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A Study of Hearing Impairment (HI) Prediction and Diagnose Based on Machine Learning Techniques

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Abstract

Hearing loss is a common problem faced by humans, especially adults. The report stated that are most of the adult are affected by the Hearing impairment (HI) who is partially or fully disable from hearing. Machine learning (ML) techniques were used to apply to predict the HI with higher accuracy. The ML is the most advanced method that can make it possible to learn any kind of complex data and provide good results. Therefore the ML is used for HI prediction and also diagnose HI with better classification models. In this work, the review of ML-based HI predictions is presented and listed the performances of literature in terms of accuracy and time consumption. Further, this work provides a better ML method to solve the HI issues by summarising the literature, comparing between the ML methods and the performances are also offered in this work.

Keyword: Hearing impairment, Machine learning, Time consumption, Diagnose HI

I. INTRODUCTION

World Health Organization (WHO) [1] stated that around 5% (430 million) of the world population Hearing impairment (HI). These issues majorly occur in the adult in a maximum number who is required for rehabilitation. Among 15% of the adults face HI issues, and 1.7 % of children are facing it. In recent times, the HI is increased in a more significant number to the adult's population. The statistic estimated that in the year 2050, over 700 million would be affected by HI, or one in each ten-member will face this HI disable issues.

Nowadays, the loss of hearing is a public health-related issue that leads a difficulty in hearing which also cause long-term defects in intellectual improvement, character, understanding and society adaptation [2]. Adults are majorly affected by HI issues from various countries for different reasons, especially noise-based environments. Researchers prove that hearing loss may be affected by environmental factors and also genetic oriented behaviour.

Industrial noise generates a continuous Gaussian noise (GN) and few complex non-Gaussian noises (NGN) frequently. This NGN is difficult to hear, which contain both non-steady and steady-state GN with high noise transients. Frequent exposure to high levels of noise by people in their working environment leads to hearing loss.

Therefore the main aim is to manage health/hazard management and predict higher noise and HI oriented issues in people in a significantly earlier stage. Predicting these issues in a fatal stage, recovering a remaining part of hearing loss is a significant possibility. Therefore the HI affected data is collected from the source and used to predict the HI problem with higher training and learning methods. For several research, the primary form of the first principle is applied. It is handled the data better for the prediction, but it cannot access the higher or complex data with a large number of samples. Inaccurate predictions are carried out in this model, so the need of learning algorithm is required for feature extraction and classification for an accurate prediction

Machine learning (ML) is applied to extract more extensive complex data to obtain higher prediction accuracy. The ML method is a mathematical derivation strategy that is broadly used to predict various fields. Some of the ML applied complex fields are applied credit card fraud (Syeda), spam detection [3], face recognition (Mian et al. 2007) and speech recognition [5]. These methods are highly effective and helpful to predict with good result exposure. Therefore, the ML model is applied to predict HI issues in terms of accuracy and time consumption.

This work reviews the Ml method-based HI problems used to predict the Auditory Brainstem system Response (ABR or ASR) at higher accuracy. In this method, some of the ML techniques are mentioned and summarised. This work resulted that the higher possible ML method to improve the ABR by predicting HI. The rest of the paper is organised as a statistic of HI in section 2 and the list of ML methods in section 3. Section 4 discusses the survey paper relevant to the HI work, and finally, the work is concluded in section 5 with a summary and references.

II. STATISTIC OF HI

Hear loss is one of the major defects that are occurred. The HI is developed as a global issue that is occurred in 80% of the people in developing and underdeveloped countries. Normal hearing is obtained at the decibel of 35 decibels (dB) for a better ear hearing. The HI is attained at the age of an adult, and also 15% of people are more than 60 years. Some of the common issues based on HI in every country are given below [1].

- For every 100 children, there will be 2 or 3 babies is under the defect of HI in one or both the ears
- The deaf child of 90 % are born to normal parents who are with well-hearing ears
- Among 15% of adults globally are affected by the HI who are with the damaged ABR
- The adult people aged 20 to 69 are affected majorly in a range of 16% for every annum.

- Last decades, the number of HI people was increased up to 21% per annum due to the industries and personal headphones and some activities
- The Men are affected by HI as double of the women percentage in the adult stage.
- There are 18 % of adults who are HI affected in both the years, and the report stated that it might improve to 23% for the next five years.
- The HI affected is varied in adults by age. For instance, adults between the age of 45 to 54 are affected as 2%, but the age of 55 to 64 is affected as 8.5 %. The others are above 74 who are almost Hearing loss in both ears.
- Generally, the statistics showed that 10% of adults are with damaged ABR system every year in all the countries.
- Most of the adults started benefits from the hearing aid, and some of the adults who are aged between 20 to 69 are benefitted from wearing hearing aids.

III. MACHINE LEARNING MODELS

ML based prediction is applied for early recovery and identification of hearing loss. In this section, few ML methods are listed .Support Vector Machine (SVM) **is mainly used for regression, classification, and outliers' detection**. It can also be used to solve both non-linear and linear problems. It has higher accuracy in many practical problems and is also very effective in huge dimensional spaces. Multiclass Support Vector Machine (MSVM), can be used to perform a multiclass classification. It is used to break the multi-classification issues into multiple binary classification issues, which is followed by SVM.

KNN model is frequently used ML methods, which is abbreviated as k-nearest neighbour. This model is used to find out the similarity between the new data and available data cases. It is used to categorise a new data case that can be the most available categories data in it.Bayes (NB) is the typical ML method is based on **Baye's principle with an independent assumption between prediction values.** It is a classifier that has a particular feature unrelated to the presented features in that class.

Hidden Markov Model (HMM) is a **statistical approach. It is majorly used for biological sequence modelling**. The output sequence is determined by a discrete stochastic process that improves through a hidden state from the observer.Convolutional Neural Network (CNN) is based on both ML and deep learning model is based on the learning data of weights and biases for different aspects/objects which helps to distinguish between objects.

Neural Network (NN) is based on the human brains operation. It consists of an input layer (obtain data), a hidden layer (used for computations) and an output layer (reading the values).

Random Forest (RF) is an ML used for **solving the classification and regression issues**. It can be used to merge several classifiers to provide better solutions to complex problems.

Decision Trees (DT) is a **graphical representation to make a decision for every situation**. For example, every DT is used to classify a feature to categorise labels or the purest classes in the dataset.

IV. LITERATURE REVIEW ON HI

Several works are developed to predict and diagnose HI and ABR using ML methods in this section. ML method to classify the ABR for a better diagnosis of HI was used to distinguish between standard and HI waveforms and predict the issue as the most acceptable process [6]. This model can be provided with a biometric marker to indicate the HI at the accuracy range of 83.33%. A perceptual linear prediction (PLP) and HI modelling based on methods where developed to support vector regression (SVR) is used for feature extraction with the PLP coefficients dataset [7]. The outcome showed that HI prediction is better and provides robust performance in different test environments.

Prediction of HI through ASR was explored which showed adults were affected [8]. Although this model is used to determine the actual and predictable age, the HI can be predicted simply. This method carried an age estimation of people in the Root Mean Square Error (RMSE) value. The result showed that the ML of RF accuracy for HI is 94%. KNN is used for determining the HI issues with a high accuracy range to imputation. The GN model is used to detect abnormal or unreliable audiograms to generate in large datasets. This model achieved a better accuracy which can be obtained an error rate for 6000 Hz threshold of 7.36 [9]. Thus, it can be more effective and consume less time to extract entire audiogram datasets.

Farmani et al. (2014) described a probabilistic model and NB for HI for an accurate prediction. However, it is more benefited with an eager extensible to complex HI models. The NB can be derived from complex issues and provides optimal results based on HI in a minimum time of 0.44ms, respectively [10].Doyle et al. (2012) presented the ML-based SVM for predicting the ABR and HI. It can be extracted based on sample size that has not in need of statistical significance. This classification is done successfully with an exact prediction from the raw EEG data. The accuracy of prediction using an SVM method is varied for a different electrode from an average of 76.3% to a maximum of 94.0%. [11]

Acoustic kernels model that is learned for every data, are represented as 20 ms duration. This model can be retrieved and solve a complex derivation for prediction. It showed that the individual's speech of HI can be provided intelligibility of human speech and achieved an accuracy of 85% by the learned kernel [12].NN can be used to extract the fractal features for HI diagnosis which is connected to various subject perception levels. Feedback NN and Feed-forward NN are provided to categorise the different levels of perception. The outcome of an intelligent HI accuracy showed as 85%, which can lead to a better diagnosis [13].

Gupta et al. (2017) implemented an ML-based hardware device by using a speech and motion-controlled. The Gesture control operates the sensor placed on the device. Several methods are attached with the device to offer an effective throughput and functionality. ML performances are a better part of this device that can be handled well and used for various applications in the future [14].

Elbasi et al. (2018) presented various methods of ML such as Artificial Immune Recognition System (AIRS), DT-J48 and RF. These methods are performed well in the prediction using Data mining. For example, the heart loss dataset is collected and handled by the ML methods and performed well in the prediction. The accuracy achieved by this method is between 99-100%, and it can also be used for massive datasets [15].Dobrowolski et al. (2016) presented an ABR with the support of SVM methods. It is used for various fields like Potential markers for an audiologists support. It can be obtained a maximum accuracy range of 97%. The performance of this method could provide better discrimination among healthy and abnormal ABR signals.[16]

Molina et al. (2016) explored the pattern-based method using ABR. It is also used for the prediction of the range between ABR signals and healthy people. This model achieved a greater accuracy of 97.6% and also applied for Potential marker to support an audiologist.[17]. Losorelli et al. (2020) discussed a speech-based ABR of musical notes and CV phones. This work can be categorised by Linear Discriminant Analysis (LDA). The performance-based on the HI prediction can be attained an accuracy as 71.5%, which can be helpful for the diagnose patients [18].Some of the works are listed to show the performance based on HI.

Table 1. Performance analysis of various Machine Learning Techniques

S.no	**Author**	**Method**	**Determination**	**Performance**
1	Osman et al. (2021)	ML review	ABR classification	83.33% accuracy
2	Charih et al (2018)	KNN	6000Hz threshold limits	Achieved a 7.36 as average
3	Ilyas et al (2019)	RF	HI diagnosis	Accuracy as 94%. And RMSE 4.1years
4	Banerjee et al (2016)	Acoustic kernels model	Complex data-based HI prediction	Accuracy is 85%
5	Paulraj et al. (2014)	NN model	distinguish perception level of hearing	85% of accuracy achieved
6	Gupta et al. (2017)	ML model	gesture-controlled device	Better performance and hardware complexity
7	Elbasi et al (2018)	AIRS, DT-J48 and RF	HI prediction	Accuracy as 99-100%
8	Dobrowolski et al (2016)	SVM	ABR prediction	Accuracy range of 97%.
9	Molina et al (2016)	Pattern-based	ABR prediction	accuracy of 97.6%
10	Losorelli et al (2020)	LDA	speech-based ABR	accuracy of 71.5%

From the performance list table based on other literature, it showed that the better results for the HI prediction is provided by the RF model in the literature of author Ilyas et al. (2019) [8] and also the hybrid ML of AIRS, DT-J48 and RF are also achieved a 99 to 100% of accuracy in prediction.

V. CONCLUSION

In this work, the survey of HI prediction based on ML methods is presented. This work is organised with statistics about HI, which is a significant problem faced worldwide. The reviews found on several ML submitted from various works. These models are listed based on their performances of ABR and HI prediction. According to the survey, the RF model achieved a maximum accuracy of 94% for HI, the hybrid of AIRS, DT-J48, and RF obtained higher accuracy of 99 to 100%. Therefore it showed that the ML is best for HI prediction and that it can be applied for various applications as a future enhancement.

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