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Covid19 Detection using Chest X-Ray images along with corresponding metadata of the chest X-Ray

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Abstract

Due to the rapid spread of coronavirus 2019(Covid 19) in the present situation ,early detection of covid 19 is very important. As per WHO [1] as of 5:26pm CEST, 5 August 2022, there have been 579,092,623 confirmed cases of COVID-19, including 6,407,556 deaths, reported globally. Lot of works have been reported to investigate covid19 using Deep learning algorithm over chest X-ray(CXR) images but as per our knowledge all have taken image data only as input to classify .In our work we have processed CNN model which can take CXR images along with corresponding the metadata(non imaging data) available with the dataset to classify Covid 19.CNN model based on Resnet 50,Dense net 121,Mobile Net,VGG-16,Inception-V3 and custom CNN have been developed to accept the multimodal data,i.e metadata along with CXR image.All the mentioned CNN have been used as feature extractor of CXR image and extracted feature have been fused with the features extracted from metadata and passed through the classifier for final classification.Some state of art Deep learning models have been run to classify the covid 19 on the same data set and compared with our best model .Experiments have been done in two phases.In the 1st phase we used CNN models on CXR image only and in the 2nd phase we ran all modified CNN models over the same CXR images with their matadata.The experimental results shows that the output of 2nd phase out performs the output of 1st phase.After that we compared our best model with other state of art models.Modified custom CNN model provides best results of 99.07 % overall accuracy

Keywords: Metadata,CNN,Covid19,Xray images,Transfer Learning

1 Introduction

Globally human can be infected by different types of human coronaviruses like HCoV-NL63,HCoV-229E,HCoV-OC43 and HCoV-HKU1 and tend to cause mild respiratory disease, but the fatality rate of novel coronavirus that was identified in December 2019 at Wuhan, China is higher than all of it's previous types [1]. Suspected COVID-19 People need to know quickly whether they are infected, so that they can be provided appropriate treatment and further spread of the virus can be stopped by self-isolating, warning the primary contacts as well .At present standard confirmatory clinical test to detect covid19 is reverse transcription-polymerase chain reaction (RT-PCR) is manual, complex, and time-consuming .Specialist equipments are required for RT-PCR and takes at least 24 hours to produce a result.The scarcity of domain experts in the hospitals and test-kits , specially in village area and due to huge increase in the number of infected patients it has become necessary to generate an automatic screening system, to identify the infected patients quickly, who require immediate isolation, further clinical confirmation and treatment [2]. For detecting COVID-19,CXR images can be taken as an alternative screening modality [2][3], where the CXR images are diagnosed by expert radiologists to look for infectious lesions associated with COVID-19.Combination of RT-PCR and Thoracic imaging,which is moderately specific in the diagnosis of COVID-19, can enhance the accuracy for the diagnosis of Covid-19.Thoracic imaging can be used to identify the false negatives of RT-PCR test[4].Due to restrictions on sample collection, a lengthy process,kit performance and a high proportion of false-positive results, many COVID-19 patients have erroneous diagnoses[5].CXR is cheap and non invasive test,which can reveal the results faster than RT-PCR test. One of the standard healthcare apparatus is CXR which is easily available in many health center even at remote villages.The advantages of Portable CXR systems are easily available and imaging can be performed in isolated rooms. People having age 60 years and more, and those having comorbidities like high blood pressure, heart and lung problems, diabetes, obesity or cancer, are at higher risk of developing serious illness due to corona viruses[1]. Patients with diabetes are vulnerable to Covid 19 infection[6, 7]. Female patients have higher antibody production and response,therefore male patients are more prone to be affected by Covid 19[8].Male,Aged people with other comorbidities like diabetes ,high blood pressure etc are very easily infected by covid 19 .Therefore the accuracy of the classification will be increased if we can take the non imaging data like patients age,gender and other comorbidities as input along with CXR image.The view of the chest X-ray plays important role in Computer added design, according to the image view shape of external lung as well as internal lung features may differ[9]. As the Covid 19 CXR dataset along with all the comorbidities that can deeply influence the accuracy of the classification are not available at present time,we have considered age,gender and view of the CXR image as the metadata(non imaging data).As soon as the dataset with all the comorbidities are available ,the same can be considered as metadata along with CXR to increase the accuracy of the classification.Since volume of Covid 19 dataset with metadata that have been used is less, we performed the same experiment on another larger dataset for validation which contains two classes either normal patient or Infiltration affected patient.As older people and female gender are more prone to be affected by Infiltration[10][11] and to maintains the consistency with earlier covid19 datasets we have considered Gender, Age and View of X-Ray image as the metadata for larger datset also.

Our main contribution of this work are as follows:

1. Non imaging data which have important role for detecting covid19, have been taken as input(Multimodal data input) along with CXR image for classification which has not been considered so far for detecting covid 19 as per our knowledge.
2. Common modification has been incorporated in the basic CNN models to accept non-imaging data along with CXR images.
3. Modified Custom CNN model gives best output for both the phases(using CXR images only with out metadata and CXR images with metadata)
4. Performance of some state of art model have been compared with our best model with metadata on the same dataset.
5. Since Covid 19 dataset along with metadata is not available with large volume, we performed the same experiment on another larger dataset for validation.

2 Related Work

Clinical studies revels that the lung infection is the most common feature of the COVID19 patients and that is why many researchers have chosen X-ray imagery for fast and automatic detection systems of Covid19[12] [13].Work has been done to predict the mortality of the patient admitted in the hospital for covid 19 using several machine learning algorithm [14].Total 375 patients blood sample were taken, out of that 201 patients who survived and 174 patients passed away due to COVID19.Ensemble tree based models obtained the best prediction scores and variables like age, days in hospital, Lymphocyte and Neutrophils are the most important variables for the mentioned prediction. In the paper[15] Author have used DenceNet architecture to examine COVID-19 using the Chest X-ray dataset with early stopping and transfer learning technique. To obtain the best accuracy for the classification of COVID-19 chest X-ray images multiple optimizers, loss functions and LR Schedulers have been compaired.Adamax optimizer with Cross Entropy loss function having Step LR Scheduler was the best and showing an accuracy of 98.45% for normal-healthy class and 98.32% for COVID-19 class. [15] proposed a CNN model consists of 3 convolutional layers followed by Max-pooling layers and 2 dense layers , ReLU have been used in the first dense layer with 256 output perceptrons and softmax function have been used in the second dense layer with two output perceptron .Categorical cross-entropy has been employed as the cost function with dropout layer and Adam optimizer. The proposed model's output performed better than that of the VGG16, VGG19, ResNet50, and Inception-v3 models..Auther [16] to combine the forecast of satellite images from the CNNs with satellite metadata, CNN model have been essambled with neural networks. There are 63 classifications and one million photos in the collection. The system achieves an F1 score of 0.797 and accuracy of 0.83. 15 classes are classified with a 95 percent accuracy rate.The author attached the combined features to a convolutional layer that is coupled to the classifier after concatenating retrieved features from ResNet50V2 and Xception.They achieved 99.50 % as an average accuracy [17] .With the addition of two fully connected layers and a dropout layer, CoroNet builds upon the Xception basic model. To identify COVID-19 from chest X-ray pictures, they implemented three scenarios of the suggested model. The first model is the primary multi-class model (4-class CoroNet) that is trained to categories four categories COVID-19, Normal, Pneumonia-bacterial and Pneumonia-viral. The other two types of 3-class CoroNet (COVID-19, Normal and Pneumonia) and binary 2-class CoroNet model (COVID-19, Normal) are variants of the primary multi-class model.Got 99% accuracy for binary classification [18].As per our literature survey none of the author have classified CXR images with corresponding metadata.

3 Back ground work

In this section we have discussed about the usage,architectural diagram,training details of the techniques used to classify CXR images like Transfer learning,Deep neural network,ResNet50,Dense Net 121,Custom CNN.

3.1 Transfer learning

Deep learning require huge amount of training date with millions of parameters ,which limits it's applications in many cases like covid19 ,here we do not have sufficient covid 19 CXR data to learn Deep learning. One of the practical solutions is Transfer learning which reduce the data required for training and tries to reuse learned knowledge for similar tasks[19] Transfer learning is the method of reusing a previously trained model on a new problem.The process of retraining the base model can be achieved by using two steps: update the architecture of the base model according to the current classification problem and retrain the model.Updation of the architecture can be done by replacing the output layers with new output layers which can provide desired number of classes at output.After that base model weight is loaded.

3.2 Deep convolution neural network

In computer vision area like classification,segmentation etc deep learning has got huge success in last decade[20].In the present time deep learning models is rapidly becoming a method for analysing X-ray images[21]. Convolutional layers make up the foundation of the CNN architecture, which accepts inputs, modifies the data from the input image, and then passes it to the next layer as an input. Each convolution layer has filters known as image kernels that are used to find patterns in the input image.In order to down-sample the input image representation, which involves lowering the dimensionality while recapturing the maximum values in the subregions, we employ a pooling layer in conjunction with a convolution layer. The input matrix, which is employed as a collection of numbers of pixels, is navigated using stride. If the stride is 1, we traverse the input matrix one pixel at a time. Additionally, it may have flatten, dropout, and fully linked layers.

3.2.1 ResNet-50 model for Classification using Image Data

ResNet-50 is an acronym for the explicit class of neural network known as the residual network, which is made up of residual blocks. When training a deeper neural network, it fixes the vanishing gradient issue by utilising skip connections discovered in the residual block. The most crucial point is that, despite the fact that the architecture is becoming more complex, the performance of the ResNet model does not degrade when compared to other architectural models[22] [23].Figure1 shows the Network Diagram of ResNet-50.We used the ResNet-50 model, which was created from scratch using the prepared dataset. We trained the Adam optimizer using a learning rate of 0.00001, a loss function of sparse categorical cross entropy, and accuracy as the measure.we trained the model for 50 epochs with a batch size of 16

3.2.2 DenseNet-121 model for Classification using Image data

A densely linked neural network, or DenseNetcite[24] for short, is a specific sort of neural network in which every layer is connected to every other layer in the network.DenseNet-121 consists of two dense blocks, three transition layers, one classification layer, and five convolution and pooling layers.Figure2 shows Network Diagram for DenseNet-121 model for Classification only using Image Data. DenseNet-121 model was created from scratch and trained on the prepared dataset. We trained the Adam optimizer using a learning rate

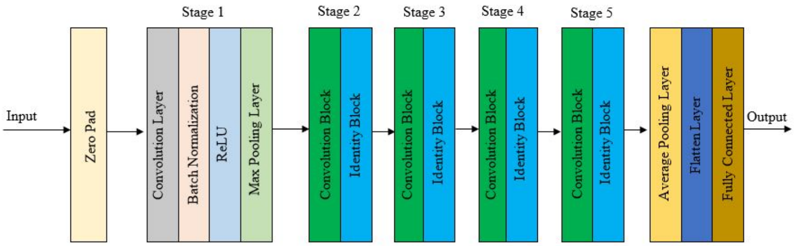


Fig. 1: Network Diagram for ResNet-50 model for Binary Classification only using Image Data

of 0.00001, a loss function of sparse categorical cross entropy, and accuracy as the measure. we trained the model for 50 iterations, with a batch size of 16.

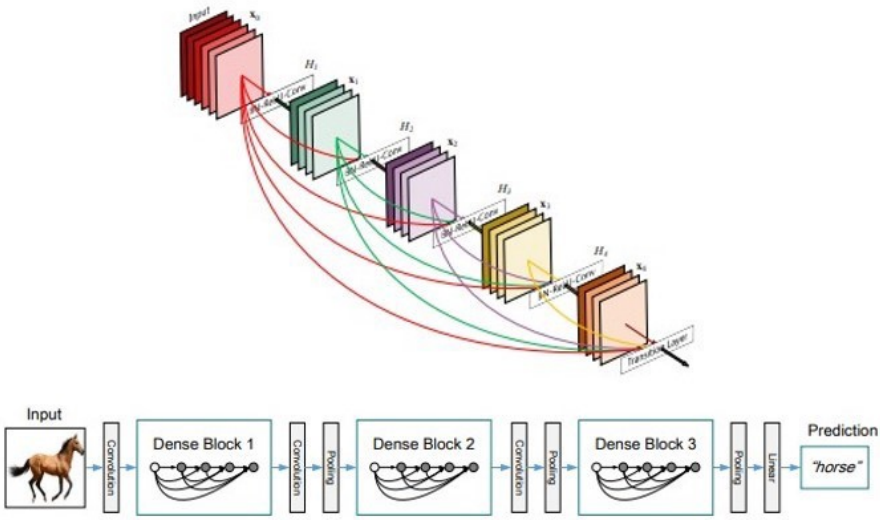


Fig. 2: Network Diagram for DenseNet-121 model for Classification only using Image Data.

3.2.3 Custom Convolutional Neural Network using image data

Let's take a closer look at each of the layers and their individual parameters in CNN [25], which comprises of a combination of convolutional layers with max pooling layers, flatten layers, and dense layers. a)The input shape, which in this case refers to the width, height, and colour channel of the input image, is (299,299,1), where 299 denotes the width, height, and colour channel, which in this case is grayscale. All of the convolution layers have been used with a kernel size of (3,3), a stride and dilation of 1, and padding set to "valid." All convolution layers use the rectified linear activation function (ReLU), a piecewise linear function that gives the output as input directly if the input is positive or zero otherwise. ReLU is widely used as an activation function in convolution layers because it resolves the vanishing gradient problem, allowing the model to learn patterns more rapidly and perform better. The first convolution layer uses a 32-bit filter, while the subsequent levels steadily increase the filter size.With a kernel size of 3,3, dilation, stride, and padding set to "valid," the convolution operation is carried out in the first convolution layer on the input image of (299,299). Due to the filter size of 32, the output size is (299-3+1,299-3+1) = (297,297), and the output shape is now (299,299,32). Using the method outlined above, we can identify the output form of each of the following convolution layers. b) Max Pooling Layers: For all of the network's max pooling layers, we use the kernel size (2,2). We can now calculate the output size of the first max pooling layer using the formula ((297-2)/2)+1, (297-2)/2)+1) = (148,148), where 297 is the output size of the previous convolution layer. Here, division is done using the integer floor value. c) Flatten Layer:The flatten layer produces a 1-D array vector using all of the pixels along all of the channels as input. The input (16,16,64) is flattened to 16384 values, for example (16x16x64). d) Dense Layer: This layer is intimately linked, meaning that each neuron in it receives input from each neuron in the layer below. Our model's output consists of three dense layers, the output layer of which has a sigmoid activation function, and two dense layers with ReLU activation functions.Figure3 shows the Network Diagram of custom CNN model for Classification only using CXR Image Data.Custom CNN has been ran with the batch size of 32. For training, we utilised the adaptive learning rate approach known as the Adam Optimizer, which uses sparse categorical cross entropy as the loss function and the accuracy metric to quantify the accuracy and loss of training and validation for various parameters. We also applied the concepts of early halting and slowing down learning. Early stopping prevents overfitting based on a metric in our example, loss, which must be minimum; as a result, anytime the model reaches the least loss, it will stop training in that epoch if the loss is not increased in the following three iterations. A factor of 0.3 is applied to the learning rate. We now start 50 rounds of training the custom CNN model on the train dataset.

4 Proposed Method

Different Deep learning models like ResNet50,DenseNet121,Mobile Net,InceptionV3 and Custom CNN have been developed by incorporating common modification on existing deep learning model to accept multimodal data.Network diagram of some of the developed models have been explained below.

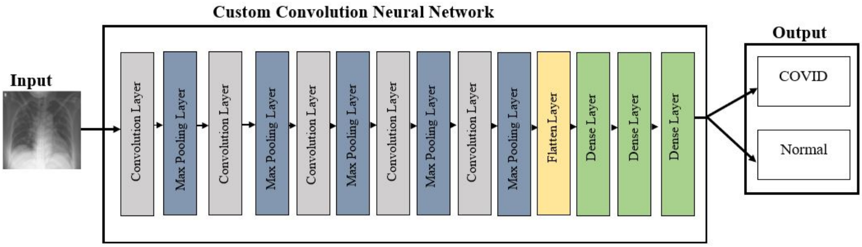


Fig. 3: Network Diagram for custom CNN model for Classification only using Image Data.

4.1 Modified ResNet-50 model for Classification using Image Data and Non-Image Data:

ResNet-50 model has been modified to accept image data as wel as non-imaging data for classification in this work as shown in figure4 below. The fully connected layer which is the output layer of ResNet-50 is replaced with a dense layer and the output of that dense layer is concatenated with the output of Fully connected neural network which takes the input as non-Image data. The concatenation layer concatenates the output of ResNet-50 model and Fully Connected Neural Network and the output of concatenation layer is passed on to the series of dense layers and at the end to the output layer which has a sigmoid activation function for classification.The Network Diagram for the Modified ResNet-50 Model for Classification Using Image Data and Non-Image Data is shown in Figure 4. With a learning rate of 0.00001, a loss function of sparse categorical cross entropy, and an accuracy metric, we used the Adam optimizer to train the system. With the same dataset, we trained the model for 50 iterations, with a batch size of 16.

4.2 Moified DenseNet-121 model using Images and Non-image Data for Classification

The Modified DenseNet-121 model for classification using Image Data and Non-Image Data used in this work is modified version of DenseNet-121 which also takes non-Image data as input together with Images as shown in figure5 below. After the Linear layer which is the output layer of DenseNet-121 a dense layer is added and the output of that dense layer is concatenated with the output of Fully connected neural network which takes the input as non-Image data. The concatenation layer concatenates the output of DenseNet-121 model and Fully Connected Neural Network and the output of concatenation layer is passed on to the series of dense layers and at the end to the output layer which has a sigmoid activation function for classification.Figure5 shows the Network

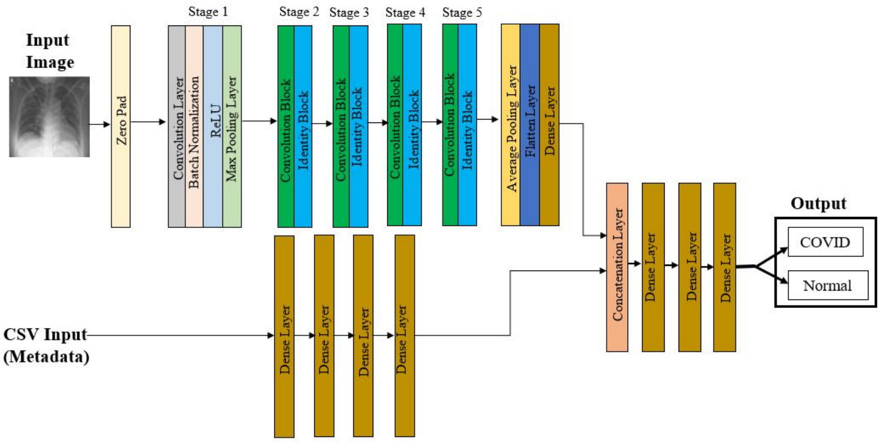


Fig. 4: Network Diagram for Modified ResNet-50 model for Classification using Image Data and Non-Image Data.

Diagram of Modified DenseNet-121 model for Classification using Image Data and Non-Image Data.DenseNet-121 model was trained on the prepared dataset from scratch.We trained the Adam optimizer using a learning rate of 0.00001, a loss function of sparse categorical cross entropy, and accuracy as the measure.

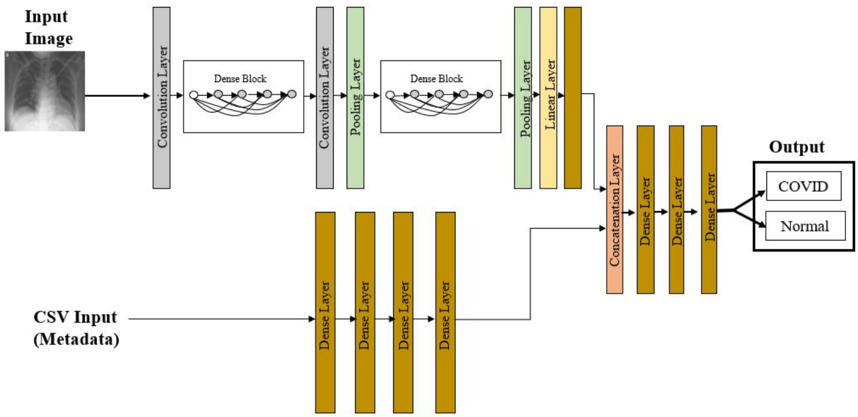


Fig. 5: Network Diagram for Modified DenseNet-121 model for Binary Classification using Image Data and Non-Image Data.

4.2.1 Modified Custom CNN based model using Images and Non-image Data for Classification

The Custom CNN model has been modified to take non imaging data along with image data(CXR) for classification as shown in figure6 below. The fully dense layer which is the output layer of Custom CNN is removed and a dense layer is added after the flatten layer and the output of that dense layer is concatenated with the output of Fully connected neural network which takes the input as non-Image data. The concatenation layer concatenates the output of custom CNN model and Fully Connected Neural Network and the output of concatenation layer is passed on to the series of dense layers and at the end to the output layer which has sigmoid activation function for classification.Figure6 shows the Network Diagram of Modified Custom CNN model for Classification using Image Data and Non-Image Data.We prepared the dataset in such a way that the input to each one of the models had one image and the corresponding non-image data together fed into the model for training. We started training the modified custom CNN model with image and non-image data with batch size of 32. The optimizer, loss function and learning rate were same used for training the custom CNN model.

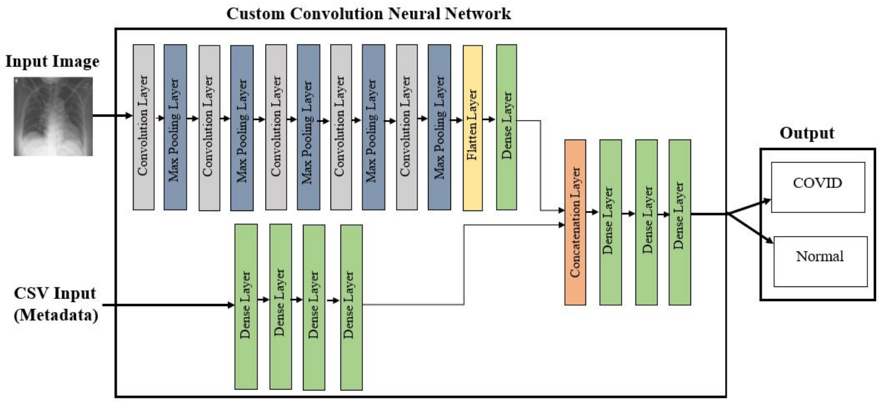


Fig. 6: Network Diagram for Custom CNN based model for Classification using image Data and Non-Image Data.

5 Results and Discussion

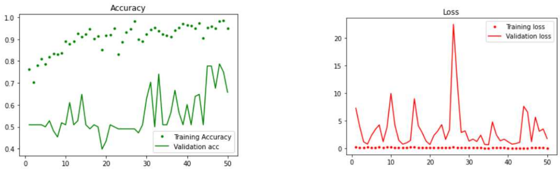
In this section we compared the results of classification by above mentioned CNN model with out metadata with the modified CNN model with metadata.Then we compared our best model ,modified Custom CNN with other state of are models and finally we ran our best model,Custom CNN on a larger dataset.

5.1 MetaData

The meaning of metadata is data about data.The nobility of this work is that we have considered some information of CXR image along with CXR image(multimodal data) as input to improve the accuracy of the classification.Metadata can be any comorbidities like Diabetics,Blood pressure,Age,Gender etc that can influence Covid19 detection.Due to unavailability of dataset we have consider only Age,Gender and view of CXR image as metadata.Convolution neural networks are designed in a way to work on 2-D data having correlation with the neighboring data just like images. However Non-Image data (metadata) are 1-D data which cannot be fed to the CNN's directly so for the work that is proposed we used keras functional API which allows us to have models with multiple inputs and also mixed inputs like images and non-image data (Multimodal). We have two input layer one is fed with image data and another is fed with non-image data, the non-image data is a csv file having features as age of patients, gender of patients and view of the Chest X-Ray image and a column as filename for the file name of the image which is used to sort the non-image data and images together so that images and non-image data are fed together to the network as both type of data are related. Fully connected neural network with dense layers takes the non-image data as input and the output is concatenated with the output of the network taking image data as input, the concatenated features are then fed to the final combination of layers and then to the output layer where the classification is made.

5.2 Data set

The Dataset consisting of COVID-19 images and normal Images with its metadata were needed for our work but due to lack of the data in single dataset we obtained data from two different sources, first one is the COVID-19 X-Ray images[26] database which is publicly available in Kaggle. This dataset consists both X-Ray images and CT scan images form which we removed CT scan images and corresponding metadata of those images, this dataset is mainly used for the COVID-19 images and Metadata.1st dataset consists 232 CXR image and corresponding metadata of covid19 patient and only 32 CXR image and corresponding metadata of Normal patient.In binary classification data imbalance contributes largely the poor performance of Deep learning. Therefore another source of dataset NIH Chest X-Ray [27] has been taken, which consists of chest X-Ray images and metadata of 14 different class, this dataset is mainly used for the normal chest X-Ray images and its metadata. The metadata we considered for our work is Gender, Age and View of X-Ray image due to consistency of these values in the both datasets.Finally we have taken 475 CXR images and respective metadata out of that 232 CXR are of Covid19 infected and rest 243 normal CXR .For the validation with another dataset [26] of total of 4986 Chest X-Ray images and its metadata was taken of which 2754 Chest X-Ray images and its metadata was for no findings class and 2228



(a) Accuracy (b) Loss

Fig. 7: Accuracy and loss graph for ResNet-50 model for classification only using image data.

Chest X-Ray images and its metadata was for Infiltration class. Further the dataset is being split in the ratio of 70:20:10 for training, testing and Validation respectively .

5.3 Evaluation metrics

We employed four types of widely used metrics to assess the classification performance attained by various strategies in the classification challenge. . 1.Accuracy (ACC):It can be defined as the proportion of samples that are correctly classified. ACC=(TP+TN)/(TP+TN+FP+FN). 2.Recall: It measures the proportion of actual positives that are correctly identified . This reflects misdiagnose proportion also. Recall/Sensitivity=TP/(TP+FN).Sensitivity is a measure of how often the model correctly classifies a positive covid 19 cases as positive 3.Precision: The percentage of detected positives that are actually positive is known as precision. Precision=TP/(TP+FP). 4.F1-score:The harmonic mean of recall and precision is measured by the F1-score. F1-score=2((Precision*Recall)/(Precision+Recall)) where The abbreviations TP, TN, FP, and FN above stand for True Positive, True Negative, False Positive, and respectively False Negative.

5.4 Classification with CXR image with out metadata

First we have classified the CXR image only,with out metadata by CNN models.

5.4.1 Classification of CXR image using ResNet- 50

The Accuracy and Loss graph,confusion matrix and performance of ResNet- 50 over CXR image data are shown in Figure 7,Figure8 and Table1 respectively.

Accuracy:66 %

Classes	Precision	Sensitivity/Recall	F1-Score
COVID-19	0.96	0.42	0.58
Normal	0.62	0.98	0.76

Table 1: Performance of ResNet-50 model for classification only using image data

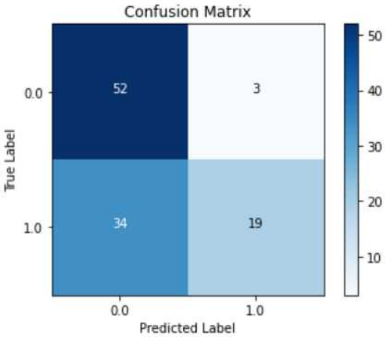
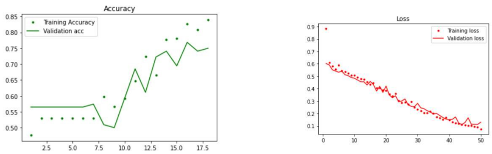


Fig. 8: Confusion Matrix for ResNet-50 for binary classification on image data.



(a) Accuracy (b) Loss

Fig. 9: Accuracy and loss graph for Custom CNN model for binary classification only using image data.

5.4.2 Classification of CXR image using Custom CNN model

The Accuracy and Loss graph,confusion matrix and performance of Custom CNN model over CXR image data are shown in Figure9,Figure 10 and table 2 respectively.

Accuracy: 75%

5.5 Classification with CXR image and metadata

In phase 1 we have classified the CXR image only by all the CNN models.In Phase2 we have used all developed models over CXR images along with it's metadata.

Classes	Precision	Sensitivity/Recall	F1-Score
COVID-19	0.77	0.80	0.78
Normal	0.73	0.68	0.70

Table 2: Performance Custom CNN model for binary classification only using image data

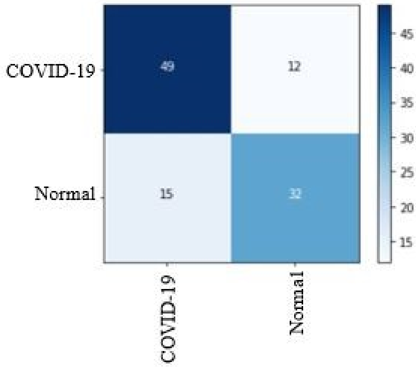
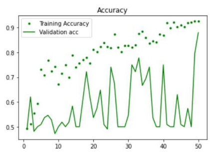
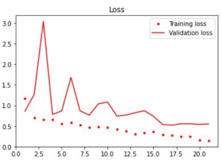


Fig. 10: Confusion Matrix for Custom CNN for binary classification on image data.



(a) Accuracy



(b) Loss

Fig. 11: Accuracy and loss graph for modified ResNet-50 model for binary classification using image data and non-Image Data..

5.5.1 Classification of CXR image with metadata using modified ResNet- 50 model

The Accuracy and Loss graph,confusion matrix and performance of ResNet-50 based model over CXR image and metadata are shown in Figure 11,Figure 12 and Table 3 respectively.

Accuracy: 88 %

Classes	Precision	Sensitivity/Recall	F1-Score
COVID-19	0.86	0.56	0.67
Normal	0.67	0.91	0.77

Table 3: Performance of modified ResNet-50 based model for binary classification using image data and non-Image Data

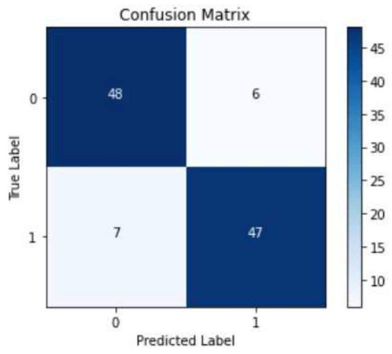
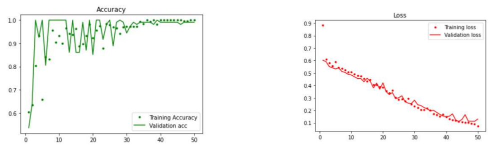


Fig. 12: Confusion Matrix for modified ResNet-50 model for binary classification using image data and non-Image Data.



(a) Accuracy (b) Loss

Fig. 13: Accuracy and loss graph for Modified Custom-CNN based model for binary classification using image data and non-Image Data.

5.5.2 Classification of CXR image with metadata using modified custom CNN model

The Accuracy and Loss graph,confusion matrix and performance of modified Custom CNN model over CXR image and metadata are shown in Figure 13,14 and table 4 respectively.

Accuracy 99.07%

5.6 Performance analysis

From Table 5 we can conclude that all the CNN models archives better results if they take metadata along with CXR images

Classes	Precision	Sensitivity/Recall	F1-Score
COVID-19	.98	1	.99
Normal	1	.99	.98

Table 4: Performance of modified custom CNN model for binary classification using image data and non-Image Data

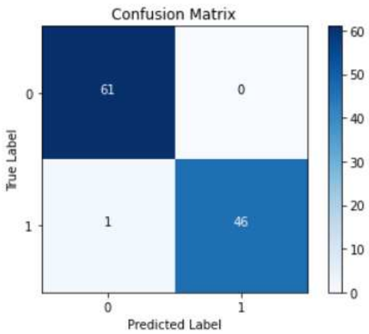


Fig. 14: Confusion Matrix for modified custom CNN based model for classification using image data and non-Image Data.

Model	Accuracy(%)	Specification
DenseNet-121	72	On CXR with out metadata
ResNet-50	66	On CXR with out metadata
MobileNet	74	On CXR with out metadata
VGG16	60.93	On CXR with out metadatay
Custom CNN	75	On CXR with out metadata
InceptionV3	68	On CXR with out metadata
Modified DenseNet-121 model	80	On CXR image along with metadata
Modified ResNet-50 model	88	On CXR image along with metadata
Modified MobileNet model	77	On CXR image along with metadata
Modified VGG16 model	66.48	On CXR image along with metadata
Modified Custom CNN model	99.07	On CXR image along with metadata
Modified InceptionV3 model	79	On CXR image along with metadata

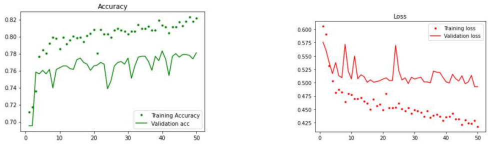
Table 5: Performance comparison of different model with different specifications

5.7 Comparison with state of art model

We have compaired our best model(modified custom CNN based model) with some state of art models.All State of Art models have been run on our dataset.From Table 5 we can see that our modified custom CNN based model performs better than all the mentioned state of Art models .

Model	Type	Precision	Recall	F1-score	Accuracy
CoroNet[16]	Covid 19	0.7	0.93	0.83	76
CoroNet[16]	Normal	0.89	0.58	0.7	
ResNet 50-transfer learning[8]	Covid 19	0.96	0.85	0.90	91
ResNet 50-transfer learning[8]	Normal	0.86	0.96	0.91	
Xception and ResNet50V2[17]	Covid 19	0.87	0.73	0.79	81
Xception and ResNet50V2[17]	Normal	0.76	0.89	0.82	
Modified Custom CNN Model	Covid 19	0.98	1	0.99	99.07
Modified Custom CNN Model	Normal	1	0.99	0.98	

Fig. 15: Comparison with state of art model.



(a) Accuracy (b) Loss

Fig. 16: Accuracy and loss graph for Custom-CNN model for binary classification using image data on larger dataset..

Classes	Precision	Sensitivity/Recall	F1-Score
Infiltration	0.71	0.42	0.53
No Findings	0.78	0.93	0.85

Table 6: Performance of custom CNN based model on Larger CXR dataset using image only

5.8 Validation with large dataset

We have performed the same experiment using the best model(custom CNN based model) over a larger dataset taking CXR images only followed by CXR image with metadata

5.8.1 Validation with large dataset taking CXR image only

The Accuracy and Loss graph,confusion matrix and performance of modified Custom CNN model over Larger data set are shown in Figure 16,Figure 17 and Table 6 respectively.

Accuracy: 77.16%

5.8.2 Validation using CXR images with metadata

The Accuracy and Loss graph,confusion matrix and performance of modified custom CNN based model over larger dataset with metadata are shown in Figure 18, Figure 19 and Table 7 respectively.

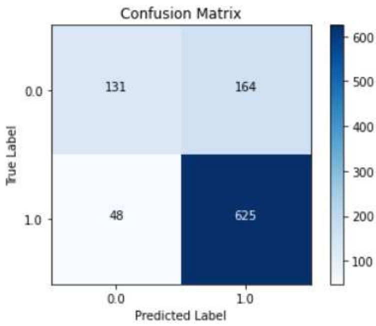
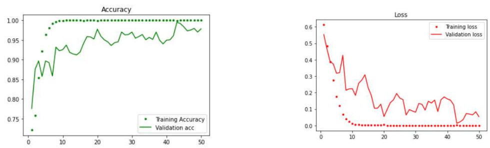


Fig. 17: Confusion Matrix for custom-CNN based model for classification using image data on larger Dataset.



(a) Accuracy (b) Loss

Fig. 18: Accuracy and loss graph of modified custom CNN based model for binary classification using image dataand metadata on larger dataset

Classes	Precision	Sensitivity/Recall	F1-Score
Infiltration	.99	.94	.96
No Findings	.97	1.00	.98

Table 7: Performance of modified custom CNN model on Larger CXR dataset with metadata.

Accuracy observed 98%

6 Conclusion

At present Covid19 pandemic has become a thread for mankind.Same can be controlled more efficiently if we can conduct automatic test of Covid19 which can provide the results quickly and accurately.In this paper we focused on increasing the accuracy of the automatic covid19 test by considering the available metadata like Age ,Gender of the patient and the view angle of the CXR images along with the CXR images.Form Table 5 it is clear that all the CNN model provides best accuracy if we consider metadata along with CXR image. The performance of our proposed CNN model for binary classification of Covid

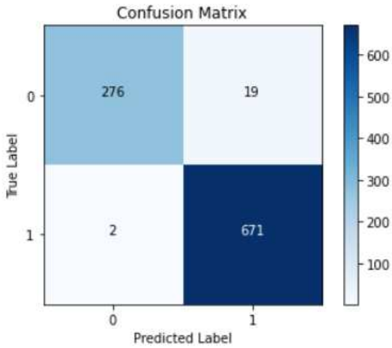


Fig. 19: Confusion matrix of modified custom CNN model for classification using CXR image and Metadata on larger Dataset.

19 detection is the best as compared to other sate of art CNN models.Table6 and table 7 show the performance of our best model that is modified custom CNN based model with another larger data set which also established the fact that if we consider the metadata along with the CXR image,the accuracy of the classification will increase.The model can be experimented on larger dataset with more metadata or clinical data like Diabetics,blood pressure etc which have deep impact on Covid19 once the CXR images with all the comorbidities are available.

Conflict of interest: The authors declare no conflict of interest.

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