ISSN No:-2456-2165

Comparison of VGG Model and Sequential Model in Predicting Lung Pathologies Using Chest X-ray Images

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Abstract: Human lungs are more prone to the diseases and need to be identified at the early stages so that appropriate treatment can be provided and minimize the complications. The utility of Artificial Intelligence (AI) in predicting the pathologies in chest X-ray images was studied. Two different neural network models were applied on the National Institute of Health (NIH) chest X-ray image datasets. These models were Visual Geometry Group (VGG) model and Sequential model with dense layers. Images were converted in to arrays and are fed into each of these models which predicted the pathologies present in the chest X-ray images. The accuracy obtained using VGG model was 65.6% and the accuracy of sequential model was 73%. Although sequential model is more accurate than VGG model, there is a need for further fine tuning the models for better accuracy.

Keywords:- *VGG Model, Sequential Model, Artificial Intelligence, Neural Network, Lung Pathologies.*

I. INTRODUCTION

In the present world, acute and chronic respiratory disorders are the most common illnesses causing morbidity and mortality in human beings. With the current pandemic of Severe Acute Respiratory Syndrome Corona Virus-2 (SARS-CoV2), the prevalence of lung diseases are on the rise. Also, the lung cancer being the most common cancers in the world adds to the overwhelming lung pathologies. There is a need to understand the diseases associated with lungs in order to treat at the earliest and minimize the complications. Due to the present pandemic, the medical fraternity across the world is channeled towards the patient care and there is dearth of doctors across the world. Hence, we studied the application of AI in identifying the lung pathologies using chest X-ray images in order to help the medical fraternity to combat the shortage of man power.

Machine learning (ML) and Artificial Neural Networks (ANN) are the most trending branches in the field of technology and science applied in various fields like education, health care sectors, research, banking etc. [1]. Deep learning is the branch of ML that defines and structures the algorithms into many layers and creates an ANN, which learns from the provided data and make an intelligent decision [1]. In this paper, we fed the arrays of chest X-ray images in two different neural network models to predict the pathologies present in the lungs and also to differentiate the malignant lesions from benign conditions.

II. METHODOLOGY

The aim of the project was to predict the lung pathologies from the chest X-ray images using VGG model and sequential models.

A. Dataset Details

The data was extracted from Random Sample NIH Chest X-ray Dataset [2]. It comprised of 1, 12,120 Chest X-ray images from 30,805 unique patients. Out of which, 5606 images were sampled from https://www.kaggle.com/nih-chest-xrays/sample [2]. All the images were annotated by the collectors and labelled with patient's identification number, age and gender. There were 15 classes (14 classes with diseases and one class with "No findings") in the dataset (Figure 1) [3][4].

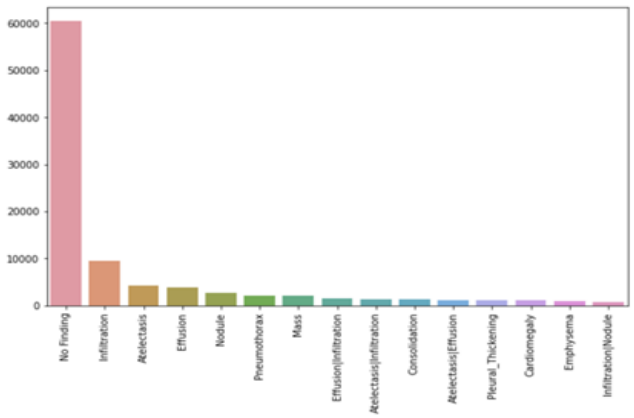

Figure 1: Different lung pathologies present in the NIH dataset

Of 5606 chest X-ray images, 516 images were selected and the distribution was balanced for different classes of lung pathologies to avoid the bias. These 516 images included 6 different classes such as 143 images of "no finding", 101 images of "Cardiomegaly", 91 images of "Fibrosis", 90 images of "Nodule", 59 images of "Emphysema" and 32 images of "Pneumonia". For the

ISSN No:-2456-2165

binary classification, the images from the selected dataset was further grouped into two classes i.e., images having the pathology as one class and images with no findings as another class [5].

B. Data Pre-processing

All the selected images were converted into arrays using NumPy array and were resized to 128X128. Each image was given the class label of either "One" or "Zero", where "One" represented the "Infiltration" and "Zero" represented "No infiltration". The arrays from all the images was taken as "X" and the arrays from the images with pathologies was taken as "Y".

The data was split into training and testing set. The 75:25 rule was applied to split so that 387 images out of 516 was used as training set. The remaining images were taken as testing set which further was sub- grouped as testing subset including 64 images and validation subset including 65 images[5].

C. VGG Model

Visual Geometry Group (VGG) neural network is one of the deep Convolution Neural Networks (CNN), first proposed by Karen Simonyan and Zisserman from the University of Oxford [6]. It uses smaller kernel-sized filters of 3x3 in 16 layers. It is difficult to train a CNN model from scratch as it requires a large training dataset and requires a huge computational and memory resources. Hence we have used a pre-trained VGG model containing 16 layers. We have added additional layers to customize and fine tune the last few layers as a part of Transfer Learning (TL). The initial few layers of VGG model learns the low level image features whereas the later layers learns the high level features which are more specific[6].

Rectifier Linear Unit (ReLU) was used as activation layer to the convolutional neural layers. By this, the negative values were removed and replaced with zeroes. This was done to avoid zero value obtained after summing up of the values [7].

The output matrix from the ReLU layer was given to max pooling layer, where the input image was shrunk and resized. The image size was further reduced by repeating the above procedure in multiple layers of convolution layer, ReLU layer and max pooling layer to finally get the smallest size image with high level features. The actual classification of the pathological class of the chest X-ray image was obtained in the fully connected layer [6].

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 128, 128, 3)]	0
block1_conv1 (Conv2D)	(None, 128, 128, 64)	1792
block1_conv2 (Conv2D)	(None, 128, 128, 64)	36928
block1_pool (MaxPooling2D)	(None, 64, 64, 64)	0
block2_conv1 (Conv2D)	(None, 64, 64, 128)	73856
block2_conv2 (Conv2D)	(None, 64, 64, 128)	147584
block2_pool (MaxPooling2D)	(None, 32, 32, 128)	0
block3_conv1 (Conv2D)	(None, 32, 32, 256)	295168
block3_conv2 (Conv2D)	(None, 32, 32, 256)	590080
block3_conv3 (Conv2D)	(None, 32, 32, 256)	590080
block3_pool (MaxPooling2D)	(None, 16, 16, 256)	0
block4_conv1 (Conv2D)	(None, 16, 16, 512)	1180160
block4_conv2 (Conv2D)	(None, 16, 16, 512)	2359808
block4_conv3 (Conv2D)	(None, 16, 16, 512)	2359808
block4_pool (MaxPooling2D)	(None, 8, 8, 512)	0
block5_conv1 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv2 (Conv2D)	(None, 8, 8, 512)	2359808
block5_conv3 (Conv2D)	(None, 8, 8, 512)	2359808
block5_pool (MaxPooling2D)	(None, 4, 4, 512)	0

Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0

Figure 2: VGG 16 model construction

D. Sequential Model

Sequential model, a pre-trained model was chosen from Keras library [8], and was formulated using the densely connected classifier. Binary Cross entropy was used as loss function which compared each of the predicted probability to the actual class output of either zero or one. Each layer in the network was dense which facilitated all the pertains that were needed for model training, testing and prediction. The model would take up the features extracted from the training set and used for validating the model after each training epochs for the selected parameter. Figure 3 depicts the training of sequential model and the corresponding output.

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```
# Train the the model
history = model.fit(
    train_features_flat,
    y_train,
    epochs=50,
    validation_data=(val_features_flat, y_val),
    callbacks=callbacks
)
```

```
Epoch 1/50
141/141 [==============================] - 6s 42ms/step - loss: 0.0164 - acc: 0.9987 - val_loss: 1.3802 - val_acc: 0.7398
Epoch 2/50
141/141 [==============================] - 6s 42ms/step - loss: 0.0164 - acc: 0.9987 - val_loss: 1.3802 - val_acc: 0.7398
Epoch 3/50
140/141 [============================>.] - ETA: 0s - loss: 0.0164 - acc: 0.9987
Epoch 00003: ReduceLROnPlateau reducing learning rate to 1.2799999282719916-09.
141/141 [==============================] - 6s 42ms/step - loss: 0.0164 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 4/50
141/141 [==============================] - 6s 41ms/step - loss: 0.0164 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 5/50
141/141 [==============================] - 6s 41ms/step - loss: 0.0164 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 6/50
141/141 [==============================] - ETA: 0s - loss: 0.0163 - acc: 0.9987
Epoch 00006: ReduceLROnPlateau reducing learning rate to 2.559999767726146-10.
141/141 [==============================] - 6s 42ms/step - loss: 0.0163 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 7/50
141/141 [==============================] - 6s 42ms/step - loss: 0.0163 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 8/50
141/141 [==============================] - 6s 42ms/step - loss: 0.0163 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 9/50
141/141 [==============================] - ETA: 0s - loss: 0.0163 - acc: 0.9987
Epoch 00009: ReduceLROnPlateau reducing learning rate to 5.1199994244299786-11.
141/141 [==============================] - 6s 42ms/step - loss: 0.0163 - acc: 0.9987 - val_loss: 1.3803 - val_acc: 0.7398
Epoch 00009: early stopping
```

Figure 3. Training the Model

III. RESULTS

The accuracy of the model for detecting cardiomegaly was high and was low for pneumonia. The validation accuracy for VGG 16 model was 65.6%. Figure 4 and figure 5 represents the VGG model accuracy for different classes of lung pathologies and the confusion matrix representing the model accuracy respectively. The validation accuracy of the sequential model was 76%. (Figure 6)

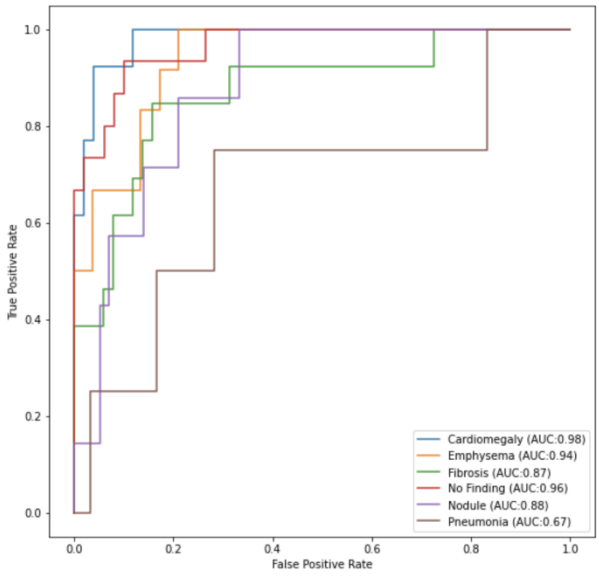

Figure 4. Accuracy of VGG model for different lung pathologies

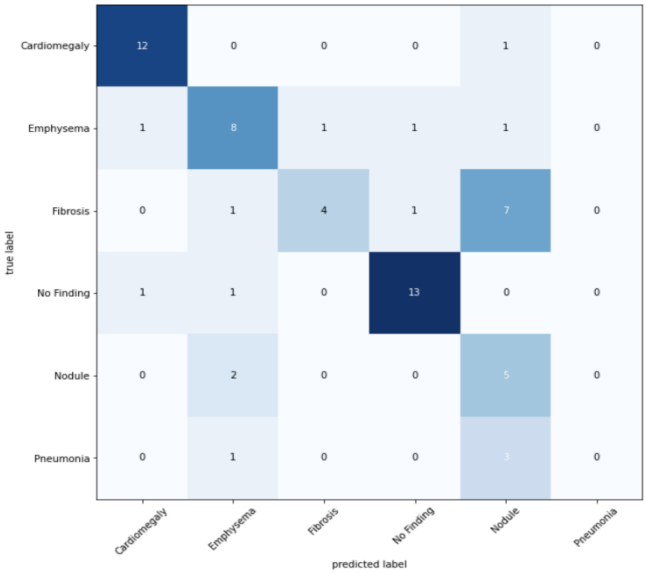

Figure 5. Confusion matrix for Multi-class lung pathologies.

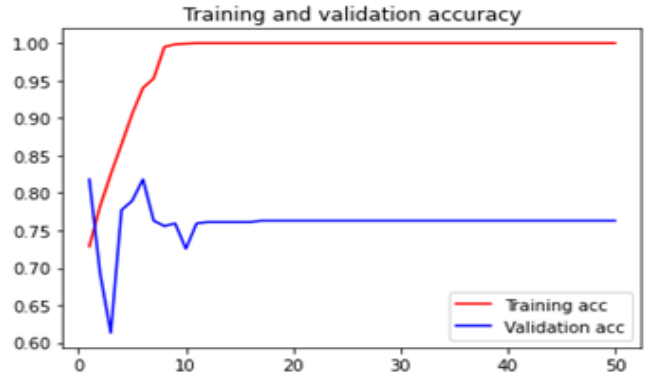

Figure 6. Validation accuracy of validation set and training set for sequential model

IV. CONCLUSION

The goal of VGG16 neural network was enhanced to classify the X-ray images containing lung disease. With this technique an accuracy of 65% was achieved. Later the sequential model with dense layers was considered for the classification of chest X-rays. With this technique an accuracy of 76% was achieved. The two different neural network architectures gave the satisfactory accuracy in classifying the images. Further work could be done in tuning the parameters of the model for better accuracy. Another future directions could be improving the time complexities of the technique by making use of better processing capabilities.

ACKNOWLEDGEMENT

I would like to acknowledge Mrs. Padma Tatuskar, School of Computer Science and Mathematics, University of Central Missouri and Dr. Rashmi P., Postgraduate in pathology, JJM Medical College, Davangere, Karnataka for their inputs in understanding and executing the research work.

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