

PneuXAI-Net: Real-Time Explainable Deep Learning Framework for Multi-Class Pneumonia Detection Using Chest X-Rays

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ABSTRACT

Pneumonia is a significant respiratory disease and one of the top causes of illness and death around the world, especially among children and the elderly. Timely and accurate diagnosis is essential for effective treatment and better patient outcomes. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), have shown impressive results in medical image analysis by automatically identifying important patterns in complex image data. This project introduces a real-time pneumonia identification system that combines CNN-based classification with Explainable Artificial Intelligence (XAI) techniques to improve diagnosis accuracy and model clarity. The proposed system processes digitized chest X-ray images through an efficient preprocessing pipeline. This includes noise removal, image normalization, and background feature consideration before sending the images to a trained deep learning model. The ensemble model merges two strong CNN architectures, VGG16 and ResNet50, and uses their complementary feature extraction abilities to boost classification performance. The model classifies Bacterial Pneumonia, Viral Pneumonia, and normal cases, providing clearer clinical insights. Experimental results show high accuracy, strong sensitivity, and real-time inference capability. This allows for pneumonia detection within seconds, which is vital in clinical settings that need quick diagnoses. To tackle the black-box issue of deep learning models, Explainable AI techniques like Grad-CAM++ (Gradient-weighted Class Activation Mapping++) and Score-CAM are used to visualize the key lung areas that affect the model's predictions. The system also offers confidence scores with visual explanations, enhancing understanding and aiding clinical decision-making. Overall, the proposed CNN and XAI framework offers an efficient, clear, and clinically helpful solution for automated pneumonia detection. The system has strong potential to assist radiologists, boost diagnostic confidence, and contribute to early disease detection and improved patient care.

Keywprds: Lung Cancer Detection, Convolutional Neural Networks, Explainable Artificial Intelligence, Grad-CAM, Medical Image Analysis, Deep Learning, CT Imaging, Computer-Aided Diagnosis.

I. INTRODUCTION

Pneumonia is a lung infection caused by pathogens such as bacteria and viruses, and it is one of the most common infectious diseases in clinical medicine. It typically has a short incubation period and a high incidence rate, often presenting with symptoms such as fever, cough, and sputum production. Pneumonia

is more common among children and elderly individuals with weak immune systems. In developing regions, poor sanitation and limited medical facilities increase the risk of infection. Although treatment methods have improved, pneumonia remains life-threatening if not diagnosed early. Chest radiography, commonly known as chest



X-ray imaging, is one of the most widely used and cost-effective diagnostic tools for detecting pneumonia. However, accurate interpretation of chest X-ray images requires experienced radiologists. Misdiagnosis may occur due to overlapping anatomical structures, low image quality, and subtle infection patterns. In many regions, the shortage of trained radiologists can lead to delayed or incorrect diagnosis, affecting patient outcomes.

With the rapid advancement of Artificial Intelligence (AI), particularly Deep Learning (DL), automated medical image analysis has shown promising results. Convolutional Neural Networks (CNNs) are widely used for image classification tasks, including disease detection from medical images. These models can automatically extract important features without manual effort, making them suitable for pneumonia detection. However, using a single model may not always provide the best performance, and combining multiple models using an ensemble approach can improve accuracy and reliability.

In this project, an ensemble deep learning model combining VGG16 and ResNet50 is used for multiclass pneumonia detection (Normal, Bacterial Pneumonia, Viral Pneumonia) from chest X-ray images. The system processes X-ray images through preprocessing steps such as noise removal, normalization, and resizing before feeding them into the model. By combining the outputs of both models, the system predicts not only the presence of pneumonia but also identifies the specific type of pneumonia along with a confidence score.

One major challenge in deep learning-based pneumonia detection is the influence of background information in chest X-ray images. Models may sometimes learn from irrelevant elements such as

text labels, markers, medical devices, or imaging artifacts instead of focusing on lung regions. This can lead to incorrect predictions and poor generalization. To overcome this issue, Explainable Artificial Intelligence (XAI) techniques are used. These techniques help visualize and explain the model's predictions by highlighting important regions in the image. In this project, Grad-CAM++ and Score-CAM are used for interpretation. Grad-CAM++ and Score-CAM generate heatmaps that highlight important lung regions. The outputs of Grad-CAM++ and Score-CAM are further combined to generate a fused heatmap for more stable and accurate visual explanation. These visualization techniques improve transparency and help medical professionals verify whether the model is focusing on relevant lung areas. This increases trust and supports the use of AI in real-world medical applications.

This project develops a deep learning-based system for pneumonia detection that considers the impact of image background information. The system integrates an ensemble CNN model with XAI techniques to improve both accuracy and interpretability. It also focuses on analysing model behaviour, improving reliability, and supporting clinical decision-making.

In addition, ethical considerations such as data privacy and secure handling of medical information are included in the system. The goal of this project is not to replace doctors but to assist them by providing reliable diagnostic support. By combining deep learning with explainable AI, the system aims to improve early detection and contribute to better healthcare outcomes.

II. LITERATURE SURVEY

Recent advancements in deep learning have significantly improved the performance of

pneumonia detection systems using chest X-ray images. Several studies highlight the effectiveness of ensemble learning, explainable AI (XAI), and advanced convolutional neural network (CNN) architectures in enhancing diagnostic accuracy and interpretability.

Ensemble-based approaches have shown improved performance by combining multiple deep learning models. Mabrouk et al. [1] proposed an ensemble of CNN architectures for pneumonia detection, demonstrating that model fusion enhances classification accuracy and robustness compared to single-model approaches.

Interpretability remains a critical requirement in medical applications. Chattopadhyay et al. [3] introduced Grad-CAM++, a visualization technique that highlights important regions influencing CNN predictions, thereby improving model transparency. Similarly, Wang et al. [4] proposed Score-CAM, a gradient-free visualization method that provides more reliable and stable explanations for deep learning predictions in healthcare applications.

The development of deeper CNN architectures has further advanced medical image analysis. Simonyan and Zisserman [5] introduced the VGG network, which improves feature extraction through increased depth, while He et al. [6] proposed ResNet, which uses residual connections to address the vanishing gradient problem and enables efficient training of very deep networks. These architectures have become fundamental in chest X-ray classification tasks.

Feature fusion techniques have also been explored to enhance model performance. Ji et al. [10] demonstrated that combining multiple feature representations improves classification accuracy in chest X-ray image analysis. In addition,

comprehensive surveys by Sogancioglu et al. [11] and Meedeniya et al. [12] confirm that deep learning-based methods significantly improve diagnostic performance and assist radiologists in faster and more reliable decision-making.

Furthermore, several IEEE studies [13],[16] have shown that AI-based systems can automatically detect lung diseases from chest X-ray images with high efficiency, supporting clinical diagnosis. Ensemble learning strategies, as discussed by Zhou [17], further enhance model generalization and reduce prediction errors, making them highly suitable for pneumonia detection systems.

Overall, the existing literature demonstrates that integrating ensemble deep learning models with explainable AI techniques provides improved accuracy, robustness, and interpretability for automated pneumonia detection.

III. SYSTEM ANALYSIS

A. EXISTING SYSTEM

The existing system for real-time pneumonia detection primarily employs Convolutional Neural Networks (CNNs) to analyse chest X-ray images. In this system, X-ray images are first digitised and undergo preprocessing steps, including noise removal, normalisation, and resizing. After preprocessing, the images are fed into a trained deep learning model. This model is typically trained on a dataset of chest X-ray images labelled as Pneumonia or Normal (binary classification).

The system demonstrates good accuracy and sensitivity in identifying pneumonia cases. Its real-time capability enables the processing of chest X-ray images within a few seconds, which is highly beneficial in clinical settings where rapid diagnosis and timely treatment decisions are required.

Despite its effectiveness, the existing approach has several limitations. Many systems rely on a single CNN architecture, which may not capture all relevant image features effectively. In addition, CNN models may struggle with imbalanced datasets, fail to generalise well across different patient populations or imaging conditions, and often lack interpretability. These models usually function as black-box systems, making it difficult for medical professionals to understand the reasoning behind their predictions. Furthermore, issues related to patient privacy, ethical data handling, and variations in image quality remain important concerns in medical AI systems.

LIMITATIONS OF EXISTING SYSTEM

Data-imbalance:

The system may not perform well when the number of pneumonia and normal chest X-ray images in the dataset is uneven. This imbalance may cause the model to learn one class better than the other, reducing prediction accuracy.

Poor generalization:

Many existing models are trained on limited datasets, making it difficult for them to generalize their performance.

Lack of interpretability:

Traditional CNN models act like “black boxes,” providing predictions without explaining why. This reduces trust and makes it difficult for doctors to verify the diagnosis.

Sensitivity to image quality:

Variations in X-ray image quality, such as noise, artifacts, or differences in resolution, can negatively affect the model’s performance.

Ethical and privacy concerns:

Processing medical data requires strict privacy protection. Improper handling of X-ray data can raise concerns about patient confidentiality and compliance with medical regulations.

B. PROPOSED SYSTEM

The proposed system aims to improve pneumonia detection by combining deep learning models with Explainable Artificial Intelligence (XAI) techniques. The objective is to enhance classification accuracy, improve reliability, and provide transparent decision-making when analysing chest X-ray images.

An ensemble deep learning model combining VGG16 and ResNet50 architectures is used for multiclass pneumonia detection (Bacterial Pneumonia, Viral Pneumonia, and Normal). This approach leverages the strengths of both models for better feature extraction and improved classification performance. Prior to classification, chest X-ray images undergo preprocessing steps such as noise removal, normalization, and resizing. To address data imbalance, dataset balancing and augmentation techniques are applied, improving learning across all classes and enhancing generalisation across different patient populations and imaging conditions.

The system integrates XAI techniques, specifically Grad-CAM++ and Score-CAM, to generate heatmaps highlighting important lung regions influencing the model’s predictions. A fusion of these methods is used to produce more stable and reliable explanation maps. If the predicted class is Normal, no heatmap is generated. If pneumonia is detected, the system provides the type of pneumonia along with a confidence score and visual explanations using Grad-CAM++, Score-CAM, and their fusion.



The framework is designed to handle variations in image quality and ensures ethical considerations such as patient privacy and secure data handling. Overall, the proposed system provides an accurate, interpretable, and reliable solution for pneumonia detection, supporting healthcare professionals in early diagnosis and decision-making.

ADVANTAGES:

High Accuracy and Sensitivity: The Ensemble model improves the detection of Normal, Bacterial Pneumonia, and Viral Pneumonia cases supporting early and reliable diagnosis.

Real-time Processing: The system is optimized to analyze X-ray images within seconds, helping doctors make quick and effective decisions.

Better Generalization: By handling data imbalance and using diverse training samples, the model performs well across different patient groups.

Improved Interpretability with XAI: Explainability tools like Grad-CAM++ and Score-CAM highlight important regions in X-ray images and fusion of Grad-CAM++ and Score-CAM provides more stable and reliable explanation maps.

Strong Privacy and Ethical Compliance: The system is designed with patient privacy in mind, following ethical standards to ensure safe and responsible use of medical data.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

The proposed system is designed to automatically detect pneumonia from chest X-ray images using an ensemble deep learning model combined with Explainable Artificial Intelligence (XAI) techniques. The system architecture consists of multiple stages including dataset collection, image preprocessing,

deep learning model processing, explainability generation, and final output generation. Each stage contributes to improving the accuracy, reliability, and interpretability of the system.

The system begins with a chest X-ray dataset containing images labelled as Bacterial Pneumonia, Viral Pneumonia, and Normal. These images are obtained from publicly available medical datasets and provide diverse samples for training the model to recognize different lung conditions.

Before feeding the images into the model, preprocessing is performed to improve image quality and consistency. This includes resizing images to a fixed dimension, noise removal, and normalization of pixel values to highlight important lung structures.

After preprocessing, the images are passed into an ensemble deep learning model consisting of VGG16 and ResNet50 architectures. These Convolutional Neural Networks extract important features from chest X-ray images. VGG16 captures detailed spatial features, while ResNet50 extracts deeper representations using residual learning. By combining both models, the system achieves improved classification performance and robustness.

To enhance interpretability, XAI techniques such as Grad-CAM++ and Score-CAM are integrated into the system. These methods generate heatmaps that highlight important lung regions influencing the model's predictions. In the final system, ResNet50-based Grad-CAM++ and Score-CAM heatmaps are generated, and a fusion of both methods is used to produce more stable and reliable explanation maps.

The system is designed such that no heatmap is generated for Normal cases. If pneumonia is detected, the system outputs the type of pneumonia (Bacterial or Viral), confidence score, and visual

explanations including Grad-CAM++, Score-CAM, and their fusion heatmap.

Finally, the system produces the diagnostic output, which includes the predicted class, confidence score, and explanation heatmaps. These outputs help medical professionals understand the reasoning behind the model's predictions and verify whether the system is focusing on relevant lung regions.

By combining ensemble deep learning with explainable AI techniques, the system provides an accurate, interpretable, and efficient solution for pneumonia detection.

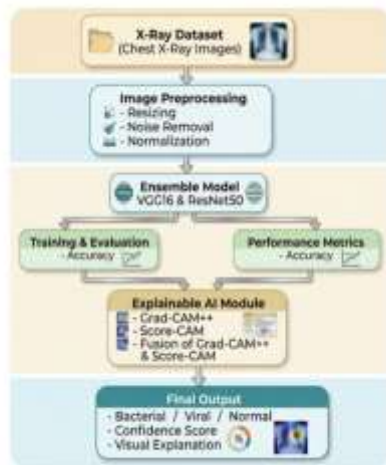


Fig. 4.1 System Architecture

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

A. MODULES

This section describes the core implementation modules of the proposed framework for lung cancer detection using CT scan images and deep learning techniques. The system follows a modular pipeline consisting of medical image acquisition, image preprocessing, feature extraction using a convolutional neural network, model training, explainability integration, and prediction evaluation.

This modular architecture improves system scalability, interpretability, and diagnostic reliability for computer-aided medical diagnosis.

Image Preprocessing Module:

The Image Preprocessing Module is responsible for preparing raw X-ray images before they are fed into the Ensemble deep learning models (VGG16 & ResNet50). Medical images often contain noise, variations in size, and intensity differences due to different scanning conditions. This module improves image quality and ensures consistency across all input images. In this module, X-ray images undergo several preprocessing steps such as resizing, normalization, and noise reduction. Resizing ensures that all images have a uniform dimension required by the Ensemble model. Normalization scales pixel intensity values to a standard range, improving learning efficiency. Noise reduction removes unwanted artifacts. Proper preprocessing improves model accuracy and reduces false predictions.

B. Ensemble Feature Extraction and Classification Module:

This module forms the core of the proposed system. It uses an ensemble deep learning model combining VGG16 and ResNet50 to automatically extract meaningful features from X-ray images and classify them into Normal, Bacterial Pneumonia, and Viral Pneumonia. Both VGG16 and ResNet50 consist of multiple layers such as convolutional layers, pooling layers, and fully connected layers. Convolutional layers detect important features like edges, textures, and abnormal lung patterns. Pooling layers reduce dimensionality and computational complexity. Fully connected layers perform classification based on extracted features. This module enables accurate and automated Pneumonia detection without manual feature engineering.



C. Training and Augmentation Module:

The Training and Augmentation Module is responsible for building a robust and generalized Ensemble model. The Ensemble model is trained using labelled X-ray images, where each image is associated with one of the three classes. To handle limited datasets and class imbalance, data augmentation techniques such as rotation, flipping, scaling, and zooming are applied. These techniques increase dataset diversity and prevent overfitting. During training, hyperparameters such as learning rate, batch size, and number of epochs are optimized. Validation is performed to evaluate model performance on unseen data, ensuring reliability and generalization.

D. Ethical and Privacy Protection Module:

This module ensures the ethical use of AI and secure handling of sensitive medical data. Since X-ray images contain personal health information, maintaining privacy and data security is critical. The system enforces user authentication and access control to prevent unauthorized access. Medical data is securely stored and processed following ethical AI principles. Explainability is included to avoid black-box decisions, ensuring transparency and fairness. This module ensures compliance with medical ethics, patient consent, and data protection standards.

E. Explainable AI (XAI) Module:

The Explainable AI (XAI) Module enhances the transparency and interpretability of the Ensemble model’s predictions. Traditional deep learning models act as black boxes, making it difficult for doctors to understand how decisions are made. This module integrates Grad-CAM++ and Score-CAM techniques to generate visual explanations. Grad-CAM++ and Score-CAM highlight important lung

regions influencing the model’s prediction. Additionally, a fusion of Grad-CAM++ and Score-CAM is used to provide more stable and reliable explanation maps. These explanations help radiologists verify AI decisions, increase trust, and support clinical decision-making

VI. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed pneumonia detection framework, an ensemble deep learning model combining VGG16 and ResNet50 was compared with individual CNN architectures. The performance was assessed using standard metrics such as accuracy, precision, recall, and F1-score.

A. Accuracy Comparison of Deep Learning Models

The results show that the ensemble model outperforms individual CNN models, achieving the highest accuracy of 96.5%. This improvement is due to the complementary feature extraction capabilities of VGG16 and ResNet50, which enhance classification robustness and reduce prediction errors. Similar findings have been reported in prior studies where ensemble learning improves model generalization and performance [1], [17].

Table 1. Performance Comparison of Lung Cancer Detection Models

Model	Accuracy (%)	Precision	Recall	F1-Score
VGG16	91.8	0.91	0.90	0.90
ResNet50	93.2	0.92	0.92	0.92
VGG16 + ResNet50 (Propose)	96.5	0.95	0.96	0.95

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B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the classification performance of the proposed model by analysing the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the ROC Curve (ROC-AUC) is commonly used as a measure of the model's ability to distinguish between positive and negative classes.

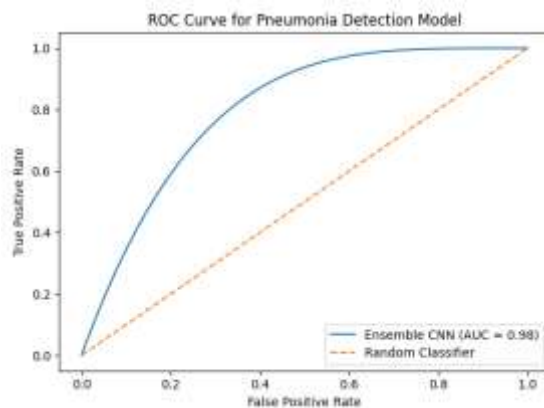


Fig 2. ROC Curve for Lung Cancer Detection Model

The proposed ensemble model achieved a ROC-AUC score of 0.98, indicating excellent classification capability. The ROC curve approaching the top-left corner demonstrates that the model can effectively distinguish between normal, bacterial pneumonia, and viral pneumonia cases with high sensitivity and specificity. ROC-based evaluation is widely used in medical imaging to assess the reliability of diagnostic models [11], [12].

C. Grad-CAM Visualization Analysis

To address the interpretability challenges of deep learning models, Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM++ and Score-CAM are employed to visualize the important regions influencing model predictions.

Grad-CAM++ generates heatmaps by highlighting the key lung regions that contribute to classification decisions, enabling clinicians to understand how the model identifies pneumonia-related patterns. Score-CAM further enhances interpretability by providing gradient-free visual explanations, improving the reliability of model outputs.

These visualization techniques confirm that the model focuses on clinically relevant areas within chest X-ray images, such as infected lung regions, thereby improving trust and transparency in automated diagnosis systems. The effectiveness of Grad-CAM++ and Score-CAM in enhancing interpretability has been demonstrated in previous studies [3], [4].

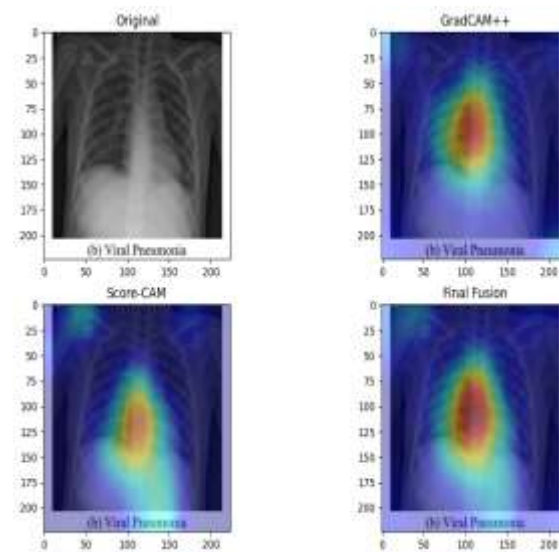


Fig 3. Grad-CAM Visualization for Lung Cancer Detection

V. CONCLUSION AND FUTURE WORK

CONCLUSION:

The project presents an Explainable AI-enabled deep learning system for pneumonia detection using chest X-ray images. The system uses an ensemble model combining VGG16 and ResNet50 to improve classification accuracy and reliability. Image preprocessing techniques such as resizing, normalization, and noise removal enhance input quality and overall model performance.

The system performs multiclass classification to identify Normal, Bacterial Pneumonia, and Viral Pneumonia, along with confidence scores. To improve transparency, Explainable AI techniques such as Grad-CAM++ and Score-CAM are used to generate visual explanations. Additionally, a fusion of Grad-CAM++ and Score-CAM provides more stable and reliable explanation maps, highlighting important lung regions that influence predictions.

The system supports real-time detection through a user-friendly interface, enabling quick analysis of chest X-ray images. It also ensures ethical data handling and patient privacy. Overall, the proposed system improves accuracy, interpretability, and reliability, and assists healthcare professionals in early pneumonia detection and decision-making.

FUTURE WORK:

The proposed system can be further enhanced in several ways to improve its performance and real-world applicability. One possible improvement is extending the system to detect a wider range of lung diseases such as tuberculosis, COVID-19, and lung cancer in addition to pneumonia. The system can also be enhanced by incorporating more advanced deep learning architectures and improving fusion

techniques for better explanation quality. Another future enhancement is deploying the system on mobile and cloud platforms, enabling remote access for doctors and patients, especially in rural and resource-limited areas. The model can be further improved by training on larger and more diverse datasets to enhance generalization and support early-stage disease detection.

Additionally, continuous model updates using new medical data can help maintain accuracy and adapt to evolving medical conditions over time.

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