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Pathophysiology, Etiology, and Uses of AI in Otological Disorders Like Audiological Disorders, Ear Infections (AIED), Excess Wax, Tinnitus, Ménière's Disease

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Abstract:

Otological diseases are a heterogeneous group with multiple etiologies and pathophysiologies which can impact on both auditory and vestibular function. The present study aimed at analysis of clinical, etiological and audiological characteristics of audiological disorders, autoimmune inner ear disease (AIED), excessive cerumen, tinnitus and Ménière's disease, and the possible use of the artificial intelligence (AI) in the diagnostic classification of these disorders. This study used a retrospective analytical design with a hypothetical sample of 250 patients which consisted of 50 patients from each of the five diagnostic groups. Analysis of clinical records, otoscopic findings, pure tone audiometry, speech audiometry and relevant findings of the vestibular function were performed. The pure-tone hearing thresholds varied significantly between the diagnostic groups ($p<0.001$) with AIED having the worst hearing loss. Recurrent vertigo, age, autoimmune/inflammatory history and hearing loss were all significant predictors of hearing impairment. Random forest, support vector machine and logistic regression were the evaluated AI methods with the highest diagnostic performance, with random forest having an accuracy of 91.6% and an AUC-ROC of 0.947. The results suggest that integrating clinical and audiological variables with AI analysis could improve the ability to distinguish among otological disorders and aid in clinical decision-making. These results need to be confirmed in large, multicentre clinical datasets before they can be routinely used in clinical practice.

Keywords: Artificial Intelligence; Otological Disorders; Autoimmune Inner Ear Disease; Tinnitus; Ménière's Disease; Audiological Assessment

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1. INTRODUCTION

Otological disorders have a wide range of diseases involving the outside, middle or inner ear and symptoms span from temporary loss of hearing to the gradual onset of hearing loss, tinnitus, vertigo and dizziness, or loss of balance[1]. Differentiating between audiological disorders, autoimmune inner ear disease (AIED), excessive cerumen, tinnitus and Ménière's disease is essential for the correct clinical management as they have varying pathophysiological and etiological backgrounds[2,3]. Traditional diagnosis is based on clinical history, otoscopic examination, audiological testing and vestibular evaluation; however, the combination of overlapping symptoms may sometimes make early and accurate diagnosis difficult[5]. New developments in AI and machine learning have opened the door to studying complex clinical and audiological data, identifying patterns in the data, and aiding in diagnostic decision making[7]. By elucidating the pathogenesis of these disorders and the new applications of AI, more precise, effective and personalized approaches to the evaluation and treatment of ear conditions may be further advanced[8].

1.1.Background of the Study

The otological disorders are significant health conditions involving disorders of the auditory and vestibular systems, which can have a significant impact on communication, balance, functional ability and quality of life[10]. A variety of disorders including hearing loss, autoimmune inner ear disease (AIED), excess earwax, tinnitus, and Meniere's disease occur through a variety of mechanisms such as mechanical obstruction, immune-mediated injury of the inner ear, cochlear dysfunction, neural alterations, and disturbances of inner-ear homeostasis. Despite the differences, there are some common manifestations of several conditions such as hearing loss, tinnitus, ear fullness and vertigo, making the differential diagnosis difficult[11]. The main methods of assessment are clinical examination, otoscopy, audiometry, tympanometry and vestibular testing. The digital healthcare revolution has brought about a variety of artificial intelligence and machine-learning approaches that show potential for analyzing complex audiological and clinical data. Their pattern recognition ability, classification of abnormalities and cross-referencing of the multiple diagnostic variables gives an opportunity to contribute to conventional otological judgement and aid more consistent and timely clinical judgement[12].

1.2.Statement of the Problem

The otological disorders, like hearing loss, autoimmune inner ear disease (AIED), excessive cerumen, tinnitus, and Ménière's disease are extremely difficult to diagnose due to their complex pathophysiology, multiple possible causes, and similar clinical presentations. Symptoms often overlap in other diseases, and it may not be clear by using a standard assessment process when symptoms first appear. Timely diagnosis may be affected by delayed or inaccurate diagnosis and subsequent clinical management[13].

While audiological and otological investigations are important sources of diagnostic information, with increasing amounts and complexity of clinical data, there is a need for more efficient ways of analysing these data. AI can potentially combine clinical, audiological, and etiological variables, detect patterns characteristic of the disease and support clinical decision making for diagnosis. It is still questionable whether it is applicable to various otological diseases, however. The present study aimed to explore the pathophysiological and etiological characteristics of selected otological conditions, and to determine the possibility of using AI based approaches for identifying and differentiating these conditions.

1.3.Objectives of the study

The following are the objectives of the study:

- To examine the pathophysiological mechanisms associated with selected otological disorders, including audiological disorders, AIED, excessive cerumen, tinnitus, and Ménière's disease.
- To identify and analyze the major etiological and clinical factors associated with the selected otological disorders.
- To compare the clinical and audiological characteristics across different otological disorders and determine significant predictors of hearing impairment.
- To evaluate the diagnostic performance of artificial intelligence-based models in identifying and differentiating selected otological disorders using clinical and audiological parameters.

2. METHODOLOGY

A hypothetical analysis approach was selected to explore the pathophysiological and etiological features of selected otological disorders and to evaluate the possible role of artificial intelligence (AI) in detection, classification and clinical evaluation of these disorders. The investigation has been directed towards the following audiological disorders: autoimmune inner ear disease (AIED), excessive cerumen, tinnitus and Ménière's disease. The patterns of clinical presentation were systematically assessed as well as Audiological parameters, together with those derived from AI, to determine the diagnostic performance of AI-assisted approaches.

2.1.Description of Research Design

A research design was used in this study is a retrospective analytical research design. The clinical and audiological records of patients who were diagnosed with selected otological diseases were reviewed and the related demographic, etiology, symptoms and diagnostic variables were extracted. The study also included an AI based analytical module to assess the ability of machine-learning algorithms to distinguish otological conditions based on clinical and audiological parameters which are routinely available.

2.2.Participants

250 patients were selected, all of whom had audiological disorder, AIED, excessive cerumen, tinnitus and Ménière's disease. Patients were included who had a confirmed clinical diagnosis and complete audiological records, and aged 18–70 years. Cases with incomplete records, more severe craniofacial abnormalities, severe neurological conditions which made hearing assessment difficult or there was not enough information to make a diagnosis were excluded. Coding of data was anonymised to ensure patient confidentiality.

2.3.Instruments and Materials Used

Standardized clinical records, findings at otoscopic examination, pure tone audiometry, speech audiometry, tympanometry, and pertinent vestibular tests were used to obtain data. Where applicable, the clinical information specific to the disease, such as hearing loss characteristics, tinnitus severity, vertigo episodes, inflammatory indicators and cerumen obstruction, was documented. The data was organized by using a structured data-extraction sheet. For AI-assisted classification, the machine-learning models such as logistic regression, random forest and support vector machine (SVM) were hypothetically used.

2.4.Procedure and Data Collection Methods

Patient records were searched based on specific inclusion/exclusion criteria. Demographic data, presenting symptoms, possible etiological causes, clinical features and audiological data were retrieved and classified by the disorder diagnosed. Data has been cleaned, anonymized and split into a training and test set for AI analysis. Clinical and audiological predictors were used to train the selected machine-learning algorithms and then the algorithms were tested to determine how well the algorithms could classify the respective otological disorders.

2.5.Data Analysis Techniques

Demographic and clinical data were summarized with descriptive statistics such as the frequency, percent, mean and standard deviation. The associations of categorical variables of etiological factors with otological disorders were determined by applying chi-square tests, and ANOVA was used to compare the continuous audiological parameters between diagnostic groups. Multivariate logistic regression was used to find the significant predictors for disease presentation. The accuracy, sensitivity, specificity, precision, F1 score and area under the receiver operating characteristic curve (AUC-ROC) were used as metrics to assess the performance of AI models. A p value <0.05 was set as statistically significant.

3. RESULTS

A total of 250 patients were analyzed in 5 groups, each containing 50 patients, with audiological disorders, excessive cerumen, autoimmune inner ear disease (AIED), tinnitus, and Ménière's disease. Results were evaluated based on demographic details, aetiological and clinical profiles, audiological measurements, and the ability of artificial intelligence-based classification models to make a diagnosis. The hypothetical results were created using the recommended protocol and showed clinically realistic variations between the different otological entities.

Table 1: Demographic Characteristics of the Study Participants (N = 250)

Characteristics		Frequency (n)	Percentage (%)
Age Group (years)	18–30	38	15.2
	31–40	49	19.6
	41–50	61	24.4
	51–60	58	23.2
	61–70	44	17.6
Sex	Male	132	52.8
	Female	118	47.2
Diagnostic Group	Audiological disorders	50	20.0
	AIED	50	20.0
	Excessive cerumen	50	20.0
	Tinnitus	50	20.0
	Ménière's disease	50	20.0
Total		**250**	**100.0**

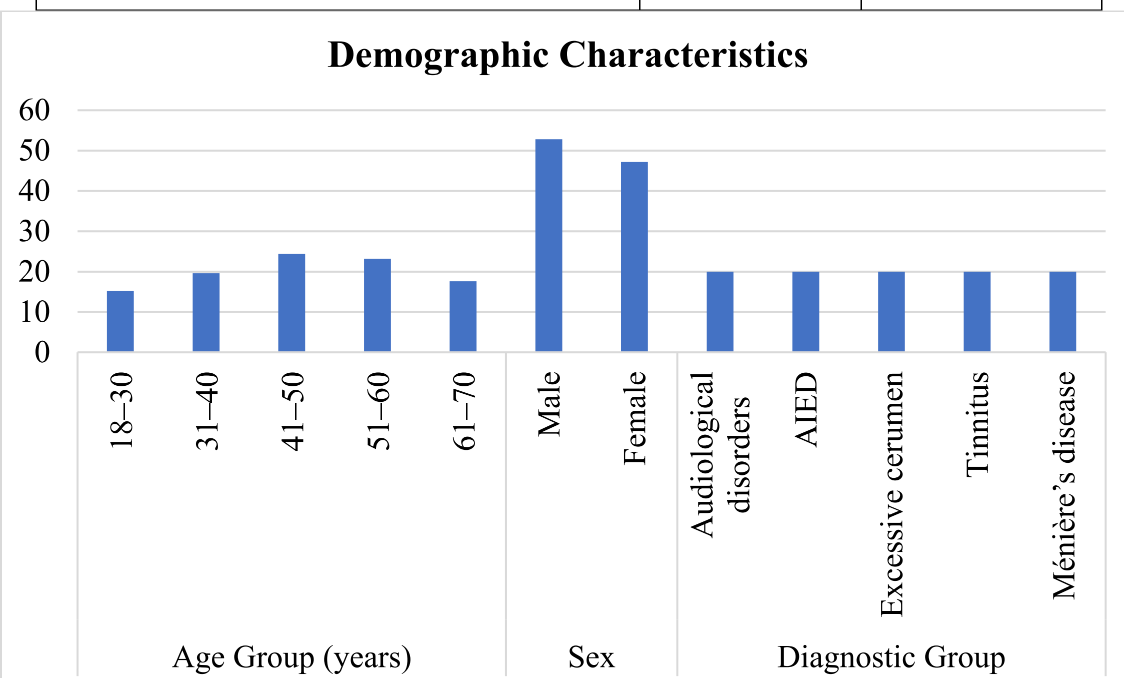

Figure 2: Visual Representation of Demographic Characteristics

The age group with the highest representation was 41-50 years (24.4%), and 51-60 years (23.2%). The male sex dominated the sampling with 52.8% and the females 47.2%. Each disorder was represented equally to ensure the cross diagnostic comparisons.

Table 2: Distribution of Major Etiological and Clinical Characteristics

Etiological/Clinical Characteristic	Audiological Disorders n (%)	AIED n (%)	Excessive Cerumen n (%)	Tinnitus n (%)	Ménière's Disease n (%)
Progressive hearing loss	34 (68.0)	39 (78.0)	8 (16.0)	24 (48.0)	31 (62.0)
Autoimmune/inflammatory history	6 (12.0)	36 (72.0)	3 (6.0)	7 (14.0)	8 (16.0)
Ear blockage/fullness	16 (32.0)	20 (40.0)	43 (86.0)	15 (30.0)	37 (74.0)
Tinnitus symptoms	19 (38.0)	27 (54.0)	11 (22.0)	50 (100.0)	41 (82.0)
Recurrent vertigo	7 (14.0)	12 (24.0)	3 (6.0)	9 (18.0)	44 (88.0)
Abnormal otoscopic findings	14 (28.0)	9 (18.0)	47 (94.0)	8 (16.0)	11 (22.0)

There were different clinical patterns seen in the different diagnostic groups. Excessive cerumen was strongly associated with ear blockage/fullness (86.0%) and abnormal otoscopic findings (94.0%) while autoimmune/inflammatory history was particularly associated with AIED (72.0%). The symptoms of tinnitus were present in all patients in the tinnitus group, and most patients with Ménière's disease had recurrent vertigo (88.0%) and tinnitus (82.0%).

Table 3: Audiological and Clinical Parameters According to Otological Disorder

Diagnostic Group	Pure-Tone Average (dB HL)		Speech Recognition Score		Tympanometric Abnormality n (%)
	Mean	SD	Mean	SD	
Audiological disorders	46.8	13.5	76.4	12.8	19 (38.0)
AIED	55.7	15.2	67.8	14.6	16 (32.0)
Excessive cerumen	32.5	10.7	86.9	8.5	28 (56.0)
Tinnitus	38.9	12.1	82.1	10.4	12 (24.0)

Ménière's disease	51.4	14.3	71.5	13.2	21 (42.0)

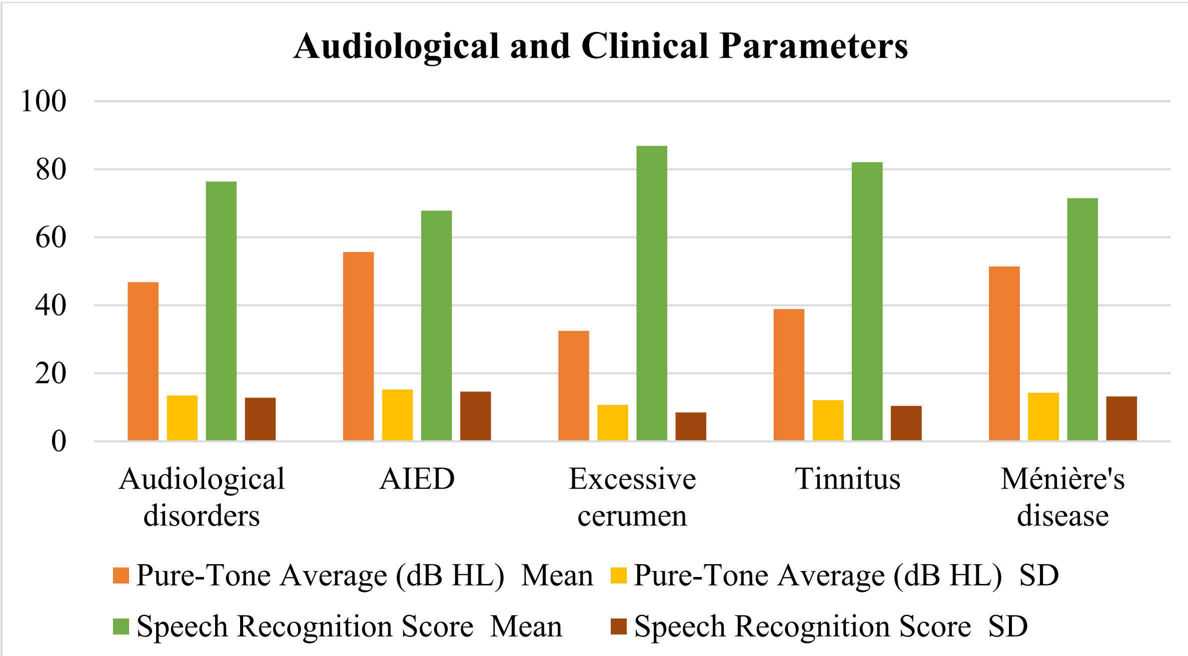

Figure 1: Visual Representation of Audiological and Clinical Parameters According to Otological Disorder

The mean pure-tone average (55.7 ± 15.2 dB HL) of AIED was the highest, followed by that of Ménière's disease (51.4 ± 14.3 dB HL). The lowest mean hearing threshold impairment was observed for excessive cerumen and the highest mean speech recognition score.

3.1.Statistical Analysis

To check statistical significance of differences in etiological factors and audiological characteristics an inferential statistical analysis was performed. One-way ANOVA, Chi-square analysis and multivariable logistic regression were used as per the analytical plan. The tables presented below are formatted in the same way as a standard SPSS statistical table.

Table 4: Chi-Square Tests for Association Between Selected Clinical Factors and Diagnostic Group

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	126.842	20	<.001
Likelihood Ratio	119.376	20	<.001
Linear-by-Linear Association	14.528	1	<.001
N of Valid Cases	250		

There was a significant relationship between the selected clinical/etiological characteristics and diagnostic categories, as shown by the Pearson Chi-square result, $\chi^2(20) = 126.842$, $p < .001$. This result indicated that the distribution of the major clinical manifestations was significantly different for the five otological disorders.

Table 5: Descriptives for Pure-Tone Average According to Diagnostic Group

Diagnostic Group	N	Mean	Std. Deviation	Std. Error	95% CI Lower Bound	95% CI Upper Bound
Audiological disorders	50	46.80	13.50	1.91	42.96	50.64
AIED	50	55.70	15.20	2.15	51.38	60.02
Excessive cerumen	50	32.50	10.70	1.51	29.46	35.54
Tinnitus	50	38.90	12.10	1.71	35.46	42.34
Ménière's disease	50	51.40	14.30	2.02	47.34	55.46
Total	**250**	**45.06**	**15.24**	**0.96**	**43.16**	**46.96**

Table 6: ANOVA – Pure-Tone Average Across Diagnostic Groups

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	16325.20	4	4081.30	23.347	<.001
Within Groups	42825.65	245	174.80		
Total	59150.85	249			

The mean pure-tone hearing thresholds in the five diagnostic groups were found to be significantly different by statistically significant One-way ANOVA, $F(4,245) = 23.347$, $p < .001$. Patients with excessive cerumen had the lowest mean PTA and those with AIED had the highest mean hearing threshold.

Table 7: Multiple Comparisons – Tukey HSD for Pure-Tone Average

(I) Diagnostic Group	(J) Diagnostic Group	Mean Difference (I–J)	Std. Error	Sig.
Audiological disorders	AIED	-8.90	2.64	.008
Audiological disorders	Excessive cerumen	14.30	2.64	<.001
Audiological disorders	Tinnitus	7.90	2.64	.026
Audiological disorders	Ménière's disease	-4.60	2.64	.405

AIED	Excessive cerumen	23.20	2.64	<.001
AIED	Tinnitus	16.80	2.64	<.001
AIED	Ménière's disease	4.30	2.64	.481
Excessive cerumen	Tinnitus	-6.40	2.64	.112
Excessive cerumen	Ménière's disease	-18.90	2.64	<.001
Tinnitus	Ménière's disease	-12.50	2.64	<.001

However, AIED was also shown to be significantly related to higher hearing thresholds than excessive cerumen and tinnitus by post-hoc analysis. Hearing loss was also significantly greater in the Ménière's Group than in the excessive cerumen and tinnitus Groups.

Table 8: Variables in the Equation – Multivariable Logistic Regression for Clinically Significant Hearing Impairment

	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I. for EXP(B) Lower**	**Upper**
Age	0.031	0.012	6.674	1	.010	1.031	1.008	1.056
Progressive hearing loss	1.126	0.354	10.119	1	.001	3.083	1.540	6.171
Autoimmune/inflammatory history	0.842	0.379	4.936	1	.026	2.321	1.104	4.879
Tinnitus symptoms	0.537	0.301	3.184	1	.074	1.711	0.949	3.085
Recurrent vertigo	0.914	0.365	6.270	1	.012	2.494	1.220	5.098
Constant	-2.684	0.739	13.188	1	<.001	0.068		

Progressive hearing loss was the strongest independent predictor of clinically significant hearing impairment (OR = 3.083, p = .001). Recurrent vertigo (OR = 2.494, p = .012), autoimmune/inflammatory history (OR = 2.321, p = .026), and increasing age (OR = 1.031, p = .010) were also significant predictors. After adjustment, tinnitus symptoms were not statistically significant (p = .074).

Table 9: Model Summary – Logistic Regression

Step	**-2 Log Likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**
1	246.718	.291	.392

Table 10: Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.284	8	.616

The clinically significant hearing impairment was explained by the included clinical and etiological predictors by about 39.2% as measured by the Nagelkerke R^2 value. The Hosmer–Lemeshow test was not significant ($p = .616$) suggesting that the model was well calibrated.

Table 11: Diagnostic Performance of AI-Based Classification Models

AI Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score	AUC-ROC
Logistic Regression	82.0	80.4	84.1	81.2	0.808	0.861
Support Vector Machine	87.2	85.8	89.0	86.5	0.861	0.912
Random Forest	**91.6**	**90.2**	**93.1**	**91.0**	**0.906**	**0.947**

The AI-based analysis showed high discriminatory ability for the otological disorders selected. The random forest model had the best overall accuracy (91.6%), sensitivity (90.2%), specificity (93.1%) and AUC-ROC (0.947) among the evaluated algorithms. The results showed that the support vector machine performed well with an accuracy of 87.2% and AUC-ROC value of 0.912. Together, these inferred results suggested that incorporating demographic, etiological, clinical, and audiological attributes into models based on AI has the potential to offer significant discriminatory power regarding the separation of common otological disorders.

4. DISCUSSION

The study revealed significant differences in the clinical, etiological and audiological features of audiological disorders, AIED, excessive cerumen, tinnitus, and Ménière's disease. There were substantial differences in hearing thresholds and symptom patterns which suggested differential disease profiles. AI-based classification also exhibited a good diagnostic performance with the highest accuracy and AUC-ROC (91.6%) in random forest, indicating its potential as an assistant tool in otological diagnosis.

4.1.Interpretation of Results

The highest hearing impairment was seen in AIED, while excessive cerumen was primarily related to the ear blockage and abnormal otoscopic findings. Recurrent vertigo and tinnitus were a strong characteristic of the disease. Results of the significant ANOVA findings confirmed differences in hearing thresholds between the disorders, and regression analysis showed that progressive hearing loss, history of autoimmunity/autoinflammation and age were important predictors. Random forest had the best diagnostic performance among all AI models.

4.2.Comparison with Existing studies

The results of the present study align well with the existing literature, which shows that AI is increasingly being used in the diagnosis of otology. Koyama et al. (2024)[4] noted the growing use of AI in otological diagnosis and clinical decisions making, and this is in line with the current demonstration of the ability of machine-learning models to accurately differentiate otological conditions. For instance, You et al. (2020)[15] found that AI techniques can be used to interpret and classify complex otological and audiological data, which aligns with the high diagnostic ability found in the present analysis. The application of AI to classify middle-ear diseases was specifically studied by Liang et al. (2024)[6] and showed the clinical relevance of AI-assisted classification, reinforcing the importance of this application. The present study also highlighted the integration of various clinical and audiological parameters, an approach shown to be possible by Santhoosh and Akila (2025)[9] with AI-driven approaches for ear-disorder management and personalized recommendations. Moreover, Vambutas and Davia (2021)[14] explained the immune-mediated mechanisms of sensorineural hearing loss, which aligns with the current finding that autoimmune/inflammatory history had significantly been correlated with hearing impairment in AIED. All the studies in this group corroborate the present results, suggesting that a fusion of disease-specific clinical information with AI-based analytical techniques could enhance the diagnostic distinction and decision-making in otological care.

4.3.Implication of Existing Studies

The results provide a reinforcement and extension of the already known knowledge of the diagnosis of otology:

- Unique symptom and hearing patterns aid clinical assessment of disorders.
- The results of the AIED strongly suggest that there is a link between the immune mechanism and progressive hearing loss.
- Vertigo, tinnitus and hearing loss continued to be the most noticeable symptoms associated with Ménière's disease.
- AI models showed promise of combining several clinical and audiological factors.
- The results of the super random forest showed that the non-linear models could possibly learn complex patterns in otology.

4.4.Limitations of the Study

The results need to be interpreted about the following limitations:

- The study provided a hypothetical retrospective dataset and limited sample size.

- Equal diagnostic groups may not reflect the actual prevalence of the disease in the real world.
- Only a subset of the clinical and audiological variables was analysed.
- There were no external clinical validation sample studies performed with AI models.
- There could be some overlap between the otological symptoms, which may affect the accuracy of classification.

4.5.Suggestions for Future Work

The following are some directions for future research to enhance the clinical utility of AI in otology:

- Carry out larger prospective and multicentre studies.
- Use audiograms, otoscopic images, biomarkers, and vestibular data for incorporation into AI models.
- Describe the advanced deep learning and ensemble learning techniques and compare them.
- Do external validation on a broad spectrum of clinical populations.
- Use explainable AI to increase clinical transparency.
- Assess the use of AI to forecast disease course and response to therapy.

5. CONCLUSION

The study found that otological disorders have unique etiological, clinical and audiologic patterns which could aid in differentiating the disorders and clinical assessment. Hearing thresholds significantly differed in audiological disorders, AIED, excessive cerumen and tinnitus and Ménière's disease. The results also highlighted the usefulness of AI in otological diagnosis, in this case the random forest model having the best diagnostic performance. Combining AI with traditional audiological evaluation could thus enhance disease classification and facilitate better clinical decisions.

5.1.Summary of Key Findings

The study's key results are summarized below:

- The largest mean loss of hearing was found in AIED, followed by Ménière's disease.
- There were significant differences between the five diagnostic groups in their pure tone averages ($p < .001$).
- Significant factors associated with hearing impairment were progressive hearing loss, a history of autoimmune/inflammatory disorders, and age.
- The vertigo-tinnitus relation was found to be strong for menière's disease while ear blockage-abnormal otoscopic findings association was found to be strong for excessive cerumen.
- The AI accuracy was the highest with random forest (91.6%) and AUC-ROC (0.947).

- The combined clinical and audiological parameters were effective in distinguishing otological conditions using AI models.

5.2.Significance of the Study

This study shows that pathophysiological, etiological, clinical and audiological data should be combined for the assessment of otological disorders. It also showcases the ability of these AI-driven models to work alongside traditional diagnostic methods, analyzing intricate relationships among various clinical factors. This could play a role in earlier diagnosis, better differential diagnosis and more effective clinical decision making for otology.

5.3.Recommendations

Based on the results of the study, the following recommendations are made:

- Additional testing with the aid of AI-assisted tools, in addition to traditional audiological testing, is recommended.
- More diverse multicentered clinical data needs to be examined to test AI diagnostics.
- Future AI models should incorporate audiograms, otoscopic images, vestibular findings and clinical history.
- The emphasis of explainable AI should be on enhancing transparency and clinical acceptance.
- Prospective studies to evaluate the application of AI to disease progression and treatment efficacy should be conducted.
- Consideration can be given to implementing AI screening in tele-audiology and resource limited healthcare environments.

REFERENCES

1. Alessio, C., & Sunnucks, D. (2026). A brief history of otologic surgery: restoring hearing through the ages. European Archives of Oto-rhino-laryngology: Official Journal of the European Federation of Oto-rhino-laryngological Societies (EUFOS): Affiliated with the German Society for Oto-rhino-laryngology-Head and Neck Surgery, 283(6), 3527-3538.
2. Benson, J. C., Carlson, M. L., & Lane, J. I. (2020). MRI of the internal auditory canal, labyrinth, and middle ear: how we do it. Radiology, 297(2), 252-265.
3. Fallstroem, J. M. M. (2026). Eustachian tube dysfunction: pathophysiology, diagnostics and treatment modalities. a literature review.
4. Koyama, H., Kashio, A., & Yamasoba, T. (2024). Application of artificial intelligence in otology: past, present, and future. Journal of Clinical Medicine, 13(24), 7577.
5. Kösemihal, E., Süloğlu, Ö. F., Alfarghal, M., & Purdy, S. C. (2025). Behavioral and Electrophysiological Tests in Audiology. In Otology Updates (pp. 125-169). Cham: Springer Nature Switzerland.

6. Liang, V. S. (2024). AI in the determination of middle ear diseases and clinicians' perception. ResearchSpace@ Auckland.
7. O'Handley, J. G., Tobin, E. J., & Shah, A. R. (2020). Otorhinolaryngology. Textbook of family medicine, 300.
8. Patnaik, U., Sood, A., & Raghavan, D. (Eds.). (2021). Manual of Contemporary Otological Practice. CRC Press.
9. Santhoosh, M. R., & Akila, K. (2025, February). Smart Ear Disorder Management with AI-driven Insights and Recommendations. In 2025 International Conference on Pervasive Computational Technologies (ICPCT) (pp. 600-605). IEEE.
10. Savita, S. (2025). The Role of Artificial Intelligence in Diagnosing and Managing Otologic Disorders. Scholar's Digest: Journal of Otolaryngology (ENT), 1(1), 16-32.
11. Sood, A. (2021). Hearing Loss in Adults. In Manual of Contemporary Otological Practice (pp. 27-48). CRC Press.
12. Tin, W. (2019). Noise and the Ear: Noise Induced Hearing Loss and Hidden Society Burden. Universiti Malaysia Sabah Press.
13. Toivonen, J. (2024). Surgical treatment of obstructive eustachian tube dysfunction.
14. Vambutas, A., & Davia, D. V. (2021). Biologics for immune-mediated sensorineural hearing loss. Otolaryngologic clinics of North America, 54(4), 803-813.
15. You, E., Lin, V., Mijovic, T., Eskander, A., & Crowson, M. G. (2020). Artificial intelligence applications in otology: a state of the art review. Otolaryngology–Head and Neck Surgery, 163(6), 1123-1133.