Udacity Machine Learning Nanodegree 2021

Capstone Project Report

Pneumonia Detection with Deep Learning

Ravee Rachakonda

Oct 2021

Domain Background

Pneumonia is an inflammatory condition of the lung primarily affecting the small air sacs known as alveoli. Symptoms typically include some combination of productive or dry cough, chest pain, fever and difficulty breathing. The severity of the condition is variable. Pneumonia is usually caused by infection with viruses or bacteria, and less commonly by other microorganisms. Identifying the responsible pathogens can be difficult. Diagnosis is often based on symptoms and physical examination. Chest X-rays, blood tests, and culture of the sputum may help confirm the diagnosis. The disease may be classified by where it was acquired, such as community- or hospital-acquired or healthcare-associated pneumonia. Each year, pneumonia affects about 450 million people globally (7% of the population) and results in about 4 million deaths. With the introduction of antibiotics and vaccines in the 20th century, survival has greatly improved. Nevertheless, pneumonia remains a leading cause of death in developing countries, and also among the very old, the very young, and the chronically ill.

The main types of pneumonia are:

- **Bacterial pneumonia**: This type is caused by various bacteria.
- **Viral pneumonia**: This type is caused by various viruses, including the flu (influenza), and is responsible for about one-third of all pneumonia cases.
- **Mycoplasma pneumonia**: This type has somewhat different symptoms and physical signs and is referred to as atypical pneumonia. It is caused by the bacterium Mycoplasma pneumoniae. It generally causes mild, widespread pneumonia that affects all age groups.
- Other pneumonias

Pneumonia is typically diagnosed based on a combination of physical signs and a chest X-ray. Imaging: A chest radiograph is frequently used in diagnosis. In people with mild disease, imaging is needed only in those with potential complications, those not having improved with treatment, or those in which the cause is uncertain. If a person is sufficiently sick to require hospitalization, a chest radiograph is recommended. Findings do not always match the severity of disease and do not reliably separate between bacterial and viral infection. X-ray presentations of pneumonia may be classified as lobar pneumonia, bronchopneumonia, lobular pneumonia, and interstitial pneumonia. Bacterial, community-acquired pneumonia classically show lung consolidation of one lung segmental lobe, which is known as lobar pneumonia. However, findings may vary, and other patterns are common in other types of pneumonia. Aspiration pneumonia may present with bilateral opacities primarily in the bases of the lungs and on the right side. Radiographs of viral pneumonia may appear normal, appear hyper-inflated, have bilateral patchy areas, or present similar to bacterial pneumonia with lobar consolidation. Radiologic findings may not be present in the early stages of the disease, especially in the presence of dehydration, or may be difficult to interpret in the obese or those with a history of lung disease. Complications such as pleural effusion may also be found on chest radiographs. Laterolateral chest radiographs can increase the diagnostic accuracy of lung consolidation and pleural effusion.

With Covid-19 rampant which has pneumonia as one of the major symptoms, I want to apply my skills to medical problems understanding the X-Ray data and determining if the given X-Ray has pneumonia detected. Based on my learning, Deep Learning is very effective at learning complex data like X-Ray images and provides reliable results. I want to build a reliable model experimenting with various deep learning algorithms and arrive at a reliable accuracy score for predicting pneumonia. The project idea is based on the data provided in the Kaggle project for detecting pneumonia using X-Ray data. With growing data in the medical field, I would like to expand my knowledge gained from X-Ray analysis to other medical and nonmedical image-based ML problems.

Problem Statement

The main goal of this capstone project is to utilize Deep Learning algorithms for detecting pneumonia in provided X-Ray. Build classifier which can score the X-Ray for detecting pneumonia and output as detected yes or no.

Datasets and Inputs

The dataset used for this capstone project is from the Kaggle project. The data is a set of chest X-Ray images in jpeg format. Dataset consists of 5956 x-ray images and is categorized into 3 categories:

- Train (5216)
  - NORMAL (1341)
  - PNEUMONIA (3875)
- Test (624)
  - NORMAL (234)
  - PNEUMONIA (390)
- Val (16)
  - NORMAL (8)
  - PNEUMONIA (8)

Solution Statement

The development of convolutional neural network layers has allowed for significant gains in the ability to classify images and detect objects in a picture. These are multiple processing layers to which image analysis filters, or convolutions, are applied. The abstracted representation of images within each layer is constructed by systematically convolving multiple filters across the image, producing a feature map that is used as input to the following layer. This architecture makes it possible to process images in the form of pixels as input and to give the desired classification as output. The image-to-classification approach in one classifier replaces the multiple steps of previous image analysis methods.

Benchmark Model

The benchmark is used from a research paper published in cell.com (https://www.cell.com/cell/fulltext/S0092-8674(18)30154-5). In the comparison of chest X-rays presenting as pneumonia versus normal, the research team achieved an accuracy of 92.8%, with a sensitivity of 93.2% and a specificity of 90.1% operating on the same data set. Research team used a transfer learning technique with CNN that was trained on various kinds of image data (Retinal, Chest X-Rays).

Evaluation Metrics

Loss, Accuracy, Precision and Recall are really good metrics for such kinds of problems as the dataset is 81.921% of Pneumonia positive. We will use the confusion matrix from the predictions and check what is the recall and precision of my model.

Project Design

Data Pre-processing

Data provided in the Kaggle project is split into train, test and validation sets. Each set contains folders for Normal and Pneumonia categories.
1. Image processing steps should be built to read in images
2. Leverage python libraries for convert image data to matrices

Kaggle input data containing the X-Ray images is pre-organized into train, val, test and classes: NORMAL, PNEUMONIA.

I have downloaded the kaggle data set, unzipped and uploaded the data to S3 bucket under data directory. As the data processing will be done with large instances using Sagemaker, it will be handy to have the data in S3 bucket. Images are grayscale and standard size of 224x224.

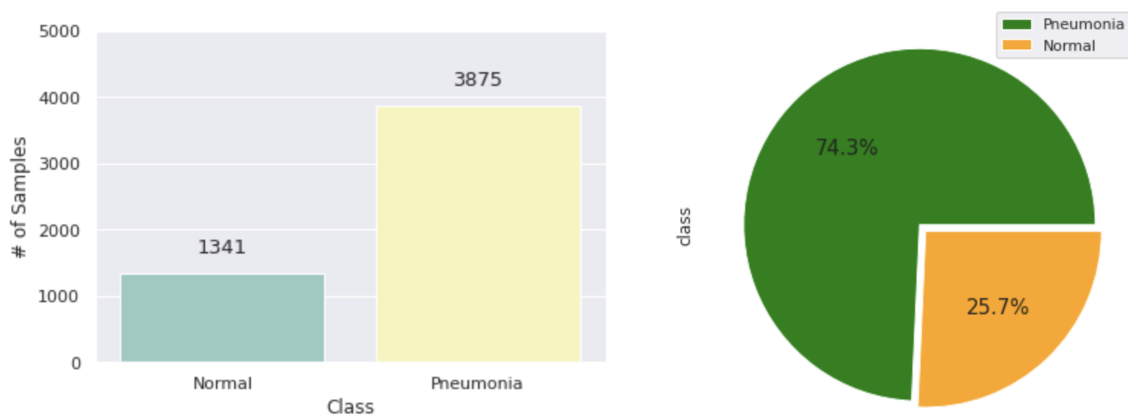

Fig 1: Training data distribution with ~3x of Pneumonia images over Normal

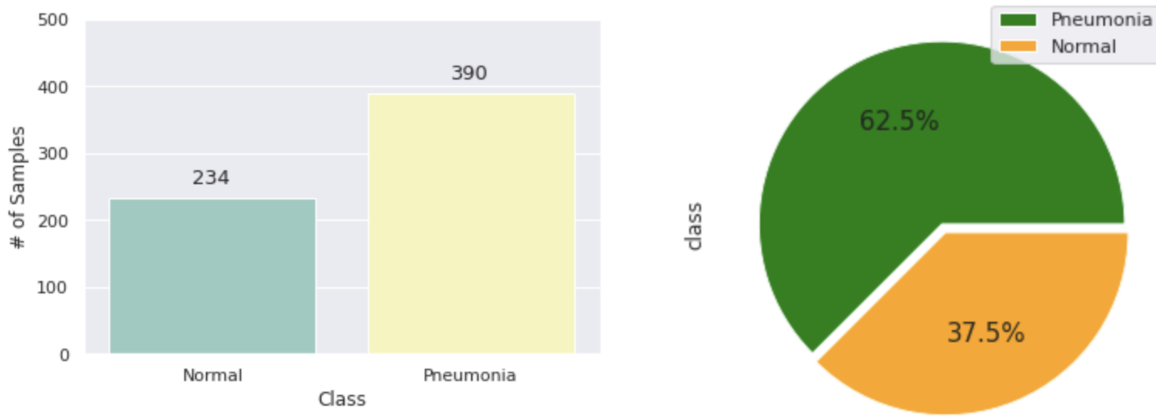

Fig 2: Training data distribution with ~1.7x of Pneumonia images over Normal

Fig 3: Visualizing the a sample of 12 x-ray images for Normal and Pneumonia

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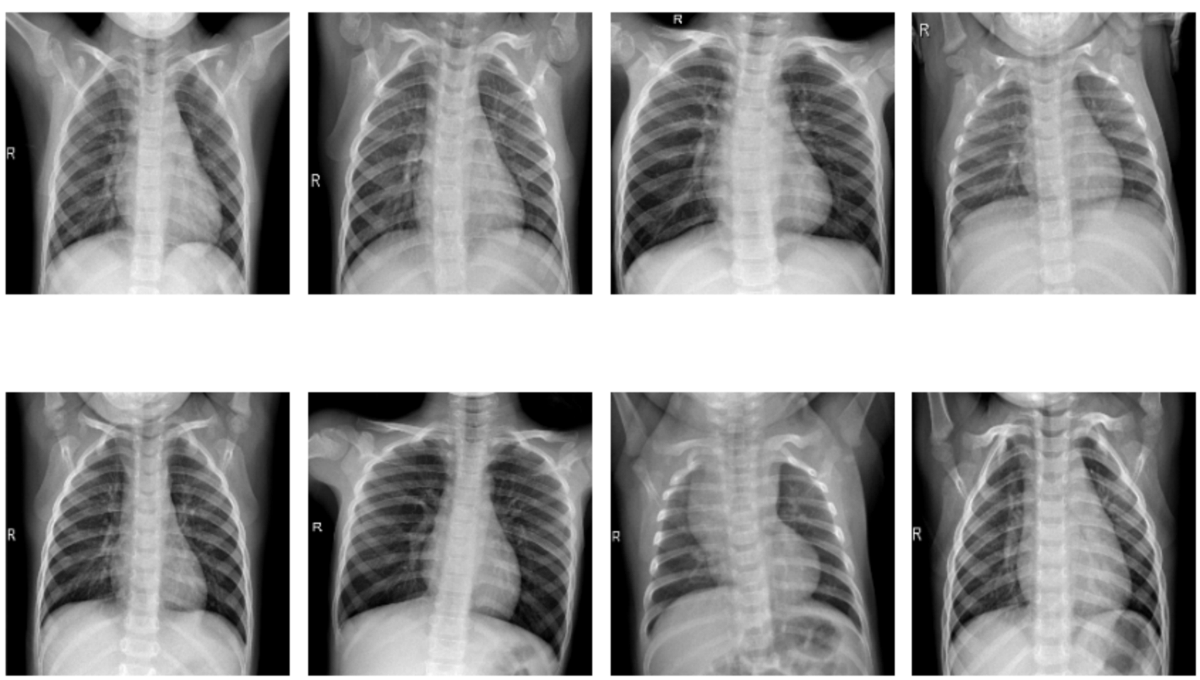
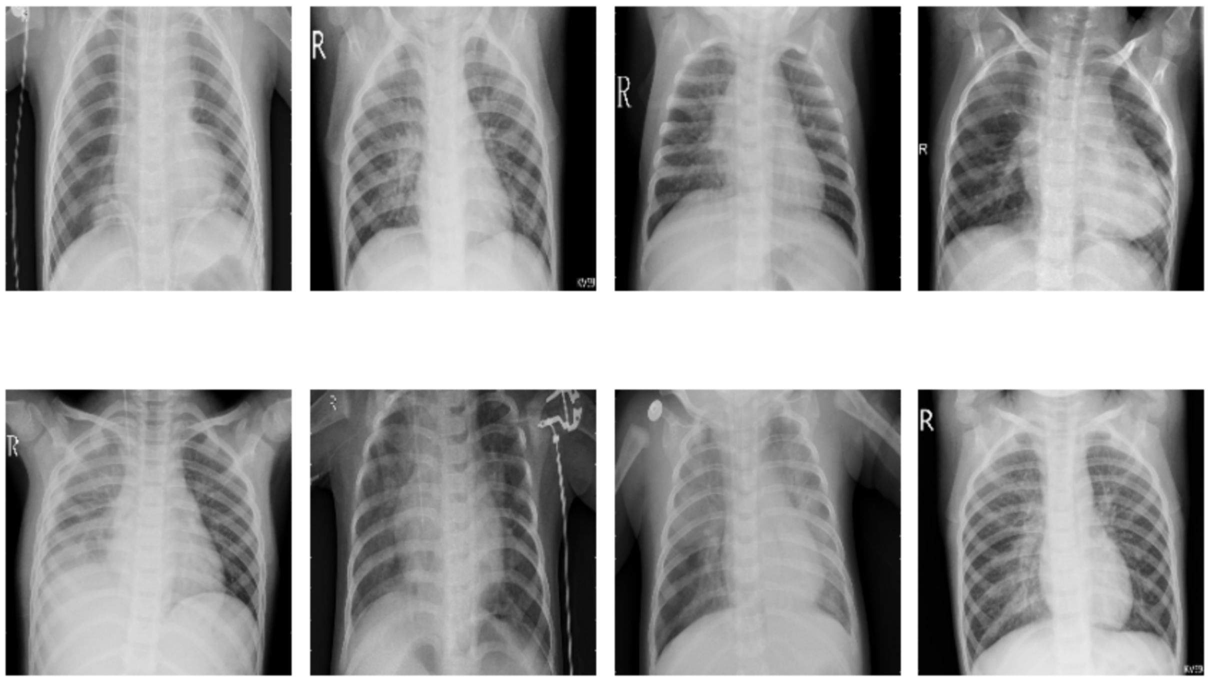
Train Set - Normal



Train Set - Pneumonia



Data Splitting

Data is already split for train, test and validation sets. We will need to randomly load the corresponding matrix data for normal and pneumonia images and create a training data set. Similarly, for test and Validation sets.

DataFrame object is created by loading all the normal and pneumonia images for training into df_train. Total of 5216 rows with class [Normal, Pneumonia] and Image path.

Training (df_train): 5126 x 2 columns
Test (df_test): 624 x 2 columns

	class	image
0	Normal	./chest-xray-pneumonia/chest_xray/train/NORMAL/NORMAL2-IM-0571-0001.jpeg
1	Normal	./chest-xray-pneumonia/chest_xray/train/NORMAL/NORMAL2-IM-0799-0001.jpeg
2	Normal	./chest-xray-pneumonia/chest_xray/train/NORMAL/NORMAL2-IM-0995-0001-0002.jpeg
3	Normal	./chest-xray-pneumonia/chest_xray/train/NORMAL/IM-0704-0001.jpeg
4	Normal	./chest-xray-pneumonia/chest_xray/train/NORMAL/NORMAL2-IM-0986-0001.jpeg
...	...	...
5211	Pneumonia	./chest-xray-pneumonia/chest_xray/train/PNEUMONIA/person967_bacteria_2892.jpeg
5212	Pneumonia	./chest-xray-pneumonia/chest_xray/train/PNEUMONIA/person1340_virus_2312.jpeg
5213	Pneumonia	./chest-xray-pneumonia/chest_xray/train/PNEUMONIA/person1679_bacteria_4450.jpeg
5214	Pneumonia	./chest-xray-pneumonia/chest_xray/train/PNEUMONIA/person585_bacteria_2414.jpeg
5215	Pneumonia	./chest-xray-pneumonia/chest_xray/train/PNEUMONIA/person1343_bacteria_3414.jpeg

5216 rows × 2 columns

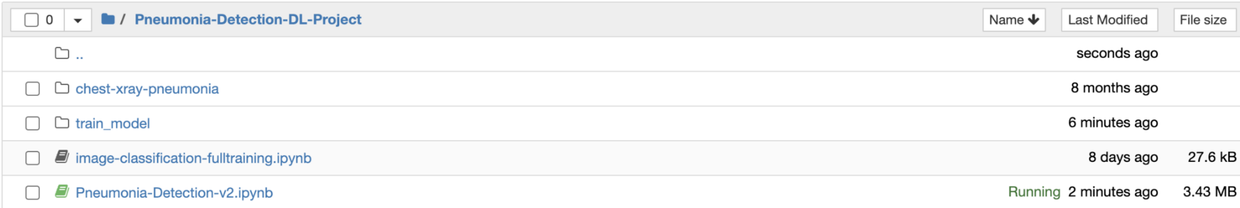
Using the train_test_split, I have split the training data into 80% and validation 20%. Keras ImageDataGenerator is used for processing the image data and creating the data set. Had issues with directly reading the files from S3 using flow_from_directory so leveraged the flow_from_dataframe by reading the images from the local directory on the sagemaker server.

Model Training

We will use Deep Learning algorithms using Convoluted Neural Network (CNN) to train and build a model. I have used Tensorflow with Sagemaker for building the model. Kernel conda_tensorflow2_36 (Tensorflow 2 with Python 3.6) is used for the execution. Along with the Sequential model, I have tried transfer learning models (ResNet152V2, DenseNet121) to compare performance.

A Sequential Model with 6 layers total. Image size of 224 x 224 with a depth of 3 is passed to the inputs_input layer.

Notebook initialized the Tensorflow function with calling entry_point of train.py which calls model.py for building the model.



Evaluation:

Testing the machine learning models with 100 epochs:

1. Sequential
2. Resnet152v2 (pretrained model)
3. DenseNet121 (pretrained model)

Performance Metrics

Model: Sequential

Metrics:

Test loss	**0.6046411311**
Test accuracy	**0.8445512652**

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.39	0.24	0.3	234
Normal (Class 1)	0.63	0.77	0.69	390
accuracy			0.57	624
macro avg	0.51	0.51	0.5	624
weighted avg	0.57	0.54	0.57	624

ROC_AUC	0.4945923734

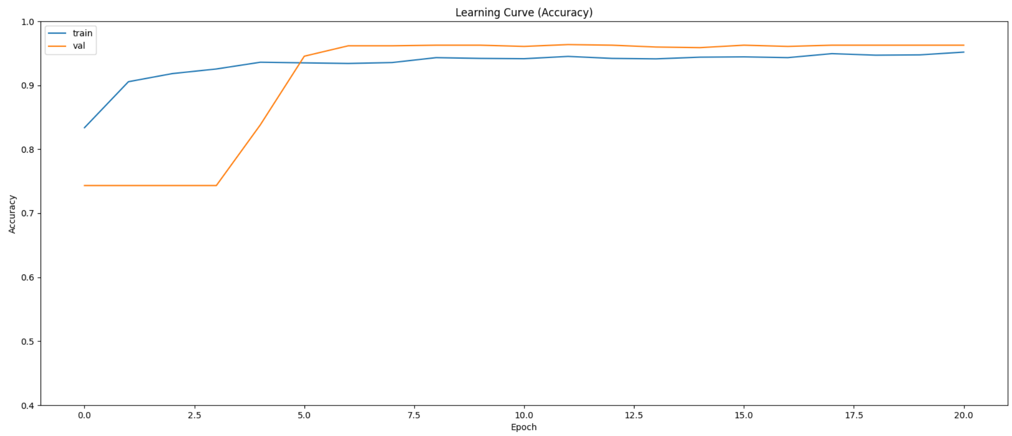


Fig 4: Learning Curve (Accuracy) - Sequential Model

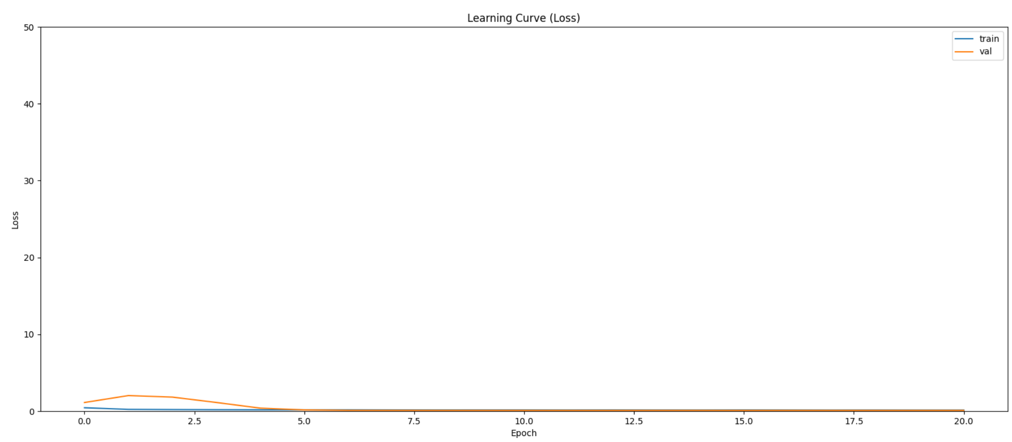


Fig 5: Learning Curve (Loss) - Sequential Model

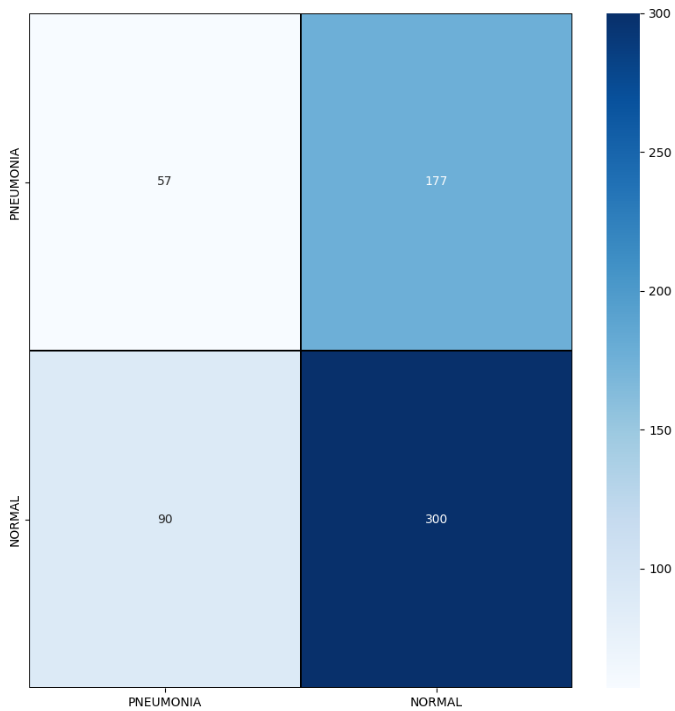


Fig 6: Confusion Matrix - Sequential Model

Sequential model, while triggered for 100 epochs, stopped at 20 epochs as the learning rate change has not been changing for a few epochs.

100 Epoch - (Resnet152v2) Transfer Learning
Resnet152v2 pretrained model is used as part of transfer learning with layers locked and run for 100 epochs. The execution was very fast and the algorithm performed better than the sequential model.

Metrics

Test loss	**0.3989337858**
Test accuracy	**0.8653846383**

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.34	0.24	0.28	234

Normal (Class 1)	0.61	0.72	0.66	390
accuracy			0.54	624
macro avg	0.48	0.48	0.47	624
weighted avg	0.51	0.54	0.52	624

ROC_AUC	0.4984056542

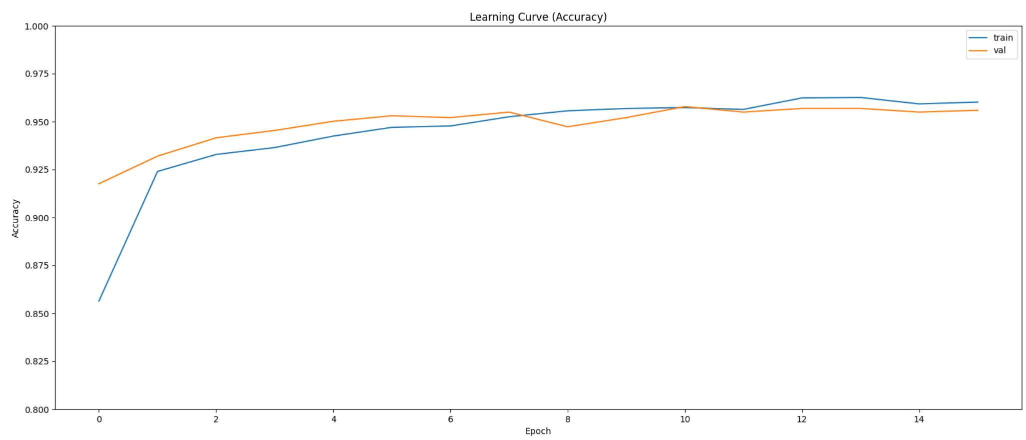


Fig 7: Learning Curve (Accuracy) - Resnet152v2 Model

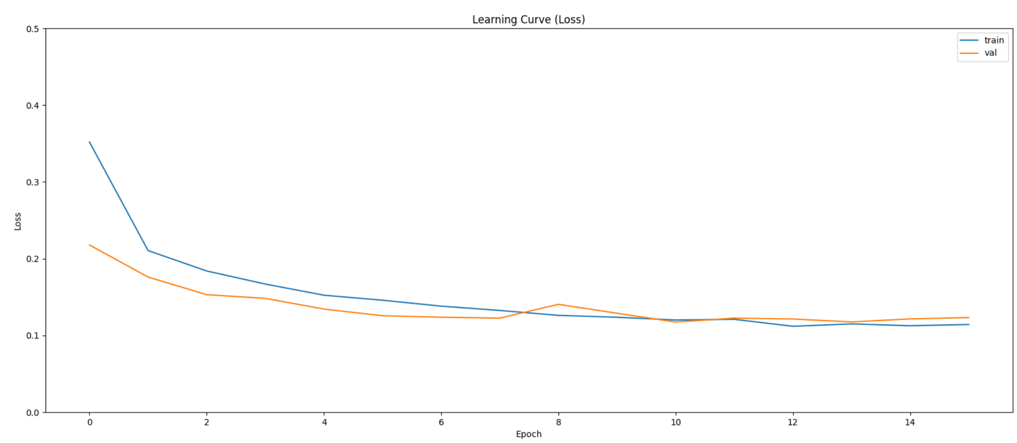


Fig 8: Learning Curve (Loss) - Resnet152v2 Model

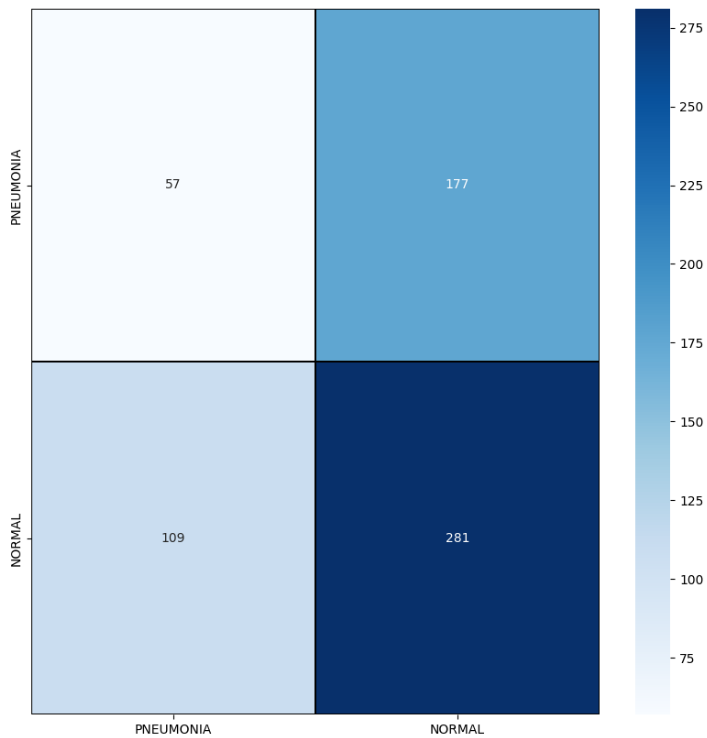


Fig 9: Confusion Matrix - Resnet152v2 Model

100 Epoch - DenseNet121
Densenet121 pretrained model is used as part of transfer learning with layers locked and run for 100 epochs. The execution was very fast and the algorithm performed better than the sequential model but a bit lesser than Resnet152v2.

Metrics

Test loss	**0.3881112001**
Test accuracy	**0.8541666865**

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.32	0.22	0.26	234
Normal (Class 1)	0.61	0.72	0.66	390

accuracy			0.53	624
macro avg	0.46	0.47	0.46	624
weighted avg	0.5	0.53	0.51	624

ROC_AUC	0.4945923734

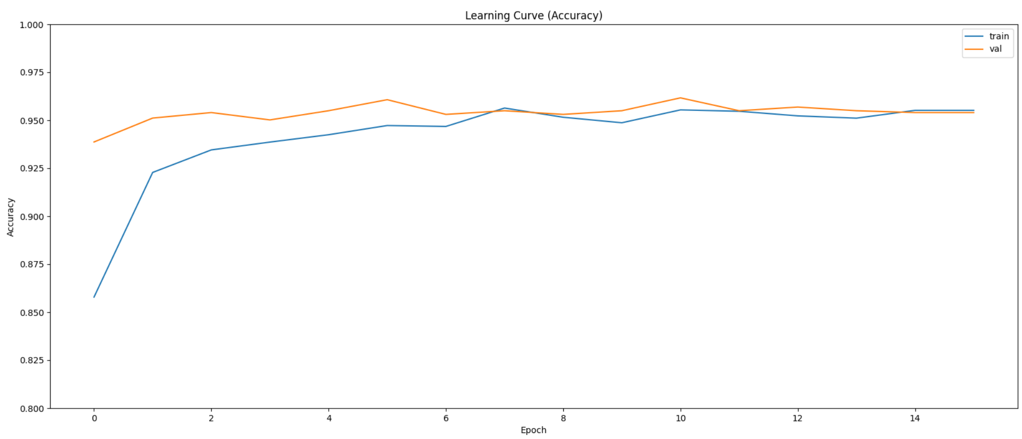


Fig 10: Learning Curve (Accuracy) - Densenet121 Model

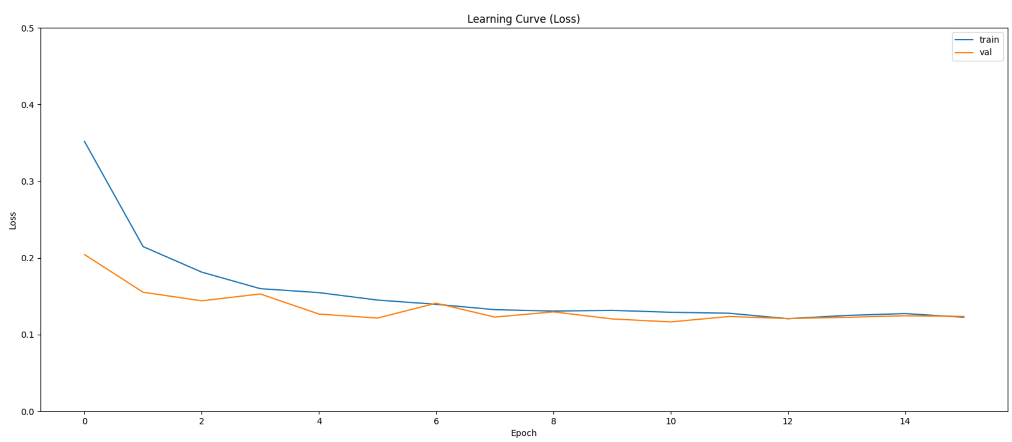


Fig 11: Learning Curve (Loss) - Densenet121 Model

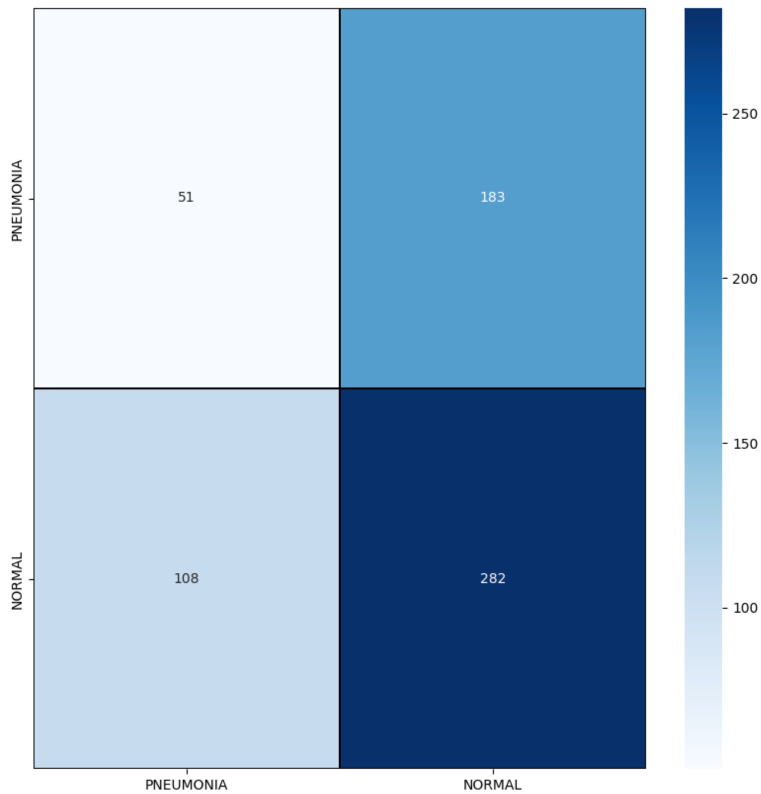


Fig 12: Confusion Matrix - Densenet121 Model

Comparison of test accuracy between the 3 models

	Sequential	**Resnet152v2**	**Densenet121**
Test loss	0.6046411311	0.3989337858	0.3881112001
Test accuracy	0.8445512652	0.8653846383	0.8541666865

Resnet152v2 has performed better than the Densenet121 and Sequential models.

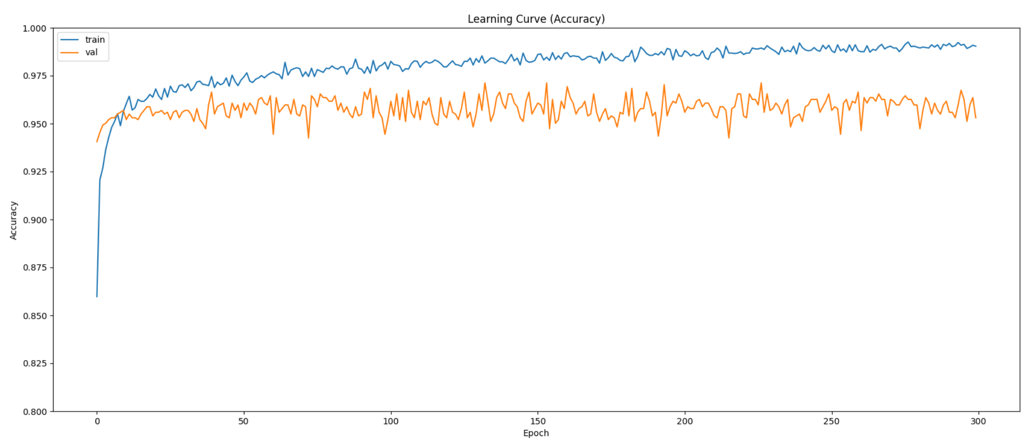
300 Epoch Transfer Learning - Resnet152v2

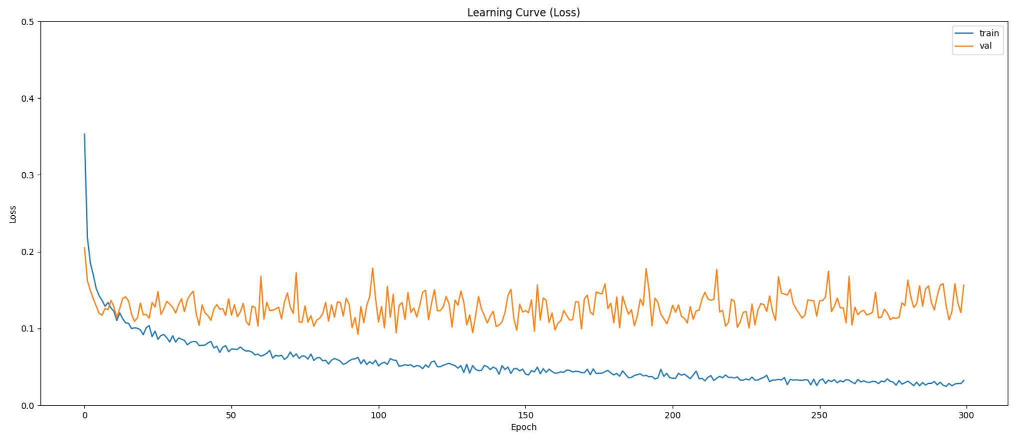
Tested with Resnet152v2 for 300 epochs the model performance has improved tremendously with accuracy of 92%.
Metrics

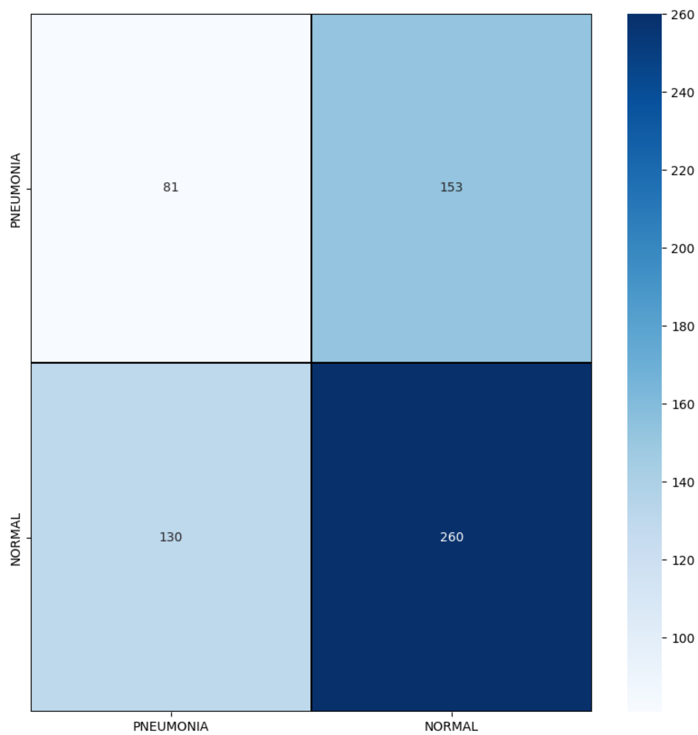
Test loss	**0.2732946018**
Test accuracy	**0.9214743376**

ROC_AUC	0.5423460443

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.38	0.35	0.36	234
Normal (Class 1)	0.63	0.67	0.65	390
accuracy			0.55	624
macro avg	0.51	0.51	0.51	624
weighted avg	0.54	0.55	0.54	624







References

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Rui Hou, William Shi, Xin Fu, Yaou Duan, Viet A.N. Huu, Cindy Wen, Edward D. Zhang, Charlotte L. Zhang, Oulan Li, Xiaobo Wang, Michael A. Singer, Xiaodong Sun, Jie Xu, Ali Tafreshi, M. Anthony Lewis, Huimin Xia, Kang Zhang
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[2] Paul Mooney https://www.kaggle.com/paultimothymooney/chest-xraypneumonia
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