A comprehensive study on COVID-19 Classification using CT images with Convolutional Neural Networks

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Abstract*—COVID-19 is one of the most contagious diseases, which has caused around 2.77 million deaths worldwide. In the earlier days, the method to fight against COVID-19 was not known. The researchers suggested the rapid diagnosis of COVID-19 and social distancing to contain COVID-19 from the community spread. The RT-PCR testing standard has been popularly preferred for the COVID-19 diagnosis all over the globe. Still, it has certain limitations of being time-consuming, costly, requires high infrastructure, and prone to manual errors. Also, studies have shown that CT scan images have higher sensitivity for COVID-19 diagnosis, which means CT scans are more accurate in the diagnosis of COVID-19. The reports have suggested that CT scans can be used as a method for improving the diagnosis of COVID-19 patients. The reading of the CT scans by experts is time-consuming and prone to human errors. The use of computer-aided automated image classification systems for accurate, rapid, and efficient diagnosis of the disease can be a preferable choice for the detection of COVID-19. In this study, we propose a methodology using Median Filter and Data Augmentation for the COVID-19 binary classification on CT images before using Deep Convolutions Networks for classification. We have observed that using Median Filter and Data Augmentation on the COVID-CT dataset before model training has contributed to an average increase in AUC of 5% considering all five models. Particularly for DenseNet169 AUC, Recall, and f1 score increased 8.21%, 16.55%, 3.82%, respectively with using Median Filter and Data Augmentation. We conducted a comprehensive study with five pretrained Convolutional Neural Networks and their ensembles on three different experimental conditions; with Data Augmentation, without Data Augmentation, and Median Filter + Data Augmentation. We achieved the best results with the DenseNet169 base model having an AUC of 90.43% and Precision, Recall, F1-score of 70.31%, 77.50%, 73.77%, respectively.

***Keywords*—Deep Convolutional Neural Networks, COVID-19, Median Filter, Data Augmentation.**

I. Introduction

COVID-19 is one of the most contagious diseases, which has caused around 2.77 million deaths worldwide [1]. The COVID-19 symptoms include fever, cough, breath shortness, fatigue, headache, loss of smell and taste, and many more. However, having these symptoms does not necessarily mean a person has a COVID-19; these symptoms are also common in pneumonia [2], [3], [4]. In the earlier days, method to fight against COVID-19 was not known. The researchers suggested the rapid diagnosis of COVID-19 and social distancing to contain COVID-19 from the community spread.

The RT-PCR testing standard has been popularly preferred for the COVID-19 diagnosis all over the globe. Still, it has certain limitations of being time-consuming, costly, requires high infrastructure, and prone to manual errors [5], [6], [7], [8]. Also, several studies have reported that the RT-PCR test has a low sensitivity of around 30% to 60%, which means the RT-PCR test misses positive cases and has a high False Negative Ratio (FNR) [9], [10].

According to medical and health protocols, Computed Tomography (CT) scans have been the easiest and recommended procedure for diagnosis during epidemics [11], [12]. The researchers have found that images can be a valuable tool for the rapid diagnosis of COVID-19 [13]. Also, studies have shown that CT scan images have higher sensitivity for COVID-19 diagnosis [14], [15], which means that CT scans are more accurate in the diagnosis of COVID-19. The reports have suggested that CT scans can be used as a method for improving the diagnosis of COVID-19 patients [16].

Notwithstanding the success of CT scans, problems are associated with the manual screening of COVID-19 from CT scans. The reading of the CT scans by experts is time-consuming and prone to human errors. The use of computer-aided automated image classification systems for accurate, rapid, and efficient diagnosis of the disease can be the preferable choice for the detection of COVID-19 [17], [18].

There have been several promising studies using Deep Convolutional Neural Networks (DCNN) for the diagnosis of COVID-19 from CT scans [19]-[25]. In this study, we propose a methodology using Median Filter and Data Augmentation for the COVID-19 binary classification on CT images before using Deep Convolutions Networks for classification. We conducted a comprehensive study with five pretrained Convolutional Neural Networks and their ensembles on three different experimental conditions; with Data Augmentation, without Data

Augmentation, and Median Filter + Data Augmentation. We have achieved the best results with the InceptionV3 base model having an AUC of 88% and weighted Precision, Recall, F1-score of 71%, 70%, 67%, respectively.

II. Background

As the prominence of the COVID-19 has been increased, researchers have been using Deep Convolutional Neural Networks for the efficient diagnosis of COVID-19. From the arrival of COVID-19, the researchers have proposed several methods for COVID-19 classification and severity detection from the CT images of patients.

In the study [19], the authors focused on COVID-19 segmentation and classification from CT images. They achieved an accuracy of 98.78% using Inception Recurrent Residual Neural Network and 99.56% for classification and segmentation of COVID-19 from CT images, respectively. However, the dataset used in the study was developed using pneumonia CT images, which makes this study less reliable.

Hu et al. [20] utilized pre-trained ShuffleNet V2 on a CT scan dataset consisting of 521 COVID-19 images and 397 healthy images. The authors have reported average sensitivity as 90.52%, specificity as 91.58%, and area under the curve (AUC) scores as 96.89%. Again the dataset used in the study was constructed by collecting CT images from various sources, which may cause the data samples repetition problem or high correlation among the chest CT Images.

In another study, Kassani et al. [21] used different pretrained Deep Convolutional Neural networks for the features extraction and Machine learning methods for training on CT images. The authors achieved maximum accuracy using the Bagging classifier on features extracted by the pretrained DenseNet121 model.

In the study [22], the authors used artificial intelligence to integrate the chest CT scan images with clinical symptoms. In a test of 279 patients, the proposed model achieved an area under the curve of 92%. Also, this method scores 17 of 25 correct predictions for COVID-19 patients, which were misclassified as non-COVID-19 by radiologists.

In another study [23], a decision fusion-based approach was considered to detect the COVID-19 cases where the authors used multiple individual model predictions to perform the final prediction. The proposed method in the study achieves around 86% accuracy, average AUC and f1 score to be 88.3% and 86.7%, respectively

Several studies also focused on the severity detection in the identified COVID-19 cases. In the study [24], the authors implemented ResNet34 to achieve an quality prediction for severity as 87.50% and non-severity as 78.46%. Zhu et al. [25] proposed an optimized CNN and VGG16 to predict the COVID-19 severity. The results of the current study were compared with the scores of radiologists on severity.

III. Methods

A. Median Filters

Median filters are very helpful for removing the Gaussian, Random, and Salt pepper noises, particularly when the density of noise's amplitude probability has periodic patterns. A sliding window approach on images conducts the process of median filtering. The median Filter works by substituting the median value of pixels covered by the sliding window at the center of each window on the image. The median Filter has an advantage in the case of long tailed noise as it highlights the edges in the images, which helps in the case of blurred images. We have applied the Median Filter on COVID-19 CT images to remove noise and focus on the edges in the image for classification. The sample Median Filter results are represented in Fig 1.

B. Data Augmentation

Data Augmentation helps overcome the problem of overfitting the model on the training dataset and extracts unique information from the augmented images. The data augmentation includes applying the random transformation to the training dataset images like horizontal and vertical flip, random zooming, color transformations, etc. In this study, we performed data augmentation by randomly flipping the CT images around the horizontal axis using Pytorch Image Data loaders, which does not separately add images to the dataset collection, but actually performs data augmentation before each epoch of model training to generate slightly different sets of images for training.

C. Convolutional Neural Networks

The functionality of the Convolutional neural networks (CNN) is motivated by the human visual system. CNN's generalized architecture constitutes a series of convolution layers, pooling layers, and fully connected layers. When an input image is passed through the CNN architecture, each convolutional layer evaluates local feature conjunctions from the previous layer. The CNN learns the simple features at the initial layers and moves towards complex features at the deeper layers. The pooling layers combine these learned features into a single feature (image) using feature map downsampling [26]. Finally, the softmax function calculates the probabilistic values between 0 and 1 for each output class for the image classification [27].

In recent years, CNN has achieved tremendous success in object detection, segmentation, and classification. Specifically, the Convolutional Neural Networks (CNN) have been popular for an automated feature extraction method for an image classification task. Researchers have developed various variants of CNN architectures, including AlexNet, VGGNet, ResNet, Inception, Xception, MobileNet, NASNet, and many more from the ImageNet challenge [28]. In the current study, we have used five pretrained convolutional neural networks for the diagnosis of COVID-19. The architectural details of these models are explained below:

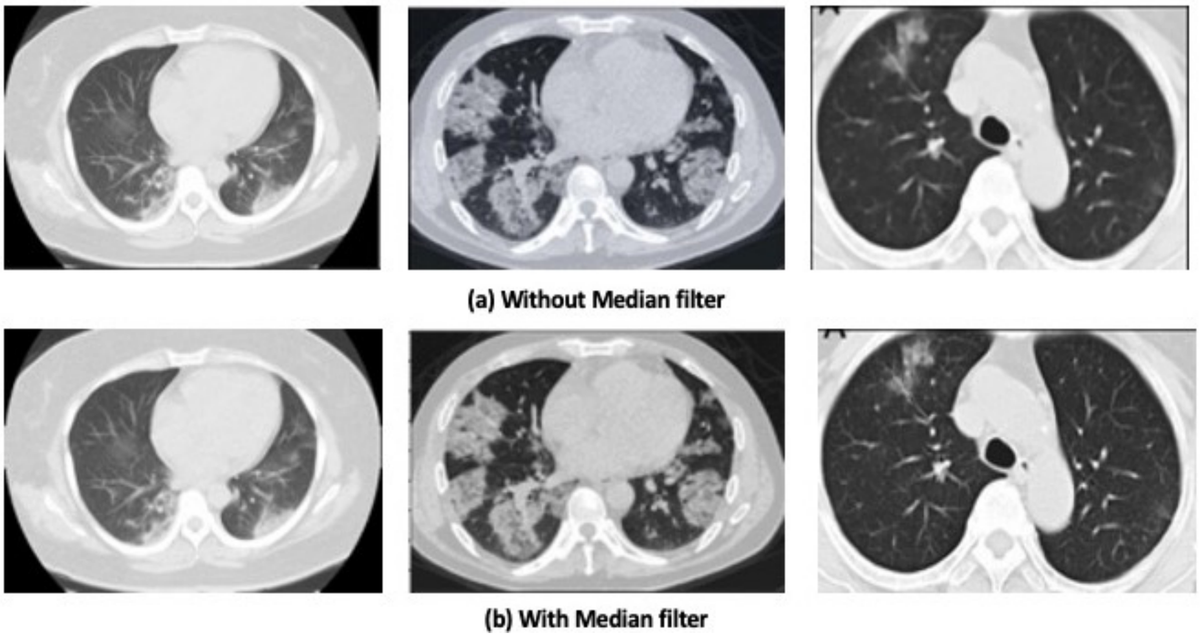

Fig 1. The visualization after applying median Filter on the sample COVID-CT samples (a) COVID-19 CT images without Median Filter. (b) COVID-19 CT images with Median Fitter

VGG

VGG was introduced by [29] in the year 2014 after the popular AlexNet architecture, which has two versions VGG-16 and VGG-19. The major improvement in the VGG architecture was that small filter sizes were used for the Convolutional Layer, which reduces the complexity of architecture and introduces deeper networks resulting in better performance. In VGG architecture, a collection of convolutional layers is followed by three fully connected layers and, finally softmax layer.

ResNet

Residual Network (ResNet) was introduced by Kaiming et al. [30] as a part of ILSVRC-2015. ResNet model has several different variants like ResNet18, ResNet50, ResNet101, ResNet164, etc., which have the same architecture but different number of layers. The architecture of ResNet included a significant concept of skip connections which bypasses several convolutional layers block in the architecture while training. The ResNet model has a lower computational complexity solving problems of overfitting and vanishing gradients.

DenseNet

The DenseNet was introduced by [31] in the year 2017. DenseNet has a compact and efficient architecture in comparison to other proposed deep convolutional neural networks. In DenseNet, element-wise addition is performed to pass inputs from one channel to another. Also, each layer in the architecture receives collective knowledge from all previous layers. The DenseNet architecture contains Batch normalization (BZ) and ReLU layers before Convolutional layers to reduce the model's complexity and size.

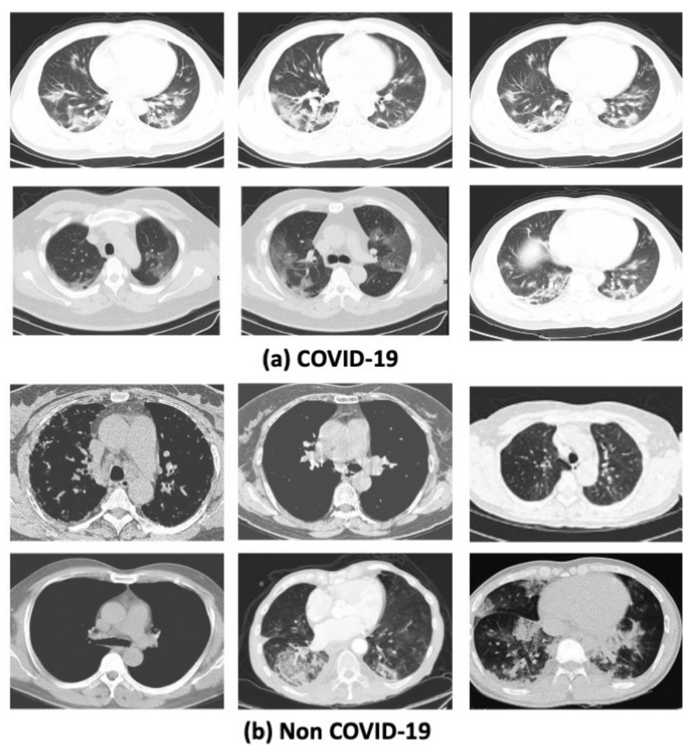

Fig 2. Sample COVID-19 CT dataset (a) COVID-19 sample CT images. (b) Non-COVID-19 samples CT images

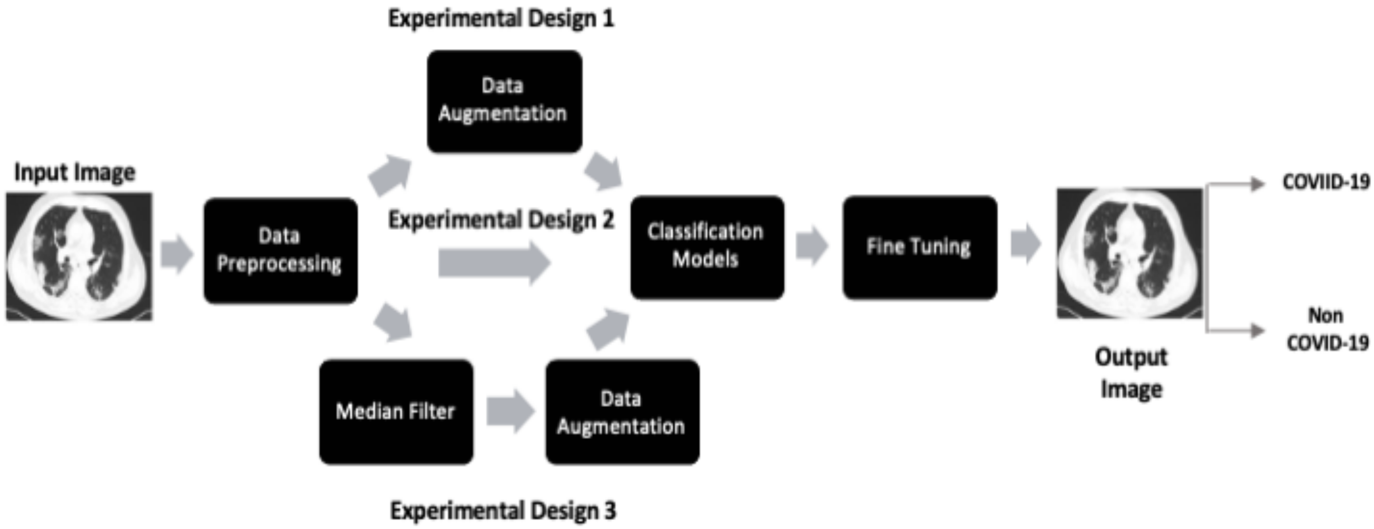

Fig 3. The Proposed Methodology for COVID-19 classification. Initially, Data Preprocessing is performed on the input dataset images. We conducted three experimental designs for the classification of CT images as COVID-19 or Non-COVID-19 using pre-trained models. Experimental Design 1: COVID-19 Classification was done using Data Augmentation on the training dataset. Experimental Design 2: COVID-19 Classification was done without using Data Augmentation, i.e., with original dataset samples. Experimental Design 3: COVID-19 Classification using Median Filter and Data Augmentation on the training dataset.

IV. Results

A. Dataset

We have used the COVID-CT dataset [32] in this study. The dataset contains 349 samples of CT images which contains novel COVID-19 and 397 non-COVID-19 samples of CT images. The CT images in the dataset were composed of high quality COVID19 studies published in either medRxiv, bioRxiv, NEJM, JAMA, and Lancet. The senior radiologist of Tongji Hospital, Wuhan, China, has reported the effectiveness and usefulness of this dataset. The sample dataset CT images of two classes, i.e., COVID-19 and non-COVID-19, are represented in Fig 2.

B. Data Preprocessing

In the preprocessing step, each image in the dataset was resized to 224 x 224 pixels resolution, similar to the study (Mandl, D. et al. 2017) using Pytorch Image Data Generator. We performed image normalization with respect to mean and standard deviation by setting values (0.485, 0.456, 0.406) and (0.229, 0.224, 0.225) respectively for the three RGB channels. The image normalization ensures that each pixel in the image has a similar data distribution, which can be helpful to extract useful features during model training.

C. Experimental Design

The implementation of the project codes was done on Google Collaboratory using Tesla P100 GPU. We have divided the total original dataset containing 746 CT images among 425 training images, 118 validation, and 203 images in the test dataset.

We conducted three experimental designs for the comprehensive study of five different pre-trained models; ResNet18, ResNet50, DenseNet121, DenseNet169, VGG16, and ensemble model for the best two performing models. The first experimental designs include using Data Augmentation and performing binary COVID-19 classification using pre-trained models. The second experimental setting includes applying Median Filter on the input dataset CT images and Data Augmentation before performing binary classification using pre-trained models. The final experimental design includes analysis without using Data Augmentation. We applied basic image normalization and image resizing steps for every experimental design. The Proposed Methodology for COVID-19 classification is represented in Fig 3.

We performed model training for 10 epochs on the training dataset for each of these experimental designs using the learning rate of 0.0001 with the Cross-Entropy loss function. We used the popularly preferred Adam optimizer with Cosine Annealing learning rate scheduler for the model training. The proposed methodology for the COVID-19 classification is to use Median Filter and Data Augmentation on CT images before final pre-trained classification models.

D. Classification Results

We have performed the performance evaluation of final classification models over AUC, Precision, Recall, and F1-score. The Precision, Recall, and F1-score can be calculated with the help of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) and are represented in equation 1, equation 2, and equation 3, respectively.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1\, score = 2\frac{(Precision)(Recall)}{Pricison + Recall} \quad (3)$$

We have got the best results with the DenseNet169 model with experimental design 3 compared to other models used in the study. The DenseNet169 has achieved an AUC of 90.43% and Precision, Recall, F1-score of 70.31%, 77.50%, 73.77%, respectively with using Median Filter and Data Augmentation. The complete results of experimental design 1, experimental design 2, and experimental design 3 are represented in Table 1, Table 2, and Table 3, respectively. In general, the best results were achieved with models in experimental design 3, followed by experimental design 1 results, and the lowest results have been achieved with experimental design 2. We observed that using Median Filter and Data Augmentation on the COVID-CT dataset before model training has contributed to an average increase in AUC of 5% considering all five models. Particularly for DenseNet169 AUC, Recall, and f1 score increased with 8.21%, 16.55%, 3.82%, respectively, using Median Filter and Data Augmentation.

Classification Models	AUC %	Precision %	Recall %	F1 score %
VGG16	79.00	60.87	90.47	72.79
ResNet18	86.00	77.45	75.23	76.32
ResNet50	88.03	79.40	79.10	78.20
DenseNet121	85.90	77.80	77.10	77.50
DenseNet169	88.06	79.43	80.95	80.18

Table 1. Experimental design 1 (With Data Augmentation) classification results for VGG16, ResNet18, Resnet50, DenseNet121, and DenseNet169

Classification Models	AUC %	Precision %	Recall %	F1 score %
VGG16	83.25	70.97	83.81	76.83
ResNet18	81.75	70.87	85.71	77.59
ResNet50	82.10	80.25	61.90	69.89
DenseNet121	85.73	70.80	92.38	80.16
DenseNet169	82.22	82.05	60.95	69.95

Table 2. Experimental design 2 (Without Data Augmentation) classification results for VGG16, ResNet18, Resnet50, DenseNet121, and DenseNet169

Classification Models	AUC %	Precision %	Recall %	F1 score %
VGG16	73.78	80.39	39.04	52.56
ResNet18	88.22	72.46	95.23	82.30
ResNet50	83.82	76.47	74.28	75.62
DenseNet121	88.75	76.00	90.47	82.60
DenseNet169	90.43	70.31	77.50	73.77

Table 3. Experimental design 3 (With Meadian Filter and Data Augmentation) classification results for VGG16, ResNet18, Resnet50, DenseNet121, and DenseNet169

V. Conclusion

COVID-19 is one of the most contagious diseases, which has caused around 2.77 million deaths worldwide. The researchers suggested the rapid diagnosis of COVID-19 and social distancing to contain COVID-19 from the community spread. The RT-PCR testing standard has been popularly preferred for the COVID-19 diagnosis all over the globe, but it has certain limitations. The reports have suggested that CT scans can be used as a method for improving the diagnosis of COVID-19 patients. The reading of the CT scans by experts is time-consuming and prone to human errors. In the current study, we propose a methodology using Median Filter and Data Augmentation for the automated COVID-19 binary classification on CT images before using Deep Convolutions Networks. We observed that using Median Filter and Data Augmentation on the COVID-CT dataset before model training has contributed to an average increase in AUC of 5% considering all five models. Particularly for DenseNet169 AUC, Recall, and f1 score increased 8.21%, 16.55%, 3.82%, respectively with using Median Filter and Data Augmentation. We achieved the best results with the DenseNet169 model having an AUC of 90.43% and Precision, Recall, F1-score of 70.31%, 77.50%, 73.77%, respectively.

In the future, we believe that the current methodology can be with ensemble-based deep convolutional neural network method, with modifications in the architecture of models to develop more efficient and robust classification results for COVID-19 classification.

VI. Authors Contribution

S.S.C. and J.R.D. designed the main idea of the project; S.S.C. handled the development of the main implementation code; M.D. modified the codes for normalization; J.R.D. included the Median Filter code in the implementation; M.D. and J.R.D. handled the implementation of codes on Google Collaboratory; S.S.C. created the figures and wrote the final report; M.D. created the presentation.

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