A Modified Deep Convolutional Network for Detection of Covid19 from Chest X-Rays Based on Concatenation of Image Preprocessing Techniques and RESnCOV

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Abstract: The fast-spreading coronavirus disease called COVID-19 has impacted millions of people worldwide. It becomes difficult for medical experts to rapidly detect the illness and stop its spread because of its rapid growth and rising numbers. One of the newer areas of study where this issue can be more carefully addressed is medical image analysis. In this study, we implemented an image processing system utilizing deep learning and neural networks to previse the 2019-nCoV using chest roentgen ray images. In order to recognize COVID-19 positive and healthy patients using chest roentgen ray images, this paper suggests employing convolutional neural networks, deep learning, and machine learning. We proposed a neural network composed of various features taken from two convolutional neural networks, ResNet50 and ResNet152V2, in order to successfully manage the intricate structural complexity of an image. We tested our network on 7940 images to see how well it performs in real-world situations. The proposed network detects normal and COVID-19 cases with an average accuracy of 95% and can be used as an aid in the radiology department.

Keywords: Chest X-ray Images, Convolutional Neural Networks, COVID-19, Deep Learning, ResNet50, ResNet152V2.

1. Introduction

The 2019-nCov rife has isolated individuals, destroyed many industries, and placed them under quarantine. People's lives have been negatively impacted by it. Because of the high contagiousness of orthocoronavirinae, identifying this illness (COVID-19) is critical in order to manage it and develop preventive strategies.

Because of a lack of detection systems and manufacturing constraints, the discovery of diseases has slowed down significantly. There is also an increase in the number of patients and victims as a result. If 2019-nCov is identified quickly, its prevalence and mortality, as well as that of other diseases, will decrease. According to the reference (Jiang et al. 2020) and WHO (2023 Jan 27), one of 2019-nCov's primary symptoms is trouble breathing, which can be identified by a chest X-ray. It is feasible to identify the presence of the disease in persons who do not exhibit any early symptoms by analyzing these images, since a computed tomography of the chest can identify the condition even when the symptoms are mild (Sun et al. 2020). The shortcomings of other instruments, such as the dearth of diagnostic devices and their production constraints, can also be overcome by using this knowledge. The advantage of using computed tomography scans and roentgen rays is that most hospitals and diagnostic facilities have access to these imaging technologies, making it simple and easy to use the necessary data for network training and detecting the disease (An et al. 2020).

Deep learning and computer vision can be used as methods when employing chest computed tomography scans or roentgen ray images to diagnose 2019-nCov. Numerous researchers have employed deep learning and machine learning techniques since the disease's outbreak and have achieved success. Because of the fragility of the COVID-19 diagnosis, one of the major challenges we face in our research is accurate diagnosis. On the other side, because there aren't many open-source data sources, we concentrate on improving detection efficiency. The intent of this paper is to improve 2019-nCov

detection and reduce 2019-nCov false positives. For this, the training parameters are improved, and two robust deep convolutional neural networks are integrated.
The remainder of the disquisition is structured as follows: the review of literature is found in Section II. Section III describes the envisaged neural network, the chest roentgen ray datasets used, and the performance measures. In Section IV, the outcomes of the suggested paradigm are discussed. The work is concluded in Part V.

2. Literature Review

Naturally, because pneumonia poses a serious health danger, the majority of earlier studies have concentrated on its detection. Research on pneumonia and its analysis has continued even after the coronavirus pandemic and widespread transmission, with a focus on its etiology because the cause of pneumonia can have a significant impact on how soon it cures with the appropriate therapy. While discussing the use of deep learning to diagnose pneumonia, new research keeps coming out. Following the coronavirus outbreak, research has also concentrated on developing the machine learning tools for quick and non-intrusive coronavirus infection diagnosis and identification. Therefore, separating 2019-nCov infections from infections that are not 2019-nCov has been the topic of numerous investigations.

A method for rapid 2019-nCov detection from chest roentgen rays was developed by (Panwar et al., 2020) using nCOVnet, a deep learning method that is mainly based on neural networks. The authors attempt to differentiate between images of COVID-19-infected lungs and those of healthy or normal lungs in their paper. The created dataset includes all of the images from the Kaggle dataset as well as 337 posterior-anterior positive roentgen ray images of COVID-19 (142 selected images). Pre-processing on these pictures included scaling, RGB, reordering, and data augmentation. To prevent data leaks, the dataset was carefully split into 30 percent for testing and 70 percent for training. The data was loaded into a model that used transfer learning, ReLU, and maxpooling layers together with VGG-16 that had been previously trained on ImageNet. For feature extraction, the proposed method uses VGG-16's upper and base layers, which are made up of five unique layers that can swap weights between them during iterations. As a consequence, the model had a sensitivity of 97.62 percent, a specificity of 78.57 percent, and an accuracy of 2.38 percent to ascertain COVID-19 in those who were actually infected. The prognosis for patients who tested positive for COVID was 97.97 percent, while the prediction for those who tested negative was 98.68 percent. The model's accuracy was determined to be 88.10 percent, and its accuracy was also shown by the ROC, which was 0.8809, which indicates good accuracy when considering the diminutive size of the training set.
The use of deep learning to discern pneumonia and 2019-nCov patients from the chest radiograph images was another area of focus for (Chakraborty et al., 2021). A total of 10040 CXR images, comprising pneumonia patients, COVID-19 cases, and normal cases, were gathered for the study from Kaggle and GitHub. After the images are inputted, they are pre-processed and segregated so that, with the exception of normalization and upscaling, all images not marked as one of the predefined categories are excluded. Lung contour masks and FC-DenseNet103 semantic segmentation method are also used to extract segmented lung areas from each image. The following breakdown of this dataset is used: 80 percent to train (of which 10 percent is used for validation) and 20 percent to the test. The ResNet18 architecture used in this model of deep learning has already been trained to perform better. To categorize data into the normal, COVID-19, and pneumonia categories, this model has additional multi-class classification layers. Maxpooling, SoftMax Layers, Convolutional, Average Pooling, Hidden, and Convolutional were all included in the model's six total layers. The accuracy and sensitivity of the model were 96.43 percent and 93.68 percent, respectively.
In (Wang et al., 2021), using deep learning, they recognized COVID-19 and then used 2D and 3D scans to section lung masses caused by orthocoronavirinae. They developed a unique convolutional neural network to categorize and help predict COVID-19 using computed tomography scans (Frid-Adar et al., 2021). To explore quantitative and qualitative analyses, COVID-Net employs the simple Residual Projection-Expansion-Projection-Extension (PEPX) design pattern (Wang et al., 2020).

Another study classified chest radiographs into the normal and COVID-19 classes using pre-trained InceptionV3, Inception ResNetV2, and ResNet50 models and transfer learning approaches (Narin et al. 2021). In reference to (Li et al., 2020), they offer COVNet to forecast 2019-nCov from computed tomography images with U-Net segmentation.

Table 1. A Summary of Previously Published Methodologies

Author	Methods	Samples	Results
Panwar et al., 2020	nCovnet	Covid (192) Normal (142)	Sen - 97.62%, Spe – 78.57%, Acc – 88.10%, F1 – 89.13%, Re – 97.62%, Pre – 82%
Chakraborty et al., 2021	Corona Nidaan Model	Covid (245) Pneumonia(5551) Normal(8006)	Acc – 95% Covid: Re – 93.54%, Pre – 93.54%, F1- 94% Normal: Re – 93.33%, Pre – 98%, F1 – 96% Pneumonia: Re -96.84%, Pre -92%, F1 -94%
Frid-Adar et al., 2021	Robust 2D and 3D Deep Learning Model	Normal (150) Covid (120)	AUC – 0.996, Sen – 98.2%, Spe – 92.2%
Wang et al., 2020	Covid-Net	No Pneumonia (8066) Non Covid Pneumonia (5538)	AUC – 93.3%, Sen – 94.0(Non Covid Pneumonia), 91.0(Covid), 95.0(Normal), PPV – 91.3(Non Covid Pneumonia), 98.9(Covid), 90.5(Normal)
Narin et al., 2021	Deep Transfer Learning (InceptionV3, ResNet50, ResNet101, ResNet152, Inception-ResNetV2)	Normal (2800) Bacterial Pneumonia (2772) Viral Pneumonia (1493)	Acc -96.1(Covid/Normal), 99.5(Covid/ Viral Pnemonia), 99.7 (Covid/Bacterial Pnemonia)
Li et al., 2020	CovNet	Covid (1296) CAP (1735) Non-Pnemonia (1325)	Covid Sen – 90%, Spe – 96%, AUC – 0.96, P-Value - <0.001 CAP Sen – 87%, Spe – 92%, AUC – 0.95, P-Value - <0.001 Non-Pneumonia Sen – 94%, Spe – 96%, AUC – 0.98, P-Value - <0.001
Wang et al., 2021	Deep Learning Inception Algorithm	Pneumonia (180) Covid (79)	Internal Acc – 89.5%, Spe – 0.87, Sen – 0.88, F1 – 0.77, AUC(95%CI) – 0.93(0.86-0.94), PPV – 0.71, NPV – 0.95, Kappa – 0.69, Youden index – 0.75 External Acc – 79.3%, Spe – 0.67, Sen – 0.83, F1 – 0.63, AUC(95%CI) – 0.81(0.71-0.84), PPV – 0.55, NPV – 0.90, Kappa – 0.48, Youden index – 0.50

*Sen – Sensitivity, Spe – Specificity, Pre – Precision, PPV – Positive Predicted Value, NPV – Negative Predicted Value, F1 – F1 Score, AUC – Area Under the Curve

3. Methodology

3.1. Proposed Neural Network

Machine-vision tasks benefit from the use of deep convolutional neural networks. They have achieved progress in a variety of industries, including disease identification, medicine, and agriculture. The robust and significant semantic features that these networks produce from the incoming data are what give them their excellence. In this case, deep networks are primarily concerned with identifying infections in x-rays, hence x-rays are classified as COVID-19 or as normal.

With one significant exception, the ResNet34 model forms the basis of ResNet50 architecture. The bottleneck in this scenario was the time required to train the layers. Here, a three-layer stack was used as opposed to the preceding two. As a result, the Resnet50 design was created by substituting a three-layer bottleneck for each two-layer block in Resnet34. In comparison to the three-layer ResNet model, it is substantially more accurate. Performance for the 50-layer ResNet is 3.8 billion FLOPS (He K et al., 1980). ResNet152V2 is a neural network with 152 layers. ResNet works by adding a direct connection channel to the network that keeps some output from the earlier network levels. The residual networks fundamental concept is to provide an effective connection channel to the proposed network, which keeps some output from the earlier network levels. This indicates that the neural network of this layer only has to learn the residual value of the output from the preceding network (Elshennawy and Ibrahim, 2020).

Our dataset's pre-processed input images have a resolution of 256x256 pixels. ResNet50 and ResNet152V2 generate a feature map from the input image's final feature extraction layer. Since both networks output feature maps of the same size, we integrated their features so that the quality of the resulting semantic features is improved by incorporating both the original and residual layers. The retrieved features from ResNet50 and ResNet152V2 are integrated, the interlinked features are concatenated into a convolutional layer, and finally a classifier is added to construct a convolutional neural network. Following the concatenation of the features, a convolutional layer was added with a kernel size of 1x1 and a 1024 filter but no activation function. This layer was introduced to transform every network into a feature map by using the spatial point-key features between all of the channels and extracting a more valuable and important semantic feature. The network learns more effectively from the combined ResNet50 and ResNet152V2 data thanks to this convolution layer. Figure 1 describes the merged network's design.

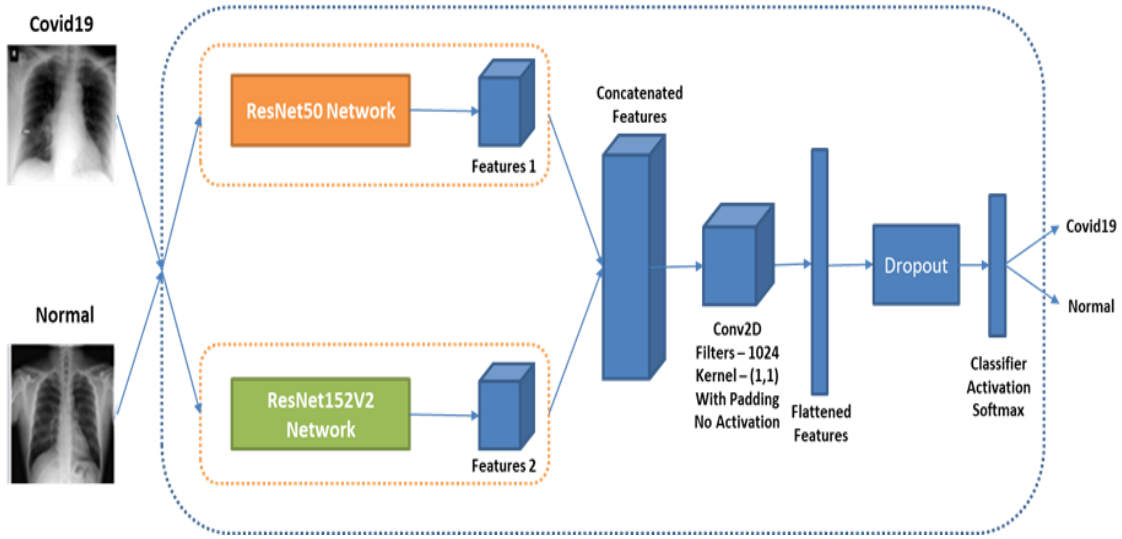


Figure 1 The Architecture of ResnCov Model

3.2. Dataset

Chest x-ray data was examined, and object detection was done using convolutional neural networks. The chest roentgen ray samples that were downloaded from Kaggle primarily consist of 2019-nCov and normal images. The images are then normalized and transformed to a (256, 256) format. The dataset are now rearranged and split into test and preliminary data. Thus, there are 6352 images and two classes in the training part. The same test part contains two categories and 1588 images. It is quite possible that the same patient's CXR images are kept in both the training and test parts, and it is indeed promising that the potentiality of the trained model is determined by the training of a validated and tested model,

even though there may be overlap. Figure 2 below shows the chest x-rays of patients who were diagnosed either positively or negatively with COVID-19.

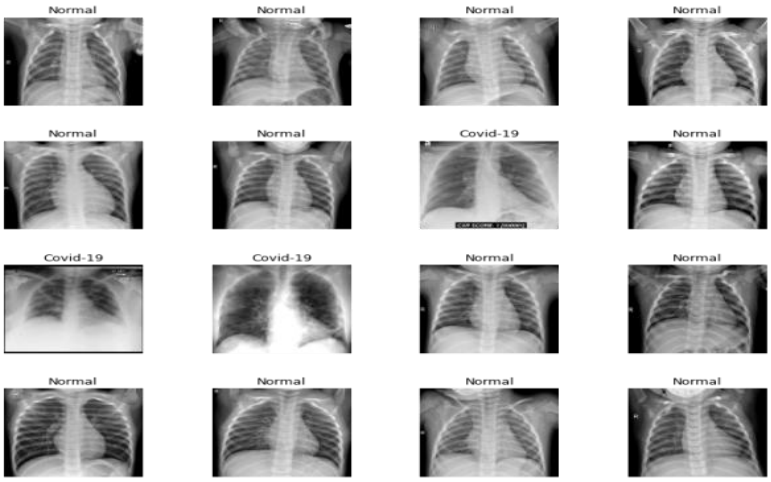


Figure 2 Covid19 and Normal Patients CXR Images

3.3. Experimental design and validation

The model was validated in two stages. The 4-fold cross-validation method, on the other hand, uses the same dataset for testing and training. On the other hand, a different dataset containing samples that weren't used during the model-training phase was applied to evaluate the model's performance. The confusion matrix was obtained. In light of the distinct classes, the F1 score, recall, and recall have been calculated. Finally, average values have been computed for each fold. Algorithm 1 in Figure 3 describes in detail the experimental setup that was used to carry out this study.

Algorithm 1: *Experimental Setup*	
Input	1. *Download Images of two categories (COVID-19, NORMAL).*
Environment	2. *Use Google CoLab and install the required libraries*
Configuration	3. *Import the images*
	4. *Configure training, testing, and validate the model using stratified 4-fold cross-validation Data Generator*
Data Generator Configuration	5. *Define an augmentation pipeline using the Compose function of augmentation library*
	6. *Create the data generator as an object of the ImageDataAugmentor library and configure the augmentation pipeline obtained in (5).*
	7. *Configure batch_size = 16.*
Directories Configuration	8. *Create two directories (DIR-1, DIR-2} of the images with their labels according the classes. DIR-1 will be used for training/testing and DIR-2 will be used for the validation.*
Training and Testing Apply 4-fold stratified cross-validation.	9. *Create the model using ResNet252V2 and dense layers with relu activation function and an output layer with a softmax activation function .*
	10. *Compile the model using the ADAM optimizer with the learning rate as .0001, Categorical Crossentropy function for loss calculation.*
	11. *Model fitting using 35 epochs and ReduceLRonPlateau function to reduce the learning rate when the metrics stop improving.*
	12. *Save the model to be used for validation testing.*
	13. *Configure testing dataset*
	14. *Generate performance score values for each fold.* a. *Sensitivity* b. *Specificity* c. *Precision* d. *Negative Predicted Value* e. *Accuracy* f. *F1 Score* g. *Model Loss Graph* h. *Model Accuracy Graph* *Note: Following steps are executed 4 times.*
	15. *Identify the best model from the outputs of training and testing phase*
Validation	16. *Load the identified model*
	17. *Load validation datasets*
	18. *Perform the validation*

Figure 3 Experimental Setup

3.4. Performance Metrics

3.4.1. Confusion Matrix

Although it is not regarded as a metric, the confusion matrix is a fundamental component that can be used to assess how well a machine learning classification model performs. It is a two-dimensional array that shows both real and predicted values in nature.

- True Positive (TP) is a category that is predicted to be true but also happens to be true (2019-nCov patients confirmed with 2019-nCov).
- True Negative (TN) is a category that is projected to be false but is also false in reality (patients who are healthy but are labeled as such).
- False Positive (FP) is a category that is predicted to be true but is actually false (healthy patients with COVID-19) and
- False Negative (FN) is a category that is predicted to be true but is actually false (patients who have COVID-19 but are healthy).

3.4.2. Accuracy

The number of precise predictions the model makes across all categories of predictions indicates accuracy in classification techniques.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \qquad (1)$$

3.4.3. Precision

The number of accurate positive predictions is known as precision. To make this calculation, divide the total number of predicted true positives (TP) by the sum of predicted true positives (TP) and false positives (FP).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad (2)$$

3.4.4. Recall

Recall displays the percentage of accurate positive predictions among all possible positive predictions made by the model. To determine this, divide the total number of true positives (TP) in the dataset by the sum of true positives (TP) and false negatives (FP). Recall, in contrast to the accuracy measure, indicates positive predictions that were not fulfilled.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \qquad (3)$$

3.4.5. F1 Score

The F1 Score determines their harmonic mean in an effort to achieve a balance between recall and precision. The maximum possible value for this precision measurement is 1. It implies perfect recall and precision.

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (4)$$

4. Results and Discussions

4.1. Results of ResnCov performance on Fold 1

The findings from the propound model's application to the 2019-nCov dataset are presented in this section. The model was evaluated on 80 percent of the dataset after it had been constructed and the relevant procedures had been followed. The 4-fold cross-validation method was used to carry out the suggested model's training. The models were trained for 35 epochs with a batch size of 16 (shown in Figures 9 (A) and 9 (B)). The model was able to distinguish between the two unique categories of normal and 2019-nCov with an accuracy score of 0.9515 on Fold1. Even after the first 35 epochs, the system was still able to attain the same validation and training accuracy. Table 2 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score on Fold1, whereas Figure 4 displays the waffle chart corresponding to each classification. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 0.9515 percent. The model's precision, recall, and F1 scores were 94.33 percent, 94.74 percent, and 94.54 percent, respectively, with a 95.48 percent total specificity performance. This demonstrates the suggested model's ability to correctly distinguish positive from negative cases.

Table 2 Results of the ResnCov Model on Fold 1

Confusion Matrix		Target		F1 Score = 0.94	
		Covid19	Normal		
Model	Covid19	666	40	Precision	0.94
	Normal	37	845	Negative Predicted Value	0.96
		Recall	Specificity	Accuracy = 0.95	
		0.95	0.95		

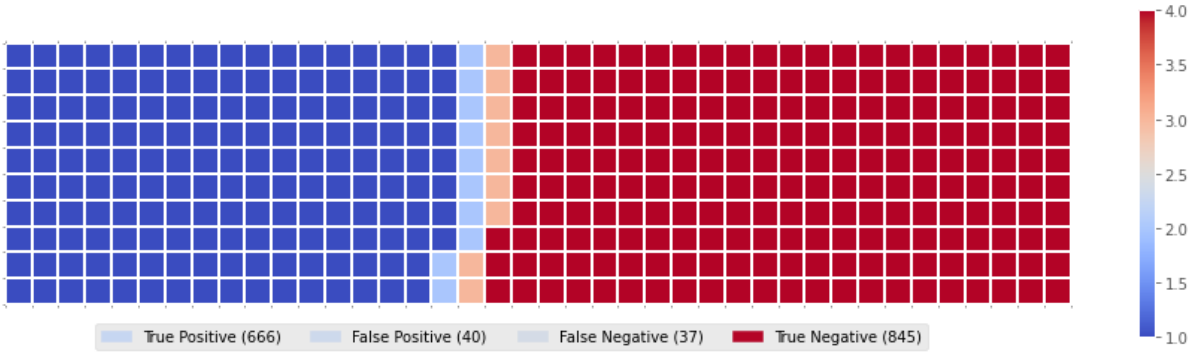


Figure 4 Waffle Chart for ResnCov Model on Fold1

4.2. Results of ResnCov performance on Fold 2

Experiments with the ResnCov model on Fold 2 yielded the following results. Table 3 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score on Fold2, whereas Figure 5 displays the waffle chart corresponding to each classification on Fold 2. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 0.9503 percent. The model's precision, recall, and F1 scores were 94.05 percent, 94.72 percent, and 94.39 percent, respectively, with a 95.26 percent total specificity performance. This demonstrates the suggested model's ability to correctly distinguish positive from negative cases.

Table 3. Results of the ResnCov Model on Fold 2

Confusion Matrix		Target		F1 Score = 0.94	
		Covid19	Normal		
Model	Covid19	664	42	Precision	0.94
	Normal	37	845	Negative Predicted Value	0.96
		Recall	Specificity	Accuracy = 0.95	
		0.95	0.95		

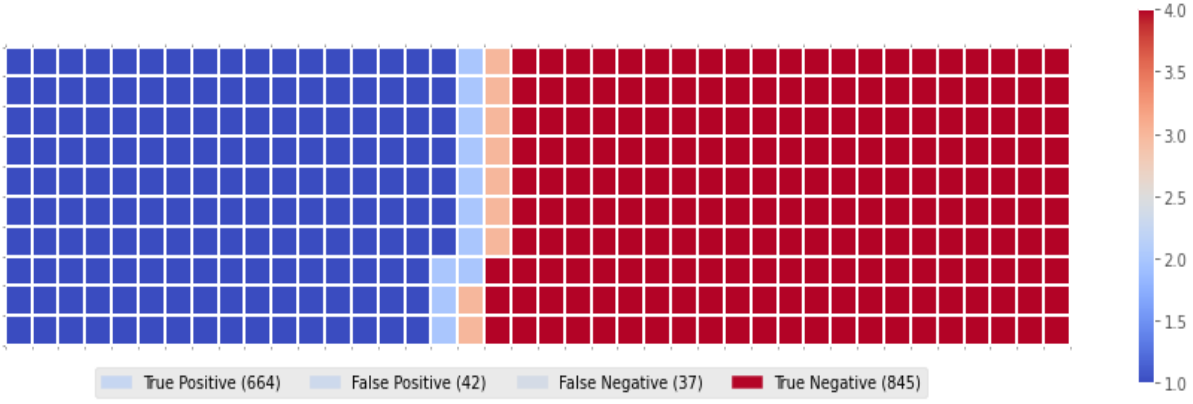


Figure 5 Waffle Chart for ResnCov Model on Fold 2

4.3.Results of ResnCov performance on Fold 3

Experiments with the ResnCov model on Fold 3 yielded the following results. Table 4 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score on Fold 3, whereas Figure 6 displays the waffle chart corresponding to each classification on Fold 3. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 0.9496 percent. The model's precision, recall, and F1 scores were 94.33 percent, 94.33 percent, and 94.33 percent, respectively, with a 95.46 percent total specificity performance. This demonstrates the suggested model's ability to correctly distinguish positive from negative cases.

Table 4 Results of the ResnCov Model on Fold 3

Confusion Matrix		Target		F1 Score = 0.94	
		Covid19	Normal		
Model	Covid19	666	40	Precision	0.94
	Normal	40	842	Negative Predicted Value	0.96
		Recall	Specificity	Accuracy = 0.95	
		0.94	0.95		

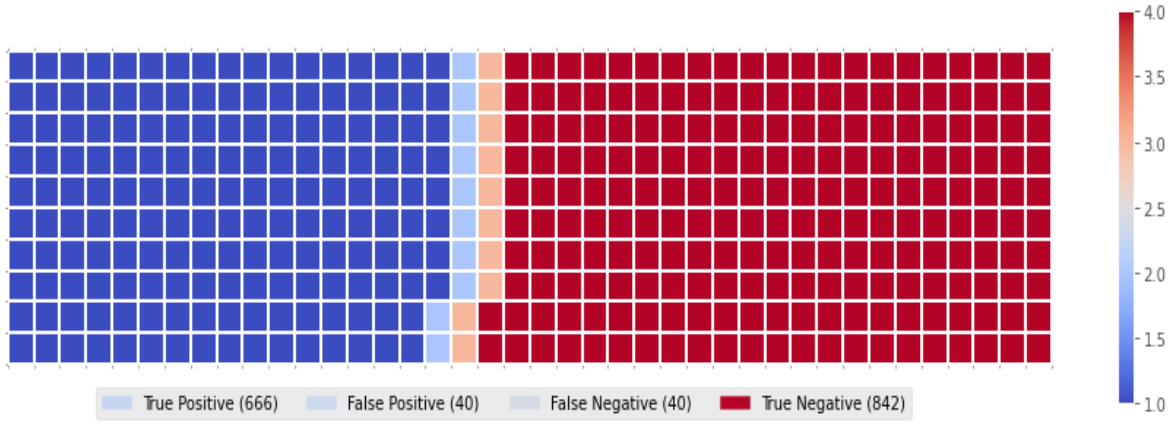


Figure 6 Waffle Chart for ResnCov Model on Fold 3

4.4. Results of ResnCov performance on Fold 4

Experiments with the ResnCov model on Fold 4 yielded the following results. Table 5 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score on Fold 4, whereas Figure 7 displays the waffle chart corresponding to each classification on Fold 4. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy is 0.9509 percent. The model's precision, recall, and F1 scores were 94.48 percent, 94.48 percent, and 94.48 percent, respectively, with a 95.58 percent total specificity performance. This demonstrates the suggested model's ability to correctly distinguish positive from negative cases.

Table 5 Results of the ResnCov Model on Fold 4

Confusion Matrix		Target		F1 Score = 0.94	
		Covid19	Normal		
Model	Covid19	667	39	Precision	0.94
	Normal	39	842	Negative Predicted Value	0.96
		Recall	Specificity	Accuracy = 0.95	
		0.95	0.96		

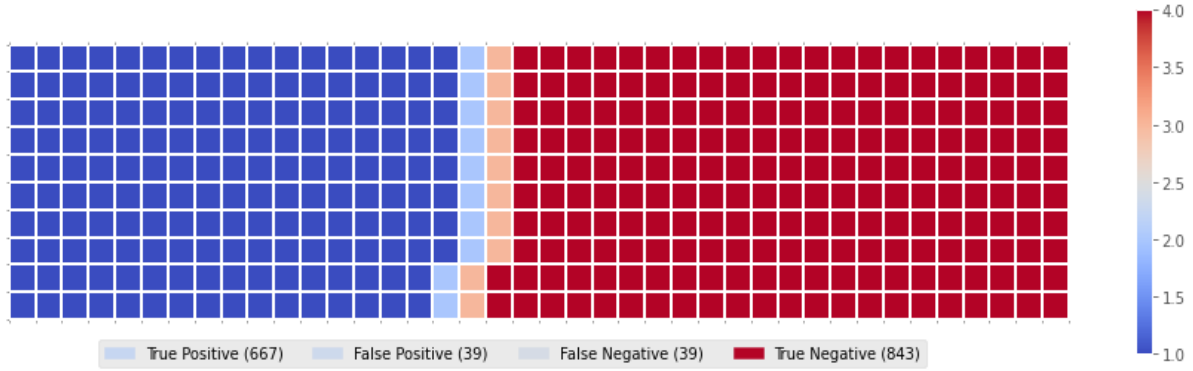


Figure 7 Waffle Chart for ResnCov Model on Fold 4

4.5. Results of ResnCov performance on each Fold

In this section, Table 6 displays the classification results for all classes in terms of recall, specificity, recall, accuracy, and F1 score on each fold and their average. The outcomes demonstrate that the suggested model performs well for all evaluation metrics. The model's overall accuracy average on each fold is 0.9506 percent. The model's average precision, recall, and F1 scores were 94.30 percent, 94.57 percent, and 94.43 percent, respectively, with a 95.44 percent total specificity performance. This

demonstrates the suggested model's ability to correctly distinguish positive from negative cases. Overall, training accuracy is inferior to validation accuracy. The two graphs below (Figure 9(A) and 9(B)) can be used to illustrate it.

Table 6 Results of the ResnCov Model on Each Fold

	Sensitivity	Specificity	Precision	NPV	Accuracy	F1 Score
Fold 1	94.74	95.48	94.33	95.80	95.15	94.54
Fold 2	94.72	95.26	94.05	95.80	95.03	94.39
Fold 3	94.33	95.46	94.33	95.46	94.96	94.33
Fold 4	94.48	95.58	94.48	95.58	95.09	94.48
Average	94.57	95.44	94.30	95.66	95.06	94.43

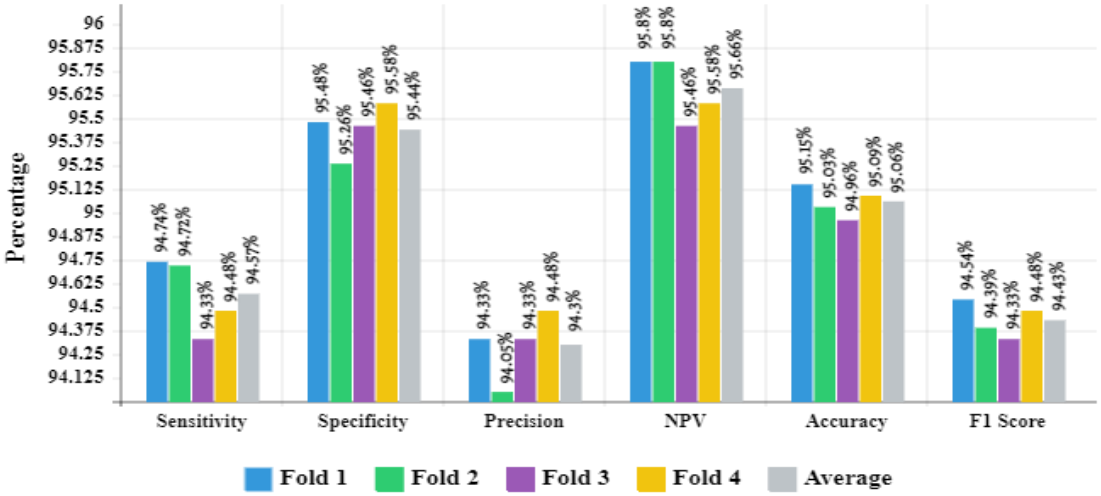
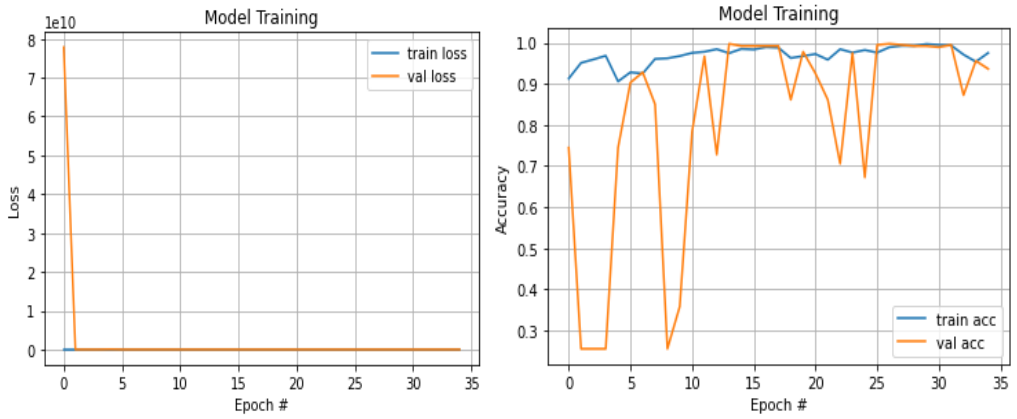


Figure 8 Performance Metrics of the ResnCov Model on Each Fold



(A) (B)

Figure 9 Model Training (A) Validation and Training Loss (B) Validation and Training Accuracy

5. Conclusions

Patients with 2019-nCov must take special care to avoid infecting healthy individuals. Let's assume nobody is aware of their 2019-nCov test result. Because they are unable to prevent 2019-nCov transmission in healthy individuals in this case, as soon as 2019-nCov findings are positive or negative, everyone should be notified. This article explains how the model can find out your 2019-nCov results quickly and affordably. With the aid of artificial intelligence and a neural network, the primary goal is to lower the cost of the 2019-nCov test and quickly obtain the findings. Using image processing and detection methods, research has been done to identify 2019-nCov from chest roentgen rays. To categorize chest roentgen ray images into two categories of normal and 2019-nCov, we developed a

coupled neural network (ResnCov) in this research that was built on the ResNet50 and ResNet152V2 networks. Our stated objective, to categorize the chest roentgen ray images as 2019-nCov or normal, can be met by our suggested model. The models we used performed well in the diagnosis of 2019-nCov, achieving a high test accuracy of 95.06 percent for the newly developed model. Although our 2019-nCov classifier is performing well, there is still room for improvement. An important addition would be additional training to help the network better distinguish 2019-nCov from other chest diseases such as viral pneumonia, bacterial pneumonia, pleurisy, etc.

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