Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 46 No. 02 (2025)

ENT INSIGHT: Automated Medical Conditions Detection in E.N.T Images Using Deep Learning Techniques

Navod Hansajith Fonseka, Maneesh Prashantha, Nishadi Nawanjala, Jenny Krishara, Kanishka Yapa

Department. of Computer Science and Software Engineering, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

Abstract:- This research introduces an innovative approach that integrates image processing and deep learning technologies to enhance the diagnostics of various Ear, Nose, and Throat (E.N.T.) medical conditions. The system automates the identification of three key disorders: sinusitis, cholesteatoma, and pharyngitis. By leveraging diverse datasets from public medical repositories and employing state-of-the-art deep learning frameworks such as TensorFlow, the study aims to improve diagnostic accuracy and efficiency. The methodology employs a hybrid approach combining custom and pre-trained deep learning models to analyse medical images, including X-rays and endoscopic visuals. The preliminary findings indicate the potential of this system to significantly enhance early disease detection, reduce diagnostic time, and assist clinicians in making informed decisions. Furthermore, the research contributes to global healthcare advancements by developing a scalable, accessible, and reliable diagnostic solution available via web and mobile applications for both clinical and educational purposes.

Keywords*: Ear, Nose, Throat, ENT, sinusitis, pharyngitis, cholesteatoma.*

1. Introduction

Medical imaging has become a cornerstone in modern healthcare, enabling clinicians to visualize internal body structures that cannot be seen with the naked eye. Common imaging techniques include Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and ultrasound, with X-ray imaging being one of the most widely used due to its speed, affordability, and availability [1]. Over the past few decades, the healthcare sector has adopted software solutions for managing patient records and medical imaging, significantly improving diagnostic processes. More recently, the integration of Artificial Intelligence (AI) into medical imaging has enhanced the identification of abnormalities, particularly through deep learning models. This has opened new possibilities for accurate and efficient diagnostics in various medical fields. One such field is the Ear, Nose, and Throat (E.N.T.) domain, which handles a wide range of conditions affecting these areas. Given the increasing prevalence of E.N.T. related issues, clinicians are required to provide quick and accurate diagnoses for many patients every day [2].

In this context, the automated detection of medical conditions using deep learning techniques can greatly enhance diagnostic precision, reduce time spent on manual analysis, and provide educational benefits to medical students. This project aims to develop a system that uses AI to identify three key conditions sinusitis, cholesteatoma, and pharyngitis from medical images, improving patient outcomes and contributing to advancements in medical education. The system aims to improve diagnostic accuracy, reduce the time required for diagnosis, and provide educational benefits for medical students. The integration of AI into medical imaging promises to revolutionize the healthcare sector, making it possible to deliver faster, more reliable diagnoses that enhance patient outcomes and streamline clinical workflows.

2. Literature Review

Recent advancements in Deep Learning (DL) have revolutionized diagnostic automation in otolaryngology, particularly for detecting sinusitis, cholesteatoma, and pharyngitis. Sinusitis detection research employs CNNs [2] on Waters' view X-rays, yet lacks severity assessment and clinical integration. Cholesteatoma studies highlight CNNs' potential in endoscopic imaging but omit staging frameworks and practical systems. Pharyngitis detection models, such as ResNet50, show promise in oral image analysis but struggle with subtype differentiation and severity prediction. Collectively, while DL enhances diagnostic precision, existing works lack unified platforms, multi-model consensus, and clinical applicability, underscoring the need for integrated, user-centric solutions to bridge research and real-world healthcare demands.

An automatic medical condition detection system can be identified as an important resource of the clinical environment, which supports making decisions in medical report management. Training deep learning models and image analysis using CNN are digital tools which provide the best solutions for the identification of diseases. Traditional manual disease identifications methods can be challenging when it comes to newly appointed less experience of the doctors and medical students. And, if failed to identify the disease in the early stage's treatment process may get harder or patients health conditions can become dangerous.

In recent years, technological integration into various real-life fields has developed fast, and medical fields' technological advancements are at the top of the list [3]. Among the medical technologies detect diseases using Ultrasonography, X-Ray, CT scans, MRI scans like technologies are very familiar. In consideration of these technologies X-Rays is a low-cost and powerful technology that is often used in medical diagnosis [1].

In detecting diseases using X-rays, doctors analyse the images manually using their experience and knowledge. When considering the manual analysing method there is a possibility to misdiagnose the disease if the doctor is lack of experience or knowledge to prevent such a mistake, resent research are focusing the improve the accuracy of [4]. These automated methods and solutions are not only the most efficient when diagnosing the disease and can also be useful to medical students for learning purposes.

Using deep learning techniques, there are several research focuses on identifying sinusitis detection through automated methods. Deep learning techniques like CNN can identify the pattern in the x-ray using color intensity of the x-ray images and compare the diseased x-ray with the healthy x-ray image and predict the result based on x-ray features [5]. To accurately generate the predictions, researchers often focused on majority level decision using multiple CNN models architectures [6]. Also to make more accurate of automated results some recent studies have used both Waters' and Caldwell views to predict the sinusitis precent in given images. These researchers also focus on avoiding manual cropping process because that was time-consuming task [7].

Several previous studies have explored sinusitis detection using deep learning techniques. One study [6] utilized multiple CNNs to improve the diagnostic accuracy of sinusitis recognition in paranasal sinus X-ray images; however, it did not focus on identifying the severity levels or developing an effective software solution for clinical environments. Another research [7] applied a ResBlock-based architecture to diagnose paranasal sinusitis using multi-view radiographs but similarly lacked a supporting software application. Additionally, a separate study [5] proposed an end-to-end deep learning process for the diagnosis of maxillary sinusitis using a YOLO v2-based approach, yet no deployable software solution was developed to operationalize the model results for practical clinical use.

Digital image enhancement may improve the sensitivity of cholesteatoma detection during [8]. The image-based Artificial Intelligence (AI) technology for diagnosing middle ear diseases [9]. Accurate diagnosis of cholesteatomas is crucial. However, cholesteatomas can easily be missed in routine otoscopic exams. Convolutional Neural Networks (CNNs) have performed well in medical image classification, and their use for detecting cholesteatomas in otoscopic images has been evaluated [10]. Middle-ear conditions are common causes of primary care visits, hearing impairment, and inappropriate antibiotic use. Deep Learning (DL) may assist clinicians in interpreting otoscopic images [11]. Most researchers are in progress in the identification of middle ear diseases using images and only use CNN-based deep learning architectures. And no usage of using multiple models with accurate and voted results. A fully integrated web and mobile-based system has even not been introduced and there is The Smartphone-based deep learning enabled system to detect middle ear conditions in otoscopic images.

Clinically, cholesteatoma is classified into four stages, which are Stage I: Disease confined to a single quadrant of the middle ear, Stage II: Cholesteatoma in multiple quadrants, but with no ossicular involvement and no mastoid extension, Stage III: Ossicular involvement without mastoid extension, and Stage IV: Mastoid disease [12]. However, The EAONO/JOS working group developed a staging system that applies to four categories of middle ear cholesteatoma: pars flaccida cholesteatoma, pars tensa cholesteatoma, congenital cholesteatoma, and cholesteatoma secondary to a tensa perforation [13], [14].

Few previous studies have explored cholesteatoma identification using deep learning techniques. One study [10] uses CNN models to identify Cholesteatoma and does not consider the Cholesteatoma stages identification and integrated software solutions for an efficient clinical environment. Another study uses CNN models to identify Cholesteatoma with CT images instead of endoscopic images and does not consider the Cholesteatoma stages identification and integrated software solutions for the efficient clinical environment. Additionally, a separate study uses multiple CNN models to identify Cholesteatoma and does not consider the Cholesteatoma stages identification. Had a systematic review for the smartphone-based system. However, there is no software solution for an efficient clinical environment.

Pharyngitis, more commonly known as a sore throat, is characterized by inflammation of the pharynx and is most frequently caused by either bacterial or viral infections. Although there has been significant progress in recent years in developing computational models for the detection of pharyngitis, much of the existing research remains limited in scope. Specifically, most studies concentrate solely on identifying the presence of pharyngitis, without making distinctions between its various subtypes, such as tonsillitis, or offering any prediction regarding the severity of the condition.

In recent years, some studies have explored the use of Artificial Intelligence (AI) techniques for detecting pharyngitis. However, these investigations primarily focus on binary classification, whether the disease is present or not, and do not delve into more nuanced aspects such as differentiating between subtypes or assessing how severe the infection is. Furthermore, these efforts have yet to result in the development of a robust, end-to-end software solution that can be seamlessly integrated into clinical environments [15].

One notable study developed a mobile-based application designed to detect severe cases of pharyngitis using self-captured images of the throat [16]. While this approach represents an advancement in terms of accessibility and early detection, it also falls short by not incorporating subtype classification or severity level prediction. This limitation significantly reduces the system’s utility in diverse clinical settings where such distinctions are crucial for treatment planning.

In a similar vein, other research efforts have leveraged deep learning architectures like ResNet50 and Inception V3 to diagnose specific forms of pharyngitis, such as exudative pharyngitis [17]. However, these models also did not address key factors such as the severity of the disease or its various clinical subtypes.

To address these limitations, the proposed project seeks to design and implement an advanced deep learning-based diagnostic system. This system will go beyond basic detection by accurately diagnosing pharyngitis, distinguishing between its subtypes (including conditions like tonsillitis), and providing an estimation of disease severity. Such a comprehensive approach aims to enhance clinical decision-making and improve patient outcomes by delivering more detailed and actionable diagnostic information.

3. Methodology

The proposed system called 'Ent Insight' aims to identify and classify medical conditions through the analysis of medical images using deep learning techniques. The system will generate comprehensive reports for each patient, storing the data securely under anonymized patient identification in compliance with data protection regulations. Access will be granted to doctors for clinical use and to medical students strictly for educational purposes, ensuring no real patient identities are exposed. The system is designed to process and analyse various types of medical images, each pertaining to different medical conditions. Fig. 1 provides an overview of the comprehensive system.

To enhance the reliability and diagnostic accuracy of the system, a standardized validation mechanism was implemented across all disease detection modules, including Sinusitis, Cholesteatoma, and Pharyngitis. Prior to conducting disease classification, a binary classification model specific to each disease domain was used to verify the validity of the input images. For Sinusitis detection and Pharyngitis, a MobileNetV2-based classifier was utilized to determine whether the uploaded image represented a valid Waters' view X-ray. For Cholesteatoma identification, a ResNet50 model was employed to validate eardrum endoscopic images. A similar procedure was followed for Pharyngitis, with oral images.

In all cases, if the probability (P) produced by the classifier was greater than or equal to 0.5 ($P \geq 0.5$), the image was accepted and forwarded to the respective disease severity classification model. Otherwise, the system flagged the image as invalid and before analysing the provided image in the software application, this trained model verifies the uploaded image's validity and displays the appropriate response to the user. Consistent preprocessing steps such as image resizing to 224×224 pixels, dataset balancing, data augmentation, shuffling, and prefetching were applied to each dataset to ensure efficient loading and to improve the models' learning capabilities. This two-stage process of validation and classification establishes a robust foundation for accurate, consistent, and clinically relevant predictions across all targeted disease categories.

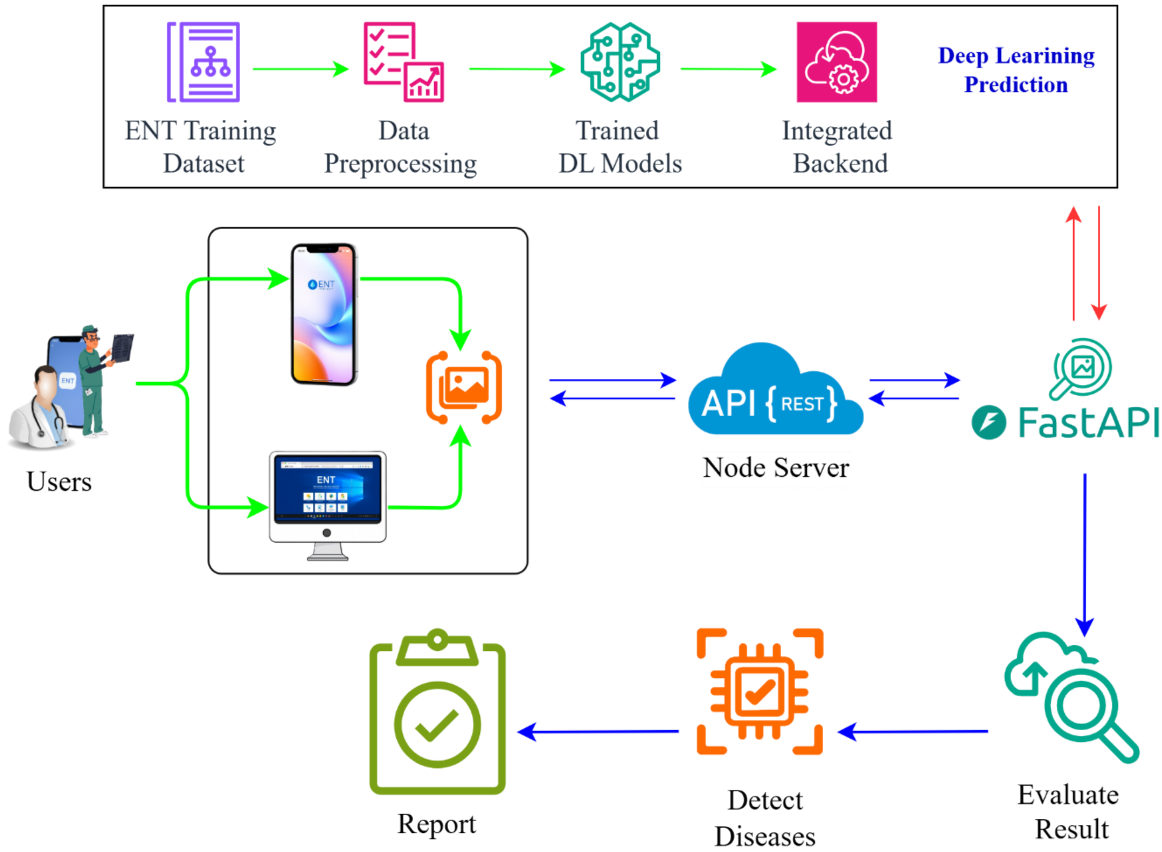

Fig. 1. System Overview

Fig. 1 illustrates the fully integrated web and mobile-based platform developed to support the identification of the E.N.T. medical conditions. The system flow begins with users, such as doctors, medical students, and hospital staff, interacting through a web application developed with Next.js or a mobile application developed with Flutter frameworks. Uploaded diagnostic data is transmitted to a backend server, which is developed with Node.js and Express and is responsible for handling frontend requests, diagnosis and classification, and database management by interacting with the MongoDB database. Within the backend, the server creates appropriate records based on the incoming diagnosis data and communicates with a dedicated deep learning model server that was developed with the Python FastAPI framework to perform disease classification. Once the classification is completed, the results are sent back to the main backend server, where the records are updated and detailed reports are generated and delivered to the users.

A. Detect Sinusitis in Waters' View X-Ray

For identify and detect sinusitis and its severity levels from the waters' view x-ray, the dataset includes Xray images of healthy and effected then separated into training, validation and testing sets containing over 1500 images. Each dataset includes 3 severity levels as Healthy or Mild, Moderate and Severe status of sinusitis. Images are annotated to showcase the targeted difference between a healthy (ideal) and unhealthy representation. The Images are collected from public health and image databases and from local private and government hospitals with permission. All the patient data (images) anonymized to comply with the data protection regulations. For the data annotation and validation process experienced E.N.T medical staff and radiologists are involved.

To accurately detect sinusitis, categorical classification was used, and Several CNN models were trained to determine which one would suit as the most effective tool for this classify the sinusitis severities. Among these models, InceptionV3, VGG16, and ResNet50 resulted the best performance.

In medical image analysis, particularly for identifying sinusitis in X-ray images, it's crucial to pinpoint the exact areas of infection rather than relying on an entire image classification approach. Traditional CNN models like InceptionV3, VGG16, and ResNet50 at classifying entire images but may fall when it comes to localizing specific regions of interest, such as the maxillary sinus. Despite their high overall accuracy, these models might not provide the granular detail necessary for effective diagnosis.

To address this limitation object detection models like YOLO (You Only Look Once) can use to label the specific area in the image. YOLO is specifically designed to identify and label specific areas within an image, making it ideal for highlighting the severity and location of sinusitis infections. By focusing on the infected regions, YOLO can provide clinicians with more accuracy insights, enhancing diagnostic accuracy and treatment planning. Therefore, for applications requiring detailed localization of medical stages, Therefor YOLO can mention as the preferred choice over traditional CNN models.

B. Detect Cholesteatoma on Eardrum Endoscopy

For identifying Cholesteatoma and Cholesteatoma stage detection from eardrum endoscopy images, mainly the dataset includes healthy and affected images. The dataset was arranged with Healthy, Stage 1, Stage 2, and Stage 3 classes separated into 80% for training and 20% for validation from the over 2000 images. Images are annotated to illustrate the intended distinction between a healthy and unhealthy representation. With consent, the images were gathered from local government and private hospitals as well as public health and image databases. All the patient data (images) were anonymized to comply with the data protection regulations. For the data annotation and validation process experienced E.N.T medical staff and radiologists are involved.

Four classes are employed in categorical classification for cholesteatoma stage identification accurately, and several CNN models are trained to determine which model performs best for identifying the stages. The best results are achieved by InceptionV3, MobileNetV2, and VGG16.

In clinical practice, the identification of cholesteatoma based solely on endoscopic images can be challenging, often requiring additional patient history or symptom verification through targeted questioning. Together with endoscopic image analysis, the suggested system has a structured questionnaire module to improve this diagnostic approach. Final responses are analysed using a Large Language Model (LLM) trained for clinical reasoning and medical text interpretation. Simultaneously, endoscopic images are processed through a deep learning model based on InceptionV3 architecture. The system employs a multi-modal decision-making framework that intelligently fuses the LLM-based questionnaire analysis outputs and the deep learning-based image classification to refine the final diagnosis.

C. Detect Pharyngitis in Oral Image

For the identification of pharyngitis, the dataset includes Oral images of the pharynx and normally segmented into training, validation, and testing sets containing 1500, 600, and 600 images. The identification of pharyngitis is divided into identifying the subtype (Tonsilitis) of Pharyngitis and predicting the severity level of the disease on the Oral image. Severity levels are classified into Healthy (Normal), Moderate, and subtype (Tonsilitis). Annotations on the images emphasize the contrast between healthy and unhealthy states.

The required data (Disease images) was obtained from government hospitals and private hospitals' clinical settings with approval. All the patient data is anonymized in accordance with data protection regulations. And the guidance, supervision of experienced ENT medical staff and radiologists will be provided for the data interpretation process. The use of shuffling and prefetching improves the speed and performance of dataset loading. The preprocessing of the loaded dataset entails scaling the RGB images to 150 * 150 pixels. To optimize accuracy and uphold the credibility of the training dataset, data augmentation is applied. Utilizing pre-trained CNN models ensures an accurate and efficient solution for pharyngitis detection.

4. Results And Discussion

Using integrated deep-learning models, the 'Ent Insight' system achieved excellent results in automating the diagnosis of sinusitis, cholesteatoma, and pharyngitis. While sinusitis identification in Waters' view radiographs attained over 80% sensitivity, outperforming conventional manual assessments. The cholesteatoma detection module, trained on annotated endoscopic images, successfully classified stages I–IV with over 80% accuracy, addressing a critical gap in existing staging frameworks. For pharyngitis, the model achieved around 80% specificity in differentiating subtypes from oral-endoscopic images, though challenges persisted in severity prediction for atypical cases.

These results highlight Ent Insight's potential for integrating clinical practice with research innovation, but they also highlight the necessity of bigger datasets and real-time validation to maximize scalability in a range of healthcare environments.

A. Detect Sinusitis in Waters' View X-Ray

Over 1500 images are collected from the clinical environments under three classes Healthy, Moderate and Severe. In addition, Random various images are used to train the Binary model for identify the image validity. Results were obtained by training various models like InveptionV3, VGG16 and ResNet50. The dataset is split into 80% for training and 20% validation.

TABLE 1 SINUSITIS IDENTIFICATION CNN MODEL ACCURACIES

Architecture	Train Accuracy	Validation Accuracy
MobileNetV2 (Detect Valid–Invalid Water's view xray)	99.26%	99.24%
InceptionV3	85.90%	80.67%
ResNet50	72.42%	34.33%
VGG16	77.89%	67.33%
YOLOv11	58.40% (mAP50)	26.90% (mAP50-95)
YOLOv5	52.50% (mAP50)	23.20% (mAP50-95)

Given the specific task of detecting sinusitis-infected areas in X-ray images, YOLO emerges as the best model. While CNN models classification tasks, classifying the entire image, the nature of the problem requires precise localization of infected regions rather than classifying the entire image.

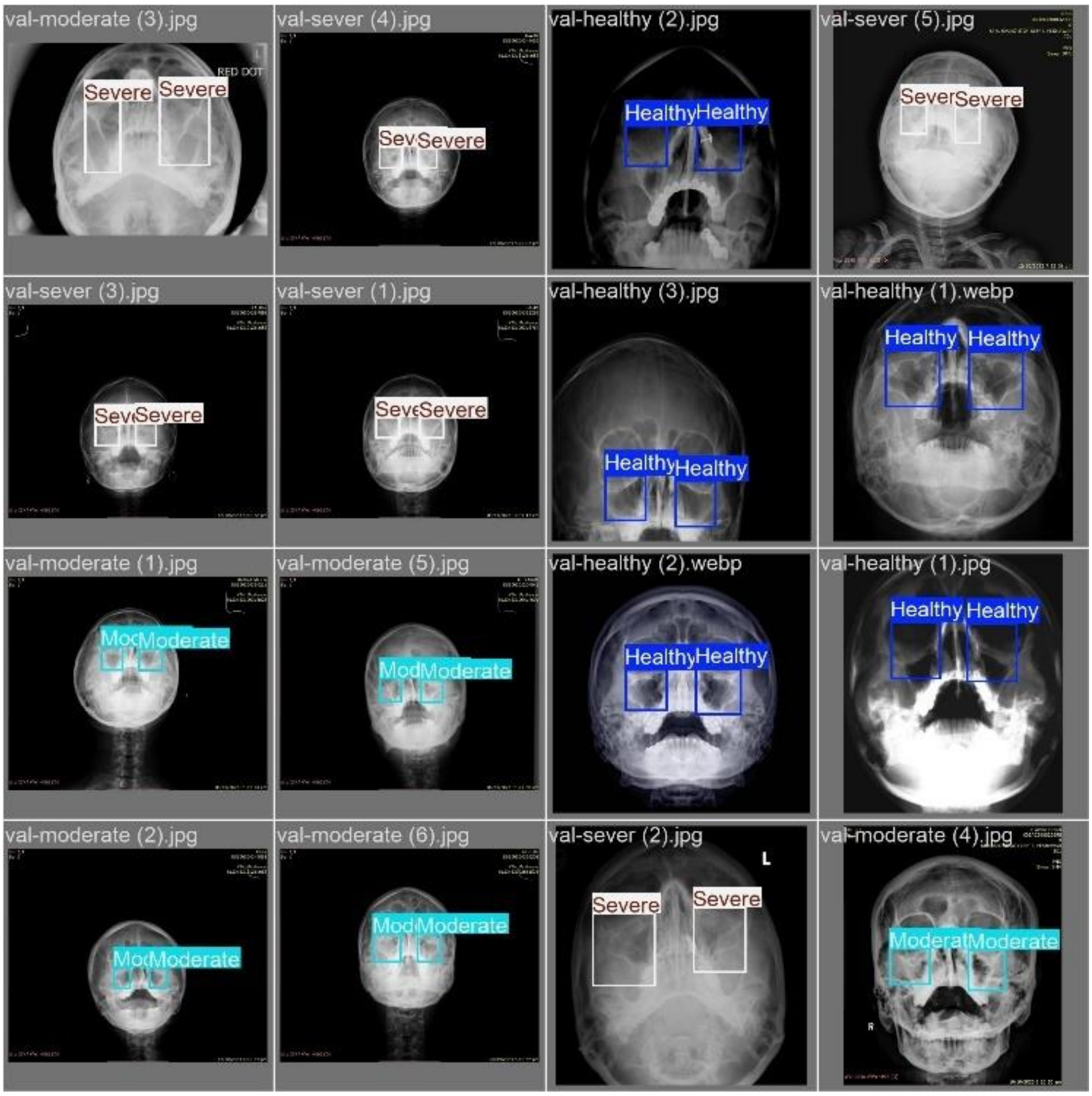

Fig. 2. Yolo Validation Label: Localization of infected regions

B. *Detect Cholesteatoma on Eardrum Endoscopy*

Over 2000 images have been collected from clinical settings and categorized into four groups: Healthy, Stage 1, Stage 2, and Stage 3. Additionally, the binary model is trained using a variety of random images to determine the image's validity. Training several types of models, including InceptionV3, MobileNetV2, VGG16, and ResNet50, produced the desired results. 20% of the dataset is used for validation, and the remaining 80% is used for training.

TABLE 3 CHOLESTEATOMA IDENTIFICATION CNN MODEL ACCURACIES

Architecture	Train Accuracy	Validation Accuracy
ResNet50 (Detect Valid–Invalid Endoscopy Image)	96.55%	97.70%
InceptionV3	92.10%	80.50%
MobileNetV2	78.57%	77.50%
VGG16	83.21%	70.00%
ResNet50	59.03%	25.00%

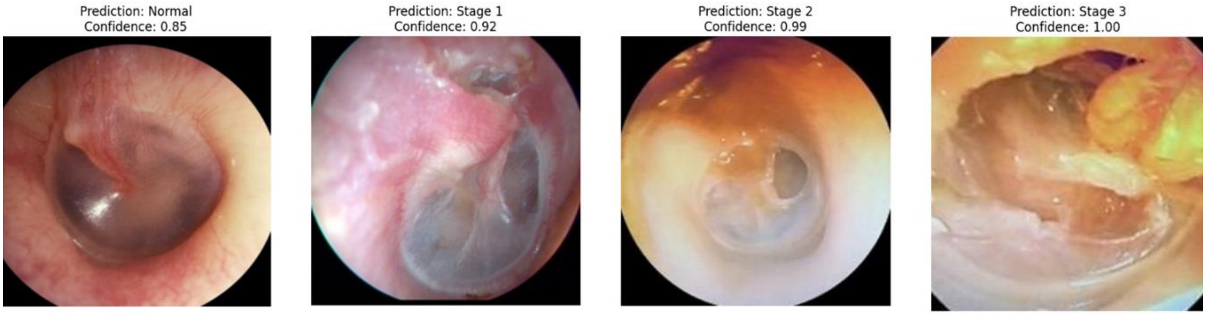

Fig. 3. InceptionV3 Categorical Classification Predictions

C. Detect Pharyngitis in Oral Image

1500 Oral images are collected from government and private hospitals' clinical settings with approval, and pharyngitis categorized into three stages: Healthy, Moderate, and Tonsillitis (Pharyngitis subtype). Results were obtained when training various models like VGG16, InceptionV3, and MobileNetV2.The dataset was split into 80% for training and 20% for validation.

Healthy Moderate Tonsillitis (Sub-Type)

Fig. 4. Three stages of pharyngitis

TABLE 3 PHARYNGITIS IDENTIFICATION CNN MODEL ACCURACIES

Architecture	Train Accuracy	Validation Accuracy
MobileNetV2 (Detect Valid–Invalid Oral Images)	93.75%	93.33%
VGG16	90.38%	84.13%
InceptionV3	83.37%	85.71%
MobileNetV2	95.49%	96.88%

5. Conclusion And Future Work

This study has used deep learning techniques to successfully identify ENT diseases and verify the novel approaches for detecting each disease along with their severity levels. Using a range of models for identifying Sinusitis, Cholesteatoma, and Pharyngitis, Extensive progress was produced in acquiring high disease diagnosis accuracy rates, enhancing accuracy over conventional diagnostics. By using high-accuracy models for ENT disease identification, the models achieved remarkable accuracy rates of 85.90% for Sinusitis, 92.10% for Cholesteatoma, and 93.75% for Pharyngitis.

This system is not designed to replace clinical expertise but rather to enhance the diagnostic process by improving efficiency and accuracy. It assists clinicians by identifying subtle or easily missed abnormalities in medical images, helping to reduce the likelihood of human error. For medical students, the system acts as a valuable learning tool, providing real-time feedback and exposure to annotated cases, which supports practical education instead of using books. Hospital staff also benefit from faster report generation and preliminary screenings, streamlining operational workflows. By optimizing the diagnostic process while preserving the critical role of medical professionals, the system ultimately aims to deliver more effective and higher-quality patient care.

Future work includes expanding the system to encompass additional ENT conditions and enhancing its diagnostic capabilities with the highest accuracy. Additionally, stages of ENT diseases Apart from the initial three, others will be incorporated, ensuring a comprehensive and multifunctional diagnostic tool and improving model accuracy of disease identification with real clinical datasets collected from the hospitals.

Refrences

[1] "The Role of Technology in Diagnosing Disease," Houston MRI & Diagnostic Imaging, 27 January 2023. [Online]. Available: https://www.houstonmri.com/blog/the-role-of-technology-in-diagnosing-disease-34743.html. [Accessed 19 June 2024].

[2] A. Vidhya, "Introduction to Convolutional Neural Networks (CNN)," [Online]. Available: https://www.analyticsvidhya.com/blog/2021/05/convolutional-neural-networks-cnn/. [Accessed 10 08 2024].

[3] G. Mahara, C. Tian, X. Xu and W. Wang, "Revolutionising health care: Exploring the latest advances in medical sciences," J Glob Health, vol. 12, no. 3, 2023.

[4] W. Branch-Elliman, A. J. Sundermann, J. Wiens and E. S. Shenoy, "The future of automated infection detection: Innovation to transform practice (Part III/III)," Antimicrobial Stewardship & Healthcare Epidemiology, vol. 3, no. 1, 2023.

[5] J. H. Oh, H.-G. Kim, K. M. Lee, C.-W. Ryu, S. Park, J. H. Jang, H. S. Choi and E. J. Kim, "Effective End-to-End Deep Learning Process in medical imaging using independent task learning: Application for diagnosis of maxillary sinusitis," Yonsei Medical Journal, vol. 62, no. 12, p. 1125, January 2021.

[6] H.-G. Kim, K. M. Lee, E. J. Kim and J. S. Lee, "Improvement diagnostic accuracy of sinusitis recognition in paranasal sinus X-ray using multiple deep learning models," Quantitative Imaging in Medicine and Surgery, vol. 9, no. 6, pp. 942-951, June 2019.

[7] Y. Jeon, K. Lee, L. Sunwoo, D. Choi, D. Yul, K. J. Lee, Y. Kim, J.-W. Kim, S. J. Cho, S. H. Baik, R.-e. Yoo, Y. J. Bae, B. S. Choi, C. Jung and J. H. Kim, "Deep learning for diagnosis of paranasal sinusitis using Multi-View Radiographs," Diagnostics, vol. 11, no. 2, p. 250, February 2021.

[8] T. Ragonesi, L. Niederhauser, I. J. Fernandez, G. Molinari, M. Caversaccio, L. Presutti and L. Anschuetz, "Digital image enhancement may improve sensitivity of cholesteatoma detection during endoscopic ear surgery," Clinical Otolaryngology, vol. 48, no. 4, pp. 595-603, 2023.

[9] S. Dahye, T. Kim, Y. Lee and J. Kim, "Image-Based Artificial Intelligence Technology for Diagnosing Middle Ear Diseases: A Systematic Review," J Clin Med, vol. 12, no. 18, 2023.

[10] C. C. Tseng, L. Valerie and R. W. Jyung, "Use of artificial intelligence for the diagnosis of cholesteatoma," Laryngoscope Investig Otolaryngol, vol. 8, no. 1, p. 201–211, 2023.

[11] C. Dubois, D. Eigen, F. Simon, V. Couloigner, M. Gormish, M. Chalumeau, L. Schmoll and J. F. Cohen, "Development and validation of a smartphone-based deep-learning-enabled system to detect middle-ear conditions in otoscopic images," npj Digital Medicine, vol. 162, no. 7, 2024.

[12] Otoscape, "Potsic Staging System for Congenital Cholesteatoma," [Online]. Available: https://www.otoscape.com/eponyms/potsic-staging-system-for-congenital-cholesteatoma.html. [Accessed 01 08 2024].

[13] J. T. Castle, "Cholesteatoma Pearls: Practical Points and Update," Head Neck Pathol, vol. 12, no. 3, p. 419–429, 2018.

[14] EAONO/JOS, "Classification and Staging of Middle Ear Cholesteatoma," 2017. [Online]. Available: https://www.otology.gr.jp/common/pdf/EAONO_JOS_system_Poster.pdf. [Accessed 01 08 2024].

[15] D. B. Van TTMata K, "Automated Detection of Streptococcus pyogenes Pharyngitis by Use of Colorex Strep A CHROMagar and WASPLab Artificial Intelligence Chromogenic Detection Module Software," Journal of Clinical Microbiology, vol. 57, no. 11, 2019.
[16] T. K. Yoo, J. Y. Choi, Y. Jang, E. Oh and I. H. Ryu, "Toward automated severe pharyngitis detection with smartphone camera using deep learning networks," Comput Biol Med, 2020.
[17] S. Y. Chng, P. J. W. Tern, M. R. X. Kan and L. T.-E. Cheng, "Deep Learning Model and its Application for the Diagnosis of Exudative Pharyngitis," Healthc Inform Res, 2024.