Group 14

Image Classification with Deep Learning

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INTRODUCTION

Image classification with deep learning refers to the task of training a deep neural network model to automatically classify images into different predefined classes or categories. It involves teaching the model to recognize and differentiate various visual patterns and features in images to make accurate predictions about the class or category to which a given image belongs.

Overview

This project implements an image classifier using deep learning techniques to classify chest X-ray images as normal or pneumonia. It involves preprocessing the dataset, defining a convolutional neural network (CNN) model architecture, training the model, and evaluating its performance using separate validation and testing datasets. Visualizations of accuracy and loss during training provide insights into the model's performance. The project aims to create an accurate and reliable classifier for diagnosing pneumonia based on chest X-ray images.

Data Understanding

The Chest X-Ray dataset is a valuable resource for pneumonia detection in chest X-ray images. It comprises a diverse collection of labeled chest radiographs representing both normal and pneumonia cases. The dataset includes images from pediatric and adult patients, covering different pneumonia types like bacterial and viral infections. The images are in JPEG format, predominantly grayscale, and exhibit variations in resolution and size. With separate training and testing subsets, this dataset enables the development and evaluation of accurate machine-learning models for pneumonia detection, offering significant potential for advancing diagnostic capabilities in the field of healthcare.

Objective and Success Metrics

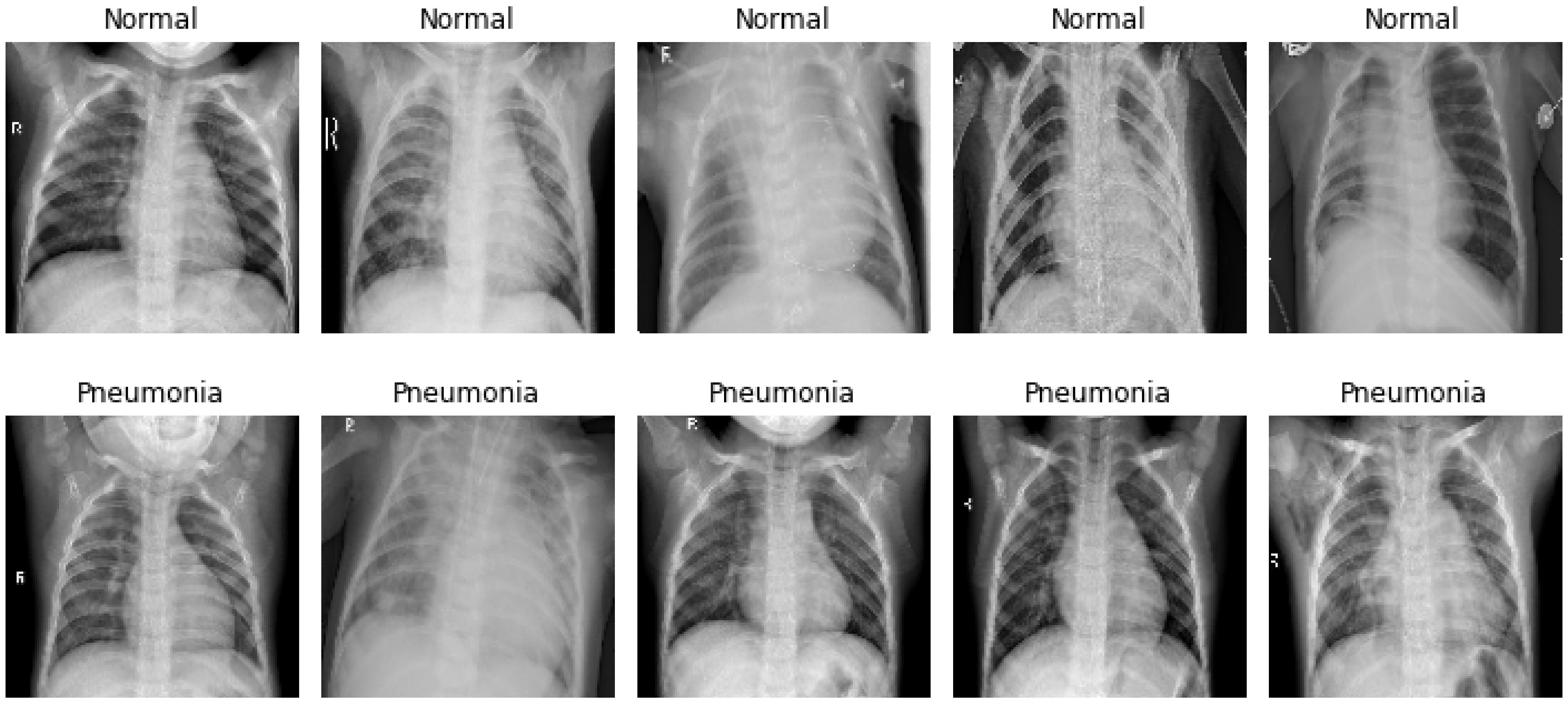
The main goal of this undertaking is to create a Neural Network model capable of reliably categorizing chest X-ray pictures as having or not having pneumonia.

Success Metrics

The performance of the model is evaluated based on:

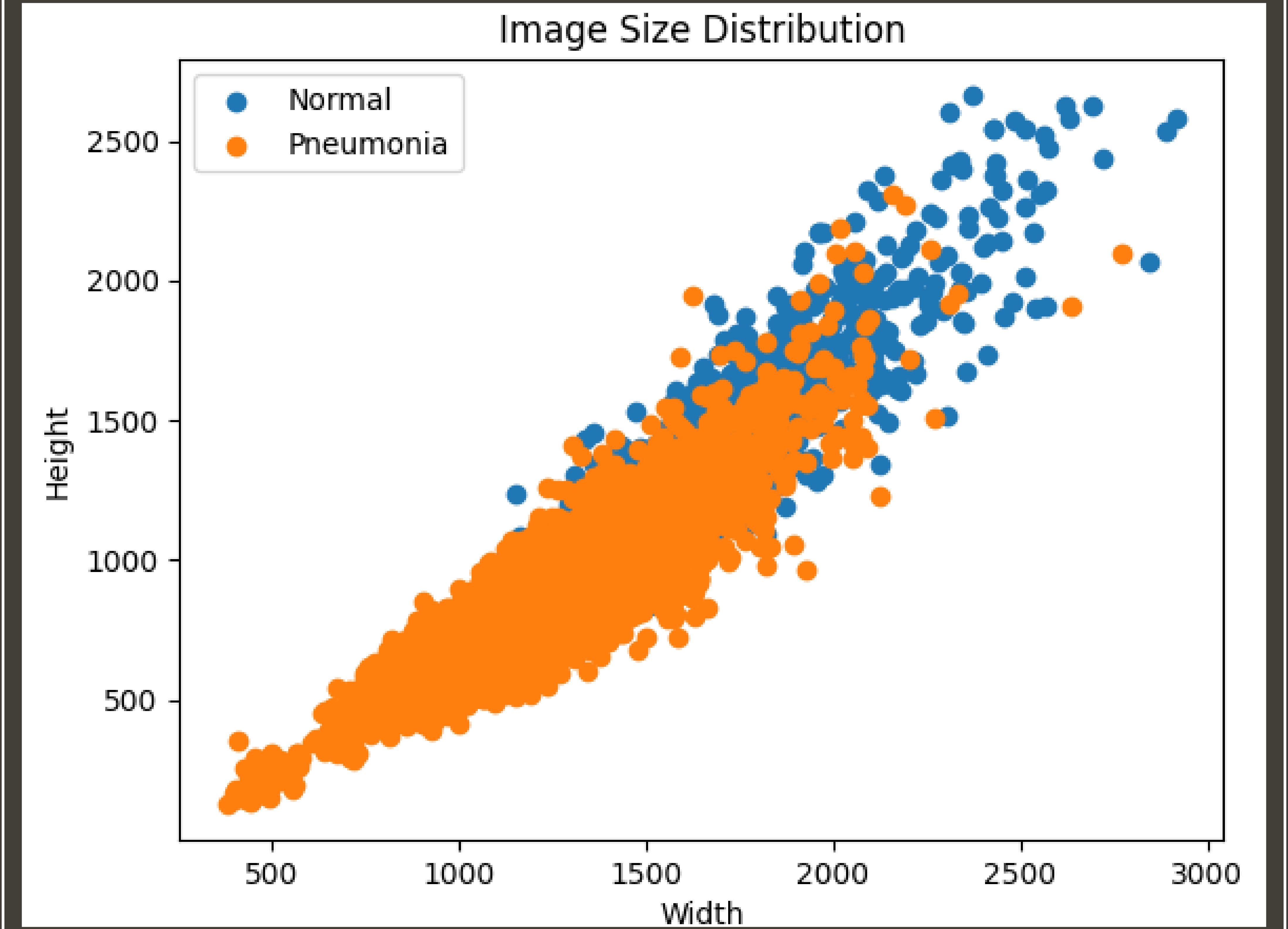
* Accuracy - achieving an accuracy of over 85%.
* Recall - achieving a recall of over 65%.
* Loss Function - minimize loss function to ensure the model is not overfitting.

Exploratory Data Analysis



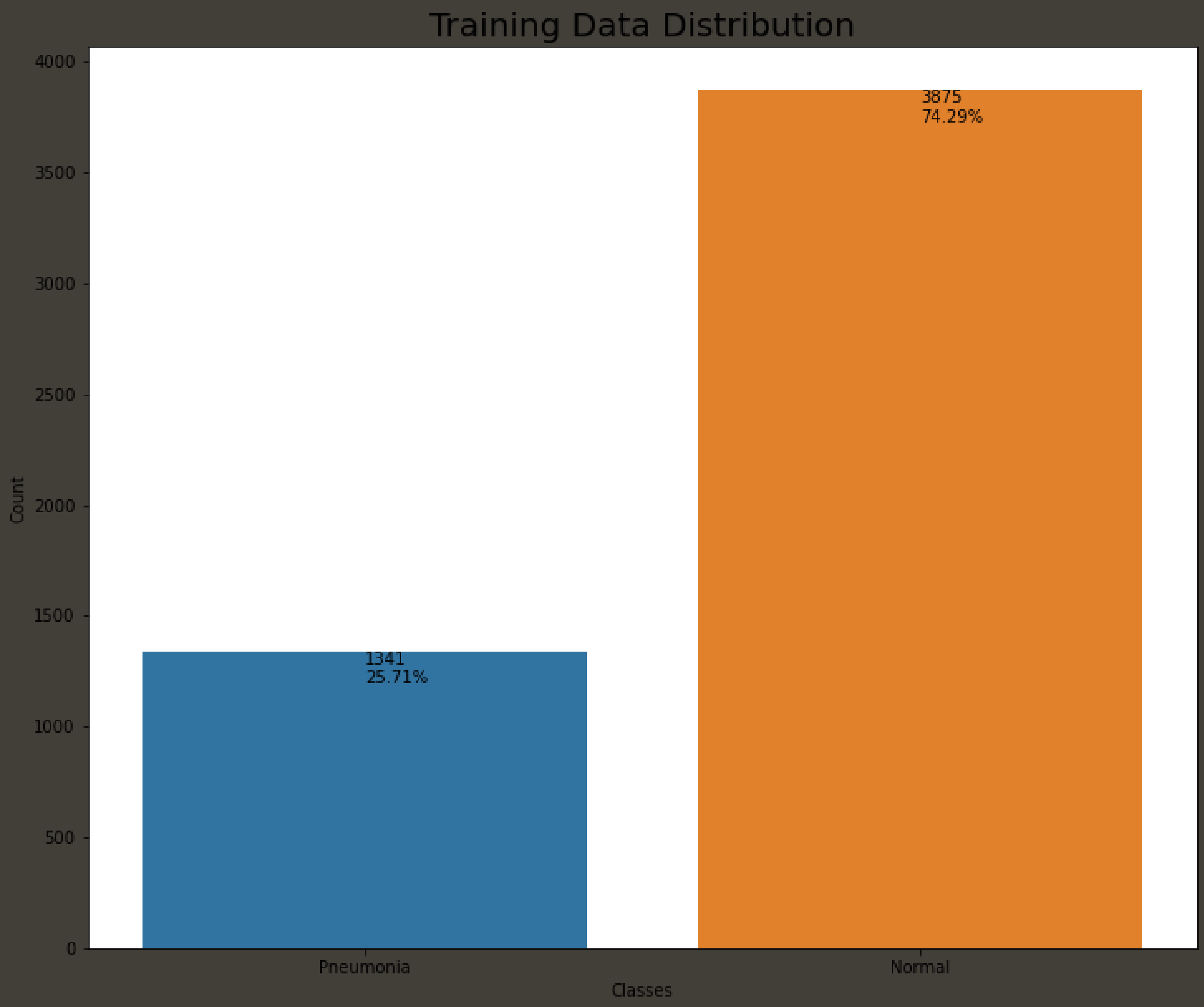
A preview of the images.

Exploratory Data Analysis



A scatter plot showing the image size distribution

Exploratory Data Analysis



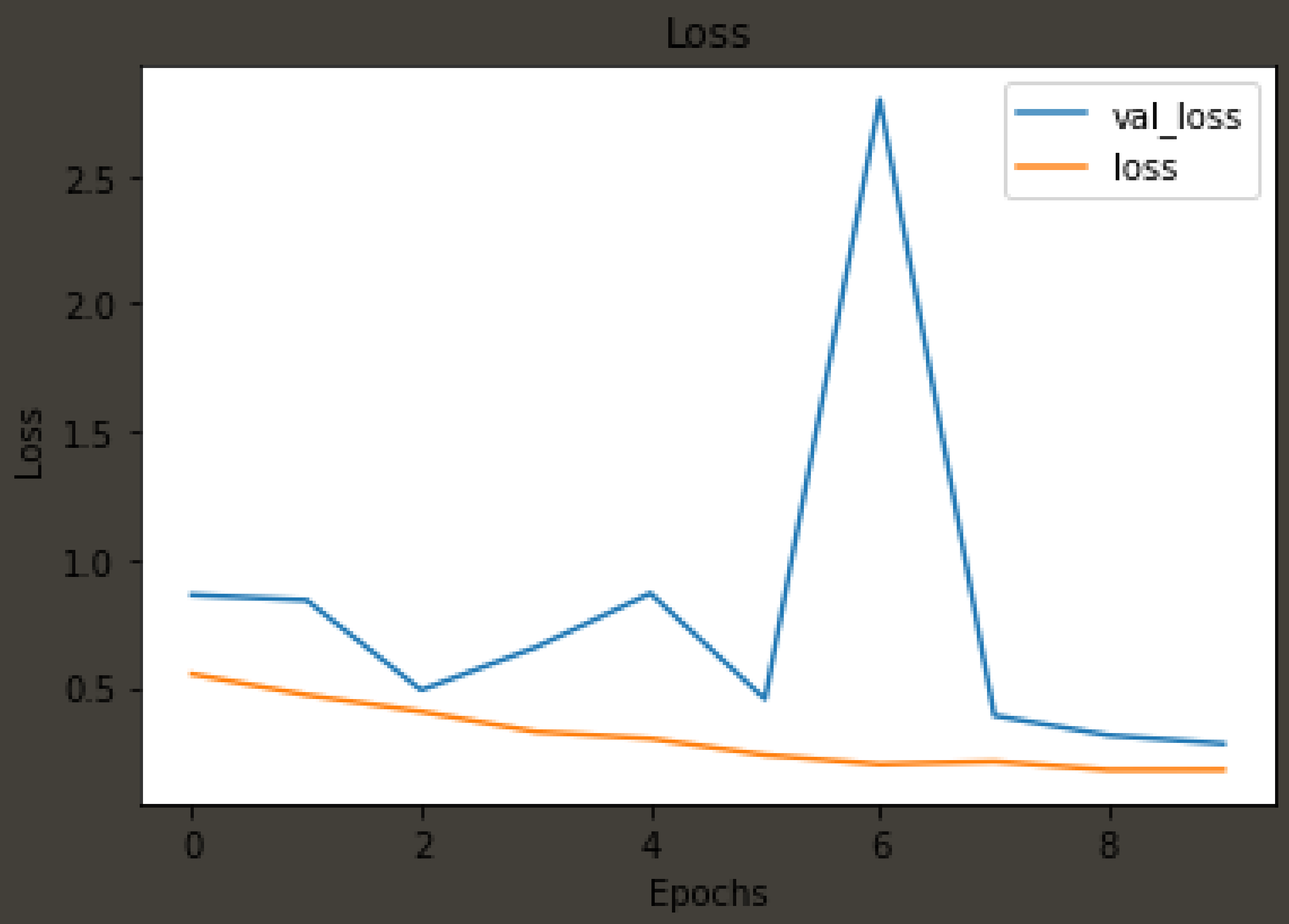
Exploratory Data Analysis

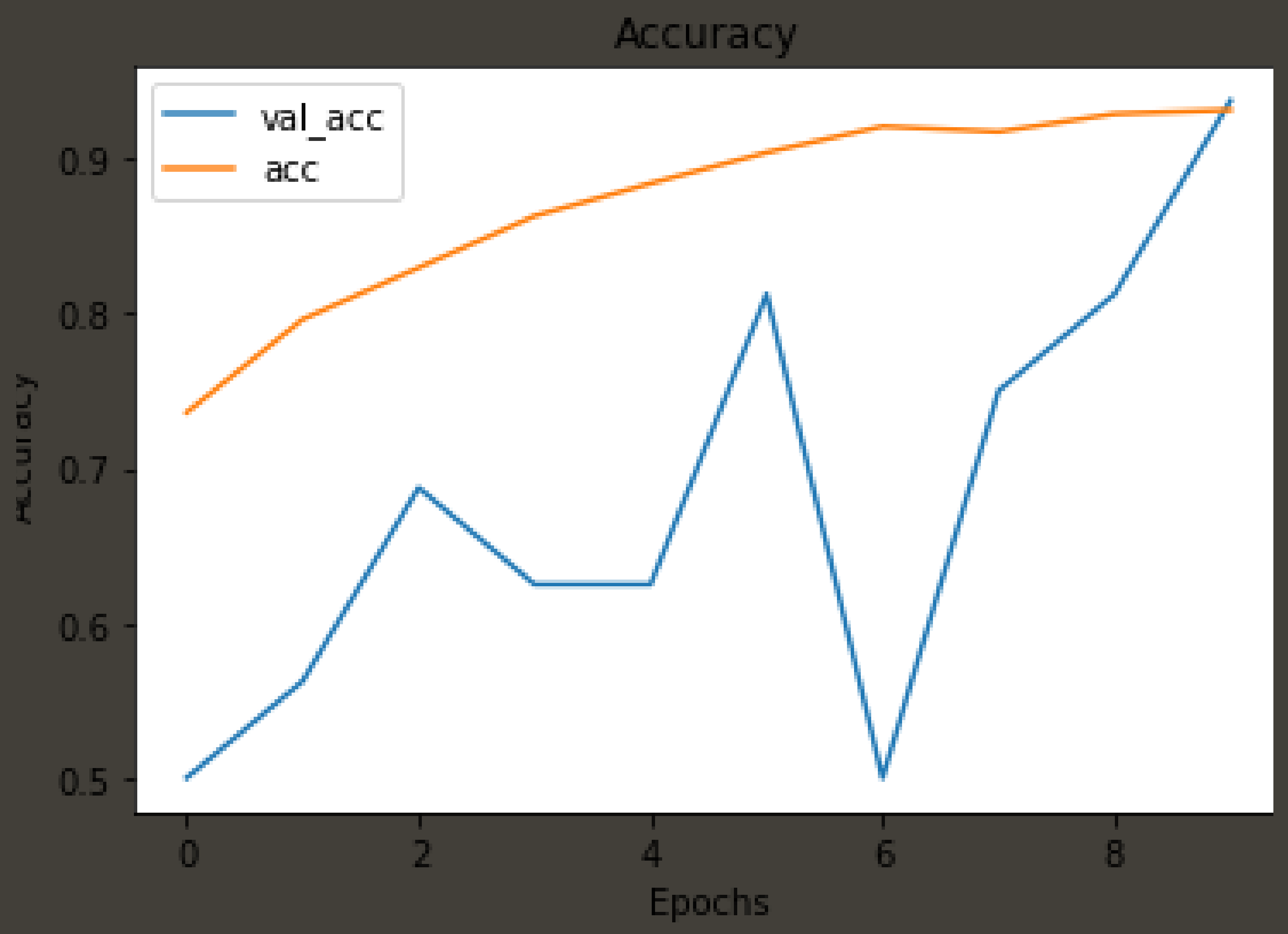
1. The dataset is divided into three folders: "train" with 5,216 images, "test" with 624 images, and "val" with 16 images. There are two classes in the dataset: "NORMAL" (representing normal chest X-rays) whose corresponding label is 0 and "PNEUMONIA" (representing chest X-rays with pneumonia) whose corresponding label is 1.
2. The "Pneumonia" class is significantly more represented than the "Normal" class. This is a common problem in medical datasets, and it can make it more challenging to train a machine-learning model that can accurately distinguish between the two classes.
3. Images of x rays of people with pneumonia seem to have a smaller width and height although not distinctively
4. There is some overlap in the distribution of image sizes for the two classes. This suggests that there are some images that are difficult to classify, even with human experts and that is why we need machine learning.

Modelling

The modeling phase of the project focused on developing a deep-learning model for pneumonia detection in chest X-ray images. The dataset, consisting of labeled chest radiographs as "normal" or "pneumonia" cases, was used for training and evaluating the model. A Convolutional Neural Network (CNN) architecture was implemented, consisting of multiple convolutional and pooling layers followed by dense layers for classification. The model was trained using the training subset of the dataset and evaluated on the validation subset. The training process involved optimizing the model's parameters using the Adam optimizer and minimizing the binary cross-entropy loss. After training for a specified number of epochs, the model's performance was assessed on the test subset using metrics such as loss and accuracy. The model achieved satisfactory results, demonstrating its potential for accurately classifying pneumonia in chest X-ray images.

Modelling


Loss
val_loss
loss
2.5
2.0
1.5
1.0
0.5
Loss
0
2
4
6
8
Epochs

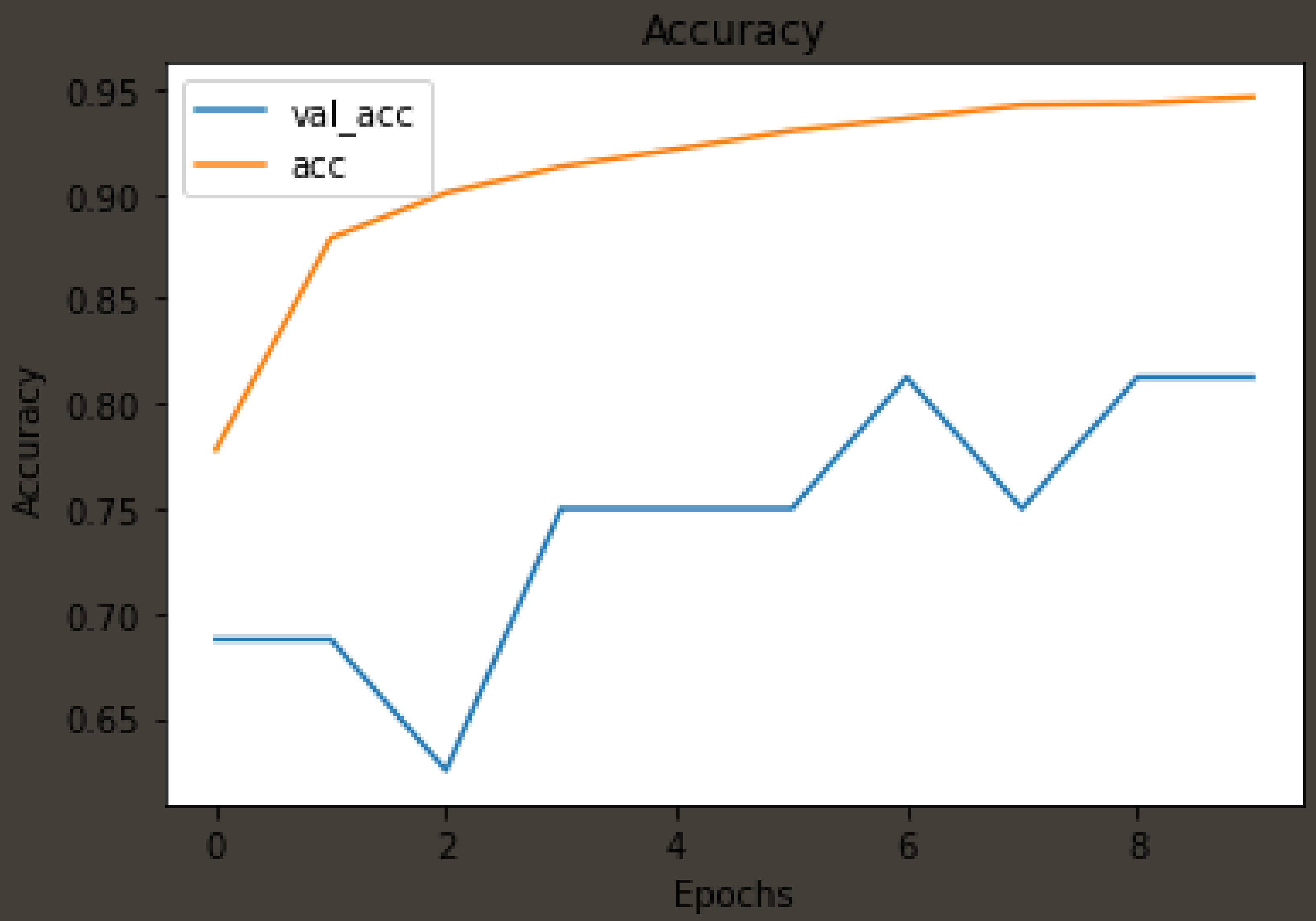

Accuracy
val_acc
acc
0.9
0.8
0.7
0.6
0.5
0
2
4
6
8
Epochs

Modelling

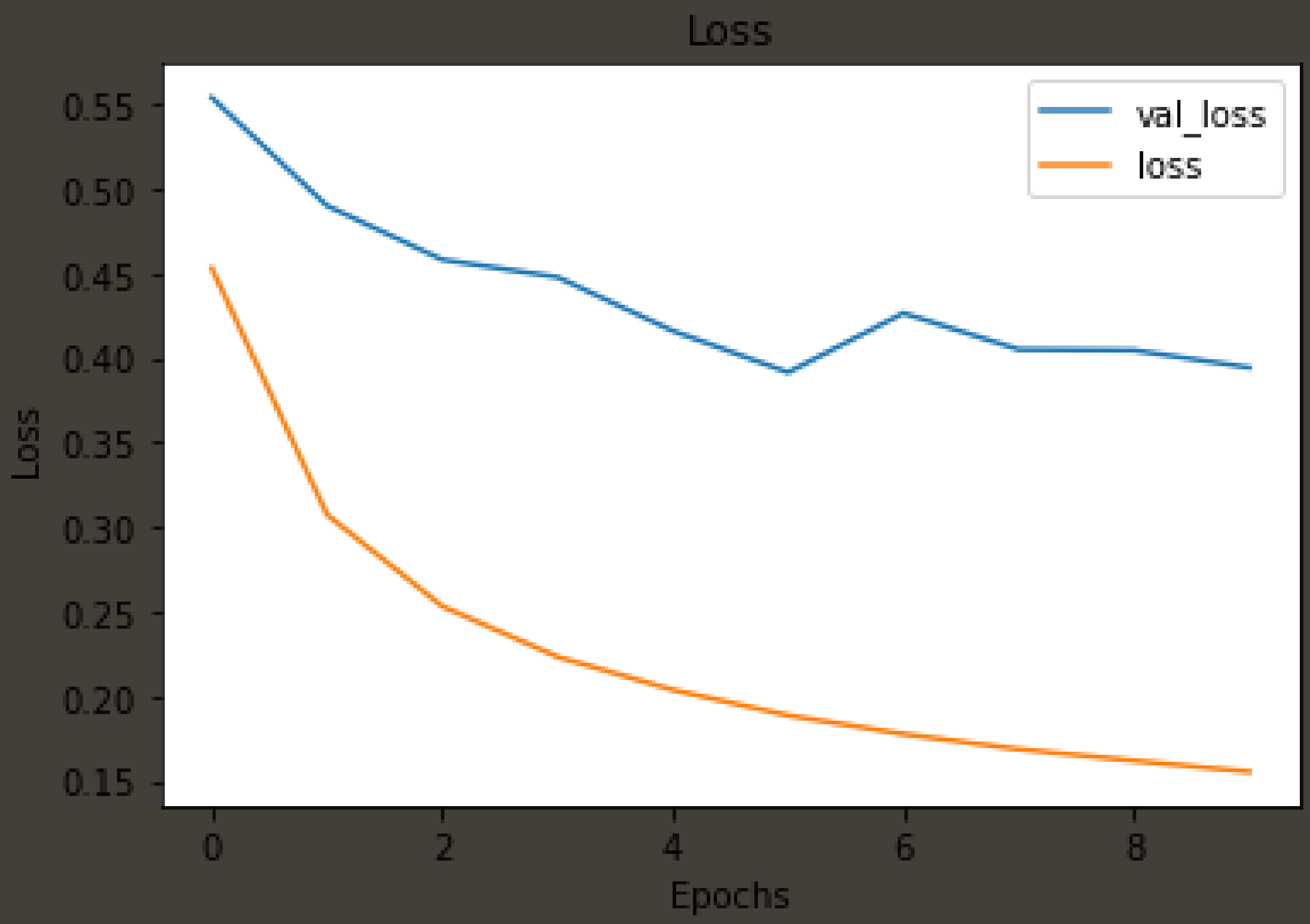
The second model is a sequential model with two convolutional layers followed by max-pooling layers and a final fully connected layer. The convolutional layers extract features from the input images, the max-pooling layers reduce the spatial dimensions, and the dense layer at the end performs the classification.

The training process yielded a training loss of 0.195 and a training accuracy of 92.4%, indicating that the model is effectively learning from the training data. Additionally, the validation loss of 0.280 and the validation accuracy of 93.8% demonstrate that the model is generalizing well to unseen data, further confirming its robustness and ability to make accurate predictions.

Modelling



Accuracy
val_acc
acc
0.95
0.90
0.85
0.80
0.75
0.70
0.65
Accuracy
0
2
4
6
8
Epochs



Loss
val_loss
loss
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
Loss
0
2
4
6
8
Epochs

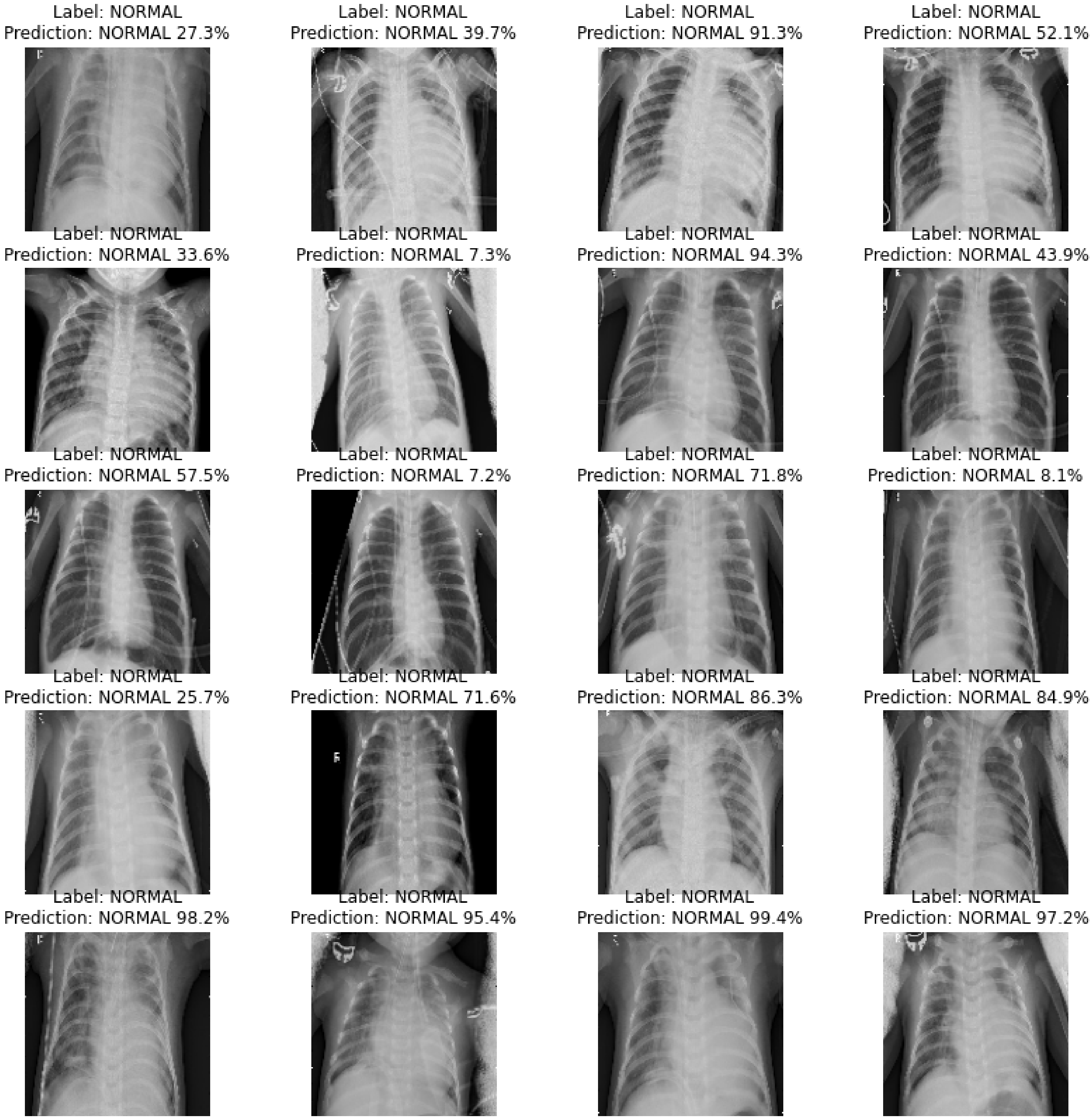
Modelling

The graphs show that the model is learning over time. The training loss decreases steadily over the epochs, and the training accuracy increases steadily over the epochs. This suggests that the model is able to learn from the training data and improve its performance. The validation loss also decreases over the epochs, but it does not decrease as quickly as the training loss. This suggests that the model is not overfitting to the training data. However, the validation accuracy plateaus after epoch 5. This suggests that the model may not be able to generalize well to new data.
Overall, the graphs show that the model is learning over time and is not overfitting to the training data.

Evaluation

The classification report provides an evaluation of the model's performance on the test dataset. The model achieved an accuracy of 83%, indicating that it correctly classified 83% of the samples. It demonstrated good precision, with 85% precision for the "NORMAL" class and 82% precision for the "PNEUMONIA" class, meaning a high percentage of predicted positive cases were indeed positive. The recall values were 67% for the "NORMAL" class and 93% for the "PNEUMONIA" class, indicating that the model effectively identified a large proportion of the actual positive cases. The F1-score, which considers both precision and recall, was 0.75 for the "NORMAL" class and 0.87 for the "PNEUMONIA" class, showing a balance between precision and recall. Overall, the model demonstrated promising performance in accurately classifying normal and pneumonia cases in the chest X-ray images.

Predictions



Predictions

These results indicate the performance of each of the models on the test dataset. Lower values for test loss indicate better performance, while higher values for test accuracy indicate higher accuracy. Based on the results, Model 2 performs the best with a test loss of 0.3740, test accuracy of 0.8317, and a recall score of 0.93 percent for pneumonia and 0.67 percent for Normal.

A recall score of 0.93 for the "PNEUMONIA" class means that the model correctly identified 93% of the actual pneumonia cases in the dataset. This indicates a high sensitivity of the model in detecting pneumonia, as it has a low likelihood of missing positive cases.

Conclusion

In summary, our image classification model achieved an accuracy of 83% in detecting pneumonia from X-ray images. While the high recall score of 0.93 indicates the model's strong ability to identify pneumonia cases, it fell short of the targeted accuracy of 85%. Factors such as limited data, the complexity of the task, model architecture, and hyperparameter sensitivity may have contributed to this outcome. Pneumonia detection from X-ray images is a challenging task due to various factors, including imaging artifacts and inter-patient variability. Despite these challenges, our model shows promise in accurately identifying pneumonia cases, but further improvements are necessary to reach higher accuracy levels.

Recommendations

- Pan African Medical Training and Research should use our CNN model for x_ray image classification in the field and also when training researcher in class.

- Deploy the developed image classification model for pneumonia detection from X-ray images in the real world. It will be useful in assisting healthcare professionals in the diagnosis of pneumonia., increase efficiency and speed in diagnosis and act as a second opinion.