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Deep hybrid models for CT images to detect COVID-19: A comparison of transfer learning approach

[1]Ebru ERDEM , [2]Tolga AYDIN

[1] Department of Computer Engineering, Ataturk University, 25240, Erzurum, Turkey
[2] Department of Computer Engineering, Ataturk University, 25240, Erzurum, Turkey

Corresponding author: Ebru ERDEM (e-mail: ebruerdem@atauni.edu.tr).

ABSTRACT The COVID-19 has become a pressing public health concern recently due to its dramatic impact. It spreads quickly, and it is beyond the ability of health staff to detect patients with the disease immediately. However, the ability to diagnose SARS-CoV-2 in a short time is critical for fighting the disease. The primary objective of this study is to develop deep neural networks to diagnose disease in a quick, safe, and cheap way. We classify the cases as normal, COVID-19, and pneumonia. Deep neural networks are developed to perform a three-class classification task. Ten deep learning models are evaluated on a large dataset. Although all DCNNs demonstrated promising potential for classification, hybrid neural networks delivered the most promising outcome with the highest accuracies. The first hybrid model is named MICOVID. The second hybrid model is named VVCOVID. These models are developed through transfer learning by using pre-trained deep learning models. Performance metrics results showed that MICOVID and VVCOVID models have an accuracy of 94% for COVID-19 detection. This is higher than other classification models. These findings suggest that two novel hybrid models that we proposed have great potential to be embedded into computer-aided systems to predict disease in radiology departments.

KEYWORDS: CNN, COVID-19, deep neural network, hybrid models

1. INTRODUCTION

Since 2019, SARS-CoV-2 has spread from China to other countries. Coronavirus disease 2019 (COVID-19) has quickly become a pandemic [1]. By April 2020, more than 30 million were confirmed as coronavirus cases, 28 million recovered, and more than 1 million deaths were reported [2]. Early diagnosis is critical to prevent infection to healthy people. The reverse-transcription polymerase chain reaction (RT-PCR) is the standard technique for diagnosing the disease. However, it may give false-negative results in the early stages of diseases. By comparison, CXR imaging or CT imaging technique is more helpful for COVID-19 detection. Bilateral and peripheral predominant ground-glass opacities (GGO) in the lobes are common initial findings on CT images. Besides bilateral multifocal GGO, septal thickening and pleural thickening are other common manifestations in the later stages [3, 4]. At the early stage of disease, it may be hard to view GGO. Therefore, images must be interpreted by only expert radiologists. Early diagnosis is getting more difficult in the face of the immense amount of the suspected cases and a limited number of expert radiologists. Computer-aided diagnosis systems (CAD) are necessary to solve such problems. Artificial intelligence solutions provide powerful tools for overcoming these difficulties.

Deep learning (DL) approaches are considered as the sub-class of machine learning (ML) methods. These methods have been used widely in the field of medicine. DL methods are capable of feature extraction and representation from raw data without any hand-craft method, augmentation, or segmentation. This situation provides an advantage compared to ML methods (thanks to improved diagnosis or smooth classification process, shorter time, and less cost). For controlling and combating novel coronavirus, DL methods can provide a quick and efficient solution. DL-based models have shown high performance in detecting COVID-19 [5- 9].

Compared to other techniques, Chest CT is considered to have sensitivity for clinical findings [10, 11]. Abbasian Ardakani et al. (2020) proposed an AI-based method for radiologists to improve the diagnosis of COVID-19. In their study, ten convolutional neural networks were used (AlexNet, VGG-16, VGG-19, ResNet-18, ResNet-50, ResNet-101, Xception, GoogleNet, MobileNet-V2, and SqueezeNet). The best performance was obtained by Xception (99.02% accuracy rate) and ResNet-101 (99.51% accuracy rate). Also, as a highly sensitive model, ResNet-101 [12] can be considered. Zhang et al. proposed another AI system developed on CT database from 3.777 patients. The AI system performance was tested by using U-net, DRUNET, FCN, DeepLabv3 (segmentation frameworks). For an accurate diagnosis of NCP, 40.880 slices were used from 260 patients (including 83 NCP patients, 86 normal patients, and 91 pneumonia patients) as a test to the classifier model. A 92.49% accuracy, a 94.93% recall, a 91.13% specificity, and a 97.97% AUROC [13] were achieved by using the proposed system. Attallah et al. constructed an efficient MULTI-DEEP CAD system based on multiple CNNs for detecting the disease. The CAD system comprises different four scenarios. Scenario I is composed of four pre-trained CNNs for classification (accuracy (78.29%). In scenario II, features were extracted from pre-trained CNNs (AlexNet, GoogleNet, ShuffleNet, and ResNet-18), and SVM was used as a classifier (accuracy (92.5%). For scenario III, the principal component analysis was applied to each feature extracted from pre-trained CNN, and selected principal components were used to train the SVM classifiers (accuracy (94%). In the last scenario, for capable of with compare scenario III, the four features were extracted from pre-trained CNN, and these features were used to train the SVM classifier (The accuracy is 94.7%). This verified system detected COVID-19 with high accuracy [14]. In another article, 386 Covid-19 and 1010 Non-Covid-19 CT lung images [15] were studied. Data were augmented with noise-adding, distortion, brightness, and contrast-changing methods. Within the scope of the study, 23-layer CNN architecture was proposed for classification. The study achieved the best accuracy rate of 93.94% and 95.70%, for 2-fold cross-validation and 10-fold cross-validation, respectively. Stephanie et al. obtained 90.8% accuracy, 93% specificity, and 84% sensitivity for the classification of 1337 patients with deep learning algorithms (Grad-CAM method) [16]. Jaiswal et al. used DenseNet-201 based deep transfer learning to detect NCP on SARS-CoV-2 CT scan images with AUC of 97%, an accuracy of 96.25%, a specificity of 96.21%, an F-measure of 96.29%, a recall of 96.29%, and a precision of 96.29% [17]. Li et al. developed a DL-based method to analyse the NCP from thick-section CT scans. The DL-based method has the ability to obtain good results with an AUC of 96.8% [18]. M. Hasan et al. built a feature extraction method comprising of DL and Q-deformed entropy algorithm.

These features were classified by employing LSTM for NCP, pneumonia, and normal cases with an accuracy of 99.68% [19]. Ko et al. utilized a 2D deep learning framework to COVID-19 pneumonia diagnosis on the lung CT image. This framework was named FCONet. FCONet framework use Xception, Inception-v3, ResNet-50, and VGG16 pre-trained models as its backbone. It showed excellent performance with a sensitivity of 99.58%, an accuracy of 99.87%, and a specificity of 100% [20].

DL-based approaches applied for automated detection of COVID-19 are summarized in Table 1 (using CXR or CT images). The CNN-based frameworks for novel coronavirus pneumonia (NCP) diagnosis were suggested in other studies. But, in usual, the effectiveness of concatenating deep models were not considered in previous research studies. To address this void in the literature, two novel hybrid deep neural networks are proposed in this article. The first hybrid model integrates MobileNet and Inception-V3 architectures (MICOVID). The second hybrid model integrates VGG16 and VGG19 architectures (VVCOVID). We also compared our proposed hybrid models with other deep learning models (DPN98, Xception, Inception-ResNet-V2, MobileNet, Inception-V3, VGG16, VGG19, SqueezeNet) in terms of model accuracy, precision, recall, f1-score, and confusion matrix. All these models were evaluated on 2019nCoVR, a large public dataset of the China National Center for Bio-information.

Table 1. A summary of previous research studies

Paper	Dataset	Method	Results
Attallah et al. [14]	347 COVID-19 397 non-COVID-19	ResNet-18	Accuracy (78.29%) AUC (83.82%) Sensitivity (76.9%) Specificity (79.9%) Precision (81%) F1-score (78.9%)
Ahuja et al. [21]	178 COVID-19 228 non-COVID-19	ResNet-18	Accuracy (99.4%) AUC (99.65%) Sensitivity (100%) Specificity (98.6%)
Dansana et al. [22]	360 COVID-19 34 non-COVID-19	VGG16	Accuracy (91%) Sensitivity (94%) Precision (100%) F1-score (97%)
Panwar et al. [23]	192 COVID-19 145 non-COVID-19	nCOVnet	Accuracy (97.62%) Sensitivity (97.62%) Specificity (78.57%)
Karar et al. [24]	69 COVID-19 237 non-COVID-19	ResNet50V2 and VGG16	Accuracy (99.90%)
Mamunur et al. [25]	260 COVID-19 600 non-COVID-19	VGG19	Accuracy (89.3%) Sensitivity (89%) Precision (90%) F1-score (90%)
Elasnaoui et al.[26]	1493 COVID-19 4594 non-COVID-19	Inception-ResNetV2	Accuracy (92.18%) Sensitivity (92.11%) Specificity (96.06%) Precision (92.38%)

			F1-score (92.07%)
Abbasian Ardakani [12]	108 COVID-19 912 non-COVID-19	ResNet-101	Accuracy (99.51%) AUC (99.4%) Sensitivity (100%) Specificity (99.02%)
Abbasian Ardakani [12]	108 COVID-19 912 non-COVID-19	Xception	Accuracy (99.02%) AUC (99.4%) Sensitivity (98.04%) Specificity (100%)
Jaiswal et al. [17]	1262 COVID-19 1230 non-COVID-19	DenseNet-201	Accuracy (96.25%) Sensitivity (96.29%) Specificity (96.21%) Precision (96.29%) F1-score (96.29%)

The general flow diagram of the study is given in Fig. 1. This study aims to develop deep learning algorithms for predicting disease in real-time. So, safety mechanisms can be utilized to prevent death and serious consequences. A deep learning framework was employed to predict disease from CT images. We use CNN features (deep learning framework) that directly predict from raw data without any need for hand-crafted features, unlike classical machine learning approaches for feature extraction (hand-crafted).

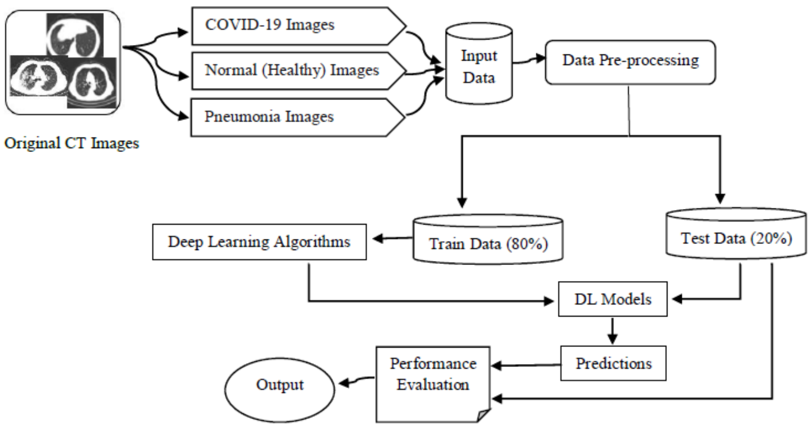

Figure 1. Flow diagram of the study

2. MATERIALS AND METHODS

2.1 DATASET

The 2019nCoVR dataset consists of CT images (2019nCoVR database, which is available at http://ncov-ai.big.ac.cn/download?lang=en). These images are constructed from the China Consortium of Chest CT Image Investigation, and they are classified as SARS-CoV-2 virus, pneumonia, and normal. This dataset is publicly available with the aim to combat disease. 31 files containing CT scans of COVID-19, 32 files containing CT scans of pneumonia, and 27 files containing CT scans of normal have been structured in the dataset [27]. We prepared a subset of CT images from the 2019nCoVR dataset. The combined dataset consists of 137.263 CT images, 114.416 training, and 22.847 testing samples. This dataset consists of 50.145 CT scans of COVID-19, 30.014 CT scans of pneumonia, and 34.257 CT scans of normal. The dataset is organized in 2 folders (train, test), as given in Table 2. CT images are resized to 256x256 before fed to DNN.

Table 2. General distribution of dataset in this study

Dataset	COVID-19	Pneumonia	Normal (Healthy)
2019nCoVR [1]	50.145	30.014	34.257
Training Set	40.114	24.011	27.444
Test Set	10.031	6.003	6.813

2.2 THE PROPOSED FRAMEWORK

In this study, ten deep learning models are applied to perform the classification. These models are a DPN98 [28] model, an Xception [29] model, an Inception-ResNet-V2 [30] model, a MobileNet [31] model, an Inception-V3 [32-34] model, a VGG16 [35] model, a VGG19 [35] model, a SqueezeNet [36] model and two hybrid models (MICOVID and VVCOVID) (Fig. 2). Transfer learning with popular pre-trained deep neural networks (DPN98, Xception, Inception-ResNet-V2, MobileNet, Inception-V3, VGG16, VGG19, and SqueezeNet) are applied to the training images of the 2019nCoVR dataset.

2.2.1 TRANSFER LEARNING APPROACH

Transfer learning is used in the field of deep-learning as a basic method. It allows a model trained on one task to be repurposed to another task through adopting. Thus, it utilizes previously learned knowledge in new classification problems. Consequently, it is able to obtain faster and better results. This approach is very useful for medical image classification.

Pre-trained models can be used for different tasks. In this study, they are used as a feature extractor (pre-trained CNN features). For classification, a classifier is trained on top of the pre-trained models. For this reason, we only fine-tune the last layer of deep neural networks (as three-class). Eight popular pre-trained models were evaluated: DPN98, Xception, Inception-ResNet-V2, MobileNet, Inception-V3, VGG16, VGG19, and SqueezeNet.

2.2.2 CNN

CNN architecture is composed of different layers: convolution, pooling and fully connected ones. The convolution layer is applied to input data (images, etc.) to produce a feature map by convolution filter (kernel). After the convolution layer, the pooling layer is generally applied to reduce the dimensions (to provide a down-sample for each feature map, to reduce the number of parameters). The output feature map and pooling process are obtained in Equation (1) and Equation (2), respectively. In Equation (1), $\boldsymbol{X_i^{l-1}}$, $\boldsymbol{k_{ij}^l}$,$\boldsymbol{b_j^l}$, and f() represent the local features, kernel (filter), bias, and activation function, respectively. In Equation (2), down() represents down-sampling process of pooling layer.

$$X_j^l = f\left(\sum_{i \in M_j} X_i^{l-1} * k_{ij}^l + b_j^l\right) \quad (1) [37]$$

$$X_j^l = down\left(X_j^{l-1}\right) \quad (2) [38]$$

Finally, a fully connected layer (the last layer) takes the output of previous layers (convolution or pooling) and predicts the label of input data for the classification decision.

2.2.3 COVID-19 DETECTION USING DPN98, XCEPTION, INCEPTION-RESNET-V2, MOBILENET, INCEPTION-V3, VGG16, VGG19, AND SQUEEZENET

Transfer learning on a dataset is used to train eight convolutional neural networks, including SqueezeNet, VGG19, VGG16, Inception-V3, MobileNet, Inception-ResNet-V2, Xception, and DPN98 to identify disease in 114.416 CT images. We evaluated these models on 22.847 CT images. So, instead of building a CNN architecture, we used some pre-trained CNN models. The detailed information about pre-trained models are as follows:

. Two of the models are the pre-trained VGG16 and VGG19, trained on the ImageNet dataset. VGG16 and VGG19 obtained good results in the ILSVRC-2014. These networks are a subset of the VGG network. VGG16 architecture consists of 16 convolutional layers. VGG19 architecture consists of 19 convolutional layers. These models are deeper CNN architectures. For both models, the default image input sizes are 224*224 with three channels.

. SqueezeNet model is a CNN architecture. The model has a convolution layer (independent, conv1), fire modules (eight, fire2-9), and the last convolution layer. Although 50 X smaller the size of this model compared to AlexNet, it gives higher performance. For this model, the dimensions of images in the input layer are 224 x 224 x 3.

. Inception-V3 CNN architecture was introduced by Szegedy et al. in 2015. The model was first introduced as a structure consisting of 22 layers (Inception-V1-GoogleNet). Later, the model was reintroduced as Inception-V2 (with batch normalization), and the final iteration has been referred to as Inception-V3 (with additional factorization). In addition Inception-V1 and Inception-V2, the Inception-V3 network uses a splitting method for dividing volume integrals. The Inception module, as a typical CNN architecture, contains convolution and pooling layers. For this model, the dimensions of images in the input layer are 229 x 229 x 3.

. Inception-ResNet-V2 is a hybrid network combining Inception architecture and residual connections [39]. Inception-ResNet-V2 is a residual version of Inception, which is roughly the computational cost of the Inception-v4 network. While Inception networks utilize filter concatenation, Inception-ResNet networks utilize residual connections.

. MobileNet is a popular deep learning model. While this CNN model has fewer parameters, it also has less calculation cost because of its general construction. Based on the depth-wise separable convolution, it has 28 layers. Except for the final layer, all layers are followed by a ReLU and a batch norm layer in the architecture. The model is designed for mobile devices and shows excellent performance for embedded industrial equipment.

. Xception was proposed by Francois Chollet. This model is another improvement of Inception-V3 deep learning model. The model contains depthwise separable convolutional layers with residual connections. For this model, image dimensions in the input layer are 229 x 229 x 3.

. DPN98 is a variation of Dual-Path Network (DPN) proposed by Yunpeng Chen, etc. It is a family of CNNs, and it has cost about fewer parameters than ResNeXt-101. DPN has the advantages of DenseNet (exploring new features) and ResNet (feature reuses). This model is very suitable for optimization and classification. It is especially used for image classification, segmentation, and object detection. DPN showed high accuracy on Places365-Standard and ImageNet-1k datasets [28]. The model has obtained the best results in the ILSVRC-2017 Challenge.

2.2.4 COVID-19 DETECTION USING MICOVID AND VVCOVID

As hybrid models, we present two novel concatenated CNN based approaches for COVID-19 detection in this study. The first proposed hybrid model is a combination of MobileNet and Inception-V3. This model is named MICOVID in the study. The second proposed hybrid model is a combination of VGG16 and VGG19. This model is named VVCOVID in the study. The proposed hybrid models have five steps as shown in Fig. 2.

These steps are as follows:

. CT scan images have been reshaped to 256*256 with three channels.

. The learned weights of the pre-trained models are used on ImageNet (for the first hybrid model: MobileNet, Inception-V3, and for second hybrid model: VGG16, VGG19). Thus, features are extracted automatically for each CT image.

. The obtained features are concatenated after applying "*GlobalAveragePooling Layer*".

. We use the stacking model to concatenate the output shape of models for each hybrid model through "Concatenate Layer". The concatenate layer returns a single tensor.

. Finally, two "*Fully Connected Layers*" consisting of 512 neurons are used. In the output layer, classification is made with the "*Softmax Layer*".

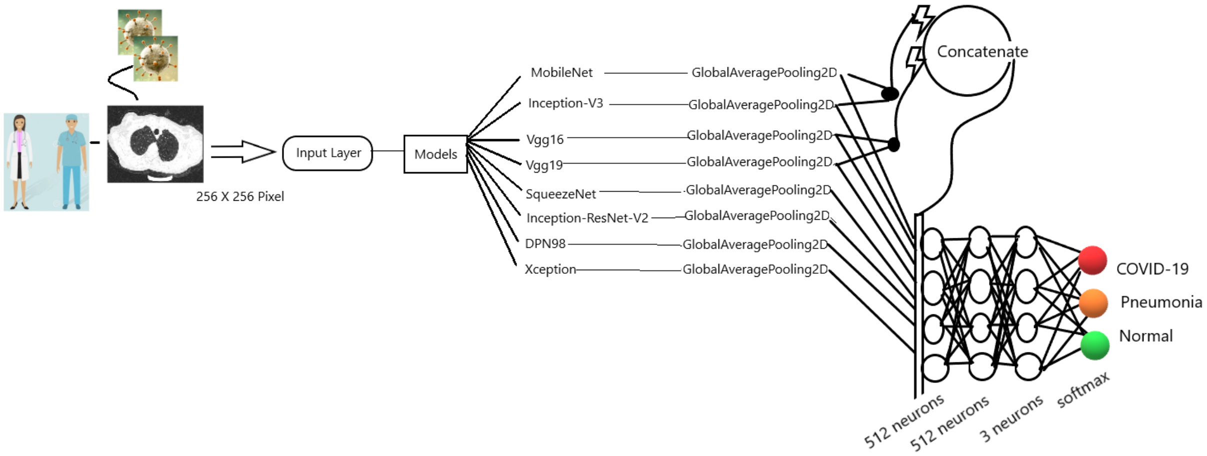

Figure 2. A general illustration of proposed framework.

MICOVID and VVCOVID layer, output shape and parameter details are given in Table 3.

Table 3. Proposed hybrid models details for detection of COVID-19

Model	Layer	Output Shape	Parameter	Total Parameter
MICOVID	input_1	(None,256,256,3)	0	
	mobilenet_1.00_224	(None,8,8,1024)	3228864	
	inception_v3	(None,6,6,2048)	21802784	
	global_average_pooling_2d_1	(None,1024)	0	
	global_average_pooling_2d_2	(None,2048)	0	26,869,219
	concatenate_1	(None,3072)	0	
	dense_1	(None,512)	1573376	
	dense_2	(None,512)	262656	
	dense_3	(None,3)	1539	
VVCOVID	input_1	(None,256,256,3)	0	
	vgg19	(None,8,8,512)	14714688	
	vgg16	(None,8,8,512)	21802784	
	global_average_pooling_2d_1	(None,512)	0	
	global_average_pooling_2d_2	(None,512)	0	35,528,067
	concatenate_1	(None,1024)	0	
	dense_1	(None,512)	1311232	
	dense_2	(None,512)	262656	
	dense_3	(None,3)	1026	

3. EXPERIMENTAL RESULTS

All model implementations and evaluations are done in Keras [40] by using a computer having an Intel(R) Core(TM) i7-7700 CPU, 24 GB memory and GeForce GT 730 GPU (NVIDIA).

3.1 DEEP LEARNING MODELS HYPER-PARAMETERS

Deep learning networks are trained for 500 epochs. The batch size is set to 32, an ADAM optimizer function and a learning rate of 0.0001. Trainable parameter, non-trainable parameter and total parameter size of DCNN models are given Table 4.

Table 4. Trainable parameter, non-trainable parameter and total parameter size of DCNN models in this study

Model	Trainable parameter	Non-trainable parameter	Total parameter
Inception-V3	23,081,635	34,432	23,116,067
MobileNet	3,995,971	21,888	4,017,859
Vgg16	15,241,539	0	15,241,539
Vgg19	20,551,235	0	20,551,235
SqueezeNet	1,249,347	0	1,249,347
InceptionResNetV2	55,327,331	60,544	55,387,875
DPN98	60,654,435	148,320	60,506,115
Xception	22,120,235	54,528	22,174,763
MobileNet+Inception-V3	26,812,899	56,320	26,869,219
Vgg19+Vgg16	35,528,067	0	35,528,067

3.2 EVALUATION METRICS

For each of the different DL models, we evaluated the classification performance in terms of sensitivity (recall), precision, accuracy, and F1-score. Table 5 and Table 6 summarize the classification performances of DCNN models. As seen in the tables, DCNN models give promising results for COVID-19 diagnosis. VVCOVID and MICOVID obtained the best accuracy rate of 94%. These hybrid models showed better performance than other DCNN models in terms of accuracy rate. VVCOVID, MICOVID, MobileNet, Inception-V3, VGG16, SqueezeNet, Inception-ResNet-V2, and Xception models obtained the sensitivity rate of ~95% ± 2%. Each model has achieved around 90% precision and F1-score rates. DCNNs have achieved the specificity rate of ~92% ± 6.7%. For COVID-19 diagnosis, the results have shown that Inception-ResNet-V2 model had the poorest classification performance with a specificity rate of 91.73%.

Table 5. Classification results of pre-trained models

	Class	MobileNet	Inception-V3	VGG16	VGG19	SqueezeNet	Inception-ResNet-V2	DPN98	Xception
Sensitivity (%)	Covid	97	92	94	87	96	97	75	96
Precision (%)	Covid	98	94	97	90	94	90	98	94
Accuracy (%)	Covid	93	86	92	86	93	89	71	93
F1-score (%)	Covid	98	93	95	89	95	94	85	95
Specificity (%)	Covid	98.51	95.79	98.55	92.22	95.27	91.73	98.75	95.27

Table 6. Classification results of deep hybrid models

	VVCOVID	MICOVID
Sensitivity (%)	96	97
Precision (%)	96	97
Accuracy (%)	**94**	**94**
F1-score (%)	96	97
Specificity (%)	97.77	97.09

The confusion matrix is a heuristic metric used to obtain the sensitivity (TPR), specificity (TNR), precision (PPV), accuracy (ACC), and F1-scores of the model, which are described in Equation (3), Equation (4), Equation (5), Equation (6), and Equation (7). Table 7 shows true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) based on three-class (COVID-19, pneumonia, and normal). So, we expressed performance metrics with subscripts for COVID-19 class as "*covid*", for pneumonia class as "*pneumonia*" and the healthy (normal) class as "*normal*". For example, TP_{covid} is the number of COVID-19 testing data correctly classified. TN_{covid} is the number of non-COVID-19 testing data correctly classified. FN_{covid} is the number of non-COVID-19 testing data misclassified. FP_{covid} is the number of COVID-19 testing data misclassified. $TP_{pneumonia}$ is the number of pneumonia testing data correctly classified. $TN_{pneumonia}$ is the number of non-pneumonia testing data correctly classified. $FN_{pneumonia}$ is the number of non-pneumonia testing data misclassified. $FP_{pneumonia}$ is the number of pneumonia testing data misclassified. TP_{normal} is the number of normal testing data correctly classified. TN_{normal} is the number of non-normal testing data correctly classified. FN_{normal} is the number of non-normal testing data misclassified. FP_{normal} is the number of normal testing data misclassified.

$$Sensitivity = \frac{\text{TP}}{\text{TP + FN}} \tag{3}$$

$$Specificity = \frac{\text{TN}}{\text{TN + FP}} \tag{4}$$

$$Precision = \frac{\text{TP}}{\text{TP + FP}} \tag{5}$$

$$Accuracy = \frac{\text{TP + TN}}{\text{TP + TN + FP + FN}} \tag{6}$$

$$F1 - score = \frac{\text{2 x precision x sensitivity}}{\text{TP + TN + FP + FN}} \tag{7}$$

Table 7. Confusion matrix of the observed deep learning algorithms on 2019nCoVR dataset

DCNNs	Actual Classes	Predicted		
		Covid	pneumonia	normal
MobileNet	Covid	9763 (TP)	252 (FN)	16 (FN)
	pneumonia	130 (FP)	6679 (TN)	4 (TN)
	normal	60 (FP)	1107 (TN)	4836 (TN)
Inception-V3	Covid	9254 (TP)	376 (FN)	401 (FN)
	pneumonia	515 (FP)	6192 (TN)	106 (TN)
	normal	24 (FP)	1742 (TN)	4237 (TN)
VGG16	Covid	9391 (TP)	572 (FN)	68 (FN)
	pneumonia	133 (FP)	6649 (TN)	31 (TN)
	normal	123 (FP)	945 (TN)	4935 (TN)
VGG19	Covid	8755 (TP)	710 (FN)	566 (FN)
	pneumonia	582 (FP)	5948 (TN)	283 (TN)
	normal	415 (FP)	714 (TN)	4874 (TN)
SqueezeNet	Covid	9603 (TP)	308 (FN)	120 (FN)
	pneumonia	471 (FP)	6199 (TN)	143 (TN)
	normal	134 (FP)	410 (TN)	5459 (TN)
Inception-ResNet-V2	Covid	9766 (TP)	168 (FN)	97 (FN)
	pneumonia	691 (FP)	6086 (TN)	36 (TN)
	normal	368 (FP)	1103 (TN)	4532 (TN)
DPN98	Covid	7562 (TP)	48 (FN)	2421 (FN)
	pneumonia	85 (FP)	3118 (TN)	3610 (TN)
	normal	75 (FP)	359 (TN)	5569 (TN)
Xception	Covid	9603 (TP)	308 (FN)	120 (FN)
	pneumonia	471 (FP)	6199 (TN)	143 (TN)
	normal	134 (FP)	410 (TN)	5459 (TN)
VVCOVID	Covid	9660 (TP)	227 (FN)	144 (FN)

	pneumonia normal	317 (FP) 55 (FP)	6331 (TN) 402 (TN)	165 (TN) 5546 (TN)
MICOVID	Covid pneumonia normal	9715 (TP) 236 (FP) 49 (FP)	298 (FN) 6557 (TN) 685 (TN)	18 (FN) 20 (TN) 5269 (TN)

4. DISCUSSION-CONCLUSIONS

Chest CT may play an important role, especially where the PCR resulting in false-negatives in COVID-19 diagnosis. Since a limited number of CXR images is publicly available for COVID-19, besides CXR images, we have resorted to CT images . We have reported a framework comprising of DCNN models for COVID-19 detection from CT images. Also, two novel deep hybrid models are developed using the images obtained. These models were trained and tested on the 2019nCoVR sub-dataset (114.416 training set and 22.847 testing set). To report a summarizing performance of deep learning models, we provide the confusion matrix, accuracy, precision, sensitivity, specificity, and f1-scores for each of these models. When the results are generally examined, this proposed framework promises using CT scan images for disease diagnostics. Besides pre-trained models, with the novel proposed deep hybrid models, the sensitivity, specificity, accuracy, precision, and F1-scores for classifying COVID-19 are obtained, and these are ~96%, ~97%, ~94%, ~96%, and ~96%, respectively. The best accuracy rate of 94% is obtained with MICOVID and VVCOVID. MobileNet- SqueezeNet-Xception (93%), VGG16 (92%), Inception-ResNet-V2 (89%), Inception-V3-VGG19 (86%), and DPN98 (71%) follows it.

Because of the mounting amount of COVID-19-infected patients, health staff is having more difficulty in combating the disease. So, the rapid development of AI methods is critical. Consequently, DCNN based-CAD systems are recommended for the diagnosis of COVID-19 in this paper. These proposed models deliver faster results than the classical PCR testing method. Thus, in addition to pre-trained models, MICOVID and VVCOVID can become rapid and efficient diagnostic tools for COVID-19.

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