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Advanced Pneumonia Detection and Severity Analysis Using CLAHE-CNN and GRAD-CAM

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Abstract: The Pneumonia is a serious respiratory infection that can lead to severe health complications and increased mortality if not diagnosed and treated at an early stage. Conventional diagnosis using chest X-ray imaging is time-consuming and highly dependent on the expertise of radiologists, which may not always be readily available in healthcare facilities. To address this challenge, this project presents an Advanced Pneumonia Detection and Severity Analysis System from Chest X-Ray Images Using CLAHE-Enhanced Convolutional Neural Networks (CNN) with Grad-CAM Visualization and Clinical Recommendation Support. The proposed system utilizes Contrast Limited Adaptive Histogram Equalization (CLAHE) as a preprocessing technique to enhance the quality and contrast of chest X-ray images, thereby improving feature extraction and classification performance. A deep CNN model is trained on labeled chest radiographs to automatically classify images as Pneumonia or Normal while also assessing the severity level of infection. The model learns discriminative patterns from enhanced X-ray images and provides accurate predictions with improved robustness. To improve transparency and interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is integrated into the framework to generate heatmap visualizations that highlight the infected lung regions responsible for the model's predictions. The performance of the proposed model is evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrate that the integration of CLAHE enhancement and Grad-CAM interpretability significantly improves diagnostic reliability and model understanding. The developed system offers an efficient, accurate, and explainable AI-assisted solution for early pneumonia diagnosis, severity assessment, timely treatment support, and improvement.

Keywords: Pneumonia Detection, Chest X-Ray, CNN, Deep Learning, CLAHE, Grad-CAM, Explainable AI, Severity Analysis, Medical Image Processing, Clinical Recommendation.

I. INTRODUCTION

The Pneumonia is a severe respiratory infection that affects the lungs by causing inflammation in the air sacs, which may fill with fluid or pus. It is one of the leading causes of death worldwide, particularly among children, elderly individuals, and patients with weakened immune systems. According to global health reports, millions of pneumonia cases are reported every year, creating a significant burden on healthcare systems. Early and accurate diagnosis is essential for timely treatment and reducing mortality rates.

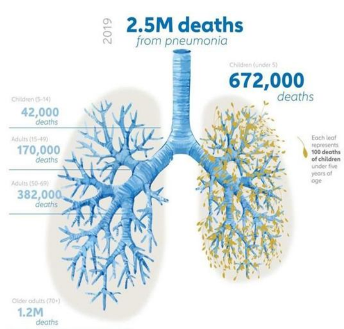

Figure 1: Pneumonia Infographic

Chest X-ray imaging is one of the most commonly used and cost-effective diagnostic techniques for pneumonia detection. Radiologists analyze chest X-ray images to identify abnormalities such as lung opacities, infiltrates, and consolidations. However, manual examination of large volumes of medical images is time-consuming and may lead to diagnostic errors due to fatigue, workload, and variations in image quality. In many healthcare centers, especially in rural and underdeveloped regions, the shortage of experienced radiologists further increases the risk of delayed diagnosis.

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Recent developments in Artificial Intelligence (AI) and Deep Learning have significantly improved the field of medical image analysis. Among various deep learning techniques, Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification and disease detection tasks. CNN- based models can automatically learn important features from chest X-ray images and provide highly accurate predictions for pneumonia detection. Despite their success, many existing deep learning models function as black-box systems, where the reasoning behind predictions is not clearly visible to medical professionals. This lack of transparency limits the trust and acceptance of AI systems in clinical environments.

To address these challenges, Explainable Artificial Intelligence (XAI) techniques are increasingly being integrated into medical diagnostic systems. One such technique is Gradient-weighted Class Activation Mapping (Grad-CAM), which generates visual heatmaps highlighting the important regions in an image that influence the model's prediction. These visual explanations help doctors understand the decision- making process of the AI model, thereby improving interpretability and clinical confidence.

In addition, image preprocessing plays a vital role in enhancing the quality of chest X-ray images for better feature extraction and classification. Contrast Limited Adaptive Histogram Equalization (CLAHE) is an effective preprocessing technique used to improve image contrast and highlight important lung structures without amplifying noise excessively. Enhanced images enable CNN models to learn more
discriminative features, thereby improving diagnostic performance.

This proposed work presents an Explainable AI-driven framework for enhanced pneumonia detection from chest X-ray images using a CLAHE-optimized CNN model. The framework combines image enhancement, deep learning-based classification, severity assessment, Grad-CAM visualization, and clinical decision support into a single integrated system. The proposed model not only detects pneumonia accurately but also evaluates the severity of infection and provides visual explanations to assist healthcare professionals in diagnosis and treatment planning.

The major contribution of this work lies in integrating explainability and severity assessment with deep learning-based pneumonia detection to create a more transparent, reliable, and clinically useful diagnostic framework. The proposed system aims to reduce diagnostic workload, improve healthcare efficiency and support medical experts.

II. LITERATURE REVIEW

Priyanka Tyagi et. al., [1] proposed a deep learning-based framework for automated pneumonia detection using chest X-ray images. The methodology utilizes a publicly available chest X-ray dataset containing Normal and Pneumonia images for model training and evaluation. Preprocessing techniques such as image resizing and normalization were applied to standardize the dataset before training. The authors implemented transfer learning using pre-trained Convolutional Neural Network (CNN) architectures including VGG16, VGG19, ResNet50, InceptionV3, and EfficientNetB3 for feature extraction and classification. The VGG16 model was configured with Image Net weights and customized classification layers to distinguish between pneumonia and normal chest X-ray images. Additionally, federated learning techniques were explored to enable collaborative model training without sharing sensitive patient data, thereby preserving privacy. The performance of the proposed system was evaluated using metrics such as accuracy, precision, recall, F1- score, and confusion matrix analysis. Experimental results demonstrated that EfficientNetB3 combined with the FedProx aggregation strategy achieved superior performance, obtaining approximately 99.32% accuracy on similar datasets and 96.98% accuracy on diverse datasets. The study concluded that deep learning and federated learning approaches can significantly improve automated pneumonia diagnosis while maintaining data privacy and reducing diagnostic workload.

P. Rajpurkar, J[2]. proposed a CNN inspired by VGG with novel pooling modules, achieving 95.5% accuracy on over 1000 CT scans, showing the potential of carefully designed architectures. Rajaraman et al. used ensembles with transfer learning on 16,000 X-rays, reaching 94–99% accuracy, highlighting the strength of model ensembles. Singh and Yow explored interpretable ProtoPNet variants, achieving 87.27% accuracy while providing visual explanations, important for clinical trust.

Hyperparameter tuning has been shown to significantly impact performance. Saboo et al. compared optimizers, batch sizes, and dropout across multiple CNNs, confirming the importance of fine-tuning. Ensemble learning is another focus; Vyas et al. combined CNNs (VGG19, ResNet50V2, DenseNet121) with traditional classifiers like Random Forest and SVM, achieving better accuracy than standalone models.

Real-time detection approaches have also emerged. Xie et al. adapted Fast-YOLO with efficient modules, improving speed and accuracy for clinical deployment. Recent reviews emphasize attention mechanisms and explainability tools (e.g., Grad-CAM) to enhance transparency and clinician trust.

III. METHODOLOGY

The proposed system, "An Explainable AI-Driven Framework for Enhanced Pneumonia Detection from Chest X-Ray Images Using CLAHE-Optimized CNN with Severity Assessment, Grad-CAM Visualization, and Clinical Decision Support," follows a systematic approach for detecting pneumonia from chest X-ray images. The methodology combines image enhancement techniques, deep learning-based classification, explainable artificial intelligence, and clinical decision support to improve diagnostic accuracy and transparency.

A. Data Collection

The pipeline initiates with the acquisition of chest X-ray images from established public repositories. These data sources primarily include standard medical benchmarks such as the Kaggle Chest X-Ray dataset, the RSNA Pneumonia Dataset, and the NIH Chest X-Ray Dataset. The goal of this step is to compile a diverse, well-labeled collection of radiographs depicting both healthy individuals and various stages of pneumonia infection to support effective model generalization.

B. Preprocessing & CLAHE Optimization

Once the raw medical images are imported, they undergo a multi-tier preprocessing phase designed to standardize the inputs and isolate essential features. The original X-rays are first subjected to resizing and noise reduction to achieve consistent matrix dimensions and clear high-frequency artifacts. The images then undergo Contrast Limited Adaptive Histogram Equalization (CLAHE) enhancement, a technique that prevents over-amplification of noise while sharpening the contrast boundaries of subtle pulmonary infiltrates. Finally, normalization maps the pixel values into a uniform scalar range, followed by data augmentation to artificially expand the training variance and prevent overfitting.

C. CNN Model Architecture & Feature Learning

The enhanced images, standardized to 224 \times 224 pixels, are fed into the deep Convolutional Neural Network (CNN) backbone. The architecture contains alternating Convolutional layers paired with Rectified Linear Unit (ReLU) activations to map spatial structures, alongside Max Pooling layers that downsample the spatial dimensions to retain dominant feature representations. The extracted abstract high-level features are subsequently routed through Fully Connected (dense) layers, regulated by Dropout layer to break co-dependencies between features, and finally passed to a Softmax output layer that computes class probabilities.

D. Pneumonia Detection (Classification)

The Softmax probabilities derived from the dense layers are evaluated by the primary classification head to perform diagnostic sorting. The framework maps the input features into one of two distinct output categories: *Normal* or *Pneumonia*. This stage acts as the primary triage layer, instantly filtering out clear, unobstructed pulmonary scans from those demonstrating radiographic signs of lung infection.

E. Severity Assessment

Scans flagged as positive for pneumonia are automatically routed to the secondary triage block for severity analysis. The system inspects the density and spatial distribution of the identified opacities to categorize the infection into three quantitative bands. A classification of *Mild* signifies a low infection profile where less than 25% of the lung field is affected. *Moderate* indicates a medium infection profile involving between 25% and 50% of the lung field. A status of *Severe* is triggered by a high infection footprint, denoting widespread infiltration covering greater than 50% of the lung area.

F. Grad-CAM Visualization (Explainable AI)

To ensure that the network's reasoning can be independently audited by clinicians, the framework incorporates Gradient-weighted Class Activation Mapping (Grad-CAM). This explainer takes the input X-ray and computes the backpropagated gradients of the target class score relative to the feature maps of the final convolutional layer. The system uses these weights to construct a 2D spatial heatmap that isolates the exact locations of the anomalies driving the prediction. This activation heatmap is then blended back onto the original scan as an overlay, ensuring that the visual evidence matches clinical observation.

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G. Clinical Decision Support System (CDSS)

The quantitative predictions and spatial maps are synthesized within an intelligent Clinical Decision Support dashboard. The software automatically displays the primary prediction result, the computed severity grading, and the visual Grad-CAM heatmap overlay. Based on the calculated severity band, the system provides automated clinical recommendations: advising regular monitoring and checkups for Mild cases, recommending medication and targeted follow-up for Moderate cases, and prompting immediate treatment and hospitalization protocols if a Severe condition is detected.

H. End-User Clinician & Radiologist Interface

The final stage closes the loop by outputting these processed metrics directly to the healthcare professional's monitor interface. The workstation displays the structural prediction alongside a calculated confidence percentage (e.g., Prediction: Pneumonia, Severity: Moderate, Confidence: 92.1%). By providing an explainable, visual map paired with clear evidence-backed insights, the interface serves as a reliable second-opinion tool to assist medical personnel in finalizing diagnoses and accelerating patient treatment pathways.

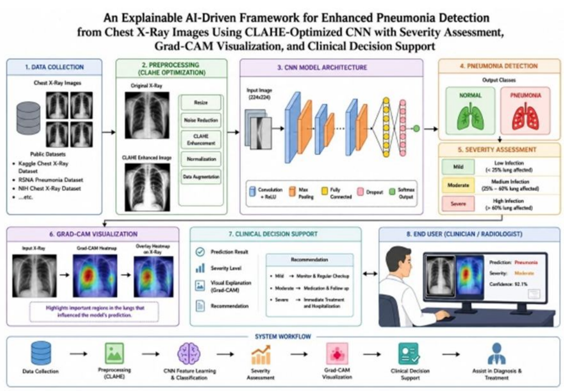

Fig 2 : System Architecture

IV. WORKING

The explainable AI-driven diagnostic framework initiates with the Data Collection stage, where raw chest X-ray images are compiled from established public repositories like Kaggle, the RSNA Pneumonia Dataset, and the NIH Chest X-Ray Dataset to provide a robust training baseline.

These raw radiographs move directly into the *Preprocessing and CLAHE Optimization* stage, where they undergo structural resizing, noise reduction filters, and Contrast Limited Adaptive Histogram Equalization to sharpen the visibility of subtle pulmonary infiltrates before being normalized and augmented to enhance model generalization. The enhanced 224 \times 224 pixel images are then fed into the CNN Model Architecture, which utilizes alternating convolutional layers with ReLU activations and max pooling to capture high-level spatial visual features, down-sampling them into dense, fully connected layers protected by dropout regularization. The final Softmax layer routes these learned features into the Pneumonia Detection module, which acts as a primary clinical triage head by executing a binary classification to sort inputs as either Normal or Pneumonia. If a scan is classified as positive for pneumonia, it is automatically passed down to the Severity Assessment module, which evaluates the total footprint of the infection to categorize the disease into three operational bands: Mild (low infection, under 25% of the lung field affected), Moderate (medium infection, 25% to 50% affected), or Severe (high infection, over 50% affected). In parallel, to dismantle the "black-box" nature of the network, the Grad-CAM Visualization engine computes the back propagated gradients of the target class score relative to the feature maps of the final convolutional layer, producing a spatial localization heatmap that is overlaid onto the original image to expose the exact regions driving the algorithm's prediction. These outputs are instantly aggregated by the Clinical Decision Support System (CDSS), which pairs the prediction, severity level, and Grad-CAM map with automated, actionable medical recommendations—such as routine checkups for mild cases, medication for moderate cases, and immediate hospitalization for severe cases. Ultimately, this entire stream of data is delivered to the End User Interface, displaying the complete visual and quantitative diagnosis with an integrated confidence percentage to serve as an interpretable, reliable second-opinion tool that assists clinicians and radiologists in making swift, confident treatment decisions.

V. RESULT

The proposed CLAHE-Optimized CNN framework was successfully implemented for pneumonia detection using chest X-ray images. The preprocessing stage enhanced image quality through contrast improvement and noise reduction, enabling better feature extraction. The CNN model effectively learned important lung features and accurately classified chest X-rays as either normal or pneumonia-infected.

The severity assessment module further categorized pneumonia cases into mild, moderate, and severe levels based on the extent of lung involvement. Additionally, Grad-CAM visualization generated heatmaps highlighting the infected regions responsible for the model's predictions, improving the interpretability and reliability of the system.

The Clinical Decision Support System combined the prediction results, confidence scores, severity levels, and visual explanations into a comprehensive diagnostic report. Overall, the experimental results demonstrate that the proposed framework provides accurate pneumonia detection, effective severity analysis, and explainable predictions, making it a valuable tool for assisting radiologists and healthcare professionals in clinical diagnosis and treatment planning.

VI. CONCLUSION

This project proposed an Explainable AI-driven framework for pneumonia detection from chest X-ray images using a CLAHE-optimized CNN model. The system successfully enhanced image quality, detected pneumonia cases accurately, and classified disease severity into different levels. The integration of Grad-CAM visualization improved the interpretability of the model by highlighting the affected lung regions responsible for the predictions.

Furthermore, the Clinical Decision Support System provided meaningful diagnostic information to assist healthcare professionals in decision-making. Overall, the proposed framework demonstrated the potential of combining deep learning and explainable AI for accurate, reliable, and efficient pneumonia diagnosis, making it a useful tool for supporting radiologists and improving patient care.

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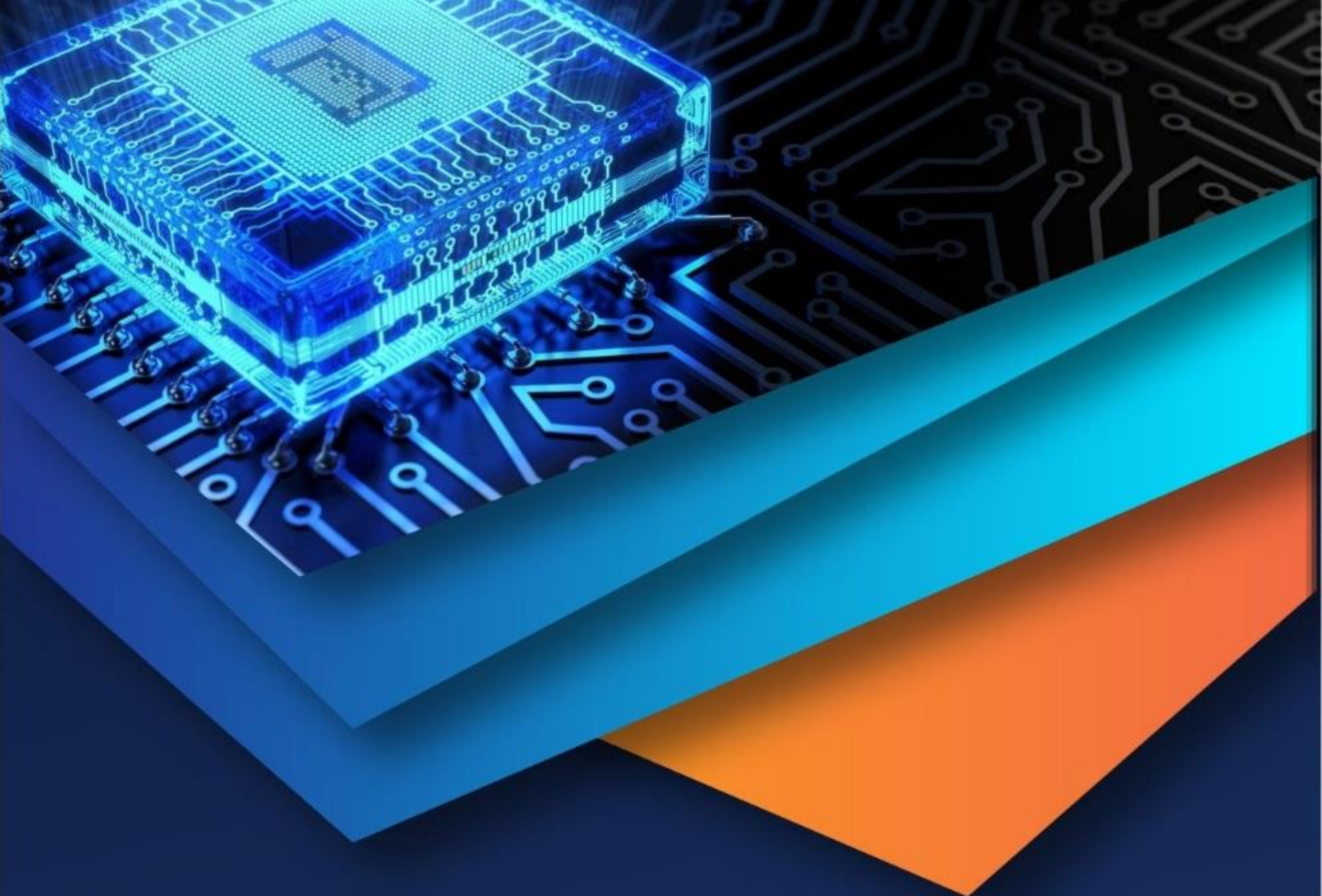

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