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Analysing most efficient deep learning model to detect COVID-19 from computer tomography images

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ABSTRACT

COVID-19 illness has a detrimental impact on the respiratory system, and the severity of the infection may be determined utilizing a selected imaging technique. Chest computer tomography (CT) imaging is a reliable diagnostic technique for finding COVID-19 early and slowing its progression. Recent research shows that deep learning algorithms, particularly convolutional neural network (CNN), may accurately diagnose COVID-19 using lung CT scan images. But in an emergency, detection accuracy simply is not enough. Determinants of data loss and classification completion time play a critical element. This study addresses the issue by finding the most efficient CNN model with the least data loss and classification time. Eight deep learning models, including Max Pooling 2D, Average Pooling 2D, VGG19, VGG16, MobileNetV2, InceptionV3, AlexNet, NFNet using a dataset of 16000 CT scans image data of COVID-19 and non-COVID-19 are compared in the study. Using the confusion matrix, the performance of the models is compared and together with the data loss and completion time. It is observed from the research that MobileNetV2 provides the highest accurate result of 99.12% with the least data loss of 0.0504% in the lowest classification completion time of 16.5secs per epoch. Thus, employing MobileNetV2 gives the best and the quickest result in an emergency.

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1. INTRODUCTION

COVID-19 was derived from the virus known as a severe acute respiratory syndrome (SARS) or coronavirus2, commonly known as SARS-CoV-2 [1]. SARS-CoV-2 is a socially transmitted virus. While the majority of COVID-19 patients present with minor symptoms, a tiny proportion develop serious or life threatening complications. Contamination may result in pneumonia, excruciating respiratory pain, multiorgan failure, and death in a growing number of real instances [2]. A crucial and essential step in combating COVID-19 is an efficient screening of infected individuals, allowing for the isolation and treatment of positive patients. Currently, the major screening technique for COVID-19 detection is CT scan imaging of the lungs. The test is performed on the patient's chest and the result is ready within minutes. The lungs of patients with COVID-19 symptoms exhibit certain visual characteristics such as ground glass opacities-hazy darker patches that may distinguish COVID-19-infected individuals from non-infected patients [3], [4].

A detection technique based on chest radiography images has a number of benefits over the traditional approach. It may be quick, evaluate many cases concurrently, increase availability, and, most significantly, such a system can be very helpful in hospitals that lack or have a limited number of testing kits and resources. Additionally, due to radiography's significance in today's health care system, radiology imaging equipment is available in every hospital, making radiography-based approaches more easy and accessible. Since 2020, there has been a rise in the number of publicly accessible CT scan images from healthy individuals, as well as those with Covid-19. This allows us to examine medical pictures and discover potential trends that may result in the illness being diagnosed automatically. Machine learning techniques for automated diagnosis have recently acquired favor in the medical sector as an auxiliary tool for professionals [5]-[9]. Deep learning, a prominent field of study in artificial intelligence (AI), allows the development of end-to-end models capable of achieving promised outcomes utilizing input data without requiring human feature extraction [10], [11]. Numerous research addresses the diagnosis of lung illness using artificial intelligence to analyze medical images. Artificial intelligence is a rapidly growing area dedicated to the creation of models from data, and its use in the development of techniques to help professionals in the interpretation of medical images has accelerated in recent years. Transfer learning, in particular, is developing as a deep learning technique in which a model created for one task is utilized as the starting point for a model on a second task. Recent efforts have shown potential in enhancing detection in a variety of medical fields, including kidney cancer detection, Lungs cancer, and breast cancer detection. Nowadays, multiple pre-trained deep learning models are utilized to detect and predict COVID-19 from CT scans or X-ray images. In this study, eight deep learning models are used to detect the COVID-19 on chest CT scan images and compared their accuracy, data loss and compilation time.

2. LITERATURE REVIEW

Researchers have been drawn to the COVID-19 classification to build algorithms to deal with this new problem. It's no secret that digital image processing algorithms have been utilized extensively in medicine to demonstrate their efficacy with acceptable outcomes. For this reason, these algorithms have been among the most popular approaches to finding a solution. Because a trustworthy method for diagnosing this viral illness is urgently required. Many new methods have recently been developed to identify and diagnose illness in its early stages to save the lives of the people suffering from it. For example, organ segmentation, disease identification and categorization, prediction, and more may be aided by image processing algorithms in the healthcare sector.

Seum *et al*. [12] performed a qualitative study to examine the performance of CNN architectures DenseNet169 and DenseNet201 in identifying COVID-19 from CT scan pictures. The U-Net segmentation technique is examined in this study to determine the performance of CNN models. The dataset, SARS-COV-2 CT-Scan, contains a record of 2481 CT scan images. DenseNet169 architecture obtained an accuracy of 89.31% without using the segmentation method, whereas DenseNet201 model achieved an accuracy of 89.67% using U-Net.

Polsinelli *et al*. [13], a light CNN architecture based on the Squeeze Net method is suggested to efficiently classify COVID-19 CT images from those of other patients suspected of having pneumonia and healthy individuals. The approach provides an accuracy of 85.03% during the first dataset layout and around 3.2% inside the second dataset layout.

Mishra *et al*. [14] used Transfer Learning to build an algorithm for detecting COVID-19 from CT scan images classified as Healthy (Normal), COVID-19, and Pneumonia. This article employs data augmentation and fine-tuning methods to enhance and optimize the VGG16 and Res-Net50 models, resulting in an average classification accuracy of 86.74% and 88.52%, respectively.

Naeem and Bin Salem [15] describes how a combination of deep learning and multi-level feature extraction methodology is used to obtain COVID-19 classification using the CT scan and chest X-ray. GIST, SIFT, and CNN are used in this method to extract features from image data. The experimental findings show that the proposed method obtained an accuracy of 98.94%.

The suggested technique from Kundu *et al*. [16] involves an ensemble method that utilizes the Gompertz function to generate fuzzy rankings for the basic classification models and adaptively fusing the base models' decision scores to construct predictions. Three transfer learning-based CNN models are being used to generate the decision scores for the proposed ensemble model that is VGG-1, WideResNet0-2, and InceptionV3. The ensemble method achieves 98.93% and 98.79% accuracy rates on the SARS-COV-2 and Harvard Data verse chest CT datasets, respectively.

Deep learning techniques based on CNN were used in [17] to classify COVID-19 and non-COVID-19 CT scan images. CTnet-10 was developed to detect COVID-19 with an accuracy of 82.1%. Additionally, different models including such DenseNet-169, VGG-16, ResNet-50, InceptionV3, and VGG-19 were assessed, with the latter showing to be better with an accuracy of 94.52%.

Most of the studies suggested or used deep learning techniques to identify, predict, and classify COVID-19 from CT scans and X-ray images of the chest. Table 1 demonstrations the summary of relevant research. This study uses deep learning techniques to classify the COVID-19, and the best models with the highest accuracy, lowest data loss, and shortest compilation time are identified.

Table 1. The overview of the related studies

Paper	Dataset Type	Source	Class	Model	Accuracy
[12]	CT scan dataset	Kaggle.com	2	DenseNet169 DenseNet201+ U-Net	89.31% 89.67%
[13]	CT scan dataset	Github.com	2	Custom Squeeze Net	85.03%
[14]	CT scan dataset	Kaggle.com + sirm.org	3	VGG16 ResNet50	86.74% 88.52%
[15]	CT scan + X-ray dataset	Kaggle.com + sirm.org	2	GIST+ SIFT+ CNN	98.94%
[16]	CT scan dataset CT scan dataset	Github.com Harvard Dataverse	2	VGG11 + WideResNet502 + InceptionV3	98.93% 98.79%
[17]	CT scan dataset	Github.com	2	CTnet-10 VGG-16	82.1% 94.52%

3. METHODOLOGY

COVID-19 detection is performed in this study using the categorization of Chest CT scan images of the lungs. CNN architectures are used to classify images. To determine which architect performs the best at identifying COVID-19 infected CT scan images, a confusion matrix of implemented models is constructed and compared. Additionally, a variety of performance parameters are accessed through the confusion matrix. Finally, in order to determine which model is the most efficient, three measures are compared: accuracy, rate of data loss, and classification completion time per epoch for the models. The study's underlying idea is to find the most efficient CNN model by identifying the model with the greatest accuracy and the lowest data loss rate in the shortest classification completion time. Figure 1 depicts the study's flow diagram.

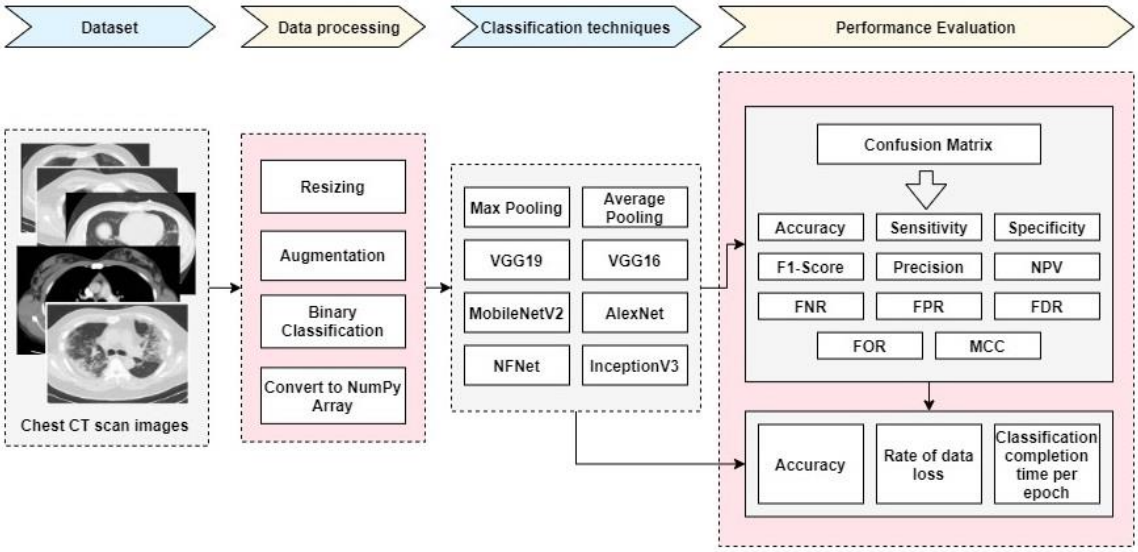


Figure 1. System architecture of proposed study

3.1. Classification models

3.1.1. Convolution neural network (CNN) architecture

CNN is a machine learning method that utilizes deep learning. It takes an input image and weights different elements, allowing it to identify one image from another [18]-[21]. The model utilizes two convolutional layers, with convolutional 2D layers in each. In both convolutional 2D layers, 'Relu activation' is utilized. It implements two Dense Layers for complete connectivity and employed 'Relu activation' for the first dense layer and 'Sigmoid activation' for the second dense layer. Apart from these levels, there are several hidden layers and an input layer. The model implementes two pooling layers: Max Pooling 2D and Average Pooling 2D.

3.1.2. Max pooling

Max pooling is used to assist in overfitting by giving an idealized version of the representation. It also reduces calculation time by lowering the amount of variables to learn and provides basic internal state performance. It performs a pooling procedure to find the largest feature map component. As the output pixel count decreases, the dimension of pictures decreases as well.

3.1.3. Average pooling

The filter's region of the feature map is used to pick the average element, which is a pooling process. Each value is added to an average and then fed to the next layer. That all data are used for feature mapping and output creation, which is a highly general calculation.

3.1.4. VGG19

VGG19 is a VGG model version comprised of 16 convolution layer, three fully connected layers, five Max Pool layers, and one Softmax. The feed to this network was a fixed-size RGB picture with a matrix with same size. Max pooling is accomplished using stride 2 across a 2x2 pixel window. Rectified linear units (ReLu) are used to incorporate non-linearity into models, which improves classification and computing performance. Three completely interconnected layers were created. Finally, as the model's final layer, there is indeed a softmax function.

3.1.5. VGG16

VGG16 uses 1x1 convolution filters, which may be thought of as a linear modification of the input channels. The input to the layer is chosen in such a way that the spatial resolution is maintained after convolution. In this model, spatial pooling is accomplished by using five max pooling layers that follow many of the conventional levels. Stride 2 is used to cover a 2x2 pixel frame when max pooling is applied. Three fully connected (FC) layers are inserted after a series of convolutional layers. The softmax layer is the last one. Layers 1 and 2 are always configured the same way in all networks.

3.1.6. MobileNetV2

MobileNetV2 is a CNN architecture optimized for mobile devices. MobileNetV2's first fully convolutional layer has 32 filters. There are 19 recurrent bottleneck layers. It is used to classify images, identify objects, and perform quantization. Two types of blocks are introduced in MobileNetv2.

- Residual block of stride 1.
- Block for downsizing with 2 stride.

Both blocks are made up of three layers. The first layer employs the ReLU6 activation function with 1x1 convolution. On the second layer, a depthwise convolution is performed, and the third layer is likewise a 1x1 convolution, except for any non-linearity. The third layer also uses the ReLu activation function MobileNetV2 performs well with fewer mathematical operations and a small number of parameters. It is about 35% quicker than its predecessor, MobileNetV1.

3.1.7. InceptionV3

When Google first demonstrated their Inception Neural Network Model in the ImageNet Classification Competition, it was called InceptionV3. The model is constructed using symmetrical and asymmetrical building elements such as convolution layers, pooling layers, concatinations, dropout, and fully-connected layers. This allows for the identification and incorporation of information from smoothed label sequences utilizing the RMSProp Optimizer and Factorized 7x7 Convolution, as well as the use of the BatchNorm in Auxillary Classifiers and a downscaling classifier.

3.1.8. AlexNet

The AlexNet consists of 8 layers, each with its own set of learnable parameters. The model consists of 5 layers, the first of which is a max pooling layer followed by three fully connected layers; each of these levels, save the output layer, uses Relu activation. Using the Relu as an activation function resulted in a nearly six-fold increase in the speed of the training process. Additionally, utilizing dropout layers keep the model from overfitting.

3.1.9. NFNet

DeepMind created NFNets to eliminate the need for normalization and boost training performance. Additionally, it adds a method called adaptive gradient clipping (AGC), which enables fast training of neural network models such as ResNet with higher batch size. The primary advantage of AGC is that it eliminates this hyperparameter. Along with AGC, dropout is utilized to mimic the regularization effect that Batch normalization provided.

3.2. Performance evaluation

The scientific community has agreed on a number of criteria for evaluating the classification system's quality [22]-[24]. The confusion matrix is used to assess the study's success using the following key parameters: true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN) where,

- TP represents COVID-19 classified by the models.
- TN indicates models that are not classed as COVID-19.
- FP indicates non-COVID-19 that the models have classified as COVID-19.
- FN denotes COVID-19 classified as non-COVID-19 by the models.

Validity metrics such as accuracy, sensitivity/recall, specificity, F1-score, precision/positive predicted value (PPV), negative predicted value (NPV), false-negative rate (FNR), false-positive rate (FPR), false discovery rate (FDR), false omission rate (FOR), and Matthews correlation coefficient (MCC) can be calculated using these parameters [25]-[30]. The mathematical formulas for these measurements are as shown in (1) to (11).

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \tag{1}$$

From (1), Accuracy is the ratio of properly predicted observations to total observations.

$$Sensitivity = \frac{TP}{\text{TP+FN}} \tag{2}$$

$$Specificity = \frac{TN}{TN+FP} \tag{3}$$

Specificity and sensitivity in (2) and (3) are used to classify data into two groups. Sensitivity is defined as the true positive rate, while specificity is defined as the true negative rate.

$$F1 - score = 2(\frac{Precision \times Recall}{Precision+Recall}) \tag{4}$$

By calculating the harmonic mean of the precision and sensitivity of a classifier, the F1-score in (4) integrates both into a single measure.

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

Precision in (5) refers to a classification model's ability to identify only relevant data items.

$$NPV = \frac{TN}{TN+FN} \tag{6}$$

In (6), NPV refers to the percentage of anticipated negatives that are truly negative. It expresses the likelihood that a projected negative value is a real negative value.

$$FNR = \frac{FN}{FN+TP} \tag{7}$$

FNR refers to the rate of determining truly positive negatives. As shown in (7) expresses the chance that an anticipated negative value is in reality a positive value.

$$FPR = \frac{FP}{FP+TN} \tag{8}$$

In (8), FPR refers to the rate of classifying a real negative as a positive.

$$FDR = \frac{FP}{FP+TP} \tag{9}$$

FDR in (9), is the percentage of ideas that all beliefs are true when they in fact false. It is the chance that all reject the null hypothesis erroneously.

$$FOR = \frac{FN}{FN+TN} \tag{10}$$

The FOR in (10) is the percentage of people who have a negative test result but have a positive actual disease.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{((TP+FP)(TP+FN)(TN+FP)(TN+FN))}} \tag{11}$$

As shown in (11) MCC is a quality metric for binary classification. where 1 represents a perfect agreement, 0 represents a prediction that is just random, and -1 represents the complete conflict between prediction and real observation.

4. RESULT AND DISCUSSION

4.1. Dataset preparation

A database of CT scan images is used in this work, which is publicly available in [31]. The dataset contains 749 images, 397 images of Non-COVID-19 (healthy lungs), and 349 images of COVID-19 are shown in Figure 2. Since not all of the images were the same size, resized all the images to 224×224 pixels. As deep learning architectures perform better with more data, the ImageDataGenerator function is used to expand the size of the dataset and create more augmentation images. The ImageDataGenerator's parameters are shown in Table 2.

Following that, all images are transformed to NumPy arrays to speed up computation. COVID-19 and NON-COVID-19 are determined using the LabelBinarizer() and categorical methods. The augmented dataset (containing 16000 images) is divided into a training set and a test set at a ratio of 80:20. The final dataset's details are shown in Table 3.

Table 2. Augmentation parameters

Rotation Range	Zoom Range	Width Shift Range	Height Shift Range	Shear Range	Horizontal Flip	Vertical Flip	Mode
20	0.15	0.2	0.2	0.15	TRUE	TRUE	Nearest

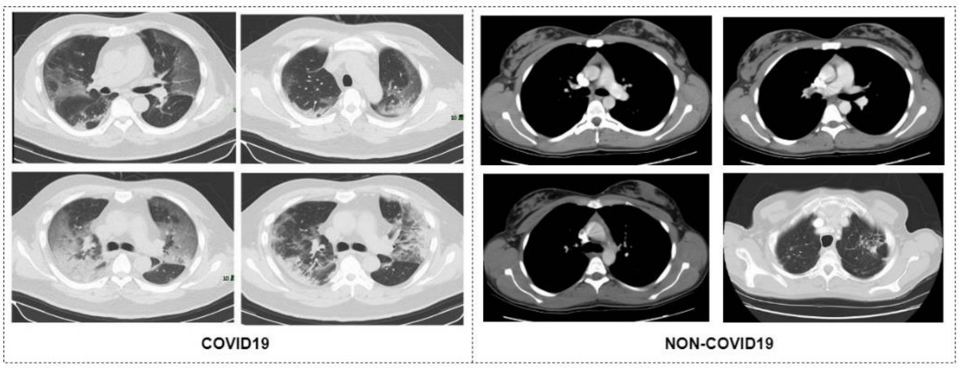


Figure 2. Data set classified sample (CT image of COVID-19 and Non-COVID-19)

Table 3. Final dataset description (After Augmentation)

Variable	Speed (rpm)
Total Number of Images	16000
COVID-19 CT Image	8000
Healthy (Non-COVID-19) CT Image	8000
Dimension (Size in Pixel)	224×224 pixels
Disease Types	2
Training Images	12800
Testing Images	3200

4.2. Result analysis

The suggested study used CNN architectures to classify COVID-19 and non-COVID-19 from Chest CT scan images. 16000 image data are used after preprocessing to gain the best classification result. Here 8 CNN architectures are used to identify the image data. The architectures are CNN Max Pooling, CNN

Average Polling, MobileNetV2, VGG16, VGG18, InceptionV3, and NFNet. Each architecture is trained and tested on 100 epochs using the RMSProp optimizer with a learning rate of 0.0000001. The outcome of the models is recorded and assessed to gain values of the confusion matrix. The confusion matrix obtained for each architecture is illustrated in the Figure 3.

In the confusion matrix the cell (1,1) represents TP, (0,1) represents FP, (0,0) represents TN and (1,0) represents FN. As stated earlier, half of the image data in the dataset are of COVID-19 and the other half are of non-COVID-19. Therefore, it can be observed from the confusion matrix that all the models could successfully identify the classes with high accuracy. However, among the models, MobileNetV2 can successfully identify the most percentage of COVID-19 and non-COVID-19 data accurately with the least percentage of an incorrect prediction. Among the 50% of COVID-19 images, MobileNetV2 efficiently identified 49.9% of data and 49.22% of data in 50% of non-COVID-19 images.

Using the elements obtained from the confusion matrix and (1) to (11), the performance of the models are measured and recorded in Table 4. From the table, it is seen that MobileNetV2 achieves the overall highest accuracy of 99.12%. The second highest accuracy is derived from VGG19 with 98.25%. It is followed by AlexNet and Max Pooling with an accuracy of 97.81% and 97.52%, respectively. Furthermore, MobileNetV2 only achieved the highest accuracy, but the highest Sensitivity, Specificity, F1-Score, Precision, NPV and MCC scores with 98.65%, 99.59%, 99.12%, 99.6%, 98.63% and 0.9824% respectively.

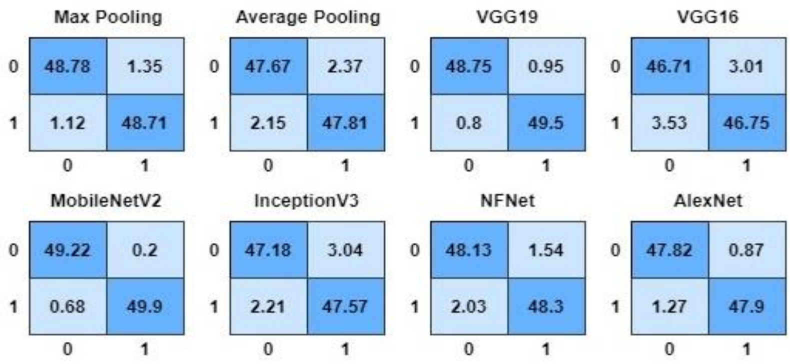
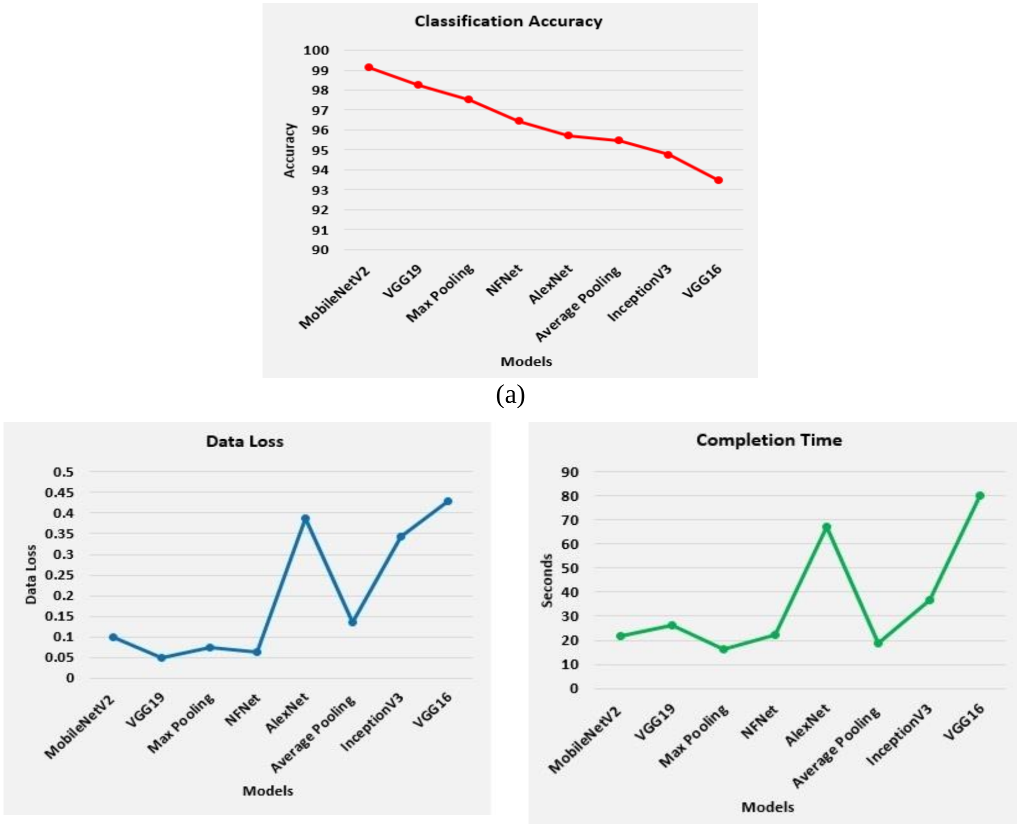


Figure 3. Confusion matrix of the models

Table 4. Performance evaluation of CNN Models

Criteria for				CNN Models				
Evaluation	MobileNetV2	VGG19	Max Pooling	Average Pooling	VGG16	NFNet	AlexNet	InceptionV3
Accuracy	99.12	98.25	97.52	95.48	93.46	96.43	97.81	94.75
Sensitivity	98.65	98.4	97.75	95.69	92.97	95.96	97.41	95.56
Specificity	99.59	98.08	97.3	95.26	93.94	96.89	98.21	93.94
F1-Score	99.12	98.26	97.52	95.48	93.46	96.43	97.81	94.77
Precision	99.6	98.11	97.3	95.27	93.95	96.91	98.21	93.99
NPV	98.63	98.38	97.75	95.68	92.97	95.95	97.41	95.52
FNR	1.34	1.59	2.24	4.3	7.02	4.03	2.58	4.43
FPR	0.4	1.91	2.69	4.73	6.05	3.1	1.78	6
FDR	0.39	1.88	2.69	4.72	6.04	3.08	1.78	6
FOR	1.36	1.61	2.24	4.31	7.02	4.04	2.58	4.47
MCC	0.9824	0.965	0.9505	0.9096	0.8692	0.9286	0.9562	0.8951

The most efficient performance of architecture depends on the accuracy of classification, classification completion time, and data loss rate. An efficient classification algorithm is characterized by its high accuracy rate in a low completion time with a low rate of data loss shown in Figure 4. From the recorded data of each model, it can be seen that from Figure 4(a), the accuracy of MobileNetV2 is the highest. From Figure 4(b), the rate of data loss is the lowest of VGG19. From Figure 4(c) the lowest classification completion time belongs to Max Pooling. However, putting the three factors together it is found that overall MobileNetV2 has the lowest completion time and lowest rate of data loss with the most accuracy. Though VGG19 has the lowest rate of data loss, it has a higher completion time and lower accuracy compared to MobileNetV2. Likewise, Max Pooling has the lowest completion time but a much poorer accuracy than MobileNetV2. The accuracy, rate off data loss and classification completion time per epoch for the MobileNetV2 are 99.12%, 0.0504%, 16.5secs/epoch.



(a)

(b) (c)

Figure 4. Performance of the models represents in (a) represents the highest accuracy of MobileNetV2, (b) represents the lowest data loss VGG19, and (c) represents the lowest classification completion time of max pooling

5. CONCLUSION

COVID-19's early diagnosis has been considered difficult because of the disease's potential to spread across society. The diagnostic procedure may be more precise and faster using deep learning methods and soft computing abilities. This study illustrated eight deep learning models that could help diagnose COVID-19 automatically. But the MobileNetV2 model has produced better accuracy than other models with the average data loss and compilation time. Though VGG19 has the lowest data loss rate, it has a higher completion time and lowers accuracy than MobileNetV2. Future studies will need the development of a hybrid deep learning method that can evaluate and perform on the high amount of images and determine how much of the lung's volume is infected.

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