Optimization Accuracy of CNN Model by Utilizing CLAHE Parameters in Image Classification Problems

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***Abstract*—This study aims to optimize popular Convolutional Neural Network (CNN) models, such as ResNet50, InceptionV4, VGG19, MobileNetV1, MobileNetV2, MobileNetV3 Small, and MobileNetV3 Large, by utilizing the CLAHE (Contrast Limited Adaptive Histogram Equalization) parameter. This research focuses on the problem of classifying retinal fundus images, which have challenges in analyzing the structure and features of the picture. This study compared the performance of CNN models, which were optimized using the CLAHE method as image pre-processing. The fundus retinal image data used is a publicly available dataset. The optimization process is done by changing the parameters in the CNN model and applying the CLAHE technique to improve image quality before the classification process. The results showed that using the CLAHE parameter significantly contributed to improving the performance of the CNN model in classifying retinal fundus images. Some CNN models optimized with CLAHE produce better accuracy than the un-optimized models. There are also variations in performance between the different models, with some models providing better results in classifying retinal fundus images. This study provides new insights regarding using CLAHE parameters in optimizing the CNN model for retinal fundus image classification problems. The results of this research can be the basis for further development in medical image processing and pattern recognition for more accurate and practical diagnostic applications.**

Keywords*—CLAHE, deep learning, CNN, classification, fundus imagery

I. INTRODUCTION

Fundus retinal images are produced by a special camera that takes pictures of the back of the eye, specifically the retina [1–5]. These images contain important information about eye health conditions and can be used to detect early various eye diseases, including diabetic retinopathy, glaucoma, and macular degeneration. Classification of retinal fundus images is one of the challenges in medical image processing because it is necessary to recognize and classify complex features in images [6–8].

Convolutional Neural Network (CNN) has become a popular method for classifying images because it can automatically study essential features through convolution layers [9–11]. Some well-known CNN models proven effective in various image processing tasks are ResNet50, InceptionV4, VGG19, MobileNetV1, MobileNetV2, MobileNetV3 Small, and MobileNetV3 Large. Each model has a unique architecture and advantages in studying complex features of images. However, retinal fundus image processing has its challenges. These images often have high variations in intensity, contrast, and lighting, which can affect the performance of the CNN model in classifying images. Therefore, it is necessary to optimize the CNN models used in the problem of retinal fundus image classification.

One technique that can be used in optimization is Contrast Limited Adaptive Histogram Equalization (CLAHE). CLAHE is a method used to improve image contrast and sharpness by improving the histogram distribution of the image. CLAHE adaptively divides the image into several small blocks, then performs a histogram equalization on each block with certain contrast limits. This technique is effective in increasing detail and improving image quality [12]. It can help improve the performance of the CNN model in the task of classifying retinal fundus images, as evidenced by related studies that have been conducted. Among them is research conducted by Shamrat et al. (2023) for the Classification of Alzheimer's Disease Stages based on Functional Brain Changes using Deep learning. In this study, the CLAHE technique is used to overcome the global method's constraints by increasing the image's local contrast. The CLAHE technique can help perform optimal classification with the tileGridSize Parameters (12, 12) and clip limit (3) [13].

Based on this, the proposed research will use different tileGridSize parameters because the higher the tileGridSize value used, the better the results will be. Jena et al. (2023) used contrast-limited adaptive histogram equalization (CLAHE) to boost the green channel since the light lesions were visible in the green channel. Green channel images were chosen for analysis because the pixel values in the green channel are less impacted by the fovea. These images were improved with CLAHE after the optic disc and vessels were removed [14]. However, the CLAHE technique in this study needed to explain the tileGridSize and clip limit values used in detail. However, the CLAHE technique was able to help CNN in solving the problems in this study. Therefore the proposed research will provide a better explanation and elaboration. In another study, Shamrat et al. (2023) performed a high-precision multiclass classification of lung diseases via MobileNetV2 adapted from chest X-ray images. Initial pre-processing of the X-ray image from the dataset uses CLAHE to increase the image's contrast to make it more straightforward. CLAHE approach employs the tileGridSize (5,5) with clip limit (0,5), tileGridSize (7,7) with clip limit (1,5), and tileGridSize (10,10) with clip limit (3) parameters. As a result, the tileGridSize parameter (10, 10) with clip limit (3) is selected as the best [15]. Based on this research, the proposed study will test these parameters on retinal fundus images and whether they can improve accuracy. George et al. (2023) used CLAHE and the Homomorphic Transformation Filter to process image pixel data and extract features from CXR to detect COVID-19 in chest X-ray images. The result is that the CLAHE Filter and Homomorphic Transformation help to improve image contrast and reduce its dynamic range. CLAHE generates non-overlapping contextual sections (also known as sub-images, tiles, or blocks) and then applies histogram equalization to each contextual area, truncating the original histogram to a specific value before redistributing the truncated pixels to each level of grayscale [16]. CLAHE in this study is used on 64x64 pixel images, while the proposed research uses 224x224 pixel images. Subsequent research was conducted by Nahiduzzaman et al. (2023) used a parallel convolutional neural network feature extractor and ELM classifier to detect diabetic retinopathy. CLAHE in this study was used to highlight the lesion on fundus images. As a result CLAHE is able to improve image quality to be clearer. CLAHE uses Parameter tileGridSize (4, 4) with clip limit (2,0) on a 124x124 pixel image [17]. While the proposed research will use CLAHE parameters and image resolution that is different from that research.

Based on previous studies, this study aims to utilize CLAHE parameters in optimizing the accuracy of the previously mentioned CNN models (ResNet50, InceptionV4, VGG19, MobileNetV1, MobileNetV2, MobileNetV3 Small, and MobileNetV3 Large) on image classification problems fundus retina. By including the CLAHE technique as image pre-processing, CNN models performance in recognizing and classifying relevant characteristics from retinal fundus pictures can be improved, contributing to better eye disease diagnosis and earlier treatment.

II. Method

A. Research Workflow

A research workflow is a series of steps or stages to plan, implement, and evaluate a study. This workflow assists researchers in organizing and directing research activities systematically. The workflow in this study is presented in Figure 1:

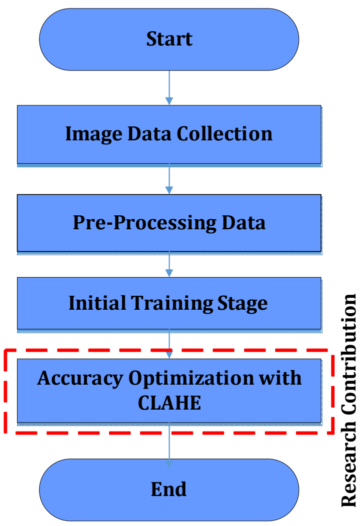


Fig. 1. Research workflow

Based on Figure 1 it can be explained as follows:

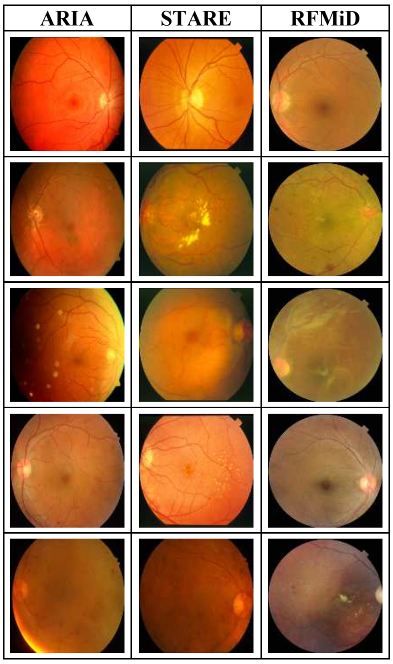
- Image Data Collection
  This stage involves collecting image data that is relevant to your research. Image data can be obtained through public databases, self-collections, or other suitable references.
- Pre-Processing Data
  Pre-Processing is a process that aims to prepare data before being analyzed. This can include changing the image format, normalizing the pixel intensity, cropping the image, or cleaning the data from noise or artifacts.
- Initial Training Stage
  This stage involves training or comparison of 7 Convolutional Neural Network (CNN) models (ResNet50, MobileNetV2, Inception, MobileNetV1, MobileNetV3 Small, MobileNetV3 Large, and VGG19) so that the best model is obtained. Based on the best-selected model, development or modification will be carried out using the CLAHE algorithm.
- Accuracy Optimization with CLAHE
  Following the initial training, the accuracy is optimized using CLAHE. The CLAHE method aims to increase the contrast and clarity of images to improve accuracy in analysis or object recognition.

B. Image Data Collection

a) The collection of datasets in this study was carried out using web scraping, namely the collection process from online sources. The dataset was obtained from Multi-Label Retinal Disease (MuReD), a combination of the ARIA, STARE, and RFMiD datasets. A total of 2208 images consisting of 20 classes [18].

TABLE I. Retina Fundus Image Data Samples

ARIA	STARE	RFMiD



After further observation, it turned out that a lot of data needed to be included (none); the total available images were only 1855 of the 20 classes. This dataset has been validated by an ophthalmologist from the SMEC Eye Hospital in Medan, Indonesia. So that the dataset that can be used for this study is only 1200 images with 12 disease classes, the following research dataset will be analyzed again so that the fundus images can be used for research.

C. Pre-Processing Data

The stages of the research in this section consist of Cleaning and Normalization of Datasets, Image Verification by Experts, Conversion of Image Format Types, Image Resizing, Split Data, and Image Data Balancing with Augmentation.

D. Training Stage

This stage is carried out after Split Data and Image Data Balancing with Augmentation have been completed. At this stage, the Hyperparameter Training used can be seen in TABLE II:

TABLE II. HYPERPARAMETER TRAINING CNN

Parameter	Information
Image Input	224x224
Batch Size	16
Epoch	50
Optimizer	Adam (lr=0.0001)
Activation Function	Softmax
Weights	'ImageNet'

Where: Input Image is the resolution of the input image used in each model. Batch Size is the number of images processed at each call in one training iteration. Epoch is the number of iterations. Optimizer is a Type of optimization. Activation Function is the Activation Function used, and Weights is the Weight Value. This study uses split data k = 3 with ratios of split data Training, validation, and Testing of 80%:10%:10%, 60%:30%:10%, and 70%:20%:10%.

E. Accuracy Optimization with CLAHE

CLAHE is an image processing technique that increases image contrast by retaining finer details in areas of low contrast levels. CLAHE is used as one of the steps to improve (optimize) accuracy.

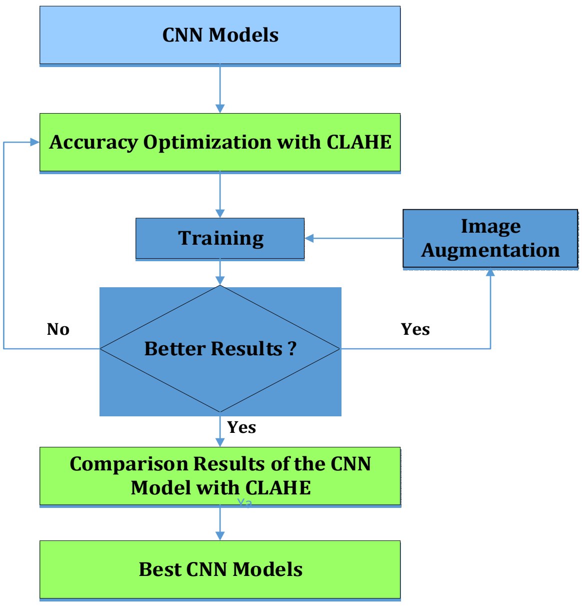


Fig. 2. Accuracy optimization flowchart with CLAHE

Based on Figure 2, it can be explained that the retinal fundus image model previously trained using 7 CNN architectural models will optimize its accuracy using CLAHE. The results of the images that have been CLAHE will be retrained; if the results are better, they will be compared with the previous initial training stage, then the results will be forwarded to be compared with each architectural model. If the results are lower (not increasing) than the initial training stage, data augmentation will be carried out continuously to obtain better results than the initial training stage. Furthermore, if the accuracy of the trained image has increased, then the next step is to compare the results of the 7 CNN models based on the CLAHE images to see the best CNN model.

III. RESULTS AND DISCUSSION

A. Pre-Processing Data

Based on the retinal fundus image dataset used for the study, after re-analysis, there were several blurry images and lens flare artifacts (reflections of light or shadows) during image capture, which would affect the research process because the photos were considered damaged and could not be used. The number of images that are not included because of this is 78 images. The sample data can be seen in Figure 3:

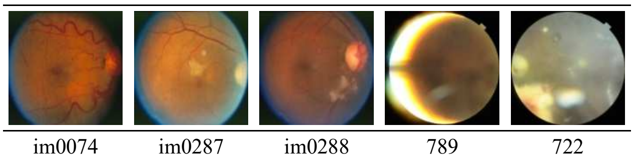


Fig. 3. Deleted image due to blur / lens artifact

After cleaning the data is complete, the image dataset, which was originally 1200, is reduced by 78 images so that it becomes 1122 images that can be used as research data. Research Dataset After cleaning, clearer data can be seen in TABLE III:

TABLE III. DATASET AFTER CLEANING DATA

Class	Diagnosis	Abbreviation	Image
1	Normal Retina	NORMAL	384
2	Diabetic Retinopathy	DR	231
3	Other Diseases	OTHER	106
4	Drusen	DN	63
5	Media Haze	MH	52
6	Optic Disc Cupping	ODC	62
7	Retinitis	RS	46
8	Age-Related Macular Degeneration	ARMD	42
9	Branch Retinal Vein Occlusion	BRVO	40
10	Central Retinal Vein Oclussion	CRVO	31
11	Optic Disc Edema	ODE	34
12	ChorioRetinitis	CSR	31
Total Image			1122

Details of the split data results based on class on data train, validation and testing can be seen in TABLE IV:

TABLE IV. RESULTS OF SPLIT DATA WITH K=3

	Class	K=1	K=2	K=3
Train	ARMD	21	28	33
	BRVO	22	24	29
	CRVO	17	20	23
	CSR	19	22	22
	DN	35	44	48
	DR	142	161	177
	MH	28	34	42
	NORMAL	228	270	314
	ODC	48	50	55
	ODE	19	22	26

	Class	K=1	K=2	K=3
	OTHER	65	73	87
	RS	28	36	40
Validation	ARMD	18	11	6
	BRVO	13	11	6
	CRVO	9	6	3
	CSR	8	5	5
	DN	19	10	6
	DR	66	47	31
	MH	19	13	5
	NORMAL	121	79	35
	ODC	9	7	2
	ODE	8	5	1
	OTHER	32	24	10
	RS	15	7	3
Testing	ARMD	3	3	3
	BRVO	5	5	5
	CRVO	5	5	5
	CSR	4	4	4
	DN	9	9	9
	DR	23	23	23
	MH	5	5	5
	NORMAL	35	35	35
	ODC	5	5	5
	ODE	7	7	7
	OTHER	9	9	9
	RS	3	3	3

The previous discussion (TABLE III) explained that each class in the dataset has an unbalanced amount, known as an unbalancing dataset. An ideal data balancing method is the Oversampling method, namely by creating additional images from the results of image augmentation in the minority class so that the number of pictures in the minority class is the same as the majority class.

The augmentation method is carried out by randomly selecting sample images in the minority class and then changing the image with the following parameters:

rotation_range = 10, horizontal_flip = True, brightness_range = (0.5, 1.5)

Fig. 4. Example of image results from augmentation

The number of images after Oversampling with the augmentation method produces many images as presented in TABLE V:

TABLE V. IMAGE DATA AFTER OVERSAMPLING

	Training	Validation	Testing
K=1	2648	1452	113
K=2	3246	955	113
K=3	3767	420	113

B. Training Stage

Based on the 7 (seven) selected models, MobileNetV1 is superior to other models used in data split ratios with k=2 and data split ratios with k=3, while MobileNetV2 is superior in data split ratios k=3. The results of the training that has been carried out based on the split data ratio with the seven CNN models can be seen in TABLE VI:

TABLE VI. RESULTS OF CNN MODEL TRAINING K=1, K=2 AND K=3

No	Model	Accuracy Training		
		K=1	*K=2*	*K=3*
1	ResNet50	25.14%	26.07	44.71
2	InceptionV4	35.47%	34.66	44.05
3	VGG19	44.42%	45.76	49.05
4	MobileNetV1	49.38%	**52.57**	**57.86**
5	MobileNetV2	**54.75%**	52.36	56.43
6	MobileNetV3_Small	28.03%	24.71	35.71
7	MobileNetV3_Large	23.97%	24.40	29.52

Based on the training results shown in TABLE 6, the highest accuracy was obtained with the MobileNetV1 model, but not too high, only 57.86%. On the other hand, there is still overfitting in the model.

C. Accuracy Optimization with CLAHE (Research Contribution)

The clip limit in CLAHE is a parameter used to limit the application of histogram equalization to each block in the image. Each block in the image will be calculated for its histogram; then, the histogram will be spread using an adaptive contrast technique that has been adjusted based on predetermined clip limits. If the clip limit is set to a low value, the histogram equalization applied to the blocks in the image will be softer and less contrast information will be lost. Conversely, if the clip limit is set to a high value, the histogram equalization applied to the blocks in the image will be sharper and more contrast information will be lost.

The flow of image quality improvement using the CLAHE method can be seen in Figure 5:

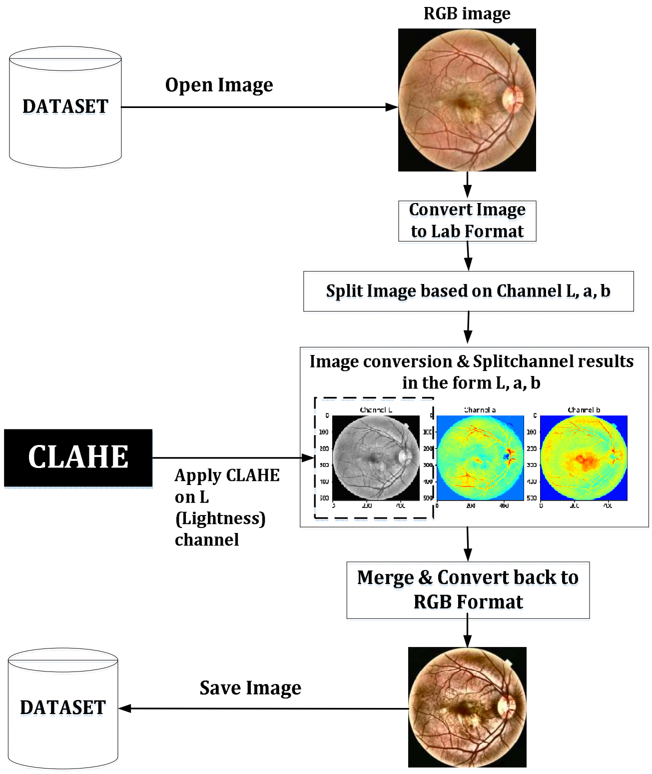
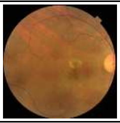
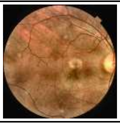
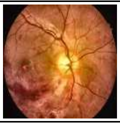
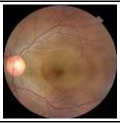
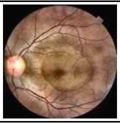
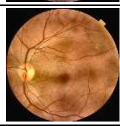
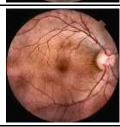
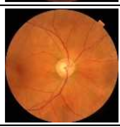
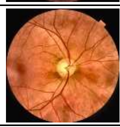
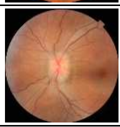
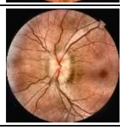


Fig. 5. Stages of the image enhancement process using CLAHE

Based on the application of CLAHE to the fundus image dataset, better image contrast is obtained than before. Image results before and after the CLAHE process was carried out for each class sample can be seen in TABLE VII:

TABLE VII. SAMPLE COMPARISON OF ORIGINAL AND IMAGE AFTER IMAGE ENHANCEMENT USING CLAHE METHOD

Class / Image ID	Original Image	CLAHE Image
Class : ARMD ID :547		
Class : BRVO ID : 1698		
Class : CRVO ID : 727		
Class : CSR ID : 172		
Class : DN ID : 203		
Class : DR ID : 38		
Class : DR ID : 681		
Class : Normal ID : 274		
Class : ODC ID : 732		
Class : ODC ID : 558		
Class : OTHER ID : im0055		
Class : RS ID : 249		

Steps to facilitate observation of the impact of increasing fundus image contrast using the CLAHE method on the CNN model, this study uses four stages of image improvement with the clip limit and tileGridSize CLAHE parameters as follows:

- Clip Limit = 3.0 ; tileGridSize = 8,8
- Clip Limit = 4.0 ; tileGridSize = 10,10
- Clip Limit = 5.0 ; tileGridSize = 12,12

Differences in image enhancement results using the CLAHE method with variations in clip limit and tileGridSize can be seen in Figure 6:

Original Image	Cliplimit=3.0 tilegridSize=(8,8)	ClipLimit=4.0 tilegridSize=(10,10)	Cliplimit=5.0 tilegridSize=(12,12)
			

Fig. 6. Image comparison with CLAHE based on clip limit and tilegridsize

Evaluation of image enhancement using the CLAHE method is carried out using Hyperparameter Training as follows:

Epoch	50
Batch_size	16
learning_rate	0.0001
Augmentasi	1000 Image
lr_schedule	return learning_rate * (0.1 ** int(epoch / 10))
Optimizer	tf.keras.optimizers.Adam(learning_rate = learning_rate, beta_1 = 0.9, beta_2 = 0.999, amsgrad = False)
Early Stopping	tf.keras.callbacks.EarlyStopping(monitor = 'loss', min_delta = 0.001, patience = 10, verbose = 1, mode = "min")
Evaluation Metrics	Accuracy, Specificity, Sensitifity / Recall, Precision

Model training uses image enhancement CLAHE results. MobileNetV1 is used as a model and a comparator of training results at this stage. MobileNetV1, in the previous step, obtained better accuracy results than the seven models compared. After the enhancement (image enhancement) using the CLAHE and training methods was carried out, the accuracy of the training data and validation data was obtained. CLAHE with clip Limit = 3 and tileGridSize = (8,8) brings an accuracy of 100% in training data and 69.33% accuracy in validation data. Image enhancement treatment using CLAHE with clip limit = 5, tileGridSize = (10,10) obtains an accuracy value on the Training data of 100% and an accuracy value on the validation data of 70.56%. While the image enhancement treatment uses CLAHE with clip limit = 6, tileGridSize = (12.12) to get an accuracy value in the Training data of 100% and an accuracy value in the validation data of 70.83%. Training results can be seen in Figure 7:

		Training Data	Validation Data
Clip Limit= 3, *tileGridSize*=(8,8)			
	Accuracy	100	69.33
	Precision	100	71.23
	Recall	100	67.67
Clip Limit = 4, *tileGridSize* = (10,10)			
	Accuracy	100	**70.83**
	Precision	100	**72.89**
	Recall	100	67.67
Clip Limit = 5, *tileGridSize* = (12,12)			
	Accuracy	100	70.67
	Precision	100	73.29
	Recall	100	**69.50**

Fig. 7. Comparison of training accuracy using mobilenetv1 based on clip limit and tilegridsize CLAHE

At this stage, MobileNetV1's performance improved by approximately ±13% compared to the previous step's training. In the last activity, the training accuracy was only 57.86% without using CLAHE image enhancement. TABLE 10 shows that the model's performance is better with clip limit = 4 and tileGridSize = (10,10). However, excessive contrast enhancement negatively impacts the model's training performance.

Comparison of 7 (seven) CNN models with CLAHE using the method and Hyperparameter Training can be seen in TABLE VIII:

Data Split Ratio	80%:10%:10%
Balancing data	Oversampling with augmentation techniques Number of training images : 1000 Image/Class
Image enhancement	CLAHE method Clip limit=4, tileGridSize(10,10)
Hyperparameter Training	
Epoch	100
Batch_size	32
Image_size	224×224 pixel 3 *channel*
Weights	ImageNet
Learning rate	0.0001
Optimizer	Adam ((learning_rate = learning_rate, beta_1 = 0.9, beta_2 = 0.999, amsgrad = False)
Activation Function	Softmax
Metrics	Accuracy, precision, recall
Callbacks	Learning rate scheduler : learning_rate * (0.1 ** int(epoch / 10)) Early Stopping : EarlyStopping (monitor = 'loss', min_delta = 0.001, patience = 10, verbose = 1, mode = "min")

TABLE VIII. ACCURACY TRAINING AND ACCURACY VALIDATION IN EACH CNN MODEL

Model	Accuracy%		*Precision%*		*Recall%*	
	Train	*Valid*	*Train*	*Valid*	*Train*	*Valid*
ResNet50	93.60	61.17	97.67	76.86	87.34	48.17
InceptionV4	99.98	73.50	99.98	76.14	99.98	72.33
VGG19	99.98	74.17	99.98	76.49	99.98	72.67
MobileNetV1	99.98	**81.17**	99.98	**83.25**	99.98	**80.33**
MobileNetV2	99.98	77.00	99.98	79.23	99.97	75.00
MobileNetV3_S	63.75	47.83	85.26	62.07	35.46	15.00
MobileNetV3_L	82.48	45.67	94.24	63.33	65.97	28.50

Based on TABLE VIII, it can be seen that the use of the CLAHE method increases the accuracy in the image classification process and is much higher than without using CLAHE.

IV. CONCLUSION

This study concludes that using the CLAHE parameter in the CNN model increases the accuracy of image classification. CLAHE helps increase contrast and eliminate luminance imbalances in images, which strengthens the ability of the CNN model to extract essential features. Implementing CLAHE as an image pre-processing stage before classification gives better results than other methods. However, properly selecting CLAHE parameters requires further exploration to ensure optimal settings for different image types and classification tasks. Overall, this study shows that using CLAHE can improve the performance of the CNN model in image classification.

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