Machine Learning Based Detection of Hearing Loss Using Auditory Perception Responses

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***Abstract*—Hearing loss or hearing impairment is the primary reason of deafness throughout the world. Hearing impairment can occur to one or both the ears. If hearing loss is identified in time, it can be minimized by practicing specific precautions. In this paper, we investigate the likelihood of detection of hearing loss through auditory system responses. Auditory perception and human age are highly interrelated. Likewise, detecting a significant gap within the real age and the estimated age, the hearing loss can easily be identified. Our proposed system for human age estimation has promising results with a Root Mean Square Error (RMSE) value of 4.1 years, and classification performance efficiency for hearing loss is 94%, showing the applicability of our approach for detection of hearing loss.**

***Index Terms*—Auditory perception; Computer-aided system; Hearing Loss; Health-care technology; Predictive model.**

I. Introduction

For several years, investigators intend to examine the hearing loss of human and interpret their causes. It has been reported by physicians and professional consultants to determine that noise is a cause of human hearing loss or impairment in the early stage of life [1].

Rendering to the World Health Organization (WHO), hearing loss is the fifth major reason for the total world population living with infirmity [2]. It may drive to numerous sicknesses such as depression [6], mental deterioration [3], social isolation [5], the occurrence inclined dementia [4], and including falls [7]. Mental deterioration and hearing loss is indicated as a fundamental reason for the hearing and brain pathway. Similarly, mental capability decreases with the mental support for the acoustic observation, which enhances the impact of hearing loss and has a direct relation to age progression. In 2012, it was declared that at the age of 65 years and higher, nearly 164.5 million individuals experienced hearing loss [8], and it is also demonstrated that the ratio of hearing loss is increasing at an early young age [9]. Carrying this interpretation, the precautionary measures for hearing loss is the primary concern for specialists [10], [11]. There is an active link between multifactorial pathogenesis and age-related hearing loss. Some pathogenic fundamentals are mention in micro-vascular syndromes like diabetes, atherosclerosis, and hypertension. It also decreases the effectiveness of mental abilities, which are related to the lifespan. There are several types of medical equipment for detection of hearing loss, such as Weber examination, Auditory Steady State Response (ASSR), Otoacoustic Emission (OE), tympanometry, audiogram, and Auditory Brain Stem Response (ABR).

Weber test is among one of the screening tests normally carried out in the clinics, in which a tuning fork is used for detection of hearing loss. [24]. It can detect single sensor neural hearing loss (inner ear hearing loss) and unilateral (one-sided) conductive hearing loss (middle ear hearing loss). A typical Weber test has a subject stating that the sound heard identically in both the ears. A person is suffering from hearing loss, if the defective ear catches the sound of Weber tuning fork louder than the average value. In tympanometry, a doctor used an otoscope with a probe set and fix it in the ear to examine the ear visually. The probe produces air stress on the ear canal, varying compression's effect to the eardrums and can be recorded for more processing. Furthermore, the audiogram also requires the support of a physician to prognosticate the hearing loss. The subject should substantially appear for the examination in the infirmary. By using computations from electrodes on the head, ABR estimates the reaction near the auditory path. OE is based on assessing low-intensity resonances, which are created by cochlea. Using a microphone, this could be estimated with or without the stimulation of the auditory system. While ASSR is done more often in sequence with the ABR test. The response of the brain to a sound can also be estimated through this analysis. All these recommended tests require a specialist in the hospital and cannot be completed without a physician.

Studies have shown the reasons behind hearing loss and subdivided them into two classes:

Non-modifiable risk factors includes race, age, and gender. Age is playing an essential role among all these features. Hearing loss and age are interrelated, such that the rate of hearing loss grows as human age rises. In the age range of 65 to 75 years, about 23% of the total population has the problem of hearing loss, while for the age of over 75, this

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value is extended to 40% and ended up in hearing impairment and deafness [14]. Current researches explain that temporary threshold shift and hearing impairment are growing among kids and youngsters. Nearly 12% of kids in the age range of 6 to 12-years-old are experiencing hearing loss [15]. Youngsters and young adults highly experience the problem of hearing impairment and tinnitus [16]. Research has also conferred that the response of the left and right ear is independent of hearing loss. The reaction to a sound is proof of genetic variance [17]. The indications of hearing loss increases if the subject has a blood group of "O". Studies has shown that due to extra involvement of outdoor activities, male subjects have higher chance of hearing loss as compared to female subjects. Noise and hearing loss are highly correlated, such that higher noise exposure causes critical hearing issues.

Modifiable risk components Several elements are linked to hearing loss caused due to modifiable components such as smoking, lack of exercise, non-use of hearing protection, diabetes, and improper diet.

Proper ear protection can decrease the risks of hearing loss associated with noise exposure. Absence of guidance, embarrassment, lack of security standards, and environment hazards can also affect the hearing of a subject [18]. Several diseases are caused by smoking, including hearing loss. Smokers have more chances to suffer from hearing loss as compared to non-smokers due to their exposure to poisonous substances. Smokers are more visible to several poisonous substances, which quickly affect hearing along with loud noises. It is stated that about 3700 adults are suffering from hearing loss because of smoking habits. Nonsmoker subjects living in the environment of smokers may have the same chances of hearing loss [19]. Hearing loss caused due to noise exposure can be controlled through proper nutrition and physical fitness. Hearing ability and cardiovascular health can be improved by practicing physical fitness [20]. Researchers recommend that with practicing physical fitness, decreases hearing loss and restores hearing due to enough supply of enough oxygen-rich blood to the internal ear [21]. Many evidences prove that dementia can also be caused due to hearing loss. To evaluate and interpret hearing is a difficult job. There are few Artificial Intelligence(AI) based applications for hearing loss detection [22], [23], and most tricky to understand and time-taking. In correspondence to the proposed methods, our system is implementing an alert mode to detect hearing loss. It can help to decrease the time for early prediction, cost, and labor work of hearing loss.

The relationship between hearing loss and auditory perception has been demonstrated [12]. While in this paper, we will investigate a novel approach for the detection of hearing loss based on auditory perception responses in comparison to clinical weber test.

II. Methods and Materials

The proposed system for detection of hearing loss consists of three main steps as shown in figure 1.

- First, by using dynamic frequency sound, the auditory system is stimulated as shown in figure.
- The collection of auditory perception responses are sent to the artificial intelligence-based system for prediction of age.
- If a notable positive variation exist between the real age and predicted age, it can be indicated that the subject may or may not suffering from hearing loss.

The flow diagram of our proposed method is shown in Figure 1, AI-based system for detection of hearing loss is presented. Mode of bilateral stimulation of the auditory system is shown in section II-A. The model for predicting human age is shown in Section II-B.

A. Acoustical stimulation

The auditory system of a subject is activated through bilateral stimulation by using a dynamic frequency sound. Our proposed system needed real-time communication. Hence, the subject should communicate with the system and respond to the audible frequencies. For greater efficiency, two tests have been conducted:

- **test-1:** A dynamic frequency sound is generated (20Hz to 20,000Hz), and the subject responds through the keyboard when he/she is no more hearing the sound. The corresponding hearable frequency F1 is registered in the database.
- **test-2:** Dynamic frequency sound from higher frequency to lowering frequency is produced (20,000 to 20Hz), and the subject has to answer when he/she begins hearing. The corresponding hearable frequency F2 is registered in the database.

The auditory system is activated by producing dynamic frequency sound by using the model below:

$$x(t) = X_0.sin(2\pi.\phi(t).t) \quad (1)$$

where $\phi(t) = \alpha.t + \phi_0$, X_0 stands for sound amplitude, t stands for time, ϕ_0 is the initialization frequency, and α stands for the increasing/decreasing value of frequency .

The frequencies F1, F2 are registered and forwarded to the prediction model for age estimation [13] and hearing loss detection.

B. Machine learning based model for detection of hearing loss

The AI based approach for age estimation is a regression model. Several regression methods are examined to determine the valid approach is chosen for age estimation through the auditory system responses. They are the Regression Forest(RF) [25], the Support Vector Regression (SVR) [26], Polynomial Regression (PR) [27], Artificial Neural Networks (ANN's) regression [28], and the Ridge Regression (RR). For all the stated regression models, 10-fold cross-validation technique has been used.

RF creates a forest of decision trees and practices mean or majority polling to aggregate results across the collection of

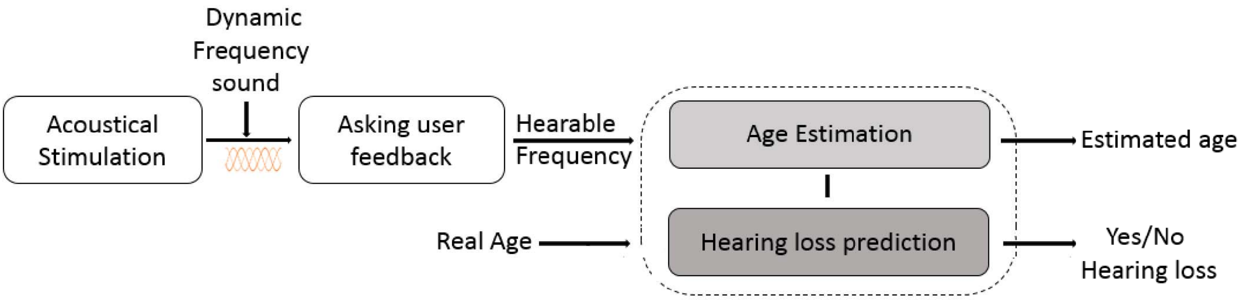


Fig. 1: Flow diagram of our proposed system

Age (Years)	Nbr of healthy	Nbr of unhealthy
<12	22	1
12-20	23	1
21-30	43	3
31-40	51	2
41-50	46	2
>50	31	7
Total:	216	16

TABLE I: Composition of dataset

trees. For classification and regression, It depends on kernel functions by utilizing non-parametric algorithms. SVR reduces the value of error and increases the boundary by determining the optimal hyperplanes. For polynomial regression, the experiments are performed by adding a polynomial function to the linear model. PR provides the best approximation relationship between the dependent and independent variables. Neural Networks (NN) are utilizes in common for regression for supervised and unsupervised learning. Ridge regression is computing a penalty phase that decreases overfitting and the penalty phase guarantees a possible solution.

III. Experimental results

To test the system, we used DELL corei7 M4700 laptop, Macbook Air Corei7, and desktop computer Dell Precision T7500. The distance for a subject to conduct the test from the laptop is 12inches.

A. Dataset collection

For this work, two experiments have been conducted: the first experiment using the proposed computed-aided methods and the second experiment conducted by using a tuning fork known as weber test.. As shown in Table I, 232 individuals participated to perform the test in the age range from 5 years to 75 years.

B. Detection of hearing loss

The efficiency of our system, using different machine learning methods such as RF, SVR, PR, RR, and NN are shown in table II. RF shows the efficiency among the proposed regression models using 10-fold cross-validation technique. The Root Mean Square Error value for RF regression model is 4.1 years. That shows that our detection model is very precise and gives a deficient error. Therefore, it can easily detect the hearing loss if the variation between the calculated age and the actual age $\triangle t$ is higher to n years (Equation 2).

$$\Delta t = (\alpha - \beta) > n(years) \quad (2)$$

with n $= \triangle + \epsilon$ and ϵ = the minimum value of auditory distrust for a person suffering with hearing loss presented by a specific amount of years.

where α is real age, β is predicted age, and $\triangle$ is the value of error rate. The higher the value error rate identify hearing loss.

In figure 2, actual vs. predicted age is shown along with the overlay regression line y=x. As the machine learning based model for hearing loss detection predicts the age precisely then all the data points would be near the center line. There are a few outliers that they are not well classified. The majority of outliers refer to the subjects below 30 years, the data points lie entirely on the line. Therefore, the proposed RF model for age estimation based on the auditory perception is very accurate, and likely be the detection of hearing loss.

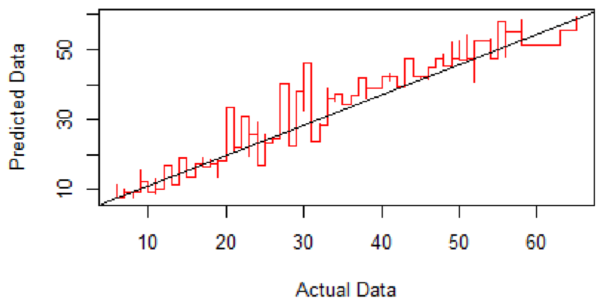


Fig. 2: RF regression model for human age estimation

C. Evaluation performances

To evaluate the performance of the system for detection of hearing loss, ten-fold cross validation for different classification models such as RF, SVM, RR, and ANN's. RF shows

Model	RMSE (years)
RF	4.1
SVR	6.1
PR	9.3
RR	8.7
ANN's	12.7

TABLE II: Regression models performances for age estimation.

Model	Accuracy	$F_1 - Score$
RF	94%	0.967
SVM	88%	0.934
RR	87%	0.927
ANN's	79%	0.880

TABLE III: Classification performances for healthy and unhealthy subjects.

the highest accuracy rate of 94% and f1_score value of 0.967 as shown in table III. For binary classification, $F_1 - score$ or F-measure is considered as a test to evaluate the precision of the model such that $F_1 - score$ gets its highest quality at 1 for ideal accuracy and recall while at 0 to the worst.

To investigate the accuracy of classification of healthy and unhealthy subjects, the confusion matrix of the classification of the datasets using RF classifier is shown in Figure 3(b). There is some healthy subjects that are misclassified as unhealthy 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 possibility of hearing loss or as decision support system to help doctor to diagnose hearing loss.

ROC curve for binary classification (healthy subjects and unhealthy subjects) using RF classifier is shown in Figure 4(b). The efficient classifier is makes limited mistakes such that the model may have a 100% True Positive Rate(TPR) and 0% False Positive Rate. Our classification model shows an AUC of 0.92. The higher value of AUC means the encouraging performance of the system for the detection of hearing loss.

D. Agying and hearing loss

In this section, the hearing loss according to age has been studied intensively. As shown in the figure 3(a), the threshold of hearing decreasing with age in a continues manner. Age-related hearing loss (presbycusis) occurs gradually with the passage of time as we grow older. We applied the grouped based trajectory to analyze the hearing loss according to age which is known as presbycusis. The goal was to use group-based trajectory interpretation to study the sequence of the hearing loss with age. The mean of the auditory responses of the individuals for every ten years.

As shown in Figure 4(a), both trajectories for the healthy and the unhealthy subjects are in decreasing order. The slope of the fitted line to the healthy auditory responses is less negative then the slope of the fitted line to the medians of the auditory responses of the unhealthy subjects. Thus, we can conclude that auditory system of unhealthy subjects with age gets a weaker faster compared to healthy subjects.

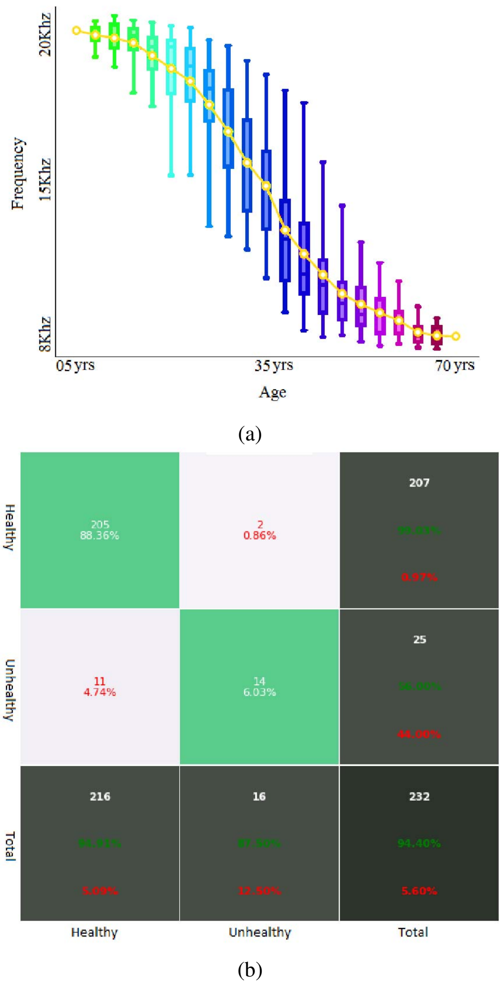
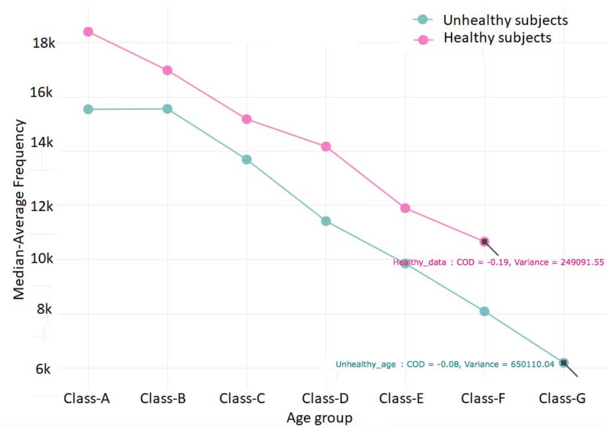


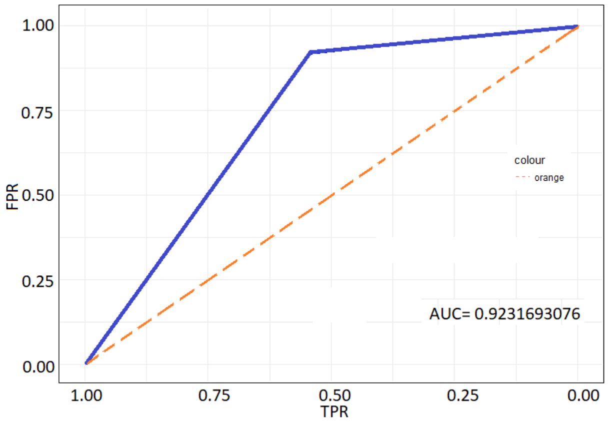
Fig. 3: Fig(a) shows trajectory of age related to hearing. Fig(b) Confusion matrix of classification performance using RF

IV. Conclusion and Future Perspective

In this paper, we deeply investigated the chances of detecting hearing loss through auditory perception responses. We demonstrated that human age and auditory system responses are interrelated. Furthermore, based on random forest regression we designed an efficient model that can predict the age of a subject with 4.1 years of RMSE value. While for prediction of hearing loss the classification performance is 94%. As a future perspective we are planning to develop an android and IOS based application to detect hearing loss. Our proposed system will offer health-care, economic, and comfortable interests.



(a)



(b)

Fig. 4: Fig(a) Shows comparison of hearing threshold of healthy and healthy subjects. Fig(b) ROC curve for classfication of healthy and unhealthy subjects

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