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Chapter 1

AI-based implementation of decisive technology for prevention and fight with COVID-19

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1.1 Introduction

Coronaviruses are a wide range of viruses, from the common cold to more extreme diseases such as severe acute respiratory syndrome (SARS-CoV) and middle-eastern respiration syndrome (MERS-CoV) diseases. Many people with pneumonia were admitted from an unexplained cause into Wuhan General Hospital in December 2019. The unknown beta-coronavirus was detected by using objective sequencing in the samples from pneumonia patients. It was a “novel coronavirus” that formed a clade within the subgenus sarbecovirus, the subfamily Ortho-coronavirinae, defined as 2019-nCoV. This novel coronavirus (Guo et al., 2020) is an unidentified entirely new strain in humans and a growing phenomenon from a safety and disease management perspective.

The novelist COVID-19 quickly spread across the world and then became a global epidemic. It has a profound impact on every daily life, global health, as well as the world economy. The new COVID-19 disease is associated with a relatively similar virus family that has SARS and perhaps some kinds of flu or cold. COVID-19 relates to the genera beta-coronavirus depending on all its phylogenetic similarities and genomic properties. Human beta-coronaviruses (SARS-CoV, MERS-CoV, SARS-CoV-2) include several similar characteristics, but also have variations in certain genomic and phenotypic composition, which may affect their pathogenesis. The key symptoms prescribed by the World Health Organisation (WHO) include shortness of breath, fever, cough, and diarrhea nCoV. The upper respiratory signs are

less common including runny nose and sneezing. Serious infections may result in pneumonia, failure of the kidneys and death.

Application of the Artificial Intelligence (AI)-driven chest scan has the potential to reduce the increasing burden on radiologists who need to track and evaluate a growing number of chest scans of patients regularly. For the future, the technology will help to predict which patients will most likely require a ventilator or medicine and who can be sent home. Deep learning is a method for studying end-to-end neural networks. It has enabled highly accurate systems for the development of various complex applications (Kumar and Shrimankar, 2017; Kumar, Shrimankar, & Singh, 2018; Kumar, 2019). A convolutional neural network (CNN) developed with various pre-trained ImageNet models in Sethy and Behera (2020) for the extraction of high-level features using X-ray images in the chest. Such extracted features were then fed into a Support Vector Machine as a machine learning classifier to detect the COVID-19 instances. A COVID-Net based on CNN architecture and transfer learning was introduced in Wang and Wong (2020) for the classification of chest X-ray images among four classes: bacterial, nonCOVID, normal, and 20 COVID-19 viral infections. COVID can best be treated with radiological imaging (Fang et al., 2020) and with imagery (Ai et al., 2020).

To learn the pattern, these systems can understand the dynamic characteristics of input data and self-process such data. Unlike traditional approaches, deep learning allows the data process features and classifications to be extracted simultaneously. Looking at the present problem of coronavirus disease, it has been advised by the WHO, to take preventive measures to safeguard ourselves. One of the main preventive measures taken by the government and WHO is to wear face mask (Leung et al., 2020; MacIntyre and Chughtai, 2020; Chu et al., 2020) while traveling outside along with social distancing. Therefore it has become essential to develop automated applications to find out if anybody wears a mask or not; so that actions can be taken accordingly.

There is no successful vaccine or treatment for the COVID-19 global pandemic and as reported to WHO, there have been 21,026,758 globally confirmed cases with 755,786 deaths as of August 15, 2020. Fig. 1.1 shows the status of COVID-19 as per WHO region (World Health Organization WHO in 2020). By motivating this, we propose two AI-based mechanisms for the prevention of COVID-19. First, a mechanism that identifies those among the crowd, who have not worn a mask. Second, a COVID-19 detection mechanism from the computed tomography (CT) scan images using a deep convolution network that classifies whether a person is a COVID-19 patient or not. The rest part of the chapter is arranged as follows: sections 1.2 and 1.3 describe related work and the proposed work, respectively. Result and analysis are given in section 1.4 followed by conclusion and references.

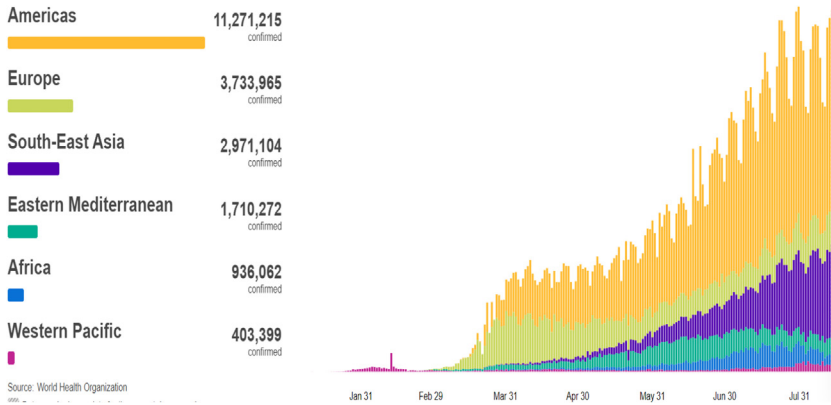


FIGURE 1.1 Global situation by WHO region. *WHO*, World Health Organisation.

1.2 Related work

[Han et al. \(2020\)](#) reported a new effort to recognize COVID-19 through weakly supervised chest CT, some underexamined, but far more feasible, scenario. This research introduced a new, attention-based deep 3D multi-instance learning (AD3D-MIL) for the global pandemic COVID-19 that monitor the poor labels and high generalization. AD3D-MIL provides a deep generator to periodically create deep 3D scenarios, an MIL pooling based on attention that aggregate deep instances into such an insightful bag interpretation, as well as a transformation function to turn the bag interpretation into a joint distribution or Bernoulli distribution for various bag classes.

[Fan et al. \(2020\)](#) proposed the innovative COVID-19 CT scans of the lung infection classification system, dubbed Inf-Net, using implicit reversed attention and clear layer-attention to enhance the detection of infected areas. Besides, the authors provided a semi-supervised viable alternative, Semi-InfNet, to reduce the lack of high reliability labeled data. Experimental findings in the COVID-SemiSeg training dataset and actual CT intensities have shown that the suggested Inf-Net and Semi-Inf-Net features perform better cutting-edge segmentation models as well as order to proceed state-of-the-art efficiency. The suggested model is capable of identifying artifacts with a small level of comparison between pathogens and natural tissues.

[Wang et al. \(2020\)](#) introduced a 3D CT metrics based weakly supervised learning system for the COVID-19 classification and lesion position. For each case, the lung section was partitioned to use a pretrained UNet; then perhaps the segmented 3D lung area was fed into a 3D neural network to determine the risk of infection with COVID-19; the COVID-19 infections are clustered by integrating the triggering regions within the classification network as well as the unsupervised associated components. 499 volumes of CT are being used for preparation and 131 volumes of CT for research. The

suggested algorithm provided 0.959 ROC AUC and 0.976 PR AUC. Use a likelihood threshold of 0.5 to distinguish COVID positive and COVID negative, an algorithm achieved a precision of 0.901, a positive predicted value of 0.840 as well as a quite high accuracy of 0.982. The methodology only took 1.93 seconds to analyze the CT volume of a single user using a solely devoted graphics processing unit (GPU).

Chung et al. (2020) reviewed the retrospective case study, chest CT scans of 21 diagnosable patients from China contaminated with 2019 new coronavirus (2019-nCoV) with a premium on recognizing and classifying the most prominent findings. Classic CT findings contained bilateral pulmonary parenchymal glazing and combined pulmonary opacities, often with flattened morphology and peripheral lung coverage. There was no lung cavitation, subtle pulmonary lesions, pleural effusions, no lymphadenopathy. Follow-up examination of a group of patients mostly during the window period of the analysis also indicated a slight to moderate worsening of the condition, as evidenced by a rise of lung opacity and density.

Scientists have shown that wearing face masks helps to reduce COVID-19's spread rate. The wearing of public masks is most effective in stopping viruses spread when enforcement is high. Li et al. (2020) established a methodology that was HGL to overcome the major issue of head pose specification with masks mostly during the COVID-19 endemic problem. This approach uses a study of the color distortion of images as well as a line depiction by retrieving and storing the pixel details from the H-channel mostly in hue, saturation, value (HSV) colored space to differentiate the facial features and mask throughout the image. This enables CNN to learn quite worthwhile information from the input image. The MAFA dataset analysis indicates that the suggested best accuracy approach (front accuracy: 93.64%, side accuracy: 87.17%) was preferable to some other specified methods. The approach to this problem also offers aid in the analysis of multiangle challenges.

Loey, Manogaran, Taha, and Khalifa (2020) proposed a hybrid model using deep and machine learning for the detection of a face mask that has two components. Resnet50 is used for feature extraction as a first component. For the second component, Support Vector Machine, ensemble algorithm, and decision trees are used for the classification purpose. For this work 99.64% testing accuracy is achieved by support vector machine (SVM) in the real-world masked face dataset (RMFD), 99.49% in simulated masked face dataset (SMFD), and 100% in the labeled faces in the wild (LFW) dataset.

Ejaz, Islam, Sifatullah, and Sarker (2019) applied the Principal Component Analysis (PCA) to identify the person in a masked and unmasked face. They found that wearing masks affect the accuracy of face resonance using PCA's extremity. YOLOv3 with Darknet-53 for the face recognition algorithm is introduced by Li, Wang, Li, and Fei (2020). This method has been trained on the CelebA and WIDER FACE datasets of over 600,000 images and received 93.90% accuracy.

1.3 Proposed work

In this study, we have implemented two AI-based preventive measures (face mask detection and CT scanning-based COVID detection) using advanced deep learning models. The first approach is to detect face masks from a crowded zone whereas the other is used to identify COVID-19 patients based on CT scan images using VGG16. Fig. 1.2 shows the overall approach for the proposed work.

Simonyan and Zisserman presented the VGG network architecture in 2014 in their paper (Simonyan and Zisserman, 2014) as shown in Fig. 1.3. This network is distinguished by its straightforwardness, using only 3×3 convolutional layers stacked in rising depth on top of each other. Max pooling is performed for a reduction of the volume size and two fully connected (FC) layers. Each one follows a softmax classifier with 4096 nodes.

1.3.1 Face mask detection

VGG16 is used to build an efficient network for the detection of face masks. The steps involved in this study are as follows:

- Perform data augmentation to get a clear view of an image sample from a different angle. Keras ImageDataGenerator function is used with rescaling, zoom range, horizontal flip, and shear_range for the proposed work.
- Used a pertained ImageNet to fine-tune the VGG16 architecture.
- Design an FC layer and then finally load the input data.

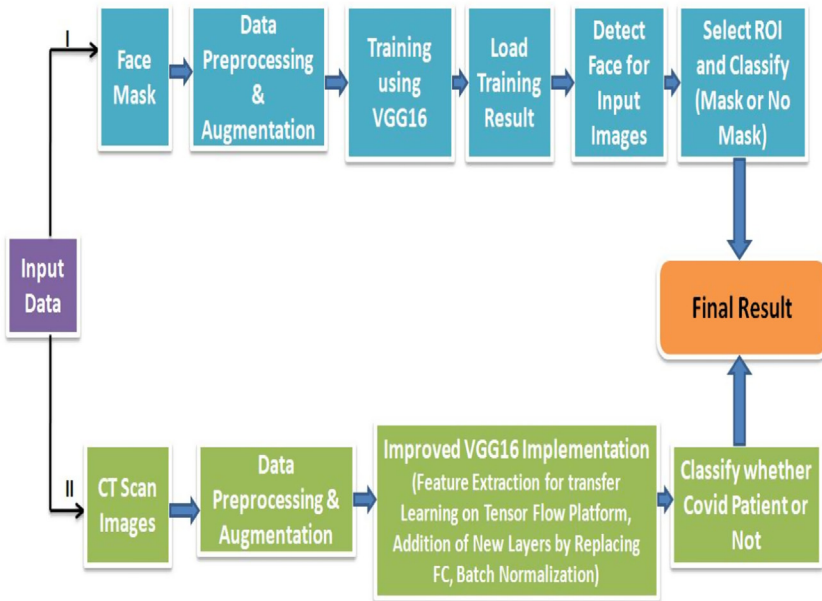


FIGURE 1.2 Proposed work block diagram.

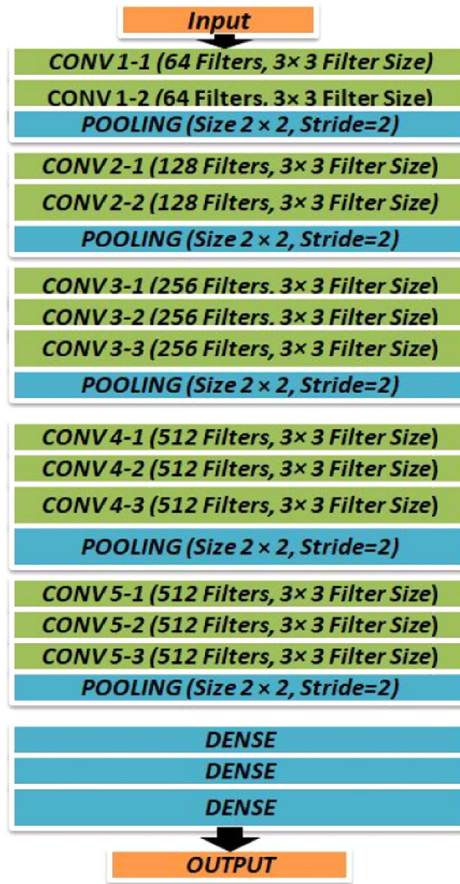


FIGURE 1.3 VGG16 architecture (Simonyan and Zisserman, 2014).

When loading the input image, it resizes to 224×224 pixels as a preprocessing. For object detection, face detection using haar-based cascade classifiers is an efficient method proposed by Paul Viola and Michael Jones in 2001 in their paper (Viola and Jones, 2001). In this machine learning technique, a cascade function is learned from both negative and positive images. It is then applied to other images for object detection. Then we need to derive haar characteristics from it. Each feature is a single value produced by subtracting the total of pixels in the white and black rectangles. If faces are identified, the positions of the detected faces are returned as Rect(x, y, w, h). Once we have these positions, we can create a face region of interest (ROI) and apply mask detection on that ROI. The proposed layered architecture of the VGG16 is shown in Fig. 1.4.

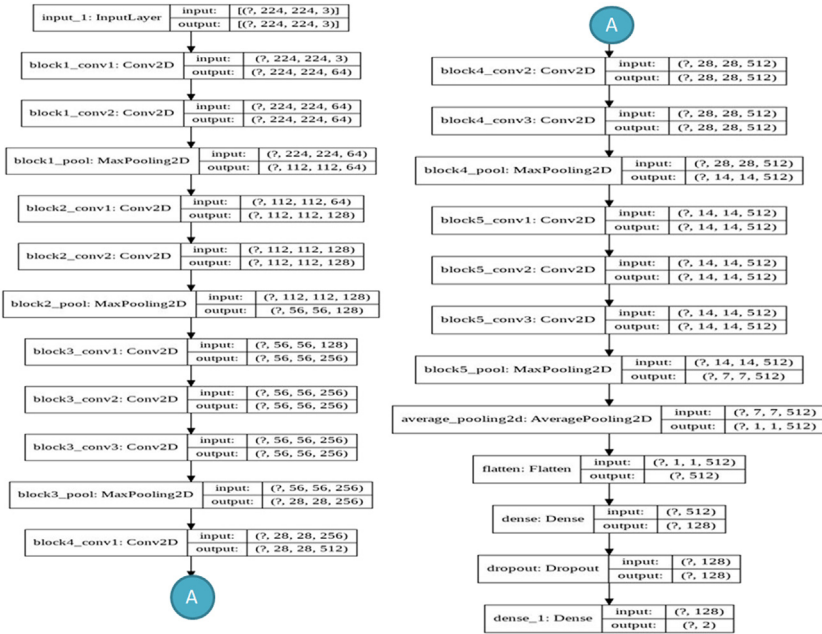


FIGURE 1.4 Proposed layered architecture of VGG16 for face mask detection.

1.3.2 Detection of COVID from CT images

The objective is to train advanced VGG16 deep convolutional model for findings of CT image patterns (vascular dilation, ground glass, traction bronchiectasis, crazy paving, architectural distortion, subpleural bands, etc.) and to classify whether a person belongs to the CT_COVID class or CT_NonCOVID class. Thus by simply uploading images of the CT scan of a patient, the proposed research would assist in the specific preliminary screening of those deemed to be positive for the deadly virus so that clinical testing can follow. Fig. 1.5 shows some sample images from CT images dataset.

The proposed work uses the concept of data augmentation, dropout, normalization, and transfer learning principle for detection. Fig. 1.6 shows the layered architecture of the VGG16 for detection of COVID from CT images. Data augmentation enriches the training data by creating new examples by transforming existing ones by random. This way we increase the size of the training set artificially, reducing overfitting. Techniques for augmenting data such as padding, cropping, and horizontal flipping are widely used to train large neural networks. In the transfer learning method, a developed model is reused for the other task.

Dropout is a regularization method that approximates the training of a large number of neural networks in parallel with various architectures.

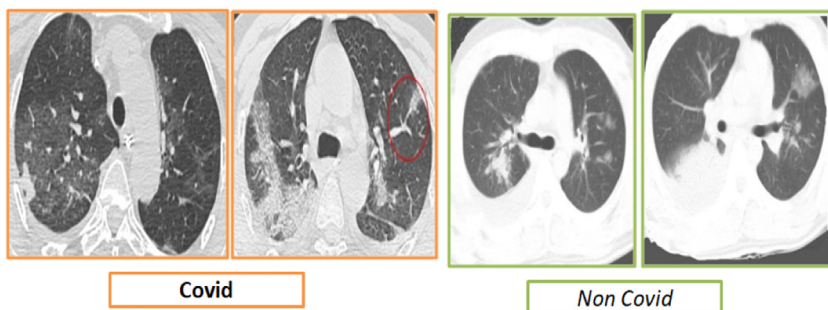


FIGURE 1.5 Sample images from CT images dataset. *CT*, Computed tomography.

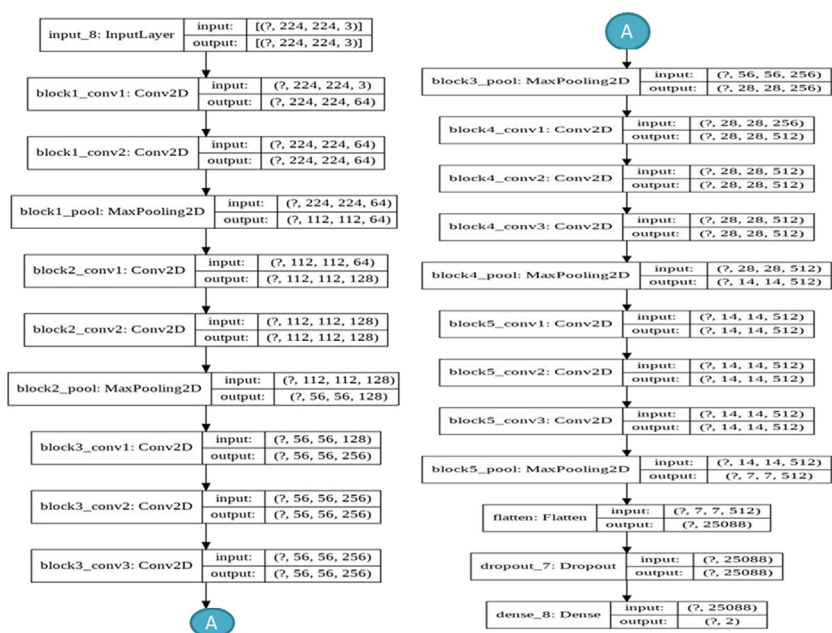


FIGURE 1.6 Proposed layered architecture of VGG16 for COVID detection from CT images. *CT*, Computed tomography.

During training, several layer outputs are randomly “dropped out” or overlooked. Batch normalization is a method used to train a deep CNN, which standardizes the inputs into one layer for each mini-batch. This results in a stabilization of the learning process and a drastic reduction of training epochs number needed for deep networks.

1.4 Results and analysis

The model is trained on Intel Core i5 6th Generation, 2.30 GHz CPU, 12 GB RAM and 2 GB of AMD Radeon R5 M330 graphics engine support on Windows 10 operating system. Accuracy curve, loss curve, confusion matrix, and classification report (precision, recall, f1 score) based analysis is performed for both the experiments. Predictions were generated by running the trained models on images of the test set. The following equation shows the mathematics behind the work.

Accuracy is the fraction of predictions that our model has been accurate.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions made}} \quad (1.1)$$

Accuracy can be measured for binary classification in terms of positives and negatives as follows:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1.2)$$

where TP = True Positives, FP = False Positives, TN = True Negatives and FN = False Negatives.

When dealing with Log Loss, the classifier will assign each class a probability for all samples. If there are N samples of the groups M , then the Log Loss is determined as follows:

$$\text{Logarithmic Loss} = \frac{-1}{N} \sum_{i=1}^N \sum_{j=1}^M y_{ij} * \log(p)_{ij} \quad (1.3)$$

Precision: It is the ratio of relevant instances to the retrieved instances.

$$\text{Precision} = TP / (TP + FP) \quad (1.4)$$

Recall: It is the ratio of relevant instances to the total amount of relevant instances that were retrieved.

$$\text{Recall} = TP / (FN + TP) \quad (1.5)$$

F1 Score: It is the weighted average of Precision and Recall.

$$\text{F1 Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (1.6)$$

1.4.1 Face mask detection

This experiment has been performed by looking without a mask or with a mask on real-time faces. In the dataset there are 1376 images, 1104 of which have been used for training and 272 for testing. Fig. 1.7 shows some sample images of masked and without masked faces with detection of face using haar-based cascade classifiers. During training, the total parameters are

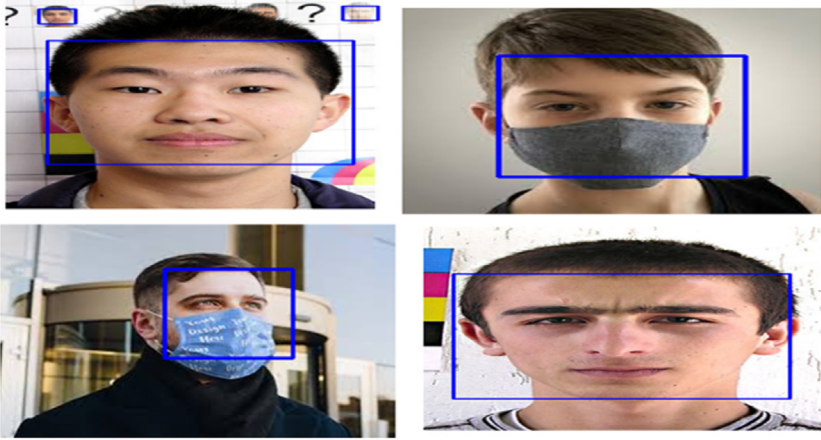


FIGURE 1.7 Sample images of masked and without masked faces with detection of face.

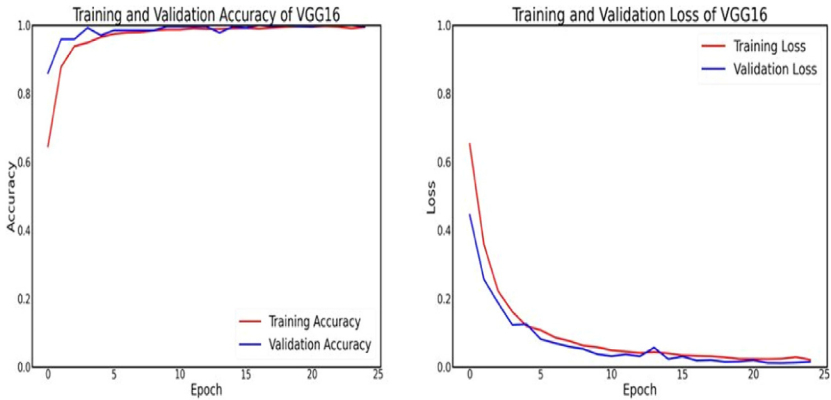


FIGURE 1.8 Accuracy and loss curve for face mask detection.

14,780,610 out of which 65,922 are trainable parameters and 14,714,688 nontrainable parameters.

The proposed work recorded training accuracy of 99.64% with the loss of logarithm 0.02 and validation accuracy of 99.63% with the loss of logarithm 0.02 in only 25 epochs with a batch size of 32 images. For the experiment, Precision, Recall and F1-Score are recorded 99.26%, 100%, and 99.63%, respectively. Fig. 1.8 displays the accuracy curve and loss curve for this experiment. Adam optimizer is used, which measures the individual adaptive learning rate for each parameter from first and second gradient moment's estimates. Confusion matrix-based analysis is done to test the results as shown in Fig. 1.9.

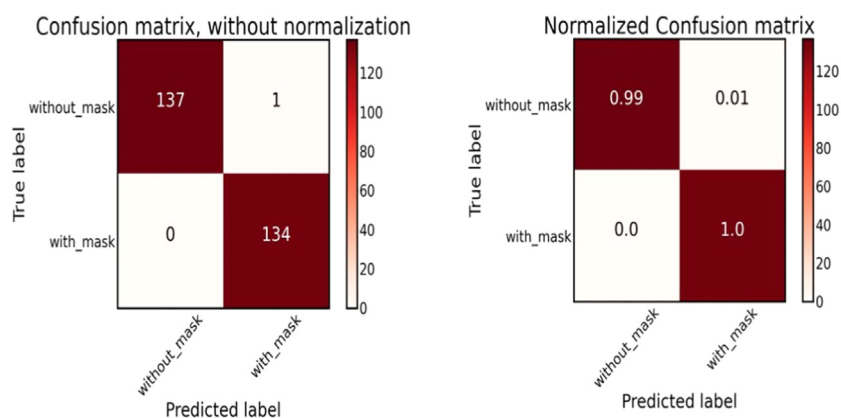


FIGURE 1.9 Confusion matrix for face mask detection.

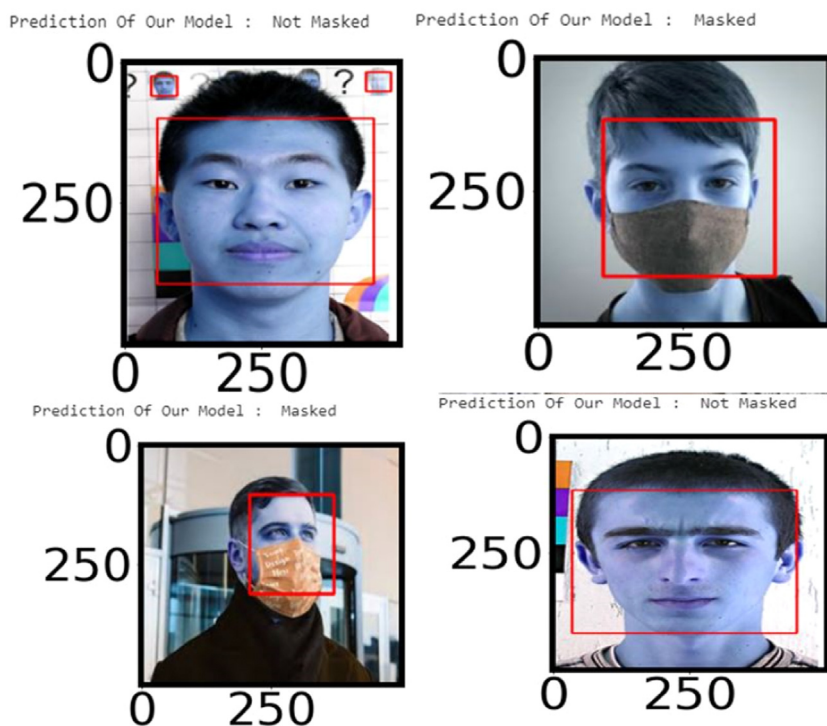


FIGURE 1.10 Prediction of random input image by the proposed model.

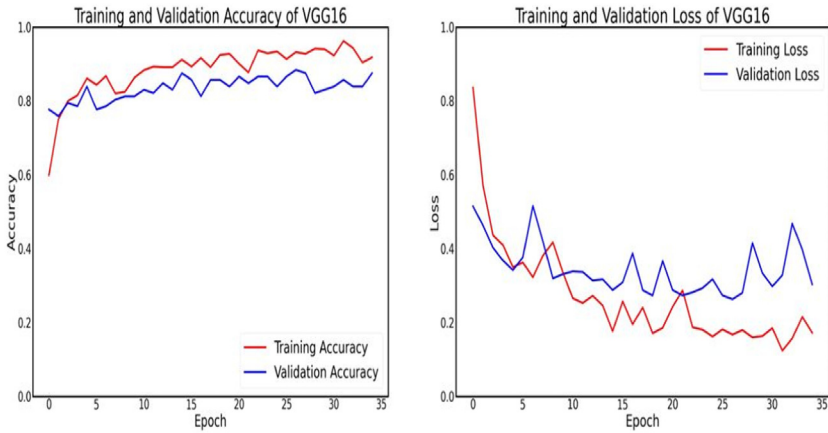


FIGURE 1.11 Accuracy and loss curve for COVID detection from CT scan images. *CT*, Computed tomography.

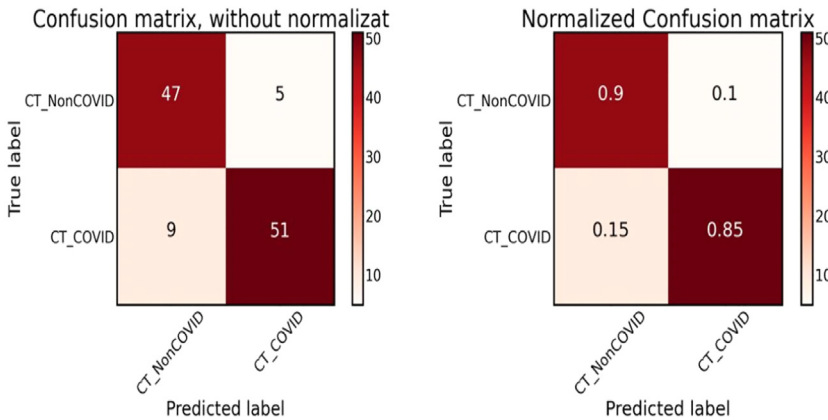


FIGURE 1.12 Confusion matrix for COVID detection from CT scan images. *CT*, Computed tomography.

Fig. 1.10 shows the true and predicted class of any arbitrary size at a given input image. It also reflects faces identified inside a bounding rectangle with their respective pixel-level image.

1.4.2 CT scan image-based COVID-19 patient identification

For this experiment, the dataset contains a total of 746 images, 634 of which have been used for training and 112 for testing. During training, the total parameters are 14,764,866 out of which 50,178 are trainable parameters and

14,714,688 nontrainable parameters. The proposed work recorded training accuracy of 97.63% with the loss of logarithm 0.07 and validation accuracy of 87.50% with the loss of logarithm 0.30 in only 35 epochs with a batch size of 32 images. Fig. 1.11 displays the accuracy curve and loss curve for the proposed model. For the experiment, overall Precision, Recall and F1-Score are recorded 91.07%, 85.00%, and 87.93%, respectively. The confusion matrix for the experiment is shown in Fig. 1.12.

1.5 Conclusion

With COVID-19, the 2020 era began and the image of these viruses is very pathetic. So far no such specific medicine has been invented and that would be the main cause of concern. Two models have been introduced in this proposed work that can be used to identify face masks and verify whether or not a patient with COVID-19 has been compromised by X-ray images, which also contribute to public healthcare. The proposed work recorded a validation accuracy of 99.63% with logarithm loss 0.02 in only 25 epochs for face mask detection and validation accuracy of 87.50% with logarithm loss 0.30 in only 35 epochs for COVID detection from CT images using the VGG16 model. Therefore AI-based face mask detection and radiography applied to CT images are a valuable prevention measure and it proves the technological viability and general applicability of a deep learning approach to enable implementation of preventive measures for global pandemic COVID-19. This technical approach will help researchers find the best possible solution to resolve the future situation.

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