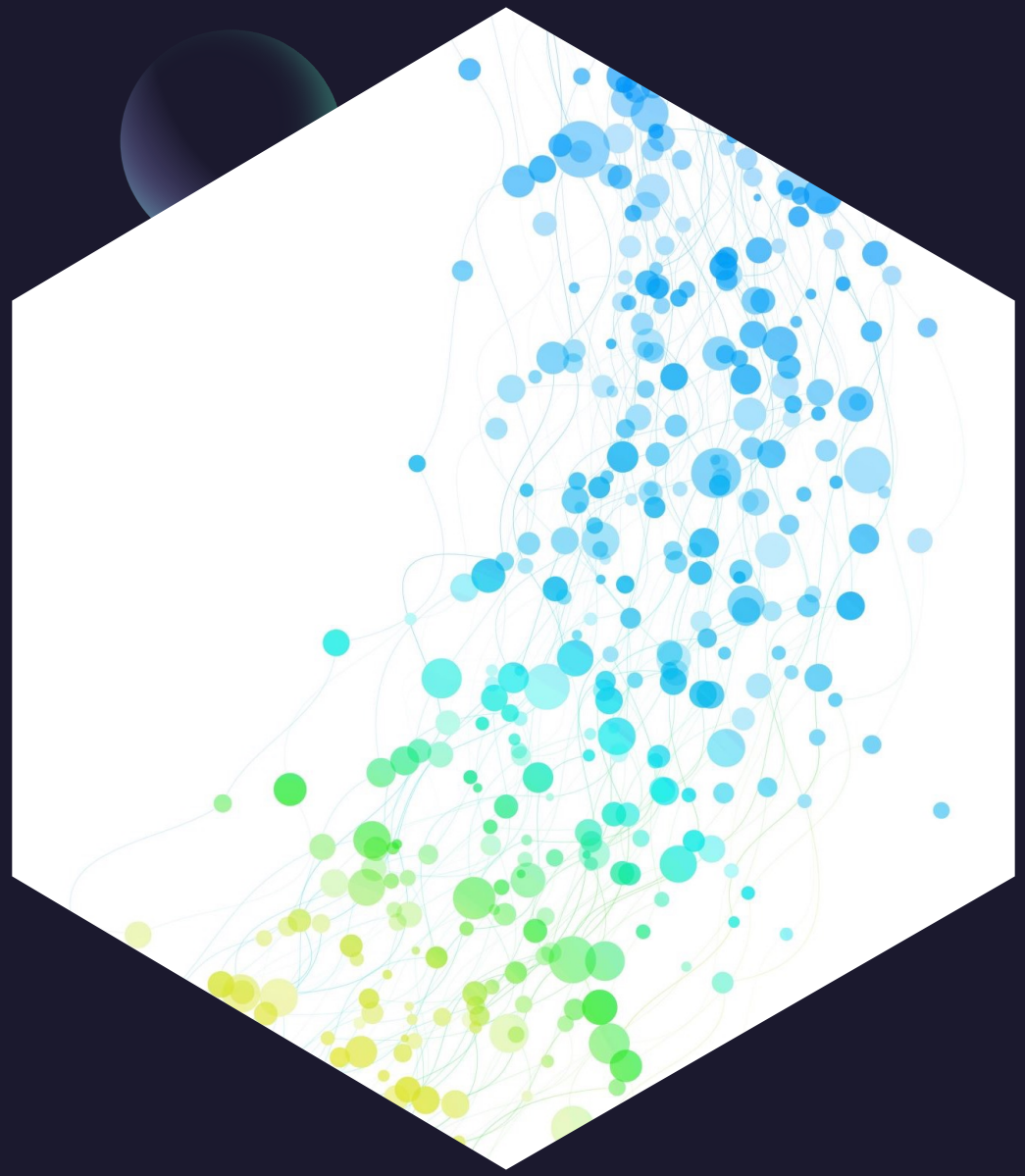
Pneumonia Detection using CNN



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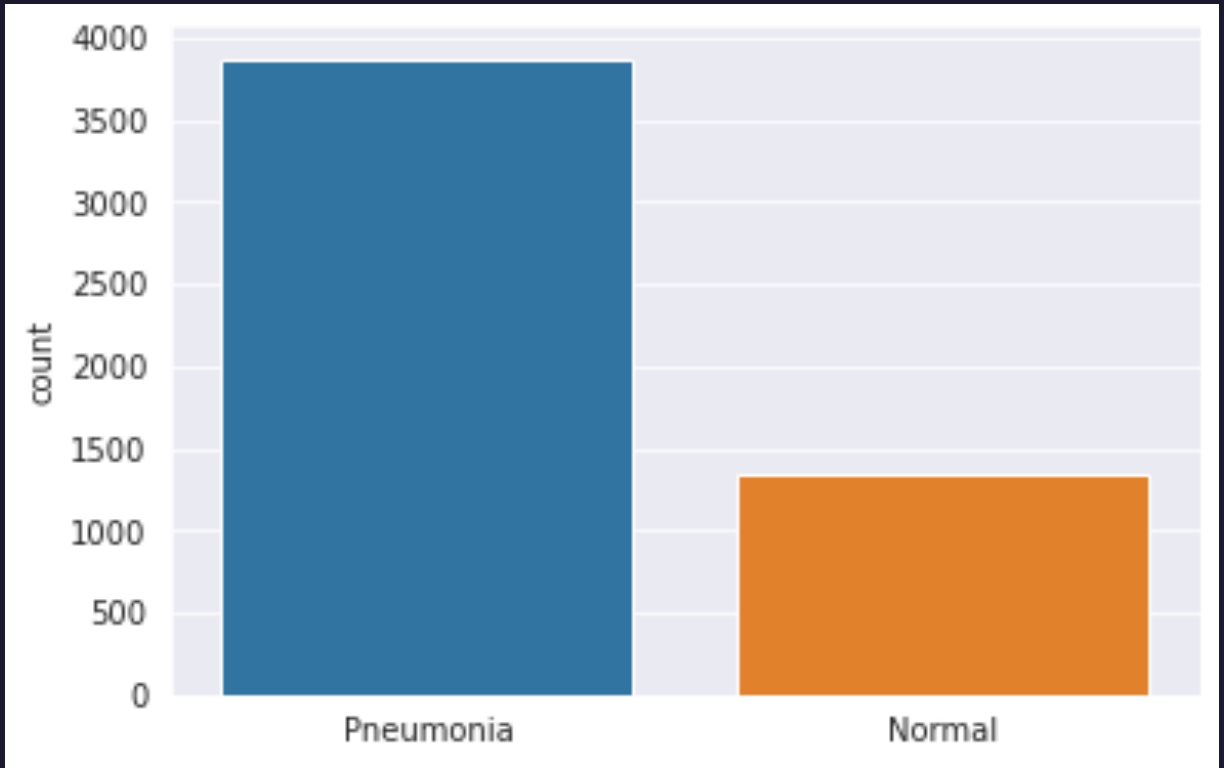
OBJECTIVES

- Develop an automated system for detecting Pneumonia in chest X-ray images using CNN and improve accuracy of pneumonia detection by reducing potential for human error or bias in diagnosis.
- To train CNN model on a large dataset of chest X-ray images with labeled pneumonia cases and normal cases to extract relevant features and use them to make predictions on new, unseen images.
- To explore the potential impact of using CNN for improving healthcare outcomes, such as reducing workload on radiologists, enabling faster and more efficient patient care.
- The overall goal of the project is to develop a reliable and accurate pneumonia detection tool that can assist doctors in making more informed diagnoses and providing appropriate treatment.

DATA DESCRIPTION

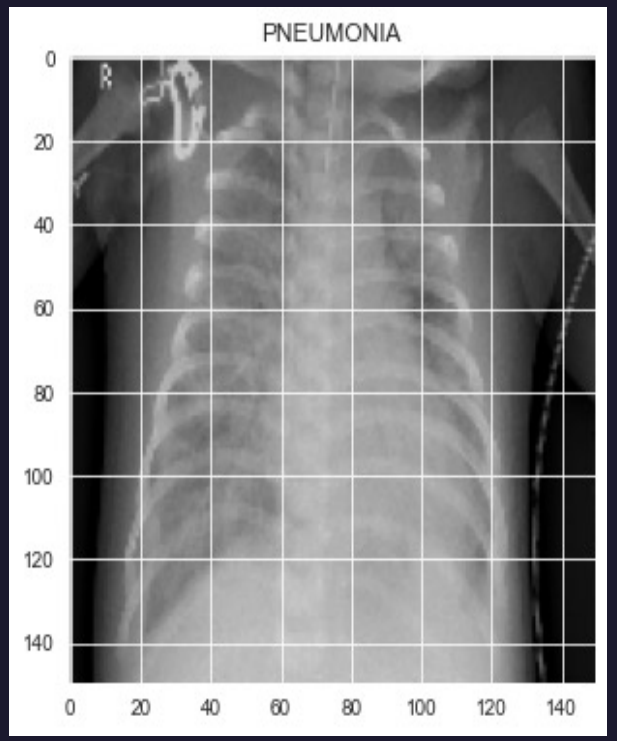
- The dataset consists of OCT Chest X-Ray images labelled as Normal or Pneumonia split into Training, Validation and Test set of independent patients.
- Optical coherence tomography (OCT) is a technique for obtaining sub-surface images of translucent or opaque materials at a resolution equivalent to a low-power microscope.
- There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).

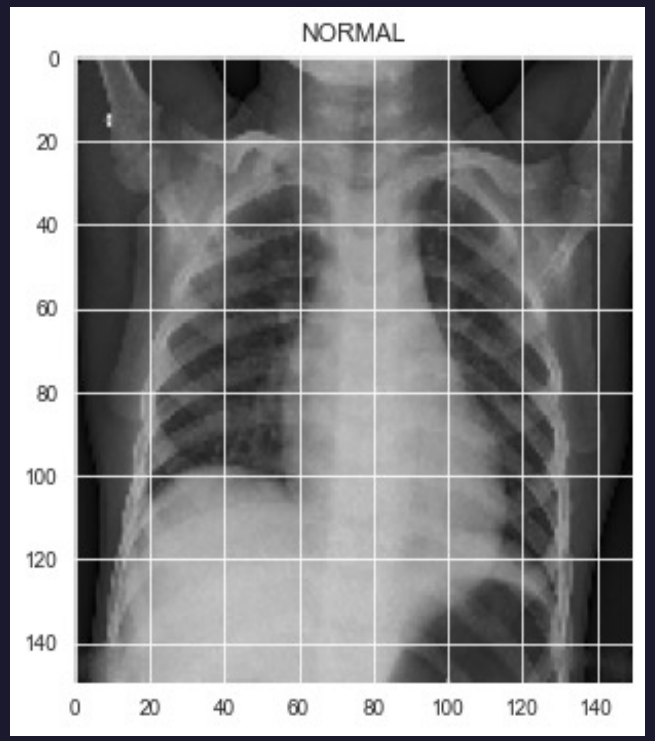
EXPLORATORY DATA ANALYSIS



- The given visualization, shows that the data is imbalanced, with one class (Pneumonia) being more prevalent than the other (Normal).
- To handle the imbalanced data, data augmentation has been performed.
- Approaches that alter the training data in ways that change the array representation while keeping the label the same are known as data augmentation techniques.

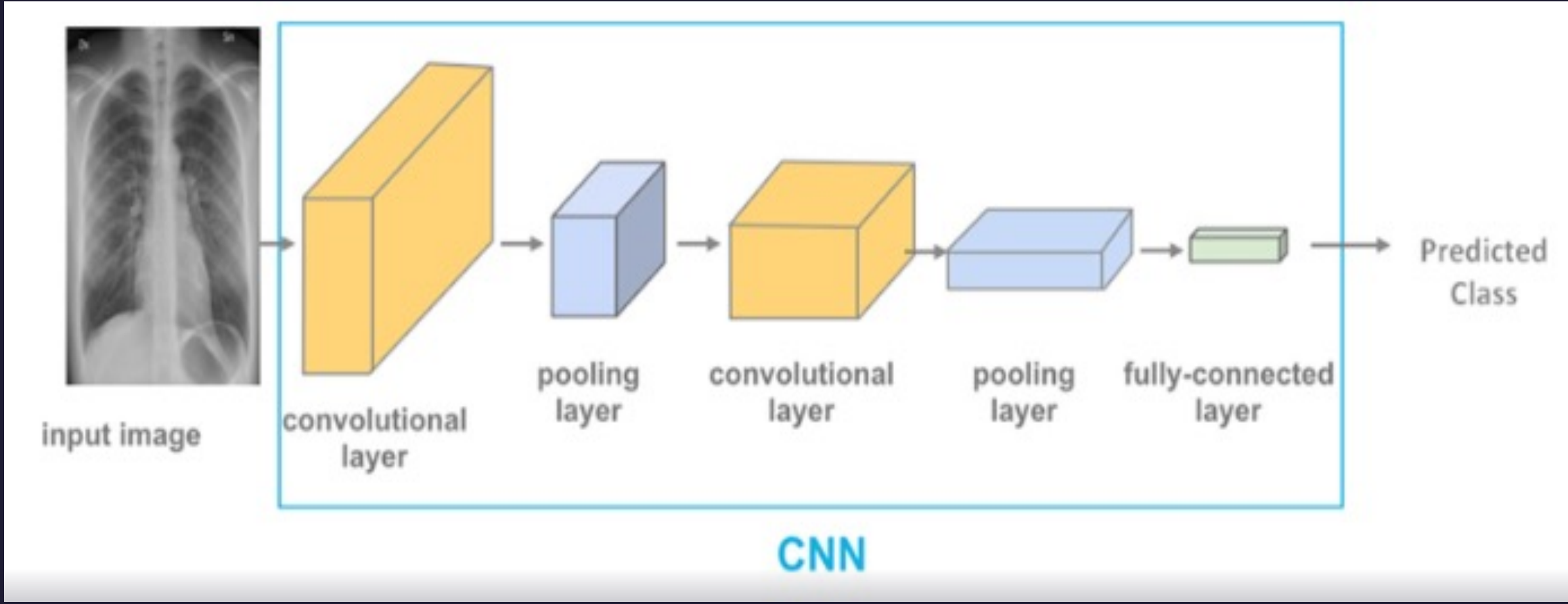
EXPLORATORY DATA ANALYSIS





- Grayscale Normalization has been performed to reduce illumination differences.
- Some popular augmentations people use are grayscales, horizontal flips, vertical flips, random crops, color jitters, translations, rotations, and much more.
- By applying a couple of transformations to train data, number of training examples can easily be doubled or tripled, and a very robust model could be created.

CNN Architecture



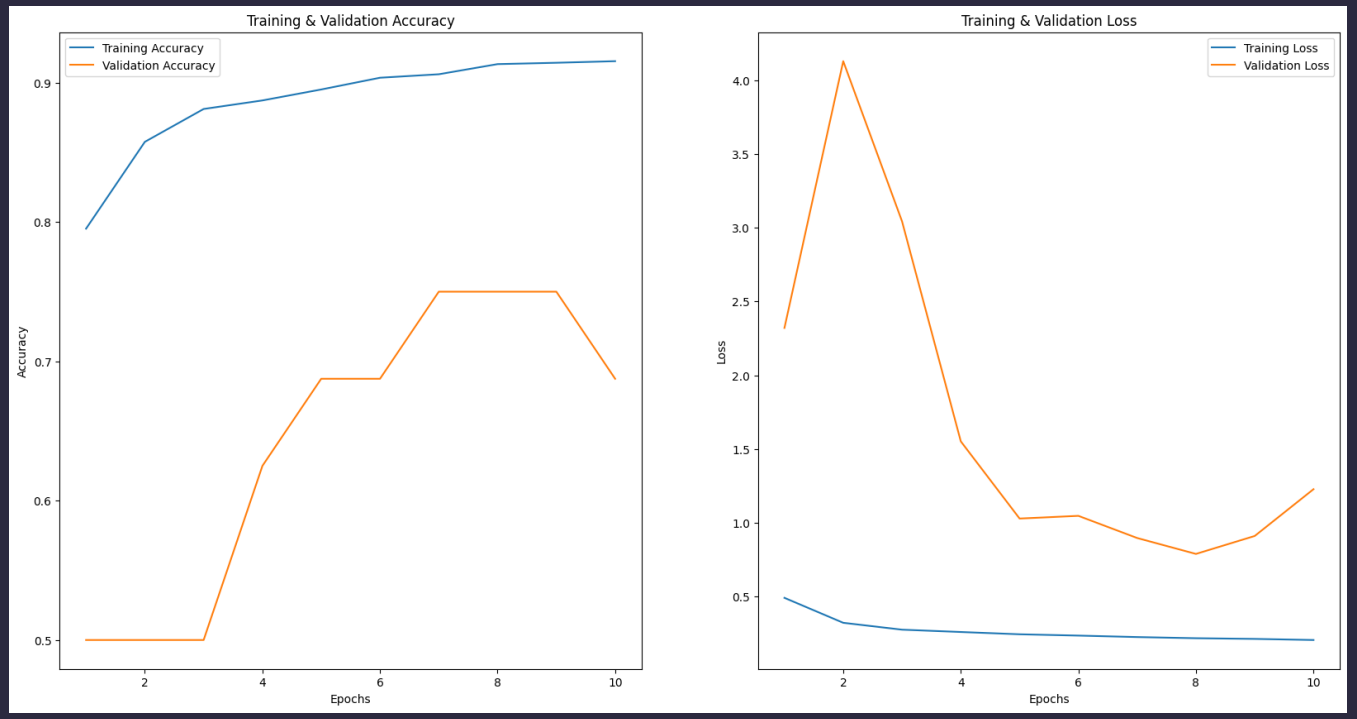
Results

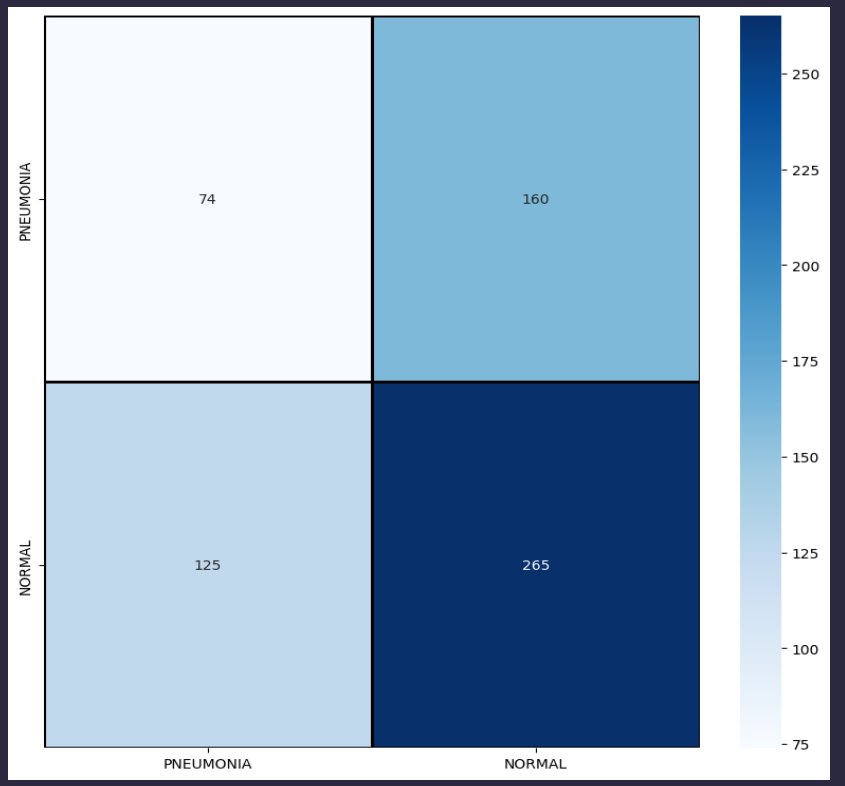
Batch Size	Epochs	Learning Rate	Precision	Recall	Accuracy	Test Accuracy	F1-Score
32	6	0.000001	0.6161	0.6051	0.5176	0.8470	0.61055
32	6	0.000010	0.6183	0.6561	0.5320	0.8814	0.63664
32	6	0.000100	0.6252	0.6974	0.5496	0.8830	0.65933
32	12	0.000001	0.6157	0.6410	0.5256	0.8525	0.62810
32	12	0.000010	0.6265	0.6282	0.5336	0.8958	0.62735
32	12	0.000100	0.6210	0.6974	0.5448	0.8910	0.65699
32	18	0.000001	0.5969	0.6076	0.4983	0.8509	0.60220
32	18	0.000010	0.6433	0.6615	0.5592	0.8926	0.65227
32	18	0.000100	0.6127	0.6410	0.5224	0.8974	0.62653

Results

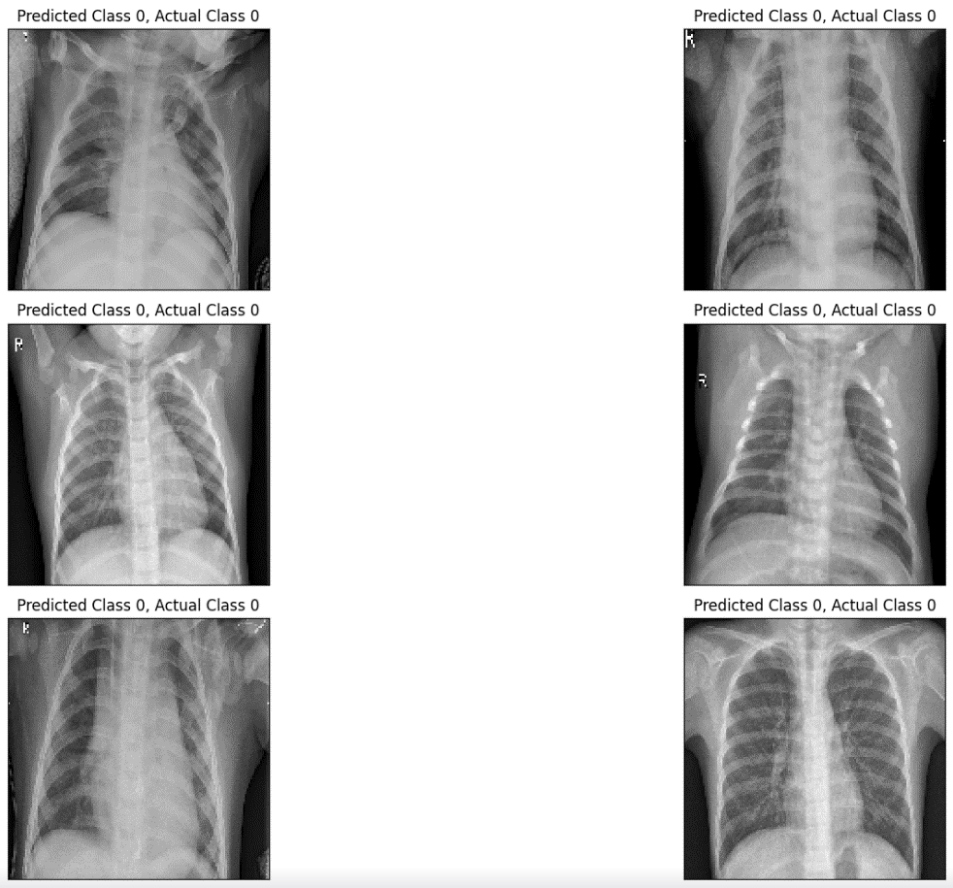
	Precision	**Recall**	**F1-Score**
Pneumonia (Class 0)	0.37	0.32	0.34
Normal (Class 1)	0.62	0.68	0.65
Test Accuracy			0.89
Accuracy			0.54
Macro Average	0.50	0.50	0.50
Weighted Average	0.53	0.54	0.53

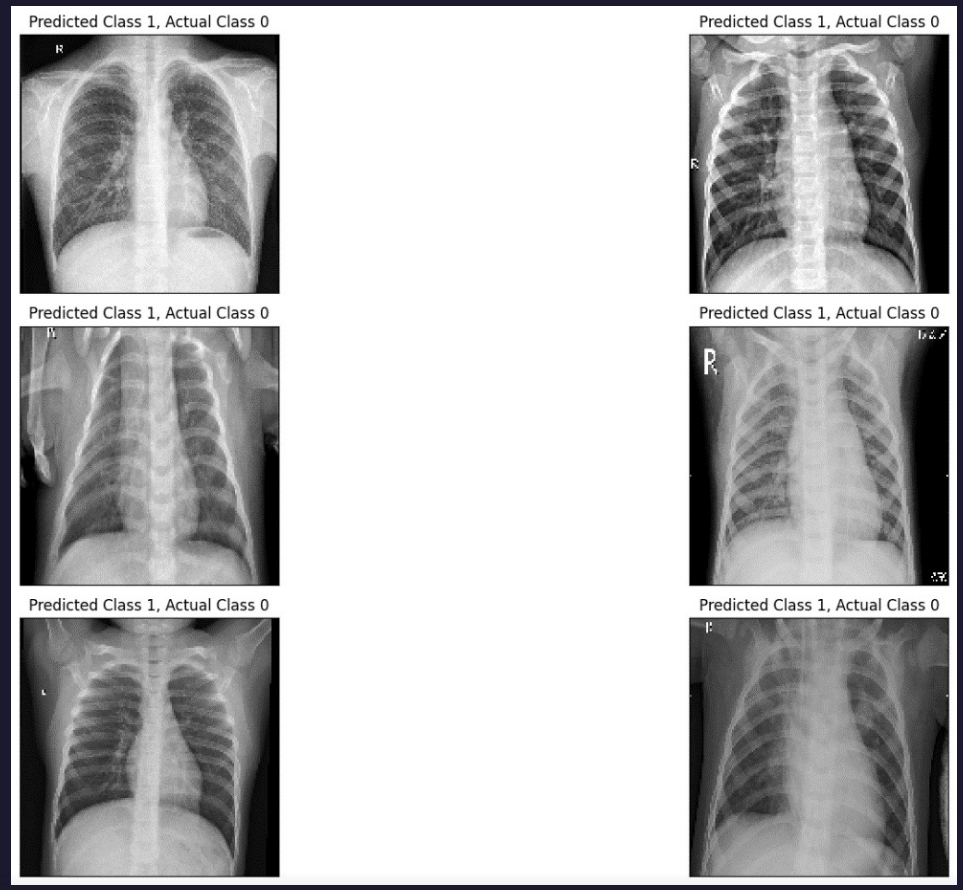
Results


Training & Validation Accuracy
Training Accuracy
Validation Accuracy
Accuracy
Epochs
Training & Validation Loss
Training Loss
Validation Loss
Loss
Epochs


PNEUMONIA
NORMAL
74
160
125
265
PNEUMONIA
NORMAL

Conclusions and Future Work





Conclusions and Future Work

Based on the experiments conducted, we can conclude that the combination of :

- Epoch = 10
- Learning Rate = 0.00001
- Batch Size = 32
- Test Accuracy = 89%

Yielded the best **Test Accuracy = 89%.**

The preferred measure for evaluation was: F1-Score = 0.65 (For Normal) and F1-Score = 0.34 (For Pneumonia) which was used to assess the model's performance.

THANK YOU