# Paediatric Pneumonia chest X-ray image classification with association to Lung cancer disease using ResNet50 Deep Learning Model

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***Abstract*—In recent disease advancement and with increasing rate of cases of Pneumonia for the past decades, this has led to the overwhelming challenges within several health systems worldwide. This problem has necessitated the need for efficient and effective measures to mediate and alleviate these challenging issues. Pneumonia is largely caused by inflammation of the lungs because of cold temperature or associated with cold weather. Any delay in treating this disease could be dangerous and could develop to lung cancer. Medical diagnoses are carried out mostly at the beginning with a chest X-ray image to ascertain the presence of pneumonia within a patient. However, this process can be laborious and time sensitive, which might produce inaccurate outcomes or results. In this study, we proposed a ResNet50 architecture to extract the characteristic features from the chest X-ray images. This architecture helps to classify the features to allow us to predict or detect the presence of pneumonia in a patient X-ray image or not. In this study, we utilized dataset extracted from Kaggle which was made up of two distinctive files (1) for training (2) for testing. The dataset was preprocessed to balance the data, and the training data was divided into two sections or parts, one for the training set and the other for the validation set. To enhance our model performance, we performed data augmentation to increase the image variations and data generator was created to reduce the memory usage during the training phase of the model. The ResNet50 architecture was customized for the task with several hyperparameter tuning and the validation data was used to experiment on the model performance validation set. The model was evaluated and measured using classification reports and confusion matrix. We performed the experiment with the following optimization algorithms, SGD, Adam, Adamax and Adagrad, each achieving the following accuracy 93%, 90%, 92% and 89% respectively. We implement the following activation functions , ReLU and ULU within the research. Different validation split ratios were implemented to ascertain the best result. The best performance was observed when 90% or 80% of the training set data was used and 10% or 20% of the validation set data was used within the training set image files.**

***Index Terms*—ResNet50, deep learning, CNN, LSTM, optimization, activation function**

## I. Background

ResNet-50 is a deep convolutional neural network (CNN) architecture with 50 layers, widely used in medical image analysis due to its ability to effectively learn and identify complex patterns in large datasets [1]. In lung cancer diagnosis, ResNet-50 has been applied to analyse medical imaging modalities, such as chest X-rays and CT scans, to detect and classify cancerous lesions. Its use of residual connections helps mitigate the vanishing gradient problem, enabling deeper networks to be trained more efficiently. This makes ResNet-50 particularly effective in distinguishing subtle features that indicate early-stage lung cancer, aiding in timely and accurate diagnosis [2].

### *A. Research Questions*

This research is crucial as it seeks to revolutionize the early detection of lung cancer by leveraging advanced deep learning techniques. Early and accurate diagnosis is vital for improving patient outcomes, yet current methods are invasive, time consuming, and expose patients to potentially harmful radiation. By developing a deep learning model capable of detecting lung cancer from pneumonia related images, this study could significantly streamline the diagnostic process, reduce risks, and enhance the accuracy of lung cancer detection, ultimately leading to more effective and timely treatment regimen.

- How accurately can a deep learning model, utilizing CNN and LSTM architectures to detect lung cancer from pneumonia related imaging data?
- What are the key differences in imaging features between pneumonia and lung cancer that the model identifies?
- How does the performance of the deep learning model compare to traditional PET/CT scans in terms of accuracy, sensitivity, and specificity for lung cancer detection?
- Can the deep learning model effectively differentiate between lung cancer and pneumonia when they co-occur in a patient?

## II. Methodology

The use of Convolutional Neural Networks (CNNs) was essential for this project due to their capability to detect subtle variations in images and identify features not easily visible to the human eye. Specifically, ResNet-50, a specialized CNN architecture, was employed to train on X-ray images of both pneumonia and normal cases. The project was carried out on Google Colab, using Python and key libraries: NumPy for data handling, Keras for building and training the ResNet-50 model, and Matplotlib for visualization. The dataset included 2,160 chest X-ray images, categorized as Pneumonia or Normal. The 2160 images belong to two classes, the validation and test images also belongs to two classes. The Images were pre-processed for the model input after performing image resizing and normalization. The model optimizer used in the experiment was SDG with a binary cross-entropy as the loss function. These help to improve the model parameters and performance. The Convolutional Neural Network (CNN) ResNet-50 was used due to its capability to detect fine details in images. The model was trained using 30 epochs with a batch size of 30, employing Colab's GPU for efficiency. It was validated with 538 images and tested on 624 images and trained on 2,698 images to assess the model accuracy and performance. Visualization of the training progress and performance metrics was achieved using *Matplotlib* which is a plotting library for Python programming language.

### A. *Results*

The results shown are good as the training accuracy does seem to show varied results but overall seem to be improving showing that the model is learning to detect pneumonia in the images as shown in Figure 2 comparing this against the normal image shown in Figure 1. This is furthered by the increase in accuracy in the training and validation accuracy chart. The model's performance was tested with 30 epochs and produced a training accuracy of 51% and a test accuracy of 59%. The original experiment was with 15 epochs, and this yielded differing results with a training accuracy of 46% and a test accuracy of 48%. The overarching loss function was 86% with a validation loss of 69%. This simply means the model is not expression as we wanted, nonetheless there were signs of improvement as we extended the number of epochs. This shows reduction in the validation loss value to 69% and the overall validation accuracy remains constant at 50% (as illustrated in Figure 3 and Figure 4).

*1) Measuring Metrics:* A Confusion Matrix was produced to measure the Metrics to evaluate the performance of the model. To further this notion, a classification report was produced producing an precision score of 0.38, recall score of 1.0 and f1-socre of 0.55 and accuracy score of 0.38 on the test images of 624. The Figure 3 and Figure 4 illustrates the performance of the ResNet50 architecture.

## III. Discussion

### A. *How to Improve the Model?*

The results from the project demonstrate that the model's performance improved with each training epoch, as reflected in the learning rate and accuracy gains. This incremental learning allowed the model to better discern between images, enhancing its potential to contribute to more accurate diagnoses in the medical field. The F1 score, which balances precision and recall, indicated that the model is on the right track but still requires further refinement.

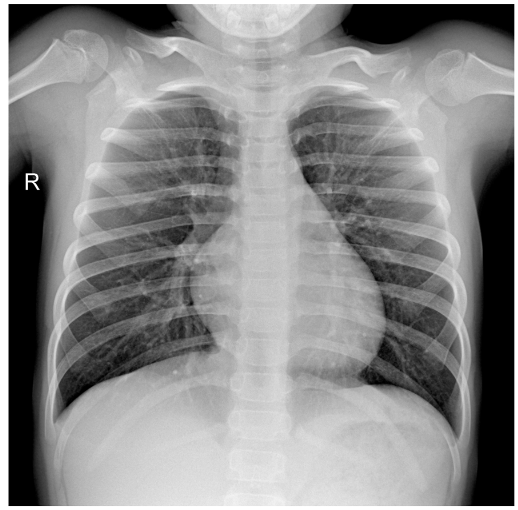


Fig. 1. Paediatric Lung X-rays of Normal Image

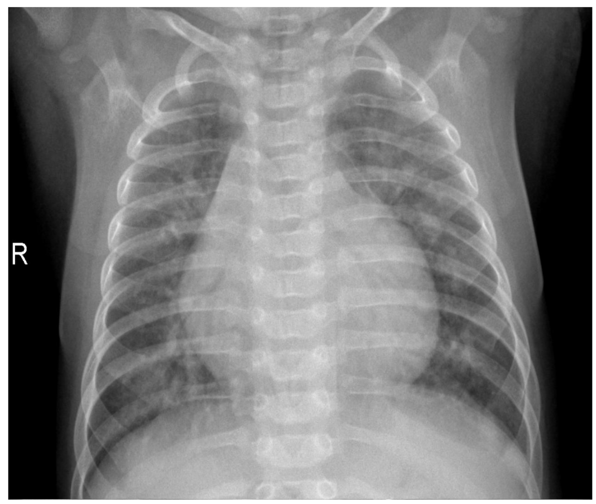


Fig. 2. Bacterial Pneumonia Image.

To truly unlock the potential of this model, several key improvements are necessary. First, extending the training using more epochs is crucial. This would allow the model to continue learning complex features, improving its ability to differentiate between pneumonia and non-pneumonia cases with greater accuracy. Enhancing the quality and diversity of the training data is also vital [4]. More representative and varied datasets would help the model generalize better to unseen images, reducing the likelihood of false positives and negatives.

In terms of fine-tuning, optimizing the model architecture by experimenting with different layers or activation functions could lead to more robust performance [3]. For example, while the Rectified Linear Unit (ReLU) has been instrumental in helping the model learn complex patterns through the introduction of non-linearity, exploring alternative activation


Fig. 3. ResNet-50 Model Training and Validation Accuracy

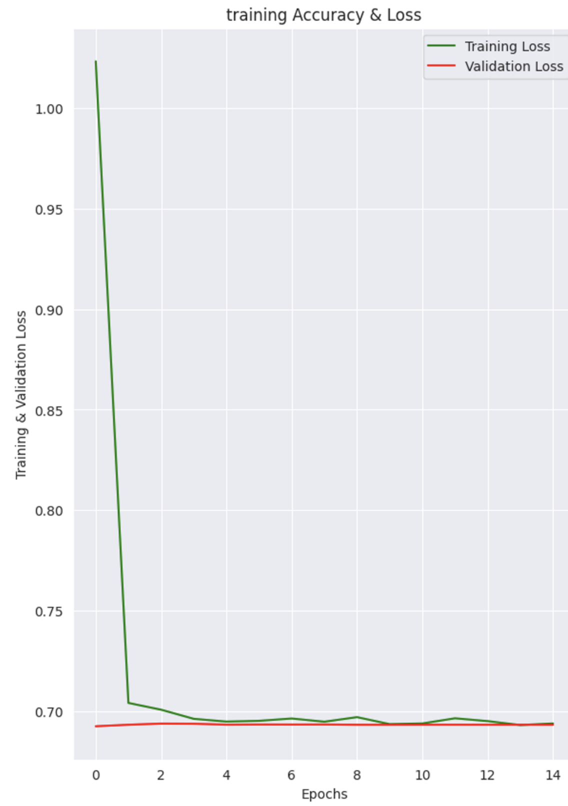


Fig. 4. ResNet-50 Model Training Accuracy and Loss

functions like the Universal Linear Unit (ULU) might yield different results. ULU offers an advantage in handling negative inputs, potentially addressing some of the limitations observed with ReLU [6]. Another possibility could be through the use of a non-linear activation function even though ReLU is not a linear function, another enhanced function may produce more varied results, but some recent studies have shown that they could improve the rate of learning in the models [5].

In conclusion, while the initial results were promising, the model still has room for improvement. ResNet-50 is an immensely powerful tool for image identification, but optimizing the training process, refining the data, and exploring alternative activation functions are critical steps to enhance its accuracy and reliability. With these enhancements, the model could significantly improve diagnosis and care in the medical field, making it an asset in the fight against diseases like pneumonia and potentially alleviating lung cancer treatment regimens.

## IV. Conclusion

The deep learning model, employing CNN and LSTM architectures, demonstrates promising but still developing performance in detecting lung cancer from pneumonia related imaging data. Initially, with 15 epochs of training, the model achieved a validation accuracy of 51%, which improved to 59% after 30 epochs, indicating ongoing learning and model iterative progression. The model distinguishes between pneumonia and lung cancer by identifying key imaging features such as lesion shape, size, and texture, with pneumonia typically presenting as diffuse opacities and lung cancer as well-defined masses or nodules. However, the model's accuracy currently lags traditional PET/CT scans, which are known for their high accuracy, sensitivity, and specificity in lung cancer detection. Additionally, while the model shows potential, its ability to differentiate between lung cancer and pneumonia when both conditions co-occur is still under development, requiring further refinement and training to enhance its performance in complex diagnostic scenarios.

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