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# Covid-19 Detection Using Deep Transfer Learning Approach Through CT Scan Images

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**Abstract:** The advancement of deep learning techniques has significantly enhanced medical diagnostics by enabling early and accurate disease detection. COVID-19, a highly infectious respiratory illness, has posed severe health and socioeconomic challenges worldwide. Early diagnosis is vital in mitigating its spread. Computed Tomography (CT) imaging has proven useful for non-invasive detection of COVID-19 due to its affordability and accessibility. However, interpreting these scans requires expert radiologists, whose assessments may vary and are subject to errors. Transfer learning offers a promising alternative for developing automated diagnostic tools with high precision. In this study, we introduce a novel 12-layer Convolutional Neural Network (CNN) model and integrate it with three established pre-trained models—VGG16, VGG19, and ResNet50—to improve classification performance. We conduct a detailed comparative analysis to evaluate the effectiveness of our proposed model against these benchmarks. The experimental outcomes demonstrate that our model surpasses the existing approaches, achieving over 98% classification accuracy, an F1 score of 0.96, and precision and recall values of 0.97. The proposed framework is not only accurate but also computationally efficient, making it suitable for rapid COVID-19 detection in clinical environments.

**Keywords:** Covid-19; Computed Tomography (CT); CNN, VGG 16; VGG 19

## 1. Introduction

The COVID-19 pandemic has emerged as one of the most disruptive global health crises, leading to widespread respiratory illness and significant mortality across the globe [1]. Beyond its direct health implications, the pandemic has adversely affected economies and social systems worldwide. According to the World Health Organization (WHO), COVID-19 has resulted in approximately five million deaths to date [2]. The manifestation of symptoms, such as mild fever, cold, and respiratory distress, varies depending on an individual's immune response, typically persisting for 2 to 14 days [3]. Radiological imaging, particularly Computed Tomography (CT) scans, is commonly used for diagnosing COVID-19 due to its affordability, safety, and fast execution. CT scans also offer the advantage of minimal radiation exposure and operational simplicity [4].

Despite these benefits, the interpretation of CT images requires experienced radiologists. Such reliance introduces the risk of inter-observer variability and diagnostic errors. Manual analysis is also time-consuming, increasing the need for automated solutions [5]. Leveraging computer-aided systems for early detection enables faster treatment, potentially reducing mortality and curbing viral transmission [6]. Given the highly contagious nature of the virus, early identification remains essential to effective containment strategies.

Recent advancements in deep learning (DL) have demonstrated notable success in medical image classification, offering tools to support radiologists in diagnosing diseases with improved accuracy. DL models can autonomously extract critical features from raw medical images, eliminating the need for manual feature engineering [7]. These methods have been instrumental in developing efficient, scalable, and rapid diagnostic tools, especially during health emergencies.

In this paper, we propose a deep learning framework tailored for the fast and cost-efficient detection of COVID-19 from chest CT scan images. Our approach involves a detailed comparison of various deep learning models, ultimately resulting in the creation of a custom 12-layer convolutional neural network specifically optimized for this classification task. The structure of the paper is as follows: Section 2 surveys recent advancements in COVID-19 detection using machine learning and deep learning techniques. Section 3 provides details about the dataset utilized. Section 4 explains the proposed methodology, followed by Section 5, which presents the experimental setup and analysis of results. Finally, Section 6 concludes the paper and suggests potential directions for future investigation. The key contributions of this study are outlined below:

- Designing and evaluating multiple state-of-the-art models with tailored layers for enhanced accuracy.
- Proposing a lightweight CNN-based architecture that reduces computational complexity while maintaining high performance.
- Performing a comparative analysis with existing models to assess improvements in accuracy and reduction in false positives.

## 2. Literature Review

This section commences several studies focusing on the deep neural networks and transfer learning have been done for detection and classification of coronavirus. This section will help researchers to accomplish and build strong foundation of knowledge in this domain and filling the gap in literature. Alsattar, H. A. et al. et al. proposed deep transfer techniques on deep CNN to detect Covid-19 patients [8]. That system is occupying on X-radiations images for the observation and classification of that virus infected patients. Detection through medical images with Deep Learning (DL) algorithms currently becomes vast early Coronavirus detection. Techniques such as CNN (Convolution Neural Network) models such as AlexNet, VGG-19, etc. are used for the classification of positive and negative cases of Coronavirus. Mezina, A. & Burget, R. studies chest X-radiation using vision transformer are the most improvable imaging techniques for the detection of Coronavirus in the early stages [9]. Barstugan and Ozkaya [10] conducted early investigations into the use of machine learning techniques for the detection of COVID-19 through CT scan images. Similarly, Khan et al. [6] explored deep learning methods aimed at enhancing classification accuracy by automatically identifying distinguishing features of COVID-19. In another study, Shah et al. [11] proposed a deep learning approach centered on Convolutional Neural Networks (CNNs), which focused on differentiating between CT images of COVID-19 positive and negative patients. Their method introduced a custom model named CT-Net-10, which achieved an accuracy of 82.1%. Additionally, several pre-trained architectures such as VGG-19 were evaluated for their performance.

Ines et al. [12] presented a Deep Transfer Learning (DTL)-based method for developing a classifier capable of detecting COVID-19 in patients using both CT and chest X-ray (CXR) images. To enhance model generalization and reduce overfitting, they employed data augmentation techniques to expand the training dataset. In a separate study, Taher et al. [13] utilized Mask R-CNN on a dataset of lung cancer patients from the Kurdistan region to analyze and detect both benign and malignant tumors at an early stage based on shape and size features.

Building on these prior works, our study provides a comprehensive evaluation of multiple pre-trained deep neural networks, including ResNet-50, VGG-16, and VGG-19, in conjunction with data augmentation strategies to improve model robustness and performance. Become aware of COVID-19 via deep learning approaches the usage of lung CT-SCAN images.

However, from this literature review we found most of the research work suffers from dissatisfaction in term of accuracy, different modalities of image quality, issue of processing/overfitting and most importantly the long training time due to higher number of layers and parameters. The comparison of different techniques is shown in Table 1.

**Table 1.** Comparison of different research work done in the field of COVID-19 detection using DL.

| | Authors | Years | Problem Addressed | Solution |
|---|---|---|---|---|
| 1 | Loey et al. [14] | 2021 | Face mask detection | Hybrid deep transfer learning model. |

| | | | | |
|---|---|---|---|---|
| 2 | Hamad et al. [15] | 2021 | Detection of coronavirus and features Detection | Proposed model with combination of LSTM and CNN. |
| 3 | Salen et al. [5] | 2020 | Early detection of coronavirus | Applied transfer learning methods |
| 4 | Behrouz et al. [16] | 2020 | Predicted and unpredicted complex disease problems | Binary classification and Regression analysis |
| 5 | Albarhi et al. [17] | 2020 | Covid-19 challenges | Proposed a solution with Artificial intelligence techniques. |
| 6 | Shambhu et al. [18] | 2022 | Covid-19 Diagnosis | Proposed novel CNN model. |
| 7 | Sevi et al. [19] | 2020 | Covid-19 Detection | Applied Deep learning approaches |
| 8 | Mangal et al. [20] | 2020 | Priorities infected patients instead of RT-PCR testing | Utilizing modern AI techniques |
| 9 | Marques et al. [21] | 2020 | Diagnosis of Covid-19 infected patients | Automated detection through Efficient Net |
| 10 | Madhu et al. [22] | 2022 | Covid-19 detection CT-Scan Images | Extreme gradient boosting |
| 11 | Chen et al. [23] | 2021 | Accurate classification of Coronavirus | DL algorithms |
| 12 | Ozsos et al. [24] | 2021 | Pneumonia Classification | DL + Pretrain model |
| 13 | Ravi et al. [25] | 2022 | Covid-19 detection and Classification | Meta classifier with DL |
| 14 | A et al. [26] | 2022 | Diagnosis coronavirus biggest challenge | CNN + ConvLSTM |
| 15 | Alakus et al. [27] | 2020 | Predicting covid-19 infection | Different DL methods |
| 16 | Taher et al. [13] | 2024 | Diagnosis of lung cancer | Mask-RCNN |
| 17 | Jenifer et al. [28] | 2024 | Fast image segmentation technique using Adaptive Histogram Equalization. | Deep CNN |
| 18 | Venkateshr et al. [29] | 2024 | Liver segmentation | UNet and ResNet |
| 19 | Trinidad et l. [30] | 2024 | Deep-Learning-Assisted Decision-Making in diagnosis | Deep CNN |

## 3. Materials and Methods

### 3.1. Dataset

The dataset used is SARS-CoV-2 CT Scan dataset that is the real patient image dataset collected from the Brazilian hospital available at the Kaggle. The dataset is updated continually, and the number of images is increasing. In this work we used dataset containing a total of 2491 images with 1252 images belonging to the patient suffering from COVID-19 disease whereas the rest of 1239 images were collected from the health patients as shown in Fig. 1. The Fig. 2 shows a random picture depicting the CT-scan image of COVID-19 and a non-COVID-19 (healthy) patient.

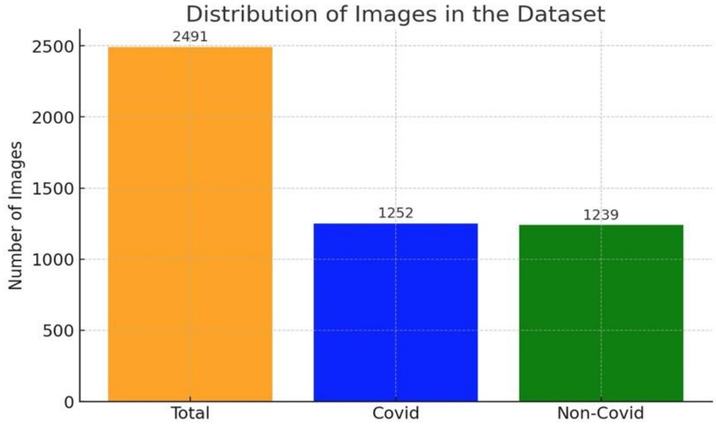


**Figure 1.** Distribution of images belonging to Covid and Non-Covid Categories.

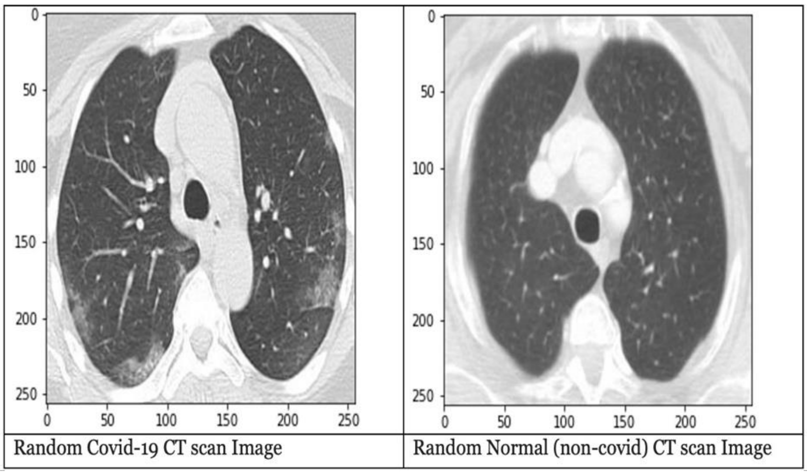


**Figure 2.** Random CT-Scan of Covid-19 Patient and Non-Covid Patient.

3.2. Methodology

The detection of Covid-19 infection from CT Scan images is a challenging task due to high variation of images in shape, size, and position. The detailed methodology used in this research work is elaborated in the figure 3 below.

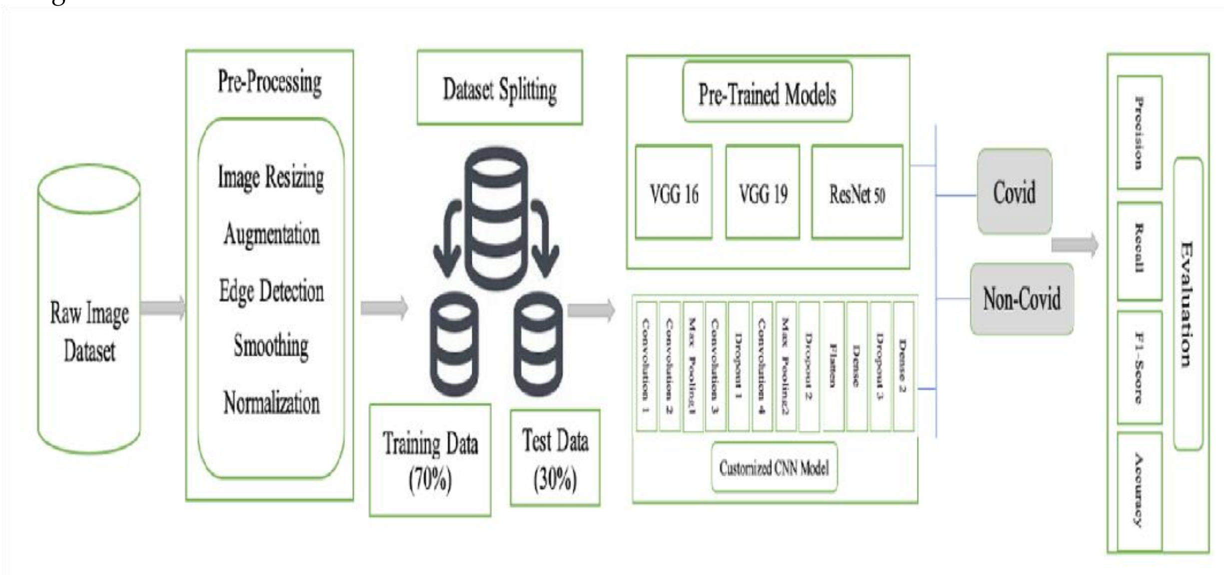


**Figure 3.** End-to-end framework for COVID-19 image classification using pretrained CNN models and a custom CNN model architecture.

After downloading the dataset images were preprocessed as the images in the dataset were of varying size. The images were properly resized to get neat and clear detection. Preprocessing was done with the reshape layer and Image Data Augmentation to give image transformation into various angles. The images were further augmented which increases the number of images, this helps us get more images for model training and learning process. Images were scaled to a size of 224 * 224 to make the model swift by managing the optimal memory usage and to ensure network trained effectively. This size helps to leverage pre-trained model directly without needing to modify the model architecture. This size allowing consistent down sampling across layers, ending in a manageable feature map size. Which helps the model to train in swift amount of time. Thus, a huge number of images could be injected into the model without exhausting its memory. The technique could serve as a trade-off among the picture quality and number of images for training in a constrained or low computational environment. To further improve the method of preprocessing we used the Gaussian filtering method which remove the noise in images and to preserve the critical edges in our CT-Scan images. The techniques of transfer leaning are employed in the worked where we have used the pre-trained model with several tweaking as per needs of optimization while keeping the structure of model unchanged. For this research work we employed following three pre-train models namely called VGG16, VGG19, ResNet50 and finally an advanced and optimized model of CNN was proposed based on different number of layers. The models were trained for 200 epochs using a batch size of 32 were executed on Google Cloud TPUs (v3-8), with TensorFlow 2.9.1 as the backend framework. Details of each classifier and their architecture is shown in next subsection.

*3.2.1. VGG16*

VGG16 is a 16-layer deep framework that has about 144 million parameters is used in this study to extract the prominent image features that could differentiate the covid and healthy patients [31]. The model is composed of 13 convolution layers with two fully connected layer and one final output layer of SoftMax. Model uses ReLU at all the hidden layers and drop out at fully connected layer. The general structure and number of parameters which helps in achieving the classification accuracy are shown in the table 2 shown below whereas the description, filters nodes and activation function used on each layer is shown in the table 3.

**Table 2.** Layer types, Output shape and no. of parameters used by VGG16.

| Layer (Type) | Output Shape | Parameters |
|---|---|---|
| input_1 | (150, 150, 3) | |
| Convl | (150, 150, 64) | 1792 |
| conv2 | (150, 150, 64) | 36928 |
| Block0l_pooling | (75, 75, 64) | |
| Block2_ convl | (75, 75, 128) | 73856 |
| Conv_02 | (75, 75, 128) | 147584 |
| Block02_pool | (37, 37, 128) | |
| Block03_Convl | (37, 37,256) | 295168 |
| Conv_02 | (37, 37, 256) | 590080 |
| Conv_03 | (37, 37, 256) | 590080 |
| Block03_pool | (18, 18, 256) | |
| Block04 convl | (18, 18, 512) | 1180160 |
| Conv02 | (18, 18, 512) | 2359808 |
| Conv03 | (18, 18, 512) | 2359808 |
| Pool | (9, 9, 512) | |
| block5 convl | (9, 9, 512) | 2359808 |
| conv2 | (9, 9, 512) | 2359808 |
| conv3 (Conv2D) | (9, 9, 512) | 2359808 |
| pool | (4, 4, 512) | |
| global_average_pooling2d | 512 | |
| batch normalization | 512 | 2048 |
| dropout | 512 | |
| dense | 256 | 131328 |
| batch normalization 1 | 256 | 1024 |
| dropout_1 | 256 | |

| | | |
|---|---|---|
| dense 1 | 2 | 514 |
| Total No. of Parameters: | 14,849,602 | |
| Total Trainable Parameters: | 133,378 | |
| Total Non-trainable Parameters: | 14,716,224 | |

### *3.2.2. VGG19*

VGG19 is a deep convolutional neural network comprising 19 layers, featuring three additional convolutional layers compared to its predecessor, VGG16. In our implementation, the architecture includes 16 convolutional layers, 5 max-pooling layers, 3 fully connected layers, and a final SoftMax layer for classification [32]. The model was trained using a batch size of 64 and a learning rate of 0.001.The general structure and number of parameters which helps in achieving the classification accuracy are shown in the table 3 whereas the description, 134 filters nodes and activation function used on each layer is shown in the table 4.

**Table 3.** Layer types, Output shape and no. of parameters used by VGG19.

| Layer (Type) | Output Shape | Parameters |
|---|---|---|
| input_01 | (224, 224, 3) | |
| Block01_conv01 | (224, 224, 64) | 1792 |
| Conv02 | (224, 224, 64) | 36928 |
| Block0l_pool | (112, 112, 64) | |
| Block02 convl | (112,112, 128) | 73856 |
| Conv02 | (112, 112, 128) | 147584 |
| Block02_pool | (56, 56, 128) | |
| Block03_ convl | (56, 56, 256) | 295168 |
| Conv02 | (56, 56, 256) | 590080 |
| Conv03 | (56, 56, 256) | 590080 |
| Conv04 | (56, 56, 256) | |
| Block03_pool | (28, 28, 256) | 1180160 |
| Block04_conv1 | (28, 28, 512) | 2359808 |
| Conv_02 | (28, 28, 512) | 2359808 |
| Conv_03 | (28, 28, 512) | |
| Conv_04 | (28, 28, 512) | 2359808 |
| Block04_pool | (14, 14, 512) | |
| Block05_conv01 | (14, 14, 512) | 2359808 |
| Conv1 | (14, 14, 512) | 2359808 |
| Conv01 | (14, 14, 512) | |
| Block05_pool | (7, 7, 512) | |
| Flatten-01 | 25088 | |
| Dense_01 | 3 | 75267 |
| Total Parameters: | 20,099,651 | |
| Trainable Parameters: | 75,267 | |
| Non-trainable Parameters: | 20,024,384 | |

**Table 4.** Description of layers along with the filters, total nodes and activation function used by VGG19.

| **Layer (Type)** | **Description** | **Filters** | **Nodes** | **Activation** |
|---|---|---|---|---|
| 1 | Conv_01 | 64 | | |
| 2 | Conv_02 | 64+Max pooling | | |
| 3 | Conv_03 | 128 | | |
| 4 | Conv_04 | 128+ Max pooling | | |
| 5 | Conv_05 | 256 | | |
| 6 | Conv_06 | 256 | | |

| | | | | |
|---|---|---|---|---|
| 7 | Conv_07 | 256+ Max pooling | | |
| 8 | Conv_08 | 512 | | |
| 9 | Conv_09 | 512 | | |
| 11 | Conv_011 | 512 | | |
| 12 | Conv_012 | 512 | | |
| 13 | Conv_013 | 512+Max pooling | | |
| 14 | FC_01 | | 4096 | |
| 15 | FC_02 | | 4096 | |
| 16 | Output layer | | 1000 | SoftMax Activation |

#### 3.2.3. *ResNet50*

ResNet50 is a variant of ResNet model which has 50 layers including the 48 layers of convolution, 1 layer of MaxPool and 1 layer of average pooling [33]. We used the categorical cross entropy during the estimation of training and validation loss. The general structure and number of parameters which helps in achieving the classification accuracy are shown in the table 5 below. The description, filters nodes and activation function used on each layer is shown in the table 6.

**Table 5.** Layer types, Output shape and no. of parameters used by ResNet50.

| **Layer (Type)** | **Output Shape** | **Parameters** |
|---|---|---|
| Convolutional | 2048 | 23587712 |
| Flatten | (2048) | |
| BN | 2048 | 8192 |
| Dense | (512) | 1049088 |
| BN_01 | (512) | 2048 |
| Dropout_01 | (512) | |
| Dense_01 | (256) | 131328 |
| BN_02 | 256 | 1024 |
| Dropout_01 | (256) | |
| Dense_02 | (128) | 32896 |
| BN_03 | 128 | 512 |
| Dropout_02 | (128) | |
| Dense_03 | (64) | 8256 |
| BN_4 | | 256 |
| Dense_4 layer | (2) | 130 |
| Total parameters: | 24,821,442 | |
| Trainable parameters: | 1,227,714 | |
| Non-trainable parameters: | 23,593,728 | |

### 3.3. Proposed Method Description

The objective of this study was to classify COVID-19 infected chest CT-Scan images, we developed a customized and modified version of Convolution Neural Network (CNN) using the strengths of CNN in extracting and retaining the complex features of images. The modified version of Convolutional neural network inherits the strength of CNN in retaining the complex features 146 from images [34]. The proposed custom model comprises of various layers such as convolution layers with varied size of kernel, filters, dropout, pooling and flatten layers. The proposed model uses Adam as an optimizer with 0.001 learning rate and batch size of 64 was used. Another objective of this modified version was to find the customized layers and activation function and its best combination of optimizer that could get the best accuracy with minimum number of parameters used, that can help in real world implementation of lightweight model.

Our model didn't used any pre-trained model weights and this results in giving auspicious output with very slight training time compared to other existing models. The said CNN model was trained and tested with different number of layers to check the impact of layers in achieving the accuracy and the no. of parameters involved.

The details of accuracy and parameters are shown in table 8 below however the best configuration was observed while working with 12 layers model with a depth of 4 layers convolution that were using an input tensor of 222 X 222. The next layer is the Maxpooling with receives the output 158 of convolutional layer was used with stride of 2 X 2 that reduces the input size to half. The data undergoes a sequence of convolutional layers before being passed through a max-pooling layer, resulting in a tensor with dimensions of 53 × 53. This output is then activated using ReLU and forwarded to a fourth convolutional layer, which contains 512 filters with a kernel size of 3 × 3 × 128 and uses a stride of 1 × 1.

The resulting tensor is flattened into 359,552 units. These units, or neurons, represent weighted values that correlate with potential COVID-19 symptoms. To mitigate the risk of overfitting, a dropout layer with a rate of 0.25 was introduced during the training phase. This is followed by a fully connected (dense) layer that compresses the output from 359,552 neurons down to 64. A ReLU activation is then applied to this output. The resulting 64-neuron tensor represents the feature vector generated by the dense layers and is subsequently mapped to a number of output neurons corresponding to the classification categories—namely, COVID-19 and non-COVID-19. The final configuration, including the structure of input layers, their respective outputs, and the total parameter count, is detailed in Table 8.

**Table 6**. Layer types, Output shape and no. of parameters used by ResNet50.

| **Layer (Type)** | **Output Shape** | **Parameters** |
|---|---|---|
| Conv_02D | (222, 222, 32) | 896 |
| Conv_02D1 | (220, 220, 64) | 18496 |
| MaxPooling_2D | (110, 110, 64) | - |
| Conv2D_02 | (108, 108, 64) | 36928 |
| Dropout | (108, 108, 64) | - |
| Conv2D_03 | (106, 106, 128) | 73856 |
| Maxpooling2D_1 | (53, 53, 128) | - |
| dropout_01 | (53, 53, 128) | - |
| Flatten | 359552 | - |
| Dense | -64 | 23011392 |
| Dropout_02 | 64 | - |
| Dense_01 | 2 | 130 |
| Total parameters | 23,141,698 | |
| Trainable parameters | 23,141,698 | |
| Non-trainable parameters | 0 | |

**Table 7.** Layer types, Output shape and no. of parameters used by ResNet50.

| **Layer (Type)** | **Number of Layers** |
|---|---|
| Convolutional | 4 |
| Pooling | 2 |
| Dropout | 3 |
| Dense | 2 |
| Flatten | 1 |

## 4. Results and Discussion

In this part of the study, we examine how well our custom model performs compared to other established deep learning models, including VGG16, VGG19, and ResNet50. To ensure a fair and thorough comparison, we applied several standard evaluation measures. These include not only the model's overall accuracy, but also its ability to correctly identify positive and negative cases (precision and recall), the balance between the two (F1-score), the number of examples evaluated for each class (support), and the detailed prediction breakdown shown in the confusion matrix. Each of these metrics is described in the following subsections to provide insight into how performance was measured and interpreted.

4.1. Accuracy

Accuracy is normally defined as total number of classifications a model correctly defined from the total number of classifications. The mathematical description of this metric is shown in Eq. 1

$$\text{Accuracy} = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \quad (1)$$

4.2. Precision

Precision refers to the proportion of correctly identified positive samples among all instances that were predicted as positive, regardless of whether the prediction was accurate or not. Mathematically precision is defined as the true positive divided by plus true positive plus false positive. The mathematical expression of precision is shown in Eq. (2)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

4.3. Recall

Recall measures a model's sensitivity by quantifying its ability to correctly detect positive cases out of all instances that are truly positive. It is computed by dividing the number of correctly predicted positive cases (true positives) by the total number of actual positives in the dataset. Recall only deals with how many numbers of samples classified correctly. It does not care about how many negative samples are classified. The mathematical expression of recall is shown in Eq. (3)

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

4.4. F-1 Score

The F1-score is a widely used evaluation metric that captures the trade-off between precision and recall by computing their harmonic mean. This measure is especially valuable when dealing with imbalanced class distributions, as it provides a more informative assessment of model performance than accuracy alone. While the F1-score is most frequently applied to binary classification problems, its formulation can be extended to handle multi-class scenarios as well. The exact mathematical representation of the F1-score is outlined in Equation (4).

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

4.5. Confusion Matrix

The confusion matrix serves as a crucial evaluation tool for classification tasks, offering a summary of the model's performance in terms of correct and incorrect predictions across various classes. Structurally, it is a tabular representation that contrasts actual class labels with those predicted by the model. For binary classification problems—such as the one in this study—the confusion matrix takes the form of a 2×2 grid. It is divided into categories that capture the predicted values (output generated by the model) and the actual values (true labels from the dataset). This allows for a clear visualization of how well the model distinguishes between the two classes.

In our experiments, a total of 1,239 CT scan images were used to evaluate the performance of the proposed model and to compare it with several pre-trained architectures. Our custom model attained an accuracy of 97%, with a precision of 97.2%, recall of 97.1%, and an F1-score of 96%. While VGG-19 showed promising results during the training phase, it displayed signs of overfitting. By contrast, the proposed model exhibited consistent and generalized performance across training, validation, and testing datasets, making it a reliable choice for real-world implementation. Figure 4 provides a graphical comparison of key performance indicators—namely precision, recall, F1-score, and accuracy—across the four evaluated models.

An analysis of the confusion matrix derived from the CT image dataset revealed that 9 COVID-positive cases were incorrectly identified as non-COVID, despite the individuals being infected. Additionally, 8 non-COVID images were mistakenly classified as COVID-positive. A comprehensive breakdown of both correctly and incorrectly classified samples is presented in Table 8, based on the confusion matrix outcomes.

**Table 8.** Confusion Matrix result for different classifiers for COVID-19 affected and Non-COVID-19 affected patients.

| Model | Actual Values | COVID-19 Affected | Non-COVID 19 |
|---|---|---|---|
| VGG-19 | COVID-19 Affected | 233 | 21 |
| | Non-COVID 19 Affected | 24 | 218 |
| VGG-19 | COVID-19 Affected | 241 | 13 |
| | Non-COVID 19 Affected | 11 | 231 |
| ResNet-50 | COVID-19 Affected | 242 | 12 |
| | Non-COVID-19 Affected | 9 | 233 |
| Proposed Model | COVID-19 Affected | 245 | 9 |
| | Non-COVID 9 | 8 | 234 |

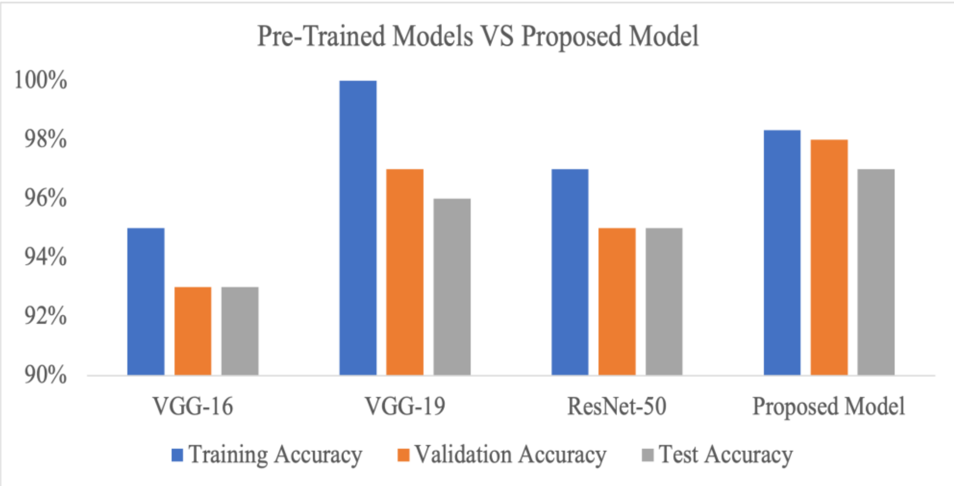


**Figure 4.** Performance evaluation of pretrained models and the custom CNN model in terms of training, validation, and test accuracy for binary classification.

The accuracy and confusion matrix obtained from the results of proposed methods has proved the reliability of model in accurately classifying model even when used with the entirely new dataset. Finally, the accuracy and loss graph of training and validation accuracy of models over 200 epochs were calculated and compared. The proposed model with 12-layers architecture achieved the highest average accuracy in testing/validation with an average value of 97%. There was about 99% training accuracy and validation accuracy was found to be approximately 96%. After getting the higher values of our model in achieving the performance metrics we have compared the values of performance metrices along with the different combination of layers used in the model. We found the different value of training and validation accuracies on the combination of layers used. The optimal number of layers that were used were 12 where proposed model achieved 98% training accuracy and 97% validation accuracy as is shown in table 11. The values of results over the different accuracies are shown in given below graph. The exceptional performance of our model can be attributed to the hyper-parameter optimization and the ideal combination of layers used. This optimality has enabled our model to efficiently generalize efficiently over unseen data of testing class, and this mitigate the risks of overfitting. This ideal combination was found to be the most consistent across both the classes, here the model avoids achieving the highest precision for one class and has poor precision for other class. Subsequently, the proposed model was benchmarked against several state-of-the-art architectures to assess its effectiveness in achieving the targeted performance metrics. Once again, our model demonstrated superior results, outperforming the compared models in terms of accuracy, precision, recall, and F1-score. A comprehensive evaluation across these metrics—including the confusion matrix—

confirms the model’s robustness in accurately distinguishing between COVID-19 and non-COVID cases in binary classification tasks.

Notably, the model's architecture relies on just four convolutional layers, which not only reduces the total number of parameters but also minimizes system complexity and mitigates the risk of overfitting. The promising outcomes achieved highlight the practical value of the proposed approach and position it as a strong foundation for future advancements in real-time, real-world medical diagnostic applications.

**Table 9.** Performance comparison between proposed model and state-of-the-art models using CT scan Images.

| Model | Precision | Recall | F1-score | Training Accuracy | Test Accuracy |
|---|---|---|---|---|---|
| VGG-16 | 91% | 90% | 94% | 95% | 93% |
| VGG-19 | 95% | 95% | 95% | 100% | 96% |
| ResNet-50 | 96% | 96% | 96% | 97% | 95% |
| Proposed Model | 97% | 97% | 96% | 98.33% | 97% |

## 5. Conclusion

The proposed model with 12-layers CNN architecture is a powerful model for classification of that virus. Three pre-train models VGG16, VGG19 and ResNet50 are used but the accuracy of proposed model is higher than the mentioned pre-train models. Mostly research develop models with the combination of different CNN layers such as 22-layers, 15 layers, 18 layers etc., but these high number of layers make the model complex by increasing the number of parameters. Also due to the higher number of parameters the computational cost of these models increases. The proposed model contains 12-layers, and the number of parameters is lesser than the previously developed models. So, the computational cost of proposed model as compared to previous models are less. Our proposed model is entirely automated which can produce 97.5% binary classification accuracy on a smaller amount of dataset that only contains 2483 images. So, this model provides better accuracy with large amount of dataset.

The proposed model holds potential for broader applications, including the diagnosis of various medical conditions and the classification of diverse data types. In future this model can be used in embedded systems with the help of IoT to address the challenges and shortages of radiologists in the rural areas. However, these models can be further improved by using the advancements and efficient features of ensemble methods. As the deep learning models are generally black boxed because it’s difficult and almost impossible to know how the model is making prediction. So, in the future, our plan is to use XAI to make the model more friendly, trustworthy, and explainable.

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