Comparison of image enhancement techniques and CNN models for COVID-19 classification using chest x-rays images

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2022 8th International Conference on Engineering, Applied Sciences, and Technology (ICEAST) | 978-1-6654-5919-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICEAST55249.2022.9826319

***Abstract*— This paper compares two image enhancement techniques with five convolutional neural network (CNN) models to classify Covid-19 chest x-ray images. a contrast limited adaptive histogram (CLAHE) and gamma correction which is method to improve image histogram are compared with the original chest x-ray image. We use five publicly available pre-trained CNN models to detect COVID-19: MobileNet, MobileNetV2, DenseNet169, DenseNet201, and ResNet50V2. Our procedure was validated using the COVID-19 radiography database, which is a freely accessible resource. MoblileNet with gamma correction is well-suited for COVIC-19 classification, achieving an accuracy score of 87.53 percent on the first epoch and 95.46 percent after training 100 epochs with the shortest computation time.**

Keywords*— *Image enhancement, COVID-19, Convolutional Neural Network, CLAHE

I. Introduction

COVID-19 is a virus-borne infection caused by the SARS-CoV-2 virus. Certain individuals who are infected with the virus develop respiratory infections that require treatment. Seniors and those with underlying medical issues are at an increased risk of developing major illnesses [1]. When it is transported to our body, it infects the cells of the inner organs and the airway. It can cause pulmonary difficulties if it enters the lungs [2]. It is possible for the lining to become irritated and inflamed. The immune system responds to inflammation. Nonetheless, some individuals had scarring in their lungs [3].

Infections are extremely contagious. To avert further inflection, a more rapid diagnosis of COVID-19 is required. Chest X-ray (CXR) is a quick and portable diagnostic tool. The X-ray equipment is readily available and less expensive than the real-time polymerase chain reaction (RT-PCR) technique [4]. The CXR film is usually diagnosed. X-ray of a patient with severe acute respiratory syndrome. It causes patchy or confluent bandlike opacity or consolidation in the peripheral and mid-to-lower lung zones [5].Artificial intelligence (AI) has the ability to drastically reduce workload and improve accuracy. By leveraging these gains, K. Srijakkot [6] demonstrated how a faster R-CNN model was utilized to detect an intruder in a power substation. It showed the high accuracy and shot computation time. Image preprocessing is another technique that has been shown to improve the accuracy of AI. K. Tenghongsakul [7] addressed the extraction of bloof vessels from retinal images by combining pre-processing and an IterNet model, which demonstrated an increase in accuracy. A. Shamila Ebenezer et al. [8] demonstrated a 94.56 percent accuracy, a 95 percent precision, a 91 percent recall, and a 93 percent F1 when using the CLAHE-based EfficientNet model. Meng Ge et al. [9] show that the DCT coefficient and the CLAHE algorithm outperform conventional image enhancement algorithms. Tawsifur Rahman et al. [10] establish the superiority of the gamma correction-based enhancement technique over other strategies. Pablo A. Vieira et al. [11] describe a novel strategy for automatically generating the optimal set of hyperparameters for the ResNet50 and VGG16 architectures that yields 97 percent accuracy when three classes are considered: COVID-19, other pneumonia, and healthy.

In this paper, we present the combination methods between CNN models and image enhancement techniques for Covid-19 Classification. Our method utilized the advantage of CNN that show the computation performance better than only image processing and increase the accuracy by using the histogram equalizer.

II. Dataset and Models

A. Dataset

In this study, we assessed our technique utilizing the COVID-19 Radiography Database [12,13]. The database was supplied with chest x-ray images of 3616 COVID-19 positive cases, as well as 10,192 normal, 6012 opacity (non-COVID lung infection), and 1345 viral pneumonia images. The images have a resolution of 299 by 299 pixels. The example original chest x-ray image and the histogram of a healthy and infected COVID-19 patient is shown in Fig. 1.

B. Models

We used pre-train published model of MobileNet, MobileNetV2, DenseNet169, DenseNet201, and ResNet50V2 [14]. We divided 90% of each subject to use as train images. The training is done using batch size 32 with maximum epoch 1, input image size 224 by 224 pixels.

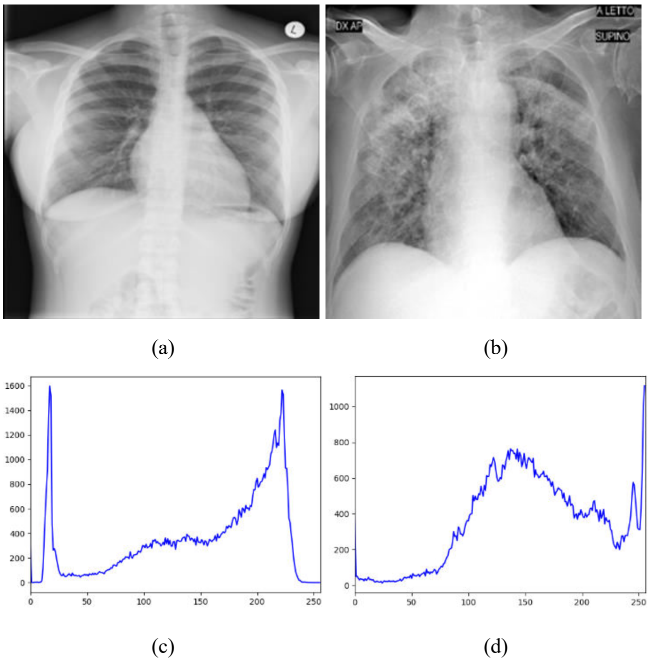

Fig. 1. Example of chest x-ray image and histogram. (a) Healthy chest x-ray image, (b) Infected COVID-19 chest x-ray image, (c) Histogram of healthy chest x-ray image, (d) Histogram of infected COVID-19 chest x-ray imageImage enhancement

Image enhancement is a fundamental image processing approach that emphasizes key information in an image while reducing or eliminating noise to improve identification quality. The purpose of image enhancement is to make the image's intended message more visible than it was in its original state.

C. *Contrast limited adaptive histogram equalizer (CLAHE)*

The contrast limited adaptive histogram equalizer [15] is a technique for improving the quality of an image. It increases the size of the histogram to the maximum and minimum values. It is possible to have an overall problem when some elements of an image are substantially different from other sections (for example, when some areas are overly bright or too dark). Increased effectiveness of certain regions will be in vain, and we will not be privy to the specifics of that sector. Furthermore, it will enhance the background noise. The adaptive histogram equalization algorithm is used to perform on the little pieces of an image referred to as tiles, which are small sections of an image. Each tile should include the solution to the complete problem. It computes the histogram for each tile on its own basis, one at a time. The problem of noise enhancement can be resolved by lowering the contrast. It does this by equally dispersing the portion of the histogram that exceeds the set contrast limit. It is possible that artifacts will remain in the tile boundaries after equalization. It is eliminated with the use of bilinear interpolation.

D. *Gamma correction*

Gamma correction [16] is a nonlinear mathematical operation that is used to alter the values of individual pixels in an image. The majority of image processing tasks involve applying linear algorithms to the entire image's pixels, such as addition, subtraction, and multiplication. To maintain a constant gamma value, it must never be both too low and too high.

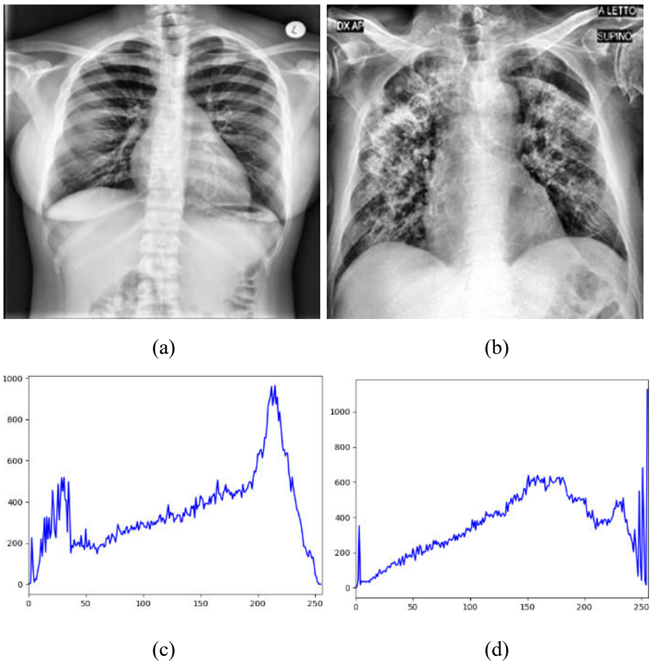

Fig. 2. Example of chest x-ray with CLAHE tecnique and histogram. (a) Healthy chest x-ray image with CLAHE, (b) Infected COVID-19 chest x-ray image with CLAHE, (c) Healthy chest x-ray histogram with CLAHE, (d) Infected COVID-19 chest x-ray histogram with CLAHE

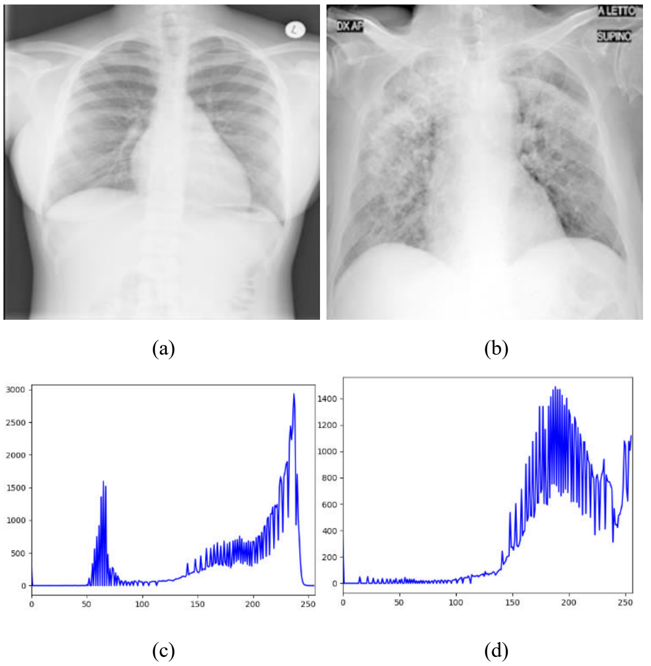

Fig. 3. Example of chest x-ray with gamma correction tecnique and histogram. (a) Healthy chest x-ray image with gamma correction, (b) infected COVID-19 chest x-ray image with gamma correction (c) Histogram of healthy chest x-ray image with gamma correction, (d) Histogram of infected COVID-19 chest x-ray image with gamma correction

III. Methodology

A. *Overview*

The outline of this research is presented in Figure 7. The dataset was divided into two parts: an X-ray of the chest of a person without COVID containing viral pneumonia and an infected coronavirus patient. The quality improvement technique processes two types of histograms: CLAHE and Gamma Correction. After training the original and processed images with one epoch on each of the five pre-trained CNN models, the most accurate model was employed for additional 100 epochs.

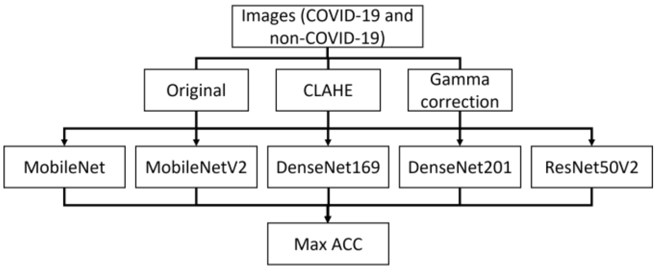

Fig. 4. Overview of our method

B. Evaluation

The performance of several networks with image enhancement techniques was evaluated and compared in the training and validation stages using three performance metrics [17]: accuracy as defined in (1), sensitivity as defined in (2), and specificity as defined in (3).

$$acc = \frac{TP+FP}{TP+TN+FP+FN} \quad (1)$$

$$sen = \frac{TP}{TP+FN} \quad (2)$$

$$spec = \frac{TN}{TN+FP} \quad (3)$$

True positive (TP) denotes the number of healthy and non-COVID-19 images that were correctly identified as healthy and non-COVID-19, true negative (TN) denotes the number of COVID-19 images that were incorrectly identified as COVID-19, false positive (FP) denotes the number of normal and non-COVID lung opacity images that were incorrectly identified as COVID-19, and false negative (FN) denotes the number of COVID-19 images.

IV. Results and Conclussion

The five published models (MobileNet, MobileNetV2, DenseNet169, DenseNet201, and ResNet50V2) were used in this investigation. The model classified using the original, CLAHE, and Gamma corrections. COVID-19, viral pneumonia, lung opacity, and normal are all represented in the collection's CXR images. Random partitioning was used to divide the database in half, with 90% going to training and 10% going to testing. Each model is trained using a single epoch. This experiment was carried out on a Windows 10 Home system equipped with an Intel Core i5-10300H processor, 8 GB of RAM, and an NVIDIA GeForce GTX 1650 4 GB GDDR6 GPU. the result of CLAHE and Gamma correction with trained model shown in Table I. Gamma correction produces the highest accuracy of 87.54 percent on the MobileNet model, according to the trial. Gamma correction and CLAHE improve the accuracy of the image in comparison to the original.

Confusion matrix in Table II show the 10 percentage of dataset that consist of 2116 images. The result of True positive (TP) is 481 images, true negative (TN) is 1539 images false positive (FP), and false negative (FN) are 48 images. The sensitivity that represented ability to correctly detect ill patients is 90.94 percentage. Specificity that refers to a test's capacity to appropriately exclude healthy individuals who do not have a problem is 96.97 percentage. The accuracy, which indicates the percentage of right predictions made out of all cases evaluated, is 95.46.

TABLE I. Results of models with image enhancement techniques with 1 epoch on trainset

Model	Enhancement technique	Train acc (%)	Val acc (%)	Time (s)
MobileNet	Original	80.98%	82.48%	103.22
	CLAHE	**84.22%**	87.48%	**67.50**
	Gamma correction	84.14%	**87.54%**	68.69
MobileNetV2	Original	83.66%	84.59%	114.99
	CLAHE	84.00%	87.29%	69.36
	Gamma correction	83.19%	86.80%	70.51
DenseNet169	Original	83.66%	87.19%	147.62
	CLAHE	82.94%	84.58%	114.59
	Gamma correction	83.27%	87.29%	122.75
DenseNet201	Original	47.91%	50.38%	70.10
	CLAHE	83.18%	86.17%	147.94
	Gamma correction	83.30%	86.41%	148.57
ResNet50V2	Original	76.38%	80.23%	80.69
	CLAHE	82.79%	84.44%	86.30
	Gamma correction	82.93%	86.94%	91.95

TABLE II. Confusion Matrix of Mobilenet with gamma correction on testset

	Actually Positive	Actually Negative
Predicted Positive	481	48
Predicted Negative	48	1539

We describe strategies for combining CNN models and image enhancing techniques for Covid-19 Classification in this paper. Our solution took advantage of the advantage of CNN, which outperforms traditional image processing in terms of computing performance, and increased the accuracy by utilizing the histogram equalization. The CNN Model (MobileNet, MobileNetV2, DenseNet169, DenseNet201, and ResNet50V2) which widely used model, were used to test with the proposed method. Our method increased the accuracy of COVID-19 detection. However, the proposed procedure was unable to considerably improve accuracy.

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