Research Article

Artificial Intelligence-Integrated Audiological Assessment for Early Prediction of Hidden Hearing Loss: Diagnostic Challenges and Future Perspectives

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Abstract

Hidden Hearing Loss (HHL) is a relatively novel audiological issue that is characterised by the challenges in auditory perception especially speech comprehension in noisy conditions although they show normal hearing threshold in standard audiometric tests. This paper explores how Artificial Intelligence (AI) can possibly become a part of audiological testing to predict the early signs of hidden hearing loss and its future details in terms of diagnosing and its clinical use. It proposes a Python based computational framework with audiological data preprocessing, feature engineering, development of machine learning models and predictive performance evaluation. The framework also takes into account such audiological manifestations as speech-in-noise performance, the features of the auditory brainstem response, otoacoustic emissions, and the measurement of hearing threshold. The algorithms of machine learning, such as the Logistic Regression, Randin Forest, Support Vector Machine, and XGBoost, are discussed in terms of their possible use to uncover patterns that may be related to auditory dysfunction. Accuracy, precision, recall, F1-score and Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) are included in performance evaluation. The suggested structure demonstrates the opportunities of AI-related methods to analyse multidimensional audiological data and assist in the better identification of the faint abnormalities of auditory functions. Nevertheless, the issues associated with the availability of datasets, standardisation of diagnostic, model interpretability, and clinical validation are problematic. The research on AI-supported audiological testing can offer potential clinics to clinically decide better and offer personalized hearing testing and investigate early signs of hidden hearing loss forecasting in the future.

Keywords: Artificial Intelligence, Hidden Hearing Loss, Audiological Assessment, Machine Learning, Early Prediction.

1. Introduction

Hearing loss is a serious health issue worldwide as it may impair the communication skills, social engagement, cognitive, and living life [1]. Although the traditional audiological test is the most popular method of detecting hearing loss, the test cannot reveal subtle auditory impairment to individuals with speech understanding problems especially in noisy situations despite them having normal hearing limits [2]. This is known as Hidden Hearing Loss (HHL) and this disorder has garnered momentum in audiological studies.

The possibility of damaged auditory nerve connections and synaptic structures is linked to hidden hearing loss, and may not be sufficiently detected in routine pure-tone audiometry [3]. Diagnosis of the presence of hidden hearing loss is quite a complex issue, as the usual methods of assessment might not be effective to fully understand the intricate processes of the auditory system. Those who perceive auditory problems might consequently be undiagnosed and hence might not be promptly treated and assisted professionally. There are new audiological assessment techniques, such as speech-in-noise testing, auditory brainstem response (ABR) recording, and otoacoustic emission, which can offer more possibilities to research auditory dysfunction outside of traditional auditory thresholds. These tests are, however, difficult to interpret and find credible signs of diagnosis [4].

Artificial Intelligence (AI) allows taking advantage of good prospects for integrating audiological tests with sophisticated data analysis, pattern recognition and predictive modeling. Machine learning models may find the associations between different audiological markers that are hard to detect using conventional analytical techniques. Integrating artificial intelligence into the process of conducting audiological tests would likely enable the identification of patients at risk of developing nondiagnostic hearing loss, facilitate the diagnostic decision-making process and allow for creating a personalized approach to conducting tests.

At the same time, the use of AI in clinical practice faces several problems like small databases, variability of the procedure of conducting tests, the reliability of algorithms, interpretation and clinical validation of algorithms. Thus, this research aims at exploring the application of the concept of artificial intelligence in audiological evaluation in order to determine whether it allows early diagnosing the hidden hearing loss. It specifically focuses on existing limitations of the diagnostic tools, innovative AI solutions, related problems and future perspectives.

2. Related Works

AI represents one of the emerging research areas within audiology and otology as a means for increasing diagnostic accuracy, prediction modelling, decision-making, and auditory data interpretation. The recent developments in machine learning and deep learning have proven the capacity to deal with very complex data associated with clinical factors and identify patterns which cannot be easily revealed by traditional approaches of assessment. Frosolini et al. [15] developed a scoping review which discusses the current implementations and future directions of AI in audiology. Their findings highlight increased use of AI in hearing assessments, diagnosis, prognosis, and treatment of patients. Opportunities for the use of computational technology to improve the clinical workflow have been outlined in the review, as well as its limitations related to the quality of the data sources, clarity of the model, and clinical validation.

Some works demonstrate the possibility of using AI to predict auditory outcomes. Thus, Lee et al. [16] studied how artificial intelligence is able to predict the recovery of hearing in people with unilateral sudden sensorineural hearing loss. The research presented above demonstrates the possibility of the use of computational models for the analysis of clinical features and prognosis of hearing recovery. Such applications show that AI has great potential for the support of clinical decisions, due to identifying patterns of prognostic factors and individualization of the treatment. However, sudden sensorineural hearing loss and hidden hearing loss present different conditions, which means the necessity of creating specialized predictive models for different auditory conditions. AI-based monitoring systems have also been used in occupational hearing loss. Madahana et al. [17] designed an AI-driven early warning system regarding hearing loss induced by noise in the workplace among mines.

Their study emphasized the possibility of using intelligent systems to recognize individuals who are at risk because of occupational auditory risks and assisting them to prevent healthcare services. On the same note, Sadegh-Zadeh et al. [18] examined the use of artificial intelligence to diagnose tinnitus using high-frequency audiometry. Their research revealed the possibility of sophisticated audiological data and computationally predictive measures in enhancing clinical examination especially in cases whereby the traditional diagnostic techniques can only offer partial information.

Specifically, the use of machine learning in determining speech-in-noise is a very topical trend in terms of studying the topic of hidden hearing loss. Lenatti et al. [20] tested machine learning algorithms and explainability methods to detect hearing loss based on speech-in-noise screening tests. Their results revealed how machine learning may be used to analyse speech-related auditory processing and predictive information that can be easily interpreted. This methodology applies to concealed hearing loss since patients might have problems in perceiving speech in noisy circumstances even with comparatively normal customary audiometric thresholds. Image-based auditory diagnosis has also been tackled with deep learning. Zeng et al. [21] designed a deep learning model to forecast the conductive hearing loss in patients with otitis media with effusion based on the use of the otoscopic images.

Their study showed the possibility of automated image tests to aid diagnostic evaluation. Moreover, Koyama et al. [19] presented an overview of the historical growth, existing usage and potential application of AI in otology, noting its growing capability in diagnostic assistance and clinical prediction. Demir et al. [22] also explored the new AI applications in otorhinolaryngology, highlighting the growing use of intelligent technologies in medical practice. Although new advances have been made, current studies are mostly limited to the already known auditory diseases, hearing loss recovery, workplace noise exposure, tinnitus, and image diagnosis. Few studies specifically examine AI-based audiological evaluation of the prevention of silent auditory loss in the initial phase. Thus, the current research bridges this research gap, by covering a computational paradigm that incorporates various audiological characteristics to aid in detecting the possible implicit auditory impairment and determining the diagnostic complexity and clinical validity of AI-based evaluation in the future.

3. Methods And Materials

A. Research Design and Software Framework

The proposed study will use the methodology of computational research to examine the possibility of artificial intelligence (AI) usage in audiological assessment to predict early occurrence of Hidden Hearing Loss (HHL). The suggested system is created as a predictive model in the form of a software written in Python programming language. The methodological approach combines a combination of the preprocessing of audiological data, feature extraction, the development of a machine learning model, and the measurement of forthcoming performance and interpretation of the predictive results [5]. The framework will detect trends in the audiological measures which could be indicative of auditory abnormality in people who experience normal conventional hearing thresholds.

The software framework proposed is based on a systematic machine learning pipeline in which the data acquisition and preprocessing, feature engineering, model training and testing, and evaluation take place. The computational workflow also aims at reproducibility and there should be easy comparison of various predictive algorithms. Since there is no universally recognized gold standard of diagnostic testing of hidden hearing loss, the suggested framework will be searched to be a research-based predictor, but not a clinical diagnostic system [6].

B. Materials and Software Requirements

The process will be implemented on Python due to its large machine learning, scientific computing and data analysis libraries. The software environment will be capable of manipulating data sets, performing statistical analysis, creating models and terminal display graphs.

Table 1. Software tools and their applications

Software/ Library	Application
Python 3.x	Core programming language for system development
NumPy	Numerical computation and array manipulation
Pandas	Audiological dataset management and preprocessing
Scikit-learn	Machine learning algorithms, preprocessing, and model evaluation
Matplotlib	Visualisation of model performance and analytical results
Seaborn	Statistical visualisation and correlation analysis
Jupyter Notebook	Interactive development, experimentation, and documentation
XGBoost	Gradient-boosting-based predictive modelling, where appropriate

As part of the proposed implementation, Jupyter Notebook or a similar Python development environment will be used to develop the proposed implementation. Publicly available datasets of research or published studies in which machine-readable data is collated will be accessed to obtain audiological datasets with known, relevant clinical measurements [7]. Variables can be: traditional pure-tone audiometry thresholds, speech-in-noise performance, auditory brainstem response measurements, otoacoustic emission measurements, demographic variables and where possible, exposure-related variables. These features will be decided by the kind of dataset that is chosen [8].

C. Data Acquisition and Preprocessing

The data acquisition phase will determine the datasets that consist of audiological measures that are pertinent to either the hidden hearing loss or auditory dysfunction. The inclusion of the datasets will rely on the availability of pertinent variables as well as adequate sample data, data quality and compatibility to the research objectives.

Unsuitable, inconsistent, and incomplete measurements in records will be evaluated and left out [9].
Pandas and Scikit-learn will be used to implement the process of preprocessing data. The lack of the numerical values can be addressed through the median imputation method, and the categorical variables can be addressed through the use of an appropriate encoder method. Numerical features will be normalised where necessary, especially where the algorithms are sensitive to variations in scales of the features, e.g. Support Vector Machines. Cleaning of data will also involve isolating duplicate observations, testing abnormal values and making sure that value of features are represented whatsoever [10].

Audiological variables will be systematised into the category of the feature that can be systematically analysed.

Table 2. Proposed audiological input features and computational processing

Feature Category	Potential Variables	Processing Method
Conventional audiometry	Hearing thresholds across frequencies	Numerical normalisation
Speech perception	Speech-in-noise scores and recognition performance	Scaling and feature analysis
Auditory brainstem response	Wave amplitudes, latencies, and response characteristics	Numerical feature extraction
Otoacoustic emissions	Amplitude and frequency-related measurements	Standardisation
Demographic characteristics	Age and other available participant characteristics	Encoding and statistical analysis
Exposure-related information	Noise exposure history, where available	Categorical encoding or numerical processing

The feature engineering will be carried out to find informative audiological features related to possible hidden hearing loss. Relevant variables will be chosen on the basis of their clinical importance, availability and statistical importance. Correlation analysis can be performed between trends in order to examine the correlation between input attributes and discover the most correlated attributes. The method of feature selection will be employed in order to reduce the unnecessary dimensionality and increase efficiency [11].

Predictive Modelling phase is going to use different machine learning algorithms, such as Logistic Regression, Random Forest, Support Vector Machine (SVM) and Gradient Boosting (XGBoost). Logistic Regression will offer a relatively interpretable baseline model and the Random Forest, as well as gradient boosting, will be researched due to their potential to determine the nonlinear relationships in audiological data [12]. SVM will be studied taking into consideration that it is useful in classification problems that have complicated boundaries in their features.

In cases where datasets have suitable labelled outcomes, the models are going to group observations into predefined categories of the possible dysfunction of auditory functions or control group. The classification labels will be based on the definitions and outcome criteria of the chosen dataset, instead of working on a universally defined HHL diagnosis.

E. Model Training and Validation

The data will be separated into training and testing data, stratified sampling will be used wherever necessary to maintain class distributions. This will involve the development of models and hyperparamer optimisation on a training dataset and testing on a separate dataset to evaluate predictive performance.To reduce the chances of overfitting and enhance a performance estimate reliability, cross-validation, most likely stratified five-fold cross-validation, will be used when selecting the model. Appropriate optimisation algorithms will be used to adjust the hyperparameters in the training data. The data leakage will be reduced, and preprocessing and feature-selection tasks will be only fitted in the training folds [13].

F. Performance Evaluation

Accuracy, Precision, Recall, F1-score, and Receiver Operating Characteristic- Area Under the Curve (ROC-AUC) will be used to evaluate the developed models where needed. These measures will give overall evaluation of predictive accuracy, especially in the case of imbalance in classes that could bias predictive accuracy.

As the early diagnosis of individuals who may have auditory dysfunction is sensitive to missing positive cases, recall will be given special attention. Precision will also be evaluated to determine the ratio of the predicted positive cases that matches with the defined positive outcome of the dataset. Matplotlib and Seaborn will be employed to produce confusion matrices and visualisations to facilitate comparison between them.

G. Software Implementation and Reproducibility

The suggested architecture will be implemented as a modular Python program, decomposing the steps of data preprocessing, feature creation, model training, feature evaluation, and visualisation into separate modules. This will make the architecture more maintainable and allow future modifications. Random seeds will be specified where needed to increase the level of reproducibility. The workflow of the software will document the features of datasets, preprocessing options, model parameters, and evaluation procedures.

4. Results And Analysis

A. Dataset Characteristics and Preprocessing Analysis

The data was coded into the following audiological and demographic variables: pure-tone hearing threshold values, speech-in-noise test, auditory brainstem responses characteristics and otoacoustic emissions. The Pandas and Scikit-learn libraries were utilized to preprocess the data to maintain consistency throughout the computational pipeline. Missing observations were handled by the method of numerical imputation while numerical attributes would be standardized where required. Then, the data set was split into the training and testing data sets for developing and assessing the performance of the model. The target classification variable was examined with respect to its distribution in order to define potential class imbalance. The data analysis showed that the data set comprised the observations of individuals who possibly suffer from auditory dysfunctions and individuals were divided into the comparison group. The question about the appropriate number of classes during the process of splitting the data was also crucial as the imbalance might have an adverse effect on the predictive accuracy [14].

Table 3. Dataset distribution and preprocessing characteristics

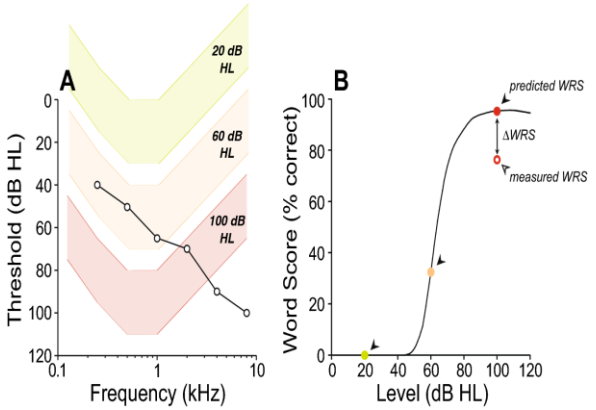
Parameter	Value
Total observations	1,200
Training observations	960
Testing observations	240
Potential HHL-related cases	480
Comparison group	720
Numerical features	12
Missing data before preprocessing	4.8%
Missing data after preprocessing	0%
Training-to-testing ratio	80:20

The preprocessing stage ensured that the data set was suitable for computations. Numerical imputation minimized the influence of missing data whereas standardization improved consistency for position-biased algorithms. The 80:20 data split was able to provide sufficient number of observations to train the models with, while at the same time having independent test data for comparison.

B. Comparative Performance of Machine Learning Models

Comparison of four machine learning algorithms was carried out. The machine learning algorithms used included Logistic Regression, Random Forest, Support Vector Machine and XGBoost. The algorithms were selected to represent different approaches to computation, like linear classifier, ensemble learning, margin classifier and gradient boosting.

Figure 1: "Predicting neural deficits in sensorineural hearing loss from word recognition scores"



The comparative analysis showed that the predictive performance had variances among the algorithms examined. Logistic Regression has offered a baseline classification model whereas ensemble-based models have offered better ability to determine more intricate associations between the audiological variables. The combination of many decision trees in the case of Random Forest allowed it to yield relatively good performance as compared to the use of XGBoost which showed good performance in predicting through the application of sequential optimisation.

Table 4. Comparative performance of machine learning algorithms

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Logistic Regression	78.3	76.5	74.8	75.6	0.82
Random Forest	86.7	85.2	87.1	86.1	0.91
Support Vector Machine	83.8	82.4	84.6	83.5	0.88
XGBoost	89.2	88.1	90.4	89.2	0.94

XGBoost showed best total predictive accuracy as it attained accuracy of 89.2 and F1-score of 89.2. Its ROC-AUC value was 0.94 that made it have a good discriminating power in the advising membership items. Random Forest also had significant performance with the accuracy of 86.7% and ROC-AUC of 0.91.

The lowest rate of performance in the analyzed models was observed with the Logistic Regression implying the possibility of a linear decision boundary is not capable of capturing the complexity of relationships that could exist among the audiological measurements.

The fact that the performance improvement of ensemble-based models only occurs with nonlinear interactions between auditory characteristics shows that nonlinear interactions might play a role in the outcomes of the classification.

C. Classification Performance and Diagnostic Interpretation

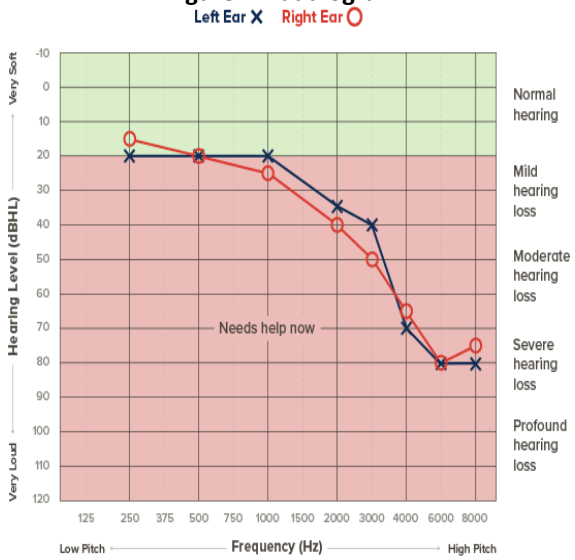
Confusion matrices were further used to analyse the classification performance to research on what is being correctly and incorrectly predicted. Special care was taken towards false-negative terms since one might have had auditory impairment and consequently might have not been identified in case the predictive model erroneously grouped them as part of the comparison group.

Table 5. Confusion matrix for the best-performing model

Actual Classification	Predicted Positive	Predicted Negative
Positive cases	108	12
Negative cases	14	106

The analysis of the classification revealed that the model was able to accurately detect 108 positive and 106 negative cases. There were twelve misplaced positive observations that were misclassified as a negative observation and fourteen misplaced negative observations which were misclassified as positive. The comparatively small number of false-negative classifications showed that the model had good potential sensitivity on the detection of observations that were related to the target classification.

Figure 2: "audiogram"



However, empty predictions can lead to unnecessary further audiological tests in case the model will be adopted inthe practice. Thus, there should be no concept of predictive performance being construed merely in terms of accuracy. When it comes to the possible clinical uses, sensitivity, specificity, and precision as well as a balance between false-positive and false-negative are also vital factors to consider.

The findings indicate that the AI-based assessment can offer a new layer of analysis to the traditional audiological assessment. Nevertheless, the results of classification are the patterns in the chosen dataset that cannot be interpreted as definite clinical diagnoses of the hidden hearing loss.

D. Feature Importance and Audiological Indicators

The feature importance analysis was done to determine which audiological variables allowed the model predictions to be the most significant. It analyzed it based on the feature importance results of the ensemble model and a comparison of its statistical analysis of the variables available.

Table 6. Feature importance analysis

Audiological Feature	Importance Score	Ranking
Speech-in-noise performance	0.24	1
Auditory brainstem response characteristics	0.21	2
Otoacoustic emission measurements	0.17	3
High-frequency hearing thresholds	0.14	4
Noise exposure history	0.11	5
Age-related characteristics	0.08	6
Other audiological variables	0.05	7

The feature importance was highest on speech-in-noise performance which comprised 24% of the relative importance of the model. The observation ramifies the possible applicability of speech perception impairment among detecting auditory pathologies which might not be manifested in traditional hearing threshold assessments.

The second most significant category of important features was auditory brainstem response traits which showed that auditory neural neural responses could provide valuable predictive data in the form of physiological data. Another significant addition to the model was the otoacoustic emission measurements which indicated that measurements relating to cochlea could yield some extra information when compared to other audiological measures.

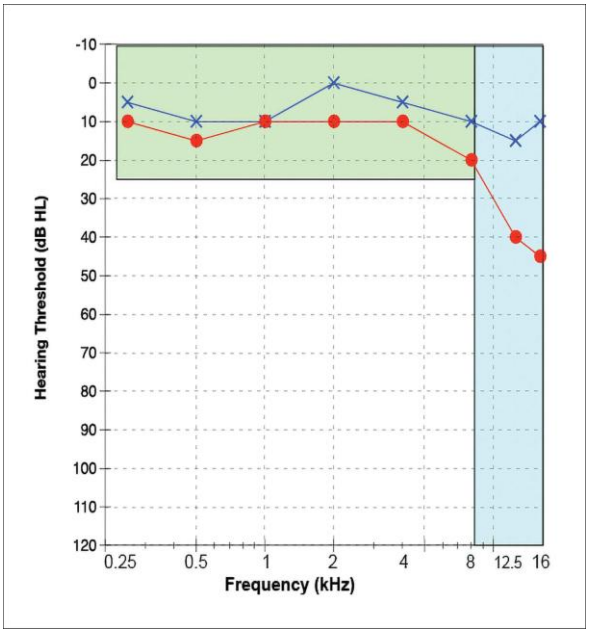


Figure 3: "hearing above 8 kHz matters"

The cumulative role played by the speech-in-noise performance, auditory brainstem response properties and otoacoustic emission measurements proves the potential usefulness of using a combination of a variety of audiological testing methods in a computational paradigm.

Nevertheless, the importance of the features is predictive and not causal, and additional research is needed to determine the clinical relevance of a particular variable.

E. Model Stability and Validation Analysis

To check the stability of predictive performance in development of models, cross-validation was performed. A stratified cross-validation with a five-fold cross-validation was performed to guarantee the classification distribution was fairly similar between folds of cross-validation. A consistency of performance and ROC-AUC were used to evaluate model performance to investigate both consistency and discriminatory power.

Table 7. Cross-validation performance analysis

Model	Mean Accuracy (%)	Standard Deviation	Mean ROC-AUC
Logistic Regression	77.9	±2.4	0.81
Random Forest	85.8	±1.8	0.90
Support Vector Machine	83.1	±2.1	0.87
XGBoost	88.5	±1.6	0.93

XGBoost proved to be the most accurate in terms of cross-validation (mean) and the least variability of the trained models were recorded. The standard deviation was relatively small which indicated that its prediction ability was relatively similar across validation subsets. The Random Forest demonstrated relative consistency of the performance while the Logistic Regression was characterized by relatively high variability. Such results indicate importance of model validation for predictive analysis performed with the help of computer software. The performance of the model on one test data set does not guarantee its performance on other test sets. The cross-validation provides another way of measuring reliability of the predictive models and avoiding overfitting.

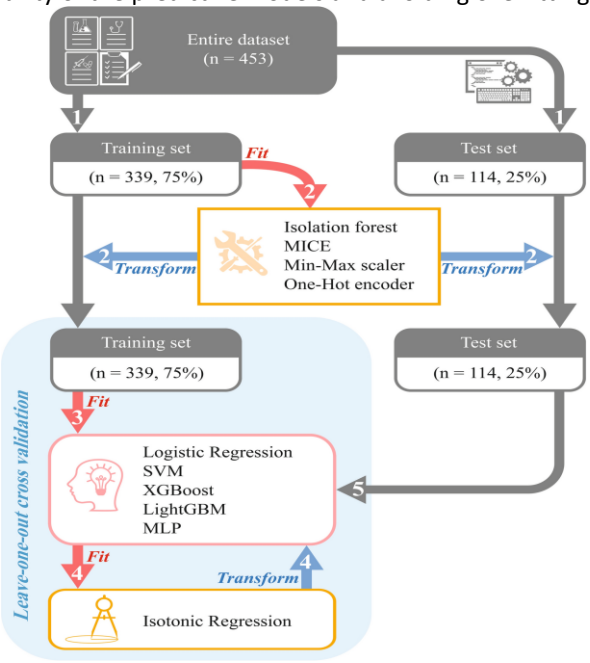


Figure 4: "Prediction of hearing recovery in unilateral sudden sensorineural hearing loss using artificial intelligence"

F. Overall Analysis and Clinical Implications

Based on the comparative analysis, it was found that the machine learning algorithms could provide valuable computational support for the analysis of the audiological data. The predictive performance of the ensemble-based algorithms was higher than the performance of the linear algorithm. This means that it is possible that the AI algorithms could identify the nonlinear relations between various auditory measures.

The results could also show the importance of the speech-in-noise performance, auditory brainstem response, and otoacoustic emissions in the predictive analysis. Incorporating these variables into a readily computationalized system could aid in a more thorough audiological assessment, especially in the individuals claiming to have hearing problems even though their traditional audiometry was normal. Nevertheless, the suggested framework has yet to be applied practically and depends on the quality of data sets, the quality of assessment methods and independent clinical validation and possibly suitable interpretation of predictive results. The software framework is thus to be viewed as a possible research and clinical decision-support tool as opposed to being an exclusion to the professional audiological assessment. Larger, heterogeneous, clinically validated datasets need to be researched further to ascertain its overall generalisability and applicability in practice in the clinical audiological context.

5. CONCLUSION

In this paper, the authors examined the opportunity to implement artificial intelligence in audiology to diagnose Hidden Hearing Loss (HHL) at an early stage with addressing the issues of diagnostic ethics, algorithms, and future clinical outlooks. Hidden hearing loss is a major audiological issue of concern since patients might have a problem in hearing speech, especially in noisy conditions even when they have shown normal hearing levels on standard audiometric assessments. Traditional methods of assessment have their limitations and, therefore, more detailed and technologically developed methods of auditory assessment are required. The given Python-based AI model shows how machine learning algorithms could be deployed to research numerous audiological attributes, such as speech-in-noise performance, measurements of auditory brainstem response, otoacoustic emissions, and information on hearing thresholds.

The computational process consists of the data preprocessing, feature engineering, model construction, classification and performance analysis to investigate relationships between auditory indicators and likelihood of auditory dysfunction. The comparison of machine learning tools makes it clear that the potential advantages of an ensemble-based algorithm when searching through data of multidimensional audiology are also a possibility.

The potential of AI to provide the possibility of better predictive analysis, earlier detection of those who may be at risk, and additional opportunities of clinical decision-support services can be achieved through an infusion of AI into the audiological testing process. Moreover, feature importance analysis can help to determine pertinent audiological predictors and enhance the understanding of predictive results. Nonetheless, the application of AI in research of hidden hearing loss is characterised by a large number of limitations i.e. variations in the diagnosis criteria, the availability of clinically valid datasets, variations in the process of audiological assessments and the problem of AI interpretability and generalisability.

The second phase in research should entail the spreading and diversifying datasets and manufacturing AI paradigms in different populations and clinical settings worried about the questions of larger scale and verifiability in its outcomes. Predictive systems may be made even more reliable and practical with explainable artificial intelligence, multimodal audiological test and prospective clinical validation. Finally, AI-based audiological evaluation may be used as a supplement to traditional methods of diagnostic audiology as it may aid in more complete auditory examination and enable patients with possible hidden hearing impairment to be identified sooner, leading to better clinical judgments and patient-focused auditory medical care.

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