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Detecting COVID 19 using Deep Learning

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Abstract: ***Corona virus disease 2019 (COVID 19) is defined as illness caused by novel corona virus now called severe acute respiratory syndrome corona virus 2 (SARS-Cov-2; formally called as 2019-nCov), which was first identified in Wuhan City, Hubei Province, China. The spreading of COVID 19 is very fast throughout the world. World economy as well as public health has been facing a devastating effect caused by COVID 19.***

Hence detecting COVID 19 is challenging task even we have multiple methods like RT-PCR, COVID kits. The RT-PCR may not available in all laboratory, even exists which take some time to process and get reports and COVID 19 test kits may not available in all places. So, the main intention of this paper is to detect COVID 19 with in low budget, less time and accurate results. We have trained deep transferred learning models like ResNet-50, ResNet-101 using COVID positive, Normal, Viral Pneumonia chest x-rays. ResNet-50, ResNet-101 is pre-trained deep learning neural network. ResNet-50 provides 98% of accuracy where ResNet-101 gives us 97% of accuracy.

Keywords: COVID 19, Deep Learning, ResNet-50, Transferred Learning, Artificial Intelligence.

I. INTRODUCTION

COVID-19, the pandemic that has brought the world to a halt, was reported in Wuhan, China in the December of 2019 for the first time, when patients with cases of unidentified pneumonia emerged. The virus responsible for the disease, named SARS-CoV-2, belongs to a family of corona viruses that are zoonotic in nature. Until SARS-CoV-2 surfaced, six types of corona viruses were known to be able to harm humans by mainly targeting the respiratory system. Among them, two had caused epidemics in the last two decades named SARS-CoV and MERS-CoV. Despite the mortality rates of these epidemics being much higher than that of COVID-19 (10% for SARS and 30-35% for MERS), the cumulative number of deaths for the latter has surpassed that of both the epidemics combined by many folds [1]. As of 28 June 2020, the total number of global cases and deaths exceed 9.8 million and 4.9 lakh respectively [2].

The common clinical characteristics of COVID-19 include a range of symptoms mutual with other viral diseases such as the common cold. In more severe or progressed cases, pneumonia, development of fluid in the lungs, acute respiratory distress syndrome (ARDS), multiorgan failure, septic shock as well as death may occur. Elderly people or people exhibiting comorbidity having a compromised immune system are highly prone to infection and severity. On the other hand, many individuals do not show any symptoms despite being carriers of the virus. This makes detection and containment of the virus even harder. Along with being a highly contagious disease, COVID-19 has a long incubation period, on average, five to six days between the contact and symptom onset phases. Thus, abiding by preventive measures such as social distancing, hygiene maintenance, and contact tracing and enabling a system that can diagnose the disease earlier and faster is paramount.

At present, the eminent standard for diagnosing COVID-19 is the reverse transcription-polymerase chain reaction (RT-PCR) which identifies the nucleotides of the virus from specimens extracted from a nasal swab or oropharyngeal swab. One of the major drawbacks of this method is the tedium involved and the time required as the fastest turn-around time is at least 24 hours. Added with the rapid spread and hence an increased number of specimens collected, the laboratories very rapidly get overwhelmed. Furthermore, it is laborious, relatively expensive, and has a low sensitivity (60%–70%) [3]. Many countries suffer from false results due to multiple plausible causes such as specimen handling, stage of disease when the specimen is collected, and quality of the specimen [4]. With limited resources i.e. testing kits, hospital beds and ICU beds, ventilators, personal protective equipment (PPE), the healthcare systems around most of the globe are loaded at the havoc and bound to make selective decisions in terms of testing, patient admission, ICU beds as well as the provision of ventilators.

Radiography chest images (X-ray and CT scan) analysis is a valuable alternative of the PCR method. They may assist in multiple ways from diagnosing the disease to sorting out the high-risk patients for quarantining and prioritizing while selective testing to identifying the false-negative PCR cases. However, since most viral cases of pneumonia' images are akin and overlap, it is very difficult and time consuming for radiologists to distinguish the fine details by vision. Artificial Intelligence models can be a prompt solution. Very recently, the deep learning (DL) approach have been very popularly and successfully used in medical image classification applications owing to its powerful accuracy.

Some of the very recent works in detecting COVID-19 involves the application of various DL approaches. Due to the problem of COVID-19 being very recent, the unavailability of immense datasets has caused most of the works to use the technique called transfer learning. For instance, Ozturk *et al.* [5] presented a new model, DarkCovidNet which was a modified form of the Darknet-19 model for automatically detecting COVID-19 from raw images (Chest X-ray). 98.08% accuracy was achieved by their model for binary classification for indicating the presence of COVID-19 and 87.02% accuracy was obtained for multi-class classification between COVID-19 and pneumonia. In another study [6], three pre-trained deep CNN based models (Inception-ResNetV2, ResNet-50, and InceptionV3) were used for the automatic identification of COVID-19 pneumonia infected patients from the X-ray radiographs of the chest. Their results indicated that ResNet-50 displayed superior performance compared to the other two models. ResNet-50 showed an accuracy of 98%, InceptionV3 had 97% accuracy and 87% accuracy was shown by the other model. Hemdan *et al.* [7] introduced COVIDX-Net, a new DL framework that was created on the basis of seven different architectures of deep CNN (Xception, VGG19, MobileNetV2, DenseNet201, InceptionResNetV2, ResNetV2, and InceptionV3). Identifying COVID-19 from X-ray images (chest) by using this framework was the main objective. The best performance in this framework was displayed by DenseNet201 and VGG19 obtaining an f1 score of 0.91 for classifying COVID-19. Moreover, in a study [8] of detecting COVID-19 pneumonia as well as viral pneumonia, the researchers developed a public database where COVID-19 and viral pneumonia along with normal X-ray images of the chest were the constituents. Their work was to test four pre-trained CNNs namely, ResNet18, AlexNet, DenseNet201, and SqueezeNet on two schemes. One scheme was COVID-19 pneumonia and normal classification whereas the other scheme was COVID-19 pneumonia, viral pneumonia as well as normal classification. From SqueezNet, both the schemes achieved 98.3% accuracy which was the highest among the networks. Image augmentation played a vital role in obtaining such a level of accuracy. Farooq *et al.* [9] presented a work where an existing pre-trained architecture named ResNet-50 was fine-tuned for its performance improvement to identify COVID-19 and other pneumonia cases (bacterial, viral). The fine-tuned version of the architecture was called COVID-ResNet. 96.3% accuracy was achieved by their model. Furthermore, a study [10] to classify the images (chest X-ray) to viral pneumonia along with COVID-19 and normal cases was done. Their classifier was CheXNet based and transfer learning was implemented. Results indicated an accuracy of 97.8% of their presented model.

In this research, a deep convolutional neural network (DCNN) based on a pre-trained model for the automatic detection of COVID-19 from two other classes (Viral Pneumonia and normal chest X-ray images) was proposed. For this purpose, we used a fine-tuned ResNet-50 previously trained on the ImageNet dataset in our model. For the experiment, we used chest X-ray images rather than CT scans to fine-tuned the ResNet-50 model for classification. X-rays are relatively cheaper, quicker, lower patient dose, and more widely available in contrast to the expensive, higher radiation exposure and time-consuming CT scan machines and scans. Furthermore, portable X-ray machines allow for testing within an isolation ward, thus reducing risks of nosocomial infections and the number of PPEs used.

Organization of the remaining parts of the paper is as follows: Section II comprises of materials and methodology that provide details of the dataset containing X-ray images (chest), data pre-processing, details of dataset splitting, and the description of the proposed deep transfer learning network architecture. Experimental results and discussion, performance evaluation, and the result comparison with the current research-based methods are presented in Section III, and lastly, the conclusion of the paper resides in section IV.

II. MATERIALS AND METHODOLOGY

A. Dataset

A total of 2947 COVID-19 chest X-ray images were obtained from kaggle; The average age for the COVID-19 group was 58.8±14.9 years, and it comprised 131 male patients and 64 female patients. Note that some patients' information is missing; this is because the dataset used in this study does not have accompanying complete metadata, because this is the very first publicly available COVID-19 X-ray image collection, and it was created in a limited time. In addition, 8926 normal and 1027 pneumonia chest X-ray images were obtained from kaggle.20 All images were in different dimensions, so they were resized to 256 × 256.

B. Design of Experiment

Actually, DCNN performs well on larger datasets than which is having smaller data. Transferred learning algorithms are most suitable when we have limited collection of data. These transferred learning algorithms are pre-trained with millions of images. In our experiment we use Deep transferred learning algorithms to train COVID 19 positive, Normal, pneumonia x-rays for the classification purpose.

The experiment starts with collecting the data, here data in terms of radiography chest x-ray images, we gone through a pre-processing and image augmentation techniques to increment variations of images and to get more accuracy score on classification of image. The classification model we used here is more powerful pre-trained transferred learning model ResNet-50, ResNet-101. ResNet-50 is 50 layer deep Convolutional neural network which was trained on millions of images with 20,000+ categories using ImageNet weights.

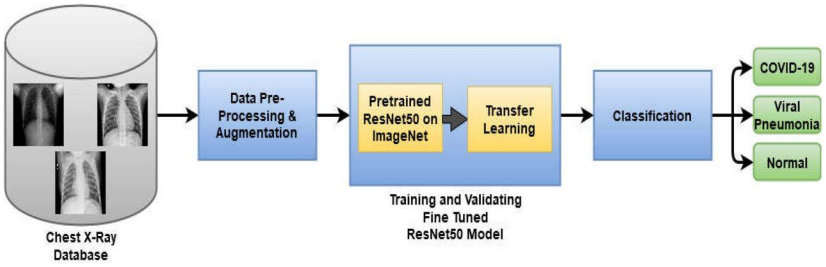


Fig 1.Workflow of proposed system for COVID-19 detection from chest X-ray images using Pre-trained ResNet50 and Transfer Learning

C. Chest x-ray Database

This database consists of COVID 19 positive, Normal and Viral phenomena radiography chest x-ray images. These images are Portable Network Graphics (PNG) and with the size of 299×299 pixels. These Normal, viral phenomena and COVID 19 positive images are collected from Kaggle and various git hub data resources. We can able to see some sample x-ray images as below.

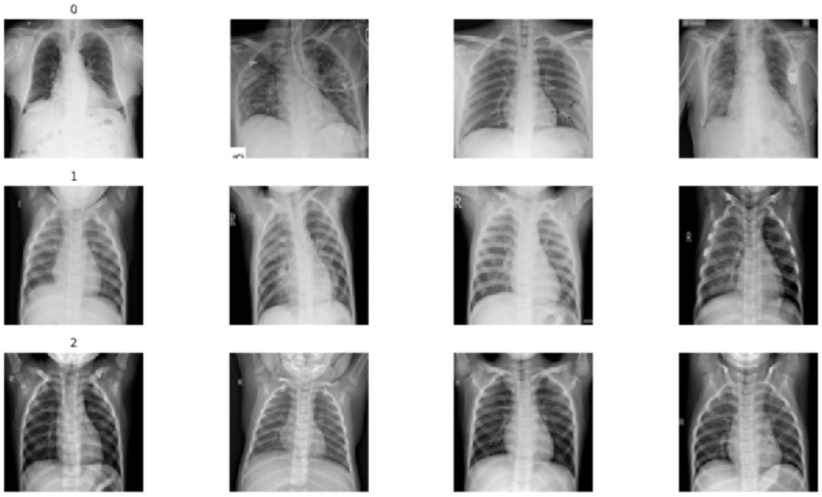


Fig II. Sample images from dataset related to three classes COVID, phenomena, Normal images

D. Data Pre-Processing

As chest x-ray images are collected from different resources over the internet so, every x-ray has its own size (height, width). We resize all chest x-rays to 299 ×299 pixels and converts into gray scale images. Every image turns to 3 channel as an input shape of 299 ×299×3 to machine learning algorithm furthermore all these are scaled to improve the speed of model training and to get greater performance. Generally we use Z-normalization / Standardization techniques used to scale the data with below formula.

$$\hat{X} = \frac{X[:i] - \mu_i}{\sigma_i} \qquad (1)$$

In this step only we have applied data augmentation technique. Using this technique we can generate more images by applying flip, zoom, shrep techniques. Which increases the size of our training dataset and model becomes more accurate by applying this technique. We have used keras 'ImageDataGeneror' method to rotate the images, zoom the some sample images.

E. Database Split

Before train our deep learning model, we have split the database into training, validation, test datasets in the ration of 80% of training dataset, 10% validation dataset, 10% test dataset. The data counts as follows after splitting the dataset

1) Training Dataset having 280 Covid 19 postive, 1200 viral pneumonia and 1200 Normal images.
2) Validation Dataset having 35 Covid 19 postive, 150 viral pneumonia and 150 Normal images
3) Test Dataset having 35 Covid 19 postive, 150 viral pneumonia and 150 Normal images.

Table I explains the distribution of images into training, validation and test sets after splitting the database.

F. ResNet-50 and Transferred Learning

ResNet, shorts for Residual Network is a classic neural network used as backbone for many computer vision tasks. This model is winner of Imagenet challenge in 2015. The fundamental breakthrough with ResNet was it allowed us train extremely deep neural networks with 150+ layers successfully. Prior to ResNet training very deep neural network was difficult due to problem of vanishing gradients. In this study, we have used 50 layer ResNet 50 the base architecture of the model and fine tuned for our classification problem.

This model is very similar to how we read the words with prior knowledge of alphabets. In similar way models can be created using the knowledge that have been trained on similar data domain. These are very useful as they are trained on very large datasets.

Hence, its not required to train deep learning model from scratch. It save our time and computational power. ResNet-50 is pre-trained model on ImageNet allow us to use its knowledge on smaller datasets. ResNet Learnt many image patterns so, we retrain our dataset and used for classification purpose known as transferred learning.

G. Proposed Transfer Learning with ResNet-50

The architecture of the proposed model for our task involves a ResNet-50 model followed by 4 additional task-specific layers. The weights of it pre-trained on ImageNet are loaded. The input size of the ResNet-50 is 299×299×3 and it uses average pooling. Figure 4 demonstrates the fine-tuned transfer learning on the ResNet-50 architecture.

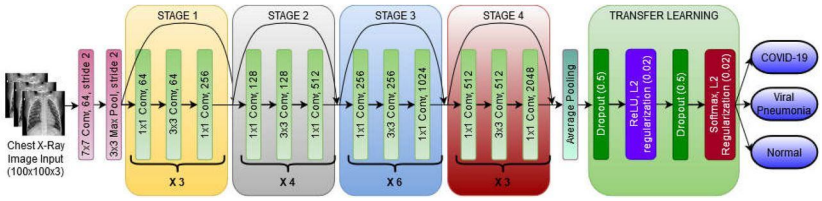


Fig III. Architecture of proposed transferred learning

In this particular work, the DCNN model was fine-tuned and transfer learning applied for classifying images (chest X-ray) to detect COVID-19. The additional layers are replacing the fully connected layer of the ResNet-50. They are a dropout layer with a dropout probability of 50% - this drops 50% of the parameters randomly and reduces over fitting. It is followed by a Rectified Linear Unit (ReLU) activation layer with L2 regularization/ridge regression. The value of the regularization parameter is 0.02. Regularization is needed to prevent overfitting of the model, and it is done so by adding a penalty with the cost function. Next is another dropout layer with 50% dropout probability. And finally is a softmax activation layer with L2 regularization (regularization parameter = 0.02) and an output size of 3 for the 3 classes of COVID-19, viral pneumonia and normal.

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. Database Split

The chest X-ray dataset consists of X-rays of three types: COVID-19, Viral Pneumonia, and Normal. In our implemented fine-tuned DCNN using transfer learning, ResNet-50, 80% data was used for training, 10% of the data for validation, and the 10% was for the testing. To train the neural network, categorical cross-entropy as the loss function for our multi-class classification problem. Moreover. This approach allows us to control the learning rate in a way that helps us travel through all the local minima during the gradient descent algorithm and thus forming multiple models in one neural network. The learning rate starts at a fixed maximum value (of 0.001 in our case), and drops quickly near local minima, and subsequently jumps to the fixed maximum value again. We have selected to have an ensemble of 3 models in this task where each model is comprised of 20 epochs, i.e. we assist the model to converge to a local minimum within 20 epochs. Throughout our experiment, we used a workstation with the Paperspace server (Windows), NVIDIA GeForce GTX 2080ti GPU, 16GB RAM. The DCNN model was executed by the use of python in Keras package, running on TensorFlow backend on Intel Xeon E3, core i5-2.4GHz processor.

B. Overall Performance Analysis

We assessed the performance of our deep transfer learning model for validation and testing dataset considering the following evaluation metrics: accuracy (ACC), precision (PPR), sensitivity or recall (SN), specificity (SP), and F1-score. The following equation measures the performance metrics

$$\text{Accuracy (ACC\%)} = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$\text{Precision (PPR)} = \frac{TP}{TP + FP} \quad (3)$$

$$\text{Sensitivity (SN)} = \frac{TP}{TP + FN} \quad (4)$$

$$\text{Specificity (SP)} = \frac{TN}{TN + FP} \quad (5)$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

The model's classification performance can be observed by the confusion matrices [15] provided in Figure 5.

It is evident that the model is demonstrating a significantly good performance in case of detecting COVID-19 X-rays with correctly predicted fraction of 1 in both validation and test datasets. Bar plot in Figure 6 shows the correctly predicted fraction values for other cases as well.

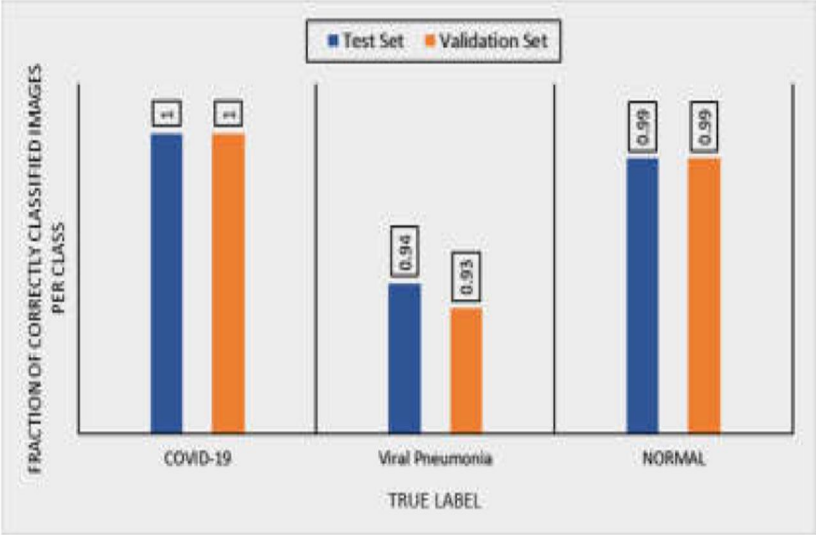


Fig IV Bar plot demonstrating number of correctly predicted images in each class

As the dataset is imbalanced, rather than solely relying on the classification accuracy as a model performance evaluating metric, we considered precision, sensitivity, F1-score and specificity evaluation to justify the preeminence of the implemented model. The model performance is depicted in below table.

Validation dataset					
Class	**Precision**	**Sensitivity (Recall)**	**Specificity**	**F1-score**	**Accurcay (%)**
COVID-19	1.00	1.00	0.99	1.00	97
Viral Pneumonia	0.98	0.93	0.99	0.95	
NORMAL	0.93	0.98	0.95	0.96	
Test dataset					
Class	**Precision**	**Sensitivity (Recall)**	**Specificity**	**F1-score**	**Accurcay (%)**
COVID-19	1.00	1.00	1.00	1.00	96
Viral Pneumonia	0.99	0.94	0.99	0.96	
NORMAL	0.95	0.99	0.95	0.97	

These performance evaluation parameters demonstrate that the model can detect COVID-19 cases with precision = 1.00, sensitivity (recall) = 1.00, specificity = 1.00, and F1-score = 1.00 scores on the testing dataset. Figure 7 and 8 illustrates the precision-recall relationship in individual cases on test and validation dataset.

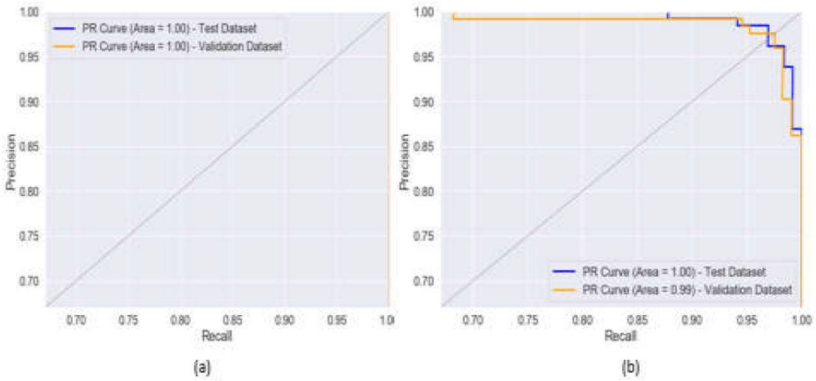


Fig V Bar Precision-Recall curves for the class: (a) COVID-19 (b) Viral Pneumonia

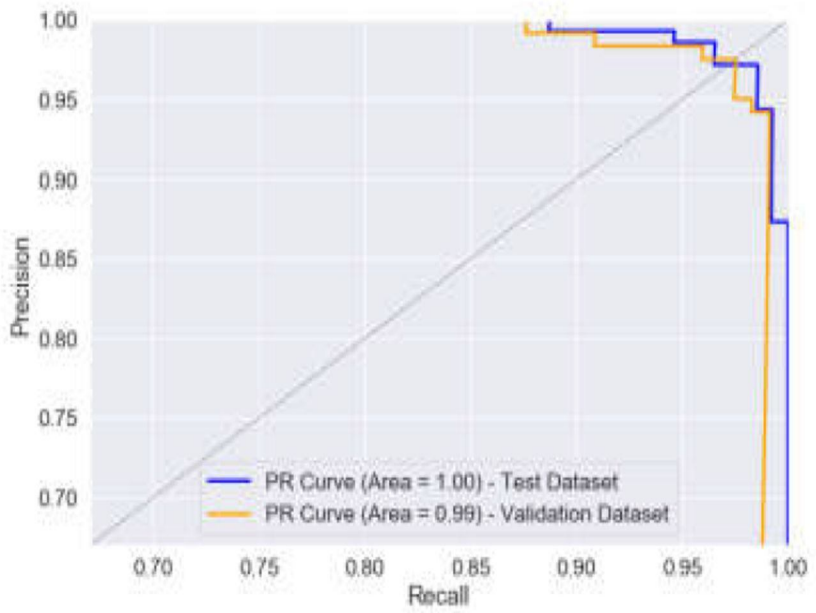


Fig VI Precision-Recall curve for the class NORMAL

The ROC curves representing the TPR and FPR on test and validation dataset for the classes COVID-19, Viral Pneumonia and Normal X-ray, provided in Figure 9 and 10. Identification of COVID-19 from the X-ray images (chest) of viral pneumonia and healthy cases can be done by the model with reasonable accuracy (AUC=100%) as understood from the ROC curves. Therefore, the deep transfer learning model presented in this paper can be a reliable method for faster and accurate COVID-19 affected case detection. However, the model's validation loss is 0.11 and the testing loss is 0.14. The training and validation loss is presented in below figure.

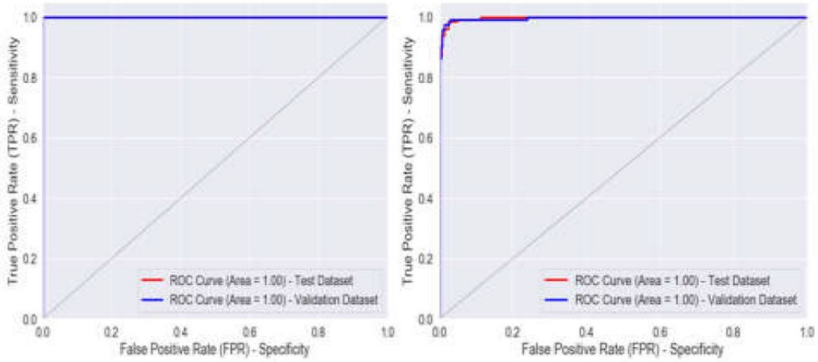


Fig VII ROC curves representing the class: (a) COVID-19 (b) Viral Pneumonia

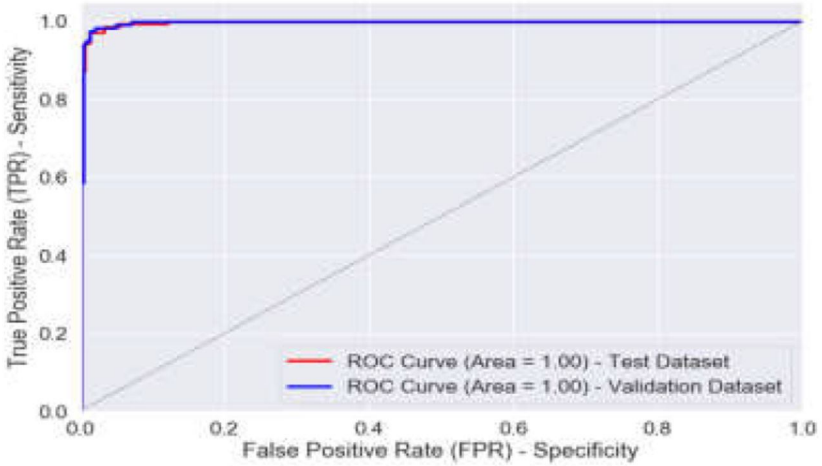


Fig VIII ROC curves representing the class NORMAL

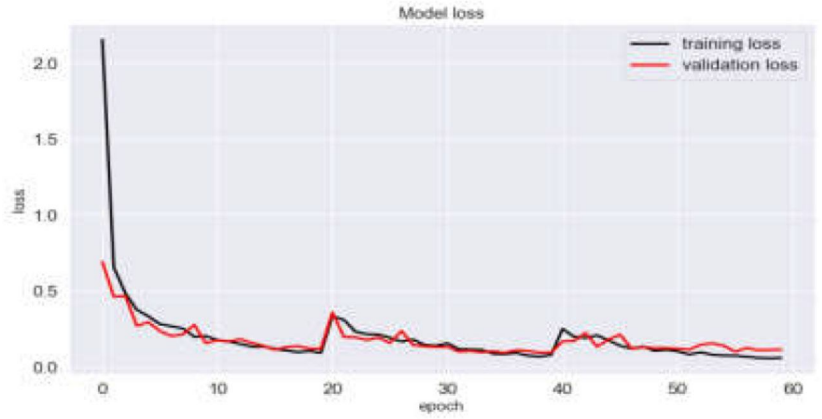


Fig IX Loss between training and validation by ResNet-50 model

To evaluate our classification, we compared our proposed COVID-19 classifier with state-of-the-art approaches. Table III provides a comparison of our proposed model's performance with the previously existing model. Our proposed model clearly outperforms some of the conventional methods in detecting COVID-19 by achieving 96.9% of average classification accuracy.

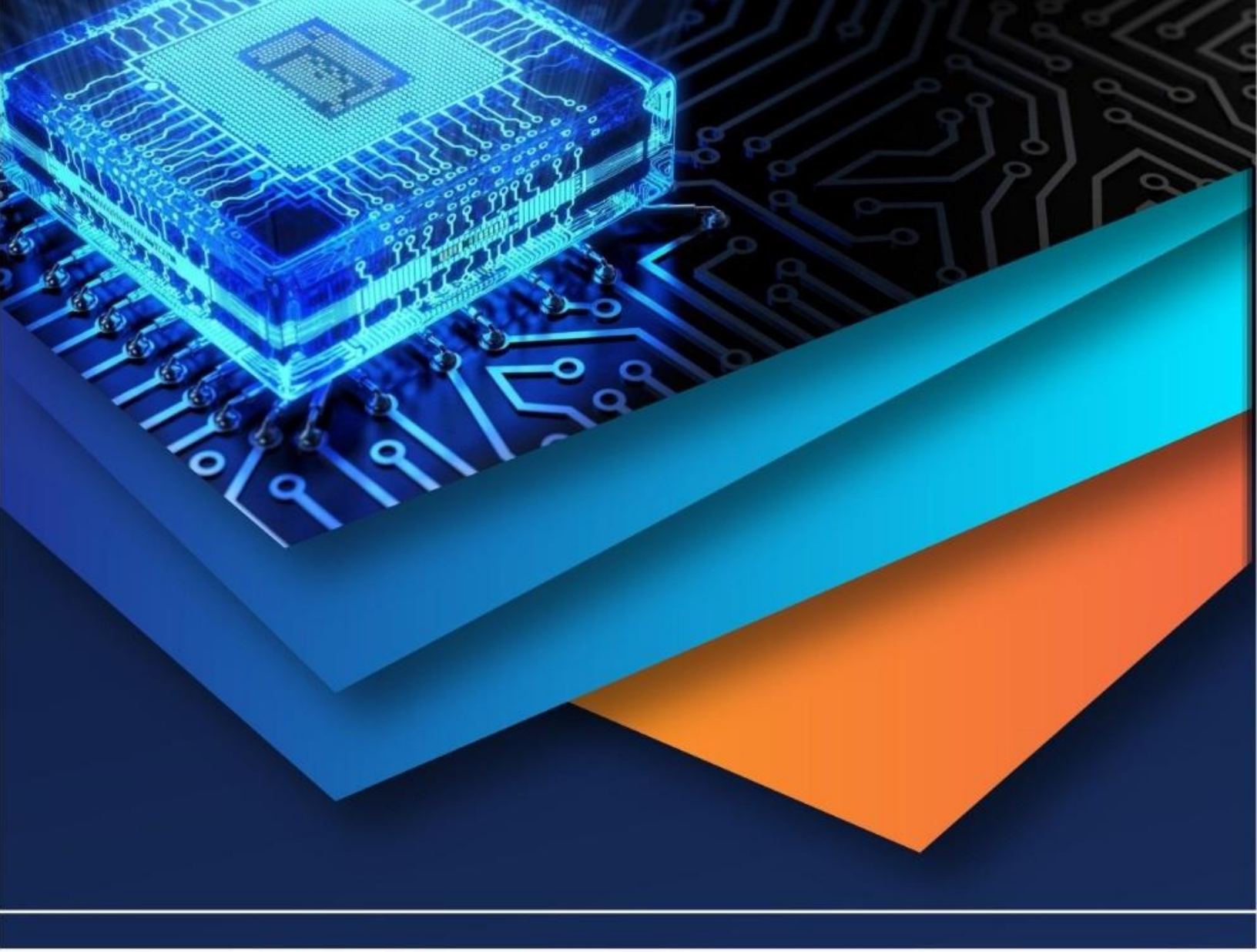
Model	Precision	Recall	F1-score	Accuracy
Proposed (Weighted average)	0.97	0.97	0.97	96.9%
ResNet-50 [6] (Binary-class)	1.00	0.96	0.98	98.0%
VGG19 [7] (Binary Class)	0.83	1.00	0.91	90.0%
SqueezeNet [8] (Multi-class)	1.00	0.97	0.98	98.3%
COVID-ResNet [9] (Multi-class)	0.97	0.97	0.97	96.2%
CheXNet [10] (Multi-class)	0.98	0.98	0.98	97.8%

IV. CONCLUSIONS

In this study, a deep transfer learning model for detecting COVID-19 automatically from images (chest X-ray) along with two other classes (Viral Pneumonia and normal chest X-ray images). The model was trained using a pre-trained network ResNet-50. Later, transfer learning is applied to the pre-trained network for faster and efficient training which improved the performance of the model. The experimental analysis confirmed that the emerging deep neural network effectively performed in detecting COVID-19 from X-ray images as opposed to existing state-of-the-art methods. Several data augmentation and preprocessing have been performed in order to increase the size of the training dataset. Performance results demonstrate that the model achieved the validation and testing accuracy of 97% and 96% respectively. Moreover, the model exhibits exceptionally well in classifying the COVID-19 cases in the test dataset with a Precision of 1.00, Sensitivity 1.00, Specificity 1.00, and F1-score of 1.00. In conclusion, we believe that this transfer learning model used in the paper, as well as other presents in the literature, will help doctors to make decisions to detect COVID-19 at its rudimentary stage as the images (chest X-ray) pose an alternate option to the PCR method. In the future, we plan to extend our research by measuring the performance of the different algorithms using a large number of datasets.

REFERENCES

[1] F. Wu et al., "A new coronavirus associated with human respiratory disease in China," Nature, vol. 579, no. 7798, pp. 265–269, 2020. CrossRefPubMedGoogle Scholar
[2] W. H. Organization, W. H. O. (WHO), and others, "Pneumonia of unknown cause--China', Emergencies preparedness, response," Dis. outbreak news, World Heal. Organ., 2020.Google Scholar
[3] X. Xie, Z. Zhong, W. Zhao, C. Zheng, F. Wang, and J. Liu, "Chest CT for typical 2019-nCoV pneumonia: relationship to negative RT-PCR testing," Radiology, p. 200343, 2020.
[4] C. Chen et al., "SARS-CoV-2--positive sputum and feces after conversion of pharyngeal samples in patients with COVID-19," Ann. Intern. Med., 2020.
[5] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images," Comput. Biol. Med., p. 103792, 2020.
[6] A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks," arXiv Prepr. arXiv2003.10849, 2020.
[7] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images," arXiv Prepr. arXiv2003.11055, 2020.
[8] M. E. H. Chowdhury et al., "Can AI help in screening viral and COVID-19 pneumonia?," arXiv Prepr. arXiv2003.13145, 2020.
[9] M. Farooq and A. Hafeez, "Covid-resnet: A deep learning framework for screening of covid19 from radiographs," arXiv Prepr. arXiv2003.14395, 2020.
[10] P. R. A. S. Bassi and R. Attux, "A Deep Convolutional Neural Network for COVID-19 Detection Using Chest X-Rays," arXiv Prepr. arXiv2005.01578, 2020.
[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.
[12] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," in 2009 IEEE conference on computer vision and pattern recognition, 2009, pp. 248–255.
[13] Z. Huang, C. O. Dumitru, Z. Pan, B. Lei, and M. Datcu, "Classification of large-scale high-resolution sar images with deep transfer learning," IEEE Geosci. Remote Sens. Lett., 2020.
[14] H.-C. Shin et al., "Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1285–1298, 2016.
[15] M. M. R. Khan, M. Siddique, A. Bakr, and S. Sakib, "Non-Intrusive Electrical Appliances Monitoring and Classification using K-Nearest Neighbors," arXiv Prepr. arXiv1911.13257, 2019.



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