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A Novel Biased Probability Neural Network (BPNN) and Regularized Extreme Learning Machine (RELM) based Hearing Loss Prediction System

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ABSTRACT: Hearing loss or hearing impairment is one of the most leading cause highly affecting the people around the world in present days. Additionally, this disease primarily affects children and adults, which has an impact on their daily lives, careers, education, and other aspects of their lives. Therefore, it has to be correctly identified and diagnosed so that early therapies can be given to save people's lives. The many kinds of automated hearing loss prediction/detection systems are created for this aim in conventional works. The majority of the current research focuses on applying prediction techniques based on machine learning and deep learning to diagnose diseases. Its shortcomings include challenging computational procedures, longer training and testing times, greater mis-prediction outcomes, and incorrect outputs. Therefore, the proposed work objects to develop a Human Age - Hearing Impairment & Level (HAHIL) prediction system by using the machine learning methodologies. In this study, we describe a computer-aided strategy to forecast hearing loss and then prevent it. Here, three distinct prediction models are deployed for age prediction, hearing loss detection, and its severity level prediction. The Biased Probability Neural Network (BPNN) technique is utilized to predict the age based on simulated human acoustical signals. Then, the Regularized Extreme Learning Machine (RELM) mechanism is deployed for predicting the hearing impairment by constructing the weight and target matrices. During evaluation, the performance of the proposed HAHIL prediction system is validated and tested by using various evaluation indicators. The effectiveness of our computer-aided hearing loss prediction methods has been proven to be very high and they can be applied to the actual application system. Also, it provides an increased accuracy up to 99%, which is highly superior than the existing prediction models.

Keywords: Hearing Impairment, Acoustic Stimulated Signals, Age Prediction, Biased Probability Neural Network (BPNN), Regularized Extreme Learning Machine (RELM), and Cross-fold validation.

1. INTRODUCTION

Hearing impairment [1, 2] is one of the developing disability in many countries, and is considered as an essential problem need to be addressed in ancient times. Among other organs, the hearing is the most significant operating function in human [3], because which allows the people to communicate with each other. According to the recent reviews, it is analyzed that the hearing impairment [4-6] is the 5th leading disability in world, and it highly correlated to social isolation, solitude, and poor cognitive health. Typically, the hearing impairment can occur in a single or both ears, which may be either temporary or permanent. The key symptoms of hearing impairments are as follows: communication difficulties, unable to understand the conversation in a noisy environment, radio/TV listening is not possible, feeling beep sound, and not attentive in a group discussions. The World Health Organization (WHO) [7-9] states that the hearing loss is common in all age genders, and it may increase according to the number of incidents. It

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also states that nearly 20 million people are having this disability in United States (US), so it is treated as the serious health problem among the people in all countries. Moreover, an untreated hearing impairment problem [10, 11] can entirely affect the people's normal life by disturbing their social life, health status, and etc. It also creates some serious health problems like depression, mental issues, dementia, and falls. Generally, the major effects of hearing impairment is categorized into two types such as regulating risk factors, and non-regulating risk factors. However, the proper diagnosis can help the hearing impaired people [12, 13] to improve their health status, which holds the processes of tuning tests, conducting physical exams, and screening words. Once the hearing impairment is detected on the people, its severity level is estimated by using various soft-computing approaches. Hence, developing an efficient and competent hearing impairment prediction and detection model is a highly demanding tasks [14-16], and supports the people to identify their disability for proper diagnosis and treatments. In the conventional works, the different types of prediction models have been developed for predicting the hearing loss in people. Specifically, the machine learning and deep learning [6, 17] techniques are extensively used for predicting the disabilities by analyzing the speech signals or acoustic signals. Yet, the conventional approaches faced the major problems [18-20] of complex mathematical operations, reduced prediction results, inefficient computations, high processing time, and error rate. Therefore, the proposed work objects to develop a novel and enhanced machine learning based prediction methodologies to predict the age, hearing impairment, and level of severity on people. The major research objectives of this paper are as follows:

- To develop a novel Human Age - Hearing Impairment & Level (HAHIL) prediction system with increased efficiency and reduced complexity.
- To accurately predict the age based on the acoustic signal frequency, a Biased Probability Neural Network (BPNN) classification model is employed.
- To predict whether the person has the hearing impairment or not based on the age and acoustic signal, a Regularized Extreme Learning Machine (RELM) based machine learning methodology is deployed.
- To predict the level of hearing loss according to the frequency of signal and age parameters, which includes normal, mild, moderate, moderate-severe, highly severe, and profound loss.
- To validate and test the performance and effectiveness of the proposed model, the cross-fold validation is also performed in this work.

The remaining portions of this paper are organized as follows: Section II reviews the conventional machine learning and deep learning based prediction models used for developing hearing impairment detection system. Also, it discusses about the pros and cons of each model based on its features and operations. Section III provides the clear description about the proposed methodology with the working model, algorithms, and descriptions. Section IV validates the performance an efficiency of the proposed classification techniques by using various measures. Finally, the overall paper is summarized with the inferences, benefits and future work in Section V.

2. RELATED WORKS

This section reviews the conventional machine learning based prediction models used for identifying the hearing loss in people. Also, it discusses about the pros and cons of each techniques according to its unique features and characteristics.

Chen, et al [21] investigated about the Noise Induced Hearing Loss (NIHL) problem by using an advanced machine learning approaches. The purpose of this work was to increase the accuracy and minimize the prediction error with the utilization of multiple algorithms. Here, the performance of the machine learning approaches were validated and compared based on the calibration performance, discrimination performance, selection tools and validation tools. From the work, it was analyzed that the machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and etc were highly suitable for the hearing loss prediction applications. *Bing, et al* [7] intended to analyze the performance of four different machine learning techniques for predicting the Sudden Sensorineural Hearing Loss (SSHL) disorder. It includes the approaches of Deep Belief Network (DBN), SVM, Multilayer Perceptron (MLP), and Logistic Regression (LR). This work mainly objects to develop a robust prediction model for hearing loss detection by automatically extracting the informative features. According to the observed results, it was analyzed that the DBN outperforms the other techniques with better performance results. *Mahmud, et al* [22] deployed a multivariate models for examining the age-related hearing impairment. Here, the efficiency of different classifiers such as KNN, Adaboost, and SVM have been validated and compared in terms of noise degraded speech detection and clear speech detection. *Biadsy, et al* [23] implemented a new sequence-to-sequence model for normalizing the speech signals for the hearing impaired application systems. In this work, the spectrogram decoder was utilized to synthesize the audio signals. *Mahmud, et al* [24] employed a parameter optimization based SVM classification technique for developing an age-related hearing loss prediction system. Due to the increased robustness of SVM, this work employed a multivariate SVM model for prediction. In addition, the hearing status was predicted according to the set of extracted Event Related Potential (ERP) features. However, it faced the problems related to the factors of difficult mathematical operations, inefficient accuracy, and prediction results.

Nayak, et al [25] intended to develop the Sensorineural Hearing Loss (NHL) prediction system by using the MRI brain images. Here, the fast fourier transform based discrete curvelet transform technique was implemented to obtain the multi-directional features from the input. Then, an integrated Principal Component Analysis and Linear Discriminant Analysis (PCA-LDA) technique was deployed to minimize the discriminative feature set. Moreover, the mutation Jaya optimization and Extreme Learning Machine (ELM) based classification methodologies were utilized to predict the hearing impairment with high detection accuracy. The major limitations of this work were increased processing time, mis-prediction outcomes, and error rate. *Bidelman, et al* [26] objects to analyze the age-related hearing impairment by using the graph theory based machine learning model. The contribution of this work was to utilize a graph theoretic approach for analyzing the brain connectivity to improve the prediction performance. Also, the SVM based classification model was deployed to predict the presence of hearing loss. Moreover the performance of this model was validated and tested according to the speech stimulus based on the measures of accuracy, area under curve, and f1-score. *Wang, et al* [27] implemented a multimodal logistic regression model for identifying the unilateral sensorineural hearing loss. Also, it deployed a double density dual tree complex wavelet transformation technique for extracting the features in order to improve the prediction performance. Moreover, the Multinomial Logistic Regression (MLR) model for detecting the classified label by using the set of optimal features. Finally, the stratified cross validation was also performed to validate the performance and efficiency of the suggested model. The key benefits of this work were optimal performance, better accuracy, and minimal computation time.

Bhat, et al [28] utilized a multi-objective learning based Convolutional Neural Network (CNN) for improving the noise quality to the hearing loss users. The main purpose of this work was to develop an efficient learning methodology with reduced processing delay and increased computational performance. Here, the nonlinear functional mapping was performed between the given inputs and expected outputs. *Tang, et al* [29] deployed a tabu search based Particle Swarm Optimization (PSO) technique for predicting the hearing loss. Also, a wavelet entropy model was used to extract the set of features from the given input. *Ilyas, et al* [30] conducted a preliminary study for predicting the hearing loss in young adults. The purpose of this paper was to investigate the major possibilities of preventing hearing impairment with respect to the auditory system response. The primary advantages of this work were reduced error rate, high robustness, and reliability. *Zhao, et al* [31] utilized a deep learning based segregation algorithm for enhancing the speech intelligibility of the hearing-loss persons. The Deep Neural Network (DNN) was mainly deployed to increase the computational efficiency and speech quality with reduced noise. *Zhu, et al* [32] developed a tracking based processing methodology for improving the gesture recognition and representation of hearing impaired persons. This work states that an efficient Artificial Intelligence (AI) techniques were highly required for developing an efficient prediction model.

Table 1. Survey on existing works

Methods & Reference	***Description***	***Pros & Cons***
Artificial Neural Network (ANN) [33]	A machine learning classification model is used to predict the hearing impairment.	Better ability to efficiently train the model, fault tolerance, and low accuracy.
Bayesian Network (BN) [34, 35]	This technique is used to predict the hearing aid by optimizing the sound.	Computational burden, more time, and better prediction rate.
Fuzzy Logic (FL) [36]	The fuzzy logic and wavelet transformation techniques are applied to predict the hearing aid based on the extracted signal features.	High precision, better accuracy, and not suitable for handling large dimensional datasets.
Deep Reinforced Learning (DRL) [37]	It aims to improve hearing perception by learning the features with the use of DRL.	High time requirement for training the data, increased accuracy, and lack of reliability.
Deep Recurrent Neural Network (DRNN) [38, 39]	A smart hearing aid system is developed with the use of DRNN, which predicts the impairment with proper learning of signal features.	Highly capable for handling large datasets, increased prediction accuracy, and more complexity.

According to this review, it is analyzed that the different types of machine learning based prediction models are developed in the conventional works for hearing loss detection. However, it faced the challenges related to the followings:

- Difficult to understand

- Complex mathematical operations
- Inefficient accuracy
- High processing time
- Increased error rate

Therefore, the proposed work objects to develop a novel prediction system for detecting the hearing impairment with high detection accuracy and performance.

3. HUMAN AGE - HEARING IMPAIRMENT & LEVEL (HAHIL) PREDICTION SYSTEM

This section presents the clear description about the hearing loss prediction system with its appropriate working flow and algorithms. The novel contribution of this work is to develop a multi-objective prediction system for predicting the human age, hearing impairment and level of hearing loss. For this purpose, a novel machine learning based classification methodologies are implemented in this work, and its working flow is illustrated in Fig 1. Here, the acoustical simulation is performed at first based on the dynamic frequency sound, and the user feedback is obtained for the prediction process. It includes the following modules:

- Acoustical simulation
- Biased Probability Neural Network (BPNN) based Age Estimation
- Regularized Extreme Learning Machine (RELM) based Hearing Impairment Prediction
- Level of hearing loss prediction

The primary advantages of the proposed Human Age - Hearing Impairment & Level (HAHIL) prediction system are as follows: simple to implement, minimal processing time, reduced computational complexity, accurate predicted results, and increased efficiency.

A. Acoustic Simulation

In this framework, the dynamic frequency sound is utilized to simulate the human acoustical signals for hearing loss prediction as shown in Fig 2. Moreover, the bilateral simulation is performed by using the following model:

$$X(t) = S_0 \times \sin(2\pi \times \varphi(T) \times T) \quad (1)$$

$$\varphi(T) = F_s \times T + \varphi_0 \quad (2)$$

Where, $X(t)$ indicates the input signal, S_0 is the sound amplitude, T denotes the time, φ_0 represents the initialization frequency, and F_s is the frequency speed. Moreover, a real time interaction is performed in this system for obtaining the available frequencies. For this purpose, the following tests are conducted in this system:

1. Case 1 – The sound generation is performed from lower to high frequency ranging from 20 Hz to 20,000 Hz, and the available frequency is considered as A1.
2. Case 2 – In this case, the higher to lower frequency sound generation is performed ranging from 20,000 Hz to 20 Hz, and the available frequency is considered as A2.

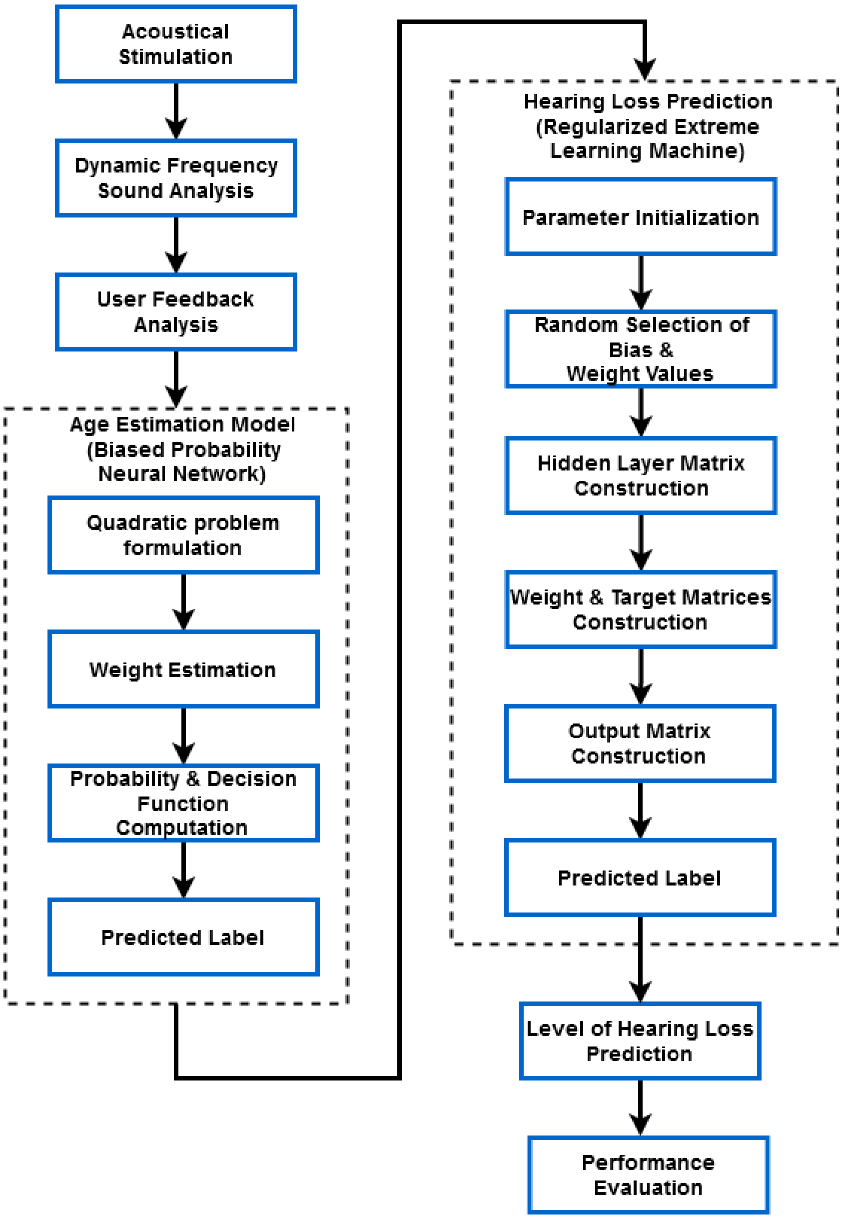

FIGURE 1. **Working flow of the proposed system**

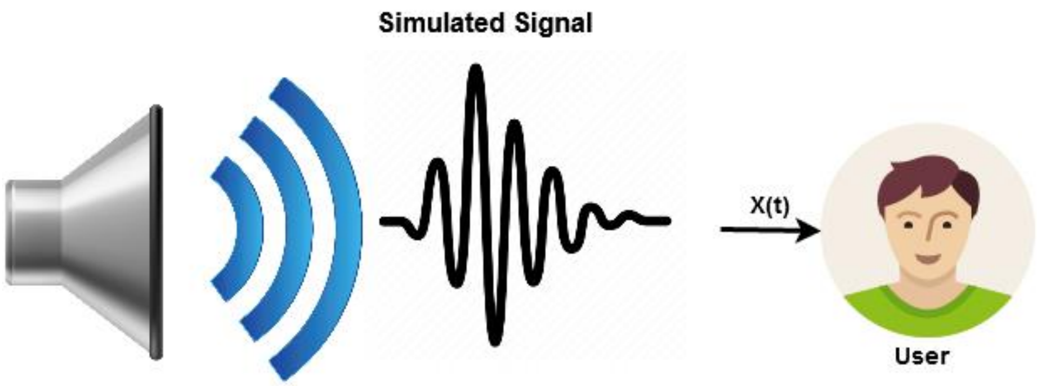

FIGURE 2. Acoustical signal simulation

B. Biased Probability Neural Network (BPNN) based Age Prediction

After signal stimulation, the age prediction is performed in this framework according to the auditory response. Here, the obtained audible frequencies are fed to the proposed Biased Probability Neural Network (BPNN) classification model. It is a type of machine learning classifier and, developed based on the conventional NN algorithm. Typically, the NN based classification methods are highly suitable for solving the complex prediction/detection problems. Hence, the NN based machine learning techniques are increasingly used in many application systems. However, the existing NN classification models limit with the problems of increased training & testing time, complex mathematical operations, high error output, and mis-prediction results. Hence, the proposed work objects to develop a new classification model by integrating the functions of Bayesian probability estimation model. The proposed BPNN is highly efficient and more suitable for the prediction applications. In this system, the BPNN is mainly deployed for predicting the human age according to the given acoustic signal inputs. Moreover, this classification model comprises the layers of input, hidden, and output, in which the input layer is more responsible for obtaining the input data. Then, the mathematical operations and calculations are performed in the hidden layer, and finally the output layer produced the predicted label as the output. Let, consider the training set having N number of data points as represented by $(x_i, y_i)_{i=1}^{N}$, where $x_i \in \delta^x$ indicates the input pattern, and $y_i \in \delta$ represents the output pattern. After that, the input x_i is mapped as $\vartheta: x_i \rightarrow \vartheta(x_i)$ into the feature space. According to this, the quadratic problem has been formulated as follows:

$$\min \omega, \alpha \left[\frac{1}{2}||\omega||^2 + W_P \sum_{i=1}^{N} \alpha_i\right] \quad (3)$$

Where, ω indicates the weight value, α is the margin value, and W_P represents the regularization parameter. Then, the probability function is computed as follows:

$$L(x_i, x) = \vartheta(x_i)^S \vartheta(x) \quad (4)$$

$$\max \gamma \left[\sum_{i=1}^{N} \gamma_i - \frac{1}{2}\sum_{i,j=1}^{N} \gamma_i \gamma_j y_i y_j L(x_i, x_j)\right] \quad (5)$$

$$\omega = \sum_{i=1}^{N} y_i \gamma_i \vartheta(x_i) \quad (5)$$

$$\sum_{i=1}^{N} \gamma_i y_i = 0, \quad 0 \leq \gamma_i \leq W_P, \forall i \quad (6)$$

Where, $\boldsymbol{\gamma_i}$ indicates the lagrange multiplier related to the training point, and $\mathbf{L}$ is the likelihood function. Based on this, the decision function $\mathbf{f(x)}$ is estimated as shown in below:

$$\mathbf{f(x) = \omega^S \vartheta(x) + t} \quad (7)$$

Where, $\mathbf{t}$ is the constant value. According to the likelihood function, it can be updated as follows:

$$\mathbf{f(x) = \sum_{i=1}^{N} \gamma_i y_i L(x_i, x) + t} \quad (8)$$

Finally, the obtained likelihood decision function is shown in below:

$$\mathbf{f(x) = sgn\left(\sum_{i=1}^{N} y_i x_i L(x_i, x_j) + t\right)} \quad (9)$$

By using this function, the classification label is predicted as whether normal, or disease affected. The algorithmic steps involved in this mechanism are represented in below:

Algorithm I – Biased Probability Neural Network (BPNN)

Input: User Feedback;
Output: Predicted label;
Step 1: At first, the input features are passed to the classifier for processing, and the patterns are mapped with the feature space.
Step 2: The quadratic problem has been formulated as follows:

$$\min_{\omega, \alpha} \left[\frac{1}{2}||\omega||^2 + W_P \sum_{i=1}^{N} \alpha_i\right]$$

Step 2: After estimating the weight value ω, the classification error rate is minimized by solving the quadratic problem; $\omega = \sum_{i=1}^{N} y_i \gamma_i \vartheta(x_i)$
Step 3: Then, the probability function is estimated with respect to each training point;

$$L(x_i, x) = \vartheta(x_i)^S \vartheta(x)$$

Step 4: The decision function $f(x)$ of classification is computed by using the probability function and bias constant;

$$f(x) = \omega^S \vartheta(x) + t$$

Step 5: Here, the probability function is completely depends on the expected outcomes, and the weight value has been updated according to the decision function;
Step 6: Consequently, the classifier has been trained with the set of distinct training samples, and based on this the weight value has been updated;
Step 7: Finally, the updated weight values are used for the testing process, and the predicted label is produced as the output; $f(x) = sgn\left(\sum_{i=1}^{N} y_i x_i L(x_i, x_j) + t\right)$

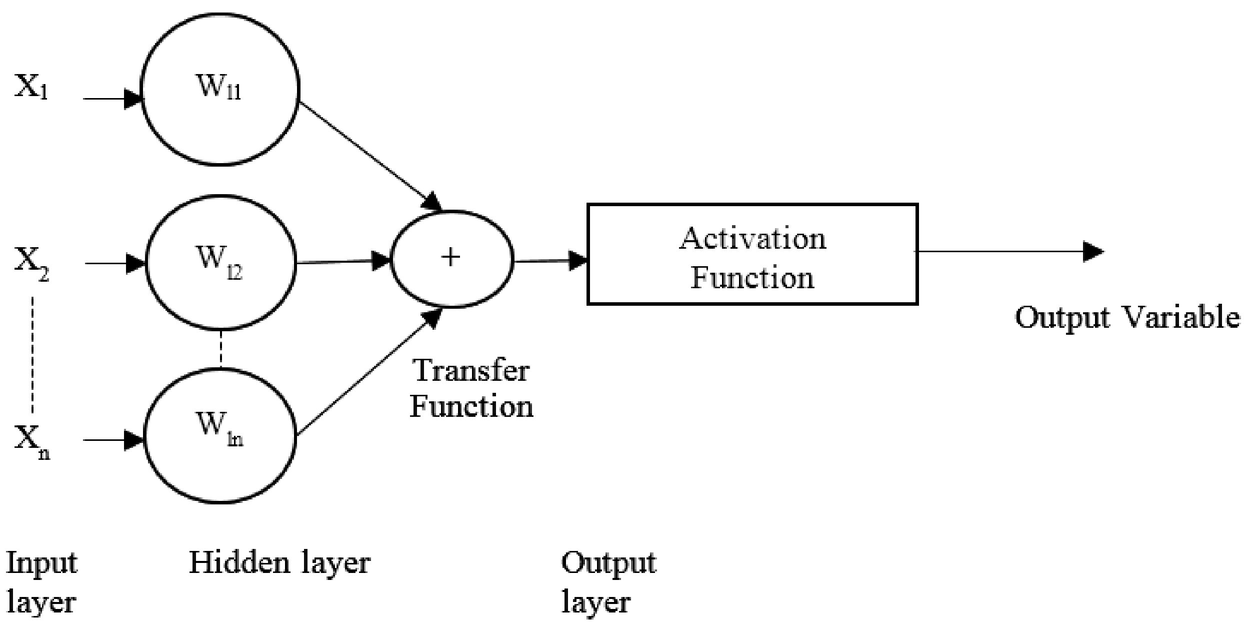

FIGURE 3. Layered architecture

C. Regularized Extreme Learning Machine (RELM) based Hearing Impairment Prediction

After predicting the age, the Regularized Extreme Learning Machine (RELM) technique is deployed to predict that if the person has a hearing impairment or not. Due to its capacity to get around the drawbacks associated with the backpropagation approach, the RELM is a classification and regression method that is employed in many applications. The RELM is superior to other classifiers due to its quick training time and lack of complexity. In contrast to gradient-based approaches, RELM assigns random values to the weights between the input and hidden layer and the hidden units biases, and all these parameters are set after learning. The hidden layer's nonlinear activation functions give the system nonlinearity. The system can then be thought of as linear. The weight between the output layer and hidden layer is the sole parameter that needs to be learned. Because RELM learns without iteration, it converges significantly more quickly than conventional algorithms. Random concealed nodes, meanwhile, promise to be able to approximate everything. According to a theoretical analysis, RELM are much more likely than conventional networks to find the best solution when given random parameters rather than all the parameters that need to be trained. In this model, the acoustic signals and the predicted age are given as the inputs for processing. Here, the RELM is the second predictive modeling approach mainly deployed for detecting the human hearing impairment. It is also one of the machine learning based classification technique, and developed based on the Feed Forward Neural Network (FFNN). Then, this network is constructed with three different layers such as input, single hidden, and output. In which, the bias and weight values of the input layer are randomly selected for processing. Then, the matrix construction and estimation processes are performed in the single hidden layer, and the output layer produced the predicted label as the output based on the updated weight value. In addition to that, the RELM is more suitable for solving the multi-class classification problems with better prediction results. The key benefits of using this technique are efficient data training and testing, reduced mis-prediction rate, high accuracy, and efficiency.

Algorithm II – Regularized Extreme Learning Machine (RELM) based Classification

Input: Parameters and training labels;
Output: Predicted class label;
Step 1: Initialize the bias and weight value for training data;
Step 2:Then, the weight ($\boldsymbol{\omega}_i$), bias ($\boldsymbol{\beta}_i$), and inputs ($\mathbf{p}_i$) are randomly selected for the input operations;
Step 3: Consequently, the matrix is constructed in the hidden layer as shown in below:

$$\mathbf{M} = \left[\mathbf{a}(\boldsymbol{\omega}_1 \cdot \mathbf{p}_1 + \boldsymbol{\beta}_1) \cdots \mathbf{a}(\boldsymbol{\omega}_m \cdot \mathbf{p}_1 + \boldsymbol{\beta}_m) \vdots \cdots \vdots \mathbf{a}(\boldsymbol{\omega}_1 \cdot \mathbf{p}_N + \boldsymbol{\beta}_1) \cdots \mathbf{a}(\boldsymbol{\omega}_m \cdot \mathbf{p}_n + \boldsymbol{\beta}_m)\right] \quad (9)$$

Step 4: Then, the weight $\boldsymbol{\delta}$ and target $\boldsymbol{\gamma}$ matrices are estimated as follows:

$$\boldsymbol{\delta} = [\boldsymbol{\delta}_1^{\gamma} \ \vdots \ \boldsymbol{\delta}_m^{\gamma}] \text{ and } \boldsymbol{\gamma} = [\mathbf{T}_1^{\gamma} \ \vdots \ \mathbf{T}_n^{\gamma}] \quad (10)$$

Step 5: After training the data, testing process has been carried out with the matrix computation;
Step 6: The hidden layer matrix $\widehat{\mathbf{M}}$ is estimated as shown in Step 3;

Step 7: The output weight values are computed by using the following model:

$$\hat{\delta} = (M^{Y}M + \lambda S)^{-1}M^{Y}\gamma \quad (11)$$

Step 8: Based on this, the output matrix is constructed as follows:

$$\rho_j = \widehat{M}\widehat{\delta} \quad (12)$$

Step 9: Finally, the testing class label $\mathbf{Out_j}$ is identified with respect to the number of classes $\mathbf{Y}$ as shown in below:

$$\mathbf{Out_j} = \arg\arg\,(\mathbf{Out_j}) \ \ j \in \mathbf{Y} \quad (13)$$

Step 10:Return the output label $\mathbf{Out_j}$;

After predicting the hearing impairment, the level of hearing loss is also predicted for estimating the severity. For this operation, the audible frequency and predicted age are considered as the inputs. Also, the cross-fold validation process is carried out among various classification methods for testing the efficiency of the proposed system. Moreover, the Root Mean Squared Error (RMSE) value is also estimated to analyze the level of severity. If the estimated value is high, it is determined that the hearing impairment is more severe. Then, the different types of classes considered in this model are as follows:

1. Normal
2. Mild
3. Moderate
4. Moderate-Severe
5. Highly severe
6. Profound loss

According to the predicted label, the improved performance, accuracy, and efficiency of the proposed model are validated using various measures.

4. RESULTS AND DISCUSSION

This section evaluates the results of the proposed HAHIL prediction system by using various evaluation measures. Also, the obtained results are compared with the recent state-of-the-art model classifiers to prove the efficacy of the proposed system. The dataset [40] used to validate the proposed HAHIL prediction system is presented in Table 1, which includes the major fields of age (years), number of healthy and unhealthy persons. Also, this dataset comprises the subjects of people in all age categories include children, teenager, young-adult, adult, and aged. Fig 3 validates the iterative analysis of the proposed HAHIL system, where the performance of classifier is validated according to the number of iterations carried in the parameter tuning. According to the results, it is analyzed that the proposed system provides an efficient solutions with minimum number of iterations, which shows the overall efficiency and performance rate of the proposed work.

TABLE 1. Dataset description

Subjects	Age (Years)	No of healthy	No 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

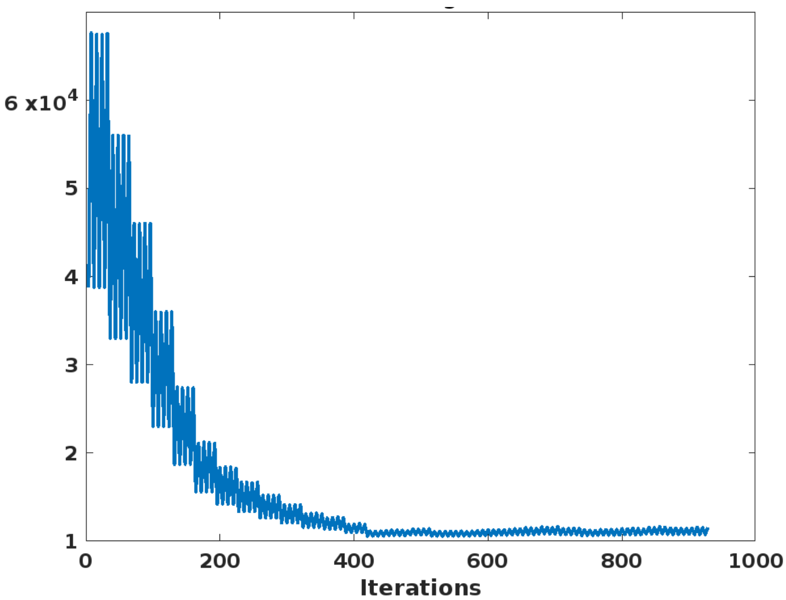

FIGURE 3. Iterative analysis

Fig 4 shows the Receiver Operating Characteristics (ROC) of the proposed HAHIL prediction system with respect to the number of True Positive Rate (TPR) and False Positive Rate (FPR). Typically, the main reason of estimating ROC is to test the efficacy and accuracy of classifier with respect to the number of truly and falsely detected samples. Moreover, this analysis includes the classes from 0 to 1, which indicates that 0 – auc = 0.98, 1 – auc = 0.97, 2 – auc = 0.96, 3 – auc = 0.97, 4 – auc = 0.95, 5 – auc = 0.98, 6 – auc = 0.94, 7 – auc = 0.96, 8 – auc = 0.97, and 9 – auc = 0.95. Based on the estimated results, it is analyzed that the proposed HAHIL prediction system provides an efficient results by accurately detecting the samples.

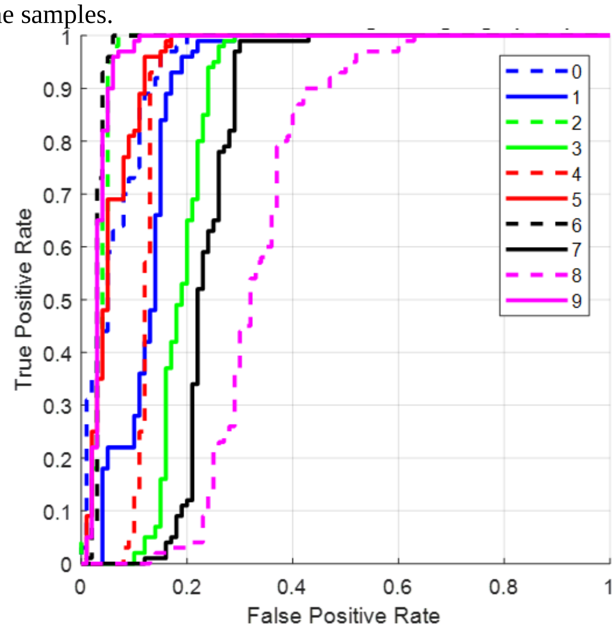

FIGURE 4. ROC analysis

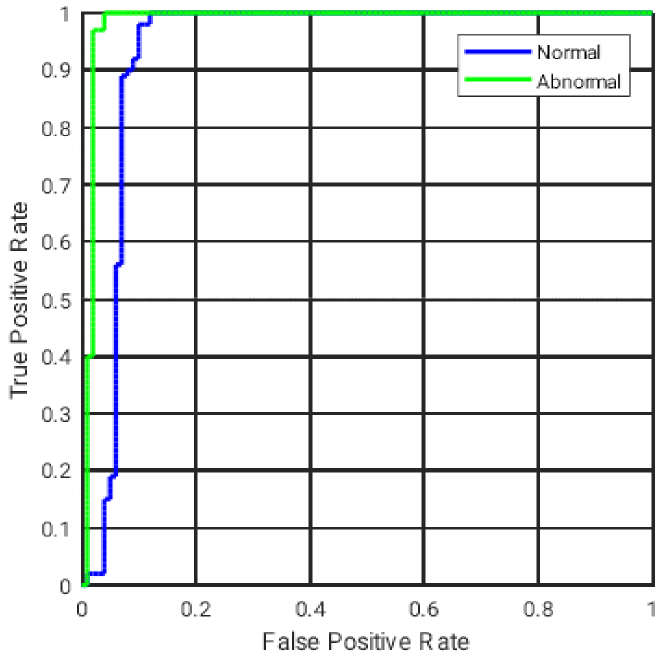

FIGURE 5. ROC analysis with healthy and unhealthy cases

Similarly, the ROC is estimated for the proposed HAHIL system for the healthy and unhealthy classes with respect to varying TPR and FPR. This analysis also depict that the proposed classifier could efficiently predict the healthy and unhealthy classes due to the proper learning and training of classification. Fig 6 presents the age distribution analysis of the proposed HAHIL system with respect to the different number of aged persons and number of subjects.

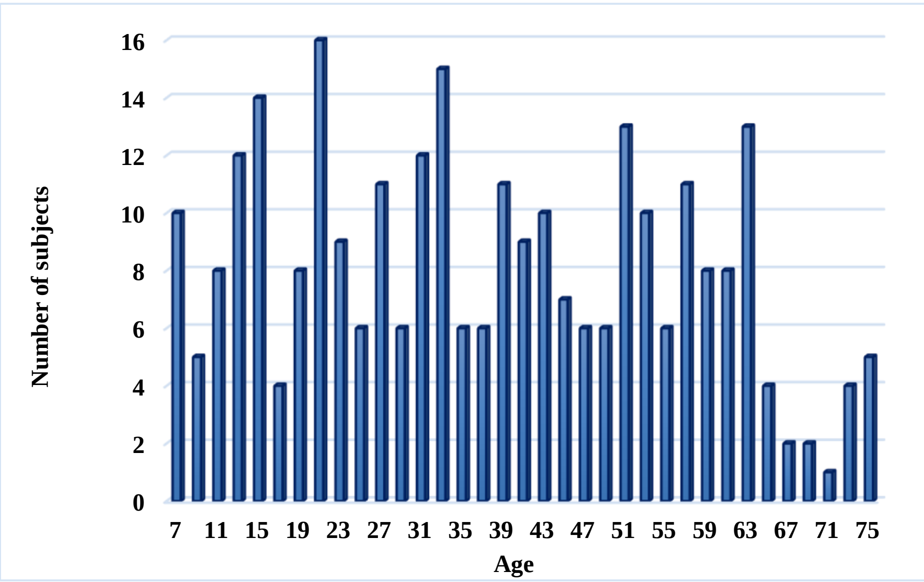

FIGURE 6. Age distribution with respect to the number of subjects

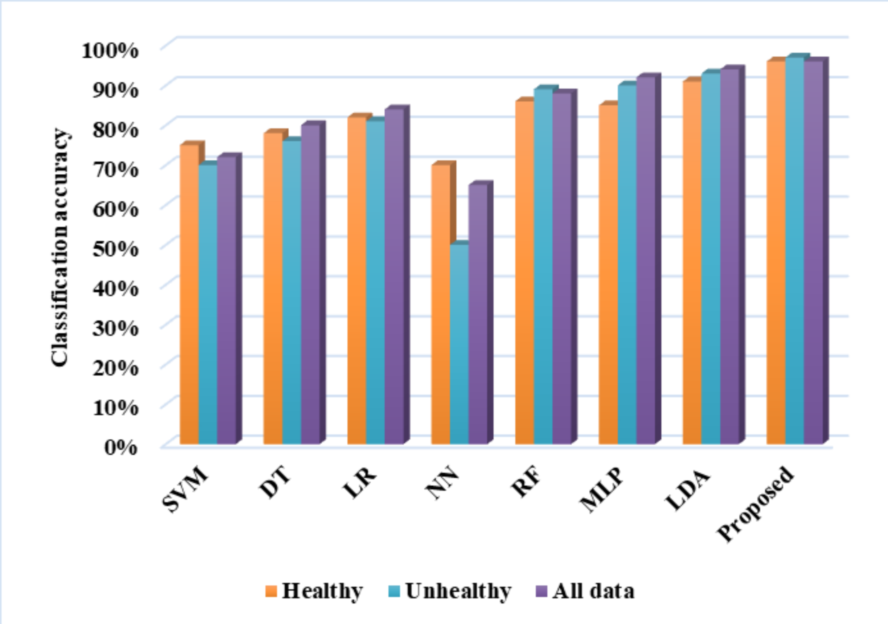

FIGURE 7. Classification accuracy analysis

Fig 7 and Table 2 validates and compares the classification accuracy of healthy and unhealthy data samples for the conventional and proposed prediction systems. The recent state-of-the-art model approaches taken for this analysis are Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), Neural Network (NN), Random Forest (RF), Multilayer Perceptron (MLP) and Linear Discriminant Analysis (LDA). In this analysis, the results are evaluated for both conventional and proposed techniques by using the developed dataset. Based on the obtained results, it is stated that the proposed HAHIL system outperforms the other approaches with increased classification accuracy.

Table 2. Healthy and unhealthy data prediction analysis

Methods	Healthy	Unhealthy	All data
SVM [41]	75%	70%	72%
DT [17]	78%	76%	80%
LR [27]	82%	81%	84%
NN [42]	70%	50%	65%
RF [43]	86%	89%	88%
MLP [44]	85%	90%	92%
LDA [45]	91%	93%	94%
Proposed	96%	97%	96%

Fig 8 and Table 3 compares the accuracy, sensitivity, and specificity of conventional and proposed classification techniques. Typically, the above mentioned measures are extensively used in the detection application systems for validating the efficiency and prediction performance of the classifier. Moreover, the increased values of accuracy, sensitivity, and specificity determines the overall improved performance of the classifier. Similarly, the precision, f1-score, and dice similarity coefficients are also considered as the important measures used to determine the performance of classifier. Fig 9 and Table 4 depicts the precision, f1-score, and dice coefficient of conventional and proposed classification approaches. The measures are computed as follows:

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100\% \quad (14)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100\% \quad (15)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (16)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \quad (17)$$

$$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision}+\text{Sensitivity}} \times 100\% \quad (18)$$

$$\text{Dice} = \frac{2 \times TP}{TP+TN+FP+FN} \times 100\% \quad (19)$$

Where, TP – True Positives, TN – True Negatives, FP – False Positives, and FN – False Negatives. From the estimated results, it is evident that the proposed HAHIL prediction system outperforms the other approaches with improved performance values of all measures. Due to the proper data training and testing, the overall detection performance of the proposed technique is highly improved over the other techniques.

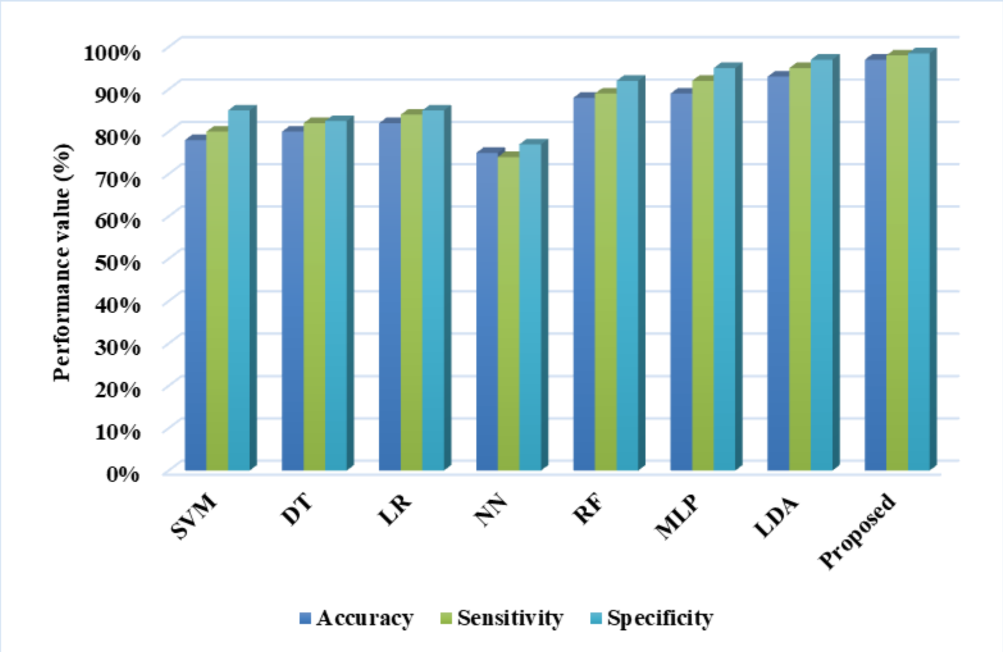

FIGURE 8. **Overall performance analysis**

Table 3. Accuracy, sensitivity, and specificity analysis

Methods	Accuracy	Sensitivity	Specificity
SVM	78%	80%	85%
DT	80%	82%	82.5%
LR	82%	84%	85%
NN	75%	74%	77%
RF	88%	89%	92%
MLP	89%	92%	95%
LDA	93%	95%	97%
Proposed	97%	98%	98.5%

Table 4. Precision, f1-score and dice similarity analysis

Methods	Precision	F1-score	Dice
SVM	79%	81%	82%
DT	83%	82%	83%
LR	84%	85%	84%
NN	76%	78%	77%
RF	90%	88%	92%
MLP	92%	91%	92.5%
LDA	94%	96%	95%
Proposed	98%	99%	98.5%

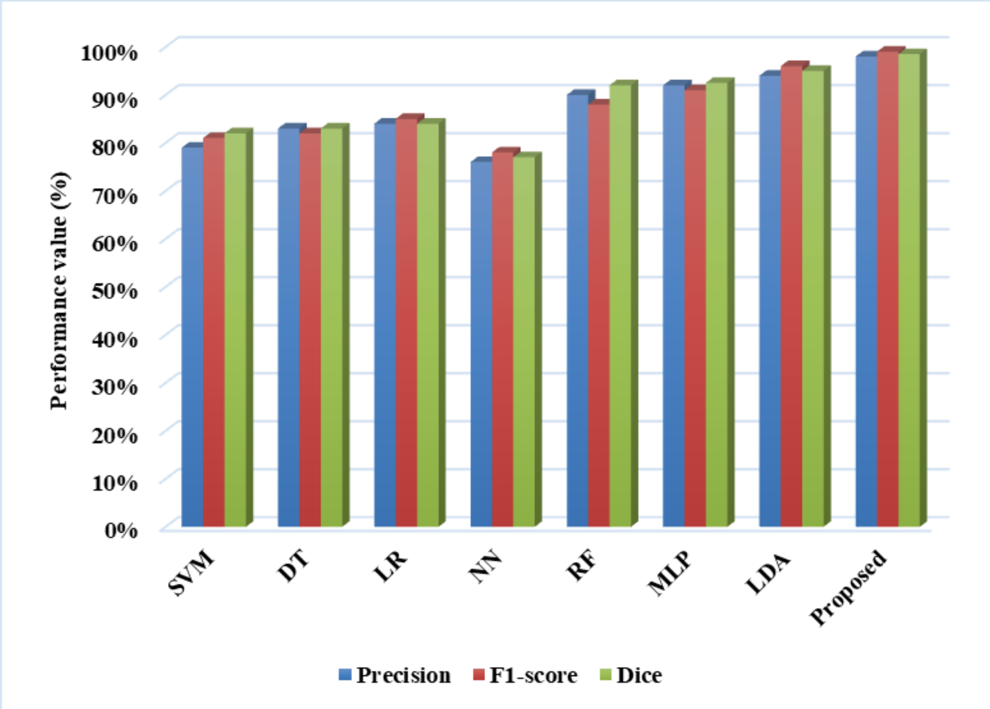

FIGURE 9. **Comparative analysis**

5. CONCLUSION

This paper presents a new prediction system, named as, HAHIL by using an intelligent machine learning methodologies. The main purpose of this work is to develop a simple and efficient prediction model by using different classification methods for predicting the age, hearing impairment, and its severity level of people. The novel contribution of this paper is to implement a computationally efficient Artificial Intelligence (AI) mechanisms to predict hearing aid with high accuracy and low computational burden. When compared to the other existing works, the proposed work has the major benefits of easy deployment, low time for training the model, and high prediction rate. In this framework, the acoustical simulation is performed at first based on the dynamic frequency sound, and the user feedback is obtained for the prediction process. After that, a bilateral simulation is performed to determine the frequencies that are available. In this framework, age prediction is carried out following signal stimulation utilizing the proposed BPNN model in accordance with the auditory response. To forecast the classified label in this model, activities like weight estimation, regularization parameter computation, and probability estimation are carried out. Then, by evaluating the acoustic waves and anticipated age, the RELM approach is applied to identify the human hearing impairment. The bias and weight values of the input layer are chosen at random for processing during this procedure, and the matrix building is carried out to estimate the output weight value. After predicting the hearing impairment, the level of hearing loss is also predicted for estimating the severity. During evaluation, the performance of the proposed technique is tested and compared by using different evaluation indicators. According to the obtained results, it is evident that the proposed HAHIL system outperforms the other approaches with increased performance values. Since the model must have a 100% true positive rate and 0% false positive rate, the correct classifier is one that makes no errors. The model that we employed to classify healthy and unhealthy subjects displays an accuracy of 99%. The system's performance in predicting hearing loss is shown to be promising by the higher value of accuracy.

In future, we intend to create a web application for anticipating and avoiding hearing loss with the use of advanced AI models. Another angle to research hearing loss and the ageing process is by linking auditory perception to other lifestyle factors.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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