# Detection of COVID-19 Infection Using Deep Neural Network and Machine Learning Technique

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***Abstract*—In the growing population expansion, automated illness identification is one of the critical subjects in the field of medical. Recently new virus named Coronavirus (COVID-19) has emerged and created a severe threat to lives and the rate of spreading is severe around the world. As the quickest diagnostic alternative, an automatic detection system should be built to detect the virus and restrict the persons to isolation and stop spreading. The objective of the work is to present a deep learning and machine learning approach combined to autonomously recognize the presence of COVID-19 using the chest X-ray images. In this system, Convolution Neural Network (CNN) with MobileNet V2 network and DesNet is used for extraction of features deeply. The extracted features are fed to classifier. The classification is performed using Multilayer Perceptron (MLP) and Support Vector Machine (SVM). The results obtained using CNN-MLP and CNN-SVM is compared. The parameters like Accuracy, F1-score, recall and precision are evaluated. The accuracy using proposed CNN-SVM is 99.18% whereas for CNN-MLP the rate of accuracy is 98.68% using MobileNet-V2. The experimental results are evaluated using Matlab tool.**

***Keywords*—X-ray data, COVID-19, neural networks, Convolution Neural Network (CNN), Support Vector Machine (SVM)**

## I. INTRODUCTION

Recent times the most dangerous virus that has spread across the world is coronavirus which is named as COVID-19. According to the report dated on July 9$^{th}$, 2020 by World Health Organization (WHO) that twelve million people had been infected and deaths around five lakhs [1]. Even in wealthier nations, health-care systems have reached a breaking point due to a scarcity of Intensive-Care Units (ICUs). Many of the infected patients having severe effect and there is adverse need of ICUs. The birth place of coronavirus is Wuhan a city in Hubei and the virus is generated from two separate symptoms, one is Severe Acute Respiratory Syndrome (SARS) and other is Middle East Respiratory Illness (MERS) [2]. Because of this virus high transmissibility, early discovery of the virus is critical for managing it. According to Chinese government recommendations [3], Reverse Transcription-Polymerase Chain Reaction (RT-PCR) is one of the major diagnosing processes for identification of SARS covid by collecting samples from respiratory system.

According to research, medical imaging can help identify viruses that are present in the lungs. Several works have built deep learning-based algorithms to detect pneumonia [4] and other diseases from medical pictures. With very modest design, several of these experiments have shown encouraging outcomes. A Convolutional Neural Network (CNN) model was employed in a study by Singh and Kumar *et al.* [5] to identify humans with COVID-19 using CT scan pictures. There are numerous other studies being conducted to identify COVID-19 in humans with the help of CT scan for lungs, based on the CT score the severity can be evaluated [6].

Li *et al.* [7] provided a completely automated system for detecting coronavirus-affected lungs in chest CT scan pictures and distinguishing them from other lung disorders. However, it stated that chest X-ray pictures are superior to other methods in the identification of virus due to their promising findings, as well as the availability of chest X-ray equipment and their cheap maintenance cost [8, 9].

Alqudah and Qazan *et al.* [10] performed research on two separate approaches, and those methods are utilized to diagnose COVID-19 utilizing the pictures of chest X-ray. Different networks are used in CNN for extraction of features and some of them are AOCTNet, DenseNet, MobileNet, etc. The extracted features from the input pictures are categorized using the classifier and different type of them are CNN-softmax, K-Nearest Neighbour (KNN), Support Vector Machine (SVM), and Random Forest (RF) algorithms. Khan *et al.* [11] used the Xception architecture to identify COVID-19 infection by classifying chest X-ray pictures from normal, bacterial, and viral pneumonia patients. Ghoshal and Tucker [12] employed a Bayesian CNN model based on drop weights to diagnose COVID-19 using images of chest X-ray. Hemdan *et al.* [13] proposed the VGG19 and Dense-Net models for diagnosing COVID-19 using X-ray pictures. The progress

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of studies on X-ray pictures for COVID-19 diagnosis was reported in [14], and the Squeeze-Net model with Bayesian optimization was supported. Cohen *et al.* [15] employed a CNN with VGG16 Network to identify the COVID-19 in human using the CT images as input. Principal Component Analysis (PCA) was used to identify the retrieved features, which were then categorized by four distinct classifiers. With the help of statistical analysis of speech spectrum properties and machine learning-based classification methods, the use of speech as a biological signal for diagnosing COVID-19 is examined [16]. The Decision Forest algorithm's performance is measured by the "recall" metric, which yields a recall value of 0.7892.

For COVID-19, Kogilavani *et al.* [17] offered many deep learning techniques. CNN architectures such VGG16, DeseNet121, MobileNet, NASNet, Xception, and EfficientNet are used in the suggested study. Mir *et al.* [18] presents five machine learning techniques: support vector machine (SVM), decision tree, nave Bayes, logistic regression, and neural network to identify and detect the COVID-19 suspicious in real time. Li and Yu [19] utilized SVM and random forest classifiers to build a model for diagnosis of COVID-19. Rondinella *et al.* [20] used deep learning Res-Net model for identification of COVID-19. COVID-QU-Ex dataset is used by Sapountzakis *et al.* [21] and deep learning is used to evaluated the dataset. Boina *et al.* [22] combine machine learning and deep learning to identify the COVID-19 using X-ray dataset. The work in this paper is outline as,

i. Chest X-ray images are considered and formed into a group of datasets to identify the COVID-19.
ii. Combination of CNN-MLP and CNN-SVM is performed to identify the COVID-19 effectively in early stages.
iii. The networks used in this study are MobileNetV2 and DenseNet201 and the results are compared.

## II. Methodology

In this part, the suggested approach for categorizing an X-ray as belonging to a healthy person or a COVID-19 person. Initially the dataset which is used for evaluating the proposed work need to be gathered. Then the procedure for extraction of features is discussed based on the theory of transfer learning [23]. Following that, discuss about the categorization approaches used as well as the procedures in their training process. Finally, specify the measures that will be used to assess the findings and compare them to other techniques. The suggested technique is depicted as a block diagram in Fig. 1 and each step is detailed in the following subsections.

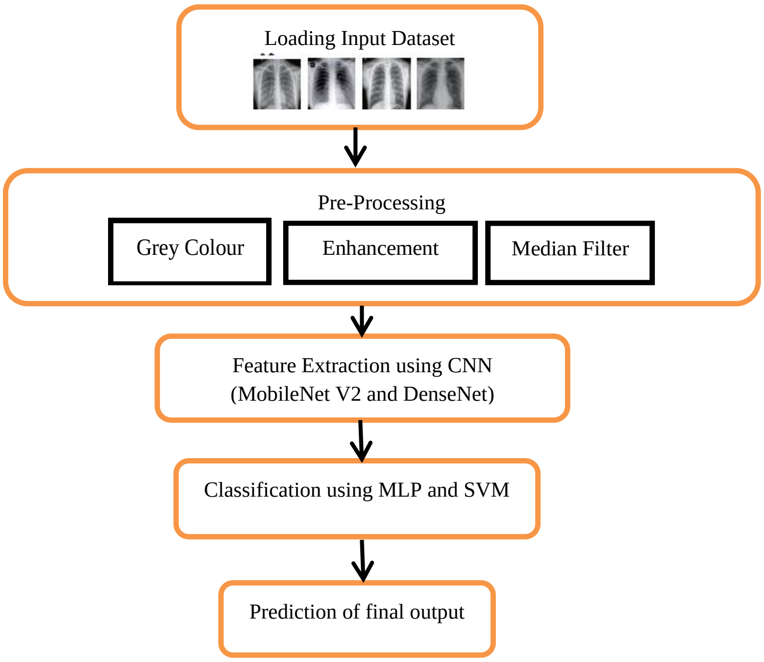



Fig. 1. Block diagram of proposed method.

### *A. Datasets*

Our investigation starts with the images of chest X-ray with frontal view. Only X-ray pictures from the Posterior-Anterior (PA) and Anterior-Posterior (AP) planes were taken. The samples considered are separated into two groups in which one group contains images of X-ray of health people and other group images of X-ray of COVID-19 people. Here a dataset is created to help us in evaluating the suggested technique. The images in database differ for health persons and will remain same for COVID-19 cases. Both the datasets which are health and unhealthy are balanced, with 189 photos of no covid and 426 numbers of images with COVID-19. The images which are used to evaluate the suggested technique were obtained from Ref. [24]. Fig. 2 depicts several example photos.

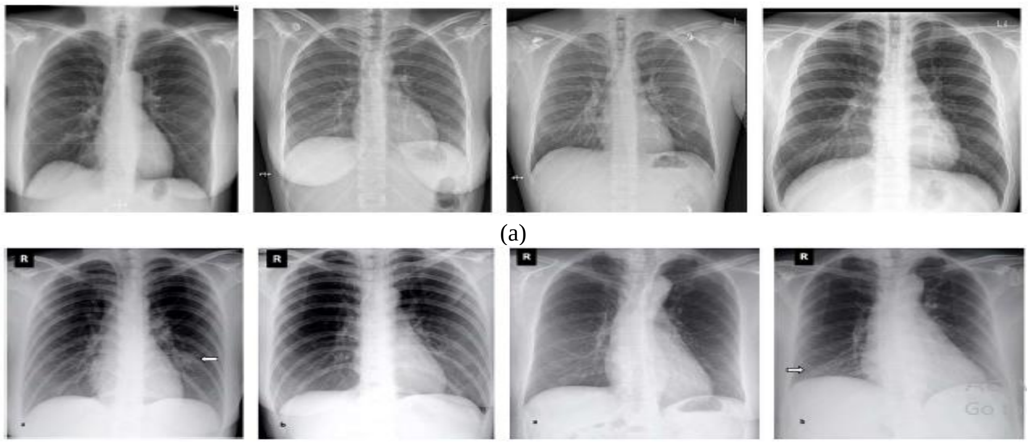



Fig. 2. X-ray images (a) COVID-19 person (b) non-COVID person.

The division and consideration of dataset used for processing the work is shown in Table I.

TABLE I. DATASET CONTRIBUTION FOR THE WORK

| Category | Dataset for Training | Dataset for Validation | Total Dataset |
|---|---|---|---|
| Normal Patients | 821 | 189 | 1010 |
| COVID-19 Patients | 2224 | 426 | 2650 |
| Total | 3045 | 615 | 3660 |

## B. *Pre-processing*

The pre-processing of the data needs to be performed before delivering the images to a pre-trained model. In this the median filter is used to eliminate noise and resize all photos to 224×224×3 pixels in size. The images are enhanced and segmented for better extraction of results. All pictures were standardized using the norms of the pre-trained model.

## C. *Feature Extraction*

For extracting of the features from the input image CNN model is utilized. In this paper, CNN model with MobileNet V2 and DenseNet 201 networks are designed. These networks use the basic model of CNN to identify the best features in identification of COVID-19 and Non COVID-19. The concept of CNN provides effective results in many areas like object identification, classification of images and most efficient in processing of medical images. The fundamental idea behind CNN is extraction of local traits from the highest layer parts and that it can extract local characteristics from high layer inputs and transmit to the layers which are lower for achieving more detailed features. The architecture and the layers present in CNN are shown in Fig. 3.

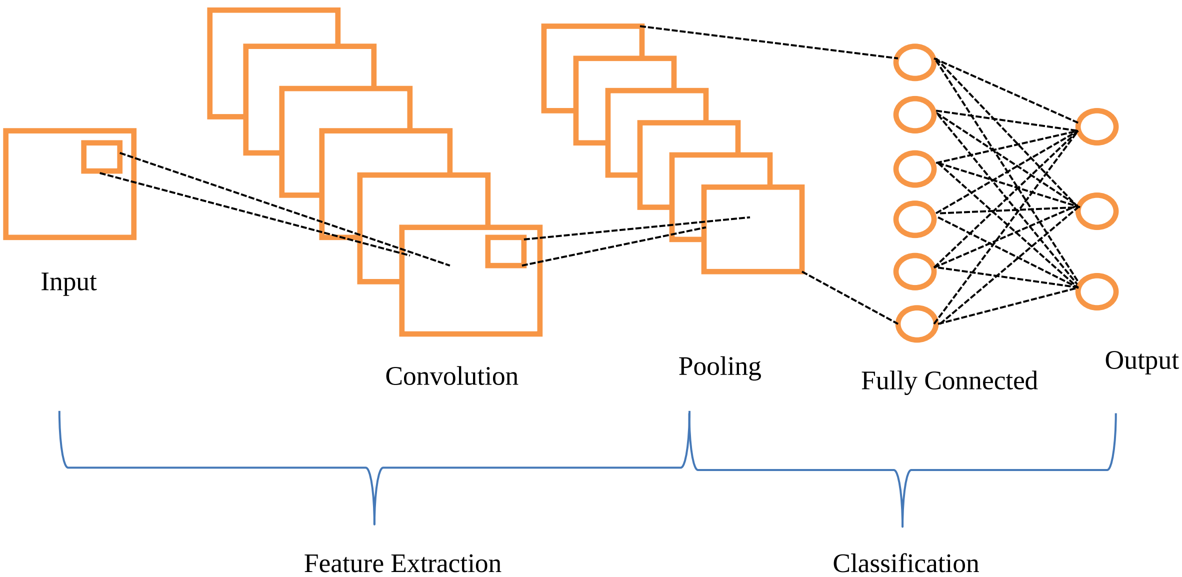



Fig. 3. CNN architecture.

A CNN is a type of multilayer perceptron, however unlike a deep learning architecture, it cannot learn complex features. CNNs have showed exceptional effectiveness in a wide range of applications [25], including classification of images, recognition of objects, and analysis of medical based images. The fundamental idea behind a CNN is that it can extract distinctive characteristics from upper layer inputs and transmit them to lower layers for more significant details. A CNN structure is designed using three layers and they are layer of convolutional, layer of pooling, and Fully Connected (FC) layers. The convolutional layer is made up of a sequence of kernels [26] that work together to generate a tensor of mapping the features. These kernels employ "stride(s)" to convolve an entire input volume into integers. When the convolutional layer is utilized to perform the striding process, the dimensions of an input volume decrease. The input volume is padded with zeros to keep the size of an input volume with lower-level characteristics, zero padding [27] is necessary. The operation of the convolutional layer is given as:

$$F(i,j) = (I \times K)(i,j) = \sum \sum I(i+m, j+n)K(m,n) \quad (1)$$

where the matrix of input is referred as "I", K denotes a size of 2D filter $m \times n$, and the output of 2D feature map is given as "F". The operation of the convolutional layer is denoted by $I \times K$. The Rectified Linear Unit (ReLU) layer is utilized in feature maps to boost nonlinearity [28]. The activation of ReLU is computed by keeping the input of threshold at zero. It is possible to express it numerically as follows:

$$f(x) = max\ (0, x) \quad (2)$$

To limit the number of parameters, the pooling layer down-samples a particular input dimension. The most prevalent approach is max pooling, which generates the highest value in each input area. The operation of classification is performed by FC layer, it helps in deciding based on information gathered from the previous layers of CNN structure [29].

In this work, the CNN uses two network models to compute and compare the performance in predicting the COVID-19, one network is MobileNet V2 and second one is DenseNet 201. The MobileNet V2 network have two blocks in which one block residual having a stride of one and the other block is shrinking having a stride of two. These two blocks have three levels. In the MobileNet V2 network use of ReLU6 is used as a first layer with 1×1 convolution. The depth-based convolution is performed in second layer. Final layer has no non linearity with 1×1 convolution. These types of networks are called as deep networks in which the power of a linear classifier on the non-zero volume part of the output domain if rectified linear unit is used [30].

DenseNet [31] creates a connection link across layers. It also makes full use of features, and alleviates the gradient disappearance problem even more. The use of a bottleneck layer, a translation layer, and the network is narrow due to slower growth rate, decreases elements, efficiently suppresses over-fitting, and the calculations are minimized.

### *D. Multilayer Perceptron (MLP)*

The training on the dataset is performed by the MLP which is a supervised learning algorithm that incorporates a function $f$ and is given as $f(.): R^m \rightarrow R^o$, in which term $m$ is the number of input dimensions and $o$ is the number of output-based dimensions. A set of features are given for the purpose of classification and the set is given as $X = x_1, x_2, \ldots, x_m$ and a supposed target is "$y$".The training in MLP Classifier is based on the method of back-propagation. The training using MLP is done on two arrays: one is array $X$ of size (n_samples, n_features), in which the samples for training are represented as feature vectors with floating points; and other is array y of size (n_samples), in which the training of samples holds the target values (class labels). After training the new samples are been predicted by the model. For training the data MLP can fit a non-linear model.

### *E. Support Vector Machine*

SVM is a widely utilized classification technique for a wide range of applications [32]. It is a system that processes information based on a simulation of a certain human process [33, 34]. Most of the linear classification is done by creating a hyper-plane. Depending on the degree of class, this hyper-plane aid separates the COVID-19 patients from the normal patients [35]. The data collected based on the hyper-plane is referred to as the decision hyper-plane, and the distance between the features and the hyper-plane is referred to as the margins. Training and testing are carried out to discover the best answer. The data that is fed into the system will be trained and tested. The 70% of data is used for training and 30% is considered for testing. After completing the training and testing of all signals the disease is predicted.

## III. EXPERIMENTAL EVALUATION

The experimental results are evaluated using Matlab software tool. The dataset which is used to evaluate the performance of suggest technique is divided into two parts for training and testing with a ratio of 70:30. The 5-fold cross-validation procedure was used to achieve the findings. The suggested network is made up of convolutional layers, which were calculated computationally. The CNN with different networks like MobileNet V2 and DenseNet 201 using MLP classification and SVM classification were implemented using Matlab software. Depending on the state of input image, the detection of COVID-19 is done. Different images will be tested using our proposed method and the performance metrics are evaluated. The experimental results evaluated using matlab tool is shown in Fig. 4.

- **Case 1: No Covid patient X-ray image as input.**

### *A. Performance Evaluation Metrics*

Based on four major metric the effectiveness of suggested work is evaluated. One is accuracy, F1-score, Precision and Recall. The finding of accuracy is based on true positive, true negative, false positive and false negative values. Here the values signify how effective the COVID-19 is predicted. The classification needs to classify perfectly to achieve correct values.

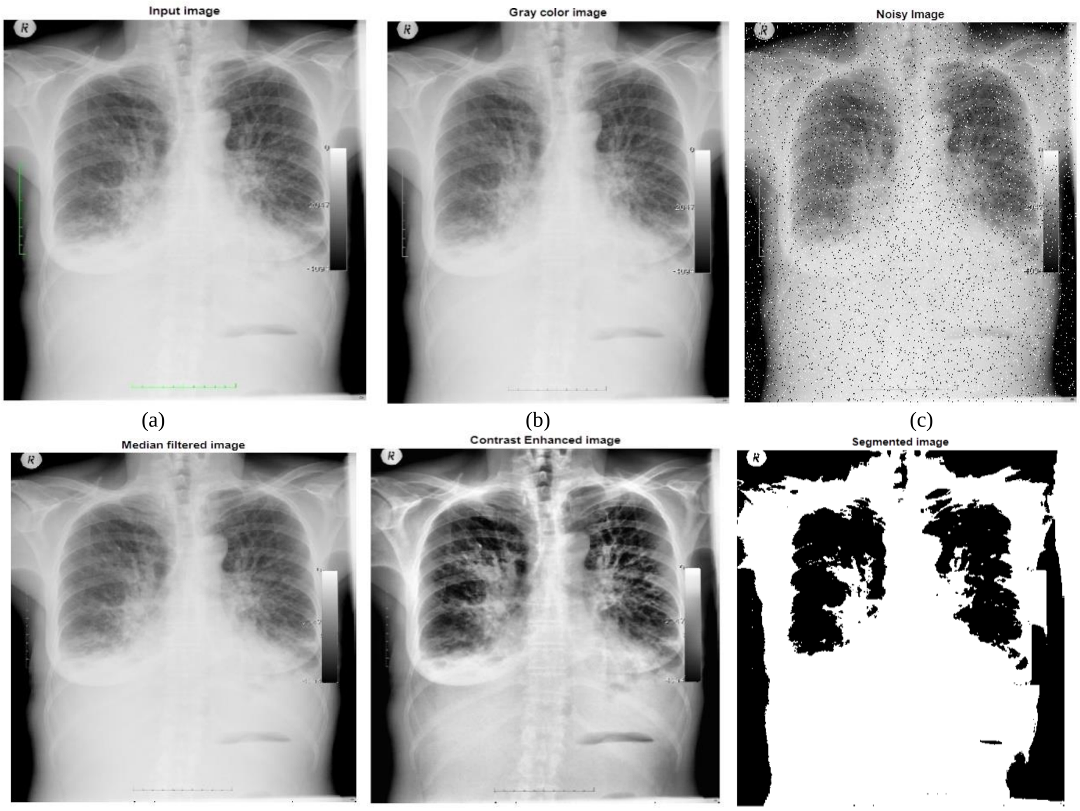



Fig. 4. Processing of image for prediction of COVID-19 or non-COVID-19: (a) Input Image (b) Grey Colour Image (c) Noisy Image (d) Median Filter Image (e) Contrast Enhanced Image (f) Segmented Image.

### *B. Accuracy*

The accuracy of a test in this work is its ability to differentiate the patient healthy and unhealthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

### *C. F1-Score*

F1-score, is a measure of a model's accuracy on a dataset. It is used to evaluate the classification systems. The F1-score is determined by taking the consonant of recall and precision.

$$F_1 = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \tag{4}$$

Precision:

$$P = \frac{TP}{TP+FP} \tag{5}$$

Recall:

$$R = \frac{TP}{TP+FN} \tag{6}$$

The parameters evaluated using different networks and classification techniques are shown in Table II. From Table II, using MobileNet V2 in CNN provides good results when compared to DenseNet 201 in CNN. When the MobileNet V2 Network using SVM classifier provides an accuracy of 99.09 and is better when compared with MobileNet V2 using MLP classifier. Further, covid patient chest X-ray is considered and the process need to evaluated using the proposed methodology. The evaluated results are shown in Fig. 5.

TABLE II. COMPARISON OF PARAMETERS

| CNN | Classification | Accuracy (%) | F1-Score (%) |
|---|---|---|---|
| MobileNet V2 | SVM | 99.18 | 98.68 |
| MobileNet V2 | MLP | 98.86 | 98.16 |
| DenseNet 201 | SVM | 95.93 | 93.40 |
| DensNet 201 | MLP | 95.77 | 93.26 |

- **Case 2: COVID-19 patient X-ray image as input.**

The effectiveness of the suggested technique for Fig. 5 is evaluated and tabulated in Table II, with accuracy and F1-score parameters. In Fig. 6(a) the results obtained using MobileNet V2-SVM Classifier is shown and Fig. 6(b) shows the results of SVM and MobileNet V2-MLP Classifier. The confusion matrix is used to validate the results. A confusion matrix is produced to visually interpret the model's outputs to receive a summary of the outcomes on a classification issue. It summarizes the right and unsuccessful predictions according to class.

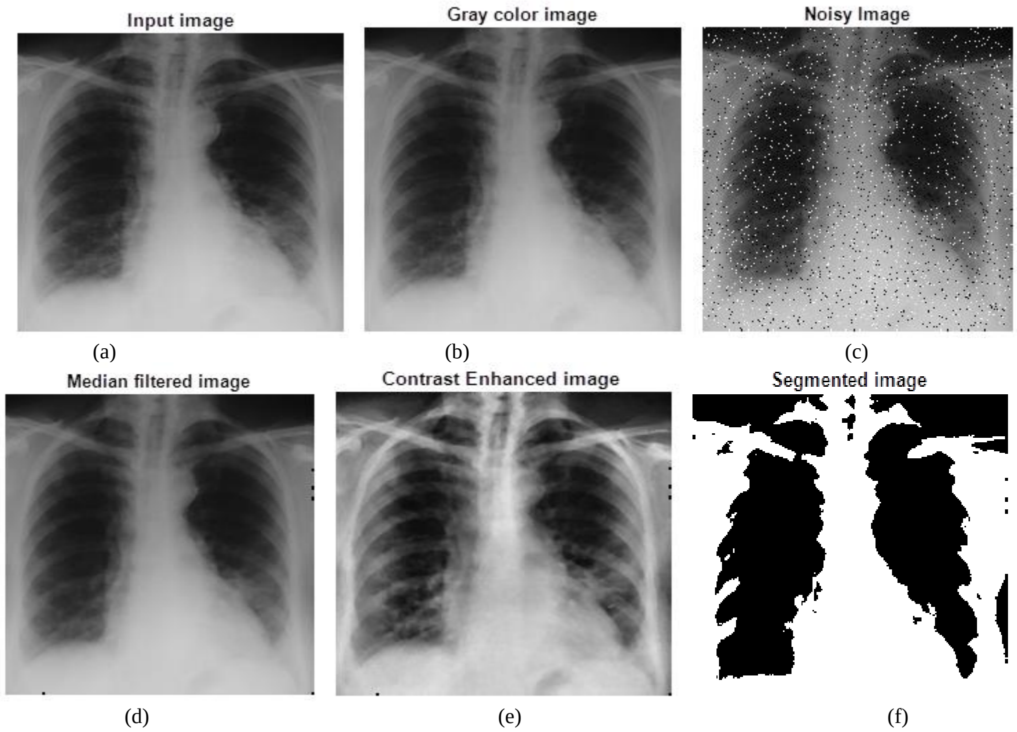
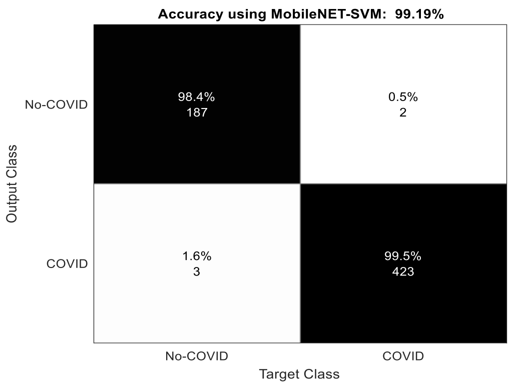
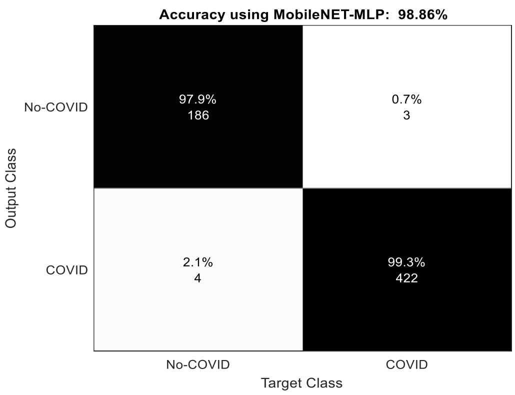



Fig. 5. Processing of image for prediction of COVID-19 or non-COVID-19: (a) Input Image (b) Grey Colour Image (c) Noisy Image (d) Median Filter Image (e) Contrast Enhanced Image (f) Segmented Image.



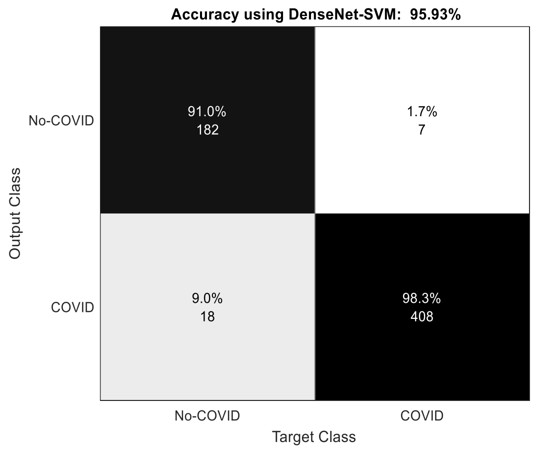

(a)



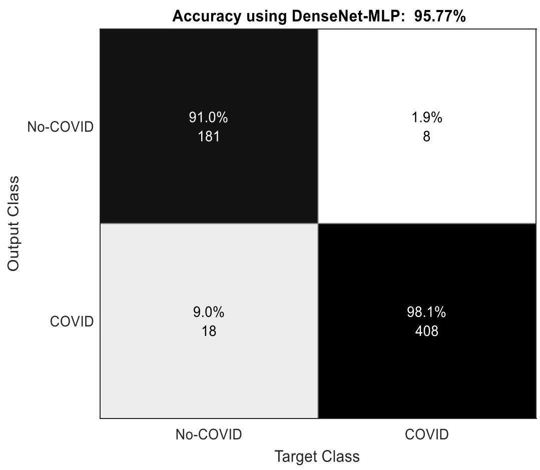

(b)

Fig. 6. Confusion matrix (a) MobileNet V2-SVM (b) MobileNet V2-MLP.

In Fig. 7(a) the results obtained using DenseNet-SVM Classifier is shown and Fig. 7(b) shows the results of SVM and DenseNet-MLP Classifier.




(a)




(b)

Fig. 7. Confusion matrix (a) DesnseNet-SVM (b) DenseNet-MLP.

The precision and recall values obtained using the proposed model is evaluated and shown in Table III.

TABLE III. COMPARISON OF PRECISION AND RECALL

| CNN | Classification | Recall (%) | Precision (%) |
|---|---|---|---|
| MobileNet V2 | SVM | 97.91 | 99.76 |
| MobileNet V2 | MLP | 97.39 | 99.52 |
| DenseNet 201 | SVM | 93.15 | 97.17 |
| DensNet 201 | MLP | 91.37 | 97.84 |

The comparison of accuracy and F1-score using various existing techniques and proposed model is shown in Table IV. From Table IV, it is shown that the proposed CNN with mobileNet V2 network combined with SVM classifier has an accuracy of 99.18% and using CNN with MobileNet V2 and MLP the accuracy is 98.68%.

TABLE IV. COMPARISON OF PARAMETERS WITH EXISTING TECHNIQUES

| Authors | | Method | Accuracy (%) | F1-Score (%) |
|---|---|---|---|---|
| T. Bessiana *et al.* [36] | | VGG19 | 98 | 98 |
| C. Kaya *et al.* [37] | | ResNet 50 | 98.75 | 98.70 |
| M. Talo *et al.* [38] | | DarkcardNet | 98.08 | 96.5 |
| S. K. J. P. Behara *et al.* [39] | | ResNet50+SVM | 95.33 | 95.30 |
| S. Kumar *et al.* [40] | | DequeezNet | 94.52 | 93.5 |
| A. K. Jaiswal *et al.* [41] | | Covidpen | 96.0 | 94.0 |
| A. K. Das *et al.* [42] | | Inception V3 | 91.6 | 91.2 |
| **Proposed work** | **Model1** | **MobileNet V2+SVM** | **99.18** | **98.68** |
| | **Model2** | **MobileNet V2+MLP** | **98.86** | **98.16** |

## IV. CONCLUSION

Increase in COVID-19 cases daily in several countries is facing resource constraints. As a result, it is very much necessary to identify the COVID-19 in humans at early stage and stop spreading. Chest X-ray images are critical in identifying COVID-19. In this paper, a deep CNN with MobileNet V2 and DenseNet 201 network is developed for detecting new COVID-19 in X-ray pictures. CNN enables data-driven direct learning of highly representative and hierarchical local visual characteristics. For the identification of disease CNN is employed for extraction of features; MLP and SVM are used as a classifier. The obtained results show that MobileNet V2 CNN with SVM classifier achieved better results with higher rate of accuracy when compared with DenseNet 201 CNN SVM. The MobileNet V2 with MLP classifier is also having good rate of accuracy when compared with DenseNet 201 MLP. Among the SVM and MLP classifiers the results shows that SVM classifier achieved good results. Further the network can be changed to improve the identification accuracy by considered MobileNet V3. Further optimization techniques can also be involved for obtained best results.

## CONFLICT OF INTEREST

The authors declare no conflict of interest

## AUTHOR CONTRIBUTIONS

M. Hema conducted the research work, developed the theory, collected the data, and wrote the paper. T. S. N Murthy conducted the research work, developed the theory, collected the data, and wrote the paper. The results are evaluated using MATLAB tool by both the authors. All authors had approved the final version.

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