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COV-RadNet: A Deep Convolutional Neural Network for Automatic Detection of COVID-19 from Chest X-Rays and CT Scans

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ABSTRACT

With the increase in severity of COVID-19 pandemic situation, the world is facing a critical fight to cope up with the impacts on human health, education and economy. The ongoing battle with the novel corona virus, is showing much priority to diagnose and provide rapid treatment to the patients. The rapid growth of COVID-19 has broken the healthcare system of the affected countries, creating a shortage in ICUs, test kits, ventilation support system. etc. This paper aims at finding an automatic COVID-19 detection approach which will assist the medical practitioners to diagnose the disease quickly and effectively. In this paper, a deep convolutional neural network, ‘COV-RadNet’ is proposed to detect COVID positive, viral pneumonia, lung opacity and normal, healthy people by analyzing their Chest Radiographic (X-ray and CT scans) images. Data augmentation technique is applied to balance the dataset ‘COVID 19 Radiography Dataset’ to make the classifier more robust to the classification task. We have applied transfer learning approach using four deep learning based models: VGG16, VGG19, ResNet152 and ResNext 101 to detect COVID-19 from chest X-ray images. We have achieved 97% classification accuracy using our proposed COV-RadNet model for COVID/Viral Pneumonia/Lungs Opacity/Normal, 99.5% accuracy to detect COVID and non-COVID classes. Among the performance of the pre-trained models, ResNext 101 has shown the highest accuracy of 98.5% for multiclass classification (COVID, viral pneumonia, Lungs opacity and normal).

1. Introduction

Coronavirus disease 2019 (COVID-19) outbreak, which has been declared by WHO as Public Health Emergency of International Concern on 30 January, 2020 and as a pandemic from 11 March till now (July, 2021). This disease is caused by an RNA virus which single stranded named Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-COV-2). This virus is mostly liable for creating respiratory illness. China informed WHO about the Pneumonia cases found in Wuhan of Hubei province in December, 2019. All these abnormal pneumonias were predicted as the outcome of attacking “SARS-COV-2” virus which is approximately 86% similar to SARS like virus. These SARS like viruses are carried by bats and this indicates the mass transmission of this virus from bat to human. This virus has mutated so many times, creating especially alpha, beta, delta variants and getting more contagious and harmful. More than 4.17 million deaths have been reported since 28 July, 2021 throughout the world due to COVID-19. Penetration of respiratory droplets in the human body through inhalation or mouth can be the major way of mass transmission of this virus. Close proximity among people increases the chance of getting infected. Even if the chance of infection is much in case of long proximity in indoor spaces. The most dangerous characteristic of this infection is that infected people may transmit the virus among people up to 20 days, whether the virus show any symptoms in his body or not [18]. In most cases, asymptomatic people are not testing usually and go undiscovered transmitting the virus among uninfected people. Those who are pre-symptomatic showing symptoms later or with a mild symptoms, spread the virus unconsciously. This is a matter of concern that at least one-third of the infected people undergo with a condition showing no symptom at all. This disease starts to show symptoms like fever, cough, etc. after 5 to 6 days incubation period and sometimes end with severe oxygen deprivation due to pneumonia. This creates emergency condition for the patient causing damage to kidney or heart and other vital organs of the body. Maintaining social distance, wearing masks in public
places, covering mouth while coughing, and making sanitization of regularly used accessories, etc. are suggested to prevent mass transmission of this virus [18].

The impact of this COVID-19 is hazardous in our normal life. The whole world has come to a steady state which has lost the regular motion of life. This situation forces to keep oneself in quarantine when he gets exposed to virus or shows symptoms. Restriction on worldwide travel, avoiding social activities, creating the new trend of “Work From Home” etc. have made the people to get habituated with a new normal life. This pandemic situation forced most of the countries to go under lockdown situation to maintain social distance. It seemed too hard to tackle with the growing number of ICU (Intensive Care Unit) demand in the developed countries also [11]. Moreover, most of the countries are facing problems due to the shortage of test kits since the number of COVID-19 infected people is growing rapidly.

Early detection of COVID-19 is very important since we have no remedial treatment or vaccine available to cope up with the situation. This early recognition of COVID-19suspected people makes them to move for isolation decreasing the risk of infecting healthy people. The majority number tests of COVID-19are done using RT-PCR (Reverse Transcription Polymerase Chain Reaction). Sensitivity for samples from nasal swab, pharyngeal swab, sputum and Broncho alveolar lavage are accordingly 63%, 32%, 75% and 90-95% [12]. Another method CRISPR gene editing tests faster than RT-PCR skipping the step of transformation from RNA to DNA. Besides antigen tests, sniff, test, antibody test, chest X-ray observation, etc. are used worldwide to detect this infection as soon as possible. Testing using the mostly used RT-PCR using samples collected from the throat, the probability of getting true positive value since the virus gradually moves down to the lungs and increases in numbers. Moreover, RT-PCR includes requirements to have specialist equipment and takes at least 24 hours to get the result. In many cases it requires a second time testing to get accurate result also. So, analysis of chest X-ray images of those people having COVID-19 symptoms can be a better way to detect and start clinical treatment of the infected people [5]. Radiologic findings of CT images and chest x-ray images showed the importance of predominant imaging of ground glass opacification [15].

Since the condition of a COVID 19 affected person is dynamic, researchers have shown interest to use different machine learning and deep learning based classifiers to differentiate COVID-19 infected people from other using their chest X-ray images. [14] proposed to use four popular deep learning based classifiers named ResNet18, ResNet50, SqueezeNet and DenseNet-121 to detect the outcome of COVID-19 in the infected lungs. They used public dataset from “Chex-Pert” containing 5000 images where 2000 images were used to train the models and the remaining portion were used to evaluate the model. They created the heat maps of the original dataset and then labeled all those data with the help of a radiologist. Since they applied their training task on pre-trained models, the initial weights were assigned from the pre-trained models. They achieved the sensitivity value around 98%±3%, depending on the threshold value of the confidence level and around 90% specificity to do this binary classification task using an imbalanced dataset. Depending on the threshold values, the sensitivity ranges from 85% to 98%. So, the model performance fluctuates with the change of the threshold values. [10] proposed to use a pre-trained model ResNet101 to distinguish between COVID and Non-COVID condition from chest X-ray images. They segmented lungs from chest X-ray using another pre-trained model U-Net. Before this segmentation task, they produced the heatmap of the training images to identify the region of interest. They achieved, on average, 97% classification accuracy to predict COVID-19 using different cutoﬀ values on the confidence score of the test images.

In recent study, researchers have found chest X-ray images to show more specificity and sensitivity to detect COVID-19 rather than RT-PCR test [12]. An automated system to detect COVID-19 from chest X-ray images will be an eye-opener in the field of medical science to provide treatments within the shortest possible time. In this paper, we have proposed a convolutional neural network to detect COVID positive or not by analyzing the chest X-ray and CT scan images where no prior knowledge will be needed. We have implemented dense layers in our proposed model to extract the features from x-ray and CT images to differentiate the globular opacity in the lungs. In our work, the main contribution is to propose a computational neural network model which will be optimized than other pre-trained deep learning models and to reduce the training time of our model in comparison with the other pre-trained models. In most cases this classification task is experimented on an imbalanced dataset. We have applied data augmentation techniques (contrast stretching) to balance our data set to generate a good balanced model.

In present diagnosis system, the importance of viral pathogen identification through nucleic acid detection cannot be denied. But insufficiency in the clinical setting like shortage in test kits, health workers, laboratories etc. make the people working in medical sector interested to accept radiographic image based COVID-19 detection techniques. Radiographic images of lungs have some utilities to be used as a screening tool. Since COVID-19 grows gradually at the early phase of infection, chest radiography may detect multiple patchy opacities relevant to the diagnosis system. Depending on the condition of the infected people, some chest radiography show eventually grown opacity making the lung “White Out Lung”. These images contain strong identical symptoms of ground class opacities, progressive opacities and consolidation at several steps of illness. Even pleural fluid in lungs (in most severe stage) can be recognized through chest radiographic images. Thin CT image slices contain strong evidence about several stage of COVID-19 caused infection like bilateral patchy area, presence of air bubbles, air bronchogram, partial collapse of lung alveoli etc. The importance of chest radiography images in COVID-19 detection strengthens our motivation in this work.

This next portion of this paper is as follows: Section 2 emphasizes on the previous works for detecting COVID positive or negative using chest X-ray. Section 3 provides details workflow of our proposed methodology, dataset description. Section 4 shows the experimental results and comparison between the previous works and our proposed methodology. Finally, this paper turns into a conclusion in Section 5.

2. Related Works

Researchers proposed to use different traditional machine learning algorithms and deep learning based classifiers to differentiate the COVID-19 infected people from other using their chest X-ray images. [14] proposed to use four popular deep learning based classifiers named ResNet18, ResNet50, SqueezeNet and DenseNet-121 to detect the outcome of COVID-19 in the infected lungs. They used public dataset from “Chex-Pert” containing 5000 images where 2000 images were used to train the models and the remaining portion were used to evaluate the model. They created the heat maps of the original dataset and then labeled all those data with the help of a radiologist. Since they applied their training task on pre-trained models, the initial weights were assigned from the pre-trained models. They achieved the sensitivity value around 98%±3%, depending on the threshold value of the confidence level and around 90% specificity to do this binary classification task using an imbalanced dataset. Depending on the threshold values, the sensitivity ranges from 85% to 98%. So, the model performance fluctuates with the change of the threshold values. [10] proposed to use a pre-trained model ResNet101 to distinguish between COVID and Non-COVID condition from chest X-ray images. They segmented lungs from chest X-ray using another pre-trained model U-Net. Before this segmentation task, they produced the heatmap of the training images to identify the region of interest. They achieved, on average, 97% classification accuracy to predict COVID-19 using different cutoﬀ values on the confidence score of the test images.
ensemble method using these classifiers. This ensemble method was applied on the basis of giving priority to model used weighted average. This additional feature of combining pre-trained models improved the classification accuracy of the average 91% to 91.6%.

[19] proposed a deep learning model 'COVIDNet' to classify chest X-ray based on 'COVID', 'Non-COVID' (pneumonia caused by other disease) and 'Normal'. They also applied pre-trained models to train the dataset and achieved highest 91% accuracy using Inception V3. Their proposed model COVIDNet achieved 93% accuracy to differentiate among these three classes. They applied a segmentation approach using Vision Pro Deep Learning tools where they made the whole image as a region of interest first and then segmented the lungs from the images. This segmentation approach improved the model performance from 93% to 95%.

[27] experimented with CT images using a modified ResNet V2 model and showed the performance of transfer learning method. They replaced the group normalization using batch normalization in every convolutional layers. They adjusted the hyper parameters, learning rate, gradient values using the dataset and random horizontal flipping was done for data augmentation. They achieved 97.9% accuracy to classify COVID, non COVID and pneumonia using CT images.

[9] initiated an automated diagnosis system to differentiate between COVID-19 and heart failure depending on the pattern of cough sounds. They proposed a model to generate features deploying DNA pattern. These features were selected through ImRMR and classification task was performed using supervised learning-based classifier, KNN (K Nearest Neighbor).

[22] implemented COVID-19 respiratory sound classification task using 10 different classes of respiratory sounds. They proposed to use LSEDP (Local Symmetric Euclidean Distance Pattern) which used Euclidean distance to generate features. Iterative-hybrid feature selector was applied to filter meaningful features. They proposed to use Bagged Tree, Linear Discriminant, KNN and SVM classifiers for this classification. They achieved highest 91.02% classification accuracy using KNN.

[16] proposed to use feature generation network and the selected features were passed through Artificial Neural Network and Deep Neural Network. They used ReliefF and iterative neighborhood component analysis based method LBP (Local Binary Pattern) for selecting features. They transformed the CT images into 2D matrices and extracted both statistical and textural features. They have shown highest 95.84% classification accuracy using DNN.

[4] proposed an exemplar deep feature extractor to extract features from CT images to detect COVID-19. They used three pre-trained deep learning-based classifiers VGG16, VGG19 and AlexNet to extract features from their fully connected layers. They filtered the features using an iterative selector and those informative features were classified using Support Vector Machine (SVM). They experimented the method on four databases and the classification accuracy fluctuates from 89.96% to 99.64%.

[26] proposed to develop a multiple input classifier using a fusion of chest X-ray images and CT images. Their novelty lied behind the addition of convolutional block attention module to improve the performance. They used features from both x-ray and CT images. They implementation Patch Shuffle technique for data augmentation and achieved 98.02% classification accuracy with the attention-based classifier.

3. Methodology

We have proposed a deep convolutional neural network “COV-RadNet” and worked on different pre-trained models to predict four classes: COVID, Lungs Opacity, Viral Pneumonia and Normal from chest X-ray images. VGG16, VGG19, ResNet 152 and ResNext 101 pre-trained models are used to implement this classification task.

3.1. COVID-19 Radiography Dataset

We have collected “COVID-19 Radiography Dataset” from Kaggle (https://www.kaggle.com/preetviraditya/COVID-19-radiography-data-set) to train and evaluate the performance of our model. A research group from different countries (Qatar, Bangladesh, Pakistan etc.) collected these dataset containing COVID, viral pneumonia, Non-COVID Lungs Opacity and Normal chest X-ray images [17,13]. Each class contains different number of images and so this dataset is an imbalanced data. For COVID, Lung Opacity, Normal and Viral Pneumonia, the number of images are accordingly 3616, 6012, 10192 and 1345. In this paper, we have implemented our work using both imbalanced and balanced data. Data augmentation technique is used to increase the number of data generating new images. Two major approaches of data augmentation are used: Horizontal Flipping and Brightness changing (through gamma correction). We have used gamma values from 0.8 to 1.1 to generate new samples. [23] used patchshuffle, a multiple way data augmentation technique. Since chest radiography images contain various kind of lung opacity information and we have four different classes where COVID-19, pneumonia and non COVID lung opacity show very close symptoms, we have implemented only two types of augmentation techniques. Each class contains 20k images for the balanced dataset.

3.2. SARS-COV-2 CT Scan Dataset

We have collected another chest CT scan (Computed Tomography) image dataset containing two classes: COVID and Non-COVID from Kaggle [2]. Chest CT scan images of this dataset is collected from patients admitted into hospitals in Sao Paulo, Brazil. Each class contains 1250 images. We have augmented the data using horizontal flipping and gamma correction with a gamma value of 0.9. After augmenting the dataset, each class contains 5000 images.

3.3. Proposed Convolutional Neural Network Architecture

The workflow of our proposed CNN model is shown in Fig. 3. We named the deep convolutional neural network “COV-RadNet” as we focused on detecting COVID or Non-COVID characteristics from chest radiographic images (X-ray and CT scans). A convolutional neural network contains multiple blocks like convolution layer, pooling layer, activation function and fully connected layer which can extract spatial trainable features adaptively using back propagation algorithms [8]. A convolution layer extracts features from images applying the convolution operation on the images using the weighted values of filters or kernels. Pooling layer reduces the number of trainable parameters, filtering the useful features only. A fully connected layer makes a combination of one or more layers in a CNN to convert the features into a one-dimensional array or vector. When the output features are connected to more than one fully connected layers, the model is called ‘Dense’ network [8]. COV-RadNet consists of eight convolution layers followed by fully connected layers and batch normalization also. In our proposed model, first the input images of size (256 × 256) are passed through the batch normalization unit. This actually estimates running mean and variance to use the values for evaluation purpose of the model. Eight convolution layers are placed sequentially with a kernel size of 3 × 3, ReLU activation function and a max pooling layer. Max pooling layer (2 × 2) reduces the image size into a factor of 2. So, after the first convolution operation, image size gets reduced to (128 × 128). The spatial information is not reduced due to convolution since we have used a padding with a value 1. All these outputs from the convolution layers are transformed into linear values using ‘Linear Layers’. From the last convolution layer, we have found 4096 convolved output values which are transferred to eight fully connected layers (Dense Layer) followed by batch normalization layers. In our COV-RadNet model, we have got the final output values from the eighth fully
connected layer. This value is mapped to the number of classes to be classified using the model. The activation function connected to the last layer is “ELU” (Exponential Linear Unit) which makes the model to converge with a good accuracy. The activation function used in hidden and output layer determines how well the model will learn the features from training data. The mostly used activation function is ReLU which decreases the impact of vanishing gradient. There exists a dead condition for ReLU when it gets negative input and returns zero. For this concern, we have applied ELU activation function for the output layer. Using ELU keeps the model safe from vanishing gradient effect. We have used SGD (Stochastic Gradient Descent) optimizer to implement this model. Learning rate for the training samples starts with 0.001 and it decays by a factor 0.1 after every 7 epochs during the training process. This technique makes the model more generalized to classify unseen samples beyond the training dataset.

3.4. Fine Tuning Pre-Trained Models and Transfer Learning

Transfer learning is such a process that makes a model using the knowledge of any previous classification task to implement a new classification task. To work with deep learning based classification algorithm, it requires enough number of training samples. In some cases, like medical data analysis, researchers lack in a suitable large dataset. Transfer learning approach initializes the previously trained weights of the pre-trained models to ensure a better learning of the pre-trained models over the new dataset [25]. The last layer output of the pre-trained model is needed to be changed with the number of classes of the new classification task. Fine tuning approach does the same. Additional feature is that the pre-trained model can be retrained in all layers like convolution layer, pooling layer including the last classification (fully connected layer).

3.5. COVID-19 Detection Using VGG Networks

VGG 16 and VGG 19 was proposed by [20] and these models consisted of accordingly 16 and 19 weighted layers. VGG networks are simpler with their architecture having $3 \times 3$ convolution layers, max pooling layers, softmax activation and fully connected layer. We have fine-tuned these pre-trained models to detect COVID-19 from chest X-ray images. Since these models are pre-trained on ImageNet dataset having 1000 classes, we have modified the last layer output, replacing with the number of classes of our COVID-19 Radiography Dataset.

3.6. COVID-19 Detection Using ResNet152

Deeper networks gradually learn features from the training set efficiently. But it arises the problem of gradient degradation also. In back propagation algorithm, the model learns feature and adjust weight values by generating gradient values. In deeper layers, the gradient values get so smaller that the initial layer weight does not change or
rarely change. To solve this issue, ResNet was proposed to add a residual layer or an identity layer which adds direct connection between the initial layers and deeper layers [7]. ResNet152 has 152 layers which is pre-trained on ImageNet dataset.

3.7. COVID-19 Detection Using ResNeXt101

ResNext101 [24] initializes a term “Cardinality” which indicates the total number of paths in a block. Using high cardinality improves the model performance by decreasing validation error instead of using a high depth model. Split, transformation and aggregation are applied to the model, thinking it as a simple neuron. In Fig. 7, the left and right sides are ResNet and ResNeXt blocks accordingly. Both blocks have the same complexity but layers are split and aggregated to increase the cardinality. We have trained our dataset on a pre-trained ResNeXt model to detect COVID-19 from chest X-ray images.

3.8. Contributions

The novelty of our work is to build up a dense network to extract features from chest X-ray and CT images. We have worked with four different classes- COVID, Lungs Opacity, Viral Pneumonia and Normal. All of these categories preserve some uniqueness in the presence though their X-rays and CT images. A deep convolutional neural network is proposed here with a combination of data augmentation technique to enlarge the dataset. The followings can be included as our contributions:

- An effective deep convolutional network, COV-RadNet, is developed to extract informative features and to recognize COVID-19 from chest X-ray and CT images.
- Generally pre-trained models like VGG16, VGG19, ResNet, ResNext etc. require more training time. These models got saturated to a certain classification peak point. We have added dropout layers...
(using max pooling) in our proposed dense network to reduce overfitting.
• COV-RadNet, a rapid and effective COVID-19 detection classifier is build up and the performance of the model signifies the importance of this automated COVID-19 detection method which already performed better than many pre-trained models (From Table 2).

4. Experimental Results

4.1. Hyper-Parameters of COV-RadNet and Pre-Trained Models

We have implemented this work on PyTorch and used hold out cross validation to split the dataset into training, test and validation set. Training, validation and test sets are 60%, 20% and 20% accordingly. We have used both Adam and SGD optimizer for the pre-trained models to adjust and minimize model loss. In both cases, we have found similar results. For our proposed COV-RadNet model, SGD is used to build the model. We have used a learning rate with a value 0.001. In all cases, 256 × 256 size input images are used and the batch size is 32. These
parameters made the training process efficient, creating a good relation between training and validation accuracy of the models [13]. From Fig. 8(a), the relationship between the training and validation accuracy is shown where the validation score gets saturated between 10-15 epochs. This positive correlation between these two indicates that the trained model is not getting over fitted and trained model will show robust performance on the evaluation samples [1].

In Fig. 8(c), we have shown that the validation accuracy fluctuated during 2 to 6 epochs with the training accuracy and in Fig. 8(d), ResNeXt 101 gradually adapted the validation accuracy with the increasing training accuracy.

4.2. Evaluation Performance

Evaluation performance of any model can be measured using various metrics like accuracy, precision, recall, sensitivity, specificity, F1 score, etc. In our work, we have applied the dataset in two conditions: Imbalanced data and balanced data with augmentation. Since calculating sensitivity and specificity for imbalanced data is more effective to evaluate a model, we have shown these metrics for both cases. Class wise precision and recall values are shown only for the balanced data. The following equations are used:

\[
\text{Sensitivity} = \frac{TP}{TP + FN}, \quad \text{Specificity} = \frac{TN}{TN + FP}
\]

\[
TP = \text{True Positive}, \quad TN = \text{True Negative}
\]  

\[
\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}
\]

\[
FP = \text{False Positive}, \quad FN = \text{False Negative}
\]

\[
\text{Accuracy} = \frac{\text{Number of Correctly Classified Images}}{\text{Total Number of Images}}
\]  

In Table 1, evaluation metrics (sensitivity, specificity, and accuracy) for the COV-RadNet model and other pre-trained models are shown. We have found the highest 96.5% classification accuracy for the ResNeXt model and our proposed model COV-RadNet has achieved 93.2% accuracy with a good sensitivity and specificity. Analyzing the per epoch time requirement to train the model, COVID-RadNet has shown a very satisfactory result. COV-RadNet is approximately 8.4 times faster than

| Model Name       | Accuracy (%) | Sensitivity (%) | Specificity (%) | Training Time (min per epoch) |
|------------------|--------------|-----------------|-----------------|-------------------------------|
| VGG 16 Adam      | 98.1         | 99.8            | 97.4            | 13.83                         |
| VGG 19 Adam      | 98.1         | 99.8            | 97.3            | 14.4                          |
| ResNet152 Adam   | 98.26        | 99.7            | 97.7            | 15.5                          |
| ResNeXt101 Adam  | 98.39        | 99.6            | 98              | 41.3                          |
| Proposed Model   | 97           | 99.6            | 96              | 4.86                          |

| Model Name       | Accuracy (%) | Sensitivity (%) | Specificity (%) | Training Time (min per epoch) |
|------------------|--------------|-----------------|-----------------|-------------------------------|
| VGG 16 SGD       | 98           | 99.8            | 97.4            | 13.83                         |
| VGG 19 SGD       | 98.1         | 99.8            | 97.3            | 14.4                          |
| ResNet152 SGD    | 98.26        | 99.7            | 97.7            | 15.5                          |
| ResNeXt101 SGD   | 98.5         | 99.8            | 98              | 41.3                          |
| Proposed Model   | 97           | 99.6            | 96              | 4.86                          |
Table 3
Comparison of COV-RadNet with Other Works.

| Reference | Methodology | Dataset | No. of Classes | Class Label | Performance |
|-----------|-------------|---------|----------------|-------------|-------------|
| [14]      | ResNet18, ResNet50, DenseNet, SqueezeNet | Chex-Pert | 2 | COVID and Non-COVID | The sensitivity ranges from 85% to 90% |
| [10]      | ResNet101 with UNet for segmentation | Collected | 2 | COVID and Non-COVID | Accuracy: 97% |
| [3]       | VGG16, DenseNet, MobileNet v2, Inception v3 | Collected | 2 | COVID, viral pneumonia and Non-COVID | Accuracy: 93% |
| [6]       | Inception v3, ResNet50v2, DenseNet2021 | Collected | 2 | COVID and Non-COVID | Accuracy: 91% |
| [19]      | COVIDNet CNN | Collected | 3 | COVID, viral pneumonia and Non-COVID | Accuracy: 93% |
| [22]      | ReliefF and RIMMR with KNN | Collected Lungs Respiratory Sounds | 10 | | Accuracy: 91.02% |
| (Ozyurt et al., 2021) | ANN and DNN with NCA,RFINCA | Collected | 2 | COVID and Non-COVID | Accuracy: 95.84% |
| [4]       | Exemplar COVID-19Fc1Net9 | Collected | 3 | COVID, viral pneumonia and Non-COVID | Accuracy: 97.60% |
| (Zhang et al., 2021) | MIDCAN, Deep Convolutional Attention Network | Collected | 2 | COVID and Non-COVID | Accuracy: 98.02% |
| Proposed work with pre-trained models | VGG 16, VGG 19, ResNet152, ResNeXt | COVID-19 Radiography Dataset [10] | 4 | COVID, lung opacity, viral pneumonia and normal | Accuracy: 98.1% |
| | | | | | Accuracy: 98.1% |
| | | | | | Accuracy: 98.26% |
| | | | | | Accuracy: 98.5% |
| Our Proposed Model | Deep Convolutional Neural Network “COV-RadNet” | | 4 | COVID, lung opacity, viral pneumonia and normal | Accuracy: 97%, Sensitivity: 99.6% |
| | “COV-RadNet” | | 3 | COVID, viral pneumonia and normal | Accuracy: 99.5%, Sensitivity: 99.8% |
| | “COV-RadNet” | | 2 | COVID, Non-COVID(Viral pneumonia + normal) | Accuracy: 99.72%, Sensitivity: 99.7% |
| | “COV-RadNet” | | 2 | COVID and Non-COVID | Accuracy: 99.5%, Sensitivity: 99.8% |

Fig. 9. Precision and Recall for COV-RadNet model(Augmented Balanced Data).

Fig. 10. Precision and Recall for ResNeXt101 model(Augmented Balanced Data).

Fig. 11. Precision and Recall for VGG 16 model (Augmented Balanced Data).

Fig. 12. Precision and Recall for ResNet model (Augmented Balanced Data).
ResNeXt. To improve the performance of our proposed model, we have trained the model with an augmented balanced dataset and achieved 97% accuracy and 99.6% sensitivity with COVID-19 class. For the models trained with a balanced dataset, we have measured the models’ precision and recall value also. In Figs. 9, 10, 11 and 12, we have shown these values with graphical representation. Our model COV-RadNet outperforms all previous works on COVID-19 detection showing 99.6% precision and recall value with respect to COVID-19 class in this work. In Fig. 13(a), (b), (c) and (d), confusion matrices for COV-RadNet, VGG16, ResNet 152 and ResNeXt are shown. Each class contains 4100 sample test images and this is balanced data for the four classes. From the confusion matrices, we can infer that COVID-19 and Normal class images are detected successfully with approximate 100% accuracy. All these models degrade their classification performance in case of Lungs Opacity and Viral Pneumonia. False positive and false negative rates between these two classes are higher than other classes. Lungs Opacity class contains such images having different types of opacities like ground glass opacity, nodular pattern, military pattern, etc. caused by pulmonary edema, pneumonia, etc. So, variation in this class is much more than other classes. We have evaluated our COV-RadNet model to classify three classes except lung opacity. This task has shown 99.5% (Figs. 12 and 13) classification accuracy to differentiate among COVID-19, viral pneumonia and normal (healthy) chest X-ray.

We have implemented binary classification to detect COVID and Non-COVID also. Using the chest X-ray dataset, we have kept all Non-COVID (lung opacity, viral pneumonia and normal) in a single class and COVID in another class. Our COV-RadNet model efficiently classified these two with 99.72% accuracy. We have worked to detect COVID or Non-COVID from chest CT scan images using our proposed model.

This binary classification is also done with 99.25% accuracy, 99.8% precision and 98.7% recall value with COVID class. In case of binary classification using chest X-ray and CT images, we analyzed the confidence scores of the test samples. The overall confidence value of COVID sample images was high enough. In the case of predicting Non-COVID samples, confidence values for lung opacity and viral pneumonia were lower than normal healthy X-ray images. So, COV-RadNet detects COVID and Non-COVID samples overcoming the inter-class similarities.
4.3. Comparison with Other Models

We have experimented with all possible cases to detect COVID-19 from chest X-ray and CT scan images using our proposed model “COV-RadNet” which has proved a promising approach to adapt for detecting COVID-19. This model performs well with respect to both sensitivity and training time. So, this detection technique will be a reliable, efficient and quick approach to detect COVID-19 and other pneumonia which will be a great advancement in medical science. COV-RadNet which are responsible for achieving the highest possible accuracy and sensitivity >97% and >99% for the four classes (COVID/Viral Pneumonia/Lungs Opacity/Normal) and two classes (COVID and non-COVID) respectively. Radiologists analyze various features from CT images to differentiate between COVID and Non COVID. Multiple lesions, ground glass opacity, interstitial changes, vascular thickening, bronchial wall thickening, pleural effusion etc. Are the major concerns to be noticed to distinguish between COVID and Non COVID.

4.4. Limitations and Future Work

Our proposed COV-RadNet model is a deep learning based classifier. At every step of training time, the model learns features using back propagation algorithms. This model tried to minimize the training error during the training phase. Besides, we have applied a data augmentation technique to enrich the database as this dataset was imbalanced. The future work may include this task as a successful part of a healthcare system to initiate the journey of automated COVID-19 diagnosis system. Our proposed model extracts and learns features on the basis of basic network concepts. In future we may include feature selection methods to train the model only with the most informative features. We may use hybrid models (combination of two or more pre-trained models) from pre-trained models and test their performance on the dataset without augmentation and multiple way data augmentation [23] also.

5. Conclusion

The ongoing pandemic situation due to COVID-19 is creating an alarming condition for the whole world. Early detection of COVID-19 for symptomatic cases will reduce the chance of mass transmission. Early detection may slow the outbreak and ensure quick medical treatment for the affected also. Since we have no strong weapons like effective vaccines availability, potential drugs to fight against this battle, we can see hope with the early detection mechanism with minimal false negative rate. Front liners like doctors, radiologists are trying to face this situation with RT-PCR screening, antimalarial drugs, remdesivir, plasma therapy, etc. In this critical situation, an automated system to detect COVID positive people from chest X-ray and CT scan images will open a new door of advancement to ensure quality medical treatment for COVID affected people. Besides, to overcome the post COVID complexities like lung infection, hypertension, black fungus attack, severe weakness, breakdown in immune system, etc., we cannot deny the importance of COVID detection at an early stage. In this paper, we have proposed a deep convolutional neural network “COV-RadNet” to detect COVID-19 from chest X-ray and CT scan images. We have experimented with the performance of the model using the “COVID-19 Radiography Dataset” and “SARS-COV-2 CT scan” dataset. We have achieved 99.6% sensitivity with COVID class for four classes (COVID, Lungs Opacity, Viral Pneumonia, Normal) classification task. This model is proved 99.8% sensitive for both chest X-ray and CT scan images to differentiate between COVID and Non-COVID class. This classification task will add a new dimension in medical science to detect COVID-19 with a satisfactory performance.

Declaration of Competing Interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.
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