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Image Pre-processing techniques comparison : COVID-19 detection through Chest X-Rays via Deep Learning

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ABSTRACT

The COVID-19 pandemic had a particularly devastating effect, spreading rapidly over the world and infecting about 36 million individuals. Chest radiography is a critical component that aids in the early detection of a variety of diseases. With the spread of the pandemic, training Convolutional Neural Networks (CNN) to detect and identify COVID-19 from chest X-rays is becoming more popular. However, there are few publicly available and medically validated datasets for COVID-19 infected chest X-Rays, resulting in the model failing to generalize successfully. It is critical to pre-process and enrich the data used to train the model in order to achieve this aim. Global Histogram Equalization (GHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Top Bottom Hat Transform are some of the pre-processing techniques available. In this study, we examine and compare all of these pre-processing methods in order to determine which is best for building a CNN model that can accurately classify an image as infected with COVID-19 or Viral Pneumonia.

Keywords: Radiography, Chest X-Rays (CXRs), COVID-19, Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Top hat Bottom Hat Transform, image pre-processing, Convolutional Neural Networks (CNNs)

I. INTRODUCTION

In December 2019, the COVID-19 pandemic [1][2][3] began in Wuhan, China. It didn't take long for the virus to spread over the globe. The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) causes the infection (SARS-CoV-2). Muscle aches, fever, sore throat, cough, tiredness, headache, shortness of breath, or a combination of these symptoms are frequent COVID-19 clinical symptoms. The most important step in fighting the pandemic is rapid and accurate screening of infected persons who are sick. The reverse transcriptasepolymerase chain reaction (RT-PCR) test, which is used to identify SARS-CoV-2 RNA from respiratory specimens, is the most widely used method for detecting COVID-19. RT-PCR, despite its enormous success, is very time-consuming, difficult, and complicated, as well as being in short supply. Radiology is a promising field, and the data obtained from images is incredibly significant and crucial in diagnosis and detection. Academics and researchers have discovered significant results in imaging studies of COVID-19. Chest x-rays (CXRs) are important in radiology because they provide the required information. Deep Learning [7][8][9] and Convolutional Neural Network (CNN) models have already been used to identify diseases and malignancies in several organs. To relieve the burden on radiologists, there is a growing trend to diagnose more and more ailments using computer aided [10] or automated techniques. Because having experienced and competent radiologists at every institution is almost impossible, an automated prediction model might make a significant impact. Artificial Intelligence (AI)-based systems are ideal for rapid COVID diagnosis because they eliminate reliance on test kits, as well as their pricing and waiting times, as shown with the RT-PCR test [12]. Many radiographic images and databases are available online, albeit not all of them have been thoroughly evaluated by radiologists. As a result, there is a paucity of validated data, and not all institutions make their patients' CXR data publicly available. As a result, it is required to pre-process the dataset used to train a CNN model in order to ensure that the network learns to classify based on relevant biological features. GHE, CLAHE, and Top Bottom Hat transform were used as pre-processing techniques in this investigation. We fed each pre-processing strategy's pictures into a CNN model to see which approach produced the best results. We also enhance the data to guarantee that it is more generic and that the model does not overfit the training set. Our CNN model, which is based on VGG-19, has 32 million parameters. We used transfer learning [13][14] and used the same design language to alter the VGG-19's head layer and add a few more layers. We use a cyclic learning rate schedule with category cross entropy loss, using Nadam as the optimizer.

Contribution: We discovered that pre-processing the data used to train the CNN to detect COVID-19 infection from chest X-rays is very important and improves accuracy. As a result, we studied a variety of pre-processing processes to determine which is the most appropriate and accurate.

II. METHODS AND MATERIAL

A. Dataset

The COVID-19 Radiography Database [26] is the dataset that was used. It includes 219 photos of COVID-19-infected CXRs, 1345 photos of patients with viral pneumonia, and 1341 photos of healthy CXRs. The dataset has been divided into train, test, and validation sets, with an 80:10:10 train/test/validation split ratio used. Because it is critical that the model be taught consistent data, the dataset only includes chest x-rays taken from the posteroanterior (PA) perspective. To solve the storage constraint, we resize all of the pictures to 512x512 pixels and then feed the images into the model after executing image pre-processing methods on them.on.

(a) COVID – 19

(b) Normal

Fig 1. Chest X-Rays in Data Set

B. Image Pre-processing

Global Histogram Equalization

Histogram Equalization [15] is an image processing technique that improves the quality of photos while preserving all of the data. By comparing pixels in the picture with similar contrast values and distributing their intensities over the histogram, this method improves the contrast of images. After dispersing their intensities over the histogram of the picture, Histogram Equalization calculates the probability mass function and the cumulative distribution function of all the image pixels according to their grey levels, and maps new grey level values into these pixels. The histogram shows the amount of pixels for each intensity value, and the Histogram Equalization technique involves increasing the picture's intensity range.

Contrast Limited Adaptive Histogram Equalization

Because the histogram of tiles in these locations is high, Adaptive Histogram Equalization [16] tends to overamplify the noise and contrast in the surrounding sections of the image. CLAHE (Contrast Restricted Adaptive Histogram Equalization) [17][18] is a better version of adaptive histogram equalization in which the amplification is restricted to prevent noise amplification. The slope of the transformation function provides the contrast amplification of pixels in Contrast Limited Adaptive Histogram Equalization (CLAHE).

(a) COVID-19

(b) Normal

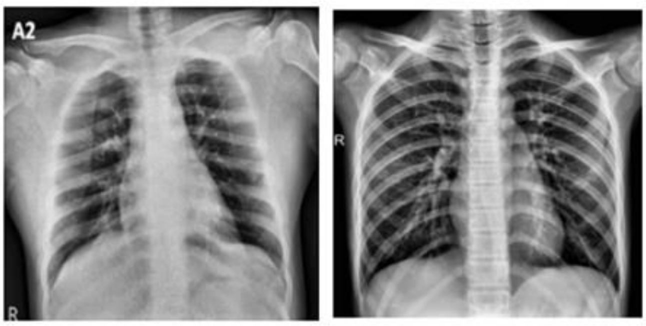
(c) Viral Pneumonia

Fig 2. GHE on Chest X-rays from the dataset

(c) Viral Pneumonia

Fig 3. CLAHE on Chest X-rays from the dataset

This slope is proportional to the slope of the cumulative distribution function (CDF) of the following pixel, and hence the value of the histogram for that pixel. By clipping the histogram at a certain value before calculating the CDF value of those pixels, the CLAHE technique limits the amplification of homogeneous regions. The CDF's slope is reduced as a result. The clip limit is the value at which the histogram is clipped, and it is determined by the normalization of the histogram as well as the size of the surrounding region. The histogram segment that exceeds the clip limit value may be redistributed uniformly over all histogram bins once again. We used a clip limit of 2.0 and a tile grid size of 1 to include CLAHE into our picture collection (8,8). (8,8). The importance of tile grid size is that for a 512x512 picture with a tile grid size of (8,8), each CXR would have a total of 4096 tiles.



(a) COVID-19 (b) Normal

Top Bottom Hat Transform (TBH)

The Top-Hat transform is a digital image processing procedure that separates small components and their characteristics from images. White tophat transformations and Black tophat (Bottom Hat) transforms are the two types of top-hat transforms. The difference between the input image and its morphological opening is denoted as the white top-hat transform. The discrepancy between the morphological closure of the image with itself is known as the Bottom Hat transform. Feature extraction and image enhancement are common uses for tophat transforms. The White top-hat transform produces a picture that includes input image components that are smaller than the structuring element and brighter than their surroundings. The Bottom hat transform, on the other hand, creates an image with sections that are smaller than the structural element and darker than their surroundings. By selecting the appropriate structural element, the size or breadth of the components recovered by these transformations may be controlled. These transform techniques are often used in image segmentation to improve non-uniform lighting circumstances and provide a better threshold pixel value for differentiating the objects in an image. Let A be a grayscale image that represents points in Euclidean space.

(a) COVID-19

(b) Normal

(c) Viral Pneumonia

Fig 4. TBH on Chest X-rays from the dataset

Let B be the chosen structuring element. Then the white top-hat transform of A is given by:

$WTH = A - (A \circ B)$ -(1)

Here, '∘' denotes the morphological opening operation. The bottom hat transform of A is given by:

$BTH = (A \cdot B) - A$ -(2)

Here, '·' denotes the morphological closing operation. The contrast enhanced version of an image is essentially the addition of the image with its White Top Hat transform and their difference with the Bottom Hat transform and is given by:

$Aenhanced = A + WTH - BTH$ -(3)

The image enhancement [19] works because we are indirectly adding the bright regions, which are the result of the white top hat transform and subtracting the dark regions which are the results of the bottom hat transform of the original image. For our work, we have taken a structuring element B as a square matrix of ones, with a size of 4x4.

C. Image Pre-processing

Following the preprocessing that we do, image augmentation [20][21] is another step that helps us produce more data. This is done to prevent the deep CNN model from overfitting to the little training data available. A model's generalization ability is determined by how well it performs on unseen test images from a different data distribution. We use transfer learning and image augmentation to improve the generalization potential of our model. In the CXRs, we use the following data augmentation techniques:

1. Rotation:
   These augmentations are done by randomly rotating the image to the left or right by a certain degree within a defined range. In our case, we require slight rotations so that the lung boundaries and edges do not go out of the image boundary. Hence, we have chosen a rotation range of 0.1 degree.
2. Width Shift:
   Images are randomly shifted on the horizontal axis by a fraction of the total width within a range to be determined by the users. Here, we need to make sure that the chosen value is such that upon translating the image towards the right or left, the lungs and their edges do not exit the image boundary. We have chosen a fraction value of 0.025 and this corresponds to a range of 12.8 pixels.
3. Height Shift:
   Images are randomly displaced on the vertical axis by a fraction of the total height within a range to be determined by the users. Again, we need to make sure that the chosen value is such

that upon translating the image upwards or downwards, the lungs and their edges do not exit the image boundary. We have chosen a fraction value of 0.025, corresponding to a range of 12.8 pixels.

4. Zoom:
   The images are randomly zoomed by a magnitude between 0 and 0.025. This range was selected to make sure that these augmentations do not make the lungs and their edges exit the image boundary.
5. Horizontal Flip: As the name suggests, the images are randomly flipped horizontally. This was done with the intuition that the model will be able to better diagnose chest radiographs of PA (posteroanterior) as well as AP (anteroposterior) view.

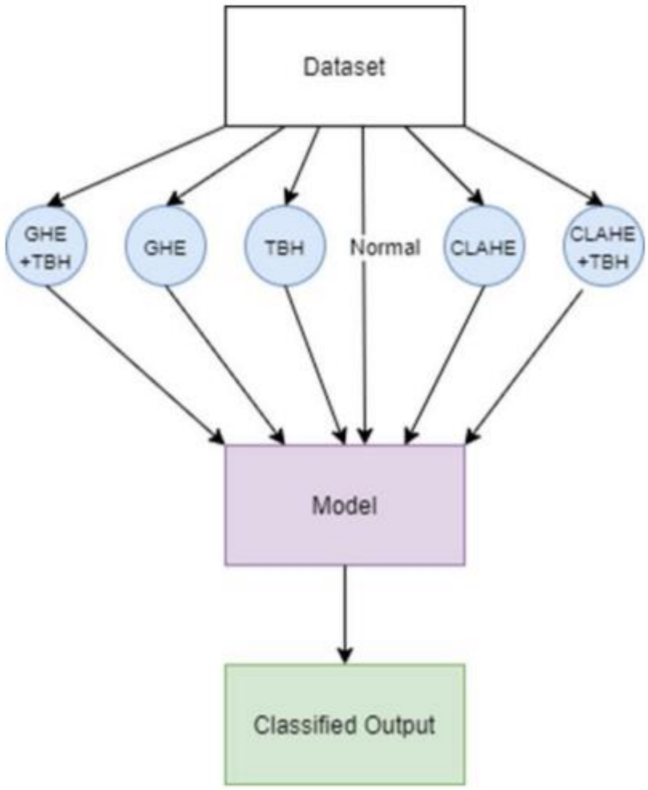


Fig 5. Process flow Diagram

D. Model Architecture

VGG-19 [22], a pre-existing deep CNN model, serves as our basis model. It is a VGG-16 variation with more than 32 million parameters. We use transfer learning [23] by removing the VGG-19's head layer and replacing it with a succession of custom layers. The FC1, FC2, and SoftMax layers are among the head layers we remove. Dense, Convolutional, Max Pooling, and ReLU layers are the most common additional layers we use. The layers were chosen in accordance with the VGG-19 model's overall architectural design, with the idea that the neural network's stability would not be jeopardized. The final model includes a Soft Max layer that separates the input into three categories: COVID-19, Normal, and Viral Pneumonia.

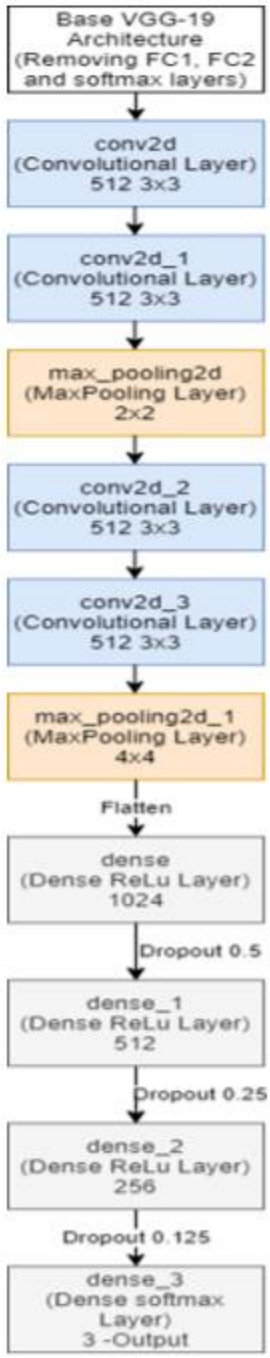


Fig 6. Proposed additional layers to the base model

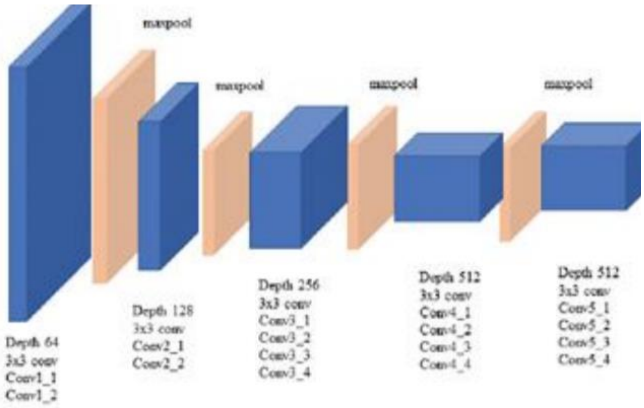


Fig 7. Base VGG-19 Architecture

E. Implementation Details

Apart from individually testing out the image preprocessing algorithms, we also test the performance of the model with sequential combinations of the techniques, namely – GHE+TBH and CLAHE+TBH.

(a) COVID-19

(b) Normal

(c) Viral Pneumonia

Fig 8. CLAHE+TBH on Chest X-rays from the dataset

(a) COVID-19

(b) Normal

(c) Viral Pneumonia

Fig 9. GHE+TBH on Chest X-rays from the dataset

The specifications of the system used to perform our analysis are as follows:

- GPU – Nvidia Tesla T4 (16 GB)
- No. of Epochs trained – 70
- Training Time – Approx. 3 hours
- TensorFlow version – 2.3.0
- Keras version – 2.4.0
- OpenCV version – 4.1.2
- Learning Rate Schedule – Cyclic (triangular2 policy)
- Base Learning Rate – 1e-3
- Max Learning Rate – 6e-3
- Loss Function – Categorical Cross Entropy
- Optimizer Function – Nadam

F. Evaluation Metrics

For the purpose of evaluation of the model, the following metrics [25] were used: precision, recall, F1 score, and accuracy.

1. **Precision**: Precision is used to evaluate a degree of exactness of the classifiers. It gives a relationship between the true positive predictive values and the fully positive predicted values.
   Precision = (TP) / (TP+FP) -(4)

2. **Recall**: Recall is also known as sensitivity which is a measure of the classifier's completeness. It is the ratio between the true positive predicted values and the summation of the true predicted positive values and the predicted false negative values.
   Recall = (TP) / (TP+FN) -(5)

3. **F1-score**: F1-score is used to handle the distribution issue with accuracy and is very useful when the dataset comprises of imbalance classes. It is an overall measure of the model's accuracy that combines precision and recall as well.
   F1 – Score = (2*TP) / (2*TP*FP+FN) -(6)

4. **Accuracy**: Accuracy is the most important metric for the results of our classifier model. It is a measure of all the correctly recognized cases.
   Accuracy = (TP+TN) / (TP+TN+FN+FP) -(7)

III.RESULTS AND DISCUSSION

After feeding the datasets after processing them with all the aforementioned image pre-processing techniques and training our proposed CNN model, the results are as follows:

Table 1. Validation Set Accuracy

Image Pre-processing Technique	Validation accuracy (%)
Normal	96.207
CLAHE	97.586
GHE	96.207
TBH	96.207
GHE+TBH	98.276
CLAHE+TBH	97.931

From the above, it is evident that the best performance is that of the dataset GHE+TBH, followed by CLAHE+TBH. The validation accuracy describes the accuracy obtained for the validation set, which was created for the purpose of training and simultaneously tuning the hyperparameters of the model. However, the real life performance of the model can only be judged on the basis of the test dataset, since these are chest x-rays which the model has never seen before. The results obtained for the same are as follows:

Table 2. Test data accuracy of the two best image preprocessing techniques

Image Pre-processing Technique	Test Accuracy (%)
GHE+TBH	96
CLAHE+TBH	94

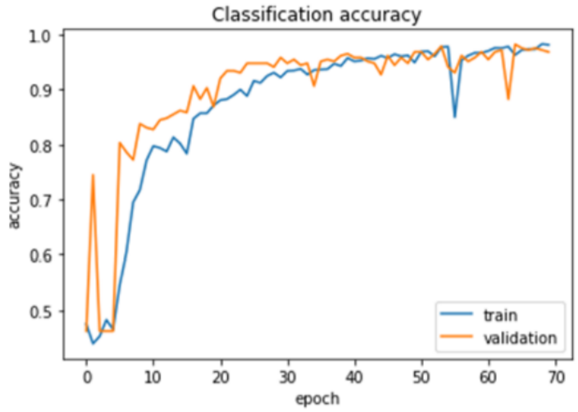


Fig 10. Training Progress of CNN model trained using GHE+TBH processed dataset

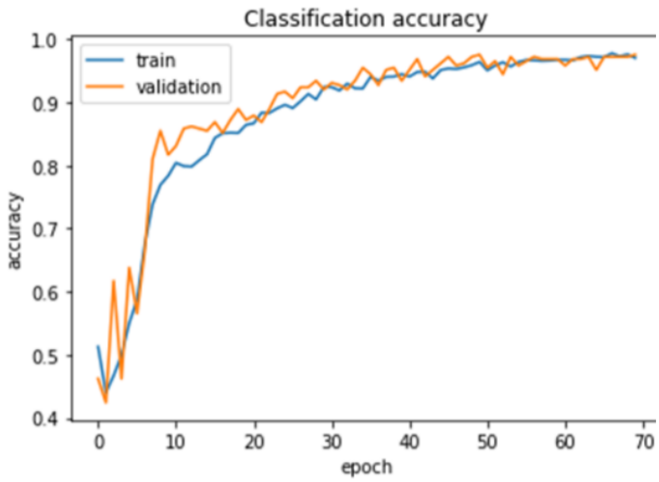


Fig 11. Training Progress of CNN model trained using CLAHE+TBH processed dataset

Now, for further comparison we also compare the evaluation metrics for the CNN models trained on these two image pre-processing techniques. First, we observe the metrics for the model trained on the dataset processed through CLAHE+TBH:

Table 3. Evaluation metrics for CLAHE+TBH

Infection Type	Precision	Recall	F1-Score
COVID-19	1.00	0.91	0.95
Normal	0.89	1.00	0.94
Viral Pneumonia	0.99	0.89	0.94

Now, the same metrics for the dataset GHE+TBH are:

Table 4. Evaluation metrics for GHE+TBH

Infection Type	Precision	Recall	F1-Score
COVID-19	1.00	0.95	0.98
Normal	0.96	0.96	0.96
Viral Pneumonia	0.95	0.96	0.96

IV.CONCLUSION

After analyzing the obtained metrics, it is clear that the model performs best when an image preparation technique is used. The top bottom hat transform followed by global histogram equalization, abbreviated as GHE+TBH, was the pre-processing approach we used that yielded the best results. The model's accuracy rate for identifying COVID-19 for the test dataset photographs is 1, which is an added advantage. We may also argue that the model's sickness detection capabilities is of high quality, since the accuracy for pneumonia is also 0.99, which is impressive. While this is far from a production-ready solution, we believe that because the model's performance in a dataset of CXRs yielded promising results, introducing a public database with multiple sources will aid in improving and further developing the model, as well as making it deployable for rapid and low-cost testing.

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