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Covi-Assist: Automatic COVID-19 Detection from Chest X-Rays

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Abstract: The spike in the number of patients with COVID-19, a respiratory virus, has put an unprecedented load over healthcare systems across the world. The early and automatic diagnosis of COVID-19 may be beneficial for countries for timely referral of patients to quarantine, rapid intubation of serious cases in specialized hospitals, and monitoring of the spread of the disease. In this work, we propose the use of chest X-Ray to detect COVID-19 infection in patients by studying the medical images and identifying possible patterns that may lead to the automatic diagnosis of the disease. This work's main contribution is proposing a deep neural network-based model for highly accurate detection of COVID-19 infection from chest X-ray images.
Keywords: COVID-19, Convolutional Neural Network, Deep Learning, Transfer Learning, Computer-aided detection tool.

I. INTRODUCTION

COVID-19 has a devastating effect on the health and well-being of the global population, caused by the infection of individuals by the severe acute respiratory syndrome Coronavirus (SARS-CoV-2). A critical step in the fight against COVID-19 is an effective screening of infected patients, such that those infected can receive immediate treatment and care, as well as be isolated to mitigate the spread of the virus. Detection of COVID-19 involves the RT-PCR test, which is a real-time reverse transcription polymerase chain reaction (rRT-PCR) test for the qualitative detection of nucleic acid from SARS-CoV-2 in upper and lower respiratory specimens (such as nasopharyngeal or oropharyngeal swabs, sputum, lower respiratory tract aspirates, bronchoalveolar lavage, and nasopharyngeal wash/aspirate) collected from individuals suspected of COVID-19 by their healthcare provider (HCP), as well as upper respiratory specimens (such as nasopharyngeal or oropharyngeal swabs, nasal swabs, or mid-turbine swabs) collected from any individual, including for testing of individuals without symptoms or other reasons to suspect COVID-19 infection. This test is also for use with individual nasal swab specimens that are self-collected. Antigen Test is a COVID-19 detection test that detects the presence of certain proteins that are part of the virus. But the existing approach has several drawbacks, it is difficult to identify the disease which requires the need of experienced Radiologists, and is expensive. With limited testing kits, it is impossible for every patient with respiratory illness to be tested using conventional techniques like RT-PCR (Reverse Transcription Polymerase Chain Reaction). The tests also have a long turnaround time and limited sensitivity. Detecting possible COVID-19 infections on Chest X-Ray may help quarantine high-risk patients while test results are awaited. In this work, we propose the use of chest X-Ray to prioritize the selection of patients for further RT-PCR testing. This may be useful in an in-patient setting where the present systems are struggling to decide whether to keep the patient in the ward along with other patients or isolate them in COVID-19 areas. It would also help in identifying patients with a high likelihood of COVID with a false negative RT-PCR who would need repeat testing. Developing a Computer Aided Detection (CAD) tool for iterative Covid-19 detection, along with an adequate description of its forming techniques which includes feature selection, extraction, and classification. It takes a chest X-Ray image as input and outputs a prediction range among two classes: Normal/COVID-19 negative and COVID-19 positive using the novel Deep Neural Network based model. This proposed approach has numerous advantages, X-Ray images are much more widespread and cost-effective, and the Transfer of digital X-Ray images does not require any transportation from the point of acquisition to the point of analysis, thus making the diagnostic process extremely quick and unlike CT Scans, portable X-Ray machines also enable testing within an isolation ward itself, hence reducing the requirement of additional Personal Protective Equipment (PPE), an extremely scarce and valuable resource in this scenario. Meanwhile, this strategy also reduces the risk of hospital-acquired infection for the patients.

II. LITERATURE SURVEY

Various Deep Learning based approaches have been developed to identify different thoracic diseases, including CheXNet[1] is one of them, which is built to detect pneumonia from chest X-Rays at a level exceeding practicing radiologists.

CheXnet is trained on ChestX-ray14, which is the largest publicly available chest X-ray dataset, and it gives better performance than previous approaches and has a simpler architecture.CheXNet is a 121-layer DenseNet-based model trained on the ChestXray14 dataset consisting of 112,120 frontal-view chest X-Ray images. The model is trained to classify X-Ray images into 14 different thoracic disease classes, including pneumonia. Given the visual similarity of the input samples, we found this to be the closest trained backbone to develop a model for identifying COVID-19 pneumonia. Apostolopoulos and Mpesiana[2] performed one of the first studies on COVID-19 detection using X-ray images. In their study, they considered transfer learning using pre-trained networks such as VGG19, MobileNet V2, inception, Xception, and Inception ResNet V2, which are the most frequently used.

Several evaluation metrics were used to evaluate the results obtained from two different datasets. MobileNet V2 and VGG19 achieved 97.40% and 98.75% accuracy, respectively, for two class experiments (COVID-19/Normal and COVID-19/Pneumonia) and 92.85% and 93.48% for three class experiments (COVID-19/Pneumonia/Normal). The final conclusion was made by the authors using the obtained confusion matrices, not the accuracy results because of the imbalanced data. A work in European Journal[3]. Uses a Convolutional Neural Network (CNN) model has been used to identify Covid-19 patients with the help of CT scan images. There are several more research works to detect the presence of the Covid-19 virus in the human lungs with the help of CT scans. In CT Image Segmentation[4], a multitask, self-supervised AI model has been developed for the diagnosis of the COVID-19 virus in human lungs with the help of CT scan images, with an accuracy of 89%.

A model using Artificial Intelligence[5] describes a fully automatic framework to detect affected lungs from Chest CT scan images and differentiated it from other lung diseases. However, Radiologic Findings[6] and Clinical Features[7] have concluded that CXR images are better than any other means in the detection of COVID-19 because of their promising results along with the availability of CXR machines and their low maintenance cost. The Survey findings are as follows, we found that Deep learning techniques can reveal image features, which are not apparent in the original images, Specifically, using Convolutional Neural Network(CNN) approaches for the detection of COVID-19 can provide promising results from several recent studies. It can be extensively utilized for image classification. The hierarchical structure and efficient feature extraction characteristics from an image make CNN a dynamic model for image classification. These approaches were tested on a small dataset. However, these need to be verified on a large dataset. The small sample size of COVID-19 images might result in a biased conclusion. Some groups have modified or fine-tuned the pre-trained networks to achieve better performance, while some groups use capsule networks. From the study, we also found that the use of chest X-ray images is beneficial over CT of the thorax, considering the amount of diagnostic time consumed.

III. OBJECTIVES AND SCOPE

1) To design and develop a COVID-19 detection system that can help in quick and accurate results.
2) To establish an early screening model to distinguish COVID-19 infected and healthy cases.
3) To overcome the problem of lack of specialized physicians in remote villages
4) To build a real-time placation useful for doctors, patients, and the rest of the world.

IV. METHODOLOGY

The whole system consists of two users, Admins/Radiologists, and Staff/Users. Admins have certain privileges such as adding new admins, and staff and uploading the chest x-ray images for prediction. Staff on the other hand can log in through the credentials provided to them by the admins and can retrieve the results stored in the database to communicate with the patients. The developed service ensures economic feasibility, which results in a low-cost setup aiming for high reach.

A. Control Flow Outline

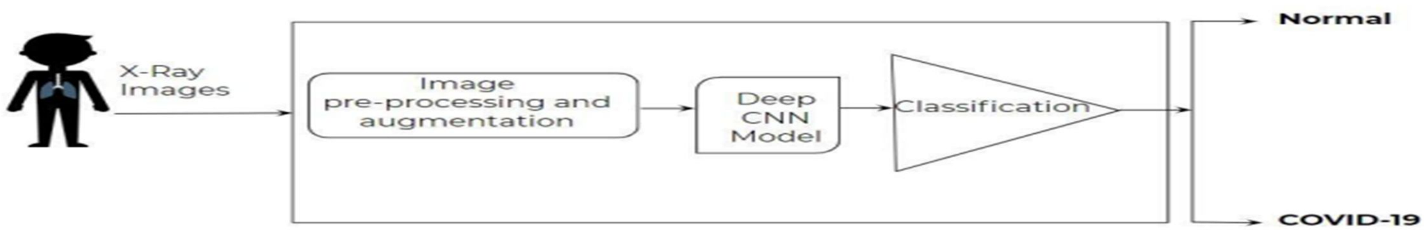

Fig. 1 Outline Overview

The raw x-ray images are pre-processed and augmented before giving it as input to the CNN model. The deeply trained CNN model takes pre-processing images as input and outputs a prediction among two classes: COVID-19 Positive and Normal.

B. Activity diagrams

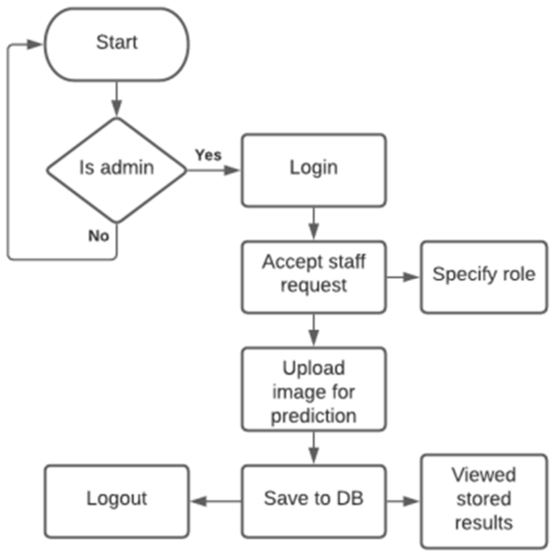

Fig. 2 For Admins

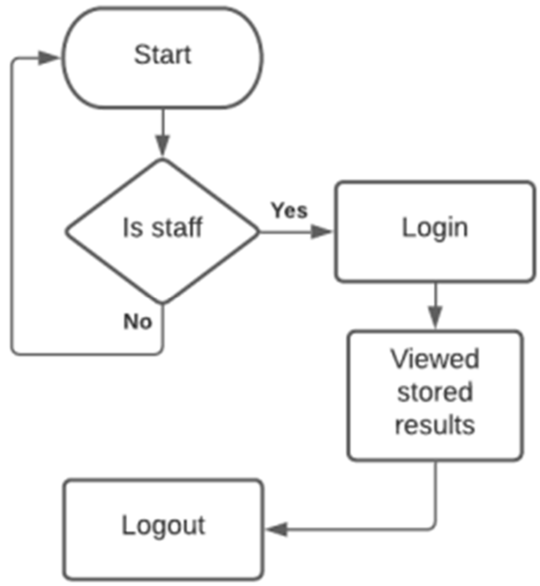

Fig. 3 For Staffs

C. Preprocessing and Pattern Recognition

For identifying possible patterns in the chest x-ray images that may lead to the automatic diagnosis of the disease, we make use of CNN. Instead of preprocessing the data to derive features like textures and shapes, a CNN takes just the image's raw pixel data as input and learns how to extract these features and ultimately infer what object they constitute. This allows for emphasizing the relevant features. To start, the CNN receives an input feature map: a three-dimensional matrix where the size of the first two dimensions corresponds to the length and width of the images in pixels. The size of the third dimension is 3 (corresponding to the 3 channels of a color image: red, green, and blue). The CNN comprises a stack of modules, each of which performs three operations. A convolution extracts tiles of the input feature map and applies filters to them to compute new features, producing an output feature map, or convolved feature (which may have a different size and depth than the input feature map). During a convolution, the filters (matrices the same size as the tile size) effectively slide over the input feature map's grid horizontally and vertically, one pixel at a time, extracting each corresponding tile's output feature map (3x3) is smaller than the input feature map (5x5). If you instead want the output feature map to have the same dimensions as the input feature map, you can add padding (blank rows/columns with all-zero values) to each side of the input feature map, producing a 7x7 matrix with 5x5 possible locations to extract a 3x3 tile. Essentially, these convolution layers promote weight sharing to examine pixels in kernels and develop visual context to classify images. Unlike Neural Networks (NN) where the weights are independent, CNN's weights are attached to the neighboring pixels to extract features in every part of the image. or each filter-tile pair, the CNN performs element-wise multiplication of the filter matrix and the tile matrix and then sums all the elements of the resulting matrix to get a single value. Each of these resulting values for every filter-tile pair is then output in the convolved feature matrix. During training, the CNN "learns" the optimal values for the filter matrices that enable it to extract meaningful features (textures, edges, shapes) from the input feature map. As the number of filters (output feature map depth) applied to the input increases, so does the number of features the CNN can extract. However, the tradeoff is that filters compose the majority of resources expended by the CNN, so training time also increases as more filters are added. Additionally, each filter added to the network provides less incremental value than the previous one, so engineers aim to construct networks that use the minimum number of filters needed to extract the features necessary for accurate image classification. CNN uses max pooling to replace output with a max summary to reduce data size and processing time. This allows you to determine features that produce the highest impact and reduces the risk of overfitting. Max pooling operates similarly to convolution. We slide over the feature map and extract tiles of a specified size. For each tile, the maximum value is output to a new feature map, and all other values are discarded. After each convolutional and max pooling operation, we can apply Rectified Linear Unit (ReLU).

The ReLU function mimics our neuron activations on a "big enough stimulus" to introduce nonlinearity for values $x>0$ and returns 0 if it does not meet the condition. This method has been effective to solve diminishing gradients. Weights that are very small will remain at 0 after the ReLU activation function.

CNN applies a Rectified Linear Unit (ReLU) transformation to the convolved feature, in order to introduce nonlinearity into the model. The ReLU function, $F(x)=\max(0,x)$, returns x for all values of $x > 0$ and returns 0 for all values of $x \leq 0$. Finally, we will serve the convolutional and max pooling feature map outputs with a Fully Connected Layer (FCL). We flatten the feature outputs to column vectors and feed-forward it to FCL.

At the end of a convolutional neural network are one or more fully connected layers (when two layers are "fully connected," every node in the first layer is connected to every node in the second layer). Their job is to perform classification based on the features extracted by the convolutions. Typically, the final fully connected layer contains a softmax activation function, which outputs a probability value from 0 to 1 for each of the classification labels the model is trying to predict.

D. CNN Architecture

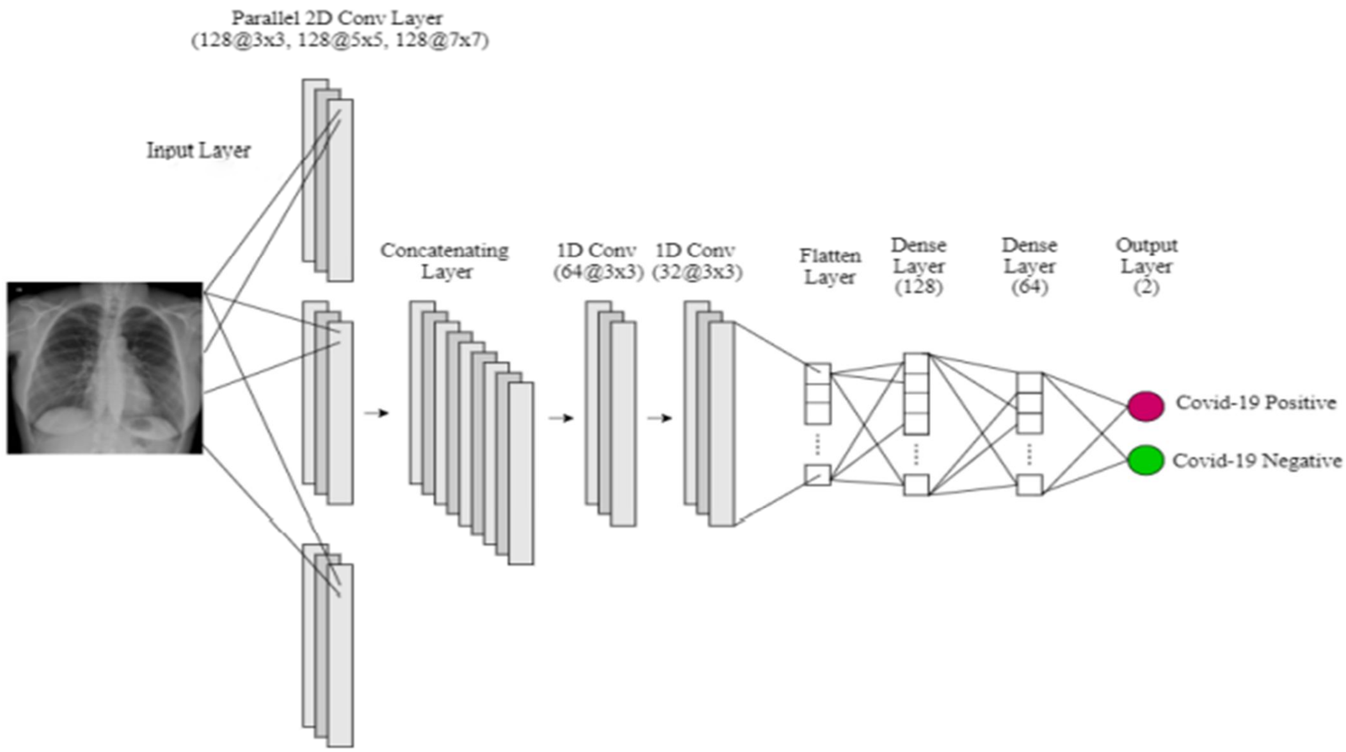

Fig. 4 CNN Architecture for COVID-19 Detection

The X-ray image is fed into the input layer of the CNN. The input layer consists of three 2-Dimensional Convolutional layers in a parallel fashion. Each 2- Dimensional Convolution Layer has 128 filters with 3 x 3, 5 x 5, and 7 x 7 filter sizes respectively. The resulting feature map from these Convolutional layers is then catered into the concatenating layer. The concatenating layer takes the list of tensors as input, all the same shape,s, and returns a single tensor that is the concatenation of all inputs. The resulting tensor passes along two 1-Dimensional layers with 64 and 32 filters with 3 x 3 filter sizes respectively. Then the flattened layer converts the pooled feature map to a single column that is passed to the fully connected layer. The dense layer is a neural network layer that is connected deeply, which means each neuron in the dense layer receives input from all neurons of its previous layer. Here the dense layer consists of 64 and 32 units respectively. The output layer is responsible for producing the final result. The output layer takes in the inputs which are passed in from the layers before it, performs the calculations via its neurons, and then the output is computed among two classes COVID-19 Positive and COVID-19 Negative. The ReLU (Rectified Linear Unit) activation function is widely used in convolutional neural networks (CNNs) because it has been shown to be effective in practice and has several desirable properties. One reason for the popularity of ReLU is its simplicity: it is defined as $f(x) = \max(0, x)$, where x is the input to the activation function.

This means that the output of the activation function is the input itself if the input is positive, and 0 if the input is negative. Another advantage of ReLU is its computational efficiency, as it does not involve any complex operations. It is also easy to implement and does not require any special initialization. Additionally, the ReLU activation function has been found to improve the training speed of a CNN, as it can help the model converge faster. Overall, the ReLU activation function has proven to be a strong performer in many deep-learning models and has become the de facto standard in many cases. While there are other activation functions that can be used in a CNN, such as sigmoid and tanh, ReLU is a good starting point and is often used as a baseline.

E. Achieving Superiority - Transfer Learning

As the use cases become complex, the complexity of the model needs to improve as well. With a few layers of CNN, one could determine simple features to classify dogs and cats. However, at the deep learning stage, one might want to classify more complex objects from images and use more data. Therefore, rather than training them from scratch, transfer learning allows them to leverage existing models to classify quickly. Transfer learning is a technique that reuses an existing model to the current model. We could produce on top of existing models that were carefully designed by experts and trained with millions of pictures. There are a few caveats that need to be followed. First, we need to modify the final layer to match the number of possible classes. Second, we will need to freeze the parameters and set the trained model variables to immutable. This prevents the model from changing significantly. One famous Transfer Learning that one could use is ResNet.A good recommendation when building a model using transfer learning is to first test optimizers to get a low bias and good results in the training set, then look for regularizers if you see overfitting over the validation set. The discussion over using freezing on the pre-trained model continues. It reduces computation time, and reduces overfitting, but lowers accuracy. When the new dataset is very different from the dataset used for training, it may be necessary to use more layers for adjustment. On selecting hyperparameters, it is important for transfer learning to use a low learning rate to take advantage of the weights of the pre-trained model. This choice of the optimizer choice (SGD, Adam, RMSprop) will impact the number of epochs needed to get a successfully trained model.

F. ResNet & ResNet50

Deep convolutional neural networks have led to a series of breakthroughs in image classification. Many other visual recognition tasks have also greatly benefited from very deep models. So, over the years there is a trend to go deeper, to solve more complex tasks, and to also increase /improve the classification/recognition accuracy. But, as we go deeper; the training of neural networks becomes difficult, and the accuracy starts saturating and then degrades also. Residual learning tries to solve both of these problems. In general, in a deep convolutional neural network, several layers are stacked and are trained to the task at hand. The network learns several low/mid/high-level features at the end of its layers. In residual learning, instead of trying to learn some features, we try to learn some residual. Residual can be simply understood as the subtraction of features learned from the input of that layer. ResNet does this using shortcut connection (directly connecting the input of the nth layer to some (n+x)th layer. It has been proved that training this form of network is easier than training simple deep convolutional neural networks, and also the problem of degrading accuracy is resolved.

As per what we have seen so far, increasing the depth should increase the accuracy of the network, as long as overfitting is taken care of. But the problem with increased depth is that the signal required to change the weights, which arises from the end of the network by comparing ground truth and prediction, becomes very small at the earlier layers, because of increased depth. It essentially means that earlier layers are almost negligible learned. This is called the vanishing gradient. The second problem with training the deeper networks is, performing the optimization on huge parameter space and therefore naively adding the layers, leading to higher training error. Residual networks allow the training of such deep networks by constructing the network through modules called residual models. ResNet50 is a variant of the ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8 x 10^9 Floating points operations. It is a widely used ResNet model, and we have explored ResNet50 architecture in depth.

As we know Deep Convolutional neural networks are really great at identifying low, mid, and high-level features from the images, and stacking more layers generally gives us better accuracy, so a question arises that is getting better model performance as easy as stacking more layers? With this question arises the problem of vanishing/exploding gradients those problems were largely handled in many ways and enabled networks with tens of layers to converge but when deep neural networks start to converge we see another problem of the accuracy getting saturated and then degrading rapidly and this was not caused by overfitting as one may guess and adding more layers to a suitable deep model just increased the training error.

G. Dataset

Chest X-ray data have been found to be very promising for assessing COVID-19 patients, especially for resolving emergency-department and urgent-care-center overcapacity.For the purpose of the experiments, several sources of

X-rays were accessed. A team of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh along with their collaborators from Pakistan and Malaysia in collaboration with medical doctors have created a database of chest X-ray images for COVID-19 positive cases along with Normal and Viral Pneumonia images. This COVID-19, normal, and other lung infection dataset is released in stages. In the first release, we have released 219 COVID-19, 1341 normal, and 1345 viral pneumonia chest X-ray (CXR) images[9].

H. The Tool

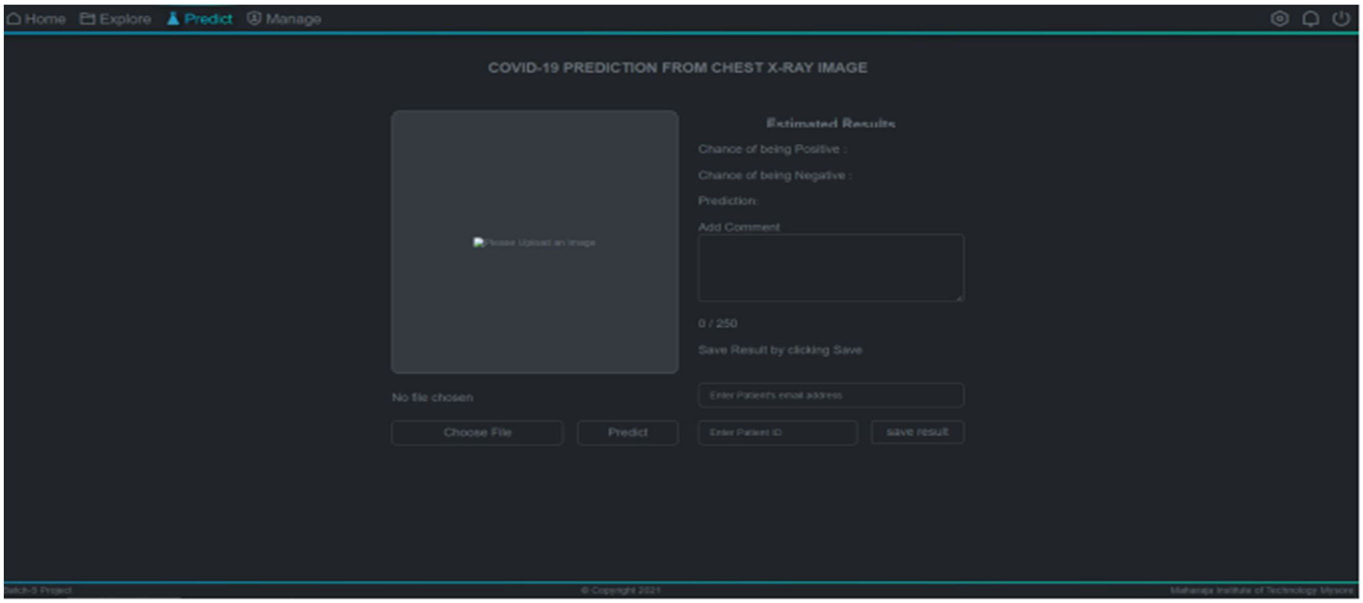

Fig. 5 Prediction Panel for uploading X-ray images.

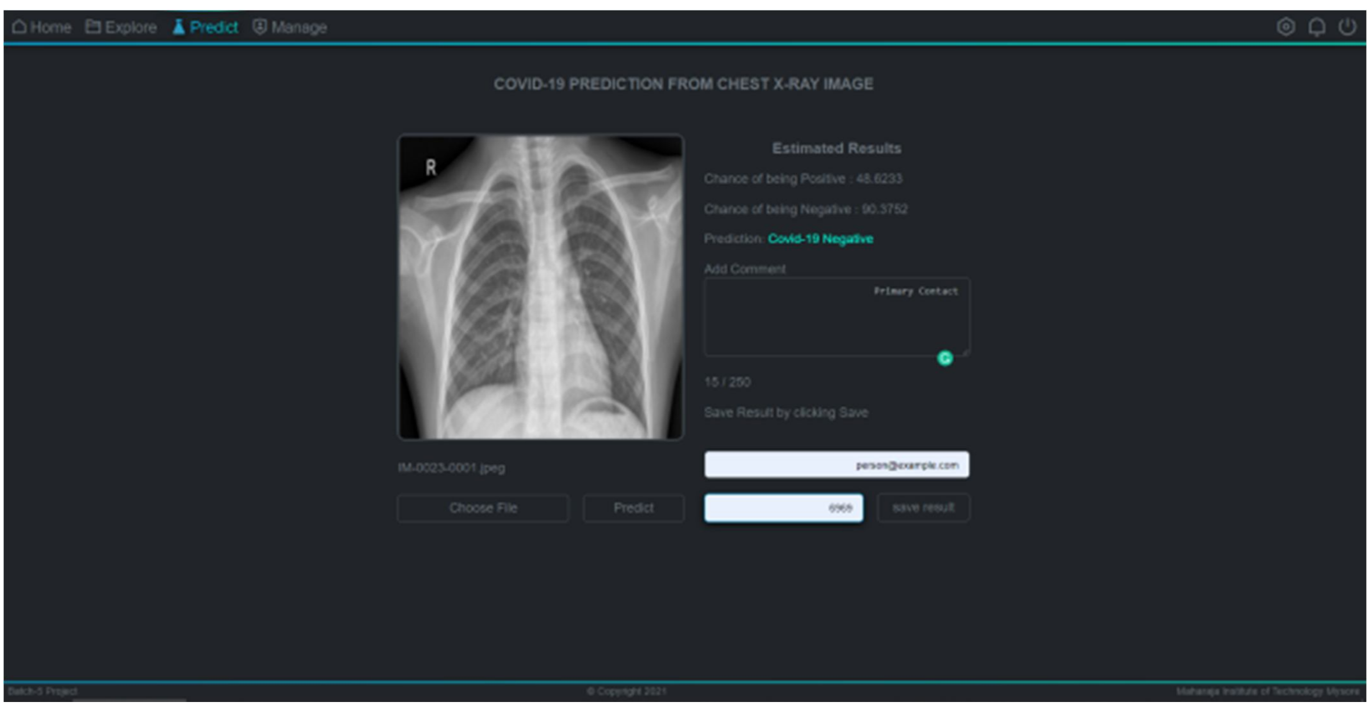

Fig. 6 Prediction Results

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Fig. 7 Explore Panel, to view and manipulate stored results.

V. EXPERIMENTS AND RESULTS

The first model trained with 3 convolutional layers were able to achieve 89% of accuracy. However, it had some flaws. It misclassified some images into the wrong class. We made use of a technique called transfer learning. Transfer learning is a technique that reuses an existing model to the current model. We could produce on top of existing models that were carefully designed by experts and trained with millions of pictures. One famous Transfer Learning we could use is ResNet. By using ResNet50, we were able to achieve 91% accuracy with less misclassification. The main aim of our project is to develop a cost-efficient and time-saving screening method for COVID-19 detection.

Evaluating the performance of this CNN is crucial in determining the accuracy and reliability of the model for predicting COVID-19 using chest X-rays. There are several metrics that can be employed to assess the performance of CNN in this context. One metric commonly used to evaluate the performance of a CNN is classification accuracy, which is the percentage of correct predictions made by the model. This can be calculated by comparing the predicted labels to the ground truth labels and counting the number of correct predictions. However, it is essential to note that classification accuracy can be misleading if the dataset is imbalanced, as the model may achieve high accuracy by simply predicting the majority class. Another metric frequently used to evaluate the performance of a CNN is the confusion matrix, which displays the number of true positive, true negative, false positive, and false negative predictions made by the model. The confusion matrix can be used to calculate other performance metrics such as precision, recall, and F1 score, which are useful for assessing the performance of a classification model. In addition to these metrics, it is essential to consider other factors such as the sensitivity and specificity of the model, which measure the ability of the model to correctly identify positive and negative cases, respectively. It is also advisable to consider the precision-recall curve, which plots the precision of the model against the recall and can provide insight into the trade-off between these two metrics. In conclusion, a combination of these metrics can provide a comprehensive evaluation of the performance of a CNN for detecting viral infection using chest X-rays.

TABLE I
PERFORMANCE EVALUATION

	Results	
	Convolutional Neural Network	Transfer Learning - ResNet50
Train Accuracy	90.18%	91.79%
Test Accuracy	89.03%	91.55%
F1 Score	0.77	0.88
Precision	0.78	0.88
Recall	0.82	0.90

VI. CONCLUSIONS

With limited testing kits, it is impossible for every patient with respiratory illness to be tested using conventional techniques like RT-PCR (Reverse Transcription Polymerase Chain Reaction). The tests also have a long turnaround time and limited sensitivity. Detecting possible COVID-19 infections on Chest X-Ray may help quarantine high-risk patients while test results are awaited. This work presents a deep CNN-based transfer learning approach for the automatic detection of COVID-19. It was observed that ResNet50 outperforms other different deep CNN networks, while image augmentation was used for training the CNN models. Despite the limitations of the current study, which are related to the data availability limitations, it opens the horizons for more specialized research into the possible existence of biomarkers related to the Covid-19 disease in X-ray images. The possible significance of those biomarkers can be confirmed or denied by other feature extraction techniques such as Radiomics in future research. The end product of the proposed work is a web application. In the future, this system can be impregnated into an X-ray machine, so that one can obtain results instantly.

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