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A COVID-19 DETECTION MODEL FROM CHEST X-RAY IMAGES USING MACHINE AND TRANSFER LEARNING FRAMEWORK

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Abstract

The new coronavirus produced by the SARS-CoV2 disease emerged in Wuhan, China, and ranges around the world. At the end of 2019, humanity was confronted with a pandemic that no one anticipated to see in the modern era: SARS is a severe acute respiratory illness. SARS CoV-2 correlated with pneumonia also recognized as coronavirus illness 2019, (COVID-19). On the other hand, the COVID-19 outburst began in Wuhan, China the epidemic's global expansion has resulted in a shortage of equipment for clinicians treating the sickness. At the period of writing, there have been over 28,000,000 verified cases and over 814,000 confirmed deaths universally. Early diagnosis of the virus is critical for the patient's complete recovery, but late detection can be deadly. This virus is relatively more dangerous due to its infectious nature. Because the virus's symptoms are similar to those of the flu, it is difficult to diagnose. This study tries to develop an automated technique for identifying Covid19 virus-infected pictures of chest X-rays images rather than simple symptoms. The suggested approach makes use of a dataset containing non-infected human chest X-rays in addition to individuals suffering from pneumonia and Covid19 virus infection. First, we train a custom CNN on a huge data set of X-ray chest pictures for non-COVID-19 before normalizing the images and performing the detection approach in the area of covid. The proposed model is then fine-tuned using the tiny COVID-19 data. Three previous transfer learning frameworks (resnet-50, VGG 16, and

VGG19) with implemented CNN have been adopted which have 96, 97, and 97% accuracy respectively. These models not only deliver an efficient detection of covid-1 x-ray images but also give a proper way for handling multiple x-ray images in a deep learning platform which gives a new perspective to society to deal with the early stage of the coronavirus. This research, combined with the GUI would assist clinicians in detecting afflicted individuals using computer-aided analysis in a matter of seconds with multiple deep-learning models. We feel that this will greatly enhance the medical field's worth.

Keywords: SARS-COV2,Covid-19,CNN,Transferlearning,resnet-50,vgg-16 and vgg-19Keyword.

Introduction

At the end of 2019, humanity was confronted with a pandemic that no one anticipated to see in the modern era: SARS is a severe acute respiratory illness. (SARS-COV-2)related pneumonia also recognized as coronavirus illness 2019, (COVID-19). On the other hand, the (COVID-19) outburst began in Wuhan, China. The epidemic's global expansion has resulted in a shortage of equipment for clinicians treating the sickness. At the period of writing, there have been over 28,000,000 verified cases and over 814,000 confirmed deaths universally. Given the time and cost of test kits necessary for diagnosis, AI and DL studies and apps have been created to assist specialists in treating patients and combating sickness [1].

Using X-ray images for automatic COVID-19 identification may be especially beneficial for nations and hospitals that cannot afford a workroom kit or do not have a CT scanner. Since no active treatment option has yet been discovered, an accurate diagnosis is critical [2]. Both viruses had genomic sequences that were 86% identical to (SARS) like viruses identified in bats, suggesting that both viruses were transferred from bats to people at some view [as seen in Fig. 1.]

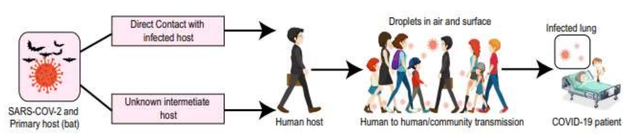

Figure 1 The transmission and spread of SARS-CoV-2 are depicted in a block diagram [3].

COVID-19 is caused by a virus that is very infectious and spreads mostly through contact with an infected person's respiratory droplets. These droplets can enter the human body by mouth or breathing [4]. As can be observed in Fig. 2, the present COVID-19 outbreak is unprecedented and is having a significant effect on the global community. It is both the most severe geopolitical event of the current generation and public health issue.

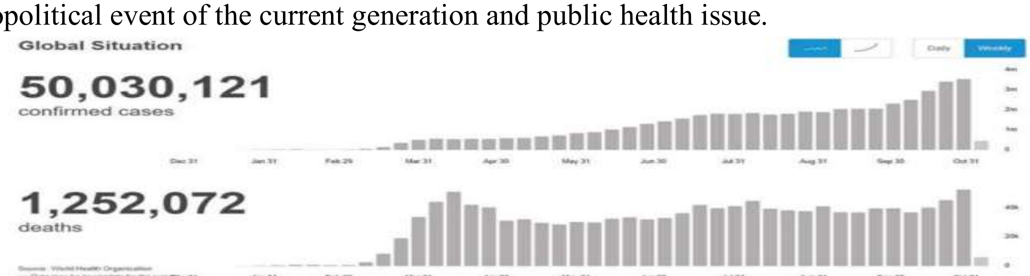

Figure 2 Global Scenarios from WHO Coronavirus Disease (Covid-19) Dashboard as of 9th November 2020.

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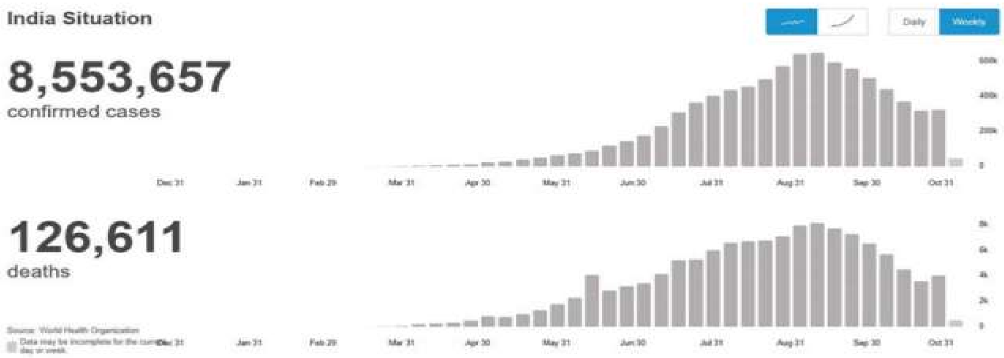


Figure 3 Indian Scenario from WHO Coronavirus (Covid-19) Dashboard as of 9th November 2020.

For the Indian Scenario in the above graph, access to ongoing research and education has never been more crucial[6]. The second most populous nation, India, which is now under lockdown and has recorded close to 59,662 cases and 1981 reduced as of May 10, 2020, owing to COVID-19 thus far (fig. 3), is particularly ready for the worst. According to one of the forecasts, India may have to cope with 300 billion cases by 2020, of which more than 4 billion may be severe. The ability to recognize people and provide assistance in time is possible with an AI-built CNN network[7]. This in turn will have a stronger effect on specialists who are focusing on severe cases to stop the pandemic from spreading. based on data from the European Centre for Virus Deterrence and Resistance. The patient's age and previous medical conditions have a significant impact on the fatality rate.

1.1 Main Contribution of Paper

Few studies have utilized just individual deep learning algorithms with CXR pictures to predict COVID-19 +ve and –ve. One project sought to create a bespoke network. Our research, however, focuses on merging numerous state-of-the-art deep learning models to increase accuracy. It is founded on the fundamental tenet that a model ensemble outperforms a single model. The goal of this study is to develop transfer learning and machine learning classifiers for sensing covid-19 in X-RAY pictures. Our framework is built on Corona Net, an open-source method for identifying COVID-19. Primary, load data and address the issue of imbalanced data. Finally, pick the models ResNet-50, Vgg-16, and Vgg-19 with excellent effect based on accuracy and loss value, Users raise their weight ratio dynamically throughout the training procedure Create a well-closed loop and iterate over it.

The remaining portions of the essay are structured as follows: - Related studies, methodologies, and techniques are outlined in Section 2. - The dataset and our recommended methodology are described in Section 3, along with background information on the cutting-edge models we used.

– In Section 4, we described the experimental setup that was used in our investigation. - The experimental results from the intended investigation are shown in Section 5, together with classification accuracy, sensitivity, and F1-score. – The study is completed with a summary of the research's findings in Section 6.

Literature Survey

Advances in picture identification, particularly in auxiliary medical diagnosis technologies. Deep learning has been used effectively to diagnose pneumonia from X-rays, outperforming radiologists. Several transfer learning models have been utilized for covid-19 identification, with each kind being employed in a different application based on the brain region of interest to investigate.

S. Calderon-Ramirez et al (2021) Planned a COVID-19 infection recognition system built on X-ray pictures of the chest with uncertainty estimation. Estimating vagueness is critical for the appropriate use of computer-aided diagnostic technologies in health applications. A skilled radiologist should carefully examine model estimates with substantial uncertainty. Using the Mix Match semi-supervised framework, we hope to enhance uncertainty estimations using unlabeled data. We put common uncertainty estimating methods, such as SoftMax scoring. We suggest employing the Jensen-Shannon distance b/w ambiguity distributions of right and wrong predictions to compare the dependability of uncertainty approximations. When using unlabeled data, our test findings demonstrate a substantial improvement in uncertainty estimations. The employment of the Monte Carlo dropout approach yields the best results [8].

K. -W. Ha and J. -W. Jeong (2021) offers an automated COVID-19 infection detection method based on chest X-ray images. 194 X-ray images of healthy people and 194 X-ray images of coronavirus patients were used to build the datasets for this inquiry. We apply the idea of transfer learning for this assignment because there aren't many photographs of COVID-19 patients that are available to the public. We modify many Image Net-trained convolutional neural network (CNN) designs to work. For the other dataset, DenseNet201 and MLP had the highest accuracy. The recommended technique thus successfully detects COVID-19 in X-ray images [9]. Calderon-Ramirez, S., and others (2020) The solution offered were tested using two freely accessible databases. This suggests that our semi-supervised system might assist increase performance levels for Covid-19 identification. In addition, we offer a semi-supervised DL boost coefficient that is designed to increase our technique's scalability and performance comparability. As a result, early, rapid, and low-cost identification of infected patients is critical. Currently, current tests are restricted and only available to those in imminent danger of serious disease. DL applied to chest X-ray images for corona identification is an appealing technique[10].

D. Hernandez et al. (2021) present a machine learning technique for identifying instances of infected individuals based on x-ray pictures of their, lungs Owing to the scarcity of accessible data and the restricted processing capacity, we propose 2 methods: I Construct a custom CNN from scratch utilizing a massive data collection of non-COVID19 pulmonary X-Rays from the past. ii) Use transfer learning with pre-trained CNN models and COVID-19 data to fine-tune the final layers [11].

W. Shi et al. (2021) Based on the direction of attention transmission, the suggested network structure may be split into instructor networks and student networks. To begin, the network captures global characteristics and focuses on infection regions to produce attention maps. With an enlarged reception field, we suggest a deformable attention module to increase infected areas' responsiveness and decrease noise in inappropriate regions. Furthermore, by integrating important information in the original i/p, attention to knowledge is transferred. Extensive studies have been carried out using publicly accessible chest X-ray and CT imaging datasets [12].

M. Qjidaa et al. (2020) For the primary identification of COVID-19 using chest x-rays, which are more readily available to patients in rural areas, advance an intelligent medical decision support system. In the end, 566 radiological images of three different types—the COVID-19 type, the Pneumonia type, and the Normal-type—were obtained. In a research study, training data from 80% of the database and test data from 20% of the database were used. They use augmentation very immediately after the pretreatment method. Our final classifier performed best with a test accuracy of (99 percent), an score of 98 percent, a precision of (98.60) percent, and a sensitivity of (98.30 %)[13].

S. D. Thepade and K. Jadhav (2020) Attempts to detect Covid19 virus-infected chest X-ray images using an automated approach. The proposed method makes use of a dataset that includes noninfected human chest X-rays. To categorize the resultant feature sets, many ML approaches and ensembles of these individual representations are employed. The findings of the experiments are obtained by 10-fold CV testing [14].

E. Irmak (2020) is a novel, powerful, and resilient using openly available information. A CNN model is created and offered as a potential COVID-19 sickness diagnosis tool. This model is used to assess whether or not a particular chest X-ray image of a patient has COVID-19 with an accuracy of 99.20 percent. Experimental results on clinical datasets are presented to support the effectiveness of the proposed approach. It is anticipated that the practice-based study recommended in this research report will help doctors recognize the COVID-19 condition. The most important effect of this new coronavirus is how contagious it is, which puts an end to life as we know it. Research on COVID-19 diagnostics will pick more steam as more details about the biology of this lethal virus become accessible [15].

S. Lafraxo and M. el Ansari (2020) It is advised to use CoviNet, a DL network, to detect the presence of COVID-19 automatically in X-ray pictures. A CNN, histogram equalization, and a filter (median) are the cornerstones of the advised planning. It is completely trained using a dataset that is available to the public. Since early discovery may limit the virus's spread, this model has a binary classification precision of 98.62 percent and a multi-class classification accuracy of 95.77 percent.

D. Haritha et al. (2020) With (99.9 percent) accuracy, the suggested model accurately detects the binary classes (COVID and normal). CHEXNET is a (CNN) network that was trained on the ChestX-ray14 dataset to detect anomalies in chest X-rays. This framework was generally expanded to perceive all 14 viruses in the (chestX-ray) 14- dataset. In our model, we applied its pre-trained model Densenet121 to identify COVID-19 from binary classes. The new coronavirus is a fast-spreading viral illness that has turned into a pandemic, posing serious dangers all over the world. It is critical to detect patients ahead of time to prevent the development of this pandemic [17].

O. EL GANNOUR et al. (2020) suggest a Deep Learning based method for COVID-19 illness recognition The Transfer Learning method is used to build this system, which utilizes six pre-trained models. The used X-Ray image library comprises 2905 pictures. This dataset has been through a variety of preparation steps. The results of this research demonstrate that the Exception network categorization is the most accurate for identifying instances infected with COVID19. This technique has a sensitivity of ninety-eight percent with an accuracy of 100 percent, respectively [18].

A. Narin (2020) Chest X-ray images that were quick and simple to collect were used because the covid19 targeted the respiratory systems. By employing residual networks to extract features from these images, classification results were obtained using support vector machines (ResNet-50). The highest overall performance values are SVM-quadratic and SVM-cubic, which are over 99 percent. Based on these encouraging findings, it is anticipated that this research-based method will benefit radiology experts and reduce the rate of false positives [19].

J. RABBAH et al (2020) A unique classification system based on the Stack Net metamodeling technique is the presented Cov Stack net. The cornerstone for feature extraction from X-ray pictures was a deep CNN. The projected model outperforms the elementary models in terms of accuracy, scoring 98% [20].

Materials and methods

In this section, we analyze data sets for detecting several images which contain pneumonia and covid-19 images.

Dataset

We use two freely available datasets that contain X-ray images in our analysis. The first dataset is an altered version of Paul Mooneys Chest Images of X-Ray Pneumonia, dataset [21], with the number of training and validation observations rebalanced to allow for a more balanced ML exercise. 5,856 observations in all are included in this collection (photos). 4,192 training observations have been made (1,082 normal cases, 3,110 lung-opacity cases). There are 624 testing observations and(1,040) validation observations (234 regular cases, 390 lung opacity cases).

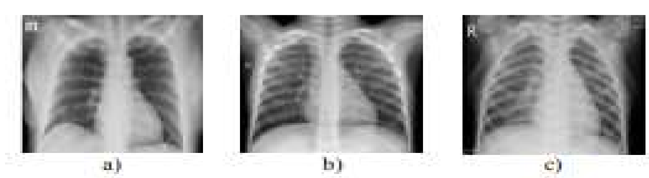


Figure 4 X-Ray dataset was utilized for some of the illustrative photos

A database of COVID-19 patients with chest X-ray or CT images makes up the second dataset [22]It includes Covid-19 instances of ARDS, MERS, and SARS.

Problems Domain

In computer vision, deep learning has already shown that it can identify images with superhuman accuracy. Further research into deep learning is being done in the field of medical image processing. However, a significant problem in the medical field is the lack of sizable datasets with high-quality ground-truth annotation. The most important effect of this new coronavirus is how contagious it is, which puts an end to life as we know it. The development of COVID-19 diagnostics will pick up steam as more knowledge about the biology of this lethal virus becomes available. The current gold standard for COVID-19 illness identification relies on time-consuming, human error-prone swabs from the nose and throat. The sensitivity of these tests is not high enough for early detection.

Proposed Methodology

Due to the scarcity of X-Ray pictures of lungs, we used two ways in patients with COVID-19.

Custom CNN model (End-to-End Trained)

A DL-CNN framework was created and trained from scratch to distinguish between healthy and sick lungs using a huge number of historical (non-COVID-19) pulmonary X-Rays from Ch experts. Simple neural networks are typically a great place to start when using deep learning to address an image categorization task. They do, however, have limitations, and beyond a certain point, the model's performance plateaus. Custom-trained convolutional neural networks (CNNs) can be used in this situation. Applications for computer vision use them frequently. And it's a concept that, in my opinion, any computer vision enthusiast needs to quickly grasp. The record established was divided into two sections: 20% for testing and 80% for training. 20% of the training data was supplied for validation.

Proposed Algorithm

Step 1: First, load the datasets

Step 2: The step-two CNN model is intended to be trained for distinguishing between healthy and unhealthy lungs.

Step 3: The data set was split in half, with 20% used for testing and 80% for training. The validation received 20% of the training data. Each training has three labels: X-ray, standard X-ray, and pneumonia.

Step 4: The model was trained with COVID-19 X-Ray pictures, further layers were added, and the model weights were frozen.

Step 5: Launch CNN

Step 6: As part of the picture processing, normalize the input (255,255).

Step 7-A, which used transfer learning, chose four models—ResNet50, VGG16, and VGG-19—that could extract features with just the right amount of fine-tuning.

Step 8: Print out each model's categorization findings.

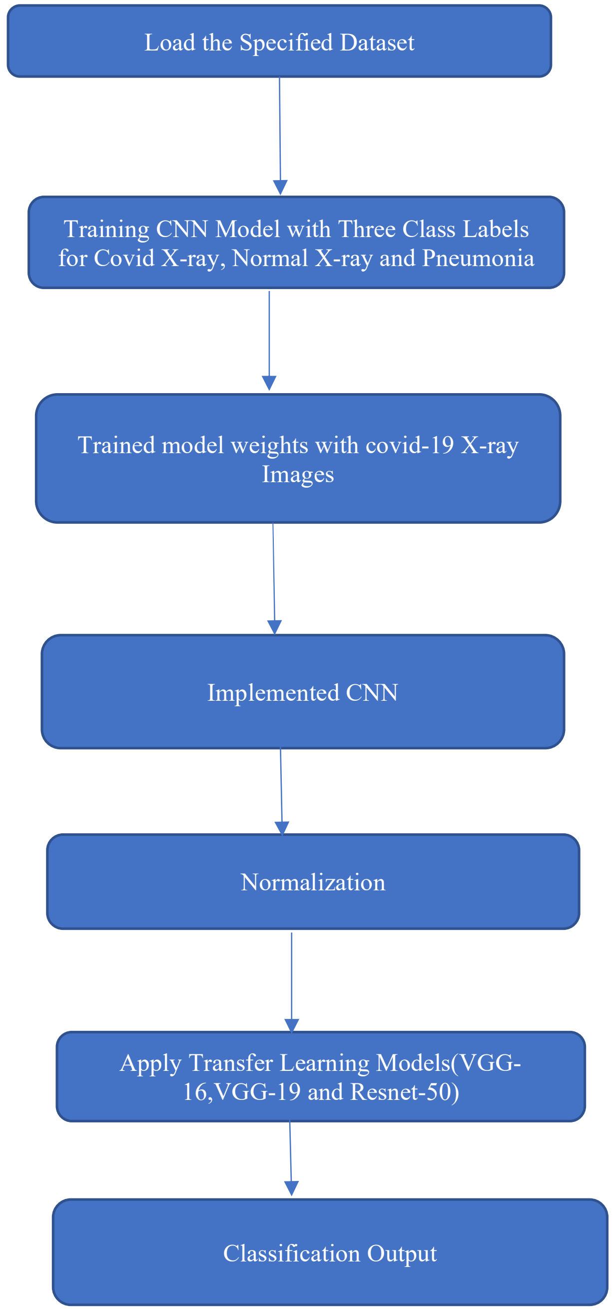


Figure 5 .A Block chart of the Proposed Approach

The abstract perspective of our suggested strategy, which includes three class labels, an 80:20 training-to-testing ratio, and a variety of deep learning and transfers learning ideas, is shown in the above image. Start by training a custom CNN with a large library of chest X-ray images that aren't from COVID-19 (expert). Then, using the scant COVID-19 data, the model is adjusted. This technique produced Model 1, which was unable of identifying COVID-19 sick people. The alternative strategy entailed importing already-trained DL models and applying COVID-19 data to train them. In this work, we created and altered three models based on ResNet50 (Model 2), VGG16 (Model 3), and VGG19 (Model 4).

2 Results and Discussion

In the simulation segment, we define planned results for detecting covid-19 in pictures utilizing several methods. For the current study, we used two of the most commonly used deep models in competitions, namely ResNet50, VGG16, and VGG19, which were capable of feature extraction and fine-tuning.

```
In [4]: for wdir in os.listdir('dataset_Xray_images'):
            print(wdir)
            wdir_total = 0
            for label in class_labels:
                total = len(os.listdir(os.path.join('dataset_Xray_images', wdir, label)))
                print(label, total)
                wdir_total +=total
            print(wdir,'-----',wdir_total)

        test
        Covid-Xray 135
        Normal-Xray 128
        PNEUMONIA 177
        test ----- 440
        train
        Covid-Xray 537
        Normal-Xray 508
        PNEUMONIA 490
        train ----- 1535

In [5]: nb_train_samples =1535
        nb_test_samples = 440
        num_classes = 3
        img_rows= 64
        img_cols= 64
        channel = 3
```

Figure 6 Load dataset with training and testing images

In the above figure, we load the dataset for x-ray images and print the class labels i.e., covid X-ray, normal x-ray, and pneumonia which have 135,128 and 177 ratios meaning a total of 440 test images. On the other hand, three labels have 537,508 and 409 training ratios which means they have a total of 1535 training ratio which has 64,64 and 3 rows, columns, and channels respectively.

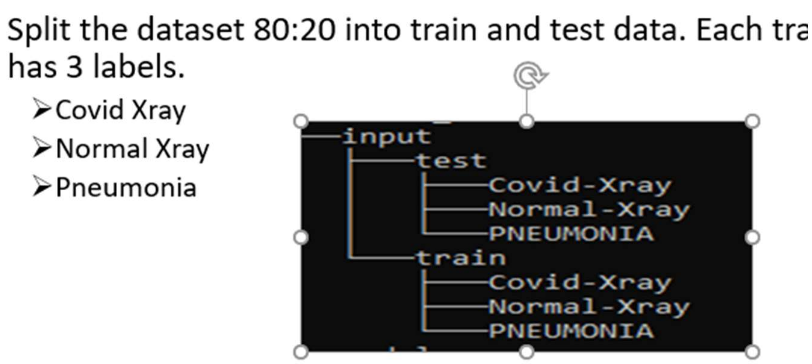
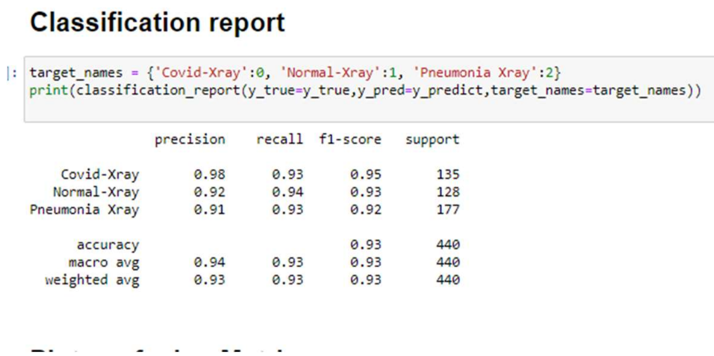


Figure 7 .Dataset with Class Labels

The above figure shows the ratio of training and testing datasets i.e., 80:20 which have three class labels.

We print the input image and normalize it as part of the image processing procedure. The crucial step of data normalization ensures that the data distribution for each input parameter is similar. This facilitates network training while accelerating convergence.



Classification report

```
target_names = {'Covid-Xray':0, 'Normal-Xray':1, 'Pneumonia Xray':2}
print(classification_report(y_true=y_true,y_pred=y_predict,target_names=target_names))
```

	precision	recall	f1-score	support
Covid-Xray	0.98	0.93	0.95	135
Normal-Xray	0.92	0.94	0.93	128
Pneumonia Xray	0.91	0.93	0.92	177
accuracy			0.93	440
macro avg	0.94	0.93	0.93	440
weighted avg	0.93	0.93	0.93	440

Figure 8 Classification Results of Implemented CNN

In the above figure implemented CNN and get the classification results as precision, recall, f1-score, and support with three class labels.

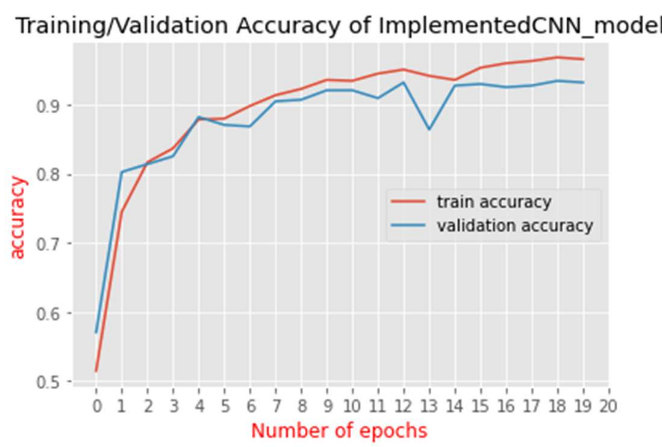


Figure 9 Training/Validation Accuracy Graph of implemented CNN

The training/validation accuracy curve of the implemented CNN model in terms of accuracy and number of epochs is shown in the above image. Validation accuracy is 97%, while training accuracy is 98%.

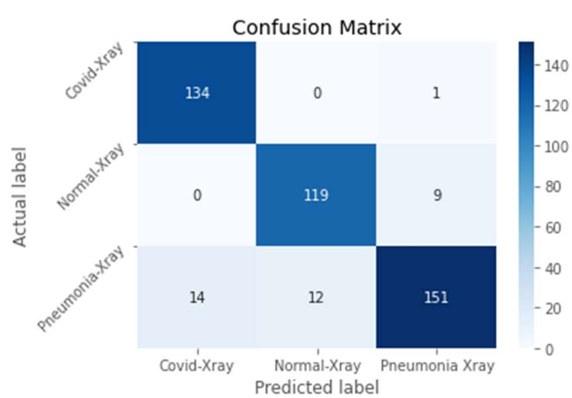


Figure 10 Confusion Matrix Graph of Implemented CNN

In the image above, the confusion matrix of implemented CNN is shown for three labels (pneumonia, standard x-ray, and covid X-ray), where the matrix is created using predicted label vs. actual label.

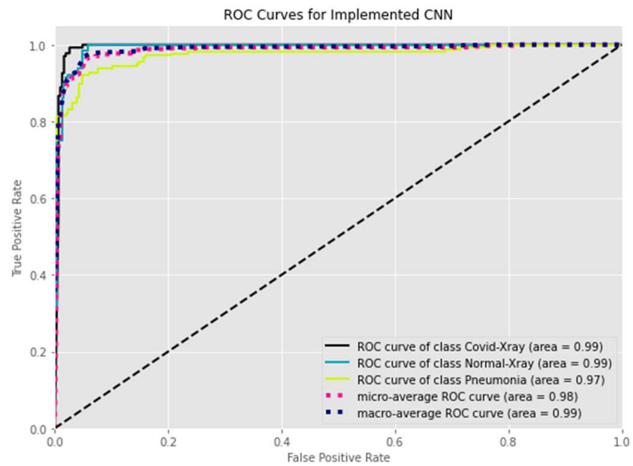
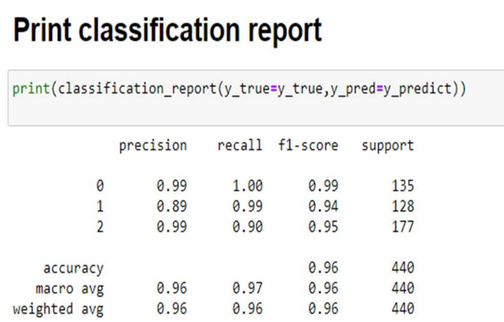


Figure 11 .ROC Curve Graph for Implemented CNN

The graph above shows the actual CNN ROC curve between the true-positive rate and the false-positive rate. We get a micro average ROC curve area of 0.98 and 0.99, respectively, for the covid X-ray class, 0..99 for the normal X-ray, 0.97 for the pneumonia X-ray, and 0.99 for the normal X-ray class.



Print classification report

```
print(classification_report(y_true=y_true,y_pred=y_predict))
```

	precision	recall	f1-score	support
0	0.99	1.00	0.99	135
1	0.89	0.99	0.94	128
2	0.99	0.90	0.95	177
accuracy			0.96	440
macro avg	0.96	0.97	0.96	440
weighted avg	0.96	0.96	0.96	440

Figure 12 Classification Results of Resnet-50

Applying ResNet-50 yields the classification results shown in the above figure as precision, recall, f1-score, and support.

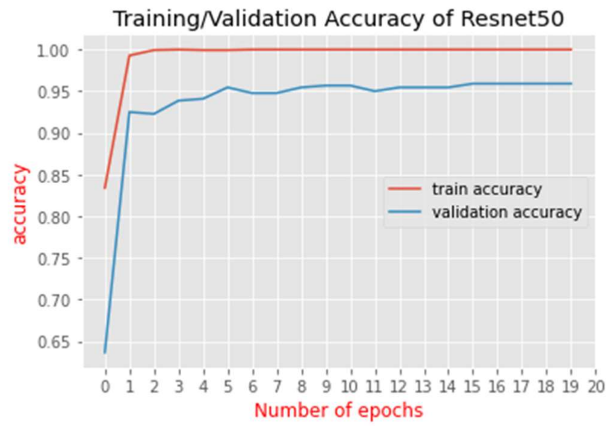


Figure 13 Training/Validation Accuracy Graph of Resnet-50

In the above figure, we get the training/validation accuracy graph of the resnet-50 model in terms of accuracy and no. of epochs. We get a training accuracy of 96% and a validation accuracy is 100%.

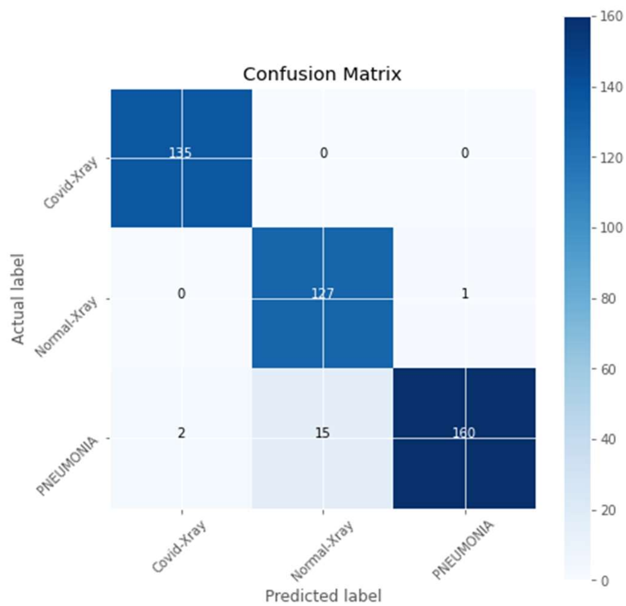


Figure 14 Confusion Matrix Graph of Resnet-50

. The confusion matrix of resnet-50 for three labels—pneumonia, normal x-ray, and COVID X-ray—is shown in the above picture, where the matrix is calculated based on the predicted label vs. the actual label.

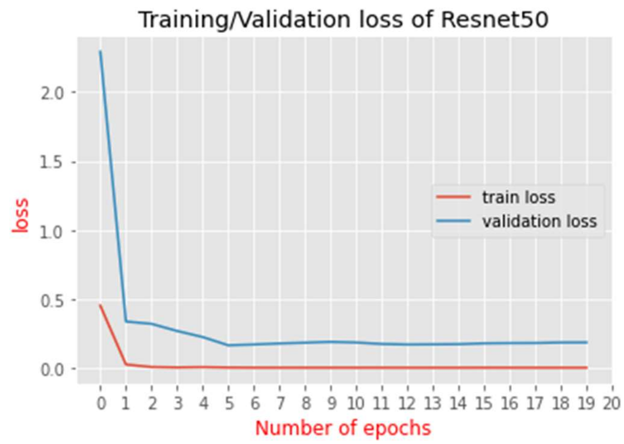


Figure 15 Training and Validation Loss of Resnet-50

The above graph displays the resnet-50 model's training and validation loss in terms of loss and the number of epochs. We demonstrate that the validation loss is 0.2 and the training loss is 0.0.

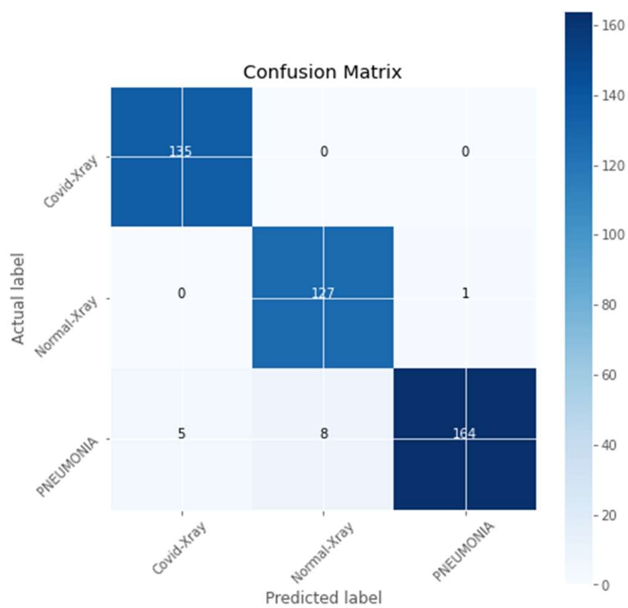


Figure 16 Confusion Matrix Graph of VGG-19

the above figure shows the confusion matrix of VGG-19 for three labels (covid X-ray, normal x-ray, and pneumonia) where the matrix is performed by predicted label vs actual label.

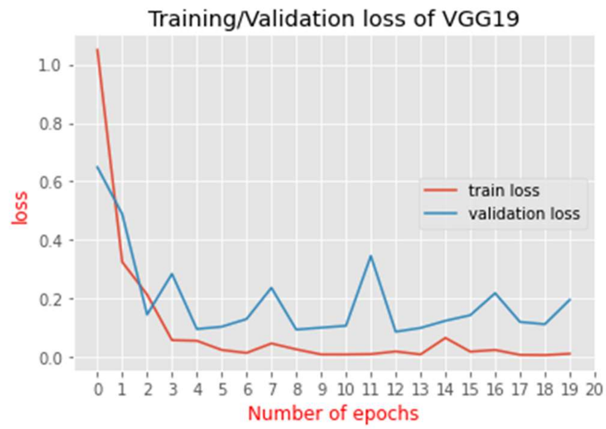


Figure 17 Training and Validation Loss of VGG-19

The above graph shows the training and validation loss of the VGG-19 model in terms of loss and the no. of epochs. we show that the training loss is 1.2 and the validation loss is 0.6.

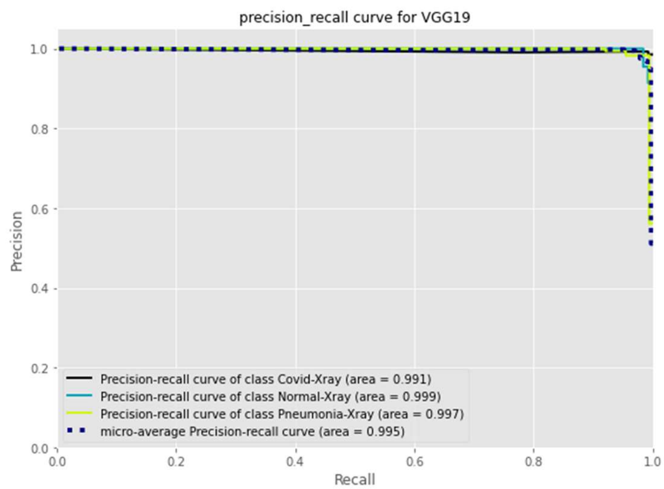


Figure 18 Precision recall curve for VGG-19

In the above figure, we can show the precision-recall curve for VGG-19 between precision and recall values. We get 0.991 area for covid X-ray class,0.999 for normal X-ray,0.997 for pneumonia X-ray and the micro average precision-recall curve area is 0.995.

Conclusions and Future Roadmap

It is critical to diagnose COVID +ve patients as soon as possible to prevent the disease from spreading and keep it under control. This study was carried out to detect COVID +ve patients using Chest X-Ray pictures in a simple and low-cost manner. First, in the approach suggested in this study, a huge data set of non-COVID-19 X-ray chest pictures is used to train a bespoke CNN, which is then used to normalize the images. The model is then fine-tuned using the tiny COVID-19 data. Four cutting-edge transfer learning models (resnet-50, VGG-16, and VGG-19) with 96,97, and 97 percent accuracy have been used. It is hoped that this research, combined with the GUI interface, would assist clinicians in detecting afflicted individuals using computer-aided analysis in a matter of seconds. We feel that this will greatly enhance the medical field's worth. The SARS-CoV2 virus, often known as a coronavirus, has killed thousands of people worldwide. Medical imaging and computer-assisted diagnostics have enabled researchers and physicians to diagnose and identification of a wide range of illnesses. The application of Transfer learning in classification has assisted in the automation of the detection procedure. The goal of this study is to talk about how to use chest X-ray pictures to diagnose Coronavirus infection in people. In the future, we will look at specific picture elements that may be used to link radiology answers with other data sources for example epidemiological histories, medical features, and hematological studies to improve diagnosis accurateness in a multi-modality integration framework. Furthermore, we will apply our transfer learning technique to a large dataset to obtain accurate and actual results. Another transfer learning model can be used to forecast more correctly.

Acknowledgements

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