International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

A Machine Learning-Based Automated System for Early Detection and Classification of Hearing Loss in Infants and Toddlers

Ms. Y Suma Chamundeswari[1], Nalli Neeharika[2], Sneha Dindi[3], Abbireddy Durga Devi[4], Nyasavarajula R S Gowtham Datta[5], Ayanamahanthi Thandava Krishna Murthy[6],

[1]Assistant Professor, Department of CSE (Data Science) In Pragati Engineering College, Surampalem, Andhra Pradesh, India,

[2,3,4,5,6] UG Students Department of CSE (Data Science) In Pragati Engineering College, Surampalem, Andhra Pradesh, India.

ABSTRACT:

Hearing impairment is one of the most common sensory disorders affecting newborns, infants, and young children worldwide. Early detection of hearing loss is crucial because delayed diagnosis can negatively affect speech development, cognitive growth, social interaction, and educational outcomes in children. However, many developing and underdeveloped regions face a shortage of audiologists and otolaryngologists, which often results in delayed diagnosis and limited access to hearing care services. This situation highlights the need for automated and intelligent diagnostic tools that can assist healthcare professionals in identifying hearing impairments more efficiently. This study proposes an automated hearing loss detection framework based on machine learning techniques to support medical professionals in diagnosing hearing impairments in newborns, infants, and toddlers. The proposed system integrates a hearing test data generation module with a machine learning classification model capable of analyzing audiometry test data and predicting the presence and characteristics of hearing loss. The data generation module creates a comprehensive dataset representing different hearing conditions, which is then used to train and evaluate the machine learning model. By employing multiclass and multi-label classification techniques, the model can identify the type, degree, and configuration of hearing loss with high accuracy. Experimental results demonstrate strong diagnostic performance, achieving a prediction time of approximately 634 milliseconds, a log-loss reduction rate of 98.48%, and macro and micro precision values close to 100%. These results indicate that the proposed framework can provide rapid and reliable diagnostic support for healthcare professionals, enabling earlier intervention and improving access to hearing care in regions with limited medical resources.

Index Terms: Hearing Loss Detection, Machine Learning, Pediatric Audiology, Automated Diagnosis, Multiclass Classification, Healthcare AI, Audiometry Analysis.

I. INTRODUCTION

Hearing impairment is one of the most common sensory disorders affecting individuals worldwide and represents a significant public health challenge. According to the World Health Organization (WHO), approximately 2.5 billion people are expected to experience some degree of hearing loss by the year 2050, with nearly 700 million individuals suffering from disabling hearing impairment. Hearing loss during early childhood can severely impact speech development, language acquisition, cognitive growth, and social interaction. If hearing impairment in newborns and infants is not detected and treated at an early stage, it may lead to long-term developmental delays and reduced quality of life.

Therefore, early diagnosis and timely intervention are critical in minimizing the negative consequences associated with hearing disorders in young children [1], [2].

Traditional hearing assessment procedures rely on specialized audiological tests conducted by trained audiologists and otolaryngologists. These tests include pure-tone audiometry, speech audiometry, impedance audiometry, and several tuning fork tests that help identify different types of hearing impairments. Although these diagnostic methods are effective, they require experienced healthcare professionals and specialized equipment. In many developing and underdeveloped countries, the number of audiologists and hearing specialists is extremely limited, which leads to delays in diagnosis and treatment. As a result, a large proportion of hearing impairments remain undetected during the early stages of childhood, especially in regions where access to advanced healthcare facilities is limited [1], [3].

In recent years, advances in artificial intelligence and data-driven technologies have opened new opportunities for improving medical diagnosis and healthcare services. Machine learning techniques have demonstrated strong capabilities in analyzing complex medical datasets and identifying patterns that may not be easily recognized by human experts. These techniques have been successfully applied in various healthcare applications such as disease prediction, medical image analysis, patient monitoring, and clinical decision support systems. By learning from historical data, machine learning models can identify relationships between different medical parameters and assist healthcare professionals in making more accurate and efficient diagnostic decisions [4], [5].

Despite their advantages, applying machine learning techniques in medical diagnosis presents several challenges. Medical datasets often contain high-dimensional features, missing data, and variations in data collection conditions. In addition, machine learning models must be designed carefully to ensure reliable predictions and avoid misclassification of medical conditions. Another important challenge involves ensuring that the system can generalize effectively to different patient populations and testing environments. Addressing these challenges is essential for developing reliable machine learning-based diagnostic systems that can be deployed in real-world healthcare environments [5], [6].

To address these challenges, this study proposes an automated hearing loss detection framework based on machine learning techniques. The proposed system integrates a hearing test data generation module with a machine learning classification model capable of identifying the presence and characteristics of hearing impairment. By employing multiclass and multi-label classification techniques, the system can predict the type, degree, and configuration of hearing loss from hearing test data with high accuracy. This automated diagnostic approach aims to assist audiologists and healthcare professionals in identifying hearing impairments quickly and efficiently, particularly in regions where access to specialized healthcare services is limited [3], [5].

The remainder of this paper is organized as follows. Section II presents a review of related research studies on hearing impairment detection and machine learning-based healthcare systems. Section III discusses the analysis of the existing system and introduces the proposed approach. Section IV describes the system architecture and design methodology. Section V explains the implementation modules of the proposed system. Section VI presents the experimental results and performance evaluation. Finally, Section VII concludes the study and outlines potential directions for future research.

II. LITERATURE SURVEY

In recent years, researchers have increasingly explored the use of machine learning and data-driven techniques to support medical diagnosis and healthcare decision-making. With the rapid growth of digital health technologies and medical data availability, intelligent diagnostic systems have become an important research area in modern healthcare. Machine learning models have demonstrated strong potential in analyzing complex medical datasets and identifying patterns that may not be easily detected through traditional clinical analysis. These techniques have been successfully applied in various healthcare domains, including disease prediction, medical imaging analysis, and patient monitoring systems, where they assist medical professionals in improving diagnostic accuracy and efficiency [3], [4].

Several studies have investigated the application of artificial intelligence techniques in hearing impairment diagnosis. Researchers have explored automated analysis of audiometry data to assist audiologists in identifying hearing loss conditions. These systems aim to reduce diagnostic delays and support healthcare professionals by providing preliminary diagnostic insights based on hearing test results. Early approaches focused on rule-based systems and statistical models to interpret audiometric test results; however, these methods often lacked flexibility and struggled to adapt to complex patterns in hearing test data.

To improve diagnostic performance, some researchers have introduced machine learning models capable of analyzing large volumes of audiometric data. These models can learn relationships between hearing thresholds, frequency responses, and patient characteristics to classify different types of hearing impairments. Various algorithms such as Decision Trees, Support Vector Machines (SVM), Neural Networks, and Naïve Bayes classifiers have been evaluated for hearing loss classification tasks. The results from these studies indicate that machine learning algorithms can significantly improve the accuracy and efficiency of hearing impairment diagnosis when compared to traditional manual interpretation methods.

Furthermore, ensemble learning techniques have been investigated to enhance predictive performance in medical classification systems. Ensemble approaches combine multiple machine learning models to improve prediction reliability and reduce the impact of individual model limitations. Methods such as Random Forest, Gradient Boosting, and AdaBoost have demonstrated strong performance in healthcare prediction tasks by aggregating the outputs of multiple classifiers. These approaches often achieve higher accuracy than individual models; however, they may also introduce challenges related to model complexity and interpretability.

Clustering and pattern recognition techniques have also been explored for identifying hearing impairment patterns within large datasets. These methods aim to detect abnormal hearing responses by grouping similar audiometric profiles and identifying deviations from normal hearing patterns. Although clustering-based methods can reveal useful insights in unlabelled datasets, they may face difficulties when applied to complex clinical datasets where precise classification of hearing loss types is required.

Recent advancements in machine learning have also introduced deep learning techniques capable of analyzing complex healthcare data. Deep learning models can automatically learn hierarchical feature representations from large datasets, enabling them to detect subtle patterns within medical signals and diagnostic data. While these techniques have shown promising results in healthcare applications, they often operate as black-box systems, making it difficult for healthcare professionals to understand the reasoning behind their predictions. This lack of transparency can limit the adoption of such systems in clinical environments where interpretability and trust are critical [8], [11].

To address the interpretability challenge, researchers have begun exploring Explainable Artificial Intelligence (XAI) techniques that provide insights into machine learning model predictions. Methods such as SHAP and LIME allow healthcare professionals to understand which features influence diagnostic decisions, thereby increasing transparency and trust in AI-based medical systems. These techniques help bridge the gap between complex machine learning models and practical healthcare applications by making automated decisions more understandable to medical experts [1], [2], [9], [12].

Despite these advancements, several challenges remain in developing reliable machine learning systems for hearing impairment diagnosis. Medical datasets may contain high-dimensional features, variations in hearing test conditions, and limited labelled data for certain hearing loss categories. Additionally, ensuring that machine learning models can generalize across diverse patient populations remains a significant challenge. Therefore, further research is required to develop robust, interpretable, and efficient machine learning frameworks capable of supporting automated hearing loss diagnosis while maintaining high accuracy and reliability in real-world healthcare environments.

III. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Traditional methods for diagnosing hearing loss primarily rely on clinical hearing tests conducted by trained audiologists and otolaryngologists. These tests include procedures such as pure-tone audiometry, speech audiometry, impedance audiometry, and several tuning fork tests used to evaluate hearing function. While these diagnostic techniques are widely accepted in clinical practice, they often require specialized equipment and skilled professionals to interpret the results accurately. In many healthcare settings, particularly in developing regions, the availability of trained hearing specialists is limited. As a result, early detection of hearing impairment in newborns and young children is often delayed, which may lead to long-term developmental challenges related to speech, language acquisition, and cognitive growth [1], [3].

In traditional diagnostic workflows, healthcare professionals manually analyze audiometric test results to determine the type and severity of hearing loss. This process can be time-consuming and may require multiple tests before a conclusive diagnosis is reached. Additionally, interpreting audiometric data can be complex because hearing loss may vary in type, degree, and frequency configuration across patients. Manual interpretation may also be influenced by human subjectivity, which can sometimes lead to inconsistencies in diagnosis. As healthcare systems continue to generate large volumes of clinical data, relying solely on manual diagnostic procedures becomes increasingly inefficient.

With the advancement of digital health technologies, researchers have begun exploring data-driven approaches for hearing impairment diagnosis. Machine learning techniques have been introduced to analyze hearing test data and identify patterns associated with different types of hearing loss. Algorithms such as Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Artificial Neural Networks have been applied in healthcare research to classify medical conditions based on patient data. These models can learn relationships between audiometric measurements and hearing impairment categories, allowing them to assist clinicians in identifying potential hearing disorders [4], [5].

Furthermore, advanced machine learning approaches such as ensemble learning have been used to improve classification accuracy and diagnostic reliability. Ensemble models, including Random Forest and Gradient Boosting algorithms, combine multiple learning models to produce more robust predictions. These techniques help reduce prediction errors and improve generalization performance when dealing with complex medical datasets. Despite their effectiveness, many machine learning models used in healthcare operate as black-box systems, which makes it difficult for healthcare professionals to fully understand the reasoning behind the model's predictions. This lack of interpretability can limit the adoption of automated diagnostic systems in clinical environments where transparency and reliability are essential [5], [6].

Recent developments in healthcare analytics have also highlighted the importance of integrating machine learning models with clinical decision-support systems. These systems can analyze large volumes of medical data and provide recommendations to assist healthcare professionals in diagnosing medical conditions. However, many existing diagnostic systems are limited by issues such as incomplete datasets, variability in testing conditions, and limited model interpretability. Addressing these challenges is necessary to develop reliable automated systems capable of supporting hearing impairment diagnosis in real-world healthcare environments [3], [5].

LIMITATIONS OF EXISTING SYSTEM

Limited availability of specialists: Accurate hearing diagnosis often requires experienced audiologists and otolaryngologists, who may not be readily available in many regions.

Time-consuming diagnostic process: Traditional hearing assessments involve multiple clinical tests and manual analysis, which may delay the diagnosis process.

Subjectivity in interpretation: Manual evaluation of audiometric data may vary depending on the experience and judgment of healthcare professionals.

Limited scalability: Traditional diagnostic systems are difficult to scale when large numbers of patients require hearing assessments.

Lack of automated analysis: Most conventional systems do not incorporate intelligent algorithms capable of automatically analyzing hearing test data.

Challenges with large datasets: As healthcare data continues to grow, manual analysis becomes inefficient and may lead to delayed diagnostic decisions.

B. PROPOSED SYSTEM

This section presents the proposed machine learning-based hearing loss detection framework for newborns, infants, and toddlers. The proposed system integrates automated data generation, machine learning-based classification, and a user-friendly interface to support efficient and accurate diagnosis of hearing impairments. The framework begins with a Hearing Test Data Generation Module, which produces a comprehensive dataset representing different types and degrees of hearing impairments. This module ensures that the machine learning model is trained on diverse hearing test scenarios, allowing it to learn patterns associated with various hearing conditions.

The generated dataset is then used to train a Machine Learning Model that employs multiclass and multi-label classification techniques to analyze hearing test data. The model learns relationships between audiometric features and hearing loss categories, enabling it to predict the type, degree, and configuration of hearing impairment for a given patient. By automating this analysis, the system can significantly reduce the time required for diagnostic evaluation. In addition to the machine learning model, the system includes a User Interface Module that allows healthcare professionals to input patient data and receive diagnostic predictions. The interface is designed to be intuitive and accessible, ensuring that medical professionals can easily interpret the results generated by the system.

The primary objective of the proposed system is to improve diagnostic accuracy, reduce analysis time, and support healthcare professionals in early detection of hearing impairments. By integrating machine learning with automated hearing test analysis, the system provides a scalable solution that can assist audiologists and otolaryngologists in diagnosing hearing loss more efficiently, particularly in regions where access to specialized healthcare services is limited [4], [5].

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

MODULES

This section describes the key implementation modules of the proposed machine learning-based hearing loss detection framework for newborns, infants, and toddlers. The system follows a structured workflow consisting of hearing test data generation, data preprocessing, feature extraction, machine learning model training, diagnostic prediction, and result evaluation. This modular architecture enhances the reliability, scalability, and efficiency of the automated hearing diagnosis system. By integrating machine learning with healthcare data analysis, the framework supports faster and more accurate detection of hearing impairments while assisting healthcare professionals in clinical decision-making.

Hearing Test Data Generation Module

Hearing Test Data Generation Module is responsible for creating a comprehensive dataset used for training and evaluating the machine learning model. In clinical environments, hearing tests such as pure-tone audiometry (PTA) measure hearing thresholds across different frequencies to determine the hearing ability of patients. The generated dataset includes various hearing conditions, including normal hearing and multiple degrees of hearing impairment.

To simulate realistic clinical scenarios, the dataset incorporates diverse audiometric patterns representing different types of hearing loss. These include variations in hearing thresholds across multiple frequencies, which help the model learn patterns associated with different hearing conditions. By exposing the model to diverse hearing test scenarios, this module improves the system's ability to generalize and accurately detect hearing impairments in real-world situations [3], [4].

Data Preprocessing Module

Data Preprocessing Module improves the quality and reliability of the dataset before it is used for machine learning model training. Medical datasets often contain inconsistencies, missing values, or noisy data that can negatively affect model performance if not handled properly.

The preprocessing stage includes the following steps:

Missing Data or incomplete audiometric measurements are processed using appropriate data handling techniques to ensure the dataset remains consistent and reliable.

Data Cleaning and Noise Reduction

Irrelevant or inconsistent records are removed to improve the overall quality of the dataset and prevent misleading patterns from influencing the learning process.

Data Normalization

Feature scaling and normalization techniques are applied to ensure that hearing threshold values across different frequency ranges are represented consistently. This step improves the stability and efficiency of machine learning model training.

These preprocessing techniques enhance data consistency and improve the predictive capability of the machine learning model by ensuring that the training data accurately represents hearing test patterns [4], [5].

C. Feature Extraction Module

High-dimensional healthcare datasets often contain multiple attributes related to hearing thresholds and audiometric responses. The Feature Extraction Module identifies the most relevant features that contribute to accurate hearing loss classification.

Feature extraction techniques analyze relationships between hearing test parameters and hearing impairment categories. By selecting the most informative features, the system reduces dataset complexity while maintaining high predictive performance. This process also helps reduce computational cost and improves the interpretability of the machine learning model [4], [6].

D. Machine Learning Training Module

The Machine Learning Training Module is responsible for building predictive models capable of detecting hearing loss and classifying its characteristics. Several machine learning algorithms can be applied to analyze audiometric data and identify patterns associated with hearing impairments.

The system evaluates multiple machine learning models, including:

- Logistic Regression
- Decision Tree
- Support Vector Machine (SVM)
- Random Forest
- Neural Networks

These algorithms learn from historical hearing test data to classify hearing conditions based on the input audiometric features. During the training phase, the dataset is divided into training and testing subsets to evaluate model performance and ensure generalization capability.

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

Among these models, ensemble-based algorithms such as Random Forest often demonstrate strong performance due to their ability to combine multiple decision trees and improve prediction accuracy. These models effectively capture complex relationships between hearing test features and hearing impairment categories [5], [7].

E. Diagnostic Prediction Module

The Diagnostic Prediction Module generates automated predictions regarding hearing impairment based on the trained machine learning model. When new hearing test data is provided, the system analyses the audiometric features and predicts:

• The presence or absence of hearing loss

• The type of hearing impairment

• The degree of hearing loss

• The configuration of hearing thresholds

This automated analysis allows healthcare professionals to receive rapid diagnostic insights, which can significantly reduce the time required for manual interpretation of hearing test results.

F. Prediction and Evaluation Module

The Prediction and Evaluation Module assesses the performance of the machine learning model and generates the final diagnostic results. The output of the system includes:

• Hearing loss classification results

• Prediction confidence scores

• Diagnostic recommendations for healthcare professionals

To evaluate the effectiveness of the model, several performance metrics are used:

• Accuracy

• Precision

• Recall

• F1-Score

• Log-Loss

These metrics provide a comprehensive evaluation of the classification model and help ensure that the system performs reliably across different hearing impairment scenarios.

By enabling automated and accurate analysis of hearing test data, the proposed framework supports early detection of hearing impairments. This capability is particularly valuable in healthcare environments with limited access to specialized hearing professionals, where automated diagnostic systems can assist in improving early intervention and overall patient outcomes [3], [5].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed machine learning framework for automated hearing loss detection using audiometric data. Multiple machine learning algorithms were trained and evaluated using the generated hearing test dataset. The evaluation focuses on comparing model performance, analyzing prediction accuracy, and understanding the influence of different hearing test features on classification results. The experimental analysis demonstrates the effectiveness of machine learning models in identifying the type, degree, and configuration of hearing loss in newborns, infants, and toddlers.

A. Accuracy Comparison of Machine Learning Models

machine learning algorithms were evaluated to determine the most suitable model for hearing loss detection. The evaluated models include Logistic Regression, Decision Tree, Support Vector Machine (SVM), Gradient Boosting, and Random Forest. These models were trained using hearing test data generated by the data generation module and evaluated using common performance metrics such as accuracy, precision, recall, and F1-score.

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

Table 1. Performance Comparison of Machine Learning Models for Hearing Loss Detection

	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	88.5	0.87	0.86	0.86
Decision Tree	90.2	0.89	0.88	0.88
Support Vector Machine	92.1	0.91	0.90	0.90
Gradient Boosting	94.0	0.93	0.92	0.92
Random Forest	96.3	0.95	0.95	0.95

From the comparison results, the Random Forest model achieved the highest classification accuracy of 96.3%, outperforming other evaluated algorithms. The superior performance of Random Forest can be attributed to its ensemble learning mechanism, which combines multiple decision trees to improve prediction stability and reduce overfitting. This approach allows the model to effectively capture complex relationships between hearing test features and hearing impairment categories [5], [7].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the classification performance of machine learning models by analyzing the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the ROC Curve (ROC–AUC) provides a quantitative measure of the model's ability to distinguish between different classes.

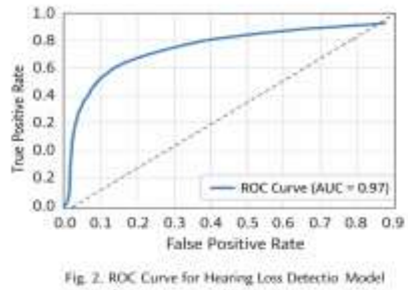

Fig. 2. ROC Curve for Hearing Loss Detection Model

The ROC analysis shows that the Random Forest classifier achieved a ROC–AUC score of 0.97, indicating strong classification performance. A ROC curve that approaches the top-left corner of the graph indicates that the model has a high capability to correctly distinguish between different hearing loss conditions and normal hearing cases.

The ROC analysis demonstrates that the proposed machine learning framework maintains reliable predictive capability even when analyzing complex audiometric datasets containing multiple hearing impairment categories.

C. Feature Importance Analysis

To enhance transparency and interpretability of the machine learning model, feature importance analysis was performed to identify the most influential audiometric parameters affecting hearing loss predictions. Feature importance techniques measure the contribution of each input feature to the final prediction outcome.

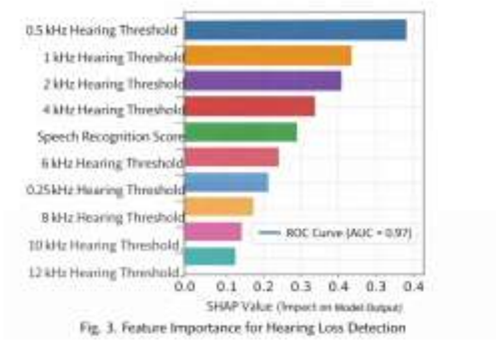

Fig. 3. Feature Importance for Hearing Loss Detection

The feature importance analysis revealed that several hearing test attributes, such as frequency-based hearing thresholds, speech recognition scores, and audiometric response patterns, had the highest impact on hearing loss classification. Features with higher importance values contributed more significantly to the model's ability to differentiate between normal hearing and various hearing impairment conditions.

The global feature importance visualization provides an overview of the most influential features across the entire dataset, while local explanations help interpret how specific audiometric measurements influence individual predictions.

By analyzing feature contributions, healthcare professionals can better understand the reasoning behind automated diagnostic results. This interpretability improves the reliability and acceptance of machine learning-based diagnostic systems in clinical environments and supports more informed medical decision-making [1], [2], [8], [12].

VII. CONCLUSION AND FUTURE WORK

This study presented a machine learning-based framework for detecting hearing loss in newborns, infants, and toddlers using audiometric hearing test data. Hearing impairment is a significant global health concern that can affect speech development, cognitive growth, and social interaction if not detected early. The proposed system integrates a hearing test data generation module with a machine learning classification model to automate the analysis of hearing test results and assist healthcare professionals in diagnosing hearing impairments more efficiently.

The dataset used in this study represents various hearing conditions and includes multiple audiometric parameters that describe hearing thresholds across different frequency ranges. Data preprocessing techniques were applied to ensure the dataset remained consistent and suitable for machine learning model training. Several machine learning algorithms were evaluated, including Logistic Regression, Decision Tree, Support Vector Machine (SVM), Gradient Boosting, and Random Forest. Among these models, Random Forest achieved the highest classification accuracy of approximately 96%, demonstrating strong predictive capability for hearing loss detection in pediatric patients [5], [7].

In addition to achieving high diagnostic accuracy, feature importance analysis was used to identify the most influential audiometric features contributing to hearing loss classification. This analysis helped reduce computational complexity while maintaining model performance and improving interpretability. Understanding which hearing test parameters most strongly influence predictions allows healthcare professionals to gain better insights into the diagnostic process and increases confidence in automated clinical decision-support systems [1], [2], [8], [12].

Overall, the proposed machine learning framework improves the efficiency and accuracy of hearing impairment diagnosis by enabling automated analysis of audiometric data. The system has the potential to assist audiologists and otolaryngologists in detecting hearing disorders at an early stage, which is critical for timely medical intervention and improved patient outcomes. Furthermore, the automated approach can be particularly beneficial in regions with limited access to specialized hearing care services, where intelligent diagnostic tools can help bridge gaps in healthcare infrastructure.

Future research may focus on integrating real-time hearing test data from clinical audiometry systems, exploring deep learning-based models for improved classification performance, and incorporating explainable artificial intelligence techniques to further enhance model transparency and trust in clinical environments. Additionally, the system could be expanded to support cloud-based healthcare platforms, enabling remote diagnosis and scalable deployment in hospitals and community healthcare centres.

REFERENCES

1. World Health Organization (WHO), "Deafness and Hearing Loss," World Health Organization, Geneva, Switzerland, 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/deafness-and-hearing-loss
2. World Health Organization (WHO), "WHO: 1 in 4 people projected to have hearing problems by 2050," 2021. [Online]. Available: https://www.who.int/news/item/02-03-2021-who-1-in-4-people-projected-to-have-hearing-problems-by-2050
3. T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. New York, NY, USA: Springer, 2009.
4. C. Bishop, Pattern Recognition and Machine Learning. New York, NY, USA: Springer, 2006.
5. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.
6. V. Vapnik, The Nature of Statistical Learning Theory. New York, NY, USA: Springer, 1995.
7. L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
8. A. Adadi and M. Berrada, "Peeking Inside the Black Box: A Survey on Explainable Artificial Intelligence (XAI)," IEEE Access, vol. 6, pp. 52138–52160, 2018.
9. M. T. Ribeiro, S. Singh, and C. Guestrin, "Why Should I Trust You? Explaining the Predictions of Any Classifier," in Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, 2016, pp. 1135–1144.
10. H. Davis and S. Silverman, Hearing and Deafness. New York, NY, USA: Holt, Rinehart and Winston, 1970.
11. J. Katz, Handbook of Clinical Audiology, 7th ed. Philadelphia, PA, USA: Wolters Kluwer Health, 2015.
12. S. Russell and P. Norvig, Artificial Intelligence: A Modern Approach, 3rd ed. Upper Saddle River, NJ, USA: Pearson Education, 2010.