Deep Hybrid Medical Vision System for Early Otitis Media Diagnosis using Otoscopic Imaging

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ABSTRACT

Otitis media includes several common inflammatory conditions of the middle ear that can have severe complications if left untreated. Correctly identifying otitis media can be difficult and a screening system supported by machine learning would be valuable for this prevalent disease. The study presents a deep learning-based automated framework for diagnosing otitis media from otoscopic images, addressing the increasing global burden of ear infections, particularly among children, where the disease remains a leading cause of hearing impairment and frequent ENT consultations. Although digital otoscopic devices generate large volumes of clinical images, diagnosis still predominantly relies on manual visual inspection by otolaryngologists, making it subjective, time-consuming, and prone to inter-observer variability, delayed detection, and fatigue-related errors, especially in resource-limited settings. Conventional assessment involves identifying conditions such as Acute Otitis Media, Chronic Otitis Media, Myringosclerosis, Cerumen Impaction, and Normal cases through expert interpretation, which lacks standardization and scalability. To overcome these challenges, the proposed system integrates image preprocessing, deep feature extraction using DenseNet121, and classification using machine learning models including Nearest Centroid Classifier (NCC), K-Nearest Neighbors (KNN), and eXtreme Gradient Boosting (XGBoost), and proposed calibrated perceptron with Dense neural network (DNN) also called as ensemble Voting model to enhance predictive performance. The dataset is divided into training and testing subsets, and the models are evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curves, and AUC metrics. Experimental results demonstrate that the Voting-based ensemble model achieves superior performance compared to individual classifiers, providing a reliable, efficient, and scalable solution for automated otitis media detection and clinical decision support.

Keywords: Early Otitis, Otoscopic imaging, Inflammatory conditions, Chronic otitis media, Conventional assessment.

1. INTRODUCTION

Otitis media (OM) is a prevalent ailment in children [1], presenting symptoms such as fever, sleep disturbances, and acute infections [2]. This illness significantly affects not only children who experience considerable pain but also their caregivers [3]. OM prevalence is high worldwide, with rates of 9.2% in Nigeria, 10% in Egypt, 6.7% in China, 9.2% in India, 9.1% in Iran, and 5.1 -- 7.8% in Russia [4]. Additionally, the incidence of OM in native Australian children is 90%, the highest worldwide [5]. Prior works have discussed OM diagnosis and treatment methods [6]. If OM is inaccurately diagnosed, it can lead to severe consequences, including hearing loss, cognitive development disorders, unnecessary surgeries, antibiotic overuse, and disease exacerbation [7]. Notably, 80% of OM patients receive antibiotics, leading to potential antibiotic resistance and unnecessary expenses [8]. Therefore, accurate diagnosis is essential to mitigate these side effects and provide effective treatment.

Figure 1. Otitis media diagnosis.

Diagnostic techniques for both acute and chronic middle ear infections have long posed challenges. Infants, in particular, present difficulties due to their narrow external ducts, which, coupled with the presence of earwax, can hinder accurate diagnosis using an ear endoscope alone [9]. Furthermore, in primary clinics and pediatrics, the accuracy of diagnosis tends to be low due to a lack of systematic training and unfamiliarity with pneumatic ear endoscopy [10,11]. To address these challenges, various approaches have been explored in the field. These include specialized training programs for medical students, the development of new otoscopic approaches and techniques, the implementation of absorbance and acoustic admittance measurements, and the integration of impedance-measuring hearing aids. Additionally, clinical trials have been conducted to compare the effects of these various approaches. However, despite these approaches and efforts, the diagnostic success rates among pediatricians and otolaryngologists in primary care settings do not exceed 70%.

2. LITERATURE SURVEY

Camalan S et al. [12] investigated an OtoPair, which uses paired eardrum images together rather than using a single eardrum image to classify them as ‘normal’ or ‘abnormal’. They also mimic the way that otologists evaluate ears, because they diagnose eardrum abnormalities by examining both ears. Their approach created a new feature vector, which is formed with extracted features from a pair of high-resolution otoscope images or images that are captured by digital video-otoscopes. The feature vector has two parts. The first part consists of lookup table-based values created by using deep learning techniques reported in our previous OtoMatch content-based image retrieval system. The second part consists of handcrafted features that are created by recording registration errors between paired eardrums, color-based features, such as histogram of a component of the color space, and statistical measurements of these color channels. Ding X et al. [13] automated interpretation of images, and the prediction of patient outcomes. Several articles have reported some machine learning (ML) algorithms such as ResNet, InceptionV3 and Unet, were applied to the diagnosis of OM successfully. The use of these techniques in the OM is still in its infancy, but their potential is enormous. They presented in this review important concepts related to ML and AI, describe how these technologies are currently being applied to diagnosing, treating, and managing OM, and discuss the challenges associated with developing AI-assisted OM technologies in the future.

Lee JY et al. [14] demonstrated the usefulness and reliability of CNNs in recognizing the side and perforation of TMs in medical images. CNN was constructed with typically six layers. After random assignment of the available images to the training, validation and test sets, training was performed. The accuracy of the CNN model was consequently evaluated using a new dataset. A class activation map (CAM) was used to evaluate feature extraction. The CNN model accuracy of detecting the TM side in the test dataset was 97.9%, whereas that of detecting the presence of perforation was 91.0%. The side of the TM and the presence of a perforation affect the activation sites. Lee H et al. [15] proposed a method of classification for tympanic membrane diseases and regression of pediatric hearing, using a deep learning model of artificial neural networks. Based on the B7 Backbone model of EfficientNet, a state-of-the-art convolutional neural network model, drop connect was applied in the encoder for generalization, and multi-layer perceptron, which is mainly used in the transformer, was applied to the decoder for improved accuracy. For the training data, the open-access tympanic membrane dataset, divided into four classes, was used as the benchmark dataset, and the SCH tympanic membrane dataset with five classes of tympanic membrane diseases and pediatric hearing was also used as the training dataset. In the benchmark using the open-access tympanic membrane dataset, their proposed model showed the highest performance among the five comparative models with an average accuracy of 93.59%, an average sensitivity of 87.19%, and an average specificity of 95.73%. Zhou Z et al. [16] proposed tympanic membrane is the only membrane in the body that is surrounded by air on both sides, under normal conditions. Despite these favorable characteristics, current examination modalities for middle-ear space utilize century-old technology such as white-light otoscopy. Viscaino M et al. [17] focused on reducing medical errors and enhancing physician capabilities using conventional artificial vision systems. However, approaches with multispectral analysis have not yet been addressed. Tissues of the tympanic membrane possess optical properties that define their characteristics in specific light spectra. Their work explored color wavelengths dependence in a model that classifies four middle and external ear conditions: normal, chronic otitis media, otitis media with effusion, and earwax plug. The model is constructed under a computer-aided diagnosis system that uses a convolutional neural network architecture. They trained several models using different single-channel images by taking each color wavelength separately.

Oghalai TP et al. [18] provided is complicated and time-consuming. To streamline data analysis and image processing, we applied a machine learning algorithm to identify and segment the key anatomical structure of interest for medical diagnostics, the tympanic membrane. Using 3D volumes of the human tympanic membrane, we used thresholding and contour finding to locate a series of objects. They then applied TensorFlow deep learning algorithms to identify the tympanic membrane within the objects using a convolutional neural network. Finally, they reconstructed the 3D volume to selectively display the tympanic membrane. The algorithm was able to correctly identify the tympanic membrane properly with an accuracy of ~98% while removing most of the artifacts within the images, caused by reflections and signal saturations. Koyama H et al. [19] improved in anatomically significant structures or diagnostic accuracy improved in conditions such as otosclerosis and vestibular schwannoma. In treatment, AI predicts hearing outcomes for sudden sensorineural hearing loss and post-operative hearing outcomes for patients who have undergone tympanoplasty. AI helps patients with hearing aids hear in challenging situations, such as in noisy environments or when multiple people are speaking. It also provides fitting information to help improve hearing with hearing aids. AI also improved cochlear implant mapping and outcome prediction, even in cases of cochlear malformation. Frosolini A et al. [20] integrated AI in audiology has evolved significantly over the succeeding decades, with 87.5% of manuscripts published in the last 4 years. Most types of AI were consistently used for specific purposes, such as logistic regression and other statistical machine learning tools (e.g., support vector machine, multilayer perceptron, random forest, deep belief network, decision tree, k-nearest neighbor, or LASSO) for automated audiometry and clinical predictions; convolutional neural networks for radiological image analysis; and large language models for automatic generation of diagnostic reports. Despite the advances in AI technologies, different ethical and professional challenges are still present, underscoring the need for larger, more diverse data collection and bioethics studies in the field of audiology.

3. PROPOSED METHODOLOGY

The proposed system is an automated medical image classification framework designed for the diagnosis of Otitis Media using otoscopic images. Initially, ear images are collected and organized into disease-specific categories. Each image is resized and preprocessed before being passed through a pretrained DenseNet121 model to extract deep feature representations using transfer learning. These extracted features are then divided into training and testing sets for model development. The system implements multiple baseline classifiers and introduces a proposed hybrid soft voting model that combines a Calibrated Perceptron and a Dense Neural Network to enhance prediction accuracy and robustness. Finally, the trained model is integrated into a GUI-based interface, enabling users to upload new ear images and receive real-time disease classification results along with performance evaluation metrics.

Figure. 2. Proposed system architecture.

The system begins with collecting otoscopic ear images categorized into different disease classes such as Acute Otitis Media, Chronic Otitis Media, Cerumen Impaction, Myringosclerosis, and Normal. The dataset is organized into separate folders where each folder represents one class label. This structured format allows automatic class identification during dataset upload. Each image is resized to 128×128 pixels to maintain uniform input dimensions. The images are converted into numerical arrays and normalized using DenseNet121 preprocessing. This ensures that the pixel values are standardized and compatible with the pretrained CNN model for effective feature extraction.

The extracted feature dataset is randomly shuffled and divided into training (80%) and testing (20%) sets. This ensures proper model validation and prevents overfitting. The training data is used to build models, while the testing data evaluates performance. Traditional classifiers such as Nearest Centroid, K-Nearest Neighbors (KNN), and XGBoost are trained using the extracted deep features. These models serve as baseline approaches to compare classification performance and analyze how different algorithms handle the feature space. The proposed system introduces a hybrid soft voting classifier combining a Calibrated Perceptron and a Dense Neural Network (DNN). The Perceptron captures linear decision boundaries, while the Dense Neural Network learns complex nonlinear patterns. Both models generate probability scores, which are averaged using soft voting to produce the final prediction. This improves robustness and generalization. The system evaluates all trained models using metrics such as Accuracy, Precision, Recall, F1-Score, Confusion Matrix, ROC Curve, and AUC Score. These metrics provide a comprehensive understanding of classification effectiveness across all disease categories. In the final stage, a user can upload a new otoscopic image through the graphical interface. The system preprocesses the image, extracts features using DenseNet121, applies the trained hybrid model, and displays the predicted disease label along with visual output. This enables real-time automated diagnosis support.

4. RESULT DISCUSSION

Figure 3. depicts the GUI of the Automated Otitis Media Diagnosis system. On the right side, there is a vertical panel of buttons allowing users to perform key functions, including uploading the dataset, performing DenseNet121 feature extraction, train-test splitting, training various models like Perceptron, NearestCentroid, KNN, and uploading a test image for prediction. The left side of the interface contains a scrollable text box that displays messages and system feedback; in this screenshot, it shows that the dataset has been successfully loaded with five classes: *Acute Otitis Media*, *Cerumen Impaction*, *Chronic Otitis Media*, *Myringosclerosis*, and *Normal*. The background image shows a clinical setting, reinforcing the medical context of the application, while the layout combines both functionality and informative status updates in a user-friendly manner.

Figure 3. GUI representation and dataset uploading of Otitis media diagnosis after admin login

Figure 4. Feature extraction of the Image dataset.

Figure 4. shows that the Images Using Deep CNNs," illustrates the completion of the feature extraction step using a deep learning model. The text area on the left confirms that "Image Preprocessing Completed" and "Xception Feature Extraction completed. Crucially, it shows the resulting dataset dimensions as "Feature Dimension: (3900, 1024)," indicating that 3,900 images were successfully processed, (or Xception, as mislabeled in the output) extracted 1,024 features per image using Global Average Pooling. The right side of the GUI displays the sequential workflow buttons, confirming the next steps are "Train Test Splitting" and training various machine learning models (Perceptron, NearestCentroid, KNN, CNN) on these newly extracted 1024-dimensional features.

Figure 5 shows the confusion matrix of the proposed Voting Classifier model demonstrates excellent classification performance across all five otitis categories. Most predictions lie perfectly on the diagonal, indicating correct classification for nearly all samples. Acute Otitis Media (107), Cerumen Impaction (120), and Normal (118) are classified with 100% accuracy. Chronic Otitis Media shows 133 correct predictions with only 1 misclassified as Myringosclerosis, while Myringosclerosis has 120 correct predictions with just 1 misclassified as Normal. The extremely low number of off-diagonal errors confirms that the proposed ensemble model effectively distinguishes between different ear conditions. Overall, the model achieves near-perfect accuracy with minimal misclassification, demonstrating strong reliability and superior performance compared to individual models..

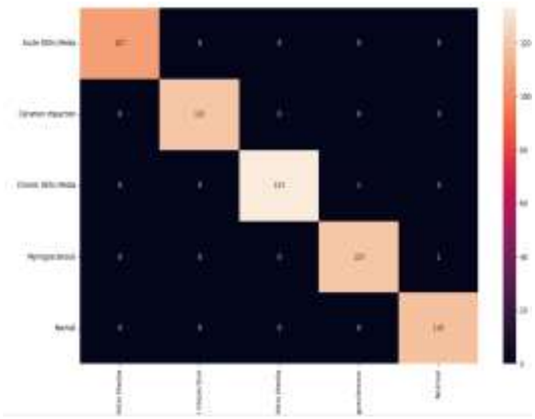


Figure 5. Confusion matrix obtained for Proposed Voting classifier

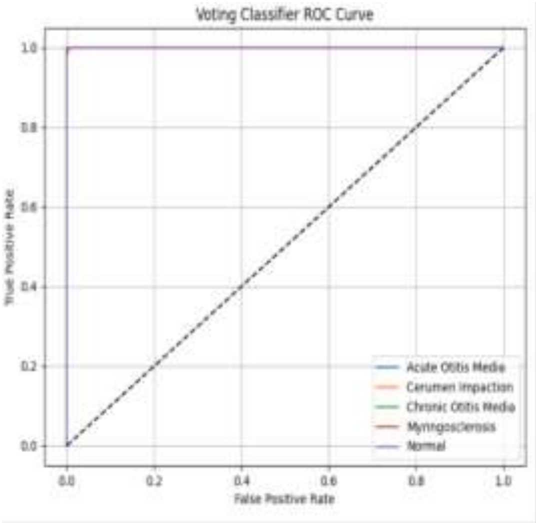
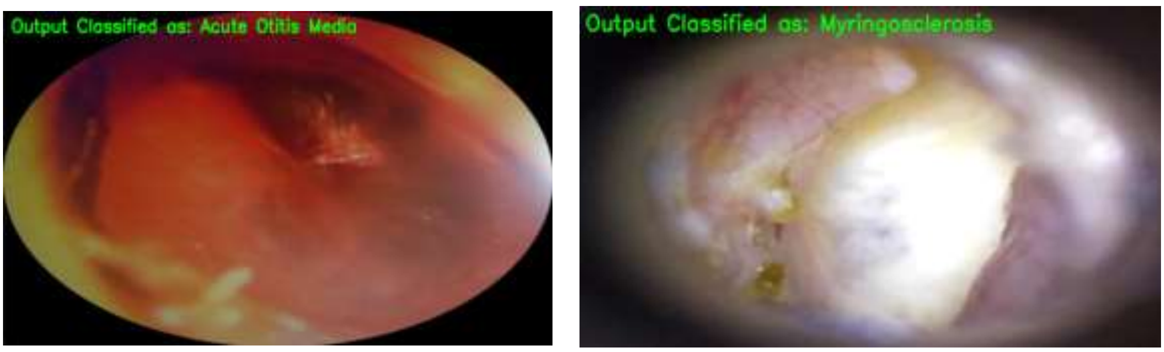


Figure 6. ROC curve obtained for voting classifier.

Figure 6 shows ROC curve of the proposed Voting Classifier model shows an almost perfect classification performance across all five classes—Acute Otitis Media, Cerumen Impaction, Chronic Otitis Media, Myringosclerosis, and Normal. The ROC curves rise sharply toward the top-left corner and remain very close to the ideal boundary, indicating a True Positive Rate near 1.0 with an extremely low False Positive Rate. This suggests that the model has excellent discriminative capability and achieves an Area Under the Curve (AUC) value close to 1.0 for all classes. Compared to the individual models (such as KNN and XGBoost, which previously showed random performance), the proposed voting ensemble significantly improves prediction reliability and demonstrates superior multiclass otitis diagnosis performance. Figure 7 displays the prediction output for a test otoscopic image classified by the Proposed voting classifier. The image itself shows a tympanic membrane that is intensely red and inflamed, consistent with clinical signs of acute infection. The green text overlay at the top left confirms the model's diagnosis: "Output Classified as: Acute Otitis Media," demonstrating that the features extracted by DenseNet121 and processed by the highly accurate voting model successfully identified the characteristic pathological features of this condition.



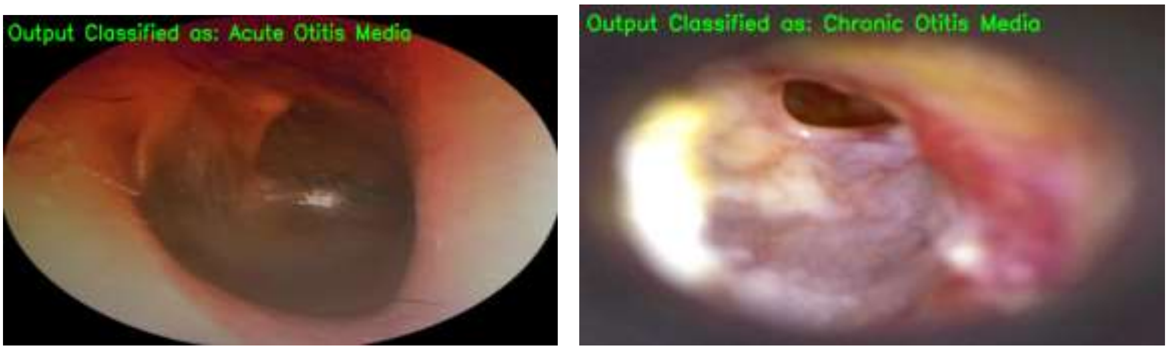


Figure 7. Prediction on test image obtained using voting classifier.

Table 1: Performance comparison for the NC, XGBoost, KNN and proposed voting models.

Algorithms Name	Accuracy	Precision	Recall	F-score
Nearest Centroid Classifier	82.33%	82.68%	82.60%	82.63%
XGBoost Classifier	17.83%	3.57%	20.00%	6.05%
KNN classifier	17.83%	3.57%	20.00%	6.05%
Voting Model	99.67%	99.67%	99.69%	99.68%

The performance comparison presented in Table 1 clearly demonstrates significant differences among the evaluated classification models: Nearest Centroid, XGBoost, KNN, and the proposed Voting Model. The Nearest Centroid classifier achieved moderate and consistent performance, obtaining an accuracy of 82.33% along with precision, recall, and F-score values around 82%, indicating that it was able to reasonably separate the classes but lacked the capability to capture more complex patterns in the feature space. In contrast, both the XGBoost and KNN classifiers performed very poorly, each producing only 17.83% accuracy with extremely low precision (3.57%), recall (20.00%), and F-score (6.05%). This suggests that these models were unable to effectively learn discriminative patterns from the extracted features, possibly due to data distribution complexity or feature characteristics that did not suit their learning behavior. The proposed Voting Model, which combines a Calibrated Perceptron and a Dense Neural Network, significantly outperformed all baseline approaches by achieving an accuracy of 99.67%, precision of 99.67%, recall of 99.69%, and F-score of 99.68%. The near-perfect and balanced metric values indicate that the ensemble approach provided highly reliable classification across all classes, minimizing both false positives and false negatives.

5. CONCLUSION

This research successfully demonstrates the effective integration of deep learning, traditional machine learning, and ensemble techniques for medical image classification. By leveraging a pretrained DenseNet121 model for deep feature extraction, the system efficiently captures discriminative patterns from otoscopic images without requiring training from scratch. The extracted deep features significantly enhance the learning capability of the classification models. Baseline machine learning algorithms such as Nearest Centroid, KNN, and XGBoost were implemented to analyze comparative performance and establish reference benchmarks. Furthermore, the proposed hybrid Voting Classifier, which combines a Calibrated Perceptron and a Dense Neural Network through a soft voting mechanism, improved prediction robustness and reliability by integrating both linear and nonlinear learning behaviors. The ensemble approach reduced individual model limitations, enhanced generalization, and provided more stable predictions across multiple disease categories.

Comprehensive performance evaluation using metrics such as accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and AUC confirmed the effectiveness of the proposed system. Additionally, the integration of a user-friendly Tkinter-based GUI and role-based authentication using TinyDB ensures practical usability and secure access control. Overall, the system offers a scalable, modular, and clinically supportive framework that can assist in early detection and automated diagnosis of ear diseases, thereby contributing toward intelligent healthcare solutions and reducing dependency on manual visual inspection.

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