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COVID-19 Infection Estimation Using Deep Learning

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Abstract: COVID-19 is an infectious disease that is spreading throughout the world, leading to a worldwide epidemic caused by the coronavirus 2 that is responsible for severe acute respiratory syndrome (SARS-CoV-2). In December 2019, the first case of COVID-19 was identified in Wuhan, China. The virus has since spread throughout the globe, leading to an outbreak across the world. The entire globe was affected within a couple of days. The SARS-CoV-2 virus can infect different organs and cells in our body. Its effects on the nose, sinuses, throat and upper respiratory tract, which includes the lungs and the windpipe, are among the most widely known. COVID-19 is mainly harmful to the lungs. This study attempted to estimate the percentage of COVID-19 lung infections by using deep learning approaches. X-rays, computerized tomography (CT) scans, and ultrasonic pictures are included in the collection. This study utilized TensorFlow and other machine learning tools to design and train deep learning models. Some of the deep learning features used to construct the model include Conv2D, Dense Net, Dropout, and Maxpooling2D. We used VGG19, CNN, customized CNN, and 10k fold. The VGG19 model has an accuracy of 78.5% and a validation accuracy of 73% with a 0.91 F1 score. The CNN model has 99% accuracy. The custom CNN has 99.63% accuracy and a 0.97 F1 score. The 10k fold model has 99% accuracy and an f1 score of 0.98, but the output is overfitted by the 10k fold model. The model with the best accuracy is a custom CNN model with a class. Overall, our study produced satisfactory results with a high level of accuracy.

Keywords: COVID-19; CNN; Python; chest CT; dataset; data augmentation; VGG19

1 Introduction

Coronavirus disease, also known as COVID-19, is a comorbid disease brought on by the acute respiratory syndrome (SARS) coronavirus 2 (SARS-CoV-2). In December of 2019, the first confirmed instance was identified within Wuhan, China [1]. The virus has since spread across the globe, causing the spread of a pandemic. During the initial outbreak in Wuhan, the virus and sickness were identified as "coronavirus" and "Wuhan coronavirus" [2]. It's also known as "Wuhan pneumonia." The WHO recommended 2019-nCoV [3] and 2019-nCoV [4] for acute respiratory illnesses in January 2020. By May 14th, 2022, COVID-19 claimed the lives of 6,286,966 people worldwide, according to world meter figures, and humankind was powerless to stop it [5]. The world government took several steps to prevent the sickness from spreading. A lot of countries are currently locked down. COVID-19 forced the closure of international crossings on many occasions. The Financial Times Stock Exchange dropped 14.3% in 2020, the lowest rate since 2008 [6]. Due to the economic slump, many people have lost their jobs or lowered their salaries. Unemployment rates have grown across the board. In addition, extensive research is being conducted in various fields to identify a practical approach to avoid loss. Computer scientists have accomplished many beneficial things, such as predicting COVID in many ways. To forecast COVID,

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they applied machine learning and deep learning.

The impact on the COVID-19 investigation was immediate, emotional, heartbreaking, and lasting. The majority of research and clinical studies in the fields of business and universities, as well as government agencies, have been halted or are already being moved to COVID-19. A majority of current clinical trials, which include ones that seek life-saving treatments, have been delayed, while the majority of studies that are still accepting new participants have ceased. The current clinical trials have been modified to permit the local community to offer medical health care and monitoring via a virtual platform, which reduces the risk of developing COVID-19 and also keeps healthcare resources from being diverted away from a widespread reaction.

The virus typically targets the lungs of the human body. It can trigger pneumonia in the most severe instances. It reduces the level of oxygen in the body. People are still getting sick from the virus, so people should still get tested and be careful not to spread it. COVID-19 is detectable through symptoms and confirmed by the RT-PCR method or by contaminated nucleic acid tests [7]. Chest CT scans, along with laboratory studies, can be used to identify COVID-19 among people who have the strongest clinical indication of being infected [8]. Antibodies produced by the body are detected by using serological tests. The body produces these antibodies in response to disease, and they can be used to identify an existing illness [7]. However, due to the fact that the number of cases is increasing quickly, it has become almost impossible to test so many patients using PCR. Testing with PCR is time-consuming and expensive. This is why alternative testing is necessary to ensure that those who are infected are quickly identified and isolated or quarantined. At present, a variety of deep learning techniques have been employed to detect viruses. However, the outcomes of these deep learning methods aren't enough to be used in a medical diagnosis system.There is also a limited number of studies estimating the severity of the infection.

Trying to combat the COVID-19 pandemic begins with recognizing the COVID-19 illness. A COVID19 infection has been detected using the reverse transcription-polymerase chain reaction (RT-PCR), X-ray scan, and computed tomography (CT-scan). Furthermore, CT scans can provide further information about the disease's course and severity and identify the COVID-19 infection. With so many COVID-19 conditions, calculating the COVID-19 percentage can assist intensive care units in freeing up ICU beds for important cases while following different protocols for patients of lower severity [9]. Medical image identification utilizing artificial intelligence and deep learning techniques, such as computed tomography (CT) scans, has been the subject of several studies and research projects. One study [10] estimated the infection rate with 99.63% accuracy.The model was created using Conv2D, Dense Net, Dropout, and Maxpooling2D. Another study [11] used the same X-ray data and achieved 98% accuracy with the InceptionV3 model.Another study [12] used CT scan data and the VGG-19 model to achieve a score of 94.52%. They also employed CTnet-10, DenseNet-169, VGG-16, ResNet-50, InceptionV3, and VGG-19, which they built themselves. Another study assessed and predicted the time with 85.91% accuracy [13].Another paper obtained a 96 percent AUC value using ResNet50 [14]. A deep CNN architecture that was derived from the chest X-ray (CXR) images to aid in COVID-19 detection was first reported in [15]. A study [16] was conducted to categorize CXR pictures into three categories, which included a transfer learning-based CNN model that was applied to COVID, non-COVID, and regular pneumonia. The CNN-based computer-aided diagnostic (CAD) method has an overall accuracy in the range of 94.5%, as per their authors. In [17] CovidGAN, an algorithm was created built on the auxiliary classifier generative adversarial networks. The accuracy was increased to 95%.In that study [18], in order to reduce complexity and improve the efficiency of memory, the authors utilized iterative pruning. They achieved an improved prediction by combining modality-specific transfer of information with iterative model pruning and ensemble learning. In [19], their objective is to design an automated deep transfer learning method for detecting COVID-19 infections with the most severe variant of the Inception model, which has 95% accuracy when used with InceptionV3. The researchers [20] developed DRE-Net and applied ResNet50 as the pretrain model. ResNet50 is an adaptation of MobileNetV2. In order to extract the details of images, they employed feature pyramid networks. This research was inspired by image data augmentation. The researchers [21] used AlexNet and GoogLeNet as well as two other DCNNs were employed to classify the images as with tuberculosis, pulmonary manifestations, and healthy. In [22], five distinct kinds of pretrained models were utilized to identify coronavirus-infected chest X-ray radiographs, including InceptionV3, the Inception ResNetV2 model, ResNet152, ResNet50, and ResNet101. In [23], they developed an algorithm for classification that was studied using VGG16 and had an accuracy rate of 95.9%. In [24], the authors used MobileNetV2 with VGG19, and MobileNetV2 was accurate 97.40% of the time. As per the study carried out by [25], the refined ResNet50 is able to achieve 92% accuracy.

Much research has been done on COVID-19 prediction in the last two years, and the findings have been quite promising. However, no study has been done on estimating the COVID-19 infection proportion. Our goal is to forecast and estimate the infraction proportion using CT scan pictures.

Our goal is to achieve high accuracy using the VGG-19 model, 10K-Fold, pre-trained CNN model, and custom CNN model. There has been very little work in estimating lung infection due to COVID; previously, most papers were about COVID-19 prediction, so our goal is to achieve high accuracy using the VGG-19 model, 10K-Fold, pre-trained CNN model, and custom CNN model. The achieved accuracy was 99.63%. Our primary goal is to get the maximum possible accuracy rate in predicting the input photos. This ensures that the final product is reputable and trustworthy. The accuracy rate is the critical goal while using this dataset. In this study, many strategies have been tried to improve accuracy.

The first section provides an introduction. The second section describes techniques and methods are explained. In section three, mathematical equations and formulas are discussed. The results are presented in section four. A comparison of performance is presented in Section 5. Section 6 also discusses the conclusion.

2 Method and Methodology

The method proposed is to calculate COVID inhalation from lung pictures using deep learning. The available datasets [26,27] were collected by codalab and Github. Then, they were merged to form a useful data set. It consists of CT scans of healthy as well as damaged lung tissue. which is part of the data.

The model has four Conv2D layers. Within the model, there are three MaxPooling2D layers, the flattened layer and two dense layers, as well as ReLU activation functions. The activation function was chosen from the final dense layer, softmax.

The accuracy of the created model is compared to that of the pre-trained model in this study using 10K Fold, Custom CNN. VGG19 is used for the pre-trained model, with some final layer changes and a head model derived from the base model. Average pooling, flattening, dense, and dropout are the customized final layers. The CNN model is well suited to image feature extraction since it extracts characteristics from provided images and learns and detects photos based on these features.

2.1Outline of Full System

The system is composed of a dataset that includes lung CT scans from COVID patients. We did some data preprocessing and data augmentation with the CT scans. Data augmentation is a technique for enhancing the variety of data available for model training without the need to collect additional data. Cropping, padding, and horizontal flipping are common data augmentation strategies used in extensive neural network training. After that, the data was fed into our model. Feature selection limits the number of input variables while developing a predictive model. Reduce the number of input variables to save money on modeling while also improving model performance in some cases.

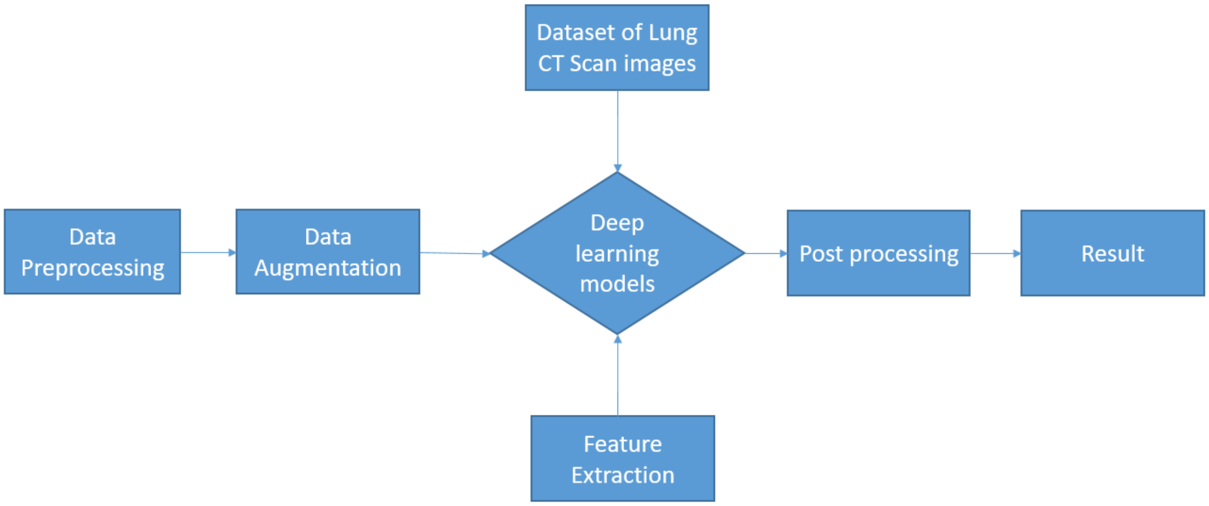


Figure 1: Block diagram of Deep Learning System

Fig. 1 shows the whole outline of our system.COVID patients' lung CT scan images are included in the system's dataset. We did some data preprocessing and data augmentation with the CT scans. Tensorflow and Keras are used in CNN data augmentation methods. The data was then entered into our model, and the results were examined.

2.2 Materials and Tools

Python is an efficient programming language used for the analysis of data. The effectiveness of deep learning-based tasks is because of Python's vast library of access. Jupyter Notebook and Google Colab were utilized to manage massive datasets and conduct online model training using a personal GPU for dataset preprocessing. They also helped keep track of all information, codes, and work in order so it could later be found through GitHub using any GPU. GitHub is also great for cooperation because it offers a teamwork and code management tracking mechanism.

2.3 Dataset Description

The accessible data sources were Codalab and Github [26,27]. The dataset is divided into three sections: training, testing, and validation. The train set has 132 CT scans, 128 of which have been confirmed to have COVID-19 based on positive reverse transcription-polymerase chain reaction (RT-PCR) results and CT scan symptoms assessed by two thoracic radiologists. There are no symptoms of infection on the other four CT scans (healthy). The Val set includes 57 CT scans, 55 of which have been confirmed to have COVID-19 based on positive reverse transcription-polymerase chain reaction (RT-PCR) results and CT scan symptoms assessed by two thoracic radiologists. There are no symptoms of infection on the other two CT scans (healthy). There are 40–70 slices in each CT scan. After data augmentation, we got a total of 3053 images in our training data.

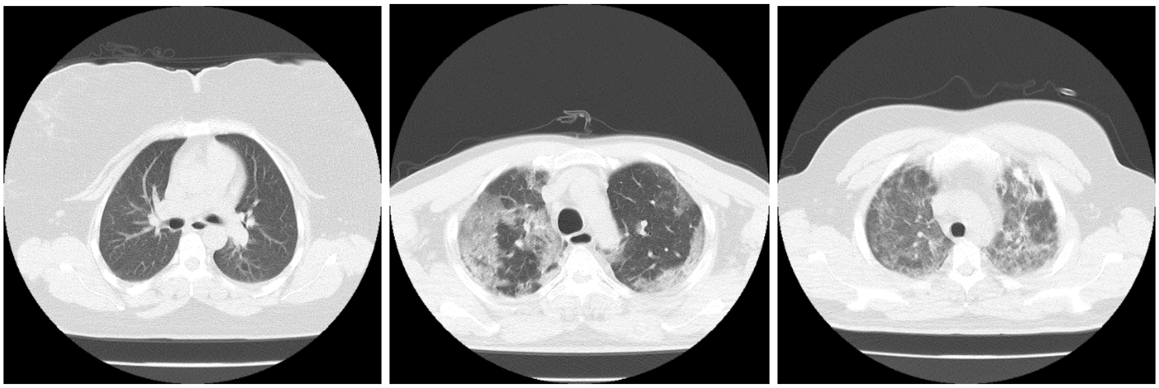


Figure 2: 0% to 100% infected lung image

In Fig.2, the leftmost lungs are 0% affected, the middle lungs are 55% affected, and the rightmost lungs are 97% affected.

2.4 System Architecture

Fig. 3 shows the system architecture. The system's architecture provides a view of the whole system. In this system, the input is a CT scanner image, while its output will be an estimate of the severity of infection. The input size is 224x224. There are 3 channels. In the first two levels of the architectural design, the size of the filter is 32. This includes padding as well as the kernel size is 3 and the activation function is called ReLU. After that, there's the maxpooling first layer with a pool dimension of 2, and strides 2. The second layer is a flat layer that converts the pooled features into one column. Then, two dense layers The first includes ReLU, which is an activation feature. The second, the tiniest layer, activation mechanism is called softmax. After preprocessing, the elements become part of the network. Fig. 3 depicts a bird's-eye view of the building.

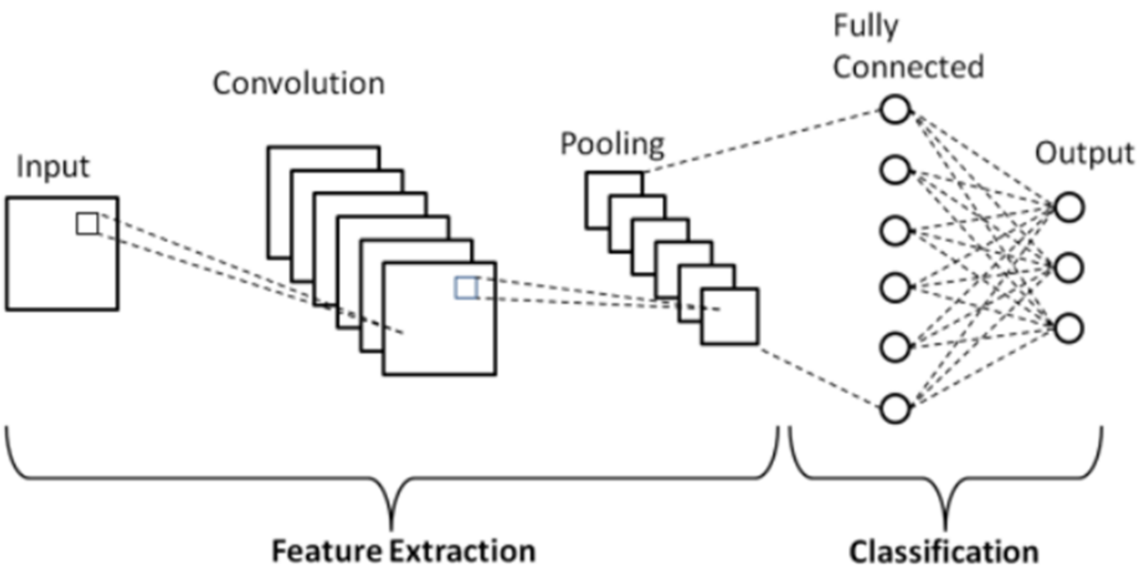


Figure 3: System Architecture[36]

2.4.1 Convolutional Layer

There are three kinds of layers which make up the CNN, which include convolutional layers, pooling layers, and fully connected (FC) layers. When the layers are stacked, a CNN structure will emerge. Alongside these three layers, there are two other important parameters, which include the dropout layer as well as the activation function.

The convolutional layer forms the core of CNN. The group is in charge of deciding the design elements. Filters process the input image within this layer. Function maps are constructed by convolution using the output of these filters. The process of multiplying weight sets by the input data is done by a convolution procedure. The filter is composed of a two-dimensional data array, which is multiplied by an input data array that has two dimensions. A single value is generated when an application of a dot product occurs to a region of the filter size between both the input and the filter. The product is used between the input's patch of filter size and the filter. The filter size is less than the input size, and it is used to multiply the input from several places with the same filter. As it systematically covers the entire image, the filter is created as a particular technique for identifying specific types of characteristics.

2.4.2 Pooling Layer

Most of the time, the convolutional layer will be followed by an underlying pooling layer. The principal goal that this layer serves is to reduce the dimensions of the feature map convolved to lower the computational cost [28]. The pooling layer allows for feature down sampling, which summarizes the presence of features. It is usually used in conjunction with the convolution layer, and it has some degree of spatial invariance. Two common pooling techniques that summarize the most active and average functions are the average pooling and the maximum pooling [29].

The pooling layer removes unnecessary features from the photos before converting them to readable images. When the layer employs average pooling, the value of its current view is averaged. Average Pooling computes the average of the elements of the predefined size of the image section. For Max Pooling, the largest element is taken from the feature map. The sum of elements within the specified section is calculated by sum pooling. It is the pooling layer that usually serves as an intermediate layer between convolutional layers and the FC layer [30]. The pooling layer is necessary to decrease the number of network parameter maps as well as feature maps while a dropout layer is employed to avoid overfitting.

2.4.3 Flatten Layer

The flattened layer transforms matrix data into a single-dimensional array that can be used within the layer that is fully linked to create a single, long and narrow one-dimensional feature. The flattening of vectors can be an alternative. Then, a fully connected layer [31] links one vector with the classification model. The full pixels are contained in a single file that has fully linked layers. The flattening process and the proper linking of layers are the final steps of CNN. To prepare for the next layer that is completely linked to the categorization of images, the image is transformed into a single-dimensional array.

2.4.4 Fully Connected Layer

Layers that are fully connected, which have proved beneficial in recognizing and classifying images within computer vision. CNN makes extensive use of these layers. Convolution and pooling are the first steps in the CNN method, which breaks the image into characteristics and evaluates them separately [32].

The Fully Connected (FC) layer comprises of biases and weights together with the neurons. It is used to link the neurons in two different layers. The layers are typically placed prior to the output layer and are the last few layers of the CNN architecture.

In this case, the input images from prior layers are flattened before being fed onto the FC layer. The flattened file is then processed by several FC layers, where mathematical functions usually take place. At this point, the process of classification begins to happen.

2.4.5 Dropout

In general, when all functions are linked with the FC layer, it could result in overfitting of the training data. Overfitting happens when a model is able to perform so well with the training data that it has an adverse impact on the model's performance when it is used on new data. To solve this issue, it is suggested to use a dropout layer wherein a small number of neurons are eliminated from the neural network during the training, resulting in a reduction in the dimensions of the model. After a dropout is reached of 0.3, 30% of the neurons are taken completely from the model.

2.4.6 Activation Functions

One of the most crucial elements in the CNN model is the activation function. They can be used to understand and approximate any complex and continuous relationship between elements in the model. In simple terms, it determines which elements from the model should be fired in the direction of forward motion and which information should remain fired at the end of the model.

It is a way to add non-linearity into the network. There are numerous commonly-used activation functions like the ReLU function, Softmax, as well as TanH, along with Sigmoid functions. Each one of these functions is used for a specific purpose. When it comes to a binary classifier, CNN model, Softmax, sigmoid, and sigmoid functions are recommended for multi-class classification, with Softmax being the most commonly used.

2.4.7 Pretrained Models

The absence of medical information or data is one of the most difficult challenges faced by researchers in the field of medical research. Data is among the most important components of deep-learning systems. Time and money are invested in the analysis of data and labeling. The benefit of transfer learning is that it doesn't require large data sets. The calculations are simpler and cost less. Transfer Learning is the technique for transferring a model that has been developed on a vast dataset to a brand new model that must be trained with new datasets that are smaller than those required. The process began with CNN training using a tiny data set for a particular task, which included a huge-scale dataset that was previously trained by the models that were previously trained. [33]. VGG 19 is a classification tool for CT scan pictures.

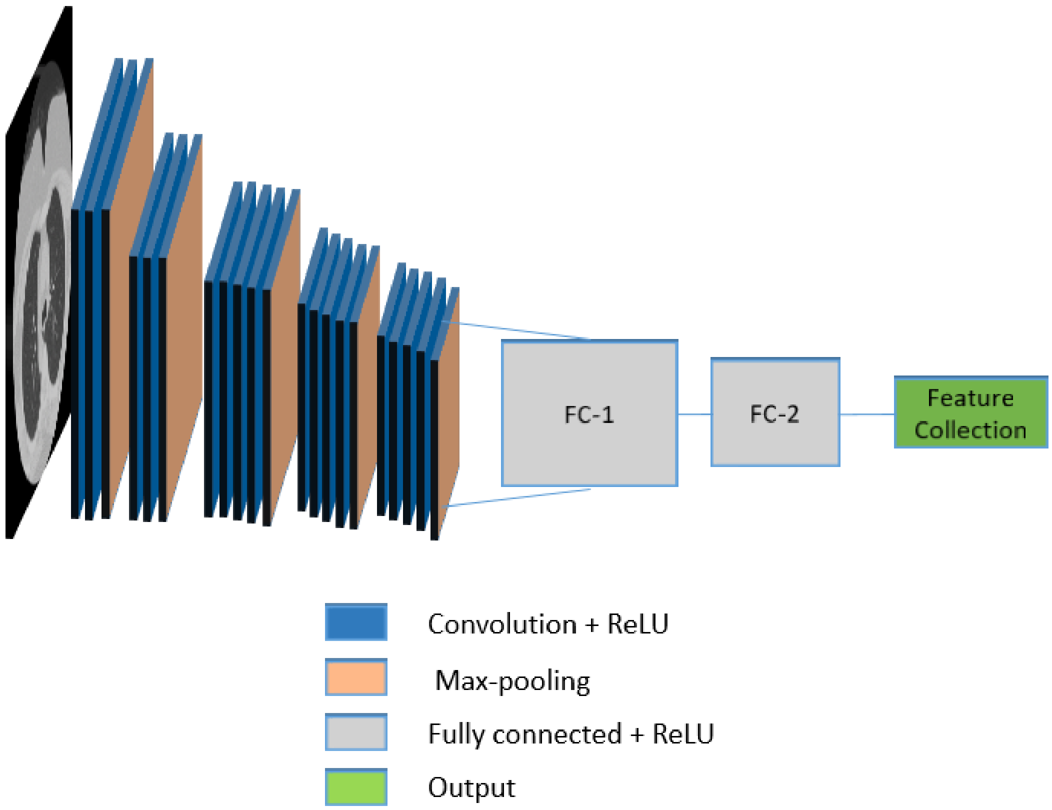


Figure 4: System architecture of the pre-trained model

Fig.4 shows the architecture of the VGG-19 model. VGG19 is a variation of the CNN model that, in short, is comprised of 19 layers (16 convolution layers, 3 fully connected layers, 5 MaxPool layers, and one SoftMax layer). There are various variations of VGG, such as VGG11, VGG16, and others. VGG19 comes with 19.6 billion FLOPS.

3. Result and analysis

After the model was trained using the model's trained generator and the validation generator, our custom CNN model produced 99.63% accuracy at the 200th epoch of our model. In this research work, we applied five CNN models. At first, we implemented VGG-19, and we got 78% accuracy.

Model	Accuracy	Validation Accuracy	Loss	Validation Loss
VGG19	78%	73%	6%	8%
CNN	99%	81%	5%	6%
10K FOLD	99%	100%	4%	6%
Custom CNN	99.63%	99.35%	1%	3%

Table 1: Histories of the accuracy and loss of the all models

From the table above we could determine the records for the precision and losses of four models. In VGG19, we got an accuracy of 78%, a validation accuracy of 73%, a loss of 6%, and a validation loss of 8%. In CNN, there is an accuracy of 99%, a validation accuracy of 81%, a loss of 5%, and a validation loss of 6%. The accuracy of 10k FOLD is 99%, the validation accuracy is 100%, the loss is 4%, and the validation loss is 6%. In custom CNN, we got an accuracy of 99.63%, a validation accuracy of 99.35%, a loss of 1%, and a validation loss of 3%.

3.1 Model Accuracy

The accuracy of training increased dramatically after each epoch, as is evident in the graph of the history of accuracy. This accuracy of 57% was observed at the initial epoch, and it increased with each successive epoch. The accuracy of the validation for the model was 55% the previous time, and it has increased from the point at which it was 55%. A line of increasing size has been established for the accuracy of training. According to the model accuracy plot, a line has been drawn for test accuracy, which is about 78% accuracy during the epoch. Fig. 5, 6 and 7 show the model accuracy, model loss, and AUC graph of the VGG-19 model, respectively.

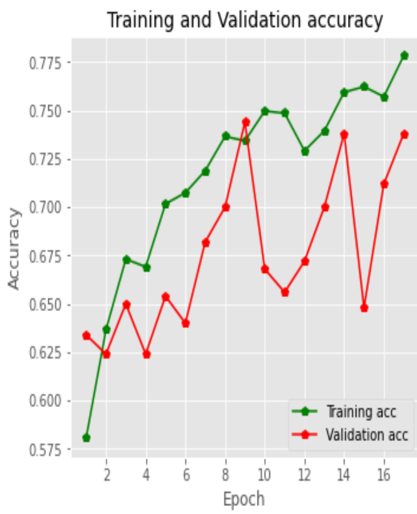
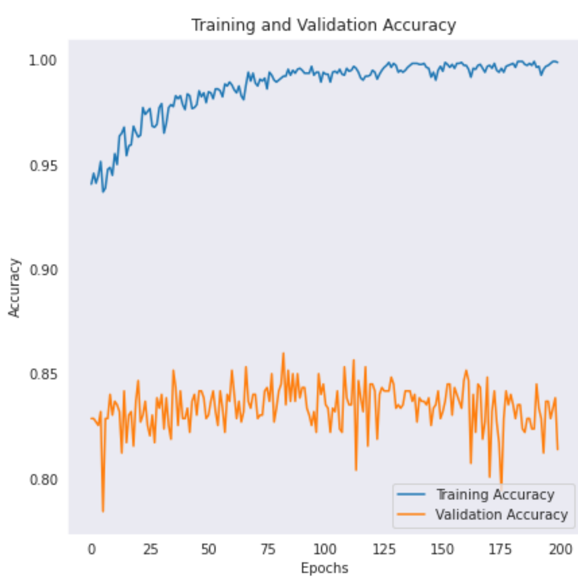


Figure 5: VGG19 accuracy Graph **Figure 6:**VGG-19 loss Graph **Figure 7 :** VGG-19 Model AUC Graph

From the graph of the model loss, it can be assumed that the lines of training loss have decreased gradually, but the validation loss hasn't decreased gradually. After the first epoch, the train loss was 45%, and after 34 epochs, it reached 6%. The validation loss was 16%, and after 34 epochs, it reached 8%. Fig. 6 shows a plot of the model loss.

Fig. 8 and 9 show the model accuracy and model loss graph of the CNN model, respectively. This training accuracy was observed at 93% of the initial epoch, and it increased with each successive epoch. At 200 epochs, the accuracy reached 99%. The validation accuracy of 83% was observed at the initial epoch. At 200 epochs, the validation accuracy reached 80%. The graph shows that the model is overfitted.



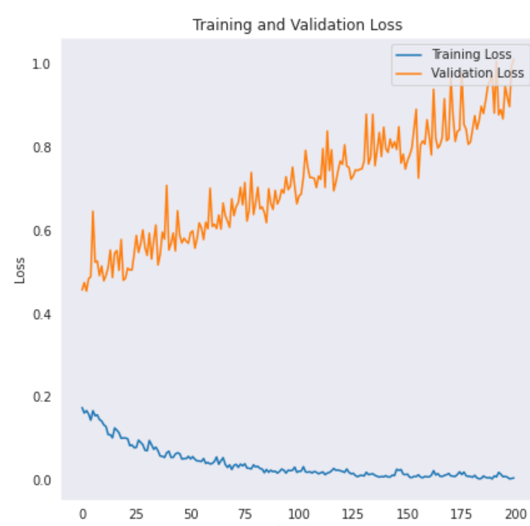


Figure 8 : CNN Model accuracy Graph

Figure 9: CNN Model loss Graph

From the graph of the model loss, it can be assumed that the lines of training loss have decreased gradually, but the validation loss hasn't decreased gradually. After the first epoch, the train loss was 19%, and after 200 epochs, it reached 5%. The validation loss was 46%, and after 200 epochs, it reached 6%.

Fig. 10 and 11 show the model accuracy and model loss graph of the 10K FOLD model. Initially, training accuracy was observed at 98%, and it increased with each successive epoch. At 100 epochs, the accuracy reached 99%. The validation accuracy of 100% was observed at the initial epoch. At 100 epochs, the validation accuracy reached 100%. The graph shows that the model is overfitted.

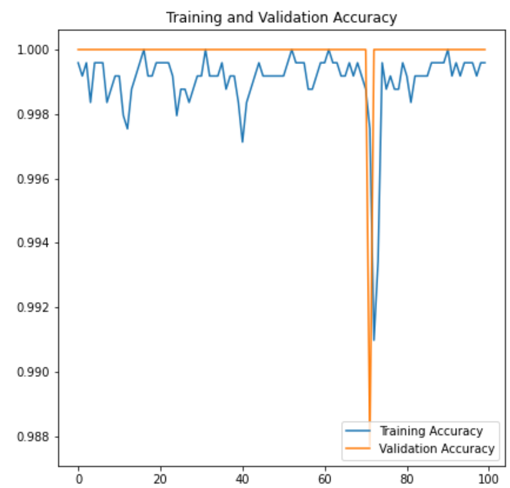


Figure 10:10K FOLD Model accuracy Graph

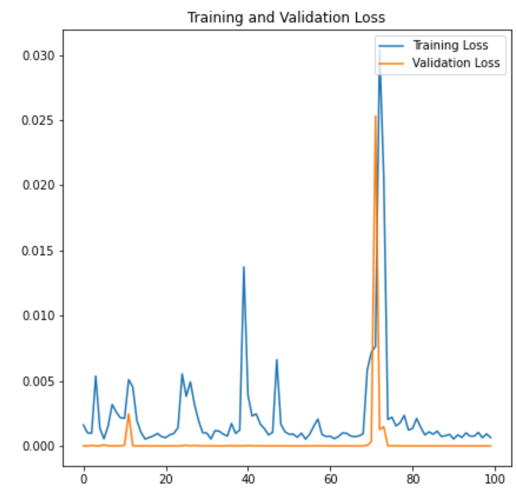
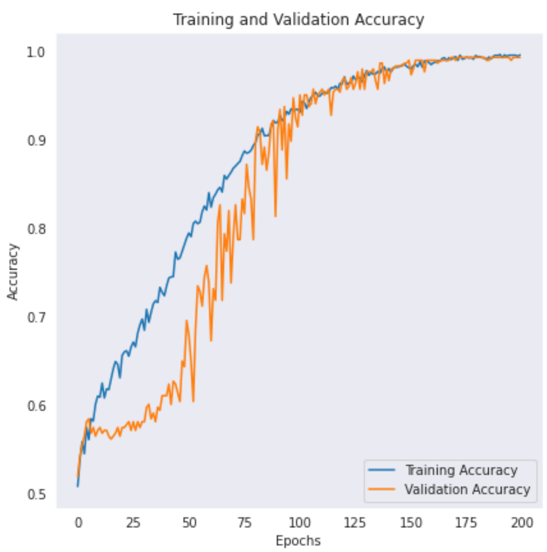


Figure 11:10K FOLD Model LOSS Graph

Fig. 12 and 13 show the model accuracy and model loss graph of the custom CNN model, respectively. Initially, 52% of the training accuracy was observed, and it increased with each successive epoch. At 200 epochs, the accuracy reached 99.63%. A validation accuracy of 55% was observed at the initial epoch. At 200 epochs, the validation accuracy reached 99.35%. The graph shows that the model is not overfitted at 200 epochs.



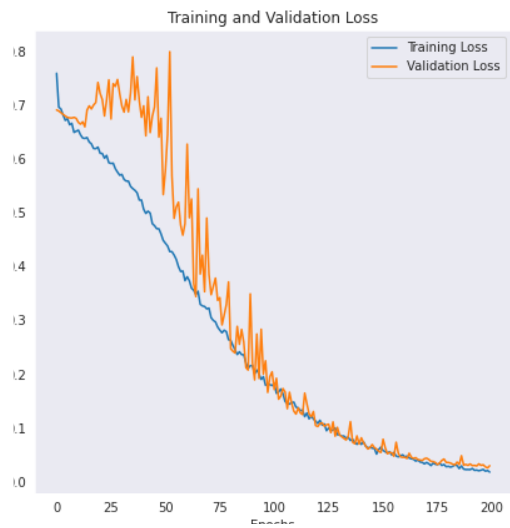


Figure 12 : Custom CNN Model accuracy Graph

Figure 13 : Custom CNN Model Loss Graph

From the graph of model loss, it could be concluded that both the lines of loss in training and test loss have been decreasing slowly. At the beginning, the loss of training was about 75%. After 200 epochs, it was 1%. The loss in validation was 70%, and after 200 epochs it was 3%.

The confusion matrix of the system is shown, including absolute values in columns as well as anticipated values displayed in rows. The confusion matrix summarizes the results of a classification model's predictions. The confusion matrix accuracy as well as incorrect forecasts are compiled and classified. The confusion matrix is illustrated in Fig. 14.

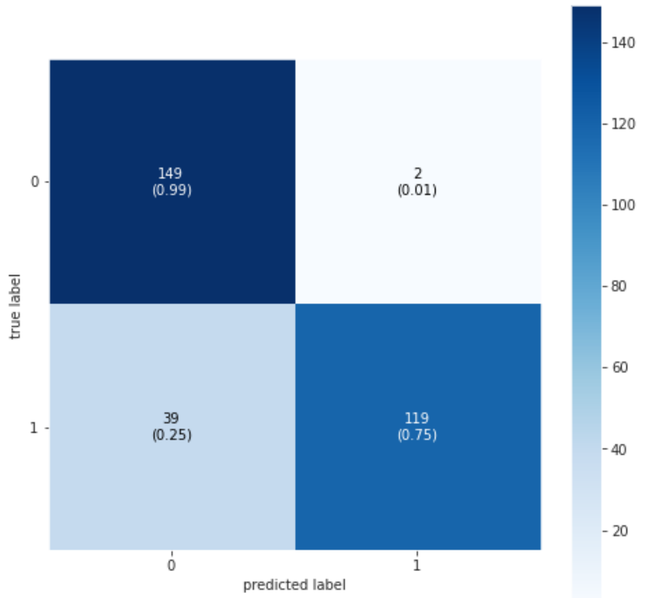


Figure 14 : Confusion Matrix

Fig. 14 illustrates that this model can adequately predict 268 photographs and wrongly predict 41 images. For error-based analysis, prediction as well as data and features are all vital. A confusion matrix will show the proportions of true positives, false negatives, true negatives and false negatives when using the prediction-based error analysis. The amount and nature of the data have an impact on the error analysis. Since the test and training sets have a significant impact on the final outcome, correctly separating the data used for testing and training is essential for error analysis. The importance of features in mistake analysis cannot be overstated. Feature engineering and regularization were also employed to eliminate mistakes.

3.4 Model Evaluation

The accuracy of the model, its precision, recall, as well as the F1 scores of models were used to judge their performance. The scores of true positive (TP), false positive (FP), and true negative (TN), as well as false negative (FN), were utilized to assess the proposed models' performance (FN). Recall, also referred to as sensitivity, is the process of accurately identifying the affected photographs from the entire image. Recall is the exact contrast to precision. The F1-score is a combination of precision and recall measurement that indicates the frequency at which the expected value is accurate. In math, it's called the harmonic average of p and r. The following are the equations.

Matrices are used to assess the system's performance and their performance once the model is created. It is important to calculate accuracy to determine how well a model system performs. (i.e., how many times the model correctly predicts the actual outcome). Eqs. 1 and 2 [34] are the mathematical formulas for finding the accuracy.

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

$$\text{accuracy}=\frac{correct\ predictions}{total\ number\ of\ example} \tag{2}$$

The probability of successfully identifying the true value of any value is referred to as recall, also known as the sensitivity. Recall can be measured through the formula in Eq. (3) [35].

$$\text{re-call}=\frac{TP}{TP+FN} \tag{3}$$

Precision refers to the amount of correct identifications. The percentage of instances when it was positive that the forecast of the model was right can be determined with the help of the mathematical formula (4). which is more dependent on the model's recognition. The precision is between 0 and 1.

$$\text{precision}=\frac{TP}{TP+FP} \tag{4}$$

The F1-score is a singular matrix that defines precision and recall. It is able to evaluate the performance of a classifier for recall as well as precision. In other mathematical terms, it is a harmonic means of accuracy and recall. The F1-score is calculated using Eq. (5).

$$\text{f1-score}=\frac{2pr}{p+r} \tag{5}$$

True positive is represented by TP, false positive by FP, and false negative by FN. The letters "p" and "r" in Eq. 5 refer to precision and recall, respectively. The model evaluation for precision as well as recall and F1-scores of our models is shown in Table 2.

Model	State	Precision	Recall	F1-score
VGG19	COVID-19	1.00	0.94	0.97
Custom CNN	Normal	0.95	1.00	0.97
10K FOLD	COVID-19	0.99	0.96	0.98
CNN	COVID-19	0.99	0.80	0.88

Table 2: Model evaluation

From the table of model evaluation, for model VGG19, we found a precision of 1.00, a recall of 0.94, and an Fl-score of 0.97. In Model Custom CNN, we found a precision of 0.95, a recall of 1.00, and an Fl-score of 0.97. We found a precision of 0.99, a recall of 0.96, and an f1-score of 0.98 in the 10k FOLD model. And in model CNN, there is a precision of 0.99, a recall of 0.80, and an fl-score of 0.88.

3.5 Model Test

The model was also put to the test in the real world, with CT scan images as input. When the model is finished, it is saved as a png file that contains the actual model. For this investigation, four png files were prepared for four different models. A new notebook file with the ipynb extension was created for the test. Individual CT scan images, comprising four models, were submitted as input to the test file. Figure 12 shows the test result, which reveals if the image is a CT scan of a COVID-19 patient.

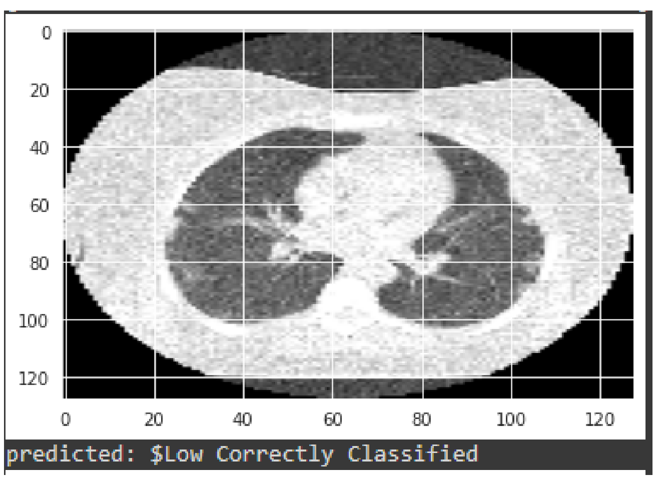


Figure 15: Screenshot of low affected image result

In Fig. 11, the affected SARS-CoV-2 CT scan was supplied as an input to the model. The model then gave its output, wherein the CT scan was of a COVID-19 low-infected patient (i.e. coronavirus infected).

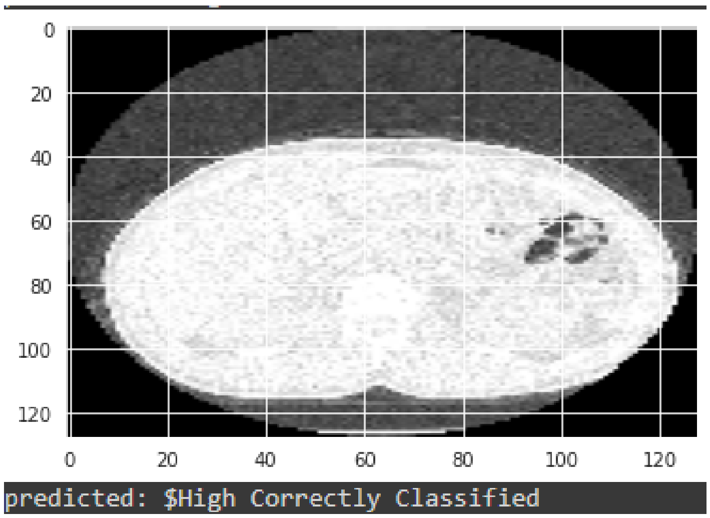


Figure 16: Screenshot of high affected image result

Following this test, a second CT scan was used as an input for the model. The image was found to be highly infected. Fig. 12 illustrates the results of the highly-infected CT scan.

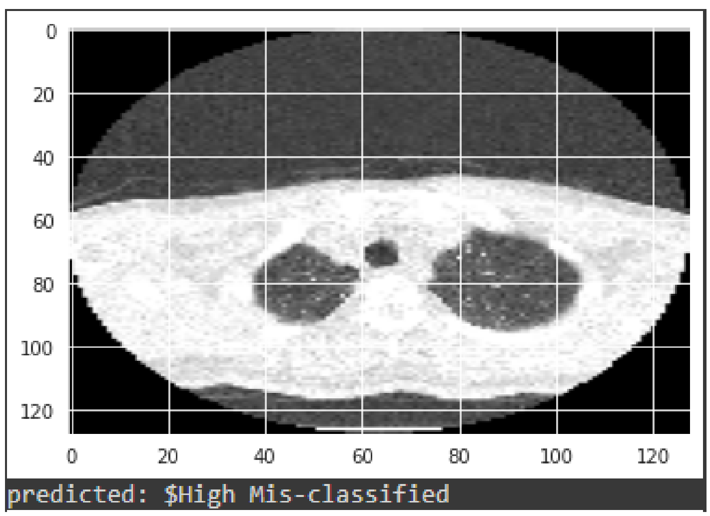


Figure 17 : Screenshot of high mis-classified image result

Fig. 13 illustrates a significant output that was misclassified. The model was able to accurately predict the patient's condition. In the study, not just the three tests conducted in conjunction with the other tests but all models were examined. Based on actual results, each model was able to pass the test.

3.5 Result Comparison

In Table 3, we compare our model results with the other paper model results.

Reference	Model Name	Accuracy	Accuracy in this study
In study [12]	VGG19	94.52%	78%
In study [12]	Custom CNN	82.1%	99.63%
In study [15]	Custom CNN	93%	99.63%
In study [16]	Custom CNN	94.5%	99.63%

Table 3: Compare results with relative works

4 Conclusion

Four CNN models were provided in this study, including a full custom CNN, pre-trained VGG19, 10K FOLD, and 2K FOLD, which were all adjusted in the final layers. The models utilized in this investigation were almost identical in terms of accuracy. SARS-CoV-2-affected and unaffected x-ray and CT scan images are included in the dataset. The 10K fold model has 99% accuracy and an F1 score of 0.98, while the VGG-19 model has 78% accuracy and an F1 score of 0.97. The pre-trained CNN model's accuracy was 98%, with an F1 score of 0.88, while the customized CNN model's accuracy was 99.63%, with an F1 score of 0.88.

As a result of this achievement, the medical sector will be forever changed. COVID-19 patients can use this technology to swiftly determine the amount of infection in their lungs, which could help with the current pandemic scenario. This type of technology will benefit humans in the future. To fine-tune the parameters and develop a reliable model that can aid humanity.

In the end, the deep learning-based COVID-19 model may be an intriguing method for research. The results can be observed as a comparison study can be carried out by altering the testing and training data ratio. Studies on survival and risk could be useful in the future for development. COVID-19 detection techniques that are based on deep learning may prove useful at the moment. In order to provide more precise results, various forms that make up CNN's architecture were created. In the future, we can enrich the dataset with more CT scans of patients with SARS-CoV-2 and use them for training, providing an excellent opportunity to observe.

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