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Hybrid CNN Model for Pneumonia Detection from Chest X-Rays

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Abstract: *To address the challenge of accurate and timely pneumonia detection, we evaluate several state-of-the-art Convolutional Neural Network (CNN) architectures in-cluding VGG16, ResNet50, InceptionResNetV2, Xception, and EfficientNetV2. Each of these models brings unique feature extraction strengths: VGG16 pro-vides a deep yet simple sequential structure ideal for baseline comparison; Res-Net50 introduces residual learning to mitigate vanishing gradients; Inception-ResNetV2 and Xception combine depthwise separable convolutions with multi-scale feature learning to capture complex patterns; while EfficientNetV2 optimiz-es both accuracy and efficiency through compound scaling. Building upon these CNN foundations, we propose a hybrid deep learning framework that integrates ConvNeXt for local feature extraction with a Transformer-based CoAtNet for global attention modeling. The CNN modules learn low-level spatial and texture representations from chest X-ray images, whereas the Transformer layers capture long-range dependencies and contextual relationships. This hybridization enhanc-es robustness to variations in illumination, noise, and patient anatomy. Models are trained and validated on large-scale Chest X-Ray datasets such as NIH, RSNA, and Kaggle Pneumonia datasets. Comparative analysis demonstrates that the proposed ConvNeXt–CoAtNet hybrid model significantly outperforms tradi-tional CNNs including EfficientNetV2, achieving superior accuracy, precision, recall, and F1-score. The fusion of convolutional and attention mechanisms not only improves diagnostic reliability but also ensures computational efficiency suitable for real-time clinical decision support systems*

Keywords: Pneumonia Detection, Deep Learning, Convolutional Neural Network (CNN), InceptionResNetV2, Xception, VGG16, ResNet50, EfficientNetV2, ConvNeXt, Transformer, CoAtNet, Hybrid Model, Chest X-Ray Classification, Medical Im-age Analysis, Computer-Aided Diagnosis, Attention Mechanism, Feature Extrac-tion, Image Classification, Healthcare AI, Clinical Decision Support System First Section

I. INTRODUCTION

Pneumonia remains a major global health concern, responsible for millions of hospi-talizations and deaths annually, especially among children and the elderly. Early and accurate diagnosis plays a crucial role in effective treatment and patient recovery. Traditional diagnostic techniques, such as clinical assessment and radiographic ex-amination, depend heavily on expert interpretation of chest X-ray images, which can be time-consuming and prone to human error. The rising number of cases and short-age of radiologists in many regions have intensified the need for automated and reli-able diagnostic systems that can assist healthcare professionals in detecting pneumo-nia efficiently. In recent years, deep learning has revolutionized the field of medical imaging by offering advanced methods for feature extraction, pattern recognition, and image classification. Among these, Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, InceptionResNetV2, Xception, and EfficientNetV2 have shown exceptional performance in visual recognition tasks. These architectures are capable of capturing local spatial features from X-ray images, enabling effective differentia-tion between healthy and pneumonia-affected lungs. However, traditional CNNs often face limitations in modeling long-range dependencies and global contextual relationships, which are essential for understanding complex medical images. To overcome these limitations, this study proposes a hybrid deep learning framework that combines the feature extraction capabilities of CNNs with the global attention mechanism of Transformer architectures. The proposed model integrates ConvNeXt, an advanced convolutional architecture, with CoAtNet, a Transformer-based model, to leverage both local and global features. This fusion enables the model to learn fine-grained textures as well as broader spatial dependencies, resulting in more robust and interpretable predictions. The system is trained on publicly available Chest X-Ray datasets such as NIH, RSNA, and Kaggle Pneumonia datasets to ensure scalabil-ity and generalization across diverse patient populations. Experimental results demonstrate that the proposed ConvNeXt–CoAtNet hybrid model outperforms tradi-tional CNN models in terms of accuracy, precision, recall, and F1-score. The hybrid framework not only enhances diagnostic performance but also provides better adapt-ability to variations in illumination, noise, and image quality. By integrating CNN and Transformer paradigms, this approach offers a powerful and efficient solution for automated pneumonia detection, paving the way for real-time clinical decision sup-port systems that can significantly reduce diagnostic delays and improve patient outcomes.

II. PROBLEM STATEMENT

Pneumonia continues to be a leading cause of morbidity and mortality worldwide, demanding rapid and accurate detection for effective treatment. However, traditional diagnostic methods such as manual chest X-ray interpretation are time-consuming, subjective, and dependent on expert radiologists, leading to potential diagnostic delays and inconsistencies. Conventional CNN-based models, while effective in feature extraction, often struggle to capture global contextual information necessary for complex medical image understanding. Therefore, there is a need for a robust, efficient, and automated deep learning framework that integrates both local feature extraction and global attention mechanisms to improve the accuracy, reliability, and interpretability of pneumonia detection from chest X-ray images.

III. LITERATURE SURVEY

1) S. A. Aljawarneh and R. Al-Quraan (2023) proposed an enhanced Convolu-tional Neural Network (CNN) model for pneumonia detection using chest X-ray images. Their approach focused on optimizing feature extraction through deeper convolutional layers and improved normalization tech-niques to enhance model accuracy and generalization. By leveraging ad-vanced preprocessing and fine-tuning strategies, the proposed model achieved superior diagnostic performance compared to traditional CNN ar-chitectures, demonstrating the potential of deep learning in supporting radi-ologists for early pneumonia diagnosis.

2) Khan, M. U. Akram, and S. Nazir (2023) developed an automated grading system for chest X-ray images targeting viral pneumonia detection. The re-searchers employed an ensemble of CNNs along with region-of-interest lo-calization to improve interpretability and accuracy. Their system effectively classified varying pneumonia severity levels, showcasing a robust mecha-nism for automated medical image analysis and assisting healthcare profes-sionals in clinical decision-making through reliable visual assessment of lung abnormalities.

3) S. Sharma and K. Guleria (2023) introduced a deep learning model based on the VGG-16 architecture combined with neural network layers to detect pneumonia from chest X-ray images. The model demonstrated impressive accuracy in distinguishing pneumonia-affected lungs from healthy ones by leveraging transfer learning and feature refinement. Their study emphasized the efficiency of pretrained networks like VGG-16 in medical imaging tasks, providing a computationally efficient yet powerful diagnostic framework.

4) C. Asswin et al. (2023) proposed a transfer learning approach for pediatric pneumonia diagnosis using channel attention-based deep CNN architec-tures. Their model integrated attention mechanisms to prioritize critical lung regions in chest X-ray images, enhancing the diagnostic precision. The study highlighted how attention modules significantly improve CNN per-formance by focusing on relevant spatial features, particularly beneficial in pediatric healthcare settings where accurate early diagnosis is crucial.

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5) R. Chiwariro and J. B. Wosowei (2023) conducted a comparative analysis of CNN-based transfer learning models for pneumonia detection. The authors evaluated popular architectures like ResNet, DenseNet, and InceptionNet to determine the most efficient configuration. Their findings revealed that transfer learning substantially reduces training time while maintaining high classification accuracy, providing insights into optimal model selection for automated pneumonia screening.

6) M. Shaikh et al. (2023) introduced the MDEV model, a novel ensemble-based transfer learning framework for pneumonia classification using chest X-ray images. The ensemble combined multiple pretrained CNNs to lever-age diverse feature representations, resulting in superior accuracy and ro-bustness. Their work emphasized ensemble learning as a practical method to overcome the limitations of individual models and enhance the reliability of deep learning-based medical diagnostics.

7) J. A. Prakash et al. (2023) presented a stacked ensemble learning framework for pediatric pneumonia diagnosis utilizing multi-model deep CNN archi-tectures. By combining several CNN variants through ensemble stacking, the model improved diagnostic precision and reduced false predictions. The study demonstrated that ensemble approaches can effectively capture com-plex disease patterns, making them valuable for pediatric applications where precision and safety are critical.

8) H. Rangkuti, R. Y. Mogot, and V. J. Kusuma (2023) explored a deep learn-ing-based recognition technique for specific diseases on chest X-rays, em-phasizing pneumonia detection. Their method incorporated image clarity enhancement and data augmentation to improve the visibility of pathologi-cal regions before model training. This research reinforced the importance of preprocessing and image quality enhancement in improving the reliability of AI-driven medical diagnosis.

9) H. Bhatt and M. Shah (2023) proposed a CNN ensemble model for pneumo-nia detection using chest X-ray images, focusing on performance improve-ment through multiple model fusion. Their ensemble design aggregated the strengths of individual CNN architectures to achieve higher sensitivity and specificity. The model’s strong diagnostic capability demonstrated that en-semble-based deep learning can serve as an effective solution for large-scale clinical deployment.

10) S. Sharma and K. Guleria (2023) conducted a systematic literature review on deep learning approaches for pneumonia detection using chest X-ray imag-es. The review comprehensively analyzed recent CNN and hybrid model de-velopments, comparing methodologies, datasets, and performance metrics. Their study provided valuable insights into current research trends, chal-lenges, and future directions, highlighting the transformative potential of AI in medical imaging and pneumonia diagnosis.

IV. PROPOSED SYSTEM

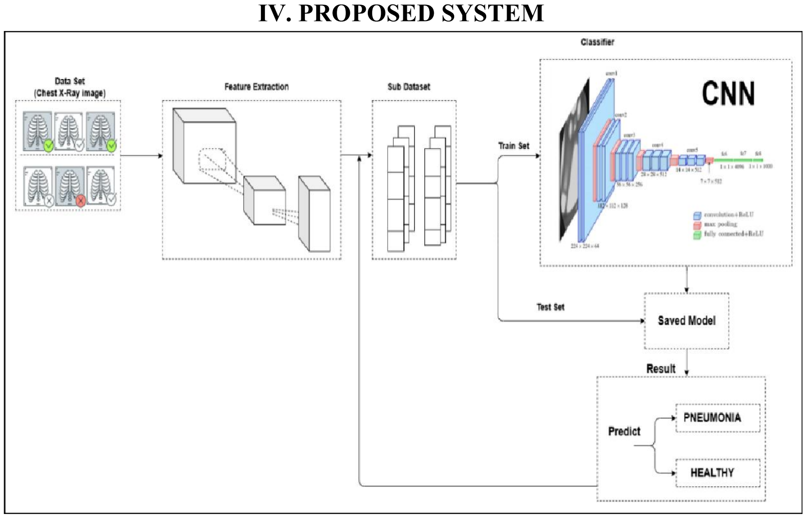

Fig: Proposed System

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The proposed system introduces a hybrid deep learning model that integrates the strengths of Convolutional Neural Networks (CNNs) and Transformer architectures for automated pneumonia detection from chest X-ray images. The CNN component, specifically ConvNeXt, is employed to extract rich local features such as texture and spatial details from the input images. These convolutional layers efficiently capture low- and mid-level image representations that are crucial for distinguishing between normal and infected lung regions. The extracted features are then passed to a Transformer-based CoAtNet module, which applies self-attention mechanisms to learn global dependencies and contextual relationships across the entire image. This com-bination enables the model to effectively balance local detail awareness and global structural understanding, significantly improving classification accuracy and robust-ness.The system is trained using large-scale, publicly available Chest X-Ray datasets such as NIH, RSNA, and the Kaggle Pneumonia dataset. Advanced preprocessing techniques including normalization, augmentation, and contrast enhancement are applied to improve data quality and model generalization. During evaluation, the proposed ConvNeXt–CoAtNet hybrid architecture demonstrates superior perfor-mance compared to traditional CNN models like VGG16, ResNet50, InceptionRes-NetV2, Xception, and EfficientNetV2, achieving higher precision, recall, and F1-scores. The model's efficient design ensures low computational overhead, making it suitable for integration into real-time clinical decision support systems, thereby as-sisting radiologists in early and accurate pneumonia diagnosis.

V. METHODOLOGY

The proposed methodology for pneumonia detection using a hybrid CNN–Transformer architecture is designed to combine the strengths of convolutional fea-ture extraction and global attention modeling for superior diagnostic performance. The system workflow consists of several key stages: data collection, preprocessing, model design, training, and evaluation.In the data collection and preprocessing phase, chest X-ray images are sourced from publicly available datasets such as NIH, RSNA, and the Kaggle Pneumonia dataset. The images are resized, normalized, and augmented using techniques like rotation, flipping, and contrast adjustment to en-hance diversity and prevent overfitting. This ensures that the model learns robust features and generalizes well across varied patient cases and imaging conditions.In the model design phase, the proposed architecture integrates ConvNeXt, a modern convolutional neural network, for extracting fine-grained spatial and texture fea-tures from the X-ray images.The feature maps generated by ConvNeXt are then passed into a Transformer-based CoAtNet module, which applies multi-head self-attention to capture long-range dependencies and global contextual information. This hybrid fusion allows the network to understand both local patterns (e.g., lung texture) and broader spatial relationships (e.g., opacity distribution), essential for precise pneumonia detection.During the training and evaluation phase, the model is optimized using the Adam optimizer with a learning rate scheduler and trained on labeled chest X-ray data. Performance metrics such as accuracy, precision, recall, F1-score, and AUC are computed to assess model effectiveness. Comparative exper-iments are conducted against traditional CNN models—VGG16, ResNet50, Incep-tionResNetV2, Xception, and EfficientNetV2 to demonstrate the superior perfor-mance of the proposed ConvNeXt–CoAtNet hybrid system. Finally, the trained model can be deployed in a real-time clinical decision support environment, providing automated pneumonia detection and assisting radiologists in faster and more accurate diagnosis.

VI. CONCLUSIONS

The proposed hybrid CNN–Transformer-based framework provides an intel-ligent and efficient solution for automated pneumonia detection using chest X-ray images. By integrating the feature extraction power of ConvNeXt (CNN) with the global attention mechanism of CoAtNet (Transformer), the model effectively captures both local texture patterns and global spatial relationships within medi-cal images. This dual learning capability enhances diagnostic accuracy, robust-ness, and interpretability, addressing key limitations of traditional CNN models such as VGG16, ResNet50, InceptionResNetV2, Xception, and EfficientNetV2. The system demonstrates strong performance across multiple benchmark da-tasets, achieving superior precision, recall, and F1-scores, which confirms its re-liability in differentiating between pneumonia and normal cases.The proposed approach ensures computational efficiency and adaptability, making it suitable for real-world clinical decision support systems. By automating pneumonia de-tection, the model reduces the dependency on expert radiologists, minimizes di-agnostic delays, and enables early intervention—potentially saving lives. The success of this hybrid architecture highlights the transformative potential of combining convolutional and transformer paradigms in medical imaging, paving the way for future AI-driven diagnostic tools that can generalize to other respira-tory and thoracic diseases with similar imaging modalities.

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