A Novel Secured Deep Learning Model for COVID Detection Using Chest X-Rays

Chhaya Gupta[1], Vasima Khan[2], Ramya Srikanteswara[3], Nasib Singh Gill[4], Preeti Gulia[5], Sindhu Menon[6]

[1, 4,5] Department of Computer Science and Applications, Maharshi Dayanand University, Rohtak, Haryana, India

[2] Computer Science & Engineering with Artificial Intelligence and Data Science, Sagar Institute of Science and Technology, Gandhi Nagar Campus, Opposite International Airport, Bhopal (M.P.), 462036

[3] Assistant Professor, Department of CSE, Nitte Meenakshi Institute of Technology

[6] Professor, School of Computing and Information Technology, REVA University, Bangalore, Karnataka, India

Emails: chhaya.rs.dcsa@mdurohtak.ac.in; drvasimakhan88@gmail.com; ramya.srikanteswara@nmit.ac.in; Nasib.gill@mdurohtak.ac.in; preeti@mdurahtak.ac.in; sindhu.menon@reva.edu.in

Corresponding Author: Preeti Gulia, Email: preeti@mdurahtak.ac.in;

Abstract

Automatic detection of a medical disease is a need of the hour as it helps doctors diagnose diseases and provide fast medical reports. COVID-19 is a deadly disease for which an automated detection system may be helpful. This study proposes a unique hybrid deep learning model, COVIDet, based on CNN and the speeded-up robust features (SURF) extraction approach to diagnose COVID-19 using chest x-ray images. SURF is utilized in this work to extract features, and the output is then transferred to a 25-layer CNN for detection using the extracted features. This investigation employed 4623 COVID-19 positive X-ray pictures or 8055 total. The suggested hybrid model also contrasts with the study's VGG19, Resnet50, Inception, Xception, and traditional CNN models. The proposed model had a 98.01% accuracy, a 97.03% F1-score, a 98.65% sensitivity, a 99% precision, and a 95.65% specificity. The proposed model can be further improved when more datasets are available and can help doctors to diagnose patients quickly and efficiently. Using chest X-ray pictures, a secured web application is also developed to identify COVID-19. The user sends the application a chest X-ray image, and in return, it determines whether an individual is COVID-19 positive or not, cutting down on testing time. In Covid times, when people are standing in long queues and waiting for their turns, this application would greatly help. The application uses the pre-trained COVIDet model in the backend.

Keywords: Coronavirus; Chest X-ray; Data Management; VGG19; ResNet 50; Convolutional Neural Network; Inception; Xception

1. Introduction

The coronavirus epidemic has spread globally and placed all the sectors on lockdown. As per the latest information from the World Health Organisation, as of 4th February 2022, 386 million active COVID cases have been recorded, with 5 million deaths [1]. The symptoms—cough, fever, shortness of breath, and acute respiratory syndrome—remain the same. The coronavirus affects the kidneys, liver, respiratory system, and even sometimes the human brain and heart. Usually, lung cancer is diagnosed by a medical professional by observing the disease's indicators and symptoms [2]. COVID-19 affects

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lungs directly by spreading the virus in them. Children have a high immunity, but COVID-19 infected them critically. If this deadly disease can be diagnosed at an early stage, then it helps control transmissibility. RT-PCR (Reverse transcription polymerase chain reaction), which requires sequencing blood samples, is used by the Chinese government to diagnose the ailment [3]. However, RT-PCR is an inefficient technique that takes 5 to 6 hours to complete, is time-consuming, and occasionally fails to produce results when the load is higher than expected. The reports are not accurate and do not come in time, due to which infected people are not detected and infect others and are deprived of receiving the correct treatment on time, which becomes a major cause of death. To attenuate the inefficiency of Covid-19 tests, many efforts have been made to propose alternative tests. The second method for diagnosing Covid-19 involves viewing infected people's chest X-rays and CT scans. Visualizing chest X-rays and CT scans is a critical step in assessing COVID-19, according to earlier studies [4].

Using X-ray imaging, many researchers have proposed and implemented various techniques to identify Covid-19 patients. Machine Learning, Deep Learning, and Computer Vision have been used to diagnose various diseases, ensuring smart healthcare. Deep learning helped detect X-ray bone suppression, prostate segmentation, skin lesions, and myocardium in coronary CT scans. The research aims to demonstrate a deep learning model that, by combining SURF, CNN, and LSTM techniques, can automatically identify COVID-19 from chest X-ray pictures. The research also proposes a secured web application using Flask to recognize COVID-19 in chest X-ray images. To extract characteristics and categorize COVID-19, the suggested hybrid model uses CNN and Surf. The dataset used for this research was pre-processed to remove noise from the COVID-19 Radiography dataset on Kaggle [5]-[6]. The main objectives and contributions are summarised below:

- The creation of a hybrid CNN-SURF model enables an accurate early detection of patients with Covid-19.
- From the gathered dataset, 8055 chest X-ray pictures were created, and noise was removed during pre-processing.
- The suggested hybrid model is contrasted with several different models applied to chest X-ray datasets.
- The performance of the new model and the current models is evaluated thoroughly, considering the F1-score, sensitivity, specificity, accuracy, confusion matrix, and ROC curves.
- A secured web application has been created to assist in identifying COVID-19 in chest X-ray images. The proposed model COVID-19 is employed in the backend to categorize the images and offer the results.

The paper is divided into the following sections: Section 2 summarizes current research on the current state of the art. In Section 3, models used to identify COVID-19 from chest X-ray images are outlined, along with a description of the suggested model, data preparation and collection information, and a description of the Flask-based web application. Section 4 presents experimental results and the contrasting efficacy of the proposed model. Section 5 concludes the essay and considers its potential future scope.

2. Related Work

Researchers have developed several methods for identifying COVID-19 through clinical imaging, CT scans, and chest X-rays. This section describes the recent work conducted in this direction.

Abdulrahman et al. [7] presented a method for analyzing COVID-19 infection and achieved an accuracy of 90%. Mukul et al. [8] analysed chest CT data to identify Covid-19 using VGG16. The Principal Component Analysis (PCA) was applied to extract features. The model's accuracy was 95%. Mandeep Singh Heer et al. [9] presented a study of IoMT (Internet of Medical Things) that controlled the spread of the COVID-19 pandemic. Nur-a-alam et al. [10] profounded a method for detecting COVID-19 from chest X-ray pictures using machine vision. Both the Histogram-oriented Gradient (HOG) approach and the CNN method were used to extract the features before being combined to train the model. The Modified Anisotropic Diffusion Filtering (MADF) approach reduced noise from the retrieved features. The proposed model had a 99.4% accuracy rate, a 95% specificity rate, and a

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93% sensitivity rate. Fairoz Kareem et al. [11] presented a review of medical image classification with the help of CNN and RNN. Nikeetha Noushini et al. [12] presented a survey on IoT-based wearables devices for the COVID-19 pandemic. Al-Wasy et al. [13] introduced an innovative multimodal deep learning system that used Butterworth bandpass filtering Equalisation to eliminate noise from chest X-ray pictures. The proposed COVID-DeepNet model's f1_score, MSE, and accuracy were all 99%. Khder Alakkari et al. [14] introduced an encoder and decoder-based LASTM model for diagnosing COVID-19. The model showed better results when compared with attention LSTM models. Rachna et al. [15] tested various deep learning-based algorithms using a dataset of chest X-ray images that uses the PA perspective, and the model achieved an accuracy of 97%. Khan et al. [16] STM-RENet, a block-based CNN model that makes use of channel boosting and transfer learning techniques, has been suggested. The proposed model had an accuracy of 96.5%. Mousavi et al. [17] describe a method that employs chest X-ray images and the CNN-LSTM model to extract attributes from the raw data. Additionally, the authors added white Gaussian noise to the original data. The model produced more than 90% accuracy in the paper, using 6 separate datasets. Harsh Taneja et al. [18] profounded a model for diagnosing the COVID-19 pandemic in a person with the help of cough sounds. The model achieved an accuracy of 78%. Manjit et al. [19] for overcoming the overfitting and hyperparameter tuning difficulties of other deep learning models, have suggested a metaheuristic-based deep COVID-19 screening model. The AlexNet architecture, which is employed for feature extraction, is the foundation of the suggested model. Haval Hussein et al. [20] introduced two new, lightweight CNN-based deep learning models for early COVID-19 patient recognition from chest x-ray images. The models correctly classified two classes with a 98.5% accuracy rate and three classes with a 96.83% accuracy rate. Isoon et al. [21] merged CNN and RNN, and RNN's fully connected layers were used in place of CNN's. The model had a 93.37% accuracy rate. Nahiduzzaman et al. [22] suggested that ChestX-ray, a lightweight CNN model, can detect many diseases besides COVID-19. The model had a 97.94% accuracy rate. Jawad Khadim et al. [23] suggested a model combining CNN and RNN with a 97.8% accuracy rate. Benbakreti et al. [24] 94.1% accuracy was attained by the model when identifying chest X-rays for COVID-19 using the ResNet 18 architecture. Celestine Iwendi et al. [25] proposed different machine learning models to analyse the open source data of COVID-19 from Mexico and Brazil. The model achieved an accuracy of 93%. Srinivas et el. [26] implemented VGG16 with Inception V3 to diagnose COVID-19 chest X-rays. The model achieved good results. Yunan Wu et al. [27] implemented a novel approach for predicting COVID-19 and the model achieved an accuracy of 76%. The literature research on the detection of Covid-19 highlighted some issues that need to be looked at. The restrictions are mentioned below:

The vast majority of research initiatives have used small datasets with fewer COVID-19 chest X-ray images that are positive. The quantity of the dataset utilized makes it impossible to determine the extent to which the models work in practice. Utilising transfer learning and other methodologies, the research conducted thus far has yielded findings with excellent accuracy utilising the pre-trained models, but little focus has been placed on developing or establishing a novel model from scratch. It is time-consuming and challenging to modify the entire architecture of any pre-trained model by either removing or adding new layers, or even by mixing new layers of two separate models. Rather than using pre-processed photos that would have compromised any pre-trained model's ability to generalise, the majority of research has been conducted on raw photographs. A lot of research has been done and many new algorithms and models have been created but none of them has been provided an application base which can be made available for end users to detect COVID-19. In order to address the issues, a brand-new hybrid model called COVIDet has been put out in this research. It is trained entirely from scratch on a massive and intricate dataset. A web application built on Flask that uses COVIDet in the backend and offers a GUI to detect COVID-19 by chest X-ray pictures has been developed.

3. Models and Materials

The Kaggle Repository was used to acquire the raw pictures, which were then put through a pre-processing pipeline to scale, shuffle, normalize, and supplement the data. The suggested innovative hybrid model COVIDet was trained on the pre-processed data. Various other models like Xception, ResNet50, VGG19, classic CNN, and Inception models are also trained on this dataset. The accuracy, specificity, sensitivity, and F1-score of the suggested model's performance were compared to those of all previously discussed models. It was observed that the suggested model yields superior outcomes.

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A. Dataset Collection

As COVID-19 is a pandemic of recent years with very few datasets available and very little labeled data, hence there is a need to collect data from different repositories. The data in this paper is collected from Kaggle repository [5]. 8055 raw chest X-ray images in total, 4623 are Covid-19 positive images, and the remaining images are standard chest X-ray images. The raw data is split into training and testing sets in an 80/20 ratio after being pre-processed, supplemented, and normalised. As of now, the research has been carried out on a 2-class classification process, but in the future, it may be taken up to 3-class and 4-class classifications also with other diseases chest X-ray scans. The main aim of collecting the data was to create a large dataset that can be used in the future for diagnosing other COVID-19 variants and to distinguish between each one of them. Fig.1 displays the 2-class visualization of the dataset, which includes the first 40 photos of Covid-19 positive cases and the first 40 images of non-Covid cases.

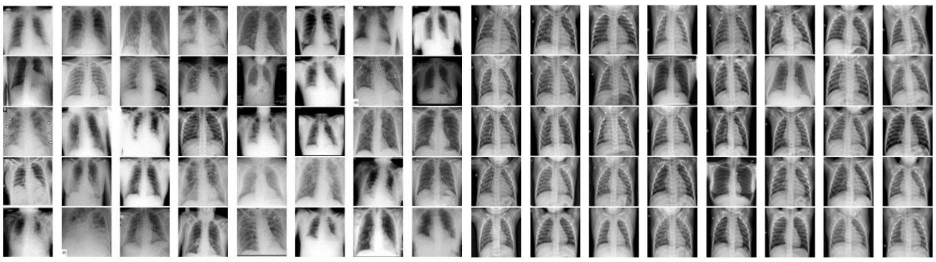

Figure 1: The first 40 Positive and Negative Covid-19 sample images.

B. Data Augmentation

A vast amount of data is needed for thorough training and for enhancing the model's performance because sometimes neural networks overfit a smaller number of samples. Data augmentation performs transformations like rotation, scaling, and reflection on original data to produce data instances. The enlarged X-ray training set enhances the model's robustness and generalization.

C. Evaluation Metrics

The following metrics: accuracy (Ac), sensitivity (Sn), F1 score (F1), and specificity (Sp) have been used to gauge how well the proposed innovative hybrid model is performing:

$$Ac = \frac{True\ Pos + True\ Neg}{True\ Pos + False\ Pos + True\ Neg + False\ Neg} \tag{1}$$

$$Sn = \frac{True\ Pos}{True\ Pos + False\ Neg} \tag{2}$$

$$F1 = \frac{2(True\ Pos)}{2(True\ Pos) + False\ Pos + False\ Neg} \tag{3}$$

$$Sp = \frac{True\ Neg}{True\ Neg + False\ Pos} \tag{4}$$

A confusion matrix is also utilized to describe a model's performance.

D. Models Trained on the Dataset

Different models like Xception, ResNet50, VGG19, classic CNN, and Inception are trained on the collected and pre-processed dataset. The experiment's photos are downsized to 224x224px dimensions because this is the optimal size for neural networks. An ImageDataGenerator is also defined in the

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experiment to train the models at modified versions of an image, such as different angles, flip rotations, or shifts. 32 batches are maintained. The models are detailed here, and attached are the findings.

1. **VGG19**

The model, which has 19 layers and is a version of the VGG, is known as VGG19. There are 19 layers, including 1 layer of SoftMax, 3 fully linked layers, 5 Maxpool layers, and 16 convolutional layers. The VGG model is the replacement for the AlexNet model. It was made by Oxford's Visual Geometry Group. Both fully connected layers and several connected convolutional layers make up the six main components of the VGG CNN. The average number of layers was between 16 and 19. Convolutional layers and activation layers are alternately used in the VGG19 algorithm. The model uses Maxpooling layers for feature extraction and ReLU as an activation function.

When the model was implemented with the current dataset, after 50 epochs, it achieved an accuracy of 94.8%. The trained model was applied to the images from the testing dataset to generate predictions. In the first test image, the trained model made the prediction shown in Fig.2. Fig.4 displays the confusion matrix with Fig.3's classification report for VGG19. Figures 5 and 6 illustrate, respectively, the area under the ROC curve, the VGG19 model accuracy, and the VGG19 model loss.

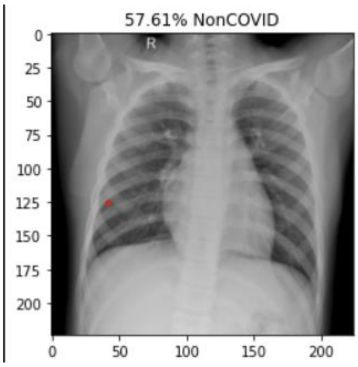

Figure 2: Prediction by VGG19 on 1st test data image.

	precision	recall	f1-score	support
0	0.88	0.93	0.95	154
1	0.93	0.88	0.93	156
accuracy			0.94	310
macro avg	0.93	0.93	0.94	310
weighted avg	0.94	0.93	0.94	310

Figure 3: Classification Report of VGG19 on current dataset.

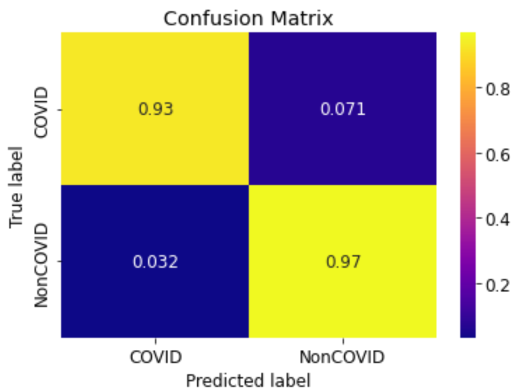

Figure 4: Confusion Matrix of VGG19.

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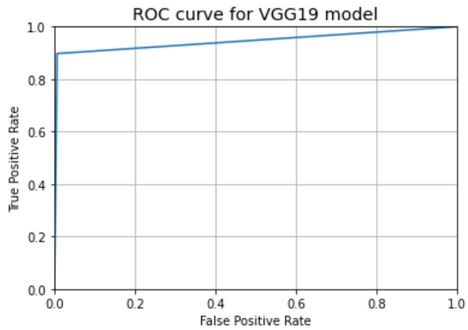

Figure. 5 Area under ROC curve for VGG19.

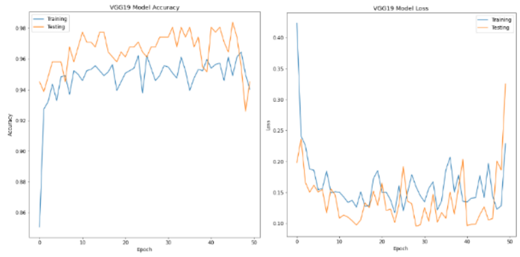

Figure 6: Accuracy and Model Loss for VGG19.

2. **Residual Network 50**

A neural network called Residual Network, often known as ResNet, serves as the foundation for a number of computer vision challenges. ResNet50 had round 152 layers. The layers in ResNet use the concept of skip connection [28]. In order to ensure that the performance of higher levels is compatible with that of lower layers, skip connections are used in the model. ResNet50 comprises five steps. Convolution and identity blocks are present in each stage. Both the blocks are composed of 3 convolutional layers.

When the model was implemented with the current dataset, after 50 epochs, it achieved an accuracy of 94.3%. The trained model was applied to the images from the testing dataset to generate predictions. Fig.7 shows the trained model's prediction on the first test image. Fig.9 shows a confusion matrix, and Fig.8 shows the classification report from ResNet50. Fig. 10 and 11 show the ResNet50 model's accuracy, loss, and area under the ROC curve, respectively.

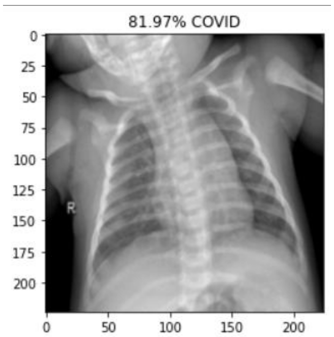

Figure 7: Prediction by ResNet50 on 1st test data image.

	precision	recall	f1-score	support
0	0.93	0.94	0.94	154
1	0.94	0.93	0.94	156
accuracy			0.94	310
macro avg	0.94	0.94	0.94	310
weighted avg	0.94	0.94	0.94	310

Figure 8: Classification report of ResNet50 on current dataset.

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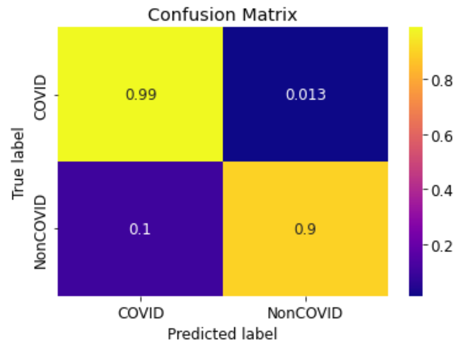

Figure 9: Confusion matrix for ResNet50.

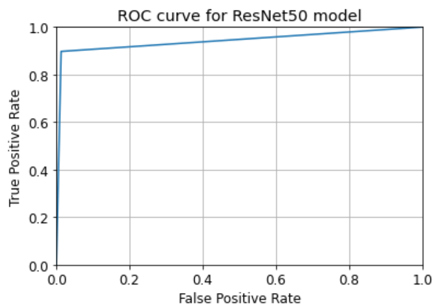

Figure 10: Area under ROC curve for ResNet50.

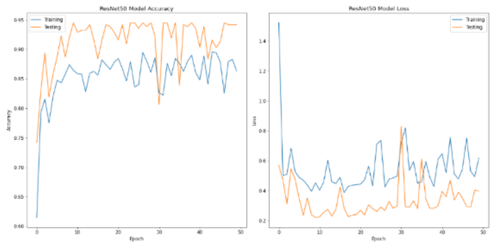

Figure 11: ResNet50 model accuracy and loss.

3. **Inception V3**

To develop CNN classifiers, Inceptions model network was an important milestone achieved. This model uses different tricks in order to boost performance of classic CNN. This model has various versions, and the most popular one is Inception version 3 which has been used on the current dataset. The model comprises of RMSProp optimizer, factorised 7x7 convolutional layers, batch norm classifiers instead of auxiliary classifiers and Label Smoothing technique. Label smoothing is a feature that stops the model from being overconfident about a class, which solves the over-fitting issue [29].

When the model was implemented with the current dataset, after 50 epochs, it achieved an accuracy of 96.1%. The trained model was applied to the images from the testing dataset to generate predictions. In the first test image, the trained model made the prediction shown in Fig.12. Fig. 13 and 14 show the InceptionV3 classification report and the confusion matrix, respectively. Fig. 15 and 16 show the InceptionV3 model's accuracy, loss, and area under the ROC curve, respectively.

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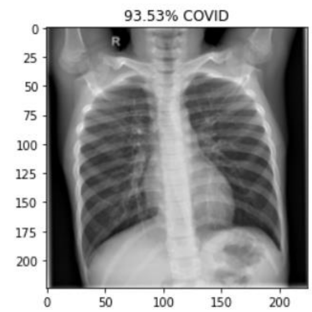

Figure: 12 Prediction by InceptionV3 on 1st test data image.

	precision	recall	f1-score	support
0	0.89	0.99	0.94	154
1	0.99	0.88	0.94	156
accuracy			0.94	310
macro avg	0.94	0.94	0.94	310
weighted avg	0.94	0.94	0.94	310

Figure 13: Classification report of InceptionV3 on current dataset.

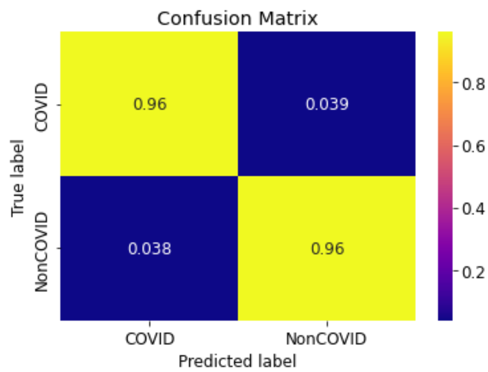

Figure. 14 Confusion matrix for InceptionV3.

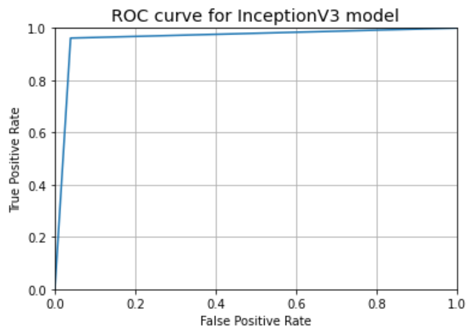

Figure 15: Area under ROC curve for InceptionV3.

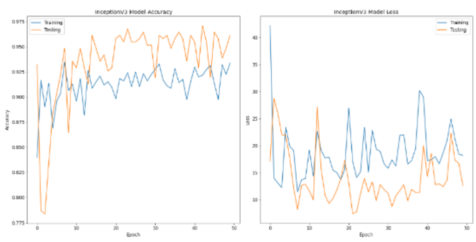

Figure 16: InceptionV3 model accuracy and loss.

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4. **Xception**

Xception refers to Inception in its most severe form. The Xception model is superior to Inception thanks to adding a modified depthwise separable convolution layer. This model adds a 1x1 convolutional layer before any spatial convolutional layer. In inceptionv3, 3x3 spatial convolutional layers were used. This model does not have any intermediate activation function like ReLU.

When the model was implemented with the current dataset, after 50 epochs, it achieved an accuracy of 93.04%. The trained model was applied to the images from the testing dataset to generate predictions. On the basis of the first test image, the trained model generated the prediction shown in Fig.17. Fig. 18 and 19 show the classification report from the Xception model and the confusion matrix, respectively. Figures 20 and 21 show the accuracy of the Xception model, loss, and the area under the ROC curve.

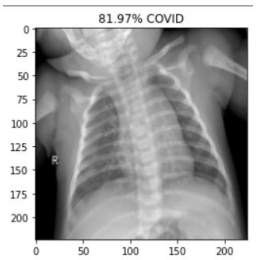

Figure 17: Prediction by Xception on 1st test data image.

	precision	recall	f1-score	support
0	0.98	0.88	0.93	154
1	0.89	0.98	0.94	156
accuracy			0.93	310
macro avg	0.94	0.93	0.93	310
weighted avg	0.94	0.93	0.93	310

Figure 18: Classification report of Xception on current dataset.

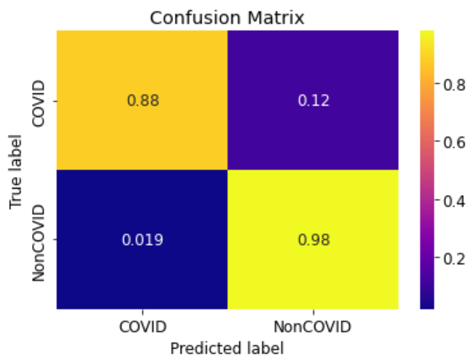

Figure 19: Confusion matrix for Xception model.

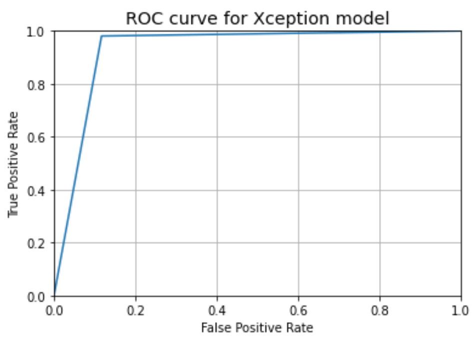

Figure 20: Area under ROC curve for Xception model.

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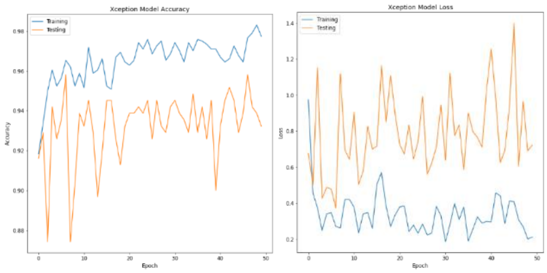

Figure 21: Xception model accuracy and loss

5. **Classic CNN**

These developments have had the greatest impact on computer vision and image processing. This model gives the computer a number array, and it calculates the likelihood that each number in the array belongs to a particular class. It resembles the human brain. To classify images, computers first analyze low-level features like curves and edges before producing high-level features. A classic CNN consists of convolutional layers, activation operation with each convolutional layer, Maxpooling, and fully connected layers.

When the model was implemented with the current dataset, after 50 epochs, it achieved an accuracy of 94.2%. The trained model was applied to the images from the testing dataset to generate predictions. Fig.22 shows the prediction made using the first test image and the trained model. Figures 23 and 24 depict the classification report for the conventional CNN model and the disagreement matrix, respectively. Fig. 25 and 26, respectively, show the ROC curve's area under it, accuracy, and loss for the conventional CNN model.

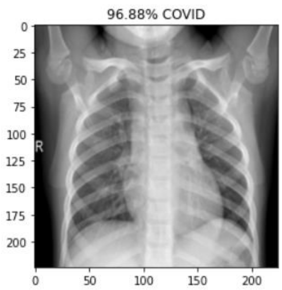

Figure 22: Prediction by Classic CNN on 1st test data image.

	precision	recall	f1-score	support
0	0.93	0.97	0.95	154
1	0.97	0.93	0.95	156
accuracy			0.95	310
macro avg	0.95	0.95	0.95	310
weighted avg	0.95	0.95	0.95	310

Figure 23: Classification report of Classic CNN on current dataset.

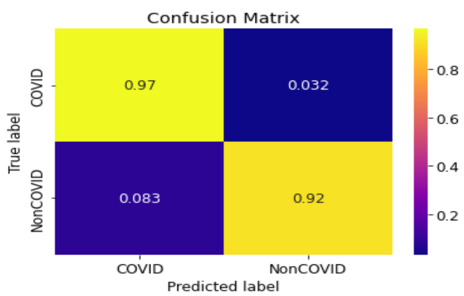

Figure 24: Confusion matrix for Classic CNN.

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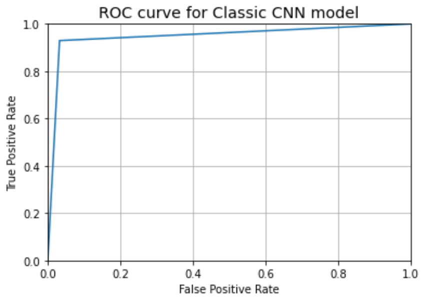

Figure 25: Area under ROC curve for Classic CNN.

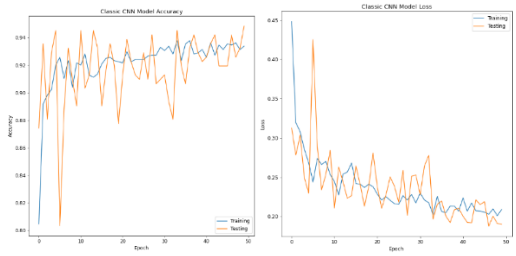

Figure 26: Classic CNN model accuracy and loss.

E. Proposed Model COVIDet and Secured Web Application

This section discusses about the proposed model COVIDet. According to the extensive literature review, researchers have developed various algorithms and models to detect COVID-19, but none of them can be used by the average person. To provide a solution for this problem, the authors in the paper developed a web application using Flask. The web application is user-friendly and provides an easy interface to the end user, which is understandable by a layman, too. In these tough times, when RT-PCR tests are unreliable and time-consuming, this app can greatly help everyone. The complete interface screenshots are provided in this section.

1. COVIDET

A total of 25 layers make up the proposed model, including 11 convolutional layers with 11 Maxpool layers, one flatten layer, and 2 thick layers. Fig.27 depicts the model's whole construction. The batch normalization is used to increase the stability of the model. The cross-entropy loss function is used with the Adam optimizer. The model is built by a series of experiments, repeatedly changing activation functions by adding and removing layers in order to choose the model that delivers the best accuracy. The research began with a 5-layer CNN model with a binary classification accuracy of 82%. After identifying the optimizer and activation function, convolutional layers and Maxpooling layers were added to the model. The optimizers, activation functions, and combination of layers make the model efficient.

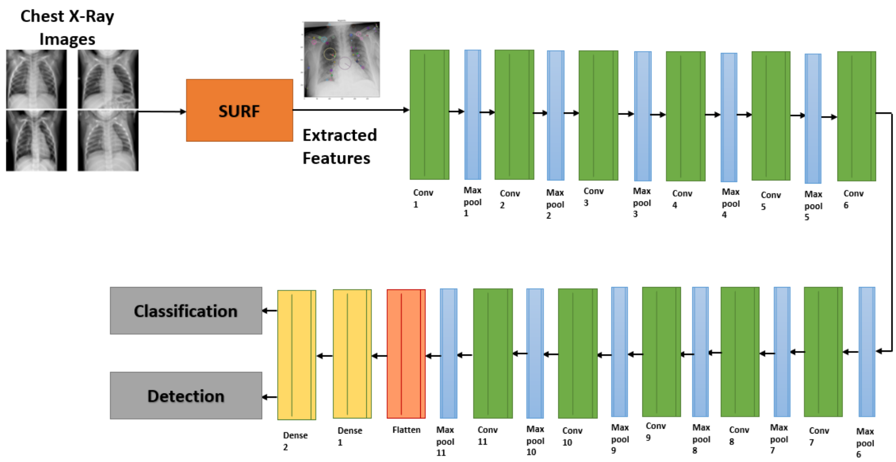

Figure 27: Architecture of proposed model - COVIDet.

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After the model was completed, the SURF approach was incorporated into the model to extract features from the photos efficiently. SURF is a fast and robust technique for feature extraction. SURF is a two-step technique: Feature extraction and feature description. For feature extraction, the technique uses Hessian Matrix as it provides better accuracy. Given a pixel (x,y), hessian of this pixel is like:

$$H\big(f(x,y)\big) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} \tag{5}$$

After the image has been filtered by the Gaussian Kernel, the hessian matrix in x at scale is determined as follows for a given point X=(x, y):

$$H(x,\mu) = \begin{bmatrix} L_{xx}(x,\mu) & L_{xy}(x,\mu) \\ L_{xy}(x,\mu) & L_{yy}(x,\mu) \end{bmatrix} \tag{6}$$

$where\ L_{xx}(x,\mu), L_{xy}(x,\mu), L_{yy}(x,\mu)$ is $convolution$ $of\ Gaussian\ second\ order\ derivative.$

Surf relies on the Hessian Matrix Determinant; to find it, use convolution with a Gaussian kernel and then the second-order derivative. It takes two steps to build an SURF feature description. First, the repeatable orientation is fixed using data from the circular region surrounding the keypoint. Next, a square region is created, aligned to the chosen orientation, and the SURF descriptor is extracted from it. In this research, SURF was implemented using OpenCV in google colaboratory and was merged with CNN. The Fig.28 provides a sample of how SURF is extracting features/keypoints from a sample image. The features are sent to the proposed model and the model classifies them detects Covid-19.

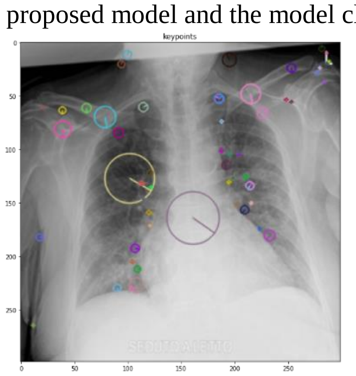

Figure 28: The features/keypoints in an image by SURF technique.

When model was implemented with the current dataset, after 50 epochs, it achieved an accuracy of 98.01%. To generate predictions, the trained model was applied to the images from the testing dataset. The trained model's prediction on the initial test image is shown in Fig. 29. The disagreement matrix is displayed in Fig.30, and Fig.31 displays the classification report for the conventional CNN model. Fig. 32 and 33 show the classic CNN model's accuracy and loss as the area under the ROC curve, respectively.

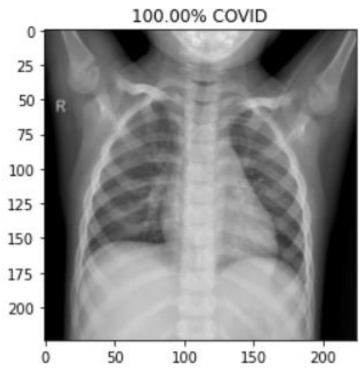

Figure 29: Prediction by COVIDet on 1st test data image.

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	precision	recall	f1-score	support
0	0.96	0.95	0.98	154
1	0.96	0.99	0.97	156
accuracy			0.98	310
macro avg	0.97	0.97	0.97	310
weighted avg	0.97	0.97	0.97	310

Figure 30: Classification report of COVIDet on current dataset.

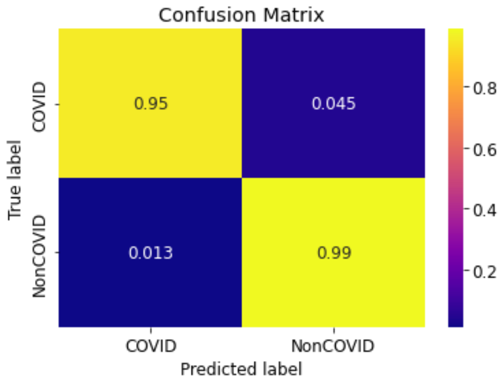

Figure 31: Confusion matrix for COVIDet.

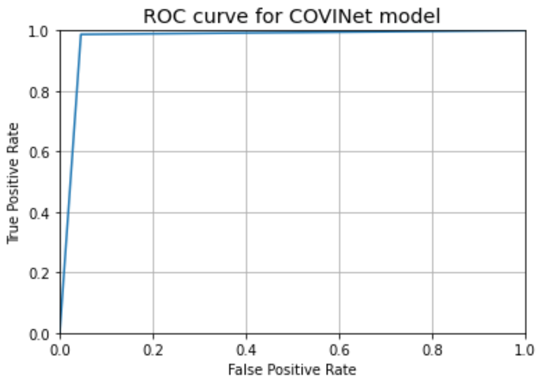

Figure 32: Area under ROC curve for COVIDet.

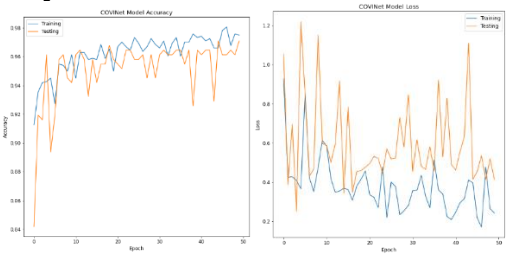

Figure 33: COVIDet model accuracy and loss.

2. Secured Web Application for COVID-19 Prediction Using COVIDet

The proposed unique paradigm was used to construct the secured web application to get beyond the RT-PCR test's drawbacks and provide data management more securely. The test is unreliable and is time-consuming. Many of the infected persons could not get proper medication on time because of hindrances of RT-PCR test. The test takes time to provide medical reports, sometimes 5-6 hours and when load is more than it might take 5-6 days and even after that it cannot be trusted. This paper proposes a secure way for managing data with the help of a web application that anyone may use to determine whether or not they have COVID-19 to get around these restrictions and benefit the community. To check whether a person is COVID-19 positive, the proposed methodology only needs an image of their chest X-ray. Fig.34 displays the application's home page. The application requests the chest X-ray image displayed in Fig.35 when the user presses the "Detect COVID" button in the top right corner.

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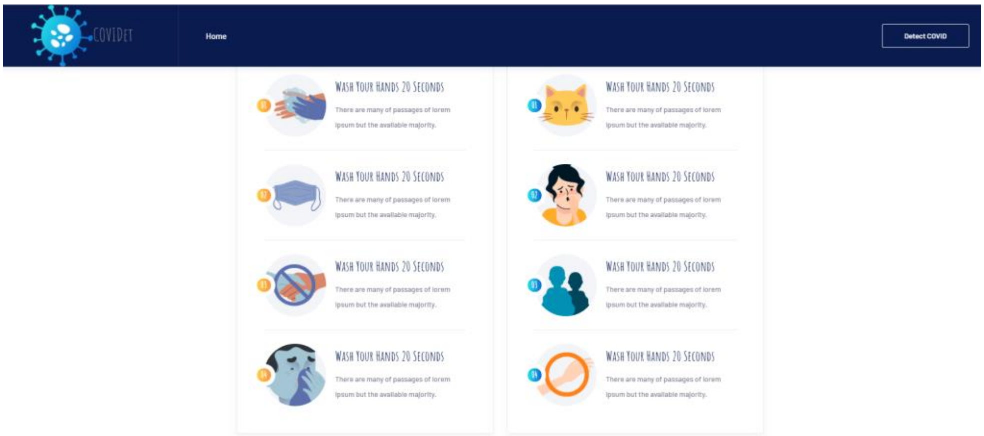

Figure 34: The Front Page of the Web Application.

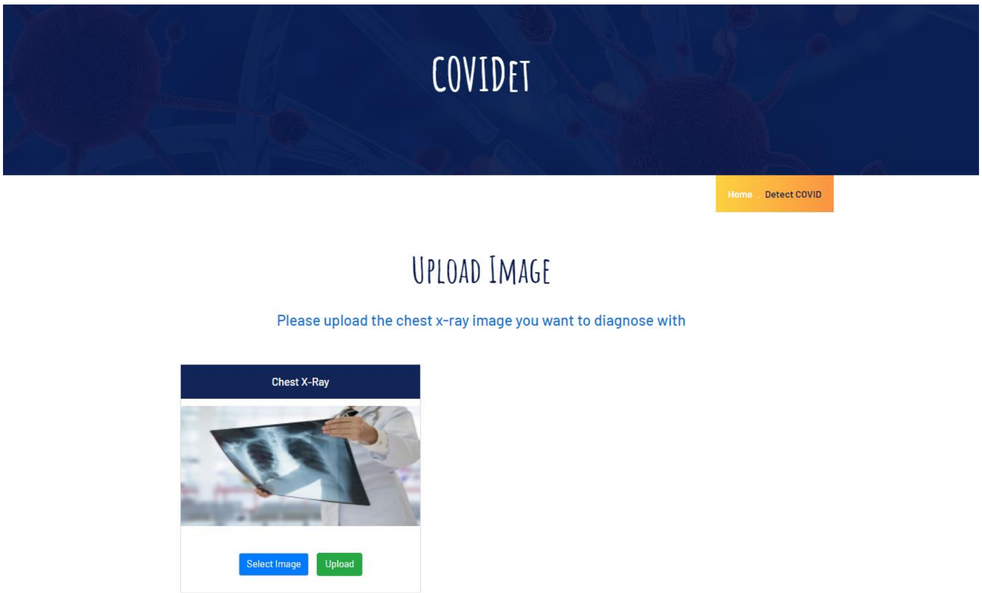

Figure 35: The Application Page for Uploading Image.

The model identifies the image once the user uploads a chest X-ray, then determines whether the person is COVID-positive. Fig.36 and Fig.37 shows a sample for both when the application detects whether a person is COVID-19 positive or not, respectively. The images for testing the application belongs to real COVID-19 data.

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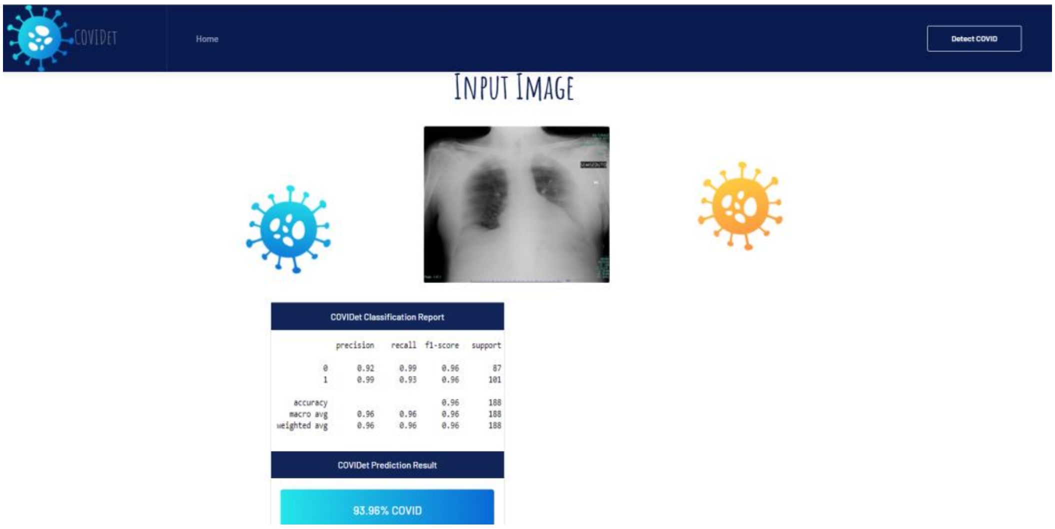

Figure 36: Sample for COVID-19 positive.

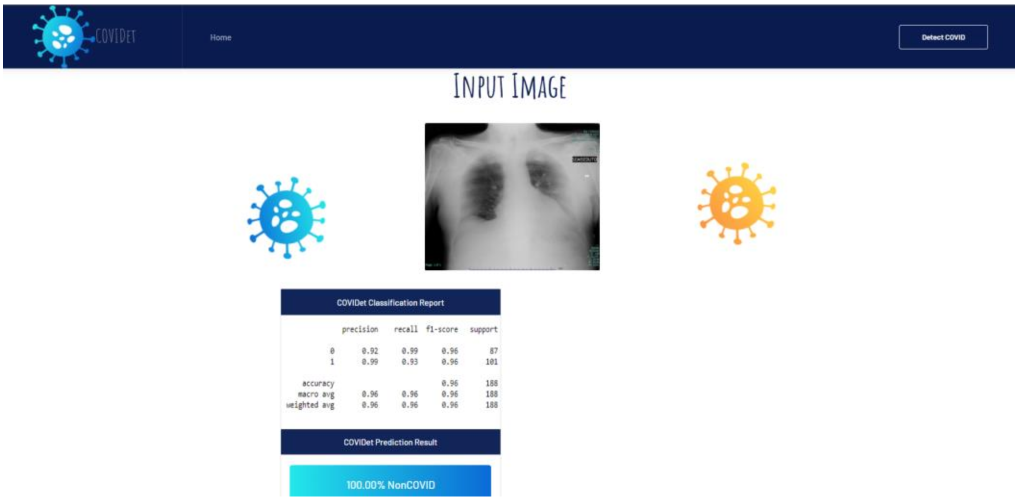

Figure 37: Sample for Non-COVID.

4. Experimental Results and Discussion

To examine the effectiveness of the proposed novel model, accuracy, recall, F1-score, sensitivity, and specificity have been calculated and are shown in fig. 36 with macro and weighted averages. This section discusses the accuracies, F1-scores, sensitivities, specificities, and recalls of all other models, namely, VGG19, ResNet50, InceptionV3, Xception, and Classic CNN, for 2-class classification. All the models have been trained on the current dataset and have provided their respective performance metrices. Table 1 provides a brief overview of the complete experiment in this research.

Table 1: Performance comparison of various models on the current dataset.

Model	Ac(%)	F1-Score(%)	Rec(%)	Prec(%)
VGG19	94.8	94.75	88.1	93.0
ResNet50	94.3	94.6	93.0	93.1

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InceptionV3	96.1	96.1	88.3	89.1
Xception	93.04	92.6	88.2	89.2
Classic CNN	94.2	94.4	93.4	93.5
COVIDet	98.01	97.03	99.1	97.0

The suggested COVIDet model produces superior results than other models when tested against the dataset utilised in this study, as shown in Table 1. Fig.38 provides a graphical representation for different models compared to the current dataset.

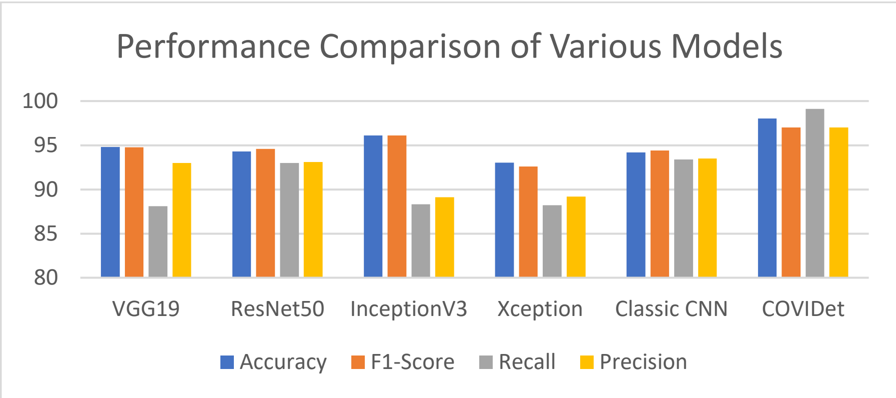

Figure 38: Performance comparison of various models.

5. Conclusion

Globally speaking, COVID-19 has had a detrimental effect. In addition to endangering people's lives, it also affected the world economy. In this study, a novel hybrid method called COVIDet is proposed to detect COVID-19 using chest X-ray pictures. A secured data managing web application is also developed as a potential replacement for RT-PCR tests in these challenging times. This web application may be helpful for every person for detecting COVID-19 with the help of chest X-ray image. RT-PCR tests are not reliable and are time-consuming, so this secure way of managing data can be a boon in these tough times. This work makes use of a big dataset of chest X-ray images. The results reveal that COVIDet obtained accuracy of 98.01%, F1-score of 97.03%, sensitivity of 98.65%, precision of 99%, and specificity of 95.65% when compared to other models, including VGG19, ResNet50, InceptioV3, Xception, and Classic CNN on the collected dataset. In future the model can be expanded to work with CT scan images as well and the web application can also be developed to work with CT scans. Since COVID-19 includes numerous variants, some parameters may need to be modified in the future to account for these variations. While the proposed COVIDet can operate with the current variations, there may be a need to modify them in the future.

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