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Auditory perception based human age estimation, classification and biometric applications

Muhammad Ilyas

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Auditory perception based human age estimation, classification and biometric applications / Estimation de l'âge chez l'Homme fondée sur la perception auditive, classification et applications en biométrie

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Acronyms

RF	Random Forest
SVM	Support Vector Machine
ANN	Artificial Neural Network
SVR	Support Vector Regression
RF	Regression Forest
AAM	Active Appearance Model
SR	Spectral Regression
LTP	Local Ternary Patterns
PCA	Principal Component Analysis
LDA	Linear Discriminant Analysis
CEA	Conformal Embedding Analysis
LPP	Locality Preserving Projections
OLPP	Orthogonal Locality Preserving Projections
CWL	Chromatic White Light
CLSM	Confocal Laser Scanning Microscopes
GEIs	Gait Energy Images
MLG	Multi-Label-Guide
GPR	Gaussian Process Regression
EVCs	Externally Visible Characteristics
AAR	Aspartic Acid Racemization
ATP	Adenosine Triphosphatase
TCR	Tooth-Coronal Index
CPCH	Coronal Pulp Cavity Height
OPGs	OrthoPantomoGraphs
PTR	Pulp Tooth area Ratio
CT	Computed Tomography
WAS	Weighted Appearance Specific

AAS	Appearance and Age-Specific
S-BS	Speakers Bilateral Simulation
H-BS	Headphone Bilateral Simulation
H-RS	Headphone Right Simulation
H-LS	Headphone Left Simulation
APDB	Auditory Perception Database
RMSE	Root Mean Square Error
PIS	Pervasive Information Systems
HTTP	HyperText Transfer Protocol
URIS	Uniform Resource Identifiers
GAA-API	Generic Authorization and Access Control-Application Program Interface
GMMs	Gaussian Mixture Models
RSA	Royal and Sun Alliance
PAs	Presentation Attacks
PAD	Presentation Attacks Detection
FRR	False Rejection Rate
FAR	False Acceptance Rate
EER	Equal Error Rate
HTER	Half Total Error Rate
DET	Detection Error Trade-off
SVM	Support Vector Machine
FFR	False Fake Rate
FLR	False Living Rate
SFAR	Spoof False Acceptance Rate
DEX	Deep EXpectation
CNN	Convolutional Neural Network
ENT	Ear Nose Throat
ABR	Auditory Brainstem Response
ASSR	Auditory Steady State Response
HC	Healthy Child
UC	Unhealthy Child
HT	Healthy Teenager
UT	Unhealthy Teenager
HA	Healthy Adult

UA	Unhealth Adult
HYA	Healthy Young Adult
UYA	Unhealthy Young Adult
HAG	Healthy AGed
UAG	Unhealthy AGed
DT	Decision Threshold

Abstract

Human age is a crucial factor in social interaction. It determines the way we interact with others. It is also a relevant forensic issue that can provide useful information in legal and criminal investigations. This is the main reason that human estimation has an extensive range of real-world based applications on human-computer interaction and forensic sciences. A novel and unique approach for the human age estimation and classification based on auditory perception is presented in the thesis. The main objective of the theory is to demonstrate that auditory perception is a biometric trait that can be used for age verification, age groups classification, and age estimation. In parallel, it is possible to develop several real-time applications in the field of biometrics. For this purpose, several techniques of machine learning, including Random Forests (RF), Artificial Neural Networks (ANN), and Vector Support Machines (SVM), are used to estimate the age of a specific subject. The data is collected from 837 tests from the subjects of different range of ages to evaluate the performance of the system. Several applications are developed through the concept of human auditory perception, such that BiometricAccess-Filter, anti-spoofing system, and prediction of hearing loss.

A comparative control access method for web security based on age estimation is proposed, where the correlation between the human age and the auditory perception is taken into account. In particular, access is denied if a person's age is not appropriate to given web content. Unlike existing web access filters, the proposed biometric approach offers greater security and protection to individual privacy. A machine learning based regression model is used to get an estimate of the age of the technical point of view. While A dataset collected from 201 persons with different ages from 06 to 60 years old, where it is considered 109 males and 82 females volunteers for training and testing purposes.

Biometric systems are considered an efficient component for identification in modern growing technologies. Biometric systems aim to verify or determine the identity of a person through his/her biological and behavioral characteristics. A biometric spoofing attack happens when an individual attempts to portray the sensor as a valid customer by displaying the falsified biometric feature of this user. This is a significant problem in biometric verification/authentication, which requires the development of new and stronger protection measures. An anti-spoofing system based on auditory perception responses. For the first time, an auditory-perception based anti-spoofing system is presented for the cause of verification according to our knowledge.

Hearing loss, hearing impairment, and deafness are increasing exponentially around the world. It is a growing health problem affecting the world today, and it is growing with a higher rate among young people and adults due to aging, hearing impairment, listening to music, and noise exposure. Treatment options for hearing loss are very limited and can be controlled by care in the early stages. Thus, proper education is required to spread awareness among people to use hearing protection, reduce exposure to loud music and other risk factors. Thus, a biometric system based on auditory perception responses is developed for prediction of hearing loss and level of hearing loss. It shows promising results compared to the clinical equipment used in daily life.

Résumé

L'âge chez l'Homme est un facteur crucial de l'interaction sociale. Il détermine la manière dont nous interagissons les uns avec les autres. Il peut également être une information pertinente fournie à la police scientifique dans le cadre d'enquêtes judiciaires ou pénales. C'est la principale raison pour laquelle l'utilisation de l'estimation de l'âge humain admet une vaste gamme d'applications : du monde réel, dans un contexte interaction homme-machine ou encore dans le domaine d'un cadre judiciaire. Une approche originale et unique de l'estimation puis de la classification de l'âge humain basée sur la perception auditive est présentée dans cette thèse. L'objectif principal de cette thèse est de démontrer que la perception auditive est une caractéristique biométrique pouvant être utilisée dans le cadre de la vérification de l'âge, la classification de groupes d'individus d'âge différent et de l'estimation de l'âge.

Nous exposerons tout d'abord les systèmes biométriques existants dans le domaine scientifique pour l'estimation, la vérification et la classification de l'âge chez l'Homme, comme le visage, l'iris, les empreintes digitales, la posture, l'ADN, etc. La biométrie est une caractéristique physique ou comportementale pouvant être mesurée et permettant l'identification et/ou la vérification d'un individu.

Les humains utilisent généralement des caractéristiques corporelles telles que la voix, le visage et la posture, ainsi que des données contextuelles supplémentaires telles que les vêtements et la position physique pour s'identifier mutuellement. L'ensemble des caractéristiques liées à une personne permet son identification.

Dans les premiers jours de notre civilisation, les gens vivaient dans de petites communautés où ils pouvaient s'identifier très rapidement. Cependant, une accélération de la croissance démographique suivie d'une polyvalence accrue dans la civilisation moderne a nécessité la mise en place de systèmes de gestion des identités capables d'enregistrer, de gérer et de trier efficacement l'identification d'une personne.

La durée de vie peut être divisée en deux phases globales: la croissance et le vieillissement, de l'enfance à l'adolescence puis de l'adolescence à l'âge adulte, respectivement. Au cours de la croissance, des changements de processus se produisent dans l'état structurel physique du corps et des caractéristiques comportementales qui sont corrélées à l'âge. Durant le vieillissement, étant donné que les capacités auditives d'un humain changent constamment en fonction de son âge, des changements radicaux s'opèrent.

Parmi les caractéristiques biométriques, l'âge en est une essentielle. Il peut-être considéré alors comme une signature pertinente. Il a été largement utilisé dans la communauté scientifique dans les domaines de la reconnaissance des formes, de la biométrie et de la vision par ordinateur.

Cette préoccupation est motivée par la demande de systèmes actifs et protégés pour l'analyse scientifique et l'interaction homme-machine. Par conséquent, la recherche sur l'âge des êtres humains intègre des outils de sécurité et de médecine légale en tenant compte des caractéristiques

physiques et comportementales humaines. La plupart des chercheurs se concentrent sur l'estimation de l'âge, que ce soit à l'aide du visage, de la voix, de la posture, de l'iris, des empreintes digitales, de la dynamique des frappes au clavier, des mains, etc.

Tous ces traits biométriques nécessitent encore davantage de mesures scientifiques pour améliorer la précision de l'estimation de l'âge humain.

Les scientifiques se sont concentrés au cours du siècle dernier sur l'estimation automatique de l'âge et son application à la classification chez l'Homme. Pour la première fois, une approche biométrique basée sur les réponses de perception auditive humaine est introduite pour l'estimation et la classification de l'âge chez l'Homme. Le mécanisme sensoriel de l'audition est connu sous le nom de système auditif humain. Il possède deux organes sensoriels pour détecter le son reconnu en tant que voix, reliés par une fibre nerveuse aux deux extrémités de la tête et reliés au tronc cérébral. Le point de connexion fondamental du cerveau est appelé le tronc cérébral. Il relie les autres composantes du cerveau aux systèmes nerveux humain. Les informations auditives sont traitées par le lobe temporal appelé cortex auditif.

Estimation de l'âge humain à l'aide de la perception auditive: L'oreille humaine est un organe fondamental (un des 5 sens). De plus, cette méthode rend difficile le transfert conjoint des détails des deux oreilles via un réseau neuronal complexe appelé le cerveau.

Un autre système de codage de données dans l'audition humaine est le principe de la volée. Les battements électriques que les cellules nerveuses produisent lors du transfert de données sont définis comme le potentiel d'action. Les potentiels d'action sont obtenus en réponse à chaque vibration lorsque les matériaux auditifs sont une cellule nerveuse de la membrane basilaire codée. Pour des fréquences inférieures à 500 Hz, un neurone délivrant un potentiel d'action oscillant à 200 battements par seconde, engendre un signal sonore de 200 Hz. Les potentiels d'action sont les résultats de la fraction déterminée de neurones du cerveau. Ainsi, le problème est immense au travers de l'oreille humaine qui permet à plusieurs cellules nerveuses de mener ce type de tâche. Dix cellules nerveuses pourraient donner 300 / s de suite à une capacité de trois mille Hz. Ce calcul inclut celui du principe de la volée jusqu'à quatre kHz, et le principe de localisation s'applique intégralement. Certaines réactions d'occurrence spécifiques créent une fibre précise dans le nerf cochléaire, connue sous le nom de principe de localisation, préservant ainsi totalement la voie auditive jusqu'au cerveau. La qualité de l'audition varie en fonction de l'âge et de l'intensité des sons.

La capacité auditive de l'homme varie en fonction de l'âge, de sorte que la fréquence audible la plus basse est de l'ordre de 18 000 Hz à l'âge de 16 ans. Elle diminue jusqu'à une valeur d'environ 15 000 Hz à l'âge de 30 ans. Cela implique que la borne supérieure en fréquence audible diminue en fonction de l'âge. Par conséquent, une forte corrélation existe entre l'âge et la fréquence audible. Ainsi, il en résulte une perte auditive dans le temps due aux dommages causés aux cellules ciliées de notre système auditif. Malgré cela, il est admis dans la littérature que l'être humain peut entendre un son de 12 Hz dans des conditions favorables et que la bande passante de son audition est comprise entre 20 Hz et 20 000 Hz. En se basant sur la perte auditive en fonction de l'âge, il est alors envisageable d'estimer ce dernier.

Dans cette thèse, nous avons abordé la question de l'estimation et de la vérification de l'âge humain en se basant sur les réponses de perception auditive. Ainsi, il a été démontré en utilisant différentes analyses discriminantes, la possibilité d'estimer puis de vérifier l'âge humain par le biais de réponses de perception auditive.

Les algorithmes de classification (par exemple, Support Vector Machine et Random Forest) sont utilisés à des fins de classification pour différents groupes d'âge. Alors que pour l'estimation de l'âge humain, un modèle de régression basé sur l'apprentissage automatique

a été conçu en utilisant une régression Random Forest. De plus une étude comparative a été réalisée avec d'autres modalités biométriques. Enfin, les performances du système ont été évaluées.

Dans ce contexte,, plusieurs techniques d'apprentissage automatique, notamment les Random Forest (RF), les réseaux de neurones artificiels (ANN), et Support Vector Machine (SVM), etc., sont utilisées pour estimer l'âge d'un sujet donné. Pour l'évaluation des performances, les données de 837 tests ont été recueillies pour différents âges. Le système d'estimation de l'âge humain proposé, basé sur la perception auditive, donne un résultat prometteur avec une précision de l'ordre de 2,6 ans en ce qui concerne la valeur d'erreur quadratique moyenne, tandis que pour la classification, la précision était respectivement de 92% pour 3 groupes d'âge et de 86% pour cinq groupes d'âge. Plusieurs applications sont développées à travers le concept d'estimation de l'âge humain utilisant la perception auditive, tel qu'un système de contrôle d'accès BiometricAccessFilter, un système anti-spoofing et enfin le diagnostic d'une perte auditive.

BiometricAccessFilter: Parmi les applications liées à l'estimation de l'âge chez l'Humain basée sur la perception auditive, BiometricAccessfilter est la première à retenir notre attention. WebAccessControl est un système de décentralisation qui permet à différents utilisateurs et groupes d'accéder aux principaux types d'informations dans lesquels les identificateurs de ressources uniformes HTTP (HyperText Transfer Protocol) identifient correctement les utilisateurs ainsi que les les groupes. WebAccesscontrol est l'élément de base des systèmes de sécurité permettant de déterminer si un utilisateur peut être autorisé à interagir avec une application spécifique. Il permet par ailleurs de garantir plus de confidentialité.

La confidentialité est une norme indispensable qui peut garantir un meilleur accès aux sources de données à toutes les phases du système. L'utilisation de cette norme sans restrictions peut toutefois rendre les ressources vulnérables aux attaques et aux menaces. C'est ce qui crée une contrainte pour la science et la technologie tout au long du développement de tels modèles. En évaluant la tâche de disponibilité au sein de Pervasive Information Systems (PIS), il a été découvert qu'il serait extrêmement nécessaire de parvenir à un équilibre entre discrétion et transparence des données, en particulier lorsqu'on envisage des applications d'accès à des sources d'informations situées dans des contextes de diffusion multiple et contrôlées par divers acteurs. En particulier pour les utilisateurs mobiles, l'évolution des PIS a créé des difficultés dans la gestion de l'accès aux données.

Ces technologies permettront simultanément - aux clients d'atteindre l'intégrité des données et - au système, en appliquant des mesures de contrôle d'accès stricts, d'assurer leur sécurité et ainsi ne pas être exposé à d'éventuelles menaces d'intrusion.

Outre la solution existante proposée, de nouveaux défis ont été mis en œuvre avec le développement technologique, tels que la difficulté de contrôler l'accès dans des environnements dynamiques. En fait, de nombreuses études ont été réalisées pour développer les outils de contrôle d'accès en tant que fondement des modèles de contrôle d'accès sensibles au contexte, mais les conceptions suggérées ne prenaient pas en compte l'importance de la facilité d'utilisation, de la prise de conscience de la situation et de l'amélioration possible des systèmes de contrôle d'accès.

Une méthode de contrôle d'accès comparative pour la sécurité Web basée sur une estimation

de l'âge est proposée, dans laquelle la corrélation entre l'âge humain et la perception auditive est prise en compte. En considérant alors que les réponses du système auditif codent des informations biométriques liées à l'âge d'une personne. Nous proposons un modèle de régression robuste capable d'estimer l'âge et un système de filtrage d'accès Web appelé BiometricAccessFilter. BiometricAccessFilter peut limiter l'accès des adultes au monde virtuel des enfants, puis prévenir les abus sexuels sur enfants dans une sphère en ligne en constante évolution. Quoiqu'il en soit, il ne fait aucun doute que l'anonymat, le cryptage sur disque dur et la protection de la vie privée sont utilisés pour mener à bien les activités illicites de pédophiles sur Internet.

En particulier, notre BiometricAccessFilter refusera l'accès à une personne si l'âge estimé de cette dernière n'est pas adapté à un contenu Web donné. Contrairement aux filtres d'accès Web existants, l'approche biométrique proposée offre une sécurité et une protection accrues de la vie privée. Le modèle de régression basé sur l'apprentissage automatique est utilisé pour obtenir une estimation de l'âge d'un point de vue technique. Un ensemble de données a été collecté auprès de 201 personnes d'âges différents allant de 6 à 60 ans, soit 109 hommes et 82 femmes volontaires à des fins de formation et de test. La proposition actuelle est sensible aux attaques d'utilisateurs cherchant à usurper le système à propos de leur âge. Dès lors, il serait possible qu'un jeune utilisateur se fasse passer pour un plus âgé. D'un autre côté, un utilisateur âgé peut également tromper le système en attendant la fin du premier mode d'expérience. Notre objectif étant de concevoir un système anti-spoofing puissant afin de le rendre plus sûr face aux attaques.

Système anti-spoofing

Les systèmes biométriques sont considérés comme un composant efficace pour l'identification dans les technologies modernes en pleine croissance. Les systèmes biométriques ont pour but de vérifier ou de déterminer l'identité d'un utilisateur à l'aide de ses caractéristiques biologiques et comportementales. La biométrie nous permet d'identifier une personne et de fournir une authentification basée sur un ensemble de données identifiables et vérifiables, qui lui sont spécifiées de manière unique. Les applications peuvent être utilisées dans le domaine de la surveillance, du contrôle d'accès et des systèmes de sécurité. En raison de la croissance scientifique des domaines de la reconnaissance des formes, de la vision par ordinateur, de l'apprentissage automatique ainsi que des progrès technologiques et de l'amélioration du stockage, du traitement et de l'acquisition de données, l'identification et la vérification des personnes sont désormais possibles. Plusieurs modalités et caractéristiques biométriques telles que le visage, l'iris, les empreintes digitales, les veines, le débit sanguin et la perception auditive peuvent permettre l'identification et l'authentification de personnes. Parallèlement, plusieurs techniques d'usurpation d'identité ont également été introduites pour leurrer ces systèmes biométriques.

Le spoofing biométrique est une technique permettant de tromper un système biométrique. Il est indispensable de pouvoir mettre en place des systèmes de protection adaptés et robustes face à une possible attaque. Par exemple lorsqu'un moule d'empreinte digitale en matériau synthétique est présenté à l'outil d'analyse biométrique en copiant les caractéristiques biologiques uniques propres à un sujet. Le système calcule les caractéristiques, de sorte que le système biométrique ne sera pas capable de reconnaître l'artefact de la cible biologique authentique. Alors, cherchant à usurper un système biométrique, l'attaquant usurpateur se présente comme un véritable utilisateur en produisant une fausse identité pour duper le capteur biométrique. Les systèmes anti-usurpation d'identité concernent le système qui rejette les attaques par usurpation d'identité. Les systèmes biométriques sans système anti-usurpation présentent un risque élevé de sécurité des données des utilisateurs. Plusieurs techniques ex-

istent pour usurper les systèmes biométriques. Pour notre système, nous avons considéré un système anti-spoofing dans le cadre d'attaques indirectes.

Nous avons conçu un système anti-usurpation basé sur les réponses de perception auditive. C'est donc la première fois, qu'un système anti-spoofing basé sur la perception auditive est présenté et utilisé dans le cadre de la vérification des individus. Le système anti-spoofing proposé, basé sur la perception auditive, est évalué à partir de 1140 essais. Les résultats obtenus sont encourageants car ils montrent la plus faible valeur EER de 2,7 %. Lors de la réalisation d'expériences, notre système a estimé l'âge de certains sujets comme étant supérieur à leur âge réel et nous nous sommes rendu compte que ces derniers avaient en réalité un problème d'audition. Dès lors, cette dernière information nous a amenés à concevoir un système de détection de la perte auditive.

Prévision de la perte auditive: La perte auditive est un phénomène très répandu et cela pour tous les âges: des adolescents aux personnes âgées. En fait, le nombre d'incidents augmente de façon exponentielle chez les enfants et les adultes. Pour les personnes âgées (plus de 65 ans), une personne sur deux souffre de perte auditive. Les sujets masculins ont plus de risques de perte auditive que les sujets féminins en raison de la participation à des activités particulièrement à risque dans leur vie quotidienne. Selon l'Organisation Mondiale de la Santé, la perte d'audition se positionne à la cinquième place en terme de handicap. Ainsi, près de 28 millions d'Américains souffrent de déficience auditive. C'est un problème de santé important qui requiert plus d'attention de la part de la communauté scientifique.

Une perte auditive non traitée peut affecter le développement d'une personne dans son cadre professionnel, mais aussi sa vie sociale, son état psychologique et son état de santé. L'impact important sur le corps ne se limitant pas uniquement à l'audition. En fait, les personnes malentendantes peuvent être confrontées à une communication déformée et incomplète qui peut affecter sérieusement leur vie professionnelle et personnelle, ce qui conduit au retrait et à l'isolement. Une perte auditive non traitée peut être à l'origine de nombreuses autres maladies telles que le déclin cognitif, l'incidence croissante de la démence, l'isolement social, la dépression et même les chutes. Les effets psychologiques sur la vie d'un sujet tels que la honte, la culpabilité, la colère, les problèmes de concentration, la tristesse, la dépression, la frustration, l'anxiété, l'insécurité, l'autocritique et un manque d'estime de soi / confiance en soi.

C'est un problème de santé majeur qui touche notre monde actuel et qui connaît une croissance exponentielle chez les jeunes et les adultes en raison du vieillissement, de l'écoute de musique et du bruit environnement. Les solutions de traitement de la perte auditive sont très limitées et ils doivent être traités dès les premiers stades de leur apparition. Par conséquent, une éducation adaptée est nécessaire pour sensibiliser les gens à l'utilisation des protections auditives, à la réduction de l'exposition à la musique diffusée à des niveaux élevés et à d'autres facteurs de risque. Nous présentons une méthode assistée par ordinateur pour prédire puis prévenir la perte auditive. Trois modèles prédictifs (estimation de l'âge humain, prévision de la perte auditive et du niveau de perte auditive) basés sur la perception auditive sont présentés.

Le modèle prédictif que nous avons conçu pour l'estimation de l'âge humain est très robuste avec une valeur d'erreur absolue moyenne (EMA) de 5,8 ans, tandis que la précision du deuxième modèle prédictif de perte auditive est égale à 94 % et le troisième modèle prédictif du niveau de la perte auditive présente une précision de 90 %.

Nos méthodes de prévision de la perte auditive assistées par ordinateur sont très promet-

teuses et peuvent être utilisées dans des systèmes d'application réels. Les résultats reposent sur 503 sujets ayant participé à la réalisation de l'expérience.

Publications

Journal publication

Ilyas, M., Othmani, A., Fournier, R., Nait-ali, A. (2019). Auditory Perception Based Anti-Spoofing System for Human Age Verification. *Electronics*, 8(11), 1313.

M. Ilyas, A. Othmani and Nait-ali A., “Human Age estimation and classification based on auditory perception using dynamic frequency sound (Under review *Journal of Multimedia Tools and Applications*).”,

M. Ilyas, A. Othmani and Nait-ali A., “BiometricAccessFilter: a Web Access Filtering System based on Forensic Age Estimation (Submitted to *journal of Electronics*).”,

M. Ilyas, A. Othmani and Nait-ali A., “Computer-Aided Prediction of Hearing Loss Based on Auditory Perception(Under review *Journal of Multimedia Tools and Application*).”,

Conference publications

M. Ilyas, A. Nait-ali , “Detection of hearing loss using machine learning based on auditory perception: A comparative study”. Accepted in SITIS Conference, 2019.

M. Ilyas, A. Othmani and Nait-ali A., “Prediction of Hearing Loss Based on Auditory Perception: A Preliminary Study.”,MICCAI2018: PRedictive Intelligence in MEDicine 11121, (2018).

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Book chapter

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Introduction

In this modern era, where technology has almost taken over every aspect of life, biometrics proposes distinguished conditions to secure our lives. The strength to recognize people uniquely and to compare particular characteristics such as their name, nationality, age, gender, and ethnicity, a legitimate identity is required to the foundation of the human community. Biometrics is a distinguishable behavioral or physical measured feature that is used for recognition, identification, or verification. Humans usually utilize body features such as voice, face, and gait beside additional contextual data such as clothing and location to identify one another. The collection of characteristics linked with an individual develops its identification. In the early days of our civilization, people used to live in small social communities, so it was easy to identify each other. Though, an acceleration in population followed by enhanced versatility in modern civilization has required the advancement of sophisticated identity administration systems that could precisely record, manage, and eliminate personal identification of people.

Life-span can be split into two comprehensive phases: aging and growth, from childhood to adolescence, and from adolescence to adulthood, respectively. During the growth, process changes occur in the state of physical body structure and behavioral characteristics that are correlated to human age. In contrast, in the aging trajectory, since the hearing capabilities of a human continuously changes according to the age and undergo drastic changes. Among biometric traits, human age is a particular essential trait and valuable signature. It gained ample recognition from scientific societies of pattern recognition, biometrics, and computer vision. The concern is motivated by the demand for active and protected systems in forensic science analysis and human-computer interaction. Hence, human age research incorporates safety and forensic tools by consideration of human's physical and behavioral features. Most of the researchers are focused on age estimation, either from the face, voice, gait, iris, fingerprint, keystroke dynamics, and hands.

The scientists concentrate in the past century on automatic age estimation and classification of human. For the first time, a biometric approach based on human auditory perception responses is introduced for human age estimation and classification. The sensory mechanism for the sense of hearing is known as the human auditory system. It has two sensory organs to detect the sound recognized as voices, linked by a brisk nerve fiber to both ends of the head and linked to the brain stem. The brain's salient connecting point is called the brain stem that bridges the other components of the brain to the human nervous system. The auditory information is processed through a temporal lobe called auditory cortex.

The human ear is a very vital organ. Furthermore, this method makes it more difficult to jointly transfer the details from the two ears through a mystifying neural network called the brain. Here is given a short story about the ear, many elusive possessions, and marvels that are poorly understood are still connected with human hearing. Another data encoding sys-

tem in human hearing is the volley principle. Those electrical beats that nerve cells produce when transferring data are defined as the potential for action. Action potentials are obtained in reactions of each round of vibration when auditory materials are a nerve cell of the basilar membrane is coded. A two hundred Hz of sound waves can be generated by a neuron that generates a two hundred/sec action potential at frequencies below 500Hz. Action potentials are the results of the determined fraction of brain neurons. Thus, this issue is immense through the human ear that allows several nerve cells to conduct this kind of task. Ten nerve cells could fire 300/sec consecutively at a capability of three thousand Hz. This calculation includes the volley principle assortment up to four kHz, and the location principle applies entirely. Some Specific occurrence reactions create an accurate fiber in the cochlear nerve, known as the place principle, fully preserved the auditory way to the brain. The quality of hearing differs according to age, along with the intensity of the sounds.

While the hearing capability of human changes according to age, such that the lowest audible frequency is almost 18,000 Hz at the age of 16. It reduces to around 15000 Hz at the age of 30 years. This implies that the greatest audible frequency declines in parallel as the age rises. Therefore, a robust correlation exists between age and audible frequency. Hence, it leads to hearing loss over time due to hair cell damage in our auditory system. Despite this, the researcher believes that humans can hear a 12Hz sound under favorable circumstances, and the frequently stated range of human hearing is between 20Hz and 20000 Hz. It is possible to estimate age using auditory perception by considering the fact of hearing loss according to age.

The main objective of the thesis is to demonstrate that human age estimation and classification is possible by using auditory perception responses and develop biometric applications in real-time based on the proposed approach.

- It is demonstrated that human age estimation and classification is possible based on auditory perception responses, which show a slight variation according to the increasing age.
- Development of a biometric access filter application based on a machine learning approach using auditory perception responses for human age estimation and classification.
- Development of a biometric anti-spoofing system using human auditory perception to verify the age of a subject based on a machine learning approach.
- Development of a health-care application for detection of hearing loss through the proposed approach of human age estimation using auditory perception responses.

Thesis Contribution

The contribution of the thesis is mentioned below:

- A novel approach for human age estimation and classification is proposed based on auditory perception responses. In this approach, a standard database has been created based on auditory perception responses in terms of audible frequencies for human age estimation and classification. Different machine learning techniques such as random forest, Support Vector Machine, and Linear Discriminant Analysis have been used to quantify the possibility of age estimation using auditory perception responses. The proposed model can be implemented in the field of forensic science and refugee immigration center.
- A web security control technique based on age estimation is introduced, taking into consideration the correlation between human age and auditory perception. In specific, if a person's age is not suitable for specified web content, entry is rejected. The biometric approach, unlike according to the current situation of internet access filters, provides higher safety and privacy protection. From the technical point of view, several machine learning approaches have been applied to the system to evaluate the performances of the system to estimate the age of the person and then provide the access according to the proposed approach. The system is analyzed by using a dataset obtained from 201 subjects aged between 06 and 60 years, where 109 males and 82 females subjects are considered.
- An anti-spoofing system is designed based on human auditory perception responses. A genuine characteristic in contrast to a false physical, synthetic sample is a significant issue in biometric verification/authentication that needs new and higher security steps to be developed. To the best of our experience, the first anti-spoofing system depending on auditory-perception is provided for verification of subjects. With 1140 trials with subjects of particular gender and age range (12-65 years of era), the implemented auditory perception-based anti-spoofing system is evaluated.
- A computer-aided system is developed for prediction of hearing loss. Three predictive models are assembled, such as human age estimation, prediction of hearing loss, and level of hearing loss based on auditory perception responses are presented. The difference between the actual age and standard estimated age using auditory perception responses from a user is indicating the hearing loss and level of hearing loss. Computer-aided hearing loss prediction techniques are observed to be very appealing and can be used in actual implementation technologies, and 503 subjects tested the system during the experiment.

Thesis Structure

In Chapter 1, state-of-the-art on human age estimation and verification using different existing biometric modalities is presented. A literature review is done on different biometric modalities such as the face, fingerprint, gait, DNA, and Dental. The contribution of biometrics traits in the field of human age estimation and verification and its noteworthy contributions in the field of biometric is intensively cited.

Chapter 2 addresses the major demonstration of human age estimation and verification based on auditory perception responses. First, it has been demonstrated by using different discriminatory analysis to prove the possibility of human age estimation and verification through auditory perception responses. The classification algorithms (e.g. Support vector machine and the random forest) are used for classification purposes of different age groups. While for human age estimation, a machine learning-based regression model has been designed by using random forest regression, and comparative study has been done with other biometric modalities. Finally, the performances of the system have been evaluated.

Chapter 3 presents an online access control system based on human age estimation using auditory perception responses to limit the access of adult to a forum which is specifically designed for kids. First, the login interface has been designed in which a user has to insert his information to create his account. Later, while signing-in, the user has to conduct a test based on auditory perception responses to estimate his age for further verification to prove his actual age. If the estimated age is higher than 18 years, this system will block his/her access while in case the system estimated the user's age below 18, access will be granted. Finally, the performances are evaluated by assessing the results.

Chapter 4 introduces a computer-aided system based on human auditory perception responses to predict hearing loss and level of hearing loss. This chapter provides details about hearing loss and its correlation to age. First, the correlation between hearing loss and aging has been demonstrated. Later, a machine learning-based system has been designed for further processing to estimate human age, and by using the difference between actual age and estimated age of a subject, the hearing loss or level of hearing loss is predicted. Finally, the results have been evaluated by calculating specificity and sensitivity.

Chapter 5 proposes an anti-spoofing system based on auditory perception responses. The system for the human age estimation system based on auditory perception is vulnerable to spoofing. An adult or child can easily fool the system by knowing his range of hearing frequency according to his age. An anti-spoofing system has been designed to enhance the performance of the biometric system against the spoof attackers. Ten different range of frequencies has been generated according to the user age, and an anti-spoofing system based on machine learning regression model decides the verification of the user. Finally, the performance of the proposed anti-spoofing system has been evaluated using the results. The thesis is concluded in Chapter 6, with detailed discussion on results and future work.

Chapter 1

State-of-art

This chapter presented the recent state of the art regarding different biometric modalities for human age estimation and offered a historical overview concerning age estimation and its evolution. The idea of human estimation using biometric traits started with human perception of body growth and studying the differences in human appearance according to age. Moreover, human age estimation has been delivered to attack by computer vision and biometric community. Computer vision community is doing research on age estimation and proposed different applications related to different biometric modalities. Previous studies proposed different methods, based on mathematical models acquired a collection of the training dataset to fix the technical parameters. These proposed models are developed and enhanced with the passage of time. A vast growth is experienced in the field of biometrics. An ultrasound used to measure a person's age from a hand is presently used at country borders to demonstrate that illegal migrants are under 18 years of age and are thus legally obligated to asylum seekers. It can be used in a home computer to restrict the access of a spoof attacker for purchasing a restricted product for minors. Moreover, digital fingerprinting, which is already prevalent on smartphones, is used more commonly to verify identity across a broader range of sites and to access more facilities. In this chapter, different biometric traits are discussed in section 1.1, used for human age estimation such as physiological and behavioral biometrics, and then the chapter is concluded in section 1.2.

1.1 Biometrics

Biometrics are physiological or behavioral features that can be utilized to define an individual in a digital way in order to provide entrance to systems, machines, or data. Biometrics has many key social applications, such as international border crossing, e-commerce, e-government, and welfare allocation, which involve reliable identification systems for individuals. Conventional subject authentication techniques based on logins and identification documents often fail to satisfy these applications' strict safety and efficiency requirements, which in-fact has encouraged active biometric identification studies. Biometrics or biometric recognition is the study of creating a person's identity based on different characteristics like iris, fingerprint, face, and speech. Biometric systems are quantified on the hypothesis that several humans physical or behavioral characteristics can be connected with a person uniquely.

The method of individual identification can be automated by recording these characteristics using suitably constructed detectors, depicting them in a digital matrix, and contrasting this captured information with information obtained from the same individual in a previous space example. Biometric recognition problems can thus be measured as a problem of pattern recog-

nition, where the machine identifies the salient characteristics (patterns) in an individual's biometric features and matches such patterns precisely. Practically, there are two primary classifications of personal biometric characteristics: physiological characteristics and behavioral characteristics [325], as shown in figure 1.1.

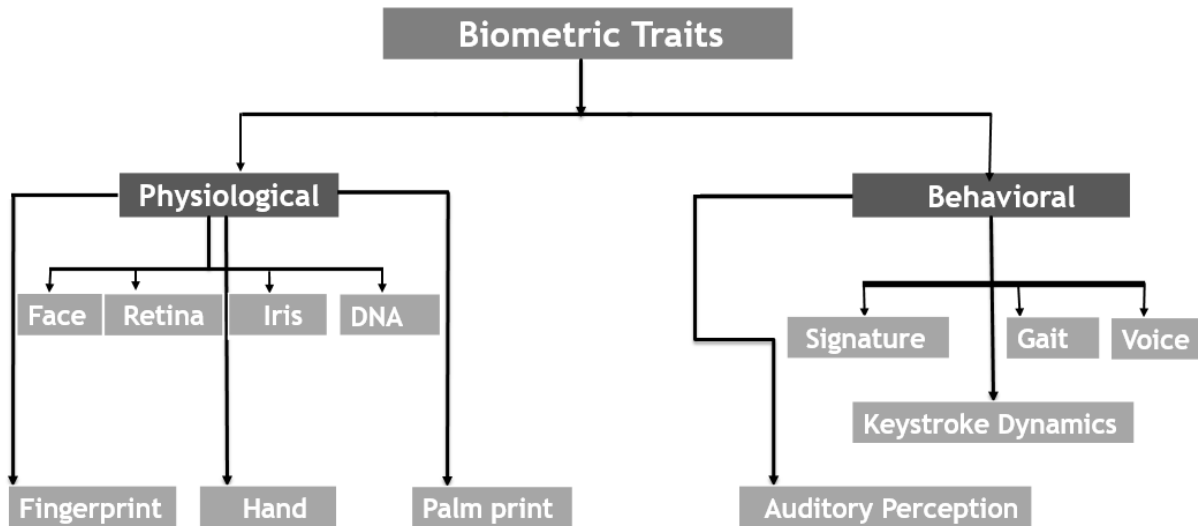


Figure 1.1: Scientific classification of biometric traits

1.1.1 Physiological Biometrics

Physiological characteristics are associated with a human body's fixed features, which shows no modification according to age. Physiological characteristics include face recognition, palm print, hand geometry, fingerprint, DNA, iris recognition, blood vein pattern, and retina.

1.1.1.1 Face

The face is a notable physical feature used by researchers for human age estimation. A human face consists of the frontal portion of the head, which is extended to the forehead, including cheeks, nose, mouth, and eyes. Face conveys an astonishing amount of data, for example, personality, passionate express, sex, ethnic group, and age. In this way, it has turned into a cooperative mode to incorporate face pictures in a few images of verification, for example, visas, ID cards, and driver's licenses. Face verification can be characterized as building up the procedure of the personality of a subject depends on their facial highlights. In its most straightforward mode, the trouble of face confirmation incorporates coordinating two face pictures and closing on the chance that they are of the indistinguishable individuals. While individuals appear to have the option to characterize the relationship of two face images acquired under different conditions, the method of automated face verification is confronting numerous difficulties. Various varieties can be found in an individual's images such as enlightenment, age, outward appearances, and posture just as show varieties in appearance because of facial hair, make-up, or adornments (for instance: contact focal point or shades). Preparing a framework to verify face images introducing such unconstrained changes is a strenuous activity, especially considering the particular psychological and neural methods related to people for the errand of face verification.

Moreover, there may exist connections inside the face images of various people, especially on the chance that they are connected with the end goal that indistinguishable twins, father and child, and so forth. Such between class connections moreover confound the issue of verification dependent on face images of people. To handle such challenges, efficient advancement has been made in the area of automatic face verification over recent decades. Methods for automated face verification has been procured with the end goal of individual verification from the video (a succession of 2D images), still 2-dimensional (2D) images, and 3D images.

The face-based biometric attribute has various points of interest that convey it ideally in different biometric applications. The face picture can be taken at a higher standoff run through non-contact sensors. Henceforth, the face is a legitimate biometric identifier in checking applications. Face conveys ID as well as feelings of an individual with the end goal that satisfaction or outrage, just as biographic information to such an extent that sexual orientation, age, and ethnicity. The automated verification of face images and related feelings is fundamental for making an intelligent system dependent on human-PC interfaces. At long last, compared to other biometric attributes like Iris and unique mark, individuals are generally additional ready to share their face pictures in the open area as appeared by the developing system in online networking applications, for example, Instagram, Facebook, Twitter, and so on, with face labeling functionalities. Because of the proposed reasons as referenced above, face verification has a wide assortment of applications in regular citizen ID, law authorization, stimulation/beguilement systems, and observation systems. The face is a striking physical element for human age estimation, utilized by researchers.

The primary method of age classification using facial features is applying the face anthropometry to derive ratios and distances with various facial zones. On the facial growth, specifically for European-descent faces, Farkas [2] presented reliable anthropometric data. In figure 1.3(a), the normal growth of the head simulates by using “revised cardioidal strain transformation” He determined face anthropometry, including dimensions of 57 landmarks on face over various ages, from (child’s) 6 to 18 years, and adults. The landmarks and required measurements are shown in figure 1.3(b). Kwon and Lobo [3] are the first who presented the studies of age classification by classifying the facial images into babies, young adults, and adults. The recommended approach was concerned about skin analysis and craniofacial development theory. They utilized six ratios of distances among facial features, along with wrinkle examination for age estimation.

The babies are identified from young adults and adults by calculating the facial ratios. Furthermore, measure the wrinkles by using a wrinkle geography map. The adults are separated from young adults and babies by calculating the index of wrinkles. To characterize the facial wrinkles, they applied “snakes” [4]. The wrinkles are observed, and ratios of faces show the face of an adult, the image is signed as a senior adult. The image is labeled as a baby if it has no wrinkles (See Figure 1.2). Since their proposed technique for a position like deformable templates and “snakes” was high in terms of computation, such the system was not so fast concerning image processing in real-time. Horng et al. [5] introduced variance for the work of Kwon and Lobo, [3] the facial images are divided into four groups for classification: babies, young adults, middle-aged adults, and old adults. The proposed model consisted of three steps: location, feature extraction, and classification into age group. In the first step, by calculating the high-frequency region, they located the facial features within the edge map of the face image. To compute the two distance ratios, these features were used to classify babies and adults.

Those characteristics were then utilized to measure two range of ratios across babies and adults. In the second step, they used Sobel filtered images, rather than “snakes,” to calculate the value of wrinkles on facial images. The advantage of the Sobel operator secured its design manageable and quicker. Many researchers continued to work with anthropometric techniques for facial age estimation.

Izadpanahi and Toygar [6] introduced a system for defining a face age group based on geometric facial features. For this model, the facial images were divided into five age groups, and 17 geometric points and ten facial measurements were extracted. Three age classifiers are used for classification, including a neural network classifier, SVM, and linear classifier, based on densities.

The anthropometry models are generally useful for the growth of young faces. However, in the anthropometric models, facial geometry is only considered without texture information. Frontal facial geometries are generally utilized in measurements when the models are sensitive to the position of the head. [7].

Based on the Active Appearance Model (AAM) [9], Lanitis et al. [8] produced a mathematical model of facial appearance, for achieving a compressed parametric representation of facial images. Several classifiers are proposed for modeling the correlation within face model parameters and age, related to their age image description, particularly the quadratic aging function. Methods based on AAM will typically analyze form and texture rather than facial geometry. Therefore, different age groups can handle these techniques slightly than especially young people [7]. From the facial images, AAM to extract a joined feature vector. The classification processes have been divided into two steps. A binary classification using SVM is used to discriminate (0-20) and adults (21-69). Growth functions (growth and adult aging) are also trained individually on the youth and adult data sets using a regression model such as Support Vector Regression (SVR). The first step in classification is to classify the objects into binary categories and then to assign the specific age to the corresponding age variable. They transformed the classifier configuration, following the extraction of the combined AAM feature vector [122] by adding a supervised Spectral Regression (SR). The feature vector dimensionality can be decreased by using SR. It the intra-class distances are maximized while minimizes the inter-class distances. To classify a face as young or adult, approximately Luu et al. [10] applied the local and holistic facial features.

The holistic AAM features are combines, which are prominent in childhood, and features important for the aged faces of Local Ternary Patterns (LTP). Geng et al. [11], applied a series of individuals aging face images all collectively to model the aging process, rather than dealing with specific aging face image individually. They used aging patterns as a number of face images distributed in age to improve their technique called AGES (AGing pattErn Subspace). AGES consists of two steps, the first step is learning, and the second step is the age estimation step. Its extracted feature vector renders all images through the Appearance Model. Instead of using restricted objects for learning, a subspace of an aging pattern is shown using Principal Component Analysis (PCA). Where the images are available for each age of the person in the dataset, the equivalent model of aging is known as the complete pattern” of aging, as opposed to the ”incomplete pattern of aging”. This approach can integrate the omitted ages by using a learning algorithm that predicts a part of the missing pattern of personal aging in each iteration by using a global pattern of aging, which is considerably examined. For an estimation of the

human age, the object feature vector is measured and used in the subspace to determine the correct age pattern by analysis for the subspace projection, which generates the minor reconstruction error. Instead, at each reasonable point in the aging process, the facial test image is tested, and the minimum reconstruction error is traditional. To enhance their earlier work, Geng et al. [12] proposed a different orientation of AGES, named $AGES_{lda}$. They include the Linear Discriminant Analysis (LDA) to the appearance model for extracting feature vectors to control the illumination, pose, and expression shifts. The system is designed to estimate the age of two layers. Next, test samples are classified with AGES into the three compatible ages. Then the exact age was defined by three individually trained subspaces. The problem of AGES strategies is that they need to face pictures at different levels of the corresponding individual, and that requirement is difficult to satisfy because at various ages and in similar situations, it is not easy to obtain a face picture of the corresponding person. In contrast, the AAM method encodes only the depth of the image without the texture pattern. There are, therefore, no facial wrinkles. Instead, the aging pattern can be identified from several individuals at various ages when studying a particular person. The age multiple is the convincing way to learn the typical pattern of aging [13–15]. Such that, Fu and Huang [121] Adopting the many embedding to obtain from multiple images at a particular age the low-dimensional aging pattern. In this approach, for a certain person, there is no requirement to do so at different ages. They used various learning techniques such as CEA, locality conservation screenings, and Orthogonal Locality Preserving Projections (OLPP).

Lanitis et al. [8] proposed an algorithm for the first time for human age estimation using facial features. Through the aging function, they represented the aging pattern. In the training set, a quadratic function is fitted as the aging function for each individual during the training process. They suggested four methods to determine the appropriate aging function for a previously invisible face image during age estimation. The Weighted Appearance Specific (WAS) method has achieved the best performance among the methods that do not rely on the external "lifestyle profiles." Later, Lanitis et al. [129], in comparison to their quadratic aging technique with several standard age estimation classification techniques. In single-layer mode as well as in three hierarchical modes, the algorithms were tested. As expected, in the hierarchical modes, all the classifiers performed well as the hierarchical structures manage the clusters of face images independently depending on age groups or appearance or both. Among them, the highest achievement was accomplished with the Appearance and Age-Specific (AAS) technique.

However, the quadratic aging feature did not demonstrate notable superiority in general efficiency over standard classifiers, according to the experimental outcomes. Age estimation is considered by the aging function-based methods as a standard function regression issue without unique design for the distinctive features of aging variation. This restriction makes it impossible for them to obtain more satisfactory results. In such methods, there may be some weaknesses. The aging function can not make good use of the temporal trait. The dependent connection between the aging faces is monodirectional, such that only those elderly images are affected by the status of a particular face. Although, a link is disclosed through the aging function is bidirectional: The aging function can be affected by any modification happens at a specific face that effects all the faces. The learning of the aging pattern of one individual is based exclusively on that person's face pictures.

Furthermore, individuals age differently, some commonality must be found among all aging habits, such that the overall trend of aging. Such standard features are essential in estimating

age, mainly when there is inadequate personal training data. For the initial unknown face image, the aging function is a linear combination of the predefined aging functions, else than generating new value from a specific model of aging patterns.

Ramanathan and Chellappa [130] proposed a model of craniofacial development characterizing growth-related differences in the form found in human faces during a young age. Hence, the work did not try to estimate the age, the significant facts in the relationship between age and face were revealed. Some research has attempted to show the mapping from one person to another.

From the technical point of view, different classifiers based on quadratic functions, shortest distance, and neural network are performed [8] while for age classification, a dropout-SVM that avoids over-fitting is used [17]. While, the error of estimation from face image was around five years ([1, 17]), it appears that human still achieves better results than machines on age estimation with an age estimation errors of 3.64 years [17].

Despite the fact, there has been far less work focused on developing systems for automatic age estimation than for human identification from face photos [16]. From the technical point of view, different classifiers based on quadratic functions, shortest distance, and neural network are performed [17] while for age classification, a dropout-SVM that avoids over-fitting is used [16].

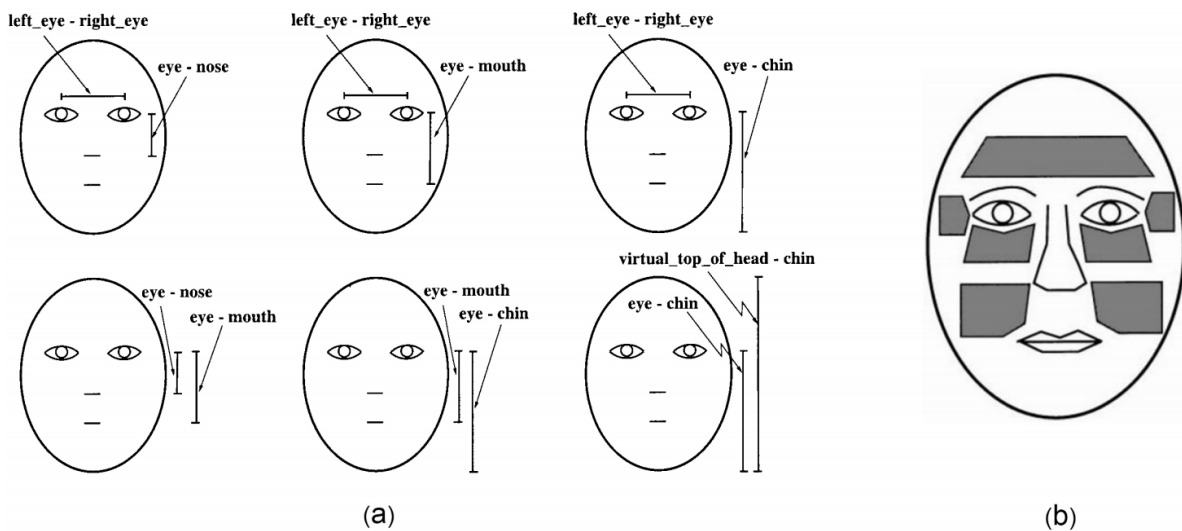


Figure 1.2: (a) 6 ratios of facial distance utilized by Kwon and Lobo in order to identify the facial characteristics of various ages. (b) areas of facial wrinkles searched [3]

1.1.1.2 Fingerprint

The structure on the top of a finger of interleaved ridges and valleys is called a fingerprint. In the late 19th to the early 20th century, the systematic use of these patterns for personal identification was introduced. The discovery of a significant amount of archaeological artifacts of human fingerprints indicates that ancestral individuals were capable of the probable uniqueness

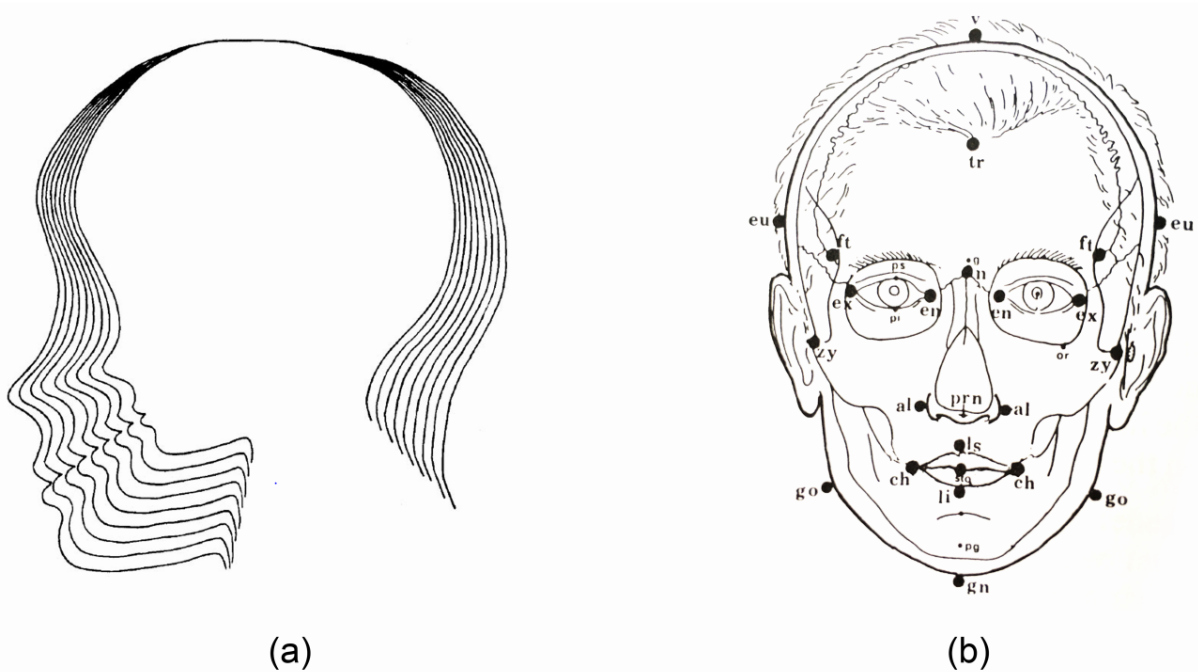


Figure 1.3: (a) Human head development modeled by using 'regulated cardiac strain transition' from childhood (innermost profile) to adulthood (outermost profile). (b) Farkas' schematic drawing of the craniofacial features of the human face [2, 16].

of fingerprints. Although the fingerprint can be taken by using ink on the tip of the finger and print it on paper, sensor technology advancement results in the design of versatile, solid-state sensors and low-cost optical and that can quickly scan the images of the fingertips and produce automated fingerprint recreations for automatically generated evaluation.

In contrast to the skin on most territories of our body, which is delicate and incorporates organs of hair and oil, the skin on the palms and soles demonstrates a stream like the example of valleys and ridges, frequently indicated as wrinkles and does not contain any hair or oil. Friction ridges are papillary ridges on a human finger that helps the hand to get a handle on things by expanding friction and improving surface unpleasantness tangible detection. The skin of the friction ridge comprises of two critical layers: epidermis (external layer) dermis (inner layer). To support friction between the palm or underside of the feet and the surface of contact, the ridges show up on the epidermis, as appeared in figure 1.4. A typical male has 20.7 ridges per centimeter in a normal while a female shares 23.4 ridges per centimeter.

Friction ridges have one more important use in the field of biometrics verification. On each finger, the design of friction ridges is shown in figure 1.4(b) is declared to be different and permanent and can be used as a sign of identification. Indeed, it is possible to distinguish even identical twins based on fingerprints. External wounds such as cuts and abrasions on the surface of the finger can change the original form in the injured area only temporarily.

Even if it was acknowledged centuries ago that fingerprints could be used as unique identifiers, their extensive use in applications demanding identification of individuals did not take place till the mid 20th decade. The criminal investigation agencies are now recording the fin-

gerprint data for investigation purposes on a tenprint card, as shown in figure 1.5 that captures the patterns of the ten fingers. Two primary uses of the fingerprints collected are:(1)Recognize perpetrators who frequently get an identity to conceal their true identity (2) To carry out a job or licensing background checks. Some other significant implementation in law enforcement of fingerprints is to create a suspect's identity based on limited fingerprints remaining in a criminal site. These are known as latent prints, as shown in figure 1.5(c). Latent prints typically have lousy image quality compared to rolled and plain fingerprints as shown in figure 1.5(a) and figure 1.5(b).

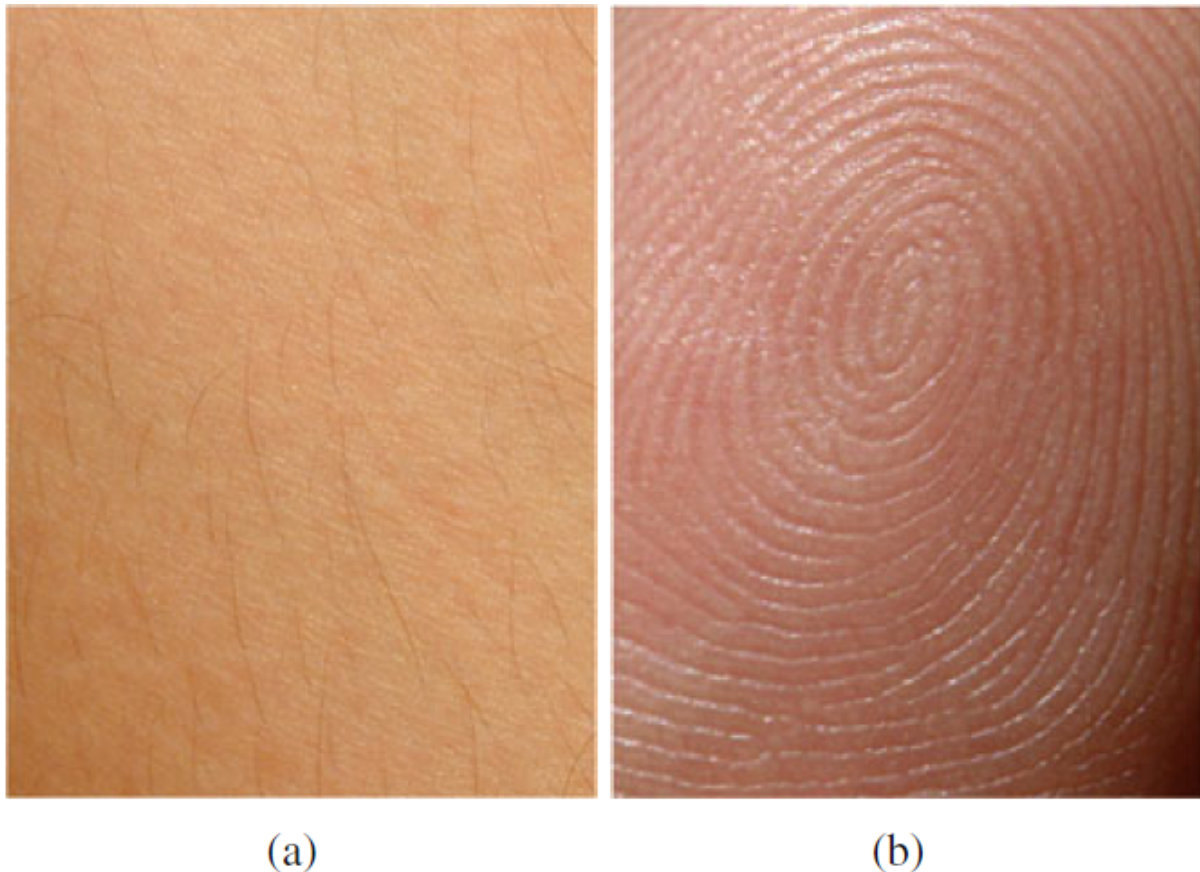


Figure 1.4: The human body has two skin kinds: (a) soft skin and (b) ridge skin with friction. A pattern of ridges interspersed with valleys is found in the friction ridge skin

[217]

In crime scene forensics, age estimation is a very significant factor. Unlike biometrics, in which age is sometimes linked to as an enrolled human's biological age, the age of traces of the crime scene forwarded to the time that has passed between trace position and the authorities capture. Determining that e agis essential for forensic investigators, connecting a trace to the moment of a crime. Suspects are very often pretending to be at a crime scene before or after the crime, specifically for masked fingerprints, which are commonly used as proof in criminal investigations [100]. Only when a latent print can connect a person to the moment of a crime concerning connecting it to the location of the crime can then print's evidence value be regarded firm in the trial. Forensic investigators have known this challenge of estimating the latent print age for even more than 80 years but not yet been appropriately resolved. The domain of capturing traces of the crime scene has recently been introduced to non-invasive, high-resolution capturing systems. These methods do not change a latent print, as opposed to

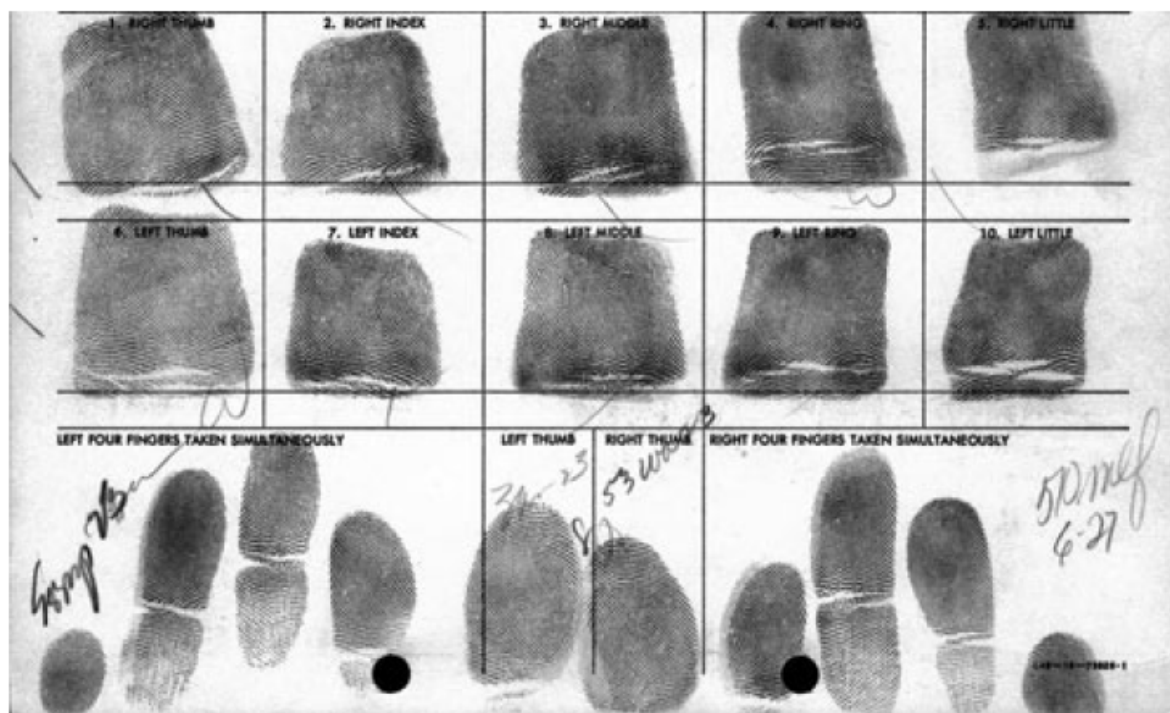


Figure 1.5: A card with tenprints. The top two rows indicate fingerprints obtained from one hand to the other by rolling each finger (so-called rolled fingerprints). The bottom row displays simple or slap fingerprints: four finger slap impressions (small to index finger) of the left side obtained concurrently are shown on the left side of the bottom row, two thumb prints are shown in the center, and four finger slap impressions (index to small finger) of the correct side obtained concurrently are shown on the correct side [217].

the conventional method of chemical or physical print improvement and lifting, thus enabling for the first time a single print to be captured in periodic periods and observed morphological modifications along with the changes in chemical structure and other characteristics happening with time. The modifications involve drying water and narrow chained fatty acid print evaporation along with the removal of height and composition while degradation process [101, 102]. High-resolution, non-invasive, capturing instruments are including infrared spectroscopes that capture chemical printing characteristics, Electrical potential sensors monitoring electrostatic characteristics, and optical devices considering morphological characteristics such that Coherence Tomography, Chromatic White Light (CWL) sensors, and Confocal Laser Scanning Microscopes (CLSM) [101]. Such non-invasiveness and enhanced resolution, however, evokes elevated buyer expenses (often more significant than €100,000 per device), demanding intensive data sharing among science professionals to guarantee repeatability and research advancement. Besides, data security is a significant consideration to understand as the devices can provide high-resolution print pictures that are deemed personal information in most European countries and the subjects to special data protection/security regulations [103].

Nia E. Archer et al. [104], investigated print degradation using chemical methods such as chromatography and mass spectrometry and focused on creating an enhanced understanding of fingerprint chemistry, in particular, latent fingerprint structure in the time of deposition, and chemical modification in lipid parts over time. Fingerprints were gathered and aged under controlled circumstances from five male donors in the age range of 25–34 years. At fixed inter-

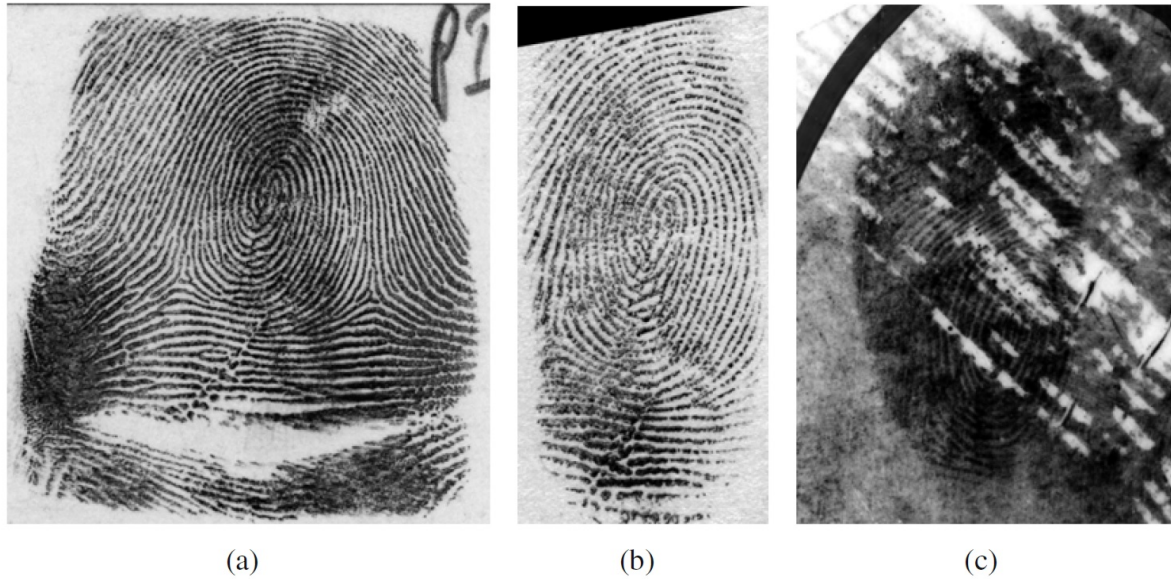


Figure 1.6: There are three distinct fingerprints of the same finger. (A) fingerprint roll, (b) fingerprint plain, and (c) fingerprint latent [217].

vals, the prints were then sampled, solvent obtained of dichloromethane, pre-derivatized with MSTFA, and evaluated using gas chromatography-mass spectrometry (GC – MS). The loss of squalene from prints stored in the sun or the dark has been shown. In the light, the loss was faster, with some donors not detecting squalene in prints after nine days of storage. Squalene was still identified in the dark for these same donors after 33 days of storage, but at much-reduced concentrations than in new prints. In the case of saturated fatty acids (tetradecanoic, palmitic and stearic acid), there was a trend towards a rise in these drugs during storage (up to about 20 days), followed by a reduction back to or below the initial concentrations. It was the case with samples stored either in the dark or in the light. A comparable pattern has been looking for palmitoleic acid. This tendency has been seen for oleic acid for specimens stored in the dark. The overall tendency was a reduction in rate over period storage for the samples, stored in the light up to 33 days.

Age estimation studies were invasive, changing a print throughout the inspection or example during physical development or print dissolution and thus it is not allowing systematic analysis of single print degradation procedures using time series. Neither of them could include specific outcomes regarding performance assessment of age and error values.

In the last decade, a few preliminary research has examined the behavior of print aging established on contactless and non-invasive chemical accession devices [113], luminescence [112], electrostatic [115], and autofluorescence [114], along with a police study [116], through microscopes and cameras. Among all these premier contactless methods are the Digi-Dak project studies [117], based on time series recorded using non-invasive, optical Chromatic White Light (CWL) detectors and Confocal Laser Scanning Microscopes (CLSM). They supplied objective performance measures and error rates for the first time for age estimation performance, using a fully digital processing chain. Although, to the best of my knowledge, no fingerprint time-series database is accessible to the signal processing society at this stage in time, that allow comprehensive and repeatable research to be carried out over several years

without significant information collection effort.

1.1.1.3 DNA

In forensics, several approaches are proposed for age estimation with DNA or dental observations. Age estimation is a critical issue in forensic science study that can present beneficial knowledge relevant to legal, criminal, and anthropological examinations. Forensic age inferring has primarily been based on morphological examination or radiography and just onward introduced to the use of molecular methods.

DNA forensic techniques have been gradually exploring the genetic code, enabling researchers to identify sex, ethnicity, eyes and hair color, and various physical characteristics out of a small sample. However, lack of efficiency or technical issues impeded the presentation of these DNA-based techniques in case-work interpretation. A notable case happened when the epigenetic signature of DNA methylation is discerned to vary while a person's lifetime continuously. During the last seven years, the number of research articles reported that DNA methylation age-related variances are steadily increased, and the forensic society has a variety of age methylation tests suitable for forensic case-work. Based on blood DNA samples, most forensic age estimation models have been generated, but in parallel, more tissues are presently also being investigated.

Age estimation of unknown corpses and human bones is a problematic area of forensic medicine, and many methods, including morphological and biochemical analyzes, have been suggested. Several new molecular methods have been suggested since the detection of many age-related DNA changes. The primary DNA-based technique to be studied widely for forensic age estimation was the analysis of human chromosome telomere repeats. Other methods have subsequently been suggested, including the assessment of mitochondrial DNA variants and more latest methods based on the assessment of T-cell sjTREC rearrangements and human genome methylation [136]. Several studies were performed to centralize the methodology, the precision, and efficiency of age determination using molecular techniques; the most encouraging results were achieved by analyzing sjTREC manipulations in blood samples and tissue methylation profile. On the other hand, many researchers have shown that the precision of both mitochondrial DNA and telomere length analyzes is not large enough to be used in forensic exercise. Although, age-related DNA changes are vulnerable to a number of factors that can change their measurement and restrict the accuracy and reproducibility of the tests; Important variables include the sort of tissue used in the assessment, the features, and lifestyle of the topic, the amount of DNA degradation owing to the impacts of environmental agents post-mortem.

For precise age estimation, the quantity of biological material is not always adequate, particularly when the body continues to be analyzed. This issue has been encouraged by scientists to create and test innovative methodologies along with the need to achieve even more precise age estimates. The latest growth of DNA analysis techniques, the outcomes of the human genome project, and the growth of the "omic" sciences have definitely resulted in the growth of fresh solutions to this difficult aspect of forensic medicine. While the first DNA-based technique to be researched widely for forensic age estimation was the analysis of human chromosome telomere repeats; Other methods have subsequently been suggested, including the assessment of mitochondrial DNA variants and more latest methods based on the assessment of T-cell sjTREC rearrangements and human genome methylation [136].

Several approaches are proposed for age estimation with DNA or dental observations. Indeed, the forensic individual age estimation with DNA approaches have gradually risen in the last five years. Morphological inspection or radiography was initially used for forensic age estimation, and later molecular approaches have been adapted. Forensic age estimation predictor used blood samples to estimate the age of humans, but in recently, the scientists are also exploring tissues to utilize it for age estimation. In recent advancements in the field of age estimation using DNA methylation, the predictive accuracy has been increased the potential of the system and its accuracy with an error value of ± 4 years [137].

Forensic Context: Forensic age estimation is utilized to obtain knowledge related to criminal, legal, or anthropological inquiries [47]. In the beginning, the age of an individual from the investigation of the remains or of the biological evidence dropped behind can help supervise the personal description of missing individuals or the crime scene [48]. Various samples can be obtained from the crime scene such as semen, blood stains, hairs, cigarette butts, and particular objects, like toothbrushes. Though, if DNA profiling does not have a good match with any DNA in the database, no suspects could be identified. To control the limitations, forensic genetics is intending to generate and approve new DNA intelligence systems. Else than presenting a person-specified genetic profile, those new tests provide knowledge about features that are given by a much smaller group of possible suspects. These features provide information about biogeographic ancestry [49] and Externally Visible Characteristics (EVCs), alternative mentioned phenotypic modality [50], that can build a flexible pond of people inquired by a proper investigation. Forensic DNA investigation could obtain a similar kind of benefit from the judgment of a person's age, as this has a definite characteristic of human physical appearance that is challenging to alter. Secondly, the recognition of age based on physical traits, such as hair color or early-onset male pattern baldness, is enhanced by identifying the DNA donor's age. Third, unknown remains of the missing person are usually found and are often defying to recognize if surviving remains are not present [51]. In general, mass disasters include various samples that need comprehensive investigation in a quick time period. The proofs will vary in the scenario from nearly well-protected to highly degraded based on the sort of incident. DNA age estimation could, therefore, be used as a testing system to boost the methods or to encourage complicated identification information. Fourth, the result of age from DNA has the great capacity to contribute characteristics to the archaeological remnants analysis [52]. Forensic anthropologists now plan to acknowledge a range of physical characteristics and the heritage of ancient skeletal remnants by using authenticated forensic DNA tests that could be extended to age-at-death estimates. Lastly, legal hearings could be approved by judging the age of DNA samples obtained from people of conflict age, such as the persuasive age of an asylum seeker or the appropriate punishment for young offenders [53]. This is a controversial topic, as gender determination in such issues requires the lowest amount of accuracy and the method that an assessment is obtained is constantly questioned in the trial because of the range of assessment scores obtained from its predictive mistake by the technique.

Primary Approaches for Age Estimation: Forensic age perception was based on the analysis of teeth and bones and teeth. Several techniques were presented that Baccino and Schmitt have outlined observed adult skeletal remains and their features [54]. The collection of the suitable methodology relevant to each age estimation outline depends on the element accessible to the analysts. Morphological investigations of the pubic symphysis, fourth rib, and clavicle from bones, sacropelvic surface, or root translucency from teeth are instructive

for the age-at-death. Recent research adopted the symphyseal face of pubic bone as a significant means to discover the age in the classification of an actual figure [55]. It is essential to perceive that whatever the process of evaluation used, the main disadvantage of the use of skeletal characteristics is their lack of informativeness for the aged since, after 65 years of age, the efficiency of age results from bones and teeth decreases considerably. The age estimation using the skeletal remains of children and adolescents can be discovered from the degree of skeletal or dental maturation [56]. In these events, the degree of mineralization of the dentition is the approved technique. Moreover, evaluation of the degree of the emergence of the third molar is particularly applicable in concluding whether a person is over or under the 18-year threshold [57]. Although it is compelling to use this method to the morphological inquiry of undocumented living individuals of a young age, the joined use of X-radiation is the main disadvantage that involves ethical concerns. For certain purposes, alternative approaches using nonionizing imaging methods such as MRI is currently being investigated [58]. In extension to skeletal techniques, molecular methods for age estimation have frequently been proclaimed in the last five years. These are based on regular modifications to biomolecules that transpire throughout the life cycle of a person's outcome of the aging process. Five basic groups of molecular remodeling have been evaluated: (1) mitochondrial DNA deletions, (2) shortening of telomeres, and (3) signal-joint T-cell, (4) advanced glycation end-products (AGEs), (5) Aspartic Acid Racemization (AAR), receptor excision circles (herein sjTREC_s). The analysis of (1), (2), and (3) are DNA-based, whereas those of (4) and (5) are protein-based methodologies. Method 1 computes the quantity of mitochondrial DNA (mtDNA) deletions that develop with age. The source for this relationship is the process of energy generation in mitochondria from the respiratory chain mechanism. Oxidation of glucose and lipids in the mitochondria to generate ATP discharges free radicals (also known reactive oxygen species) and causes destruction in the mtDNA directing to the collection of deletions. In special, the 4977 nucleotides (nt) deletion has been examined as a subject for age estimation. Though scientific problems and a deficiency of precision have hindered its importance in forensic examples, since ample assurance periods were required and the correlation was close to the utmost of age: young (under 20 years) versus old (over 70 years) [59].

Method 2 explores the features of telomeres building the structures found at the edge of the chromosomes that contain up to many thousand tandem redos of the series TTAGGG. The compression of telomeres happens in each cell after every mitotic division. To control these cells can provoke the interpretation of the enzyme telomerase, which combines repeat progressions to the end of the telomeres. However, this method loses efficiency as time passes. However, age-estimation tests have sought to estimate telomere contracting, as with mtDNA deletions, scientific reasons direct to imprecise results with a usual lack of recreative ability [60]. Method 5 studies AGEs that constitute a heterogeneous group of compounds originated from the glycation of proteins. They gather throughout the lifetime of a person in various tissues and have been determined to build the generally perceived color variations (yellow-to-brown) measured utilizing a colorimeter or spectrophotometer. The intensity of color variations can be applied to understand the age of the person. Although a reduction of regulated modes and the tremendous heterogeneity of this group of biomolecules have prevented its usefulness for age estimation. Furthermore, for the process to have enough precision, it is only suitable for the interpretation of an individual aged 45 years and over [61]. Technically, the various scientific age-estimation systems are achieved by technique 4, examining AAR with an estimation error of ± 3 years [62]. The racemization is a chemical process that turns pure enantiomers (L or D) into a hybrid of both. In mammals, particularly, L-amino acids are fused through protein creation. As the ages

of the subjects, racemization takes place, and the level of D-amino acid enantiomers starts to develop. AAR is based on the chromatographic computation of D-aspartic acid, and this method is individually suitable to dentine as an optimal tissue for study. Furthermore, the precision of the technique is high, and the method is devastating, and so lacks wide-scale utilization. Although, the vulnerability of the teeth to high temperatures presents bias to the decisions, prominently in the verification of burned human bodies.

Method 3, which investigates levels of sjTRECs, presents probably the most viable molecular approach based on the appearance of a remarkable species of DNA in the blood. The sjTRECs identified are circularized DNA molecules that result from T-lymphocyte DNA shuffle. An age-related decay in the levels of Rec-J sjTREC happens through the person's lifespan. Though the same precision of the test is considered (the estimation error is approximately ± 9 years), the method is restrained to blood samples, and diseases affecting the immune system can possibly hinder the estimates made [63].

Human Aging and Epigenetics Human aging has been defined as "a gradual, time-dependent change of a collection of various biological roles" [18]. It does a continuous loss describe a natural process of physiological probity affected by the growth of cellular destruction during a person's lifespan, with time, this activates the growth of age-related complications, neurodegenerative disorders, cardiovascular diseases, including cancer, diabetes, etc. [19]. By conducting physical phenotypic changes with age, human aging also includes noticeable variations to physical features. Regular balding in men, hair graying, as well as facial wrinkles, decrease in elasticity of muscles, are the prominent standard features that can serve to explain the scene in the lifespan of a person. A complete summary of the cellular and molecular characteristics after the physical or outer aging changes have been fully explained away [19].

The shape of a genome is produced through several epigenetic marks such as DNA methylation [20], posttranslational alteration of histones [23], chromatin remodeling [22], and noncoding RNAs [21]. To modify the appearance of a gene, all epigenetic marks experience dynamic remodeling. They operate in a sequence as a network, and the downstream result of the timing of their modulation is what establishes the epigenetic code [24] or human epigenome.

The mitotically modification in gene regulation is reversibly covered by epigenetic patterns. It happens without any remodeling to the primary DNA sequence [65]. Although currently, the concept of transgenerational epigenetics is under debate, and also related to as the epigenetic heritage, [64], is obtaining empirical proof and thus is admitted as a method [66–69]. This non-Mendelian heritage indicates epigenetic modifications in progenitors such that epigenetic marks caused by the environment [70]. It may not be completely reset after fertilization by epigenetic remodeling and could consequently be assigned through the germline to descendants among generations. [71]. In 2011, in *Caenorhabditis elegans*, transgenerational longevity heritage was first recorded, promoting the possibility of expanded life due to epigenetic modifications inherited from a restricted amount of prior generations [72]. This idea could have a substantial effect on society. More study is required to handle the challenges which go beyond its scope.

During the growth process or childhood/adulthood, the variations in epigenetic designs happen. The primary distinction is that modifications in the epigenetic landscape are biologically reprogrammed during embryonic, and germ cell growth and are essential for lineage measure-

ment and cell identification [73, 74], While this regeneration of epigenetic marks represents age-related deleterious occurrences in adult somatic cells [75]. Consequently, epigenetic modifications have a significant impact on the process of human aging [76]. These changes – grouped as "epigenetic drift" or "epigenetic clock" [77] – this is the consequence of ongoing genetic-environmental interactions that happen during the lifetime of the person.

1.1.1.4 Dental

The human age estimation from dental observations has studied, and several techniques have been proposed. They are based on dental maturation for children and can be split into those using the strategy to the atlas and those using ranking schemes. Morphologic and radiological methods are used for adults.

Dental age estimation in scientific literature presents several data sources on various approaches, the technical execution, and the mechanisms following them. Growth features such as mineralization, gingival clinging, cementation of quantities or decrease of pulp space can be used to evaluate dental age. Also associated with the calendar era are degenerative alterations such as tooth attrition or periodontal involution. A combination of other parameters, fluorescence strength, dentin density, aspartic acid racemization or dentinal sclerosis-assist in evaluating age-related alterations in dental tissue, and it can be used to specify human calendar age [78]. A range of biochemical, morphological and histological methods are used to determine the personal calendar age at the moment of the death, according to the "Skeleton Age and Sex Diagnosis Recommendations" [79]. The teeth are often the only structures that fit for examination in instances of decomposition. This is due to the much-reduced extent of their harm to the environment livestock, moisture, microbial activity, mechanical forces, and elevated temperatures. It is shown conclusively that even cremated teeth provide enough material to determine the calendar age relatively accurately [80].

Different literature studies have provided several strategies. The strategies were generally categorized into three categories, the methods of Kvaal, Ikeda, and Cameriere, all based on secondary dentin deposition of the tooth. In an attempt to determine the calendar era in cross-sections, Gustafson includes six age-dependent factors (attrition, periodontal binding, secondary dentine, cement accumulation, root resorption, and root dental clarity) [81]. Each of the parameters' morphological appearance enables their verification with a coefficient of 0 to 3. The aggregate outcome determines the age with the linear regression equation of Gustafson, which should apply to each sort of tooth [82]. In 1971, Johanson launched another science strategy, implementing a fresh scheme for attributing coefficients to the initial method of Gustafson. He also introduced a range of linear regression models and found that the translucency of root dentin depended on most on the calendar era, and secondary dentin came. [83]. Whereas secondary dentin apposition can be analyzed using several non-invasive, easy, and convenient radiological methods. The pioneers on this topic were Kvaal and Solheim. They estimated an adult's age from measuring the volume of the pulp on complete mouth dental x-rays without tooth removal and destruction [84].

Only radiographic measurements were used to introduce a methodology. Using the six-teeth periapical radiographs, pulp and tooth length were evaluated as well as width, and ratios between the dimensions of length and width were calculated. Based on the assessment consequence, the width ratios seemed to have a greater correlation than the length ratio, and the

regression determination coefficient was discovered to be the highest when the ratios from both jaws were used for all six teeth. Bosmans et al. implemented Kvaal's form on electronic orthopantomographs (OPGs) and contrasted the initial method using periapical radiograph readings. They acquired an age estimate similar in adolescents to those based on the initial Kvaal technique, notably when all six kinds of teeth were used [85]. Similarly, So also, in a German populace, Paewinsky et al. affirmed the appropriateness of Kvaal's procedure to digitized all-encompassing radiographs and noted improved exactness and more prominent coefficients of connection. The outcomes uncovered the most grounded connections between's the readings and age at stage An of the upper horizontal incisors and a straight coefficient of relationship $r=-0.916$ with a standard deviation of 6.4 years [86]. Meinel et al. evaluated the utilization of the improvement of the relapse recipe by Kvaal and Paewinsky to OPGs from an Austrian populace and found that immediate execution of the relapse formulae brought about a genuine age underestimation going from 31.4 to 47.1 years [87].

From there on, various investigations were discharged breaking down the method connected by Kvaal and Paewinsky utilizing unmistakable sorts of a tooth from numerous ethnicities, and each indicated particular exactness, precision, and unwavering quality [88–94]. Almost all investigations have demonstrated that relationships between's ordered age and dental proportions are littler than those detailed by Kvaal and Paewinsky. A new file, called the Tooth-Coronal Index (TCI), was made by another system called the method of Ikeda (1985). The TCI depends on two straight components of human teeth separated dental radiographs, the stature of the crown (CH) and Coronal Pulp Cavity Height (CPCH). The division between the anatomical crown and root is a straight line followed between the bond polish intersections on the mesial and distal parts. The CH was surveyed vertically from the cervical line to the tip of the biggest cusp, and the CPCH from the cervical line to the tip of the biggest mash horn was evaluated vertically. They demonstrated that there is a significant connection between's the length of the mash pit and the sequential age. They utilized dental radiographs of 116 extricated teeth (53 incisors, 63 molars) to gauge the length of the coronal mash hole and teeth crown and determined the TCI for every tooth [96]. In 1997, Drusini and friends tried Ikeda's system in digitalized OPGs utilizing mandibular back teeth and affirmed the more prominent relationship among's TCI and age. For manly molars ($r=-0.92$), the primary straight relapse conditions were created, and the connection was especially significant. They deduced that the TCI is not just a reliable screening instrument for evaluating the time of death in skeletal remains, yet besides, a helpful apparatus for deciding the time of living people [95].

Cameriere et al. [97] propelled another age appraisal radiography procedure utilizing the Pulp Tooth area Ratio (PTR) to measure the utilization of optional canine dentin in digitized periapical radiographs. The concentrate established of 100 Italian white Caucasian inhabitants (46 guys, 54 females) in skeleton stays matured around in the age range of 18 and 72 years. The mash/tooth proportion, tooth length, mash/tooth length proportion, mash/tooth district, and mash/tooth width proportions were determined to utilize a computer helped to draft program. Statistical investigations demonstrated that the mash/tooth' region' proportion was best connected with age, bringing about raised coefficients of relapse ($r^2=0.85$). The approach was at first to look at the PTR of maxillary canine, however, in the end, included different teeth, to such an extent that incisors, premolars, molars, utilizing orthopantotomographs just as intraoral periapical radiographs to gauge age, and the journalists accomplished raised rates of age conjecture exactness (mean mistake of 2,58-5,4 years) [97]. What is more, irrefutably the remaining blunder normal between ordered period and evaluated age was for the most part un-

derneath four years.

Cameriere et al. [97]. approach at first determined the upper canine PTR, yet was persistently tried utilizing periodical radiographs and OPGs on numerous teeth, enormous example sizes, and various populaces. Ongoing examinations contended that to accomplish the extreme precision, more populace express conditions with a well-conveyed age gathering ought to be created in more significant samples. A new methodology, not expressed above, was utilized distinctly by one research. In mandible molars, Tsatsoulis et al. [98] investigated the effects of age on mash chamber morphology and width. They researched 494 mandibular molars (262 first and 232-second molars) and assessed four separations with explicit tourist spots on OPGs, two edges, and two proportions. The creators demonstrated that age is occluso-gingivally identified with diminished mash chamber measure, and the expansion rate of roof thickness of the mash chamber is like the thickness of the mash chamber floor. While these discoveries have given the connection among age and mash chamber roof floor separation of multi-root teeth, any age gauge relapse equations dependent on estimation [98].

In different clinical and scientific fields such as pediatric dentistry, orthodontics, anthropology, paleontology, and forensic dentistry, determination of dental age is needed. An unidentified person's age can be evaluated by correlating an individual's physical, skeletal, and dental maturity. Many techniques for evaluating dental development have been suggested, usually referred to as dental aging. There are two types of dental aging: tooth mineralization and patterns of tooth eruption, both biological and developmental patterns. Eruption relates to the appearance of the tooth via gum instead of the bone formation or entering the occlusal plane. It is making it difficult for skeletal remains in forensics to use eruption for age estimation. Local exogenous variables such as infection, obstruction, crowding, and premature removal of the deciduous predecessor or neighboring permanent teeth can considerably influence the development of the tooth.

The literature is now entirely consistent that local and systemic factors are hardly influenced by techniques of dental age assessment based on an assessment of the mineralization and development of the teeth, [131] but rely on population genetics because ethnic variability is demonstrated [132]. The age assessment through the research of continuous teeth calcification has shown reliable and precise techniques and results. The use of various techniques in current literature and procedures, the creation of fresh techniques for the implementation of the most appropriate method, should be used to estimate age in a given population [132]. Several techniques are convenient for determining the dental age as introduced by Nolla's, [133] Haavikko's, [134] Demirjian's, and modified Demirjian method by Willems et al. [135] many researchers have proposed a distinct amount of radiographic phases to quantify the ongoing process from the first traces of cusp mineralization through root apex closures. Demirjian et al., the technique for dividing dental development into 8 phases and criteria for these phases have been provided for each tooth individually. One score was assigned to each phase of the left jaw, seven teeth, and the amount of the score evaluated the dental maturity of the subject, and the dental age was calculated by using gender tables. In the use of this technique, fewer phases contribute to the end of dental maturation to make a significant jump in the dental age through a single-phase change. The research by Nolla was one of the first to longitudinally evaluate and quantify tooth growth. This technique has provided a total of tooth results per year of age that are used to estimate age in groups of one year of age, and that also gives each tooth an age at each point. Haavikko et al. screening one of the 12 radiographical phases of

each permanent tooth was recommended as a technique of age estimation. The challenge with the Haavikko technique was to decide whether to include incomplete analyzed kids who were significantly delayed in one tooth to compare with other techniques. They are based on dental maturation for kids and can be split into those who use the atlas strategy and those who use scoring processes. For adults, morphological and radiological techniques are used [138].

Periapical radiographs and OPGs have been mostly used in the measurement of pulp and tooth size, and recent use of Computed Tomography (CT) and cone-beam CT. Many studies conducted to calculate pulp chamber volumes using the three-dimensional digital radiographic pictures of teeth, and the authors achieved promising outcomes for age estimation based on the pulp-tooth volume ratio [99]. Although multiple methods for determining radiological dental age that indirectly quantified secondary dentinal deposition in living adults were feasible, countless trials conducted on these methods showed different accuracy, accuracy, and reliability. For more reliable outcomes, forensic odontologists should apply distinct methods, conduct repetitive measurements, and gather extra experimental information from distinct ethnicities. They should also continuously develop new methods and validate the existing methods.

1.1.1.5 Hand

Hand and wrist radiography is helpful as it is simple, cheap and non-invasive to estimate age. The age estimation techniques frequently used for hand and wrist skeleton are Greulich – Pyle (GP), Tanner – Whitehouse (TW) and Fishman [140–148]. The Greulich – Pyle technique is based on the entire hand's visual comparison. The reference population includes kids from Cleveland, Ohio, and information were gathered until 1942 [140]. The Tanner – Whitehouse technique is focused on visual similarity of each bone, using a numerical scheme that has undergone a sequence of revisions to enhance precision. The reference data were gathered from people having different nationalities, including Japan, but mostly from European countries and the United States. In the 1990s, the recent Tanner – Whitehouse 3 dataset was gathered [144, 145]. In the orthodontic sector, the Fishman technique is mainly well-known [147–150]. This technique was first suggested in 1982 and is based on information gathered from American kids. This technique utilizes the notion of dichotomous tracing on a systematic monitoring system [147, 148]. The observation system begins with the first SMI, its existence or lack will move to another SMI, and so on.

Stern et al. [326] presented a Deep Convolutional Neural Network (DCNN) architecture for age estimation based on 3D MRI bone. Following the method of Tanner-Whitehouse 2, DCNN comprises of identical per-bone phase assessment (SE) frames, which measures the ossification phases of hand bones individually. They are aimed at reducing the dimensionality of appearance characteristics in 3D bone volumes, capturing age-related characteristics defined by the ossification process. The fusion of independent age results from each bone is introduced in DCNN in order to obtain a constant biological age prediction by linking the outputs of all stage estimation parts in a fully linked layer. In the state-of-the-art automatic biological age estimation method, resulting in a mean error of 0.36 ± 0.30 years between estimated and ground truth biological age.

Sunpatch B. et al. [139] assess the precision and efficiency of the three age estimation techniques frequently used: Greulich – Pyle, Tanner – Whitehouse, and Fishman. They collected the database of three hundred and sixty-five hand and wrist radiographs were gathered retrospectively from Thai patients aged 8–20 years between 2011–2016. Greulich–Pyle, Tan-

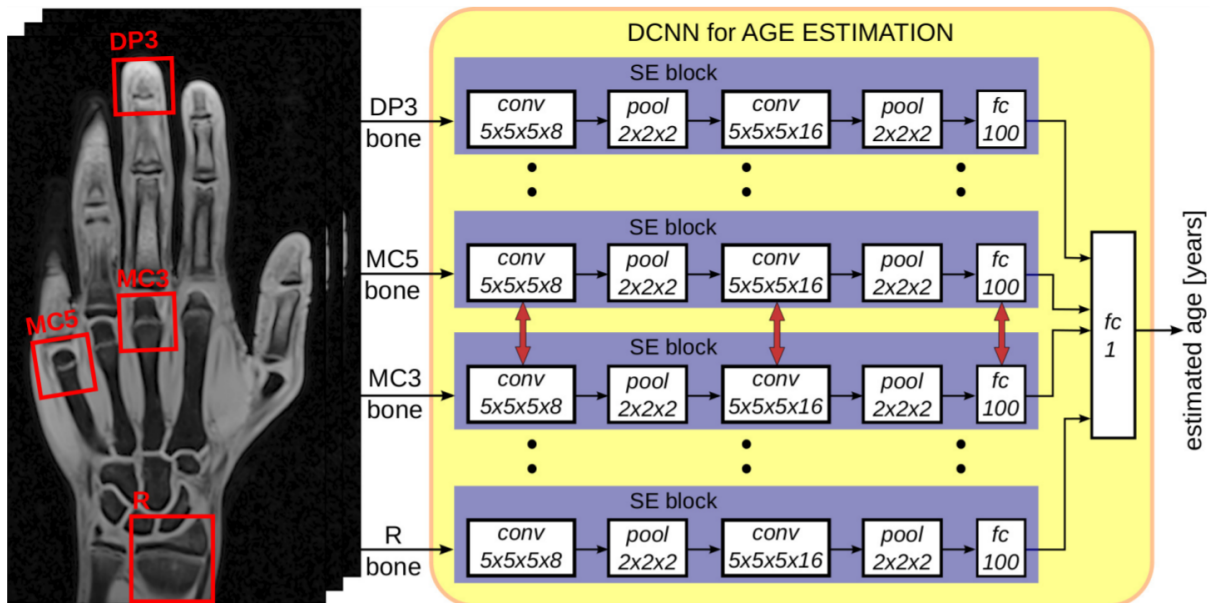


Figure 1.7: DCNN Architecture for hand based human age estimation [326]

ner–Whitehouse 3, for each radiograph, radius, ulna, chosen short bones (RUS) and Fishman technique were used. Comparisons were made using Wilcoxon signed rank test with Bonferroni correction between the estimated era of each technique and the chronological age. On the significant legal age thresholds in Thailand (10, 13, 15 and 18 years old), sensitivity, specificity, and precision tests were carried out. Weighted kappa evaluation assessed the reliability of intra- and inter-observers. The estimated ages from the three methods were significantly different from the chronological age, except for Tanner–Whitehouse 3 RUS in males. With regard to the legal age thresholds, Greulich – Pyle showed the greatest precision for the 10-year legal age limit, (83.2% for women and 79.63% for men). The Fishman technique showed the highest precision of 13 (77.5% for women and 74.31% for men) and 15 (83.08% for women and 73.77% for men) for the legal age limit. Greulich – Pyle showed a precision of 53.85% for women and 54.44% for men for an age limit of 18 years old.

1.1.2 Behavioral Biometrics

Behavioral biometrics is related to the measurement of patterns in human activities that are special in identification and measurement. Methods of behavioral biometric evaluation include keystroke dynamics, gait analysis, voice identification, features of mouse use, signature analysis, cognitive biometrics and auditory perception.

1.1.2.1 Keystroke dynamics

Keystroke dynamics are studied as well from the perspective of age detection. With the help of this technique, the exact age cannot be estimated, but it can be utilized to differentiate between kids and adults.

Scientific findings indicate links between this easy assignment and the age, gender, dominant hand, general health of a subject, and if he or she puts maximum energy to the challenge.

Because utilizing a keyboard is like continually pressing a button, the same features may occur in distinct typing patterns. To alter the outdated method of using passwords as a login system, keystroke dynamics are initially used for user authentication. For instance, Joyce and Gupta [119] presented diagram latencies to identify a valid user and an impostor, and the outcome indicates that the impostor has been able to verify successfully very few times. Though, subjects are categorized according to a computer used to write a text presented by Tsimperidis and Katos [118]. They used empirical data, which is a public dataset, having keystrokes in several languages to confirm the language dependency assumption while the performances of the different classifier are evaluated. This approach was able to identify the gender and classify the subjects with a probability success value of 70%.

Finally, Idrus et al. [120] in a study effort to retrieve data from dynamic keystroke templates with the capacity, such as recognize a user's age category when typing a password or passphrase on a keyboard. The dataset was collected from 110 subjects who were requested to type 5 sentences in length between 17 and 24 characters using a SVM classifier, divided users into two age groups, those under 30 and those over 30, and obtained a classification precision between 65% and 82%.

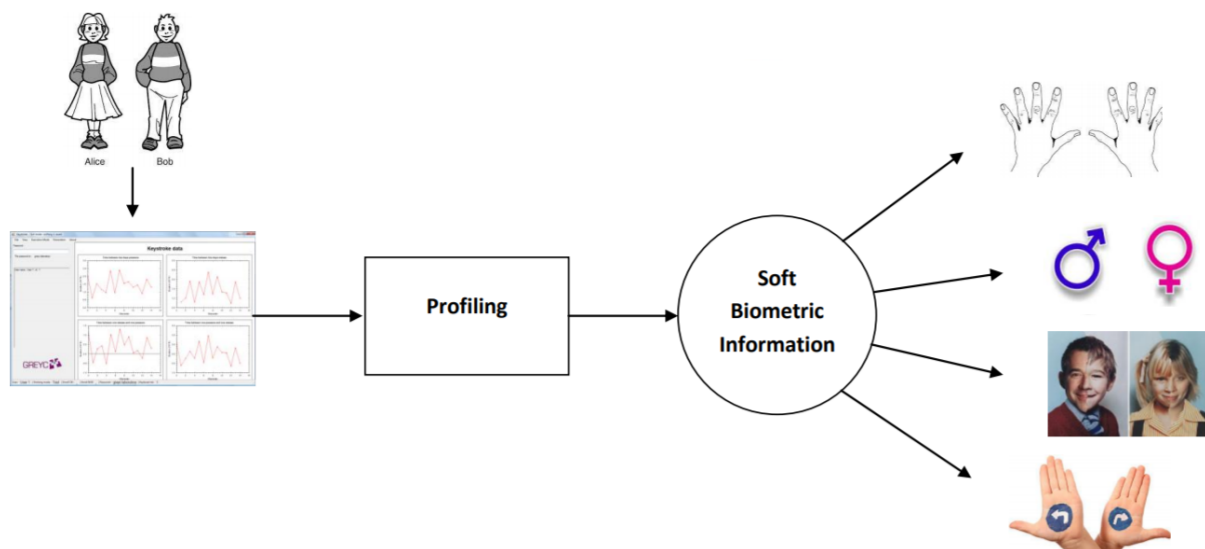


Figure 1.8: soft biometric information [124]

Idrus et al. [327] presented information about soft biometrics as shown in figure 1.8. It comprises evaluating the writing method of the user by identifying the amount of fingers used to write (one or two), sex, age range, and handedness, with successful results. The identification level for a ratio above 50% is significantly lower than that for other soft standards, such as between 65% and 82%. Avar pental [123] presented that many of the subject's operations are deliberate and other involuntary, but user applications are generally intended to respond only to deliberate instructions. The unintentional activity of the user, however, includes many hints about a user, which can be useful to take into consideration when developing a suitable reaction. Concentrating on these unintended clues, which have been left behind by utilizing standard input devices, keyboard and mouse, and precisely, to forecast gender and age for people. Keyboard and mouse information included in this research are gathered from a total of 1519 topics in six distinct systems from 2011 to 2017. The present exam, though, is frequency-based text mining characteristics that have comparable effects on rhythm typing and if there are

essential variations between distinct age groups and gender groups in typing velocity. When predicting both user age or gender, some monitored machine learning models produce f-scores above 0.9.

Keystroke dynamics are studied as well from the perspective of age detection. With the help of this technique, the exact age cannot be estimated, but it can be utilized just to differentiate between kids and adults. A multi-layer perceptron show that the age can be detected with a probability that it is far from the uniform distribution with a rate of success of 72% for two classes and 64% for four classes [152]. In previous work, distinguishing child Internet users from adults show that the accuracy rates above 90% was achievable with support vector machine or linear discriminant analysis classifier [153].

1.1.2.2 Gait

Gait signature is also one of the best behavioral biometric modalities for estimation of human age. By using gait features, it is possible to differentiate between gender even if they belong to the same age group. However, there are very less scientific studies done on gait-based age estimation and age group classification than face-based studies. Due to advance requirements for visual surveillance, gait biometrics have lately gained more attention. Gait has many benefits compared to other biometrics such as irises, faces, and finger veins. It can be perceived from such a low-resolution picture at a more considerable distance from a camera. Besides, gait is indeed implicit conduct that individuals usually do not deliberately hide the gait and do not need the collaboration of the person. Mostly research concentrate on gait-based identification or verification [25–27], that can be utilized directly for several applications such as monitoring, criminal investigations and forensics, and [28–30]. Human recognition and verification studies play a significant role in acknowledging other human features such as ethnicity, age, and sex. Human age estimation is among them, an exciting and productive field of studies. Gait-based estimation of human age has some specific benefits, especially in surveillance situations, whereas under such circumstances, gait can still be well understood. Human age estimation based on gait, therefore, offers most prospective advantages, including the situation of automatic counting of clients in which age groups are of concern to the marketing of products based research or automatic access control based on age to a particular region. Besides, gait or more practically talking, a composition of gait and shape, is viable to estimate human age just because it includes discriminative age indications. Such that Davis [31] presents the difference of gait between a child and an adult in terms of the frequencies of the leg length, steps, and step width.

Ince et al. [32] demonstrated that a child's head-to-body ratio differs from an adult. Almost identical results have also been reported in [37] by evaluating commonly used physical appearance-based gait description is known as Gait Energy Images (GEIs) [38] or average silhouettes [39] containing data on gait and overall shape. As shown in figure 1.9 , GEIs has an average over people for each age range to provide more proof for this, as the head-to-body ratio is changing as childs grow up. Moreover, a middle-aged dispersed and stop appear as individuals get older. Such modifications in appearance-based gait depiction, therefore, offer the option of estimating human age. Additional techniques for estimating human age based on gait typically consist of two components: description of features and algorithms for estimating human age. With the depiction of features, because of its easy yet efficient characteristics, GEI is the most frequently used [33, 37]. Several approaches [34, 35] use multiple age learn-

ing methods on GEI to discover a low-dimensional depiction capturing GEI's inherent data allocation and geometrical structure. Primarily there are two types of human age estimation algorithms: regression-based techniques [35, 37] and classification-based techniques [33]. In classification-based methods generally, consider an individual class is assigned with age label, then uses a multi-class classification algorithm to address the issue of estimating human age, while regression-based methods directly address an issue of regression from a gait and human age, which is natural as a steady value fundamentally defines an age. Though, all of such research on gait-based assessment of estimating age used a singular age group-independent assessment approach, irrespective of the reality is the aging process of gait changes considerably among all age groups such as kids, adolescents, and elderly people, which can readily be seen in figure 1.9 so that children development rate is much quicker than adults. Hence, the differences between age groups may not be handled well by a single age group-independent assessment, which results from big errors of age estimation when variation in age becomes big. Thus, age group-dependent structure is suggested for the gait-based assessment of human age to address this issue, that's considered as a fusion of regression-based and classification methods.

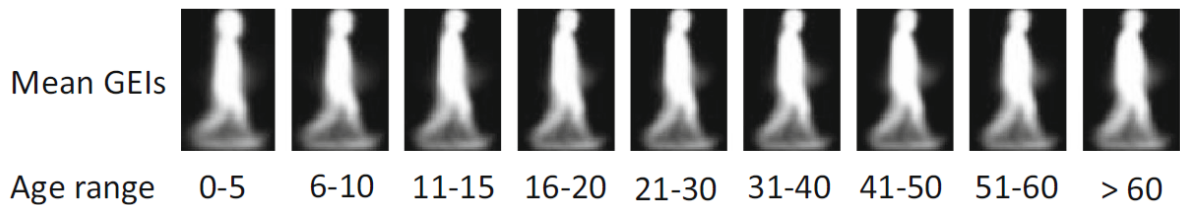


Figure 1.9: Different age groups with Mean GEIs
[124]

Gait-based classification techniques generally utilize linear and kinematic characteristics. Davis [31], used the characteristics of step width, leg length, and step frequency to distinguish two age groups: kids age range of 3–5 years and adults age range of 30–52 years. Begg et al. [46] used minimum foot clearance information to classify younger individuals 28.4 years mean age and 6.4 years is the standard deviation and elderly individuals 69.2 years mean age and 5.1 years is the standard deviation. Characteristics including head-to-body proportion, stride length, and appearance have been used in [45] to classify adults and kids depending on randomly marked datasets.

In [44], longitudinal spatiotemporal and transverse silhouette predictions throughout a gait cycle are utilized to depict the spin of the arms, the angle of the head, the slumped position, and the duration of the gait, which showed a significant separation between young and old. For the classification of the human age group, some techniques used appearance-based gait characteristics. For example, frequency domain characteristics are used by Mannami et al. [36, 43] for three classes: children (below the age of 15), adults (in the age range 15 and 65) and the elderly (over the age of 65). Though, there are several constraints of the prior techniques of classification of the human age group, such that owing to restricted age spectrum and a tiny amount of quite rough age ranges, there is inadequate scientific validity.

Estimation of human age based on gait is a fairly fresh area of research, and thus a restricted amount of studies have been carried out so far. The earliest research on this subject was released by Lu and Tan [33] through an efficient label encoding system, they first transformed every age value in a binary sequence. On the GEIs and their Gabor representations, Multi-

Label-Guided (MLG) subspace learning technique was implemented to accurately classify and relate a person's age data to estimate human age. Lastly, instead of traditional classification techniques, they conducted multilabel k-nearest neighbors classification, which regarded each age group as a class and decoded the label vector age data. Makihara et al. [37], subsequently suggested a standard algorithm for age estimation based on gait signature using Gaussian Process Regression (GPR) [41], which indicated excellent efficiency in the facial based human age estimation [42] in combination with a silhouette-based gait characteristic.

The statistics using a generation-wide gait database along with 1728 topics with a broad age category (2 to 94 years of age) stated the capacity for application of gait-based estimation of human age in real-world. Furthermore, research has been done to estimate human age, use the fusion of gait and face characteristics [40]. They first used averaging feature to fuse gait characteristics from different gait phases and face characteristics from many angles, then combining these separately fused characteristics in a single-function vector. At the end, in order to get the estimated age, a comparable age estimation technique as [33] was used. Though, all of these research used a single age range-independent assessment method, irrespective of the reality that aging gait method varies considerably between age categories for example kids, adolescents, and the elderly, and therefore results from big estimation errors as the age variability rises.

Age related studies based on auditory system was presented for the first time in 1987 by Morrongiello et al [328]. The discrimination was studied for three age groups using specific signals and silence situation. It was mentioned that discriminated duration changes of 20 ms, 15ms and 10ms was experienced for infants, child's and adults.

1.2 Conclusion

In this chapter, existing works in the field of human age estimation has been reviewed. While some exciting and interesting work can be found based on distinct biometric modalities dealing with age estimation, such as face, finger, DNA, etc. Studies have shown that the existing works used statistical methods to present a model using specific dataset as training data. While in recent works based on machine learning and deep learning techniques, the databases are divided into training data and testing data such that the testing data also belongs to the parent database. In physical features, face trait has shown promising results for human age estimation, classification, and verification. while considering the physiological characteristics DNA shows the higher accuracy for human age estimation, classification, and verification. In this theses, a novel trait has been introduced in the field of biometrics for human age estimation, classification, verification and authentication based on auditory perception responses.

Chapter 2

Human age estimation and classification using auditory perception

This chapter provides information about auditory perception responses, which can vary according to age and demonstrate the possibility of human age estimation and classification through auditory perception responses. The assessment of human age has a wide variety of applications linked to human-computer interaction and forensic sciences. A novel method for classification and assessment of human age is created based on auditory perception. The primary input involves demonstrating that auditory perception is a biometric characteristic that can be used based on auditory perception to identify age groups and classify age groups and estimate age. Age estimation and age classification protocols will be regarded after a fast analysis of various popular methods used in the age estimation sector and after showing some generalities on the auditory system. Several machine learning methods, including Random Forests (RF) and Support Vector Machines (SVM), are used for this purpose to assess the volunteer's age. Data from 837 trials were gathered with varying ages varying from 6 to 60 years old to assess the performance of the auditory.

2.1 Sound, Ear and hearing

Basic details concerning sound and how the human auditory system performs the listening process is presented in this section. The basic function is extensively described that affects the hearing in daily lives, such as environmental effects that complicate human hearing.

2.1.1 Introduction to sound

Hearing enables us to define and acknowledge entities in the universe depending on the sound they generate, and listening enables us to interact. Sound is obtained from artifacts that vibrate in a sound transmitting environment, such as wind, creating strain differences. A sound origin propagates a pressure wave downward. The vibration can be imparted to that item when the pressure wave meets another item and the pressure wave propagates in the object's environment. The sound wave from the item can also be reflected or it can diffract around the item. A sound wave that spreads away from a vibrating item can thus touch a listener's eardrum, triggering the eardrum to vibrate and start the listening cycle.

Sound waves can be categorized into two different domains, such as time domain and frequency domain). Sound is defined in the time domain as a series of changes in pressure (oscil-

lations) occurring over time. The spectrum defines sound in terms of the tonal elements which make up the sound in the frequency domain. Tonal noise is characterized by a time-domain in which the sound pressure comes as a regular (sinusoidal) feature of the moment. There are three basic physical attributes of a sound waveform: frequency, temporal variation, and amplitude. Frequency refers to the number of times the vibratory pattern oscillates (in the time domain). Amplitude relates to the pressure of the sound. The temporal variation of sound, such as sound duration, has many elements. Sound pressure is equal to the intensity of sound (in power or energy units), so it is possible to measure sound magnitude in pressure, power, and energy systems. The popular sound level measurement is the decibel (dB), while decibel is the logarithm of the ratio of two sound pressures or two sound intensities. Frequency is evaluated in hertz (Hz) units, cycles per second. Time measurements are represented in different temporal divisions or can be converted into linear degrees measured phase.

2.1.2 Auditory system

The ear acts as an effective transducer (an energy form changing device), changes the pressure of sound in the air through signal (neural-electrical), which translated via the brain in the form sound (music, noise speech, etc.). Brain and each part of the ear (external, middle, inner) play a definite part in the process of transformation is shown in figure 2.1

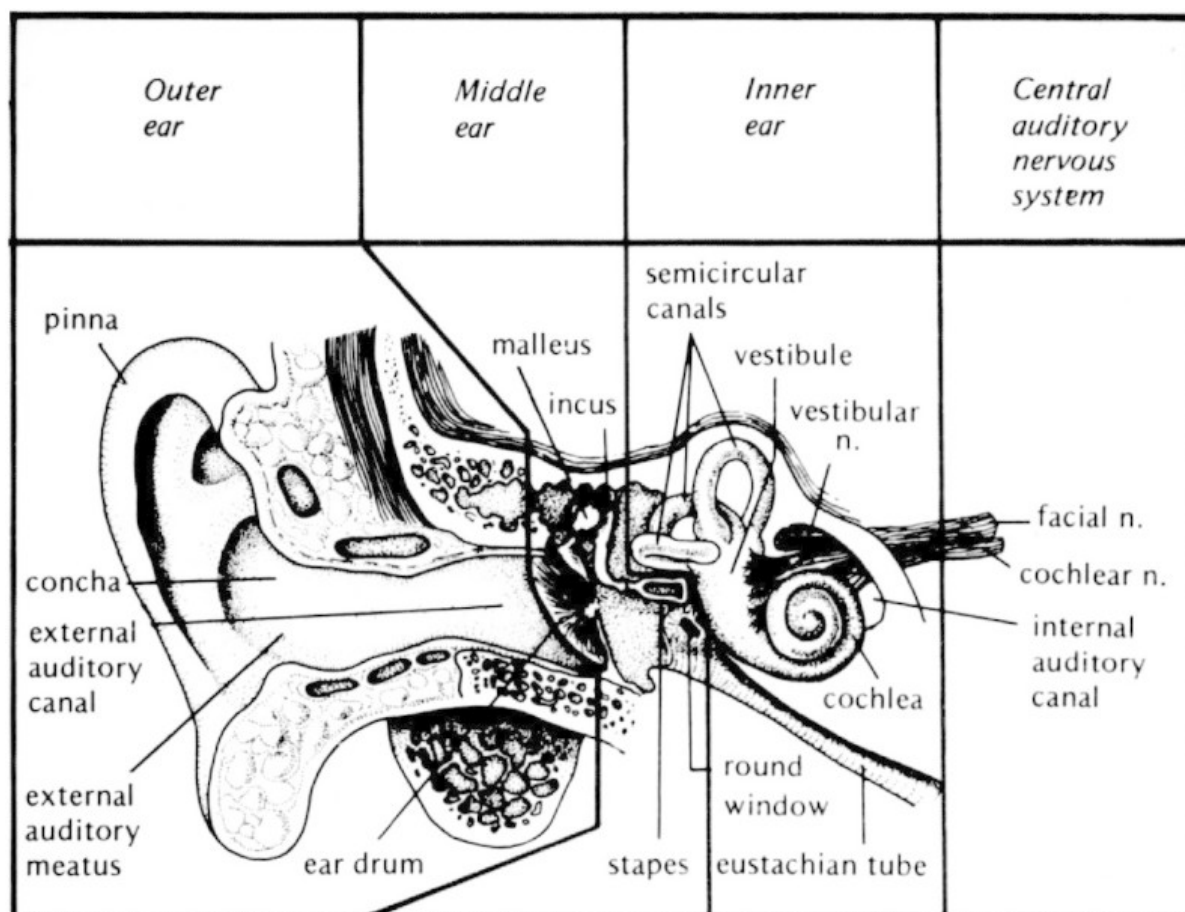


Figure 2.1: Flow diagram of the proposed approach

The external part of the ear (external ear) consists of a structure called pinna through which the sound is captured from the surrounding. Now the sound is pass to the eardrum (tympanic

membrane) by the canal channel of the external ear and splits the external and middle parts of the ear. The eardrum, with the help of three middle ear bones (malleus, incus, and stapes), helps in the transfer of sound pressure in air to the inner ear having fluid and tissue. Most of the sound pressure is reflected when it is transferred to a dense medium environment of the inner ear. Consequently, the inner ear suggests impedance to directing the pressure of a sound to the inner ear (fluid and tissue region). This transmission and resistance of sound pressure are stated as “admittance” and “impedance” respectively. The whole transfer process within the middle ear is described by a special term “acoustic immittance” (a combination of two words impedance and admittance (im + mittance)). Due to this impedance, there is approximately 35dB loss of sound pressure transmission to the inner ear. However, most of this loss is overcome when the outer ear, tympanic membrane, and ossicles cooperate when there is a sound to emphasize the sound pressure into the inner ear. Hence, the inner ear fluids and tissue regions start vibration in the response of sound in a very effective way.

Normally sound waves are transferred into the staple footplate through the ossicular middle ear chain. In the oval window of the inner ear, the footplate rocks and sets in motion the fluids of the inner ear. The parameters of the motion are dependent upon the intensity, frequency or time of the signal. Both the vestibular mechanism belongs to the inner ear, the sense that keeps the balance and cochlea which underlier the sense of hearing. Three separate fluid chambers exist in cochlea; two of them include perilymph (scala vestibuli and scala tympani), identical to the extracellular fluid of the body, and the other scala medium incorporates endolymph, comparable to intracellular fluid.

The compositions of the cochlea fluctuate in response to a particular sound in a specific pattern of vibration. This vibrational pattern provides the inner hair cells and their joints to the sensory nerve to convey signals to the brainstem and brain regarding the sound’s vibration and its frequency content. That is, the cochlear vibration traveling wave motion helps to separate out the frequency information of any sound, so that feedback about the sound frequency elements is coded in the neural replies that are sent to the brainstem and brain.

The more severe the sound, the higher the number of neural discharges forwarded to the brainstem and brain by the auditory nerve. Through the auditory nerve, the cochlea carries neural data about the three physical characteristics of sound to the brain and brainstem: speed, temporal difference, and concentration. The cochlea’s biomechanical reaction is very susceptible to sound, is specific in high frequency, and acts in a nonlinear way. Much of this sensitivity, frequency selectivity, and nonlinearity is a feature of the outer hair cells motility.

The skull bones start to vibrate at 60 dB SPL, nullifying the system of middle ear. This skull’s immediate vibration can trigger the cochlea to vibrate and therefore the hair cells to bend and begin the hearing cycle. Its not the efficient way as it represents a hearing loss of at least 60 dB in this way to stimulate the auditory nervous system.

The peripheral auditory system is made up of the outer, center, and internal eyes along with the auditory nerve, and the brain and brain form the main auditory nervous system. Hearing and auditory perception are the responsibility of the peripheral and core nervous systems together.

2.1.3 Auditory perception

Perception is the capacity of humans to interpret data received from the surroundings by our distinct senses. The audition is the meaning that enables us to perceive and locate sounds. Therefore, the capacity to obtain and interpret these sounds which reach the ears, or the human auditory system through audible frequency waves transferred by air or other means is called auditory perception [161].

The human hearing may provide us a path to: Communicate with each other applying human speech such as to interact with an administrator who is presenting oral guidance, process information- sounds alert, such as respond to an auditory warning and Determine the spatial location of a sound source such as the location of a train based on its sound.

There is a variety of fundamental understanding of how the visual system enables sound, informative sound handling, and sound localization-based interaction. Listeners can detect the existence of a part, discriminate modifications in frequency, locate a sound's origin, level, and time, recognize distinct sounds of expression, and identify and acknowledge distinct forms of sound. Often, when there are many locations generating sound at about the same moment, the auditory system must perform these job duties so that the sound from one origin may conflict with the capacity to "feel" the sound from another origin. The sound that interferes can render it hard to detect another sound, discriminate between distinct frequencies, or recognize a specific sound. A listening impairment can render it hard to execute one or all of these duties even in the lack of sounds intervening, but particularly in the presence of sounds intervening.

2.1.4 Sound detection

With frequencies varying from about 20 to 20000 Hz, the healthy and young hearing system can identify sounds in silence. The figure indicates the uniform average thresholds for determining distinct frequency tonal signals when the length of the signals is about 500 milliseconds (ms). The sounds to be detected can be provided in a calibrated free-field setting (Minimal Audible Pressure (MAP), measurements) or from a loudspeaker (Minimal Audible Field (MAF), measurements). The headphones can be circumaural, such that with a headphone cushion fitting around the pinna and the earphone microphone lying on the outside of the outer ear canal, or with earphones fitting into the outer ear canal can be inserted. The thresholds are displayed as SPL decibels, where null (0) dB SPL implies that the amount of sound pressure is 20 micropascals such that 20 micro pascals is the reference sound pressure. The figure also shows the upper listening boundaries, showing the highest SPL that the auditory system can accept. Thus, in the frequency region where the human auditory system is most vulnerable (between 500 and 4000 Hz), the dynamic range of listening includes about 130 dB. The thresholds for identifying a tonal sound rise as the length of the sound to be identified reduces below 500 ms at durations but remains roughly continuous as the length rises above 500 ms.

The young person, ontologically healthy in a workplace, can, therefore, detect the sound signal across the frequency limit 20 to 20000Hz, but depends on variables such as sound frequency, sound duration and any sound other than the signal sound that may occur at, or close to, the same time. Masking implies that the object sound identification limit has been increased by the masking sound appearance. Pitch and loudness related to the sound's perceived characteristics, which are extremely linked to both sound level and frequency. Specifically, the

comparable sound is more probable to mask one another than spectrally comparable sound. The signals that occur simultaneously with a masker and signal may be most difficult to detect, but they could mask as the signals and masks do not flap temporarily. All these auditory perception interventions can be significantly impacted if an individual is suffering from hearing loss.

2.1.5 Human discrimination through sound

Listeners can distinguish a variation in sound level of about one decibel and about half one percent change in tonal frequency across a spectrum of frequencies (approx. 500 to 4000 Hz) and at concentrations (approx. 35 to 80 dB SPL) in which people are sensitive. For example, a 50 dB SPL sound could be distinguished by a 51 dB SPL sound, and a 2000Hz noise by a 2010 Hz sound could be discriminated. High level and frequency variation levels can result in a lack of hearings, rendering it hard for the individual with a lack of hearing to distinguish the tiny distinctions that often follow transition in the waveform of the voice.

Sounds for long durations involve a significant shift in duration for discrimination than for smaller time frame recordings, but many variables are dependent on the precise connection between duration and its discrimination. Listeners can distinguish between a sound that has a fluctuating total level (the sound is modulated with frequency) when the general rates of output fluctuate less than 50Hz. A signal modulated by amplitude comprises a transmission sound, called the modulator, with a distinct stage. The sound level of the receiver rises in a way determined by the modulator and reduces over time.

Such sound discrimination procedures do not alter noticeably as soon as the sensor sound is easily detectable, depending on the existence of masking objects. Many persons with a problem of hearing loss, in particular, the aged people, have trouble handling the temporal sound framework. More such individuals generally have elevated time differences and involve rapid frequency fluctuation levels in order to distinguish a fluctuating sound from a continues to sound. So individuals with these kinds of problems may not be prepared to track some of the fast sound intensity changes that are visible in many daily activities, like expression and different kinds of music.

Thus, minor modifications in sound, amplitude, and length can be discriminated in the workplace, even when there are some masking sounds. As soon as the sound level is not too fast, subjects should be prepared to determine that the sound fluctuates (in loudness) at the workplace. Hearing deprivation is often less effective than individuals who have an ordinary listening when performing those auditory discrimination activities.

2.1.6 Human auditory system: generalities

While we are 16 years old, our highest audible frequency is around 18000Hz. At 30 years old, it decreases to around 15000Hz. This means that with the increase in age, the highest audible frequency decreases as well. Consequently, there is a correlation between the age and the audible frequency [158–161]. Therefore, hearing loss occurs over time due to the damage of hair cells in our auditory system [154–157].

Considering hearing loss as a factor, the auditory system can estimate age. Some research has been done to study the peak frequency. A human being can tolerate it by pulling people's attention through the sound of the mosquito frequency. Nevertheless, it is stated in the literature that humans can hear a sound 12Hz under favorable circumstances [157], and the commonly stated range of human hearing is from 20Hz to 20,000Hz [158–160].

Contrariwise, research in the field of human age estimation through auditory perception has been introduced in our previous work [161] for the first time. An accurate and enhance system is introduced with better performance. To better study the correlation between age and auditory perception, three objectives are to be achieved in this work:

- Demonstrating the feasibility: the separability between different age groups based on the auditory perception is studied.
- Classifying human age onto an age group using the auditory perception: different age groups are used, and the performances of the classification are compared.
- Estimating human age from the auditory perception: different regression models are compared to find the best one for forensic age identification from the auditory perception.

2.2 Human age estimation and classification

2.2.1 Protocol of simulation

According to the following model, human auditory system is stimulated by producing dynamic sound waves:

$$\begin{cases} x(t) = A_0 \cdot \sin(2\pi \cdot \phi(t) \cdot t), \\ \text{where } \phi(t) = \alpha \cdot t + \phi_0, \end{cases} \quad (2.1)$$

A_0 stands for sound amplitude, t stands for time, ϕ_0 is the initialization frequency, and α stands for the increasing/decreasing frequency speed.

In this experiment, four different protocols with speaker (S) and headphone (H) are considered, namely: Bilateral Stimulation (S-BS), Bilateral Stimulation (H-BS), Right Stimulation (H-RS), and Left Stimulation (H-LS). In the first protocol, the stimulation duration is set to t_1, t_2, t_3, t_4 , and t_5 . This protocol enables the system to choose the appropriate time of stimulation for the experiment. While headphones are used in the remaining three protocols:

- Bilateral Stimulation (H-BS),
- Right Stimulation (H-RS),
- Left Stimulation (H-LS).

Therefore, each volunteer is supposed to participate in eight experiments, as represented in Figure 2.2.

For each protocol, the system requires interactivity, as shown in Figure 2.2. The dynamic sound is generated with an increasing frequency. Each volunteer should achieve a manual action to stop the system if no sound is heard. Basically, the stimulation is conducted according to two modes:

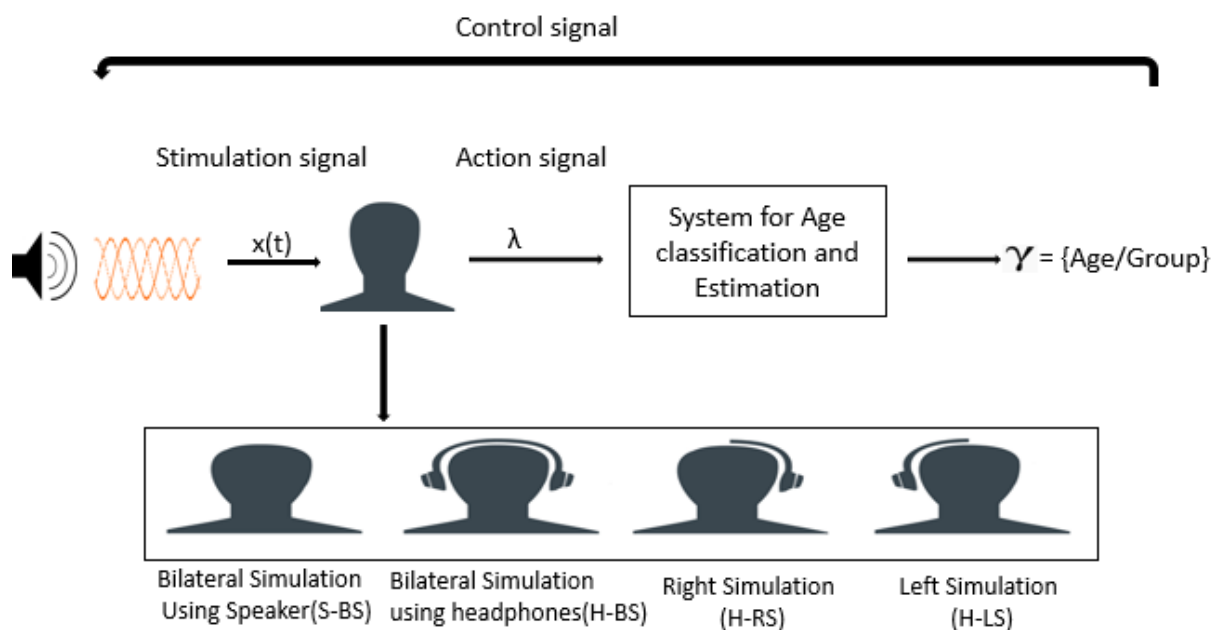


Figure 2.2: Flow diagram of the proposed approach

- first mode: the sound is generated and increased from the lower frequency (20Hz) to the higher frequency (20,000Hz). The volunteer stops the stimulation (e.g. keyboard action), once no sound is perceived,
- second mode: a second stimulation is triggered automatically once the volunteer completes the first mode action. In this case, the generated sound frequency decreases from the higher frequency (20,000Hz) to the lower frequency (20Hz). The volunteer stops the stimulation once the sound is perceived.

2.2.2 Discrimination of age groups based of auditory perception

Human auditory perception is a powerful biometric feature that distinguishes the age of a person. Linear Discriminant Analysis (LDA) is used to demonstrate the auditory perception characteristics [163]. LDA is a technique used to locate a linear combination of characteristics in statistics, pattern recognition, and machine learning that defines or distinguishes the classes of objects or occurrences. The combination can be used before subsequent classification as a linear classifier or, more frequently, for dimensionality reduction. Assuming that all the classes are sharing similar dimensional matrix of covariance and the model suits each class with a Gaussian density. The ratio of in-class variance to inter-class variance is maximized with this methodology in order to reduce information variability in the same class and increase class segregation. Therefore, solid boundaries are built between classes by defining it as a linear classifier. The linear sequence of features that categorize or distinct classes is found using LDA, which offers a better understanding of the distribution of data features [162].

LDA can deal with cases where there is an unequal amount of volunteers in each class. It is performed on condition sub-sets using three features corresponding to three frequen-

cies (the registered frequency from the first test, the registered frequency from the second test, and the average frequency from the two). The matrix of three-dimensional characteristics is projected onto a lower-dimensional room by maximizing the variance between classes while minimizing the variance between classes. The axes of the predicted information are called linear discriminant and show the maximum distance between the distinct age groups, thus offering a visual proof or not that age groups appear to be well distinguished or not taking into account the recorded hearable frequencies.

2.2.3 Human age estimation and classification

The second part concerns the classification into age groups of the various auditory perceived reactions. Two supervised learning techniques are used: Support Vector Machine (SVM) and Random Forest (RF) support. While their performance guarantees have been demonstrated, these two classifiers are among the most commonly used in computer vision and pattern recognition applications.

Support Vector Machine (SVM): were originally proposed by Boser, Guyon and Vapnik in 1992 [164, 171]. SVM optimizes the "margin," and therefore depends on the "distance" idea between distinct points, and the user has to decide how much the distance is important. SVM provides you with "support vectors," which are points for each class nearest to the class border. It depends on the choice of analysis of their own. SVMs constructs a set of hyperplanes that maximize the separation, or margin, between samples of the different classes. In their original space, the sets to discriminate might not be linearly separable. Thus, the initial finite-dimensional space was suggested to be mapped into a much higher-dimensional space, probably making it simpler to separate in that space. There are evaluations of several transformations or kernel features. Multiple values for gamma and cost has been tested ($gamma = 0.5, 0.8, 1, 2$ and $cost = 10^{-1}, 10^1$). The best results were achieved with radial kernel, $gamma = 2$ and $cost = 10$.

Random Forest (RF): were proposed by Leo Breiman in 2001 [168]. With a combination of mathematical and categorical characteristics, Random Forest operates well. It's also okay when characteristics are on different scales. Approximately, you can use information as they are with Random Forest. RF is a set of larger decision trees that are created on bootstrap samples of the training data by using a random selection of variable subsets. Every tree of the forest then votes to determine the sample's class, and a majority vote makes the final decision. Breiman builds the RF classifier with suggested values for the number of decision trees equal to 500 and the number of characteristics used to divide the node in Mtry's decision tree growing phase. It is fixed to 0.10, which is quite close also to the recommended value by Breiman ($Mtry = \sqrt{p}$ where p is the feature vector size, p in our experiment is 3).

Approach of classification: SVM and RF classifiers with $k=10$ are used to perform stratified k-fold cross-validation. Cross-validation is a method for evaluating predictive models by dividing the initial sample into a model training set and a test set for evaluating it [165–167]. Cross-validation loops are used to optimize the algorithm parameters

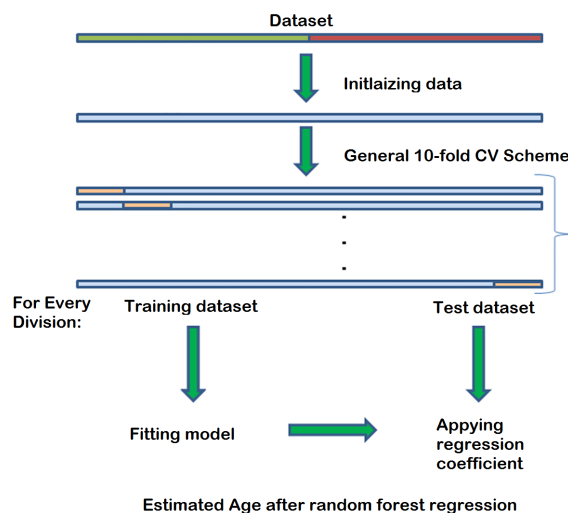


Figure 2.3: 10 fold cross-validation using random forest

by further dividing each of the ten initial training datasets into smaller training datasets and validation datasets. Cross-validation efficiency is calculated for each combination of the classifier parameters, and then the best performing parameters are selected within the loop. Classification with the highest parameters will then be implemented to the initial test data set [169, 170]. This method, which was constructed using the training dataset, acquired the ultimate output. 10-fold cross-validation based approach for testing and evaluation is summarized in Figure 2.3.

After statistically quantifying the datasets, each age group is well discriminated. A regression model has been designed in order to estimate the age of a subject after conducting the experiment.

Two types of techniques have been used for human age estimation, such as Regression Forests and Support Vector Regression. Regression Forests (RF) is an ensemble of various forests of regression. Using various nonlinear regression, they predict true valued figures at leaf nodes. Support Vector Regression (SVR) utilizes the same classification principle as SVM by optimizing the regression generalization boundaries. In the estimation of real numbers, a tolerance margin (epsilon) is counted, and a loss function is identified that ignores errors that are stimulated to the true value within a certain range.

2.2.4 Experimental results

To asses the system, different machines are used such as DELL corei7 M4700 computer, MacbookAir 2018, and desktop computer dell Corei7 Z800. The minimum distance between the computer and the subject while conducted the experiment is 12 inches. The sound intensity A_0 generated by our system is set to 95db and, the duration $t_1 = 10s$, $t_2 = 15s$, $t_3 = 20s$, $t_4 = 40s$ and $t_5 = 60s$.

The collection of the data from the subject will be described in the section below, including the age group discrimination assessment method. Subsequently, the discrimination

based on auditory perception between the distinct age groups is emphasized. Finally, the results of age estimation are explained in detail with comparison to other biometric modalities.

2.2.4.1 Auditory Perception Database(APDB)

In this experiment, around 282 subjects from different ages and gender participated in each protocol, and 1117 tests are performed, which represent the total number of samples in the database. The required time to conduct the complete test is 10 minutes. Some of the subjects were unable to complete the entire eight tests because it was time-consuming and irritable. This is why, the number of subjects for each protocol is not balanced as required as shown in Table 2.1, Table 2.2.

The collected dataset is subdivided into three and five age groups for classification purposes to demonstrate the separation better. As shown in Table 2.1, a volunteer belong to:

- Child: if the volunteer conducting the experiment is less than 12 years old,
- Teenager: if the age of the volunteer conducting the experiment is between 12 to 18 years old,
- Adult: if the volunteer conducting the experiment is more than 18 years old.

The number of subjects in child and teenager age groups is almost balanced, while more subjects participated in an adult group for the experiment. As shown in Table 2.2, the two age groups of child and teenager are kept the same as in the dataset of three age groups. The adult age group is further subdivided into three more groups:

- Young adult: if the age of the volunteer conducting the experiment is between 19 and 29 years old,
- Adult: if the age of the volunteer conducting the experiment is between 30 and 50 years old,
- Aged: if the volunteer conducting the experiment has more than 50 years old.

About 25 subjects participated in the experiment on each of the eight tests, with the exception of the adult age group (30-50 y), in which we have over 40 samples. During the next steps of data analysis and handling, weighting down the group is implemented to balance the distinct age groups.

2.2.4.2 Results

First, the protocol S-BS for $t_1 = 10s$ has been considered so that it is divided into three age groups and then subdivided into five age groups. The LDA has been carried out, and the samples are predicted on the first two linear discriminating axes (LD1 and LD2). The peculiarity of LDA is to define the distribution of predictor individually in each of the response classes and then uses the theorem of Bayes to estimate the probability. The data of all the groups are not well discriminated, and each group somehow overlap each other, as shown in figure 2.4. While for the second protocol $t_2 = 15$, LDA is also performed,

Table 2.1: Number of volunteers in each group of the three age groups within the six datasets

Datasets	Child < 12	Teenager 12 – 18	Adult > 18	Total
With Speaker				
S-BS (10s)	22	26	91	139
S-BS (15s)	22	26	93	141
S-BS (20s)	22	26	93	141
S-BS (40s)	22	26	90	138
S-BS (60s)	22	26	89	137
With Headphone				
H-BS	22	26	95	143
H-RS	22	26	91	141
H-LS	22	26	87	137

Table 2.2: Number of volunteers in each group of the five age groups within the six datasets

Datasets	Child < 12	Teenager 12 – 18	Young adult 19 – 29	Adult 30 – 50	Aged > 50	Total
With Speaker						
S-BS (10s)	22	26	29	41	21	139
S-BS (15s)	22	26	29	43	21	141
S-BS (20s)	22	26	29	43	21	141
S-BS (40)	22	26	28	41	21	138
S-BS (60s)	22	26	28	40	21	137
With Headphone						
H-BS	22	26	32	42	21	143
H-RS	22	26	27	43	21	141
H-LR	22	26	25	41	21	137

the projected data shows overlap among all the given groups and the data is not very well discriminated as shown in figure 2.5.

Considering the protocol S-BS for $t_3 = 20s$, such that it has been divided into three age groups and then in five age groups. The projected data are presented in Figure 2.6-a and show a higher separation among the three age groups of child, teenager, and adult. However, the boundary of the teenager class is not well drawn. The data is projected in three-dimensional space, as shown in Figure 2.6-b. The three age groups can be identified well and consequently. It can be demonstrated that there is a good separation between the three age groups based on the auditory perception responses. In order to check the separability and discrimination, LDA was further performed through the dataset of S-BS for $t_3 = 20s$, which is divided into five age groups. The child and teenager age groups are well separated, but the three age groups of young adult, adult and aged are quite overlapped as shown in the projection of data on the two linear discriminants (Figure 2.6-c) and on the three linear discriminants (Figure 2.6-d).

Considering the second dataset of the first S-BS protocol $t_4 = 40s$, LDA was conducted in three and five age groups for the second dataset. The sample projection into linear discriminants is shown in Figure 2.7 and it has a nice separation between the different age groups but is not very well isolated compared to the S-BS dataset. $t_4 = 40s$. The protocol of S-BS for $t_4 = 40s$ It is not very effective as a child, and teenager age group information is not well segregated.

The third dataset for the first S-BS protocol $t_5 = 60s$ is considered for statistical evaluation. LDA is performed, and the results are shown in Figure 2.8. A big similarity between the results is experienced in the projection of the dataset S-BS for $t_4 = 40s$ and the dataset S-BS for $t_4 = 60s$. In fact, samples from the age group are extremely mixed up. Samples are confused among the different age groups and are not well separated in comparison with S-BS $t_2 = 40s$ dataset.

Consequently, in the first protocol S-BS for $t_3 = 20s$ acts better than the protocol of S-BS for $t_4 = 40s$ and S-BS for $t_5 = 60s$. It shows better discrimination of the different age groups. Considering the same procedure as done for the dataset of S-BS for $t_3 = 20s$, the analysis of the protocols such that H-BS for $t_3 = 20s$, H-RS for $t_3 = 20s$ and H-LS for $t_3 = 20s$ are studied to compare and perceive the best protocol that gives the best discrimination among the different age groups.

LDA is performed upon the dataset of H-BS for $t_3 = 20s$ (Figure 2.9). It shows through the projection into the linear discriminant less separability between the different age groups than the dataset of first protocol S-BS for $t_3 = 20s$ (Figure 2.6). The teenager age group is confused with the child and adult age groups while the five age groups are not well segregated.

In Figure 2.10 and Figure 2.11, the results of the LDA for the third protocol dataset of H-RS for $t_3 = 20s$ and the fourth protocol H-LS for $t_3 = 20s$ after quantifying it for three and five age groups respectively are presented. The results show that the data is not

separated properly as compared to the first protocol S-BS for $t_3 = 20s$ dataset.

In conclusion, the protocol of S-BS for $t_3 = 20s$ according to the LDA, the age groups are more separable than the other protocols. The resulting perceived auditory answers from this protocol can be used to discriminate against age groups. This separability is statistically quantified as follows: first, by defining which a unique observation belongs to the set of age groups and then by studying the data distribution using statistical hypothesis testing.

SVM and RF classifiers are used to classify auditory perception into three and five age groups. With SVM and RF classifiers, ten fold cross-validation is repeated 100 times. The final classification results are calculated and shown in Table 2.3. The best accuracy is achieved for the three age groups with 92% and the S-BS for $t_3 = 20s$ dataset by using RF classifier. For five age groups, the maximum accuracy of classification of 86% is also achieved with the S-BS for $t_3 = 20s$ dataset and the RF classifier.

To explore the classification accuracy rate for each age group, the confusion matrices of the classification of the S-BS for $t_3 = 20s$ dataset are shown in (Table 2.4) using RF classifier into three age groups, and the confusion matrices for five age groups is shown in (Table 2.5) are studied. It is examined in Table 2.4 that the teenager age group has a higher number of subjects that are misclassified into the adult age group. Furthermore, from Table 2.5, it can be seen that the most frequently expected misclassified responses are one of the closer age groups. A more feasible understanding is that within each age group the a-priori age range is not well defined and may be different for our application.

For this experiment, RF shows higher accuracy for classification as compared to SVM. To conclude, the separability between the different age groups is important and evident. Thus, in the first S-BS protocol for $t_3 = 20s$, which corresponds to the shortest duration and most discriminating experiment, the auditory perception is well discriminated. A shorter interval provides better results. The listening fatigue might be the reason because it requires a great deal of effort and energy to listen. It can make a subject very tired because of the loss of energy, while it is a little harder for a subject to conduct the experiment in good order.

Univariate analysis is applied to the S-BS protocol dataset for $t_3 = 20s$, after the statistical evaluation to find the most effective protocol among all the datasets. Using univariate T-Tests on the average frequency of the two tests to select those displaying a statistical difference, the samples of the different age groups were systematically compared.

To quantify the concept of the statistical importance of proof, the T-test is based on null hypothesis testing. A likelihood value (p-value) is calculated using a collection of random variables to quantify the probability of a specified statistical model. In other words, it measures the magnitude of the change within the data samples relative to the variation. A graphical interpretation using boxplots is shown in Figure 2.12 and Figure 2.13 relation to the descriptive analysis of the separability of age groups. The boxplots show variations in samples of the three or five populations (age groups) provided and point to variability or correlation intra and inter-class.

Table 2.3: Performances of the classification into three or five age groups

	Random Forest		Support Vector Machine	
	3 Groups	5 groups	3 groups	5 groups
S-BS (10s)	61%	57%	55%	47%
S-BS (15s)	79%	73%	51%	48%
S-BS (20s)	92%	86%	80%	65%
S-BS (40s)	91%	84%	67%	56%
S-BS (60s)	86%	80%	65%	45%
H-BS	86%	81%	69%	47%
H-RS	86%	80%	66%	50%
H-LS	84%	81%	56%	41%

Table 2.4: Confusion matrix of the classification using RF classifier of S-BS for $t_1 = 20s$ dataset into three age groups

	Child	Teenager	Adult	Omission	Commission
Child	21	1	0	5%	0%
Teenager	0	25	3	11%	4%
Adult	0	0	93	0%	3%
Correctly classified	21	25	93		
Total	21	26	96		
Overall accuracy	92%				

Table 2.5: Confusion matrix of the classification using RF classifier of S-BS for $t_1 = 20s$ dataset into five age groups

	Child	Teenager	Young adult	Adult	Aged	Omission	Commission
Child	21	1	0	0	0	5%	0%
Teenager	0	25	1	0	0	4%	4%
Young adult	0	0	29	0	0	0%	3%
Adult	0	0	0	40	0	0%	2%
Aged	0	0	0	1	20	5%	0%
Correctly classified	21	25	29	40	20		
Total	21	26	30	41	20		
Overall accuracy	86%						

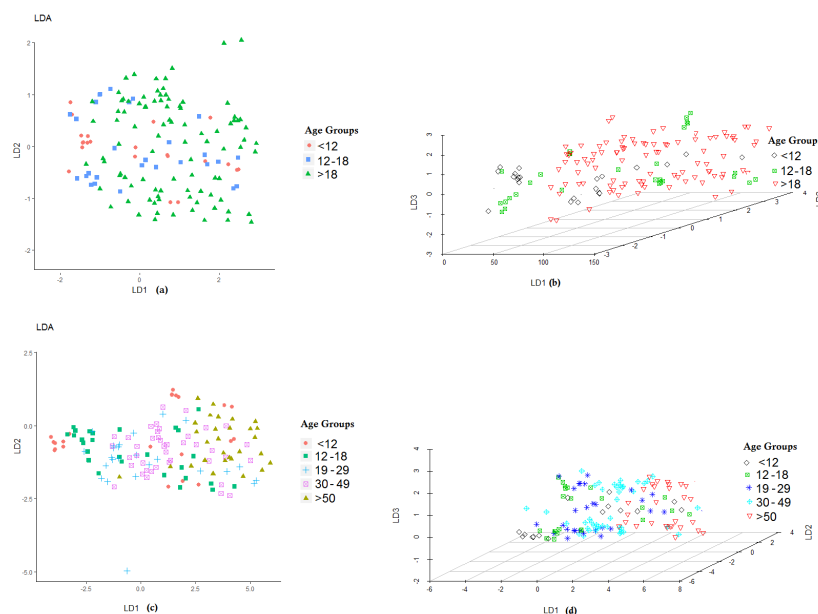


Figure 2.4: LDA applied to S-BS for $t_1 = 10s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

The p-value among the three age groups of a child, teenager, and adult are inferior to 10^{-8} . The three age groups are therefore very different and discriminating on the basis of the volunteers' hearable frequencies. The distribution of volunteers within the adult age group is more widespread, meaning that within this group there is great variability.

The division of this age group into three groups demonstrates that the five age groups are also different and well divided according to the p-value of the T-test. The p-value is also below 10^{-8} . The distribution of adult age group samples is the most dispersed, and there is confusion about data from young adults and older groups. It is also the case with young adult age group samples, some samples may be misclassified as adult samples. Consequently, despite the outliers samples, the p-value is a matter-of-fact that the estimation of age is possible using the auditory perception.

The results of the age estimation regression analysis using RF and SVR are summarized in table 2.2.4.2. In fact, 10-fold cross-validation using RF regression demonstrates the highest efficiency rate of 98.2% and for S-BS $t_3 = 20s$ dataset, the smallest Root Mean Square Error (RMSE) of 2.6 years. The resulting model is stable, and the average value of the estimated ages is small, represented by the variance, and corresponds to 4.14 years. SVR shows lower accuracy than RF for S-BS for $t_3 = 20s$ dataset. Consequently, the 10-fold cross-validation regression model constructed using Regression Forests is the most precise approach to age estimation using auditory perception.

In addition, the present proposal is vulnerable to user assaults that attempt to spoof the system about their era — considering the fact that we are in the process of creating for our suggested strategy, a powerful anti-spoofing scheme in the future.

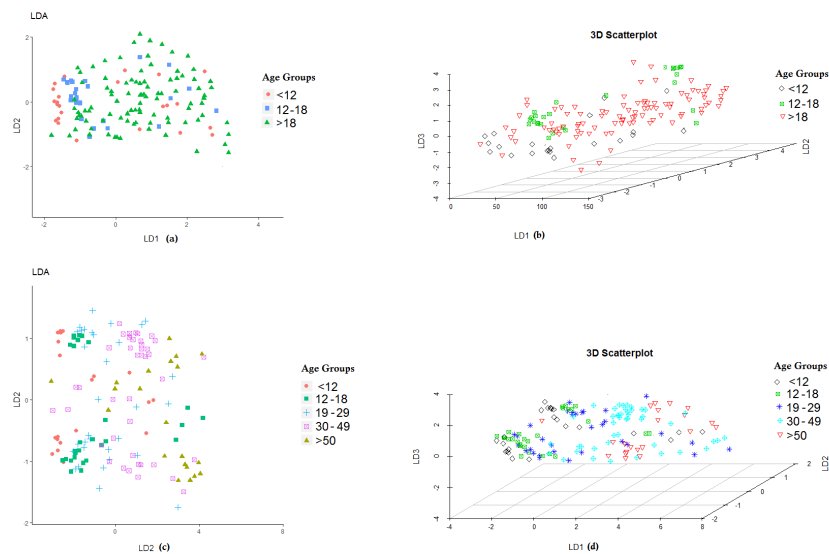


Figure 2.5: LDA applied to S-BS for $t_2 = 15s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

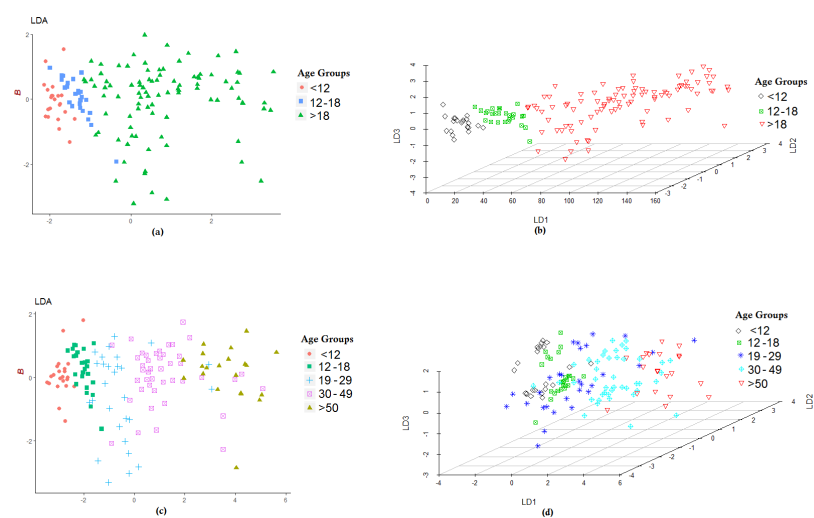


Figure 2.6: LDA applied to S-BS for $t_3 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

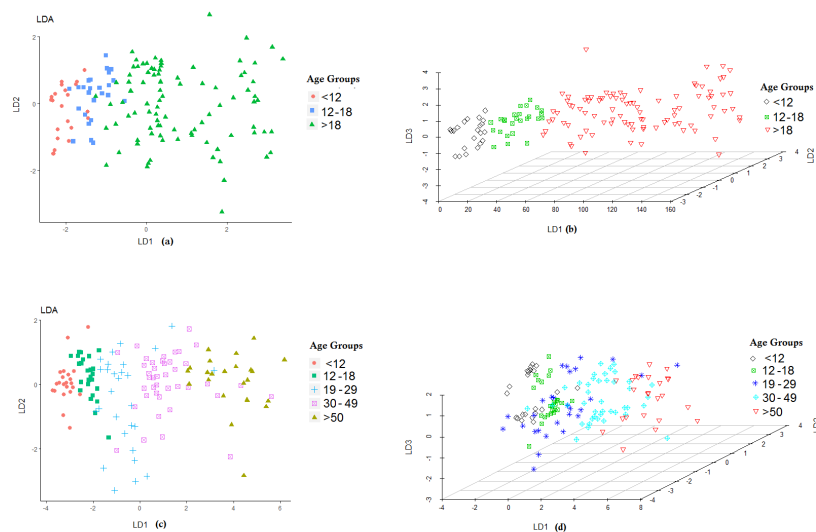


Figure 2.7: LDA applied to S-BS for $t_4 = 40s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

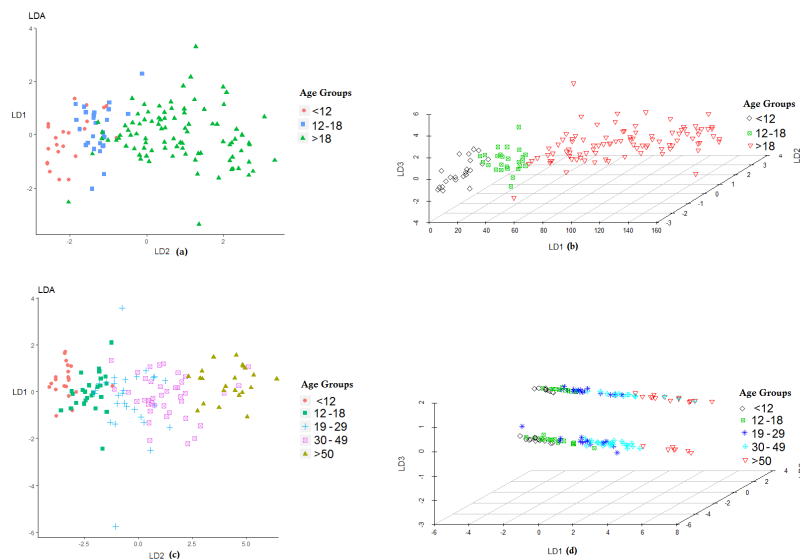


Figure 2.8: LDA applied to S-BS for $t_5 = 60s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

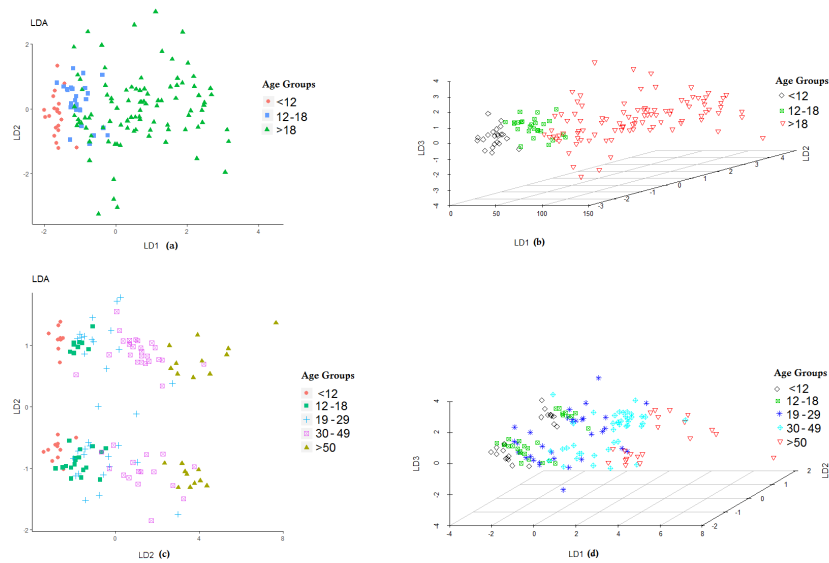


Figure 2.9: LDA applied to H-BS for $t_3 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

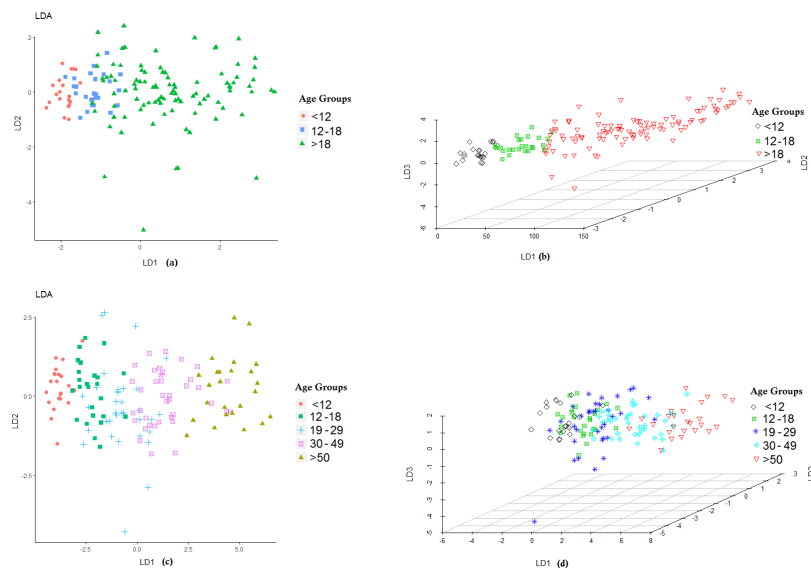


Figure 2.10: LDA applied to H-RS for $t_3 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

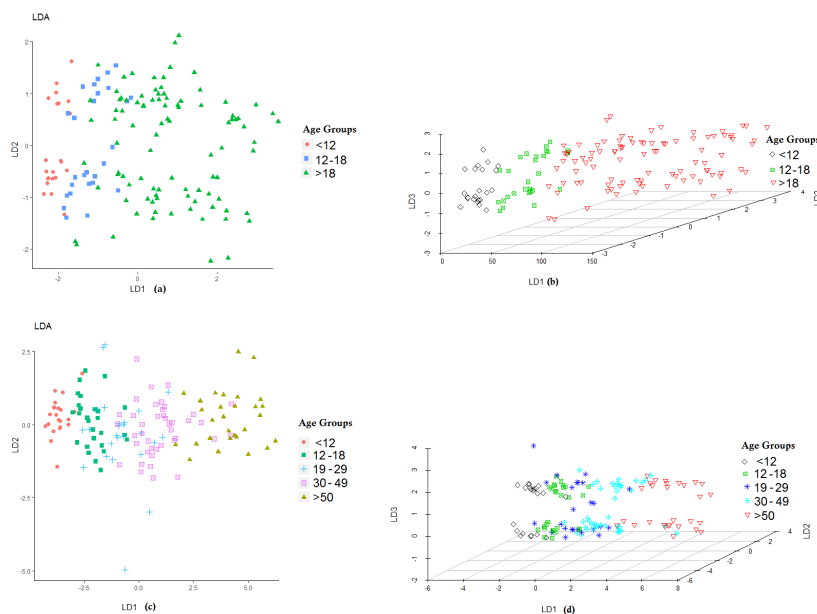


Figure 2.11: LDA applied to H-LS for $t_3 = 20s$ dataset divided into three (top) and five age groups (bottom): data projected on axes LD1 and LD2 (a,c) and on axes LD1, LD2 and LD3 (b,d).

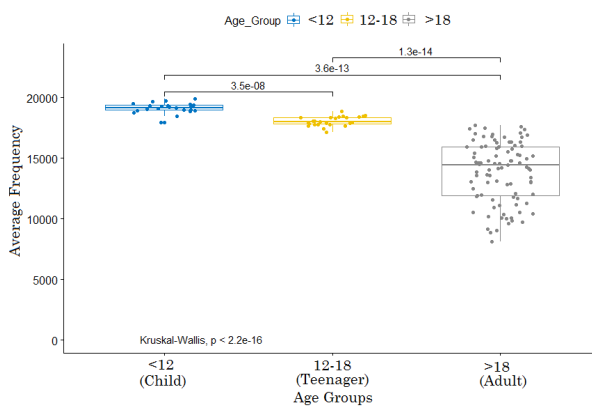


Figure 2.12: Boxplot of the data according to the best discriminating protocol of S-BS for $t_1 = 20s$ for three age groups

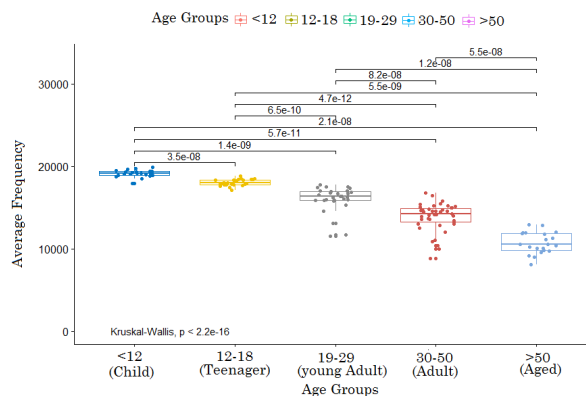


Figure 2.13: Boxplot of the data according to the best discriminating protocol of S-BS for $t_3 = 20s$ for five age groups

Datasets	Accuracy		RMSE		Variance	
	RF	SVR	RF	SVR	RF	SVR
With Speaker						
S-BS (10s)	55.0%	49.1%	11.2	12.5	40.7	48.4
S-BS (15s)	72.3%	69.9%	8.8	8.1	15.6	29.3
S-BS (20s)	98.2%	95.7%	2.6	6.6	4.1	27.1
S-BS (40s)	98.0%	95.5%	2.8	6.7	4.3	25.9
S-BS (60s)	97.2%	95.7%	3.5	5.8	5.1	15.7
With Headphone						
H-BS	97.6%	96.3%	3.1	5.5	4.4	17.7
H-RS	97.4%	94.5%	3.8	6.9	8.7	28.8
H-LS	97.6%	93.1%	3.2	5.8	4.9	19.4

Table 2.6: Performances of the age estimation

2.2.5 Comparison to other biometric modalities

In tables 2.7 and 2.8 present, respectively, the age classification and assessment and comparative results. The existing approaches shown in the classification of age groups Table 2.7 are extracted from published papers [1, 8, 17, 152, 153].

Edinger et al. [17] presented different aspects of the suggested human age classification system design based on the Gallagher benchmark and the Audience list. The age groups in the two benchmarks are divergent, the difficulties represented by each data set can not be compared directly. The "accurate" ranking as the average precision of anticipating the real age label across all age classes. "1-off" means collecting mistakes in branding, one age group divided as right from the real label. Dropout 0.5 indicates dropoutSVM with a 50% chance of losing characteristics; Dropout 0.8 indicates 80% of the entry characteristics fell from two parts of the entry feature vector, spontaneously and separately. The highest accuracy for human age classification is 66.6% by the proposed system by Edinger et al.

Syed et al. [324] presented a voice based approach for human classification. The fusion of many classifiers trained from distinct sources was regarded in the current work to classify the age of a speaker. The voice information was split into six vowel segments to decrease the difficulty of the data distribution in n-dimensional feature space. Subsequently, age ranking based on vowel was conducted to handle the information. Fuzzy information fusion is subsequently used to fuse the decisions of the classifiers trained in the preceding phase. Compared to the evaluation precision of each band or vowel autonomous ranking, the general precision of the choice fusion shows a significant enhancement. The highest accuracy shown by the proposed system is 60.8% for three age groups. Moyses [1] presented a review for human age classification based on voice and highest accuracy was nearly 70% for 5 age groups.

Ioannis et al. [37] presented an incident response method is suggested to handle authentication failure detections in applications using adaptive biometric authentication and, more precisely, keystroke user identification. The approach's primary element is

a multi-layer perceptron that focuses on a user's age classification. Causal inference indicate that the classifier can identify the individual's birth with a likelihood that is far from a standardized random sampling, thus rendering the suggested technique appropriate for offering encouraging yet forensic evidence during e-discovery. For two classes they found an accuracy of 73% while for four classes the accuracy was 66%. Uzun et al. [153] presented a binary classification technique with an accuracy of 90%. The auditory perception-based approach achieves the highest results for age classification than the face, voice and keystroke-based methods. Meanwhile for three age groups and five age groups, the classification performance based on auditory perception is promising.

On the other hand different biometric modalities are also used for human age estimation such as face, voice, gait, DNA etc. Lanitis et al. [8] presented an experimental assessment of the problem of automatic age estimation, evaluating the performance of a quadratic function classifier, the shortest distance classifier, and neural network-based classifiers. Whenever a single step classification technique was utilized and when hierarchical age estimation techniques were utilized, the classifiers in question were assessed. The results obtained from the automatic estimation of age compare favorably with the results obtained by humans on the task of estimating age based on face images. In general, human observers were tested on a comparable but significantly smaller database for an age estimation error of 3.64 years.

The human age can also affects the voice of a an individual. Moyses et al. [1] have shown in his review upon different biometric techniques used by researches and demonstrated the influence of age on human voices. Age estimation through human has shown an absolute error scores that was higher in older as compared to young individuals, such that 11.37 and 10.14. In parallel to that, the absolute error of 6.83 years, has found in older individuals that estimated less accurately such as 6.30 years 5.91 years as compared to face images. As a conclusion the the absolute error is mention as in the range of 4.7 years to 10 years.

Gait is also considered a potential biometric trait for human estimation. From distance to distance human age estimation has several real-time applications, that include surveillance, tracking in public sectors and airports, sensitive entrances inside a building. Jiwen et al. [121] presented a technique to characterize better the nature of human gait and improve the robustness of the proposed age estimation process, we extract a collection of over-complete Gabor features including both Gabor magnitude and Gabor step details of gait sequences and perform several feature fusion to boost age estimation efficiency. The experimental setup using gait features demonstrated the effectiveness of the proposed approach with the absolute error value of 6 years. Yashuki et al. [132] provided a baseline algorithm based on gait signature for age estimation integrated by Gaussian process regression, which was effective in the face-based age estimation field, in accordance with silhouette-based gait characteristics such as an average silhouette (or Gait Energy Image) that was commonly utilized in many gait recognition algorithms. While the performance of the proposed system was demonstrated with a mean absolute error value of 8.2 years.

The estimation of forensic age was originally based on morphological examination and radiography and molecular methods only began to follow later. Nevertheless, the imple-

mentation of these DNA-based techniques for investigation evaluation was delayed by lack of accuracy and technical problems. The epigenetic pattern of DNA methylation was determined to alter slowly during a person's lifetime and considered as a turning point. While more research has been required to increase predictor accuracy and to develop a wider range of tissues for which tests can examine the most suitable sites, a number of predictors of the forensic era have been recorded that provide reliable data on their prediction accuracy (predictive error of ± 4 years).

As shown in Table 2.8, the auditory perception based human age estimation approach has a significantly smaller mean absolute error of age estimation than the existing approaches based on face [8], voice [1], gait [33, 37] and DNA [137]. Last but not least, this result obviously shows that auditory perception leads with a much better classification and estimation of age compared to conventional biometric methods.

	Ref	Age classification				
		2 groups	3 groups	4 groups	5 groups	7 groups
Face	[17]					66.6%
Voice	[324]		60.83%			
	[1]				$\cong 70\%$	
Keystroke	[37]	73%		66%		
	[153]	$\cong 90\%$				
Auditory Perception	our approach		92%		86%	

Table 2.7: Performance comparison of several approaches of age groups classification

	Ref	Mean Absolute Error (Years)	
Face	[8]	Quadratic Classifier	4.87
		Shortest Distance	5.02
		MLP	3.64
		Human	5
Voice	[1]		4.7 to 10
Gait	[124]		6
	[37]		8.2
DNA	[137]		4
Auditory perception	our approach		2.6

Table 2.8: Performance comparison of several approaches of age estimation

2.3 Conclusion

A novel approach is introduced in the field of biometric about forensic age classification and estimation based on the auditory perception. The first protocol S-BS for $t_3 = 20s$ is demonstrated as more descriptive and separable according to the age sub-division. Among all the classifiers, Random Forest has shown the promising and most accurate results for human age classification and estimation. Using the first protocol S-BS for

$t_3 = 20s$ and Random Forest classifier, a good classification rate of 92% accuracy has been achieved for three age groups while 86% of accuracy is achieved for five age groups respectively. An efficient regression model is also built by using Random Forest Regression, and it shows an accuracy rate of 98.2% and a root mean square of error of 2.6 years. After demonstrating the possibility of human age estimation, we feel the need for real-time implementation of this approach to propose possible applications.

Chapter 3

A Web Control Access System Based On Human Auditory Perception For Children Protection

Security problems fall into being along with the development of web interfaces. Practical tools are needed to control entry and filter unwanted web content. Access control filter is a safety method that controls who and what should be accessed or viewed by an individual in a computing atmosphere. An internet security system is introduced, based on age estimation using auditory perception responses, taking into consideration the connection between human age and auditory perception responses. In specific, the access is canceled if the subject age is not suitable to given web content. Compared to the existing web access filters, the BiometricAccessFilter technique proposed higher security and data protection to an individual's privacy. Different machine learning regression models have been analyzed to enhance the performance of the BiometricAccessFilter system. The primary contribution of the proposed approach is human age estimation, which is proceeded to an open-source web access filter to prevent the access of adults to a web application specially designed for kids.

3.1 Introduction

WebAccessControl is a decentralization system that allows various users and groups to access major types of information in which HyperText Transfer Protocol (HTTP) Uniform Resource Identifiers (URIs) correctly identify users and groups. WebAccesscontrol is the basic element of security systems answerable to assess if a user can be allowed to operate in a specific way on a certain application. It can guarantee more privacy and confidentiality. According to Brandeis and Warren's study [185], privacy can be defined as the right to be let alone. Transparency is the main quality that can guarantee greater access to data sources throughout all system layers. Along with the rising advancement of networking capacities, telecommunications systems, traditional information systems, Software, and hardware system, have developed to ensure greater transparency, operability, and better sharing of data between the various sub-components of a data system that generally related to heterogeneous stages of confidentiality. Scientific developments and the incorporation of emerging technological advancement in everyday applications for

the well being of humans have allowed faster connections and increased availability to data resources. The whole advancement allowed the users to communicate freely and access various resources of data "anytime, anywhere and anyhow", this is how the system would become ubiquitous or omnipresent.

Secrecy is a much-needed standard that can guarantee greater access to sources of data at all system phases. Using this standard without restrictions, though, it can render resources susceptible to attacks and threats on security. This is what creates a constraint to science and technology that stands throughout the manner of such model's development. Evaluating the availability task inside Pervasive Information Systems (PIS), it is discovered that it would be extremely necessary to achieve an equilibrium between data discretion and data transparency, particularly when considering access applications to sources of information situated within multi-distributive settings and controlled by various officials. In particular, for mobile users, the evolution of PIS has brought challenges in managing data access. Such technologies will enable customers to attain data integrity simultaneously and the system through the application of rigid access control measures, which can ensure its security and keep from being exposed to intrusion threats. Along with the proposed, existing solution, there are new challenges that have been implemented with technological development, such as the difficulty of controlling access in dynamic environments. As a matter of fact, many research studies have been done to develop the role back access control mechanism as a ground for context-aware models of access control, but the suggested designs did not bring the significance of usability into consideration, situational awareness, and enhancing possibilities for access.

Due to the heterogeneousness of computers, operating systems, information designs, and programming languages used for application development, the handling of distributed information has always been a difficult issue to solve. Though, the standard for the web has changed according to the situation, such that the aim is offering a connection protocol among computers, are known as "web services," which composed of a service-oriented architecture which makes it possible to easily transform and distribute information sources that have become accessible everywhere. In the era of system-oriented interfaces and considering the multi-distributive existence of access control proposals that manage sources of information in pervasive environments, access control efforts have been directed towards decision-making from multiple distributed access policies, managed by different services, and sometimes generated in real-time.

In the era of modern computing systems, when individuals around the globe appreciate every aspect of information technology, the security of information has become a very challenging and complicated issue. Security breaches to secured data may result in inconceivable destruction. The internet rapidly became a significant tool for debate, trade, and company after a brief span of being no more than a hobby. Rather than keeping data that the whole globe could see, web pages were also used to obtain telephone, economic documents, and other private or proprietary data that were intended to be accessed by people or organizations only. The ultimate goal of many security scientists and technicians is to provide a safe, versatile, neutral strategy and yet easy to manage access control model. Different access control technologies were suggested, offering some benefits, but a full, excellently-studied system also needs to be constructed. The web access control

system is one of the promising solutions to solving access control tasks.

Access control has primary entities that are active targets that access certain passive items that are secured. The main flaws in access control are the significant amount of subjects and items that need to be managed, particularly in a distributed setting where users and resources are dispersed. The concepts of "group", "role", "compartment", "level", etc. were implemented to fix this issue. It is possible for a group of subjects with the same access rights enters into another group. Likewise, for safety reasons (such as top-secret, secret, confidential, etc.), objects can be categorized into distinct levels. Besides, access authorizations can be collected into priority lists to modify the management of access control. Analyzing the administration of security policy while enhancing the expressive authority of access control systems to provide flexible, tailored strategies was and remain the primary objective of an ideal model of access control.

3.1.1 Access control

The computer security conventional core of attraction is known as access control. This is where computer science intersects with security engineering. Its primary role is to regulate which director has access to which source of data or information in the system (people, methods, equipment). Such as, which documents you can access, which operation you can run, how you distribute information with other managers, etc [174].

Access control is about deciding valid members to permit operation, mediating any effort by a customer to access a source of data in the system. Following effective user authentication, full access is given in some systems, but most applications involve a more advanced and complicated control system. Authentication would be any method through which the system confirms that the person he says to be is legitimate. It generally includes a login and password but can include any other technique of showing identities such as smart card, retina, speech recognition, or fingerprints.

In relation to the authentication process, how approvals are organized is concerned with an access control system. The authorization is to figure out if the individual is allowed to access the tool once authenticated. It is recognized by analyzing applications against related activities, determining that the measures required can be given.

3.1.1.1 Life cycle of access control system

The access control life cycle begins with an access request given by a topic who requests the scheme to conduct an activity on a certain item, as shown in figure 3.1. The system will review the authorizations issued to this institution according to features and background of the user, and it will respond to his application with binary replies: a "Yes" will permit the topic to execute the required behavior on the item or a "No" that can reverse that application. It provides next, the meanings of the primary organizations that occur in an approval scheme to simply comprehend this system.

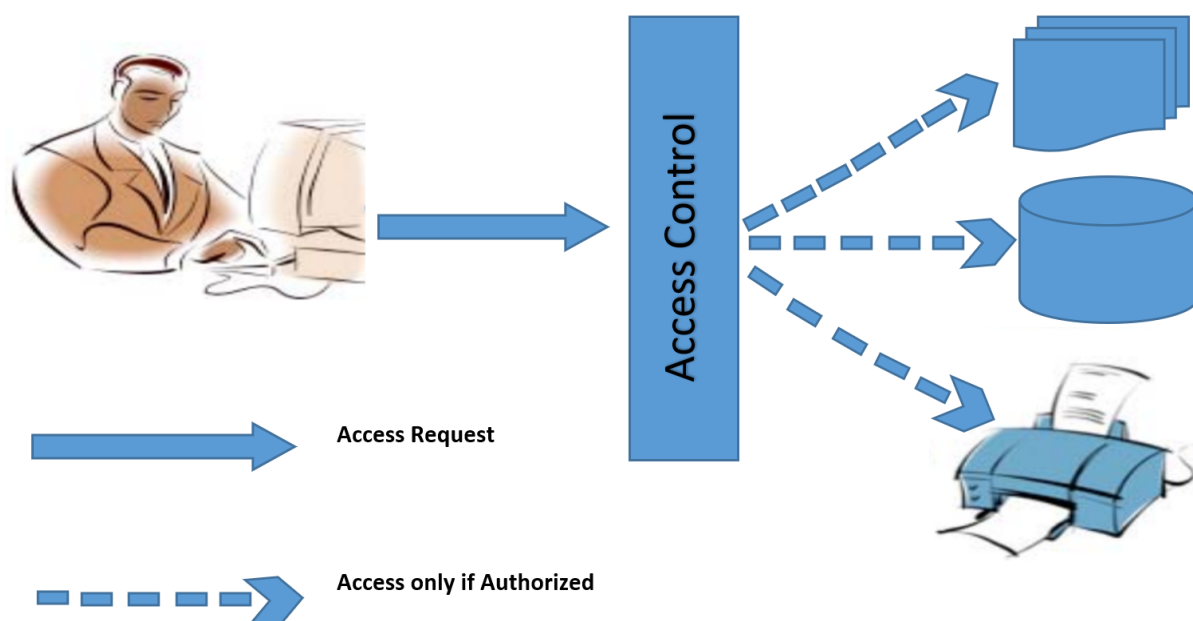


Figure 3.1: Life cycle of access control system

Subject is a live entity in the state of a human, process, or instrument which creates data to seep between different entities or can modify the form of the system [186].

Object: An object containing data or receiving it. Access to an item may involve access to the data contained therein. Explanations of objects are records, blocks, fields, pages, files, segments, directories, processes, directory trees, and programs, along with video displays, processors, clocks, keyboards, network nodes, and printers. The class of artifacts [186] may also include equipment's like, electrical switches, disk-drives, relays, and mechanical elements linked with a computer system.

Action/Operation is an active process initiated on items by a topic; for example, various activities are conducted with a particular record (write, read, execute, delete, etc.).

Permission (privilege) is the approval of executing some intervention on the system allocated to a subject. The word authorization relates to a certain combination of items and procedures in most computer security literature. A specific procedure used on two various items reflects two separate permissions, and likewise, two different activities implemented to an item constitute two separate access rights [187].

3.1.1.2 Access Control execution

Interacting with private sources of data within the same centralized system needs processes for access control, which can safeguard these resources from any risk. To ensure complete security, availability should be regulated throughout all interaction lines beginning from software point, middleware level, working unit tier and lastly via a network, the features of appropriate entry command are outlined in these levels [188]:

Application level are the processes of access control that the customer considers at the

stage of the implementation can convey a diverse and complicated security policy. It could be accomplished through properly comprehensive authentication and verification checks based on the sensitivity of the application's, tracking rights to guarantee the access that are the minimum needed for the present company requirements of the customer, using time limitations on entry as suitable, recording access to safety occurrences and subsequently using a software.

Middleware is an addition to applications that can be published, for example, a database management system or a package of keeping books that invoke a range of protective characteristics. Such that, a book-keeping program may need to make sure another ledger for the same amount is credited to a transaction that charges for a certain quantity for one account.

Operating system provides the facilities to middleware. As this develops resources from lower-level elements such as documents and communications ports, it takes on the obligation to provide methods to regulate access to them. Effective access control should be carried out by: (1) ensuring access to the services of the system, (ii) limiting and tracking special access, (iii) registering and tracking user's or program access to delicate sources and alarming safety occurrences, (iv) upgrading safety patched working systems and (v) securing equipment's that can be used.

At **network level** access control should be highly ensured. It operates to provide security against unlawful access through various levels of access controls. Organizations must organize network servers, applications, information and customers into security domains such that untrusted external networks, exterior service suppliers or multiple inner customer devices), create suitable access criteria within and between each security domain, introduce suitable technical checks to continuously satisfy these access demands and follow cross-domain access for safety policy violation and illegitimate processes.

Lastly, the entry checks of the operating system will generally depend on the processor's hardware characteristics or related memory management hardware. These checks can be accessed, which memory handles the process.

3.1.1.3 Access control management

In general, the application of an access control system is focused on three primary ideas [184]: access control strategies, designs, and processes.

Making secure access to some systems and applications is a serious matter, and thus, biometric technology provides a solution to the proposed problems. Biometrics can offer notable solutions for a person's identification to make our life more secure and private.

Access control policies defines the guidelines for regulating access controls. Access control strategies are generally vibrant in nature, as they must represent changing company variables, public laws, and economic circumstances. Policies are conditions of high-level that indicate how to control access and who, under what conditions, can access data.

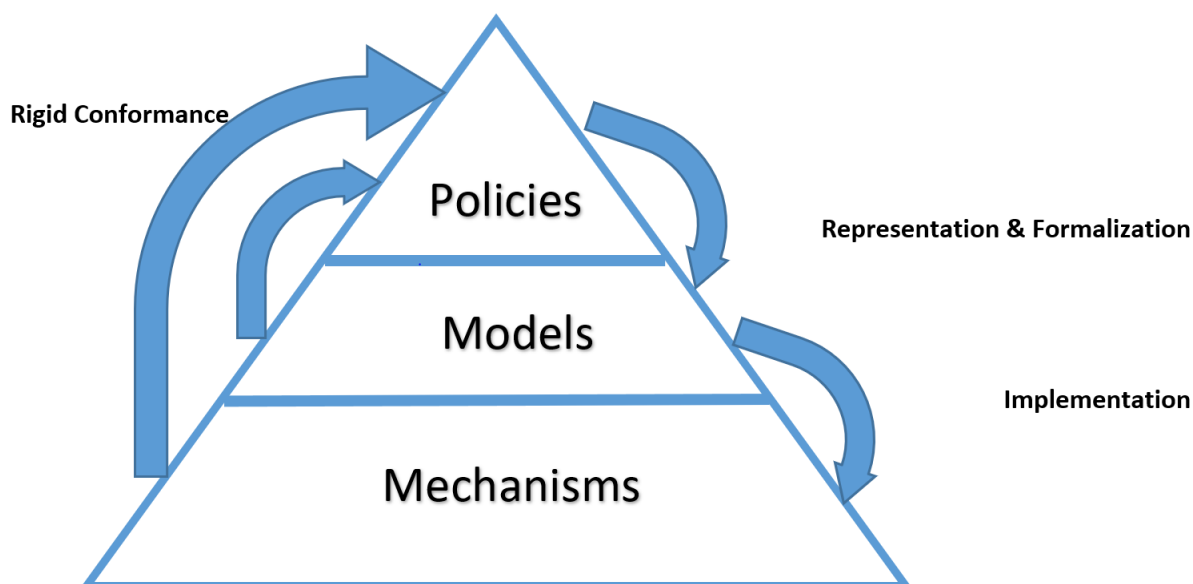


Figure 3.2: Implementation concept of access control

Access control model provides an official description of the security measures of access control. The conceptual model enables the security characteristics supplied by the constructed access control system to be demonstrated. Security designs are helpful in proving the theoretical constraints of a system as comprehensive demonstrations of the security policy imposed by the system.

Access control mechanism usually they arrive at a low level of abstraction where they implement such high-level access control measures and transmit the user application for entry to the particular framework provided by the system.

Access control designs are important because of the capacity to bridge the gap between user strategies and processes. Instead of just trying exclusively at the mechanism level to assess and analyze access control systems, access control designs are generally published to define the security properties of an access control system.

Biometric approaches provide a sophisticated guide with three components to solve the problems of access control. The first concern the data acquisition of distinctive, unique, and measurable characteristics used to describe individuals. The second component takes care of the compression and the processing of the data to make it suitable for different situations. The third component concerns the verification process.

During the last few years, biometric applications for web security and web control access have been developed based on the physical and behavioral features of humans. What lies ahead is a huge task of protection of sensitive and confidential information in this digitized era. Access to one's account's information on the internet is traditionally secured by the help of usernames and passwords or pins.

These techniques could not be trusted to the extent that they can not identify an indi-

vidual who has obtained the data required for validation [190]. Biometric techniques, like pseudo-intrusion and anti-spoofing, are utilized to secure a person or an institution's private information.

3.1.2 Non-biometric approaches for web access control

Username and passwords are mostly used among internet access methods to limit/give access to the content of a webpage. Many organizations have webpages that require limited access. For those who want to access, the administration first needs a centralized and genuine login. The access control system also used the ticket assignment strategy for consumers to access a suggested website. This rendered designing processes might limit entry to webpages possible. The commonly utilized system is to encourage the customer for a username and password before a website's data can be viewed.

Fu, Kevin et al [172]. proposed that a constant cause of web-based issues is client authentication. Despite this, many well-studied authentication methods, websites remain to use profoundly weak authentication systems, particularly in non-company settings such as storefronts. Such flaws are sometimes caused by the reckless misuse of web cookies authenticators. They reduced client authentication on two schemes, acquired unlawful entry on eight of the twenty-seven locations we researched, and derived from one of the secret keys utilized to mint authenticators. They include a summary of Web customer authentication, particular constraints, specifications, and safety designs. It involves introducing the exclamatory opponent, an attacker that is amazingly strong, and can modify to request a website. They offer a number of tips to develop a safe authentication system for clients. Using these suggestions, They show the layout and evaluation by the interrogative opponent of a straightforward authentication system that is safe against forgeries. Together with Secure Sockets Layer, they provide a system that is safe from forgery by the competent opponent.

Bauer L et al. [173] explains how a new web access control system is designed, implemented, and executed. In order to obtain higher flexibility in the implementation of access control policies – in specific to enable better interoperability across administrative limits – they proposed a scheme on the proof-carrying authorization concepts. With the concept of objectives and meetings, an extended model of proof-carrying authorization and a module system is added to the language of evidence. They proposed an access control system that allows the location and use of security policy bits allocated throughout random users. It offers a system to hide components of the security policy from unauthorized customers. The system is introduced as modules extending a conventional web server and internet browser to utilize proof-carrying permission to monitor the web page's access. By iteratively collecting proof elements, the web browser produces proofs mechanically until proof can be built. They proposed an iterative approval whereby a server may need a browser to demonstrate a number of problems. Execution involves a sequence of optimization, such as speculation proofing, and modularization and caching proofing, and shows that generalization, flexible, and integration objectives are consistent with decent results.

In a web-based application, controlling access is the basic element of the design. Systems assigning certificates such as kerberos ticket [191] or an X.509 certificate [192] is issued to a user for the verification to authorize him/her to access a specific webpage. These kinds of systems have not yet achieved a wide range of appreciation, and it fails to provide compatibility between administrative domains. International Standard describes a structure for records and attributes of public-key certificates. Other standards authorities can use these frameworks to describe their implementation to public key infrastructures and privacy control infrastructures. The above Proposal International Standard also sets out a structure for providing Directory authentication facilities to its customers. It defines two stages of verification: easy verification, using a password as requested identity verification, and strong verification, comprising signatures created using cryptographic methods. Even as basic authentication provides some restricted security against unlawful access, only strong authentication should be used as the grounds for safe service delivery.

Several approaches have been proposed for web control access and intrusion detection [193, 194]. Existing intrusion detection operates to secure the systems in isolation from access command. The failure of communication and interoperation between such parts makes it impossible to track and react to continuing assaults in real-time before causing harm. To handle it, vibrant permission methods are used to help the detection and reaction capacities of fine-grained access command and implementation tier interference. The Generic Authorization and Access Control-Application Program Interface (GAA-API) is integrated to provide the Apache Web Server with vibrant intrusion detection and reaction. The GAA-API is a generic API that can be used for many applications to allow such vibrant approval and responses to intrusion. [193].

W. Hu et al. [194] have introduced two internet intruder prevention algorithms built on Adaboost. A traditional Adaboost internet method is used in the first algorithm where choice stumps are utilized as soft classifications. An enhanced online Adaboost method is suggested in the second algorithm, and soft classifiers are proposed for online Gaussian Mixture Models (GMMs). They also suggested a disperse intrusion detection structure, in which each node uses the internet Adaboost algorithm to build a local parameterized detection model. In every node, a global detection model is constructed by using a limited number of samples in the node to combine the local parametric models. While utilizing an algorithm centered on particle swarm optimization and supporting vector machines, this combination is achieved. A global model is used for detecting intrusions in each node. Experimental results suggest that the enhanced online method of Adaboost with GMMs achieves a higher rate of detection frequency and a very low false alarm rate as compared to the traditional online method of Adaboost using decision stumps. Almost both algorithms excel previous algorithms for intrusion detection. It is demonstrated that in each node of particle swarm optimization and Support vector machine-based algorithm efficiently incorporates the local detection models into the comprehensive system, the global system in a cluster can manage the kinds of interference discovered in other nodes without exchanging the specimens of these kinds of interference.

Puder et al. [175] provided a reliable website viewing network equipment controls and transfers every application from a user's browser across the whitelist of pre-approved websites only if it is on the whitelist. Such that, the query will be substituted by pre-

arranged information and transferred to the user's web browser as a reaction. It can be possible to monitor the port that came through the user's application against authorized whitelist ports and send answers from the internet against authorized whitelist pages. The network appliance is summarized in a safe cabinet so that it can be unlocked and accessed by only an approved administrator with a unique key. The safe cabinet can be created as a distinct hardware element physically intervene between a router and the device of a client, or as a safe software running on or operating with a network server.

However, to crack existing command access systems, many intrusion blocker software is accessible. Every intrusion system is intended for a particular access control system, and the main drawback is the ability to acclimate to new people. Indeed, as there are often new intrusion schemes, we cannot rely completely on the existing control access designs.

3.1.3 Biometric approaches for web control access

Biometrics has been proposed as one of the solutions to solve intrusion problems. The field of biometrics has become a user-friendly technology as it also provides an alternative approach for personal verification. Biometric technologies such as fingerprints, facial recognition, and retinal scans produce accurate and unique identifiers. The identification using such modalities are reliable [175, 195, 196].

In human physical features, fingerprint and face verification became very popular by replacing pins and passwords. Thus, it provides a secure verification for critical websites such as e-banking and official email.

Hu, B. et al. [175] show multiple solutions to limit the access of users to a specific webpage. With the steady rise in internet multimedia usage as well as the fast distribution and exchanging of multiple data, individuals are paying more and more critical to the daily power usage data. The power companies apply and enroll their government reports to create their government site in an attempt to understand the relationship between power companies and user information about energy usage. Building interactive service software to transmit information safely is the fundamental objective. They proposed constructing integrated web-based business software to guarantee system safety and efficiency, which is of excellent study importance. The campaign for socialist modernization is continuously advancing, the living standard of people is continually improving, and the social service quality demands are reaching a tremendous height. Due to the fast growth of communication, the steady rise of internet multimedia usage, as well as the fast distribution and exchanging of multiple data, people are paying increasing attention to daily power usage data. The safety processes, such as identification, verification, access control, non-repudiation, software fault tolerance, resource control, and many more, could be implemented through the software codes as per system security level. The software could only be called after identity verification when customers login implementation software. As the login system for users may utilize assorted identification such as hardware or software certificate, Royal and Sun Alliance (RSA) token, fingerprint, and so on, except the password for the user name. The model regulates the access rights of operating objects, such as interface (feature and key) operation, company (techniques) procedure,

to avoid the safety of unlawful access from being violated. Access to the implementation software utilizes the Servlet Filter method to regulate the rights of object activity in the presentation layer. Likewise, access to the web interface utilizes the WebService Handler technique for the company activity rights command. Besides, the company module calls on the owners to regulate information rights. To regulate the revision and continuous access to the same correct item, the Token technology can be used. A database is created containing the usernames and fingerprint impressions. A user inputs username and the fingerprint impression. If there is a match, the user is granted access to the webpage. Otherwise, access is denied [198]. There is always a problem that does exist by having a minor cut on the finger, which may affect the results [197].

Various initiatives are competing for the top spot technologies in the field of biometric. The combination also includes Microsoft (GAFAM), Facebook, Google, Amazon, and Apple. All existing tech giants of software now released their conceptual findings within the areas of face analysis, image recognition, and artificial intelligence on a regular basis in an effort to enhance the knowledge as quickly as feasible. The GaussianFace algorithm created by Hong Kong University scientists in 2014 accomplished 98.52% accuracy for face recognition relative to the 97.53% attained for animals. An outstanding performance gave despite storage ability and calculation periods [177]. Facebook again declare the implementation of DeepFace program in 2014, that can establish if two images refer to the same individual, with a precision level of 97.25% while in 97.53% of the cases, or just 0.28 times greater than the Facebook program, while subjects respond when performing the same experiment [178]. Google got a higher performance with FaceNet, a novel identification mechanism with unrivaled scores: 100% precision with Labeled Faces comparison test in The Wild, and 95% on the database collected as YouTube Faces DB. Implementation of an artificial neural network and the latest algorithm, the organization from the Mountain View has attempted to connect the face of the owner with nearly ideal results [179]. MIT scientists discovered that Microsoft, IBM, and China-based Megvii (FACE++) techniques had elevated error rates relative to lighter-skin males when detecting females with darker skin [180]. Ars Technica stated that Amazon had been strongly introducing to law enforcement agencies on a cloud-based face recognition product called Rekognition. The option can acknowledge as much as 100 individuals in a specific image and match the face in the databases with millions of names [181]. Newsweek revealed that 28 representatives of the US Congress were mistakenly recognized by Amazon's facial recognition technology as individuals detained for offenses.

It is also possible to use iris recognition to access internet command. It has a very comprehensive and distinctive model for centuries and stays continuous. Iris has one more property that can not be harmed or altered until a forger generates a similar artificial eye. Iris scans a small infrared beam through the eye's pupil. This method is precise and efficient, but it is also very invasive and awkward [182]. A benefit of this strategy is that the iris pattern can be captured even if the person is a few feet away. For example, It will be hard to authenticate the identification of a user engaged in e-business operations where prospective customers and vendors have no physical meeting. The high ratio of hacking on the internet and several networks is also a point of interest. A remote login scheme using iris templates is used to give valid customers entry and refuse illegitimate user's entry to it. The model introduced was evaluated to Nigerian native black iris infor-

mation kits (depicting the black race population), whereas the response is benchmarked with that acquired from the famous CASIA iris database, global and conventional. The proposed approach ensures an extremely high standard of protection. The system testing was performed using black and white populace eye pictures [183].

Voice could be used for detection in individual cognitive characteristics. Many web-based access control systems were intended via his speech to identify an individual automatically. Voice characteristics can enable gender, era, and language to be identified without supplying the scheme with any prior data. It can also be used in the identification of answering machines for unwanted or meaningless telephone call processing. Voice biometric technology is mostly used for fraud and theft identification by call center businesses [199]. In another technique, the user has to speak a number of sentences to the speaker, which are then used as his identity markers along with a smartcard. The user inserts the smartcard in the slot and then communicates with the computer through a microphone. The Speech pattern is compared with the stored data in the system through the smartcard, and then access is granted if they match [200].

Signatures are widely used around the globe and a powerful tool of identification. Signatures are still used for verifying cheques. One of the methods is by visual inspection. Another method is to compare a new signature with images of the signature stored in the database. Every human being has a habit of writing certain alphabets in his own style. The key in identification of a signature is to tell between those perpetual portions from which that vary with almost every signing [201].

Same as a hand-written signature, keystrokes dynamics has some neurophysical impression which can be utilized to identify an individual. The time-lapse between keystrokes normally shows a unique timing pattern, which can be utilized as a feature to identify a person. For identification and verification, an individual has to generate a reference profile through his keyboard. Then a test person can take a test and compare his profile with the existing one. If the difference is large between the two profiles, the access to the system is denied [201].

3.2 Proposed Approach

The flow chart of the proposed approach for human age estimation is shown in Figure 3.3. In the beginning, the auditory system is stimulated through a dynamic frequency sound, and a test person has to interact with the system through his keyboard when a sound is heard. The corresponding frequencies of the user feedbacks are saved (Section 3.2.1). Using the result of the tests, the regression model should verify the age of the volunteer. Access accepted to the web application if the volunteer is below or equal to 18 years old, and else access is denied (Section 3.2.2).

3.2.1 Protocol of stimulation

The human auditory system is stimulated by generating dynamic sound waves, according to the stated model:

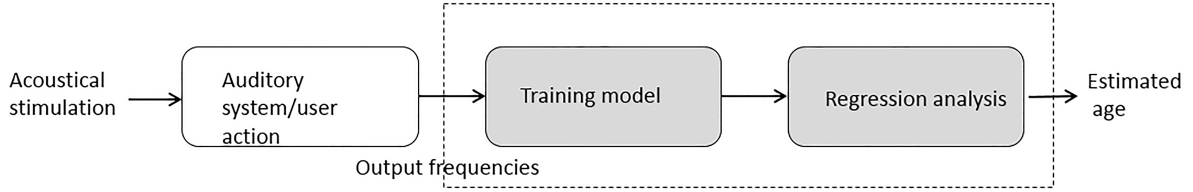


Figure 3.3: Flowchart of the proposed auditory perception based age estimation approaches

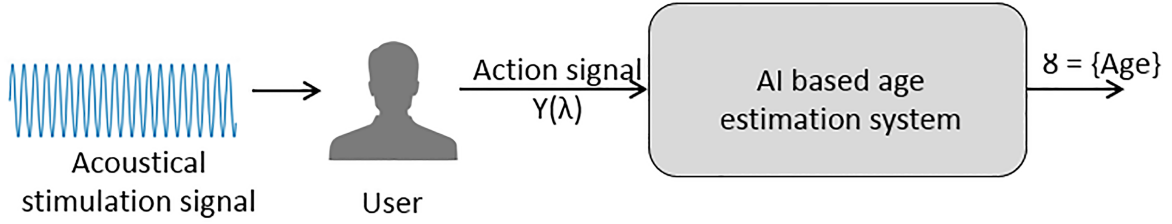


Figure 3.4: Flow diagram of our proposed approach

$$\begin{cases} s(t) = A_0 \cdot \sin(2\pi \cdot \phi(t)), \\ \text{where } \phi(t) = \alpha \cdot t + \phi_0, \end{cases} \quad (3.1)$$

A_0 stands for sound amplitude, t stands for time, ϕ_0 is the initialization frequency, and α stands for the increasing/decreasing frequency speed.

In this experiment, the stimulation duration of t is set to 20sec. The system demands a real-time interaction, as shown in Figure 3.4. A dynamic frequency sound is generated. Each volunteer should react to the system while he/she stops hearing the sound or starts hearing the sound. Basically, there are two tests conducted for the stimulation:

- first test of stimulation: the sound is generated in an increasing manner from the lower frequency (20Hz) to the higher frequency (20,000Hz). The volunteer ends the first test (e.g, keyboard action), once no sound is perceived,
- second test of stimulation: a second stimulation is triggered automatically once the volunteer completes the first mode action. In this case, the sound is generated by decreasing the frequency from the higher frequency (20,000Hz) to the lower frequency (20Hz). The volunteer ends the second test once the sound is perceived.

The average of the two test frequencies has been calculated. A feature vector bringing together the frequency of the first test, the frequency of the second test, and the average of two frequencies are created.

3.2.2 Age estimation based on the auditory perception

The second part of this work concerns the age estimation of the two auditory perceived responses. For that, a regression model has been presented in order to estimate the age

of a volunteer.

In this work, two types of techniques have been used: Regression Forests and Support Vector Regression. These two regression models are among the most widely used in computer vision and pattern recognition applications although their performance guarantees have been proven.

Regression Forests (RF) are an ensemble of different regression trees. They predict real-valued numbers at leaf nodes using multiple non-linear regression. From the original data, we have drawn n_{tree} bootstrap samples. We select a number of predictors $M_{try} = p$ for bootstrap samples. A majority of votes decide about the final age of a volunteer. SVR is using the same principle of SVM for classification. SVR built a set of hyperplanes that maximize the separation or margin and to minimize the error between samples. Artificial Neural Networks (ANNs) illustrates the initial neural network model using the least-squares method to calculate the weights that are then used for calculating the activation function. The proposed approach is that the transformed samples have a common structure of sparsity in each class, unlike other methods. The least square regression model imposes an inter-class sparsity restriction that significantly reduces the sample margins of the same class, whereas samples from different classes will show an increase. Such variables support the way regression is transformed more compactly and discriminated, thus producing better results than others.

Stratified k-fold cross-validation is performed using SVR and RF models with $k=10$. Cross-validation is a method for evaluating predictive models by dividing the initial sample into a model training set and a test collection for evaluation. [165–167]. To optimize the parameters of the algorithm, loops of cross-validation are used by further splitting each of the ten original training datasets into smaller training datasets and validation datasets. For every combination of the parameters of the classifiers, cross-validation performance is computed, and then the best performing parameters inside the loop are chosen. Then, regression with the best parameters is applied to the original testing dataset. The tuned SVR model with a specific parameter such as the radial kernel, gamma with the best value of 2, and cost value is 10.

The RF classifier is built with standard values proposed by Breiman such that the valuation of decision trees which is equal to 500 and the number of features used to split the node in the decision tree growing process denoted by M_{try} . It is fixed to 0.10, which is quite close also to the recommended value by Breiman ($M_{try} = \sqrt{p}$ where p is the size of the feature vector (p in our experiment is 3)).

3.3 Experiments and results

In this section, the required conditions are explained, then the process of dataset collection and analysis discrimination of the two age groups is briefly explained. Finally, the results of age estimation are provided.

3.3.1 Condition of the experiment

To assess the system while conducting the experiment Dell precision COREi7 M4700 is used, and it also been tested with Macbook pro, desktop computer Z800 core i7. The

calculated between the computer and the subject was 12 inches. While the intensity of generated sound was recorded as 95db at its maximum for the duration of 20 seconds experiment, the results can be affected if conditions are modified as required for the standard experiment, and the output will have a higher rate of error.

3.3.2 APBDB(Auditory Perception-based Biometric Access Filter Database)

In this experiment, 201 subjects participated from different ages and gender for database collection. To complete one test, it requires 2 minutes for a subject. The number of subjects for the two classes according to the age are quite balance as mention in Table 3.1.

The collected database is then sub-divided into two classes. As shown in Table 3.1, a subject belongs to:

- Child: if the volunteer conducting the experiment is less than 18 years old,
- Adult: if the volunteer conducting the experiment is more than 18 years old.

The number of subject in both the groups are nearly equal, for the child groups from 06 years to 18 years 41 males and 59 females volunteers participated. In total, we have 100 samples for the child group. In the adult group from 19 years to 65 years, we have 68 males and 23 females. In total, we have 101 samples for the adult group.

Algorithm 1 Biometric control access filter

```

1: procedure ACCESS VERIFICATION
2: Access = false
3: login = Enter-login()
4: Age ← Enter-age()
5:   while Access == false & age ← ≤ 18 do
6:   Sound ← acoustical-stimulation(20, 20000)
7:   F1 ← User-feedback (Sound1)
8:   Sound ← acoustical-stimulation(20000, 20)
9:   F2 ← User-feedback (Sound2);
10:  Fa = F1 + F2 / 2
11:  Feature-vector = [F1, F2, Fa]
12:  Estimated-age = Age-Estimation (Feature-Vector, regression-model)
13:  ( Estimated-age ≤ 18 )
14:  Access = True
15: else
16:  Access = False
17: return ← login()

```

3.3.3 Results

3.3.3.1 Dimensionality reduction of the auditory perception responses

A technique of dimensionality reduction is used to explore the auditory perception in a linear discriminant space. Linear Discriminant Analysis (LDA) is used [163]. The ratio

Table 3.1: Number of volunteers in each group based on gender

Age groups	Below 18 years		Above 18 years	
Gender	Male	Female	Male	Female
No.	41	59	68	23
Total	100		101	

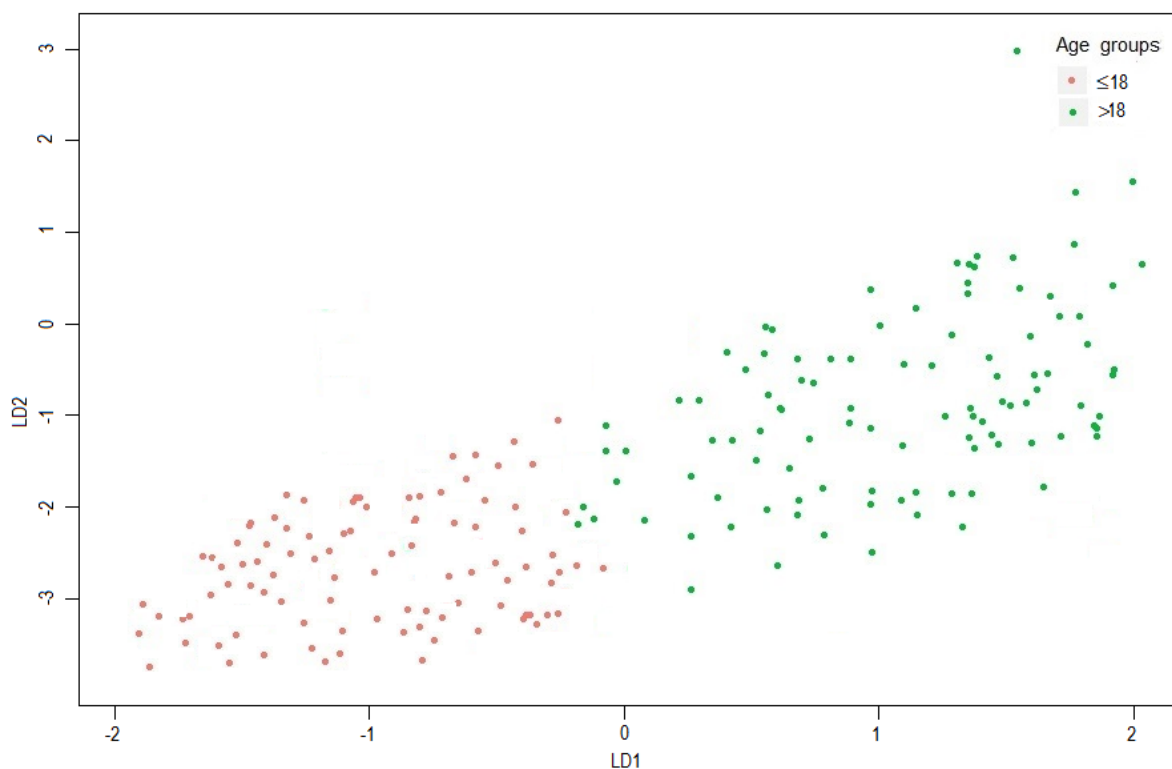


Figure 3.5: LDA applied to the dataset divided into two age groups.

of within-class variance to the between-class variance is maximized with the objective of reducing the variation of the data in the same class and increasing the separation between classes. Therefore, among the classes, solid boundaries are built, to make it a linear classifier.

It is performed on subsets of conditions using three features that correspond to three frequencies (the registered frequency from the first test, the registered frequency from the second test, and the average of the two frequencies). The samples are projected on the two first linear discriminant axes (LD1 and LD2). The projected data are presented in Figure 3.5. In fact, there are a few points overlapping between the two classes, but in general, the dataset is pretty separable. This good separation shows that the auditory perception responses are highly correlated to the age, and the age group of persons can be identified from its auditory perception responses.

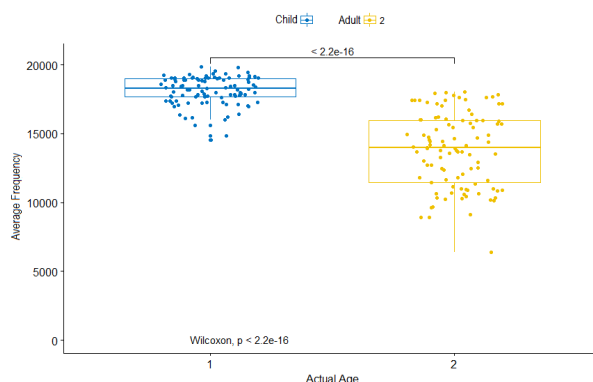


Figure 3.6: Boxplot of the two age groups

3.3.3.2 Quantification of the separability between the two age groups

After the statistical analysis, univariate analysis is applied to the dataset divided into two age groups. By using univariate T-Tests, the samples of the two age groups show variability by considering average frequencies. In order to testify the statistical significance of the evidence, a T-test is proposed, which is based on a null hypothesis. Likewise, it calculates the differences among the variables in a dataset. A detailed interpretation to discriminate the two age groups is presented using boxplot, as shown in Figure 3.6. The boxplots display variation in samples of the age groups and point out the intra and inter-class variability or correlation.

The p-value between the two age groups is inferior to 10^{-16} . Consequently, the two age groups are very different and discriminating according to the hearable frequencies of the volunteers. The distribution of the adult age group is a little spread out. It means there is big variability inside this group. Some samples can be misclassified, and despite the outliers samples, the p-value is a matter-of-fact that there are big discrimination and separation between the adult and child age groups. Thus the auditory perception may be used for the age estimation of a person.

3.3.3.3 Classification of adult and child age groups

In this section, the classification of the auditory perception into two groups is performed using SVM, RF, Adaboost, LDA, and Neural Network(NN) classifiers. Tenfold cross-validation technique is used for all the classification approaches. The final calculated classification rate is shown in Table 3.2. To conclude, there is an obvious separability between the two age groups. Comparing the classification accuracy of the different classifiers, RF shows the best accuracy of 95% for two age groups. The confusion matrix using RF classifier into two age groups is shown in Table 3.3. The most misclassified samples come from the child group, and It means that it is easier to recognize an adult than a child. Thus, the proposed web filter could easily recognize an adult and prevent his access to children's applications.

Table 3.2: Classification of the two age groups

Model	Accuracy
Random Forest	95%
SVM	89%
Adaboost	87%
LDA	85%
Neural Network	79%

Table 3.3: Confusion matrix of the classification using RF classifier

RF	Child group	Adult group	Omission	Commission
Child group	90	10	1.09%	10%
Adult group	1	100	9.09%	0.99%

3.3.3.4 Age estimation based on the auditory perception

The performances of the regression analysis for age estimation using RF, SVR, Adaboost, and Neural Network(NN) is summarized in table 3.4. RF regression using 10-fold cross-validation shows the best rate of efficiency of 97% and the smallest root mean square of error (RMSE) of 2.6 years. The resultant model is stable, and the spread out of the estimated ages from their average value is small, it is represented using the variance and corresponds to 8.71 years. All the other regression models show lower accuracy than RF for our proposed dataset. Therefore, the proposed regression model using RF in 10-fold cross-validation is the most accurate approach for age estimation using the auditory perception.

Table 3.4: Performances of the age estimation

Model	Accuracy	RMSE	MEAN ERROR	VARIANCE	STD DEVIATION
SVM	95%	7.25	4.72	30.49	5.52
RF	97%	4.17	2.95	8.71	2.95
Adaboost	92%	9.31	6.12	24.23	9.91
NN	83%	11.17	7.51	33.12	12.16

The age of the child group is estimated more accurately than the adult group, as shown in Figure 3.7. The difference between the actual age of a volunteer and the estimated age for the child group is very less comparing to the adult group. While Mean Error Value for age estimation is 2.95 years.

The scatter plot of the known actual vs. the predicted age and overlay the line $y=x$ are shown in Figure 3.7. If the model predicts the age perfectly, then all the data points would lie on this line. There are only a few outliers that do not fit well the line with few years of difference. We can also see that below 20 years, the data points lie perfectly on the line. Therefore, our approach can predict the age of a child with high accuracy.

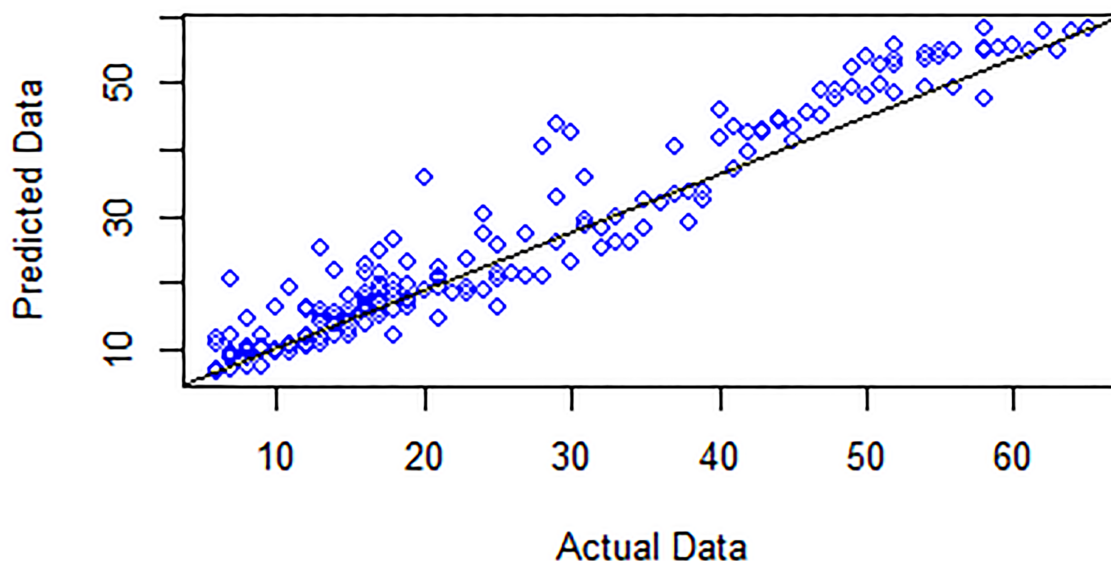


Figure 3.7: Actual and predicted age for the best-fitting model

3.3.3.5 Objective Performance Evaluation

The objective evaluation shows how much the results and the references are determined as the same person by using auditory perception. To evaluate the performance of the system, volunteers of different ages and gender have tested our designed system. For real-time evaluation, the regression model trains the model with the reference database and tests the model with a volunteer's data, which does not exist in the system's database. This evaluation checks the likelihood that the volunteer belongs to the same age class, and then the similarity is evaluated based on the accuracy and the thresholds. While handling a biometric system, Objective evaluation techniques are based on two factors: the FAR (False Acceptance Rate), which is calculated as a fragment of impostor scores overshooting the threshold, and the FRR (False Rejection Rate), which is calculated as a fragment of genuine scores falling below the threshold. There is no admissible way to determine if a system with a lower FAR and a higher FRR value performs better than a system with a higher FAR and a lower FRR. Therefore, the equal error rate (EER) of a system can be used. The minor the value of EER, the better is the performance of the system. The ROC (Receiver Operating Characteristic) curve is created in order to choose the prime threshold; we obtain 113 genuine scores and 3 impostor scores through some volunteers of different ages and gender. By considering the definition of FAR and FRR, the value of EER can easily be calculated. The ROC curve for our proposed model after testing is shown in Figure 3.8. It is concluded that the system's performance is quite satisfying; hence the EER is 1.4%. However, it is obvious that the performance can be affected by changing the standardized parameters (distance from the computer, using headphones or speaker, and sound intensity), and hearing loss is also a factor that can affect the results.

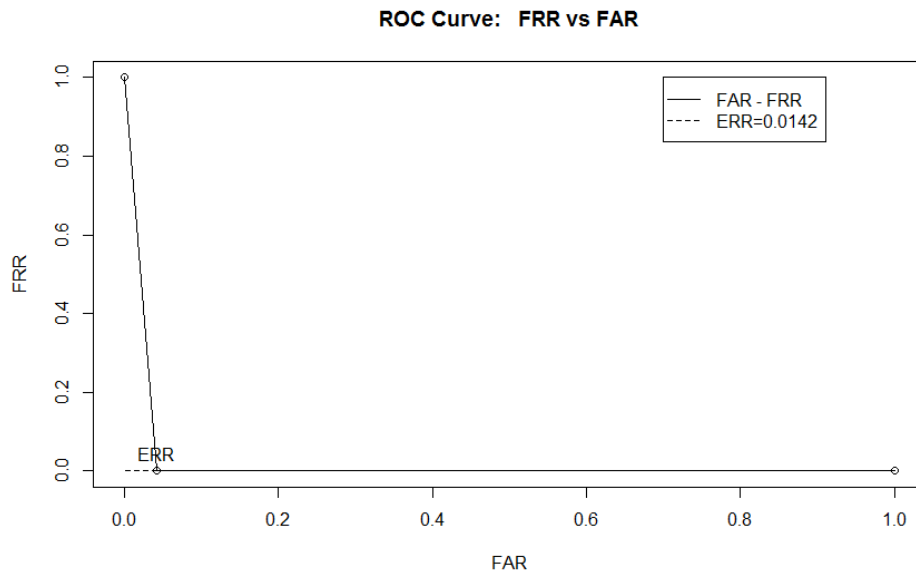


Figure 3.8: EER of the proposed model on ROC curve

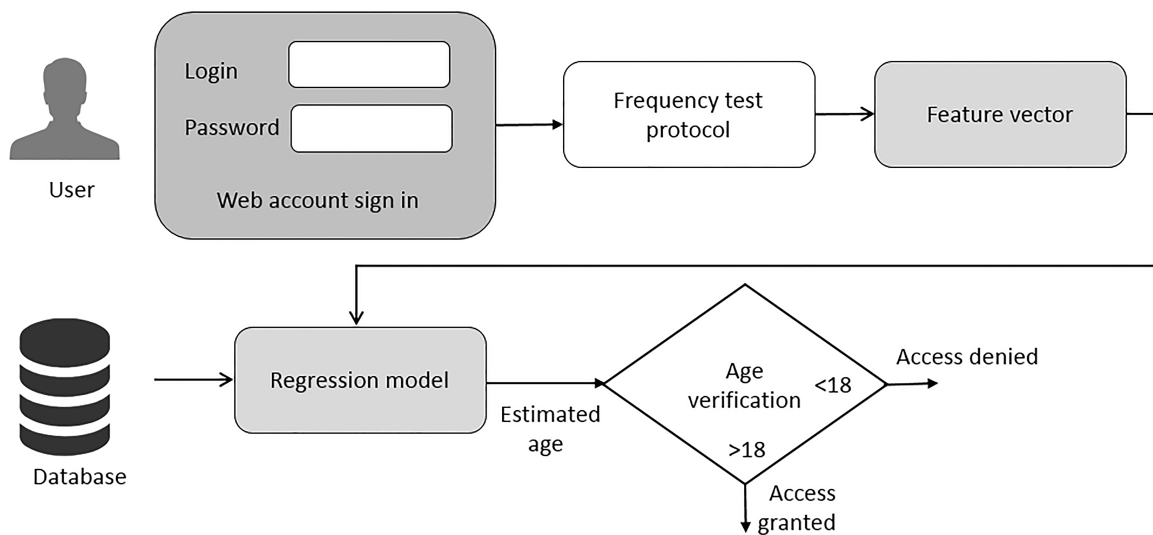


Figure 3.9: BiometricAccessFilter-based web application

3.4 Biometricaccessfilter: A web application

By considering that the auditory system responses encode biometric information about the age of a person. We build a robust regression model that can estimate the forensic age and a web access filtering system called BiometricAccessFilter. A web application which uses this filter is available (<http://54.218.80.4:9004/>).

In Figure 3.9, We explained how a user could create an account on our online web interface. It requires some data to be inserted manually, such as email address, name, and password. After the Creation of an account successfully, on the Login page, we present an age verification step to give access right to the user who is less than 18 years old. The test person takes the test by listening to the sound, and he should press 'ENTER' when he started hearing the sound. The corresponding frequency is registered, and the test is repeated a second time. The regression model is used to predict and estimate the age of new subscribers. If the estimated age of the subscriber is higher than 18 years, then the access will be denied, and if his/her age is lower than 18 years, the account will be created for further use.

The current proposal is sensitive to attacks of users who try to spoof the system about their age. Such that it would be possible, a young user, to impersonate an older one. On the other hand, an old user might also deceive the system by waiting until the first mode of the experiment ends. Considering the fact we felt to design a strong anti-spoofing system to make it more secure to attacks.

BiometricAccessFilter can limit the access of adults to the virtual world of kids and then prevent child sexual abuse in an ever-evolving online sphere. Regardless, there is no doubt that anonymity, hard-drive encryption, and enhanced privacy are used to carry out illicit activities of internet pedophile [202]. With this web application, we hope to change the practice and introduce new ways of developing more secure web applications using smart biometric approaches. Consequently, forensic biometrics can help in a wide range of applications in cybercrime detection. It can overcome the loopholes of traditional anonymous identification systems.

Our designed system is stronger and secure than the existing web access control systems. Besides, our system requires a smart interactive way of cooperation with the user. Moreover, our system is robust compared to the traditional modalities for the verification system.

3.5 Conclusion

BiometricAccessFilter is an application based on newly developed biometric trait auditory perception. It is a completely new approach to access control systems. It is based on auditory perception. It is successfully demonstrated that we can limit the access of an adult to a web-page specially designed for children, and similarly, the access of kids

can also be controlled. It is proved that the proposed system can limit the access of users within certain age groups most discriminating, and the Regression Forest is the most accurate for age estimation. A robust regression model is also built, and it has an accuracy rate of precision to control the access. The designed system is vulnerable to spoof-attacks. Thus we planned to build a strong anti-spoofing system based on auditory perception responses.

Chapter 4

Auditory perception biometric anti-spoofing system and countermeasure for age verification

Biometric systems are considered an efficient component for identification in modern growing technologies. The aim of biometric systems is to verify or determine the identity of a user through his/her biological and behavioral characteristics. A real trait in variation to a fake physical, synthetic sample is an important problem in biometric verification/authentication, which requires the development of new and stronger protection measures. In this article, we are presenting an anti-spoofing system based on auditory perception responses. To the best of our knowledge, for the first time, an auditory perception-based anti-spoofing system is presented for subjects verification. The proposed auditory perception-based anti-spoofing system is evaluated with 1140 trials with subjects of different gender and age range (12-65 years of age).

4.1 Introduction

Biometrics allows us to identify a person and provide authentication based on a set of an identifiable and verifiable dataset, which are uniquely specified to them. It can be used for surveillance, access control, and security systems [217]. Due to the scientific growth in the field of pattern recognition, computer vision, machine learning, and also the technological advancement and improvement of storage, processing, and data acquisition, person identification and verification is now possible. Several biometric modalities and traits such as the face, iris, fingerprint, vein, blood flow, and auditory perception can successfully allow people identification and authentication. In parallel, several spoofing techniques also introduced to crack such biometric systems.

Biometric spoofing is a technique to deceive a biometric system. Where a false object such as a fingerprint mold made of artificial material is presented to the biometric scanning tool that copies the unique biological features of a subject. The system computes the features so that the biometric system will not be able to recognize the artifact from the genuine biological target. Therefore, aiming to spoof a biometric system, the spoof attacker presents himself as a real user by producing a fake identity to fool the biometric

sensor. Anti-spoofing systems are concerned with the system that rejects the spoofing attacks [228]. Biometric systems without an anti-spoofing system have a high risk of security of user's data. Several techniques exist to spoof biometric systems [246,247]. In previous studies eight different points have been explained for spoofing attack [248,249] which are divided into two groups direct attacks and indirect attacks.

Direct attacks [235] are possible with the generation of synthetic samples, and this is the first unsafe point at the sensor level of a biometric security system. For direct attack, no particular information is needed about the system, such as matching algorithm, features extraction, and format of data, etc. It is working in the analog domain, out of the digital boundary of the system. Therefore, digital protection techniques such as digital signatures, watermarking are not useful. For direct spoofing, the attacker targets the acquisition sensor typically. Because several biometric modalities can be constructed by using some common types of equipment to copy actual biometric reading such as printers, audio recorders, and stampers. Concerning that, the biometrics community proposed spoofing benchmarks. It allows the biometric systems to work on the concepts of anti-spoofing systems. Face, iris, and fingerprint are important modalities for which spoofing detection has been investigated. Each of them shares a common characteristic for benchmarks such as video-based or image. For iris, spoofing attacks usually occur with printed iris images [272] or cosmetic contact lenses [273,274]. For faces, a digital video or a photograph can be used for a spoof attack [275]. A 3D mask is also a logical entity for face spoof attacker [276]. While for fingerprint, artificial replicas are modeled in a supportive way for spoofing [277]. A mold of the fingerprint of an authentic user can also duplicate the real user on a specific material such as silicon, play-doh, gelatin.

Indirect attacks requires all the information and knowledge about the system to spoof it. While to manipulate a biometric system, indirect attacks require the knowledge about the specific feature extraction procedure, the matching algorithm used, possible weak links in the communication channel, and database access. Indirect attacks are performed inside the system, such as bypassing the feature extractor or the comparator, manipulating the biometric references in the biometric reference database, and exploiting possible weak points in communication channels [278]. The dependency of a biometric system concerns to the expert, who knows which features to be captured for acquisition that remains secure from the spoofing attacker. Proposing the possible constraint to limit the access of the attacker and even a small modification in the system needs to reconstruct the whole system from scratch.

The threats to the biometric system regarding spoofing attacks are now acknowledged. While the anti-spoofing systems are still facing challenges. To enhance the performance of the biometric system, spoofing countermeasures are also introduced. The countermeasure is a binary classifier; its job is to distinguish between spoofed and genuine trials. Spoofing countermeasures directly influence the entire performance of the biometric system, while aiming to minimize vulnerabilities to spoofing; it also has the capability to reject genuine trials. In the future, anti-spoofing systems require more intensive study and attention.

Human age estimation and classification based on auditory perception responses are pre-

sented for the first time in 2017. In this article, we are presenting an anti-spoofing system for a pre-existing biometric system for age estimation and classification using auditory perception [161].

Several biometric modalities are briefly explained in the section below:

4.1.1 Fingerprint

Fingerprints are likely the best recognized and prevalent among biometrics due to their characteristics: durability, universality, and uniqueness. As previously implemented, it has been shown that fingerprint applications are susceptible to demonstration attacks. "Fingerprints cannot lie, but liars can make fingerprints". Sad to say, on many occasions now, this paraphrase of an ancient quote ascribed to Mark Twain has been proved correct. As when the implementation of fingerprint technologies continues to grow year after year in such diverse settings as airports, laptops, or mobile phones, individuals are also becoming more acquainted with their use in daily lives and, as a consequence, the safety flaws of fingerprint detectors are now becoming more widely recognized. As a result, fingerprint became among the most used biometric features that have attracted the greatest focus from not only scientists and manufacturers, but also from the public and clients concerning its vulnerability to Presentation Attacks (PAs) known as spoofing [312]. The involvement of the biometric community in the safety assessment of fingerprint recognition technologies against presentation attacks has resulted in the development of countless and very varied projects in this sector: the publishing of countless study articles that reveal and evaluate distinct solutions to presentation attacks for fingerprint. Several projects have shown the priority provided to improving system safety by all sides engaged in the growth of fingerprint-based biometrics and the need to suggest and create particular techniques of security against PAs in an attempt to make practical use of this quickly evolving technology. Researchers have thus concentrated on designing particular countermeasures that allow fingerprint recognition technologies to identify and deny false samples, thus enhancing the robustness of the proposed application. In the field of fingerprint, in addition to other Presentation Attack Detection (PAD) approaches such as the use of multibiometric or challenge-response methods, the so-called liveness identification techniques have received unique interest from scientists and the business community. To differentiate between true and false characteristics, these algorithms use distinct physiological characteristics. Liveness evaluation methods are a difficult engineering issue because they have to meet certain challenging demands [295]: (i) In no case should the technique be damaging to the person or involve improper interaction of the user (ii) individuals would not hesitate to utilize it because it is user-friendly (iii) Results must be produced quickly, and at a very low interval since the user cannot be invited to communicate with the sensor for a long time (iv) Low cost, widespread use cannot be anticipated if the price is too big (v) The performance will not devalue the identification efficiency such as false rejection of the biometric system in relation to getting a decent fake identification level.

There are two main groups of fingerprint spoofing detection techniques: hardware-based and software-based. Both kinds of techniques have certain benefits and disadvantages over the other and, in particular, a mixture of both would be the most appealing protection strategy to enhancing biometric system safety. Hardware-based systems generally

pose a greater false identification rate as a crude contrast, whereas software-based methods are generally less costly (as no additional unit is required) and less intrusive as their application is open to the consumer. Moreover, since they work straight on the obtained sample (and not on the biometric characteristic of its own), software-based methods may be integrated with the function extractor module, making them possibly capable of identifying other kinds of illegal break-ins efforts not simply categorized as display assaults. Software-based techniques can secure the system toward preserved or synthetic samples being injected into the channel of communication between the sensor and the extractor. Hardware-based spoofing detection quantifies extra sensitive sensors and software-based solutions related to the acquisition sensors of the verification system [227]. A common countermeasure for the detection of spoof attacks using fingerprint is liveness detection, and it can be a hardware or software-based system. In hardware-based techniques, the system uses the features of liveliness such as electrical conductivity of the skin, the temperature of a finger, skin resistance, and pulse oximetry [229, 230, 234]. These techniques require supplementary hardware in combination with the biometric sensor, and that makes it more costly. In the liveness detection system, an electro tactile pattern is studied during authentication by transmitting electric pulses to the fingertip [250]. The odor-based anti-spoofing system, an array of chemical sensors, is designed as an acquisition system that detects the characteristic pattern of an odor. The voltage decreases when the odor is exposed to gelatin or skin, although exposing the sensor to silicon and latex, the voltage is increases [251].

4.1.2 Iris

The viability of spoofing attacks was recognized for the first time by Daugman [253]. He used a Fast Fourier transform for the verification of high-frequency spectral magnitude inside the frequency domain. These developments have drawn attention to increasing the number of products, journals, and applications from scientists and companies. The first devices for iris recognition were created to function as stand-alone systems [296]. In recent days, iris recognition technology is included in some of the most significant working applications such as Android, Microsoft Windows, and devices like laptops or desktops, smartphones as an authentication system. The primary benefits of iris can be summed up as follows:

- During prenatal gestation, the iris is produced and shows extremely discrete models. These kinds of patterns are comprised of complicated, colors, and irrelevant shapes. The extremely discriminating features of the iris enable identification algorithms to achieve similar performance with the most precise biometric methods [297].
- the genetic incidence of the iris is restricted, so irises are distinct from individuals with mutual genes. A person's irises are regarded as distinct cases that do not suit one another.
- the iris is an internally noticeable organ of the eye. it could be acquired at a range and the progress made on procurement systems makes it easy to incorporate iris recognition into electronic devices [298].

In actual implementations, the rapid deployment of iris recognition technology has raised worries about its safety. Iris biometrics applications provide a range of various scenarios and

security levels, such as banking, authentication of smartphone users, and government ID programs. Resilience against threats occurs as one of the most effective study fields in the latest literature on iris biometrics, among all problems connected with biometric structures. Users are challenging the safety of commercial iris systems. In 2017, the chaos computer club revealed to the Samsung Galaxy S8 iris printer their effective assault using a straightforward image and a contact lens [299]. In biometric applications, submission threats are described as presenting individual features or artifacts immediately at the request of a biometric model that attempts to interfere with its ordinary procedure [300]. It includes Spoofing attacks, evasion attacks, and so-called zero-effort attacks. Most of the iris PAD study in literature focuses on detecting spoofing attacks. In the literature, the word liveness identification is also used to suggest systems that can be classified between bona fide specimens and artifacts used to manipulate biometric devices. The attackers can be categorized into two kinds based on their intentions:

- **Impostor:** The intruder attempts to imitate the identity of other subjects by utilizing his own iris such as, zero-effort attacks or an artifact that imitates the spoofed identity iris such as photo, video or synthetic iris. Such an attack needs a specific amount of understanding of the genuine user's eye and the features of the eye detector to boost the attack's achievement.
- **Identity concealer:** The intruder attempts to avoid awareness of the iris. Examples in this situation include enrolling people with false irises (for example, synthetically produced) or altered irises (for example, textured contact lenses). These instances are a method to mask true identity.

In the state-of-art, several solutions are available to detect the liveness of iris, which rely on the special acquisition hardware [254–256] as well as a software-based solution that uses pattern of someone's iris on the contact lenses to analyze the textural effects of the spoof attacker [257]. Software-based solutions also investigated pupil construction [260], cosmetic contact lenses [258, 259, 264, 265] and multibiometrics EEG and iris together [261]. For image quality measures such as motion, occlusion, focus, and pupil dilation, 22 images were used by Galbally et al. [262]. Sequential floating features selection is used for best features selection and then forwarded a quadratic discriminant classifier [263]. To analyze printing regularities in irises, some peak values inside the frequency spectrum are concerned with spoof attackers mention. Iris anti-spoofing methods investigate strong features through texture patterns, bags-of-visual-words, and image-quality metrics. A strong variation is found from dataset to dataset as concerning the performances [252].

4.1.3 Face

Face recognition is currently one of the most ubiquitous of all existing biometric traits. The face has been studied as a biometric trait from the 1960s for recognition and verification purposes and later achieved an evolutionary standard in the field of computer vision in the 1990s [301]. Several exciting features of the human face for biometrics are distant acquisition, anti-intrusive, and the excellent discriminating features of the body for identity verification. For several reasons, face is currently one of the biometric attributes with the biggest economic and social effect:

- In spite of consumer quota, the face is the second most widely used biometric worldwide straight after fingerprints [302]. Every day, more and more manufacturers, like Apple, with its Face ID technology, include face recognition in their products.

- In most identification documents, such as the biometric passport compliant with ICAO [303] or national ID cards [304], face features have been used.

Because of their strong implementation level, attacks with a face verification system as their goal are no longer limited to theoretical situations, becoming a huge threat. Several types of applications do exist and delicate data that attackers can easily manipulate. Providing a suitable amount of safety for each face recognition application, as achieved with other biometric traits, such as iris or fingerprint, should be a key concern. Historically, the primary aim of face recognition studies has been on improving efficiency in checking and identity duties, such that faster identification between subjects using stored facial data. A face recognition system should be developed to optimize the distinctions between the facial characteristics of each person to accomplish this objective and for a similar user in the same way. There are occlusions, low resolution, distinct viewpoints, graphics, etc., within the variable factors that can influence the efficiency of face recognition systems. Strengthening the efficiency of identification technologies in the existence of these variable variables in face recognition studies is presently an effective sector. In contradiction to their efficiency optimization, the security vulnerabilities of face recognition systems have been much less researched in the past, and focus has been paid to identifying distinct kinds of assaults in the latest years only [305]. PAD detects if a biometric attribute derives from a working individual or is false in relation to these vulnerabilities.

The face-based anti-spoofing techniques are categorized into four different groups [245], user behavior modeling, methods relying on extra devices, methods relying on user cooperation, and data-driven characterization methods. User behavior modeling concerns the user behavior in front of the camera, some researchers considered motion detection such as involuntary movements of parts of the face and head [236, 237] and eye blinking [238, 239]. The methods rely on extra devices, allow a user to use specific anti-spoof hardware, it can be deployed near thermal or infrared images [241]. The use of multiple of 2-D cameras or 3-D cameras can also provide additional protection [240]. The methods rely on user cooperation is that the system is still influenced by small head tilts of the user, which simulate the movement of head displaying a genuine user. The data-driven approaches include the surface texture of facial skin. Through facial texture, it's easy to calculate specific values that classify the optical qualities of the facial skin for optical-flow analysis [244] and compare the live people with non-live ones [243].

For many decades, users are practicing masks or facial disguises for not being identified. In the modern era, this trend is developed; a newer version to modify one's appearance is the use of plastic surgery. The procedure of plastic surgeries is performed because of its affordable cost and the speed of perfection. In spite of all this, recently, a robust algorithm is designed to detect the facial surgery changes [266–268]. While the problem of face recognition after going through the operation of plastic surgery is still a challenging task [269], even without going through a permanent treatment, a temporary make-up can also affect the performance of a face-based biometric systems [240]. All the above techniques are used to hide the identity of a person, such as face masks, plastic surgery, and make-up. The adult tries to impersonate to child; a male can try to impersonate as female etc. It has also been demonstrated that female intruder impersonates to male successfully by wearing some make-up [271].

4.1.4 Gait

Recognition of a person through his walking style is known as biometric gait. Recently this has become a subject of excellent concern in studies on biometrics. Gait is possibly advan-

tageous compared to some other biometric modalities as it can be obtained from a range and does not involve communication or customer collaboration. This leaves it an appealing choice in applications for video surveillance. Recent state-of-the-art technologies demonstrate that individuals using gait identification can be recognized using Silhouette or model-based methods [306]. In order to identify the wandering topic, both methods begin by analyzing image information. Approaches based on Silhouette have experienced the best performance. Those using the average Silhouette in specific have demonstrated to be the most common [307]. The selection of characteristics has been implemented to recognize the attributes of the silhouettes that most add to acceptance [308]. Earlier time model-based methods used pendular designs to measure the slope variety while walking [309]. Currently, in combination with vertex-based locations, these designs were used. This approach tracks and describes people by shifting their joints. Such model-based techniques were also resistant to functional image selection, which discovered that motion components could have greater discriminative ability than structural components. Another region of studies is the camera viewpoint's impact on the traveling path of the subject. Implying the human is a strong artifact, walking periodically across a linear route for two gait phases can attain identification that is equal to the direction of the road compared to the camera [310]. The covariate variables are of equivalent significance, and the degree to which internal variables obstruct gait appreciation is of importance. Evaluation of covariate variables, along with clothing and footwear, has shown that carrying a trench coat or carrying flip flops can influence identification efficiency considerably [311]. It is expected because carrying garments that hide the entire corpse will obviously avoid any biometric gait. Furthermore, when carrying ordinary boots, the running fashion compatible with drop flops is understood to vary, although no study has parameterized this impact. In recent literature, to explore the nature of the variability within the class and the difference in gait as a biometric between classes.

For Gait recognition, spoof attacks are not studied intensively as needed. A high-quality video of valid subjects played back in front of the cameras can affect the system. Gait is a behavioral biometric and may not remain the same, especially over a long duration of time, body weight, and special injuries [272]. Synthetic devices attack cannot affect the performances of gait biometrics.

Meanwhile, four different existing spoofing mechanisms have been explored. The gait motion is captured through the accelerometer sensor, which provides the signature. A traditional approach, such as a vision-based gait recognition system, is more potential and practical than a sensor-based approach.

The first spoofing attack for gait signature, the individual walks behind the genuine target by copying his moves. This kind of spoofing can be identified such that spoofing attempt has a lower match scoring than the genuine. The second spoofing attack is related to the response of an accelerometer sensor connected to the leg, which is projected on a wall. A spoof attacker is visualizing and try to match the moves with the target, and it is used on the basis of identification. This technique has an accuracy of 60% to spoof the biometric gait system. For the third spoofing attack, an accelerometer is used as the previous approach and focus on their performance through practice. Only those spoof attackers were successful, which are closely matched to the genuine signature, and with practice, the performance of the gait signature can be affected. The fourth study uses how a target impersonates the clothing of a genuine subject to spoof the gait recognition system. It is among one of the straightforward and robust meth-

ods used for spoofing. It is used to enter a secure environment where a formal type of dress or uniform is common. Clothing impersonation is one of the most efficient methods used for spoofing gait signature.

Using targeted attacks and clothing impersonation can spoof a gait recognition system. No artificial detection exists for such kinds of attacks, and it is specifically challenging.

4.1.5 Signature

Biometric user authentication applications have been highly deployed in many appropriate industries in recent years, such as safety, e-government, healthcare, schooling, finance, or insurance [313]. This development was made feasible by two primary variables: (1) technological development and enhancement of sensor quality [314], which reduced the costs of personal-purpose phones (smartphones and phones) and hence society's elevated awareness of their use; and (2) the development of technology for biometric identification in particular [315–317]. It is essential to remember, however, that these biometric authentication technologies must resist various kinds of potential threats [318]. Here the main focus is on Presentation Attack (PA) internet handwritten biometric identification systems situations. Through enhanced tag procurement situations, including machine interoperability [319] and reading entries, these systems have gained important publicity in recent years. In terms of spoofing attack, signature-based biometric verification is facing two kinds of spoof attacks [320]:

- Random imposter: where no user information is recognized and impostors submit their own request pretending to be another customer of the system
- Skilled imposter: Where impostors have some degree of knowledge about the system being attacked, such as information about the client and attempt to forge their records claiming to be the consumer in the system.

Galbally et al. recently addressed various methods in [321] to document precise possible results in handwritten signature checking using learning gained from vulnerability assessment of Presentation Attacks (PA). They regarded qualified impostors to be a specific situation of biometric PAs conducted against a biometric cognitive trait in several occasions referred to as mimicry. The important difference between physical PAs and mimicry needs to be highlighted such that conventional PAs are using some physical artifacts like a fake mask and molded fingerprints and can easily be detected at sensor level at some occasions while in mimicry the interaction with the system is entirely similar to that of normal attempt. Galbally et al. [321] updated the conventional designation of impostor identity situations such that random and skilled following the normal biometric PAD.

The researchers introduced a mechanism of off-line identity checking and forgery detection, relying on faded modeling [321]. Actual signature checking and forgery detection were accomplished through angle characteristics obtained by using a grid method. An exponential membership function fuzzified the derivative characteristics, which was altered to include two structural parameters relating to differences in handwriting styles and other variables influencing a signature's scripting. Experiments proved the system's ability to detect even the simplest signature modifications.

Brault et al. [322] provided an initial effort to assess, experimentally, and a priori from the coordinates selected during their execution, the trouble that a typical imitator might experience in reproducing that mark both mentally and flexibly. They first obtained a functional model of what a typical imitator has to do to duplicate any signature to accomplish this objective dynamically. For a specified signature, a particular coefficient of trouble was then numerically predicted. Experimenting specifically focused on the reproduction of the mark showed the model's efficacy. Three distinct reports contrasted the classification of the checked documents provided by the complexity index: the views of the imitators themselves, those of an experienced paper reviewer, and the classification provided by a particular pattern recognition algorithm. They are also given a request for an instance. This task was one of PAD's first efforts to verify handwritten signatures internet using a unique pad connected to a digitizer (Summagraphic Inc. Model MM1201). The sampling frequency was 110 Hz, with 0.025 inches of spatial resolution [322]. Reillo et al. [323] introduced PAD techniques centered on the use of certain global characteristics such as the complete amount of shots and the signature time. They obtained a new database largely based on 11 elements of PAs concerning the forger's stage of understanding and instruments. The conclusions obtained in this task using the suggested PAD decreased the EER to below 3.0% from a ratio near to 20%.

4.1.6 Multimodal

For a multimodal biometric system, a fusion of multiple liveness detectors is used, such as finger liveness detector, fake based detector, and live based features detector. Multimodal biometric can also be defined as a fusion of matcher and liveness detector or multiple biometric systems without liveness detection.

A variety of spoofing attacks exist for Multimodal Biometric Systems (MBS) [233]. They are categorized into different categories, such as first, second, etc. For type first type of attack, a fake biometric input is presented to the system along with the sensors. In the second type of attack, a signal is captured from a genuine user and reuses it for spoofing. In the third type of attack includes feature extractor such as a trojan horse. In the fourth type of attack, the features extracted from the system are replaced with another feature set. While in the fifth type of attack includes corrupting the matcher to modify the match score, which is preselected. The sixth type of attack is related to change the template of the database and seventh type of attack concerns attacking the channel between the matcher and the stored template.

While the anti-spoofing system extracts a different kind of features for each biometrics trait. Ridge lets are used to extract features from the face while from fingerprint level-1 (local orientation and frequencies) and level-2 (minutiae) extract the required features. The local ternary pattern is calculated for iris. Finally, all the features are fused and fed to the classifier for classification.

For all biometric modalities such as iris, face, gait etc, there are spoofing detection methods. Indeed, we believe that existing solutions based on deep representations might be a valuable direction to this field of research, allowing the construction of systems with little effort even to image-based attack types yet to come. An anti-spoofing system for auditory based human age estimation and classification system is presented for the first time.

4.2 Potential vulnerability of the auditory perception based biometric system to spoofing

4.2.1 Auditory perception based biometric system for age estimation and verification

The ability of a human to receive and interpret different sounds that reach the ears of the human auditory system through audible frequency waves transmitted through the air or other means is known as auditory perception. The auditory perception is highly correlated with human age. The auditory perception response varies with age, such as the age increases, the highest audible range of frequency decreases. The decrease in the highest audible frequency leads to hearing loss.

The flow chart of the proposed auditory perception-based age estimation and classification approaches are shown in Figure 4.1. First, the auditory system is simulated using dynamic frequency sound waves. The hearable frequencies are recorded and used to estimate the age of a person. After, the responses of the auditory system are registered in a dataset to analyze the separability between the different age groups, to classify the perceived responses into an age group and estimate the age of the subject.

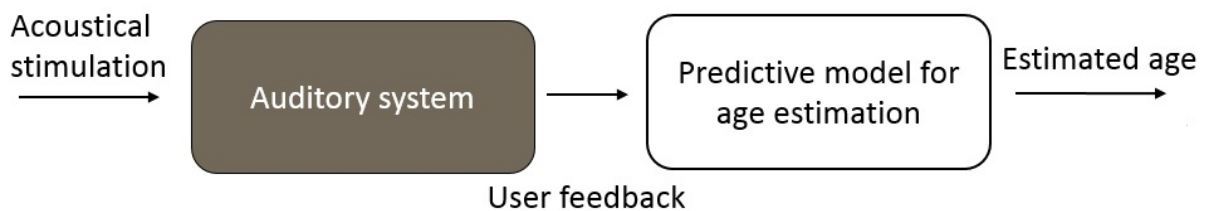


Figure 4.1: Daigram of the auditory perception based human estimation system

4.2.2 Protocol of stimulation

By generating dynamic frequency sound waves human auditory system is stimulated according to the following model:

$$\begin{cases} x(t) = A_0 \cdot \sin(2\pi \cdot \phi(t) \cdot t), \\ \text{where } \phi(t) = \alpha \cdot t + \phi_0, \end{cases} \quad (4.1)$$

A_0 stands for sound amplitude, t stands for time, ϕ_0 is the initialization frequency, and α stands for the frequency speed.

The stimulation duration of t is set to 20sec. A user has to interact with the system in real-time. A dynamic frequency sound is generated. Each user should respond while he/she stops hearing the sound or starts hearing the sound. The subject should conduct two tests:

- first test: the sound is generated from the lower frequency (20Hz) to the higher frequency (20,000Hz). The user ends the first test (e.g. keyboard action), once no sound is perceived,

- second test: the second starts automatically. In this case, the sound is generated from the higher frequency (20,000Hz) to the lower frequency (20Hz). The user ends the second test once the sound is perceived.

Both the frequencies are registered in data, and the system then calculates the average of the two frequencies (first test frequency and second test frequency). The average of the two test frequencies has been calculated. The three frequencies are the feature vectors that are used to describe the auditory perception of each test person. Two objectives have been achieved: Classifying human age into an age group using the auditory perception such that different age groups are used, and the performances of the classification are compared. Estimating human age from the auditory perception is carried out using Random forest regression model is designed for forensic age identification from the auditory perception.

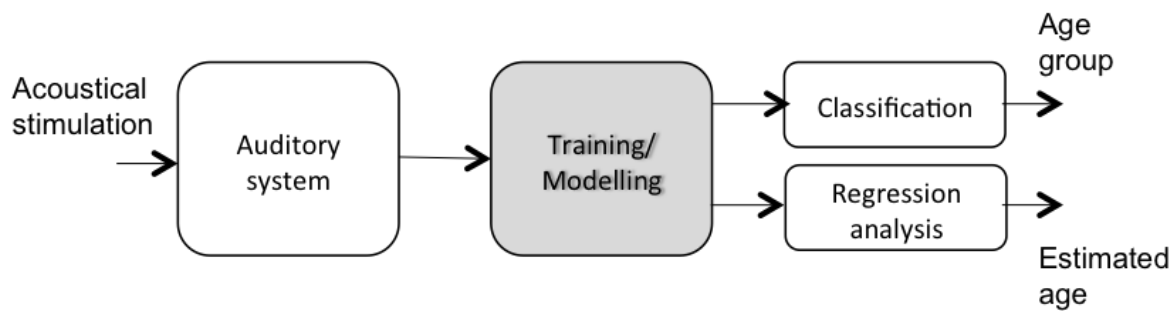


Figure 4.2: Flow chart of the proposed auditory perception based age classification and estimation approaches

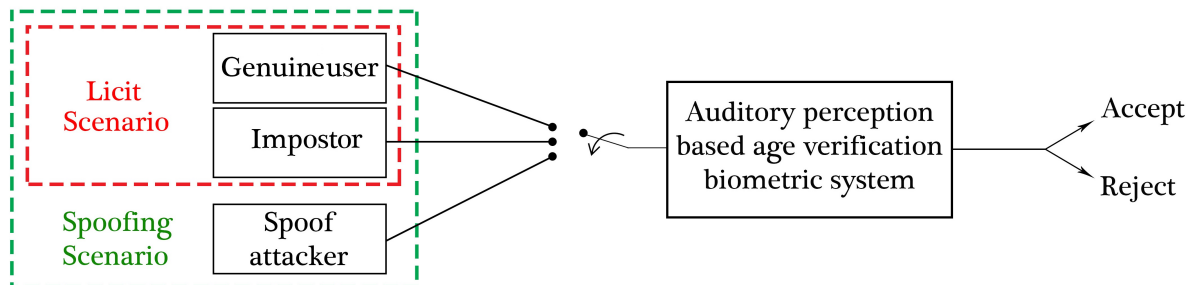


Figure 4.3: Auditory perception based anti-spoofing system

The proposed approach of age estimation based on auditory perception shows a good classification rate of 92% and 86% for three and five age groups, respectively. A robust regression model is also built, and it has an accuracy rate of 98.2% and a root mean square of error of 2.6 years. On the other hand, the proposed approach is tested on licit scenario for assessing the baseline performance using genuine and zero-effort imposter trails. The auditory perception-based system for age estimation and classification shows promising results. Although it is very sensitive to spoof attacks, a user can easily spoof the system such that a user can easily spoof the system with his age. Two scenarios exist to spoof the system:

- An old user to impersonate a young one, just by finishing the experiment with a high-frequency in the first test and respond after some seconds as the second test of experiment. A young user to impersonate an old one, by finishing the first test with lower-frequency, and respond with a higher delay for the second test.

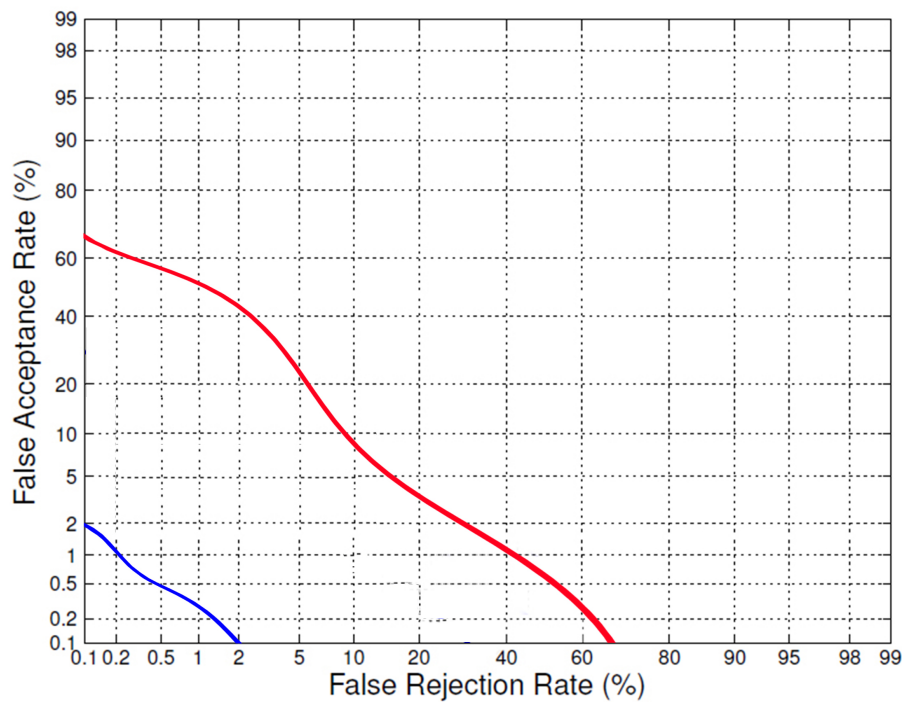


Figure 4.4: Licit scenario vs spoof scenario of biometrics system for auditory based human age estimation

The comparison of the auditory perception-based system under licit scenario and spoof scenario is shown in figure 4.4. The EER value for licit scenario is nearly 2% while under spoof scenario is increased to 60%. We can conclude from that the need for anti-spoofing measures for the auditory perception-based biometric system.

4.3 Anti-spoofing measure for auditory perception biometric system

The proposed biometrics system is vulnerable and easy to spoof as shown in section 4.2. Therefore, we presented an anti-spoofing system as shown in Figure 4.3 to prevent indirect attacks [329] The digitize limits of the biometric system can only taken into consideration.

A test subject is required to take the test for age estimation using auditory perception, as shown in Figure 4.2. As the auditory perception-based system estimate the age of the subject, our proposed anti-spoofing system will verify his age. To quantify that, ten random frequencies are generated by considering the estimated age of the subject. It is hard for a spoof attacker to guess the hearable and unhearable frequencies in the set of generated frequencies. A certain number of hearable and unhearable random frequencies are generated for a subject of a corresponding input age. To make it more vulnerable to spoofing attack, some of the hearable generation frequencies are repeated to ensure that the test person gives the same feedback. According to our previous study, the minimum and the maximum value of hearable and unhearable frequencies for each age are assigned from a reference database. Every feedback for each generated frequency has a value $1/b$ of the final score, where b is the total number of randomly generated frequencies. The final score has to be greater than a decision threshold τ to genuine

and verify the input age.

Spoof trials concerning to a high score compared to the optimized value of τ are misclassified to genuine trials. The decision threshold is optimized to curtail an a posteriori evaluation standards given by:

$$\tau_{EER}^* = \arg.\min |FAR(\tau, D_{dev}) - FRR(\tau, D_{dev})| \quad (4.2)$$

Where the decision threshold τ is set in order to equalize the False Rejection Rate (FRR) and the False Acceptance Rate (FAR). The baseline performance of the algorithm can also be illustrated as a function of decision threshold τ_{EER}

As FAR and FRR are inversely related, the decision threshold can be set to equalize the FAR and FRR. Therefore, the posterior performance criteria to minimize could be the Half Total Error Rate (HTER):

$$\tau_{EER}^* = \operatorname{argmin}.HTER(\tau, D_{dev}) \quad (4.3)$$

$$HTER(\tau, D_{dev}) = \frac{FAR(\tau, D_{dev}) + FRR(\tau, D_{dev})}{2} \quad (4.4)$$

D_{dev} is development dataset used to determine the decision threshold. More details about the algorithm is given in Algorithm 2.

Algorithm 2 Auditory perception based anti-spoofing system for age estimation system

```

1: procedure OUTPUT: AGE VERIFICATION
2:   a=real-age,
3:   b= nbr-freq,
4:   c= nbr-randomn-hearable-freq,
5:   d=nbr-repetition-hearable-freq,
6:   Input: a, b, c, d, e( $\tau_{EER}$ )
7:   a  $\leftarrow$  insert()
8:   F3, F4 = [min-f(a), max-f(a)]
9:   F1, F2 = [min-f(a), max-f(a)]
10:  TAB : rand-f(b)
11:  for i=1:b do
12:    TAB[i]=0
13:  end for
14:  hearable-indices [ ]  $\leftarrow$  c
15:  for i=1:length(hearable-indices) do
16:    TAB[hearable-indices(i)] = (F1,F2)
17:  end for
18:  for i=1:d) do
19:    d  $\leftarrow$  rand[ ]
20:    d = TAB[position]
21:  end for
22:  for i=1:b) do
23:    if TAB[i]  $\neq$  0
24:      TAB[i] = (F3,F4)
25:    endif

```

```

26:   end for
27:   for  $i=1:b$  do
28:     play sound(<TAB[i])
29:     user feedback[i] ← ask user feedback >
30:   end for
31:   nbr-correct-answers ← check user feedback(user-feedback[])
32:   if ( $nbr-correct-answers \geq \tau_{EER}$ ): verified-age ← True
33:   else
34:     verified-age ← False
35:   end

```

4.4 Experiments and results

4.4.1 Auditory perception Anti-spoofing Database

Three datasets are collected as shown in Table 4.4.1 under two different scenarios such as licit scenario and spoof scenario by using algorithm 2 :

-The development dataset: is utilized to decide for the optimization of threshold and efficient performance at a specific operational value. The total number of trials for the development dataset is 360 for both genders (males and females) subjects. - The anti-spoofing dataset is used to assess the vulnerability of the proposed anti-spoofing system with the required threshold τ value. While 410 trials were conducted for the anti-spoofing dataset.

- The countermeasure dataset is a two-class dataset to identify genuine and spoofed trials, although 370 trials have been conducted by all the (both males and females) subjects in the age range of 12 to 51 years. The test set is utilized to determine the performance for a proposed threshold computed through the development set. The test set is equally distributed into enrolment and probe subsets.

Datasets	Development dataset		Anti-Spoofing dataset		Countermeasure Dataset	
	Male	Female	Male	Female	Male	Female
Licit Scenario	200	80	220	108	320	56
Spoofing Scenario	60	20	60	22	66	24
Total trials	360		410		470	

Table 4.1: Number of subjects in each dataset

4.4.2 Decision threshold optimization

The development of the dataset is utilized for the optimization of the decision threshold. The baseline performance of the biometrics system is assessed on a licit scenario with genuine and zero-effort imposter trials. The function of the decision threshold (τ) is illustrated in Table 4.2, and the best threshold which minimizes the HTER is set to 80% of the total experiments. As the number of repetitions or experiment is fixed in this work to ten, imposters trails correlating to a score little higher than eight trials will be misclassified as genuine trials, such that the genuine trials with correct answers less than eight trials will be misclassified as imposter trials. The score distribution for licit scenario is illustrated in Figure 4.5 Still, a little flap exists between the distribution of genuine and imposter trail. Thus the system will not make a lot of errors

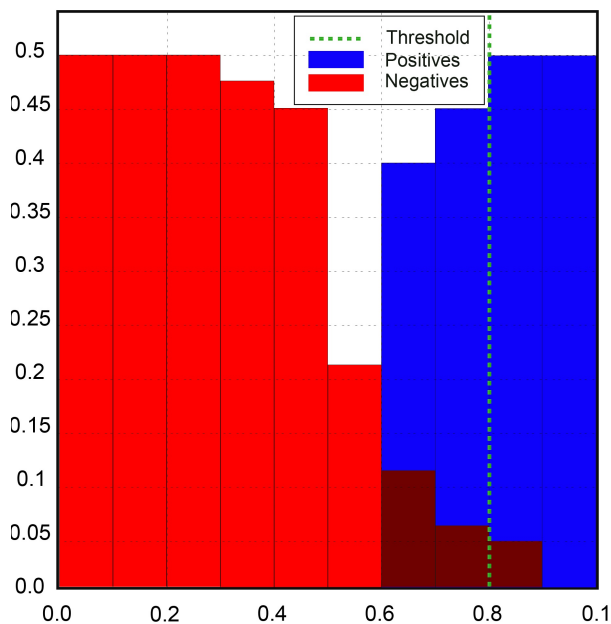


Figure 4.5: Score distribution of genuine users and zero-effort imposters while a decision threshold τ is determined with a vertical dashed line.

in distinguishing them. It illustrates the behavior of the system for varying decision threshold τ . It also shows the trade-off between genuine and imposter trials. The decision threshold τ at 80% shows the minimum misclassification of imposter trials as genuine. The efficiency of the proposed biometrics system can be demonstrated with the Detection Error Trade-off (DET) profile, as shown in Figure 4.6. Under the licit scenario the EER value 2.2% for the proposed anti-spoofing system.

The predetermined threshold is utilized to estimate the efficiency of the system using a test set D_{test} (FAR, FRR, and HTER of D_{test}).

4.5 Assessment of the anti-spoofing measure

In the field of biometrics, we considered the binary classification to determine the genuine and spoof trials. Like other biometric systems, it also gives rise to two other kinds of error False Fake Rate (FFR) and False Living Rate (FLR). The FFR represents the value of genuine trials misclassified as spoofed trials, while The FLR represents the value of spoofed trials misclassified as genuine trials.

In Figure 4.7 the blue line shows the baseline of the biometrics system without spoofing attack and without countermeasures of development dataset. The cyan line shows the efficiency of the system while having the same configuration of the baseline under licit scenario. The red line shows the performance of the system, equipped with an auditory perception-based anti-spoofing system with baseline configuration under a spoofing attack. In order to quantify how many genuine users are misclassified as spoof attackers and to recapitulate all of the above configurations we are required to study the system under a complex contact of the integrated system with spoofing attack.

The overall efficiency of a biometric system is the main concern; there is always an as-

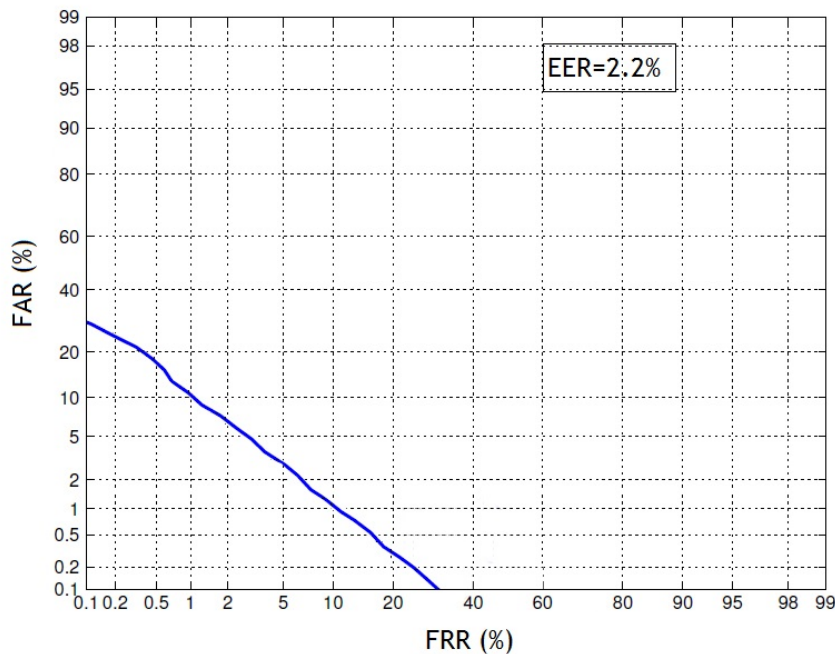


Figure 4.6: Detection of error trade-off (DET) plot showing an equal error rate (EER) of 2.2%

assessment of unconventional performance. The first configuration is specified for baseline configuration, while the second is simple with no countermeasures and open to spoof attacks. A separate configuration is required to be applied, which can support the licit scenario under a spoof attack. However, the third approach allows the system to stay secure under a spoof attack and can be evaluated for overall performance.

Hence, the value of FAR/FRR/SFAR can decide the overall efficiency of a biometric system under the required conditions. The performance depends upon the requirement and security of the system such that for some application, the FAR is more important than FRR and vice versa. In our case, the overall performance can be determined by the value of EER. The EER for baseline, baseline under licit scenario and baseline with spoofing scenario is 2.2%, 9.5%, and 5.5%

4.5.1 Assessment of vulnerabilities to spoofing

The performance of the anti-spoofing system based on auditory perception is evaluated with the spoofing scenario such that the subset of zero imposters is replaced by spoofed trials. It can be illustrated that for score distribution, the overlap between spoofed trails and genuine is greater than imposter and genuine trails.

The vulnerability of the system is quantitatively measured and expressed in terms of Spoof False Acceptance Rate (SFAR). SFAR is the percentage value of the spoofed trails, which are classified as genuine for a given decision threshold τ . An example is presented in Figure 4.10 to briefly illustrate the SFAR profile as a threshold function τ . As a function of τ , the difference between FAR (licit scenario) and FRR (licit scenario) thus represents the vulnerability of the system. In Figure 4.11, the DET plot presents both the spoof (SFAR vs FRR) and licit (FAR vs FRR) scenarios. To express the vulnerability at a certain point is very important, thus EER for

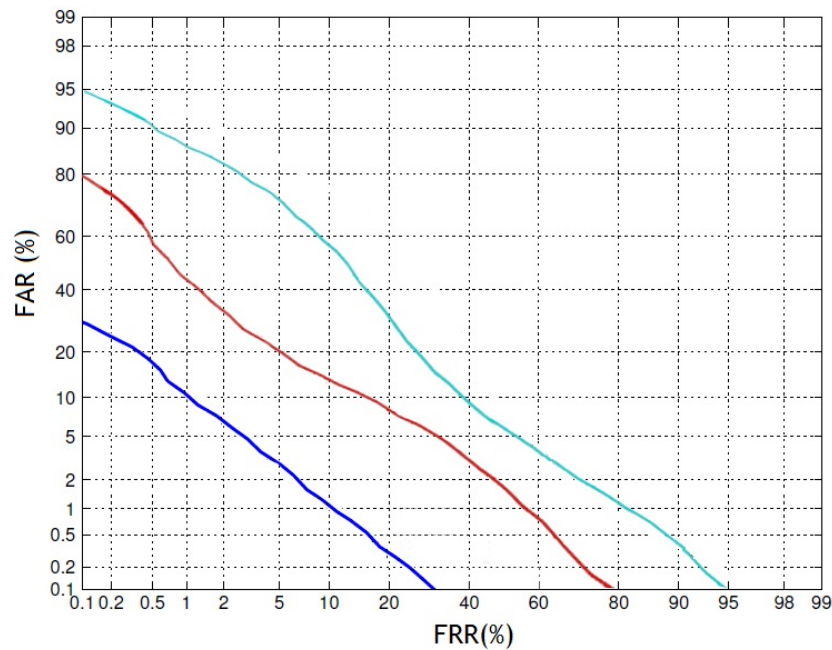


Figure 4.7: The FAR and FRR of a biometric system with/witout spoofing attack

DT (τ)	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
FAR	100%	100%	100%	94%	91%	42%	13%	6.8%	5.7%	0%
FRR	0%	0%	0%	5.7%	8.5%	8.5%	3.4%	4.6%	20.5%	25.7%
FAR-FRR	100%	100%	100%	88.3%	82.5%	33.5%	9.6%	2.2%	14.8%	25.7%
HTER	50%	50%	50%	49.4%	49.75%	25.25%	16.4%	5.7%	23.35	12.8

Table 4.2: Optimization for Decision Threshold (τ) (DT) for auditory perception

SFAR and FAR for a common FRR is shown in Figure 4.11. The FRR is 4%, as shown in the example, and FAR is 7%, while SFAR is mentioned as 14%.

4.6 Assessment of the anti-spoofing countermeasure

The countermeasure is action, device, procedure or technique which minimizes the danger that it causes, or discovers, and reports a threat, a vulnerability, or attack, by eliminating it or preventing it. The increasing importance of anti-spoofing systems, countermeasures, several combinations of countermeasure approaches and algorithms in the state-of-art gives assistance to the researcher to introduce countermeasures. While not developing robustness to particular attacks, fused countermeasures allow an adjustable anti-spoofing structure by which recently developing vulnerabilities can be immediately covered with flexible fusion approaches or the extension of modern countermeasures. The fusion of two biometric modalities, facial features, and auditory perception approaches are used for human age estimation as a countermeasure. As shown in Figure 4.14, countermeasure sub-systems are alternatively integrated, in series not in parallel, with the biometric system. Countermeasure is consist of is two steps:

- Human age verification using facial features
- Human age verification using auditory perception responses

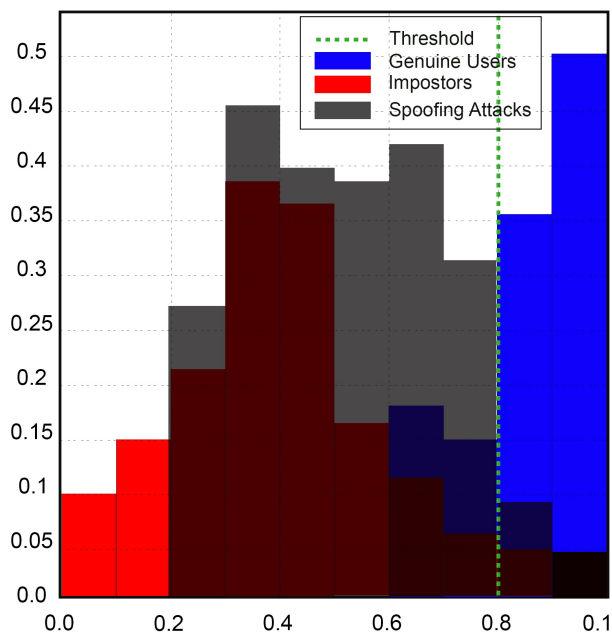


Figure 4.8: Score distributions of Zero-effort imposters, genuine and spoof attackers with the Spoof False Acceptance Rate

To conduct the test, a subject's image is taken in real time through a camera and the DEX((Deep EXpectation) based CNN system estimate the age through facial features. If the subject successfully conducted the test, another test based auditory perception has been conducted for age verification.

4.6.1 Automatic age estimation using face feature

For age estimation using facial feature, we used DEX (Deep EXpectation) from the state-of-art [215]. In this section the pipeline of the proposed approach is briefly explained.

4.6.1.1 Face alignment

Many datasets utilized for this work do not show centered frontal faces for DEX technique but rather faces, and the detection occurs, and the faces are aligned for training and testing.

For some face images, it was hard for the detector to identify faces. In such cases, the entire image is used as the face image. The efficiency improves while studying the context throughout the face also. Thus, the face is detected face by using 40% of the image height and width on every side. In case, the face is very wide, then keep it as it is, the final pixel at the edge is reappeared. This assures that the face in the image will always be kept in the corresponding position. As the phase ratio of the resultant image may change and compressed to 256*256 pixels. It provides the input to the deep convolutional neural network.

4.6.1.2 CNN Architecture

A conventional Convolutional Neural Network (CNN) is designed for estimating the age of an individual begins with a particular face image as an input. This needs an aligned face with the setting as input and delivers a detection for the age. On a face image with known age, CNN is

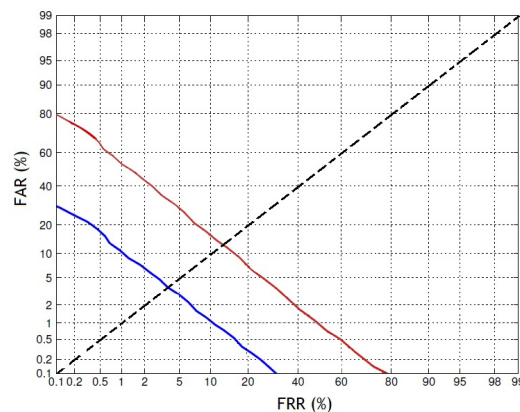


Figure 4.9: DET determines the Spoof False Acceptance Rate (SFAR), EER on the decision threshold τ illustrated from the development dataset

trained.

CNN with VGG-16 has been used in this method as shown in Figure 4.12. The reason to choose this architecture is that the architecture is deep and easy to manage, having promising results over ImageNet challenge [214] and considering the truth that, in this case, the VGG-16 executes with a low-resolution image (256x256) that allows the model good classification model which are publicly available. VGG-16 is much deeper as compared to earlier architecture, such as AlexNet [216], 13 convolutional, and three fully connected layers, entirely having 16 layers. AlexNet, in comparing to VGG-16 uses the considerable larger value of filters measures up to $11 * 11$ at a stride of 4. Whereby all filter in VGG-16 catches manageable geometrical structures and in comparison provides much-complicated logics by its expanded depth.

4.6.1.3 Evaluation protocol

To quantify evaluation in Figure 4.14, provides the Detection Error Trade-off (DET) Curve with different profiles under a spoof attack. A clear view of the efficiency of different systems has been demonstrated by calculating the EER value under a spoof attack. The evaluation involves three different kinds of system configurations to generate a different DET profile. The first configuration (blue profile) demonstrates the efficiency of the biometric countermeasure system (under spoof attack). While the second configuration (green profile) demonstrates the efficiency of the auditory perception-based anti-spoofing system while constrained to spoof attacks. The third configuration (red profile) demonstrates the enhancement in the efficiency of the active countermeasures.

The value of EER is improved based on our proposed approach, which is cited with regards to the baseline system and auditory perception-based system. We conclude that the proposed countermeasure based group feature vectors in the system alignment for verification are considered universal. The EER value is 3.5% for the countermeasure under spoof-attack and considered a promising result. In parallel, the FRR value is higher than the required value in comparison to the anti-spoofing system based on auditory perception.

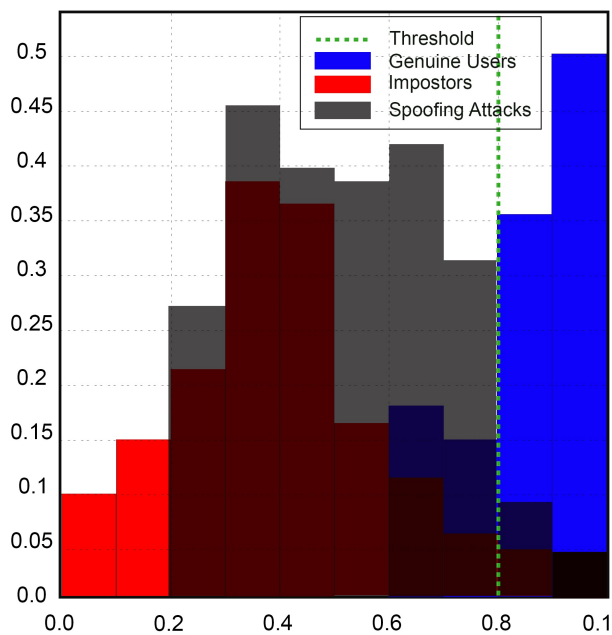


Figure 4.10: Score distributions of Zero-effort imposters, genuine and spoof attackers with the Spoof False Acceptance Rate

4.7 Conclusion

The past work, human age estimation based on auditory perception, is distinguished by the lack of a standard evaluation methodology and its status of vulnerability to spoofing. This paper introduced a promising knowledge to standardize the evaluation method.

We conclude that the proposed anti-spoofing system is robust by having an EER value of 5.5% under the spoof attack scenario while further scientific work is needed in order to expand and alter the methodologies through the previous work. While the proposed spoofing countermeasures provided a reason for optimism, showing EER value of 3.5%. Their generalization of existing spoofing attacks is still not clear by having a higher value of FRR. This position contributes to a range of forward-looking study strategies, including merged countermeasures and classification techniques. As it is a new trait, more challenging databases are needed to keep biometric system developers safe from the spoof-attacker. Although highly hard, they are estimating the effectiveness of countermeasures in practical implementation situations will be critical, inclusive not only in the capacity to identify spoof attacks but also the effect on the suitability of the model. While demonstrating the anti-spoofing system, several subject's age was estimated more than their actual age, which leads us to develop a system for the detection of hearing loss.

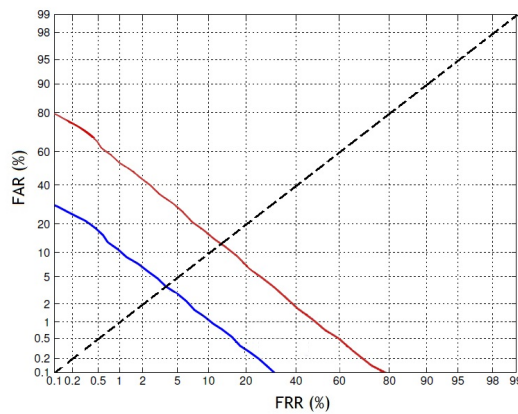


Figure 4.11: DET determines the Spoof False Acceptance Rate (SFAR), EER on the decision threshold τ illustrated from the development dataset

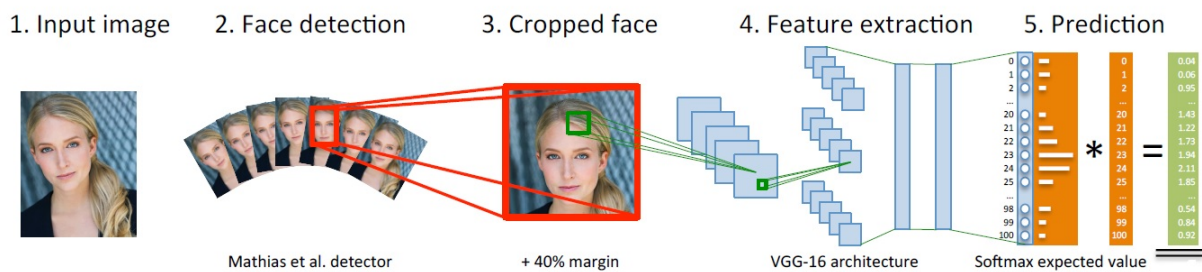


Figure 4.12: Pipeline of DEX architecture

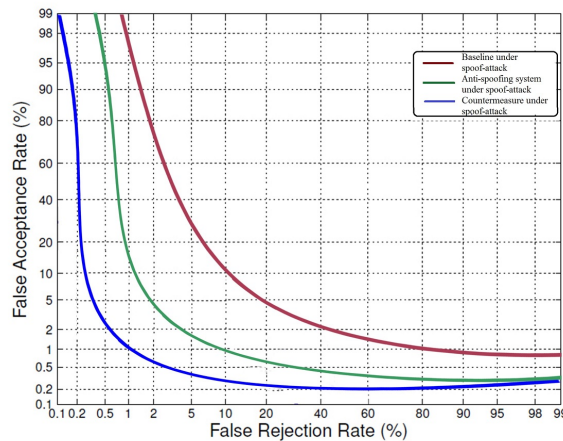


Figure 4.13: The Detection Error Trade-off (DET) profiles are obtained for baseline, auditory perception based biometric anti-spoofing system, and countermeasure approach under spoof-attack

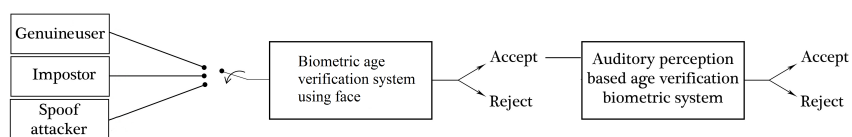


Figure 4.14: Spoofing countermeasure integrated with biometric system

Chapter 5

Computer aided prediction of hearing loss using auditory perception responses

Hearing loss is the principal cause behind hearing impairment and deafness around the world. It is a significant health problem affecting our world today, and it is growing exponentially among both young people and adults due to aging, hearing impairment, listening to music, and noise exposure. Treatment options for hearing loss are very limited, and it can only be fully controlled by taking precautions in the early stages. Thus, proper education is required to spread awareness among people to use hearing protection, reduce exposure to loud music and other risk factors. A computer-aided method to predict and then prevent hearing loss is presented. Three predictive models (human age estimation, prediction of hearing loss, and level of hearing loss) based on auditory perception are presented.

5.1 Introduction

Hearing loss is a partial or total inability to hear. The individual suffering from it will experience difficulty in hearing speech and sounds. Hearing loss may happen in one or both ears, and it may be permanent or temporary. Symptoms of hearing loss are:

- Difficulty following a conversation
- Hard to understand conversations in a noisy atmosphere
- Listening to the radio or TV on a high volume
- Beep sound or ringing in ears(tinnitus).
- Feeling tired in group conversations.

Recently hearing loss has become very common amongst all ages, from teenagers to older people. In fact, the number of incidences is increasing among children and adults exponentially [203, 204]. For elderly people (over the age of 65), every second person suffers from hearing loss [205]. Male subjects have a bigger chance of hearing loss when compared to female subjects, due to the involvement of extra activities in daily life. According to the World Health Organization, hearing loss is the fifth major reason for living with disability [206]. Such that, nearly 28 millions of Americans are suffering from hearing loss [203]. It is a significant

health problem and needs more attention not only from the scientific community but from everyone.

Untreated hearing loss can affect a person's professional development as well as social life, psychological, and health status. It has a big impact on the body, which is not only limited to hearing. In fact, those who are suffering from hearing loss can experience things such as distorted and incomplete communication, which can seriously affect their professional and personal lives and thus lead to withdrawal and isolation. Untreated hearing loss may cause so many other diseases, such as cognitive decline [207], inclined incidence of dementia [208], social isolation [209], depression [210] and even falls [211]. The physiological effects on a person's life can be feelings of shame, guilt, anger, difficulty concentrating, sadness, depression, frustration, anxiety, insecurity, self-criticism, and low self-esteem/self-confidence [212].

A subject can inherit a mutated gene or genes that cause hearing loss, or a subject may inherit undesirable genes. Hearing loss can be syndromic if present at birth, meaning the subject may have other health issues such as problems with balance, vision, or even heart problems. Nearly 30% of inherited hearing loss corresponds to a syndrome [213]. Age-related hearing loss, also known as presbycusis, occurs over time and is due to changes in the inner ear such as changes in blood flow, or damage done to hair cells. There are hair cells inside the human ear; people are born with nearly 16,000 hair cells, and hearing loss is only detected when about 30-50% of the hair cells are destroyed or damaged [209]. The damage done to hair cells in the Corti within the cochlea of the inner ear is involved in the mechanism of hearing loss. Unfortunately, there are limited resources to detect the early stages of hearing loss. By the time it can be detected, too many hair cells are damaged or destroyed, and cell destruction cannot be restored by using a hearing aid.

If hearing loss is felt by a subject, it is important to conduct a hearing test with an otologist, otolaryngologist, or ENT (Ear, Nose, Throat) specialist, to diagnose the disease properly. There are several tests available to precisely predict the type and severity of hearing loss, such as air conduction or audiometry, bone conduction, word recognition, acoustic immittance, Otoacoustic Emissions (OAE's), and Auditory Brainstem Response (ABR). For these tests, a subject is required to follow a proper mechanism in the presence of a specialist or a doctor. In fact, computer-aided systems are needed for preliminary tests and for preliminary diagnoses. Such systems can provide economic, health-care, and wellbeing benefits. To the best of our knowledge, there is no scientifically proved system that exists currently.

We developed an efficient computer-aided system for prediction and prevention of hearing loss. It can help to reduce the cost, labor work, and time for healthy people facing hearing problems. It can also prevent hearing loss if diagnosed in the early stages.

5.1.1 Human auditory system: generalities

The human auditory system is the sensory mechanism for the sense of hearing. It has two sensory organs to hear the sound known as ears, which are connected to both the sides of the head and connected to the brain stem through a brisk nerve fiber. The salient linking point of the brain is called brain stem, which provides a bridge to the human nervous system to the other parts of the brain. The auditory information is processed through a temporal lobe called the auditory cortex.

The human ear is extremely an intricate organ. This process is making difficulty furthermore when the information from the two ears is collectively transferred through a mystifying neural network called the brain. Here just a short story about the ear is presented; many elusive possessions and poorly understanding marvels are still found associated with human hearing.

Figure 5.1 explains the main processes and their structures that cover a normal human ear. The outer ear, which is the combination of two portions, the observable flap of skin and cartilage attributed to the head side, and the canal of an ear, a tube nearby 0.5 cm in diameter ranging around 3 cm into the head region. These structures forward the surrounding effects to the middle and inner ear organs located securely inside the bone of the skull. Stretched transversely found at the ear canal end is a tinny sheet of tissue named eardrum (tympanic membrane). It causes a vibration when the Sound waves stick to it. The middle ear is a combination of small bones that forward the vibration of the eardrum to the cochlea (inner ear) to convert into neural impulses. The cochlea is a tube-like structure filled from liquid about 2 mm in width and 3 cm in length. Though revealed straight in figure 5.1, the cochlea of the ear is curly in shape, which looks like a small snail shell. In reality, the cochlea is a derivative of the Greek word used for a snail.

At that time, when a wave of sound efforts to cross air state to liquid, so only a small portion of these waves are diffusing into surrounding whereas the remaining energy is reflected due to truncated mechanical impedance (low acoustic pressure and high particle velocity resulting from low density and high compressibility) of air as compared to liquid having high mechanical impedance. It is concluded that the mechanical impedance difference mostly reflected the sound waves in the air medium or fluid.

The network function of the middle ear increases a portion of the energy of the sound while entering the inner ear liquid medium. Mostly this impedance alteration is coming from the difference in zone amongst the eardrum (sound received from the air) and the oval window (see figure 5.1). The zone of the eardrum and the oval window is roughly estimated as 60mm² and 40mm², respectively. So, the applied pressure is equal to force separated through a zone, and this zone difference increases the pressure of sound waves approximately 15 times.

There is a basilar membrane inside the cochlea works like supporting building composed of usually 12,000 sensory cells which form the cochlear nerve. This membrane is present in a solid form adjacent to the oval window and turns elastic form towards the opposite end, permitting it to perform the role of the frequency spectrum analyzer. Because of exposure to the high-frequency signal, this membrane vibrated due to its rigid nature and exited the nerve cells to move near the oval window and vice versa. This association makes fibers specific in the cochlear nerve as a result of specific frequencies responses named place principle, which is well-preserved through the aural path mad about the brain.

Volley principle is another information encoding scheme in the hearing of humans. And those electrical beats which are produced by nerve cells when transfer information is term as action potentials. Action potentials are generating in responses of every round of vibration when a nerve cell of the basilar membrane code auditory materials. E.g., a two hundred Hz of sound waves can be produced through a neuron generating an action potential of two hundred/sec at frequencies lower than 500Hz. It is the determined fraction of brain neurons to

produced action potentials. So, this problem is overwhelming through the human ear, which permitting many nerve cells to perform this type of task. A given example will clarify this statement. A three thousand Hz capacity might be signified by ten nerve cells consecutively fire 300/sec. This calculation covers the assortment of volley principle up to four kHz, and above this figure, the place principle completely applies. Some Specific occurrences responses make a precise fiber in the cochlear nerve, which is known as place principle, preserved the auditory way to brain completely.

In Table [3], the interrelationship between perceived loudness and sound intensity is briefly explained. To indicate the sound intensity on a logarithmic scale is known as decibel SPL (Sound Power Level). 0 dB SPL has a sound wave power of 10-16 watts/cm², about the lowest intensity of sound perceived by a human ear. A typical speech is about 60 dB SPL, while severe damage can occur to the ear at nearly 140 dB SPL.

The difference between the faintest and loudest sounds is that humans can hear about 120 dB. A person can quickly detect the change in loudness of sound when the signal is modified by about 1 dB (a change of 12% in amplitude). While there are about 120 levels of loudness that a human can perceive from the low whisper to the thunder. The human ear has an amazing sensitivity while listening to the low-frequency sound, and the eardrum vibrates much lesser than the diameter of a molecule!

The range of human hearing is usually considered between 20 Hz to 20,000 Hz, but the sensitivity to sound starts from 1000 Hz and 4000 Hz. For example, a person can detect sound as lower as 0 dB SPL at 3000 Hz but needs 40 dB SPL at 100 hertz (an increased amplitude to 100). A person can judge that the two sounds are different if the frequencies differ by more than 0.3% at 3000 Hz and increase to 3% at 100Hz. A good example is that adjacent keys of a piano differ by 6% in frequency.

The first advantage of having two ears is the capability of identifying the direction of the sound. The human can detect the difference between two sources sound that is put as far as three degrees apart, about 10 meters to the width of the person. The information about direction is received in two different ways. First, the frequencies above 1000 Hz are strongly tracked by the head such that the ear near to the sound source gets a stronger signal as compared to the ear on the other side of the head. The second sign to directionality is that the ear which is far from the sound source side hears the sound slightly later compared to the near ear, due to its more considerable distance from the sound source.

While human hearing can quickly determine the direction of a sound source and identification of the distance to the sound source is poor. The reason is that very few signs are available in a sound wave that can provide such information. Human hearing poorly perceives that low-frequency sounds are distant while the high-frequency sounds are nearby [28].

The rest of the chapter is organized as follows. In this Section, briefly explain different categories of hearing loss and precautions for the prevention and discuss the existing systems in the state-of-art for prediction and prevention of hearing loss. In Section III, the proposed auditory perception-based methods for the three predictive models are discussed. In Section IV, evaluations and performances of the different proposed approaches are discussed. Finally, in the last Section V, a conclusion to this work, a set of perspectives and paths for our future

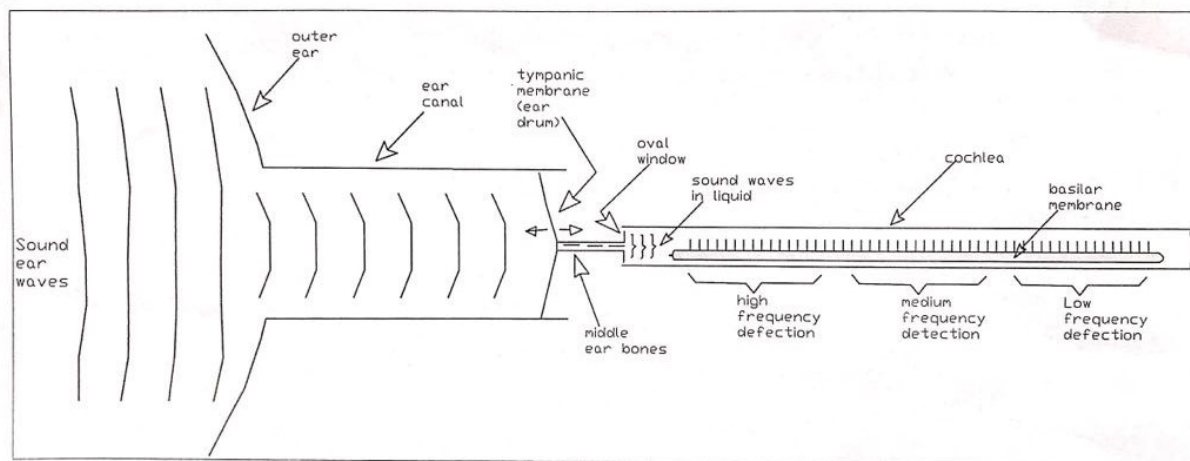


Figure 5.1: Functional diagram of ear

work is delivered.

5.2 Hearing loss and causes

There are many causes of hearing loss that can be subdivided into two categories; the first category concerns the non-modifiable risk factors, and the second category concerns the modifiable risk factors. The first category of causes cannot be prevented, whereas the second category can. Therefore, efforts should be made to prevent hearing loss when one of the factors of the second category occurs.

5.2.0.1 Non-modifiable risk factors

comprise of race, genetics, age, and gender. Age is a central factor among all of these aspects. Hearing loss is directly proportional to increasing age. As age increases, the value of hearing loss also increases [161]. About 40% of the population suffers from hearing loss above the age of 75 years. Approximately 23% between the age of 65 and 75 years of age suffer from full or partial hearing loss [279].

Studies have shown that temporary threshold shift and hearing impairment is increasing exponentially among children and teenagers. Between the age of 6 to 12 years old, 12% of children suffer from hearing loss, while teenagers and young adults are suffering from hearing impairment and tinnitus [280, 281]. The right and left ear have different responses to hearing loss. Research proves that an individual in blood group O has a bigger chance of hearing loss and impairment. Due to extra involvement in different activities, boys have more chance of experiencing hearing loss when compared to girls [280].

5.2.0.2 Modifiable Risk factors

are related to external and non-genetic factors such as non-use of hearing protection, lack of exercise, smoking, unbalanced diet, and diabetes.

watts/cm ²	Decibel	Effects/Examples
10 ⁻²	140	Jet airoplane at 30 meters, severe pain, damage in seconds
10 ⁻³	130	
10 ⁻⁴	120	Loud rock concert, pneumatic chipper at 2 meters, threshold of pain
10 ⁻⁵	110	Damage from 30 minutes per day exposure
10 ⁻⁶	100	Noisy factory, siren at 30 meters, damage from 8 hours per day exposure
10 ⁻⁷	90	Inside a heavy truck; damage from prolonged exposure
10 ⁻⁸	80	Loud radio, classroom lecture
10 ⁻⁹	70	Noisy office, busy traffic
10 ⁻¹⁰	60	Normal conversation
10 ⁻¹¹	50	Average office, soft music
10 ⁻¹²	40	Average home
10 ⁻¹³	30	Quiet home
10 ⁻¹⁴	20	Whisper at one meter distance
10 ⁻¹⁵	10	Rustle of leaves
10 ⁻¹⁶	0	Threshold of hearing at 1000 Hz
10 ⁻¹⁷	10 ⁻¹	weakest audible
10 ⁻¹⁸	10 ⁻²	

Table 5.1: Sound intensity levels and intensities

Non-use of hearing protection is due to lack of knowledge and discomfort associated with the age. Most individuals are unaware of the risk of hearing the loss in a noisy environment, so that's why they are reluctant to use ear protections [283]. The fact is that 60% of teenagers have experienced temporary hearing loss or tinnitus because of attending clubs and loud concerts [282].

Smoking causes many health issues, including hearing loss. With a loud noise, the hearing of smokers can largely be affected because they are exposed to many toxic substances [284].

lack of exercises and bad nutrition are also related to hearing loss. Teenagers and young adults can enhance their hearing capabilities by doing proper exercise and maintaining cardiovascular fitness [285]. Physical fitness and exercise can reduce temporary hearing loss, which occurs because of noise exposure. Researchers suggest that with physical fitness, the inner ear gets more oxygen-rich blood, which reduces hearing loss and strengthens hearing [286].

Tooth loss, heart diseases, and diabetes are strongly associated with hearing loss [287, 288]. It has been found that hearing loss is more prominent among individuals who have many tooth loss. Tooth loss causes hearing impairment due to abnormal activity of muscles on the auditory tube. Diabetes increases the risk of hearing loss at an early age. The typical sound transmission is disturbed due to high blood sugar, which narrows the blood vessels inside the inner ear.

Cognitive impairment Studies have shown that hearing loss has a connection with the brain function decline or loss of brain tissues known as cognitive decline. The size of the brain shrinks, which is a natural part of aging. An older subject loses brain mass faster due to hearing loss when compared to a normal subject [289].

5.2.1 Hearing loss diagnosis

A variety of preliminary tests are available to diagnose hearing loss such as a physical exam, general screening tests, and tuning fork tests.

Physical exam: a doctor looks into the ear to check the causes of the hearing loss, such as inflammation due to infection or earwax. The doctor also looks for structural causes of the hearing problems.

General screening tests: the doctor may cover one ear at a time to see how well a subject hears words spoken at various volumes and how he/she responds to other sounds.

Tuning fork tests: simple tests with tuning forks can help a doctor to detect hearing loss. A tuning fork easily evaluates the hearing loss caused by damage to the vibrating parts of the middle ear (including eardrum), damage to sensors or nerves of the inner ear, or damage to both.

After the detection of hearing the loss in the preliminary tests, the level and severity of hearing loss can be diagnosed by using several machine-based approaches:

- **Otoacoustic Emissions Testing (OAE):** Otoacoustic Emissions Testing (OAE) is measuring the inner ear (cochlear) function. During the test, a tiny probe is placed in the ear, and the tones are played. Then it is sent to the ear canal from the probe speaker and through the middle ear to the cochlea. In the cochlea, the outer hair cells get excited and respond to the generated acoustic reaction. In the reverse direction from the cochlea, the generated response moves back to the ear canal and is detected by the probe microphone. The mechanism of OAE shows that within normal limits, the hair cells function normally.
- **Impedance Testing:** Impedance testing provide information about the functionality of the middle ear. The processing time for each ear is 3 to 30 sec. This involves different conditions of pressure over the eardrum to determine if any problems exist in the middle ear.
- **Auditory Brainstem Response (ABR):** for Auditory Brainstem Response (ABR), three different electrodes are placed on the head of an individual, and then a sound is played. The response of the brain is then measured with equipment. This test does not measure the reaction of the auditory system; it determines the brain's activity response.
- **Audiometry:** Audiometry involves several sounds generated from low to high pitches and soft to loud intensity in a silent room. An audiologist records all the responses of the subject to every sound.
- **Auditory Steady-State Response (ASSR):** ASSR is often done in combination with the ABR test. This test also measures the brain's response to sound. All the proposed tests need to be done in the hospital and are not possible to achieve without a physician.

Some online web-based applications are also available to detect hearing loss such as Bel-tone [291], Miracle-ear [290], Phonak [292] etc. In Beltone, a subject has to enter all their information, including age and gender. In this hearing test, the subject hears combinations of three words and three numbers. During the test, there is rushing noises that will change in volume. Each time, there are three images to select of three heard words. The results will be sent through email. Miracle-ear is also an online interface for the detection of hearing loss. Six different sounds are generated in a noisy environment, and the subject has to interact with

the system by responding to some questions. Phonak is another online interface; different frequency sounds are generated during the experiment, and the subject has to interact with the system in real-time. While using all these interfaces, it is hard for a subject to follow the steps, and sometimes they will get lost in the middle.

The better hearing institute is also an online hearing loss prediction interface [293]. It has a different mechanism than the above-mentioned online hearing loss prediction systems. At the start of the experiment, the system asks some question to the subject about hearing problems he/she may experience, such as:

- Have a problem hearing over the telephone.
- Have trouble following the conversation when two or more people are talking at the same time.
- Have trouble understanding things on TV.
- Have to strain to understand conversations.
- Have to worry about missing a telephone ring or doorbell.
- Have trouble hearing conversations in a noisy background, such as a crowded room or restaurant.
- Get confused about where sounds come from.
- Misunderstand some words in a sentence and need to ask people to repeat themselves.
- Especially have trouble understanding the speech of women and children.
- Have trouble understanding the speaker in a large room, such as at a meeting or place of worship.
- Many people I talk to seem to mumble (or do not speak clearly).
- People get annoyed because I misunderstand what they say.
- Misunderstand what others are saying and make inappropriate responses.
- Avoid social activities because I cannot hear well and fear I will reply improperly.
- Family members and friends have told me they think I may have a hearing loss.

To answer these questions, a subject has to choose a number in the range of 1-5. Each answer has a specific score which determines the intensity of the hearing loss. A scoring value above 30 indicates a hearing loss [294].

To the best of our knowledge, no scientific studies illustrated in scientific papers are behind the systems mentioned above, in order to prove the reliability of these systems.

In order to study these systems and their limitations, we asked nearly 15 subjects to try the above online systems for hearing loss detection without providing any information about the steps to follow. After completing the test, we asked the subjects to provide a review of each system. Each of the online systems has a common issue of time; the proposed systems are

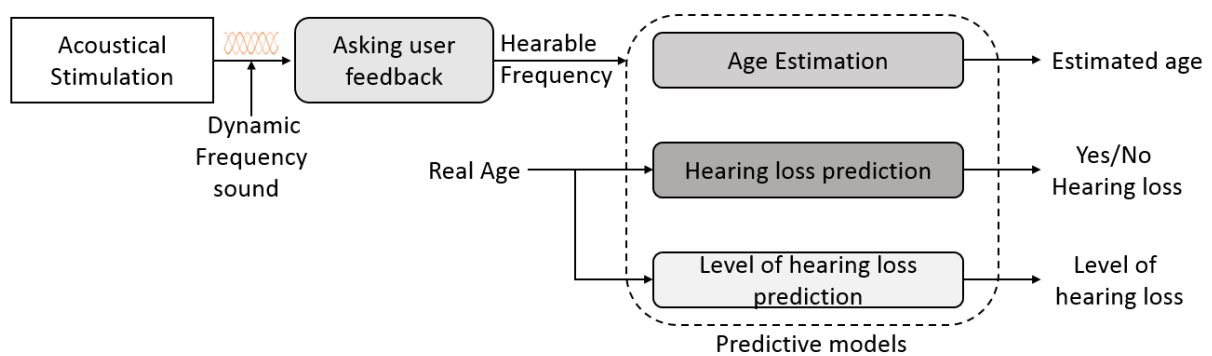


Figure 5.2: Flow diagram of our proposed approach

time-consuming. Secondly, it is hard for the subjects to follow the steps of the experiment. According to the subjects, different experiments are complex. The third drawback of these systems is that they are unable to find out the severances of hearing loss of a subject or its level, which is an important factor.

5.3 Proposed approach

The flow chart of our proposed hearing loss prediction system approach is shown in Figure 5.2. First, the auditory system is stimulated using a dynamic frequency sound [161] (see Section 2.2.1). A user feedback is required, and audible frequencies are fed to three predictive models:

- the first predictive model is built to estimate the human age (Section 5.4.4.1), only the auditory perception responses are given as input,
- the second predictive model is built to predict hearing loss (Section 5.4.4.2), the auditory perception responses and the real age are given as input,
- the third predictive model is built to predict the severity or level of hearing loss (Section 5.4.4.3), the auditory perception responses and the real age are given as input.

The human auditory system is stimulated using dynamic frequency sounds (see Fig. 5.3). A bilateral stimulation with the speaker is realized according to the following model:

$$x(t) = A_0 \cdot \sin(2\pi \cdot \phi(t) \cdot t), \quad (5.1)$$

where $\phi(t) = \alpha \cdot t + \phi_0$, A_0 stands for sound amplitude, t stands for time, ϕ_0 is the initialization frequency, and α stands for the frequency speed.

The proposed system needs real-time interaction. Thus, the subject must interact and respond to the system when he/she hears sounds. Two tests are to be conducted:

- **First test:** the sound is generated from lower frequency to higher frequency (20Hz to 20,000Hz), and the user has to respond through keyboard action when he/she stops hearing. The correspondent audible frequency $F1$ is saved.

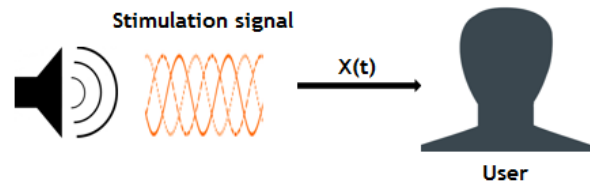


Figure 5.3: Protocol of bilateral acoustical stimulation

- **Second test:** the sound is generated from a higher frequency to lower frequency (20,000 to 20Hz), and the user has to respond when he/she starts hearing. The correspondent audible frequency F_2 is saved.

The two audible frequencies F_1 , F_2 and the mean of both are saved and fed to the different predictive models.

5.4 Experiments and results

To conduct the test, we used different laptops such as DELL corei7 M4700 computer, Macbook Air Corei7, HP pavilion corei7, and desktop computer Dell Precision T7500. The minimum distance for a volunteer to take the test from the computer is 12inches. The sound intensity A_0 generated by our system is set to 95db and the duration 20s. This section describes how the data were collected, the correlation between human age and the auditory perception was studied, the performance of the three predictive models was evaluated, and finally aging of hearing loss was considered.

5.4.1 Auditory Perception Based Database To Predict Hearing Loss

Two experiments have been conducted in this work: the first experiment using the proposed computed-aided methods and the second experiment using an audiogram. Five hundred three (503) subjects participated in conducting the test, as shown in Table 5.2. The age distribution of the subjects is presented in Fig. 5.6, and they belong to all ages from 7 years to 75 years. There is no big difference between the number of subjects per age.

The collected dataset is unbalanced, and it presents more healthy subjects than unhealthy subjects, more adult subjects than the rest and more males than females. All the subject was in the range of 6 to 75 years old. In order to balance the different age groups, weighting down groups is applied during the next steps of data analysis and processing. The proposed protocol requires 2-3 minutes for a volunteer to conduct the test successfully.

The medical test using the audiogram is conducted by a doctor.

The intensity of sound is measured in units called decibels (dB). Here are some examples of decibel levels for some common sounds Normal household: 50 dB, Normal conversation: 60 dB, Rock concert: 120 dB, and Gunshot: 140 dB To determine the permanent hearing loss, the standard method is as follows:

- the threshold level (dB) of average hearing at 250, 500, 1000, 2000, and 4000 Hz is calculated for each ear,

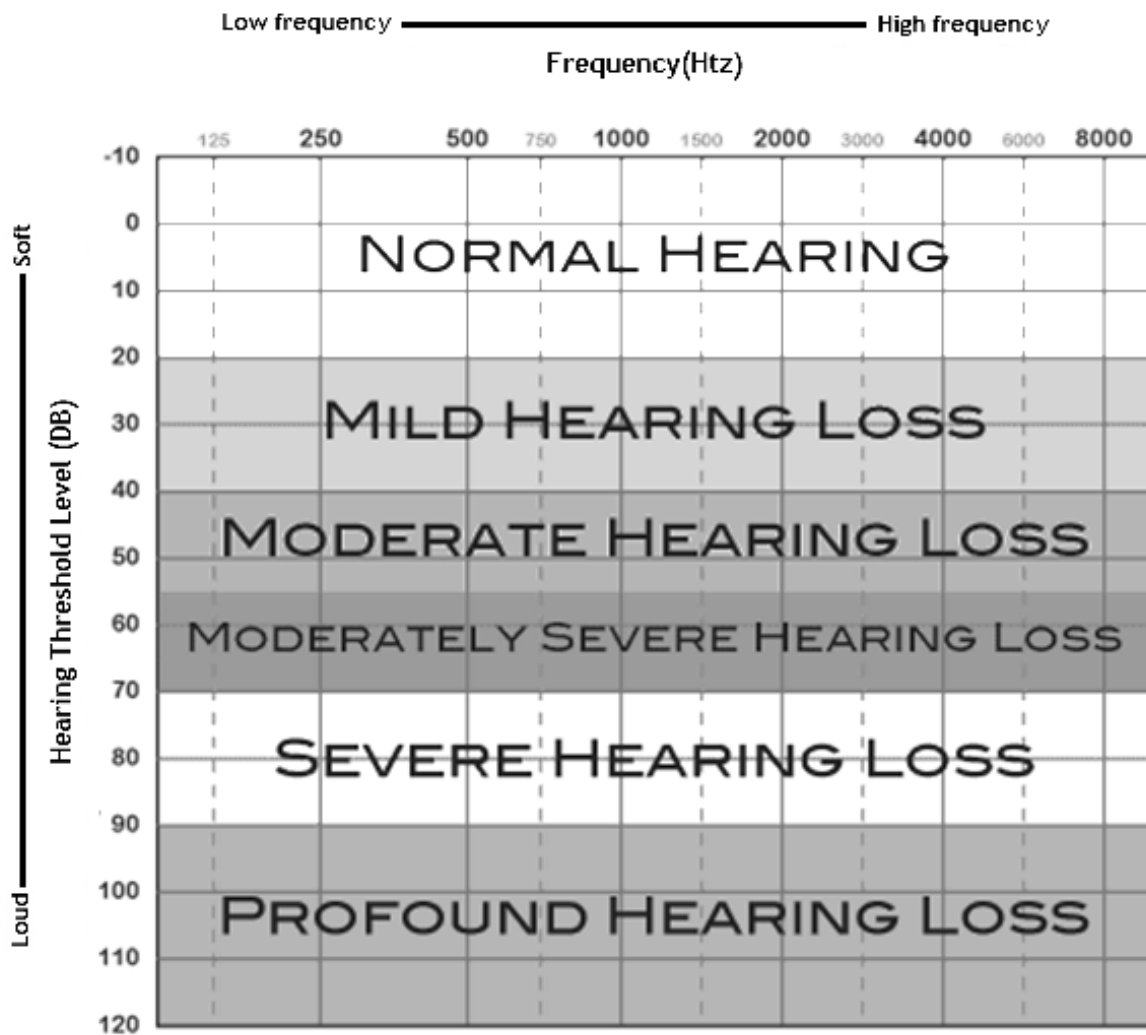


Figure 5.4: Hearing threshold level according to the audiogram [97]

- The total hearing loss (dB) of left and right ear is calculated by multiplying the smaller hearing threshold (better ear) by five, adding it to the larger hearing threshold (poorer ear), and dividing the total by six.

We assessed the hearing loss by using the proposed grading system such that Normal: > 25 dB, Mild hearing loss: 25 to 40 dB, Moderate hearing loss: 40 to 55 dB, Moderate-to-severe hearing loss: 55 to 70 dB, Severe hearing loss: 70 to 90 dB, and Profound loss: 90 dB or more.

As shown in Fig. 5.4, the top of the graph frequency is plotted, from lower frequencies (250Hz) to higher frequencies (8000Hz). On the left side of the graph from top to bottom, sound level in dB is plotted from faint sound (-10dB) up to very intense sounds (-120dB)

Hearing thresholds for the left ear are represented by blue x and thresholds for the right ear are represented by the red circles as shown in the example Fig. 5.5. The subject has normal hearing for lower pitches specified by a red circle corresponds to 15 dB for 250 Hz and 20 dB for 500 Hz. In the high pitches, the hearing threshold fall into the severe level of hearing loss, for 2000 Hz is 40 dB, 65 dB for 4000 Hz and 75 dB for 8000 Hz.

While for left ear, the subject has normal hearing for 20dB for 250 Hz, 500 Hz and 1000

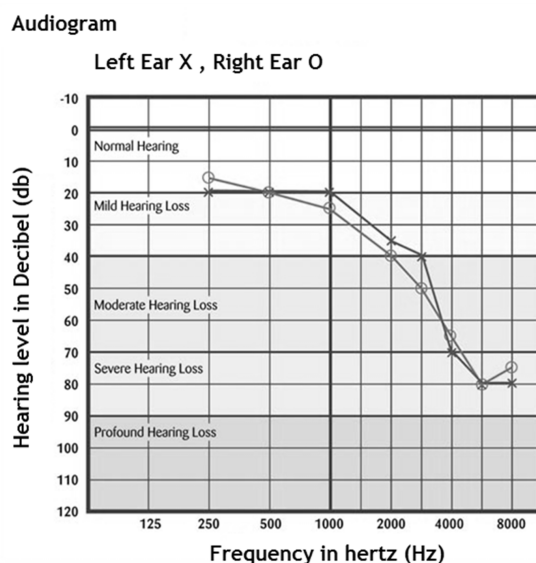


Figure 5.5: Hearing threshold level according to the audiogram for the right and left ears [97]

Subjects	Age (Years)	Nbr of healthy	Nbr of unhealthy
Child	<12	44	3
Teenager	12-18	47	4
Young-Adult	19-29	85	7
Adult	30-50	156	7
Aged	>50	94	58

Table 5.2: Composition of dataset

Hz at lower pitches correspond to blue x. For high pitches, hearing threshold falls into severe hearing loss, 35dB for 2000 Hz, 70dB for 4000 Hz and 80 dB for 8000 Hz.

5.4.2 Classification of healthy and unhealthy subjects

In order to study the correlation between the human age and the auditory perception, the distribution of the different age groups is compared using a univariate T-tests. The average frequency of the two tests is considered to show the separability between the different age groups. The T-test is based on null hypothesis testing in order to quantify the idea of statistical significance of evidence. A T-test compares the means of two independent groups of samples, and probability value (p-value) is computed to quantify the probability for a given statistical model via the set of samples.

To understand and interpret the auditory responses inside each group, a graphical interpretation using boxplots are shown in Figure 5.7 and Figure 5.8 for three and five age groups, respectively. According to the boxplot, the three age groups of a child, teenager, and adult are well separated. Furthermore, the p-value of all the statistical tests among them is below 10^{-5} , as shown in Figure 5.7. The biggest p-value is between the child and the teenager age groups, and thus, the auditory responses of a child can be more easily misclassified as a teenager than with other age groups. The distribution of auditory responses of the adult age group is more spread out; it means there is big variability inside this group. The statistical tests show that the

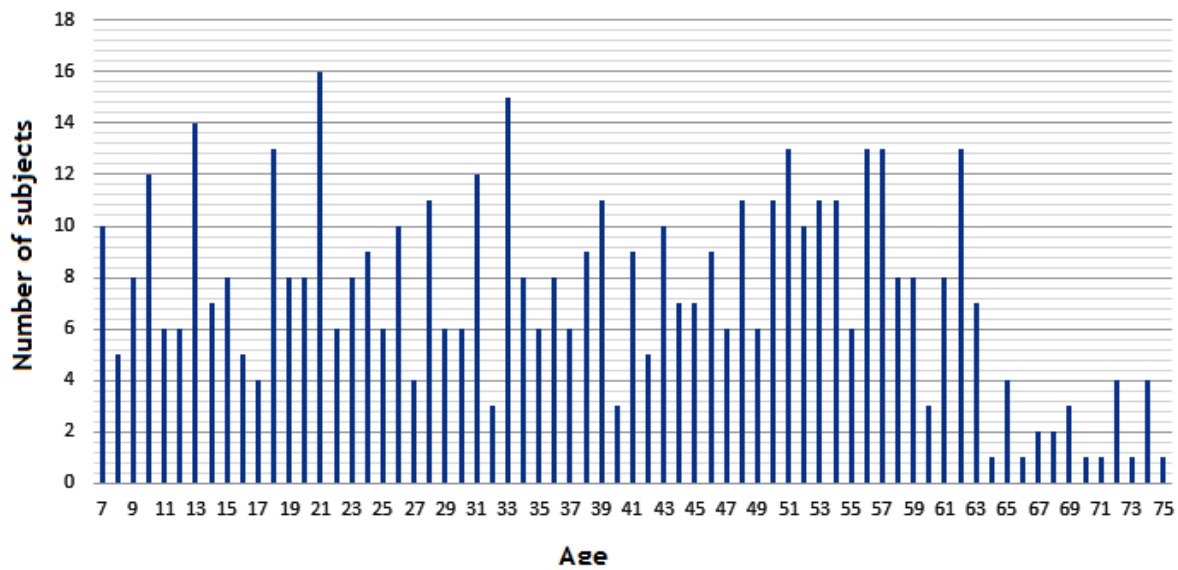


Figure 5.6: Age distribution of the subjects

three age groups are well discriminated according to the hearable frequencies of the volunteers inside each age group.

As the adult age group is very spread, it is divided into three age groups (young adult, adult, and aged), and the distribution of the five age groups is shown in Figure 5.8. According to the p-value of the different T-tests, the five age groups are also well separated despite the outliers. The samples of the aged group are the most dispersed, and they are confused mainly with the adult age group. The audible frequencies decrease with age, and then it is more probable that the audible frequencies of one age group to be confused with the audible frequencies of the closest age groups.

The different statistical tests demonstrate that there is a good separability between the auditory responses belonging to the different age groups, therefore, it is interesting to study the estimation of human age based on the auditory perception.

Age-based classification of auditory responses: In this section, the classification of the auditory responses into age groups is performed using RF, SVM, adaboost, LDA and NN classifiers. For age based classification, the dataset is divided into three and five age groups. Three tests are performed and shown in Table 5.3 and Table 5.4:

- classification of the healthy subjects into three/five age groups,
- classification of the unhealthy subjects into three/five age groups,
- classification of all (healthy and unhealthy) subjects into three/five age groups.

The final classification rate for three age groups is shown in Table 5.4. The best accuracy of 94% for healthy subjects, 95% for unhealthy subjects, and 92% for all data are achieved using RF classifier for three age groups. While, for five groups, as shown in Table 5.3, the best accuracy of 85% for healthy subjects, 88% for the unhealthy subjects while 87% for all subjects is achieved. RF shows the highest accuracy for the subjects (healthy, unhealthy, and all) divided

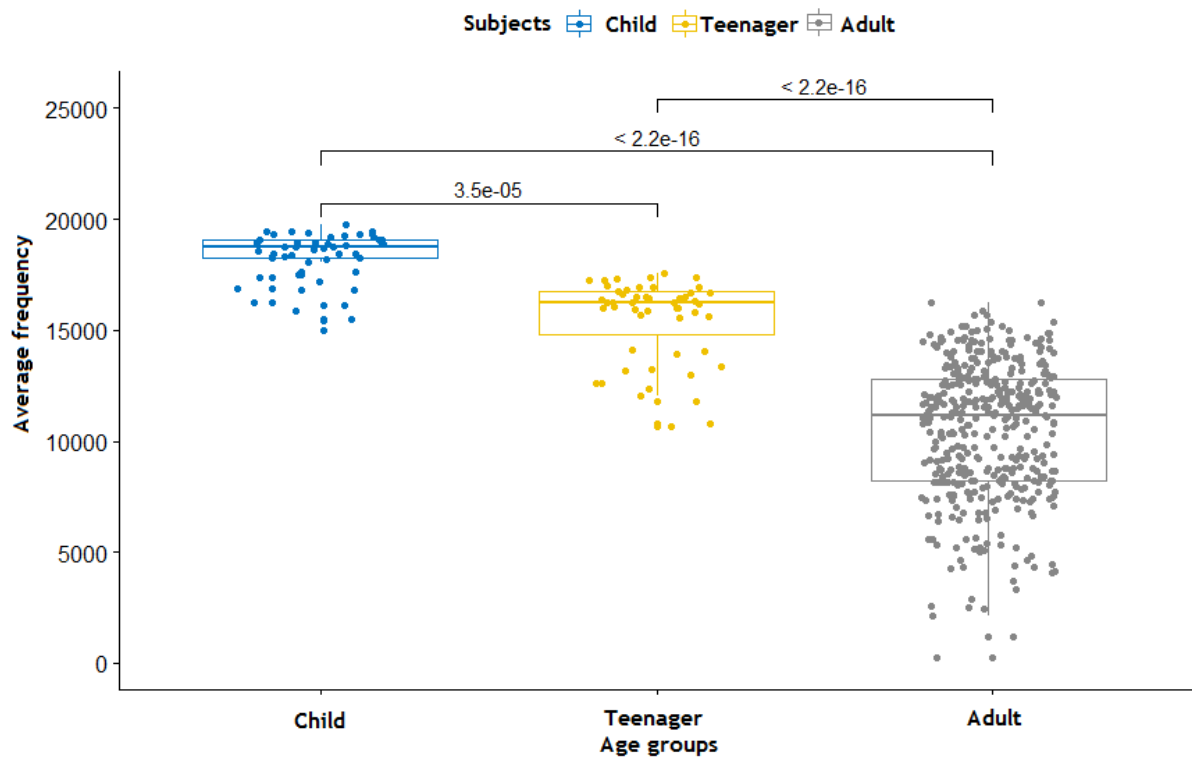


Figure 5.7: Boxplots of the average frequency of the three age groups

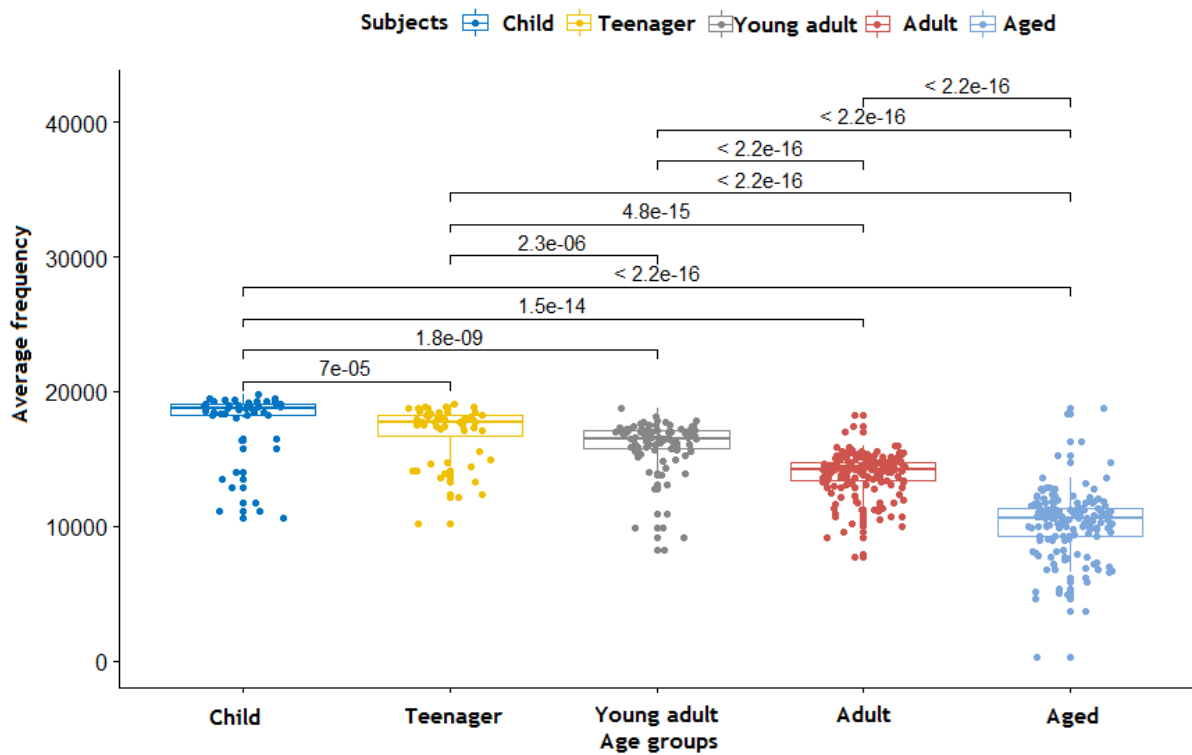


Figure 5.8: Boxplots of the average frequency of the five age groups

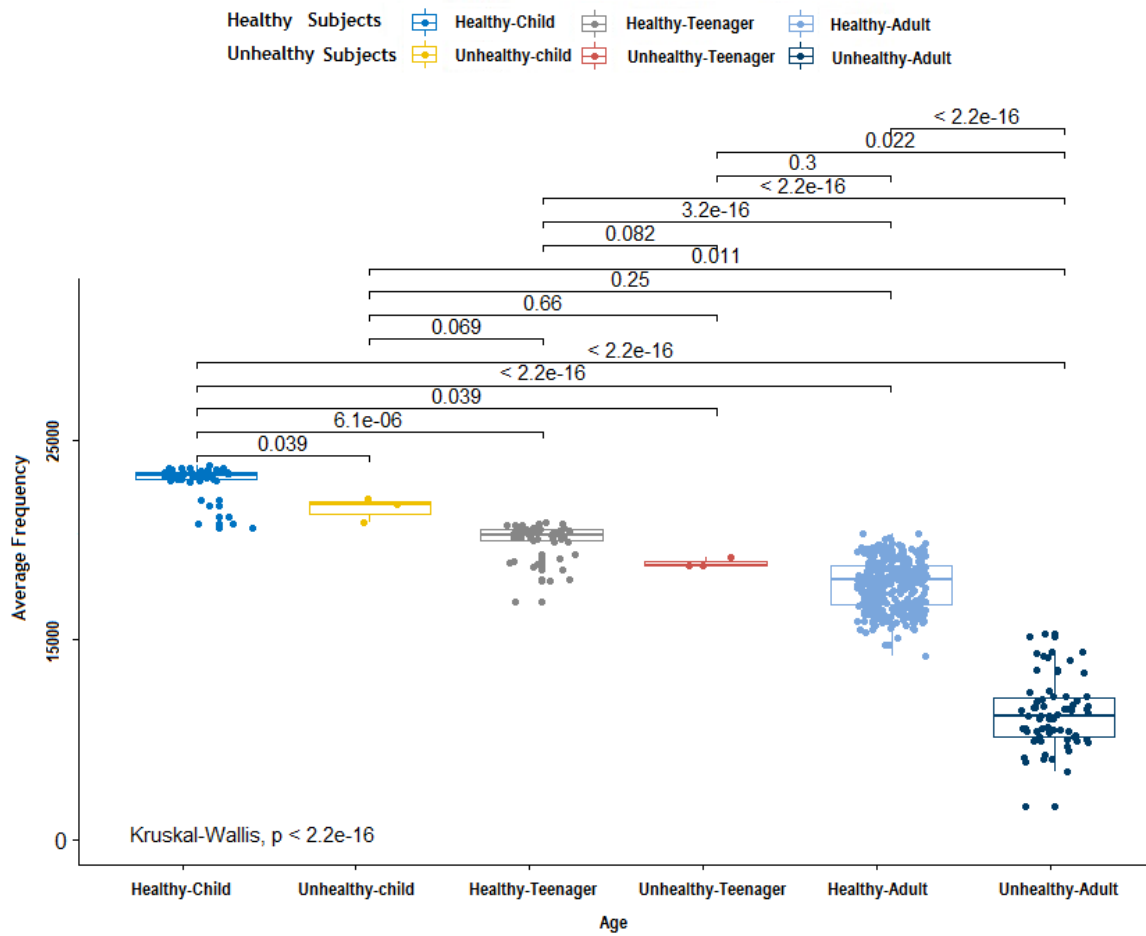


Figure 5.9: Boxplots of the average frequency of the six groups

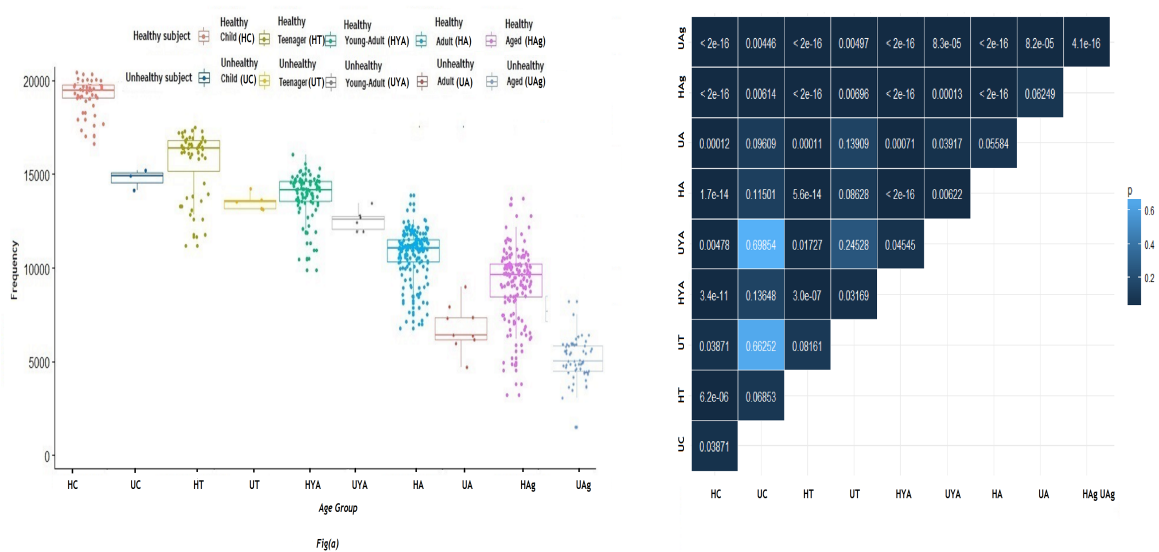


Figure 5.10: a) Boxplots of the average frequency of the ten groups, b) P-value of the T-tests between the different groups

Classifier	Case		
	Healthy	Unhealthy	All data
RF	85%	88%	87%
SVM	73%	69%	70%
LDA	51%	65%	59%
Adaboost	76%	61%	73%
NN	71%	45%	61%

Table 5.3: Performances of the classification into five age groups of healthy, unhealthy and all subjects

Classifier	Case		
	Healthy	Unhealthy	All data
RF	94%	95%	92%
SVM	91%	91%	87%
LDA	71%	77%	71%
Adaboost	88%	89%	86%
ANN	83%	90%	80%

Table 5.4: Performances of the classification into three age groups of healthy, unhealthy and all subjects

into three and five groups. The accuracy of the classification into three groups is better than the classification into five groups. It is harder for the classifier to classify unhealthy subjects than healthy subjects. The confusion matrices of the healthy, unhealthy and all subjects using RF classifier into three age and five age groups are shown respectively in Fig 5.11, and 5.12

A set of conclusions can be made from the different confusion matrices:

- the misclassified subjects of the healthy and unhealthy belong mainly and mostly to the closest age groups,
- the auditory responses of child are mainly misclassified as teenager and vice versa,
- the auditory responses of adult are mainly misclassified as aged and vice versa.

Consequently, there is a big separability between the age groups according to auditory responses. After demonstrating the high correlation between the human age and the auditory perception, the separability of healthy and unhealthy subjects inside the same age group is studied in the next section.

Classifier	Case	
	Six Groups	Ten Groups
RF	93%	90%
SVM	84%	81%
LDA	41%	56%
Adaboost	69%	65%
NN	73%	69%

Table 5.5: Performances of the classification of the all data into six groups and ten groups

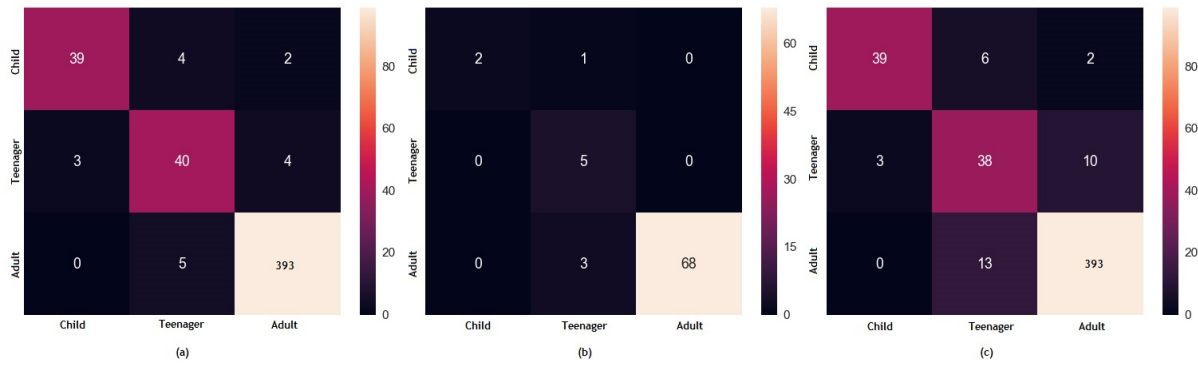


Figure 5.11: (a): Confusion matrix of the classification of the healthy subjects into three age groups using RF classifier. (b): Confusion matrix of the classification of the Unhealthy subjects into three age groups using RF classifier. (c): Confusion matrix of the classification of all subjects into three age groups using RF classifier

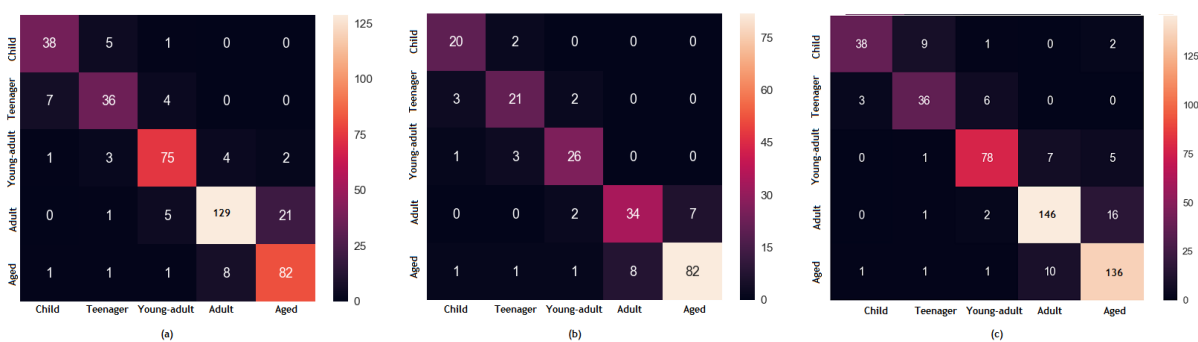


Figure 5.12: (a): Confusion matrix of the classification of the healthy subjects into five age groups using RF classifier. (b): Confusion matrix of the classification of the Unhealthy subjects into five age groups using RF classifier. (c): Confusion matrix of the classification of all subjects into five age groups using RF classifier

5.4.3 Impact of the state of health in the classification of the auditory perception

In this section, the impact of the state of health in the age based-classification of the auditory perception is studied. For that, first, the distribution of the healthy, and the unhealthy subjects inside each age group is studied and after, the performances of several classifiers in the classification of the auditory responses into healthy and unhealthy age groups are summarized.

Study of the distribution of the healthy and the unhealthy age groups: The healthy and unhealthy subjects are considered independently inside the three age groups of child, teenager and adult and six age groups are thus created: Healthy Child (HC), Unhealthy Child (UC), Healthy Teenager (HT), Unhealthy Teenager (UT), Healthy Adult (HA), Unhealthy Adult (UA).

The boxplots of the average frequency of the six groups are shown in Figure 5.9. The healthy and unhealthy subjects inside the same age group are more misclassified than the subjects between two age groups as can be seen from the p-value equal to 0.039 of T-test between the healthy and the unhealthy child age groups or also the p-value equal to 0.082 of the T-test between the healthy and the unhealthy teenager age groups. Contrariwise, the p-value of the T-test between the healthy and the unhealthy adult age groups is lower than 10^{-15} . Thus, the loss of hearing is more marked with age, and it is easier to discriminate with adults. We can also notice that the audible frequencies of the unhealthy age groups are closer to the audible frequencies of its senior age groups, the p-value of T-test between the unhealthy child and healthy teenager is equal to 0.069 while the p-value of T-test between the unhealthy teenager and healthy adult is equal to 0.3. Consequently, we can conclude that hearing loss is manifested by an aging of the auditory system, and the auditory responses of an unhealthy subject are closer to the auditory responses of an older healthy subject.

Like in the study of correlation between age and auditory perception and for more separability, the adult age group is divided into young adult, adult and aged and ten groups were studied: Healthy Child (HC), Unhealthy Child (UC), Healthy Teenager (HT), Unhealthy Teenager (UT), Healthy Adult (HA), Unhealthy Adult (UA), Healthy Young Adult (HYA), Unhealthy Young Adult (UYA), Healthy AGed (HAG), Unhealthy AGed (UAG).

According to the different T-tests and their corresponding p-values, as shown in Fig. 5.10, the same conclusions like the previous analysis of the six groups are made. Besides, we conclude that the unhealthy child is the easiest to confuse with the unhealthy teenager or the unhealthy young adult.

Classification of auditory perception into healthy and unhealthy age groups:

Health and age-based classification performances are shown in Table 5.5. The best classification performance of 93% and 90% for respectively, six groups, and ten groups are achieved using RF classifier. The state of health does not have a big impact on the age and health-based classification of the auditory perception. The values of variance and standard deviation of all the age groups for healthy and unhealthy subjects are shown in Table 5.6. The healthy adult, Unhealthy adult, healthy aged, and unhealthy aged shows a higher value. The responses are spread away from the mean value, which corresponds to a higher variation of the data.

HC	38 7.45%				1 0.20%		39 97.44% 2.56%
UC	2 0.39%	3 0.59%			3 0.59%		8 37.50% 62.50%
HT	5 0.98%		32 6.27%				37 88.49% 13.51%
UT	7 1.37%		5 0.98%	3 0.59%	1 0.20%		16 18.75% 81.25%
HA	3 0.59%				328 64.31%	10 1.96%	341 96.19% 3.81%
UA					12 2.35%	57 11.18%	69 82.61% 17.39%
sum_col	55 69.09% 30.91%	3 100% 0.00%	37 88.49% 13.51%	3 100% 0.00%	345 95.07% 4.93%	67 85.07% 14.93%	510 90.39% 9.61%
	HC	UC	HT	UT	HA	UA	sum_lin

Figure 5.13: Confusion matrix of the classification of the six groups using RF classifier

To evaluate the performance of the classification for each age group, the confusion matrices of the classification of the dataset into six groups and ten groups are shown in Figure 5.13 and Figure 5.14. The main misclassifications concern:

- H-adult misclassified as U-adult,
- H-aged misclassified as U-aged and vice versa.

With age, the auditory responses of unhealthy subjects are closer to the auditory responses of healthy subjects having the same age. Thus, the aging of the auditory system manifests as a hearing loss problem.

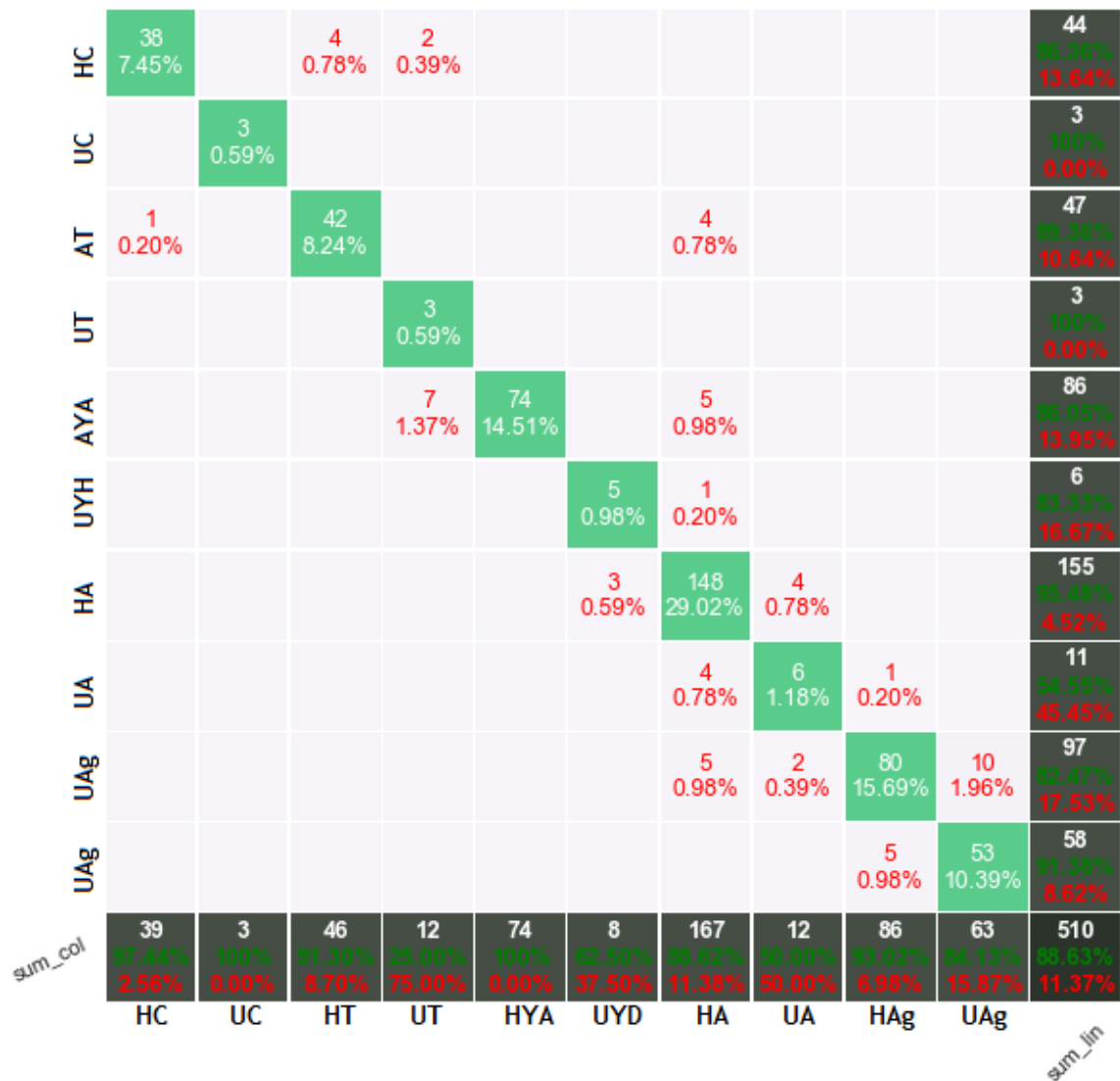


Figure 5.14: Confusion matrix of the classification of the ten groups using RF classifier

Subjects	Variance	Standard Deviation
Healthy-Child	0.34	0.58
Unhealthy-Child	0.020	0.14
Healthy-Teenager	0.33	0.55
Unhealthy-Teenager	0.031	0.16
Healthy-Young-Adult	0.32	0.52
Unhealthy-Young-Adult	0.022	0.14
Healthy-Adult	2.6	1.6
Unhealthy-Adult	3.5	1.8
Healthy-AGed	1.65	1.28
Unhealthy-AGed	2.57	4.45

Table 5.6: The variance and the standard deviation of the auditory responses inside each group

0	412 76.01%	2 0.37%					414 99.52% 0.48%
1	2 0.37%	36 6.64%	3 0.55%	1 0.18%	3 0.55%		45 80.00% 20.00%
2	5 0.92%	2 0.37%	41 7.56%				48 85.42% 14.58%
3	7 1.29%		1 0.18%	12 2.21%	2 0.37%		22 54.55% 45.45%
4	3 0.55%				4 0.74%	3 0.55%	10 40.00% 60.00%
5			1 0.18%			2 0.37%	3 66.67% 33.33%
sum_col	429 96.04% 3.96%	40 90.00% 10.00%	46 89.13% 10.87%	13 92.31% 7.69%	9 44.44% 55.56%	5 40.00% 60.00%	542 93.54% 6.46%
	0	1	2	3	4	5	sum_lin

Figure 5.15: Confusion matrix for prediction of hearing loss

Model	Case		
	Healthy	Unhealthy	All data
RF	4.1	8.33	5.8
SVR	6.9	11.01	7.9
Adaboost	11.1	13.3	12.6
ANN	12.9	15.1	14.5

Table 5.7: Performances of the predictive models of age estimation based on auditory perception

5.4.4 Prediction of hearing loss and level hearing loss

5.4.4.1 Age estimation based on auditory perception

Multiple regression analysis is performed using four classifiers to estimate the human age based on the auditory responses: Random Forests (RF), Support Vector Regression (SVR), Adaboost, and Artificial Neural Networks (ANN). The performances of the different classifiers are summarized in Table 5.7. RF shows the best accuracy with the smallest Mean Absolute Error (MAE) of 4.1 years for the dataset containing only healthy subjects, 8.3 years for unhealthy subjects, and 5.8 for the dataset combining both healthy and unhealthy subjects. It is more difficult for the classifier to estimate the age of the unhealthy than the healthy subjects. An MAE of 5.8 is a good accuracy for age estimation, and it is bigger than the age range inside each age group, and thus even when the predictive model badly estimate the age of a person, there is a big chance that the estimated age belong to the same age group, for example, when estimating the age of a child, it is hard to be estimated as an aged person.

The scatter plot of the actual vs. the predicted age and the overlay regression line $y=x$ are shown in Figure 5.16. If the model predicts the age perfectly, then all the data points would lie on this line. There are only a few outliers that do not fit well the line with a few years of difference. We can also see that the majority of outliers belong to an early age, and below 30 years, the data points lie perfectly on the line. Therefore, the proposed RF model for age estimation based on the auditory perception is very accurate, and it can be used in many applications like the prediction of hearing loss and level of hearing loss.

5.4.4.2 Prediction of hearing loss based on auditory perception

The second predictive model based on the auditory perception is for predicting hearing loss. Its accuracy is shown in table 5.8. The RF classifier has the highest accuracy of 94%. The sensitivity of our system is equal to 95%, while specificity is equal to 97%. Thus, the predictive model is not very sensitive while it is very specific.

To investigate the accuracy of the classification of healthy and unhealthy subjects, the confusion matrices of the classification of the datasets using RF classifier is shown in Figure 5.17. There are more unhealthy subjects that are misclassified as healthy subjects. To conclude, there is an important and obvious separability between auditory responses of healthy and unhealthy subjects. Thus, our proposed predictive model can predict with good accuracy the hearing loss, and it can be then used as a preliminary test for checking the possibility of hearing loss or as a decision support system to help a doctor to diagnose hearing loss.

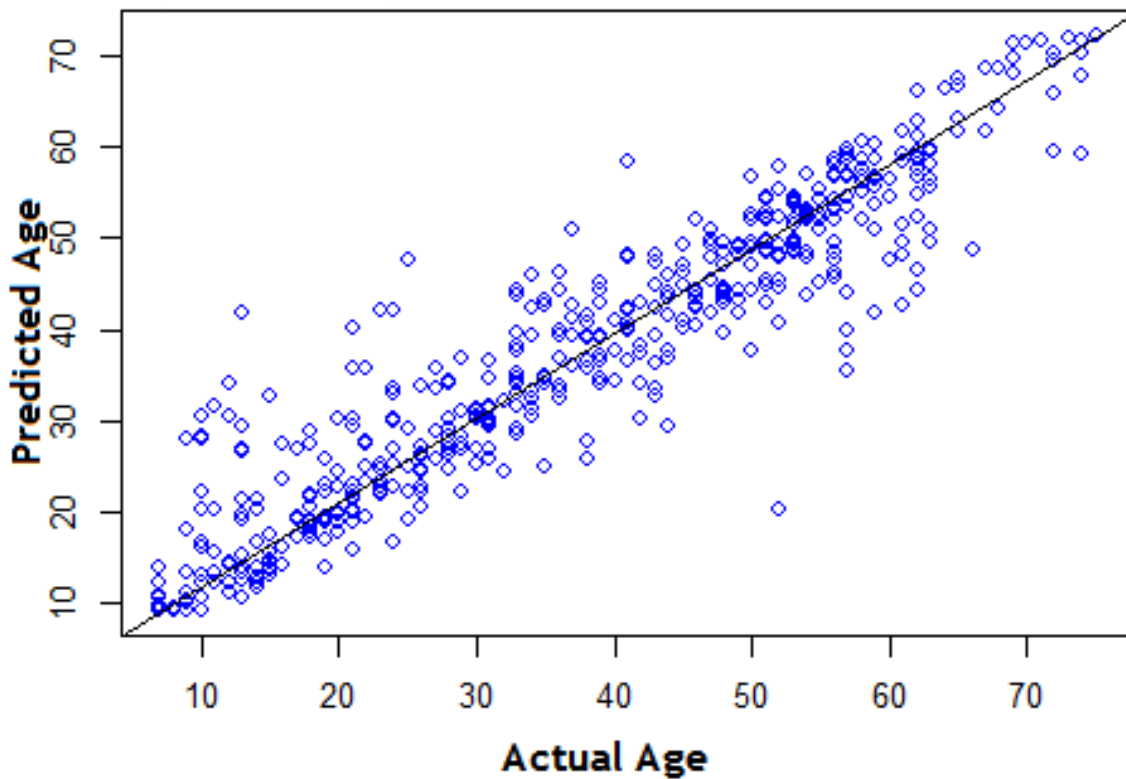


Figure 5.16: Actual vs. predicted age results of the predictive model of age estimation

Model	Accuracy	Sensitivity	Specificity
Random Forest	94%	95%	97%
SVM	91%	45%	99%
Adaboost	91%	39%	99%
LDA	87%	85%	91%
Neural Network	89%	95%	91%

Table 5.8: Performances of the classification into healthy and unhealthy subjects

5.4.4.3 Prediction of the level of hearing loss

The level of hearing loss is the third predictive model of our auditory perception-based system. Six classes are considered according to the level of hearing loss such as normal, mild, moderate, moderate severe, severe and profound. In Table 5.9, the performances of the different classifiers (RF, SVM, Adaboost, LDA, and NN) are presented and RF shows the highest accuracy of 90%. The RF classification model is built using LOOCV to get the most accurate results.

To explore the accuracy of the RF classifier, the confusion matrix is shown in Figure 5.15. It can be seen that the misclassified subjects belong to a close hearing loss intensity class which make sense, for example, 2 normal are misclassified as mild, 3 mild are misclassified as moderate, 2 mild are misclassified as normal, etc. Predicting the level of hearing loss is a complicated task as the system should be able to separate healthy and the unhealthy subjects and discriminate the severity of hearing loss. Despite the difficulty of the task, the proposed predictive model performs very well and gives a good accuracy which make it operable in

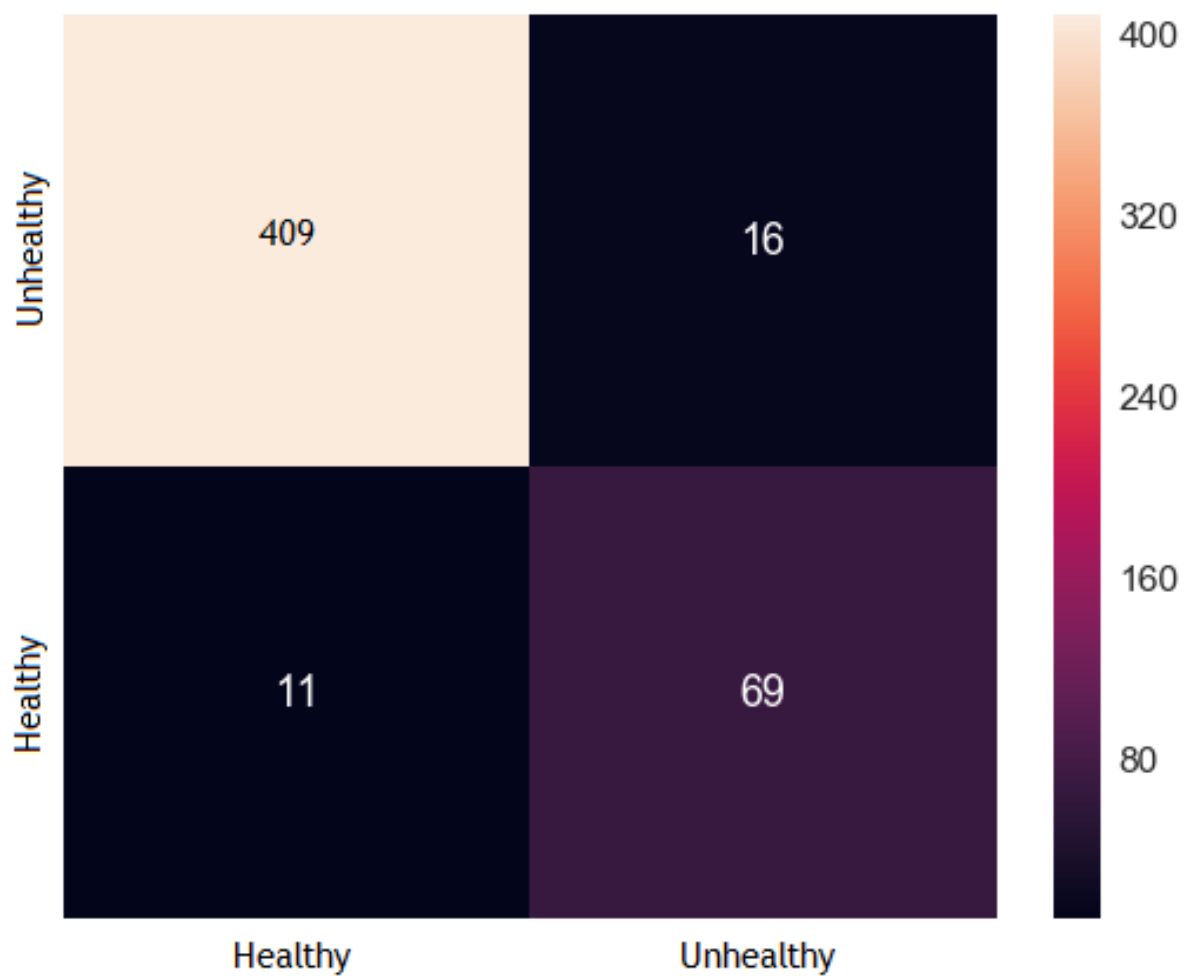


Figure 5.17: Confusion matrix of the classification using RF classifier for the dataset divided into healthy and unhealthy subjects

medical applications.

Model	Accuracy
Random Forest	90%
SVM	87%
Adaboost	75%
LDA	63%
Neural Network	59%

Table 5.9: Classification of the hearing loss intensity (Normal, Mild, Moderate, moderate severe, and profound)

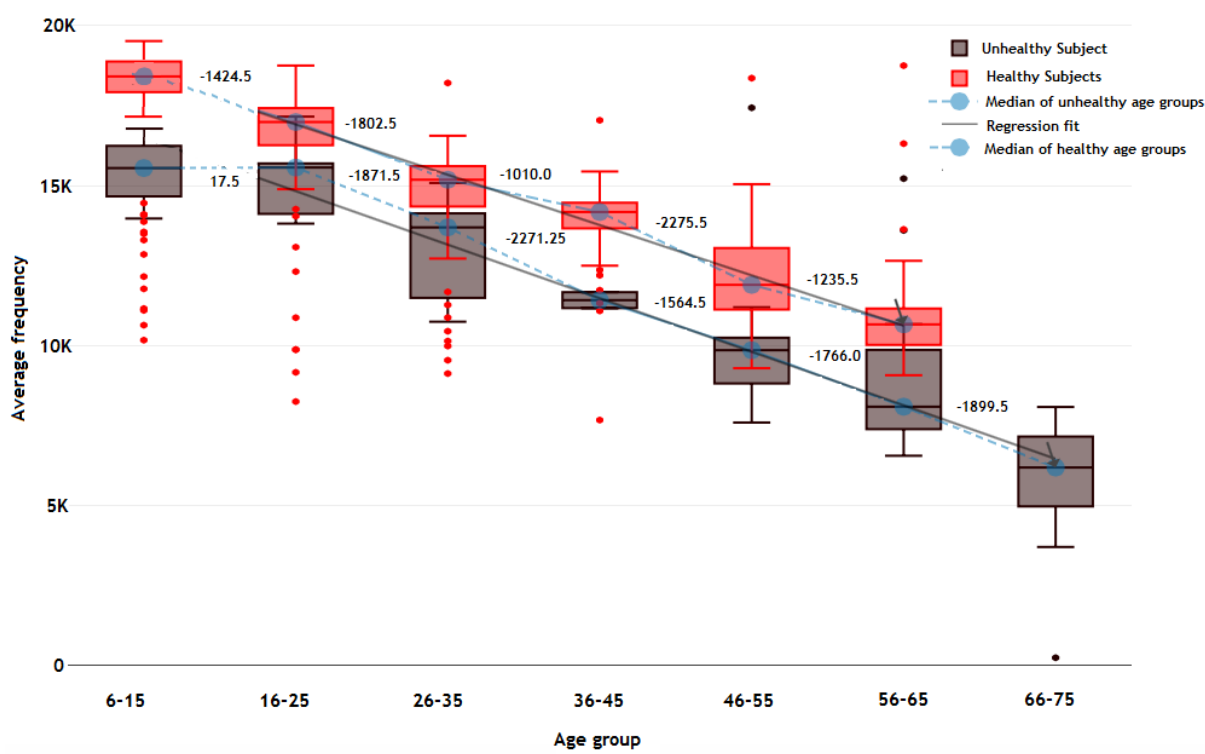


Figure 5.18: Trajectory analysis of the aging of auditory system of healthy and unhealthy subjects

5.4.4.4 Performance Evaluation

To evaluate the performance of predicting hearing loss, we used tenfold cross-validation for different classifiers such as RF, SVR, Adaboost, and ANNs. In each round of cross-validation, 90% of the data was randomly selected as training data, and the remaining 10% of the data is used as the testing data to test whether the trained classifier can predict the hearing loss of a subject that corresponds to a specific age group. The classification accuracy is calculated to assess the performance by using the sensitivity which is defined as $TP/(TP+FN)$, and the specificity $TN/(TN+FP)$. In addition, AUC is also demonstrated, which is defined as the area under a receiver operating characteristic (ROC) curve. ROC measures the performance of overall hearing loss prediction in comparison to RF classifier for six groups based on their health

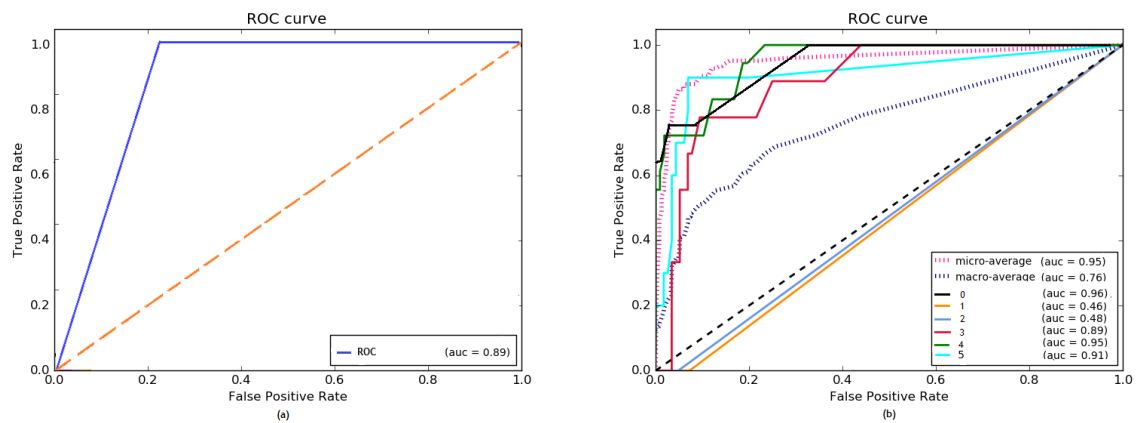


Figure 5.19: (a) ROC curve for binary classification (Healthy and Unhealthy). (b) ROC curves of different age groups. The ROC curve of an ideal classifier should be passing three points: the origin (0, 0), the top-right corner (1, 1) and the top-left corner (0, 1). The ROC curve of a random-guess classifier is just a straight line connecting the origin (0, 0) and the top-right corner (1, 1). The red curve, produced by the proposed RF, is the closest to the ideal curve.

condition, both healthy subjects and unhealthy subjects; each group is very well classified according to the Figure 5.19(a). ROC curve is obtained by varying the discrimination threshold for each group. If the value of AUC is closer to 1 that means, a model is performing very well. The performance of the proposed approach is more precise for all the groups, while the AUC values are 0.96, 0.46, 0.48, 0.89, 0.95, and 0.91 for the hearing level from 0-5. We can demonstrate that each group is well separated and accurately classified while for hearing loss levels 2 and 3 has some misclassification responses.

Further, ROC curve for binary classification (healthy subjects and unhealthy subjects) using RF classifier is shown in Figure 5.19(a). The accurate classifier is the one that makes zero mistakes such that the model must have a 100% true positive rate and 0% false-positive rate. The model we used for the classification of healthy and unhealthy subject it shows an AUC of 0.88. The higher value of AUC indicates the promising performance of the system for the prediction of hearing loss.

5.4.5 Aging of auditory system

To study the correlation between human age and auditory perception, we start by studying the discrimination of auditory responses of different age groups. For that, the collected dataset is sub-divided into three age groups and five age groups. As shown in Table 5.2, a volunteer belong to:

- Child: if the volunteer conducting the experiment is less than 12 years old,
- Teenager: if the age of the volunteer conducting the experiment is between 12 to 18 years old,
- Adult: if the volunteer conducting the experiment is more than 18 years old.

Child and teenager age groups are almost balanced, while more volunteers are participating in the adult age group. The adult group presents a big range of age and then big variability inside

this age group. Thus, the two age groups of child and teenager are kept the same as in the dataset of three age groups and the adult age group is subdivided into three groups:

- Young adult: if the age of the volunteer conducting the experiment is between 19 and 29 years old,
- Adult: if the age of the volunteer conducting the experiment is between 30 and 50 years old,
- Aged: if the volunteer conducting the experiment has more than 50 years old.

5.5 Conclusion

The motivation of the proposed techniques is to build a computer-aided system to detect and facilitate the people suffering from hearing loss or hearing impairment. Throughout the world, there is a deficiency in educating people to care about the precautionary measures to prevent hearing loss. A clinical system for prediction of hearing loss and level of hearing loss is under development. This facility will provide special and more robust results and concurrently teach the prevention of many causes of hearing-impairment.

A computer-aided prediction of hearing loss based on auditory perception is introduced. Three predictive models for age estimation, hearing loss prediction, and level of hearing loss prediction are presented after demonstrating the high correlation between auditory perception and the human age. The performances of the predictive models are evaluated on a dataset of 503 of healthy and unhealthy subjects. The RF predictive models show high accuracy with an MAE of 5.8 years for age estimation, 94% of good classification for the prediction of hearing loss, and 90% of good classification for the level of hearing loss.

Chapter 6

Conclusion and perspectives

In the final chapter, the review has been presented of the research and further discuss the future research directions is also presented.

This thesis introduced auditory perception responses as a novel biometric modality for human age estimation, classification, and real-time application related to it. This modality demonstrated the possibility of several developed applications such as Biometric Access Control, Anti-spoofing system, prediction of hearing loss.

The main objectives of the thesis are:

- Human age estimation and classification using auditory perception response
- Development of biometric applications based on auditory perception responses
 - Biometric, Access Control system, based on auditory perception responses
 - Anti-Spoofing system using auditory perception responses
 - Machine learning based prediction of hearing loss using auditory perception responses

with the objective of the thesis several questions are successfully demonstrated:

- **Is it possible to use auditory perception responses human age estimation and classification?**

As hearing loss has a strong connection with human age. A subject experience some hearing loss if he/she lives long enough — it's part of the ordinary aging cycle. Hearing loss related to age is known as presbycusis, happens slowly across both ears, generally. Bringing this into consideration, a system is designed to specify the maximum hearable frequency of people of different ages to create a standard database. By using several techniques, it is justified that there is huge discrimination among the data, it is demonstrated that subjects of different ages are separable with respect to their auditory frequency responses. A novel approach has been introduced based on machine learning technique using random forest regressor and random forest classifier for human age estimation and classification. This system provided promising results as compared to other existing biometric systems for human age estimation and classification.

- **What are the possible application in real-world based on auditory perception responses** Based on the demonstration by using auditory perception responses for human age estimation and classification, we tried to make it possible to develop several applications in the field of biometrics:
 - Biometric Access Filter
 - Anti-spoofing system
 - prediction of hearing loss

The above-mentioned application has been developed based on auditory perception responses, and all of them show promising results after being analyzed.

6.1 Thesis Contribution

The main contribution of the thesis is as follows:

- , A novel approach for human age estimation and classification, is proposed based on auditory perception responses. Data from 837 trials were gathered with ranging from 6 to 60 years of age to assess the performance of our experiment.
- Biometric Access Filter: A web security control technique based on age estimation is introduced, taking into consideration the correlation between human age and auditory perception.
- A computer-aided system is developed for prediction of hearing loss. Three predictive models are assembled, such as human age estimation, prediction of hearing loss, and level of hearing loss based on auditory perception responses are presented.
- An anti-spoofing system is designed based on human auditory perception responses. A genuine characteristic in contrast to a false physical, synthetic sample is a significant issue in biometric verification/authentication that needs new and higher security steps to be developed.

A novel approach is introduced in the field of biometric about forensic age classification and estimation based on the auditory perception. The first protocol S-BS for $t_1 = 20s$ is demonstrated as more descriptive and separable according to the age sub-division. Among all the classifiers, Random Forest has shown the promising and most accurate results for human age classification and estimation. Using the first protocol S-BS for $t_1 = 20s$ and Random Forest classifier, a good classification rate of 92% accuracy has been achieved for three age groups while 86% of accuracy is achieved for five age groups respectively. An efficient regression model is also built by using Random Forest Regression, and it shows an accuracy rate of 98.2% and a root mean square of error of 2.6 years. The proposed method can be used in the field of forensics for human age estimation and classification. For optimum precision, multiple techniques are always used in conjunction. The investigator may predict the minimum age of the subject and/or his or her most likely age, depending on the legal issues at hand. In determining whether an individual has reached the age of legal majority, the biometric age estimation concept can be used. It is intended to guarantee that virtually all subjects categorized as adults have actually achieved a legal majority, although some other subjects will be categorized as minors wrongly.

Based on the approach of auditory perception-based human age estimation and classification, we presented a biometric access filter, which is a completely new approach for access control systems. With the help of biometric access filters, we can limit the access of adults or kids to webpage or document. It is demonstrated that we can limit the access of users within a certain age group most discriminating, and the Regression Forest is the most accurate for age estimation. A robust regression model is also built, and it has an accuracy rate of 97.04% and a root mean square of error of 4.17 years. The EER value is 1.4%.

The past work, human age estimation based on auditory perception, is characterized by the lack of a standard evaluation methodology and its status of vulnerability to spoofing. This article presents what is to the best of the authors' knowledge for the standard evaluation method. We conclude that the proposed anti-spoofing system is robust by having an EER value of 5.5% under the spoof attack scenario. While further work is required to extend and adapt the methodology in view of the lessons learned through recent work. While the performance of spoofing countermeasures proposed so far gives cause for optimism, showing EER value of 3.5%. Their generalization of previously unseen spoofing attacks remains unclear by having a higher value of FRR.

A computer-aided prediction of hearing loss based on auditory perception is introduced. Three predictive models for age estimation, hearing loss prediction, and level of hearing loss prediction are developed. After demonstrating the high correlation between auditory perception and the human age. The performances of the predictive models are evaluated on a dataset of 503 of healthy and unhealthy subjects. The RF predictive models show high accuracy with an MAE of 5.8 years for age estimation, 94% of good classification for the prediction of hearing loss, and 90% of good classification for the level of hearing loss.

Note: The results achieved is based on the dataset collected, it can be varied according to, profession, gender, living habits, working area.

6.2 Future perspective

Many difficulties were encountered in the course for this research, and issues have been posed that direct us to more improvements and potential work. These views for the prospective are provided below:

The dynamic sound generated for the proposed experiments to estimate human age or classify into a specific group is irritating and it was difficult for the subject to tolerate it after repetition. As a future perspective, it required a more sophisticated model for sound generation to reduce the feelings of fatigue. More advanced equipment such as otoacoustic emission tests is used to measure the maximum threshold of hearing in a more accurate meaning to enhance the performance of the system. Another perspective, as an anti-spoofing system, has been developed for the proposed system for auditory perception-based human age estimation and classification, while it can be enhanced by considering the countermeasures with other scientifically proven biometric modalities such as gait, face, finger, etc. To analyze the potential attacks in parallel to countermeasures with other biometric modalities in order to develop high performance anti-spoofing biometric systems. This perspective can overcome the vulnerabilities of future biometric applications based on age estimation with auditory perception.

It's also demonstrated during collecting the dataset that male has more chances of hearing loss as compared to females. The category of gender is to assess the sex of an individual, such that to identify the subject as male or female, depending on their biometric signs. The binary evaluation of males and females for gender classification can be identified as 1 and 0. Recognition of gender is fundamentally an issue of the classification of two classes. Whereas other biometric characteristics, such as gait, are also be used to classify gender, face-based methods are still the most common for gender discrimination. As a future perspective, it can be considered by collecting a more dataset to analyze the difference between the highest frequency threshold of the subjects to identify the gender along with age estimation and classification similar to other biometric modalities.

This status leads to a variety of research directions for the future, including fused counter-measures and one-class classification strategies. As the field is new and so more challenging, databases will be essential in order for biometric system developers to stay one step ahead of the fraudsters. While extremely difficult, it will be critical to estimate the reliability of counter-measures in practical application scenarios, including, not just their ability to detect spoofing, but also their impact on system usability.

Concerning the application based on human age estimation such that in continuation of a computer-aided system for prediction of hearing loss and level of hearing loss, a mobile application can also be developed, and the system can be tested under the proposed standard of World Health Organization in clinical laboratories. This application can also provide awareness about the precautionary measures to prevent hearing loss among teenagers and young adults.

The method of anti-spoofing system based on human auditory perception can also replace "CAPTCHA" to identify human and robot. CAPTCHA stands for "Completely Automated Public Turing Test to Tell Computers and Humans Apart," a term that includes its role and purpose: a machine-administered exam that confirms genuine people and removes malicious bots injecting spam and harvesting messages. CAPTCHAs were recognized as irritating-but-bulletproof from 2000 and onward, but today this view is questioned specifically for the "bullet-proof" portion. CAPTCHA became vulnerable as several companies challenged its precision. The biometrics community is also looking for alternative solutions so we can present a strengthened and scientific solution to replace CAPTCHA with an auditory perception-based system in the future.

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