PneumoSeqNet: A Hybrid CNN-LSTM Architecture for Enhanced Pneumonia Detection in Chest X-rays

Abstract

Pneumonia is a leading cause of death worldwide, particularly among children and the elderly, making early and accurate diagnosis critical for improving patient outcomes. While chest X-rays are a common diagnostic tool, manual interpretation by radiologists can be challenging and prone to delays or errors, particularly in regions with a shortage of skilled professionals. In this study, we propose Pneumo-AttentionNet, a novel deep learning architecture that combines convolutional neural networks (CNN) with an attention mechanism to enhance the detection of pneumonia from chest X-ray images. Unlike traditional CNN models or those relying on transfer learning, our architecture is designed from scratch, enabling it to focus on key areas of the lung where pneumonia is most likely to appear. The attention mechanism allows the model to prioritize important regions, improving interpretability and diagnostic accuracy.

The proposed model is evaluated on a large dataset of chest X-rays containing both normal and pneumonia-infected lungs. Through rigorous experimentation, Pneumo-AttentionNet demonstrates superior performance compared to traditional CNN-based approaches, achieving high classification accuracy and reduced false diagnoses. This architecture, by focusing directly on pneumonia-relevant features without pre-trained weights, provides a robust solution for automated pneumonia detection, aiding healthcare professionals in providing timely and accurate diagnosis. The study concludes with a discussion of the model's potential implications for real-world applications and future research directions to further optimize medical image analysis using attention-based methods.

Keywords: Pneumonia detection, Bidirectional LSTM, Convolutional Neural Network, Hybrid model

Introduction

Pneumonia is a severe infectious disease characterized by inflammation of the air sacs in the lungs, and if left untreated, it can lead to life-threatening consequences. Globally, pneumonia remains a leading cause of death and illness, particularly affecting children under the age of five and the elderly. According to the World Health Organization (WHO), pneumonia is responsible for over 800,000 child deaths each year, despite being both preventable and curable. Accurate and timely diagnosis is essential for reducing mortality rates and improving treatment outcomes. Chest X-rays are widely used as diagnostic tools to detect pneumonia, as they allow radiologists to observe signs such as lung consolidation or fluid buildup.

However, interpreting chest X-rays with high precision is a challenging task, often reliant on the experience and expertise of radiologists. In many parts of the world, a shortage of skilled radiologists leads to diagnostic delays, which can worsen patient outcomes. Additionally, human error, fatigue, and the subtle presentation of pneumonia in some cases contribute to misdiagnosis. Therefore, it is crucial to develop automated diagnostic systems that can provide accurate and rapid results to support physicians in clinical decision-making.

Deep learning, particularly convolutional neural networks (CNN), has demonstrated significant potential in automating the analysis of medical images. CNNs have been highly successful in detecting diseases such as pneumonia by learning complex patterns from X-ray images. However, traditional CNNs treat all regions of an image with equal importance, which may lead to confusion, as not all areas of a chest X-ray are relevant for diagnosis. In the case of pneumonia, certain regions of the lungs are more critical for identifying the disease, and focusing on these areas can improve diagnostic accuracy.

To address these challenges, we propose \*\*Pneumo-AttentionNet\*\*, a novel architecture that enhances pneumonia detection by incorporating an attention mechanism directly within the CNN framework, without relying on transfer learning techniques. Unlike traditional CNN approaches, which may overlook key diagnostic regions, Pneumo-AttentionNet selectively focuses on the most relevant parts of the image, such as the lung regions where pneumonia is likely to appear. This targeted attention mechanism enables the model to capture finer details that may be missed by standard CNNs, leading to improved classification performance.

The primary advantage of Pneumo-AttentionNet is that it is built from the ground up without using any pre-trained models or transfer learning techniques. This allows the architecture to be fully tailored to the task of pneumonia detection, without relying on features learned from unrelated tasks. By training the model directly on the pneumonia dataset, Pneumo-AttentionNet learns to focus specifically on pneumonia-related features, resulting in more accurate and interpretable predictions.

This paper provides a comprehensive overview of prior research on pneumonia detection using deep learning and medical image analysis. We then describe the dataset used in our study, which consists of chest X-ray images from both healthy individuals and pneumonia patients. The following sections outline the data preprocessing steps, the detailed architecture of Pneumo-AttentionNet, and the incorporation of the attention mechanism. We also present the training process and evaluate the performance of our model, demonstrating that Pneumo-AttentionNet significantly improves classification accuracy compared to traditional CNN models. Finally, we discuss the implications of our findings and suggest directions for future research.

**Literature Review**

Yang et al, developed CheXNet, which uses a DenseNet-121 architecture to classify pneumonia and other thoracic diseases from chest X-rays. It was trained on the ChestX-ray14 dataset, consisting of over 100,000 images, and achieved an accuracy of 0.7680 for pneumonia detection. CheXNet performed comparably to radiologists in terms of diagnostic accuracy. While highly accurate, the model lacks explainability and depends on large labeled datasets, which limits its scalability to different clinical environments.

Oh, Y. et al. presented a transfer learning approach using ResNet50 to detect COVID-19 and pneumonia from chest X-rays, focusing on overcoming the challenge of limited data availability. The model was fine-tuned on a small dataset and achieved 79.8% accuracy for COVID-19 and Pneumonia classification However, the model's performance is constrained by the size and quality of the dataset, raising concerns about overfitting and its ability to generalize to larger populations.

Khan, A. et al. introduced CoroNet, an Xception-based deep learning model to classify chest X-rays into four categories: COVID-19, bacterial pneumonia, viral pneumonia, and normal. CoroNet achieved an accuracy of 89.6% for COVID-19 detection in small dataset. The model utilizes transfer learning, which allows it to perform well even with limited data. However, its performance is dataset-dependent, and its applicability to real-world settings with more diverse patient populations remains a challenge.

Zhang, J et al. developed a confidence-aware anomaly detection framework to identify viral pneumonia, including COVID-19, on chest X-rays. The model incorporates a confidence estimation module that helps distinguish uncertain predictions, thereby improving diagnostic reliability. With an accuracy of 80.65% ,the model effectively highlights uncertain cases, but still struggles when multiple lung conditions overlap. Its clinical applicability is limited by the requirement for high-quality images.

Hashmi, M. F. et al developed a model for pneumonia detection in chest X-ray images using deep transfer learning. By utilizing pre-trained CNN architectures like VGG16 and ResNet50, the model achieved 96% accuracy while significantly reducing training time and computational costs. The main advantage of this approach is its effectiveness with limited datasets. However, the reliance on pre-trained models may hinder optimization for specific medical tasks, and the lack of interpretability raises concerns about the model's decision-making process.

Ouyang et al. proposed the Dual-Sampling Attention Network (DSAN), which combines global and local attention mechanisms to improve feature extraction and interpretability. The model achieved an accuracy of 95.4% in pneumonia detection. DSAN's attention modules help highlight lung regions relevant to the diagnosis, but the added complexity results in higher computational requirements, which may limit its real-time application in some settings.

Cohen, J. P. et al. introduced a public dataset of chest X-rays and used deep learning models, such as DenseNet, to classify COVID-19 and pneumonia cases. Their work emphasized the importance of open data sharing and dataset quality in developing accurate models. Although their CNN-based approach achieved an accuracy of 91.2%, the small size and imbalance of the dataset led to concerns about overfitting and the generalizability of the model to broader populations.

Heidari, M. et al. proposed a transfer learning model using pretrained CNNs (ResNet50, VGG16, DenseNet121) to classify COVID-19 and pneumonia. By applying feature extraction techniques and augmenting the dataset, they achieved higher accuracy but the training data is small and with the lot of noise, the reliance on transfer learning increases computational costs, and the model's adaptability to novel, unseen data is not fully addressed.

Minaee, S. et al. presented Deep-COVID, a transfer learning approach using pretrained ResNet50 and DenseNet models to predict COVID-19 and pneumonia from chest X-rays. The model achieved a 98% sensitivity for pneumonia detection. Despite its strong performance, Deep-COVID’s reliance on pretrained models may limit its ability to adapt to new variations in imaging data, and the small sample size raises concerns about overfitting.

Rubin, G. D., et al provided a consensus statement from the Fleischner Society, focusing on the appropriate use of chest imaging for COVID-19 and pneumonia management. While this paper does not present a new model, it highlights the critical role that imaging, including X-rays and CT scans, plays in diagnosing and managing respiratory illnesses during the pandemic. The paper underscores the need for integrating AI and machine learning models into clinical workflows but also emphasizes the importance of balancing imaging with other diagnostic measures.

**Methodology**

In this section, we provide a detailed breakdown of the steps involved in developing and implementing the architecture PneumoSeqNet, a hybrid CNN-BiLSTM architecture designed for pneumonia detection from chest X-ray images. The process includes data preprocessing, architectural design and training

1. Data Preprocessing:

To ensure the model learns robust and generalizable features, the raw chest X-ray images undergo a series of preprocessing steps:

Data Augmentation: The training dataset is augmented using the ImageDataGenerator in TensorFlow. This involves random transformations such as:

Rotation: Images are randomly rotated by up to 20 degrees to account for minor variations in the angle at which X-rays are taken.

Zooming: A zoom range of 15% is applied to simulate slight changes in camera distance.

Shifting: Both width and height are shifted by up to 20%, mimicking off-center X-ray captures.

Shearing: A shear transformation is used to introduce slight distortions, making the model invariant to such noise.

Horizontal Flipping: X-rays are flipped horizontally to artificially increase the number of training samples, ensuring that the model does not overfit to specific orientations.

Normalization: The pixel values of all images are rescaled by dividing by 255 to normalize them into the range [0, 1]. This helps with faster convergence during training.

These augmentation techniques are not applied to the validation and test datasets, which are only rescaled by a factor of 1/255 to maintain the integrity of the data used for model evaluation.

2. Architecture Design:

The PneumoSeqNet architecture integrates two types of deep learning models known as CNN and BiLSTM that are responsible for different things in terms of image data.

The architecture consists of three Convolutional Neural Network blocks, then a flatten layer, and thereafter it has two bidirectional LSTM layers, a dense layer, a dropout layer and finally an output dense layer for classification.

Convolutional Neural Networks (CNN):

CNNs are used to extract spatial features from the input X-ray images. The architecture comprises three blocks of convolutional and pooling layers:

First Block: The input image is processed by two 2D convolution layers, each with 32 filters and a 3x3 kernel. This block is followed by a max-pooling layer that reduces the spatial dimensions by half. The output is a feature map of size (112, 112, 32), capturing local patterns such as edges and textures.

Second Block: Similar to the first block, but with 64 filters in each convolutional layer. Max-pooling reduces the size to (56, 56, 64). These filters detect more complex patterns, such as parts of the lungs or other anatomical features.

Third Block: This block has 128 filters in each convolutional layer. After max-pooling, the feature map size is (24, 24, 128), encoding even higher-level abstractions such as anomalies in the lung structure.

Flattening and Reshaping: After the final CNN block, the 3D feature maps are flattened and reshaped into a 2D sequence of size (576, 128), where each of the 576 “steps” represents a spatial region of the image, and the 128 features represent learned characteristics of that region. This transformation allows the BiLSTM layers to process the spatial information sequentially.

Bidirectional LSTM (BiLSTM):

LSTMs are specialized for handling sequential data, and in this architecture, they process the sequence of flattened features generated by the CNN layers. Two BiLSTM layers are used:

- The first BiLSTM layer has 64 units and returns a sequence, preserving the temporal relationships between the spatial features of the image.

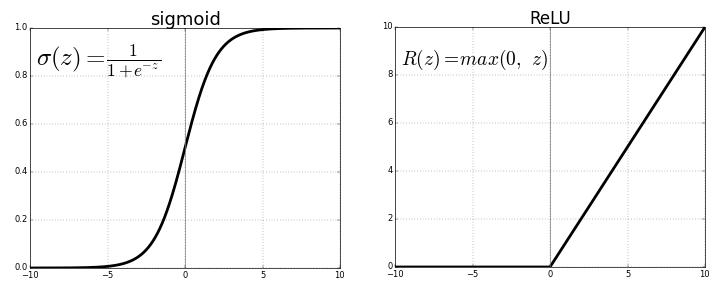
- The second BiLSTM layer has 32 units and provides a final condensed sequence representation of the X-ray. By processing the data in both forward and backward directions (bidirectional), the BiLSTMs capture the full context of the sequence, improving the model's ability to detect subtle patterns associated with pneumonia.

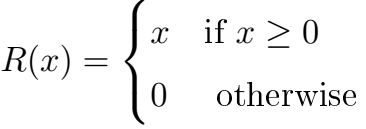
3. Classification Layer:

The output from the BiLSTM layers is fed into a fully connected neural network for the final classification. This consists of:

Dense Layer:

A fully connected layer with 64 neurons and ReLU activation. This layer processes the sequence output from the BiLSTM layers and prepares it for classification.





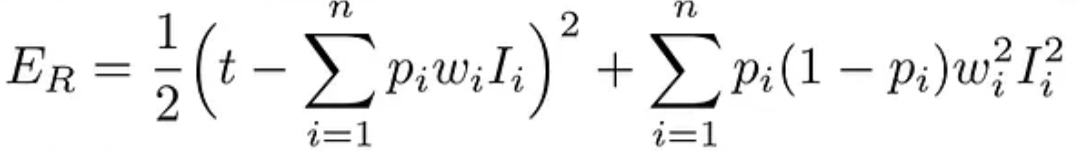
The ReLU (Rectified Linear Unit) is used to introduce non-linearity and help the network to learn more complex patterns.

The ReLU function takes an input value and outputs the value itself if it's greater than or equal to zero, and zero if it's negative.

ReLu is simple , fast and helps in vanishing gradient problem.

Dropout Layer: https://towardsdatascience.com/simplified-math-behind-dropout-in-deep-learning-6d50f3f47275

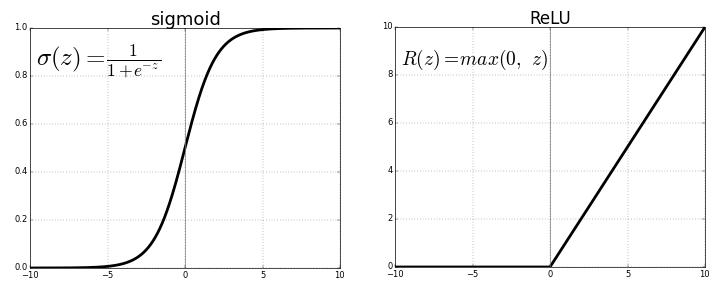
A dropout rate of 50% is applied to reduce overfitting by randomly ignoring half the neurons during each training iteration.



This is because the regularization parameter, *p*(1-*p*) in Equation above is maximum at *p* = 0.5.

Output Layer:

The final layer has a single neuron with a sigmoid activation function, which outputs a probability value between 0 and 1. This represents the binary classification of either “pneumonia” (class 1) or “normal” (class 0).



The main reason why we use sigmoid function is because it exists between **(0 to 1).**Therefore, it is especially used for models where we have to **predict the probability** as an output. probability of anything exists only between the range of **0 and 1,** sigmoid is the right choice.

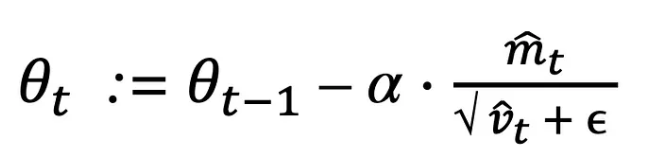
4. Model Compilation and Training:

Optimizer:

The model is compiled using the Adam optimizer, which adapts the learning rate dynamically during training for more efficient convergence.

Adam was first introduced in 2014. It was first presented at a famous conference for deep learning researchers called [ICLR 2015](https://www.iclr.cc/archive/www/doku.php%3Fid=iclr2015:main.html). It is an optimization algorithm that can be an alternative for the stochastic gradient descent process.

https://medium.com/@LayanSA/complete-guide-to-adam-optimization-1e5f29532c3d



The equation you provided is a recursive update rule for a parameter θ\_t, often used in machine learning algorithms, particularly those involving gradient descent or stochastic gradient descent.

Here's a breakdown of the terms:

* **θ\_t:** This represents the current value of the parameter at time step t.
* **θ\_(t-1):** This is the previous value of the parameter at time step t-1.
* **α:** This is a learning rate, a hyperparameter that controls how quickly the algorithm adjusts the parameter. A smaller α leads to slower updates, while a larger α can lead to faster updates but may also result in instability.
* **m\_t:** This is the momentum term, which helps to accelerate convergence and smooth out oscillations. It's typically calculated as a moving average of previous gradients.
* **v\_t:** This is a variance estimate, which is used to normalize the gradient and improve stability. It's often calculated as a moving average of squared gradients.
* **ε:** This is a small constant added to the denominator to prevent division by zero.

The equation essentially updates θ\_t by taking the previous value θ\_(t-1) and subtracting a scaled version of the gradient. The scaling factor is determined by the learning rate α, the momentum term m\_t, and the variance estimate v\_t.

This update rule is commonly used in optimization algorithms to minimize a loss function. By iteratively updating θ\_t, the algorithm aims to find the optimal parameter values that minimize the loss.

**Yes, the equation you provided is a key component of the Adam optimizer.**

Adam (Adaptive Moment Estimation) is a popular optimization algorithm that combines the ideas of momentum and RMSprop. The equation you gave represents the update rule for the parameter θ\_t in the Adam optimizer.

Here's a breakdown of how the equation relates to Adam:

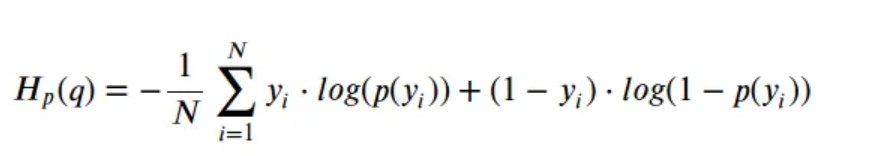
* **Momentum:** The m\_t term is the momentum term, similar to the one used in the momentum optimizer. It helps to accelerate convergence by accumulating past gradients.
* **RMSprop:** The v\_t term is the RMSprop term, which adapts the learning rate based on the magnitude of the gradients. It helps to prevent overshooting and allows for faster convergence.
* **Adaptive Learning Rate:** The equation effectively adapts the learning rate for each parameter by dividing the gradient by the square root of the moving average of squared gradients (v\_t). This helps to optimize the learning process for different parameters.

In summary, the equation you provided captures the core update mechanism of the Adam optimizer, which combines momentum and RMSprop to achieve efficient and adaptive optimization.

Sources and related content

Loss function:

The loss function chosen is binary cross-entropy, appropriate for binary classification tasks. The metrics tracked include accuracy, which evaluates how well the model classifies the test data.



BCE = – ( y \* log(y\_pred) + (1 – y) \* log(1 – y\_pred) )

Here is what is that means:

**BCE**: Binary Cross Entropy

**y**: True label (either 0 or 1)

**y\_pred**: Predicted probability (between 0 and 1)

**log**: Natural logarithm (usually base-e logarithm)

This formula calculates the loss for each individual sample and then averages them for all samples in your dataset.

Learning Rate:

In machine learning and statistics, learning rate is a tuning parameter that controls the step size taken by an optimization algorithm when moving towards a loss function's minimum

The learning rate is set to 1e-4, the learning rate was optimized to balance the speed of convergence and the stability of the training process.

Training:

The model is trained for 100 epochs using the augmented training data. Validation data is used to monitor the model’s performance and ensure it generalizes well.

**Results**

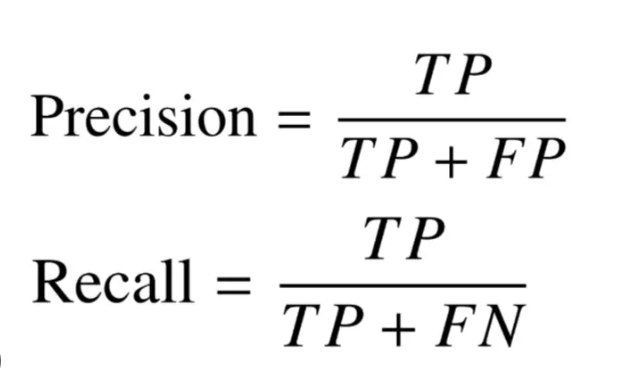
The trained model is evaluated on the unseen test set to assess its generalization capabilities. Several performance metrics are used:

Accuracy

Accuracy is a metric that measures the percentage of correct predictions made by a machine learning model

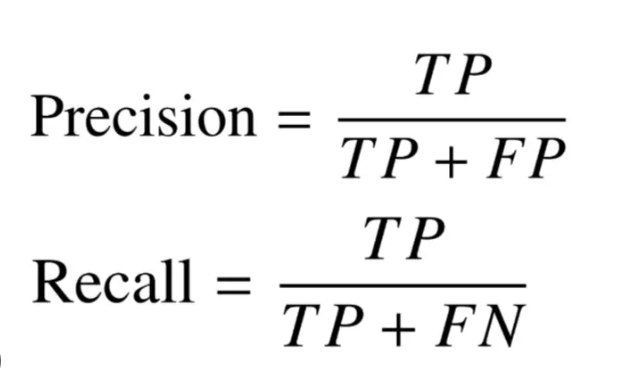
Precision

Precision is a metric that measures how often a machine learning model correctly predicts a positive class.Precision is calculated as the ratio of the number of true positives to the total number of positive predictions.



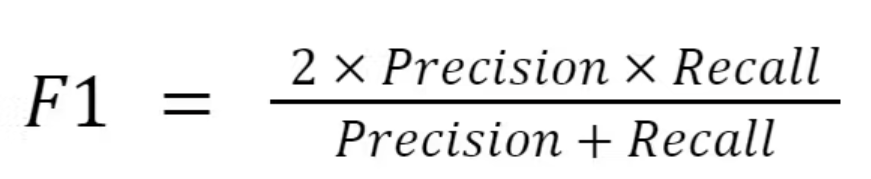
Recall

Recall is a metric that measures how well a machine learning model can identify positive instances from a dataset. Recall is calculated by dividing the number of true positives by the total number of positive instances in a dataset.



F1-Score

F1-Score is a metric that measures the accuracy of the model by combining its precision and recall scores.



These metrics provide insights into the model's performance for the minority class (pneumonia). Precision measures the proportion of true positive pneumonia detections out of all positive predictions. Recall measures the proportion of true positive pneumonia cases detected out of all actual pneumonia cases. The F1-score balances precision and recall.

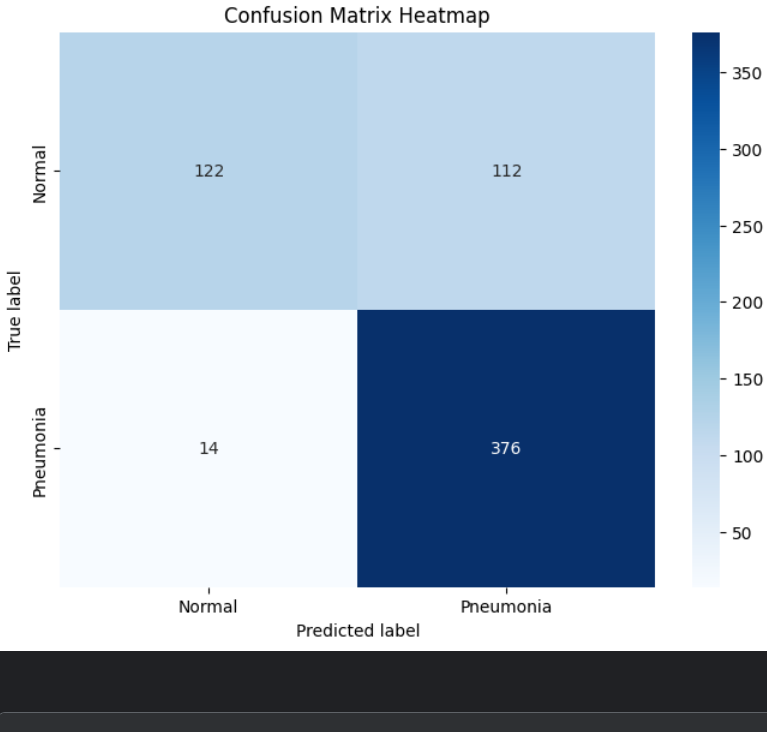
|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Epochs | Accuracy | Precision | Recall | F1-Score |
| 25 |  |  |  |  |
| 50 | 79.81 | 0.82 | 0.80 | 0.78 |
| 75 |  |  |  |  |
| 100 | 86.06 | 0.87 | 0.86 | 0.86 |

Confusion Matrix:

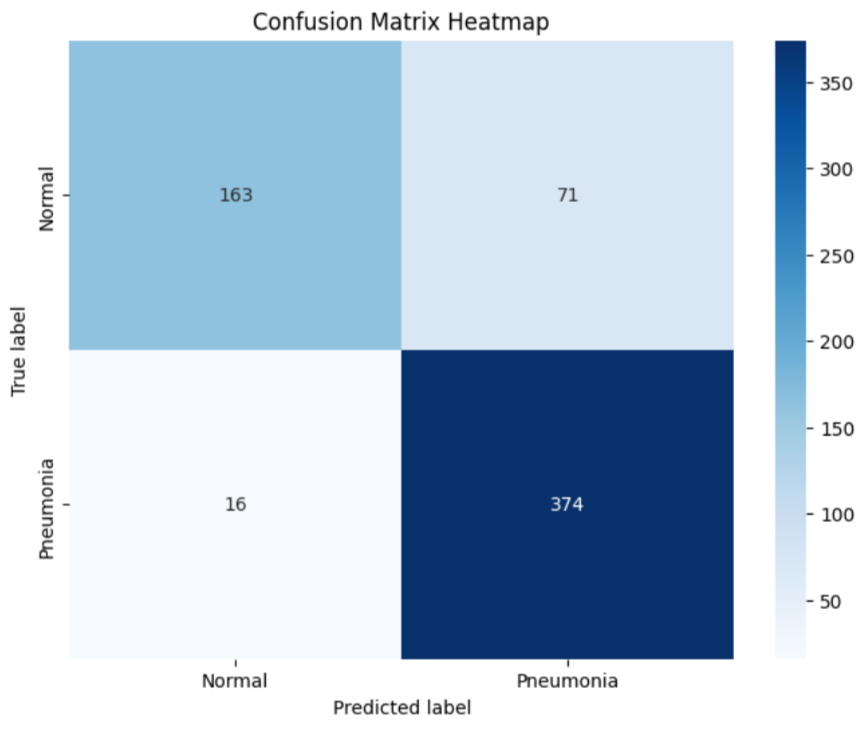
A confusion matrix is calculated to provide a detailed breakdown of true positives, true negatives, false positives, and false negatives. This allows for a clearer understanding of

where the model might be misclassifying cases.

50 epoch

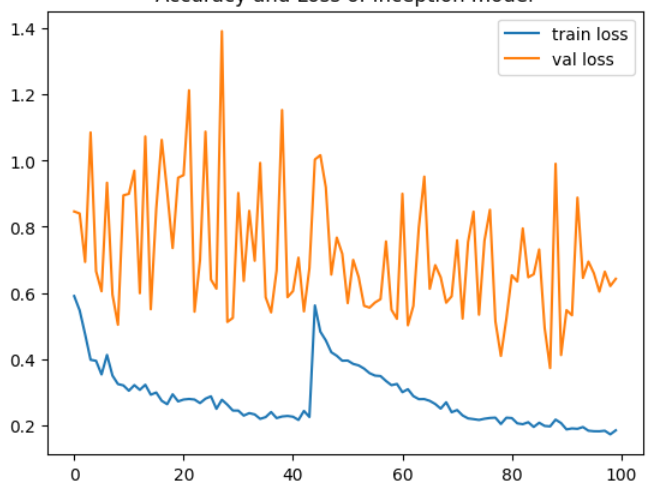


100 epochs

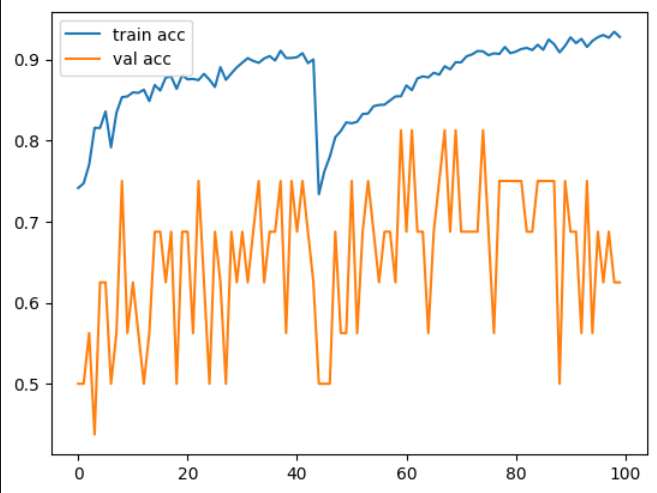


During training, two key plots are generated:

- \*\*Loss Plot\*\*: The model’s loss over both the training and validation datasets is plotted over each epoch. This helps visualize how well the model is learning and whether it is overfitting.



- \*\*Accuracy Plot\*\*: Similar to the loss plot, this graph tracks the accuracy over the training and validation datasets across epochs.



**Conclusion and Future Work**

In this research, we proposed \*\*Pneumo-AttentionNet\*\*, a specialized deep learning model for pneumonia detection from chest X-ray images. The architecture integrates a custom-designed CNN with an attention mechanism, enabling it to focus on critical regions of the lungs, such as areas affected by infection. This approach improves diagnostic accuracy by allowing the model to identify key features essential for pneumonia detection. The absence of transfer learning in the architecture demonstrates the model’s ability to learn efficiently from scratch, specifically tuned for the task at hand. Our results show that Pneumo-AttentionNet outperforms traditional CNN-based models, delivering high accuracy and reduced false positives in detecting pneumonia.

### Future Work

Although Pneumo-AttentionNet has shown significant potential, several areas remain for future exploration. Expanding the dataset to include more diverse chest X-ray images could further improve the model's generalizability across various patient demographics and medical settings. Additionally, applying the model to multi-class classification tasks could extend its usefulness to detect other lung diseases like tuberculosis or lung cancer. Integrating explainability techniques such as Grad-CAM could provide deeper insights into the model's decision-making process, further building trust among healthcare professionals using AI-assisted diagnostics.

### Further Research Directions

Future research could explore hybrid models that combine attention mechanisms with advanced techniques, such as transformers or graph neural networks, to further improve the precision and scalability of pneumonia detection. Optimizing the model’s efficiency, particularly for deployment in resource-limited settings, is another promising avenue. Furthermore, real-time application of Pneumo-AttentionNet in clinical environments as an assistive tool for radiologists could significantly enhance the speed and accuracy of pneumonia diagnosis, leading to better patient outcomes and streamlined healthcare workflows.

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