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Comparative Analysis of Identification of COVID-19 Using Chest X-Ray Images and Machine Learning

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ABSTRACT

The novel coronavirus or COVID-19 is a contagious disease that is severely affecting millions of lives around the world. To date, chest X-ray images and CT scans are widely used to detect if a person is infected with COVID-19. This paper studies some of the recent existing machine learning and deep learning architectures used to classify the Chest X-ray images so that we can identify a COVID-19 infected person. Different machine learning algorithms are used for the identification of COVID-19 and a comparative analysis is done so that it will be easier for the people to identify the infected or those who are suspected to be infected as soon as possible and not spread the disease without being aware of being infected and prevent loss of life. In this paper, four different methods (Resnet50, InceptionResnetV2, Xception, and EfficientNetB7) are used to analyze the chest X-Ray images of the COVID-19 infected patients. A comparative study is also done to analyze their accuracy and other related factors. This paper hopes to bring out the performance of the models that are used under study.

Keywords: *Covid-19, X-Rays, Machine Learning, Deep Learning*

1. INTRODUCTION

COVID-19 or novel coronavirus is a highly infectious disease caused by the SARS-Cov-2 virus. World Health Organization (WHO) declared this outbreak as a pandemic on the 11th of March 2020 whereby 13th May 2021, over 161,566,997 cases were identified globally in 188 different countries, and has over a total of 3,352,365 fatalities and 139,420,292 people also have recovered. This disease has large host ranges and is mostly seen in bats.

Early identification of COVID-19 should be done to quarantine the infected and prevent the spread of the disease as well as loss of life. This can be done by using machine learning approaches. With machine learning, it has become possible for us to understand and identify COVID-19 as early as possible.

2. BACKGROUND

Many approaches and algorithms were used to identify, detect or predict if people are infected or are suspected to be infected with COVID-19 with the help of their chest x-ray images within a short span of 9 to 10 months. These algorithms are introduced to help improve the accuracy and performance of identification. These algorithms are given below in a tabular format along with their accuracies. Das et al. [5] used Xception (Fig. 1) model on chest X-ray images to detect COVID-19. The dataset used here consists of three classes, namely, COVID-19 positive, pneumonia positive, and COVID-19 negative. 70% of the dataset is used for training. The remaining 20% and 10% are used to test and validate respectively. The training model provided an accuracy of 99.5% and the testing model gave an accuracy of 97.4%.

Narin et al [6] used three architectures - InceptionV3, Resnet-50, and Inception-ResNetV2 to detect COVID-19 in chest X-rays. The dataset contains the chest X-ray images of 50 COVID-19 patients and 50 healthy patients [7]. All images in this combined dataset were resized to 224x224 pixel size. The accuracy of InceptionV3 model was 97%, pre-trained ResNet-50 model provided the classification performance of 98% accuracy, and the classification performance of pre-trained Inception-ResNetV2 model was of 87% accuracy.

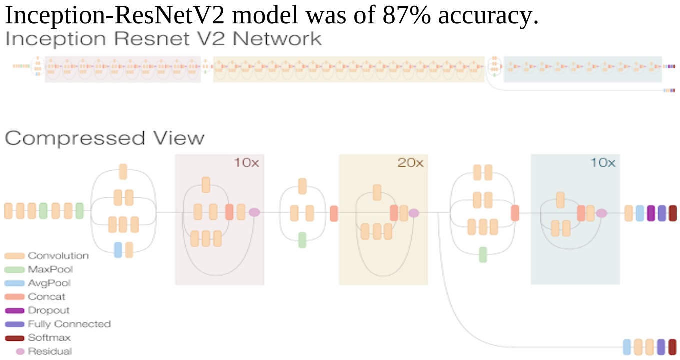

Fig. 1. Schematic diagram of the InceptionResnetV2 Architecture [21]

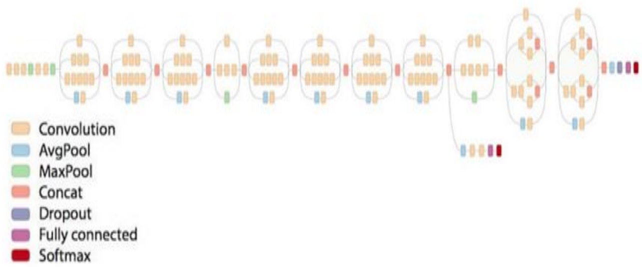

Fig. 2. Schematic diagram of the InceptionV3 Architecture [20]

Table 1. Literature survey of machine learning approaches for identification of COVID-19

	Image type	*Method used*	*Accuracy*	
Das et al. [5]	X-ray	Extreme version of the Inception (Xception) model	Testing: 99.5% Training: 97.4%	
		InceptionV3	97%	
Narin et al. [6]	X-ray	ResNet-50	98%	
		Inception-ResNetV2	87%	
Ozturk et al. [8]	X-ray	DarkNet	98.08% for two classes ('Covid-19' and 'No findings') 87.02% for 3 classes ('Covid-19', 'Pneumonia' and 'No findings')	
Shibly et al. [9]	X-ray	VGG-16 (Faster R–CNN) framework	97.36%	
Hemdan et al. [10]	X-ray	COVIDX-Net framework based on 7 classifiers:		
		i) VGG19	90%	
		ii) DenseNet201	90%	
		iii) ResNetV2	70%	
		iv) InceptionV3	50%	
		v) InceptionResNetV2	80%	
		vi) Xception	80%	
		vii) MobileNetV2	60%	
Farooq et al. [11]	X-ray	COVID-ResNet	96.23%	
Hassantabar et al. [14]	MRI	DNN and fractal features Classification (with feature extraction)	83.4%	
		CNN (without feature extraction)	93.2%	
Altan et al. [15]	X-ray	EfficientNet-B0	95.24%	
		EfficientNet-B0 (2D curvelet transform)	96.87%	
		EfficientNet-B0 (2D curvelet transform-CSSA)	99.69%	
Tuncer et al. [16]	X-ray	ResExLBP and IRF based feature selection using the following 5 classifiers:	LOOCV (%)	10-fold CV (%)
		i) Decision Tree (DT)	92.83	96.63
		ii) Linear discriminant (LD)	99.07	99.11
		iii) kNN	97.20	96.63
		iv) SVM	99.69	99.55
		v) Subspace discriminant (SD)	99.07	98.70
Yoo et al. [17]	X-ray	Deep learning-based decision-tree classifier	95% (of 3rd Decision Tree)	

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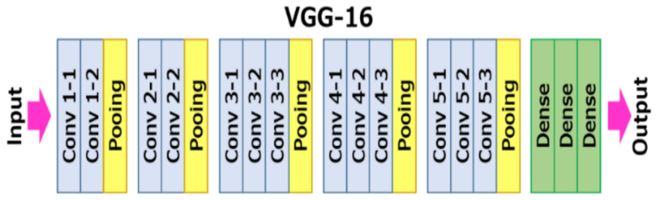


Fig. 3. VGG-16 Architecture [9]

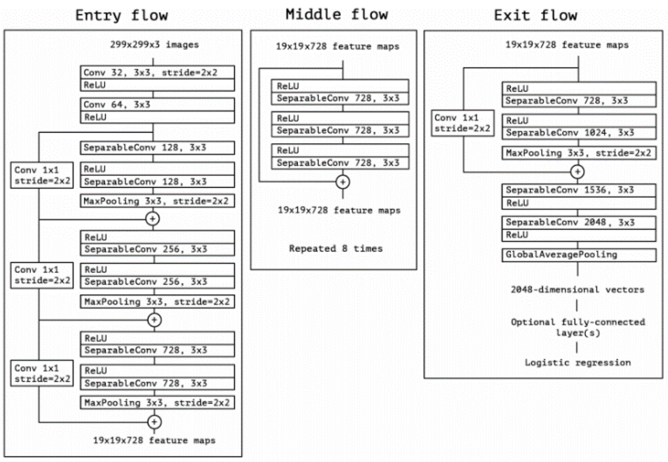


Fig. 4. Xception Model Architecture [26]

Farooq et al [11] built a CNN framework to differentiate COVID-19 and pneumonia. The authors used the open-sourced and open accessed COVIDx [13] dataset. COVIDx dataset consists of 5941 chest X-ray images divided into 4 different classes which are COVID-19, bacterial, viral, and normal. They built COVID-ResNet [12] model using a pre-trained ResNet-50 architecture to improve its performance. This approach achieved an accuracy of 96.23% (on all the classes) with 41 epochs. Hassantabar et al [14] used two methods which are Deep Neural Network (DNN) method with fractal feature and Convolutional Neural Network (CNN) on CT scan images. There are 682 X-Ray images of lungs in the dataset. The CNN method provided a higher accuracy of 93.2% and 96.1% sensitivity whereas the accuracy of DNN method was 83.4% and sensitivity was 86%. They also used another dataset called COVID-SemiSeg dataset to detect infected tissues for segmentation using CNN techniques. The accuracy of the segmentation process is found to be 83.84%.

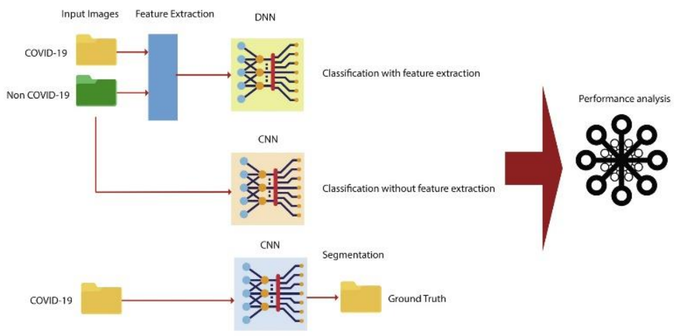
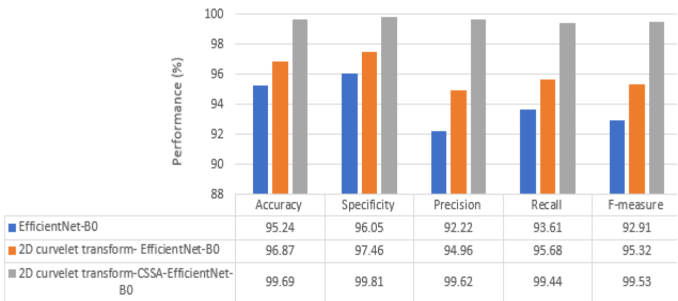


Fig. 5. Conceptual Diagram of the model [14]

Altan et al [15] proposed a hybrid model which consists of 2D curvelet transformation, chaotic salp swarm algorithm (CSSA), and deep learning technique to determine infection of coronavirus from X-ray images. They used a combined dataset of X-ray images consisting of a total of 2905 images of 10241024 pixels. The test images data contains 60 images from each of the classes. The remaining images data were used for training the model. The authors produced 5075 synthetic image data by using image processing techniques. 472 chest X-ray images from each class of the synthetic data are used as test data. In their model, they applied 2D Curvelet transformation on the images to obtain a feature matrix. EfficientNetB0 model, is used to diagnose the COVID-19 disease. The performance results of the aforementioned models under study are shown below.



	Accuracy	Specificity	Precision	Recall	F-measure
EfficientNet-B0	95.24	96.05	92.22	93.61	92.91
2D curvelet transform- EfficientNet-B0	96.87	97.46	94.96	95.68	95.32
2D curvelet transform-CSSA-EfficientNet-B0	99.69	99.81	99.62	99.44	99.53

Fig. 6. Performance results of (i) EfficientNet-B0, (ii) 2D curvelet transform - EfficientNet-B0, and (iii) 2D curvelet transform - CSSA - EfficientNet-B0

Tuncer et al [16] proposed ResExLBP model which automatically detects the COVID-19 virus. The dataset consists of 87 X-ray images of COVID-19 infected patients. The patients' ages were observed to be at least 50 years. During image pre-processing, the input X-ray images are converted into grayscale images and resized to 512×512. Residual Exemplar Local Binary Pattern (ResExLBP) method is used for feature generation and a novel iterative ReliefF (IRF) is used for feature selection. The performance of the two classification methods using LOOCV and 10-fold CV are shown in Fig. 7 and Fig. 8.

	CAC	SEN	SPE	BCAC	GM	Number of errors
DT	92.83	86.21	95.3	90.75	90.64	23
LD	99.07	96.55	100	98.28	98.26	3
kNN	97.2	89.66	100	94.83	94.69	9
SVM	99.69	98.85	100	99.43	99.42	1
SD	99.07	96.65	100	98.28	98.26	3

Fig. 7. Performance measurements using the LOOCV [15]

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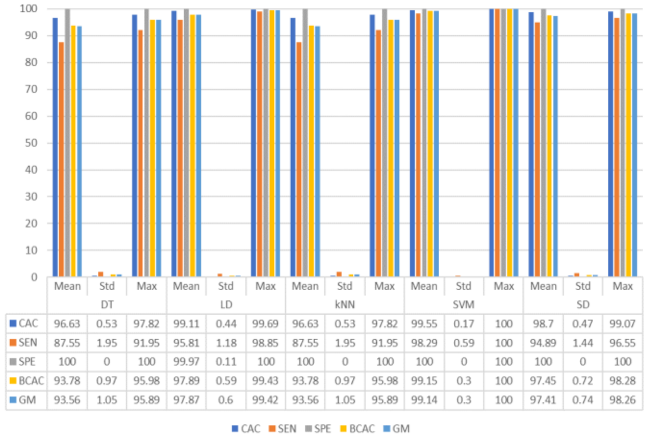

Fig. 8. Performance measurements using the 10-fold CV. [16]

Yoo et al [17] proposed a decision-tree classifier based on deep learning to detect COVID-19 from Chest X-Ray images. They also investigated the feasibility of the model. The authors proposed a classifier comprising three binary decision trees. The first decision tree classified the CXR (chet x-ray) images as normal or abnormal. The second decision tree identified the abnormality in images. The third decision tree classified the abnormality in images for COVID-19. The accuracy of the first decision tree is 98%, and for the second decision tree is 80%. The average accuracy of the third decision tree is 95%.

3. OTHER RELATED WORKS

Some of the related works related to classifying and identifying COVID-19 from X-Ray images are discussed below. Demirović et al [22] studied the performance of some image processing algorithms using TensorFlow framework. They executed the image processing algorithms parallelly using multicore CPUs and GPUs. Their results are shown in Table 2.

Table 2. CPU and GPU specifications used in experiment [22]

Processor	CPU	GPU
Number of cores	2	2 x 2496
Max. clock frequency	3.0 GHz	875 MHz
Global memory size	46080 kB	2 x 12 GB

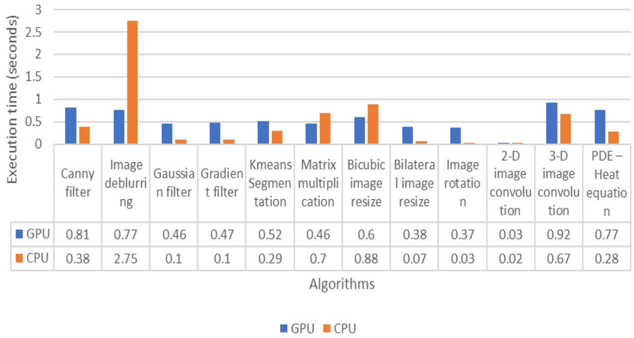

Fig. 9. Speedups for smaller data size

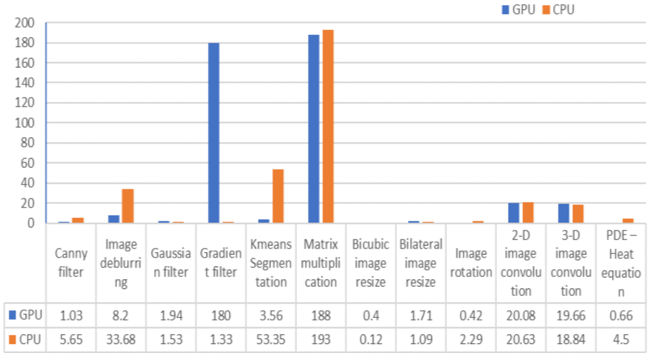

Fig. 10. Speedups for larger data size

Table 3. Deep Learning Architectures used and their performance

Deep Learning Architectures	*Proposed by*	*Accuracy (%)*	*Precision (%)*
CNN	Chellapilla et. al., 2006	84.18	94.05
VGG16 [18]	K. Simonyan and A. Zisserman, 2014	86.26	87.73
VGG19 [18]	K. Simonyan and A. Zisserman, 2014	85.94	80.39
InceptionV3 [27]	Szegedy et. al., 2014	94.59	93.75
Xception [26]	Chollet, 2017	83.14	95.77
DenseNet201 [31]	Huang et.al., 2018	93.66	99.01
MobileNetV2 [32]	Sandler et. al., 2018	96.27	98.06
InceptionResnet V2 [30]	Szegedy et. al., 2016	96.27	98.61
Resnet50 [28]	He at al., 2016	96.61	98.49

Altaf et al [23] studied the recent developments made in medical imaging analysis using machine learning/deep learning methods. The authors explained the unique machine learning and Computer Vision perspective taken on the advances of deep learning in medical imaging. This paper helps us recognize the challenges we will face during our research and understand the machine learning and deep learning techniques to deal with those challenges. Shorten et al [24], in their study, talked about Data Augmentation, to solve the problems a researcher faces due to limited data as earlier, many neural networks were heavily dependent in big data to avoid overfitting. The authors put forward many techniques to improve the size and quality of the training dataset. In this paper, many image augmentation algorithms are introduced in detail. The authors also discussed the application of augmentation methods based on Generative Adversarial Networks (GANs) [25]. ASNAOUI et al [29] used recent Deep - CNN architectures to automatically detect and classify normal and pneumonia images. These architectures included are listed in Table 3. They performed a comparative

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analysis of the abovementioned algorithms. They introduced a publicly available image which consists of 5856 images. In their study, intensity normalization and CLAHE methods are used for image pre-processing. They normalized input images to the standard normal distribution using min-max normalization. They resampled the dataset by using data augmentation techniques where 2 new images are generated from each input image. Resnet50, MobileNetV2, and InceptionResnetV2 showed high performance at more than 96% accuracy with an increase in the rate of training and validation. However, the remaining models showed low performance of at least 84% accuracy.

4. DATASETS USED

In this article, a single dataset is taken Chest X-ray images [35]. The dataset consists of train and test images under three categories. They are COVID-19, Normal, and Pneumonia. There are a total of 6432 X-ray images present in the dataset. 20% of the total images are contained as test data and the rest 80% of them are train data. Fig 11. and Fig 12. shows the number of images in each of the three categories for the train images and test images data respectively.

	Category	Number of images
0	Normal	1266
1	Pneumonia	3428
2	COVID19	460

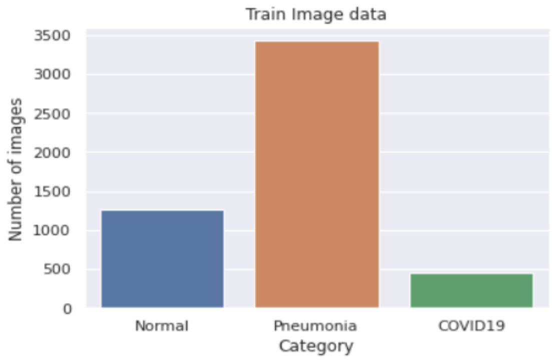

Fig. 11. Train Images Data

	Category	Number of images
0	Normal	317
1	Pneumonia	855
2	COVID19	116

Fig. 12. Test Images Data

Here, we can see that the highest number of images fall under Pneumonia category, then comes the Normal category, and the COVID-19 category has the least number of the images. Pneumonia category has total of 4313 images (3428 in train data and 885 in test data), Normal category has total of 1583 images (1266 in train data and 317 in test data), and the COVID-19 category has total of 576 images (460 in train data and 116 in test data). Some of the images in the three categories (COVID-19, Normal, and Pneumonia) are shown in the figures below.

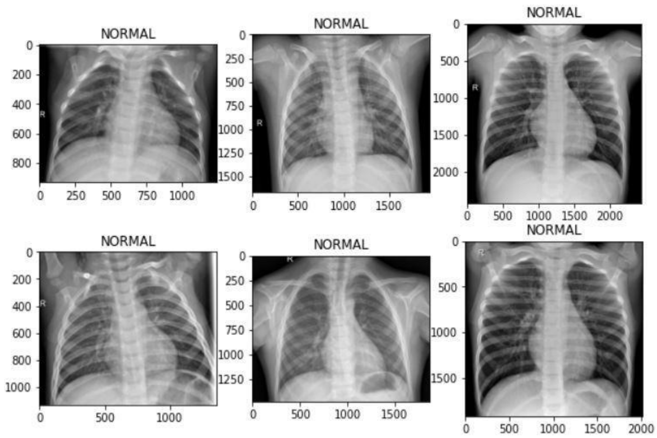

Fig. 13. Sample Normal Images data

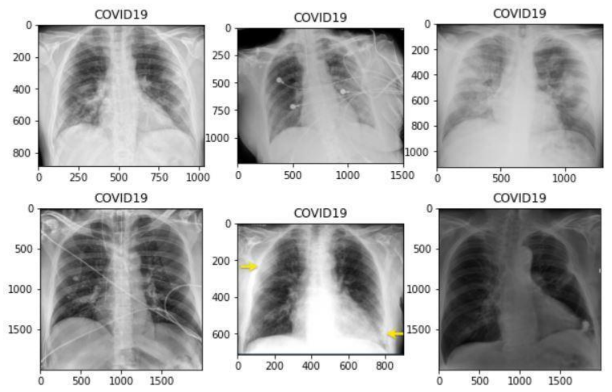

Fig. 14. Sample COVID-19 Images data

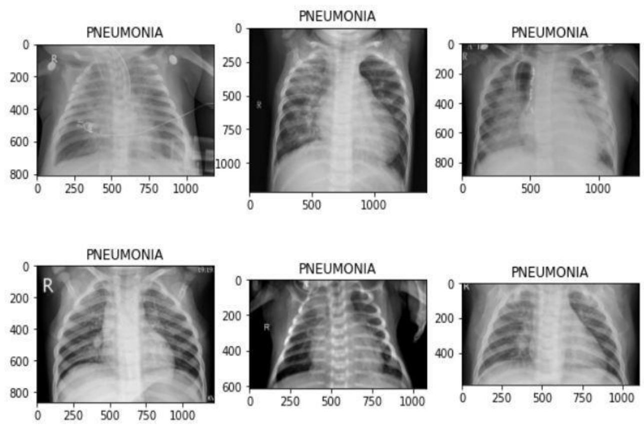

Fig. 15. Sample Pneumonia Images data

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5. EXPERIMENTS AND RESULTS

The dataset images were resized to size 224x224 pixels and then data augmentation. Four Deep Learning models are used in our current study to classify the images – InceptionResnetV2, Resnet50, EfficientNetB7[20] and Xception. The accuracy, loss, and confusion matrix of the four models are shown in Fig.16, Fig. 17, and Fig. 18, respectively. The average accuracy and loss values of the abovementioned models are shown in Table 3. The train accuracy is found to be highest in Xception model (92.34%), then InceptionResnetV2 shows second highest train accuracy (90.62%). Resnet50 has the third highest train accuracy (75.63%) and lastly, EfficientNetB7 shows worst training efficiency of 32.53%.

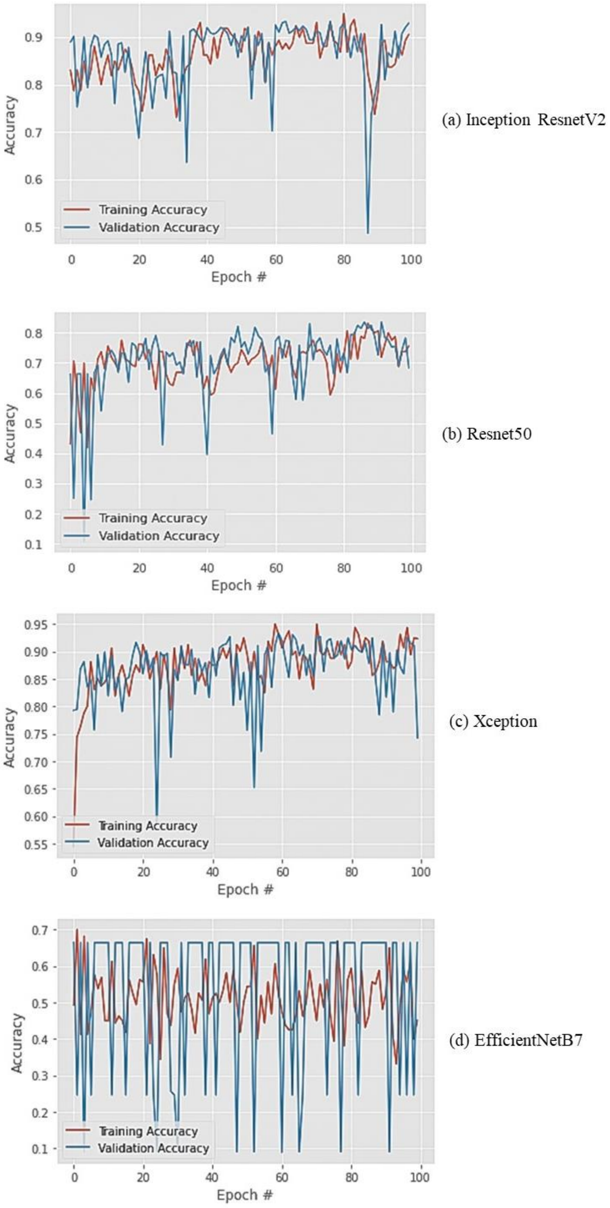


Fig. 16. Accuracy graph of (a)InceptionResnetV2 (b) Resnet50 (c)Xception and (d) EfficientNetB7

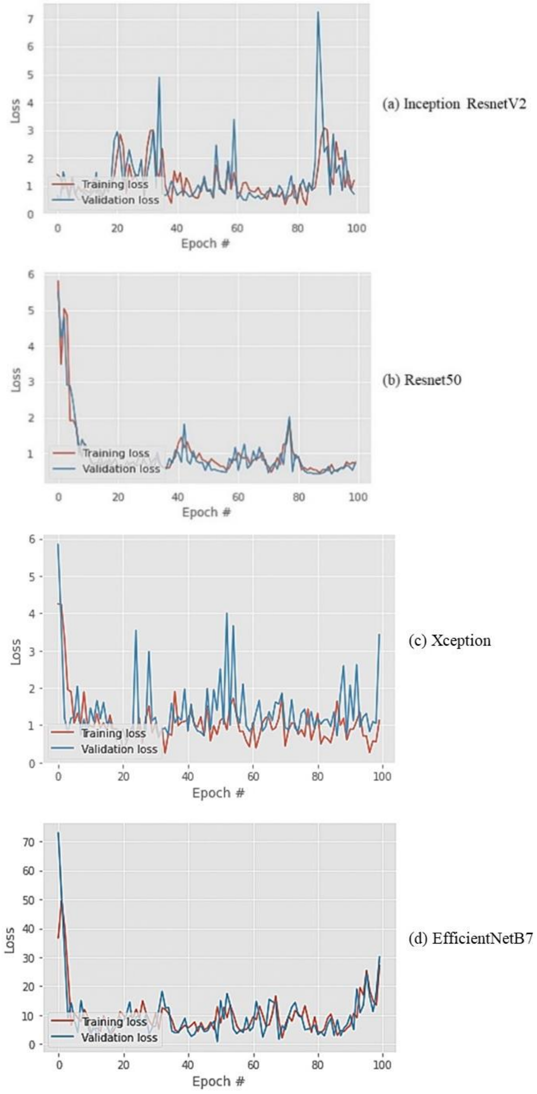
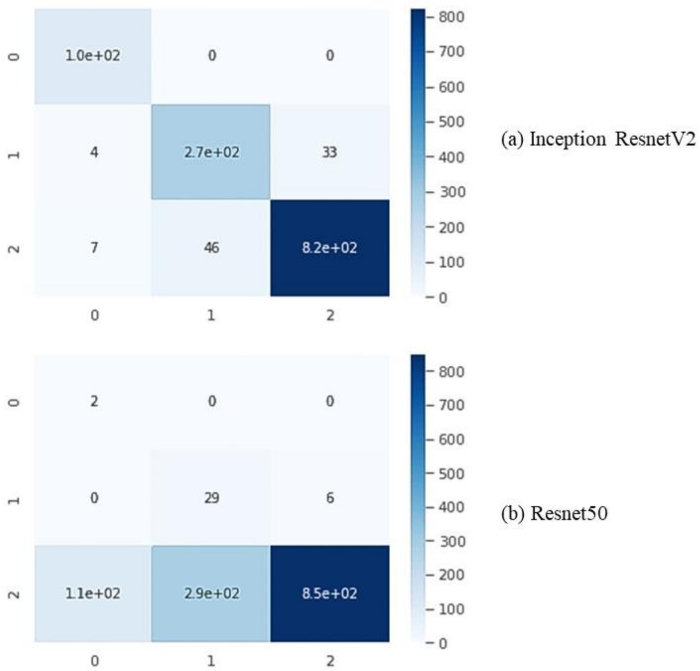


Fig. 17. Loss graph of (a)InceptionResnetV2 (b) Resnet50 (c)Xception and (d) EfficientNetB7



Volume 11, Issue 1
February 2022

ITEE Journal
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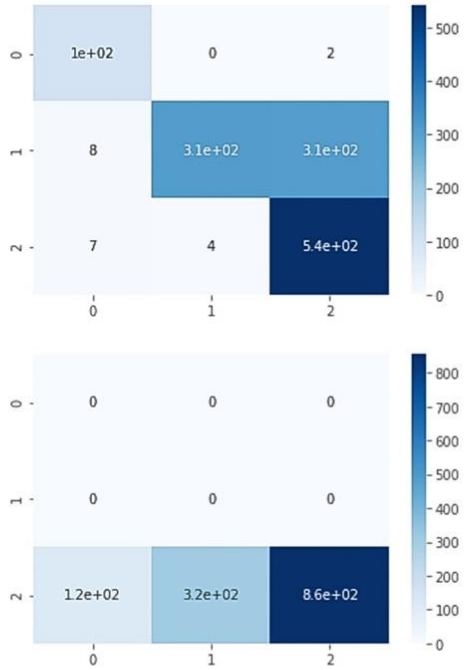

(c) Xception

(d) EfficientNetB7

Fig. 18. Confusion Matrix of (a)InceptionResnetV2 (b)Resnet50 (c)Xception and (d)EfficientNetB7

Table 4. Accuracy and Loss values of the models used under study on the train data

Model Under Study	*Accuracy*	*Loss*	*Validation Accuracy*	*Validation Loss*
InceptionResnet V2	0.9062	1.2071	0.9301	0.7120
Resnet50	0.7563	0.7120	0.6832	0.7582
EfficientNetB7	0.3253	23.60	0.6638	30.14
Xception	0.9294	0.8954	0.7422	3.4272

Table 5. Performance results of the models under study on the test data

Model Under Study	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-score (%)*
InceptionResnet V2	93.01	93.13	93.01	93.04
Resnet50	68.32	96.69	68.32	78.76
Xception	74.22	82.62	74.22	72.79
EfficientNetB7	66.38	100.0	66.38	79.79

6. CONCLUSION

Multitude of people around the world have been infected with COVID-19. A lot of them have lost their lives. Therefore, it is very important to identify this disease at the earliest. In our study, we used four different Deep Learning algorithms to identify COVID-19 in chest X-ray images. All the models have performed differently, and we can conclude that InceptionResnetV2 had the highest accuracy i.e., 93.01% out of the four. This study helped us understand the use of deep learning algorithms for identifying a particular disease and how much potential it has in the field of medical science. The main challenge for us currently is the availability of enough data and new machine learning approaches to work in this field. In our future work, we hope to build our own model to achieve greater accuracy in identifying COVID-19.

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