



Optimization of Mount Merapi Image Classification Through the Implementation of the CLAHE Algorithm

Awang Hendrianto Pratomo^{1,3*}, Azhar Fikri Haryodwiseno¹, Andika Bayu Aji²,
Eko Teguh Paripurno³, Johan Danu Prasetya³, Nurul Akmar Emran⁴, Sanusi Azmi⁵,
Norharyati Binti Harum⁵, Anidah Robani⁴

¹ Informatics Study Program, Department of Informatics, Faculty of Industrial Engineering, Universitas Pembangunan Nasional "Veteran" Yogyakarta, Indonesia

² Center for Geological Disaster Technology Research and Development (BPPTKG) DIY, Indonesia

³ Master in Disaster Management Study Program, Department of Environmental Engineering, Faculty of Mineral Technology and Energy, Universitas Pembangunan Nasional "Veteran" Yogyakarta, Indonesia

⁴ Applied Data Engineering Department, Faculty of Information and Communication Technology, Technical University of Malaysia Melaka, Malaysia

⁵ Department of Software Engineering, Faculty of Information and Communication Technology, Technical University of Malaysia Melaka, Malaysia

Received : September 15, 2026	Revised : September 21, 2026	Accepted : September 22, 2026	Online : October 7, 2026
-------------------------------	------------------------------	-------------------------------	--------------------------

Abstract

Continuous monitoring of Mount Merapi's volcanic activity by the Center for Volcanology and Geological Hazard Mitigation (BPPTKG) is frequently hindered by poor visual image quality caused by adverse weather, heavy cloud cover, dense fog, and insufficient nighttime illumination. These visual constraints impede accurate visibility assessment, which can delay disaster risk assessment and timely early warnings. This study aims to automate the visibility classification of Mount Merapi images using a deep learning model based on the VGG-16 Convolutional Neural Network (CNN) architecture. To address visual impairments, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied as a preprocessing step to enhance local image contrast without inducing excessive noise. Specifically, the base VGG-16 architecture was modified via transfer learning by replacing the original fully connected layers with a Global Average Pooling (GAP) layer and reducing the first Dense layer to 512 neurons to lower computational complexity and mitigate overfitting. Image data were collected via web scraping from the official BPPTKG gallery and categorized into six visibility classes. Experimental results show that applying CLAHE with an optimal clip limit of 5 provides the most effective contrast enhancement. Using the Adam optimizer with a learning rate of 0.0001, a batch size of 32, a 70:20:10 data split, and 200 epochs of training improved validation accuracy from 84.36% to 89.25% and testing accuracy to 91.67%. The most significant gain occurred under low-light conditions (the "Night Obscured" class), achieving 100% precision.

Keywords *Mount Merapi, Computer Vision, Image Classification, VGG-16, CLAHE*

INTRODUCTION

Mount Merapi is one of Indonesia's most active volcanoes, with a long history of persistent eruptive activity. Rising to 2,986 meters above sea level, the volcano spans four administrative regions: Sleman Regency, the Special Region of Yogyakarta, Boyolali Regency, and Klaten Regency. A distinctive characteristic of Merapi's eruptions is the occurrence of pyroclastic density currents, locally known as *wedhus gembel*. Historical records indicate that Merapi experienced frequent explosive eruptions between 1587 and 1872. Although volcanic activity has decreased since then, lava avalanches continue to occur today. The volcano therefore continues to pose a significant threat to surrounding communities. For example, the major eruption in 2010 destroyed 2,411

Copyright Holder:

© Awang, Azhar, Andika, Eko, Johan, Nurul, Sanusi, Norharyati, & Anidah. (2026)

Corresponding author's email: awang@upnyk.ac.id

This Article is Licensed Under:



buildings, claimed hundreds of lives, and forced more than 350,000 residents to evacuate.

The institution responsible for monitoring Mount Merapi is the Center for Volcanology and Geological Hazard Mitigation for Mount Merapi (BPPTKG). To continuously observe volcanic activity, BPPTKG operates several monitoring stations surrounding the volcano (Afif, 2020). These stations collect various types of observational data, including visual imagery (Afif, 2020; ALAMIN, 2024; A. H. Pratomo et al., 2025), seismic activity (Ramdhan et al., 2020), ground deformation (Affan Syamaidzar, 2025), lava avalanche events, and other geophysical measurements. Volcanology experts then analyze the collected data to support volcanic activity assessment and provide timely early-warning information to the public (Gelgel et al., 2023).

The CLAHE algorithm was selected because it offers substantial advantages over its predecessor, Adaptive Histogram Equalization (AHE), particularly in handling visual degradation caused by fog and low-light conditions. Its main advantage is its ability to reveal hidden details in dark regions by applying a clip limit to the histogram, enhancing local contrast while preventing excessive noise amplification in homogeneous foggy areas (Hayati et al., 2023). Nevertheless, CLAHE also has several limitations. When directly applied to the RGB color space, histogram equalization may introduce color distortion, resulting in visually unnatural images. Furthermore, an excessively large clip limit can amplify background noise and generate artificial block artifacts. To overcome these limitations, this study applies CLAHE exclusively to the L (Lightness) channel of the LAB color space. This strategy effectively corrects illumination imbalance and reconstructs the spatial features of dark and fog-obsured Mount Merapi images while preserving their original color characteristics, thereby enabling the classification model to learn more representative visual features and achieve higher classification accuracy.

LITERATURE REVIEW

State of the Art

Machine learning is a branch of artificial intelligence (AI) that develops computational models by learning patterns from data through mathematical optimization, enabling tasks such as prediction, classification, and clustering (Eriana & Zein, 2023). Image classification is one of its most widely used applications, allowing computer systems to recognize and categorize images by extracting and matching discriminative visual features from complex datasets (Chen et al., 2021; Fan et al., 2022; Xu et al., 2024). These visual features generally represent distinctive characteristics that differentiate one image class from another. Commonly used features include color information, object edges (Gonzalez & Woods, 2018; Wardhani & Dwiasnati, 2024), and hierarchical features learned by deep neural networks (Li et al., 2021; Raza et al., 2025).

Several previous studies have applied machine learning techniques to classify Mount Merapi image visibility conditions. Afif (2020) investigated the K-Nearest Neighbors (KNN) algorithm combined with Chi-Square and Correlation-based Feature Selection (CFS). The proposed approach achieved 90% classification accuracy while requiring only 0.001822 seconds of computation using 27 selected features. Subsequently, ALAMIN (2024) employed a deep learning approach based on the VGG-16 convolutional neural network (CNN) architecture. Trained for 50 epochs using the Adam optimizer, the proposed model significantly outperformed previous approaches, achieving a maximum classification accuracy of 99.15%.

Despite these promising results, image visibility classification remains challenging because different visibility categories often exhibit highly similar visual characteristics under unfavorable weather and illumination conditions. Such similarities increase the likelihood of misclassification and consequently reduce model performance. Therefore, an effective image enhancement technique is required to improve image quality and facilitate feature extraction (Nilasari et al., 2022). In this study, the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm is

employed as a preprocessing technique to enhance image contrast while preventing excessive contrast amplification. By limiting histogram amplification through a predefined clip limit, CLAHE effectively improves image contrast while preserving image quality (Hayati et al., 2023).

RESEARCH METHOD

This study employed a quantitative research approach with an experimental design. To validate the hypothesis that applying the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm improves the performance of Mount Merapi image visibility classification, the research was conducted in several sequential stages, as illustrated in Figure 1. These stages include problem analysis, data collection, data preprocessing, model training, model evaluation, and model testing.

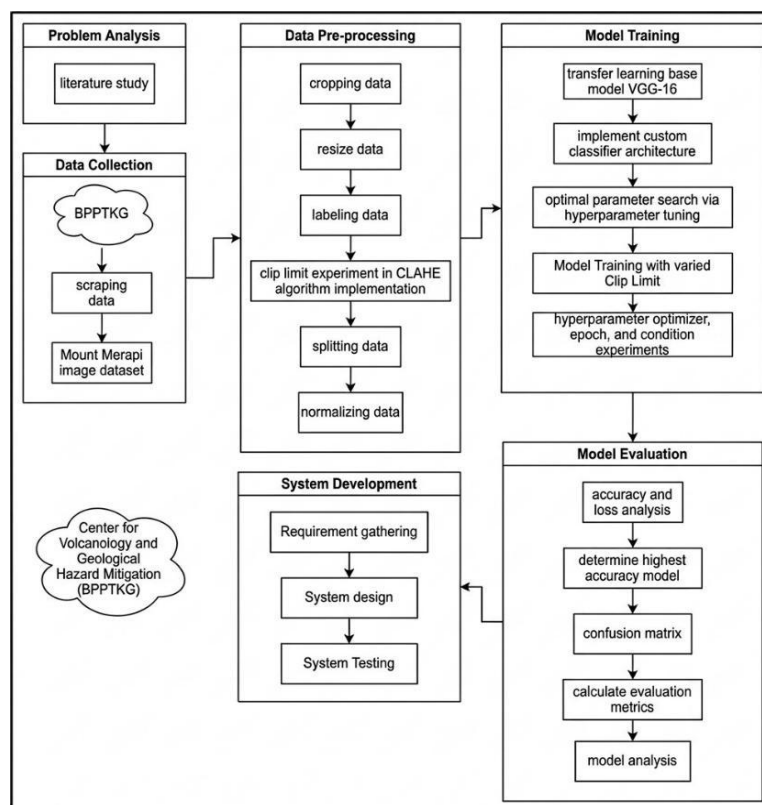


Figure 1. Research Methodology

Data Collection

This study used a web scraping approach to automate data acquisition, enabling efficient collection of thousands of images (Khder, 2021). One common web scraping technique involves downloading images from HTML elements on a webpage (El Asikri et al., 2020). In this study, Mount Merapi images were collected directly from the BPPTKG website at <https://cendana15.com/gallery/>. The scraping process used the Selenium Python library to automate browser interactions, including navigating web pages, accessing daily directories, scrolling until target elements became visible, and extracting and downloading large numbers of images in a structured manner. The scraped images have an original resolution of 300 x 200 pixels and are stored in JPEG (.jpg) format. Data collection was conducted from January to December 2025.

Preprocessing Data

In this study, image preprocessing prepared the raw images for model training. As

illustrated in Figure 2, the preprocessing pipeline consists of six stages: image cropping, image resizing, data labeling, CLAHE implementation, data splitting, and data normalization.

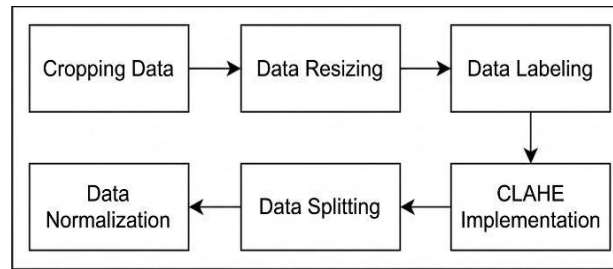


Figure 2. Data Preprocessing Pipeline

Visibility labels were subsequently assigned through visual interpretation. Based on the proportion of clouds or fog obscuring the mountain, the images were classified into three visibility categories. The Clear class represents images in which the entire mountain is fully visible without visual obstruction. The Partially Closed class represents images in which clouds or fog obscure part of the mountain, while the major contours remain distinguishable. In contrast, the Closed class represents images in which the mountain is completely obscured by dense clouds or thick fog, leaving little or no visible information about the main object, as shown in Figure 3.



Figure 3. Representative images for each visibility class

Implementation CLAHE

Limited Adaptive Histogram Equalization (CLAHE) is an image enhancement technique developed to overcome the limitations of its predecessor, Adaptive Histogram Equalization (AHE). CLAHE effectively improves local image contrast while preventing the excessive noise amplification commonly associated with AHE due to uncontrolled contrast enhancement (Hayati et al., 2023;

Lionnie & Alaydrus, 2024). This redistribution preserves balanced, visually natural image contrast while preventing excessive enhancement in homogeneous regions (Mudjirahardjo, 2024).

Procedurally, the CLAHE algorithm consists of five main stages (Haddadi et al., 2024; Wiliani et al., 2025):

1. The input image is divided into a number of small, non-overlapping regions known as tiles (or local grids).
2. The histogram of each tile is clipped using a predefined clip limit (threshold). The clip limit is calculated using.
3. The excess pixel counts resulting from histogram clipping are then redistributed uniformly across all histogram bins.
4. Local histogram equalization is subsequently performed on each tile using the cumulative distribution function (CDF), as defined in Equation (1)

$$CDF(i) = \sum_{j=0}^i H(j) \quad (1)$$

Where:

$CDF(i)$: cumulative distribution function at intensity level i

$H(j)$: number of pixels with intensity value j in the histogram

i : intensity level (0–255 for an 8-bit image)

5. Finally, the output pixel values are generated using bilinear interpolation to ensure smooth transitions between adjacent tiles and eliminate artificial tile boundaries.

Figure 4 illustrates the implementation process of the CLAHE algorithm.

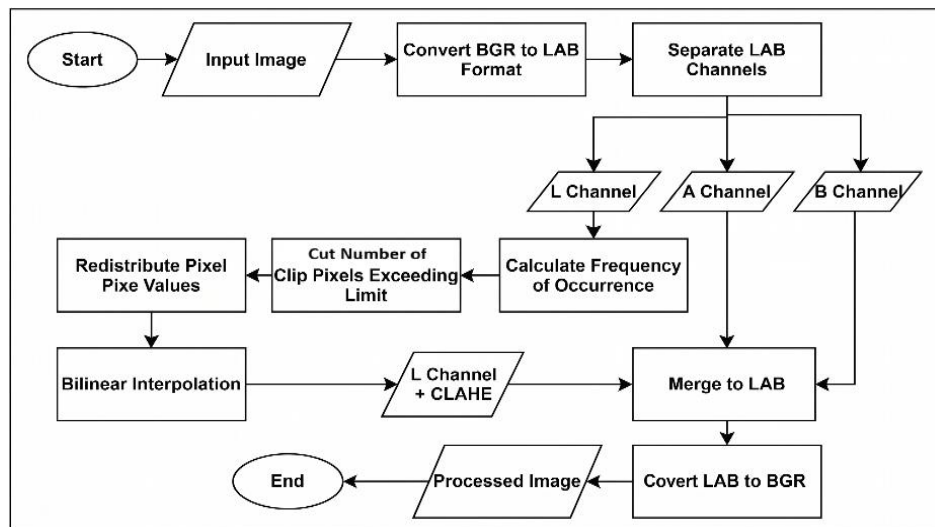


Figure 4. Implementation Steps of CLAHE in the L Channel

First, the input image is converted from the RGB color space to the LAB color space. LAB consists of three channels: the L channel, which represents lightness, and the a and b channels, which represent the green–red and blue–yellow color components, respectively. The L channel ranges from 0 (black) to 100 (white), while the a and b channels range from –128 to +127, representing the green–red and blue–yellow color axes, respectively.

Data Splitting and Normalization

The dataset was divided into three subsets: training, validation, and testing. This study

evaluated two split ratios: 80:10:10 and 70:20:10. Subsequently, all image matrices were normalized by scaling pixel intensity values to the range $[0, 1]$ to facilitate weight computation during neural network training.

VGG-16 Transfer Learning

In this study, the transfer learning approach was applied to the VGG-16 CNN architecture to optimize the training process for classifying Mount Merapi image visibility conditions. As shown in Figure 5, the transfer learning architecture consists of two main components: frozen layers (non-trainable parameters) and trainable layers (trainable parameters).

The trainable layers consist of a Global Average Pooling (GAP) layer, a Dense layer with the ReLU activation function (1024 neurons), a Dropout layer with a rate of 0.3, a second Dense layer with the ReLU activation function (512 neurons), another Dropout layer with a rate of 0.3, and the final output layer. During training, the model iteratively updates the parameters in these trainable layers, enabling it to adapt to the six visibility classes of Mount Merapi.

VGG-16 is a Convolutional Neural Network (CNN) architecture widely adopted for computer vision tasks because of its simple yet deep network design (Shodiq et al., 2024). Its key characteristic is uniformly stacking 3×3 convolutional filters with a stride of 1 and same padding, which reduces trainable parameters while improving hierarchical extraction of texture boundaries and object contours (Juslan & Muhammad, 2025; Omideyi et al., 2025). Designed for 224×224 -pixel input images, VGG-16 consists of 16 learnable layers, including 13 convolutional layers for feature extraction and five Max Pooling layers for spatial downsampling. In transfer learning applications, researchers often replace the original computationally intensive Fully Connected layers with a Global Average Pooling (GAP) layer or a lightweight dense classifier. This architectural modification substantially reduces trainable parameters, mitigating overfitting and lowering computational complexity, particularly when the model is trained on domain-specific image datasets (Chen et al., 2021), as shown in Figure 5.

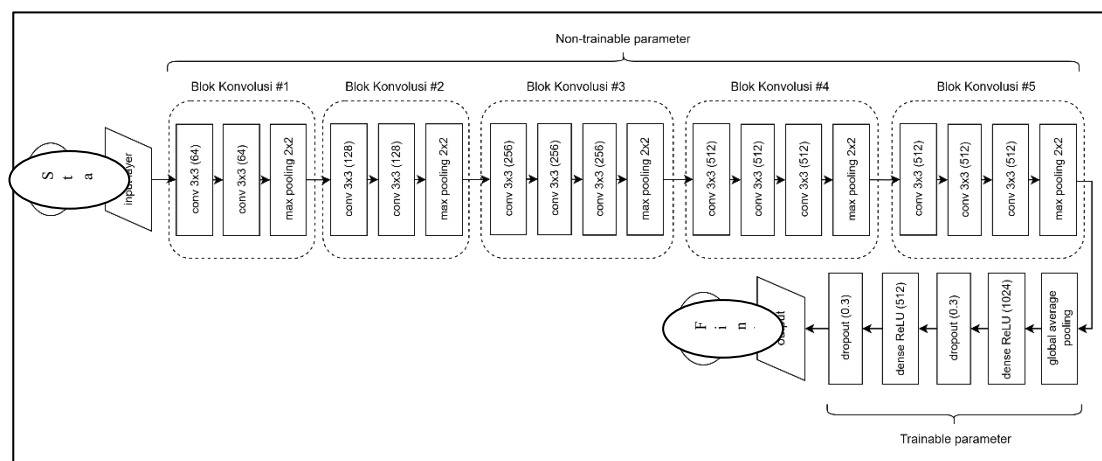


Figure 5. Baseline Model Architecture

Initially, this study adopted the baseline classifier architecture proposed by Alamin (2024). However, the number of parameters in each layer significantly affects computational efficiency and the model's ability to learn data patterns for accurate prediction (Lu et al., 2022). Therefore, this study modifies the baseline architecture by reducing the number of neurons in the first Dense layer from 1024 to 512, as shown in Figure 6. This reduction decreases the model complexity, lowers computational memory requirements, and minimizes the risk of overfitting, particularly when the

model is trained on an imbalanced dataset.

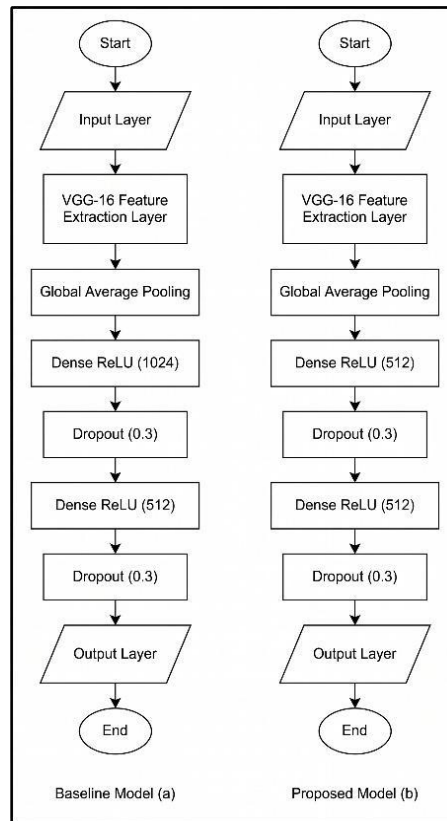


Figure 6. Comparison of the Baseline Model Architecture and the Proposed Model

Model Training

During training, the input images are first processed through forward propagation. According to [Pratomo et al. \(2025\)](#), forward propagation transforms data from the input layer to the output layer to generate predictions, which are then evaluated using a loss function. At this stage, the input images pass through the non-trainable VGG-16 feature extraction layers to generate visual feature representations. These features then pass through the Global Average Pooling layer and subsequent classification layers to produce prediction probabilities for the six Mount Merapi visibility classes.

After obtaining the loss value, the training process continues with backpropagation to compute error gradients with respect to the model parameters. According to [Goodfellow \(2016\)](#), backpropagation is the primary learning algorithm used in neural networks to compute gradients and update model parameters. In this study, backpropagation is performed only on the trainable layers, whereas the weights of the VGG-16 feature extraction layers remain unchanged.

Feature Extraction

Image classification in convolutional neural networks relies on the network architecture's ability to transform raw pixel values into meaningful feature representations. In this study, feature extraction is performed through a sequence of layers in the modified VGG-16 architecture, including convolution, spatial dimensionality reduction, and final classification.

This study evaluates the proposed model through several experimental scenarios using different hyperparameter configurations. These experiments assess the effectiveness of the proposed preprocessing method in improving classification performance on Mount Merapi

visibility images and identify the optimal model based on the highest classification accuracy.

FINDINGS AND DISCUSSION

FINDING

Optimal Hyperparameter Results

The initial experiment identified the optimal hyperparameter configuration for the proposed model before applying CLAHE preprocessing. Table 1 summarizes the results of the fourteen experimental scenarios.

Table 1. Model Training Results for Optimal Hyperparameter Selection

No	Dataset	Model	Optimizer	Epoch	Ratio split	Learning rate	Batch size	Train acc	Val acc
1	Balanced	usulan	adam	200	70:20:10	0.0001	16	88.99%	83.39%
2	Balanced	usulan	adam	200	70:20:10	0.0001	32	86.57%	84.36%
3	Balanced	usulan	adam	250	70:20:10	0.0001	32	89.09%	82.74%
4	Balanced	usulan	adam	300	70:20:10	0.0001	32	89.09%	82.41%
5	Balanced	usulan	adam	350	70:20:10	0.0001	32	90.76%	84.36%

Scenario 1, which adopted the hyperparameter configuration from the baseline study, achieved relatively low performance, with a training accuracy of 77.59% and a validation accuracy of 78.03%. Experimental results showed that balancing the dataset through downsampling and modifying the classifier architecture improved the classification performance.

Among all evaluated configurations, Scenario 11 achieved the best overall performance. This configuration employed the balanced dataset, the proposed architecture, the Adam optimizer, a 70:20:10 data split ratio, a learning rate of 0.0001, a batch size of 32, and 200 training epochs. The model achieved 86.57% training accuracy and 84.36% validation accuracy.

Hyperparameter Tuning Results

Subsequently, the model trained using the optimal clip limit of 5 was evaluated under three optimization algorithms, namely SGD, RMSProp, and Adam. As shown in Table 2, the SGD optimizer performed poorly, with training accuracy remaining between 35% and 64% even after 200 epochs. SGD's inability to adaptively regulate gradient updates led to slow convergence and limited optimization performance.

In contrast, the adaptive optimization strategies employed by RMSProp and Adam produced substantially better learning performance. As shown in Figure 7, the Adam optimizer maintained stable convergence throughout training, achieving 93.84% training accuracy and 89.25% validation accuracy after 200 epochs.

Table 2. Hyperparameter Tuning Results

No	Data Condition	Optimizer	Epoch	Clip limit	Train acc	Val acc
19	Balanced	RMSProp	150	5	89.74%	85.99%
20	Balanced	RMSProp	200	5	92.16%	87.30%
21	Balanced	Adam	50	5	84.79%	83.39%
22	Balanced	Adam	100	5	89.37%	85.67%
23	Balanced	Adam	150	5	91.42%	85.67%
24	Balanced	Adam	200	5	93.84%	89.25%
25	Balanced	Adam	350	5	96.36%	89.90%

The experiment conducted using the Adam optimizer for 350 epochs achieved a training accuracy of 96.36%, as illustrated in Figure 7a. However, the corresponding loss curves (Figure 7b) confirmed recurring overfitting. These results indicate that the model became excessively specialized in learning minor characteristics of the training data, thereby reducing its ability to generalize to unseen samples.

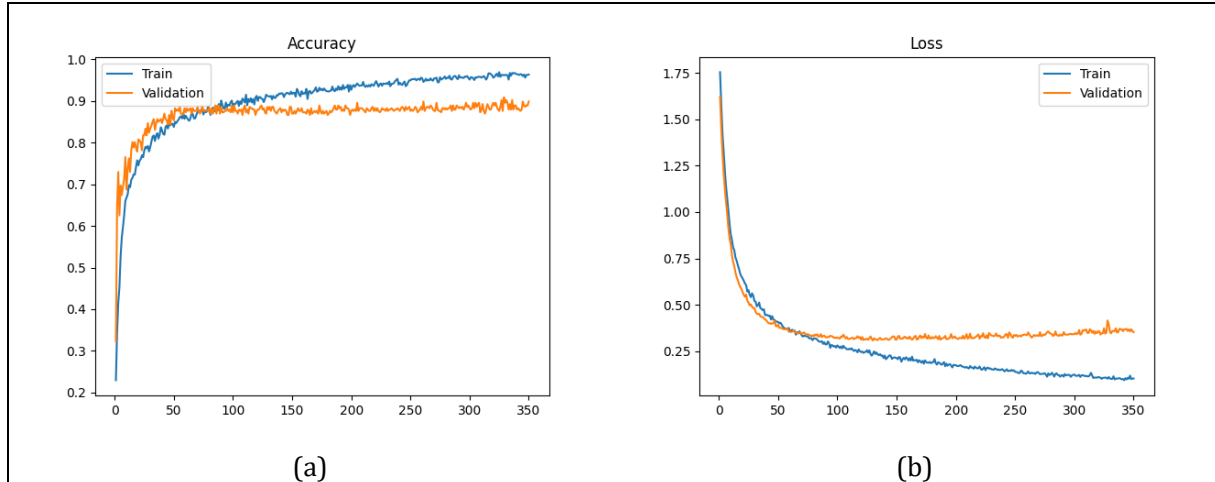


Figure 7. Accuracy and Loss Curves Using the Balanced Dataset, Adam Optimizer, and 350 Epochs

Discussion

Although overall classification performance was high, an analysis of misclassified samples revealed that several prediction errors stemmed from external factors rather than model limitations. One example involved images captured at 05:05 WIB, which were labeled as Night solely based on predefined time intervals, even though the scene already showed dawn illumination comparable to daytime conditions. These labeling inconsistencies impaired learning because the model relied exclusively on visual information rather than acquisition time. Another source of error involved incandescent lava flows, whose brightness became excessively enhanced after CLAHE preprocessing, causing them to resemble thin cloud formations and consequently increasing the likelihood of misclassification. These findings suggest that future volcanic visibility classification systems should not rely exclusively on predefined time intervals or subjective human interpretation. Instead, image labeling should incorporate objective illumination measurements (e.g., luminance or illuminance thresholds) together with morphological feature analysis to minimize subjective bias.

Furthermore, the choice of optimization algorithm played a crucial role in classification performance during hyperparameter tuning. Comparative evaluation showed that Stochastic Gradient Descent (SGD) failed to converge satisfactorily, with classification accuracy remaining below 65%, primarily because it could not adaptively regulate gradient updates. Although RMSProp produced considerably better learning performance, Adam consistently achieved the best results. Its adaptive optimization strategy maintained stable loss convergence while enabling the model to learn discriminative feature representations more efficiently throughout training.

CONCLUSIONS

Based on the findings of this study, the proposed preprocessing approach using the CLAHE algorithm applied to the L (Lightness) channel in the LAB color space effectively enhanced low-contrast images affected by cloud interference and low-light conditions. The proposed model, configured with a modified Dense layer containing 512 neurons, 200 training epochs, a 70:20:10 data split ratio, a learning rate of 0.0001, and a batch size of 32, achieved a training accuracy of

86.57% and a validation accuracy of 84.36%. These results represent improvements of 8.98 and 6.33 percentage points, respectively, compared with the baseline configuration. Through hyperparameter optimization, we identified a clip limit of 5 as the optimal configuration for improving the model's generalization performance. Under this configuration, validation accuracy increased from 84.36% to 89.25%, while test accuracy reached 91.67%. These findings demonstrate that the proposed CLAHE-based preprocessing method effectively enhances the visual separation between the main object and weather-related disturbances, particularly dense fog.

LIMITATIONS & FURTHER RESEARCH

Despite the encouraging results, several limitations identified in this study provide opportunities for future research. First, labeling daytime and nighttime images based solely on predefined time intervals introduced labeling bias. Future studies should consider replacing this approach with an image-labeling strategy based on objective illumination measurements derived directly from the image. Second, the visibility labels Partially Covered and Covered were assigned through manual visual interpretation. Future work should use an objective visibility estimation method based on detecting the visible mountain contour, for example, by using an edge detection algorithm such as the Canny Edge Detector to estimate the percentage of mountain coverage. This approach would reduce the subjectivity of manual visual labeling and improve dataset consistency.

ACKNOWLEDGMENTS

The authors would like to thank Universitas Pembangunan Nasional “Veteran” Yogyakarta for providing facilities and financial support under Grant Research International Collaboration No. 283/UN62.21/PG.00.00/2026, and Universiti Teknikal Malaysia Melaka under Grand Research No NTARABANGSA(IRMG)-UPNVY/2026/FTMK/A00105.

REFERENCES

- Afif, R. (2020). *Pemodelan pemilahan citra Gunung Merapi secara otomatis pada BPPTKG Yogyakarta* [Undergraduate thesis, Universitas Islam Indonesia].
- Alamin, D. (2024). *Implementasi metode convolutional neural network pada klasifikasi citra Gunung Merapi* [Undergraduate thesis, UPN “Veteran” Yogyakarta].
- Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y. (2021). Review of image classification algorithms based on convolutional neural networks. *Remote Sensing*, 13(22), 4712.
- El Asikri, M., Knit, S., & Chaib, H. (2020). Using web scraping in a knowledge environment to build ontologies using Python and Scrapy. *European Journal of Molecular & Clinical Medicine*, 7(3).
- Eriana, E. S., & Zein, A. (2023). *Artificial intelligence (AI)*.
- Fan, Q., Bi, Y., Xue, B., & Zhang, M. (2022). Genetic programming for feature extraction and construction in image classification. *Applied Soft Computing*, 118, 108509.
- Gelgel, R. A., Pramudita, M. A., & Silalahi, J. E. (2023). Penggunaan media sosial Instagram dalam komunikasi bencana kesiapsiagaan erupsi Gunung Merapi. *COMMENTATE: Journal of Communication Management*, 4(2), 151–165.
- Gonzalez, R. C., & Woods, R. E. (2018). *Digital image processing* (Global ed.). Pearson Education.
- Goodfellow, I. (2016). *Deep learning*. MIT Press.
- Haddadi, Y. R., Mansouri, B., & Khodja, F. Z. I. (2024). A novel medical image enhancement algorithm based on CLAHE and pelican optimization. *Multimedia Tools and Applications*, 83(42), 90069–90088.
- Hayati, M., Muchtar, K., Maulina, N., Syamsuddin, I., Elwirehardja, G. N., & Pardamean, B. (2023). Impact of CLAHE-based image enhancement for diabetic retinopathy classification through deep learning. *Procedia Computer Science*, 216, 57–66.

- Juslan, W., & Muhammad, A. H. (2025). Evaluasi kinerja metode peningkatan kontras (CLAHE & HE) pada klasifikasi ras kucing menggunakan VGG16. *Edumatic: Jurnal Pendidikan Informatika*, 9(1), 246–255.
- Khder, M. A. (2021). Web scraping or web crawling: State of art, techniques, approaches and application. *International Journal of Advances in Soft Computing and Its Applications*.
- Li, C., Miao, F., & Gao, G. (2021). A novel progressive image classification method based on hierarchical convolutional neural networks. *Electronics*, 10(24), 3183.
- Lionnie, R., & Alaydrus, M. (2024). Studi efek ekualisasi histogram dan CLAHE dalam mendeteksi fitur wajah manusia. *Jurnal Teknologi Elektro*, 15(2).
- Lu, Y., Huo, Y., Yang, Z., Niu, Y., Zhao, M., Bosiakov, S., & Li, L. (2022). Influence of the parameters of the convolutional neural network model in predicting the effective compressive modulus of porous structure. *Frontiers in Bioengineering and Biotechnology*, 10, 985688.
- Mudjirahardjo, P. (2024). The effect of grayscale, CLAHE image and filter images in convolution process. *International Journal of Advanced Multidisciplinary Research Studies*, 4(3), 943–946.
- Nilasari, N. K. N., Divayana, Y., & Hartati, R. S. (2022). Perbandingan metode median filtering dengan CLAHE dalam mengidentifikasi koloni bakteri. *Majalah Ilmiah Teknologi Elektro*, 21(1), 71.
- Omideyi, D. A., Isiaka, R. M., & Babatunde, R. S. (2025). Development of a web-based platform utilizing a hybrid CNN architecture for real-time fecal image classification. *Ajayi Crowther Journal of Pure and Applied Sciences*, 4(4).
- Pratomo, A. H., Attamimi, P. I. K., Santoso, A. B., Paripurno, E. T., Prasetya, J. D., & Azmi, M. S. (2025). Classification of Merapi Volcano images based on HSV color feature extraction and local binary pattern texture feature extraction using the K-nearest neighbors method. *RSF Conference Series: Engineering and Technology*, 4(1), 463–476.
- Ramadhan, M., Kristyawan, S., & Sembiring, A. S. (2020). Seismisitas di wilayah Jawa Tengah dan sekitarnya berdasarkan hasil relokasi hiposenter dari empat jaringan seismik menggunakan model kecepatan 3-D. *EKSPLORIUM*, 41(1), 61–72.
- Raza, S. M., Raza, A., Babeker, M. I. A., Haq, Z. U., Islam, M. A., & Li, S. (2025). Efficient citrus fruit image classification via a hybrid hierarchical CNN and transfer learning framework. *Journal of Food Measurement and Characterization*, 19(1), 356–377.
- Shodiq, U., Maimunah, M., & Avizenna, M. H. (2024). Klasifikasi jalan rusak menggunakan transfer learning arsitektur VGG16. *JOISIE (Journal of Information Systems and Informatics Engineering)*, 8(1), 75–85.
- Syamaidzar, A. (2025). *Penentuan deformasi vertikal Gunung Merapi menggunakan interferometric synthetic aperture radar (InSAR) tahun 2023 hingga 2024* [Undergraduate thesis, Universitas Gadjah Mada].
- Wardhani, E., & Dwiasnati, S. (2024). Deteksi pelat nomor dengan menggunakan optical character recognition berbasis algoritma LSTM. *Faktor Exacta*.
https://journal.lppmunindra.ac.id/index.php/Faktor_Exacta/article/view/19216
- Wiliani, N., Khawa, T., & Ramli, S. (2025). Peningkatan kontras pada preprocessing gambar permukaan solar panel dengan histogram. *Innovation and Technology*, 2(1).
- Xu, S., Chen, S., Xu, R., Wang, C., Lu, P., & Guo, L. (2024). Local feature matching using deep learning: A survey. *Information Fusion*, 107, 102344.