Deep Pre-Trained Convolutional Neural System for High-Accuracy Covid19 Forecasting from Chest X-Rays

2022 IEEE 7th International conference for Convergence in Technology (I2CT) | 978-1-6654-2168-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/I2CT54291.2022.9825048

Faraz Bagwan
School of Computer Engineering & Technology
MIT World Peace University
Pune, India
farazbagwan11@gmail.com

Dr. Nitin Pise
School of Computer Engineering & Technology
MIT World Peace University
Pune, India
nitin.pise@mitwpu.edu.in

Abstract*—The continuous battle against the variants of Corona Virus demands speedy treatment and quick diagnostic reporting on priority basis. With millions of people contracting the infection every day and a mortality rate of 2%, our goal is to solve this growing problem by developing an important and substantive method for diagnosing COVID19 patients. Due to a proportionally reduced number of medical practitioners, testing kits, and other resources in densely populated nations, the exponential development of COVID19 cases is having a significant impact on the health care system, making it increasingly important to identify infected patients. The goal of this work is to develop an exact, productive and time-saving algorithm to identify positive corona patients that addresses the aforementioned issues. In this paper, a Deep Convolution Neural Network model called "EfficientNet" is implemented and explored that can reveal significant diagnostic characteristics to enable radiologists and medical specialists locate COVID-19 infected patients using X-ray pictures of the chest and aid in the fight against the pandemic. The experimental findings conclusively indicate that an accuracy rate of 99.71 percent was obtained for binary classification of Non-COVID and COVID Chest X-ray pictures. Our pretrained Deep Learning classification model can be a significant contribution to recognizing COVID-19 inflicted individuals due to its high diagnostic accuracy.

***Keywords*—Corona-virus, radiography, chest X-rays, deep-learning, convolution neural networks, pretrained**

I. Introduction

Corona-virus is a family of deadly viruses that attacks the lungs of the host. Its initial symptoms are common cold with shortness in breath, however, when left untreated it may progress to respiratory failure due to low oxygen levels in the body. The first outbreak of Covid19 was found in Wuhan district of China in 2019. It entered the Indian soil in January, 2020. Many countries' healthcare systems are collapsing as a result of millions of individuals getting infected and a scarcity of testing kits and diagnosis systems. To date, no effective medication, therapy, or vaccine for the treatment of infected patients has been developed. It turns out that quick detection and isolation of affected individuals [1] are required in order to combat viral spread [2]. The most used detection method i.e. Reverse Transcription Polymerase Chain Reaction (RT PCR) test for determining COVID-19 is time-consuming and in limited supply because of the huge outbreak. [1] It also poses strict environment constraints with respect to hygiene and sterilized equipment.

As a result, medical professionals and government officials rely on diagnosis techniques to properly isolate affected persons and restrict the spread of pandemics. Patients' chest X-ray scans may prove to be a less expensive, more efficient, and faster approach of diagnosing COVID-19. Medical practitioners have been known to use chest X-ray pictures to diagnose patients with lung diseases such as pneumonia, MERS-CoV, SARS-CoV, ARDS, and others in the past. Lung infections, fractures, bone injuries, Pneumonia, and malignancies can all be diagnosed with scanned X-ray pictures. For some time now, researchers have been exploring for alternate screening approaches, such as deep-learning implemented on patient chest X-rays, which has shown encouraging results. Regardless of their success, we observe that these approaches have a significant computational cost, which is why they are tough to obtain and available. As a result, the goal of this research is to create a model for predicting COVID-19 using chest X-ray images that is both stable and efficient

In the following study, we used Deep Convolution Neural Networks (DCNNs) to construct an automated model for forecasting COVID-19. The goal of our research was to create a supervised Deep Learning model that could classify chest X-ray pictures into two categories. Normal (i.e., a healthy person) and COVID-infected (i.e., a person infected with Corona Virus). We also used COVID19 vs. non-COVID19 chest X-ray images to do binary classification. Multiple open-source web sources were used to compile the dataset. These resources were provided for free for study purposes. We were able to train complicated Deep Neural Networks using these publicly available datasets, and the results were really rewarding.

EfficientNet [3] is the proposed Deep Learning model. It extracts features using Deep Convolution Neural Networks (DCNNs) that have been pre-trained. DCNNs are cutting edge and most active learning algorithms that are extensively used in a variety of practical applications, including pattern identification and picture classification in computer vision. They provide the most intuitive approach to grasp the visuals and the most likely outcomes. It is well-known for its ability to classify data that is very non-linear. Our suggested technique unambiguously concludes that X-ray pictures are a superior tool for detecting Coronaviruses quickly and accurately. Accuracy was chosen as an assessment measure for this model.

This paper's goal and key contribution are summarised below:

1. We suggested fine-tuned EfficientNet, a model based on deep convolutional neural networking that is apt to distinguish COVID19 X-ray from a healthy patient's X-ray with a test accuracy of 99.71 percent. In the categorization of medical picture data, it showed to be a powerful and robust ML model.

2. We gathered distinct datasets totalling 15264 chest X-ray images. There were 7628 X-rays of patients which were diagnosed as positive with COVID-19, and 7636 X-rays of healthy people.

3. The study includes a full implementation of the model, "EfficientNet," as well as a discussion of the experimental results.

4. The goal of our proposal was to assist medical practitioners and nursing personnel in dealing with the constantly increasing COVID-19 cases and performing a speedier and automated diagnosis of patients.

The remainder of the research is structured as follows: We addressed the previously published studies and their shortcomings in Section 2. We attempted to better our work and results by capitalizing on such flaws. Section 3 delves into the essential and preparatory principles needed to comprehend this research. We described and reviewed the proposed system architecture. It also refers to the data collection that we used to perform our study. In Section 4, we discussed the implementation decisions of our proposed EfficientNet model for two-class categorization. Section 5 contains an experimental analysis, findings, and comments. Conclusions and Future efforts are discussed in sections 6 and 7 respectively

II. LITERATURE SURVEY

This section uses the Chest X-ray pictures to evaluate the overview of previously published research deployed in this domain for distinguishing and categorizing of COVID-19 inflicted patients. Because of the rapid spread of this new virus around the world, there aren't many studies on detecting COVID-19 using chest X-ray pictures. The majority of the writers used pre-trained DCNNS to extract useful features and then performed classification using three-class classification (COVID-19 vs. Pneumonia vs. Normal) and two-class classification (COVID vs. Non-COVID). We compared the performance of our CoVNet-19 model to that of these previously published research.

The research authors of [6] compared several topologies using a small collection of 55 X-ray pictures of the chest region with 26 confirmed COVID-19 positive cases.

CovidX-Net is a system developed to aid health workers in instantly assessing Covid-19 using X-rays of chest. It is centered on deep neural network frameworks like customized VGG19 (Visual Geometry Group Network), DenseNet201, InceptionV3, ResNetV2, Inception-ResNet-V2, Xception, and the 2nd edition of Google-obileNetV2. The ImageNet dataset was used to train these networks. At the conclusion of the experiments, the following results were obtained: VGG19 [7] and Dense Convolutional Network (DenseNet201) [8] models performed similarly well on COVID-19 detection, with F1 scores of 0.92 and 0.88, respectively, for Covid-19 positive and healthy. The InceptionV3 architecture had the poorest results, with F1 scores of 0.68 for normal cases and 0.00 for COVID-19 instances.

Increasingly inspired by the need for quicker interpretation of radiological images to combat viral transmission, the authors of [9] develop COVID-Net, a novel CNN architecture that can categorize CXR pictures into COVID-19, pneumonia, and normal. The dataset utilized in this situation is substantially greater than in earlier studies. It includes of 13,800 CRX photos from 13,645 patient cases, 182 of which are COVID-19 patients. According to the outcomes, an overall accuracy of 92.3 percent was achieved whereas sensitivity was 80.01 percent.

Superior findings, [10] were reported than the previously described COVID-Net, providing 96.22 percent accuracy and an absolute sensitivity of 100 percent for COVID-19. They then tweaked ResNet50 [11] by training it on a dataset with 4 classes i.e., pneumonia-viral, pneumonia-bacterial, COVID-19 positive and healthy.

It's crucial to note the issue presented in [9] contains an additional class, making the dataset a part of the data utilized in [6]. 69 Covid-19 radiographs from 46 Covid-19 patients were utilized in the dataset here. There were around 1200 instances of no-pneumonia, 930 pneumonia-bacterial, and 660 non-Covid-19 pneumonia-viral cases.

Researchers of [12] compiled collection of 1,144 X-ray pictures from various available datasets. Only 90 are associated to COVID-19, with the remainder falling into one of the total 6 categories: 5 different varieties of pneumonia along with a healthy type. The multilayered assessment was conducted in order to find COVID-19 patterns on CXR pictures. To extract information from X-rays, several approaches are utilized, one of which is based on CNNS (V3-Inception [13]). SVM, Random Forest, KNNs, MLPs, and Decision Trees were also among the classifiers explored by the researchers. [4] for classification. The COVID-19 class had an F1- score of 0.890. Notwithstanding the fact that the two contributions have a strong relationship, we assert that a high correlation is inappropriate due to the uniqueness of the datasets each model utilizes.

CoroNet, the model used in [14], was pre-trained on ImageNet [5] and utilizes the Xception CNN architecture [15]. The authors trained and tested it using a constructed dataset made up of X-ray data from two separate public datasets. An accuracy of 89.01 percent and a precision rate of 92.9 percent for Covid-19 positive cases and 92 percent for four classifications (Pneumonia-bacterial, Covid-19, Pneumonia-viral and Normal).

Since there was limited amount of COVID-19 X-ray scans available, most models were created on an imbalanced dataset of X-rays, according to the findings. We believe that by gathering a more diverse and balanced dataset and using an efficient feature extraction approach, we may improve these results even further. The next step in this study is to create classification model that can be used to efficiently categorize X-ray data. We also provide a full comparison report of our suggested technique with some previously published publications.

III. PROPOSED MODEL

Given a chest X-ray picture as input, the system must determine whether or not the person is inflicted with Covid-

19. We have a collection of supervised X-ray pictures that have been meticulously tagged by radiologists on which to train the model. A model like this can assist health care workers detect COVID-19 instances [16] considerably faster than a radiologist going through each scan one by one, especially when a considerable number of individuals must be assessed in a relatively brief period of time.

The task at hand is to create an algorithm to solve a binary classification issue. The challenge of categorising cases into one of two classes is known as binary classification in machine learning. Provided a front-view of a chest X-Ray as input, we must generate a vector of two category probabilities as output. These numbers denote the likelihood that the input corresponds to one of the two classes ("COVID-19" or "Normal" in current scenario).

We utilized the EfficientNet to retrieve our stated target. The EfficientNet is a deep artificial neural network family that achieves 84.5 percent top one and 97.1 percent top five accuracy on ImageNet while being 8.5 times smaller and 6.10 times quicker on inference than the existing ConvNet. The Mobile Inverted Bottleneck Conv (MBconv) Block [4], represented in Fig. 1, is its major component.

The EfficientNet neural network series is intended to take-off as a comparatively improved yet compact prediction model and then systematically maximize each of its features using a set of scaling parameters. As shown in Fig. 2, an EfficientNet is strictly characterised by three dimensions: depth, breadth, and resolutions. On the dataset, we utilise data augmentation. The ImageNet [5] dataset is then used to perform transfer learning. The notion of progressive scaling is a valuable technique for improving accuracy. Finally, we tested our model against our data.

We chose EfficientNet, a deep CNN architecture with scaling approach that evenly expands all dimensions of depth, width and resolution using a compounding coefficient, rather than constructing a new architecture from scratch, because of its promising results. Indeed, the EfficientNet evenly adjusts the network features i.e., depth, width and resolution with pre-set scaling coefficients, rather than arbitrarily scaling these elements as is common practice.

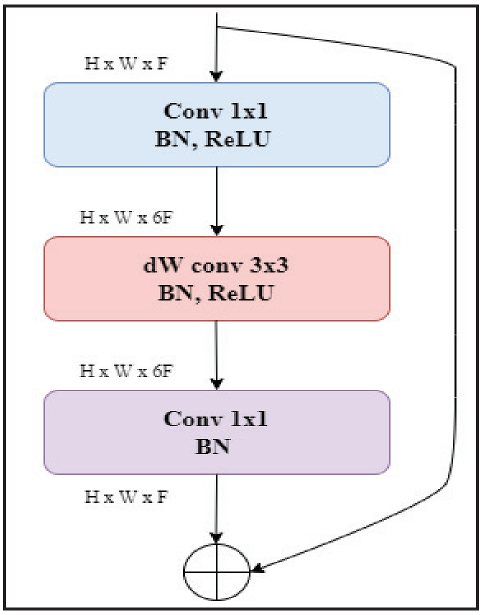

Fig. 1. MBconv Block (where, dW is depthwise, BN is Batch Norm, H x W x F is tensor shape in height x width x depth)

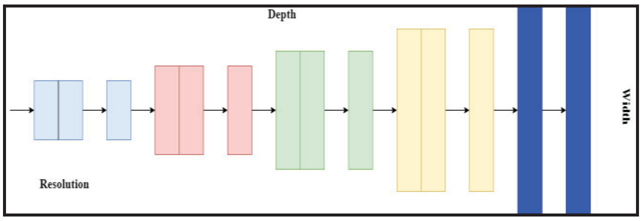

Fig. 2. EfficientNet with three parameters (Depth, width and resolution)

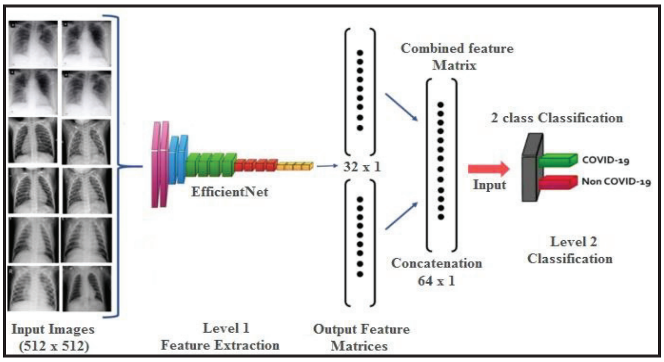

Fig. 3. Architecture diagram of proposed efficientNet model

The architecture diagram of our proposed DeepCNN model using efficientNet is shown in Fig. 3. With our proposed working method and design, the model provides an optimal understanding of data. EfficientNets' visualisation is more complicated than VGG19's [7]. As a result, we've attempted to depict a simplified blueprint of EfficientNet's architecture. Algorithm 1 depicts the working procedural algorithm of our suggested deep learning categorization approach. To achieve binary classification, the same model architecture was built and trained independently, i.e., EfficientNet model was trained for binary class feature extraction.

Algorithm 1: X-Ray classification using "EfficientNet" model

Input: (512x512x3) dimensional Chest X-Ray images.

Output: Predicted class label for the image (0: COVID-19, 1: Normal).

1. Extracting features from the image

1.1. Image is passed through multiple conv., ReLU Activation and Max Pooling layers of EfficientNet

i. Convolution Operation between the Filter (L) of size (w x z) and Image(I) to give Feature Map (F):

$$\mathbf{F(p,q)=(1*L)(p,q)=\Sigma w \Sigma z}\ \boldsymbol{I(p+w,\ q+z)L(w,z)}$$

ii. ReLU Activation Function to introduce non-linearity:

$$\boldsymbol{f}\mathbf{(x)= max\ (0,\ x)}$$

iii. Max Pooling:
It is a Down-sampling layer to reduce the dimension of feature maps.
Returns: (32x1)
Feature Vector: $\mathbf{X1 = [\alpha_0, \alpha_1, \alpha_2 \ldots\ldots \alpha_{32}]^T}$

1.2. Image is passed through multiple Convolution, Max Pooling and Relu Activation Layers of EfficientNet
Returns: (32x1)

Feature Vector: $\mathbf{X2} = [\beta_0, \beta_1, \beta_2 \ldots, \beta_{32}]^T$

2. Augmentation of both Feature Vectors

$$\mathbf{X} = (X_1^T|X_2^T) = [\alpha_0, \alpha_1, \alpha_2 \ldots, \alpha_{32}, \beta_0, \beta_1, \beta_2 \ldots, \beta_{32}]$$

Returns: (64x1) Feature Vector

3. The formed feature vector is given as input to perform Classification.

   The proposed trained DCNN model returns the class label.

A. Dataset Description

The training dataset is made up of 15264 (512x512 pixel) pictures identified by an experienced radiologist. The test dataset has 400 pictures from the same distribution.

People without Covid-19 (negative) and with (positive) Covid-19 are depicted in the images below.

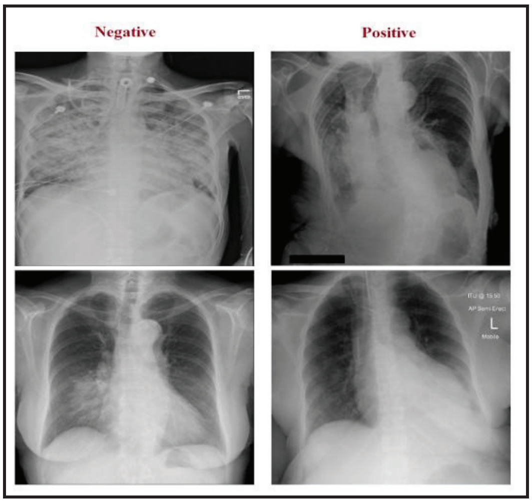

Fig. 4. Sample Images from Dataset

IV. IMPLEMENTATION

The following section discusses about the implementation decisions taken after careful evaluation at each stage of model creation and training.

A. Learning Rate:

While a lower learning rate results in greater convergence [17], it does not always equate to the highest test accuracy. It's possible that the problem is that the algorithm hasn't yet learnt the weights that result in the lowest error for the test set. On the other side, a faster learning rate may cause the algorithm to exceed the ideal set of weights. We tried with 10e-3, 10e-4, and 10e-5 learning rates and discovered that 10e-4 had the lowest error rates for the test dataset.

B. Batch Size:

When we increased the batch size to 256 or even 64, we ran into memory troubles and had to settle for a smaller batch size. We attempted with 32 and 16 as well. With a learning rate of 10e-4, the batch size of 32 produced the lowest error rates of the two batch sizes. In this study, the interaction between Learning Rate, Batch Size, and Accuracy has been thoroughly examined. We started with a lower learning rate (lr=0.0001 instead of 0.001), which proved out to be the superior decision afterwards, and followed the rule of thumb of setting the batch size to 32, which is a standard practice in deep learning.

C. Pre-trained model

When deciding which pre-trained model to employ, we initially evaluated the accuracy of multiple pre-trained models and the number of parameters in the model. Computer vision [18] is a rapidly expanding discipline in which new models are constantly being created. Initially, we planned to utilize VGG16 or Resnet50 [19], but after reading about Efficientnet, decided to go with Efficientnet. Since, we had an RTX 2070 GPU, the model we could utilize was limited by the constraints of its hardware. We began using Efficientnet version b7, but the GPU immediately gave up as the model didn't fit in its memory. Hence, had to kill multiple jobs on b7, b6, b5 and b4 models.

D. Epochs:

With a model like EfficientNet b3 having 12 million parameters and tens of thousands of training dataset instances, it is very easy to overtrain a model. In reality, while training the model using 20 Epochs, we obtained a training accuracy of 1. For various learning rate and batch size combinations, we utilized epochs ranging from 1 to 30.

E. Sampling:

No sampling was performed initially. Interestingly, the model classified all of the test situations as "1," against my anticipation of "0." The issue, we believed, here was that the test images were not converted in the same way that the training images were, and the untransformed test images resembled the transformed training images of label "1." Then, in the training dataset, we utilized a weighted random sampler, which resulted in a nearly 50–50 representation of the 0 and 1 classes. However, it also resulted in a reduction in the entire training dataset size from 15000 to little under 3000. With this sample approach, the accuracy improved but plateaued at roughly 0.86. Following that, we oversampled from the minority class to equalize the quantity of images from both classes. As a result, my training dataset grew from 15000 to 26000.

F. Tuning:

To acquire the best possible outcome, we tweaked the hyper-parameters. We experimented with several epochs and discovered that after 11 epochs of training, we obtained the best test accuracy for this dataset with the pre-trained model, learning rate, and batch size we used.

V. RESULT AND ANALYSIS

The training accuracy and cross-entropy loss are plotted over iterations. There are 7227 batch iterations in all, and the graphic depicts how these values change over time. The experimental setup and findings are presented in this section. The computational studies are carried out using the Jupyter Notebook execution environment [24] and the Pytorch Python framework [22] [23].

We used EfficientNet for binary classification to differentiate COVID19 and Non-COVID19 chest X-rays. The training and validation, accuracy and loss curves for the EfficientNet DCNN model is shown in Fig. 5, 6 and 7. EfficientNet achieved 98.47 percent, 99.03 percent, and 99.71, training, validation, and test set efficiency, respectively. For binary classification, EfficientNet showed an improvement in all evaluation metrics. Table 1 shows all of EfficientNet's training, validation, and testing evaluation metrics. The confusion matrix of EfficientNet on the test set is shown in Fig. 8. It achieved total training and validation accuracy of 99 percent and 99.03 percent, respectively, for binary classification, and a test set accuracy of 99.71 percent.

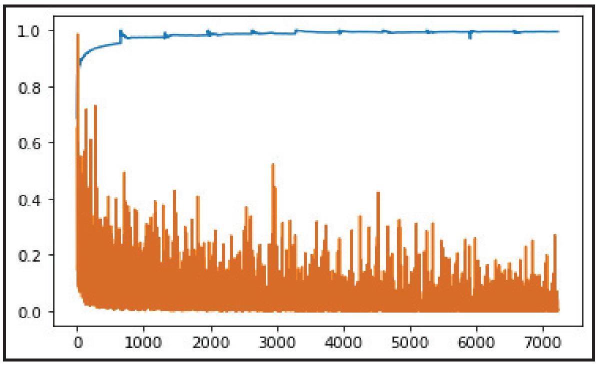

Fig. 5. Accuracy and Loss graph of efficientNet model for training (Blue:Accuracy, Orange:Loss, x-axis: Epochs, y-axis: loss and accuracy measure)

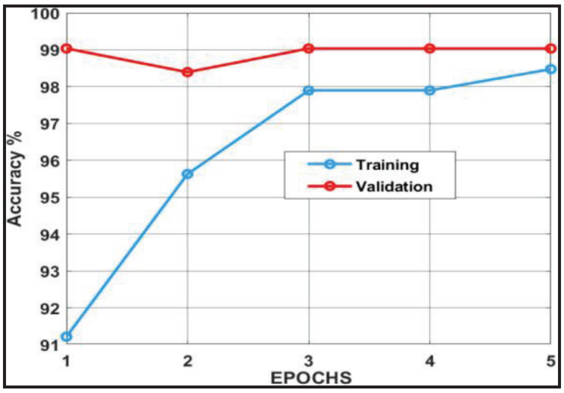

Fig. 6. Accuracy graph of efficientNet model

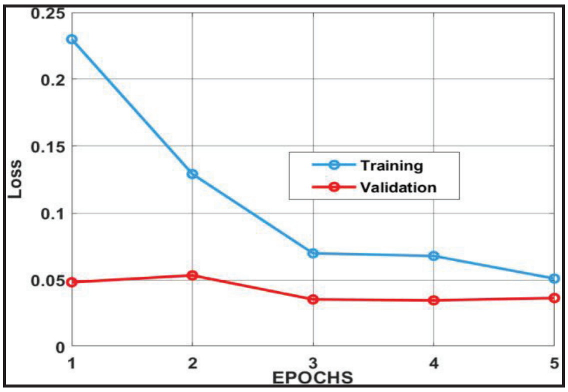

Fig. 7. Loss graph of efficientNet model

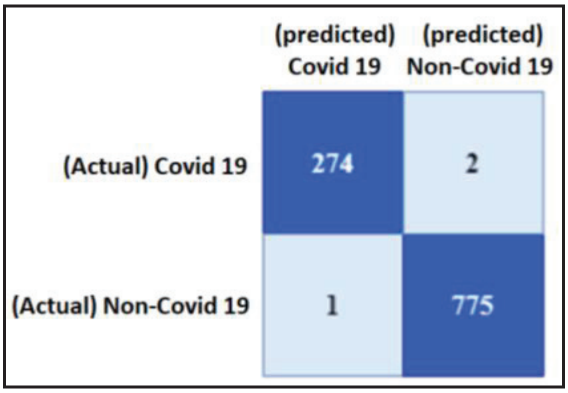

Fig. 8. Confusion Matrix of EfficientNet Model on Test Set (Accuracy: 99.71%, Sensitivity: 99.63% Specificity: 99.74%)

TABLE I. EFFICIENTNETS' EVALUATION METRICS WITH RESPECT TO ACCURACY AND LOSS FOR BINARY CLASSIFICATION

Metrics	***Training***		***Validation***		***Test***	
Efficient Net	98.47%	0.023	99.03%	0.022	99.71%	0.021

VI. CONCLUSION

The findings demonstrated that our EfficientNet classification model could detect COVID-19 among individuals with higher accuracy. The results indicate that the DCCN, EfficientNet, assisted us in achieving the greatest classification accuracy by extracting valuable complex features. As a result, medical institutions may benefit from an automated Deep Learning approach for COVID-19 diagnosis utilizing chest radiography tablatures. The EfficientNet model was trained on a variety of X-ray image datasets and achieved a high overall binary classification test-data accuracy of 99.71 percent. Since a good medicine and/or vaccination isn't accessible to humanity, it's critical to accurately detect all positive COVID19 cases and halt the virus from spreading. Because of the pandemic's rapid spread, every case must be reported properly. With millions of individuals infected, the epidemic has outrun many nations' medical resources and testing tools. We anticipate that EfficientNet will give considerable aid and support to medical practitioners and nursing personnel in dealing with the rapidly increasing number of COVID-19 cases and performing faster and more accurate patient diagnosis. Millions of people are still at risk from this deadly disease, which should be addressed sensibly by equipping ourselves with everything we have at our disposal. We believe that with automation [6] [10] at the expert level, this technology can play a significant role in combating the COVID-19 epidemic, and that further development with a bigger database would be even better.

VII. FUTURE WORK

According to the findings, it can therefore be proven that employing Deep Convolutional Neural Networks can assist us in extracting valuable information from X-Ray photos, which can then be utilized to diagnose and detect COVID-19 infected people. By removing the restrictions of our work, more research may be done based on our suggested study. Much more patient data, mainly of COVID-19 individuals, may be used to provide a significantly more trustworthy in-depth study. Other physical and physiological aspects of the patient may be noted and utilized as input features to the Deep Learning Classification [20] model using chest X-ray pictures. Apart from COVID-19, only instances of Pneumonia were included in this investigation. Other related viral and pneumonia-based illnesses, such as SARS and MERS, can be included in a better and broader scaled categorization model. Due to a lack of processing resources, all of the Convolutional layers of the pre-trained DCNNs [21] were not fine-tuned.

If the entire DCNN is fine-tuned with the training data, the classification results may improve. For multi-class classification jobs with three or more unique classes, instead of obtaining a (32x1) feature vector from one DCNN, the number of features can be extended to 64 or 128. EfficientNet may be improved and changed into its lighter version. It may then be engineered to run effectively on low-power devices such as smartphones and Arduinos. The camera on cellphones may be used to collect X-ray images and detect COVID-19. The public will be able to examine the diagnosis findings on their cellphones by taking a snapshot of the X-ray image.

As a result, the given study contributes to the feasibility of a cheaper, faster, and more efficient method of automatically detecting the condition, and it can be a valuable tool for medical practitioners and nursing personnel dealing with the constantly increasing COVID-19 cases. This strategy has the potential to help manage the rapidly growing number of infections by prompting infected people to stay confined and prevent others from coming into contact.

REFERENCES

[1] L.-P. Béland, A. Brodeur, and T. Wright, "The short-term economic consequences of COVID-19: Exposure to disease, remote work and government response," IZA Discuss. Pap., no. 13159, p. 90, 2020.

[2] W. McKibbin and R. Fernando, "The Global Macroeconomic Impacts of COVID-19: Seven Scenarios," Asian Econ. Pap., pp. 1–55, 2020.

[3] M. Tan and Q. V Le, "EfficientNet : Rethinking Model Scaling for Convolutional Neural Networks," 2019.

[4] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear bottlenecks," in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2018, pp. 4510–4520.

[5] L. Fei-Fei, J. Deng, and K. Li, "ImageNet: Constructing a large-scale image database," J. Vis., vol. 9, no. 8, pp. 1037–1037, 2010.

[6] 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," 2020.

[7] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc., pp. 1–14, 2015.

[8] Y. Huang et al., "GPipe: Efficient Training of Giant Neural Networks using Pipeline Parallelism," no. NeurIPS, 2018.

[9] L. Wang and A. Wong, "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images," pp. 1–12, 2020.

[10] M. Farooq and A. Hafeez, "COVID-ResNet : A Deep Learning Framework for Screening of COVID19 from Radiographs."

[11] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "the Impact of Residual Connections on Learning," pp. 4278–4284.

[12] R. M. Pereira, D. Bertolini, L. O. Teixeira, C. N. Silla, and Y. M. G. Costa, "Computer Methods and Programs in Biomedicine COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios," Comput. Methods Programs Biomed., vol. 194, p. 105532, 2020.

[13] C. Szegedy, V. Vanhoucke, and J. Shlens, "Rethinking the Inception Architecture for Computer Vision," 2014.

[14] A. Iqbal, J. Latief, and M. Mudasir, "Computer Methods and Programs in Biomedicine CoroNet : A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images," Comput. Methods Programs Biomed., vol. 196, p. 105581, 2020.

[15] C. Google, "Xception : Deep Learning with Depthwise Separable Convolutions," pp. 1251–1258, 2014.

[16] Hemdan E.E.-D., Shouman M.A., Karar M.E. 2020. COVIDX-net: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images. http://arxiv.org/abs/2003.11055. [Google Scholar]

[17] Pathak Y., Shukla P.K., Tiwari A., Stalin S., Singh S. Deep transfer learning based classification model for COVID-19 disease. Irbm. 2020;1:1–6. doi: 10.1016/j.irbm.2020.05.003. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[18] Tougaçar M., Ergen B., Cömert Z. COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches. Comput. Biol. Med. 2020 [PMC free article] [PubMed] [Google Scholar]

[19] Ucar F., Korkmaz D. Covidiagnosis-net: Deep Bayes-squeezenet based diagnostic of the coronavirus disease 2019 (COVID-19) from X-ray images. Med. Hypotheses. 2020 [PMC free article] [PubMed] [Google Scholar]

[20] Goodfellow I., Bengio Y., Courville A. MIT press Cambridge; 2016. Deep Learning. http://www.deeplearningbook.org. [Google Scholar]

[21] Deshpande Adit. 2016. A beginner's guide to understanding convolutional neural networks. https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/ [Google Scholar]

[22] Chollet F. first ed. Manning Publications Co.; USA: 2017. Deep Learning with Python. [Google Scholar]

[23] 2020. Tensorflow, Transfer learning with a pretrained ConvNet. https://www.tensorflow.org/tutorials/images/transfer_learning (Accessed June 15, 2020) [Google Scholar]

[24] T. Carneiro, R. V. M. Da Nobrega, T. Nepomuceno, G. Bin Bian, V. H. C. De Albuquerque, and P. P. R. Filho, "Performance Analysis of Google Colaboratory as a Tool for Accelerating Deep Learning Applications," IEEE Access, vol. 6, pp. 61677–61685, 2018