CNN For Detecting Pneumonia from X-ray Images

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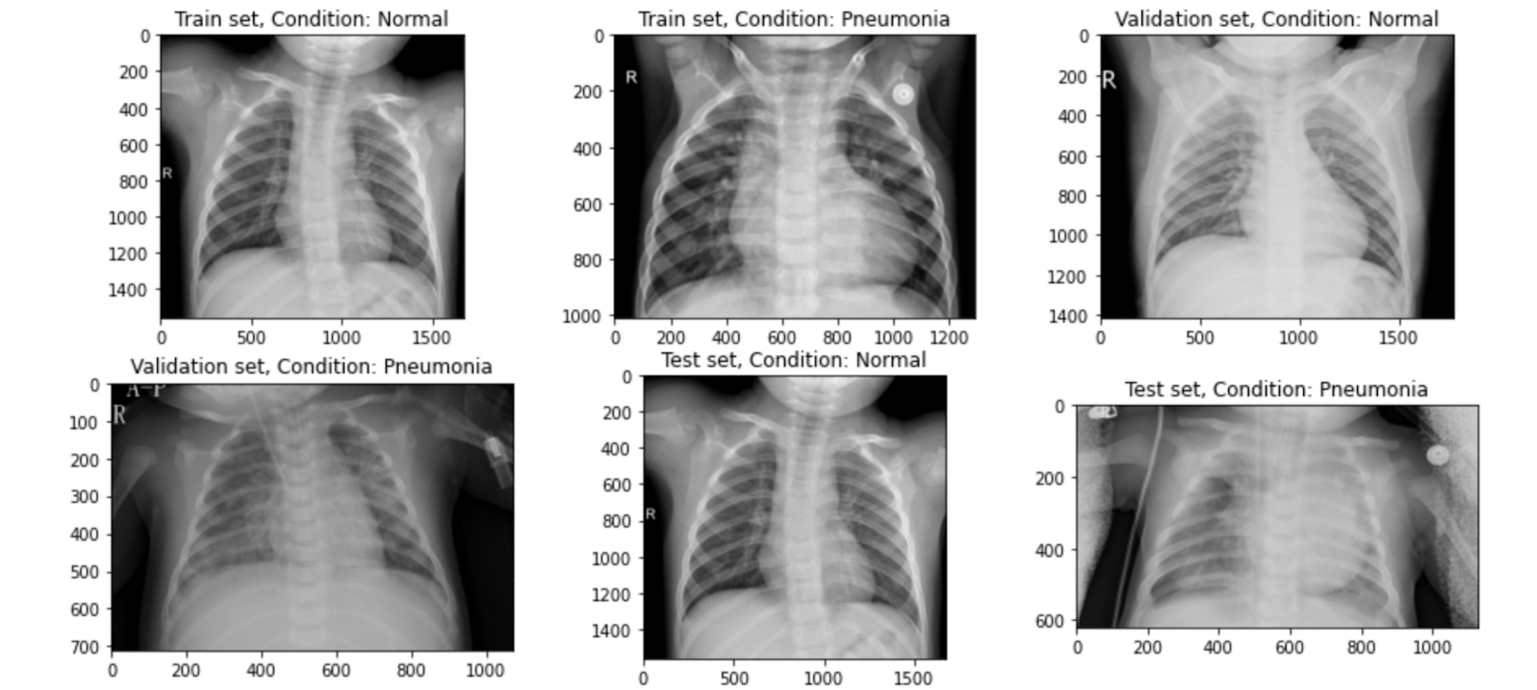
Springboard

Contents

Problem Statement

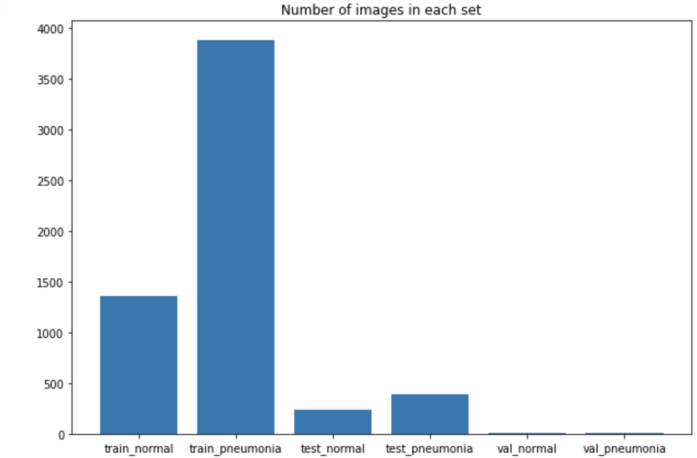
- Globally, 450 million get infected by pneumonia in a year
- 4 million people die from the disease in the world
- 50 thousand people die from the disease in the United States of America
- Analyzing and classifying chest x-rays can be very tedious for radiologists
- Artificial intelligence-based solutions can provide support for experts in the medical domain in performing time-consuming works

Dataset


Train set, Condition: Normal
Train set, Condition: Pneumonia
Validation set, Condition: Normal
Validation set, Condition: Pneumonia
Test set, Condition: Normal
Test set, Condition: Pneumonia

Dataset

- https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia
- Organized into 3 folders (train, test, val)
- 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia / Normal)




```
Number of images in train_normal_dir: 1354
Number of images in train_pneumonia_dir: 3875
Number of images in val_normal_dir: 8
Number of images in val_pneumonia_dir: 8
Number of images in test_normal_dir: 234
Number of images in test_pneumonia_dir: 390
```

Figure 1. *Number of images in each set*

Data Acquisition Using Colab

- Keras
  - High level library for building deep learning models
  - Tensorflow framework backend
  - Leverage backend engine to compute on GPU
- Google Colab
  - Jupyter notebook environment running Python in Cloud
  - Access to GPU resources
  - Free

Data Preprocessing

- ImageDataGenerator
  - reads images from disk and convert them to float32 tensors and feed them to the network
  - sets up generators that are capable of loading the required amount of data directly from the source folder, converting them into training data
  - rescales the images
  - performs data augmentation
    - zoom_range =0.3 and vertical_flip = True
- flow_from_directory
  - load images from the disk, applies rescaling, and resizes the images into the required dimensions.

Application of CNN

- Input
  - ImageDataGenerator
- Convolutional Base
  - Four convolutional layers
  - Max Pooling – downsampling
  - Batch normalization – speed up training
  - Learns patterns at different scales
- Dense Classifier
  - Four dense layers
  - Dropout layers – prevent overfitting
  - Sigmoid – binary classification problem

Baseline Model

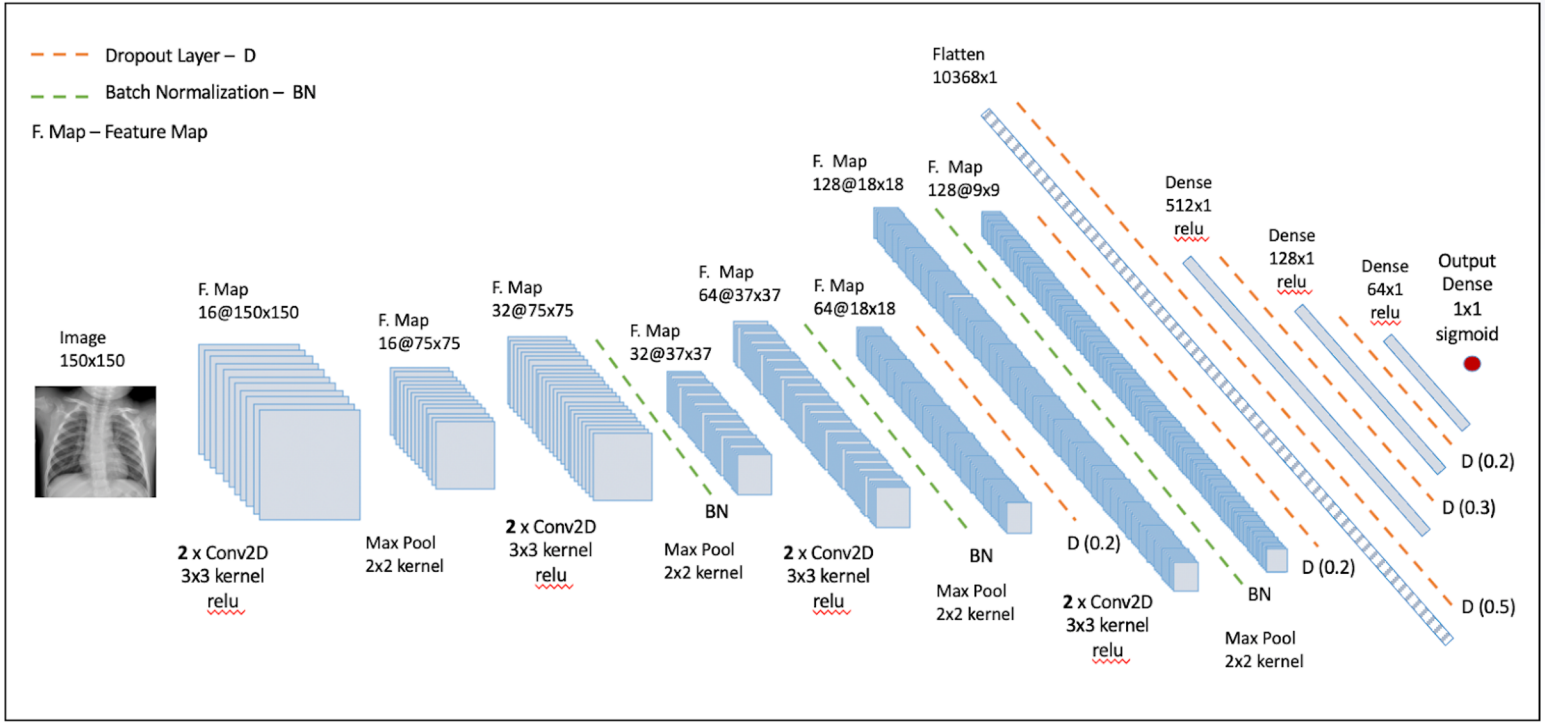


Figure 2. *Baseline Model*

Compiling the Model

Loss Function	Optimizer	Output Metrics
How performance is measured on training data	How network parameters are updated during training	What measures to record during training
Binary – cross entropy (two classes – 'normal' and 'pneumonia')	Adam - automatically adapts the learning rate during training	Accuracy

Training the Model

Callback Functions		
ModelCheckpoint	ReduceLROnPlateau	EarlyStopping
Saves model or weights at some intervals so the model or weights can be loaded later to continue the training.	Monitors a quantity and if no improvement is seen for a 'patience' number of epochs, the learning rate is reduced.	Prevents overtraining of the model by terminating the training process if it's not really learning anything.

```
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint

checkpoint = ModelCheckpoint(filepath='best_weights.hdf5', monitor='val_loss', save_best_only=Tru
e, save_weights_only=True)
lr_reduce = ReduceLROnPlateau(monitor='val_loss', factor=0.3, patience=2, verbose=1, mode='max')
early_stopping = EarlyStopping(monitor='val_loss', min_delta=0.1, patience=5, mode='auto',verbose=
1)
```

Evaluating the Model

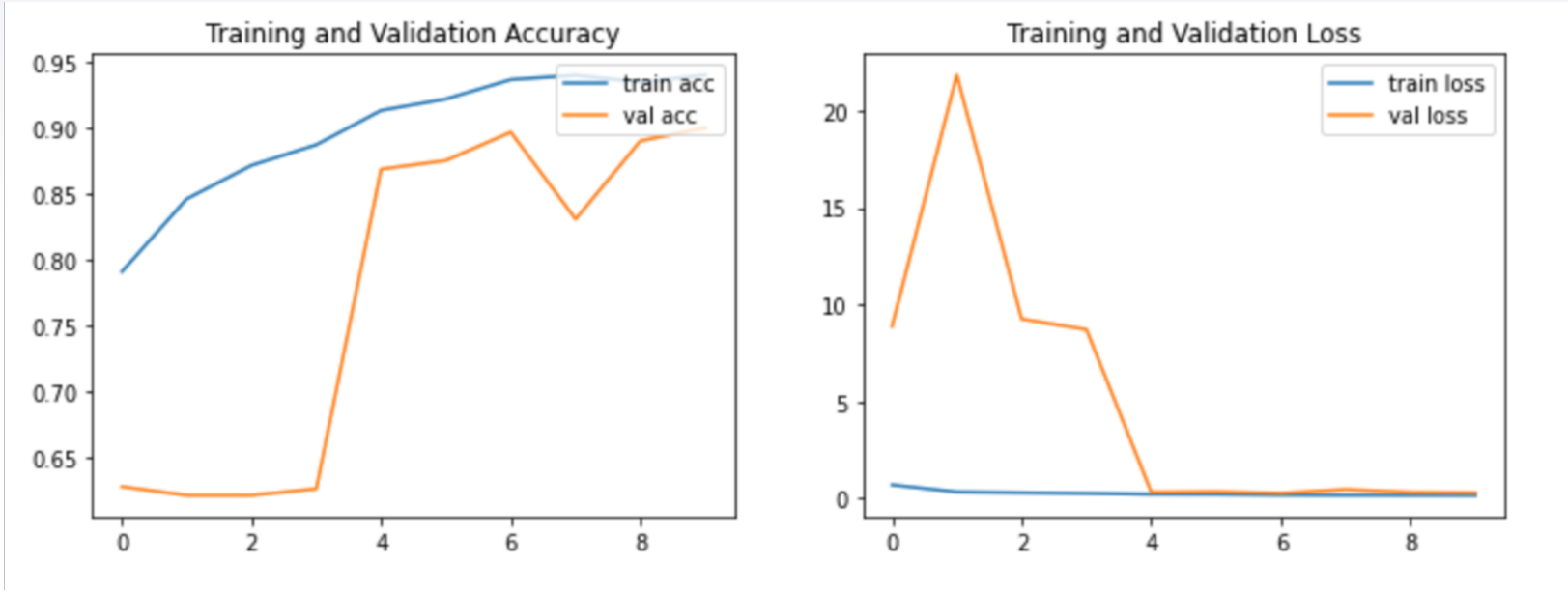


Figure 3. *Training History Plots*

Model Performance

Overall accuracy on test data: 90% with 0.29 loss

	precision	recall	f1-score	support
0	0.95	0.77	0.85	234
1	0.88	0.97	0.92	390
accuracy			0.90	624
macro avg	0.91	0.87	0.89	624
weighted avg	0.90	0.90	0.89	624

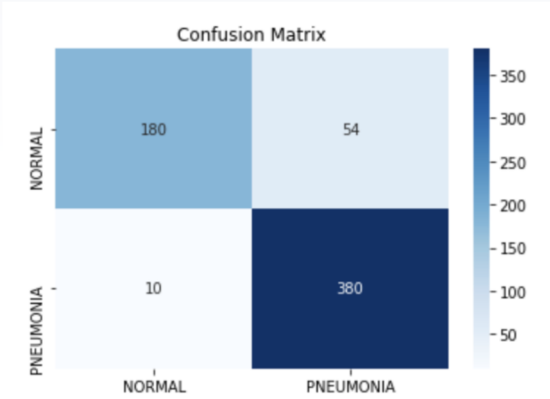
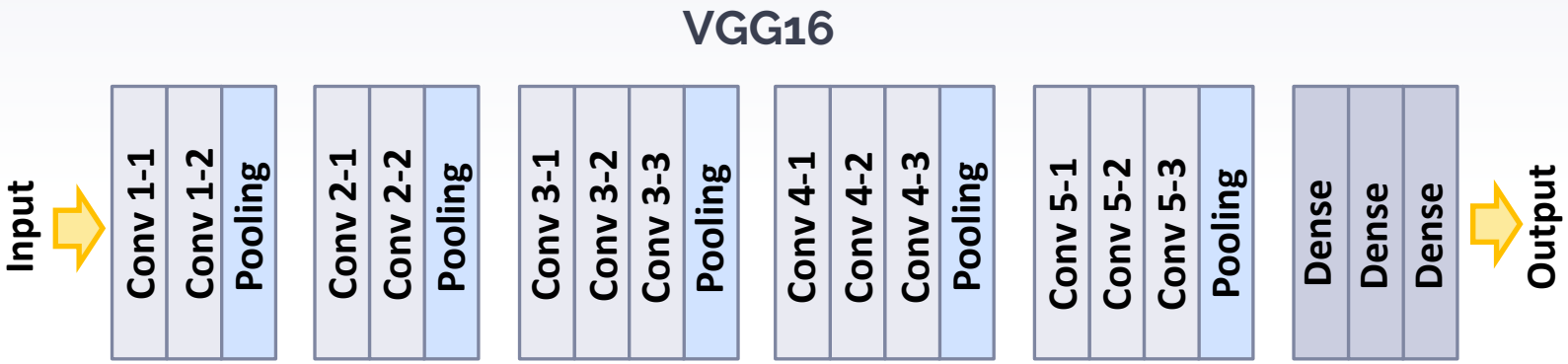


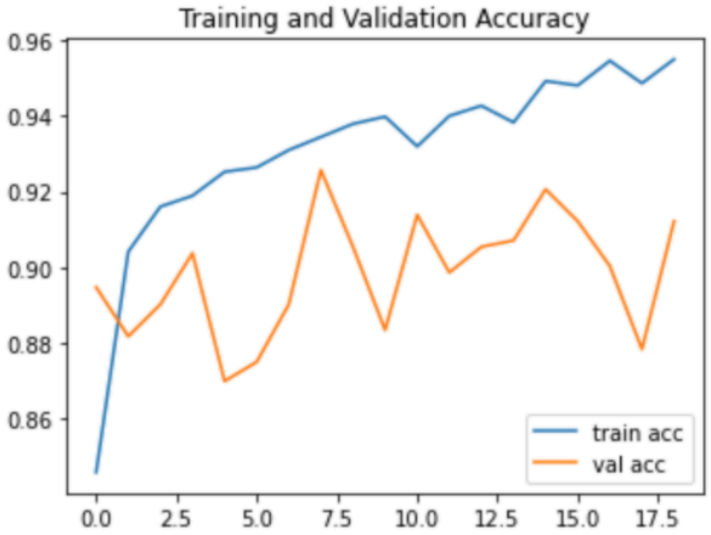
Figure 4. *Classification Report and Confusion Matrix*

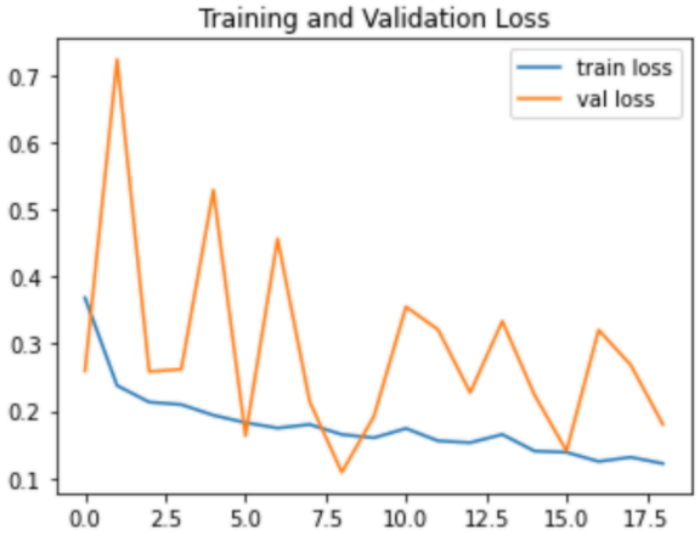
Transfer Learning with VGG16

- Model Summary:

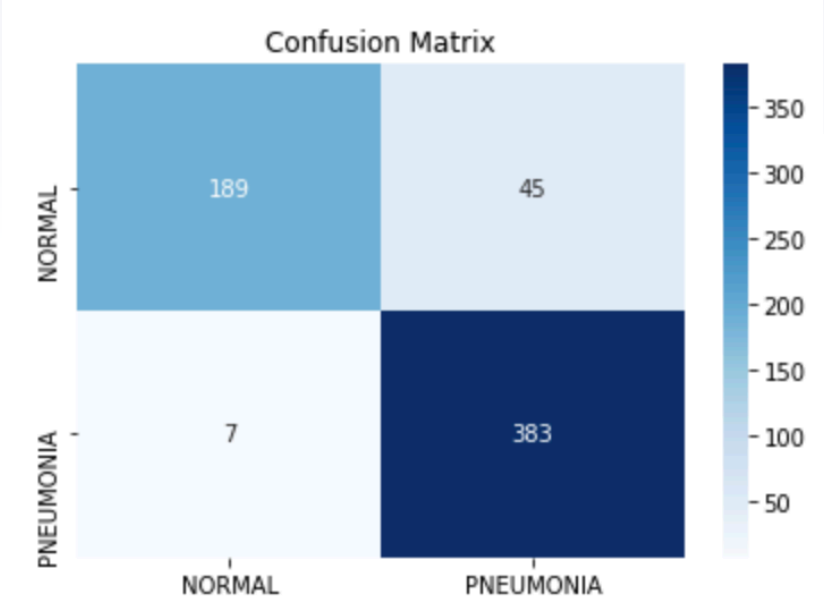


VGG16 Training Performance





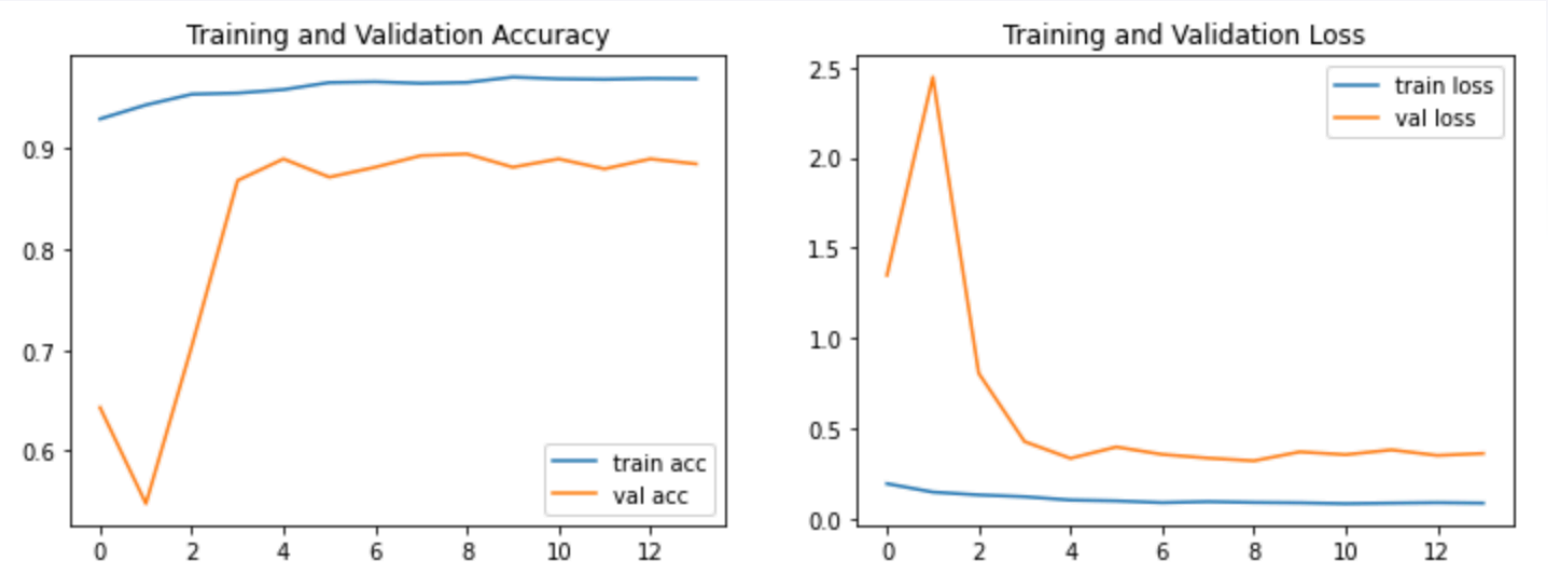
VGG16 Test Performance



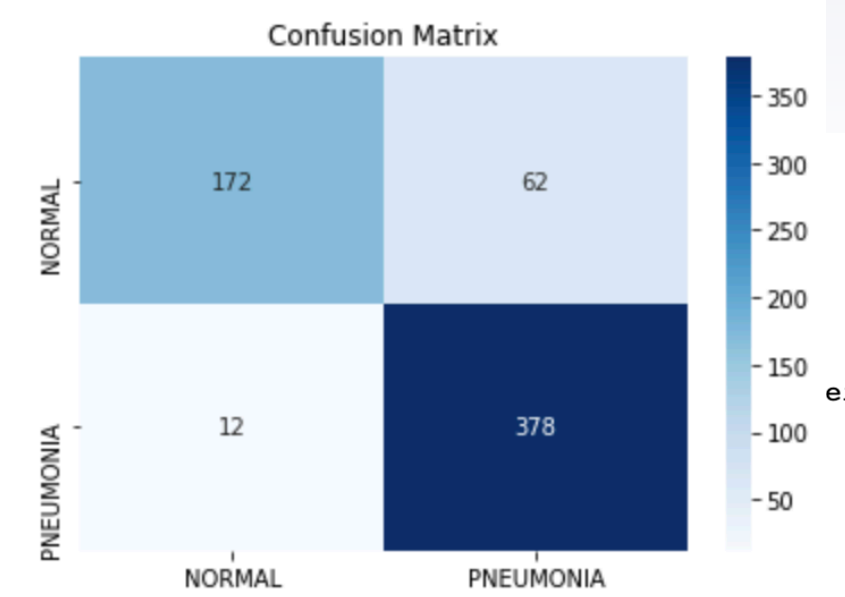
- Classification Report

	precision	recall	f1-score	support
0	0.96	0.81	0.88	234
1	0.89	0.98	0.94	390
accuracy			0.92	624
macro avg	0.93	0.89	0.91	624
weighted avg	0.92	0.92	0.91	624

CNN on DCGAN Generated Images



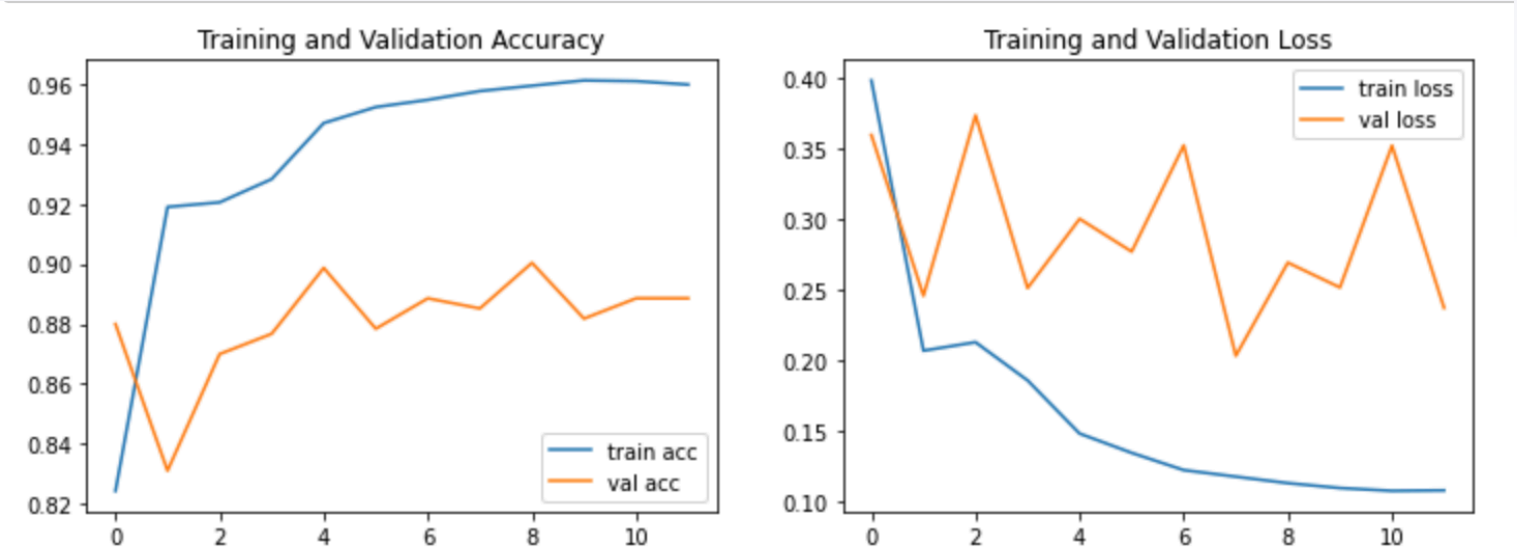
CNN on DCGAN Generated Images



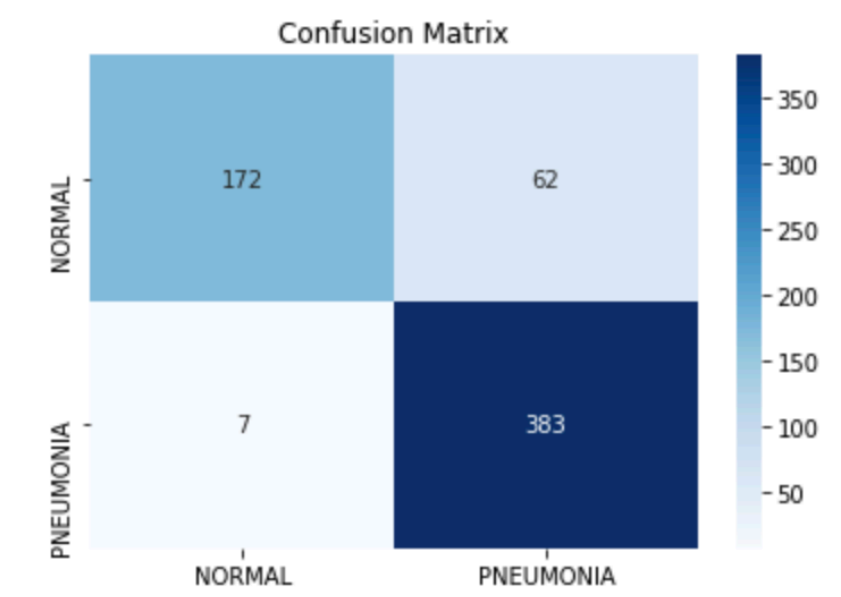
- Classification Report

	precision	recall	f1-score	support
0	0.93	0.74	0.82	234
1	0.86	0.97	0.91	390
accuracy			0.88	624
macro avg	0.90	0.85	0.87	624
eighted avg	0.89	0.88	0.88	624

VGG16 on DCGAN Generated Images



VGG16 on DCGAN Generated Images



- Classification Report

	precision	recall	f1-score	support
0	0.96	0.74	0.83	234
1	0.86	0.98	0.92	390
accuracy			0.89	624
macro avg	0.91	0.86	0.88	624
weighted avg	0.90	0.89	0.89	624

Summary of Results

- Used Google Colab to apply the architecture (using Keras)
- Applied Deep Learning with CNN to classify chest x-ray images
- Applied VGG16 to classify chest x-ray images
- Generated x-ray images with DCGAN
- Applied CNN and VGG16 to DCGAN generated images
- All the approaches resulted with ~90% accuracy

Follow-on Work

- Improve baseline model accuracy with different approaches
  - Increase the number of convolutional layers
  - Change predetermined values (batch size, epochs, callbacks…)
- Increase the number of data using
  - Data augmentation with different hyperparameters
  - Different GAN models
- Train the data using other ‘Transfer Learning’ techniques

Thank you!

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Project @ https://github.com/Meralbalik/Capstone-Project-2