A deep learning-based approach for hearing loss detection

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ABSTRACT

Millions of people across the world are affected by hearing loss and early detection is very important for effective intervention. The traditional hearing screening methods are effective but they often rely on specialized equipment and clinical resources, making them less accessible to common people. Hearing loss is a state that affects the ability to communicate, socially interact and overall quality of life. The advancements in recent years have aimed to enhance the accessibility and efficiency of hearing tests, mainly in remote areas. The accurate classification of hearing loss is essential for effective detection and treatment in audiology. This study presents a deep learning (DL)-based approach based on a feedforward neural network (FNN). This paper focuses on common causes like cerumen impaction, otitis media, and otosclerosis. The study tries to explore ways to improve the diagnosis of hearing loss. The goal is to develop solutions that make hearing screenings more accessible and cost-effective for populations with limited access to healthcare resources. The results show the advantages of DL models in supporting automated accurate classification of hearing loss for intelligent diagnostic systems in audiological healthcare.

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1. INTRODUCTION

Hearing disorder is a common health condition that affects many individuals across the world irrespective of their age, gender, and socioeconomic boundaries. It can significantly affect one's ability to communicate, engage in social interactions and maintain overall quality of life. There could be several causes for hearing loss. It is broadly categorized into two types namely sensorineural or cochlear hearing and conductive hearing loss. Sensorineural hearing disorder occurs because of injury to the inner part of the ear and conductive hearing loss results due to obstructions or abnormalities in the outer part or middle ear. This hearing loss is caused as a result of ear infections, the buildup of earwax, otosclerosis and other forms of ear obstruction. These conditions are treatable, but they still contribute significantly to hearing impairment across the world. The global burden of hearing loss is huge with nearly 466 million people worldwide experiencing some form of disabling hearing loss. Of these, conductive hearing loss, which is less severe than sensorineural hearing loss affects a large part of individuals. It is responsible for impairing the ability to hear sounds clearly thus disrupting daily communication and social interactions.

The quality of a person's life can be greatly impacted by hearing impairments. Effective intervention and rehabilitation of hearing loss depend on early detection, especially in populations that are at risk, such as infants, the elderly, and people who are exposed to noise at work. Traditional audiometric testing techniques frequently use subjective assessment and could not always offer the accuracy needed to identify mild hearing loss at its earliest stages. Tympanometry and audiometry testing are two examples of the specialized tools that have historically been used. These techniques frequently need expensive equipment, skilled personnel, and access to medical facilities which may not be available in rural locations.

According to Barbour *et al.* [1], an online machine learning (ML) based audiometry technique was presented that estimates hearing thresholds throughout the entire frequency range. The approach improves the assessment's efficiency by providing more audiogram details that conventional methods do not. Digital methods for automated audiometric testing with ML algorithms are discussed in [2]. The authors examined 27 automated hearing test techniques and highlighted how ML lowers the number of trials needed for pure-tone audiometry (PTA), resulting in reasonably priced audiometric evaluations. The study in [3], [4] created a deep learning (DL) model to predict conductive hearing to properly diagnose conductive hearing loss brought on by otitis media, and otoscopic pictures were analyzed. The model showed an accuracy of 81%, which is trained on a dataset of more than 2,000 otoscopic pictures.

Schlittenlacher *et al.* [5] demonstrated how ML techniques, like Bayesian active learning, can maximize PTA's effectiveness in the most uncertain regions. Gathman *et al.* [6] used decision tree algorithms, namely light gradient boosting machine (LGBM), to predict audiometry-based hearing levels for predicting hearing loss using demographic and clinical data. The accuracy obtained by the model was very high. AlSamhori *et al.* [7] discussed how AI and ML might help to prevent hearing loss. The study demonstrates that AI algorithms can be included into audiometric devices to improve the efficiency and in diagnosing hearing loss. Shin *et al.* [8] created and compared several ML models like gradient boosting, recurrent neural networks, and multilayer perceptrons.

Weng *et al.* [9] examined the application of ML models to predict sound perception. It analyzed 16 research studies with 5,058 cochlear implant users, both adults and children. To classify pure-tone audiogram data, Dou *et al.* [10] suggested a hybrid ML approach that blends decision trees with DL methods. The model classified various types of hearing loss with an accuracy range of 96.75% to 99.85%. ML methods were used in [11] to identify middle-ear disorders such as otosclerosis and ossicular disarticulation.

Several ML models were used [12]. The use of DL models for categorizing audiometric data and identifying hearing loss is discussed [13]. Crowson *et al.* [14] investigated the application of DL to automate audiometric examinations by increasing the accessibility and affordability of hearing loss identification in environments with limited resources. Calabrese *et al.* [15] presented deep neural networks for audiogram estimation. Hepsiba and Justin [16] showed that deep neural networks can be used to improve speech comprehension for people who make use of hearing aids. Shin *et al.* [17] explained that hearing loss detection can be improved when pure-tone audiograms are combined with speech recognition data. An advancement for telemedicine and mobile health applications is proposed in [18] for the real-time classification of hearing loss using DL models.

The application of convolutional neural networks (CNNs) in order to automate the classification of audiometric results is discussed in [19]. According to their research, CNN-based models are capable of accurately classifying audiograms with high precision as close to professional audiologists. The authors in [20]–[22] demonstrated how artificial neural networks (ANN) are used in the detection of hearing loss. Their study shows that by analyzing the audiometric data in a very precise and scalable manner, ANNs can anticipate the severity of impairments and identify different forms of hearing loss. The study in [23]–[25] highlighted that ML and signal processing methods might be combined to predict hearing loss. By combining the advantages of DL with signal processing, this hybrid technique can detect hearing loss that are more precise and trustworthy.

Detecting the hearing loss is difficult, especially in environments with limited resources. Artificial intelligence has transformed several areas of healthcare in the last ten years by means of precision medicine, automating diagnostic procedures, and improving patient outcomes. Conventional audiometry depends heavily on trained audiologists to interpret results. This poses challenges in large-scale screenings. This has made it necessary to create DL-driven models that can improve the performance.

The key contribution of this research paper includes a feedforward neural network (FNN) was designed to automatically classify common types of hearing loss. The proposed DL model helps in early detection by showing great accuracy in classifying hearing loss. This paper checks the feasibility of audiometric evaluation through DL techniques for the early identification of hearing impairments. Including DL to audiometric testing makes the diagnosis process better. It also leads to scalable and cost-effective solutions in both clinical and remote settings. This paper aims to investigate novel approaches to improve the diagnosis of hearing loss to enhance accessibility for individuals affected. It aims to identify solutions that can be applied in low-resource environments by investigating cutting-edge techniques.

2. METHOD

This section outlines the methodology followed in the proposed DL model for hearing loss. The steps proposed include data collection, data preprocessing, and model development. Each step is designed to ensure robust feature extraction, accurate learning, and reliable prediction performance of the proposed model.

2.1. Data collection

Collection of the audiometric details is the initial stage for developing the proposed DL model. The data was collected from the UCI Audiology dataset. This dataset includes both categorical and numerical information, which is mostly utilized for the classification of hearing loss. An FNN for multi-class classification of hearing loss is presented in this research. The dataset is made up of audiological test data that has characteristics which help in the detection of hearing loss in various contexts. The various features in the dataset were patient attributes such as age, sex, and audiological test results. The categorical features include test types, ear side (left or right) and certain test results such as loss or condition. Numerical features included values such as the patient's age, audiometric results, and various measurements related to hearing thresholds and impedances. This dataset presents a challenge because of the variety of feature types. Preprocessing approaches are needed to normalize numerical features and transform categorical variables into a format that can be used. The goal was to predict one of five possible classes of hearing loss: normal, conductive, mixed, cochlear, and retro cochlear.

2.2. Data preprocessing

The preprocessing of data is performed in order to prepare the dataset that is applicable for DL model training. This step ensures data consistency, reduces noise, and improves overall data quality. There were multiple steps in this phase, which are listed as follows:

i) Categorical encoding: the one-hot encoding was used to transform the categorical features, like test kind and ear side, into binary vectors. Each category in the feature has its own binary column created in this stage. For example, the ear side was represented as binary columns for the left part of ears and right ears, and the test type feature was encoded into separate columns for each test type.
ii) Feature scaling: standardization was used to standardize numerical features which scales the features to have unit variance and zero mean value. This helps in more efficient training by preventing characteristics from having an uneven effect on the model's learning.
iii) Data splitting: the data is randomly grouped into training set and validation set as an 80/20 split. This division allows the model to be evaluated on new data, which helps to minimize the risk of overfitting.
iv) Tensor conversion: after preprocessing the dataset was converted into PyTorch tensors, which is a necessary format for training DL models in PyTorch. The data was then packaged into data loader objects for mini-batch training that allows for more efficient processing and helps to manage memory consumption during model training.

2.3. Model development

The proposed model is designed to capture relevant patterns from the input data. The model is made up of multiple interconnected layers that enable hierarchical feature learning and improved prediction accuracy. The proposed model is explained as follows:

i) Input layer: the input layer corresponds to the features in the preprocessed dataset. Each node represents one feature, including both categorical and numerical features. This layer serves as the interface between the raw input data and the DL model.
ii) Hidden layers: the model has two hidden layers. The first layer has 128 neurons, which is activated by the rectified linear unit (ReLU) activation function that helps to add non-linearity to the model. A dropout rate of about 0.3 was applied to this layer to minimize any overfitting. The next layer is made up of 64 neurons which also uses the ReLU activation function and a 0.3 dropout rate to further prevent overfitting and enhance generalization.
iii) Output layer: this layer has 5 neurons representing one of the five potential classes of hearing loss. A SoftMax activation is applied to this layer to transform the raw values to a probability distribution. The highest probability class is chosen as the predicted output.

2.4. Model training

The model training process is a critical phase that determines the learning efficiency of the proposed approach. It focuses on minimizing prediction errors. The model training process involves selecting appropriate optimization techniques, loss functions, and evaluation metrics:

i) Loss function: the cross-entropy loss was applied as the loss function. This is ideal for the task of multi-class classification. This function combines SoftMax activation with a log loss to compute the difference between the probability of the predicted class and the actual labels.

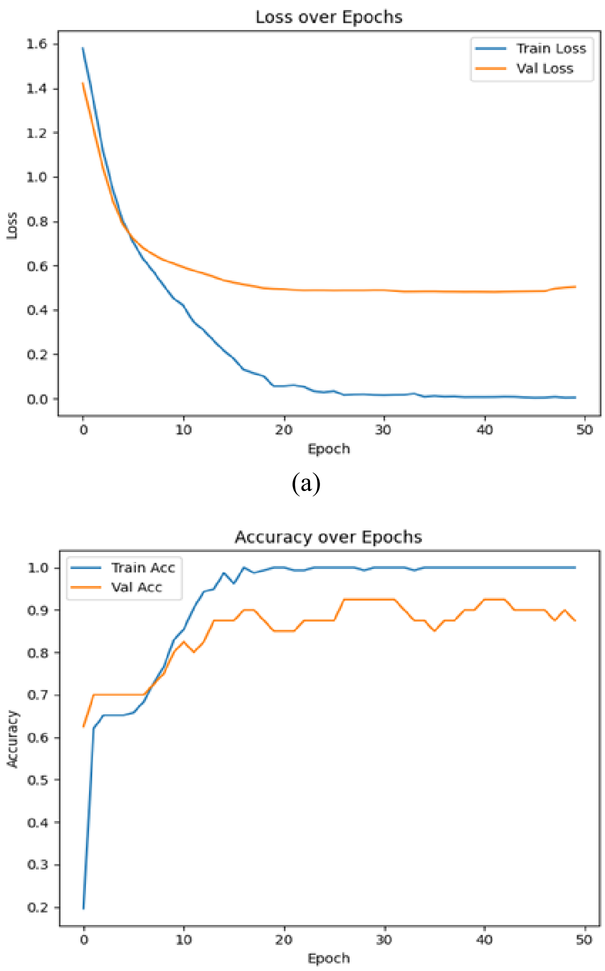
ii) Optimizer: Adam optimizer was used to train the model. This optimizer is recognized for its efficiency and capacity to adjust learning rates during the training process. Adam optimizer uses the advantages of both momentum and adaptive learning rates for faster convergence.

iii) Training process: the proposed model was trained for 50 epochs. In each epoch the entire training dataset was fed into the model and the weights were adjusted based on the calculated gradients. Dropout was used during the training process so as to prevent any overfitting. The performance was evaluated on the validation set after each epoch to monitor development and guarantee strong generalization to unknown data. The hyperparameters like the learning and dropout rate were adjusted in response to validation results so as to maximize the performance.

3. RESULTS AND DISCUSSION

The results of the proposed DL model for multi-class classification of hearing loss are presented in this section. The dataset used was the UCI Audiology dataset. The effectiveness of the model was evaluated based on its ability to classify hearing loss into five categories: normal, conductive, mixed, cochlear, and retro cochlear. The metrics like accuracy, precision, recall and F1-score were used to determine the model's performance. The train-validation split of 80/20 was used to train the model for 50 epochs. Cross entropy loss was used as the loss function in the training phase, and the Adam optimizer was used. The learning rate was set to 0.001. To avoid overfitting, dropout regularization was done to both hidden layers at a rate of 0.3.

Figure 1 shows the graph of training and validation loss (Figure 1(a)) as well training and validation accuracy (Figure 1(b)). The training loss decreased consistently over the 50 epochs. The accuracy on the training set increased steadily. The validation loss showed a similar trend. The model demonstrated effective convergence, as indicated by the stable loss and high accuracy towards the end of training.



(a)

(b)

Figure 1. The graph of (a) training loss vs validation loss and (b) training accuracy vs validation accuracy

In this study, the proposed model was evaluated against support vector machine (SVM) and random forest (RF). The detailed study of the performance of these models is presented as follow. The focus is on their effectiveness in predicting the five hearing loss categories: normal, conductive, mixed, cochlear, and retro cochlear. The proposed model demonstrated very good overall performance obtaining an accuracy of 85% across all categories. The proposed model's classification report is summarized in Table 1.

The proposed model performed well for predicting cochlear hearing loss with a 0.93 precision, 0.93 recall, and an F1-score of 0.93. The mixed class demonstrated a balanced result with a precision of 0.60, recall of 0.75, and an F1-score of 0.67. Although the model demonstrated strong recall for this class there is a scope for improving precision. The retro cochlear class also performed well, with a precision of 1.00 and a recall of 0.67. This highlights good precision but suggests that the model could improve in finding all instances of retro cochlear hearing loss. For the conductive class, the model gave a good performance with a precision of 0.67, recall of 0.67, and an F1-score of 0.67 showing good performance. The normal class, with only 2 samples in the dataset, was difficult to classify. The model was able to generate a precision of 0.50, recall of 0.50, and F1-score of 0.50, reflecting the difficulty in accurately classifying this small class. The proposed model performed well for cochlear and mixed classes. It achieved a good accuracy and F1-scores. The results were more balanced across the various classes as compared to SVM and RF.

Table 1. The proposed model classification report

Class	Precision	Recall	F1-score
Normal	0.50	0.50	0.50
Conductive	0.67	0.67	0.67
Mixed	0.60	0.75	0.67
Cochlear	0.93	0.93	0.93
Retro cochlear	1.00	0.67	0.80

SVM is a widely used supervised learning method which is effective in handling high-dimensional data. It aims at finding an optimal hyperplane that maximizes the separation margin among different classes. SVM classification report is presented in Table 2. The SVM generated an overall accuracy of 82%. Like the proposed model, the SVM model performed well on the cochlear class, achieving a precision value of 0.85 and recall of 1.00 resulting in an F1-score of 0.92. This represents that SVM was highly effective in classifying cochlear hearing loss. Conductive class showed an impressive precision of 1.00 but with a recall of 0.67 and F1-score of 0.80. The mixed class showed poor result with an F1-score of 0.33. The precision of 0.50 and recall of 0.25 indicate that the SVM model struggled significantly with this class. Like the proposed model, the Retro cochlear class was another strength of the SVM model where the precision score was 1.0, recall was 0.67 and F1-score was 0.80. The normal class was not classified correctly by the SVM model, with all scores being 0.00 showing that the SVM struggled to recognize instances of normal hearing loss. The SVM model substantially failed with the normal and mixed categories but did well overall on the cochlear and retro cochlear classes.

Table 2. The classification report of SVM

Class	Precision	Recall	F1-score
Normal	0.00	0.00	0.00
Conductive	1.00	0.67	0.80
Mixed	0.50	0.25	0.33
Cochlear	0.85	1.00	0.92
Retro cochlear	1.00	0.67	0.80

RF is a technique that makes use of multiple decision trees. The RF classifier achieved an accuracy of 82% with performance variations similar to those of SVM. RF classification report is shown in Table 3. The cochlear class was well-predicted by the RF model scoring a precision of 0.90, recall of 0.96, and 0.93 F1-score. This confirms model's effectiveness in classifying instances of cochlear hearing loss. The conductive class achieved decent results with a precision score 0.67, a recall of score 0.67, and F1-score of 0.67. The performance was balanced but did not have ideal accuracy. The mixed class showed a moderate performance with an F1-score of 0.57, where the precision was 0.67 and recall was 0.50. This indicates that the model was somewhat effective but failed to correctly classify instances of mixed hearing loss. As in the SVM model the retro cochlear performed well with a precision of 1.00 and recall of 0.67 and 0.80 F1-score. Similar to SVM the normal class posed a challenge for the RF model with all scores at 0.00.

Table 3. The classification report of RF

Class	Precision	Recall	F1-score
Normal	0.00	0.00	0.00
Conductive	0.67	0.67	0.67
Mixed	0.67	0.50	0.57
Cochlear	0.90	0.96	0.93
Retro cochlear	1.00	0.67	0.80

All models performed well for the cochlear class scoring a F1-scores that are close to or above 0.90. The proposed model and SVM models exhibited almost perfect recall while RF showed a slightly higher precision (0.90) than the other two models. The SVM model had the highest precision for the conductive class (1.00) but the proposed model and RF had more balanced performance with F1-scores of 0.67 each. The proposed model performed the best on the mixed class with 0.67 F1-score. The retro cochlear class was classified properly by all the models scoring F1-scores above 0.80 and almost perfect precision for the proposed model and SVM. The normal class was not classified properly by all models because of its small sample size (only 2 instances) and all models struggled to classify this class correctly. The proposed model was also compared with existing methodologies [3], [25]. The comparative analysis is presented in Table 4.

The model proposed in this paper showed better results than all the other compared models in terms of overall accuracy (85%). It demonstrates a good performance across most classes especially in predicting cochlear and mixed hearing loss. Based on the results, the proposed model provides an effective solution for this classification task. There is a potential for further improvement by model tuning, data augmentation or using more advanced architectures. The results depict that the proposed FNN model can achieve high classification accuracy for hearing loss prediction. Future improvements could involve fine-tuning the model, exploring deeper architectures and including additional features to further improve classification accuracy.

Table 4. Comparative analysis with exiting method

Model	Accuracy (%)
DL [3]	81
ML [25]	78
Proposed model	85

4. CONCLUSION

The diagnosis and management of hearing loss have made a significant difference in recent years. Early detection of hearing loss and intervention are very critical for preventing any long-term disability. The continuous research in the field of new diagnostic technologies, as well as the development of affordable treatment is essential to ensure that individuals can benefit from timely interventions. The model that is proposed in this paper showed promising results in classifying hearing loss of different types, achieving an overall accuracy of 85%. However, there are still challenges with minority classes which can be dealt with by using methods such as data augmentation or adjusting the weights of class. The experimental findings show that the proposed DL models are effective tools for the automated classification tasks in healthcare.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable. This study utilizes a publicly available dataset from UC Irvine Machine Learning Repository, with no identification of personal information or involvement of individuals requiring informed consent.

ETHICAL APPROVAL

Not applicable. This study uses a publicly available dataset from UC Irvine Machine Learning Repository and does not involve human or animal subjects; thus, no institutional review board approval or compliance with the Helsinki Declaration is required.

DATA AVAILABILITY

The data that support the findings of this study will be available in UC Irvine Machine Learning Repository at https://archive.ics.uci.edu/ml/machine-learning-databases/audiology/audiology.standardized.data.

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