DOMAIN AWARE HYBRID CNN TRANSFORMER FRAMEWORK FOR EXPLAINABLE PNEUMONIA DETECTION

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Abstract:

Pneumonia is a serious respiratory disease that affects millions of people worldwide and can lead to severe health complications if not detected early. Traditional diagnostic methods rely heavily on manual examination of chest X-ray images by medical experts, which can be time-consuming and prone to human error. Recent advancements in artificial intelligence and deep learning have enabled automated medical image analysis systems that assist clinicians in disease detection. This study proposes a domain-aware hybrid CNN-Transformer framework for explainable pneumonia detection using chest X-ray images. The hybrid architecture combines the feature extraction capabilities of Convolutional Neural Networks with the global contextual learning ability of Transformer models. The domain-aware component incorporates medical knowledge to enhance the model's understanding of lung structures, while explainable AI techniques provide visual interpretations of the model's predictions. Experimental results demonstrate improved detection accuracy and better interpretability compared to traditional deep learning models. The proposed framework can assist healthcare professionals in making faster and more reliable diagnostic decisions for pneumonia detection.

Keywords: Pneumonia Detection, Deep Learning, Hybrid CNN Transformer, Explainable AI, Medical Image Analysis, Chest X-ray Analysis, Artificial Intelligence in Healthcare.

I.INTRODUCTION

Pneumonia is a life-threatening respiratory infection that affects the lungs and can cause severe complications, particularly among children, elderly individuals, and patients with weakened immune systems. Early detection and timely treatment are essential to reduce mortality rates associated with this disease. Chest X-ray imaging is one of the most widely used diagnostic tools for identifying pneumonia; however, manual interpretation of medical images requires significant expertise and may lead to diagnostic errors. With the advancement of artificial intelligence, deep learning models have shown remarkable success in medical image analysis tasks. Convolutional Neural Networks are particularly effective in extracting spatial features from medical images, while Transformer-based architectures have demonstrated strong capabilities in capturing long-range dependencies and contextual information. Integrating these two approaches into a hybrid framework can improve diagnostic accuracy. Additionally, explainable AI techniques play a crucial role in providing transparency and interpretability in medical decision-making systems. This research introduces a domain-aware hybrid CNN-Transformer framework designed to enhance pneumonia detection accuracy while providing interpretable results to support clinical diagnosis.

II.LITERATURE SURVEY

Several studies have explored the use of artificial intelligence and deep learning techniques for pneumonia detection using chest X-ray images. Convolutional Neural Networks (CNNs) have been widely applied in medical image analysis due to their ability to extract important spatial features from images and achieve high accuracy in disease classification tasks. Researchers have also investigated the use of transfer learning techniques where pre-trained models are fine-tuned to improve performance with limited medical datasets. Recently, Transformer-based architectures have gained attention for their ability to capture long-range dependencies and global contextual relationships within images, which enhances the understanding of complex medical patterns. Hybrid models that combine CNN and Transformer architectures have been proposed to leverage the advantages of both approaches, improving feature extraction and contextual learning simultaneously. Additionally, explainable artificial intelligence techniques such as Grad-CAM and attention maps have been introduced to provide visual explanations of model predictions, allowing healthcare professionals to better understand how AI systems identify pneumonia from chest X-ray images.

III.EXISTING SYSTEM

Existing pneumonia detection systems mainly rely on traditional deep learning models such as convolutional neural networks for analyzing chest X-ray images. These models focus on extracting spatial features from medical images and classifying them into pneumonia or normal categories. While these systems have shown promising accuracy in detecting lung abnormalities, they often face limitations in capturing global contextual relationships present in complex medical images. Moreover, many existing systems function as black-box models, providing predictions without clear explanations of how the decision was made. This lack of interpretability can reduce the confidence of healthcare professionals in using AI-assisted diagnostic systems. Additionally, traditional CNN-based models may require large labeled datasets and may not effectively incorporate domain knowledge related to lung anatomy and disease patterns.

IV.PROPOSED SYSTEM

The proposed system introduces a domain-aware hybrid CNN-Transformer framework for explainable pneumonia detection from chest X-ray images. The architecture integrates convolutional neural networks to extract local spatial features and Transformer layers to capture global contextual relationships within the images. This hybrid structure improves the model’s ability to analyze complex patterns associated with pneumonia. A domain-aware component is incorporated to utilize medical knowledge related to lung structures and pneumonia characteristics, enabling more accurate detection. Furthermore, explainable artificial intelligence techniques are applied to generate visual explanations of the model’s predictions, highlighting important regions in chest X-ray images that contribute to the diagnosis. This approach not only improves detection accuracy but also enhances transparency and reliability, making the system more suitable for real-world clinical applications.

V.SYSTEM ARCHITECTURE

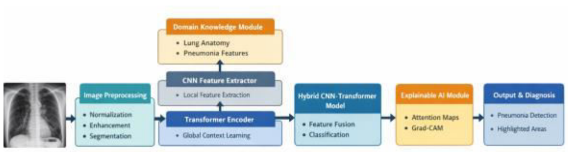

Fig 5.1

The system architecture for the Domain Aware Hybrid CNN-Transformer Framework for Explainable Pneumonia Detection is designed to automatically analyze chest X-ray images and identify pneumonia using advanced deep learning techniques. The architecture begins with the image acquisition stage, where chest X-ray images are collected from medical imaging systems or healthcare datasets. These images serve as the input for the detection system.

1. Chest X-ray Image Input

The system begins by collecting chest X-ray images from medical imaging devices or publicly available medical datasets. These images serve as the primary input for the pneumonia detection framework and contain visual information about lung structures and possible infection areas.

2. Image Preprocessing

In this step, the collected chest X-ray images are processed to improve their quality and consistency. Operations such as image resizing, normalization, noise removal, and contrast enhancement are performed to ensure that the images are suitable for deep learning analysis.

3. CNN Feature Extraction

The preprocessed images are then passed to the Convolutional Neural Network (CNN) module, which extracts important spatial features from the images. These features represent local patterns in the lung regions that may indicate pneumonia-related abnormalities.

4. Transformer Encoder Processing

The Transformer encoder analyzes the extracted features to capture global contextual relationships within the chest X-ray images. This step helps the system understand long-range dependencies and complex patterns present in lung structures.

5. Hybrid CNN-Transformer Model

The features obtained from the CNN and Transformer modules are combined in the hybrid model. This integrated framework performs feature fusion and classification to determine whether pneumonia is present in the chest X-ray image.

6. Explainable Output and Diagnosis

Finally, the system generates the prediction results and applies explainable AI techniques such as Grad-CAM or attention maps to highlight the important regions of the X-ray image. The results are displayed to healthcare professionals, assisting them in making accurate and interpretable diagnostic decisions.

VI.IMPLEMENTATION

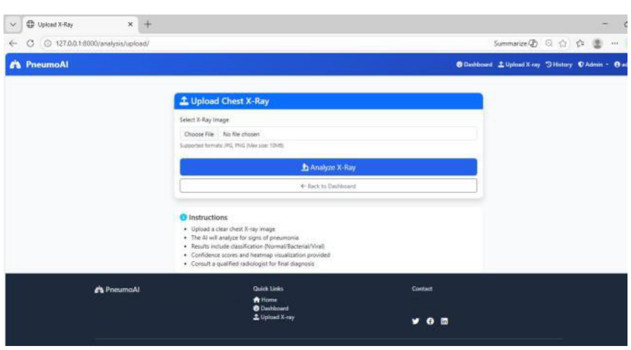

Fig 6.1

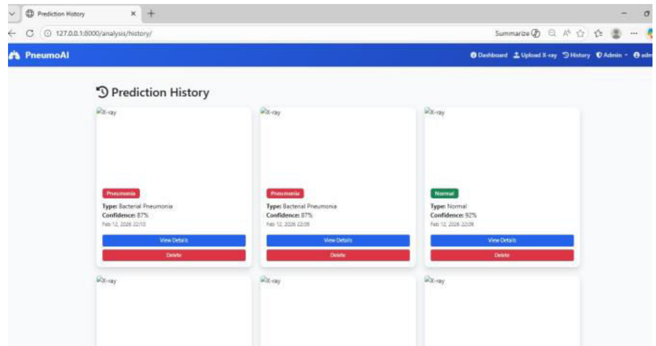

Fig 6.2

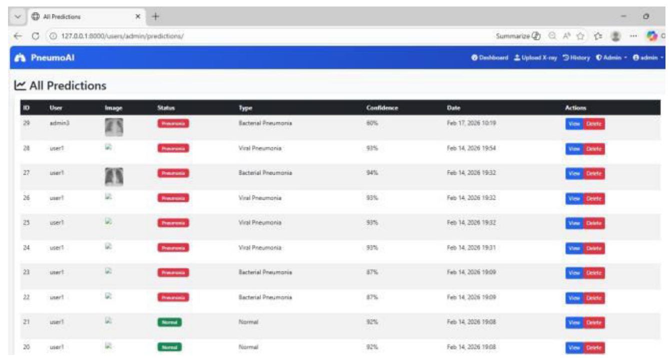

Fig 6.3

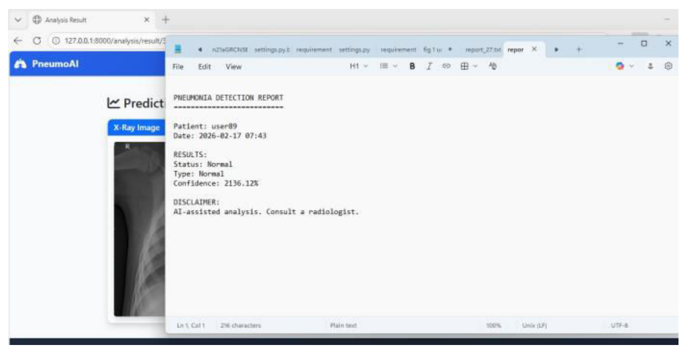

Fig 6.4

VII.CONCLUSION

The Domain Aware Hybrid CNN Transformer Framework for Explainable Pneumonia Detection provides an efficient and intelligent approach for detecting pneumonia from chest X-ray images. By combining the strengths of convolutional neural networks and transformer architectures, the proposed framework is able to capture both local spatial features and global contextual relationships within medical images. The integration of domain knowledge related to lung anatomy further improves the model's ability to identify pneumonia patterns accurately. Additionally, the use of explainable artificial intelligence techniques enhances the transparency of the model by highlighting important regions in the X-ray images that influence the prediction. This system can assist healthcare professionals in making faster and more reliable diagnostic decisions, ultimately improving patient care and reducing the risk of misdiagnosis.

VIII.FUTURE SCOPE

The proposed system can be further improved by incorporating larger and more diverse medical datasets to enhance the robustness and accuracy of the model. Future research may focus on integrating advanced transformer architectures and more powerful hybrid deep learning models to improve pneumonia detection performance. The framework can also be extended to detect multiple lung diseases such as tuberculosis, COVID-19, and lung cancer using the same architecture. Additionally, integrating the system with hospital information systems and cloud-based platforms can enable real-time analysis of medical images. The development of mobile or web-based applications for AI-assisted diagnosis could further help healthcare professionals access diagnostic tools easily in clinical environments.

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