An Efficient Approach for Automatic detection of COVID-19 using Transfer Learning from Chest X-Ray Images

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***Abstract*—The coronavirus disease 2019 (covid 19), which was declared a pandemic by the World Health Organization (WHO) in December, causes significant alveolar damage and progressive respiratory failure, resulting in death. The only laboratory technique available, RT–PCR, has an accuracy of about 73 percent. Medical specialists may benefit from early detection using CXR. Using deep convolutional neural network architecture, we propose a Com-puter Aided Diagnosis (CADx) for the diagnosis of coronavirus disease 2019.The chest x-ray dataset is used for testing and training of neural networks. The CXR images are segmented using a U net model, and the segmented image is then used to train a classification model using the Inception v3 model, which distinguishes covid 19 from pneumococcal records and safe records. Training of inception v3 is done with different resolutions of Chest X-rays (CXR) and for further optimization adam optimizer is used. This model produces high computational efficiency with an accuracy of 0.97 per-cent. Based on the promising results obtained the proposed method can be used for effective diagnosis of covid 19 during this pandemic.**

***Index Terms*—Chest X-rays ,inception v3,UNet**

I. Introduction

The coronavirus disease covid19 has spread worldwide and was declared a pandemic by the World Health Organization in March 2020. (WHO). COVID-19 is caused by the virus SARS-CoV-2. According to the phylogenetic study, SARS-CoV-2 originated in bats and was later transmitted to humans via other animal carriers in the Human wet market [26].As of July 28, 2020, WHO had received reports of 16,301,736 confirmed cases of COVID-19, with 650,069 deaths.[29].COVID-19 patients have symptoms ranging from a dry cough, sore throats, and fever to organ failure, septic shock, extreme pneumonia, and Acute Respiratory Distress Syndrome (ARDS)[27].

Early detection is the only way to ensure a quick recovery. The only method for detecting COVID-19 is to use a laboratory-based technique called reverse transcription–polymerase chain reaction (real time RT–PCR), which is checked by taking samples from the infected person's respiratory tract. It is time consuming and gives low sensitivity results, moreover there is a shortage of this diagnosis kit .Due to which chest scans such as x-ray and CT is taken for people with pneumonia symptoms for early detection and treatment. However the discrimination of covid-19 and pneumonia is an hard process as they have indistinguishable image characteristics. With the advent of Artificial intelligence, the deep learning technique is being used for the detection and classification of many diseases in the medical field. Using computed tomography (CT) images, deep learning techniques can be used to diagnose COVID-19 earlier and more accurately.[23]. CT images share common characteristics between pneumonia and COVID-19 and the other disadvantage of CT images is that routine role of CT imaging is arduous in terms of safety for both health workers and other patients[3] .

Early findings using chest x-rays(CXR) is a tedious process even for thoracic radiologists. As a result of which they rely on deep learning based applications for better accuracy in detection. This paper proposes a method for detection of covid-19 by training the Convolution neural networks (CNN) using the chest x-rays (CXR). We used multiple dataset from Kaggle and from Johns Hopkins dataset for COVID 19[38][39].These data are used to train the neural network .In this system prior to image classification we perform preprocessing which involves semantic segmentation. It is pixel level classification often known as dense prediction where each pixel represents a particular class[28].The UNet architecture, a well-known neural network for biomedical image segmentation, is used for semantic image segmentation. Since there aren't enough datasets based on covid-19 x rays to train really deep neural networks, transfer learning is a better choice.[21].hence we use a deep neural network namely Inception V3 for transfer learning process where feature extraction is done by CNN and image classification is done by fully connected layer and softmax. Thus in our proposed model we perform semantic segmentation followed by image classification for early detection and classification of COVID-19 from other pneumonia. This model gives a better accuracy as the segmentation and computational training enables the network to extract better localized features from the segmented images, and help in alleviating the insufficiency of CXR data to train from.

II. Literature Survey

Real time analysis and detection of COVID-19 has currently been conducted in various domains but not limited to image recognition and classification. The widely used domain has been Neural Networks because of the advancement in Deep Learning and Bio-Technology. Neural network was previously used for pneumonia detection, brain tumour classification and several other diseases[20][23]. These proposed models gave results by extracting CT images of lungs. However, a trustworthy and essential model is of prior importance COVID-19 must be classified and evaluated. Reverse transcription has been found to be less accurate than computed tomography (CT) imaging (RT-PCR)[14]. A thing of concern was when there were relatively inadequate datasets available. It was difficult to train the model through deep learning, so instead it was done using domain extension transfer learning (DETL)[8][17][15]. Along with this, transfer learning models such as Alexnet, Googlenet, Resnet18, VGG16 CNN and Resnet50 have been selected for the investigation of COVID-19[10][14]. In Neural Networks the main milestone has been the Inception Network which gives accurate results with considerably sparse datasets[1][23].

Apart from the inception network they have also gone a step further by introducing the residual connections architecture, ResNet50V2 and Xception in order to increase the training efficiency of the inception network as well[2][23].A slight change was done to improvise the model by using Residual Attention Network in order to get an exact outcome[16]. Further research was done which gave an extensive statistical output from the datasets of Chest X-ray (CXR) and CT images which aimed at removing the bias from the dataset. It was considered very important to classify the images into different classes more accurately[3]. To show the detection transparency of COVID-19, Gradient Class Activation Map (Grad-CAM) was put into use which was very useful in identifying as to where the model paid more attention during the classification step[5]. The different protocols which were used to detect COVID-19 were compared. It was observed that by removing significant parts of the lung image from the X-ray, the results obtained were the same as that of the X-RAY with the whole view of the lungs. This showed that it was very difficult to propose a precise protocol and further increased the need for a more reliable model. As a result of this task, an idea was suggested that combined the NIHs, CHE, and KAG training sets, as well as 10 folds of COV, and pre-trained using AlexNet to recognise the image source dataset. They also selected a dataset from NIH, CHE, and KAG to be left out of the training set and included in the testset to further validate it.They then trained AlexNet on the training sets of two datasets from NIH, CHE, and KAG on 10 folds of COV, and then checked it on the left-out dataset's test set and the remaining fold of COV. This was done three times, once for each option in the dataset that was left out. As a result, the above experiment provided a solution to the problem of developing a new protocol as well as some steps to assess biasness[6]. Another breakthrough was whenAn Auxiliary Classifier Generative Adversarial Network (ACGAN)-based model called CovidGAN was used to create synthetic chest X-ray (CXR) images which were used when it was difficult to get radiographic images in a short span of time[22]. Another domain which was used for the classification of COVID-19 using chest X-rays was Supervised UMAP. UMAP uses manifold learning for dimension reduction and hence produces the required output[11]. In future, more advanced technologies were used for the study.

III. Methodology

A. Preprocessing and Dataaugmentation

1) Preprocessing: Preprocessing involves transferring raw, inconsistent data into understandable format . It aims in reducing errors and increasing computational efficiency. In medical image processing, preprocessing plays a major role in reducing noises and segmentation process helps in the converting raw data into multiple segments. This is further used in prediction and classification. In this process we use semantic segmentation also known as dense prediction. In semantic segmentation each pixel is labeled according to the class being represented.

2) Unet-Segmentation: In the proposed system from the CXR image, segmentation is done using Unet architecture. We train Unet on a kaggle dataset. UNet is used for image segmentation in the biomedical field. It consists of two parts: contracting path and expansion path. In the contracting path, the input image is sentenced to three 3x3 convolution layerIt is divided into two sections: a contracting path and an expansion path.s where each layer is followed by 2x2 max pooling. The kernel (feature mapping) is doubled so as to improve its performance.Between the contraction and expansion routes, UNet has a bottleneck section.It's made up of two 2x2 convolution layers with no pooling.This is followed by an expansion path. The number of expansion blocks is the same as that of contraction blocks. Here transposed convolution is performed where the size of the image is expanded. Each CNN layer is followed by an up sampling layer. Each input consists of feature extraction of the corresponding CNN layer. The expansion path image not only regains its original size but also retains the spatial information. UNet is able to do image localisation by predicting the image pixel by pixel.

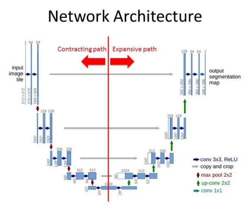

Fig. 1. Structure of UNet

3) Data Augmentation: Image pre-processing and augmentation becomes important because of the huge discrepancy in image resolutions of the CXR dataset. Data augmentation is done only for training set of data. Before processing by CNN, images are normalized using Batch normalization.It is used for normalizing the value distribution before going into the next layer. To combat the internal covariate shift problem, it normalises each layer's inputs.

$$Y = F\left(BN\left(W \cdot X + b\right)\right) \tag{1}$$

Over a mini batch, a batch normalisation transform was applied to activation x.
INPUT : Values of x over a mini Batch:

$$B = \{x_1..m\}\, Parameterlearned = \gamma, \beta \tag{2}$$

Mini-batch mean is done by finding the mean for values of x

$$\mu\beta \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \tag{3}$$

And then the mini batch variance is calculated

$$\sigma^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m}\left(x_i - \mu\beta^2\right) \tag{4}$$

Batch normalisation, which normalises the output of a previous activation layer by subtracting the batch mean and dividing by the batch standard deviation, is used to ensure the stability of neural networks.

$$\hat{x_i} \leftarrow \frac{x_i - \mu\beta}{\sqrt{\sigma_\beta^2 + \epsilon}} \tag{5}$$

The weights in the next layer are no longer optimal after this shift/scale of activation outputs by some arbitrarily initialised parameters. If there is a way to minimise the loss function, SGD (Stochastic gradient descent) undoes the normalisation.

The normalized output is multiplied by a "standard deviation" parameter (gamma) and add a "mean" parameter (beta).

$$y_i \leftarrow \gamma\hat{x_i} + \beta \equiv BN_{\beta,\gamma}\left(x_i\right) \tag{6}$$

OUTPUT:

$$BN_{\beta,\gamma}(x_i) \tag{7}$$

B. Transfer Learning

Training a CNN from scratch is a tedious process and in case of covid the dataset available is scarce and it is wise to use transfer learning than supervised learning in which we have the pertained model.We will be able to pass weights learned over hundreds of hours of training on several high-powered GPUs because this model was trained on such a large dataset. Transfer learning reduces the convergence, training time and increases the computational capacity. It overcomes insufficient data and training time. In neural networks the lower layers learn features from pre trained models and higher layers learn features that are more application specific. As a result of which in the transfer learning process it is enough to fine tune the last few layers as the weights in the early layers are retained.

C. Inception V3

In this proposed system we use inception v3 transfer learning based architecture for CXR image classification, regression and feature extraction.which is then followed by a fully connected layer for classification. Inception v3 is primarily a network structure developed by Kara's, which is pre-trained in Image Net. It is a 48 layers deep network.The network's learning rate is 0.000001. 4. At the ILSVRC 2015 competition, Inception v1 came in second place. Inception-v3 is an Inception module that extracts features using multiple convolutional layers and concatenates them as the output.

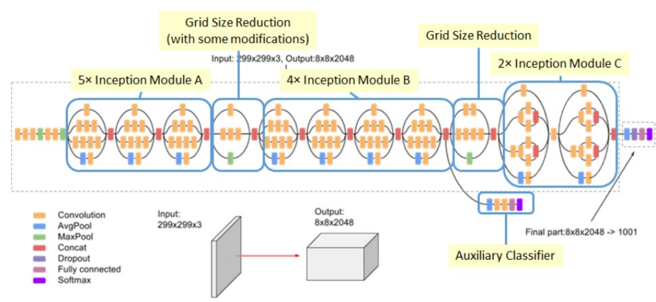

Fig. 2. Inception V3 Architecture

D. Working

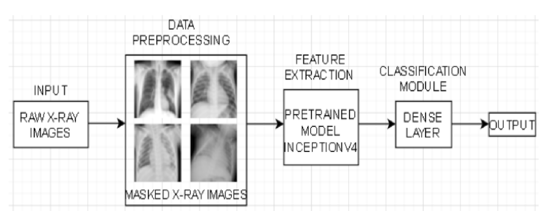

Fig. 3. Workflow Diagram

In order to obtain accurate and effective results, semantic fully connected layer for classification. Inception v3 is primarily a network structure developed by Kara's, which is pre-trained in Image Net. It is a 48 layers deep network.. Learning rate of the network is 0.000001. 4. Inception v1 was the first runner up at the ILSVRC 2015 competition. Inception-v3 is an Inception module that uses multiple convolutional layers for feature extraction and concatenates extracted features as the output.segmentation is performed on the dataset using U-net Architecture followed by image classification. This approach allows us to obtain more accurate and rich image features from the dataset.Balancing the data to be unbiased is of utmost importance while training any model. Considering the less amount of data available, augmenting the existing dataset will improve the training model and will enhance the prediction to be more accurate. Hence, data augmentation is further performed for the training set to eliminate any discrepancy caused by lack of data. The images are then normalised using Batch normalisation technique and further pre-trained using Convolutional Neural Network architecture.

To remove features, the Transfer Learning approach is used. as it is proved to reduce errors and produce effective results with faster training duration. inception v3 based architecture is used as this method has proven to be burning less computational power and also providing better and accurate results compared to other architectures. Specifically, the pre-training process is performed on an image-net dataset and its weights are loaded. The last fully-connected layers are replaced with new layers. These lower layers are fine-tuned keeping the higher layers frozen, in order to prevent overfitting.Proper parameter tuning, using proper regularization methods is also performed during the training of the model.After successfully training the model, testing the model with data unseen by the model is also of prior importance. This will allow us to evaluate the performance

IV. Experimentation result

A. Dataset

In this paper, we have used datasets of the CXR images of patients affected by COVID 19, bacterial pneumonia and no infection. The datasets were obtained from 3 different sources which are publicly available online. Covid-19 chest x-ray dataset was obtained from Cohen JP's github repository [38]and his kaggle dataset[39] This dataset was developed by Cohen at al. by gathering images from various publications and websites.It includes cases of COVID 19 and other bacterial pneumonia diseases, as well as chest X-ray/CT images (MERS, SARS, and ARDS) Each image has a metadata field that contains the Patient ID, sex, age, and other pertinent information. To maintain a balanced dataset, we used 358 frontal chest x-ray images of COVID positive events, 358 images of Pneumonia- Bacterial cases, and 358 standard CXR scanned images at the time of our experimentation.The other source was a dataset created by Kermany D, Goldbaum M, Cai W et al.[37] This dataset contains validated normal chest x-ray images.The images present are in black and white. These grayscale images are processed to obtain 2D arrays and further normalised. The images are resized uniformly at (224,224) pixels. We further extract features from the image using CNN.

B. Experimentation setup

The experiment was conducted on a windows 10 system 64 bit using the MATLAB R2019A software. The coding language used was Python programming. The experiment is conducted with the specified model to get accurate results from the experiment and validation process. The detailed experimentation is as follows, the model comprises of CNN layer part and then the detection layer. The experiment is run on a coaction as it is proved to reduce errors and produce effective results with faster training duration. inception v3 based architecture is used as this method has proven to be burning less computational power and also providing betmputer with given configurations, 8 Gb of RAM and 4 Gb of NVIDIA G-force GTX 1060-ti graphics card. In order to show the superiority of our model we have compared our models output with the majorly used classification ML model SVM (support Vector Machine) .The raw data is obtained from the Kaggle dataset[39] . This data is obtained and then categorized into train and test directories of random nature and an indexed csv file is created for the training purpose. The categorization of train and test is on random scale at an 80:20 ratio. The experiment is conducted for both the CNN developed and the the SVM setup.The experimental results are as follows.

C. Experimental results for SVM and Transfer learning using inception v3

a) True Positives (TP): These are the positive values that were correctly predicted which indicates that the worth of the actual(true) group is yes, as is the value of the expected batch.E.g. if true class value depicts that they have been actually affected by the disease or they are not affected by the disease and they are normal and the predicted class also confirms this.

b) True Negatives (TN): These are the non-positive values that were rightly predicted, that is, the value of the actual(true) group as well as for the contemplated class is also nil. E.g. if the true class tells they were not affected by the disease and the predicted group also confirms this. False positives and false negatives arise when the real class differs from the expected class .

c) False Positives (FP): When true batch is no and contemplated class is not no(yes). E.g. if the true group says they were not pretentious by the COVID disease, but the planned class tells you that they are not affected.

d) False Negatives (FN) : When the definite(true) group is yes but anticipated batch is not yes. E.g. if true class value predicts that they were affected by COVID-19 and the predicted class depicts they are diseased.

TABLE I
The confusion matrix for Testing on SVM

	Predicted			
	Stages	Normal	Pneumonia	Covid
Actual	Normal	28	1	3
	Pneumonia	2	25	0
	Covid	1	1	71

Using Confusion Matrix of SVM specification the parameters for normal class normal call is TP=28,TN =97,FP=4,FN =3 for other pneumonia class TP=25,TN=103, FP=2, FN=2 for covid class TP=71, TN=56, FP=2, FN=3 Using Confusion

TABLE II
THE CONFUSION MATRIX FOR TESTING ON CNN

	Predicted			
	Stages	Normal	Pneumonia	Covid
Actual	Normal	31	3	0
	Pneumonia	0	23	0
	Covid	0	1	74

Matrix of developed inception v3 model the parameters for normal class TP=31,TN =108,FP=3,FN =0 for other pneumonia class TP=23,TN=106, FP=4, FN=0 and for covid class TP=74, TN=57, FP=1, FN=0 respectively are found. Once these four parameters are met then we can calculate Precision, Recall and F1 score.

e) Precision : Precision is calculated as the ratio of the proportion of predicted true observations to the aggregate of correctly predicted positive considerations.The low false positive confidence is related to high precision.

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

f) Recall (Sensitivity) : The proportion of positive factors to every consideration in the actual class(yes) can be used to calculate recall.

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

g) F1 score: The F1 Score can be determined by multiplying the value of precision and Recall and then averaging it. If we have uneven class distribution then F1 score is typically more beneficial than precision.

$$F1score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{10}$$

TABLE III
VALUES OF PRECISION/RECALL/F1-SCORE AND SUPPORT FOR EACH CLASS IN SVM SPECIFICATION IN PERCENTAGE

Metrics	Precision	Recall	F1-score
Normal	88	90	89
Pneumonia	93	93	93
Covid	97	96	97

TABLE IV
VALUES OF PRECISION/RECALL/F1-SCORE AND SUPPORT FOR EACH CLASS IN TRANSFER LEARNING USING INCEPTION V3 SPECIFICATION IN PERCENTAGE

Metrics	Precision	Recall	F1-score
Normal	91	100	95
Pneumonia	100	85	92
Covid	99	100	99

h) Accuracy: The most intuitive success metric is accuracy, which is measured as a proportion of correctly predicted considerations to the total number of observations. If we get higher accuracy then our model works better.

$$Accuracy = \frac{\sum(TP) + \sum(TN)}{\sum(TP) + \sum(TN) + \sum(FP) + \sum(FN)} \tag{11}$$

i) Macro-Average: The macro-average is the mean of all groups' precision/recall/F1.

j) Weighted average: The total number in TP(true positive of all classes) divided by the total number of objects in all classes yields the weighted average.

TABLE V
ACCURACY,MACRO-AVERAGE,WEIGHTED-AVERAGE FOR PRECISION/RECALL/F1 OF ALL CLASSES IN SVM SPECIFICATION IN PERCENTAGE

Metrics	Precision	Recall	F1-Score
Accuracy			94
Macro Avg.	92	93	93
Weighted Avg.	94	94	94

TABLE VI
ACCURACY,MACRO-AVERAGE,WEIGHTED-AVERAGE FOR PRECISION/RECALL/F1 OF ALL CLASSES IN TRANSFER LEARNING USING INCEPTION V3 SPECIFICATION IN PERCENTAGE

Metrics	Precision	Recall	F1-Score
Accuracy			97
Macro Avg.	97	95	96
Weighted Avg.	97	97	97

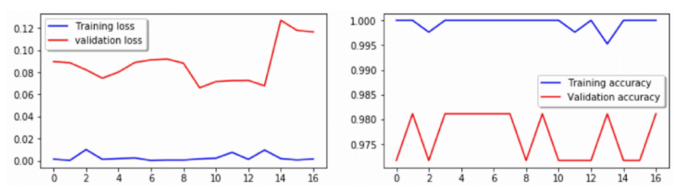

Fig. 4. The above graph shows the training ,validation loss and also training,validation accuracy

By the experimentation done we could achieve better accuracy compared to the existing or traditional Support Vector Machine(SVM) . The accuracy was increased drastically by the improved model where segmentation is initially done and the accuracy for SVM and CNN were 94% and 97% respectively.

V. CONCLUSION

In this paper we propose an idea which differentiate COVID- 19 from pneumonia records.Computer Aided Diagnosis(CADx) has been used for the diagnosis of COVID-19 using deep convolutional neural network model.Subsequently, CXR images are processed using a U net model for accurate segmentation.The segmented image is then used for training and classification using the Inception v3 model.The idea behind using Inception v3 as it gives far better resolutions of Chest X-rays (CXR) when compared to other techniques.In addition, this model produces an accuracy of 0.97%. Based on the promising efficiency which the model showcases the proposed method can be used for effective and quick diagnosis of COVID-19 during the pandemic.Although we have obtained this result there is a scope for future improvisation wherein other models may give even more greater accuracy, computational efficiency and training flexibility.

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