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A Data Augmented Approach to Transfer Learning for Covid-19 Detection

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Abstract. Early Covid-19 detection can help with efficient treatment and isolation plans to prevent its spread. Recent transfer learning methods are constrained by the size of labeled datasets, affecting the reliability of the Covid-19 diagnosis. Motivated by the success of data augmentation for various classification problems, in this work, we adopt an approach called contrast limited adaptive histogram equalization (CLAHE) to train the last layer of the various popular convolutional neural networks models. This optimization to transfer learning aims to mitigate the bias prevalent in insufficient labeled Covid-19 datasets. Specifically, we transfer learned AlexNet, ZFNet, VGG-16, ResNet-18, and GoogLeNet using the CLAHE-augmented dataset. Experiment results reveal that the CLAHE-based augmentation demonstrates better performance in contrast to models fine-tuned under non-augmented datasets.

INTRODUCTION

Transfer learning uses pre-trained models to accelerate learning for various computer vision applications, such as robotics and video processing. More precisely, transfer learning takes benefits from the correlation of datasets to develop classification algorithms suitable for dynamic environments [1]. Specifically, the transfer learned patterns on a source dataset are used to build an optimized deep learning (DNN) solution for a closer target application, where the pre-trained model is fine-tuned for the target dataset [2]. Conventional image classification techniques are computationally expensive and are time-consuming [3]. These challenges are addressed by popular convolutional neural networks (CNNs). One of the major shortcomings of CNNs is that they require a large number of relevant training samples to achieve good accuracy. Transfer learning is a popular solution to address these limitations and works efficiently with smaller training datasets [4].

Early and faster Covid-19 detection can help to contain the disease while offloading significant pressure from healthcare [5]. Popular Covid-19 screening techniques include reverse transcriptase quantitative polymerase chain reaction (RT-qPCR), computed tomography (CT) imaging, thermal screening, and X-Ray imaging [6]. These screening techniques, however, have some serious drawbacks. For example, in the RT-qPCR test, viral RNA is extracted from nasal swabs using a fluorescent dye that is invasive requiring significant time and effort [7].

Most image processing solutions to Covid-18 detection are used to assist the clinician with a second opinion [8]. In this context, various deep learning approaches to image classification have been reported in the literature. Hemdan et al. [9] proposed a deep learning model called COVIDX-Net based on seven CNNs to diagnose Covid-19 using X-ray images. Similarly, [10] has introduced a deep model for Covid-19, called COVID-Net to classify Covid-19 and non-Covid-19 patients. These deep learning approaches assume a large labeled X-ray dataset to train the deep learning models, an expensive and tedious process.

One serious challenge to machine learning classifiers is bias prevalent in the dataset. This bias reflects errors where certain features/classes are heavily weighted/represented than other classes. This can result in poor classification accuracy, analytic errors, and poor generalization. These challenges to Covid-19 detection are alleviated using the potential of transfer learning that results in high-quality DNN models with a small dataset [11]. Data augmentation is a viable solution to reduce overfitting problem due to smaller training dataset. This issue is common in medical diagnostics where collection of samples requires significant resources and time. In computer vision, this issue is addressed by generating new data points from existing using semantics-preserving transformations known as data augmentation [12].Bias in transfer learning can be alleviated using appropriate data augmentation techniques. These augmentation approaches, however, only slightly alter the train samples affecting the reliability of transfer learning. In contrast to these simple augmentation methods, this work adopts Contrast Limited Adaptive Histogram Equalization(CLAHE)-based optimization to transfer learning [13]. This method locally enhances the low-contrast X-ray images and provides better feature details.

Specifically, this research proposes transfer learning models based on using CLAHE-based augmentation. It evaluates the performance of CLAHE-based augmentation to the popular pre-trained models and compares with the transfer learning without augmentation.

CLAHE-AUGMENTED TRANSFER LEARNING FOR COVID-19 DETECTION

CLAHE is a contrast enhancement algorithm that improves image quality by highlighting image features and information. Image contrast is achieved through local and global pixel processing. Traditional contrast enhancement algorithms, such as histogram equalization (HE), adaptive histogram equalization (AHE), and hybrid cumulative histogram equalization (HCHE) redistribute the brightness of each image with the help of histograms [14]. CLAHE overcomes the issue of global histogram equalization due to noise amplification from the homogeneous regions. The algorithm computes different histograms and utilizes them to redistribute the lightness value [13]. Primarily, CLAHE enhances the low-contrast medical images with the help of control image enhancement quality parameters including block size (BS) and clip limit (CL).

Algorithm 1 illustrates the steps involved in data augmentation to address the issue of the imbalanced dataset of lung X-ray images. Line 1 of Algorithm 1 shows that the Algorithm 1 takes the Covid-19 dataset as an input. Lines 6 to 11 illustrate the steps to perform augmentation on the Covid-19 dataset using the CLAHE algorithm. Line 7 outlines the steps of selecting random images and applying a 20-degree rotation using ImageDataGenerator(). A random rotation with a limit of 25 degrees ensures that the representative class features are not removed by cropping. Line 8 and line 9 transforms the images horizontally and vertically. Line 10 represents the process to flip random images to generate new ones. It also applies the default likelihood of flipping to each image. Line 11 presents the process of filling points residing outside the boundary of the input image using the nearest points.

Finally, line 12 shows the CLAHE-based augmentation by calling the AHE() method. Line 15 adds a CL of 0.03 to the images using the CLAHE. CLAHE divides an image into several non-overlapping regions of equivalent size. It determines histograms for each region that are redistributed such their height do not exceed 0.03. CLAHE algorithm generates multiple images after applying the contrast enhancement mechanism. Class imbalance of the dataset is addressed before applying augmentation. This results in an increase in the dataset to 1847 Covid-19 labeled images.

```
Input Data: Chest X-ray Images (X,Y), Y = y/y ∈ Covid − 19
 1: loop
 2:     for all x ∈ X                        ▷ Apply ImageDataGenerator to all images
 3:     x ← ImageDataGenerator(x)
 4: function ImageDataGenerator (x)
 5:     rotate( random( x,20))               ▷ Rotate images at 20
 6:     shift(width, 0.01)                   ▷ Shift width to 0.01
 7:     shift(height,0.01)                   ▷ Shift height to 0.01
 8:     flip(random(x, horizontal)           ▷ Flip horizontally
 9:     fill(mode=nearest)                   ▷ Fill points outside boundaries
10:     x ← AHE(x)                           ▷ Apply AHE to input images
11: end ImageDataGenerator()
12: function AHE (x)
13: CLAHE(clip_limit=0.03)                   ▷ Apply CLAHE algorithm with contrast enhancement
14: end AHE()
```

Algorithm 1: CLAHE-based image augmentation algorithm.

CLAHE-AUGMENTED TRANSFER LEARNED MODELS FOR COVID-19 DETECTION

The models used for transfer learning based on CLAHE-based augmentation are discussed below.

AlextNet AlexNet is a CNN model that won the ImageNet Large Scale Visual Recognition (ILSVRC) for detecting objects and classifying images in 2012 [15]. The model consists of five convolutional layers and three fully connected layers. The first two convolutional layers of the model are backed by normalization and max-pooling layers that use a 3×3 filter and a stride size of 2. The next two convolutional layers are linked straight with a max-pooling layer followed by the last convolutional layer in the model. The output of the max-pooling layer is passed to two fully connected layers, of which the second fully connected layer uses a softmax activation function. The filters present in the first and second convolutional layers are of size 11×11 and 5×5, respectively.

ZFNeT ZFNet is a CNN architecture built as an extension to AlexNet. The model uses 7×7 kernels rather than 11×11 to reduce the number of weights. The model aims to prevent pixel information due to the large filter and uses ReLu as the activation function [16]. It not only reduces the number of network parameters but also increases the accuracy of the classification.

VGG-16 VGG-16 is a deep CNN that consists of sixteen layers. The architecture of this model involves five stacks of convolutions. Spatial resolutions are retained after 3×3 convolution layers with the aid of 1-pixel padding and 1-pixel stride. There are five max-pooling layers with stride 2 that trail some convolutional layers. The classifier part consists of three fully connected layers, the first two layers having 4096 channels and the third layer having as many channels as the number of classes. The third fully connected layer that performs the classification is followed by the Softmax layer that yields class probabilities [17].
ResNet-18 ResNet is renowned for its use of residual blocks. This model architecture consists of a continuous connection between residual blocks to address gradient disappearance issues caused by the stacking of deeper layers in CNN. Residual block is a fundamental concept that attaches input x to output $F(x)$ to prevent gradient disappearance while using a 3×3 convolution layer twice. The model consists of eight modules, each of which has two convolutional layers aided by batch normalization [18].
GoogLeNet GoogLeNet is based on 22 layers to reduce the computational complexity associated with traditional CNN. The model uses fewer network parameters than AlexNet and VGG. The model incorporates inception layers based on different kernel sizes. These kernels perform dimensionality reduction to avoid computationally expensive layers.

Covid-19 Detection using Transfer Learned Models

All the selected models for Covid-19 detection are pre-trained on the ImageNet dataset consisting of 1.2 million high-resolution images from 1000 classes. These pre-trained models cannot directly extract features from the ImageNet dataset to classify the images. To address this challenge, these models are fine-tuned on the X-ray image dataset to extract Covid-19 features. During fine-tuning, the output produced by the fully connected layer of all the selected models is modified from 1000 to 2.Finally, this output is passed to the Softmax function that computes the probability distribution values that sum up to one [19].The initial learning rate of all the selected models is set to 0.04 which is decreased to 0.01 after every 4 epochs to accelerate convergence. The CLAHE-enabled transfer learning proposed in this work uses Adam optimizer as the loss function that converges faster. It uses a fewer number of iterations to reach the local minima of the loss function.

Line 1 in Algorithm 2 shows that all images from the dataset are taken as input. Line 2 shows the expected output where the images in $x \in X$ are correctly labeled as$y \in Y$. Line 1 shows a call to Algorithm 1 to perform CLAHE-based data augmentation on images labeled as Covid-19. Line 5 represents the method to flip the images horizontally, where the probability to select an image for flipping is set to 0.5. Line 7 normalizes the image using the mean and the standard deviation. Line 8 downloads various pre-trained models D for transfer learning, i.e., AlexNet, ZFNet, VGG-16, ResNet-18, and GoogLeNet. Line 10 calls fit () mechanism where all the models are fine-tuned and transfer learned. Line 16 to 17 shows the process of applying a learning rate of 0.01 for each model. Line 19 explains the training of the fine-tuned models for 5, 10, 15, 20, and 25 epochs. Line 20 indicates that, for each training episode with a batch size 16, the model parameters are updated using backpropagation after four training epochs. Lines 11 to 12 show the process of loading test data $x \in X_{test}$ to make predictions by using a fine-tuned model from D.

Input Data: Chest X-ray Images (X,Y); $Y = y/y \in Covid-19, normal$
$X \leftarrow$ *Algorithm 1(X)* ▷ Generate augmented images by using Algorithm 1 **while** $X! = \emptyset$ **do**
end
resize(x, 224×224) ▷ Modify image dimension
rotate(random(x,20)) ▷ Rotate images at 20
flip(x, horizontal):$P(r(x)) = 0.5$ ▷ Flip horizontally with probability of rotation 0.5
$x \leftarrow \bar{x}(0.485, 0.456, 0.406) \& std(0.229, 0.224, 0.225)$ ▷ Normalize each image
$D \leftarrow$ {AlexNet, ZFNet, VGG-16, ResNet-18, GoogLeNet} ▷ Download and fine-tune models **for** *all* $d \in D$ **do**
end
$d \leftarrow fit(d)$
foreach $x \in X_{test}$
d.predict_Covid-19(x)
function ***fit*** (d)
replace(classifier($d(2, dim = 1)$)) ▷ Replace last layer of each pre-trained model
$\mu \leftarrow 0.01$
end fit()
for $epoch \leq 25$ **do**
end
$d \leftarrow fit(d)$
foreach $batch(X_i, Y_i) \in (X_{train}, Y_{train})$
update(d, param) ▷ Update parameters of model
$epoch \leftarrow epoch + 5$ **if** *(loss(epochs,4) increases)* **then**
end
$\mu \leftarrow \times \times 0.01$ ▷ if loss increases for 4 epochs

Algorithm 2: CLAHE-enabled transfer learning for Covid-19 detection.

Performance Analysis of CLAHE-augmented Transfer learning

Dataset The dataset used for this work combines X-ray images from two other datasets, i.e., COVID-Chestxray-Dataset published by Joseph Paul Cohen [20] and ChexPert dataset [21]. The combined dataset consists of 2,031 images for training and 3,040 images for testing. The resultant dataset is combined with the positive Covid-19 images after consultation with a board-certified radiologist. The training dataset consists of 31 Covid-19 positive images, and 2000 non-Covid-19 images. The test dataset has 40 Covid-19 and 3000 non-Covid-19 images. The resultant dataset is highly imbalanced with a small number of positive Covid-19 images that necessitates the need to apply augmentation. The augmented dataset includes 6,887 images, out of which 3,847 images are used for training, and 3,040 images for testing. After augmentation, the training dataset consists of 1,847 Covid-19 and 2,000 non-Covid-19 images. On the other hand, the test dataset with 40 Covid-19 images and 3,000 non-Covid-19 images.

Figure 1 (a) represents the confusion matrix obtained while testing the ResNet-18 model. Out of the 40 Covid-19 positive images, 28 images are categorized as true positives (TPs) and 12 as false negatives(FNs). These predictions are valid for the 50 positive classes that are correctly classified, with only 11 images as incorrectly classified as Covid-19 positive. The confusion matrix based on the testing of the VGG-16 model trained for 10 epochs is illustrated in Figure 1 (b). The model demonstrates excellent performance by characterizing 35 out of 40 images as true positive and misclassifying only 28 images as positive.

Figure 1 (c) presents the confusion matrix of ZFNet model trained using 20 epochs. The model performance is relatively acceptable with 30 TPs and 10 FNs. Similarly, only 14 images are classified as FPs. Classification for Covid-19 positive classes is approximately 90% making the model a good fit for Covid-19 detection. The confusion matrix for the AlexNet model trained on 10 epochs is shown in Figure 1 (d). It demonstrates good performance to classify the Covid-19 images with 33% TPs out of 40 Covid-19. It also lists only 21 images as FP that appears reasonable to classify TNs correctly from the 2979 images. Figure 1(e) depicts the confusion matrix for GoogleNet based on 14 epochs. The model successfully classifies 25 images as TPs out of the 40 Covid-19 positive images. This indicates a forecast of over 50% with only 5 images as FP of healthy patients.

Figure 3 (a) shows the sensitivity of each model trained at different epochs. AlexNet demonstrates the highest sensitivity of 90% when trained on 5 epochs, whereas ZFNet achieves a sensitivity of 82.5%. Both models show a decrease in the rate of sensitivity when trained with a higher number of epochs. AlexNet modelś sensitivity fluctuates with a further ascent in sensitivity level at 15 and 25 epochs. On the contrary, the ZFNet modelś sensitivity is only increased with 25 epochs. VGG-16 achieves the highest sensitivity with an estimation of 92.5% when trained at 15 epochs. From 14 onward, the modelś performance diminishes with a slight ascent in 25 epochs. ResNet-18 shows weak performance in terms of sensitivity with a maximum of 70% when trained with 5 epochs. Among all the models, GoogleNet demonstrates the weakest sensitivity rate of 50% when trained on 25 epochs. GoogleNet shows the lowest sensitivity value of 77.5% sensitivity. Figure 3 (b) delineates the TNR of the 5 models used for Covid-19 detection trained on augmented data. Both GoogleNet and ResNet-18 show 99.63% specificity when trained on 5 epochs.

These models show a marginal degradation in performance when trained on 10 epochs. However, the model demonstrates an increase in performance with an increase in the number of epochs. GoogleNet achieves the highest specificity of 99.87% when trained on 20 epochs. Specificity value of the GoogleNet and ResNet-18 is almost the same when trained on 25 epochs. ZFNet presents an average performance in terms of specificity with 99.53% being the highest when trained using 25 epochs.VGG-16 demonstrates the least performance while AlexNet with 98% when trained on 5 epochs. The model, however, improves its performance to 99% on 10 epochs. VGG-16 shows a maximum specificity of 99.07% when trained on 10 epochs.

Figure 3 (c) shows the accuracy of all the models trained on augmented data. Among all the models, the GoogleNet demonstrates the highest accuracy of 99.34% when trained on 15 epochs. On the other hand, the AlextNet and VCG-16 when trained on 5 epochs demonstrate the accuracy of 97.93%, 98.62%, respectively. However, the accuracy of both the models improves to 99.08% and 98.91% when trained on 10 epochs. The ResNet-18 model shows an accuracy of 99.24% for 5 epochs. ZFNet shows an average performance with 99.21% accuracy when trained on 20 epochs.

We assess the quality of classification using MCC on a highly imbalanced dataset. Figure 3 (d) reflects the MCC estimations of different models. It can be observed from the Figure that the GoogleNet achieves highest MCC score of 0.72 when trained on 10 and 15 epochs. ZFNet achieves an MCC value of 0.71 when trained on 20 epochs. For the 5 epochs, both the ResNet-18 and ZFNet show an MCC score of 0.71 and 0.69, respectively. The model with the lowest MCC value of 0.56 was AlexNet when trained on 25 epochs.VGG-16 shows average results with a maximum MCC score of 0.69 when trained for 10 epochs.The above analysis reveals that VCG-16 demonstrates best performance in terms of sensitivity. AlextNet and ZFNet also show better sensitivity when trained on 5 epochs.

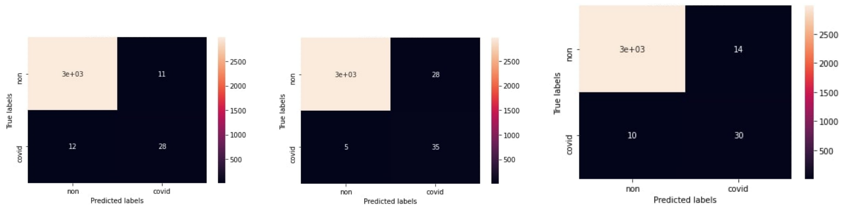
Performance Analysis of Transfer Learning Models without Augmentation

All the non-augmented images are down-sampled to 224×224 before feeding it to all the selected models for transfer learning.

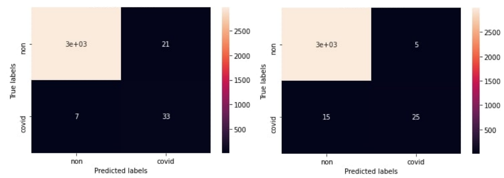
Figure 2 (a) presents the confusion matrix of ResNet-18 model trained using 20 epochs. It classifies only 19 images as TP out of the 40 Covid-19 positive images. In contrast to this, ResNet-18 with augmented data only classifies three images to FP. The confusion matrix of VGG-16 model trained for 15 epochs is given in Figure 2 (b). It can be seen from Figure, the model achieves 17 TPs and 3 FPs. Even with non-augmented data, the model tends to have a decently low number of FPs. Figure 2 (c) depicts the confusion matrix of the ZFNet model trained for 25 epochs. The model provides good results with 0 FP for classifying health patients. On the other hand, for the infected individuals, the ZFNet underperforms and classifies only 16 images as TP while 24 images as FN. Figure 2 (d) displays the confusion matrix of the AlexNet model trained on 25 epochs. AlextNet shows good performance by classifying Covid-19 patients accurately, i.e., 35 TP out of 40 images. Transfer learned model also characterizes the Covid-19 images with good accuracy by classifying only 6 images as FP. The confusion matrix of the GoogleNet model trained on 15 epochs is depicted in Figure2 (e). The model performs well with only 3 Covid-19 images as FP. As far as Covid-19 positive classification is concerned, the model incorrectly classifies 21 images as FN. The model precisely classifies 19 images as TP that is half of the total Covid-19 positive images fed into the model.

Figure 4 (a) presents the sensitivity of various Covid-19 detection models when trained on non-augmented images. For sensitivity, AlexNet demonstrates the best performance with a value of 95% when trained using 15 epochs. Other models show sensitivity below 60% with VGG-16 with the least sensitivity when trained for 5 epochs. Once trained for 15 epochs, AlexNet, GoogleNet, and VGG-16 achieve a sensitivity of 80%, 47.5%, and 42.5%, respectively. ResNet-18 shows a sensitivity of 57.50% when trained on 5 epochs

The specificity observed by different models trained on non-augmented images is shown in Figure 4 (b). All the models except AlexNet demonstrate stable performance. AlexNet presents a fluctuating value of 98.17%, 99.47%, 98.10%, 99.80%, and 99.73% when trained on 5, 10, 15, 20, and 25 epochs. ZFNet and VCG-16 show performance

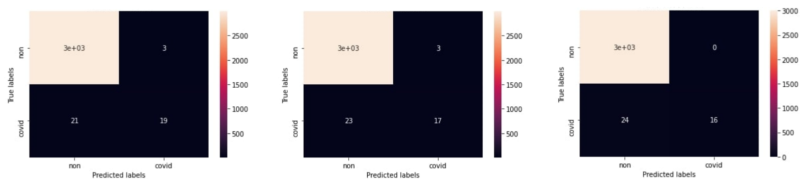


(a) ResNet-18. (b) VGG-16. (c) ZFNet.

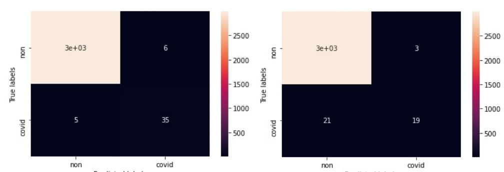


(d) AlexNet. (e) GoogleNet.

FIGURE 1. Confusion matrices of deep learning approaches with CLAHE-enabled augmentation



(a) ResNet-18. (b) VGG-16. (c) ZFNet.



(d) AlexNet. (e) GoogleNet.

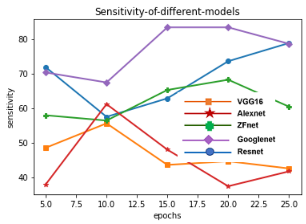
FIGURE 2. Confusion matrices of deep learning approaches without augmentation

with a specificity of 100% when trained on 5 epochs. GoogleNet and ResNet-18 also show noticeable specificity of 99.93% and 99.77% when trained on 5 epochs.

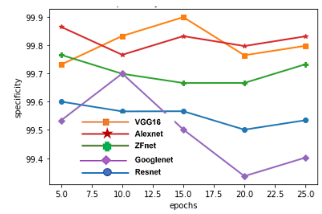
The accuracy of each model on non-augmented images is presented in Figure 4 (c). As with the specificity, all models demonstrate a stable performance with the exception of AlexNet. The accuracy demonstrated by the AlexNet is 97.93%, 99.28%, 98.10%, 99.64%, and 99.54% when trained on 5, 10, 15, 20, and 25 epochs. AlexNet shows the best accuracy when trained on 25 epochs. Apart from AlexNet, ResNet-18 and GoogleNet show the best accuracy of 99.21% and 99.14% when trained on 5 epochs. ZFNet and VGG-16 also show good accuracy of 99.01% and 98.85% when trained on 5 epochs.

Figure 4 (d) shows different values of MCC when the models are trained on non-augmented data for the Covid-19 classification. Among all the models, AlexNet achieves the highest value of 0.86 when trained on 20 epochs. VCG-16 demonstrated an MCC value of 0.35 when trained on 5 epochs. ResNet-18 shows the best MCC value of 0.66 when trained for 5 epochs. For 15 epochs, GoogleNet, ResNet-18 and VGG-16 show a value of 0.64, 0.63, and 0.60, respectively. Among all the models, ZFNet demonstrates a value of 0.63 when trained on 25 epochs.

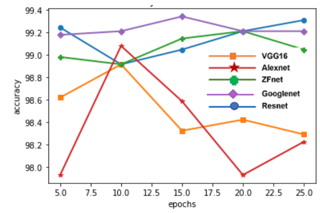
An analysis of Figure 3 and Figure 4 show that some classifiers without CLAHE-enabled augmentation, such as Alexnet tend to achieve a better mix of all the confusion matrix categories, i.e., true positives, false negatives, true negatives, and false positives, and react proportionally good both to the positive and negative classes. These classifiers outperform as data augmentation help to learn more generalizable knowledge using a larger dataset. It is critical to treat both the false positives and false negatives equally, specifically, it is essential to not diagnose a Covid-19 patient positive case as negative, resulting in its widespread in the community. Figure 3 (a) and Figure 4 (a) show that



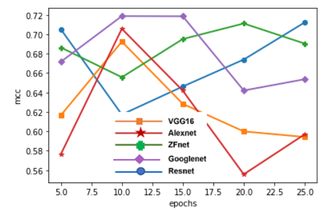
(a) Sensitivity.



(b) Specificity.

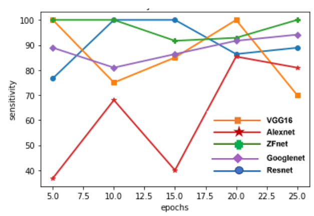


(c) Accuracy.

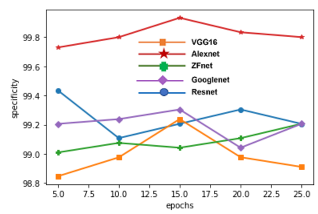


(d) MCC.

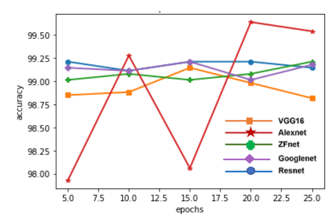
FIGURE 3. Performance of deep learning models with CLAHE-enabled augmentation



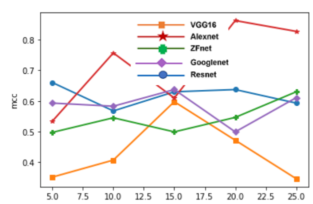
(a) Sensitivity.



(b) Specificity.



(c) Accuracy.



(d) MCC.

FIGURE 4. Performance of deep learning approaches without augmentation

the sensitivity of most of the classifiers is not affected by the increased size of the dataset using CLAHE-enabled augmentation. From a clinical aspect, this ensures that only a few false negatives are leading to missed Covid-19 infection diagnosis. Figure 3 (b) and Figure 4 (b) depict that the augmentation of the dataset improves the specificity of most of the classifiers, such as Resnet, VGG16, and ZNFnet. The high specificity of these classifiers ensures that Covid-19 negative predictions are negative for the majority of the cases. This shows that the prediction results achieved using the CLAHE-enabled augmentation are reliable for Covid-19 diagnosis in contrast to without augmentation.

The accuracy of all the classifiers in Figure 3 (c) and Figure 4(c) shows that the CLAHE augmented increase in the dataset improves the accuracy of most of the classifiers, such as Googlenet and ZFnet. This supports the potential of CLAHE-enabled augmentation to transfer learning, although they are known to work well with limited datasets. This suggests that pretraining of the large, out-of-held dataset with CLAHE-enabled augmentation ensures excellent performance in case of limited training data. Evaluations reveal that the majority of models perform better for Covid-19 detection when trained on CLAHE-augmented data. The specificity of majority deep learning models trained on non-augmented data is higher. On the other hand, transfer learned models when trained on CLAHE-augmented data achieve higher sensitivity. Our results suggest that almost all the models demonstrate Covid-19 detection accurately with high sensitivity when X-ray images are augmented using the CLAHE method.

CONCLUSION AND FUTURE WORK

Deep learning techniques incur higher training costs due to extensive parameters tuning with a requirement of large datasets. Although the dataset used for model training is relatively large with 5071 Chest X-ray images consisting of both Covid-19 and normal class images [22], the dataset remains unbalanced with only 31 images classified as Covid-19 positive for model training. To address this issue with the data, in this work we select various pre-trained models, including AlexNet, ZFNet, VGG-16, ResNet-18, and GoogLeNet, and transfer learned to create stable models for Covid-19 predictions. Specifically, we demonstrate how we can augment X-ray images data by using CLAHE to train the last layer of the selected models to improve model performance. Primarily, we propose transfer learning methods based on various deep learning approaches, i.e., AlexNet, ZFNet, VGG-16, ResNet-18, and GoogLeNet. Our results suggest that the transfer learning based on CLAHE-augmented data improves the accuracy and sensitivity of Covid-19 detection as compared to the transfer learned models using nonaugmented data. Our results reveal that the VCG-16 shows excellent performance with a sensitivity of 95% when trained using 15 epochs on CLAHE-augmented data. On the contrary, AlexNet performs well in terms of sensitivity even when trained on non-augmented data. Other models, however, show poor performance in terms of sensitivity with a value of less than 60%, once trained on non-augmented data.

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