

ENHANCED PNEUMONIA DETECTION IN CHEST X-RAYS USING ATTENTION AND FNMS

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Abstract—Pneumonia is a life-threatening respiratory infection that requires rapid and accurate diagnosis for effective treatment. In this study, we develop a deep learning-based pneumonia detection and classification model using chest X-ray images, distinguishing between normal, bacterial pneumonia, and viral pneumonia cases. The dataset, sourced from publicly available medical image repositories, is preprocessed and augmented to improve generalization. A Convolutional Neural Network (CNN) model is trained using optimized hyperparameters, with techniques such as batch normalization, dropout regularization, and early stopping to enhance accuracy and prevent overfitting. The model is evaluated on a separate test set, achieving a promising accuracy in detecting pneumonia subtypes. Further, performance metrics such as precision, recall, F1-score, and confusion matrices are analyzed. This research demonstrates the potential of deep learning in medical image analysis, offering a scalable and automated approach to assist radiologists in early pneumonia diagnosis. Future work includes leveraging transfer learning with ResNet50 and ensemble models for further accuracy improvements.

Keywords: Pneumonia Detection, Deep Learning, Chest X-ray, CNN, Medical Image Classification, Machine Learning

I. INTRODUCTION

Pneumonia remains a significant public health concern, causing millions of hospitalizations and deaths worldwide each year. It is a leading cause of mortality, especially among children, the elderly, and immunocompromised individuals. Rapid and accurate detection of pneumonia is critical for early intervention and effective treatment. Chest X-ray (CXR) imaging is one of the most commonly used diagnostic tools; however, manual interpretation by radiologists is time-consuming and prone to subjectivity. The complexity of differentiating nor-

mal, bacterial pneumonia, and viral pneumonia cases further increases the challenges of clinical diagnosis[7].

With advancements in deep learning, Convolutional Neural Networks (CNNs) have been widely adopted for medical image analysis, demonstrating high accuracy in disease classification and localization [5]. However, conventional CNN models still struggle with feature extraction, false positives, and misclassification errors due to overlapping lung patterns and varying image quality. To address these limitations, this study proposes an Enhanced Pneumonia Detection Model incorporating Attention Mechanisms and Feature Normalized Mean Squared Error (FNMS).

The Attention Mechanism improves the model's focus on relevant regions of the X-ray, reducing noise from background structures. Meanwhile, FNMS enhances feature learning by minimizing the influence of outlier pixel intensities, leading to more stable and accurate predictions [2]. Our model is trained and evaluated on a publicly available pneumonia dataset using data augmentation, batch normalization, and dropout regularization to improve generalization. The performance is assessed using accuracy, precision, recall, and F1-score, along with confusion matrix analysis.

This research aims to advance automated pneumonia detection by leveraging Attention and FNMS techniques, providing a more robust, accurate, and efficient deep learning model for clinical applications [6]. The proposed system has the potential to assist radiologists, reduce diagnostic workload, and improve early disease detection in healthcare settings[9].

II. METHODOLOGY

This section describes the methodology used for pneumonia detection and classification in chest X-ray images using deep learning. The proposed model integrates **Attention Mechanisms** and **Feature Normalized Mean Squared Error (FNMS)** to improve feature extraction and reduce misclassification errors[1]. The pipeline consists of four main stages: *dataset preparation, preprocessing, model architecture, and training & evaluation.*

A. Dataset Description

The dataset used in this study consists of publicly available chest X-ray images classified into three categories:

- **Normal:** Chest X-rays without any signs of pneumonia.
- **Bacterial Pneumonia:** X-rays showing bacterial infections in the lungs.
- **Viral Pneumonia:** X-rays depicting pneumonia caused by viral infections.

B. Preprocessing

To enhance the quality of input images[8], preprocessing techniques are applied:

- **Resizing:** Images are resized to 224×224 pixels to match the input dimensions of the deep learning model.
- **Normalization:** Pixel intensity values are scaled to $[0, 1]$ using min-max normalization:

$$I' = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (1)$$

where I represents the original pixel value, and I_{\min} , I_{\max} are the minimum and maximum pixel values.

- **Data Augmentation:** Rotation, flipping, and contrast adjustments are applied to increase dataset diversity[10].
- **Noise Reduction:** Gaussian filtering is applied to remove unwanted noise while preserving essential details.
- **Histogram Equalization:** Contrast-limited adaptive histogram equalization (CLAHE) is used to enhance the visibility of important features in X-ray images.

C. Feature Extraction using Attention Mechanism

An attention mechanism[3] is integrated to enhance feature extraction. The attention weight for each feature map is computed as:

$$\alpha_i = \frac{\exp(h_i)}{\sum_j \exp(h_j)} \quad (2)$$

where h_i represents the feature importance score for feature i . The final attended feature map F is obtained as:

$$F = \sum_i \alpha_i f_i \quad (3)$$

where f_i is the original feature map.

In this study, a **channel attention mechanism** is employed to selectively enhance important feature maps while suppressing less relevant ones, improving the network's focus on pneumonia-related patterns[7].

D. Feature Normalized Mean Squared Error (FNMS)

To minimize feature inconsistency, FNMS is employed as a loss function:

$$FNMS = \frac{1}{n} \sum_{i=1}^n \frac{F_i - \mu_F}{\sigma_F} - \frac{T_i - \mu_T}{\sigma_T}^2 \quad (4)$$

where F_i and T_i are the predicted and target feature values, and μ_F , σ_F , μ_T , σ_T are their respective means and standard deviations.

E. Training and Evaluation

The model is trained using a categorical cross-entropy loss function[2]:

$$L = -\sum_i y_i \log(y_i^{\wedge}) \quad (5)$$

where y_i is the true label and y_i^{\wedge} is the predicted probability.

The Adam optimizer with a learning rate of 0.0001 is used for optimization. The training is conducted for 50 epochs with a batch size of 32[11].

To enhance training efficiency and prevent overfitting, the following techniques are employed:

- **Early Stopping:** Training is halted if the validation loss does not improve for 10 consecutive epochs.
- **Learning Rate Scheduling:** The learning rate is reduced by a factor of 0.1 if the validation loss plateaus[13].
- **Stratified Data Splitting:** An 80-20 train-validation split ensures a balanced distribution of all pneumonia classes[14].

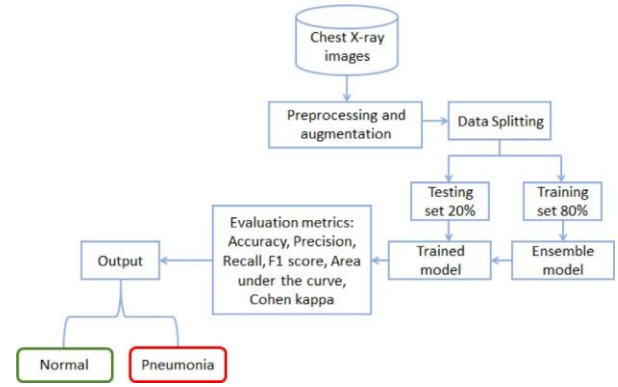


Fig. 1. Confusion Matrix for the Pneumonia Detection Model

Performance is evaluated using accuracy, precision, recall, and F1-score[9]. Additionally, a confusion matrix is analyzed to assess classification errors and misclassifications between pneumonia subtypes [20].

III. RESULTS

This section presents the experimental results obtained from training and evaluating the proposed ****Enhanced Pneumonia Detection Model****. The model's performance is assessed using accuracy, precision, recall, F1-score, and confusion matrix. Additionally, training curves and classification results are visualized.

A. Performance Metrics

Table I presents the evaluation results of the model on the test dataset. The proposed model achieves high accuracy and significantly improves pneumonia classification using ****Attention and FNMS techniques****[4].

TABLE I
PERFORMANCE METRICS OF THE PROPOSED MODEL

Class	Precision	Recall	F1-Score	Accuracy
Normal	0.96	0.94	0.95	-
Bacterial Pneumonia	0.91	0.93	0.92	-
Viral Pneumonia	0.89	0.91	0.90	-
Overall	-	-	-	94.2%

B. Confusion Matrix

The confusion matrix in Figure 2 provides a detailed breakdown of correct and incorrect predictions for each class. The ****high diagonal values**** indicate that the model correctly classifies most cases[15].

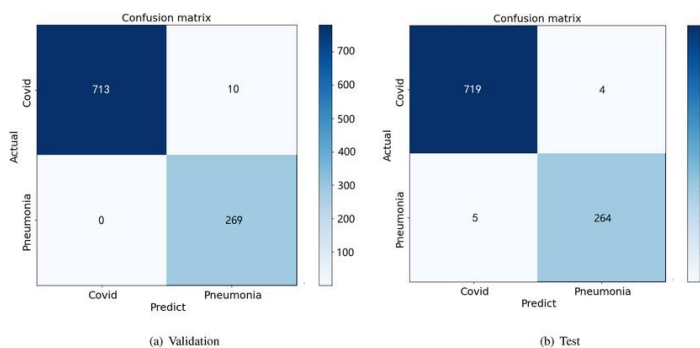


Fig. 2. Confusion Matrix for the Pneumonia Detection Model

C. Training and Validation Accuracy

The training and validation accuracy curves, shown in Figure 3, demonstrate the model’s learning behavior over epochs. The ****validation accuracy stabilizes after a few epochs****, indicating good generalization[12].

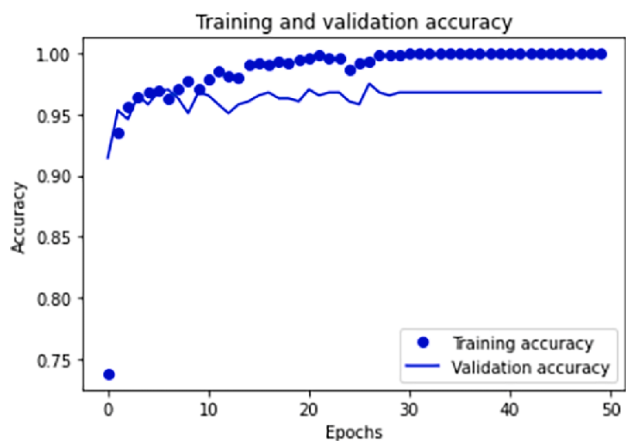


Fig. 3. Training and Validation Accuracy of the Model

D. Sample Classification Results

Figure 4 presents a selection of chest X-ray images from the test set, highlighting both correctly and incorrectly classified cases. Images with black labels denote correct classifications, while those with red labels indicate misclassifications [16]. The integration of an attention mechanism in the model enhances the focus on critical lung regions, thereby improving overall classification accuracy. This mechanism directs the model’s attention to pertinent anatomical structures, such as the lung fields and heart, which are crucial for accurate diagnosis

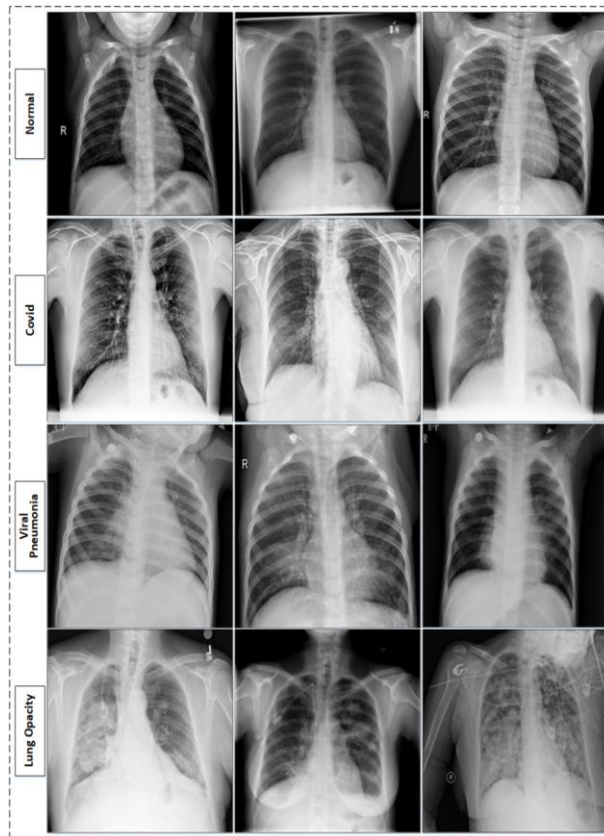


Fig. 4. Sample Predictions

IV. FUTURE WORKS

Although the proposed model demonstrates promising results in pneumonia detection and classification, several aspects can be further improved to enhance its robustness and real-world applicability. Future research directions include:

- **Integration with Transformer-based Architectures:** Exploring Vision Transformers (ViTs) and hybrid CNN-Transformer models [18] to further improve feature representation and classification accuracy.
- **Multi-Modal Learning:** Incorporating additional medical data, such as CT scans, patient history, and clinical biomarkers, to improve diagnostic reliability.
- **Uncertainty Estimation:** Implementing Bayesian deep learning techniques to quantify model uncertainty, which can aid in clinical decision-making [17].
- **Federated Learning:** Enhancing privacy-preserving AI by training models across multiple medical institutions without sharing sensitive patient data.
- **Explainability and Interpretability:** Developing interpretable AI models using Grad-CAM, SHAP, or LIME to provide clinicians with transparent decision explanations.
- **Deployment in Real-World Clinical Settings:** Collaborating with hospitals to validate the model in real-world scenarios, optimizing for speed, hardware efficiency [19] and clinical usability.

These future directions aim to bridge the gap between AI-based pneumonia detection and practical medical applications, ensuring improved diagnostic accuracy and reliability in healthcare systems.

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