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Deep Convolutional Neural Network With Image Processing Techniques And Resnet252v2 For Detection Of Covid19 From X-Ray Images

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Abstract

The 2019 coronavirus disease, or SARS-CoV-2, is a rapidly spreading viral infection that has affected millions of people around the world. Due to its rapid spread and increasing numbers, it becomes overwhelming for health professionals to quickly diagnose the disease and prevent its spread. Therefore, automation of the diagnostic procedure has become essential. This improves work efficiency and keeps healthcare workers protected from exposure to viruses. Medical image analysis is one of the emerging fields of research where this problem can be addressed even more precisely. This paper presents the prediction of SARSCoV- 2 using chest roentgen rays images and the implementation of an image processing system using deep learning and neural networks. This

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study presents a methodology that utilises deep learning techniques, including machine learning and convolutional neural networks, to predict the presence of SARS-CoV-2 infection in patients based on the analysis of chest radiographs. The utilisation of deep architectures is essential in the categorization of roentgen rays images due to the intricate nature of their structures. In light of this, we present a neural network including a sequential arrangement of ResNet50 and Res Net152V2 networks. The network demonstrated superior accuracy by employing various features derived from two robust networks. In order to assess the performance of our network, a comprehensive evaluation was conducted on a dataset consisting of 15,602 images. This evaluation aimed to determine the accuracy achieved by the network under real-world conditions. The network under consideration has an average accuracy of 93% in detecting both SARS-CoV-2 and normal cases, rendering it a potentially valuable tool inside the radiology department.

Keywords: Chest roentgen rays Images · Convolutional Neural Networks · Coronavirus · COVID-19 · SARS-CoV-2 · Deep Learning · ResNet50 · ResNet152V2. 2 Kavitha Rajalakshmi. D et al.

1 Introduction

The global dissemination of the coronavirus has resulted in the implementation of quarantine measures and significant disruptions across several businesses, leading to a profound deterioration in individuals' overall well-being. The diagnosis of SARS-CoV-2 is of significant importance in the management and containment of the disease, owing to its highly contagious nature. This process is crucial for implementing effective control strategies and developing preventive measures.

The delayed identification of diseases due to insufficient availability and manufacturing constraints of detection technologies has contributed to the escalation

in the number of patients and victims. The prompt detection of SARS-CoV-2 can contribute to a reduction in the occurrence of other diseases, as well as a drop in the prevalence and fatality rates associated with this particular virus.

Based on the citation provided [1] and the World Health Organisation (WHO) [2], one of the primary indicators of SARS-CoV-2 is respiratory distress, which can be identified by the utilisation of a chest roentgen rays. A chest CT scan has the capability to detect the presence of a disease, even in cases when symptoms are moderate or absent. By studying these images, it is feasible to identify the condition in individuals who are suspicious or asymptomatic [3]. The utilisation of this information can additionally address the constraints associated

with alternative technologies, such the absence of diagnostic kits and their restrictions in production. One notable benefit associated with the utilisation of CT scans and roentgen rays is the widespread accessibility of CT equipment and roentgen rays imaging systems within the majority of medical facilities and research laboratories. Additionally, the simplicity in handling the requisite data for training the network enables efficient illness identification. According to the cited source, when common symptoms such as fever are not present, the use of CT scans and chest roentgen rays can be considered as effective diagnostic tools for the disease. The utilisation of computer vision and deep learning techniques can be valuable in the diagnosis of SARS-CoV-2, as it is one of the diagnostic procedures involving chest CT scans or roentgen rays image processing. Numerous researchers have employed machine vision and Deep Learning techniques to attain favourable outcomes in light of the disease's proliferation. The difficulty of diagnostic accuracy is a significant concern in our research due to the sensitivity associated with the identification of SARS-CoV-2. However, given the scarcity of available open source data, our primary objective is to enhance the efficiency of detection. The objective of this article is to enhance the identification of SARS-CoV-2 and mitigate the occurrence of false positive results associated with SARS-CoV-2. In this approach, two robust deep convolutional neural networks are integrated, and the training parameters are fine-tuned for optimal performance. The subsequent sections of the paper are structured in the following manner. Section II of the document encompasses the literature review.

In this section, we outline the neural network model that is being presented, as well as the chest roentgen rays datasets that were utilised in the study. Additionally, we discuss the performance measures that were employed to evaluate the effectiveness of the proposed model. The findings of the suggested model are elucidated in Section IV. The final section of the text serves as the concluding part.

2 Literature Survey

Undoubtedly, the majority of prior research has been on the identification of pneumonia due to its significant implications for public health. Despite the occurrence of the coronavirus pandemic and its subsequent global dissemination, research on pneumonia and its categorization persists, with a special emphasis on its aetiology. This emphasis stems from the recognition that the origin of pneumonia plays a crucial role in determining the efficacy of appropriate therapeutic interventions. Ongoing investigations are yielding new findings in the realm of pneumonia diagnosis through the utilisation of machine learning techniques. Following the outbreak of the coronavirus pandemic, scholarly investigations have increasingly prioritised the exploration of machine learning applications aimed at expediting and non-invasively identifying cases of coronavirus infection. Hence, numerous research endeavours are being directed towards distinguishing between SARS-CoV-2 infections and non-severe acute respiratory syndrome coronavirus 2 infections.

In their study, Panwar et al. [5] examined the advancement of a strategy aimed at swiftly identifying SARS-CoV-2 in chest roentgen rays. This approach employed a deep learning method known as nCOVnet, which is based on neural networks. The authors of the study want to differentiate between photos depicting lungs afflicted with SARS-CoV-2 and those portraying lungs in a normal or healthy state. The dataset that has been created consists of a compilation of positive X-ray images of SARS-CoV-2, specifically 337 posterior-anterior images. Additionally, the dataset includes the entirety of the Kaggle dataset, which comprises 142 selected photos. The photos underwent pre-processing techniques including scaling, RGB conversion, reordering, and data augmentation.

The dataset was meticulously partitioned, allocating 70% of the data for training purposes and reserving the remaining 30% for testing, so guaranteeing the absence of any data leakage. The data was inputted into a model that comprised of VGG-16, which had been pre-trained on the ImageNet dataset, using transfer learning. The model also included ReLU and maxpooling layers. The technique that has been built utilises both the top and base layers of the VGG-16 model for the purpose of feature extraction. These layers are composed of five bespoke layers that possess the ability to adjust the weights in a bidirectional manner during the iterations. Consequently, the model successfully identified SARS-CoV-2in patients who were genuinely infected, exhibiting an error rate of 2.38%, a sensitivity of 97.62%, and a specificity of 78.57%. The accuracy rates for predicting positive COVID-19 instances and non-COVID cases were 97.97% and 98.68% respectively, indicating a high level of accuracy in both categories.

In general, the model's accuracy was determined to be 88.10%. Additionally, the ROC value, which represents accuracy, was found to be 0.88095. These re sults suggest a high level of accuracy, particularly when considering the limited quantity of the training dataset.

Chakraborty et al. [6] conducted a study that aimed to differentiate between instances of SARS-CoV-2 and cases of pneumonia based on analysis of chest roentgen rays utilising deep learning technology. The study obtained a dataset comprising 10,040 chest X-ray (CXR) pictures from reputable sources such as Kaggle and GitHub. The dataset encompassed instances of pneumonia, SARS-CoV-2 , as well as normal cases. Once the photos are provided as input, they undergo a pre-processing and segmentation process. This ensures that only images classified as belonging to the required categories are retained, while any other images are rejected, save for cases involving normalisation and upscaling. Furthermore, the FC-DenseNet103 semantic segmentation technique is employed alongside lung contour masks to get segmented lung areas from individual images. The dataset is partitioned into three subsets: 80% for training, with an additional 10% allocated for validation, and the remaining 20% reserved for testing purposes. The deep learning model employed in this study utilises the ResNet18 architecture, which has been pre-trained to enhance its performance.

The employed model incorporates additional multi-class classification layers to effectively categorise data into three distinct classes: SARS-CoV-2, pneumonia, and normal. The model was comprised of a total of six layers, encompassing convolutional, hidden, maxpooling, average pooling, and SoftMax layers. The model successfully attained an accuracy of 96.43% and a sensitivity of 93.68%.

In the study conducted by the authors [9], an innovative Convolutional Neural Network (CNN) was employed to classify and make predictions regarding SARS-CoV-2 utilising lung computed tomography (CT) scans. In a study conducted by the author [10], the application of deep learning techniques was employed to identify the presence of SARS-CoV-2. The study further utilised both two-dimensional (2D) and three-dimensional (3D) imaging methods to accurately segment lung masses that were attributed to the coronavirus. The COVIDNet framework employs the PEPX (Residual Projection-Expansion-Projection- Extension) design pattern, which is known for its lightweight nature, to facilitate both quantitative and qualitative analysis [11]. A different research study employed pretrained ResNet50, InceptionV3, and Inception ResNetV2 models, together with transfer learning approaches, to categorise chest roentgen rays into two classes: normal and SARS-CoV-2 [12]. With regards to the aforementioned topic. In their study, the authors [13] propose the utilisation of COVNet, a predictive model, to identify cases of SARS-CoV-2 based on U-net segmented CT scans.

3 Methodology

3.1 Proposed Neural Network

Deep convolutional neural networks (CNNs) have proven to be highly advantageous in the field of machine vision. Significant progress has been achieved across various domains, including agriculture, medical disease diagnosis, and industry.

The networks' superiority can be attributed to their ability to derive robust and valuable semantic features from the input data. The primary objective of deep networks is to identify infections in X-ray images, specifically classifying them as either normal or indicative of SARS-CoV-2 infection.

The ResNet50 architecture is based on the ResNet34 model with one important difference. In this case, the building block was transformed into a bottleneck model due to the time required to train the layers. A 3-layer stack was used here instead of the previous 2. Therefore, each 2-layer block in Resnet34 was replaced by a 3-layer bottleneck, forming the Resnet50 architecture. It has much higher accuracy than the 3-layer ResNet model. The 50-layer ResNet achieves a performance of 3.8 billion FLOPS[7]. ResNet152V2 was a 152-layer neural network.

The basic idea of ResNet is to add a direct connection channel to the network, which preserves some output from the previous network layers. This means that the neural network of this layer does not need to learn the entire output, but learns the residual value of the previous network output [8].

The input images in our collection have been pre-processed to a resolution of 256 × 256 pixels. ResNet50 and ResNet152V2 generate a feature map by processing the input image through the last layer of feature extraction. The integration of the feature maps from both networks, which are of equal dimensions, enhances the quality of the semantic features obtained by incorporating both the original and residual layers. The creation of a convolutional neural network involves the fusion of the retrieved features from ResNet50 and ResNet152V2 models. These characteristics are subsequently concatenated and utilised as input for a convolutional layer. Finally, the convolutional layer is integrated with a classifier. The convolutional layer that followed the concatenation of features had a kernel size of 1 × 1, consisting of 1024 filters, and did not include an activation function.

A layer was incorporated in order to extract a semantic feature of higher value from the spatial point data across all channels, so transforming each channel into a feature map. The inclusion of this convolution layer facilitates enhanced learning capabilities within the network by leveraging the amalgamated features

extracted from ResNet50 and ResNet152V2. The architectural composition of the integrated network is depicted in Figure 1.

3.2 Dataset

Convolutional neural networks were used to detect objects and chest X-ray data were analyzed. The chest X-ray samples downloaded from Kaggle basically contain images in two categories: normal and SARS-CoV-2. The images are then converted to (256,256) format and normalized. At this point, the images are rearranged and divided into preliminary and test data. The training part therefore has 1441 images and 2 classes. There are 360 images and 2 categories in the same

test section. There are many possibilities that CXR images of the same patients are stored in both training and test sections. It may overlap, but it is promising that the training of a tested and validated model determines the ability of

the trained model. Chest roentgen rays of SARS-CoV-2 positive and negative patients in Figure 2 below.

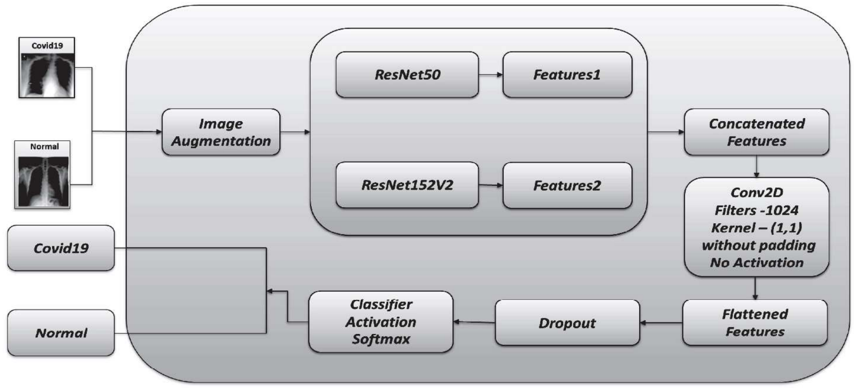


Fig. 1: Architecture of Concatenated Model. Fig.

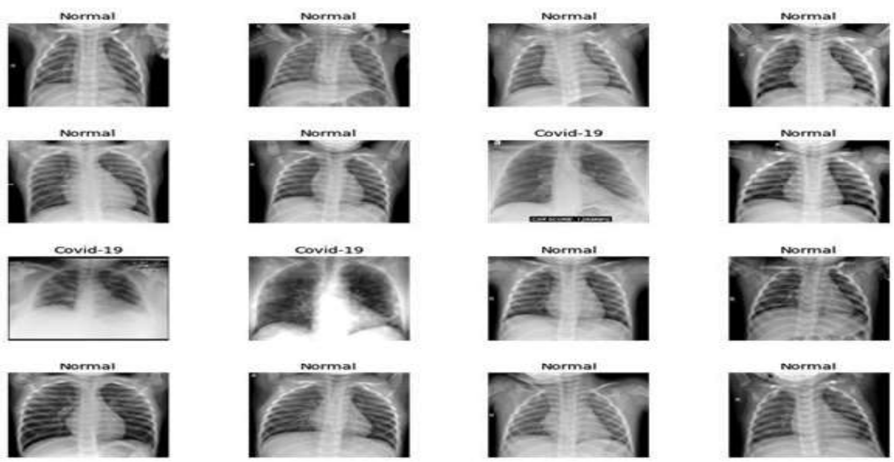


Fig. 2: Covid19 and Normal Patients CXR Image.

3.3 Performance Metrics

Confusion Matrix The confusion matrix is a basic element that can be used to measure the performance of an ML classification model, but is not considered a metric. In nature, it is a two-dimensional array that displays actual values and predicted values.

- True Positive (TP) - the category is predicted to be true and is also valid in reality (covid19 patients and diagnosed covid19);

- True Negative (TN) - class predicted as false and false in reality (patients who are healthy and diagnosed as healthy);
- False positive (FP) - class predicted as true but actually false (patients who are healthy but diagnosed with covid19); and
- False Negative (FN), a class predicted to be false but actually true (patients with SARS-CoV-2 but diagnosed as healthy).

Accuracy Accuracy for classification problems is the number of correct predictions the model makes for all types of predictions.

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

Precision Precision indicates how many positive predictions were correct. To calculate this, you divide the number of true positives (TP) by the total number of positives predicted by the classifier (TP, FP).

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall Recall shows the proportion of correct positive predictions out of all positives that the model could have made. To calculate this, you divide all true positives in the dataset by the sum of all true positives and false negatives. In this way, unlike the accuracy measure, recall signals unfulfilled positive predictions.

F1 Score F1 Score tries to find a balance between precision and recall by calculating their harmonic mean. This is a measure of test precision with a maximum possible value of 1. It indicates perfect precision and recall.

$$Precision = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

4 Results

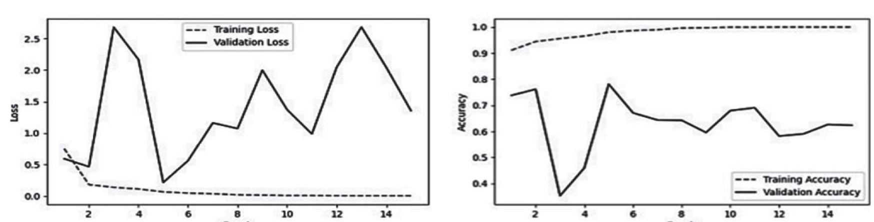
In this section, the results of the detailed experiment with ResNet50 and ResNet152V2 pre-trained CNNs to evaluate the efficacy of transfer learning for SARS-CoV- 2 cases detection from the chest roentgen images and the application of the ResNet252V2 model to the SARS-CoV-2 dataset are reported.

4.1 ResNet50 Model

The ResNet50 model was evaluated on 80 percent of the dataset after it had been constructed and the relevant procedures had been followed. The models were trained for 35 epochs with a batch size of 16 (shown in Figures 3a and 4b). The model was able to distinguish between the two unique categories of normal and SARS-CoV-2 with an accuracy score of 0.77. Table 1 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score, whereas Figure displays the confusion matrix corresponding to each classification. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 77.22 percent. The model's precision, recall, and F1 scores were 76.09 percent, 53.85percent, and 63.06 percent, respectively, with a 90.43percent total specificity performance.

Table 1: Results of the Res Net 50 Model

<table>
<tr><td colspan="2" rowspan="2">Confusion Matrix</td><td colspan="2">Target</td><td colspan="2" rowspan="2">F1 Score = 0.63</td></tr>
<tr><td>Covid19</td><td>Normal</td></tr>
<tr><td rowspan="2">Model</td><td>Covid19</td><td>70</td><td>22</td><td>Precision</td><td>0.76</td></tr>
<tr><td>Normal</td><td>60</td><td>208</td><td>Negative Predicted Value</td><td>0.78</td></tr>
<tr><td colspan="2" rowspan="2"></td><td>Recall</td><td>Specificity</td><td colspan="2" rowspan="2">Accuracy = 0.77</td></tr>
<tr><td>0.54</td><td>0.90</td></tr>
</table>



(a) Training and Validation Loss of ResNet50 Model

(b) Training and Validation Accuracy of Res Net 50 Model

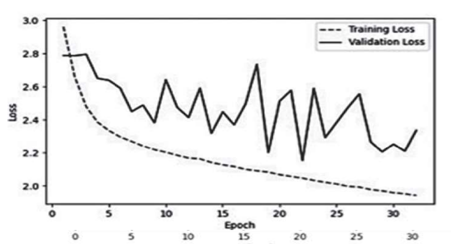
Fig. 3: Training and Validation Loss/Accuracy of ResNet50 Model

4.2 ResNet152V2 Model

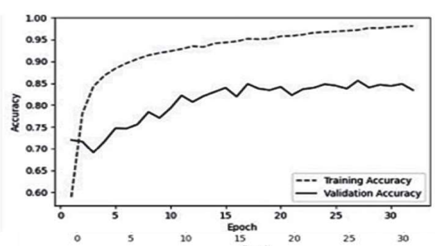
The ResNet152V2 model was evaluated on 80 percent of the dataset after it had been constructed and the relevant procedures had been followed. The models were trained for 35 epochs with a batch size of 16 (shown in Figures 4a and 4a). The model was able to distinguish between the two unique categories of normal and SARS-CoV-2 with an accuracy score of 0.80. Table 2 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score, whereas Figure displays the confusion matrix corresponding to each classification. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 80.56 percent. The model's precision, recall, and F1 scores were 81.52 percent, 58.59percent, and 68.18 percent, respectively, with a 92.67percent total specificity performance.

Table 2: Results of the ResNet152V2 Model

<table>
<tr><td colspan="2" rowspan="2">Confusion Matrix</td><td colspan="2">Target</td><td colspan="2" rowspan="2">F1 Score = 0.68</td></tr>
<tr><td>Covid19</td><td>Normal</td></tr>
<tr><td rowspan="2">Model</td><td>Covid19</td><td>75</td><td>17</td><td>Precision</td><td>0.81</td></tr>
<tr><td>Normal</td><td>53</td><td>215</td><td>Negative Predicted Value</td><td>0.80</td></tr>
<tr><td colspan="2" rowspan="2"></td><td>Recall</td><td>Specificity</td><td colspan="2" rowspan="2">Accuracy = 0.80</td></tr>
<tr><td>0.58</td><td>0.93</td></tr>
</table>



(a) Training and Validation Loss of ResNet152V2 Model



(b) Training and Validation Accuracy of ResNet152V2 Model

Fig. 4: Training and Validation Loss/Accuracy of ResNet152V2 Model

4.3 ResNet252V2 Model

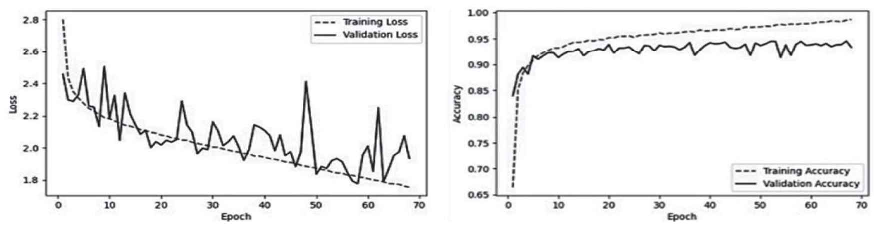
The proposed ResNet252V2 model was evaluated on 80 percent of the dataset after it had been constructed and the relevant procedures had been followed. The

models were trained for 35 epochs with a batch size of 16 (shown in Figures 5a and 5b). The model was able to distinguish between the two unique categories of normal and SARS-CoV-2 with an accuracy score of 0.93. Table 3displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score, whereas Figure displays the confusion matrix corresponding to each classification. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 92.81 percent. The model's precision, recall, and F1 scores were 93.48 percent, 81.13 percent, and 86.87 percent, respectively, with a 97.64 percent total specificity performance. This demonstrates the suggested model's ability to correctly distinguish positive

from negative cases. 4.4 Comparison of ResNet252V2 with ResNet50 and ResNet152V2 According to the findings (see Figure 6), ResNet252V2 consistently outperforms other pre-trained models in terms of performance. During evaluation, it was discovered that the pre-trained ResNet152V2 model outperformed the ResNet50 model. So, instead of using the ResNet50 model when the dataset is small, a pretrained ResNet152V2 model can be employed.

Table 3: Results of the ResNet252V2 Model

<table>
<tr><td colspan="2" rowspan="2">Confusion Matrix</td><td colspan="2">Target</td><td colspan="2" rowspan="2">F1 Score = 0.87</td></tr>
<tr><td>Covid19</td><td>Normal</td></tr>
<tr><td rowspan="2">Model</td><td>Covid19</td><td>86</td><td>6</td><td>Precision</td><td>0.93</td></tr>
<tr><td>Normal</td><td>20</td><td>248</td><td>Negative Predicted Value</td><td>0.93</td></tr>
<tr><td colspan="2" rowspan="2"></td><td>Recall</td><td>Specificity</td><td colspan="2" rowspan="2">Accuracy = 0.93</td></tr>
<tr><td>0.81</td><td>0.98</td></tr>
</table>



(a) Training and Validation Loss of ResNet252V2 Model

(b) Training and Validation Accuracy of ResNet252V2 Model

Fig. 5: Training and Validation Loss/Accuracy of ResNet252V2 Model

5 Conclusion

The most important responsibility of SARS-Cov-2 patients is not to spread SARS-Cov-2 to healthy people. Let's say no one knows their SARS-Cov-2 result. In this case, they cannot control the spread of SARS-Cov-2 in healthy people, so everyone should know about the positive or negative results of SARS-Cov-2 as soon as possible. This article is about how the system can know your SARSCoV- 2 results as early as possible at a low cost. The main motive is to reduce the cost of the corona test and get the results as soon as possible with the help of neural networks and artificial intelligence. Research has been done to identify SARS-CoV-2 from chest roentgen rays using detection. In this paper, we presented a coupled neural network based on ResNet50 and ResNet152V2 networks to classify chest roentgen rays images into two classes of normal and SARS-CoV- 2. Our proposed model can achieve our stated goal, which was to classify chest roentgen rays images either as SARS-CoV-2 or normal. The models we used performed well in the diagnosis of SARS-CoV-2, achieving a high test accuracy of 92.8% for the newly developed model. Although our SARS-CoV-2 classifier is performing well, there is still room for improvement. An important addition would be additional training to help the network better distinguish SARS-CoV-2 from other chest diseases such as viral pneumonia, bacterial pneumonia, pleurisy, etc.

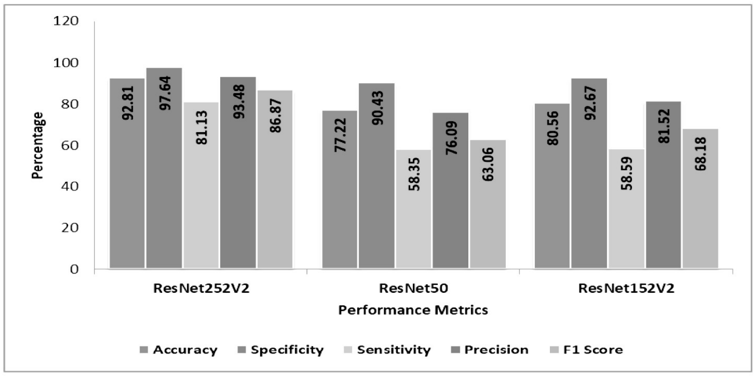


Fig. 6: Performance Metrics of ResNet252V2, ResNet50, ResNet152V2

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