MJFAS
Malaysian Journal of Fundamental and Applied Sciences

RESEARCH ARTICLE

Coronavirus Classification based on Enhanced X-ray Images and Deep Learning

Fallah H. Najjar [a,c,*], Safa Riyadh Waheed[b,c], Duha Amer Mahdi[a]

[a]Department of Computer System Techniques, Technical Institute of Najaf, Al-Furat Al-Awsat Technical University, Iraq; [b]Computer Techniques Engineering Department, Faculty of Information Technology, Imam Jaafar Al-Sadiq University, Baghdad, Iraq; [c]Faculty of Engineering, School of Computing, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia

Abstract In light of the fact that the global pandemic of Coronavirus Disease 2019 (COVID-19) is still having a significant impact on the health of people all over the world, there is a growing need for testing diagnosis and treatment that can be completed quickly. The primary imaging modalities used in the respiratory disease diagnostic process are the Chest X-ray (CXR) and the computed tomography scan. In this context, this paper aims to design a new Convolutional Neural Network (CNN) to diagnose COVID-19 in patients based on CXR images and determine whether they are COVID or healthy. We have tested the performance of our CNN on the COVID-19 Radiography Database with three classes (COVID, Pneumonia, and Normal). Also, we proposed a new enhancement technique to enhance the CXR image using the Laplacian kernel with Delta Function and Contrast-Limited Adaptive Histogram Equalization. The proposed CNN has been trained and tested on 15153 enhanced and original images, COVID (3616), Pneumonia (1345), and Normal (10192). Our enhancement technique increased the performance metrics scores of the proposed CNN. Hence, the proposed method obtained better results than the state-of-the-art methods in accuracy, sensitivity, precision, specificity, and F measure.

Keywords: Coronavirus, COVID-19, classification, X-ray, deep learning.

Introduction

The pandemic caused by COVID-19 continues to affect health all over the world. However, COVID-19 is a global pandemic that requires rapid and accurate diagnostic testing in healthcare facilities. It is critical to distinguish between viral and bacterial pneumonia and other respiratory infections, such as tuberculosis, using chest imaging technology when dealing with infection control decisions and diagnosis and planning treatment regimens [1]. In addition, the symptoms of many infectious respiratory diseases, such as wheezing, coughing, and fever, are similar. On the other hand, deep learning has significantly impacted artificial intelligence [2]. Machine learning uses deep learning to solve complex problems with state-of-the-art computer vision and image processing capabilities [3-6]. Therefore, deep learning models have dramatically improved medical image detection, classification, and segmentation [7]. Several papers have been published, and efforts have been invested in presenting integrated deep-learning models to diagnose COVID-19 in patients based on CXR images and determine whether they are COVID-19 or not. Some of this research proposed combining two or more deep learning models [8-11]. However, one question comes to mind; we have already dived deep; why dive more...? In the context of the previous question, this paper proposed a new image enhancement method to enhance medical images. We also developed a new CNN architecture to identify COVID-19 in patients based on CXR images.

However, the rest of this paper is accomplished as follows. First, section two demonstrates the related work. Then, section three describes the methodology of the proposed method. After that, section four illustrates the obtained result. Finally, section five concludes the whole study.

***For correspondence:**
fallahnajjar@atu.edu.iq

Received: 2 Nov. 2022
Accepted: 11 April 2023

10.11113/mjfas.v19n3.2909

Related Works

Several research studies have been published on diagnosing and predicting COVID-19 from 2019 until now. Among them are those based on deep learning to increase research productivity in this field. However, this section focuses on COVID-19 articles that used a pre-processing technique and classified the CXR images into two or multiclass classification using deep learning approaches. For example, R Hertel and R Benlamri [12] proposed a new COVID-19 segmentation and classification technique. However, the authors used the ResUnet in segmentation while combining three CNNs classifiers, namely, VGG-16, DenseNet-201, and ResNet-152, to classify their proposed dataset into three classes COVID, Normal, and Pneumonia, or two categories, of COVID and other.

R Hertel and R Benlamri [8] present a COV-SENT model based on a pre-trained DenseNet-121 network. The proposed COV-SENT was modified by adding dense, dropout, and three class SoftMax layers and retrained under the transfer learning scheme utilizing 112,120 CXR images. M Mamalakis *et al*. [13] proposed DenResCov-19 using DenseNet-201, but the DenseNet-201 was combined with the ResNet-50 by adding extra layers to concatenate the two CNNs. However, the proposed method was evaluated using four datasets and classified image datasets into four classes, COVID, healthy, tuberculosis, and pneumonia.

Ieracitano *et al*. [14] proposed a pre-processing technique by manually removing empty black and text from the CXR images. Then, all images are resized into 800×900 pixels. After that, the fuzzy edge detector was used to extract the fuzzy features from the CXR images. Finally, a CovNNet was used to classify the pre-processed images into COVID or No-COVID.

Saad *et al*. [15] present a new image enhancement method to enhance the datasets. First, alI input images were resized into 227*227 pixels. Then, the authors used the Unsharp filter to sharpen the input images. After that, the histogram equalization was used to adjust the intensities of the input images. Finally, the image complement was used to reduce the black region of the input images. Additionally, the enhanced dataset images are used to retrain the SqueezNet under the transfer learning scheme to classify the CXR images into three classes, COVID, Pneumonia, or Normal.

K Shankar and E Perumal [16] present a new technique to extract features from the fusion of local binary patterns with the deep features (through the Inception-v3 network) calculated from Gaussian-filtered images. The proposed method classified the dataset images into four classes, COVID, healthy, SARS, and pneumocystis.

Materials and Methods

This paper proposed a new image enhancement procedure to enhance the CXR image. Also, we developed a new CNN consisting of 26 layers to identify COVID-19 in patients based on CXR images and determine whether they are COVID or healthy. Then, we used COVID-19 Radiography Database (COVID-Dataset) with three classes (COVID, Pneumonia, and Normal). Next, we applied our enhancement technique to the COVID-Dataset [17-19]. Finally, the enhanced dataset images are trained with our CNN to generate a model to classify the images into COVID, Pneumonia, or Normal. However, in order to implement the proposed method, an Intel Core i7-11800H processor (2.30 GHz, 16 CPUs), 16 GB DDR4 RAM, and an NVIDIA GeForce RTX 3050 TI GPU were used in conjunction with Windows 11. For the programming, MATLAB (R2022a) was used.

Dataset

The COVID-Dataset is used to test the proposed method in this study. The COVID-Dataset consists of four classes, COVID (3616), Lung Opacity (6012), Normal (10192), and Viral Pneumonia (1345) CXR images. Hence, we used only the COVID, Pneumonia, and Normal classes. However, samples of dataset images are shown in Figure 1.

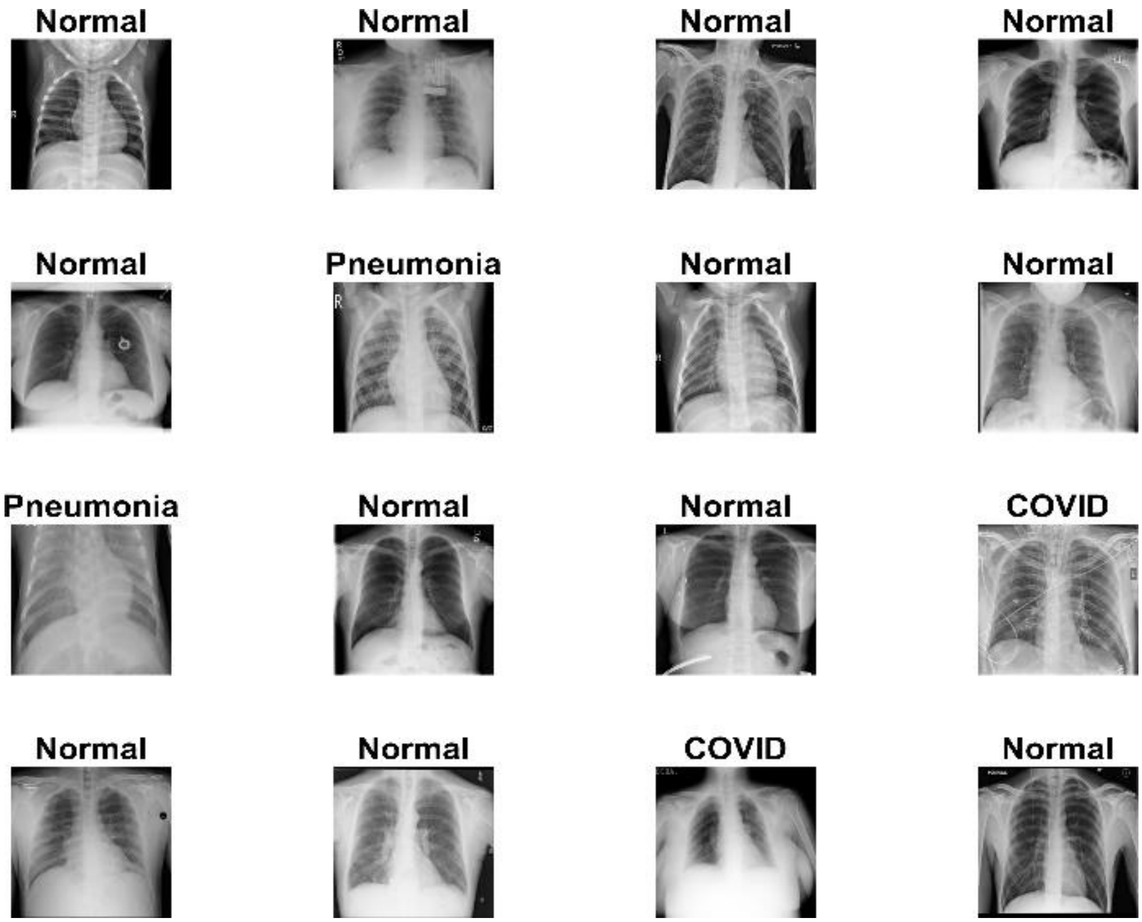


Figure 1. COVID-Dataset samples images [17]

The proposed image enhancement

This section presents the image enhancement methodology, which is based on the Laplacian Filter (LF) with Delta Function (DF) and Contrast Limited Adaptive Histogram Equalization (CLAHE). First, all dataset images are resized into 224×224. Then, we used the Laplacian filter combined with the Delta function and Scaling factor. Laplacian filters are edge detectors that compute the second derivatives of an image, which measure the rate of change in the first derivatives of an image. This value change in neighboring pixels indicates edge or continuous progression. However, the LF is shown in Figure 2

-1	-1	-1
-1	9	-1
-1	-1	-1

Figure 2. Laplacian filter.

On the other hand, the DF is a widespread function or distribution over real numbers with zero value everywhere except at zero. However, the DF is shown in Figure 3.

0	0	0
0	1	0
0	0	0

Figure 3. Delta function.

10.11113/mjfas.v19n3.2909

We add a Scaling Factor (SF) to the LF and DF to generate a new Convolution Filter (CF) using equation 1:

$$CF = LF + SF \times DF \tag{1}$$

where CF represents the proposed filter, LF represents the Laplacian kernel, DF represents the Delta function, and SF represents the Scale Factor. Note that: the SF value is from 1 to 255, including fractional numbers. In all experimental testing, the SF value is 1.5.

Improved image contrast can be achieved using Adaptive Histogram Equalization (AHE). It redistributes the image's luminance values by computing several histograms corresponding to a different image section. Because of this, it is a good choice for boosting local contrast and sharpening image edges in different parts of an image. On the other hand, AHE tends to overamplify noise in areas of an image that are relatively homogenous. In CLAHE, a variant of AHE, the amplification is limited. Readers are recommended to see [20]. Additionally, the proposed image enhancement method is shown in Figure 4.

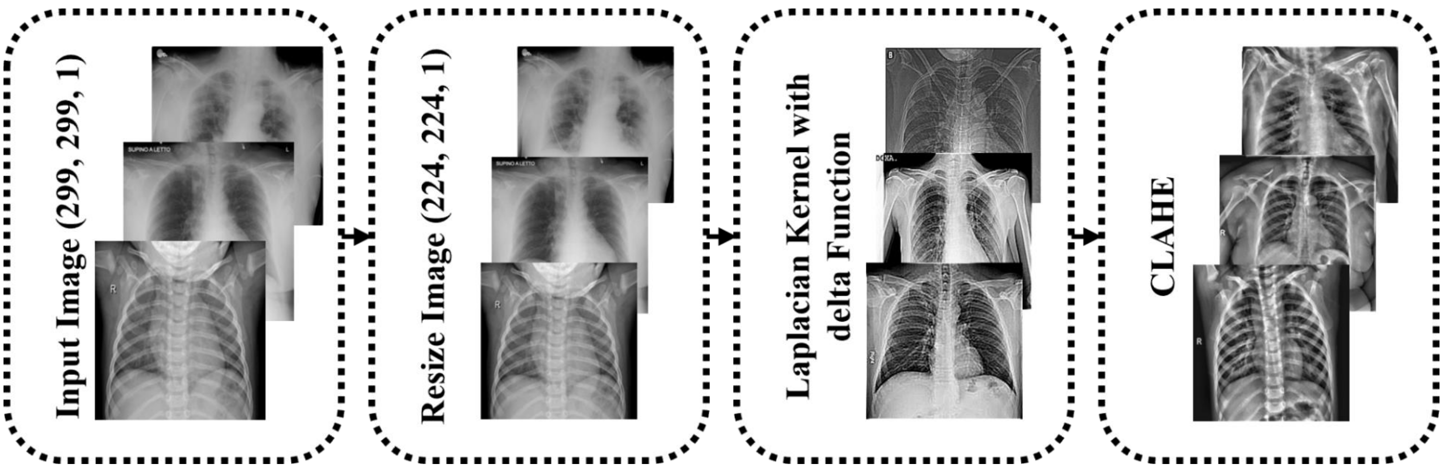
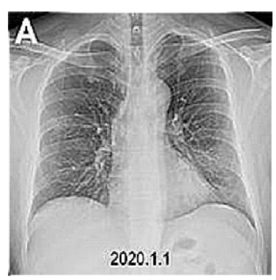
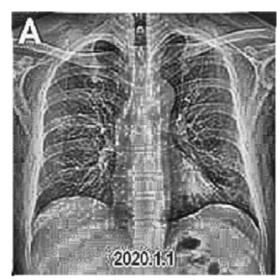


Figure 4: Applying the proposed image enhancement technique to the dataset

However, Figure 5 displays the results of applying the proposed image enhancement technique to the input images.

Class	Original Image 299×299	Resized Image 224×224	Applying CF	Applying CLAHE
COVID				
Pneumonia				

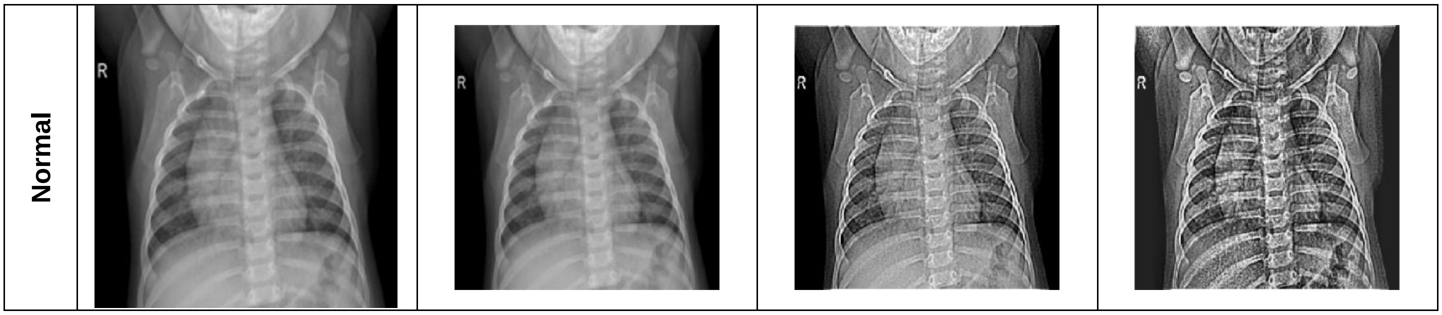


Figure 5: Applying the proposed image enhancement to the COVID-Dataset.

Proposed CNN

We designed a new CNN consisting of 26 layers to diagnose COVID-19 in patients based on CXR images and determine whether they are COVID, Pneumonia, or Normal. In addition, to further improve the performance of the proposed CNN, the learning rate scheduler utilizing Adam optimizer is applied. Figure 6 depicts the proposed CNN schematic with processed data.

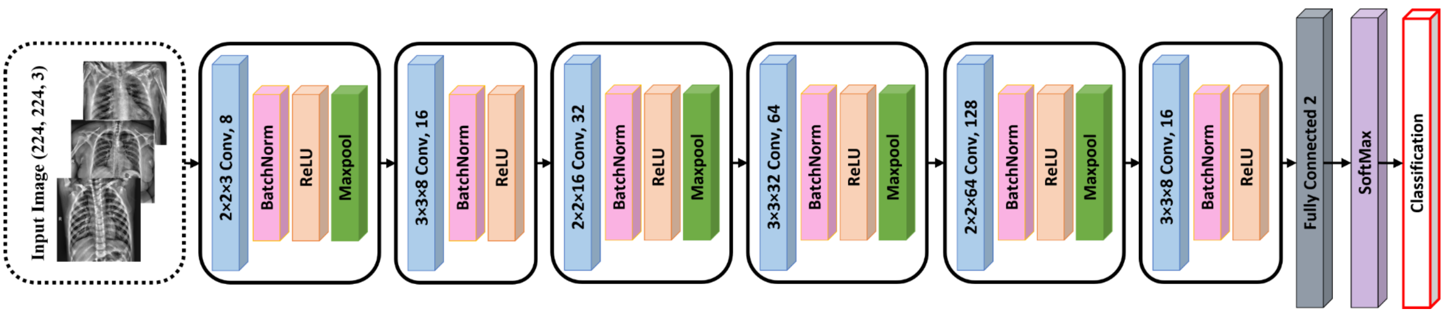


Figure 6: Architecture of the proposed CNN.

Design of the proposed method

The architecture of the proposed approach is shown in Figure 7. First, again, the COVID-Dataset images are enhanced by the proposed pre-processing. Next, the enhanced and original images are used to train the proposed CNN.

In this study, we have computed the performance parameters, namely Precision (PRE), Sensitivity (SEN), Accuracy (ACC), Specificity (SP), also F1 score (F1), to consider the data label imbalance [21]. One of the literatures most widely used and extensively discussed accuracy measurements is the F1 score [22-25].

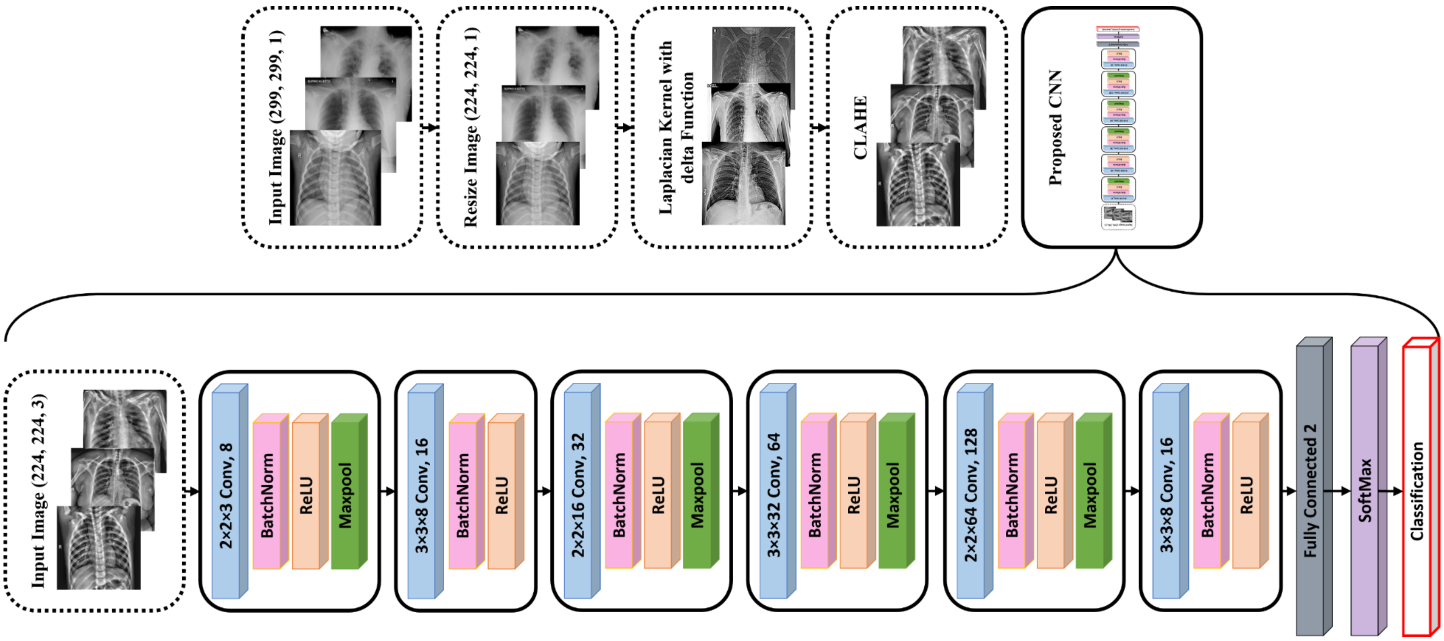


Figure 7. Flowchart of the proposed method.

Results and Discussion

This section demonstrates how well the proposed image enhancement methods and the CNN perform when classifying segmented CXR images for COVID, pneumonia, and Normal. However, first, we used the enhanced and original dataset images to train the proposed method. Henceforth, the enhanced and original dataset's images are split randomly into train 90% and testing 10% sets. Also, the train images are divided randomly into train 90% and testing 10% sets. Finally, the proposed CNN was established with 20 epochs, five frequency iterations for each epoch, a constant learning rate schedule with a learning rate of 0.001, and a single GPU.

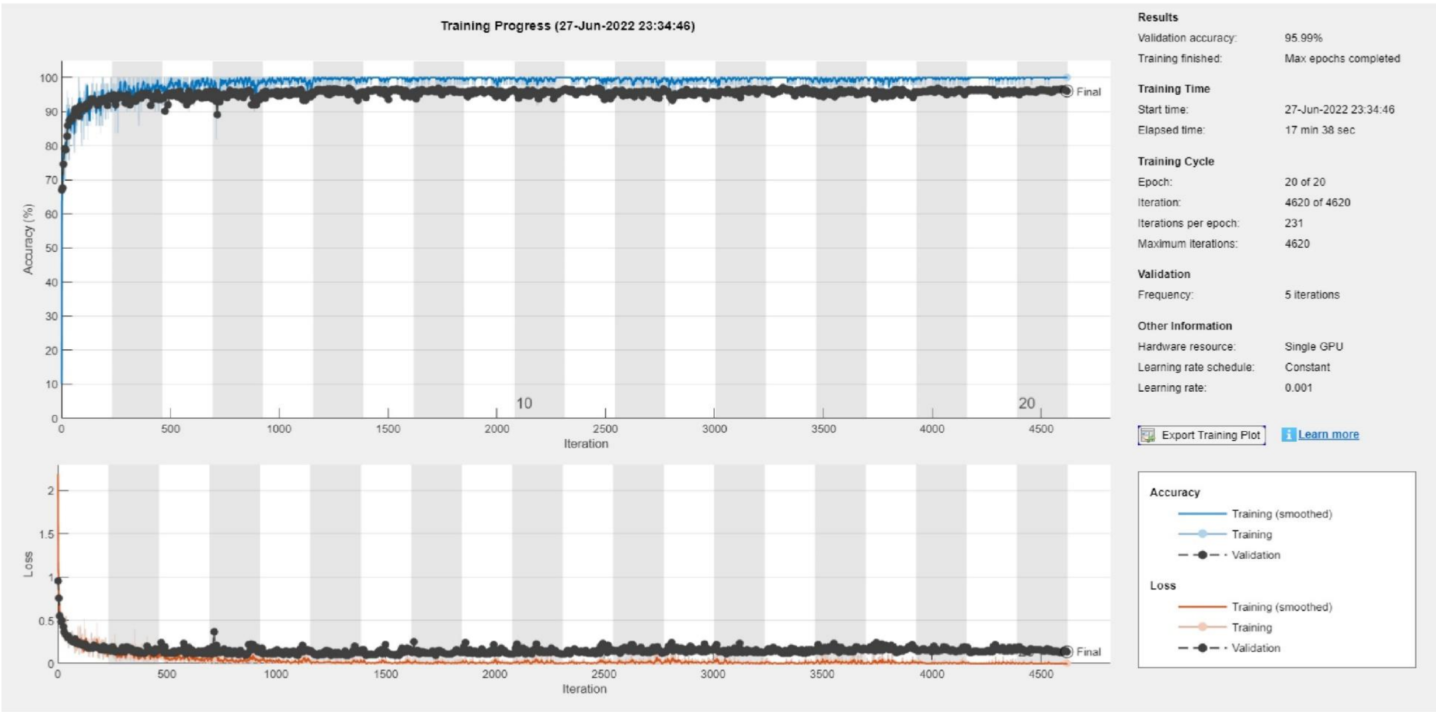


Figure 8. Training progress of applying the proposed CNN to the original dataset images.

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In comparison, the training progress using the proposed image enhancement method is shown in Figure 9. The validation accuracy was 97.51%, whereas the training took 18 minutes and 21 seconds. Therefore, the proposed image enhancement method increases the validation accuracy.

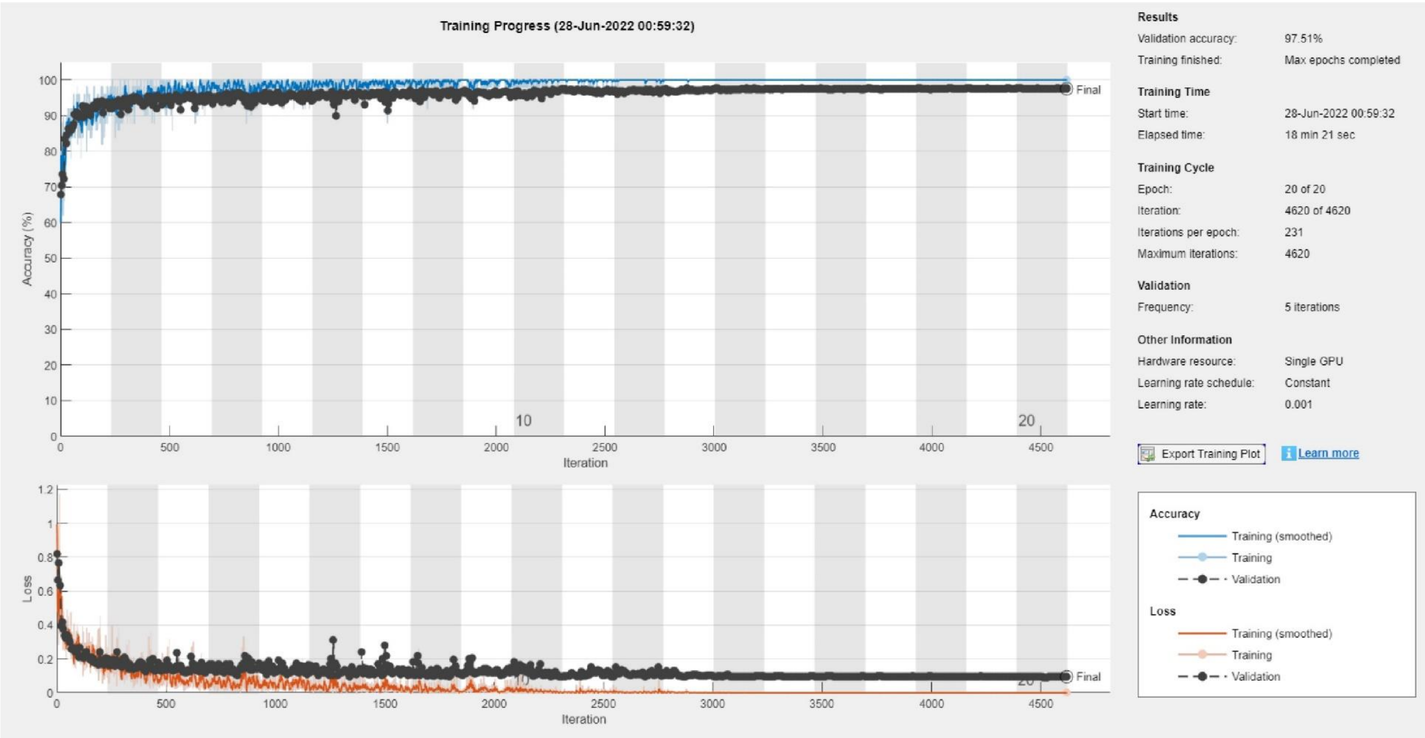

Figure 9. Training progress of applying the proposed CNN to the enhanced dataset images

The performance measures of the proposed CNN, applied to the enhanced images dataset, are shown in **Error! Reference source not found.**.

Table 1. Performance metrics after training on original dataset images

Class	TP	TN	FP	FN	ACC	PRE	Sen	F1	SP
COVID	339	1134	19	23	0.9723	0.9469	0.9365	0.9417	0.9801
Normal	997	473	23	22	0.9703	0.9775	0.9784	0.9779	0.9556
Pneumonia	130	1374	7	4	0.9927	0.9489	0.9701	0.9594	0.9971

The performance measures of the proposed CNN, applied to the original dataset images, are shown in **Error! Reference source not found.**.

Table 2. Performance metrics after training on enhanced dataset images

Class	TP	TN	FP	FN	ACC	PRE	Sen	F1	SP
COVID	347	1142	11	15	0.9828	0.9693	0.9586	0.9639	0.9870
Normal	1008	481	15	11	0.9828	0.9853	0.9892	0.9873	0.9776
Pneumonia	129	1376	5	5	0.9934	0.9627	0.9627	0.9627	0.9964

A total of 1515 test images are represented by their confusion matrices, shown in Figure 5. (1019 Normal images, 362 COVID images, and 134 pneumonia images). These matrices display the data, with each cell of the confusion matrix indicating the proportion of the total test images contained within it.

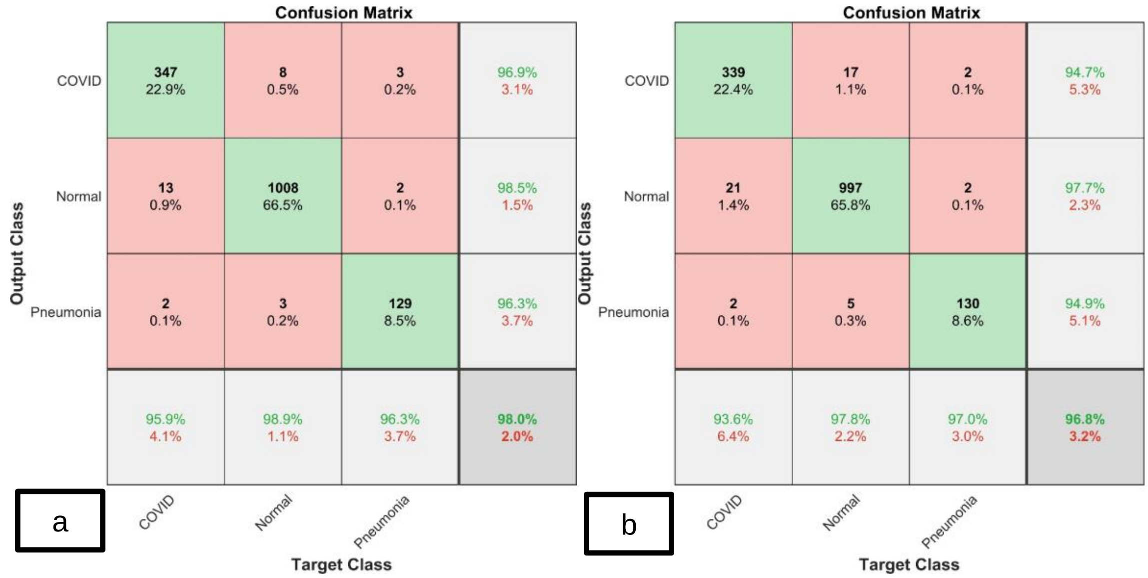

Figure 10. Confusion matrix: a: Enhanced images, b: Original images

Finally, to determine how well our proposed method performs compared to existing state-of-the-art deep learning methods for detecting COVID-19 from CXR images, see Table 3.

Table 3. Weighted average performance metrics. The best results are specified in bold

Method	Avg ACC	Avg PRE	Avg Sen	Avg F1	Avg SP
Apostolopoulos and Mpesiana [18]	93.33%	-	90.66%	-	95.23%
Ieracitano *et al*. [14]	80.9±6.2%	85.2±4.5%	82.5±11.9%	-	78.6±6.9%
Shankar and Perumal [16]	95.11%	-	93.15%	-	96.50%
Hertel and Benlamri [11]	89.44%	84.33%	84.33%	84.33%	92.03%
Hertel and Benlamri [12]	89.40%	84.21%	84.21%	84.21%	92.02%
A. Bhattacharyya *et al*. [26]	96.60%	-	95.00%	-	97.40%
Our proposed method	**98.64%**	**97.95%**	**97.95%**	**97.95%**	**98.98%**

Conclusions

This paper proposed a new CNN to diagnose COVID-19 in patients based on CXR images and determine whether they are COVID, Pneumonia, or Normal. Also, we proposed a new enhancement technique to enhance the CXR image using the Laplacian kernel with Delta Function and Contrast-Limited Adaptive Histogram Equalization. We have tested the performance of our CNN on the COVID-19 Radiography Database with two classes (COVID and Normal). The proposed CNN has been trained and tested on 13808 enhanced and original images, COVID (3616) and Normal (10192). The enhancement technique increased the performance metrics of the proposed CNN. Hence, the proposed method obtained better results than the state-of-the-art methods in PR, SEN, SP, ACC, and F1. In the future, we intend to implement the proposed approach on other datasets.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

Acknowledgment

This work is part of a research project, FRGS19-090-0699, supported by the Ministry of Higher Education, Malaysia and University Technology of Malaysia.

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