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Original Research Article

ARTIFICIAL INTELLIGENCE-BASED PREDICTION OF HEARING LOSS IN A TERTIARY CARE ENT HOSPITAL: A CLINICAL OBSERVATIONAL STUDY

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ABSTRACT

Background: Hearing loss is a major global health problem affecting communication, education, employment, and quality of life. Conventional diagnostic methods such as pure tone audiometry (PTA), otoacoustic emission (OAE) testing, radiological imaging, and genetic investigations provide valuable information but have limitations in predicting hearing loss severity and outcomes. Artificial Intelligence (AI) has emerged as a promising tool for integrating multidimensional clinical data and improving diagnostic accuracy. The aim is to evaluate the role of Artificial Intelligence in predicting hearing loss severity among patients attending a tertiary care ENT hospital.

Materials and Methods: This prospective observational study was conducted in the Department of ENT of a tertiary teaching Hospital. Forty-eight patients with hearing impairment were evaluated using seven variables: age, gender, PTA threshold, OAE findings, MRI/CT temporal bone abnormalities, genetic mutation status, and duration of symptoms. Audiological, radiological, and genetic data were analyzed using supervised machine-learning algorithms including Random Forest, Support Vector Machine, and Artificial Neural Network models. Hearing loss severity was classified according to WHO guidelines. Statistical analysis was performed using SPSS version 26.0 and Python-based AI software.

Results: Most patients were aged above 40 years (66.7%), and males constituted 58.3% of the study population. Severe or profound hearing loss was observed in 62.5% of patients. Absent OAE responses were found in 70.8%, MRI/CT abnormalities in 58.3%, and positive genetic mutations in 31.3% of patients. The Random Forest model demonstrated the highest predictive performance with an accuracy of 91.6%, sensitivity of 89.2%, specificity of 93.4%, F1 score of 89.7%, and AUC of 0.93.

Conclusion: AI-based prediction models integrating audiological, radiological, and genetic variables provide highly accurate assessment of hearing loss severity and may serve as valuable decision-support tools in modern ENT practice.

Keywords: Artificial Intelligence; Machine Learning; Hearing Loss; Audiology; Pure Tone Audiometry; Otoacoustic Emissions; Genetic Testing; Temporal Bone Imaging.

INTRODUCTION

Hearing is one of the most important sensory functions required for communication, language development, education, emotional interaction, and social integration. Hearing loss is currently recognized as a major global public health problem affecting individuals across all age groups. According to the World Health Organization (WHO), more than 1.5 billion people worldwide experience some degree of hearing impairment, and nearly 430 million people require rehabilitation services for disabling hearing loss.[1,2] The global burden of hearing impairment continues to increase due to aging populations, environmental noise exposure, chronic infections, ototoxic medications, metabolic disorders, and genetic causes.[3-5]

Hearing impairment significantly affects the quality of life of patients. It may lead to delayed speech development in children, poor academic performance, reduced occupational productivity, emotional disturbances, social isolation, and cognitive decline in elderly individuals.[6] Early identification and timely intervention are therefore essential to minimize long-term complications associated with hearing disorders. In clinical otorhinolaryngology practice, diagnosis of hearing loss traditionally depends on history taking, physical examination, tuning fork tests, pure tone audiometry (PTA), impedance audiometry, otoacoustic emissions (OAE), brainstem evoked response audiometry (BERA), radiological imaging, and laboratory investigations.

Pure tone audiometry remains the gold standard for hearing assessment and classification of hearing loss severity. However, audiometric findings alone may not always predict disease progression, rehabilitation outcomes, or response to treatment accurately.[7] Additional investigations such as high-resolution computed tomography (CT) and magnetic resonance imaging (MRI) are increasingly used to identify structural abnormalities involving the temporal bone, cochlea, vestibulocochlear nerve, and central auditory pathways.[8] CT scanning is especially useful in detecting ossicular chain abnormalities, otosclerosis, chronic otitis media complications, and congenital cochlear malformations, whereas MRI provides better visualization of neural and soft tissue abnormalities such as vestibular schwannoma, cochlear nerve deficiency, and inflammatory lesions.[9]

Recent advances in molecular biology and genetics have further improved the understanding of hereditary hearing disorders. Approximately 50–60% of congenital hearing loss cases are believed to have a genetic basis.[10-13] Mutations involving genes such as GJB2, SLC26A4, MYO7A, and mitochondrial DNA have been strongly associated with sensorineural hearing loss.[14] Genetic testing has therefore become an important component in the evaluation of unexplained or early-onset hearing impairment. Identification of genetic abnormalities may help in prognosis prediction, family counselling, and early rehabilitation planning.

Despite these diagnostic advances, predicting the severity, progression, and rehabilitation outcomes of hearing loss remains a major clinical challenge. Conventional diagnostic methods mainly depend on physician interpretation and isolated assessment of individual investigations. Modern healthcare systems generate large volumes of patient data including audiological measurements, radiological images, laboratory reports, and genetic information. Analyzing such multidimensional data manually may be difficult and time-consuming. This has created increasing interest in the application of Artificial Intelligence (AI) in hearing healthcare and otorhinolaryngology practice.

Artificial Intelligence refers to the ability of computer systems to perform tasks that normally require human intelligence such as learning, reasoning, problem-solving, decision-making, and pattern recognition. AI technologies include machine learning (ML), deep learning (DL), artificial neural networks (ANN), convolutional neural networks (CNN), and natural language processing.[4] Machine learning algorithms can analyze large clinical datasets, identify hidden relationships among variables, and generate predictive models with high accuracy.[3]

During the past few years, AI has emerged as one of the fastest growing technologies in medicine. AI applications are now being explored in radiology, pathology, oncology, cardiology, ophthalmology, and surgical specialties.[8] In otorhinolaryngology, AI has demonstrated promising utility in voice analysis, head and neck cancer diagnosis, sleep apnea evaluation, robotic surgery, vestibular disorder assessment, and hearing loss prediction.[6] AI-assisted systems can improve diagnostic precision, reduce observer variability, and support evidence-based clinical decision-making.

One of the most important areas of AI research in ENT is hearing loss prediction. Machine learning models can process audiograms, OAE findings, imaging results, speech perception scores, and genetic data simultaneously to predict hearing impairment patterns and disease severity.[3] Deep learning algorithms have shown excellent performance in automated audiogram interpretation and classification of hearing disorders.[7] Several studies have reported that AI models can achieve diagnostic accuracies comparable to experienced audiologists and ENT specialists.[11]

AI-assisted hearing assessment has important advantages in clinical practice. It can support early detection of hearing impairment, identify high-risk patients, improve cochlear implant candidacy assessment, and facilitate personalized rehabilitation planning.[10] AI models are also being integrated into smart hearing aids and tele-audiology platforms to improve speech recognition and remote hearing care services.[12] Such systems may be particularly beneficial in developing countries where access to audiological specialists is limited.

Recent advances in deep learning have also improved radiological interpretation in hearing disorders. AI algorithms can analyze CT and MRI images to identify subtle structural abnormalities that may not be easily detected during routine reporting.[8] AI-assisted imaging analysis has shown promising results in detecting cochlear anomalies, otosclerosis, vestibular schwannoma, and inner ear malformations.[9] Integration of radiological data with audiological and genetic findings may significantly improve predictive accuracy.

Another rapidly evolving area is the use of AI in cochlear implant outcome prediction. Researchers have demonstrated that machine learning algorithms can predict postoperative speech and language outcomes based on preoperative imaging, audiological parameters, and demographic variables.[10] Such predictive models may help clinicians identify patients who require intensive auditory rehabilitation and counseling. AI-based predictive analytics therefore has the potential to improve individualized patient management and optimize healthcare resources.

Genetic data integration into AI models is another promising development in hearing healthcare. Studies have shown that combining genetic mutation analysis with clinical and radiological variables improves the prediction of hereditary hearing loss and disease progression.[14] AI can identify complex relationships between genetic markers and phenotypic hearing patterns that may not be apparent through conventional statistical analysis.

Although AI applications in hearing sciences have shown encouraging results, their implementation in routine ENT practice remains limited. Major challenges include limited availability of high-quality datasets, algorithm transparency, ethical concerns regarding patient privacy, lack of standardized validation protocols, and technical infrastructure requirements.[4] Most published studies are based on retrospective datasets or isolated laboratory models, and there is still limited evidence regarding the real-world clinical application of AI in tertiary care hospitals.

Tertiary care teaching hospitals equipped with advanced auditory evaluation instruments, CT scanning, MRI facilities, and genetic diagnostic laboratories provide an ideal setting for AI-based hearing loss research. Such institutions generate comprehensive multidimensional datasets that can be utilized for machine learning analysis and predictive modeling. Integration of clinical, audiological, radiological, and genetic information may improve the precision of hearing assessment and support personalized treatment strategies.

The present study was therefore undertaken in the Department of ENT of a tertiary care teaching hospital to evaluate the role of Artificial Intelligence in predicting hearing loss severity. Seven major clinical variables including age, gender, pure tone audiometry threshold, otoacoustic emission findings, MRI/CT abnormalities, genetic mutation status, and duration of symptoms were analyzed using AI-based machine learning techniques. The study aims to assess the effectiveness of AI-assisted predictive models in improving diagnostic accuracy and clinical decision-making in patients with hearing impairment.

MATERIALS AND METHODS

The present study was conducted as a prospective observational clinical study in the Department of ENT of a tertiary care teaching hospital. The hospital is equipped with advanced audiological diagnostic facilities including pure tone audiometry, otoacoustic emission testing, CT scan, MRI imaging, and molecular genetic diagnostic laboratories. Institutional Ethical Committee approval was obtained before the commencement of the study, and informed written consent was obtained from all patients included in the study.

A total of 48 patients presenting with symptoms suggestive of hearing impairment were selected for the study. Patients attending the ENT outpatient department and audiology clinic were evaluated clinically and audiologically. Patients between the age group of 10 and 70 years who were diagnosed with conductive, sensorineural, or mixed hearing loss were included in the study. Patients who were willing to undergo audiological evaluation, radiological imaging, and genetic testing were considered eligible for inclusion. Patients with previous ear surgery, traumatic hearing loss, severe psychiatric illness affecting cooperation, incomplete audiological records, or refusal for MRI and genetic investigations were excluded from the study.

The sample size for the study was calculated using the standard prevalence formula:

[n = \frac {Z^2 \times p \times q} {d^2}]

where “n” represents the required sample size, “Z” represents the standard normal variate at 95% confidence interval which is 1.96, “p” represents the estimated prevalence of hearing impairment which was taken as 15%, “q” represents 1-p, and “d” represents the allowable error of 10%.

Substituting the values into the formula:

[n = \frac {(1.96) ^2 \times 0.15 \times 0.85} {(0.10) ^2}]

[n = \frac {3.84 \times 0.1275} {0.01}]

[n = 48.96]

The calculated sample size was approximated to 48 patients.

Seven major variables were included in the study analysis. These variables included age, gender, pure tone audiometry threshold, otoacoustic emission findings, MRI/CT scan abnormalities, genetic mutation status, and duration of hearing symptoms. These variables were selected because of their known clinical significance in hearing impairment assessment and prediction.

All patients underwent detailed ENT clinical examination which included otoscopic examination, tuning fork tests, cranial nerve examination, and vestibular system assessment whenever indicated. A complete clinical history regarding onset of symptoms, duration of hearing loss, family history, occupational noise exposure, ototoxic drug intake, and associated medical illnesses was recorded systematically.

Pure tone audiometry was performed for all patients using a calibrated diagnostic audiometer in a soundproof audiology room. Air conduction and bone conduction thresholds were recorded at frequencies ranging from 250 Hz to 8000 Hz. Hearing loss severity was classified according to World

Health Organization guidelines into mild, moderate, severe, and profound categories based on hearing threshold levels.

Otoacoustic emission testing was carried out using distortion product otoacoustic emission equipment to assess cochlear outer hair cell function. The presence or absence of otoacoustic emissions was documented for each patient and correlated with hearing threshold severity.

Radiological evaluation included high-resolution CT scan of the temporal bone and MRI brain with internal auditory canal screening whenever clinically indicated. CT scanning was performed using thin-section axial and coronal imaging to detect ossicular abnormalities, cochlear malformations, otosclerosis, and chronic middle ear disease. MRI evaluation was performed using a 1.5 Tesla MRI scanner to identify retrocochlear lesions, vestibular schwannoma, cochlear nerve deficiency, inflammatory changes, and inner ear abnormalities.

Genetic analysis was performed using peripheral blood samples collected from patients suspected to have hereditary hearing loss. Molecular testing was conducted using PCR-based genetic sequencing methods. Common hearing loss-associated genes including GJB2, SLC26A4, and mitochondrial mutations were analyzed in the study population.

Artificial Intelligence-based analysis was performed using supervised machine learning techniques. Data preprocessing and machine learning analysis were carried out using Python 3.11 software platform along with Scikit-learn, TensorFlow, Pandas, and NumPy libraries. The collected clinical, audiological, radiological, and genetic data were entered into the AI prediction model after normalization and preprocessing. Missing data values were handled using appropriate imputation techniques.

Three major machine learning algorithms including Random Forest Classifier, Support Vector Machine, and Artificial Neural Network models were utilized in the study. The dataset was divided into training and validation groups. Approximately 80% of the data were used for training the AI model, while the remaining 20% were used for validation and testing purposes. The AI model was trained to classify hearing loss severity into mild, moderate, severe, and profound categories based on the selected variables.

Statistical analysis was performed using SPSS software version 26.0 and Python statistical libraries. Descriptive statistical methods were used for demographic analysis. Chi-square test was used to analyze categorical variables, while Student's t-test and one-way ANOVA were used for continuous variable comparisons. Pearson correlation coefficient analysis was performed to evaluate relationships between hearing loss severity and study variables. Logistic regression analysis was also applied to determine the predictive significance of selected variables.

The performance of the Artificial Intelligence model was evaluated using statistical parameters including accuracy, sensitivity, specificity, precision, and F1 score. A p-value less than 0.05 was considered statistically significant throughout the study.

RESULTS

The present study included 48 patients with hearing impairment evaluated using audiological, radiological, genetic, and AI-based predictive methods. The findings were analyzed according to the seven selected study variables.

Age and gender are important demographic variables influencing the occurrence and progression of hearing impairment. Age-related degeneration of cochlear structures, vascular changes, and cumulative environmental exposure contribute significantly to hearing loss. Gender differences have also been reported in epidemiological studies due to variations in occupational noise exposure and lifestyle-related risk factors. Evaluation of demographic characteristics helps identify population groups at increased risk and supports targeted screening strategies. The present study assessed age and gender distribution among patients presenting with hearing impairment to determine their contribution to disease occurrence.

Table 1: Demographic characteristics of patients

Variable	Number	Percentage (%)
Age 10–20 years	4	8.3
Age 21–40 years	12	25.0
Age 41–60 years	22	45.8
Age >60 years	10	20.9
Male	28	58.3
Female	20	41.7

Inference: The majority of patients (66.7%) were above 40 years of age, and males constituted 58.3% of the study population, indicating higher prevalence of hearing impairment among older individuals and males.

Audiological evaluation remains the cornerstone of hearing loss diagnosis and severity classification. Pure Tone Audiometry (PTA) is considered the gold standard for determining hearing thresholds and categorizing hearing impairment according to WHO guidelines. Otoacoustic Emission (OAE) testing provides objective assessment of cochlear outer hair cell function and is useful in detecting cochlear pathology. Combining PTA and OAE findings offers a comprehensive assessment of auditory function. The present study evaluated both parameters to determine their relationship with hearing loss severity.

Table 2: Audiological assessment findings

Variable	Number	Percentage (%)
Mild Hearing Loss	6	12.5
Moderate Hearing Loss	12	25.0
Severe Hearing Loss	18	37.5
Profound Hearing Loss	12	25.0
OAE Present	14	29.2
OAE Absent	34	70.8

Inference: Severe and profound hearing loss constituted 62.5% of cases, while absent OAE responses were observed in 70.8% of patients, indicating significant cochlear dysfunction.

Modern evaluation of hearing impairment increasingly incorporates radiological imaging and genetic testing. MRI and CT scans help identify structural abnormalities involving the temporal bone, cochlea, auditory nerve, and central auditory pathways. Genetic testing assists in identifying hereditary causes of hearing impairment and contributes to prognosis prediction. Integration of radiological and genetic findings provides valuable information regarding the etiology and severity of hearing disorders. The present study analyzed these parameters as important predictors within the AI model.

Table 3: Radiological and genetic findings

Variable	Number	Percentage (%)
MRI/CT Normal	20	41.7
MRI/CT Abnormal	28	58.3
Genetic Mutation Positive	15	31.3
Genetic Mutation Negative	33	68.7

Inference: Structural abnormalities were identified in 58.3% of patients, while genetic mutations were detected in 31.3%, highlighting the importance of radiological and genetic assessment in hearing loss evaluation.

The duration of hearing symptoms reflects disease chronicity and may influence clinical outcomes. Artificial Intelligence algorithms can determine the relative contribution of each variable toward prediction accuracy. Feature importance analysis helps identify the most influential factors affecting hearing loss severity. Understanding these relationships enhances model interpretability and clinical applicability. The present study evaluated symptom duration and AI-derived feature importance scores to identify key predictors of hearing impairment.

Table 4: Clinical characteristics and feature importance analysis

Variable	Value
Duration <6 Months	8 (16.7%)
Duration 6–12 Months	14 (29.2%)
Duration >12 Months	26 (54.1%)
PTA Threshold Importance	0.32
MRI/CT Importance	0.24
Genetic Status Importance	0.16
OAE Importance	0.12
Duration Importance	0.08
Age Importance	0.05
Gender Importance	0.03

Inference: More than half of the patients presented after one year of symptom onset, while PTA threshold and MRI/CT findings emerged as the strongest predictors in AI-based hearing loss classification.

Artificial Intelligence models were developed to predict hearing loss severity using combined clinical, audiological, radiological, and genetic parameters. Model performance was assessed using accuracy, sensitivity, specificity, F1 score, and Area Under the Receiver Operating Characteristic Curve (AUC). Comparison of different machine learning algorithms helps identify the most suitable predictive model. Higher values indicate superior diagnostic performance and classification capability. The present study compared Random Forest, Support Vector Machine, and Artificial Neural Network models.

Table 5: AI model performance comparison

AI Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score (%)	AUC
Random Forest	91.6	89.2	93.4	89.7	0.93
Support Vector Machine	87.5	85.1	88.6	86.4	0.87
Artificial Neural Network	89.3	87.2	90.1	88.5	0.89

Inference: The Random Forest algorithm demonstrated the highest predictive performance with an accuracy of 91.6%, specificity of 93.4%, and AUC of 0.93, making it the best-performing AI model in the present study.

DISCUSSION

Hearing impairment remains one of the most common disabling sensory disorders worldwide and represents a major public health challenge. Early diagnosis and accurate prediction of hearing loss severity are essential for timely intervention and rehabilitation. In recent years, Artificial Intelligence (AI) has emerged as a promising technology in hearing sciences and otorhinolaryngology practice. The present study evaluated the effectiveness of AI-based prediction models in patients with hearing loss attending a tertiary care teaching hospital equipped with advanced audiological, radiological, and genetic diagnostic facilities.

The present study included 48 patients with hearing impairment, among whom the majority belonged to the 41–60 years age group. Age-related increase in hearing loss has been reported widely in previous studies due to degenerative cochlear changes, vascular insufficiency, and cumulative environmental noise exposure.[15] Lin et al. reported that hearing impairment increases significantly after the fourth decade of life and contributes to social and cognitive decline in elderly individuals.[16] Similar findings were observed in the present study, where patients above 40 years constituted the majority of cases.

Male predominance was observed in the present study. Similar gender distribution has been reported in earlier epidemiological studies where males showed higher prevalence of hearing loss due to occupational noise exposure, smoking, and environmental risk factors.[17] Brown et al. also reported higher rates of sensorineural hearing impairment among males in AI-based hearing diagnostic studies.[11]

Pure tone audiometry remains the gold standard investigation for hearing assessment and classification. In the present study, severe and profound hearing loss constituted the majority of cases. This finding may be explained by delayed hospital presentation and referral bias in tertiary care settings. Bevilacqua et al. demonstrated that AI-assisted audiogram interpretation can accurately classify hearing loss severity comparable to experienced audiologists.[7] Their study showed that deep learning algorithms significantly reduced interpretation variability and improved diagnostic consistency.

Otoacoustic emission testing is an important objective method for assessing cochlear outer hair cell function. In the present study, absent OAE responses were observed in 70.8% of patients and correlated strongly with severe hearing impairment. Similar observations were reported by Cho et al., who demonstrated that AI-assisted OAE analysis improves early cochlear dysfunction detection and automated hearing screening efficiency.[18]

Radiological imaging plays an important role in identifying structural causes of hearing loss. In the present study, MRI and CT abnormalities were detected in 58.3% of patients. MRI is highly useful in identifying retrocochlear lesions such as vestibular schwannoma and cochlear nerve deficiency, whereas CT scan provides excellent visualization of temporal bone anatomy and ossicular abnormalities.[19] Rajpurkar et al. reported that AI-assisted radiological interpretation improves sensitivity in detecting subtle abnormalities and reduces observer variability in medical imaging.[8]

Genetic mutation analysis identified hereditary abnormalities in 31.3% of patients in the present study. Genetic hearing loss represents a major etiological factor, especially in congenital and early-onset sensorineural hearing impairment.[14] Kim et al. demonstrated that mutations involving GJB2 and SLC26A4 genes are among the most common causes of hereditary deafness worldwide.[14] Integration of genetic information into AI prediction models may significantly improve diagnostic accuracy and individualized patient care.

One of the major findings of the present study was the high predictive accuracy achieved using AI-based machine learning algorithms. The AI model demonstrated an overall accuracy of 91.6%, sensitivity of 89.2%, and specificity of 93.4%. Artificial Intelligence provides significant advantages in modern hearing healthcare because it can process multidimensional clinical data rapidly and accurately. In the present study, AI models successfully integrated audiological, radiological, and genetic variables to improve prediction of hearing loss severity. Machine learning algorithms are particularly useful in identifying complex nonlinear relationships among clinical variables that may not be easily recognized through conventional statistical methods. AI-assisted prediction systems may help ENT specialists in early diagnosis, individualized rehabilitation planning, cochlear implant candidacy assessment, and long-term prognostic evaluation. The findings of the present study support the growing role of AI as a valuable clinical decision-support tool in tertiary care otorhinolaryngology practice. Similar performance levels have been reported in previous studies evaluating AI applications in hearing diagnostics. Patel et al. demonstrated that machine learning algorithms effectively classify hearing loss patterns using multidimensional audiological datasets with high diagnostic precision.[16] Their study emphasized the importance of feature extraction and supervised learning techniques in predictive hearing analysis.

The present study utilized supervised machine learning methods including Random Forest Classifier, Support Vector Machine (SVM), and Artificial Neural Networks (ANN). Random Forest algorithms are particularly useful in medical prediction models because they can handle multiple clinical variables simultaneously and reduce overfitting.[18] Support Vector Machines have also shown excellent performance in classification-based hearing assessment studies.[19]

Artificial Neural Networks simulate biological neural pathways and are highly effective in recognizing complex nonlinear relationships among variables. Several recent studies have shown that ANN models outperform conventional statistical methods in predicting hearing outcomes and cochlear implant performance.[20] Arriaga et al. reported that AI-assisted cochlear implant outcome prediction improves rehabilitation planning and patient counselling.[10]

Another important advantage of AI in hearing healthcare is its ability to integrate multidimensional data from different diagnostic modalities. Conventional clinical evaluation often analyzes audiological, radiological, and genetic findings separately. AI systems can simultaneously process these variables and identify hidden relationships that may not be easily recognized by clinicians.[13] Mehta et al. emphasized that predictive analytics using AI may become an important component of future ENT practice.[13]

The use of AI in tele-audiology and remote hearing screening has also gained increasing attention. AI-assisted smartphone audiometry and cloud-based hearing analysis systems may improve access to hearing care services in rural and resource-limited regions.[12] Singh et al. demonstrated that tele-audiology integrated with AI significantly improves hearing screening efficiency and reduces diagnostic delays in underserved populations.[20]

Despite the promising findings, several challenges remain in implementing AI in routine ENT practice. One of the major limitations is the requirement for large high-quality datasets for effective machine learning training.[4] Small datasets may reduce model generalizability and increase algorithm bias. Ethical concerns regarding patient privacy, data security, and algorithm transparency also require careful consideration before widespread clinical implementation.

Another important limitation is the “black-box” nature of certain deep learning algorithms where clinicians may not fully understand the reasoning process behind AI predictions.[21] Explainable AI models are therefore increasingly being explored to improve physician trust and clinical acceptance. Shahnaz et al. highlighted the importance of ethical and transparent AI systems in hearing healthcare applications.[4] Swanepoel and Hall,[22] suggested that AI-based systems have the potential to enhance tele-audiology services, facilitate early detection of hearing impairment, and improve access to hearing healthcare, particularly in underserved populations.

Lee and Park,[23] reviewed and concluded that machine learning techniques improve classification accuracy and support clinical decision-making by identifying patterns that may not be evident through conventional statistical methods. Kumar and Sharma,[23] demonstrated that their findings suggested automated imaging analysis enhanced diagnostic efficiency and facilitate early identification of structural causes of hearing impairment. Green and Bhutta,[24] emphasized reported that integration of genomic information with clinical and audiological findings improves disease characterization, prognostic assessment, and personalized treatment planning. Wilson and Dorman,[25] proposed that AI-driven signal processing, predictive outcome modeling, and adaptive auditory training systems may significantly improve speech perception, rehabilitation outcomes, and long-term patient satisfaction among cochlear implant recipients.

The present study has certain limitations. The sample size was relatively small and derived from a single tertiary care center. Long-term follow-up and external validation studies were not performed. Future multicentric studies involving larger populations and advanced deep learning architectures may provide more robust evidence regarding the clinical utility of AI in hearing loss prediction.

Nevertheless, the study demonstrates that AI-based predictive models have significant potential in modern otorhinolaryngology practice. Integration of audiological, radiological, and genetic variables using machine learning techniques can improve diagnostic accuracy, facilitate early intervention, and support personalized rehabilitation planning. AI-assisted systems may eventually become routine clinical tools in tertiary care ENT hospitals and hearing rehabilitation centres.

Limitations of the Study

The present study was limited by a small sample size and single-center design, which may affect generalizability. Long-term follow-up was not performed. Only selected genetic mutations were analyzed, and advanced deep learning models requiring larger datasets were not included. Environmental and socioeconomic factors influencing hearing loss were also not assessed in the study.

CONCLUSION

AI-based prediction models integrating audiological, radiological, and genetic variables provide highly accurate assessment of hearing loss severity and may serve as valuable decision-support tools in modern ENT practice.

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