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A FRAMEWORK FOR EFFECTIVE PREDICTION AND CLASSIFICATION OF CORONA VIRUS (COVID-19) DISEASE BASED ON DIFFERENT CONVOLUTIONAL NEURAL NETWORK

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Abstract

Corona virus (Covid-19) is one of the severe diseases that affects pneumonia and impacts our different body parts. This virus was origin from Wuhan city of China in December 2019 and later, it became a global pandemic disease rapidly spreading all over the world. To prevent viral spread, positive cases must be identified early and infected patients must be treated as soon as possible. The demand for COVID-19 testing kits has grown, and many developing countries are running out of them as new cases emerge every day. In this case, current research using radiology imaging (such as X-ray and CT scan) has been shown to be effective in detecting COVID-19, as CT scan images offer vital information about the disease caused by the COVID-19 virus.. In order to handle these problems, we have proposed different CNN models (like traditional Convolutional, Dilated Convolution and Separable Convolution) for the accurate and rapid prediction of the disease, assisting in mitigating the problem of scarcity of testing kits. The architecture consist of three convolution layers of 32 filters with kernel size of 3x3, pooling size of 2x2 and fully connected layer 1024. For performance assessment, 11,000 CT Scan images has been collected from COVID-19 CT-Scan dataset and performed three k-fold validation (3-fold, 5-fold and 10-fold) process. Experimental results shows that 10-fold cross validation model for the Covid-19 disease classification outperformed the other two k-fold cross validation (3-fold and 5-fold) by achieving 94.85%, 96.85% and 97.18% of accuracy respectively.

Keywords: *Corona virus, Covid-19, k-fold validation, Disease Classification, CT scan images, convolutional neural networks, D-CNN and seperable convolution.*

I. INTRODUCTION

The Coronavirus (COVID-19), which was first appeared at the end of 2019, caused a global epidemic that spread so fast from person to person in the community [1]. According to data from the World Health Organization (WHO), the rate of COVID-19 infection in China ranges from 16 to 21%, with a mortality rate of 2-3% [2]. As a result, to deal with COVID-19, people must take the necessary quarantine precautions and take safety measures. To diagnose COVID-19, the clinical symptom must be present, as well as positive X-ray and CT images, and also a positive pathological test [3]. When a person is infected with COVID-19, they will have a variety of symptoms, including fever, cough, severe throat, headache, muscle pain, and respiratory issues [4]. However, many patients suffer serious respiratory distress until they die. This is a problem for people all around the world, because, in addition to demographic factors like gender and age, environmental factors like temperature and humidity can influence the disease's frequency and transmission.

Furthermore, with these symptoms, positive X-ray and CT findings should be performed. Evaluating the virus's RNA sequence is another COVID-19 diagnostic approach. Due to the considerable time it takes to diagnose, this method is not particularly effective. It also has a 30-50% accuracy rate in diagnosis. As a result, multiple diagnostic tests should be performed. For the detection of COVID-19, radiological imaging techniques are necessary. The COVID-19 virus exhibits the same features in early and late stages on X-rays and Computer Tomography (CT) images [5]. Although it shows a circular distribution within an image, it may exhibit similar characteristics with other viral epidemic lung diseases. This makes it challenging to detect COVID-19 from other viral cases of pneumonia [6]. The following is a summary of the book chapter. The literature review and research on COVID-19 using Machine Learning (ML) and Deep Learning (DL) approaches are discussed in Section 2. The proposed technique for early diagnosis of COVID-19 from CT image datasets using different deep learning models are described in Section 3. The experimental results, performance metrics and evaluation are presented in Section 4. Finally, Section 5 concludes the research results.

II. RELATED WORKS

In the development and application of systems to automatically classify, especially in the medical field, it is rapidly growing and gaining popularity by making additional medical practitioners tools. Deep learning, a branch of artificial intelligence research, allows for input data analysis without the requirement for manual feature extraction process. Deep learning techniques have been used to diagnose and identify breast cancer, classify skin cancer, and classify diseases in the brain. Deep learning has also been used to classify diseases in the brain and detect pneumonia from chest x-ray images. With the advancement of existing deep learning techniques, it is predicted that the problem of classifying COVID-19 will be overcome. The authors of [9] developed a traditional machine learning approach for feature extraction from CT images of COVID-19 infection regions based on their observation that several false-negative results are produced. While [10] demonstrated that the study has a relatively low positive rate when evaluating COVID-19 in the early stages of disease identification. The aim of [11] is to develop a model of deep learning based quantitative CT images, the authors concentrating on the logistic regression model for predicting the severity of COVID-19. The author [12] describes how to predict COVID-19 using Lasso regression screening and multivariate logistic regression.

COVID-19 is detected from chest X-ray images using a convoluted network called COVID-Net, according to further research. Researchers also looked at the COVID-Net model throughout the prediction stage to learn more about COVID-19-related parameters that could aid doctors in early screening. COVID-Net has a high level of accuracy, with 93.3 percent test accuracy [13]. The same subsequent study used a Convolutional Neural Network's pre-trained network to recognize x-ray images automatically, with the goal of assisting medical doctors, particularly physicians, in the diagnosis of COVID-19 patients [14], [15]. The first experiment deployed models based on convolutional neural networks such as ResNet50, InceptionV3, and InceptionResNetV2. There are 100 data points in this research dataset, which are classified into two categories: COVID-19 and Normal. However, most of previous researches have focused their pre-trained deep learning models such as VGG-16, VGG-19, Inception and ResNet-50 on either X-ray images or CT Scan images and presented their results in terms of whether COVID-19 or Not. The pre-trained models require large number data and also it occupies more time consumption. In order to reduce the time consumption and data set lacking, we have introduce the three Convolutional Neural Network (Traditional CNN, Dilated CNN and Depth wise Separable Convolutional model)

III. PROPOSED WORKS

The Convolutional Neural Network is a special kind of neural network and its design is inspired by the concept of a biological neuron called the receptive field to imitate the connectivity pattern of neurons within the human brain. The CNN model is feed forward neural network, which is a stack of filters (convolutional layer) and sub-sampling layers (pooling layer) which repeat themselves alternatively and it has one or more completely connected neurons (fully connected layer/dense) at the end. Even though this model is applied in various domains, it gets optimized results in image processing applications. The CNN is built by concatenating individual blocks or layers. These layers are putting together for performing a series of tasks. Figure 1 shows the general architecture of the traditional convolutional neural network, which contains following layers.

- Convolutional Layer
- Pooling Layer (Down-Sampling/ Up-Sampling)
- Fully Connected Layer (one dimensional data)
- Output Layer (Classification)

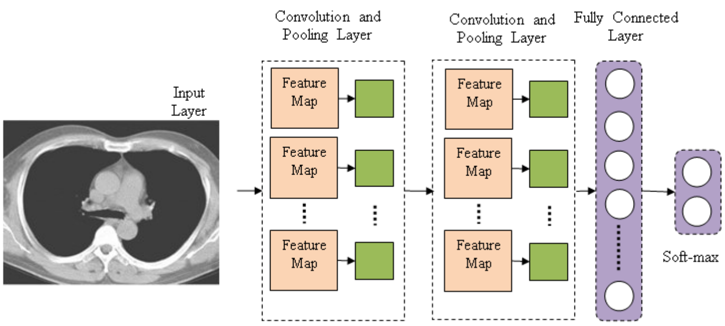

Fig. 1 The architecture of Covid-19 Disease prediction Model

3.1. Traditional CNN Model

3.1.1. Convolutional Layer

The convolution layer is one of the primary building components of a CNN and the name "Convolutional Neural Network" comes from it. The convolution layer has a series of filters or kernels whose parameters must be learned, and its aim is to learn feature representations from the inputs. As a convolution operational activity, it executes linear multiplication to extract high-level features such as lines, edges, and internal shape from the input image. This layer is a three dimensional matrix with size of h×w×c with corresponding weight for each point, where h represents the height of the inputs, w represents the width of the inputs and c represents the depth of the channel. The kernel size, of k×k is convolved with the input shapes. As shown in Figure 2, starting from top-left corner of the input, each kernel is moved from left to right, one element at a time. Once the top-right corner is reached, the kernel is moved one element in a downward direction, and again the kernel is moved from left to right, one element at a time. This process is repeated until the kernel reaches the bottom-right corner. By this process, this layer plays an important role to extract different level features such as edges, lines, corners, structures and shapes from the input image.

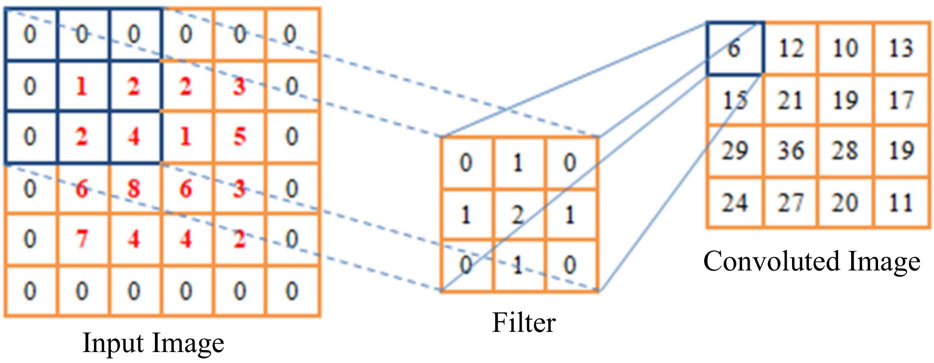

Fig. 2 Convolution process for input images

3.1.2. Activation Function

The Rectified Linear Unit is the activation function that is used (ReLu). The kernel or filter size utilised for each convolution layer is 3 3 in order to speed up the training process and improve identification accuracy. The activation function of the ReLU is defined as follow:

$$b_{i,j,k} = \max\,(a_{i,j,k}, 0) \tag{1}$$

where, $a_{i,j,k}$ is the input of the activation function at location (i, j) on the k-th channel. In this layer we remove every negative value from the filtered images and replace it with zeros. The procedure of ReLU activation function is depicted in Figure 3.

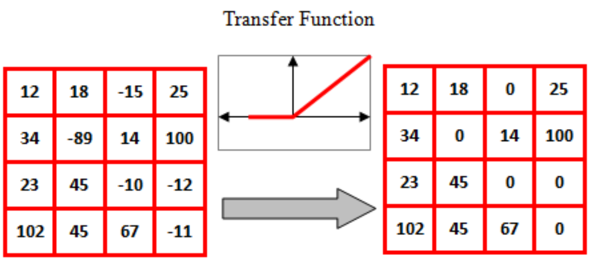

Fig. 3 Working principles of Activation Function

3.1.3. Pooling Layer

Pooling layer is a sub-sampling operation which is added after the convolutional layer and activation function. The main objective of a pooling layer is to reduce the feature maps while maintaining the most important

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information. Thus, it reduces the number of parameters to learn and the number of computations to be performed in the network. It also helps to keep away from the overfitting problem. When we select the images as an input matrix I with dimensions I = (Ix, Iy), we can write the output size of the corresponding matrix as O = (x, y) stated in equations 2 and 3.

$$x = \frac{I_x - (W_x - S_x) + 2 \cdot P_x}{S_x} \tag{2}$$

$$y = \frac{I_y - (W_y - S_y) + 2 \cdot P_y}{S_y} \tag{3}$$

where, $I = (I_x, I_y)$ is a two dimensional matrix of the feature map as input image, $W = (W_x, W_y)$ is represented as pooling window size, $S = (S_x, S_y)$ is an stride length which is used to determine by how many pixels the window will be shifted, $P = (P_x, P_y)$ is padding parameter and $O = (x, y)$ is an output of the pooling result as a two dimensional matrix. There are three common pooling methods, namely max-pooling, min-pooling and average-pooling to summarize the most activated presence of a feature, least activated presence of a feature and average presence of a feature respectively.

Max and Min Pooling

The max-pooling finds out the maximum value for each patch of the feature map. Similarly min-pooling finds out the minimum value for each patch of the feature map. In this case we have the pooling window size W = (2, 2) and the size of stride length S = (2, 2). It means that the size will be reduced to half of the size. If the input matrix for pooling layer is 4×4 matrix, the output of the pooling values will be 2×2 as shown in Figure 4.

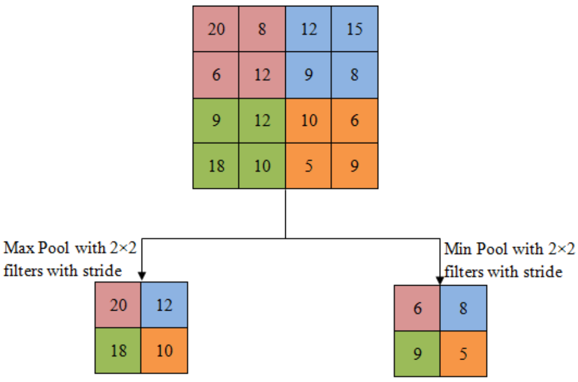

Fig. 4 Max and Min-pooling operation

3.1.4. Flatten and Fully Connected Layer

The aim of a fully connected layer is to classify the image into a label by taking the results of the convolution/pooling process. Normally, CNN uses at least one fully connected layer at the end of the model. The output from all convolution and pooling layers is a stack of feature maps. Fully connected layer is used to flatten a stack of feature maps into a one-dimensional feature space. Then it connects all flattened neurons for summarizing those feature maps. This layer goes through its own backpropagation process to determine the most accurate weights. Each neuron receives weights and prioritizes the most appropriate label. Finally, it computes the score for each class based on the neuron's vote on each of the labels and the winner of that vote is considered as the classification decision. This process is illustrated in Figure 5, where a 3×3 feature map is converted into one dimensional data and 9 neurons are fully connected to 3 neurons. In the task of classification, to output the probability of each class, a soft-max layer is connected to the last fully connected layer.

3.2. Dilated CNN Model

In this subsection, we have utilized the dilated convolutional neural network as a replacement for the standard CNN for enhancing CT images scene classification accuracy. The new dilated convolution filter extends the receptive field while keeping the parameters the same. As a result, we may improve the model's performance while also reducing its computing time. The typical CNN model with small convolution kernels must learn more relevant information with a deep convolutional network, which increases to the computational complexity.

3.3. Depth wise Separable CNN Model

In this subsection, we have used the depth wise separable convolutional neural network as a replacement for the standard CNN for enhancing CT images scene classification accuracy. A depthwise separable convolutional network, which has been explicitly implemented in MobileNet architecture[19]. The depth-wise separable convolution is made up of two convolutions: one for depth wise and one for point wise. 3×3 convolutions are separated into a 3×3 depth-wise convolution and a 1×1 point-wise convolution through depth-wise separable convolution. In a single step, traditional convolution performs both channel and spatial computations. Traditional convolution uses one kernel for each input channel, and the convolved output is the sum of all the channels convolved results. On the other hand, Depthwise Separable Convolution divides the process into two steps: Depth-wise convolution is a type of channel-wise convolution that uses individual input channels to execute the convolution. Then, similar to traditional convolution with kernel size 1×1, perform point-wise convolution. The outputs of each channel are combined using point-wise convolution.

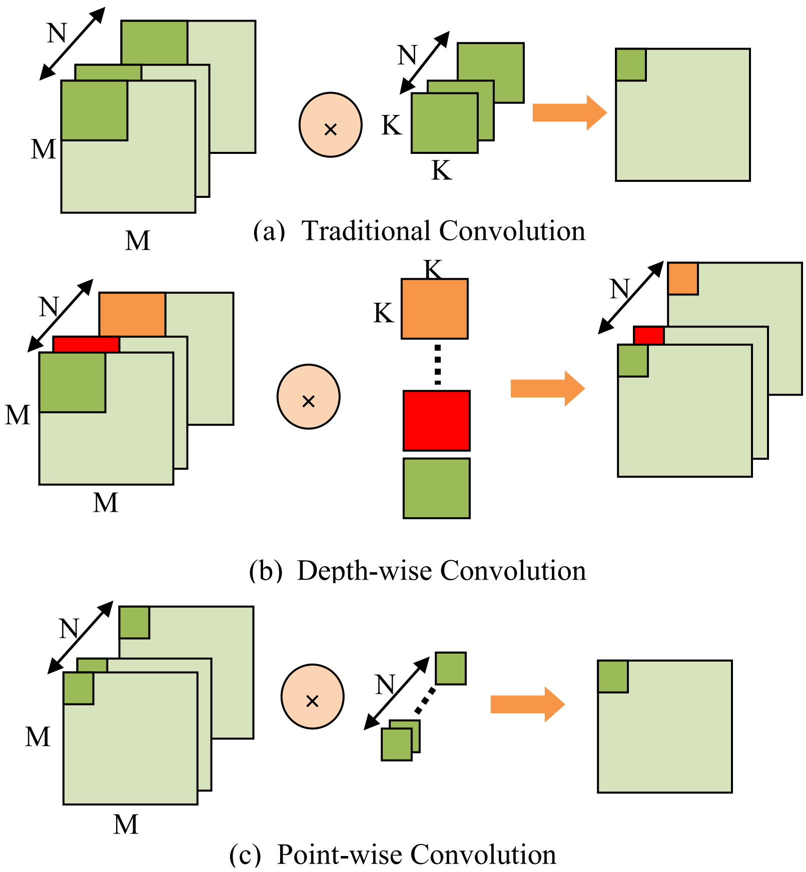

Fig. 5 Conceptual illustration of traditional and Depth-wise Separable Convolution; (a) traditional convolution (b) Depth-wise convolution; (c) point wise convolution

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Various experiments are conducted to portray the effectiveness of the proposed approach and a detailed comparative analysis and discussion on the results are presented in this section. The experiments are conducted in Jupyter Notebook and Anaconda Prompt IDE with different deep learning libraries such as Open CV, Numpy, Matplotlib and sklearn. The three proposed models (traditional CNN, Dilated CNN and Depth wise separable CNN model) was trained and tested with X-Ray images using Keras and TensorFlow in corei7 CPU 2.6 GHz, 1TB hard disk drive and 8-GB of RAM.

4.1. Dataset Descriptions

Dataset plays a crucial role in developing and evaluating various scene classification models. We have used X-Ray medical image datasets for effective prediction and classification of corona virus (Covid-19) diseases. The

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dataset is COVID-19 CT scan image, which consist of 2 classes (COVID-19 and Normal) and totally 11,000 images. Each class contains 5,500 images with resolution of 128×128. To evaluate the effectiveness of the proposed approach, we have chosen K-Fold validation for prediction of COVID-19 disease. The sample images from datasets are shown in Figure 8.

The dataset divided into three parts namely Training, Validation and Test. In each class, there are 100 images used for Testing. As mentioned in the Table 1, the Training and Validation of dataset is divides based on the K-Fold validation techniques.

Table 1 Training and Validation dataset split

K-Fold	Training	Validation	Test
3	3600	1800	100
5	4320	1080	100
10	4860	540	100

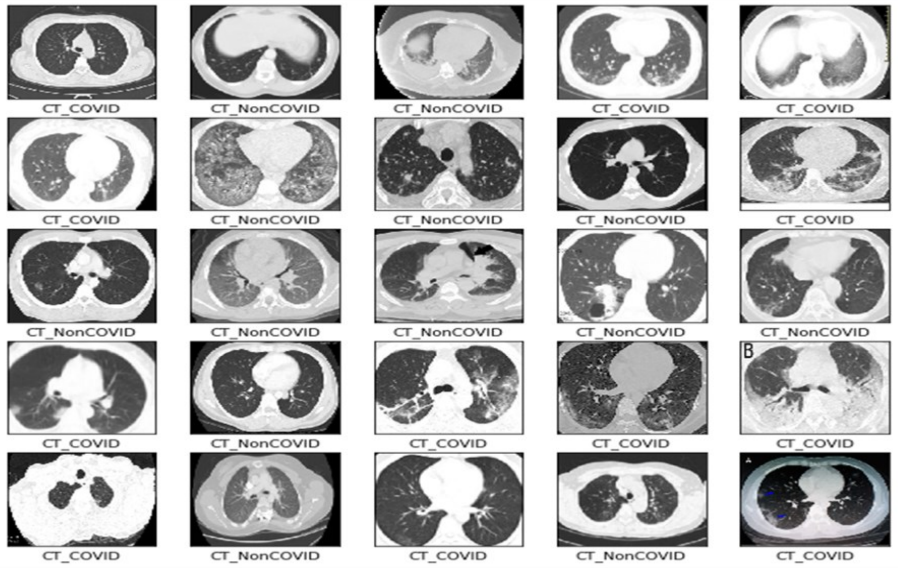

Fig. 6 Sample CT_Scan dataset for prediction and classification of COVID-19

4.2. Performance Metrics

The performance of the proposed model is evaluated by using various performance metrics such as K-Fold validation, Precision, Recall, Accuracy and F1-measure. The confusion matrix is a two dimensional table as shown in Table 2, is used to calculate the above mentioned metrics. In this matrix actual values are in column side and predicted values are in row side. Let TP, TN, FP and FN denote the number of True Positive, number of True Negative, number of False Positive and number of False Negative respectively. The TP is an outcome, where the models correctly predict the positive class. The TN is an outcome, where the models correctly predict the negative class. The FP is an outcome, where the models incorrectly predict the positive class. The FN is an outcome, where the models incorrectly predict the negative class.

K-Fold Validation

The purpose of K-Fold validation is opportunity to train and validate all the images in the model. K-fold cross-validation is a type of cross-validation in which we iterate k times over a set of data. We partition the dataset into k parts for each round: one part is used for validation, and the remaining k-1 parts are merged into a training subset for model evaluation, as illustrated in Figure 9.

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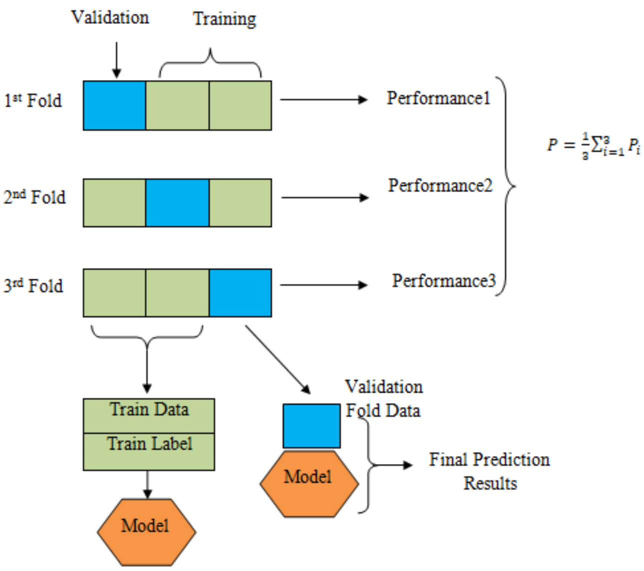

Fig. 7 The concepts of K-Fold cross validation

4.3. Result Analysis of three CNN Models

The experimental results of our three proposed models are worked with same parameter and configurations. The experimental setting of traditional CNN, Dilated CNN and Depth wise separable CNN model consists of three convolutional layers, three max pooling layers, followed by one fully connected layer and one softmax classifier. For avoiding the problem of over fitting concepts, we have used dropout and Adam optimizers.

Like traditional CNN model, the proposed dilated convolutional with dilation rate of 2 is as it same as parameter and configuration but, the receptive field is increased as 5×5. So, in order to increases of receptive field is incorporated with more relevant information and increase the performance of proposed model as well as reduce the computational time. Similarly, the depth wise convolutional also perform same number of parameters and configuration. As shown in Table 3 and Figure 10, the performance metrics of CT- Scan dataset for 15 epochs on three CNN models (Traditional CNN, Dilated CNN and Depthwise Separable convolution) using the 3-fold validation techniques.

Table 2. Performance metrics of Covid-19 dataset with 3-Fold Validation

S. No.	Dataset	Model	Accuracy	Precision	Recall	F1-Score
1	Covid-19 Dataset	Traditional CNN	84.34	85.17	85.20	85.15
2		Dilated CNN	86.71	87.35	86.71	86.42
3		Depthwise Separable CNN	88.85	88.49	88.43	88.37

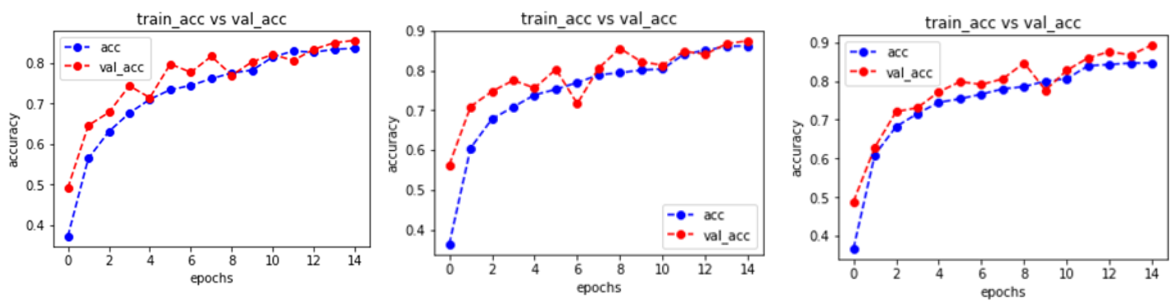

Figure 8. Classification accuracy for Covid-19 with 3-Fold validation

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In the second experimental set, the training and validation techniques increased as 5-fold and 10-fold cross validation. In case 5-fold validation means, the total dataset is divided into 5; one part is for validation and remaining four parts for training set. So when ever increase the k-fold values the performance of model also increase. As shown in Table 4 and Figure 11, the performance metrics of CT- Scan dataset for 15 epochs on three CNN models (Traditional CNN, Dilated CNN and Depthwise Separable convolution) using the 5-fold validation techniques.

Table 3. Performance metrics of Covid-19 dataset with 5-Fold Validation

S. No.	Dataset	Model	Accuracy	Precision	Recall	F1-Score
1	Covid-19 Dataset	Traditional CNN	89.88	90.19	90.28	90.69
2		Dilated CNN	91.76	92.27	91.76	91.61
3		Depthwise Separable CNN	92.35	92.16	92.15	92.10

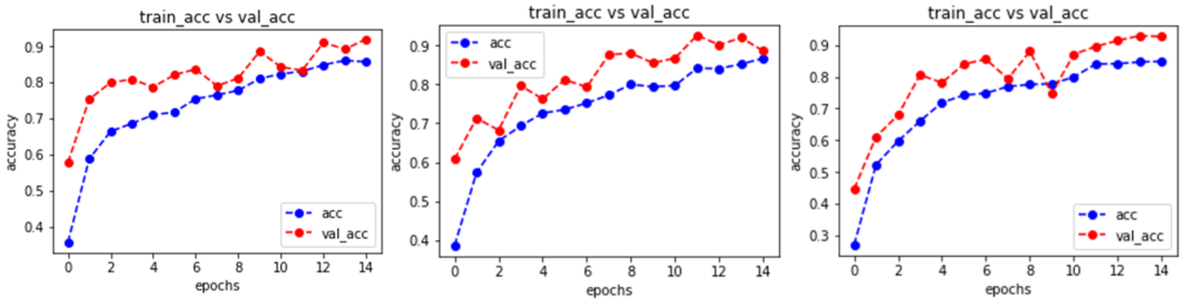

Fig. 9 Classification accuracy for Covid-19 with 5-Fold validation

Table 5. Performance metrics of Covid-19 dataset with 10-Fold Validation

S. No.	Dataset	Model	Accuracy	Precision	Recall	F1-Score
1	Covid-19 Dataset	Traditional CNN	94.85	95.44	94.86	94.89
2		Dilated CNN	96.85	97.17	96.86	96.89
3		Depthwise Separable CNN	97.18	97.41	97	96.98

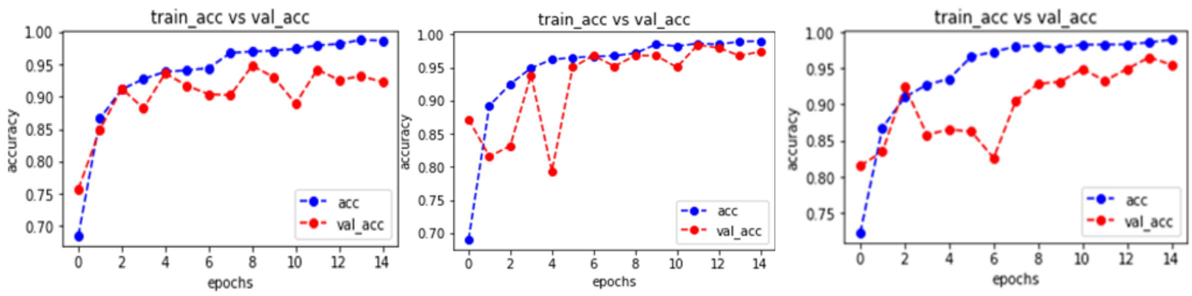

Fig. 10 Classification accuracy for Covid-19 with 10-Fold validation

Based on experimental results show that, the Dilated CNN and Depthwise Separable CNN model has higher accuracy than traditional CNN model and also computation time is less compared to traditional model. Similarly, the 10–Fold cross validation has higher accuracy than 5-fold and 3-fold cross validation.

CONCLUSION

In this paper, we have proposed effective framework for prediction and classification of corona virus (COVID-19) Disease using different Convolutional Neural Networks such as Traditional CNN, Dilated and Depthwise Separable CNN model. The CNN models act as a feature extractor and classifier for the given training and validation images. The Dilated CNN model is reduced the computation time of model and also increase the receptive filed of model without changing the parameters. Also the Depthwise Separable CNN model fetches the more information in the convolution layer. In order to demonstrate the efficiency of proposed models, experiments are conducted using K-Fold validation (3-fold, 5-fold and 10-fold cross validation) from COVI-19 CT-scan dataset and achieved the accuracy as 89.85%, 94.7% and 96.5% respectively for 10-fold validaion. We have observed that all the three proposed CNN models with 10-fold cross validation have given better accuracy than 3-fold and 5-fold cross validation. In future, we have planned to incorporate our proposed convolutional neural network models will be implemented in GPU environment for reducing the computational time.

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