Pneumonia detection using CNN

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Abstract

Pneumonia is a severe a respiratory disorder that mainly involves the lung tissues continues to be a significant global health issue. It poses a high risk to vulnerable groups such as young children, elderly individuals, and people with weakened immune systems. Each year, hundreds of millions of cases are reported worldwide, making it one of the leading causes of high mortality rates, especially in children below five and older adults. Early and precise diagnosis plays a vital role in successful treatment outcomes; however, conventional techniques like chest X-ray evaluation depend significantly on trained radiologists, potentially causing delays or diagnostic errors, especially in underserved regions. The development of deep learning techniques within artificial intelligence has considerably improved the identification of pneumonia in chest X-ray images. Convolutional Neural Networks (CNNs) are commonly utilized due to their ability to automatically learn and extract important visual patterns associated with the disease. Modern approaches also incorporate methods such as residual connections, dropout, and advanced pooling strategies to enhance model efficiency and prevent overfitting. Research based on large-scale medical imaging datasets has shown that these models can achieve very high accuracy, often exceeding 95%, along with strong model performance indicators such as precision and recall, F1-score, and AUC. Overall, advanced CNN-based techniques have proven to outperform conventional diagnostic approaches methods. These intelligent systems provide a fast, dependable, and cost-efficient solution, helping medical professionals make better decisions and improving patient care outcomes.

Keywords: Pneumonia Detection, Chest X-ray, Deep Learning, CNN, Attention Mechanisms, Explainable AI, Medical Imaging

1. Introduction

Pneumonia remains a critical global health concern, significantly contributing to rates of illness and death, with a significant impact on children under five years of age and the elderly population. Around 450 million people are affected by pneumonia globally each year, leading to millions of deaths, particularly in low- and middle-income countries [1]. Despite its high prevalence, access to timely and adequate medical care remains limited, with only about half of the affected population receiving prompt diagnosis and treatment [2]. This delay in intervention often leads to severe complications and increased mortality rates.

It can further aggravate the patient's condition, reducing the chances of successful treatment. In many cases, late diagnosis places additional pressure on healthcare systems and increases overall medical costs.

Traditional diagnostic approaches, including chest X-ray analysis, are widely used for pneumonia detection; However, these approaches are often time-intensive, require substantial resources, and rely heavily on the expertise of skilled radiologists [3]. Moreover, the radiographic features of pneumonia frequently overlap with other pulmonary conditions, making accurate diagnosis challenging and increasing the likelihood of misclassification [4]. These limitations are particularly evident in resource-constrained settings, where the availability of skilled healthcare professionals and diagnostic infrastructure is inadequate. Over the past few years, deep learning methods have greatly improved medical image analysis. CNNs are especially effective in automatically identifying important features from chest X-ray images, leading to better results in classification and detection tasks [5]. Many studies have used advanced CNN models like ResNet, DenseNet, VGGNet, and EfficientNet, which help in training deeper networks and solving problems like vanishing gradients [6], [7]. In addition, transfer learning with pre-trained models is commonly used to improve performance, especially when medical data is limited [8].

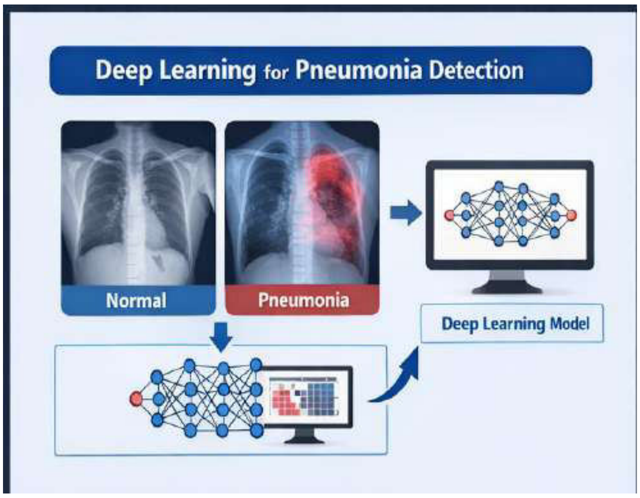
n spite of these improvements, existing systems still face several challenges. Data imbalance, variations in image quality, and the subtle and heterogeneous nature of pneumonia features continue to affect model robustness and generalization [9]. Many studies use single models, which may not capture complex features in medical images effectively. Moreover, deep learning-based models are often difficult to interpret, which creates concerns in clinical use. In addition, they demand substantial computational resources, thereby limiting their suitability for real-world use, especially in low-resource settings [10].

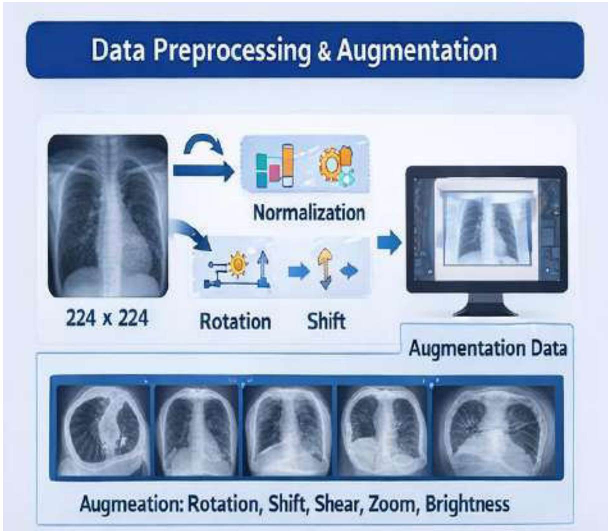
To address these challenges, recent studies focuses on hybrid models that combine multiple CNNs along with attention and feature fusion techniques. These approaches aim to enhance feature representation, improve classification accuracy, and provide more robust and efficient diagnostic support frameworks [11]. Overall, the adoption of deep learning techniques in pneumonia detection shows strong potential in supporting healthcare professionals, enabling earlier diagnosis, and helping to reduce the global impact of the disease.

2. Related Work

Over throughout the last decade, deep learning has significantly been widely studied for automatically detecting pneumonia and other chest diseases using X-ray images. A notable breakthrough in this field was reported by Rajpurkar et al. [19], who developed a deep CNN capable of detecting pneumonia at a performance level comparable to, and in some cases exceeding, that of radiologists. This work highlighted the potential of deep learning approaches in medical imaging and contributed to the development of future research in automated diagnosis.

After this, many studies have focused on improving diagnostic accuracy and handling the challenges in pneumonia detection. Recent research shows that it is often difficult to differentiate pneumonia from other lung infections because their X-ray features can appear similar, especially in children [20]. To emphasize this challenge, ensemble learning approaches have been introduced, combining multiple pre-trained CNN models to enhance classification performance and achieve high sensitivity and AUC values. Lightweight architectures have also been known for their efficiency in real-world applications. In [21], a MobileNet-based model was introduced to provide a quick and computationally efficient solution for pneumonia detection, achieving strong accuracy and recall while reducing training time and resource requirements. Similarly, methods using transfer learning and different optimization methods have been explored to solve the problem of limited data. For example, a multi-level optimization framework was proposed in [22] to improve model performance by utilizing knowledge from source domains, thereby compensating for limited annotated medical datasets. Attention mechanisms have become an important improvement in deep learning models, allowing networks to focus on the most relevant areas of medical images. A comprehensive survey in [26] emphasized the versatility and effectiveness of attention-based approaches across various applications. Building on this concept, several studies have incorporated attention modules with deep CNN architectures to improve feature representation and classification accuracy. For example, models combining architectures such as ResNet and DenseNet with attention-based feature selection have shown substantial improvements in diagnostic performance. Similarly, the incorporation of channel attention mechanisms, such as Squeeze-and-Excitation (SE) blocks, has been found to improve the identification of critical features in chest X-ray images.





In parallel, advancements in feature fusion techniques have further improved the capability across deep learning models. Multi-path and attention-based feature fusion networks have been proposed in recent studies to extract and combine complementary features from different layers and architectures, resulting in improved classification accuracy across various medical imaging tasks. These developments demonstrate the increasing trend toward hybrid and more sophisticated models for robust pneumonia detection.

Despite these advancements, problems such as limited data continue to exist imbalance, variability in imaging conditions, and the complexity of pneumonia patterns continue to limit model generalization and real-world applicability. Consequently, ongoing research is focused on developing more efficient, interpretable, and scalable deep learning systems that offer dependable diagnostic assistance in various clinical settings.

3. Materials and Methods

This study presents a transparent and an explainable deep learning framework for detecting pneumonia in chest radiographs. Unlike conventional convolutional neural network-based approaches that operate as black-box systems, the proposed method explicitly integrates attention mechanisms and visualization-driven components to improve interpretability while maintaining high diagnostic performance. The framework is designed not only to boost classification results and provide important clinical interpretation of the model's decisions.

3.1 Data Preparation and Augmentation

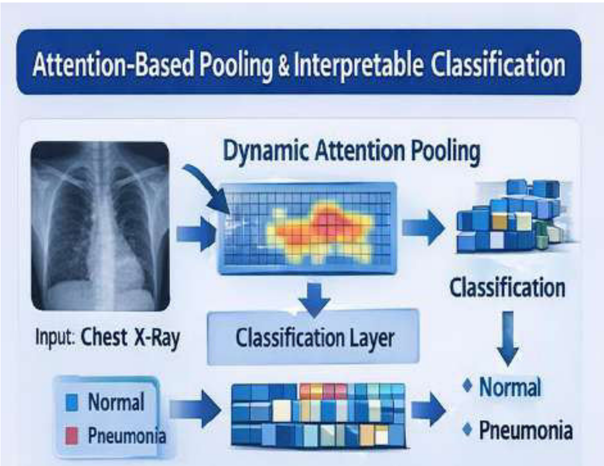
The experimental dataset consists of chest X-ray images categorized into normal and pneumonia classes, consistent with widely used datasets in prior studies [16], [17]. All images were resized to a consistent size to ensure efficient computation and compatibility with deep learning models. Pixel intensity normalization was applied to stabilize the training process.

To achieve better generalization and avoid overfitting, different augmentation techniques were employed, including random rotations, spatial translations, zooming, and brightness adjustments. These augmentation strategies simulate real-world variability in medical imaging conditions and enhance model robustness, as demonstrated in previous works [14], [24]. Careful parameter tuning was applied to ensure that clinically relevant features were preserved without introducing unrealistic distortions.

3.2 Hybrid Feature Extraction with Attention

To capture rich and discriminative representations from chest X-ray images, this study puts forward a hybrid backbone architecture that combines EfficientNet and DenseNet. EfficientNet provides an optimal trade-off between model complexity and performance through compound scaling, whereas DenseNet facilitates effective feature reuse and gradient propagation via dense connectivity [25].

Deep convolutional models have exhibited high effectiveness in medical image classification tasks [12], [13], [17]; however, they often lack interpretability. To overcome this limitation, attention mechanisms are embedded within during the feature extraction phase. These modules allow the model to focus on important regions related to diagnosis, such as areas showing lung opacity or infection, while reducing the influence of less useful background details. The use of attention is inspired by prior advancements in attention-based learning [26].



3.3 Attention-Driven Feature Fusion

A key innovation of this work lies in the design of an attention-guided feature fusion strategy. In contrast with traditional methods that utilize simple concatenation or averaging, the proposed method adaptively weights feature maps obtained from EfficientNet and DenseNet.

This mechanism allows the model to selectively emphasize complementary information from both networks, leading to a more informative and balanced feature representation. Similar techniques have exhibited enhanced effectiveness in recent studies [25], [26]. Additionally, residual skip connections are integrated during the fusion process to preserve spatial and semantic information while ensuring stable gradient flow.

3.4 Dynamic Attention-Based Pooling

Traditional pooling operations, such as max pooling and average pooling, often contribute to the loss of important spatial information, thereby contributing to the difficulty in understanding deep learning based-models. To address this limitation, this work introduces a dynamic attention-based pooling mechanism.

This module evaluates the relative importance of different spatial regions prior to aggregation, ensuring that diagnostically significant areas are retained during the downsampling process. Such attention-driven improvements in feature representation have been highlighted in prior research .

3.5 Classification Head and Regularization

Following feature extraction and enhancement, the refined feature representation the complexity in understanding deep learning models classification into normal and pneumonia categories. To improve generalization while minimizing overfitting, techniques like dropout and batch normalization are applied, consistent with established deep learning practices [10], [11].

The model outputs probability distributions over the target classes rather than binary decisions. This probabilistic output provides additional diagnostic insight by quantifying prediction confidence, which is particularly valuable in clinical decision-support systems [19], [20].

3.6 Enhancing Model Transparency and Interpretability

A central primary contribution of this work is the explicit focus on improving model transparency. To emphasize the black-box limitation, multiple explainability techniques are incorporated into the framework, including attention map visualization and gradient-based localization methods.

These techniques produce visual explanations that show the areas of the chest X-ray image that have the greatest impact on the model's predictions. Analogous methods have been explored in prior studies to enhance interpretability in medical imaging [6], [8], [9]. Such visualizations allow clinicians to verify whether the model is identifying on medically relevant anatomical structures, thereby increasing trust and usability.

By combining attention mechanisms, interpretable feature fusion, dynamic pooling, and visualization-based explanations, the proposed framework transforms a traditionally opaque learning-based model into a transparent and clinically meaningful diagnostic tool.

4. Results and Discussion

The proposed model was tested against standard architectures like VGG19 and ResNet50 using evaluation metrics such as accuracy, precision, recall, F1-score, specificity, and AUC. The model achieved an accuracy of 95.19%, precision of 98.38%, recall of 93.84%, F1-score of 96.06%, specificity of 97.43%, and an AUC of **0.9564**, indicating effective performance in distinguishing between normal and pneumonia-affected lungs. While existing models like VGGNet, ResNet, and DenseNet show high accuracy in medical image classification [4], [6], [8], [9], [23], [25], they typically behave as black-box models with low interpretability [1], [2], [10]. To address this limitation, the proposed framework integrates attention-based mechanisms, including feature fusion and dynamic pooling, to enhance both feature representation and transparency.

Furthermore, explainability techniques such as attention maps and gradient-based localization were incorporated to provide visual insights into the model's predictions. These visualizations highlight clinically relevant regions, improving trust and interpretability in line with prior research [1], [3].

Overall, the proposed model achieves a balance between high diagnostic performance and interpretability, effectively addressing the black-box issue while maintaining reliability for clinical applications [9], [10], [18].

5. Conclusion

This research successfully demonstrates a novel, transparent deep learning system created to reduce the gap between high-performance AI and clinical trust in pneumonia diagnosis. By moving away from "black-box" models and integrating **EfficientNetB0** with **DenseNet121** via a multi-stage attention framework, we have shown that diagnostic precision does not have to come at the expense of interpretability. Ultimately, this interpretable framework offers a robust, scalable solution for clinical environments—particularly those with limited radiological resources. By providing both a high-accuracy classification and a visual justification for its findings, this system serves as a reliable secondary diagnostic aid, enhancing trust in AI-driven medical interventions.

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