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Detection of COVID 19 using X-ray Images with Fine-tuned Transfer Learning

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Recently, COVID-19 infection has been spread to a wider human population worldwide and deemed a pandemic for its rapidity. The absence of medicine or immunization for the “COVID-19” illness, along with the requirement for early discovery and isolation of affected persons, is critical in reducing the risk of infection in healthy population. Blood specimens, or “RT-PCR” are primary screening technique for “COVID-19”. However, average positive “RT-PCR” is expected as 30 to 60%, leading to undiscovered infections and potentially endangering a broad population of healthy persons with infectious symptoms. With the quick examination approach, chest radiography as a common approach for identifying respiratory disorders is straightforward to execute. A board-certified radiologist indicated the presence of disease in these radiographs. Four transfer learning techniques to COVID-19 illness identification were trained using 2,000 X-rays: VGG-16, GoogleNet, ResNet, and SqueezeNet. The result of the experimental assessment shows that the VGG-16 network fine-tuned with Keras achieved sensitivity of 100% with specificity of 98.5% and accuracy of approximately 99.3%.

Keywords: COVID 19, Transfer learning, VGG-16, X-ray

Introduction

Worldwide Lung related diseases are the most prevalent medical conditions in humans.[1–3] In “March 2020”, “World Health Organization (WHO)” authoritatively proclaimed outbreak of “COVID-19”, the sickness brought about by “SARS-CoV-2. “COVID-19” is exceptionally irresistible and might possibly develop into fatal “acute respiratory distress syndrome (ARDS)”. Early discovery and determination are basic essentials for controlling “COVID-19” spreading. Greatest well-known screening technique to recognize it is “Reverse-Transcription Polymerase Chain Reaction (RT-PCR)” testing. In any case, it is relentless strategy and a few examinations revealed its low responsiveness in beginning phases. Chest scans like “X-rays and Computer tomography (CT) scans” have been used to recognize morphological examples of lung lesions linked with “COVID-19”. Regardless, precision of assurance of “COVID-19” of Chest scans unequivocally hinge upon subject experts and Deep learning strategies concentrated as a device to modernize and help with finding. Corona-virus illness is a new type of lung infection that was recently found COVID-19.[(4)] Temperature, dry cough, loss of taste, and respiratory illness are the main indications of this virus.[5] Researchers worldwide are on various fields are now concentrating on the diagnosis and management, such as diagnostic instruments for the identification of COVID- 19 and vaccines for the management. Efficient in regulating the spread of COVID-19, patient screening is important.[6] Overally, our policymakers are unlikely to minimize the population distribution of it, for the following reasons: i) inadequate detection kits ii) drug therapy and vaccines are not feasible until[7] CAD systems help detect COVID-19 pneumonia in lung radiography image-based detection are highly desired.

Professional radiology advice is required for reliable, and rapid diagnosis of “COVID-19” with “chest X-ray”. A daunting challenge intended for healthcare professionals is the effective and reliable management of COVID-19 illness. But a big problem is the restricted supply of traditional COVID-19 detection kits. For COVID-19 identification with imaging sense modality, an automated diagnostic model is therefore needed to minimize the

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hand-operated intervention in disease detection with an X-ray of lung images. One of the simplest ways to diagnose this disease is to look at radiology and radiography photographs.[8] The current study attempts to determine and localize COVID-19 immediately using “x-ray” images. A three-step detection process is designed: a) Data-augmentation, b) disease-detection, and c) improving the detection accuracy using fine tuning. However, a small quantity of free “COVID-19” disease “X-rays” are open to scientific community. All these images are added to the shear, rotate, and translational activity to resolve need for wide databases training needs and over-fitting problems. In step 2, X-rays are classified into 3 classes, “COVID-19”, Pneumonia and Normal with deep-learning-based techniques. In addition, four pre-trained models based on a deep CNN, like VGG-16, GoogleNet, ResNet18, and SqueezeNet. Based on assessment of typical output parameters for models, the best training model is obtained. In step 3, accuracy improvement of COVID-19 detection using fine tuning of VGG-16 network to perform as a best pretrained ‘transfer learning’ model is presented.

SqueezeNets are completely convolutional and custom Fire modules having a squeeze layer of 1 × 1 convolutions that tremendously cuts boundaries as it can restrict the number of input channels in each layer. This makes SqueezeNets to have very low latency, notwithstanding the reality that they don't have thick layers. VGG represents Visual Geometry Group. It is described by pyramidal shape, in which bottom layers closer to picture are huge, though top layers are deep. VGG model, or VGGNet, upholds 16 layers- VGG16, which is “convolutional neural network” model. VGG16 model achieves practically 92.8% top-5 test accuracy in “ImageNet”. VGGNet is an extraordinary structure block for advancing as it is clear to execute. It is an excellent design for benchmarking on a specific undertaking. ResNet stands for Residual Network. In solving local gradient problem, Resnet is better than VGGnet with the help of Identity function, it would not allow the vanishing gradient problem to occur.

Related Works

Precise and fast diagnosis of “COVID-19” alleged cases in the beginning phase assumes a significant part in apt quarantine and clinical treatment, that is likewise vital for patients' prognosis. Yet, an enormous quantity of alleged patients want to go through scanning that have made a huge burden to proficient clinical staffs, and serious lack is likewise a significant test in the Pandemic circumstance; besides, radiologists' filmictiredness would elevate possible risks of misused diagnosis for a rareslight lesions. Deep learning, core technology of increasing “artificial intelligence (AI)” as of late, has been accounted for with essentially diagnostic accuracy in clinical imaging for programmed identification of lung illnesses. Most Deep learning-based techniques for infection diagnosis expects to clarify the injuries, particularly for disease detection. Clarifying lesions of “COVID-19” costs an enormous measure of endeavors for doctors, isn't satisfactory when “COVID-19” is scattering fastly and there are extraordinary deficiencies for radiologists. This means, performing “COVID-19” discovery in weakly-supervised way is vital. One of the most straightforward marks for “COVID-19” discovery is patient-level, i.e., showing patient as “COVID-19 positive or negative”. In this manner, goal of current work is to examine capability of a “deep learning-based model” for automatic “COVID-19” detection utilizing “X-ray” checks for fast judgement of “COVID-19” to counter the outbreak. Christodoulidis *et al.*[9] worked on six publicly available texture databases and on huge color image databases like ImageNet, to pretrain networks with the framework, then fine-tuned on the on medical imaging data. This method has produced sufficiently decent results in numerous applications and resulted in F1 Score as 0.8817.

A variety of COVID-19 based on advanced methods were developed in response to the demand for fast and accurate analysis of radiography pictures as mentioned in Table 1. The use of CNN-based architectures has been proposed, with promising results. We used a comparably big dataset for study, which included “chest X-ray” pictures on “COVID-19 pneumonia, bacterial pneumonia”, normal patients, and have trained on four models on transfer learning concepts such as VGG-16, ResNet-18, GoogleNet and SqueezeNet architectures. Researchers have mainly analyzed[10] chest CT pictures of patients with COVID-19. Towards COVID-19 infection, CT has been demonstrated to have sensitivity 98%, whereas RT-PCR sensitivity is just 71% in recent investigations. The X-ray, however, is more effective in COVID-19 diagnosis because it can offer a full view of the lung and can thus be adequately detected in connection with the existence of abnormality. But there is minimal supply of X-ray chest photographs of positive cases. “Transfer learning with data augmentation” thus seen to be valuable tool for the identification of anomalies.

The “transfer-learning” for “COVID-19” detection classifies an X-ray of lungs into 3 classes- “Normal, Pneumonia, and COVID-19”. Numerous architectures applied during the detection process are VGG-16, GoogleNet, ResNet18, and SqueezeNet. Size of training augmented images altered depending on the compatibility with many transfer model used for study. The size requirement is: VGG-16 (224 × 224 × 3), GoogleNet (224 × 224 × 3), ResNet18 (224 × 224 × 3) and SqueezeNet (227 × 227 × 3). Based on class labels applied to the training dataset, pre-trained models will identify small chest X-ray or radiography dataset of the patient. In addition to COVID-19 identification, several attempts have been made to anticipate feast of COVID-19 disease. Furthermore, the corrective feedback Polynomial Neural Network used for forecasting COVID-19 pandemic spreading with a significantly lesser prediction error.

Table 1 — Description of methods of deep learning for study of “COVID-19”

Data used	Performance of the model
COVID-Positive[14]	For binary classification 98.08% accuracy and 87.02% for multiclass (normal, pneumonia, COVID)
“X-ray” pictures of 102 positive “COVID-19” cases and pneumonia cases[15]	with Resnet50 and VGG16, an accuracy of 89.2% and an AUC of 0.95 is obtained.
“COVID-Xray”-5k dataset and ChexPert dataset[16]	Used ResNet18, ResNet50, SqueezeNet, and DenseNet, obtained sensitivity of 97.5% and specificity of 90%.
Used 224 COVID-19 images[17]	96.75 percent, 98.62 percent and 96.48 percent accuracy, sensitivity and precision gained with transfer learning, respectively.
100 chest X-ray images of “COVID-19” positive cases and 1431 images of pneumonia[18]	With deep learning model, achieved sensitivity of 96.05% and specificity of 70.62%
50 X-ray pictures of each of COVID and normal cases[19]	Utilised “ResNet50, InceptionV3 and Inception-ResNetV2”, accuracies “ResNet50 (98%), Inception ResNetV2(87%) and InceptionV3 (97%)”.

Materials and Methods

In current study, we considered large database for the detection of COVID-19, the problem can be solved using the augmentation method. Pre-trained model labels by extracting from trained augmented data. The suggested three-step COVID19 detection process using lung X-ray slices is represented hierarchically in Fig. 1. Data collected from dataset, containing three types of images as normal, COVID-19 or Pneumonia is subjected to pre processing and then augmentation along with resizing was performed before training process. Then a detection model is developed.

Data Augmentation

It is a method that can help researchers substantially increase the variety of data, without actively gathering new data. In order to train broad networks, strategies for rising data such as cropping, folding, and horizontal flipping were employed. The proposed methodology was implemented on data-set containing “X-ray” pictures[11] of chest “COVID-19” positive, Pneumonia, and Normal. Dataset comprises 397 COVID-positive pictures of 216 patients and 397 X-ray pictures of “Pneumonia and Normal “patients.

In the present study, we need to resize the images[12,13], so that they are compatible to apply as input for the Transfer Learning architectures. We performed two pre-processing steps (Augmentation and resize) before applying to transfer learning. Before and after augmentation, the data sizes are shown in Table 2.

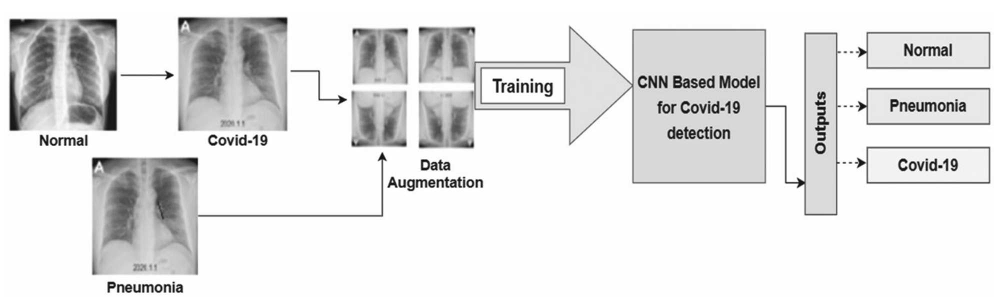

Fig. 1 — Flow diagram for COVID-19 detection

Table 2 — Details of input data used

Category	Training Data		Validation-Data	Testing-Data
	No-Augmentation	Augmentation		
COVID(343)	172	1548	76	95
Pneumonia(397)	228	2052	97	72
Normal(397)	228	2052	97	72

Deep Learning

The transfer-learning detection model categorizes an X-ray of lungs into 3 classes, such as “Normal, Pneumonia and COVID-19”. In this research, analysis was utilizing X-ray pictures collected from two separate sources. Cohen JP was creating “COVID-19” X-ray reference archive utilizing pictures from numerous open access outlets. Website is continually modified with images that researchers from several regions. Currently 343 X-ray pictures with “COVID-19”. Various architectures applied during the detection process are “VGG-16, GoogleNet, ResNet18, and SqueezeNet”. Trained augmented images size is altered depending on compatibility with many transfer models used for the study. Based on class labels applied to training dataset, the pre-trained models will identify "X-ray images.[14,15] The imbalance problem in the data can be avoided using 397 Normal and 397 pneumonia frontal chest X-ray pictures randomly from “Kaggle” database. Retrain pre-trained one through upgrading completely linked layers as per input modified database in order to identify new objects. A)’adam ’optimizers, b) mini-batch size: 64, c) testing is carried out upto 50 epochs, d) validation” frequency: 3, e) pre-quantified initial learning rate of testing is $3e^{-4}$, which are the parameters chosen for the proposed model. Measures such as sensitivity, precision, F1-score, consistency, the best achievement of various transfer-learning networks is analyzed. In addition, in X-ray pictures of COVID-positive events, the deeper layer better performing architecture is identified and used as abnormality identification.

In step-3 of the proposed methodology, the FC of a layer of the pre-trained network is fine-tuned with Keras. We develop new fully-connected layer, then insert it at the end of the existing design during fine-tuning phase. The new FC layer head is connected to the existing network's body. Then, to ensure that any previously learnt strong features by CNN are not vanished, previous convolution layers of network were freezed. Then, only train the fully linked layer heads. The final step is to unfreeze portions or all of the network's convolution layers and perform the second training pass.

Table 3 — The layers and parameters of the proposed model (VGG-16)

Type-of-Layer	Output-shape	Parameters
Input layer	[224,224,3]	0
ConV-2d	[224,224,64]	1792
ConV-2d	[224,224,64]	36928
MaxPooling 2d	[112,112,64]	0
ConV-2d	[112,112,128]	73856
ConV-2d	[112,112,128]	14586
MaxPooling 2d	[56,56,128]	0
ConV-2d	[56,56,256]	295168
ConV-2d	[56,56,256]	590080
ConV-2d	[56,56,256]	590080
MaxPooling 2d	[28,28,256]	0
ConV-2d	[28,28,512]	1180160
ConV-2d	[28,28,512]	2359808
ConV-2d	[28,28,512]	2359808
MaxPooling 2d	[14,14,512]	0
ConV-2d	[14,14,512]	2359808
ConV-2d	[14,14,512]	2359808
ConV-2d	[14,14,512]	2359808
MaxPooling 2d	[7,7,512]	0
Avg-Pooling2d(3)	—	—
Flatten	[None,512]	0
Dense	[None,64]	32832
Linear	[None,3]	130
Total Params	14,747,650	—
Trainable Params	32,962	—
Non-Trainable Params	14,714,688	—

Deep Learning Model

Proposed models have the benefits like (a) limited data collection pre-processing, (b) quicker learning, (c) time-complexity that has been modified by the various parameters, and (d) performs well on the finite database, hence comfortable for the role of classification of medical images.

Training is used in the conceptual work transition for grouping of “chest x-ray” photographs into 3 categories. The VGG-16 Googlenet Resnet18 and Squeezenet are used with these 4 distinct pre-trained models. The CNN models are equipped to classify from the image net database into 1000 object categories. For the identification data of a chest x-ray into 3 groups. VGG-16 model has 16 weight layers, was based on the LeNet and AlexNet designs. For all layers, convolution filter size is 3 × 3. Layers of Conventional VGG-16 are given in Table 3. There are 64 feature maps in each of these convolution filters. After that, there are two layers with three convolutions each, tailed by max-pooling and 3 FC layers. VGG-16 model is most effective. Its design is shown in Fig. 2. Fog-assisted IoT enabled

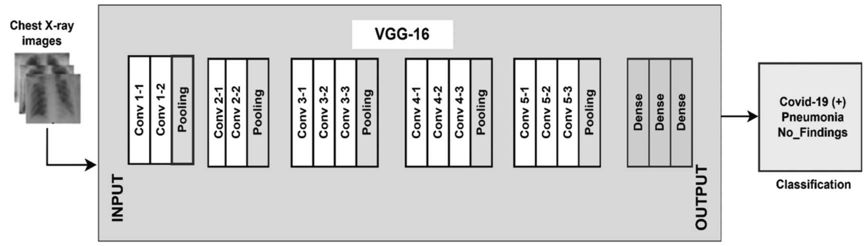

Fig. 2 — Architecture of proposed model

framework helps in remotely monitoring the healthcare data through the smart gateways. Here, the event triggering data transmission methodology could be used for analyzing the patient's health data based on the temporal health index.

To make consistent pre-trained network, the input images are pre-processed, i.e. a 256 × 256 × 3 image transformed to 224 × 224 × 3. The layers of convolution and applied filter for scanning input image. Then a feature map is generated by the convolution layer to estimate class probabilities of each obtained feature map. First convolution layer's (conv1), furnishes low level characteristics such as colour, edges, gradient activity, etc. Deeper convolution operation offers high-level characteristics, such as abnormality in X-ray images found in deeper layer in the proposed work. The spatial scale of features of convolution is limited by layer of pooling. In the pooling layer, the dominant features such as spatial invariants and rotational ones are obtained. The flattened contribution from the pooling layer is obtained by the fully linked layer (FC) and functions as feed-forward network.

The performance is constrained within [0, 1] by Softmax matrix. Softmax layer thus estimates probability of input vector of certain class that has been studied. The SqueezeNet is often used to compare the efficiency of chest X-ray image recognition on smaller neural networks for deep learning. The squeeze net is a model of 68 layers which includes an input image size of 227 × 227 × 3. With squeeze net, while time complexity is overcome, performance on the proposed model is not satisfactory. Freezed all convolution layers in network as in Fig. 3(a) when we started the fine-tuning phase and then allowed the gradient to back-propagate via the fully-connected layers. This allows warming up our network. Once the fully-connected layers had the opportunity to warm up as in Fig. 3(b), we can unfreeze all or any of layers in network earlier and therefore enable each as fine-tuned.

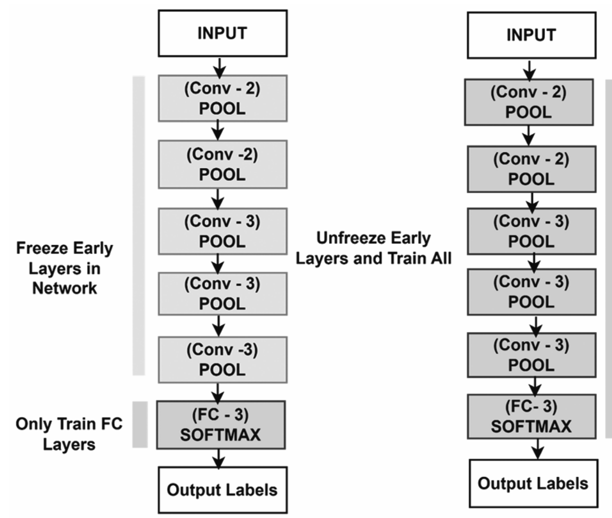

Fig. 3 — (a) Freeze all convolution layers in network (b) unfreeze all or any of layers to fine-tune

The pretrained VGG-16 model used for the X-ray image classification is 16 layers deep and includes a 224 × 224 × 3 as image for the input. For preparation, the "adam" optimizer is used. ResNet18 architecture was also used with 177-layers deep. In comparison, the 347-layer ResNet-18 is also more complicated than remaining residual models. The input size of '224 × 224 × 3' is needed by the network. In all the pretrained models, the initial learning rate used is 3e −4. Due to its ability to efficiently refine, converge faster, and improve the precision with enhanced range, the residual model is picked. However, increase in the layers of each residual network, increases time utilization. A new layer is replaced by the FC layer for transfer learning using for VGG-16. Number of output classes is equal to X-ray data groups the model is being trained on. Thus, in the proposed model, new convolution layer and number of filtering equal to output categories replaced by the last layer.

Fine-tuning VGG-16 with Keras

Fine-tuning improves an accuracy of pre-trained networks.[16,17] We know that the last layers in VGG-16 are “FC layers” with “soft-max”. There’s a question, though, because our convolution layers already trained deep, discriminative filters (using the ImageNet dataset). Instead, we let our FC head "warm-up" by "freezing" all Convolution layers within the network’s body to circumvent this problem, as depicted in Fig. 3 (left). Fine-tuning necessitates not just modifying but also retraining the CNN design to recognize different types of objects (classes). We fine-tune a pre-trained CNN by removing the final layer (usually VGG, ResNet, and GoogleNet). Filters were used on datasets other than those on which the network was built to forecast class labels. We must undertake network operation and update the real architecture so that we can retrain parts of network, rather than merely using a pre-trained network. We can unfreeze the remaining network and continue training if we want to. Using fine-tuning, we can employ pre-trained networks to recognize classes on which they were not initially trained. Moreover, this method has the potential to be more accurate than transferring learning through feature extraction.

Results and Discussion

Many deep learning models[18,19] discussed are performing better for detection. A three-class classifier is implemented to distinguish COVID, pneumonia and normal cases.

We used 4 transfer-learning models (VGG-16, GoogleNet, ResNet18, and SqueezeNet). Training accuracy, 99.82% (the validation accuracy 97.32% attained with the VGG-16 model. The output compared to transfer learning architectures utilized for the present work using VGG-16 is presented in Fig. 4. Convergence graph of training-validation accuracy of VGG-16 architecture and loss function for 50-epochs (8:2 training-validation data) is displayed in Fig. 5. This graph depicts Training loss and accuracy, Validation loss and accuracy with respect to number of epochs of the VGG-16 model. As the number of epochs increases, the training loss and validation loss decreases, training accuracy and validation accuracy increases. Training accuracy starts with 95% for 5 epochs and increases upto 100% as the number of epochs increases. The functioning of a classifier can be compared based on criteria: Sensitivity, Specificity, Precision, F1score and total accuracy. Testing precision of 99.4% was achieved by the VGG-16 transfer learning architecture and important findings are: (i) Total dataset is rated as 98.6% precision and 100% sensitivity, and (ii) Area Under Curve (AUC) of 0.99 as in Table 3. TP = Truepositive (correctly classified COVID positive cases); TN = True-negative (correctly classified normal cases); FP = False-positive (Normal class classified as COVID positive); FN = False-negative (COVID positives class classified as normal) outline the output parameters. The performance comparison of proposed methodology for identification of COVID using chest radiography is presented in Table 4. The overview of Deep Learning techniques for analysis of the COVID-19 is presented in Table 5. The ROC

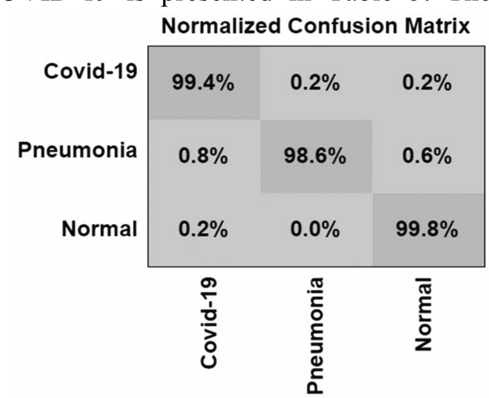

Fig. 4 — Confusion matrix using VGG-16 model

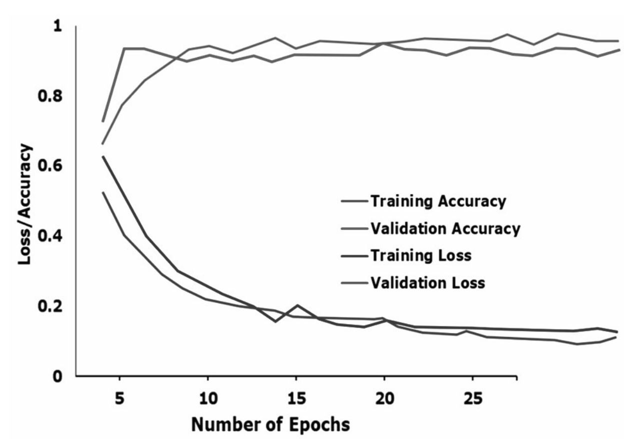

Fig. 5 — Accuracy and loss function graph using model VGG-16

Table 4 — COVID-19 detection performance metrics

	Sensitivity	Specificity	Precision	F1-score	Accuracy
VGG-16 (Fine tuning)	100%	98.5%	99.1%	99.4%	99.3%
ResNet-18	99%	97.3%	97.8%	98.4%	98.7%
GoogleNet	97.8%	95.9%	96.8%	97.3%	97.1%
SqueezeNet	95.8%	94.3%	95.7%	95.5%	95.3%

Table 5 — Overview of Deep Learning techniques for analysis of the COVID-19

Approach	Performance
X-ray images 224 “COVID-19”, 700 Pneumonia, 504 Healthy[13]	93.48% accuracy with VGG-16
CT 229 normal and 313 positive cases[14]	3D CNN with UNet and accuracy 90.8%
Images 50 “COVID-19” (+) and “normal” cases[15]	“ResNet-50” (98%), “Inception-V3” (97%), and “Inception-ResNetV2” (87%)
“X-ray” images of 25 “COVID19”(+) 25 COVID-19 (-)[17]	95.38% accuracy with ResNet50+SVM
“X-ray” of normal (25) and COVID positive (25)- [20]	With deep new learning model COVIDXNet, accuracy of 90.0%
With CT Normal (175),Viral pneumonia(224), “COVID-19” positive(219)[21]	with ResNet accuracy of 86.7%
“X-ray” images of 53 “COVID19”(+), 5526 “COVID-19” (-), 8066 Healthy[22]	92.4% accuracy with COVID-Net
343 “COVID-19” (+), 397 Normal, 397 Pneumonia.(Proposed Study Chest X-ray	“VGG-16” (Fine-tuning), Accuracy 99.4%

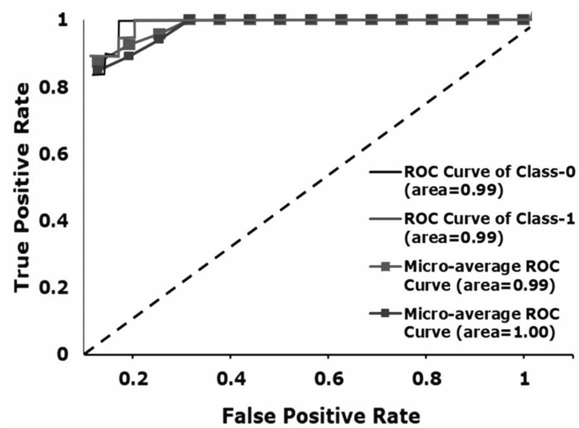

Fig. 6 — Roc graph using VGG-16 model

curve using VGG-16 classification is shown in Fig. 6. Here, to plot this curve we have considered COVID-19 as one class (class 0) and Pneumonia and Normal are considered other class (class 1). The area under the curve for class 0 is 0.99 and for class 1 also 0.99. Here, to plot this curve we have considered COVID-19 as one class (class 0) and Pneumonia and Normal are considered other class (class 1). The area under the curve for class 0 is 0.99 and for class 1 also 0.99.

Conclusions

The three-step COVID-19 illness classification model is applied to X-ray pictures with ‘transfer learning’ in this study. Data augmentation is performed in step 1 on X-ray pictures, step 2 involves using four different ‘transfer learning models’ to classify the X-ray dataset: VGG-16, GoogleNet, ResNet, and SqueezeNet. The best performing model is fine-tuned with Keras in step 3 to boost the precision of chest X-ray in positive COVID-19 events. With the VGG-16 transfer learning model, the maximum accuracy of 99.82% for training and 97.32% for validation is obtained. The measurement knowledge yields 99.4% accuracy, 100% efficiency, 98.6% precision, and 0.9965 AUC. The suggested framework would definitely assist in the fast and precise identification of the signature of COVID-19 from lung radiographs. We plan on applying our concept in the future on real-time datasets.

Conflict of Interest

The authors declare no conflict of interest.

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