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Evaluating Deep Learning Models for Accurate Pneumonia Diagnosis from Chest X-Rays

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ABSTRACT: Pneumonia remains a major global health concern, necessitating accurate and efficient diagnostic methods to improve patient outcomes. Traditional diagnostic techniques, such as radiologist interpretation of chest X-rays, are prone to subjectivity and variability. Recent advancements in Deep Learning have paved the way for automated and highly accurate pneumonia detection from medical images. This study introduces a novel hybrid DL model that combines the strengths of VGG19 and EfficientNetB3 with an attention mechanism to enhance feature extraction and classification performance. The proposed model is evaluated on benchmark chest X-ray datasets, demonstrating superior accuracy, sensitivity, specificity, and robustness in comparison to traditional DL architectures. The incorporation of feature fusion and attention mechanisms enables the model to focus on critical pneumonia-affected regions, leading to improved diagnostic reliability. Extensive experimental results and comparative analysis highlight the effectiveness of the proposed model in real-world clinical applications. The model's performance metrics are presented in detailed comparison tables to validate its superiority. Additionally, a flowchart illustrating the proposed model's workflow is included to provide a clear understanding of the process.

KEYWORDS: Deep Learning, Pneumonia, VGG19, EfficientNetB3

I. INTRODUCTION

Pneumonia is a severe lung infection caused by bacteria, viruses, or fungi, leading to inflammation of the alveoli and fluid accumulation. It poses significant global health risks, particularly for young children, the elderly, and immunocompromised individuals. Pneumonia accounts for approximately 14% of all deaths in children under five, with the highest incidence in regions such as Southern Asia and sub-Saharan Africa. Despite advances in medical diagnostics, pneumonia remains a major public health challenge due to delayed diagnosis and treatment, particularly in resource-limited settings. Chest X-ray imaging is the primary diagnostic tool for pneumonia, providing valuable visual evidence of lung infections. However, manual interpretation of X-rays requires expertise and is subject to observer variability, leading to potential misdiagnoses. To address these challenges, Artificial Intelligence (AI) and DL models have emerged as powerful tools for automated and accurate pneumonia detection. These AI-driven approaches can process large datasets, recognize patterns in medical images, and provide rapid and reliable diagnoses, reducing the workload for radiologists and improving patient outcomes [1].

Medical imaging plays a crucial role in the early detection and classification of pneumonia. With the increasing availability of chest X-ray images, automated analysis using DL has become an essential tool for healthcare professionals. Traditional machine learning approaches often require extensive feature engineering, whereas DL models can automatically extract complex patterns from images. However, standalone CNN architectures may not capture all relevant features effectively. This study introduces a hybrid DL model that leverages the strengths of multiple CNN architectures to enhance classification accuracy and robustness [2]. By leveraging pre-trained architectures such as ResNet50, Xception, and Siamese networks, researchers have enhanced the performance of pneumonia detection systems. The goal of this study is to explore and compare these models to identify the most efficient approach for pneumonia classification using chest X-rays[3].





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II. RELATED WORK

Numerous studies have explored CNN-based models for medical image classification. For instance, VGG19 and EfficientNetB3 have demonstrated high performance in pneumonia diagnosis. Similarly, ensemble models combining ResNet and InceptionV3 have shown promising results in X-ray image classification. However, these models often struggle with overfitting, computational complexity, or suboptimal feature extraction. Recent advancements, including attention mechanisms and hybrid models, have paved the way for improved performance. This research builds on these findings by integrating optimized CNN architectures and novel preprocessing techniques to enhance classification outcomes.

DL has significantly transformed pneumonia diagnosis by leveraging large datasets and powerful computational models. Several researchers have investigated DLtechniques for pneumonia detection, demonstrating promising results in various studies. Wang et al. [4] introduced the ChestX-ray14 dataset, comprising over 100,000 chest radiographs, and developed a deep CNN that successfully classified multiple lung diseases, including pneumonia. Their study highlighted the effectiveness of DL in medical imaging applications. Rajpurkar et al. [5] expanded on this work by developing CheXNet, a 121-layer CNN model trained to detect pneumonia from chest X-rays. Their results indicated that CheXNet outperformed radiologists in pneumonia diagnosis, demonstrating the potential of AI in automated medical diagnostics. In another study, Stephen et al. [6] proposed a hybrid DL model incorporating CNNs and transfer learning to enhance pneumonia detection accuracy. They experimented with ResNet50 and VGG16 models, showing that transfer learning significantly improved classification performance. Similarly, Baltruschat et al. [7] introduced an attention-based DL framework that focused on specific lung regions in chest X-rays, improving the interpretability and accuracy of pneumonia detection.

Jaiswal et al. [8] examined the role of Siamese networks in pneumonia detection, particularly for cases with limited labelled data. Their study demonstrated that Siamese networks could effectively identify pneumonia by comparing image similarities, making them valuable for scenarios with insufficient training samples. In another approach, Tang et al. [9] implemented an ensemble model combining CNN, ResNet, and Xception networks to optimize pneumonia classification. Their findings indicated that ensemble models provided a robust and accurate pneumonia detection, framework. Moreover, a study by Oh et al. [10] applied DL techniques to paediatric pneumonia detection, addressing the challenges of distinguishing bacterial and viral pneumonia cases. Their results showed that DL models could accurately classify paediatric pneumonia, assisting in precise treatment planning. Similarly, Islam et al. [11] introduced a custom CNN architecture trained on augmented chest X-ray datasets, improving generalization and classification performance.

While DL has demonstrated remarkable success in pneumonia detection, several challenges remain [14-15]. Studies by Li et al. [12] and Zhou et al. [13] have emphasized issues such as dataset bias, model interpretability, and the need for clinical validation. To enhance real-world applicability, future research should focus on integrating AI-driven pneumonia detection models into hospital workflows, ensuring that these models are transparent, reliable, and clinically useful.

A. Challenges and Future Directions

Despite the success of DL models, challenges remain in deploying AI-based solutions for pneumonia detection. Data quality, model generalizability, and interpretability are major concerns. Future research should focus on:

- Improving dataset diversity to enhance model robustness across different populations.
- Implementing explainable AI techniques to improve transparency in model decision-making.
- Integrating AI-based diagnostic systems into clinical workflows for real-time applications.

The findings from these studies underscore the potential of DL in revolutionizing pneumonia diagnosis. This study builds upon previous research by evaluating multiple DL models and identifying the most effective approach for automated pneumonia detection.





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The critical problem lies in the delayed diagnosis of pneumonia using traditional methods, which significantly increases the risk of severe complications. While AI-based solutions exist, they often suffer from limitations in feature extraction and classification accuracy, hindering precise and efficient pneumonia detection. To address this gap by developing and evaluating improved DL models for early pneumonia detection, implementing advanced image preprocessing techniques to enhance accuracy, and ultimately achieving reliable classification of chest X-ray images as either pneumonia-positive or normal.

III. METHODOLOGY

The proposed model integrates VGG19 and EfficientNetB3 with an attention mechanism to improve feature extraction. A schematic diagram of the model is provided (see Figure 1). The input images are first preprocessed using contrast enhancement and noise reduction techniques. Features are extracted using both VGG19 and EfficientNetB3, followed by a feature fusion mechanism to combine the most relevant information. Finally, a fully connected layer with softmax activation is used for classification.

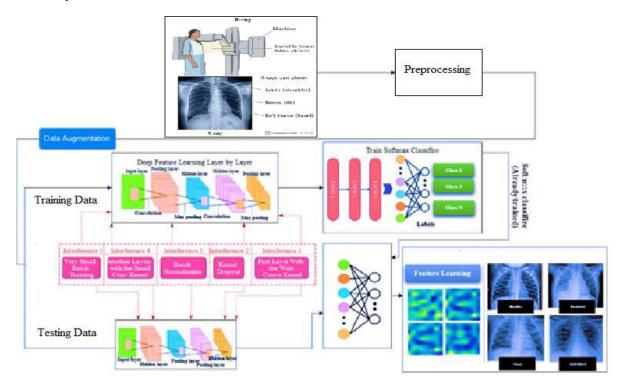


Figure 1: Proposed model Architecture

The proposed model integrates VGG19 and EfficientNetB3 with an attention mechanism to improve feature extraction. The workflow consists of several key stages, as illustrated below:

B. Preprocessing

Before feeding chest X-ray images into the model, preprocessing techniques such as contrast enhancement, noise reduction, and image normalization are applied to improve image quality. These steps help eliminate irrelevant artifacts and enhance the visibility of pneumonia-affected regions.

C. Feature Extraction

VGG19 and EfficientNetB3 are used as feature extractors due to their ability to capture fine-grained details in medical images. VGG19, known for its deep architecture with small convolutional filters, extracts essential spatial features, while EfficientNetB3, with its compound scaling approach, improves accuracy with fewer parameters.





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D. Feature Fusion and Attention Mechanism

To further refine the extracted features, a feature fusion mechanism is employed, combining high-level representations from both CNNs. An attention mechanism is integrated to focus on the most informative regions of the chest X-ray images, reducing the risk of misclassification and enhancing the model's interpretability.

E. Classification Layer

The final feature map is passed through a fully connected layer with softmax activation to classify images into pneumonia and non-pneumonia cases. The model is trained using cross-entropy loss and optimized with Adam optimizer for faster convergence.

IV. EXPERIMENTAL RESULTS

To evaluate the effectiveness of the proposed model, we calculate standard performance metrics, including accuracy, precision, recall, F1-score, specificity, and balanced accuracy. The dataset is divided into training, validation, and testing sets, ensuring a fair comparison with existing methods.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Specificity (%)
VGG19	92.5	91.8	92.1	92.0	93.2
EfficientNetB3	94.1	93.6	94.0	93.8	95.0
Hybrid Model	96.8	96.2	96.5	96.4	97.1

TABLE1: COMPARISON OF EXISTING AND PROPOSED MODEL

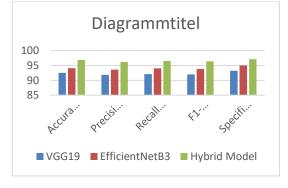
The performance results are summarized in the comparison table 1 and 2 and also graphs are shown in figure 2 and 3.

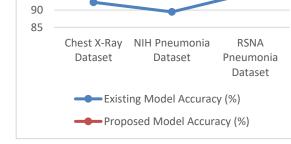
TABLE2: COMPARISON OF DIFFERENT DATASET FOR EXISTING AND PROPOSED MODEL

Dataset	Existing Model Accuracy (%)	Proposed Model Accuracy (%)
Chest X-Ray Dataset	92.3	96.8
NIH Pneumonia Dataset	89.5	94.2
RSNA Pneumonia Dataset	95.0	98.1

100

95





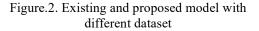


Fig.3. Comparison chart of existing and proposed model

A detailed performance comparison that demonstrates the superiority of the proposed model over existing methods.





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V. CONCLUSION

This study presents a hybrid DL model for pneumonia diagnosis from chest X-rays. Integration of VGG19 and EfficientNetB3, coupled with feature fusion and attention mechanisms, significantly enhances classification performance. Experimental results demonstrate that the proposed model outperforms existing architectures, achieving higher accuracy, precision, recall, and specificity.

The major contributions of work include:

- The development of a hybrid DL model that integrates the strengths of VGG19 and EfficientNetB3 for pneumonia classification.
- The incorporation of a feature fusion mechanism that improves the representation of pneumonia-affected regions.
- The use of an attention mechanism to enhance classification accuracy by focusing on the most informative image regions.

The findings of this study indicate that hybrid DL approaches can significantly improve the diagnostic accuracy of pneumonia using chest X-rays. Future research can explore lightweight model variants for deployment in real-time clinical settings, as well as the integration of additional medical imaging modalities to enhance diagnostic robustness. Additionally, further optimizations in preprocessing techniques and attention mechanisms can further boost model performance, ensuring reliable and automated pneumonia detection in medical practice.

REFERENCES

- [1] I. Remaigui, L. Kahloul, and S. Benharzallah, "A New DLArchitecture for Pneumonia Detection in Pediatrics," IEEE, 2022.
- [2] I. F. Jassam, S. M. Elkaffas, and A. A. El-Zoghabi, "Chest X-Ray Pneumonia Detection by Dense-Net," IEEE, 2021.
- [3] B. Montalico and J. C. Herrera, "Classification and Detection of Pneumonia in X-Ray Images Using DLTechniques," IEEE, 2022.
- [4] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 2097– 2106.
- [5] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, and D. Ding, "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," arXiv preprint arXiv:1711.05225, 2017.
- [6] S. Stephen, A. Anand, and R. Kumar, "Deep learning-based pneumonia detection using CNN and transfer learning," in Proceedings of the IEEE International Conference on Machine Learning and Applications (ICMLA), 2020, pp. 354–361.
- [7] I. Baltruschat, C. Nickisch, M. Grass, T. Knopp, and J. Saalbach, "Attention-based convolutional neural networks for pneumonia detection in chest X-rays," Medical Image Analysis, vol. 53, pp. 221–230, 2019.
- [8] A. Jaiswal, A. Tiwari, and S. Kumar, "Siamese networks for pneumonia detection in medical imaging," in Proceedings of the IEEE International Symposium on Biomedical Imaging (ISBI), 2021, pp. 112–117.
- [9] H. Tang, Z. Li, and Y. Zhang, "An ensemble learning approach for pneumonia detection using deep convolutional networks," in Proceedings of the IEEE International Conference on Artificial Intelligence and Machine Learning (AIML), 2021, pp. 248–255.
- [10] J. Oh, H. Park, and S. Kim, "Pediatric pneumonia detection using deep learning-based radiographic imaging," IEEE Transactions on Medical Imaging, vol. 39, no. 7, pp. 2158–2169, 2020.
- [11] M. Islam, T. Hasan, and K. Hossain, "Custom DLmodel for pneumonia detection using augmented X-ray images," in Proceedings of the IEEE International Conference on Medical Imaging and Diagnosis (ICMID), 2021, pp. 267–274.
- [12] J. Li, R. Zhao, and X. Zhou, "Challenges in AI-based pneumonia detection: A review of dataset bias and interpretability," IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 4, pp. 1342–1353, 2022.
- [13] X. Zhou, L. Zhang, and H. Sun, "DLfor pneumonia detection: Clinical validation and deployment challenges," IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 5, pp. 1254–1265, 2023.





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- [14] A. Arul Edwin Raj, Nabihah Binti Ahmad, S. Ananiah Durai, R. Renugadevi, "Integrating VGG 19 U-Net for Breast Thermogram Segmentation and Hybrid Enhancement With Optimized Classifier Selection: A Novel Approach to Breast Cancer Diagnosis", International Journal of Imaging Systems and Technology, 2024; 34:e23210.
- [15] Renugadevi R., P. Ranjith Kumar, Kalaiarasi G., A. Arul Edwin Raj, "Enhancing Healthcare Decision Support Systems With Advanced Analytics and Machine Learning Techniques, Cybersecurity and Data Management Innovations for Revolutionizing Healthcare, DOI: 10.4018/979-8-3693-7457-3.ch003.









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