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# Effect of image transformation on EfficientNet model for COVID-19 CT image classification

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ABSTRACT

The Novel Corona Virus 2019 has drastically affected millions of people all around the world and was a huge threat to the human race since its evolution in 2019. Chest CT images are considered to be one of the indicative sources for diagnosis of COVID-19 by most of the researchers in the research community. Several researchers have proposed various models for the prediction of COVID-19 using CT images using Artificial Intelligence based algorithms (Alimadadi e al., 2020 [19], Srinivasa Rao and Vazquez, 2020 [20], Vaishya et al., 2020 [21]). EfficientNet is one of the powerful Convolutional Neural Network models proposed by Tan and Le (2019). The objective of this study is to explore the effect of image enhancement algorithms such as Laplace transform, Wavelet transforms, Adaptive gamma correction and Contrast limited adaptive histogram equalization (CLAHE) on Chest CT images for the classification of Covid-19 using the EfficientNet algorithm. SARS- COV-2 (Soares et al., 2020) dataset is used in this study. The images were preprocessed and brightness augmented. The EfficientNet algorithm is implemented and the performance is evaluated by adding the four image enhancement algorithms. The CLAHE based EfficientNet model yielded an accuracy of 94.56%, precision of 95%, recall of 91%, and F1 of 93%. This study shows that adding a CLAHE image enhancement to the EfficientNet model improves the performance of the powerful Convolutional Neural Network model in classifying the CT images for Covid-19.


## 1. Introduction

Novel Coronavirus is a wide group of viruses that cause everything from a regular cold to more chronic infections like Middle East Respiratory Syndrome (MERS) and severe acute respiratory syndrome (SARS). In Wuhan, China, a new coronavirus (COVID-19) was found in 2019. This is a newly discovered coronavirus that has never been seen in people earlier. The majority of people affected with the COVID-19 virus will have minor to medium respiratory symptoms and this will recover fully without requiring additional care and treatment. Adults over the age of 65, including those with underlying health conditions such as cardiovascular disease, diabetes, chronic respiratory disease, and cancer, are at an increased risk of developing a serious illness. On January 30, 2020, the World Health Organization (WHO) announced a worldwide health emergency. To minimize the spread of illnesses, early treatment of illnesses is among the first lines of defense against this epidemic. Table 1 descibes various deep learning applied in this of research [1,2,5,6,9,11] along with the corresponding results.

Presently, the starting point for diagnosing COVID-19 is a positive nucleic acid testing (NAT) report using reverse- transcriptase polymerase-chain-reaction (RT-PCR) technology. The conventional testing tool, RT-PCR, is well- known, but recent investigations have found that it has a significant risk of false negatives. The RT-PCR method for determining COVID-19 has a few shortcomings. As a result, chest CT has become an accurate imaging technique for COVID-19, which is performed in addition to clinical symptoms and epidemiological findings to identify the illness. CT scan images are also helpful for detecting COVID-19 with greater specificity and sensitivity, according to studies. To begin with RT-PCR, test kits are inadequately available, require additional time for testing, and checking sensitivity also varies. The CT scan images were effective in diagnosing COVID-19, resulting in more lives saved. In endemic areas, a CT scan of the chest is found to be crucial for COVID-19 identification. Due to the sensitivity and specificity results of CT

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**Table 1**
Comparison of Different Deep learning Methods using Transfer Learning Techniques to identify COVID 19 patients or non-COVID patients by CT scan images ([1,2,5,6,9], and [11]).

| S.No | Pre-trained Models | Accuracy |
|---|---|---|
| 1 | VGG-16 | 89% |
| 2 | DenseNet169 | 93.15% |
| 3 | InceptionV3 | 53.4% |
| 4 | Inception ResNet | 90.90% |
| 5 | ResNet50 | 60% |
| 6 | AlexNet | 82% |

scans, many different countries. Now uses a clinical detection threshold based on optimal CT scan imaging symptoms. As a result, the images of the CT scan are a good replacement for the RT-PCR method. This paper aims to reduce the number of false-positive and false-negative where to try to save the human life and can provide better accuracy with other deep learning approaches.

## 2. Related works

Coronavirus is a subclass of RNA viruses that can cause dangerous serious diseases in people and animals. There have been more than 24.6 crore cases reported of coronavirus worldwide as of today, with around 44.3L of these instances leading to the death of the person infected. There are 216 countries, areas, or territories got affected by the coronavirus. The top four countries with the most instances are the United States, Brazil, India, and Russia.

COVID-19 testing involves evaluating items that show the presence of severe acute respiratory syndrome-associated coronavirus. Several researchers have proposed various models for the prediction of COVID-19 using CT images using Artificial Intelligence based algorithms (Alimadadi e al., 2020 [19], Srinivasa Rao and Vazquez, 2020 [20], Vaishya et al., 2020 [21]). The state-of-the-art of Convolutional Neural Networks (CNNs) for diagnosing COVID-19 from chest X- rays automatically (CXRs) is presented in [12]. Different types of deep learning algorithms were investigated and identified the best algorithms were for the classification of CXR images. Investigations were done using 1345 viral images, 1341 healthy CXR images for deep analysis of COVID-19. From the observations, VGG16 and Mobile net were able to provide an accuracy of 98.28%. Still larger data set is required to weigh the performance of transfer deep learning with F1 score, specificity, sensitivity, and precision.

Automated detection of Covid-19 in X-ray and CT images using a machine learning approach is presented in [7]. For this approach, accurate feature extraction is playing a major role in learning. This method is considered a pool of methods of deep learning approaches. They are mobileNet, DenseNet, Xception, ResNet, IncepptionNet, NasNet, InceprtionResNet and VGNet. The extracted features were then fed into several machine learning classifiers to classify subjects as either a case of COVID-19 or a normal case. The findings of this research on a chest X-ray and CT dataset shows Densenet architecture trained by Bagging tree classifier was able to provide good accuracy on extracted features for classification of the images. The investigation on the elements that influence the quality of ImageNet pre-trained features by transfer learning [4]. The process of developing high-performance learners by means of easily assessible data collected from various areas is called transfer learning [13]. The objective of this paper [4] was to establish the importance of feature learning for training data, rather than to evaluate various neural network topologies. Using transfer learning, a significant reduction was observed in several images or the number of classes for training the data.

A new automatic prediction of COVID 19 disease using CT images with the integration of deep learning and machine learning techniques are developed in [10]. The DenseNet201 model has the best training results, with a good accuracy rate. The DenseNet201 model and KNN algorithm had the best result when combining pre-trained models with ML algorithms and were able to achieve very good accuracy. An integrated approach of five different transfer learning architectures such as Densenet 201, VGG19, Efficient Net, Mobile net, and ResNet to detect Covid-19 images[8]. The findings of this research reveal that transfer learning-based frameworks could be a viable alternative to the existing methods for detecting the occurrence of the infection in victims. The impact of using standard Histogram Equalization and Contrast Limited Adaptive Histogram Equalization on lung scans is also examined in the study. The VGG-19 architecture, when integrated with a dataset that uses Contrast Limited Adaptive Histogram Equalization, provided the highest overall results, with 95.75 percent accuracy.

KarNet, a simplified two-dimensional DL architecture, works well in identifying COVID-19 patients using lung CT scan images [3]. Karnet was a deep learning framework that combined the pre-trained models such as DenseNet201, VGG16, ResNet0V2, and MobileNet. This integrated model acted as the backbone of Karnet. Each model of this approach was developed and tested using both augmented and unaugmented datasets. Karnet model that utilized DenseNet201 produced a better identification ability when compared with other pre-trained models. DenseNet was able to produce 97% accuracy for the dataset.

## 3. Materials and methods

The SARS-CoV-2 computed tomography (CT) scan dataset [14], which is openly accessible, is used in this study. The dataset comprises a collection of 2482 CT scans, out of which 1252 CT scans are of those positive for COVID-19 infection followed by 1230 CT scans for patients who are not infected by COVID-19. The information was gathered from genuine patients in a hospital in Sao Paulo, Brazil. The goal of this dataset is to promote the product development of artificial intelligence systems that can determine whether a person is affected with SARS-CoV-2 by analyzing his or her CT scans. Fig. 1 illustrates a few samples obtained from the dataset for COVID and NON-COVID CT scans.

### 3.1. Image preprocessing and enhancement

The images were pre-processed and the dataset size is enhanced with brightness augmentation. Further, we applied the following five image transformation to enhance the images before it is fed to the EfficientNet algorithm. The adaptive gamma correction transformation technique is used to increase the visibility of the detailed information present in an image. This is done by increasing the brightness and contrast of an image without affecting any visual artifacts. The adaptive gamma correction defines the function which has intensity transformation based on the input image. It has several steps which include color transformation, image classification, and intensity transformation, enhancement of low-contrast image, and enhancement of the high- or moderate-contrast image.

The wavelet transform is to choose a function as the basic wavelet whose integral is zero in the time domain. We can obtain a family function by expanding and translating the fundamental wavelet, which could serve as a framework for the function space. By projecting the image onto the framework, we decompose the original image. Several scaling in the wavelet transform domain can give a time-scale expression to an image in the original time

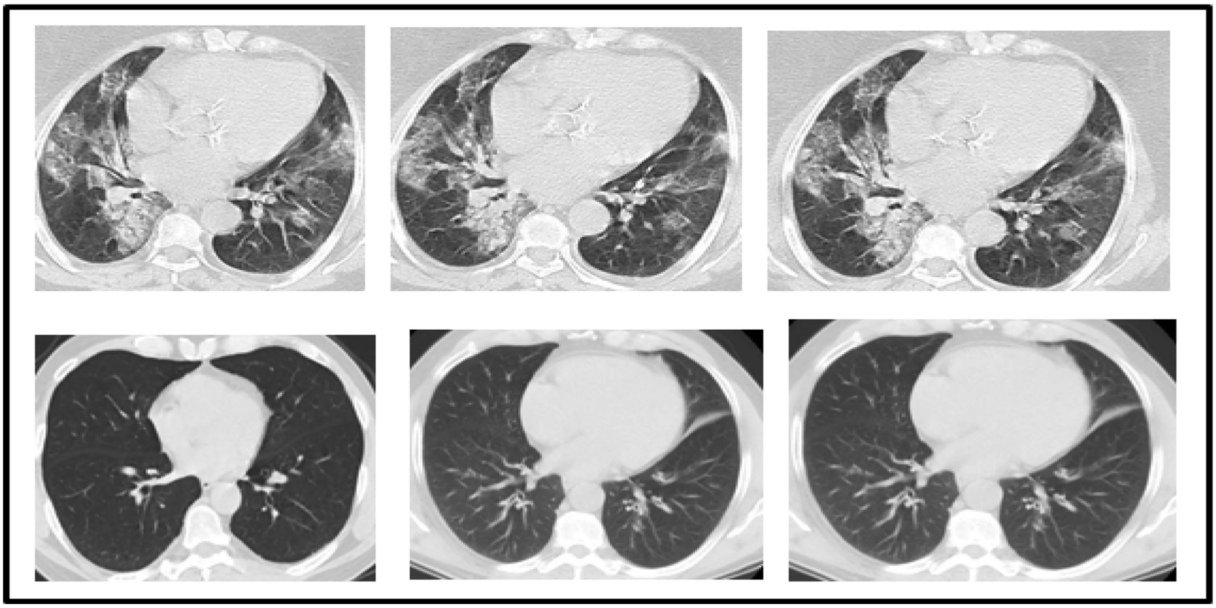

**Fig. 1.** CT Scans of people with COVID (top 3) and without COVID (bottom 3).

domain. Then we may get the most efficient image transformation domain. Fig. 2 illustrates the original image with the output acquired from the four image transformation techniques.

CLAHE is a histogram-based image enhancement method that limits amplification based on the clipping done in the histogram to limit it to a predefined level. It is a methodology for allocating projected intensity levels in medical data that has proven to be effective. The approach looks at a histogram of intensity in a contextual region focused on every pixel and adjusts the displayed brightness at that pixel to the ranking of that pixel's intensity in its histogram. The obtained histogram is a customized version of the standard histogram, in which the method's image contrast is shown at each intensity level [15]. CLAHE works by minimizing contrast enhancement, which is commonly achieved by a technique called Histogram Equalization [16], which also results in noise augmentation. As a result, desired outcomes were attained in circumstances where noise became excessively noticeable by enhancing contrast, such as medical photos, by restricting contrast augmentation in Histogram Equalization. In simple terms, contrast enhancement is the slope of the function that connects the input picture intensity value to the desired resultant image intensities. The slope of this related function can be limited to reduce contrast [17]. In our work, the inclusion of CLAHE has aided in enhancing the overall accuracy rate.

### 3.2. EfficientNet algorithm

The EfficientNet algorithm was originally introduced by [18] by offering an incredible method for scaling neural network models by enhancing depths, breadth, and precision. It is a convolutional neural network (CNN) design and scaling technique that applies a compounded coefficient to scale up all depth, width, and resolution dimensions evenly.

The EfficientNet scaling method consistently increases network breadth, depth, and resolution with a set of preset scaling parameters, contrasting standard practice, which adjusts these factors randomly The researchers started by creating a base network using a technique called neural architecture search, which automates the building of neural networks. On floating-point operations per second which in short is known as the "FLOPS" level, it optimizes both effectiveness and precision. The movable inversion bottleneck convolution called "MBConv" has been utilized in this architecture. Furthermore, the authors then scaled up the base network to create the EfficientNet class of deep learning methods.

Fig. 3 shows the EfficientNet-B0 setup, which is the most efficient. There are a total of 18 convolution layers, each having a k (3,3) or k(3,3) kernel (5,5). The size of the input image is 224 by 224 pixels. The next layers are reduced in resolution to lower the size of the feature map but increased in width to improve accuracy. The second convolution layer, for example, has W = 16 filters, whereas the next convolution layer has W = 24 filters. For the last layer, which is sent to the fully connected layer, the maximum number of filters is D = 1, 280.

The hyperparameters are set up during the model's training. To avoid overfitting during the training phase, an early stopping approach was adopted. At the moment where the validation loss value was the best, the models were registered. The models were trained using the Adam optimization technique. In this optimization, the learning rate is initially set to 0.0005.

Fig. 4 depicts the flow diagram carried out in our work. Initially, we have performed the necessary and requisite data processing methodology. This is followed by an image-enhancing step with the aid of the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. Once the enhancing process is completed, we load the reconstructed enhanced data into the EfficientNet algorithm. The obtained results for the proposed work are evaluated in terms of accuracy rate, precision, recall, and F1-score.

## 4. Results and discussion

In this study, the effects of image transformation algorithms such as SMQT, Wavelet transform, Laplace transform and CLAHE were analyzed on the EfficientNet algorithm in the classification of the COVID-19 CT images. This study was conducted in a system with a corei5 processor 7th generation, 16 GB RAM, and Nvidia GeForce 940MX GPU. The SARS-COV-2 CT scan dataset consists of 2482 images. The training set comprises 1984 images and the testing set comprises 497 images in the ratio of 8:2 approximately. The effect of five image transformations such as CLAHE, Wavelet transform, adaptive gamma correction, and Laplace transform are eval-

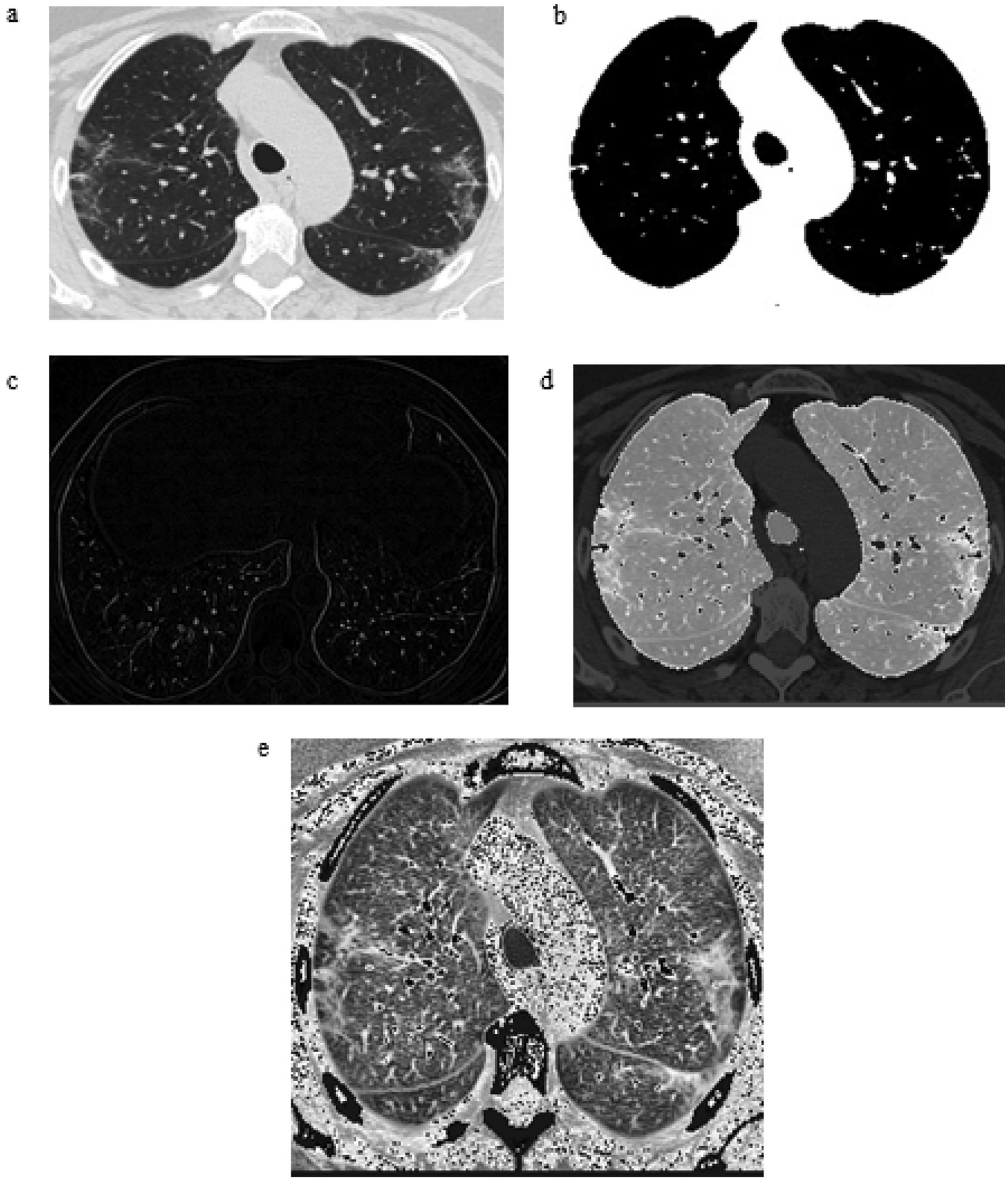


**Fig. 2.** (a) Original Image; (b) Adaptive Gamma Corrected Image; (c) Laplace Transformed Image (d) Wavelet Transform Image (e) CLAHE Enhanced Image.

uated on the EfficientNet algorithm. The accuracy and loss of the EfficientNet algorithm without image enhancement are shown in Fig. 6. The model achieved a validation accuracy of 90.15%.

However, few of the evaluated image transforms showed a significant difference in the classification accuracy. Fig. 6 shows the accuracy and loss of the EfficientNet algorithm with Laplace transformed images. The accuracy was comparatively lower than the EfficientNet algorithm without Laplace transformation. Fig. 8 shows the accuracy and loss with adaptive gamma-corrected images. Though there is a slight increase in the accuracy there was no significant improvement. Fig. 8 shows the accuracy and loss with Wavelet transform. Either the wavelet transform did not show a significant improvement. Fig. 9 shows the accuracy and loss with CLAHE transformation. It is observed that there is a significant increase in accuracy compared to the other image transforms. In this work, a 10-fold cross validation has been performed whose results are elaborated in Table 2 respectively.

Fig. 5 shows the training and validation accuracy of the EfficientNet model. The model achieved a validation accuracy of 90.15%.

Fig. 6 shows the training and validation accuracy and loss of the EfficientNet model with Laplace image transformation. The model achieved a validation accuracy of 75.90%.

Fig. 7 shows the training and validation accuracy and loss of the EfficientNet model with adaptive gamma- corrected images as input. The highest accuracy is achieved during the epoch. The model achieved an accuracy of 90.94%

Fig. 8 shows the training and validation accuracy of the EfficientNet model with wavelet transformation. The model achieved a validation accuracy of 92.55.

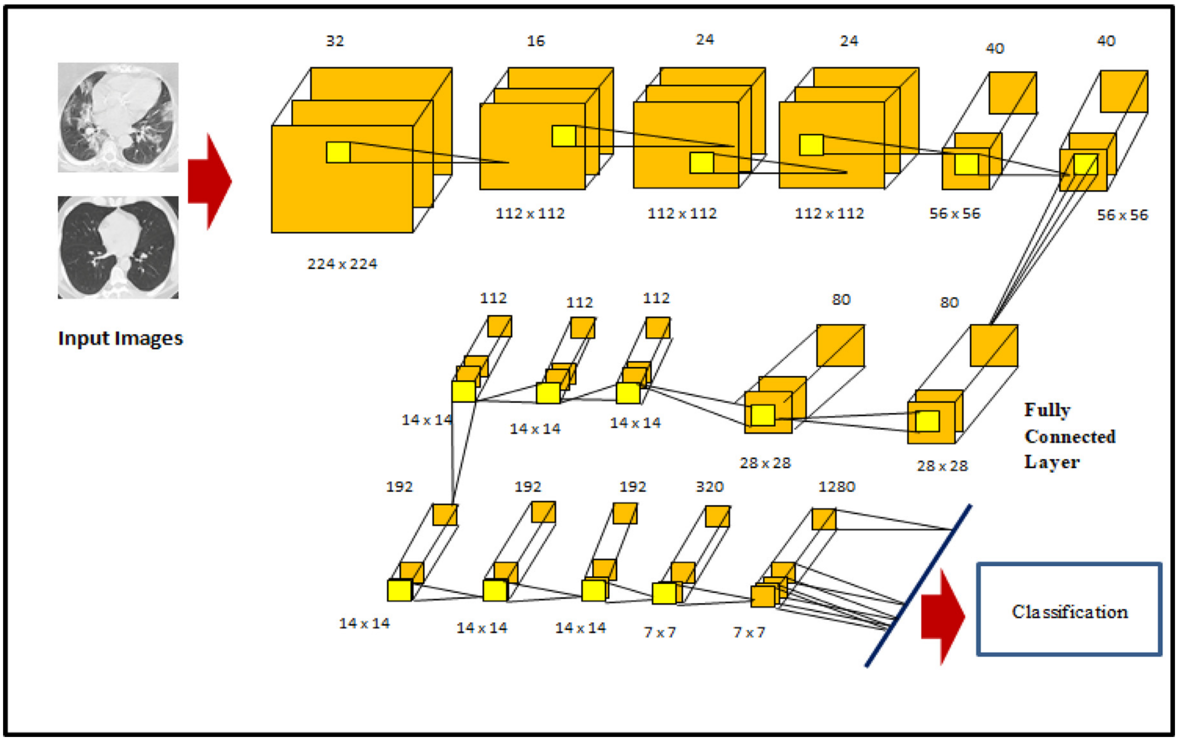


**Fig. 3.** EfficientNet: Detailed Architecture Diagram.

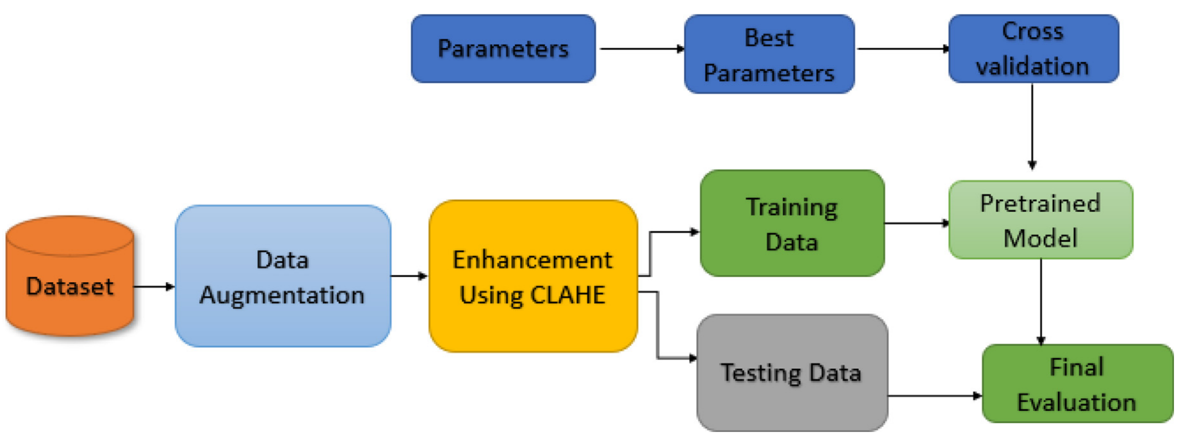


**Fig. 4.** Flow Diagram for the Proposed Work.

Fig. 9 shows the training and validation accuracy of the EfficientNet model with CLAHE image transformation. The model achieved an accuracy of 94.56%. The effect of the CLAHE transform was comparatively significant on the accuracy of the model.

The average of the 10 fold cross validation is given in Table 3. As shown in Table 3 the performance metrics such as precision, recall and F1 for CLAHE transform are high compared to the other image transforms on the EfficientNet model.

## 5. Conclusion

This paper provides an efficient image classification using EfficientNet for COVID-19 detection using CT images. We used preprocessing to enrich the images before implementing the algorithm in this investigation. Our method can increase the visibility of the given image without affecting the visual artifacts of the image. Several transformation techniques were executed on EfficientNet such as Wavelet transform, Laplace transforms, adaptive gamma, and CLAHE. Among them, we were able to achieve an accuracy of 94.56% using CLAHE transformation on EfficientNet. Finally, chest CT imaging provides high sensitivity for COVID-19 diagnosis. To detect COVID-19 via CT images, we provide a very efficient approach using CLAHE transformation on EfficientNet strategy that outperforms state-of- the-art approaches.

## CRediT authorship contribution statement

**A. Shamila Ebenezer:** Conceptualization, Methodology, Validation. **S. Deepa Kanmani:** Data Curation, Formal Analysis, Review. **Mahima Sivakumar:** Resources, Visualization. **S. Jeba Priya:** Writing - review & editing.

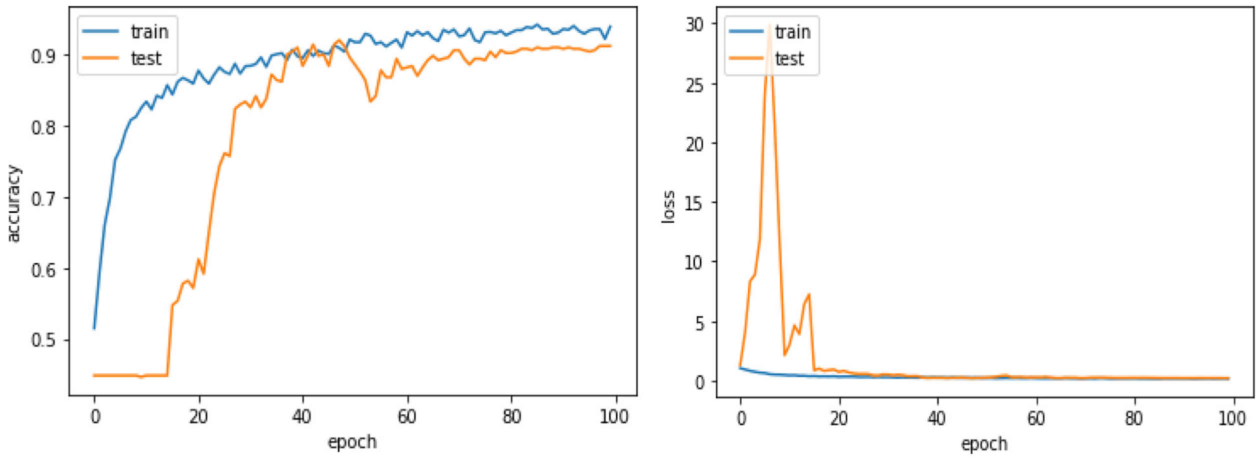


**Fig. 5.** Training and validation accuracy of EfficientNet model.

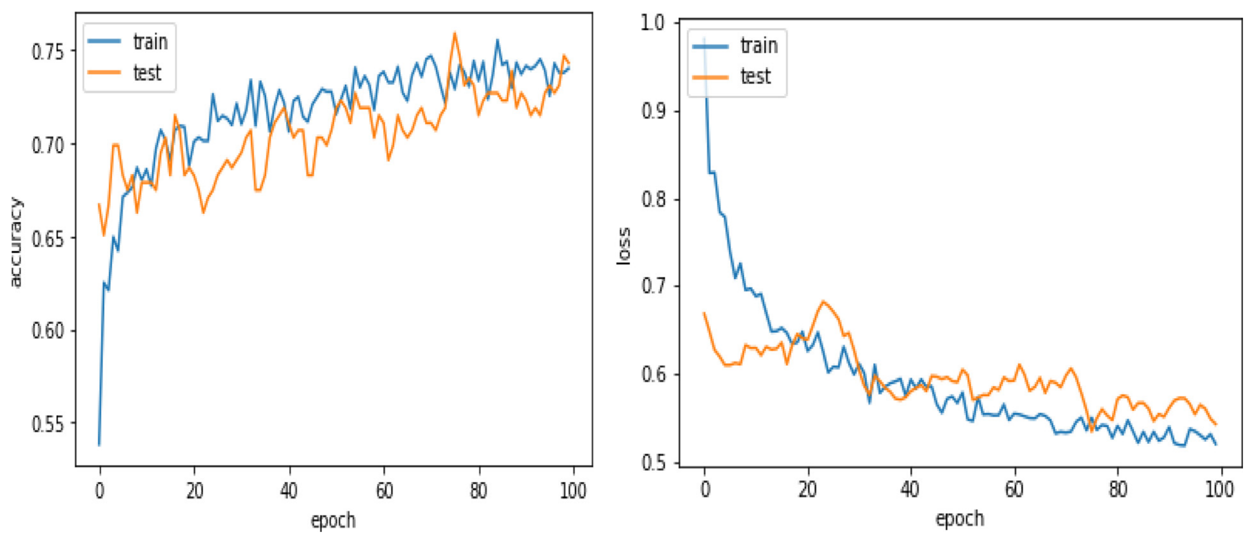


**Fig. 6.** Training and validation accuracy of Laplace transformed images on EfficientNet model.

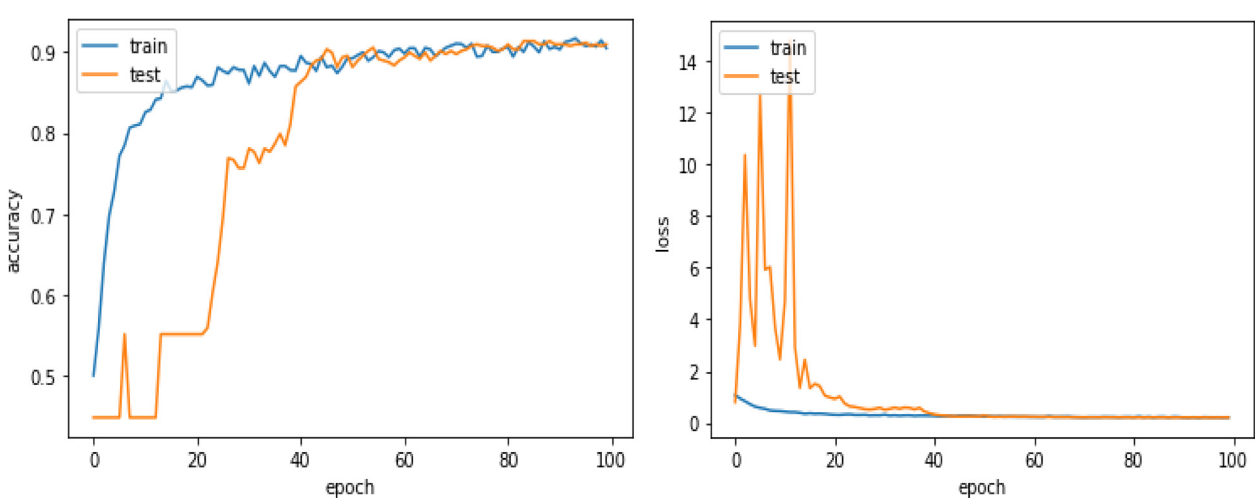


**Fig. 7.** Training and validation accuracy/loss of adaptive gamma-corrected images on EfficientNet model.

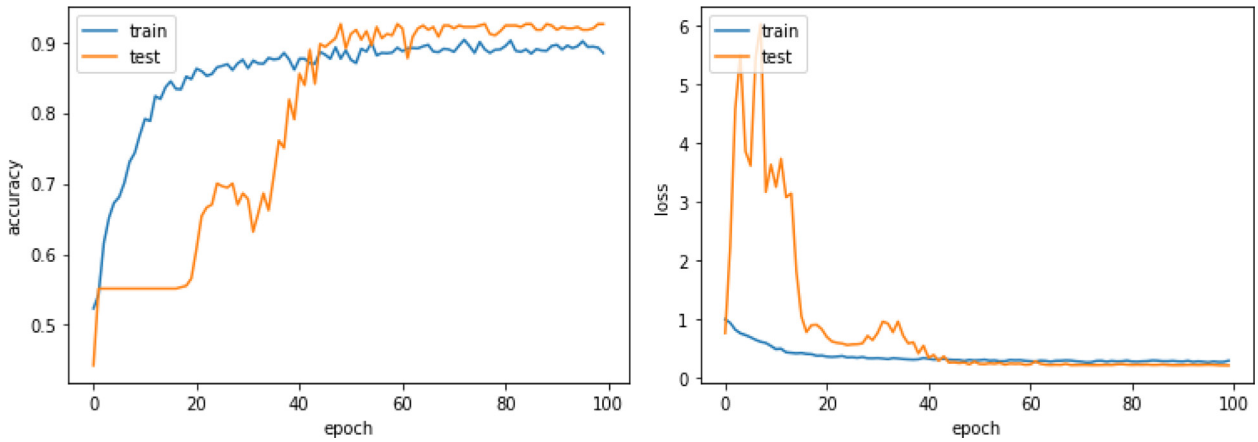


**Fig. 8.** Training and validation accuracy/loss of wavelet transformed images on EfficientNet model.

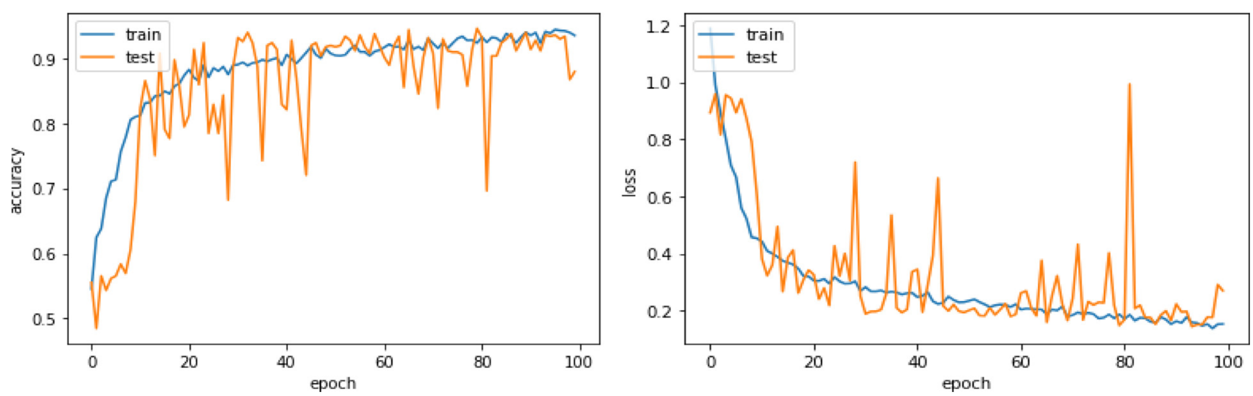


**Fig. 9.** Training and validation accuracy/loss of CLAHE transformed images on EfficientNet model.

**Table 2**
Results of 10-Fold cross validation.

| Fold | Accuracy | Precision | Recall | F-1 Score |
|---|---|---|---|---|
| 1 | 94.80% | 93.01% | 91.00% | 91.00% |
| 2 | 94.12% | 94.60% | 91.00% | 94.00% |
| 3 | 93.54% | 93.33% | 90.89% | 93.00% |
| 4 | 92.72% | 92.70% | 92.00% | 92.00% |
| 5 | 92.52% | 92.31% | 90.00% | 92.00% |
| 6 | 95.67% | 94% | 91.00% | 94.00% |
| 7 | 96.52% | 98.44% | 91.00% | 93.90% |
| 8 | 96.52% | 98.39% | 91.10% | 93.80% |
| 9 | 94.74% | 97.45% | 91.00% | 92.10% |
| 10 | 94.48% | 95.78% | 91.00% | 94.20% |
| Average | 94.56% | 95.00% | 91.00% | 93.00% |

**Table 3**
Average values of performance metrics.

| Model | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Laplace transform | 0.7590 | 0.68 | 0.72 | 0.64 |
| Adaptive gamma correction | 0.9094 | 0.91 | 0.91 | 0.92 |
| Wavelet transform | 0.9255 | 0.93 | 0.90 | 0.93 |
| **CLAHE transform** | **0.9456** | **0.95** | **0.91** | **0.93** |

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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