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EFFECT OF IMAGE PRE-PROCESSING METHOD ON CONVOLUTIONAL NEURAL NETWORK CLASSIFICATION OF COVID-19 CT SCAN IMAGES

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Abstract. *The presence of abnormalities on CT lung images of COVID-19 patients, such as ground-glass opacity and consolidation, can be used to aid in the detection of COVID-19. These abnormalities can be ambiguous and obscure, resulting in false detection by the doctor. This paper evaluates several image pre-processing methods for automatic detection of COVID-19 based on CT images. First, we used Watershed segmentation to separate the lung cavities. We retained the interior of the lung cavity, where the features of COVID-19 were located. Next, we evaluate the addition of a smoothing image method of Median and Gaussian filters to remove blood vessel spots. We also assess the contrast improvement-based methods using Histogram Equalization (HE) and Contrast Limited Adaptive Histogram Equalization (CLAHE) to highlight the features of COVID-19 further. Multi-dimensional extension of CLAHE (MCLAHE) is also used as an optimization of CLAHE method. In addition, the Inverted Threshold to Zero method is utilized to segment the COVID-19 features. We used transfer learning Convolutional Neural Network (CNN) in VGG-19, ResNet50, Xception, and DenseNet201 for the classification process. The results show that classification accuracy can be improved by adding appropriate pre-processing techniques. CLAHE and MCLAHE have the highest accuracy with 91.20% and 91.60%, respectively.*

Keywords: CNN, COVID-19 classification, CT scan, Image pre-processing, Transfer learning

1. Introduction.

The presence of specific abnormalities in lung CT scan radiological imaging of COVID-19 can be another alternative for detecting COVID-19 in addition to Polymerase Chain Reaction (PCR) tests. This radiological imaging may show bilateral opacities, sub-segmental consolidation, lobar or collapsed lung or nodules, and a ground glass appearance. Ai et al. [1] reported that chest CT scan has a high sensitivity for the diagnosis of COVID-19. Although chest CT scan shows excellent potential for diagnosing COVID-19 pneumonia, manual identification of radiographic features sometimes has low specificity in differentiating COVID-19 from other types such as bacterial pneumonia [2].

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Faint abnormal signs, poor image quality, and doctor's experience in analyzing radiological images are some factors that result in differential diagnoses, especially if there are small details [3]. Therefore, the use of appropriate image pre-processing can help to clarify COVID-19 features in CT images.

The contribution provided in this article is an evaluation of the pre-processing image method before being included in the classification process. This contribution is collected because the image processing before it was included in the classification process has been found to play a significant role. Hu et al. [4] produced an average accuracy of 89.2% with the input image of a COVID-19 CT scan image that has been segmented first. Koonsanit et al. [5] researched image enhancement applications on typical digital x-ray images. Koonsanit et al.'s research shows that the combination of the Normalization function and the CLAHE method (N-CLAHE) improves the pre-processing correction for digital chest radiography. Siddiqi et al. [6] researched HE filters for CT images of the abdomen bearing liver tumor. Siddiqi et al. stated that CLAHE is a better choice for image enhancement as compared to HE and Two-Step Adaptive Histogram Equalization (TSAHE) methods.

This paper combined the Watershed segmentation method with several image quality enhancement methods such as Median filter, Gaussian filter, HE, CLAHE, and Inverted Threshold to Zero. We evaluated whether applying appropriate pre-processing methods to CT scan COVID-19 images would improve image quality and produce a higher classification accuracy. Watershed segmentation is used to separate the feature area from the background. The feature area used is the inside of the lung cavity. Smoothing filters, such as Median and Gaussian filters, minimize blood vessel contamination and focus on COVID-19 features. Improving the quality of image contrast in the form of HE and CLAHE is intended to highlight the features of COVID-19. We also evaluated using the Inverted Threshold to Zero segmentation method to segment the COVID-19 features in the lung cavity. To assess the use of the pre-processing method, we compared the classification results without the pre-processing process with the results of the classification that went through the pre-processing process first. We used several CNN models to perform the classification process using a transfer learning mechanism. The CNN models we used are VGG19, ResNet50, Xception, and DenseNet201. The use of appropriate pre-processing is expected to achieve the highest accuracy.

The paper is organized as follows. Section 2 presents the related works to this paper. Section 3 provides a description of the sources and methods used. Section 4 shows the scenario and experimental results. Section 5 contains a discussion that analyzes the outcomes of the experiment. Section 6 shows the conclusions to complete the paper.

2. **Related Works.** The following are some studies that are related to this paper. Some of the studies below discuss the manual detection of COVID-19 on a chest CT scan image, pre-processing image method, and the use of CNN in the medical imaging field.

Chest CT scan imaging is one of the methods used to help detect the presence of COVID-19 in the lungs. Ai et al. [1] reported that chest CT scan has a high sensitivity for diagnosing COVID-19. Data and analysis from Ai et al.'s research show that chest CT scans can be considered for screening for COVID-19, periodic evaluations, and follow-up actions for COVID-19 sufferers, especially in areas with high case rates. Chest radiography may show bilateral opacities, consolidation subsegmental, lobar or collapsed lung or nodules, ground-glass appearance [7]. A few small patches with noticeable interstitial changes may appear in the peripheral lung in the early stages, developing into multiple ground-glass opacities and infiltrating both lungs. In severe cases, lung consolidation can

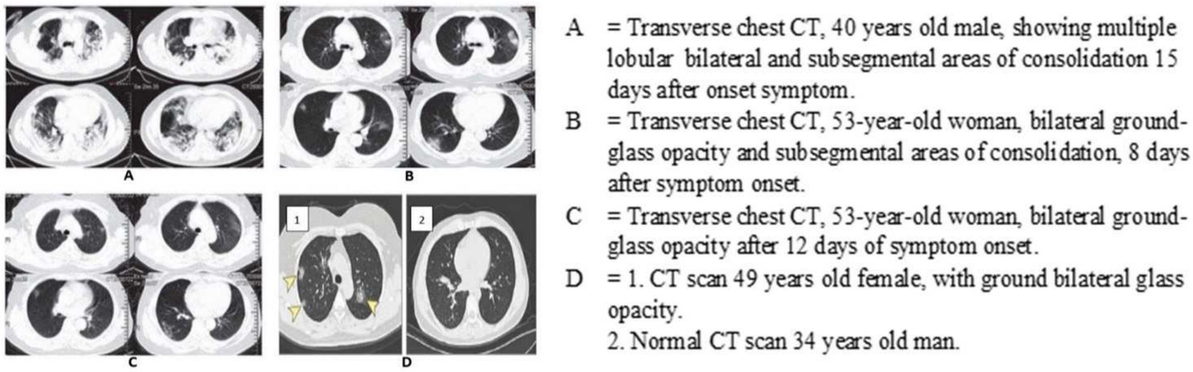

FIGURE 1. Chest CT scan of a COVID-19 pneumonia patient [1,9]

occur and lead to a "white lung" condition. Figure 1 shows signs of abnormality on a chest CT scan.

Conventionally, paramedics can detect the presence of COVID-19 in the lungs by observing signs of abnormalities that appear on CT scan images of the lungs. However, as we can see in Figure 1, these abnormalities are sometimes vague and unclear. There is also noise in small spots of blood vessels and unnecessary components outside the lung cavity. These things can sometimes cause disagreements diagnoses among doctors, especially if there are small details. The ambiguity of abnormal features and the presence of annoying noise can be minimized by using the correct pre-processing technique. Horry et al. [8] used image enhancement in the form of CLAHE as pre-processing on X-Ray, CT scan, and ultrasound image data. N-CLAHE is used to minimize the effects of sampling bias by normalizing the image and highlighting finer details for attention to the machine learning classification process. Abdullah et al. [9] compared different segmentation methods applied to CT scans to focus on areas of the lung cavity. From the comparison, the result obtained is that the Otsu threshold accuracy is 99.00%, Watershed segmentation is 99.85%, and K-mean Clustering is 99.02%.

Another study on image pre-processing from Siddiqi et al. [6] studied the Histogram Equalization filter to enhance CT scan images. Siddiqi et al. stated that CLAHE is better for improving CT images than HE and TSAHE methods. Koonsanit et al. [5] have researched image enhancement applications for digital X-ray images. Koonsanit et al.'s study shows that the proposed NCLAHE method significantly improves pre-processing correction for digital chest radiographs. Stimper et al. [10] formed MCLAHE simultaneously on all dataset dimensions. This method allows for better visualization and emphasizes the features of multi-dimensional images.

There are several methods to detect COVID-19 on CT scan images. Saygili [11] used histogram of oriented gradient and local binary pattern to perform feature extraction of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). They used 10-fold cross-validation for classification methods of k-nearest neighbors, bag of tree, support vector machine, and kernel extreme learning machine. In their study, it yielded an accuracy training of 98.11%. Soares et al. [12] used an eXplainable Deep Learning approach to classify the SARS-CoV-2 CT-scan dataset. Without pre-processing, they achieve an accuracy training of 97.38%. Alshazly et al. [13] used the CNN transfer learning model ResNet101 to automatically extract the features of COVID-19. The results of Alshazly et al.'s research with the datasets that did not go through the pre-processing process have an average accuracy training of 92.9%. Transfer learning is a method of extracting features that uses a pre-trained CNN that can be retrained through fine-tuning [14]. To train a CNN from scratch, a large number of images and computational resources are required. The transfer learning approach, on the other hand, becomes a viable option when the dataset is small and computational resources are limited [15]. Because the available dataset is relatively small, the CNN transfer learning with fine-tuning strategy is used in this work. Additionally, it has been found that CNN model needs less preliminary processing than other classification techniques [16].

3. **Material and Methods.** We present an evaluation of image pre-processing for COVID-19 CT scan image classification in three primary operations: data preparation, classification stage, and system evaluation. The dataset used in this study is described in dataset collection. A further description of the proposed image pre-processing method has been presented in the data preparation section. The parameters in the training process of the CNN model and the classification process are described in the classification stage. System evaluation is intended to measure the level of accuracy of the proposed model. The methods used in calculating the model's accuracy are also described in the system evaluation section. The system design of the proposed model is shown in Figure 2.

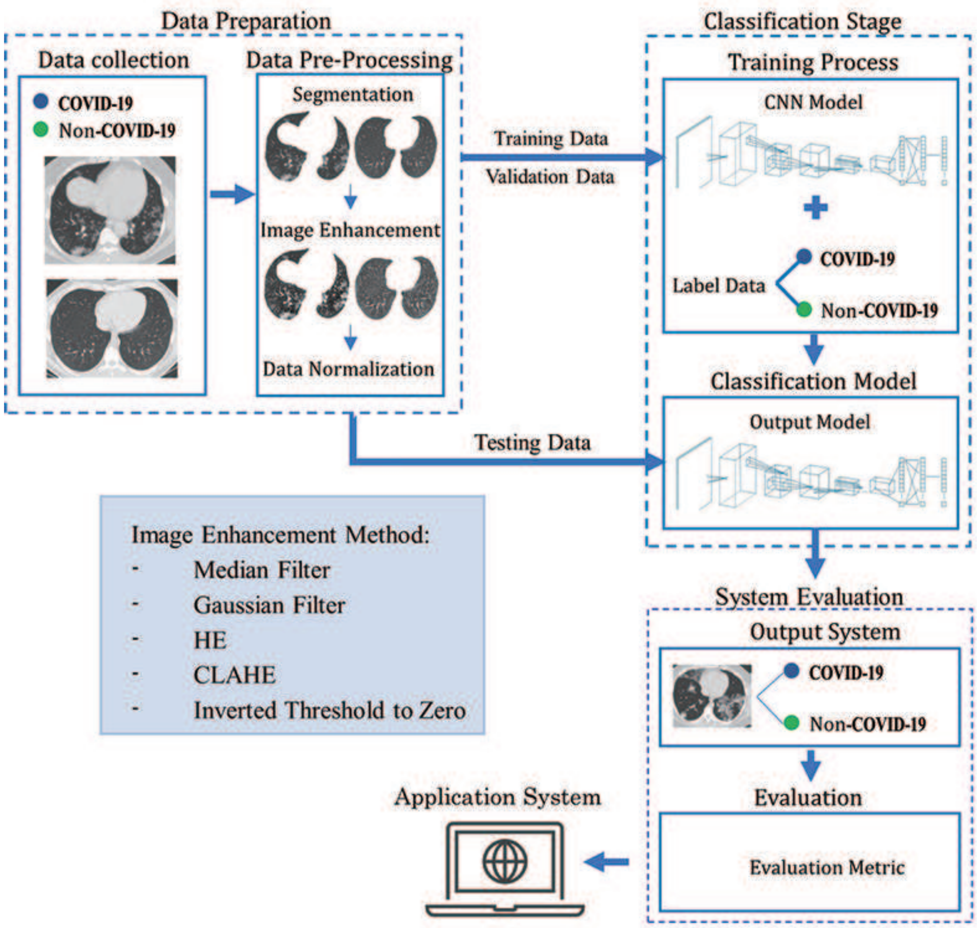

FIGURE 2. System design

3.1. **Data collection.** The dataset used in this research is a CT scan image of the lungs for COVID-19 and non-COVID-19 (not suffering from COVID-19, such as normal and pneumonia caused by bacteria). The total dataset used is 2481 data consisting of 1252 COVID-19 and 1229 non-COVID-19. These data have been collected from actual patients

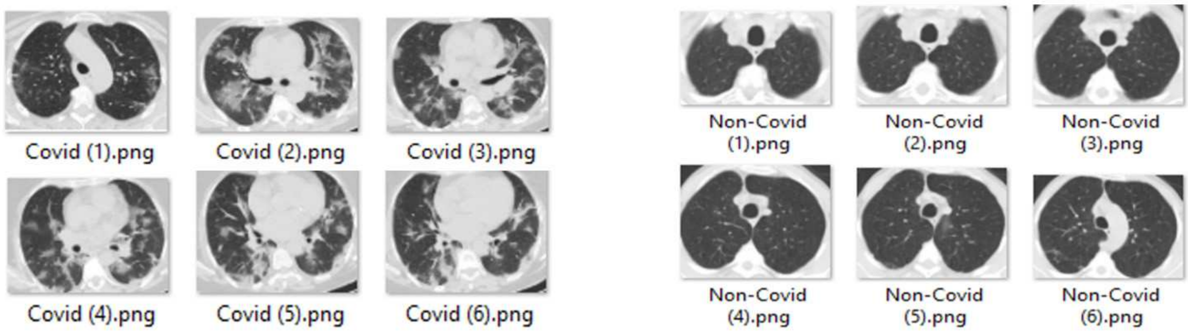

FIGURE 3. The example of CT scan dataset: (a) COVID-19 and (b) non-COVID-19

in Sao Paulo Hospital, Brazil [12]. Furthermore, the data is divided into two parts. There are 2231 training data (consisting of 1127 COVID-19 and 1104 non-COVID-19) and 250 testing data (consisting of 125 COVID-19 and 125 non-COVID-19). An overview of the dataset used can be seen in Figure 3.

3.2. **Data preparation.** At this point, we do some image pre-processing to improve image quality. We propose a preprocessing method that combines lung cavity segmentation with several image quality enhancement methods such as smoothing filters, image contrast improvement, and image thresholding. We used Watershed segmentation to separate the lung cavities' outside and inside in the initial stage. We retain the interior of the lung cavity, where the features for detecting COVID-19 are located. Next, we evaluate the addition of a smoothing image pre-processing method in the form of a Median and Gaussian filter to remove blood vessel spots. We also assess the use of contrast improvement-based pre-processing methods in the form of HE and CLAHE, which aims to highlight the features of COVID-19 further. Furthermore, the CLAHE method is optimized using MCLAHE. In addition, we also evaluated the use of the Inverted Threshold to Zero method to segment the COVID-19 features in the lung cavity.

3.2.1. *Lung segmentation using Watershed algorithm.* The first pre-processing process is the segmentation of the lung cavity. The segmentation process is carried out to eliminate other features on the CT scan image that are unnecessary (such as bone images, medical information, and others). This process is performed because the identifying characteristics of COVID-19 are found only inside the lung cavity. Therefore, only part of the lung cavity will be left at this stage, and the background will be removed. The segmentation process is solved using the Marker-controlled Watershed segmentation algorithm. This algorithm modifies the Watershed technique that aims to overcome the over-segmentation problem in the watershed transformation [17]. Marker-controlled Watershed segmentation is done first by identifying certain digital image elements. Figure 4 shows the output of the lung cavity segmentation process.

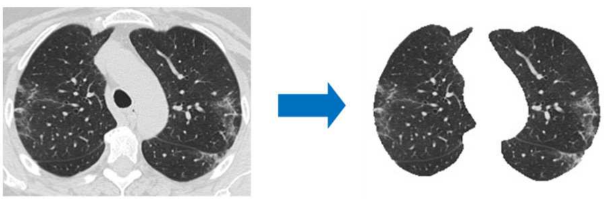

FIGURE 4. Segmentation of the lung cavity

The aim of the Watershed segmentation algorithm is to extract and segment the image's pixels based on their degree of similarity [18]. The basic concept of Watershed segmentation works is assumed that a hole is made at the regional minimum. Then the entire topography is flowing with water coming from that hole at a constant speed. A dam is built to prevent the merger when water rising from two catchment basins is about to merge. The water flow will reach the desired level and stop flowing when only the top of the dam is visible. This visible edge of the dam is called the Watershed line [19]. This Watershed line is the result of segmentation, assuming that the Watershed line is the edge of the object to be segmented. Figure 5 shows the illustration of Watershed morphology.

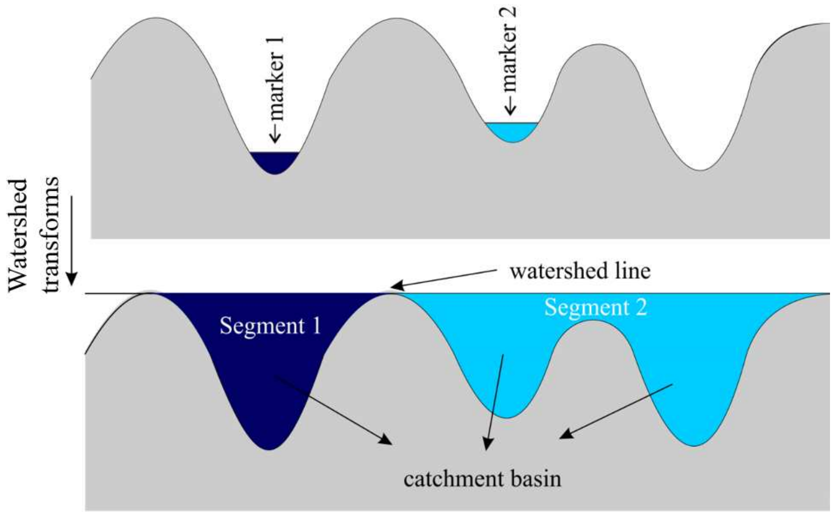

FIGURE 5. Basic concept of Watershed morphology

3.2.2. *Smoothing filter.* Smoothing filters are mainly used to reduce noise in an image and blurring. Blurring is used to remove unimportant information from the image before features are extracted. This paper uses smoothing filters such as Median and Gaussian filters to minimize blood vessel spots in the lung cavity.

The Median filter is one of the most popular and powerful non-linear filters for reducing noise in both 1-dimensional and 2-dimensional data [20]. It is widely used because it effectively removes noise but still retains edges. The Median filter works by moving from pixel to pixel in an image, replacing each value with the median value of the neighboring pixel. Median filtering is calculated by first sorting all the pixel values of the window into numerical order and then replacing the pixels with the center pixel values. The original value of the pixels is included in the median computation. The Median filter provides excellent noise-reduction capabilities, with significantly less blurring than a linear smoothing filter of the same size. The Median filter is particularly effective in the case of bipolar and unipolar impulse noise. However, when the Median filter window size is too large, it tends to spoil image details [21]. The Median function is represented by Equation (1).

$$\widehat{f}(x,y) = \underset{(s,t)\in S_{xy}}{median}\{g(s,t)\} \tag{1}$$

The $g(s,t)$ represents pixel intensity value that is located with s and t coordinates inside the kernel. xy notation represents the intensity value positioned on the x and y coordinates.

A Gaussian filter is a linear filter with a weighting value for each member selected based on the Gaussian function. The Gaussian filter kernel runs in 2D convolution to smooth the image and remove noise. The correlation of an image $f(x, y)$ that is convoluted to the kernel w, which has size $m \times n$, denoted as $(w * f)(x, y)$, is given by Equation (2) [22].

$$(w * f)(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s, t) f(x - s, y - t) \tag{2}$$

where a is given by $\frac{m-1}{2}$, and b is provided by $\frac{n-1}{2}$. The function $f(x, y)$ defines a Gaussian filter function according to the Gaussian distribution in Equation (3).

$$f(x, y) = \frac{1}{2\pi\sigma} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3}$$

The Gaussian filter has two parameters: the window's dimension and standard deviation σ. The higher the σ value, the higher the image smoothing effect.

3.2.3. *Contrast improvement method.* One of the symptoms that occurs on the CT scan image of COVID-19 is the appearance of ground glass in the lobes of the lung. This ground glass sometimes appears as a fuzzy smooth spot. From there, one way to reinforce the features of these COVID-19 is improving the contrast of the image. Some methods that can enhance the image's contrast are HE and CLAHE. This method is expected to enhance image contrast and further highlight the features of COVID-19.

HE is a non-linear contrast enhancement method that can redistribute the original image's histogram to produce uniform population density. This method is often used in contrast enhancement because of its simple and practical function. The result of this function is that it can change image brightness significantly because of histogram flattening. This histogram equalization process used a cumulative distribution because the gradient equalization of the cumulative distribution is carried out in this process. The function of HE that is used for an image with a grayscale of k bits is defined as Equation (4).

$$K_o = round\left(\frac{C_i \cdot \left(2^k - 1\right)}{w \cdot h}\right) \tag{4}$$

where K_o is the result of the histogram equalization, C_i is the cumulative distribution of the grayscale values of the original image on i-pixel. *Round* is a function that rounds to the nearest number. The w and h are the width and height of the image.

CLAHE is a development of Adaptive Histogram Equalization (AHE), which will apply HE on small blocks of the image. When in the application of the HE method, there is noise in the image, then the contrast of the image will be increased. To avoid increasing the contrast of the image that is too high, contrast limiting is applied. If any histogram bins are above the specified contrast limit, those pixels are cropped and distributed uniformly to other bins before applying histogram equalization. Figure 6 shows the difference between the use of HE and CLAHE.

The CLAHE algorithm can be divided into several steps [23]. First, split the original CT image into contextual areas. Then, find the local histogram for each pixel. After each pixel's local histogram is found, merge each local histogram at the clip level. Next is to rearrange the histogram using bilinear interpolation and integrate histogram to improve pixel values. How to calculate the clip limit of a histogram can be defined by the following Equation (5).

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{\max} - 1)\right) \tag{5}$$

where β is the clip limit, M is the region size, and N is the grayscale value (256). α is the clip factor that expresses the addition of the limitations of a histogram with a value between 0 to 100, and $S_{\max}$ is the maximum slope.

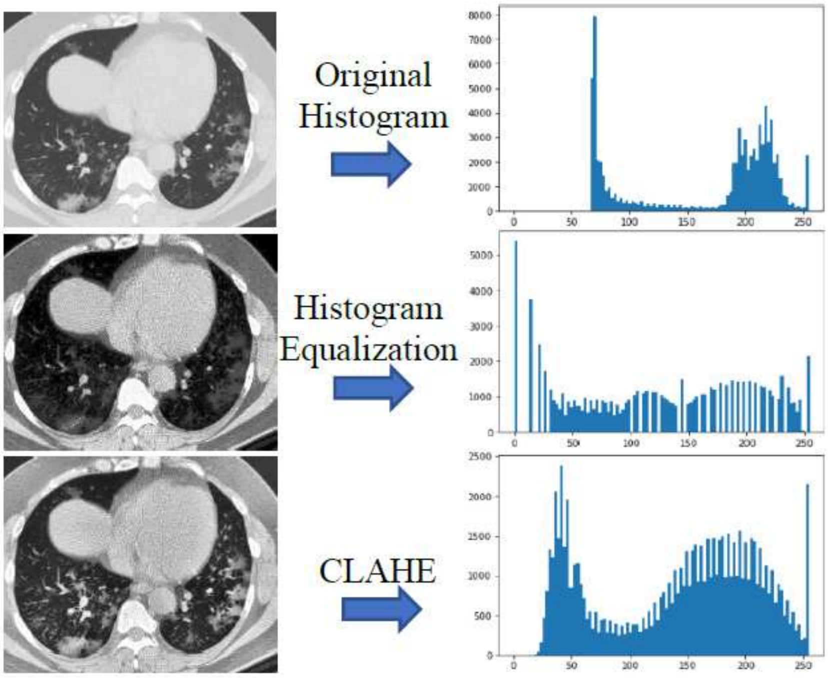

FIGURE 6. The difference between HE and CLAHE

MCLAHE is an extension of CLAHE where this method can provide better visualization and discernment of multi-dimensional image features [10]. The first step in extending the CLAHE method to MCLAHE is to add padding around the D-dimensional edges of the image. D is the number of data dimensions in positive integers. The data that has been padded is then divided into small kernels according to the desired size. Each kernel will be subjected to a histogram distribution and cut histogram according to the specified clip limit. The output of this stage is then subjected to Cumulative Distribution Function (CDF) normalization. Intensity mapping at each D-dimensional pixel was calculated by multilinear interpolation of transformed intensities among the normalized CDFs in the pixel's nearest-neighbor kernels. In the last stage, the contrast-enhanced output data are generated by applying the intensity transform to every pixel in the input data.

3.2.4. *Feature segmentation using simple thresholding.* The thresholding method can be applied to an image to obtain image segmentation. This method converts the grayscale image to a binary image based on the specified clip level [24]. Inverted Threshold to Zero is an application of thresholding by setting the destination pixel value to zero if the source pixel value is greater than the threshold. Otherwise, it is set to the source pixel value. This paper used the Inverted Threshold to Zero to separate COVID-19 features from the lung cavity area. Let $f(x, y)$ be the value of the gray color of the image in pixels (x, y) and T be the specified threshold value, and the output of the thresholding image is defined in Equation (6).

$$g(x, y) = \begin{cases} 0 & \text{if } f(x, y) > T \\ f(x, y) & \text{if } f(x, y) \leq T \end{cases} \tag{6}$$

3.3. **Classification stage.** In this study, we used the CNN algorithm for the feature extraction and classification process. After the CT scan image has passed the pre-processing process, the image is subjected to a feature extraction process using a pre-trained CNN network model. Before entering the basic model of the pre-trained network, the CT scan image is first subjected to the Conv2D process. This process has three filters with a size of 3×3 per kernel. This stage aims to fit the input image in the form of a grayscale image with the basic model of the pre-trained network to be used. In our model, the feature extraction output is then performed by Global Average Polling (GAP), Batch Normalization (BN), Dropout, ReLU activation function, second BN, second Dropout, and finally the SoftMax activation function. GAP is used to collect feature information by combining the latest input feature map into a whole, which has advantages in retaining feature information and accelerating the computation [25]. BN is used to make the model more stable, more efficient, and improve deep network generalization [26]. Dropout is a regularization technique that has shown promising results in preventing a model from overfitting [27]. Figure 7 shows the proposed CNN model to classify COVID-19.

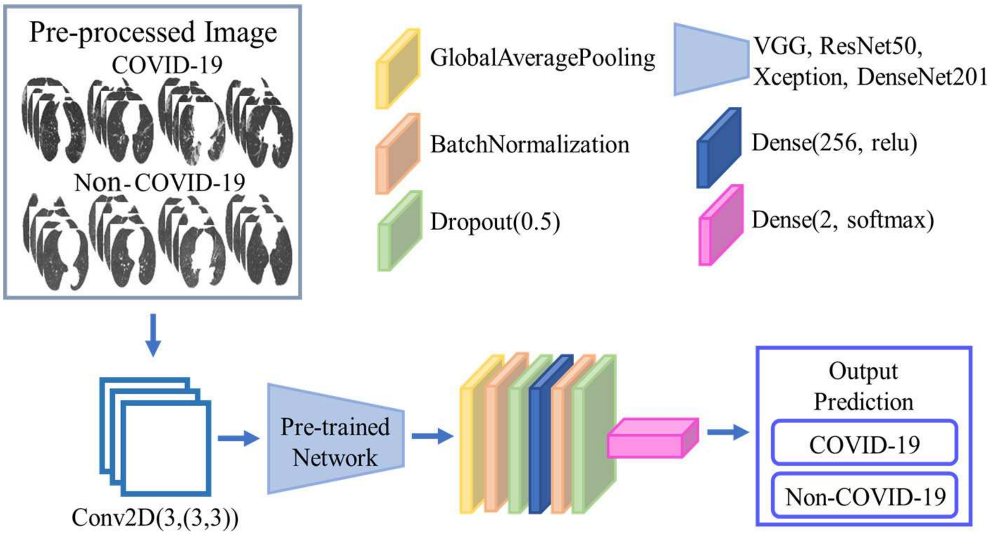

FIGURE 7. The proposed CNN model

Several CNN architectures have proven their effectiveness in the ILSVRC image classification competition. These include the Visual Geometry Group (VGG) and the Inception module from GoogLeNet, demonstrating the benefits of increasing network depth and width. The CNN ResNets architecture builds a residual block learning model through identity mapping shortcut connections. This allows the neural network model to pass through hundreds or even thousands of layers. At this stage, the feature extraction process is carried out using the pre-trained network VGG-19, ResNet50, Xception, and DenseNet201.

3.4. **System evaluation.** For the case of binary classification, the evaluation of classification training can be defined based on the confusion matrix [28]. The confusion matrix is a statistical metric used to implement machine learning classification algorithms to determine the accuracy of a model [29]. The confusion matrix consists of True Negative (TN), True Positive (TP), False Positive (FP), and False Negative (FN). The values of TN and TP indicate the value of the positive and negative classification results that are classified correctly according to ground truth. In contrast, FP and FN indicate the number of positive and negative classification errors.

To assess the performance of the proposed model, the system evaluation process is carried out by calculating the level of accuracy, error rate, precision, sensitivity, specificity, and F1-score. Accuracy is the proportion of correct results out of the total number of samples tested. Error rate measures the ratio of incorrect predictions to the total number of samples evaluated. Precision is used to measure which positive samples out of the total number of predicted samples in the positive class were predicted correctly. Sensitivity is used to measure the proportion of positive samples that are correctly classified. Specificity is used to measure the ratio of negative samples that are correctly classified. The F1-score is a number between 0 and 1 and is the harmonic mean of precision and recall. The sample mentioned above consists of COVID-19 and non-COVID-19 data. Equation (7) until Equation (12) show the formulae for accuracy, error rate, precision, sensitivity, specificity, and F1-score.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{7}$$

$$Error\ Rate = \frac{FP + FN}{TP + FP + TN + FN} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Sensitivity\ or\ Recall = \frac{TP}{TP + FN} \tag{10}$$

$$Specificity = \frac{TN}{TN + FP} \tag{11}$$

$$F1\text{-}score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{12}$$

4. **Experiments and Results.** This experiment is divided into two scenarios. The first scenario is to carry out a feature extraction and classification process using the original dataset without going through the data pre-processing process. The second scenario is to pre-process the image before entering the feature extraction and classification process. A summary of the scenarios used is presented in Table 1.

Table 1. Scenario experiment

Methods		Scenario 1				Scenario 2					
		1.1	1.2	1.3	1.4	2.1	2.2	2.3	2.4	2.5	2.6
Pre-processing	Watershed					✓	✓	✓	✓	✓	✓
	Median					✓					
	Gaussian						✓				
	Inverted Threshold to Zero							✓			
	HE								✓		
	CLAHE									✓	
	MCLAHE										✓
CNN	VGG-19	✓									
	ResNet50		✓			✓	✓	✓	✓	✓	✓
	Xception			✓							
	DenseNet201				✓						

4.1. **First scenario.** In this scenario, the CT scan COVID-19 and non-COVID-19 datasets are directly processed for feature extraction and classification without pre-processing. We added a Conv2D layer before the CNN transfer learning model in the feature learning process. After the CNN transfer learning model, we added GlobalAveragePooling2D, BatchNormalization, and Dropout(0.5). In the classification process, we used BatchNormalization, Dropout(0.5), and the ReLU activation function. The parameters used in the training process are a learning rate of 0.002, batch size of 32, an epoch of 200, and

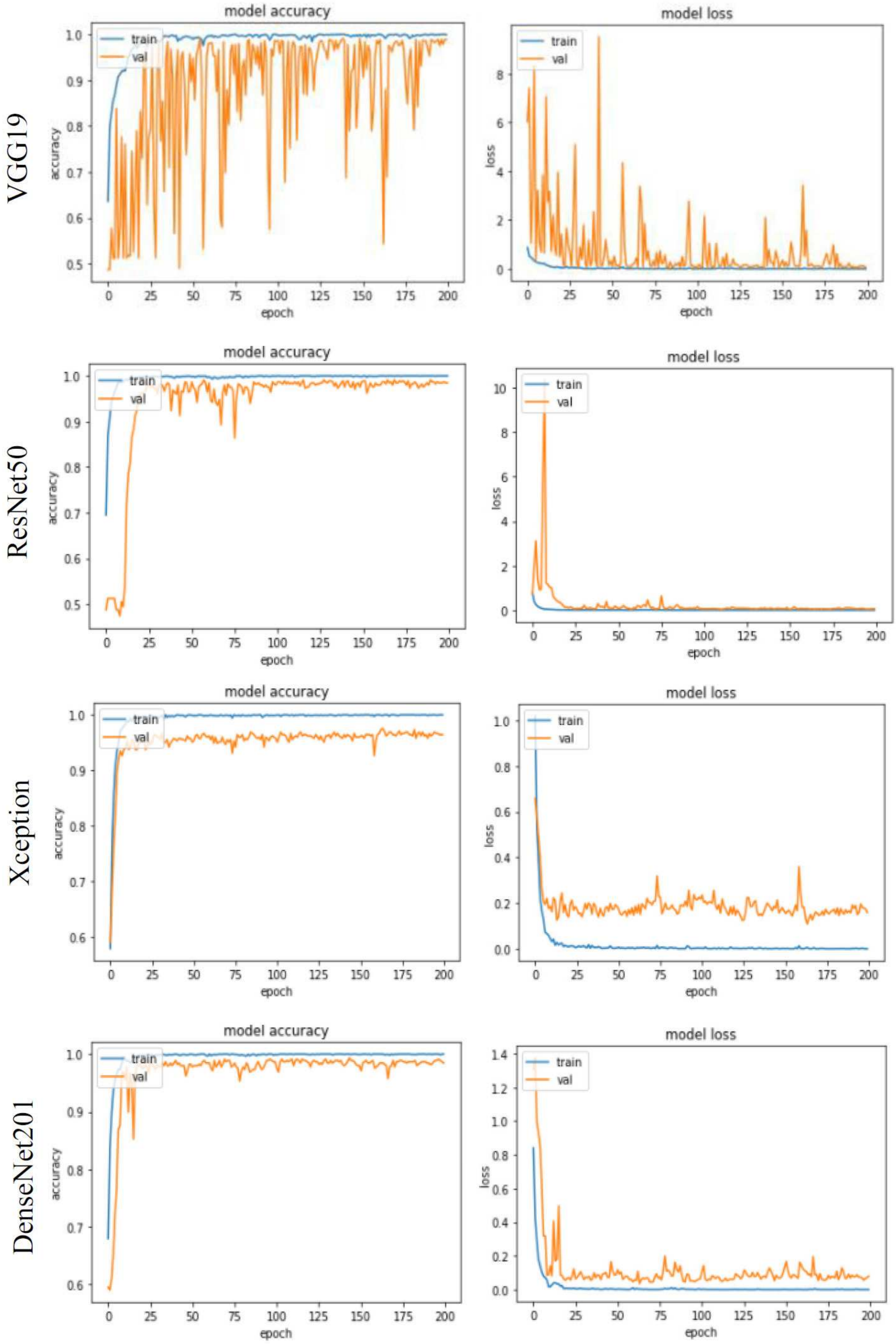

FIGURE 8. Graph of accuracy and loss training

the Adam optimizer. Figure 8 shows the training process results of several pre-trained networks that have been used.

From the results of the training graph in Figure 8, ResNet50, Xception, and DenseNet-201 show more stable results than VGG19. Compared to other methods that have been tested, ResNet50 has the smallest distance between the training and validation results. Furthermore, to measure the performance of each CNN model on our testing data, we used the calculation of accuracy, error rate, precision, sensitivity, specificity, and F1-score. From the measurement results, ResNet50 has a better performance compared to other methods that have been tested. Table 2 shows the results of the performance calculation on the testing data.

Table 2. Performance calculation from the original image. The bolded text represents the models' best performance for each metric performance calculation outcome.

Experimental results on training data						
Scenario 1	Accuracy	Error rate	Precision	Sensitivity	Specificity	F1-score
VGG-19	99.11	8.9	**99.13**	99.13	**99.08**	99.13
ResNet50	**99.33**	**6.7**	**99.13**	**99.56**	**99.08**	**99.35**
Xception	97.99	20.1	97.83	98.25	97.71	98.04
DenseNet201	99.11	8.9	**99.13**	99.13	**99.08**	99.13
Experimental results on testing data						
Scenario 1	Accuracy	Error rate	Precision	Sensitivity	Specificity	F1-score
VGG-19	75.60	24.4	78.07	71.2	80.0	74.48
ResNet50	**86.40**	**13.6**	**86.99**	**85.6**	**87.2**	**86.29**
Xception	81.60	18.4	81.10	82.4	80.8	81.75
DenseNet201	85.20	14.8	84.92	85.6	84.8	85.26

4.2. **Second scenario.** In this scenario, we added pre-processing of COVID-19 and non-COVID-19 images before the feature extraction and classification process. The first step of image pre-processing is the segmentation of the lung cavity to remove unneeded features. This process is carried out using the Marker-controlled Watershed segmentation method. The marking of the segments in the Watershed method is done manually with a mouse click. Figure 9 presents the process of segmentation of the lung cavity.

(a) (b) (c)

Figure 9. The segmentation process: (a) Marking using a mouse click; (b) find contour; (c) inserting original CT image into Watershed output

From left to right, the CT scan image is first marked on the inside and outside of the lung cavity. Furthermore, the find contour algorithm will search for the contour that has been formed by mouse marking. After the contour is found, the segmentation process carried out using the Watershed method will mark the pixels around the contour to be the same value as the contour according to the Watershed distribution. In this process, the lung cavities are colored black, other than the lung cavities are colored white. The last segmentation step is to insert the original CT scan image into the image resulting from the Watershed process.

The next step in the image pre-processing process is applying the image enhancement methods: Median filter, Gaussian filter, Inverted Threshold to Zero, HE, CLAHE, and MCLAHE alternately. The output of each image enhancement method is then subjected to a classification stage. Figure 10 shows a sample of the application of the image enhancement method.

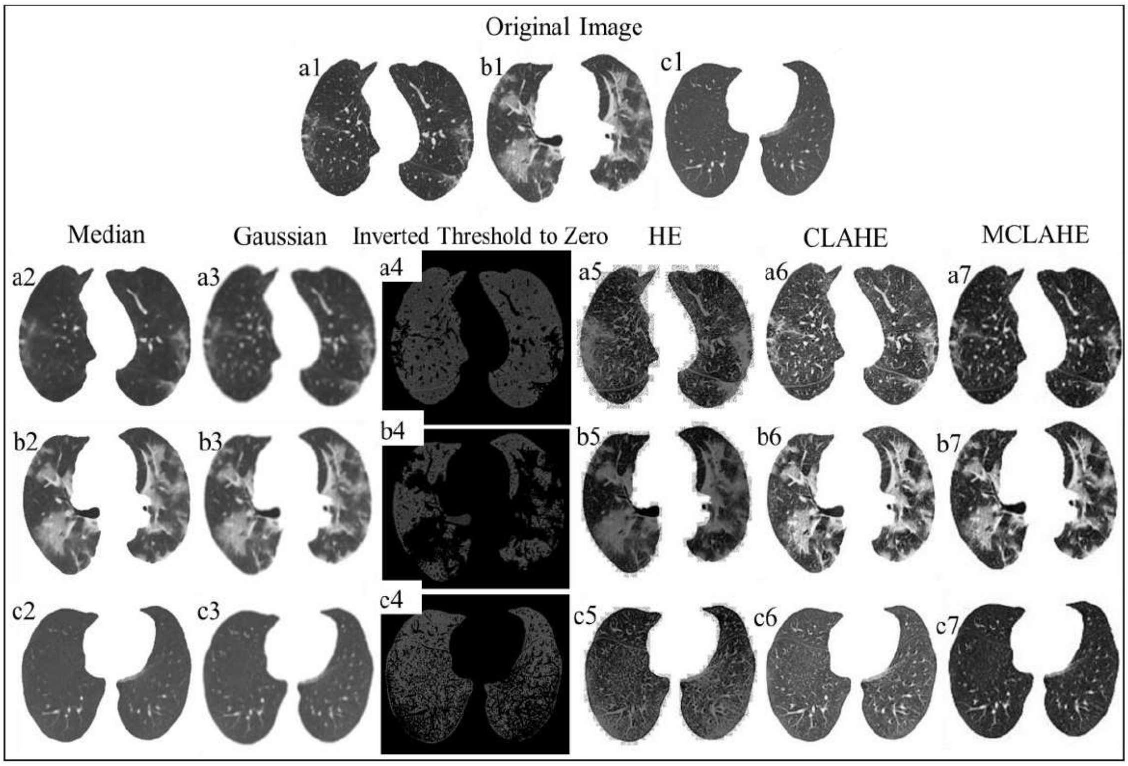

FIGURE 10. The application of the image enhancement method. (a) and (b) are CT scan images of moderate and severe COVID-19. (c) is non-COVID-19 CT scan image. (1) Original image, (2) Median, (3) Gaussian, (4) Inverted Threshold to Zero, (5) HE, (6) CLAHE, (7) MCLAHE.

From Figure 10, it can be observed that the Median and Gaussian filters can minimize noise by blurring the image according to the kernel filter level. However, these methods can also cause the nebulous features of COVID-19 to be eroded. Inverted Threshold to Zero can less increase the difference in features from COVID-19 and non-COVID-19. CLAHE can further enhance the contrast of vague COVID-19 features to highlight those features more than HE. Furthermore, as seen in Figure 10, the application of the MCLAHE method can further clarify the features of COVID-19 than the regular CLAHE method. Table 3 shows the results of the performance calculation after applying each image enhancement method.

The feature extraction and classification process in Table 3 are completed using the ResNet50 model because, in scenario one, ResNe50 models produce better performance than the other models. From this calculation, the use of segmentation with the addition of Median filter, Gaussian filter, HE, CLAHE, and MCLAHE can increase the performance

Table 3. Performance calculation from pre-processed images. The bolded text represents the models' best performance for each metric performance calculation outcome.

Experimental results on training data						
Scenario 2	Accuracy	Error rate	Precision	Sensitivity	Specificity	F1-score
Median	98.39	1.61	98.10	98.78	97.98	98.44
Gaussian	**98.66**	**1.34**	**98.27**	**99.13**	**98.17**	**98.70**
HE	98.21	1.79	98.25	98.25	**98.17**	98.25
CLAHE	**98.66**	**1.34**	**98.27**	**99.13**	**98.17**	**98.70**
Inverted Threshold to Zero	96.87	3.13	96.14	97.82	95.87	96.97
MCLAHE	97.99	2.01	97.41	98.69	97.25	98.05
Experimental results on testing data						
Scenario 2	Accuracy	Error rate	Precision	Sensitivity	Specificity	F1-score
Median	90.40	9.60	86.33	96.00	84.80	90.91
Gaussian	88.40	11.60	86.92	90.40	**86.40**	88.63
HE	90.40	9.60	86.86	95.00	85.60	90.84
CLAHE	91.20	8.80	87.59	96.00	**86.40**	91.60
Inverted Threshold to Zero	86.00	14.00	80.82	94.40	77.60	87.08
MCLAHE	**91.60**	**8.40**	86.62	**98.40**	84.80	**92.13**

of the classification process. In an experiment using testing data, MCLAHE method can produce better accuracy values than the other methods.

5. **Discussion.** These signs of abnormalities on CT scan COVID-19 imaging are sometimes subtle. These signs occur when the disease has recently attacked the lungs or the patient has mild symptoms. Poor image quality can also cause features from COVID-19 to be less visible. This poor image quality is one of the causes of CNN's low accuracy of COVID-19 detection results. This problem is usually solved by using image pre-processing to improve image quality and highlight features. The selection of the proper method in the image pre-processing process can help to improve the classification accuracy results.

In this paper, we present the evaluation of several pre-processing methods to improve the image quality for COVID-19 automatic detection. The pre-processing is done by lung cavity segmentation and image quality enhancement. Because the features for the recognition of COVID-19 are only found inside the lung cavity, the first step of pre-processing is done by eliminating other features on the CT scan image that are not needed (such as ribs, heart, and medical markings). Therefore, at this stage it will only leave part of the lung cavity. Removing unneeded features is done by segmenting using the Watershed method. The Watershed method that is used to distinguish the segmented parts is performed by clicking the mouse and manually marking. Using this method, good results have been obtained in separating the inside of the lung cavity (along with COVID-19 features) and the outside of the lung cavity that is not required. The segmented image is then subjected to image enhancement in the form of Median filter, Gaussian filter, Inverted Threshold to Zero, HE, and CLAHE alternately. The experimental results found that the combination of Watershed segmentation and CLAHE image enhancement has the highest classification accuracy rate of 91.20%. After it was found that CLAHE has the highest accuracy value, the CLAHE performance improvement was carried out using MCLAHE. This method can allow better visualization and discernment of multi-dimensional image features. The MCLAHE method obtained the highest accuracy of 91.60%.

The Median filter and Gaussian filter image enhancement methods have 90.40% and 88.40% accuracy results, respectively. Both methods show lower results than the CLAHE method. These results happen because during the image blurring process it not only removes blood vessel spots but also erodes the small and faint features of COVID-19.

The HE method shows a higher accuracy with a value of 90.40% than the Median filter, Gaussian filter, and Inverted Threshold to Zero. These results happen because the HE method can increase the contrast value of the image so that it can clarify the faint features of COVID-19. However, in the HE method, the image's contrast enhancement is generally carried out in one whole image so that the feature highlighting process is not as good as CLAHE. On the other hand, CLAHE improves the image quality by dividing the image into small parts to highlight the faint features in the area. Inverted Threshold to Zero has the smallest accuracy value, 86.00%. The small value of this accuracy is because this method cannot clarify the features of COVID-19. The use of Inverted Threshold to Zero can even eliminate some features due to inaccuracies in selecting the threshold value.

All experiments in scenario 2 were carried out with CNN ResNet50 pre-trained network. This model was chosen based on scenario 1, which shows that ResNet50 produces the highest accuracy than other models. This is because ResNet50 used the Identity Connection, which helps protect the network from vanishing gradient problems.

6. **Conclusions.** The selection of pre-processing suitable for certain cases can improve the results of feature extraction and classification of a CNN model. The above experiment showed that the addition of pre-processing images in the form of lung cavity segmentation accompanied by the CLAHE image enhancement method could produce a higher level of accuracy than Median, Gaussian, Inverted Threshold to Zero, and HE image enhancement. It also shows a higher level of accuracy when compared to the classification output of the original image without pre-processing. The MCLAHE is used to optimize the performance of the CLAHE method and is proven to increase the accuracy of the results to 91.60%. The MCLAHE can produce better visualization and discernment of multi-dimensional image features. However, with a larger and more representative sample size, this percentage may be elevated. As a future direction, this result could be enhanced by incorporating more pre-processing processes or further refining the MCLAHE method. Furthermore, automatic lung cavity segmentation using a deep learning algorithm may facilitate segmentation speedup in future study.

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REFERENCES

[1] T. Ai et al., Correlation of chest CT and RT-PCR testing for coronavirus disease 2019 (COVID-19) in China: A report of 1014 cases, *Radiology*, vol.296, no.2, pp.32-40, 2020.

[2] T. Yan, P. K. Wong, H. Ren, H. Wang, J. Wang and Y. Li, Automatic distinction between COVID-19 and common pneumonia using multi-scale convolutional neural network on chest CT scans, *Chaos, Solitons and Fractals*, vol.140, 110153, DOI: 10.1016/j.chaos.2020.110153, 2020.

[3] M. Polsinelli, L. Cinque and G. Placidi, A light CNN for detecting COVID-19 from CT scans of the chest, *Pattern Recognit. Lett.*, vol.140, pp.95-100, DOI: 10.1016/j.patrec.2020.10.001, 2020.

[4] S. Hu et al., Weakly supervised deep learning for COVID-19 infection detection and classification from CT images, *IEEE Access*, vol.8, no.4, pp.118869-118883, DOI: 10.1109/ACCESS.2020.3005510, 2020.

[5] K. Koonsanit, S. Thongvigitmanee, N. Pongnapang and P. Thajchayapong, Image enhancement on digital x-ray images using N-CLAHE, *2017 10th Biomedical Engineering International Conference (BMEiCON)*, pp.1-4, 2017.

[6] A. A. Siddiqi, G. B. Narejo, M. Tariq and A. Hashmi, Investigation of histogram equalization filter for CT scan image enhancement, *Biomed. Eng. – Appl. Basis Commun.*, vol.31, no.5, pp.1-10, DOI: 10.4015/S1016237219500388, 2019.

[7] E. Burhan et al., *Pneumonia COVID-19 Diagnosis & Management in Indonesia*, Perhimpunan Dokter Paru Indoneisa, Jakarta, 2020.

[8] M. J. Horry et al., COVID-19 detection through transfer learning using multimodal imaging data, *IEEE Access*, vol.8, pp.149808-149824, 2020.

[9] M. F. Abdullah et al., A comparative study of image segmentation technique applied for lung cancer detection, *Proc. of the 9th IEEE Int. Conf. Control Syst. Comput. Eng. (ICCSCE2019)*, pp.72-77, DOI: 10.1109/ICCSCE47578.2019.9068574, 2019.

[10] V. Stimper, S. Bauer, R. Ernstorfer, B. Schölkopf and R. P. Xian, Multidimensional contrast limited adaptive histogram equalization, *IEEE Access*, vol.7, pp.165437-165447, 2019.

[11] A. Saygılı, A new approach for computer-aided detection of coronavirus (COVID-19) from CT and X-ray images using machine learning methods, *Appl. Soft Comput.*, vol.105, 107323, DOI: 10.1016/j.asoc.2021.107323, 2021.

[12] E. Soares, P. Angelov, S. Biaso, M. H. Froes and D. K. Abe, SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification, *medRxiv*, DOI: 10.1101/2020.04.24.20078584, 2020.

[13] H. Alshazly, C. Linse, E. Barth and T. Martinetz, Explainable COVID-19 detection using chest CT scans and deep learning, *Sensors*, vol.21, no.2, 455, DOI: 10.3390/s21020455, 2021.

[14] R. Patel and A. Chaware, Transfer learning with fine-tuned MobileNetV2 for diabetic retinopathy, *2020 International Conference for Emerging Technology (INCET)*, pp.1-4, 2020.

[15] A. J. Santoso and R. E. Saragih, Automatic face mask detection based on MobileNet V2 and DenseNet 121 models, *ICIC Express Letters*, vol.16, no.4, pp.433-440, 2022.

[16] S. Liawatimena, E. Abdurahman, A. Trisetyarso, A. Wibowo, I. S. Edbert, M. K. Ario and F. Effendi, Performance optimization of maxpool calculation using 4D rank tensor, *ICIC Express Letters, Part B: Applications*, vol.13, no.7, pp.767-776, 2022.

[17] R. Sarma and Y. K. Gupta, A comparative study of new and existing segmentation techniques, *IOP Conference Series: Materials Science and Engineering*, vol.1022, no.1, DOI: 10.1088/1757-899X/1022/1/012027, 2021.

[18] K. Lv, W. Wang, Z. Zhou and X. Wang, An improved Watershed algorithm on multi-directional edge detection for road extraction in remote images, *International Journal of Innovative Computing, Information and Control*, vol.18, no.3, pp.851-866, 2022.

[19] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 3rd Edition, Pearson, New York, 2007.

[20] I. Pitas and A. N. Venetsanopoulos, Order statistics in digital image processing, *Proc. of IEEE*, vol.80, no.12, pp.1893-1921, 1992.

[21] T. Sun, M. Gabbouj and Y. Neuvo, Center weighted median filters: Some properties and their applications in image processing, *Signal Processing*, vol.35, no.3, pp.213-229, 1994.

[22] R. E. Woods, S. L. Eddins and R. C. Gonzalez, *Digital Image Processing Using MATLAB*, 2nd Edition, Gatesmark Publishing, United States of America, 2009.

[23] D. A. Ragab and O. Attallah, FUSI-CAD: Coronavirus (COVID-19) diagnosis based on the fusion of CNNs and handcrafted features, *PeerJ Comput. Sci.*, vol.6, e306, DOI: 10.7717/peerj-cs.306, 2020.

[24] N. Anusha, K. B. Sai and K. Srujana, Image segmentation using ToZero method and ToZero inverse methods, *ARPN J. Eng. Appl. Sci.*, vol.13, no.16, pp.4678-4682, 2018.

[25] Z. Bi, L. Yu, H. Gao, P. Zhou and H. Yao, Improved VGG model-based efficient traffic sign recognition for safe driving in 5G scenarios, *Int. J. Mach. Learn. Cybern.*, vol.12, no.11, pp.3069-3080, 2021.

[26] L. Huang, J. Qin, Y. Zhou, F. Zhu, L. Liu and L. Shao, Normalization techniques in training DNNs: Methodology, analysis and application, *arXiv.org*, arXiv: 2009.12836, 2020.

[27] B. A. Skourt, A. El Hassani and A. Majda, Mixed-pooling-dropout for convolutional neural network regularization, *J. King Saud Univ. Inf. Sci.*, 2021.
[28] M. Hossin and M. N. Sulaiman, A review on evaluation metrics for data classification evaluations, *Int. J. Data Min. Knowl. Manag. Process.*, vol.5, no.2, pp.1-11, DOI: 10.5121/ijdkp.2015.5201, 2015.
[29] A. A. Salih and A. M. Abdulazeez, Evaluation of classification algorithms for intrusion detection system: A review, *J. Soft Comput. Data Min.*, vol.2, no.1, pp.31-40, 2021.

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