Analysing X-Ray Images to Detect Lung Diseases Using DenseNet-169 technique

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***Abstract* - Lung disease is a common affliction around the world. Pneumonia, Tuberculosis, Chronic obstructive pulmonary disease, asthma, COVID-19, fibrosis, etc. fall into this category. In this paper, the main focus is on Pneumonia, Tuberculosis, and Covid-19. In developing countries where middle-class population often lives in poverty and is exposed to pollution, lung disease poses a major concern. This has led to the development of numerous machine learning and image processing models. Convolutional neural networks (CNNs), Densely connected Convolutional networks, VGG, and Residual Networks (ResNets) are some of the available deep learning approaches that have been used to predict lung diseases. The approach, used here are two such deep learning neural networks, namely VGG-16 and Densenet-169. A composite dataset containing x-ray images of lungs from the Kaggle repository was used as the dataset. VGG-16 and Densenet-169 are both used on this dataset to classify the x-ray into one of four categories: normal, pneumonia, COVID-19, and tuberculosis. To improve disease identification reliability, a cross-validation strategy in which both the VGG-16 and Densenet-169 models ran simultaneously was used. The VGG-16 Architecture gave an accuracy of 86% and the Denesenet-169 architecture gave an accuracy of 91%.**

***Keywords* - VGG-16, DenseNet-169, ResNet, CNN, COVID-19**

I. INTRODUCTION

Lung illness is very widespread all around the world. COPD, pneumonia, asthma, TB, fibrosis, and other respiratory diseases are among them. Lung disease affects tens of millions of individuals worldwide [1]. As a human being we all expand and relax our lungs thousands of time which leads to intake of oxygen and outtake of carbon dioxide. Lung disease can develop when any portion of the respiratory system is compromised. Your airways branch into tiny tubes (bronchioles) that lead to alveoli, which are clusters of air sacs. The majority of your lung tissue is made up of these air sacs. Diseases of the lung which affect the alveoli are usually caused by bacteria or viruses, some of these diseases are pneumonia, and Tuberculosis. The viruses also include coronaviruses which causes COVID-19.

Lung diseases also pose a significant threat, particularly in emerging and economically under-privileged nations, where tens of thousands of people dwell in a state of poverty and are exposed to polluted air [2]. Chronic lung diseases are one of the main causes of mortality around the world [3]. Most lung disorders are discovered when they have progressed to a late stage. This pattern indicates a troubling societal scenario. It shows there's a huge disparity in the diagnosis of lung diseases in advanced stages which are usually out of scope for treatment in contrast to earlier stages of the disease. Delayed diagnosis hence significantly deprives one of an efficient treatment regimen and as a result, it greatly declines a patient's chances of recovery. But with timely detection, better diagnosis and proper treatment plan can be provided to support the quality of living for the patient as well as increase the recovery rate. The advantages of early diagnosis and treatment, as well as the disadvantages of delayed diagnosis of lung illnesses, highlight the need for current research efforts to identify faster ways to categorise diseases for improved treatment and care.

For this, machine learning and deep learning can be extremely useful [4]. Digital technology has recently grown in importance around the world. The goal is to point doctors and other researchers in the right direction for using deep learning to detect lung illness. In general, as a dataset, a huge amount of X-ray images of the lungs are used. The system proposed in this work will be substantially beneficial in detecting lung diseases with increased accuracy, using which many vulnerable people can be protected and as a result, there will be a decline in the disease rate. For this objective, development of numerous machine learning and image processing models. Convolutional neural networks (CNNs), Densely connected Convolutional networks, VGG, and Residual Networks (ResNets) are some of the available deep learning approaches are used. For this work VGG-16 and Densenet-169 was used. A composite dataset containing x-ray images of lungs from the Kaggle repository was used as the dataset. VGG-16 and Densenet-169 are both used on this dataset to classify the x-ray into one of four categories: normal, pneumonia, COVID-19, and tuberculosis. To improve disease identification reliability, a cross-validation strategy was utilised in which both the VGG-16 and Densenet-169 models ran simultaneously.

II. LITERATURE SURVEY

Subrato Bharti et al [5] proposed a hybrid deep learning method that utilizes the combination of VGG, spatial transformer network (STN) with a convolutional neural network. They called this new neural network VGG Data STN with CNN (VDSNet). This hybrid neural network yields a validation accuracy of 73%. The authors have stated that their hybrid model requires less training time at the cost of reduced validation accuracy.

Guk Bae Kim et al [6] used high-resolution computed tomography (HRCT) images to differentiate and classify patterns of interstitial lung diseases (ILDs) using deep learning techniques. The classification model they used consisted of a CNN with six learnable layers, among which four were convolution layers and two were fully connected layers. They also compared this result with the vanilla SVM classifier and found that CNN gave better accuracy.

Matthew Zak and Adam Krzyżak et al [7] implemented convolutional neural networks on three pre-trained networks, which were VGG. Resnet-50 and InceptionV3, They designed a pipeline system that was used to segment chest x-ray images and they compared the results with existing methods and solutions. for non-segmented chest X-ray images their accuracies were in the range from 0.64 - 0.81 whereas for segmented chest X-ray images it was from 0.70 to 0.82.

Joel Than Chia Ming et al [8] proposed a classification system that consists of features from multiple different deep neural networks. Their results were compared with the conventional Gray-level Co-occurrence Matrix. The authors have used a small dataset of 96 images with five levels of HRCT slices. The networks used were Alexnet, VGG16, Res-50 and Res101. Moreover, they also introduced five classifying algorithms Decision tree, SVM, LDA, regression and K nearest neighbours. They achieved a maximum performance of 96% for decision tree, 100% for SVM . 97.40 for PCA and KNN.

Rahib H. Abiyev et al [9] proposed convolutional neural networks (CNNs) for the diagnosis of chest diseases. For the detection of chest disorders, backpropagation neural networks (BPNNs) and competitive neural networks (CpNNs) are used for comparison with the CNN. The same chest X-ray database is used for training and testing for CNN, BNN, CpNN. The accuracy, error rate, and training time of each network were addressed.

TABLE I. Comparison of previous works

Author	Technique/Algorithm	Dataset	Accuracy
Subrato Bharti et al	VDSNet	X-ray images	73%
Guk Bae Kim et al	CNNs	HRCT images	81.27 - 95.12%
Matthew Zak et al	VGG-16, ResNet-50 and InceptionV3	X-ray images	1. Non-segmented 64-81% 2. Segmented 70-82%
Joel Than Chia Ming et al	Alexnet, VGG16, Res-50 and Res101 With Decision tree, SVM, LDA, regression and KNN	HRCT images	1. Decision Tree 96% 2. SVM - 100% 3. KNN & PCA - 97.40%
Rahib H.Abiyev et al	CNNs	X-ray images	92.4%

III. DATASET

The dataset used here is a composite dataset consisting of 7135 X-ray images belonging to 4 classes. The 4 classes are: Normal, Covid-19, Pneumonia, and Tuberculosis. The Pneumonia dataset, consisting of 5,863 Pneumonia and Normal X-ray images, was collected from the Kaggle repository [10]. The Tuberculosis dataset was also gathered from the Kaggle repository [11], which consists of 700 Tuberculosis X-ray images. The Covid-19 dataset was obtained from the open-source GitHub repository [12], containing 468 Covid-19 X-ray images. These x-ray images were combined into a single dataset consisting of 4 classes, that is, Normal, Covid-19, Pneumonia, and Tuberculosis, and used for training the models.

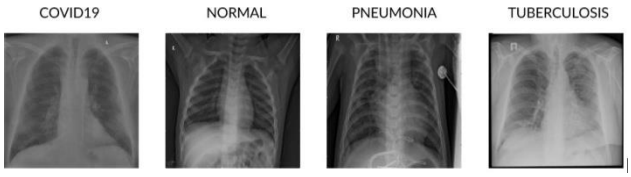

Fig. 1. Sample Image for each class

IV. PROPOSED SYSTEM

I. Data Preprocessing

Integration of several image datasets that included Covid-19, Tuberculosis, Pneumonia, and Normal Chest X-ray images into a single dataset with four classes: Covid-19, Tuberculosis, Pneumonia, and Normal. Pneumonia, Normal, Tuberculosis, and Covid-19 pictures made up 54 percent, 19 percent, 17 percent, and 10% of the data set, respectively. To generate a balanced dataset, random selection of 1000 images from each of Pneumonia and Normal, as well as 890 augmented images for Covid-19 and Tuberculosis, for a total of 1000 images for each class. The obtained images were originally of various sizes ranging from 700 x 400 to 2400 x 1900 pixels, these

were resized to 350 x 350 pixels. Rescaling by the factor of 1/255 because the original dataset images are RGB which are in the scale of 0-255, this range of values is too high for a model to process. This transformation is done because it is highly beneficial to treat all images in the same manner. Neural networks tend to yield better results when the inputs are normalized.

II. Modelling

The preprocessed images were fed into VGG-16(Visual Geometry Group) and DenseNet-169 for Training the network.

1) VGG-16

As previously stated, usage of a pre-trained Neural Network named VGG-16 to classify chest X-ray images into Tuberculosis, Covid-19, Pneumonia, and Normal. VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford [13] it was trained using the ImageNet Dataset which consists of over 14 million high-resolution images amongst 22,000 different categories. VGG-16 has thirteen convolutional layers, five max-pooling layers, and three dense layers which makes a total of 21 layers, of which only 16 layers are weighted layers. VGG-16 architecture is shown in Figure 2**.**

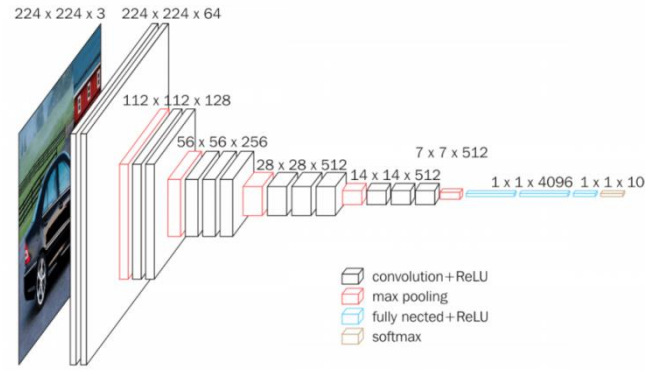

Fig. 2 VGG-16 architecture

This model makes use of Imagenet weights, the input sizes for this model were changed according to preferences and are mentioned in the model summary table [Table 1] It has a total of 14,919,492 parameters among which 204,804 are trainable parameters and 14,714,688 are non-trainable parameters.

Flattening the output of the last block of the Maxpooling2D layer and add a Dense layer with four neurons for the classification of four classes. The model was trained for 6 epochs on softmax activation function and Adam optimizer. The softmax function is utilised as the activation function in the output layer of neural network models that predict a multinomial probability distribution. Among the adaptive optimizers, Adam is the best. It works well with sparse data: the adaptive learning rate is ideal for this sort of dataset, and the learning rate value is irrelevant.

TABLE II. VGG-16 model summary

Sr. No	Layer	OutputShape	Parameters
1)	InputLayer	350 x 350 x 3	0
2)	Conv2D Layer1 (Block1)	350 x 350 x 64	1792
3)	Conv2D Layer2 (Block1)	350 x 350 x 64	36928
4)	MaxPooling2D (Block1)	175 x 175 x 64	0
5)	Conv2D Layer1 (Block2)	175 x 175 x 128	73856
6)	Conv2D Layer2 (Block2)	175 x 175 x 128	147584
7)	MaxPooling2D (Block2)	87 x 87 x 128	0
8)	Conv2D Layer1 (Block3)	87 x 87 x 256	295168
9)	Conv2D Layer2 (Block3)	87 x 87 x 256	590080
10)	Conv2D Layer3 (Block3)	87 x 87 x 256	590080
11)	MaxPooling2D (Block3)	43 x 43 x 256	0
12)	Conv2D Layer1 (Block4)	43 x 43 x 512	1180160
13)	Conv2D Layer2 (Block4)	43 x 43 x 512	2359808
14)	Conv2D Layer3 (Block4)	43 x 43 x 512	2359808
15)	MaxPooling2D (Block4)	21 x 21 x 512	0
16)	Conv2D Layer1 (Block5)	21 x 21 x 512	2359808
17)	Conv2D Layer2 (Block5)	21 x 21 x 512	2359808
18)	Conv2D Layer3 (Block5)	21 x 21 x 512	2359808
19)	MaxPooling2D (Block5)	10 x 10 x 512	0
20)	Flatten	51200	0
21)	Dense	4	204804

2) Densenet-169

Densenet-169 model is one of the DenseNet group of models which was proposed by G. Huang et al [14] and it was the ImageNet competition's winner in 2017. The additional input gathered from all earlier layers is transmitted to the feature maps to all subsequent layers in Densenet. Each layer collects information from the levels above it. The network may be narrow and tighter since each layer receives feature maps from all preceding layers, resulting in fewer channels(and hence improved computational and memory efficiency).The architecture of Densenet-169 is shown in Figure 3.

Densenet-169 model is also pre-trained on the ImageNet dataset like the VGG-16. The DenseNet-169 model was trained on the same dataset of 1000 images each of Covid-19, Pneumonia, Tuberculosis and Normal for training, 771 images for testing, and 38 images for validation. Flattening the output of the last layer and add a Dense layer with four neurons as was done for the VGG-16 model, the model has a total of 13,448,260 parameters of which 805,380 are trainable parameters: and 12,642,880 are non-trainable parameters. Softmax activation function and Adam optimizer were used for this process.

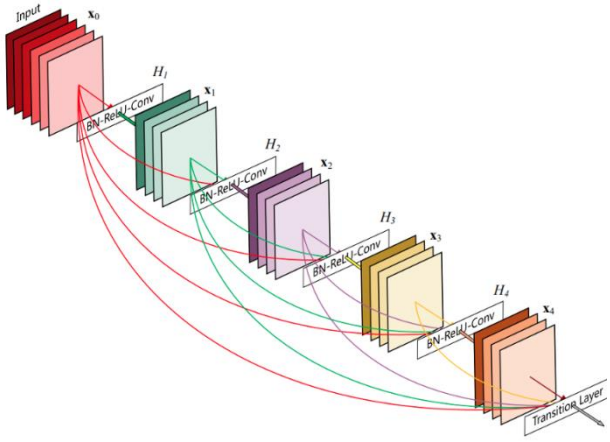

Fig. 3 Densenet-169 architecture

Both these neural network models were interfaced to the streamlit platform, streamlit is an open source framework which makes python scripts into web application platform. This system was created such that a single X ray image is passed through both VGG-16 andDensenet-169 models simultaneously, the output will only be provided if both models had consensus on the result classification.

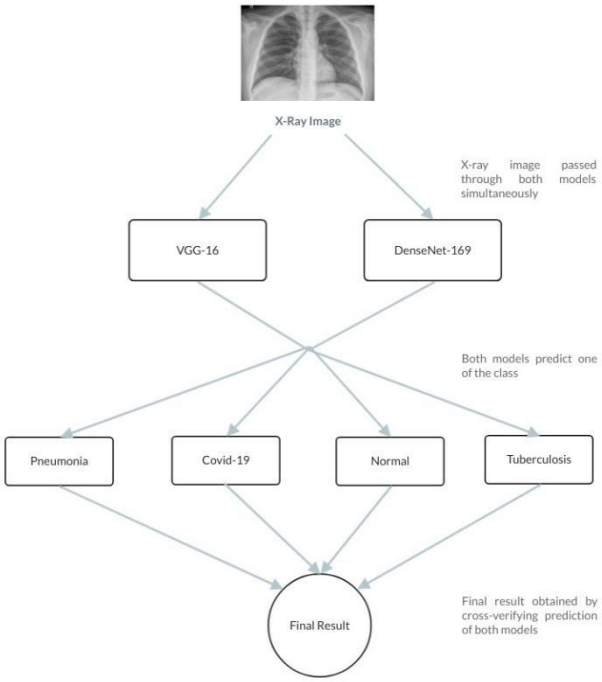

Fig. 4 Flowchart of proposed cross-verification method

V. EXPERIMENTAL RESULTS

The performance results of the proposed VGG-16 and Densenet-169 models are discussed here.

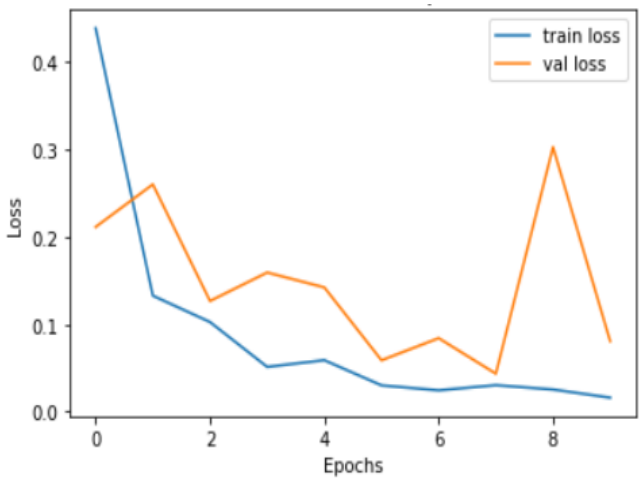

Fig. 5 VGG-16 Loss Graph

Figure 5 depicts the graph of loss with respect to epochs in range of 0.0 to 0.5 for 10 epochs for VGG-16 model. As can be seen from the figure the model was run for 10 epochs, at 10th epoch the least value for training and validation loss was obtained.

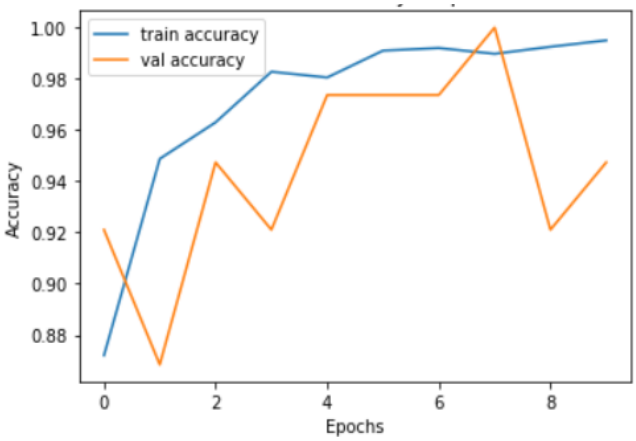

Fig. 6 VGG-16 Accuracy Graph

Figure 6 depicts the graph of accuracy with respect to epochs in range of 0.88 to 1 for 10 epochs for Densenet-169. As can be seen from the figure the model was run for 10 epochs, at 7th epoch the optimal value for training and validation accuracy was obtained.

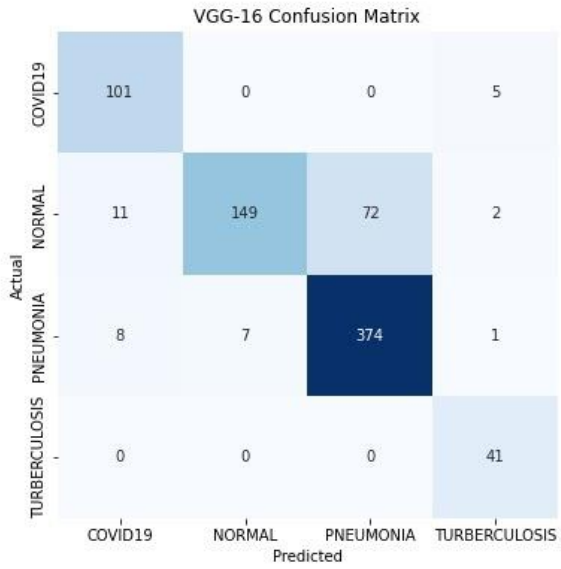

Fig. 7 VGG-16 Confusion Matrix

Figure 7 shows the confusion matrix for the VGG-16 model classified for 4 classes. A total of 771 x-ray images were tested, among which 106 were of COVID-19 out of which 101 were correctly predicted, 234 were NORMAL out of which 149 were correctly predicted, 390 PNEUMONIA out of which 374 were correctly predicted, 41 TUBERCULOSIS out of which all were correctly predicted.

TABLE III. VGG-16 classification report

	Precision	**Recall**	**F1-Score**	**Accuracy**
COVID-19	0.84	0.95	0.89	0.95
NORMAL	0.96	0.64	0.76	0.63
PNEUMONIA	0.84	0.96	0.89	0.95
TUBERCULOSIS	0.84	1.00	0.91	1.00
Macro Average	0.87	0.89	0.87	0.86
Weighted Average	0.87	0.86	0.86	0.86

Table 2. shows the classification report for VGG-16 model. In this it can be seen that the true positive rate (precision) is 87%, recall is 89%, and the weighted harmonic mean of precision and recall (F1 Score) is 87%. While the overall accuracy is 86%.

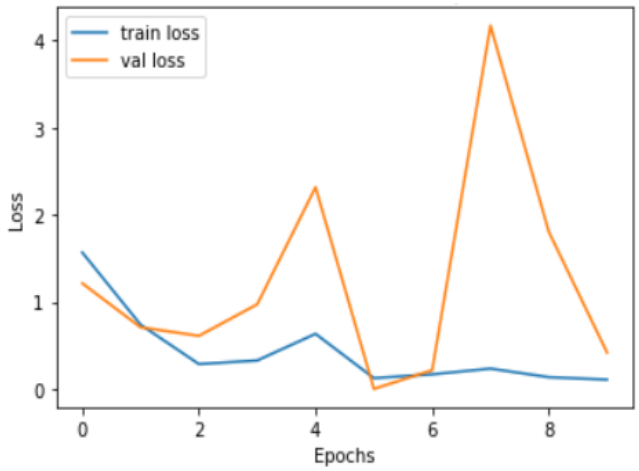

Fig 8. Densenet-169 Loss Graph

Figure 8 depicts the graph of loss with respect to epochs in range of 0.0 to 0.5 for 10 epochs for Densenet-169 model. As can be seen from the figure the model was run for 10 epochs, at 5th epoch the least value for training and validation loss was obtained.

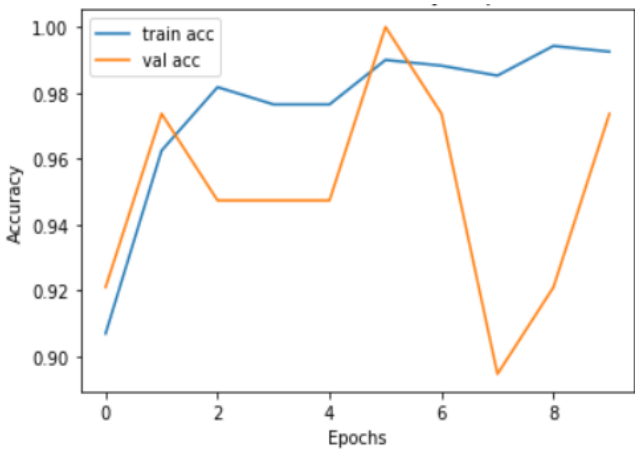

Fig. 9 Densenet-169 Accuracy Graph

Figure 9 depicts the graph of accuracy with respect to epochs in range of 0.90 to 1 for 10 epochs for Densenet-169 model. As can be seen from the figure the model was run for 10 epochs, at 5th epoch the optimal value for training and validation accuracy was obtained.

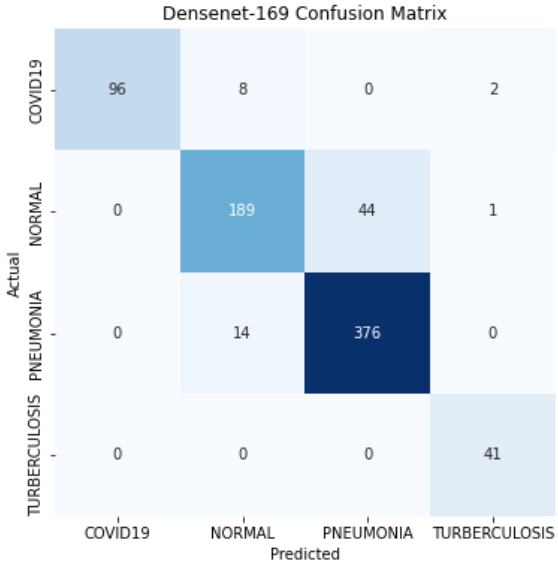

Fig. 10 Densenet-169 Confusion Matrix

Figure 10 shows the confusion matrix for the VGG-16 model classified for 4 classes. A total of 771 x-ray images were tested, among which 106 were of COVID-19 out of which 96 were correctly predicted, 234 were NORMAL out of which 189 were correctly predicted, 390 PNEUMONIA out of which 376 were correctly predicted, 41 TUBERCULOSIS out of which all were correctly predicted.

TABLE IV. Densenet-169 classification report

	Precision	**Recall**	**F1-Score**	**Accuracy**
COVID-19	1.00	0.91	0.95	0.90
NORMAL	0.90	0.81	0.85	0.80
PNEUMONIA	0.90	0.96	0.93	0.96
TUBERCULOSIS	0.93	1.00	0.96	1.00
Macro Average	0.93	0.92	0.92	0.91
Weighted Average	0.91	0.91	0.91	0.91

Table 3. shows the classification report for Densenet-169 model. In this it can be seen that the true positive rate (precision) is 93%, recall is 92%, and the weighted harmonic mean of precision and recall (F1 Score) is also 92%. While the overall accuracy is 91%.

VI. CONCLUSION

For the time being our proposed work consists of two models used to implement the classification process, in the later future various other improved models can be tested, fine-tuned, and implemented. VGG-16 and Densenet-169 were chosen due to their high reliability for real-time usage, these models gave the optimal F1 score.

The deep learning models used here can be highly beneficial in the medical industry helping medical personnel for highly accurate diagnosis of diseases like Covid-19, Tuberculosis, and Pneumonia with just chest X-ray images. The models used for the classification of these diseases were VGG-16 with an accuracy of 87% and Densenet-169 with 91% accuracy.

Available X ray images are used to train convolutional neural networks to get accurate results. This can help in diagnosing diseases like Covid-19 much more easily with readily available infrastructure in the hospitals compared to its costlier diagnostic counterpart RT-PCR method. This will help in getting a faster diagnosis accurately for timely treatment of the ill.

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