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Pneumonia Detection and Severity Classification in Chest X-Rays through Region Based Isolation and Optimized CNN Architectures

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***Abstract* - Globally, pneumonia is still a major health concern, particularly in areas with poor diagnostic facilities. This paper compares two CNN architectures, ConvXNet and a CustomCNN, for deep learning-based pneumonia identification using chest X-ray pictures. Preprocessing methods were used, including data augmentation, contrast enhancement, normalization, and grayscale conversion. A segmentation framework based on U-Net and ResNet32 was also implemented in order to separate lung regions and extract information unique to each region.**

CustomCNN demonstrated strong generalization capabilities with a high training accuracy of 96.04%, while ConvXNet excelled in validation and test performance, achieving 88.94% validation accuracy and 90.75% test accuracy. Notably, CustomCNN showcased superior recall 98.5%, making it highly effective in minimizing missed pneumonia cases, whereas ConvXNet achieved slightly better precision 86.4%, ensuring fewer false positives. These findings highlight the complementary strengths of both architectures, emphasizing their potential in supporting accurate and reliable pneumonia detection and severity classification, especially in resource-constrained healthcare settings.

Keywords: Pneumonia Detection, Severity Classification, Chest X-ray Analysis, Deep Learning, Convolutional Neural Networks (CNN), U-Net, ResNet34, Lung Segmentation.

I. INTRODUCTION

Acute respiratory infections like pneumonia, which impact the lungs, continue to pose a serious threat to world health. The World Health Organization (WHO) reports that pneumonia was the biggest infectious cause of mortality globally in 2019, accounting for 2.5 million deaths. This startling figure emphasizes the serious public health threat this illness poses, especially to susceptible groups like young children and those with compromised immune systems.

Pneumonia's effects go much beyond its death rate. Significant morbidity from the illness results in extended hospital stays, chronic respiratory issues, and a lower standard of living. In low- and middle-income countries (LMICs), where access to healthcare is often limited, this cost is even greater. In these areas, children are disproportionately affected by pneumonia, which kills hundreds of thousands of children under five every year.

The recent COVID-19 pandemic has further highlighted the challenges posed by respiratory infections. Both pneumonia and COVID-19 share overlapping symptoms such as fever, cough, and shortness of breath, making differential diagnosis challenging, especially in resource-constrained settings. This overlap has strained healthcare systems globally, emphasizing the need for rapid and accurate diagnostic tools.

Chest X-rays have long been the mainstay of pneumonia diagnosis. Their non-invasive nature, affordability, and accessibility make them a valuable tool, particularly in LMICs. However, the interpretation of X-rays relies heavily on the expertise of clinicians, making it susceptible to human error and subjectivity. This highlights the need for more objective and automated methods for pneumonia detection.

Traditional methods for diagnosing pneumonia, such as physical examination and chest auscultation, are often time-consuming and lack sensitivity and specificity. Moreover, relying on the expertise of clinicians for interpreting X-rays can lead to inconsistencies and delays in diagnosis, particularly in regions with limited healthcare resources.

The shortcomings of the present pneumonia diagnostic techniques may be addressed by promising improvements provided by developments in computer vision and artificial intelligence (AI). The accuracy, effectiveness, and accessibility of diagnosing pneumonia could be greatly increased with the creation of automated AI-powered systems for examining chest X-rays. This could therefore result in better patient outcomes and lower healthcare expenses, especially in environments with limited resources.

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The goal of this project is to create a reliable and precise AI-powered system that can identify pneumonia from chest X-rays and categorize the infection's severity. This dual functionality allows for improved healthcare outcomes, quicker turnaround times, and better decision-making and better patient care prioritization, which eventually enhance patient outcomes and maximize the use of resources in healthcare environments.

II. RELATED WORK

Mudasir Ali et al. [1] implemented and evaluated six deep learning models, including EfficientNetV2L, using a collection of 5,856 chest X-ray pictures in order to identify pneumonia. Their study demonstrated that EfficientNetV2L outperformed other models, achieving an accuracy of 94.02%. However, challenges such as overfitting, the need for additional datasets, and image quality issues were noted as limitations.

Samyak Shrimali [2] conducted a comparative analysis of transfer learning-based CNN architectures for using a dataset of 5,863 chest X-ray pictures, pneumonia was detected. The best accuracy, 92.53%, was obtained by a hybrid model that combined VGG16 and DenseNet121, with an F1-score of 83.41%.Despite these promising results, dataset limitations and class imbalance issues were highlighted as challenges.

Jovito Colin and Nico Surantha [3] explored interpretability in deep learning-based pneumonia detection by integrating techniques such as Class Activation Maps (CAMs), Layer-wise Relevance Propagation (LRP), and a Spatial Attention Mechanism (SAM) using ResNet50. Their model's interpretability score (MRS) was 85%, its sensitivity was 90%, and its specificity was 92%.However, the study emphasized trade-offs between accuracy and interpretability, as well as dataset bias concerns.

Mabrouk et al. [4] utilized an ensemble of pretrainedCNN models such as Vision Transformer (ViT), DenseNet169, and MobileNetV2, for pneumonia detection. Their ensemble approach yielded an accuracy of 93.91% but required extensive hyperparameter tuning and faced challenges related to variance and bias in ensemble learning.

Gupta et al. [5] focused on lightweight CNN architectures trained with preprocessing techniques such as augmentation, standardization, and normalization. Their model achieved a remarkable 98.89% accuracy and an AUC-ROC score of 0.99. However, the study pointed out the necessity of validating the model on diverse populations due to limited generalizability.

N. Shilpa et al. [6] leveraged transfer learning with ResNet50, MobileNetV2, AlexNet, EfficientNetB0, and Xception, alongside preprocessing techniques like CLAHE and 5-fold cross-validation. EfficientNetB0 achieved 99.78% accuracy with 100% precision, recall, and F1-score. Nevertheless, potential overfitting due to the relatively small dataset size was identified as a limitation.

Mihai Bundea and Gabriel MihailDanciu [7] investigated pneumonia classification using DenseNet architectures 5,856 chest X-ray pictures using the DenseNet121, DenseNet169, and DenseNet201 dataset. Although the models achieved up to 96% accuracy, there were issues with their low interpretability and restricted generalizability for clinical use.

Sadman Sadik Khan et al. [8] applied deep learning strategies, including MobileNetV2, InceptionV3, and custom CNN architectures, for pneumonia identification in chest X-rays. MobileNetV2 achieved the highest accuracy of97%, yet the study highlighted the need for further tuning and dataset expansion for improved generalization.

Mr. M. Rajeev Kumar and Dr. B. Geetha Vani [9] proposed a deep learning approach incorporating attention mechanisms with VGG16 and Inception V3. Their model achieved 98.53% accuracy but required further validation and tuning to ensure generalizability across diverse clinical settings.

Jagan Mohan Dudala [10] developed a custom CNN with data augmentation, down sampling, and dropout to address class imbalance in pneumonia detection. With an AUC of 0.99, the model's overall accuracy was 98.03%, and its validation accuracy was 99.78%.However, potential misclassification of some cases led to concerns regarding false positives and negatives.

VisheshTanwar [11] designed a CNN-based model to classify pneumonia into bacterial and viral categories, alongside normal chest X-rays. The overall accuracy was 80%, with bacterial pneumonia recall reaching 99%, while viral pneumonia recall remained significantly lower at 26%, indicating a need for further model optimization.

MohitBeri et al. [12] employed pre-trained CNN models as feature extractors and classifiers for pneumonia detection, achieving 93% accuracy for pneumonia cases and 92% for normal cases. Despite high F1-scores (~0.9), the study acknowledged limitations related to dataset diversity, overfitting risks, and the need for clinical validation.

Fadzai Ethel Muchina et al. [13] explored the use of LIME segmentation to enhance interpretability in CNN-based pneumonia classification. Their approach achieved a VGG16 accuracy of 97.95% and a ROC-AUC of 0.993. However,

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subjectivity in LIME-based interpretations and limitations in dataset diversity restricted real-time deployment feasibility.

Tina Babu et al. [14] designed a robust CNN architecture incorporating multiple Conv2D layers, ReLU activation, max-pooling, and fully connected layers. Their model achieved a training accuracy of 98.16%, validation accuracy of 98.45%, and test accuracy of 92.1%. However, limited dataset diversity and potential overfitting posed challenges for broader clinical applications.

Vinay K et al. [15] examined the effectiveness of CNN-based deep learning models with transfer learning. Using optimizers like Adamand architectures like VGG16, ResNet50, and DenseNet121, their best-performing model achieved 90.93% accuracy. Challenges related to model interpretability and dataset diversity emphasized the need for further optimization.

III. METHODOLOGY

This study intends to thoroughly assess the effectiveness of different convolutional neural network (CNN) architectures for chest X-ray-based pneumonia identification in light of the shortcomings noted in current approaches. It seeks to determine the architecture that best utilizes the potential of the data while maintaining accuracy, scalability, and efficiency by expanding on already-effective models.

A. Dataset Properties

Kaggle provided the dataset used in this study, which is called "Chest X-Ray Images for Pneumonia Detection." It includes chest X-ray pictures created especially for classification applications. The dataset is organized in a hierarchical manner and is divided into three main folders: validation, test, and train. There are subfolders for the image categories of pneumonia (infected lungs) and normal (healthy lungs) in each of these folders.

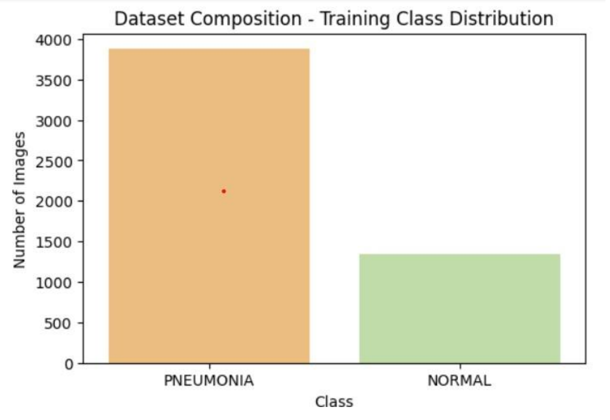

Figure 1: Bar graph representing the distribution of images in the training dataset across the two classes

The dataset includes 5,856 JPEG-formatted chest X-ray pictures in total. Pediatric patients' chest X-ray pictures were gathered. To ensure its applicability in actual clinical settings, all X-rays were obtained as part of standard clinical care. The use of pediatric-only chest X-rays introduces dataset bias and limits generalizability to adult populations. Due to anatomical and clinical differences, the models may underperform on adult cases. Broader datasets including adults are needed to improve robustness.

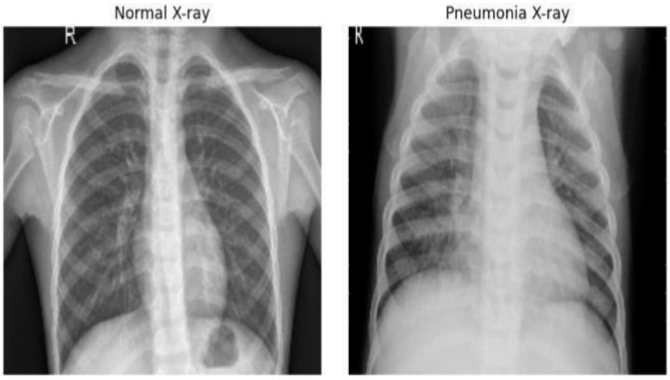

Figure 2: Sample images from chest X-rays dataset classified as Normal and Pneumonia

B. Data Preprocessing

To ensure high-quality input data, the chest X-ray images were first extracted and organized into separate directories for training, validation, and testing. The images were converted to grayscale to emphasize key textural features essential for pneumonia detection. To ensure uniformity and speed up processing, all images were scaled to 224 × 224 pixels.

In order to improve model robustness and reduce overfitting, data augmentation was applied to the training dataset using TensorFlow's Image Data Generator. Various transformations were incorporated to introduce diversity in the dataset and simulate natural variations encountered in real-world medical imaging. These included random rotations, translations, zooming, shearing, and brightness adjustments. Moreover, horizontal flipping was applied to introduce variations in orientation, and a suitable fill mode was used to handle any distortions at image boundaries.

The validation and test datasets were only rescaled without augmentation to maintain consistency during model evaluation. This preprocessing pipeline ensured that the model could learn robust and generalizable features for pneumonia classification.

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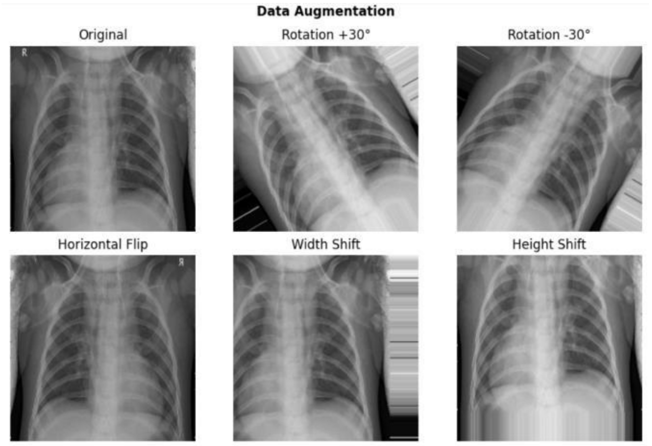

Figure 3: Examples of data augmentation techniques applied to Chest X-ray images from dataset

C. CNN Model Design and Selection

This research explores pneumonia detection and severity classification in chest X-rays using custom CNN architectures. Two models, ConvXNet and CustomCNN, were developed to evaluate their effectiveness. These architectures were designed to leverage different convolutional configurations for enhanced feature extraction.

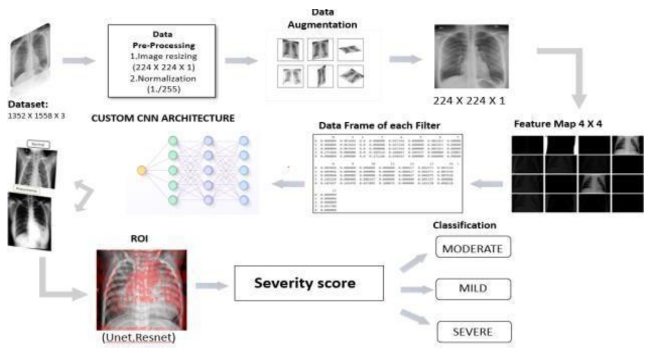

Figure 4: Architecture Diagram

ConvXNet features multiple convolutional layers with progressively increasing filters (32, 64, 128, and 256) and max- pooling layers, capturing both low-level and high-level features. This structure enables deeper feature representation, improving classification performance.

CustomCNN, on the other hand, uses a simpler and lightweight structure that applies small filters (with sizes 16, 32, 64, and 128) to analyze the images. This design reduces complexity while still maintaining good classification performance. Additional pooling layers help in reducing computation and focusing on important features.

To improve severity classification, a segmentation-based approach was integrated. A pre-trained segmentation model was utilized to isolate pneumonia-affected lung regions. The extracted regions were then analyzed to quantify the spread of pneumonia, classifying severity levels as Mild, Moderate, or Severe based on the affected lung area.

Grayscale chest X-ray pictures that had been reduced to 224 × 224 pixels were used to train both models. To enhance generalization, a variety of data augmentation techniques were used, including flipping, rotation, zooming, and brightness fluctuations. For the best training, the binary cross-entropy loss function and Adam optimizer were used. To avoid overfitting, the models were trained for 50 epochs with early stopping.

Table I: Comparison of CNN Architectures

ModelName	Key Architectural Features	Strengths	Potential Limitations
ConvXNet	Multiple convolutional layers(32,64, 128,256)with max pooling	Capturesboth low- and high-level features,deep feature extraction	Largermodel size,potential overfitting
CustomCNN	Compact structure with filtersizes(16, 32,64,128) andpooling layers	Efficient, optimizedfor feature extraction, reduced complexity	Maysacrifice some feature depth for efficiency
HybridModel	Combinationof ConvXNet and CustomCNN feature representations	Potential for improved accuracyand robustness	Increased complexity, requires careful integration

The selected CNN architectures (ConvXNet and CustomCNN) exhibit unique advantages, contributing to diverse performance in pneumonia detection. ConvXNet excels in deeper feature extraction, while CustomCNN focuses on efficiency with a lighter structure. Additionally, the segmentation-based severity classification provides more detailed pneumonia assessments. The hybrid model, combining the strengths of both architectures, offers potential improvements in classification accuracy. However, challenges such as model generalizability, data imbalance, and interpretability remain, necessitating further research for real-world clinical applications.

D. Lung Segmentation and Severity Classification

This study uses lung segmentation in addition to pneumonia detection to better classify severity and isolate

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pneumonia-affected areas. To make sure the classifier concentrates on pertinent regions, lung regions were extracted from the chest X-ray images using a U-Net-based segmentation model using ResNet32 (pre-trained on ImageNet) as the encoder.

The lung regions that are segmented were further analyzed to quantify the spread of pneumonia, determining severity levels as follows:

- MildPneumonia:<10%lungarea affected
- ModeratePneumonia: 10-40%lungarea affected
- SeverePneumonia: >40%lungarea affected

Clinicians may now make well-informed judgments based on the amount of infection rather than merely binary classification thanks to this segmentation-based severity classification, which improves the model's interpretability. However, lung shape variations, X-ray quality, and possible noise in the dataset all affect segmentation accuracy, which can make it difficult to classify severity precisely.

By integrating region-based isolation through lung segmentation, this approach goes beyond traditional pneumonia classification. The severity estimation adds clinical relevance, helping in treatment prioritization and monitoring disease progression. However, balancing segmentation accuracy and classification performance remains an ongoing challenge, necessitating further fine-tuning and dataset augmentation techniques.

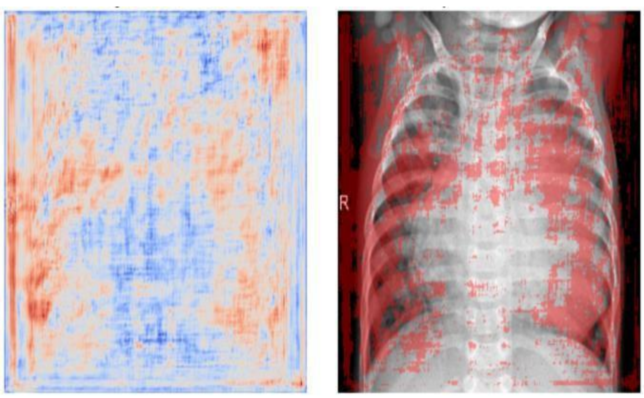

Figure 5: Segmentation masks highlighting pneumonia-affected lung regions along with severity classification

IV. EXPERIMENTATION AND RESULTS

The suggested system's results show that it can identify pneumonia and categorize its severity in chest X-ray pictures with good accuracy, robustness, and efficiency. To improve classification performance, the system makes use of a variety of deep learning models, such as an improved CNN architecture (ConvXNet) and a bespoke CNN (CustomCNN). These models were selected because of their powerful feature extraction capabilities, efficient architectural layout, and capacity to differentiate between healthy lungs and lungs damaged by pneumonia.

A carefully selected dataset of chest X-ray pictures was used to thoroughly train and evaluate the models. Comprehensive data augmentation techniques, including rotation, shifting, shearing, zooming, brightness modifications, and horizontal flipping, were used to improve performance even more. The model's capacity to generalize across a range of patient situations, such as changes in lung opacities, location, and X-ray quality, was much enhanced by these augmentation techniques.

With a training accuracy of 96.04%, the CustomCNN model outperformed ConvXNet, which had a training accuracy of 94.33%. ConvXNet, on the other hand, demonstrated superior generalization, attaining a higher validation accuracy of 88.94% as opposed to CustomCNN's 87.3%. Measures like precision, recall, and F1-score provide additional evidence of both models' efficacy in differentiating between pneumonia and normal patients. While false positives and false negatives are kept to a minimum, the confusion matrix analysis shows that both models accurately categorize the majority of test samples, with CustomCNN reaching a test accuracy of 90.55% and ConvXNet achieving a slightly higher test accuracy of 90.75%. Furthermore, the ROC-AUC scores show good classification performance; CustomCNN and ConvXNet both have significant discriminatory power, with CustomCNN obtaining an AUC of 0.97 and ConvXNet coming in second at 0.96.

One of the key innovations of this system is its pneumonia severity classification, which integrates a U-Net and ResNet32 segmentation model to isolate affected lung regions and determine severity based on the percentage of pneumonia-affected lung area. This segmentation-based severity assessment categorizes pneumonia cases into Mild, Moderate, and Severe, providing crucial insights for clinical decision-making. The visualization of segmented lung regions overlaid on X-ray images offers an interpretable and intuitive understanding of the affected areas.

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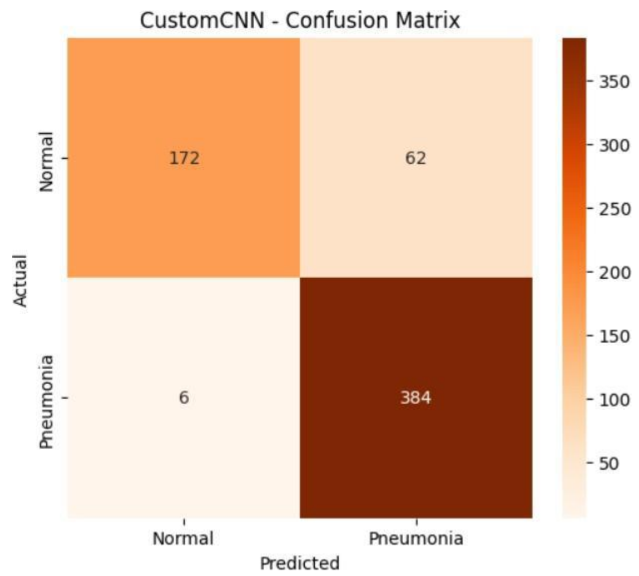

Figure 6: Confusion matrix for Custom CNN model

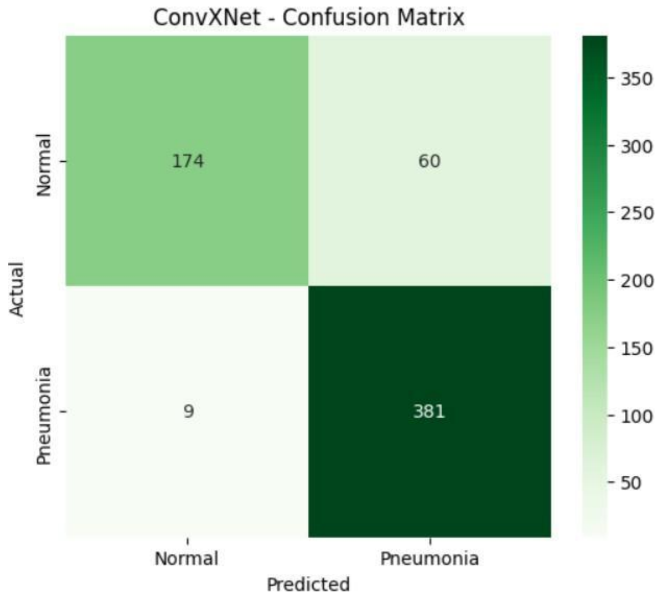

Figure 7: Confusion matrix for ConvXNet model

All things considered, this system improves pneumonia identification and assessment by fusing deep learning innovations with medical imaging, making it a useful diagnostic tool for radiologists and other healthcare professionals. The ability to classify severity levels further enhances its clinical applicability, potentially aiding inearly intervention and better treatment planning. The success of this system underscores the potential of artificial intelligence in revolutionizing pneumonia diagnosis, optimizing healthcare workflows, and advancing medical imaging analysis.

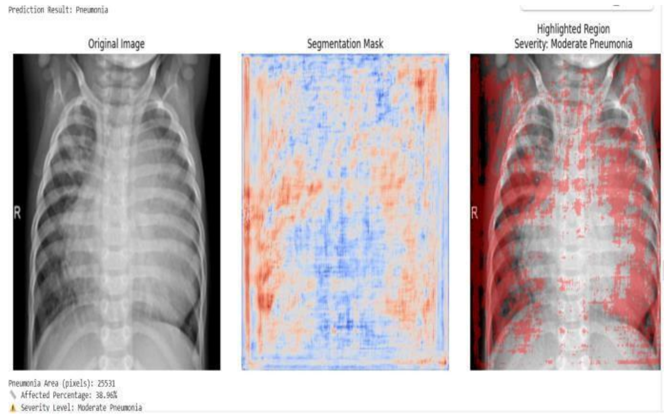

Figure 8: Final output showing pneumonia detection and severity classification

V. CONCLUSION

The proposed pneumonia detection and severity classification system effectively utilizes deep learning-based image classification and segmentation techniques to achieve accurate identification of pneumonia cases and their severity levels. By employing a custom CNN model and ConvXNet, the system achieves reliable classification performance. The CustomCNN model achieved a higher training accuracy of 96.04%, while ConvXNet exhibited slightly better generalization with a validation accuracy of 88.94% compared to 87.3% for CustomCNN.

On test data, ConvXNet achieved a marginally higher test accuracy of 90.75%, whereas CustomCNN recorded 90.55%. Additionally, CustomCNN achieved a higher AUC of 0.97, indicating superior discriminatory capability over ConvXNet's AUC of 0.96. Both models effectively capture complex patterns in chest X-ray images, showcasing their potential for real-world clinical applications.

To further enhance pneumonia analysis, the system integrates a U-Net and ResNet32 segmentation model, allowing for the isolation of pneumonia-affected lung regions. This enables severity classification into Mild, Moderate, and Severe categories based on the percentage of affected lung area. The segmentation model effectively highlights pneumonia regions, offering a visual representation of infection extent and severity.

To confirm the models' dependability, a thorough performance evaluation was carried out utilizing important measures like accuracy, precision, recall, F1-score, and AUC-ROC. To improve generalization and guarantee reliable performance on unseen X-ray pictures, sophisticated data augmentation techniques like as rotation, shifting, zooming, and brightness alteration were used. The CustomCNN model performs better in classification, according to comparative

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analysis, and the segmentation-assisted severity classification improves the evaluation of pneumonia.

To ensure usability in real-world medical scenarios, the system provides automated severity analysis alongside pneumonia classification, enabling more informed clinical decision-making. By integrating deep learning-based classification, region-based segmentation, and severity quantification, the project demonstrates a practical AI-powered solution for pneumonia diagnosis and severity assessment, with significant potential for clinical application and radiological research.

Table II: Performance evaluation metrics for CNN Models

Model	Training Accuracy	Test Accuracy	F1-Score	KeyPoints
CustomCNN	96.04%	90.55%	91.8%	Designed for pneumonia detection; works better when combined with lung segmentation.
ConvXNet	94.33%	90.75%	91.5%	General-purpose CNN; performs well but slightly less optimized for pneumonia-specific features.

VI. ETHICAL CONSIDERATIONS

While this study demonstrates promising results for pneumonia detection and severity classification, it is important to acknowledge potential ethical challenges. Models trained primarily on pediatric chest X-rays may not generalize across adult or elderly populations, leading to biased outcomes. Moreover, deploying AI tools in low-resource settings raises concerns about equity, as limited access to high-quality imaging and computing infrastructure may hinder effective usage. Ensuring model transparency and clinical validation across diverse populations is crucial to avoid unintended harm and promote equitable healthcare delivery.

VII. FUTURE WORK

Future work can focus on enhancing the proposed CNN architectures through advanced hyperparameter tuning, integration of attention mechanisms, and adoption of more efficient segmentation models to improve accuracy and generalization. Expanding the study to larger and more diverse real-world datasets will help assess model scalability and clinical applicability. In particular, future efforts should address the current dataset bias by incorporating adult chest X-rays alongside pediatric cases to improve model generalization across age groups. Incorporating clinical metadata and exploring ensemble learning strategies could further boost diagnostic performance. Additionally, deploying the system on lightweight, mobile-compatible platforms can make it more accessible in low-resource healthcare settings, ensuring real-time, reliable pneumonia detection and severity assessment in practical scenarios.

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