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Covid-19 Prediction from Chest X-Ray and CT scan Using Deep Learning Methods

Aarthy. R[1], Kasiraja Gunasekarn[2], Danish Maqbool Sheikh[3], Mallipeddi Jai Sivasankar[4], Balaji Selvarajan[5]

[1]Assistant Professor, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur
[2]Student, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur
[3]Student, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur
[4]Student, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur
[5]Student, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan Engineering College, Perambalur

ABSTRACT

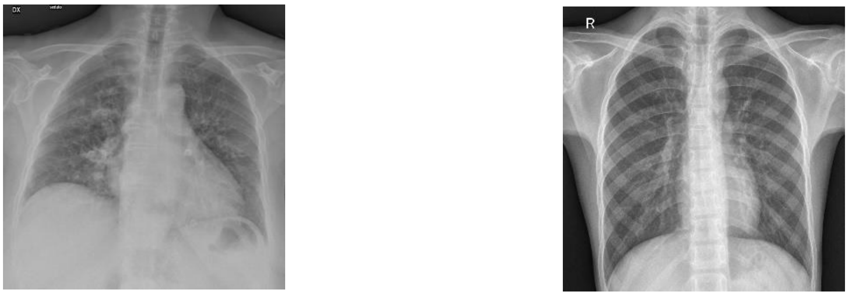
The novel coronavirus disease of humans, COVID-19, is now thought to be the deadliest sickness it has ever produced. A limited number of COVID-19 test kits are accessible in hospitals because of a shortage of radiologists, and this is also accompanied by a shortage of equipment due to the daily increase in cases as a result of an increase in the number of COVID-19-infected individuals. To Overcome this Several convolutional neural networks (CNN)-based techniques for computer-aided COVID-19 detection based on lung computed tomography (CT) scans and Chest X-ray Images (C-X-rays) have been developed as of late. In this proposed model we used a hybrid dataset of Chest X-ray and CT scans in a single dataset to train the model and predict the COVID-19 cases with both the Chest X-ray and CT scan. However, the presentations of COVID-19 in CT scans and Chest X-Rays are classified into two classes Covid 19 and Normal. Chest X-rays and CT scans provide a different method for detecting Coronavirus early in the disease phase. Using VGG16 and CNN deep learning algorithms, the model identified characteristics from Chest X-ray images and CT scans and categorized them into two groups: Normal and COVID-19. The model had trained with 1600 pictures of two folders test and validation with 2 classes of each folder to test their realism in practical settings. The traditional CNN model has less accuracy in detecting COVID-19 cases, for the betterment of prediction it needs the improved CNN model. The proposed model has the highest accuracy of 94% when compared to the traditional CNN model.

Keywords: CNN, VGG16, COVID-19, Chest X-ray, CT scan, Deep Learning.

I. INTRODUCTION

One of the most lethal diseases, COVID-19, began to spread around the end of 2019 and had considerable growth by the middle of 2020. It is a disease that can spread quickly from one person to another through direct or indirect contact. It can also be referred to as a serious lung condition that impairs breathing and affects the lungs. Despite such high rates of mortality and societal impact, COVID-19 diagnostic tests are still far from adequate [1], and the rate of dissemination was higher than the rate at which COVID tests were conducted globally. Several tests were conducted in that situation to identify the infected patients, but the reverse transcription polymerase chain reaction (RT-PCR) proved to be the most successful method. which can identify SARS-Cov-2 RNA in respiratory samples taken from the nasopharynx or oropharynx [2]. Throughout the 14-day observation period, several tests are conducted to guarantee the accuracy of the RTPCR test results [3]. Although there were not many test subjects available, RTPCR was the most frequently used and gold standard test. Yet these test kits weren't sufficient to conduct tests everywhere in the world. The chest X-ray and lung CT scan were the second-most-often used medical images to diagnose COVID-19-infected patients since RTPCR was insufficient and took too long. It took less time and was still a cost-effective way to diagnose COVID-19. Early diagnosis, quick isolation, and early treatment are the primary means of controlling COVID-19 disease. The procedures used in radiography aid in both the differential and final diagnosis of the disease. Pneumonia in the lungs is the illness's most notable symptom. A chest X-ray is the first imaging technique that doctors choose [4]. Chest X-rays are most frequently used for diagnosis since CT scans by doctors are time-consuming and labor-intensive, especially with the present rise in patient numbers, which generally increases the workload of radiologists and impairs diagnostic efficiency [5].

In recent years, the identification of diseases like brain tumors, kidney stones, bone cancer, etc. using radiological pictures like X-rays, MRI and CT scans has seen the most widespread application of machine learning and deep learning, branches of artificial intelligence. Using both chest X-rays and CT scans, deep learning was applied in this case to the diagnosis of COVID-19 prediction. The implementation of deep learning in disease diagnostics relies heavily on the convolutional neural network (CNN) approach. CNN's ground-breaking capabilities allowed medical professionals to employ it for a variety of purposes [6]. The



(a) (b)

Figure 1: (a) COVID-19 CXR and (b) NORMAL CXR

(a) (b)

Figure 2: (a) COVID-19 CT scan and (b) NORMAL CT scan

implementation of multiple ML/DL approaches to identify and classify COVID-19 is insufficient.

Despite the introduction of several detection schemes to deal with the spread of COVID-19, the deep learning method is still mostly employed in COVID-19 diagnosis. A lot of data is needed for the ML-based techniques to develop the detection models. Since only a small number of medical photos are accessible, the DL approaches only offer improved results and practical answers to tackle pandemic conditions. Researchers and radiologists must be involved in medical image mining because it takes a lot of time and money. Spatial information loss was seen by COVID-19 ML-based screening models, which is still a major concern [7].

Many neural networks, including VGG16, ResNet, DenseNet, and AlexNet, are used in CNN. ShuffleNet, MobileNet, etc., to implement the diagnosis of COVID-19 with better accuracy. In the suggested approach, we used a VGG16 neural network to more accurately diagnose the COVID-19 condition with the hybrid dataset of both Chest X-ray and CT scan combined. In contrast to other processes, including blood tests, viral tests, and RT-PCR, the chest X-ray (CXR) and CT scan were the cost-efficient and low-time-demanding processes that we employed to forecast the COVID-19 patients faster. The developed neural network model was trained to predict COVID-19 instances more accurately and successfully utilize these medical images.

II. RELATED WORK

In this section, we evaluated some of the research similar to our project that has been conducted by various authors and researchers utilizing deep learning techniques to predict COVID-19 cases and the norm using medical pictures such as chest X-rays and CT scans.

Kapil Gupta and Varun Balaji [8] for the automated screening of COVID-19, two pre-trained deep learning models (DLMs), namely MobileNetV2 and DarkNet19, as well as a newly-designed lightweight DLM, are used. For the training, validation, and testing of deep learning models, a repeated ten-fold holdout validation procedure is used. With transfer-learned DarkNet19, the greatest classification accuracy of 98.91% is attained. Further CT scans can be used to test the suggested framework. To demonstrate the viability of the proposed study, simulation results using the publicly accessible COVID-19 CT scan image dataset are supplied. They used the dataset which contains 1252 COVID-19 images and 1230 non-COVID-19 images of CT scans.

Amiya Kumar Dash and Puspanjali Mohapatra [9], put up an original paradigm for identifying the COVID-19 infection. On top of this deep convolutional neural network, which has already learned discriminative features such as edges, colors, geometric changes, shapes, and objects, they added a new simplified, fully connected layer set that is initialized with some random weights. They removed the fully connected layers of the well-established model VGG-16 in this case. They seize all the layers in the network body to warm up our FC head and then unfreeze all the layers to allow for fine-tuning to prevent the risk of damaging the network's rich features. The proposed classification model identified COVID-19 with an accuracy of 97.12%, 99.2% sensitivity, and 99.6% specificity. The dataset contains medical images from three classes COVID-19, non-COVID-19 Pneumonia, and Normal. The dataset contains 147 images of COVID-19, 600 images of non- COVID-19 Pneumonia, and 525 Normal class.

Nallamothu Sri Kavya, Thotapalli Shilpa, N. Veeranjaneyulu, and D. Divya Priya [10], used VCG16 and ResNet50 deep learning algorithms, they identified characteristics from chest X-ray pictures and divided them into three groups: viral pneumonia, normal, and COVID-19. We tested the models on 15,153 photos to evaluate how accurate they were under actual conditions. The VGG16 model has an average COVID-19 case detection accuracy of 89.34%, while ResNet50 has an accuracy of 91.39%. However, a larger dataset is required when using deep learning to identify COVID-19. Accurate scenario detection is the desired outcome.

Shaline Jia Thean Koh, Marwan Nafea, and Hermawan Nugroho [11] Describe a different approach that can be used on edge devices to analyze chest X-ray pictures and deliver an effective and precise diagnosis of COVID-19. The strategy makes it possible for the deep learning model to be used in real-world scenarios. By utilizing transfer learning techniques, the convolutional neural network models used in this study were created to accurately predict COVID-19 and pneumonia infection from chest X-ray pictures. The generated model had a 98.13% accuracy, 97.79% sensitivity, and 99.1% specificity. To highlight the critical regions in the X-ray pictures that drive the model to its decision or prediction, we employed the Gradient Class Activation Map (Grad-CAM). After processing the dataset consist of 1095 images in the train set and 480in the test set. That Each class contains 635 training data and 160 testing data.

Lobna M. AbouEI-Magd, Ashraf Darwish, Vaclav Snasel, and Aboul Ella Hassanien [12], To detect COVID-19 with unbalanced data sets, this research suggests a pre-trained convolutional neural network (VGG16) with capsule neural networks (CapsNet). Due to the Caps Net's capacity to specify concepts like perspective, direction, and size. To prevent the creation of outliers or changes in data distribution, Synthetic Minority Over-sampling Technology (SMOTE) was used to ensure that new samples were generated near the sample center. The Gaussian optimization method has been utilized to optimize the capsule network parameters (capsule dimensionality and routing number) because changing them may alter the outcomes.

R. G. Babukarthik, V. Ananth Krishna Adiga G. Sambasivam, D, Chandramohan and J. Amudhavel [13], The purpose of this study is to develop a method for using CXR pictures to distinguish between pneumonia caused by COVID-19 and healthy lungs in a normal person. The deep learning method is one of the impressive techniques used to extract a high-dimensional feature from medical photos. Modern methods like genetic deep learning convolutional neural networks (GDCNN) are employed. It is trained from scratch to extract features for separating COVID-19 photos from other types of images. It can be seen through training a GDCNN from scratch that the suggested approach outperforms alternative transfer learning techniques. In COVID-19 prediction, a classification accuracy of 98.84%, precision of 93%, sensitivity of 100%, and specificity of 97.0% are attained. The highest nominal rate in the identification of COVID-19 disease prediction in an unbalanced environment is revealed by the research's top classification accuracy. The new classification model that has been developed outperforms previous models like ReseNet 18, ReseNet 50, Squeezenet, DenseNet-121, and Visual Geometry Group (VGG-16).

Nirmala Devi Kathamuthu and Shanthi Subramaniam [14], proposed a study that examines several CNN methods based on deep transfer learning for detecting the presence of COVID-19 in chest CT images. The base models in this study are VGG16, VGC19, Desenet 121, InceptionV3, Xception, and Reset50. A confusion matrix and numerous performance metrics, including accuracy, recall, precision, f1 score, loss, and ROC, were used to assess each model's performance. In this investigation, the VGG16 model performed significantly better than the other models (98.00% accuracy). The virtues of the suggested strategy for identifying and keeping track of COVID-19 patients have been demonstrated by promising results from experiments. A dataset of 2481 photos from Kaggle, representing CT scan images, was used to train the model. The

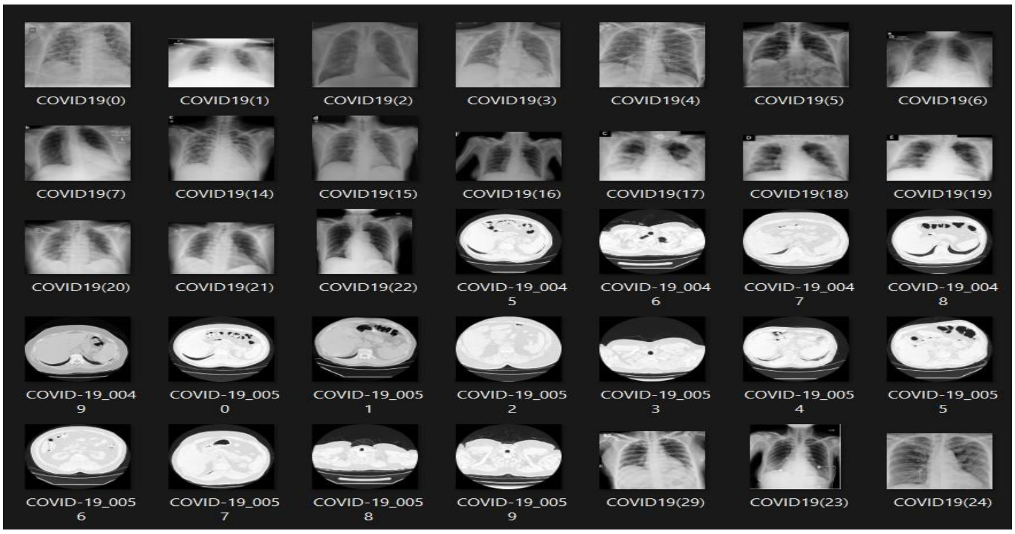


Figure 3: Hybrid dataset of COVID-19 medical images

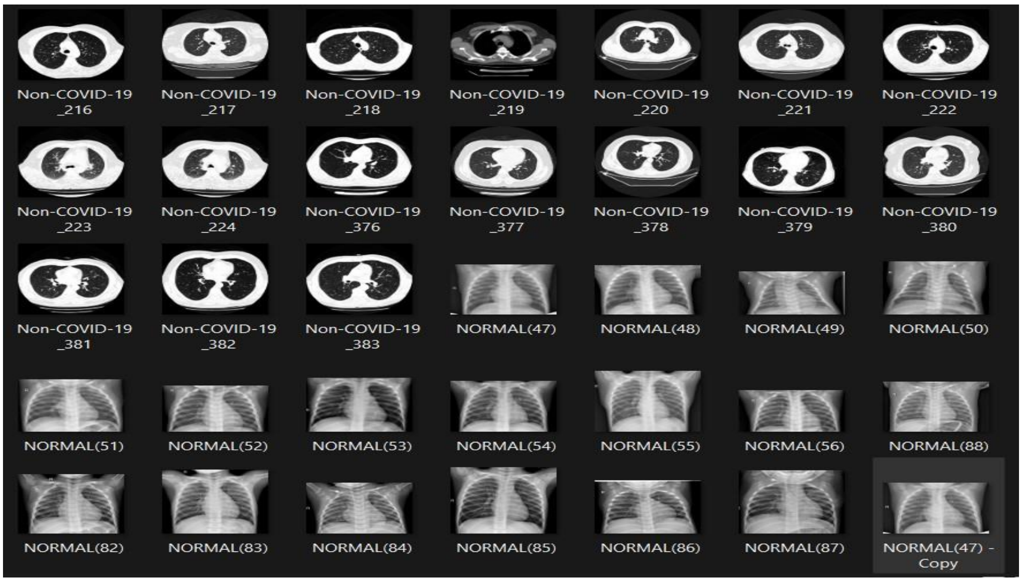


Figure 4: Hybrid dataset of Non-COVID-19 medical images.

information was then divided into COVID and non-COVID groups. Whereas the non-COVID class only had 1229 CT pictures, the COVID class has 1252. In this study, the model was trained using 80% of the data from lung CT scans, then tested using the remaining 20%.

III. DATASET

In this study, the model was trained using a hybrid dataset that contains medical images of both a CT scan and a Chest X-ray (CXR). The data was gathered from open sources like GitHub and Kaggle. A total of 9736 images, including 7281 COVID CT scans, 729 non-COVID CT scans, 460 COVID chest X-rays, and 1266 non-COVID Chest X-rays, were gathered from public resources. From there, we filtered 800 CT scans, 400 of which had COVID and 400 of which were Non-COVID-19, as well as 800 chest X-rays, 400 of COVID and 400 which of Non-COVID, in both the training and validation folders. Figure 3 and Figure 4 show the hybrid dataset of COVID-19 and Non-COVID-19 medical images.

IV. VGG16 ARCHITECTURE

In the paper "Very deep convolutional network for large-scale image recognition" K. Simonyan and A. Zisserman introduced the VGG16 algorithm. 13 convolutional layers and 3 fully linked layers make up the VGG16. Five blocks make up the convolutional layer [12]. Since it only uses filters of size 3 x 3 with one stride for convolutional filters and 2 x 2 pooling with two

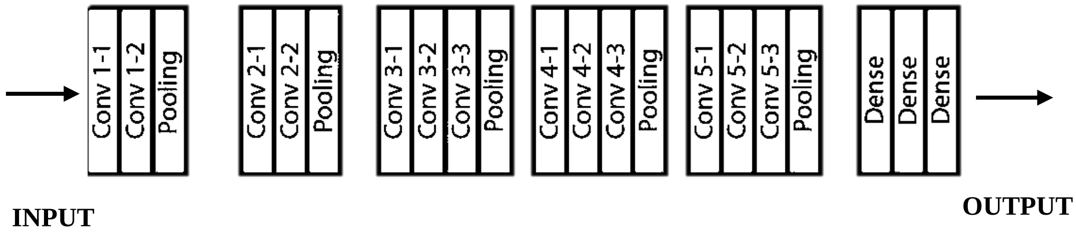


Figure 5: Architecture of VGG16

strides in all layers, the model's architecture is consistent and fluid.

V. METHODOLOGY

In this section, we discussed the methods and modules of our proposed system with VGG16 architecture.

Class Formulation

The chest X-ray and CT scan images that were gathered from multiple open sources, including GitHub and Kaggle, were divided into two classes: COVID-19 and Non-Covid-19, in each train and validation folder. Each class consists of 400 images, with 800 images in the train folder and 800 images in the validation folder, each of which had two classes. To train the model, a total of 1600 photos were used for the class formulation.

Importing Pre-trained Model

We used a VGG-16 pre-trained model in this proposed system by utilizing transfer learning. Using the Keras library, we imported the VGG16 model from Keras, where the model was trained using the ImageNet dataset. There are 1,281,167 training photos in the ImageNet dataset, which is enormous. 100,000 test photos and 50,000 validation photos are included. The final three layers were fully connected layers using sigmoid as an activation function, while the first thirteen levels were convolutional layers with ReLu as an activation function. The layers in the VGG16 model are depicted in Figure 6, along with the total number of parameters.

The activation function employed for the VGG16 model is typically softmax. However, as it is a binary classification, we employed the sigmoid activation function. Given that its value can range from 0 to 1, the sigmoid is the optimal activation function for binary classification. Convolutional layer pooling layers are there between them. There are various kinds of pooling layers, including maximum, minimum, and average pooling. However, we used a pre-trained model and the maximum pooling layer, which is the standard pooling layer, in the VGG16 model. The flattened layer, which is used to turn the two-dimensional array into a single-dimensional array so that the fully connected layer can anticipate the output, comes before the fully connected layer.

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 224, 224, 3)]     0
 block1_conv1 (Conv2D)       (None, 224, 224, 64)      1792
 block1_conv2 (Conv2D)       (None, 224, 224, 64)      36928
 block1_pool (MaxPooling2D)  (None, 112, 112, 64)      0
 block2_conv1 (Conv2D)       (None, 112, 112, 128)     73856
 block2_conv2 (Conv2D)       (None, 112, 112, 128)     147584
 block2_pool (MaxPooling2D)  (None, 56, 56, 128)       0
 block3_conv1 (Conv2D)       (None, 56, 56, 256)       295168
 block3_conv2 (Conv2D)       (None, 56, 56, 256)       590080
 block3_conv3 (Conv2D)       (None, 56, 56, 256)       590080
 block3_pool (MaxPooling2D)  (None, 28, 28, 256)       0
 block4_conv1 (Conv2D)       (None, 28, 28, 512)       1180160
 block4_conv2 (Conv2D)       (None, 28, 28, 512)       2359808
 block4_conv3 (Conv2D)       (None, 28, 28, 512)       2359808
 block4_pool (MaxPooling2D)  (None, 14, 14, 512)       0
 block5_conv1 (Conv2D)       (None, 14, 14, 512)       2359808
 block5_conv2 (Conv2D)       (None, 14, 14, 512)       2359808
 block5_conv3 (Conv2D)       (None, 14, 14, 512)       2359808
 block5_pool (MaxPooling2D)  (None, 7, 7, 512)         0
 flatten (Flatten)           (None, 25088)             0
 fc1 (Dense)                 (None, 4096)              102764544
 fc2 (Dense)                 (None, 4096)              16781312
 dense (Dense)               (None, 2)                 8194
=================================================================
Total params: 134,268,738
Trainable params: 134,268,738
Non-trainable params: 0
_________________________________________________________________
```

Figure 6: Layers and Parameters in VGG16

Model Compilation

The final stage of model creation is the compilation. We can start the training step after the compilation is finished. We used categorical cross entropy, a loss function that is frequently used in the VGG16 model for the multiclass picture classification, in the model compilation step of the suggested model. Also, we employed an SGD optimizer with a momentum of 0.9 and a learning rate of 0.0001. While the momentum weight takes prior weight changes into account when updating current weights, the learning rate sets the step size towards a minimum of the loss function while following the gradient.

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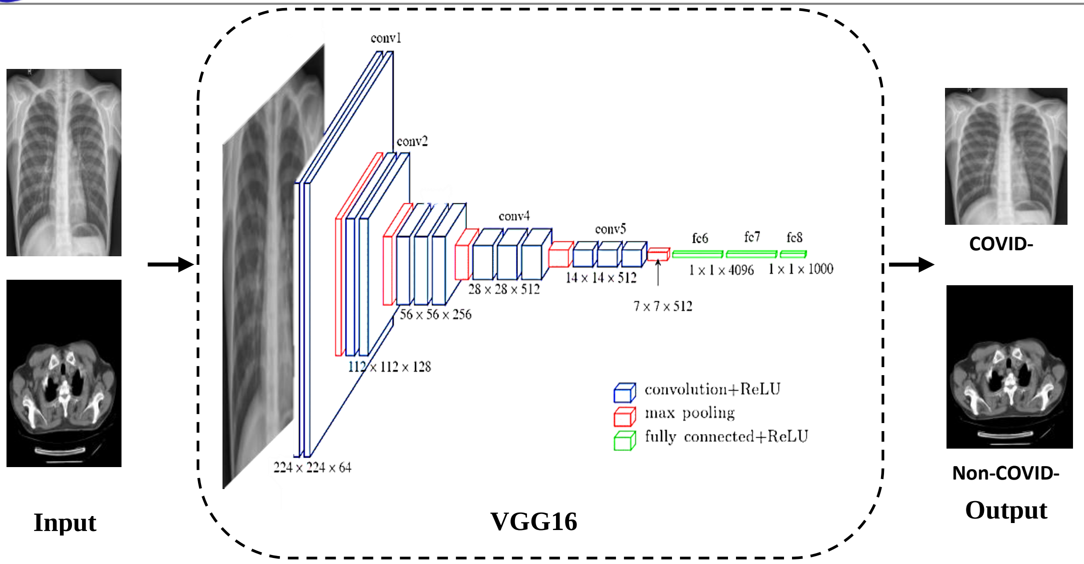
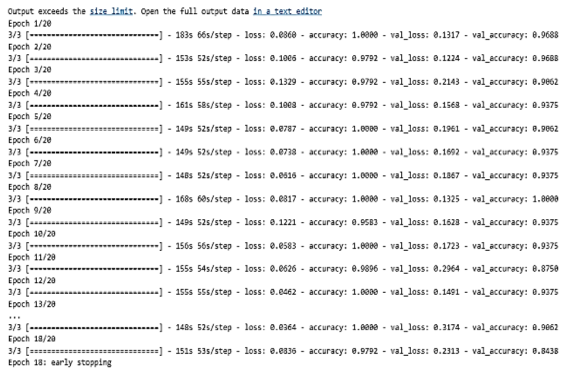


Figure 7. Architecture of Proposed system

SGD stands for Stochastic Gradient Descent which rectifies the previous drawbacks by other optimizers with momentum by denoising the gradients. Weight updates depend on noisy derivatives; therefore, convergence time will shorten if we can denoise the derivatives in some way. The goal is to use an exponential weighting average to denoise the derivative while giving greater weight to recent updates than to older ones. It reduces fluctuation in the irrelevant direction and accelerates convergence in the relevant direction. One extra hyperparameter is employed in this method known as momentum, denoted by "y". Typically, the momentum term is set to 0.9 or a comparable value. Momentum at time t is estimated using all previous updates, with more weight being given to recent changes than to older ones. This causes the convergence to accelerate.

Model Fit

In the section on model fit, we used Checkpointing and Early halting. As a model is being trained, checkpointing is used to save the best model. Here, the mode is maximal, and the accuracy value is monitored. The accuracy value of maximum will be saved throughout this checkpoint as the best model in the folder indicated by the file path. Epoch is also used to describe the save frequency, which means that the best model will be overwritten with the previous model in the file directory after each epoch. Early stopping is used to stop the training of the model if there is no improvement in the monitored value after the mentioned epoch in the patient. Here we monitored the value accuracy and the patience was mentioned as 10. In the model fit, we applied to fit the training set as steps per epoch are 3, the number of epochs is 20, and we have validation data and callbacks. Figure 8 shows the result of the trained model.



```
Output exceeds the size limit. Open the full output data in a text editor
Epoch 1/20
3/3 [==============================] - 183s 66s/step - loss: 0.0860 - accuracy: 1.0000 - val_loss: 0.1317 - val_accuracy: 0.9688
Epoch 2/20
3/3 [==============================] - 153s 52s/step - loss: 0.1006 - accuracy: 0.9792 - val_loss: 0.1224 - val_accuracy: 0.9688
Epoch 3/20
3/3 [==============================] - 155s 55s/step - loss: 0.1329 - accuracy: 0.9792 - val_loss: 0.2143 - val_accuracy: 0.9062
Epoch 4/20
3/3 [==============================] - 161s 58s/step - loss: 0.1008 - accuracy: 0.9792 - val_loss: 0.1568 - val_accuracy: 0.9375
Epoch 5/20
3/3 [==============================] - 149s 52s/step - loss: 0.0787 - accuracy: 1.0000 - val_loss: 0.1961 - val_accuracy: 0.9062
Epoch 6/20
3/3 [==============================] - 149s 52s/step - loss: 0.0738 - accuracy: 1.0000 - val_loss: 0.1692 - val_accuracy: 0.9375
Epoch 7/20
3/3 [==============================] - 148s 52s/step - loss: 0.0616 - accuracy: 1.0000 - val_loss: 0.1867 - val_accuracy: 0.9375
Epoch 8/20
3/3 [==============================] - 168s 60s/step - loss: 0.0817 - accuracy: 1.0000 - val_loss: 0.1325 - val_accuracy: 1.0000
Epoch 9/20
3/3 [==============================] - 149s 52s/step - loss: 0.1221 - accuracy: 0.9583 - val_loss: 0.1628 - val_accuracy: 0.9375
Epoch 10/20
3/3 [==============================] - 156s 56s/step - loss: 0.0583 - accuracy: 1.0000 - val_loss: 0.1723 - val_accuracy: 0.9375
Epoch 11/20
3/3 [==============================] - 155s 54s/step - loss: 0.0626 - accuracy: 0.9896 - val_loss: 0.2964 - val_accuracy: 0.8750
Epoch 12/20
3/3 [==============================] - 155s 55s/step - loss: 0.0462 - accuracy: 1.0000 - val_loss: 0.1491 - val_accuracy: 0.9375
Epoch 13/20
...
3/3 [==============================] - 148s 52s/step - loss: 0.0364 - accuracy: 1.0000 - val_loss: 0.3174 - val_accuracy: 0.9062
Epoch 18/20
3/3 [==============================] - 151s 53s/step - loss: 0.0836 - accuracy: 0.9792 - val_loss: 0.2313 - val_accuracy: 0.8438
Epoch 18: early stopping
```

Figure 8. Result of model training in Epoch 18.

VI. EVALUATION METRICS

We achieved an accuracy of 94% after the model was fitted and trained and an accuracy of 84% after validation. Early stopping ended the training at the 18th epoch because the accuracy of the validation did not improve. And for the accuracy, loss, validation accuracy, and validation loss, we plotted a graph. Five evaluation measures were utilized to assess the performance of the suggested model: accuracy, precision, recall, specificity, and F1 Score The plotted graph for the model training is shown in Figure 9

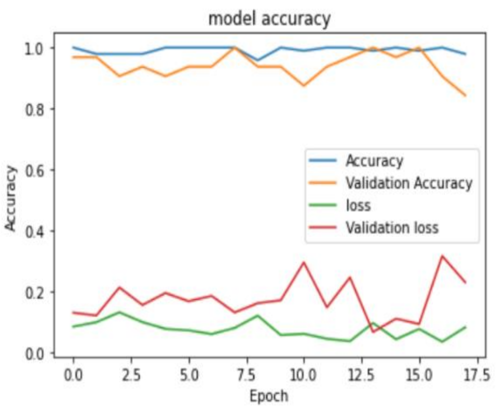


Figure 9. Accuracy and loss graph

Confusion Matrix

The confusion matrix is an important matrix to create to find the precision, F1 score, specificity, sensitivity, and accuracy. A confusion matrix is used to find the False Negative, False positive, True Negative, and True positive values of the prediction of the trained model. To explain how effectively a categorization system performs, a confusion matrix is utilized. A confusion matrix displays and summarises the effectiveness of a classification method. Figure 10 shows the confusion matrix of the proposed model.

True positive: The cases where we predicted as COVID-19 and even actually it is the positive case. True positive prediction is 389.

True negative: The cases where we predict as Non-COVID-19 and even actually it is a negative case. True negative prediction is 364.

False positive: The cases where we predict COVID-19, but it is a negative case. The false positive prediction is 36.

False negative: The case where we predict Non-COVID-19, but it is a positive case. The false negative prediction is 11.

Accuracy

The statistics known as accuracy are used to evaluate the effectiveness of classification and regression algorithms. The accuracy value for the proposed model is 94 percent.

Accuracy = (TP + TN) / (TP + TN + FP +FN)

= (389 + 364) / (389 + 364 + 36 + 11)

= 0.94125

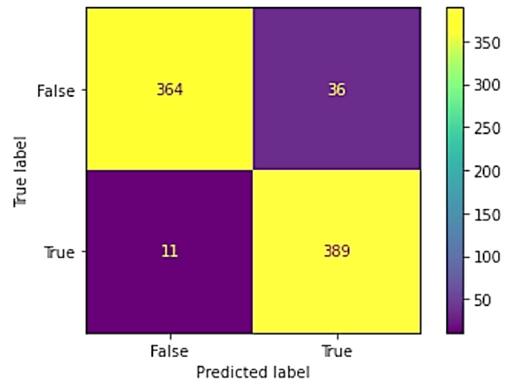


Figure 10. Confusion matrix of Proposed model

Precision

Precision is a measure of how well the suggested model classified the positive photos. The number of true positives divided by the number of true positive predictions is an indicator of the model's success and is explained by the number of positive predictions produced. The precision value of the proposed model is 91 percent.

Precision = TP / (TP + FP)

= 389 / (389 + 36)

= 0.915

Recall

Recall refers to positive findings that are correctly classified as positive. What it is referred to as is a real positive rate. The Recall value of the proposed model is 97 percent.

Recall = TP / (TP + FN)

= 389 / (389 + 11)

= 0.97

Specificity

It looks that how effectively the model predicts negative outcomes. Similar to sensitivity, but from the perspective of undesirable outcomes, is specificity. The specificity value of the proposed model is 91 percent

Specificity = TN / (TN + FP)

= 364 / (364 + 36)

= 0.91

F1 Score

The "harmonic mean" of sensitivity and precision is the F-score. It considers both false-positive and false-negative cases and is appropriate for datasets with imbalances. The proposed model has an F1 score of 94 percent.

F1 Score = 2 * ((precision * sensitivity) / (precision + sensitivity))

= 2 * ((91 * 97) / (91 + 97))

= 0.94

VII. RESULT AND DISCUSSION

The pre-trained model that we employed in this study was imported from Keras. Millions of photos from the ImageNet dataset were used to pre-train this model. 800 photos from the training set and 800 images from the validation set comprise the 1600 images used to train this proposed VGG-16. This suggested model was trained using a hybrid dataset and achieved an accuracy of 94% when compared to other VGG-16 models. With a 94% accuracy rate, this model is used with a hybrid dataset. Table 1 provides values for recall, specificity, F1 Score, accuracy, and precision.

Network	Acc	Prec	Recall	Spec	F1
VGG16	0.94125	0.9152	0.9725	0.91	0.9430

Table 1. Values of evaluation metrics

VIII. CONCLUSION AND FUTURE WORK

When employing medical pictures like CT scans and chest X-rays to identify COVID-19 instances, the suggested approach uses VGG16 neural networks. The advantage of the proposed method is that the model is trained using a hybrid dataset that incorporates information from a chest X-ray and a CT scan. Furthermore, the accuracy rate of our proposed model is 94%. We will employ additional techniques, including the K-fold technique, in upcoming studies to improve the model's accuracy and functionality. Also, additional neural networks like MobileNet and ResNet will be employed to increase the prediction of COVID-19 in deep learning.

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