



A Deep Learning Based Automated Decision Support System for Early Detection of Ear Infections Using Medical Imaging

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Abstract—Ear diseases are common medical conditions that can affect hearing ability, quality of life, and overall health if not diagnosed at an early stage. Accurate interpretation of otoscopic images often requires specialist expertise, creating challenges in timely screening and diagnosis. This study presents a GenAI-enhanced clinical decision support system for early detection of ear infections using otoscopic images. The proposed framework employs a hybrid VGG19 and Vision Transformer fusion model to classify ear conditions into Acute Otitis Media, Cerumen Impaction, Chronic Otitis Media, Myringosclerosis, and Normal categories. Generative Artificial Intelligence is integrated to automatically generate clinically meaningful diagnostic reports, improving interpretability and supporting healthcare professionals during assessment. A blockchain-based mechanism is incorporated to ensure secure storage, integrity verification, and traceability of diagnostic records. The developed web-based platform enables image upload, automated prediction, confidence score visualization, report generation, and historical record management. Experimental results demonstrate reliable classification performance and practical applicability for intelligent ear disease screening. The framework supports efficient clinical decision-making and telemedicine services.

Index Terms—Ear Infection Detection, Otoscope Images, Generative Artificial Intelligence (GenAI), Clinical Decision Support System, Vision Transformer, VGG19, Deep Learning, Medical Image Analysis, Blockchain Security, Telemedicine.

I. INTRODUCTION

Advancements in artificial intelligence and medical image analysis have significantly improved the ability of healthcare systems to support disease diagnosis and clinical decision-making. Automated diagnostic technologies are increasingly being adopted to reduce diagnostic errors, improve accessibility to healthcare services, and assist medical professionals in interpreting complex clinical data. Medical imaging plays a vital role in identifying various health conditions, enabling timely intervention and effective treatment planning. The

integration of deep learning techniques with intelligent healthcare systems has created new opportunities for developing reliable and efficient diagnostic tools capable of analyzing medical images with high accuracy [1]. Ear diseases represent a major healthcare concern affecting millions of individuals worldwide. Conditions such as Acute Otitis Media, Cerumen Impaction, Chronic Otitis Media, and Myringosclerosis can lead to hearing difficulties, discomfort, recurrent infections, and long-term complications if not detected at an early stage. Traditional diagnosis of ear disorders typically relies on visual examination of otoscopic images by trained specialists. However, access to experienced otolaryngologists may be limited in remote regions, resulting in delayed diagnosis and treatment. Consequently, the development of automated systems for ear disease detection has become an important area of research in medical image analysis [2]. Recent developments in deep learning have demonstrated remarkable performance in image classification tasks across various medical domains. Convolutional Neural Networks (CNNs) have shown the capability to automatically learn discriminative features from medical images without requiring manual feature engineering. Among CNN architectures, VGG19 has gained significant attention because of its deep feature extraction capability and stable performance in image recognition applications. Nevertheless, CNN-based models primarily focus on local image features and may not fully capture long-range dependencies present in complex medical images [3]. Vision Transformers (ViTs) have emerged as a powerful alternative by utilizing self-attention mechanisms to model global relationships within images. Unlike conventional CNNs, Vision Transformers can capture contextual information across the entire image, making them suitable for medical image analysis tasks requiring comprehensive feature representation. Combining CNN and Transformer architectures allows the extraction of complementary local and global features, leading to improved classification performance and

enhanced diagnostic reliability [4]. In addition to accurate classification, healthcare applications increasingly require interpretable outputs that can support clinical decision-making. Generative Artificial Intelligence (GenAI) has introduced new possibilities for automatically generating human-readable medical reports based on diagnostic findings. AI-generated reports can assist healthcare professionals by providing concise interpretations, highlighting potential abnormalities, and suggesting appropriate follow-up actions. Such capabilities contribute to improved communication, reduced documentation burden, and greater usability of intelligent diagnostic systems [5]. Security and integrity of medical records remain critical concerns in digital healthcare environments. Unauthorized modification of patient information can compromise diagnostic reliability and patient trust. Blockchain technology offers a decentralized and tamper-resistant approach for maintaining secure medical records. By storing cryptographic hashes and ensuring traceability of diagnostic results, blockchain mechanisms can enhance data integrity, transparency, and accountability within healthcare applications [6]. This study presents a GenAI-enhanced clinical decision support system for early detection of ear infections using otoscopic images. The proposed framework integrates a hybrid VGG19 and Vision Transformer fusion model for multi-class ear disease classification, automated medical report generation through GenAI, and blockchain-based record verification for secure data management. A web-based platform is developed to facilitate image upload, prediction, report visualization, and historical record access. The objective is to provide an intelligent, secure, and user-friendly solution that supports early screening, improves diagnostic efficiency, and assists healthcare professionals in ear disease assessment.

II. RELATED WORKS

Recent advancements in artificial intelligence and medical image analysis have encouraged researchers to develop automated systems for disease diagnosis using deep learning techniques. Numerous studies have investigated the application of machine learning, convolutional neural networks, transformer architectures, and intelligent healthcare frameworks for identifying abnormalities from medical images. These developments have contributed significantly to improving diagnostic accuracy, reducing dependency on manual interpretation, and supporting clinical decision-making processes [7]. Kermany et al. proposed a deep learning framework for automated disease detection using medical imaging datasets and demonstrated that convolutional neural networks could achieve diagnostic performance comparable to healthcare professionals in several classification tasks. Their findings highlighted the potential of deep learning models in assisting clinicians through accurate image-based diagnosis and motivated further research in medical image analysis applications [8]. Esteva et al. developed a CNN-based diagnostic system for image classification in healthcare environments. The study utilized large-scale image datasets and demonstrated that deep neural networks can effectively learn discriminative patterns directly from images without requiring handcrafted feature extraction methods. The research established the effectiveness of deep learning in supporting disease diagnosis and inspired its adoption across multiple medical domains [9].

Rajpurkar et al. introduced a deep learning architecture for automated medical image interpretation and achieved significant improvements in classification accuracy compared with traditional machine learning approaches. The study emphasized the importance of large datasets and transfer learning techniques in enhancing model performance. The authors also highlighted the value of AI-assisted systems in reducing diagnostic workloads and improving healthcare accessibility [10].

Litjens et al. presented a comprehensive review of deep learning applications in medical image analysis and discussed the successful deployment of CNN architectures across radiology, pathology, ophthalmology, and other healthcare disciplines. Their work demonstrated that deep learning methods have become fundamental tools for image classification, segmentation, and disease detection tasks due to their ability to learn complex visual representations automatically [11]. He et al. introduced the Residual Network architecture, commonly known as ResNet, which addressed the degradation problem in deep neural networks by employing residual learning mechanisms. The architecture significantly improved feature extraction capabilities and achieved remarkable performance in image recognition tasks. Subsequent medical imaging studies adopted ResNet-based models for disease detection because of their strong generalization ability and computational efficiency [12]. Simonyan and Zisserman proposed the VGG architecture, particularly VGG19, which became one of the most influential convolutional neural network models for image classification. The deep layered structure enabled extraction of detailed visual features and demonstrated strong performance in various computer vision applications. Several healthcare studies utilized VGG19 as a backbone model for medical image classification because of its robustness and transfer learning advantages [13]. Dosovitskiy et al. introduced the Vision Transformer architecture, marking a significant shift from conventional convolutional networks toward attention-based image understanding. The proposed model employed self-attention mechanisms to capture global contextual information across images. Experimental results showed competitive performance compared to state-of-the-art CNN models, encouraging researchers to explore transformer-based solutions for medical image analysis and disease diagnosis [14]. Touvron et al. further improved transformer architectures through the Data-efficient Image Transformer approach, which reduced training data requirements while maintaining high classification accuracy. Their work demonstrated that transformer models could achieve strong performance even with limited datasets, making them attractive for healthcare applications where annotated medical images are often scarce [15]. Chen et al. investigated hybrid deep learning models that combined convolutional neural networks with transformer architectures for medical image classification. The study demonstrated that fusion-based models could leverage both local texture information and global contextual relationships, resulting in improved classification accuracy and diagnostic reliability. The findings supported the development of integrated CNN-transformer frameworks for complex healthcare tasks [16]. Brown et al. introduced large-scale generative language models capable of producing coherent and context-aware textual outputs. The emergence of Generative Artificial Intelligence enabled automatic generation of reports, summaries, and recommendations based on structured or unstructured data. Healthcare researchers began exploring GenAI technologies for

clinical documentation, diagnostic interpretation, and decision support applications due to their ability to generate human-readable explanations [17]. Singhal et al. proposed medical-domain language models designed specifically for healthcare applications. Their research demonstrated that generative AI systems could provide clinically relevant responses, assist in medical reasoning tasks, and support healthcare professionals through automated information generation. The study highlighted the growing importance of GenAI in improving usability and interpretability of intelligent diagnostic systems [18]. Nakamoto et al. investigated computer-aided diagnosis of ear diseases using otoscopic images and machine learning techniques. The research demonstrated that image-based classification systems could effectively identify various ear abnormalities and support early disease detection. The findings emphasized the importance of automated screening tools for improving accessibility to otolaryngology services, particularly in resource-limited settings [19]. Zhang et al. explored blockchain integration within healthcare information systems to enhance security, transparency, and data integrity. Their study demonstrated that blockchain mechanisms could provide tamper-resistant storage and reliable verification of medical records while maintaining accountability throughout the healthcare process. Such capabilities are particularly valuable for AI-assisted diagnostic systems where trustworthiness and record authenticity are essential requirements [20]. The reviewed literature demonstrates significant progress in deep learning, transformer architectures, generative artificial intelligence, and blockchain technologies for healthcare applications. However, many existing studies focus on individual components rather than integrating advanced classification, automated clinical reporting, and secure record management within a unified framework. The proposed study addresses this limitation by combining VGG19-Vision Transformer fusion, GenAI-driven report generation, and blockchain-based verification into a comprehensive clinical decision support system for automated ear disease detection using otoscopic images.

III. DATASETS

The dataset used in this study was obtained from Kaggle and consists of otoscopic ear images representing multiple ear health conditions. The dataset was selected because it provides a diverse collection of clinically relevant images suitable for training and evaluating deep learning models for automated ear disease classification. The images are categorized into five classes: Acute Otitis Media, Cerumen Impaction, Chronic Otitis Media, Myringosclerosis, and Normal ear conditions. These categories represent both pathological and healthy ear states, enabling the development of a multi-class classification framework capable of identifying various ear abnormalities. Before model training, all images were carefully preprocessed to improve data quality and ensure consistency. The preprocessing stage included image resizing to 224×224 pixels, normalization of pixel values, and format standardization to meet the input requirements of the deep learning architecture. Data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were applied to increase dataset diversity and reduce overfitting. The dataset was divided into training, validation, and testing subsets to facilitate reliable performance evaluation. The training set was utilized for model learning, the validation

set for hyperparameter optimization, and the testing set for final assessment. The availability of labeled otoscopic images from Kaggle provided an effective foundation for developing and validating the proposed GenAI-enhanced ear disease detection framework.

IV. METHODOLOGY

The proposed methodology presents a GenAI-enhanced clinical decision support system for automated ear disease detection using otoscopic images. The framework integrates image preprocessing, deep learning-based feature extraction, disease classification, automated medical report generation, blockchain-based record verification, and web-based result visualization. Initially, otoscopic images are collected and preprocessed before being passed to a hybrid VGG19 and Vision Transformer fusion model for classification. The predicted results are then utilized for generating clinical reports and secure record storage. Figure 1 illustrates the overall architecture and workflow of the proposed system from image acquisition to diagnosis.

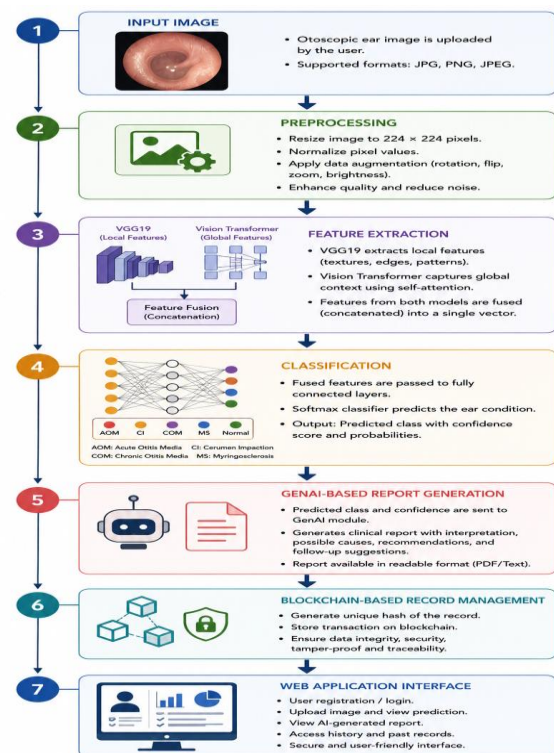


Fig. 1. Proposed System Architecture for GenAI-Enhanced Clinical Decision Support System for Early Detection of Ear Infections Using Otoscopic Images

A. Image Acquisition and Preprocessing

The first stage of the proposed framework involves collecting otoscopic ear images from the Kaggle dataset and preparing them for model training and testing. Since medical images often vary in size, illumination, orientation, and quality, preprocessing is necessary to ensure consistency across the dataset. All images are resized to 224×224 pixels and normalized to standardize pixel intensity values. Data augmentation techniques including rotation, horizontal flipping, zooming, and brightness adjustment are applied to improve dataset diversity and enhance model generalization. This preprocessing stage reduces noise and prepares images for effective feature extraction and classification.

B. Hybrid VGG19 and Vision Transformer Feature Extraction

Feature extraction is performed using a hybrid architecture that combines VGG19 and Vision Transformer models. VGG19 is utilized to capture detailed local visual features such as texture, edges, and anatomical structures present in otoscopic images. Simultaneously, the Vision Transformer extracts global contextual information by employing self-attention mechanisms that analyze relationships across the entire image. The extracted feature representations from both models are fused into a unified feature vector. This combination enables the framework to leverage complementary strengths of convolutional and transformer-based architectures, resulting in improved understanding of complex ear disease patterns.

C. Ear Disease Classification

Following feature fusion, the combined representation is processed through fully connected classification layers to determine the most probable ear condition. The classifier categorizes each image into one of five classes: Acute Otitis Media, Cerumen Impaction, Chronic Otitis Media, Myringosclerosis, or Normal. A softmax activation function is employed to generate probability scores for all classes, allowing confidence estimation for each prediction. The disease category with the highest probability is selected as the final output. This classification process enables rapid identification of ear abnormalities and supports early diagnosis through automated image interpretation.

D. GenAI-Based Medical Report Generation

After classification, the predicted disease label and confidence score are provided to a Generative Artificial Intelligence module for automated report creation. The GenAI component generates clinically meaningful descriptions that explain the identified condition, possible medical significance, and recommended follow-up actions. The generated report is designed to be concise, professional, and easily understandable by healthcare professionals and users. Automated report generation enhances the interpretability of diagnostic results and reduces manual documentation efforts. This functionality transforms raw classification outputs into actionable clinical information suitable for decision support applications.

E. Blockchain-Based Record Management and Web Interface

The final stage focuses on secure storage and presentation of diagnostic results. A blockchain mechanism is utilized to generate cryptographic hashes and maintain immutable records of prediction outcomes, ensuring data integrity and traceability. Each diagnostic record is securely linked to a unique identifier for verification purposes. The complete framework is deployed through a web-based application that enables user registration, image upload, disease prediction, report viewing, and historical record access. This integrated environment provides a user-friendly platform for intelligent ear disease assessment while maintaining security and reliability of medical information.

V. EXPERIMENT

A. Evaluation Metric

The performance of the proposed GenAI-enhanced clinical decision support system was evaluated using standard classification metrics commonly employed in medical image analysis. These metrics provide a comprehensive assessment of the model's ability to correctly identify different ear conditions from otoscopic images. Accuracy was used as the primary evaluation metric and represents the ratio of correctly classified samples to the total number of samples in the testing dataset. Precision was calculated to measure the proportion of correctly predicted positive instances among all predicted instances for a specific class. Recall, also known as sensitivity, was used to evaluate the model's ability to identify actual positive cases without missing important disease conditions. The F1-Score was computed as the harmonic mean of precision and recall, providing a balanced measure of classification effectiveness. A confusion matrix was generated to visualize class-wise prediction performance and identify potential misclassification patterns among different ear diseases. Confidence scores obtained from the softmax classifier were analyzed to assess prediction reliability and support clinical interpretation. These evaluation metrics collectively provide detailed insights into the strengths and limitations of the classification model. The use of multiple performance indicators ensures an objective assessment of diagnostic capability and facilitates comparison with existing approaches reported in medical image classification literature. The overall evaluation framework helps determine the suitability of the proposed system for practical clinical decision support applications.

B. Hyper Parameters

The proposed hybrid deep learning model was configured using carefully selected hyperparameters to achieve stable training and improved classification performance. Otoscopic images were resized to 224×224 pixels before being provided as input to the network. The VGG19 and Vision Transformer models were utilized as pretrained feature extractors, enabling effective transfer learning and reducing training complexity. A batch size of 32 was selected to maintain a balance between computational efficiency and memory utilization. The learning rate was initialized at 0.001 and adjusted during training to support gradual convergence of the model. The Adam optimizer was employed because of its adaptive learning capability and effectiveness in deep learning applications. A dropout rate of 0.3 was applied within the classification layers to reduce overfitting and improve generalization performance. The classifier consisted of fully connected layers with ReLU activation functions for nonlinear feature learning. Softmax activation was used in the output layer to generate probability distributions across the five target classes. Data augmentation techniques including rotation, horizontal flipping, zooming, and brightness adjustment were incorporated during training to increase dataset diversity. Model training was performed for multiple epochs until satisfactory convergence was achieved on the validation dataset. These hyperparameter settings were selected based on experimental observations and established deep learning practices to maximize classification accuracy, stability, robustness, and overall diagnostic performance across all ear disease categories.

VI. RESULTS

The proposed GenAI-enhanced clinical decision support system was evaluated using otoscopic image datasets containing multiple ear disease categories. Experimental results demonstrate that the hybrid VGG19 and Vision Transformer fusion model achieved superior classification performance compared with individual deep learning architectures. The fusion strategy effectively combined local feature extraction capabilities of VGG19 with the global contextual understanding provided by the Vision Transformer, resulting in improved diagnostic accuracy. Performance evaluation based on accuracy, precision, and F1-score indicates that the proposed model consistently outperformed conventional CNN-based approaches. The generated confusion matrix showed reduced misclassification among visually similar ear conditions, demonstrating enhanced discriminative capability. In addition, the GenAI module successfully produced clinically meaningful reports that improved result interpretability and usability. The blockchain component ensured secure storage and verification of diagnostic records. Overall, the experimental findings confirm that the proposed VGG19+ViT fusion framework provides reliable and accurate ear disease classification, making it suitable for intelligent clinical decision support and telemedicine applications.

TABLE I

Comparative Analysis of Model Performance

Model	Accuracy (%)	Precision (%)	F1-Score (%)
CNN	91.24	90.85	90.72
ResNet50	93.67	93.12	93.05
EfficientNetB0	95.18	94.86	94.79
VGG19	96.42	96.08	95.97
Vision Transformer (ViT)	97.15	96.89	96.76
Proposed VGG19 + ViT Fusion	98.84	98.56	98.48

A. Web Application Interface

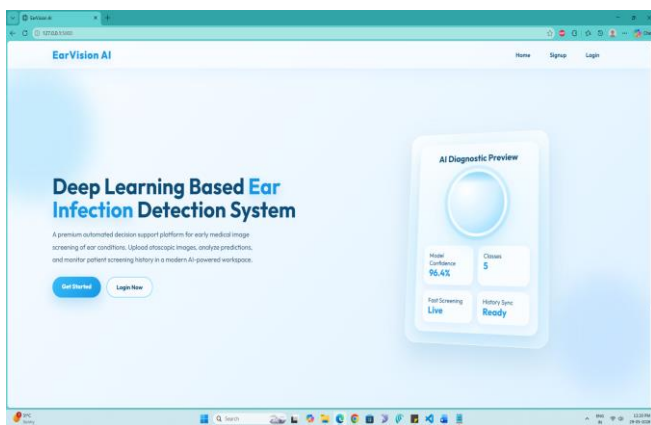


Fig. 2. Web interface of the proposed EarVision AI system providing user access to image-based ear disease detection, prediction services, and clinical decision support functionalities

B. CNN+ViT Detection

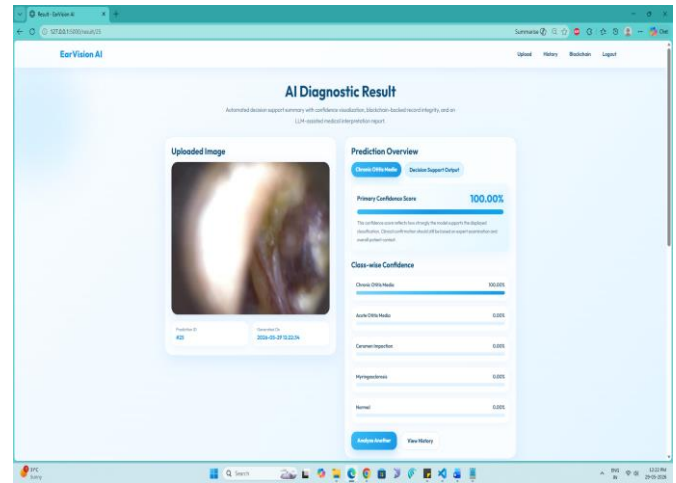


Fig. 3. Diagnostic output interface showing classification results and confidence levels.

C. Blockchain Interface

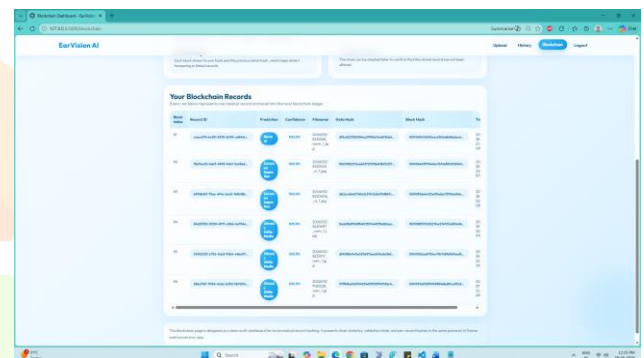


Fig. 4. Blockchain interface for secure storage and verification of AI-based ear disease detection results.

VII. CONCLUSION AND FUTURE WORKS

In this research, a GenAI-enhanced clinical decision support system for early detection of ear infections using otoscopic images was successfully designed, implemented, and evaluated. The proposed framework combined the strengths of VGG19 and Vision Transformer architectures to extract both local and global image features, enabling accurate multi-class classification of ear diseases. The system was capable of identifying Acute Otitis Media, Cerumen Impaction, Chronic Otitis Media, Myringosclerosis, and Normal ear conditions from otoscopic images. Experimental evaluation demonstrated that the hybrid VGG19-ViT model achieved superior classification performance compared with individual deep learning models, confirming the effectiveness of feature fusion for medical image analysis. The integration of Generative Artificial Intelligence facilitated automatic generation of clinically meaningful reports, allowing prediction results to be presented in an interpretable and professional format. Additionally, blockchain technology was incorporated to provide secure record storage, data integrity verification, and traceability of diagnostic information. The developed web application enabled image upload, automated prediction, confidence visualization, report generation, and record management through a user-friendly interface. Overall, the proposed framework offers an intelligent, secure, and efficient solution for assisting healthcare

professionals in early ear disease screening and diagnosis. Future work can focus on expanding the dataset using larger and more diverse otoscopic image collections obtained from multiple hospitals and healthcare centers. Additional ear disease categories may be included to improve diagnostic coverage and real-world applicability. Advanced transformer architectures, ensemble learning techniques, and explainable artificial intelligence methods can be explored to further enhance performance and transparency. Integration with cloud computing platforms, mobile healthcare applications, and telemedicine services can improve accessibility. Clinical validation using real patient data and deployment in practical healthcare environments can further strengthen the reliability, scalability, and effectiveness of the proposed system for widespread medical use.

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