ILKOM Jurnal Ilmiah Vol. 18, No. 2, August 2026, pp. 351-362
Accredited 2nd by KEMDIKTISAINTEK No. 10/C/C3/DT.05.00/2025; E-ISSN 2548-7779 | P-ISSN 2087-1716

Research Article Open Access (CC–BY-SA)

Improved Coffee Beans Detection Using Contrast Limited Adaptive Histogram Equalization and Unsharp Masking

Srivan Palelleng [a,1,*]; Nugra Tasik Allo [a,2]; Juprianus Rusman [a,3]
[a] *Program Studi Teknik Informarika UKI Toraja, Jl. Nusantara No. 12, Tana Toraja 91811, Indonesia*
[1] *srivan_palelleng@ukitoraja.ac.id;* [2] *nugra@ukitoraja.ac.id; rusman.jr@ukitoraja.ac.id*
* *Corresponding author*

Article history: Received October 18, 2025; Revised November 05, 2025, 2026; Accepted June 04, 2026; Available online August 10, 2026.

Abstract

Contrast Limited Adaptive Histogram Equalization (CLAHE) is widely used to enhance image contrast, but it has limitations in improving edge sharpness and may amplify noise. Meanwhile, Unsharp Masking (USM) is effective for edge enhancement, yet it is less optimal when applied to low-contrast images. To address these weaknesses, this study proposes a hybrid image enhancement method combining CLAHE and USM for coffee beans quality analysis. The dataset consists of four classes: Biji-Kopi Normal (normal), Biji-Kopi Pecah (broken), Biji-Kopi Hitam (black), and Biji-Kopi Berlubang (hollow). All images were trained at a resolution of 512×512 pixels for 2000 iterations without transfer learning to ensure fair and unbiased evaluation. Histogram-based analysis demonstrates significant improvements after enhancement, including a 50.19% increase in mean intensity, a 217.9% increase in variance, a 78.38% rise in standard deviation, and a 22% increase in skewness, along with a 37.42% reduction in kurtosis. Performance evaluation using YOLOv4-Tiny shows that the proposed method improves AP50 from 96.51 to 97.7 and AP75 from 59.91 to 66.24, while AP95 remains unchanged at 0.01. The most notable improvements are observed at AP70 to AP90, indicating that the hybrid approach not only enhances classification performance but also strengthens object localization accuracy, making it effective for coffee bean defect detection.

Keywords: Coffee Beans; Object Detection; CLAHE; Unsharp Masking; YOLOv4.

Introduction

Coffee is one of the leading commodities with high economic value, ranking second after petroleum in terms of international trade volume [1]. Among the well-known varieties is Toraja Coffee, which is widely recognized in both domestic and international markets as a premium coffee with distinctive flavor characteristics. The quality of coffee beans plays a crucial role in determining their export competitiveness, encompassing factors such as bean size, moisture content, and the overall defect rate [2]. In addition to sensory attributes, coffee quality also reflects other aspects, including certification, sustainability, and the social footprint associated with the beans. One automation technique that can help ensure consistent coffee bean quality is computer vision. As a branch of artificial intelligence, computer vision is capable of analyzing, recognizing, and classifying objects more efficiently, particularly when dealing with large volumes of coffee beans. To guarantee reliable model performance, coffee bean images must meet sufficient quality standards to facilitate accurate processing by computer vision algorithms. This includes maintaining appropriate resolution, lighting, contrast, and sharpness, so that essential features such as color, shape, and texture can be optimally extracted. Without high-quality images, computer vision algorithms risk producing erroneous interpretations, which may compromise both classification accuracy and the detection of coffee bean quality.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is an image enhancement method that improves image quality by locally increasing contrast and refining the distribution of intensities between bright and dark regions of an image [3], [4]. The principle of CLAHE involves dividing the image into several sections (tiles), and then applying Histogram Equalization (HE) to each section. Its main advantage lies in the contrast limiting or clipping mechanism, which constrains excessively high contrast values [5], [6]. These excessive contrast values are redistributed to other histogram bins before equalization, thereby preventing over-enhancement effects [7], [8]. Due to its adaptability to variations in contrast and the support of contrast limiting, CLAHE has become a popular technique in various image processing applications. However, although contrast is enhanced, fine details or textures in the image are not always improved, which may result in the loss of important visual information [9], [10].

http://dx.doi.org/10.33096/ilkom.v18i2.3120.351-362

Another image enhancement method is Unsharp Masking (USM). Despite the term *unsharp* in its name, this method is actually employed to sharpen images. Its working principle involves generating a blurred version of the original image, which is then used as a mask to extract high-frequency details. These details are subsequently added back to the original image with an amplification factor, making edges and important features appear clearer and sharper [11], [12]. However, USM has a limitation related to image contrast: when the image contrast is low (dark), the enhancement process becomes less effective [13].

The study in [14] employed CLAHE to address issues of over-exposure and artifacts that frequently occur in conventional methods. The localized contrast enhancement mechanism in CLAHE is able to overcome the limitations of previous approaches. In medical imaging, low image quality caused by device luminance often leads to suboptimal outputs. Therefore, [15] applied CLAHE since it can improve image contrast without the need to increase radiation dosage, which carries the risk of misdiagnosis. Furthermore, a survey conducted by [16] reported that low contrast makes the USM method highly sensitive, thus producing artifacts in the image.

This study introduces a hybrid image enhancement strategy that integrates Contrast Limited Adaptive Histogram Equalization (CLAHE) and Unsharp Masking (USM) to address the limitations of single-method enhancement in coffee bean image analysis. The proposed approach leverages CLAHE to improve local contrast while utilizing USM to reinforce edge sharpness and texture details, thereby generating more discriminative visual features. The primary contribution of this work is the systematic evaluation of the combined enhancement pipeline as a preprocessing stage for a YOLOv4-Tiny based detection framework, aiming to improve robustness against low-contrast and low-detail imaging conditions. By explicitly optimizing both contrast distribution and structural clarity, this research provides a more effective preprocessing solution to enhance automated coffee bean quality assessment performance.

Method

This section provides a detailed description of each stage conducted in the research, starting from data processing to model evaluation. In addition, the discussion also elaborates on various phenomena observed during the experiments, thereby offering a comprehensive overview of the research workflow and the resulting findings.

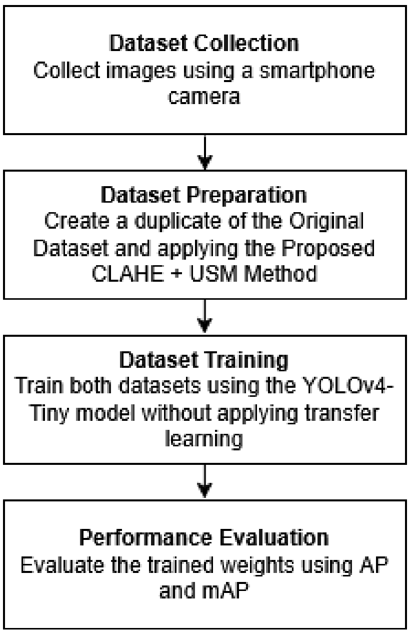


Figure 1. Research Workflow

A. Dataset Preparation

This stage represents the initial step, which involves preparing the dataset to be used in the study. The coffee beans were categorized into four different classes: *Biji-Kopi Normal*, *Biji-Kopi Pecah*, *Biji-Kopi Hitam*, and *Biji-Kopi Berlubang*. The images were captured using an iPhone X smartphone with a 12 MP f/2.4 52 mm camera under moderate lighting conditions. The data collection scenario was conducted for each class with a fixed camera-to-object distance of 35 cm. After collection, the images were annotated using the Roboflow tool. The initial dataset consisted of 379 images: 101 *Biji-Kopi Normal*, 90 *Biji-Kopi Pecah*, 100 *Biji-Kopi Hitam*, and 89 *Biji-Kopi Berlubang*. To increase data diversity, augmentation techniques such as flipping and rotation were applied, resulting in an expanded dataset of 1,137 images.

B. Original Images

Original images refer to the raw, unprocessed images that have not undergone any form of image enhancement. These images serve as the baseline reference, enabling objective comparison with images that have been processed using proposed enhancement techniques. By establishing the original images as a benchmark, it becomes possible to systematically evaluate the impact of each enhancement method on image quality. The use of original images is particularly important because they represent the actual visual conditions captured during data collection without any artificial modifications. As such, they provide an unbiased starting point for analysis, ensuring that the improvements or degradations observed in the enhanced images can be directly attributed to the applied techniques rather than pre-existing manipulations. To further assess the baseline quality of the dataset, histogram analysis then applied to the original images. Conducting this step is essential, as it offers a quantitative overview of the dataset prior to enhancement. The resulting histogram characteristics serve as a foundation for understanding the limitations of the raw images and for measuring the effectiveness of subsequent image enhancement methods.

Table 1. Example of Original Images

Biji-Kopi Normal	***Biji-Kopi Pecah***	***Biji-Kopi Hitam***	***Biji-Kopi Berlubang***
			

From **Table 1**, examples of image samples from each class in the dataset are presented. It can be observed that important image features, such as color, edges, and shape, have not yet been optimally extracted. This condition may cause machine learning algorithms to face difficulties in accurately recognizing and learning the image characteristics. Therefore, the application of appropriate image enhancement methods is required to maximize these features, thereby supporting the performance of the algorithms during the training process.

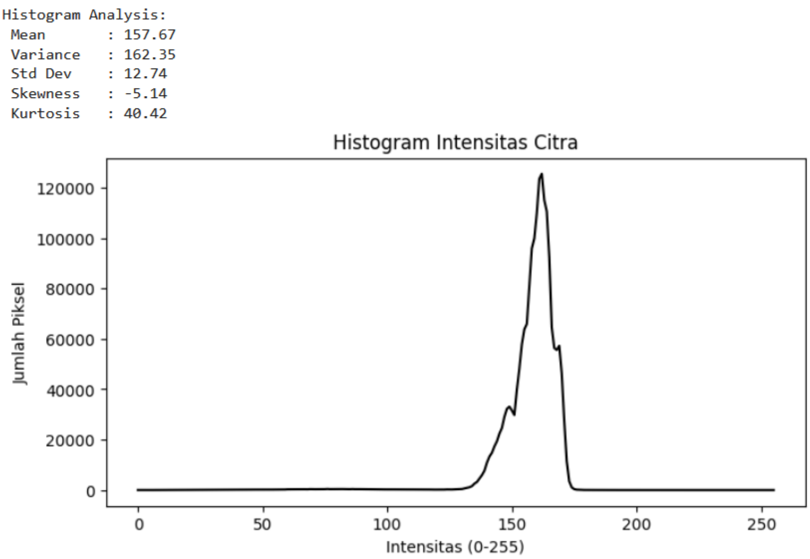


Figure 2. Histogram Analysis of Original Images on *Biji-Kopi Normal*

Histogram analysis is an image analysis method that utilizes the distribution of pixel intensities in an image to evaluate its quality or characteristics [17], [18]. A histogram is a graphical representation that plots intensity values (X-axis) against the number of pixels (Y-axis). In this context, histogram analysis represents the distribution of contrast and brightness within an image [19]. This analytical method is well-suited for the images used in this study, as it provides a quantitative evaluation that can serve as a reference for comparison. The image analyed in **Figure 2** uses a *Biji-Kopi Normal* sample and produces several statistical values, including Mean, Variance, Standard Deviation, Skewness, and Kurtosis [20], [21]. The Mean indicates the average brightness level, where higher values correspond to brighter images (range of 0–255). Variance measures the extent to which pixel values deviate from the mean; a higher variance indicates greater image contrast (range of 0–255). Standard Deviation (Std. Dev.) reflects how far the pixel values deviate from the average; low-contrast images yield smaller values, while high-contrast images produce larger ones. Skewness measures the asymmetry of the intensity distribution, where a value of 0 indicates symmetry, values less than 0 represent images dominated by bright regions, and values greater than 0 indicate images dominated by dark regions. Lastly, kurtosis quantifies the sharpness or peakedness of the histogram distribution. Unlike mean and skewness, which describe central tendency and symmetry, kurtosis emphasizes whether the distribution peak is sharp or flat [17], [22], [23], [24], [25].

C. CLAHE And USM

Histogram Equalization (HE) is a contrast enhancement method that equalizes the distribution of pixel intensities across the entire image [26]. However, its application often leads to excessive enhancement (over-enhancement), particularly in the presence of noise [27], [28]. To address this, HE was further developed into Adaptive Histogram Equalization (AHE), which operates by dividing the image into smaller regions (tiles) and then applying HE within each region [29]. AHE performs better in enhancing local contrast across different regions of the image, but it also has the drawback of amplifying noise [30]. The limitations of AHE subsequently led to the development of Contrast Limited Adaptive Histogram Equalization (CLAHE), where the histogram equalization process within each tile is regulated using contrast limiting to suppress noise amplification [14]. CLAHE works by dividing the image into tiles, applying contrast limiting, and then performing intensity transformation within each tile to improve contrast. Finally, the transitions between neighboring tiles are smoothed using bilinear interpolation to produce a visually consistent image [31].

Unsharp Masking (USM) is an image processing technique used to enhance image sharpness. The method operates by generating a blurred version of the original image, then calculating the difference between the original and the blurred image to extract edge details. These details, referred to as the *mask*, are subsequently amplified by a certain factor and added back to the original image. As a result, object edges appear more distinct, making the image visually sharper [11], [12].

Although both methods are widely used, they still exhibit several limitations in practice. CLAHE does not effectively highlight object edges, resulting in images that appear flat, less sharp, and with poor distinction between objects and the background. While CLAHE improves contrast distribution, it does not necessarily enhance fine details or image features, meaning that important information may remain unaffected. In other words, CLAHE effectively increases global and local contrast but falls short in improving object–background separation. On the other hand, USM is capable of producing dominant sharpening effects, yet it remains ineffective when applied to images with inherently low contrast.

Based on the limitations of the two methods described above, this study proposes the integration of CLAHE and USM to improve the quality of images to be detected. The combination is designed to complement the weaknesses of each technique. The issues in CLAHE, such as noise amplification, insufficient edge enhancement, and the lack of improvement in fine image details, can be addressed by USM, which enhances important edges and improves texture sharpness. Conversely, the limitation of USM that ineffectiveness in low-contrast images can be mitigated by CLAHE through its tile-based contrast limiting mechanism. Thus, objects with minimal contrast and weak features can be optimized using the combined approach. The algorithm for integrating these two methods is illustrated in Algorithm below.

Algorithm CLAHE + Unsharp Masking	
Input:	Grayscale image I
	Tile size of M x N

Clip limit C
Blur radius r
Factor k

Output: Enhanced image

1. Divide the input image I into tiles of size M x N
2. For each tile:
   a. Compute histogram of pixel intensities
   b. Clip the histogram using threshold C
   c. Redistribute the clipped excess uniformly across all bins.
   d. Compute the cumulative distribution function
   e. Map the pixel values of the tile using the distribution function
3. Apply bilinear interpolation between tiles to avoid artifacts
4. Combine to produce image I'
5. Apply gaussian blur to the image I'_{blur}
6. Extract mask as the difference $Mask = I' - I'_{blur}$
7. Add the detail back to the original I' image with amplification k, $Result = I' + k \times Mask$
8. Result = CLAHE + USM

In the proposed method, CLAHE enhances both global and local contrast in the image, after which USM reinforces details and edge features once the contrast has been improved. As shown in Table 2, the results of applying CLAHE and USM, when compared to Table 1, demonstrate more evenly distributed contrast and sharper object representation.

Table 2. Example of CLAHE and USM

Biji-Kopi Normal	***Biji-Kopi Pecah***	***Biji-Kopi Hitam***	***Biji-Kopi Berlubang***
			

Figure 3 presents the quantitative representation of histogram analysis after applying CLAHE and USM to the *Biji-Kopi Normal* image shown in Table 2. Compared to the original image, the mean intensity (brightness) increased by 79.046, from 157.57 to 236.61. The variance, which reflects the contrast distribution, also improved significantly, from 162.35 (std 12.74) to 516.08 (std 22.72). Prior to enhancement, the image appeared relatively flat. The skewness value of -5.14, which indicated a predominance of darker regions, became less extreme at -4.01 after enhancement. Although the change is not substantial, the reduction suggests an improvement in dark-region detail visibility. Finally, kurtosis can be decreased from 40.42 to 25.30, indicating that the CLAHE and USM image exhibits greater variation in intensity distribution, as the sharp concentration of pixel values is no longer clustered in a single region.

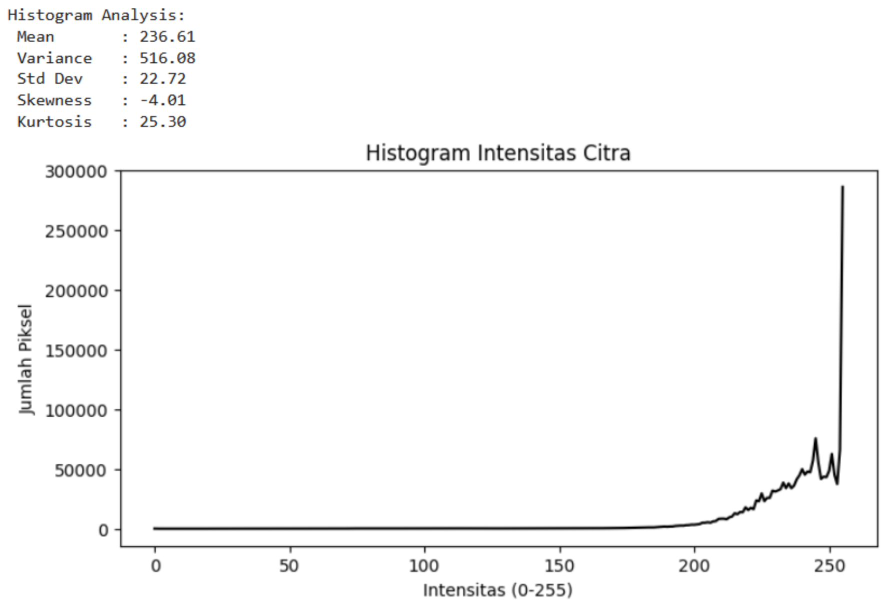


Figure 3. Histogram Analysis of CLAHE and USM on *Biji-Kopi Normal*

D. YOLOv4-Tiny

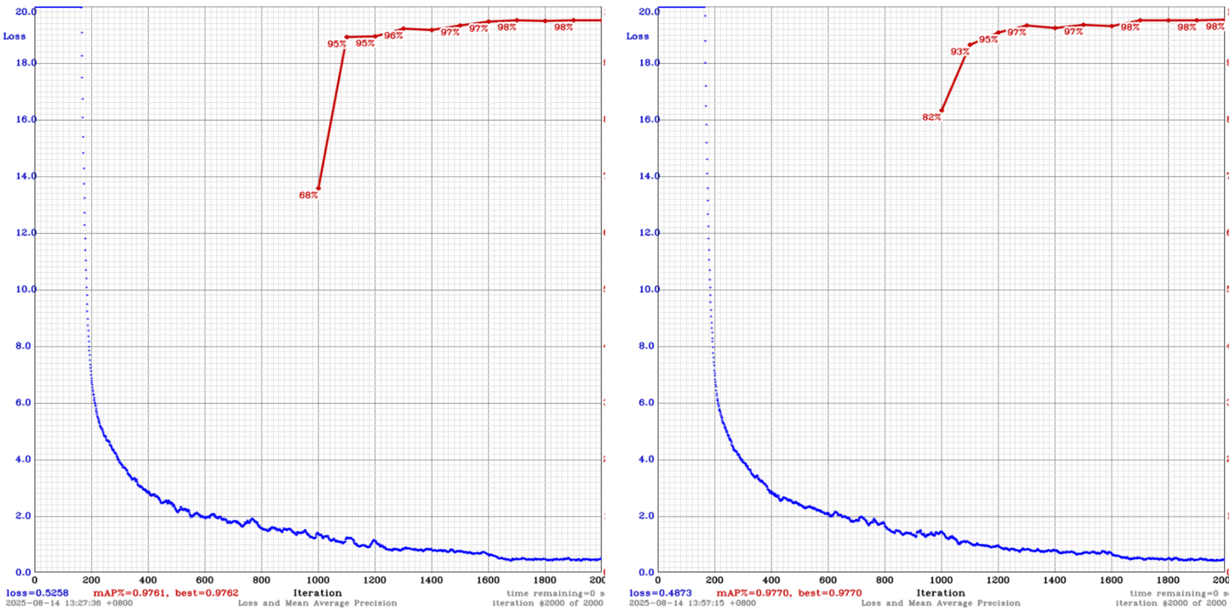
In the study referenced in [32], a comprehensive benchmark evaluation was conducted on more than 550 YOLO variants across four different datasets. The results indicate that YOLOv3 and YOLOv4 achieved the best performance in terms of the accuracy–latency trade-off, demonstrating a more optimal balance between detection accuracy and inference speed compared to other YOLO variants evaluated in the study. YOLOv4-Tiny is a lightweight variant of YOLOv4 specifically designed for low-computational requirements. This model is capable of performing object detection in real time with higher speed compared to the full YOLOv4 version, although with a simpler architectural complexity. In this study, the Darknet framework was employed, with the YOLOv4-Tiny architecture consisting of 39 layers, including convolutional, route, upsample, shortcut, and YOLO head layers. The training was implemented using NVIDIA RTX 4050 (4GB VRAM) with CUDA 11.8 and CuDNN 8.9.7 on Linux Debian 12. Both the original dataset and the dataset enhanced using the CLAHE and USM method were trained under the same configuration, namely batch = 64, subdivision = 32, width = 512, height = 512, max_batches = 2000, and steps = 1600, 1800. To ensure the purity of the experimental results, the entire training process was carried out without applying transfer learning.

E. Performance Evaluation

The evaluation stage was conducted to assess the extent to which the developed model is capable of detecting objects accurately and consistently. This process involved measuring the model's performance using relevant metrics, thereby enabling the results to be described quantitatively. In this study, the primary metric employed is Average Precision (AP), calculated across multiple Intersection over Union (IoU) thresholds ranging from 50, 55, 60 up to 95. The AP values at each threshold reflect the model's ability to identify objects with varying levels of precision, where higher thresholds indicate a stricter evaluation of the alignment between predictions and ground truth. Furthermore, to provide a comprehensive overview of overall performance, the mean Average Precision (mAP) is used, which represents the average of all AP values across the IoU thresholds [33], [34]. Accordingly, mAP offers a robust measure of the balance between precision and recall achieved by the model under different threshold levels.

Results and Discussion

This section presents the experimental results of the YOLOv4-Tiny model using two types of data, namely the Original Images and the enhanced images generated through the CLAHE and USM method. The analysis focuses on a comparative evaluation of model performance, illustrated through training process visualizations, assessment of AP values for each class, and a discussion of the differences in object detection performance across the classes.



(a) (b)

Figure 4. Performance Comparison of (a) Original Images Performance and (b) CLAHE and USM Performance on YOLOv4-Tiny

The performance comparison demonstrates that the CLAHE and USM approach achieved superior results, with an AP50 of 97.70 compared to 96.61 obtained from the Original Images. A higher AP value indicates that the model is capable of detecting objects with greater accuracy in terms of both localization and classification. Moreover, a higher mAP reflects the model's ability to reduce detection errors, such as false positives and false negatives. This finding is further supported by the training curves, where **Figure 4** (Original Images) shows that the AP initially starts at 68, while **Figure 4** CLAHE and USM begins at 82, illustrating the benefits of contrast equalization and feature enhancement in facilitating the model's learning process. Additionally, the loss values of both models differ, with CLAHE and USM achieving a lower loss of 0.4873 compared to 0.5258 for the Original Images. A lower loss indicates better learning capability of the model on the dataset. Since loss and AP are closely related, a smaller loss typically corresponds to a higher mAP, and vice versa. A comprehensive comparison of AP values across classes is presented in **Table 3**.

Table 3. AP50 to AP95 Comparison for Each Dataset

Dataset	AP50	AP 55	AP 60	AP 65	AP70	AP75	AP80	AP85	AP90	AP95	mAP
Original	96.61	95.91	94.17	89.92	79.43	59.91	33.53	11.32	1.66	0.02	56.248
CLAHE + USM	97.7	97.05	95.7	91.83	83.41	66.24	40.29	15.19	2.1	0.02	58.953
Rel. Improv. (%)	**1.13**	**1.19**	**1.62**	**2.12**	**5.01**	**10.58**	**20.13**	**34.17**	**26.51**	**0.00**	**4.81**

To further evaluate the model's performance across different thresholds, Table 3 illustrates that the dataset enhanced with CLAHE and USM consistently outperforms the Original Images at every threshold level. This comparison is crucial for providing a clearer understanding of the model's performance consistency. Based on the Relative Improvement (%) values presented in Table 3, the performance gains achieved by CLAHE and USM are relatively modest at lower thresholds, such as AP50, AP55, and AP60. This phenomenon occurs because the model already possesses sufficient capability to perform coarse detection at these levels. However, more substantial performance differences emerge when the evaluation thresholds increase to AP70 through AP90. At these higher levels of precision, the application of preprocessing with CLAHE and Unsharp Masking contributes to improving image quality by enhancing contrast and sharpness, thereby enabling the model to generate more accurate bounding box predictions.

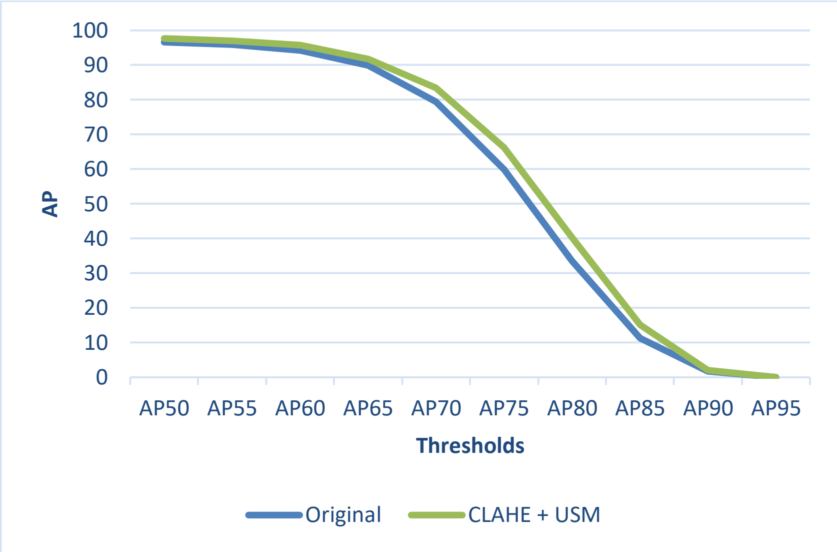


Figure 5. Comparison of AP Between the Original Dataset and CLAHE With USM

Figure 5 presents a visualization comparing the AP values obtained from training on the Original Dataset (blue) and the CLAHE and USM enhanced dataset (green). It can be observed that CLAHE and USM outperforms the Original Dataset across nearly all AP thresholds, with the exception of AP95. At AP95, the model is required to produce extremely strict predictions, where any Confidence Score below 95 is immediately classified as incorrect. Further evaluation, as shown in Table 3, indicates that the mean Average Precision (mAP) of CLAHE and USM increases by 4.81%. This comparison provides additional proofs that the applied preprocessing techniques contribute to improving the performance of the object detection model. A more detailed comparison and analysis will subsequently be conducted by evaluating the model's performance for each class at three specific thresholds: AP50, AP75, and AP95.

Table 4. Comparison of Each Class at AP50

AP50	*Biji-Kopi Normal*	*Biji-Kopi Pecah*	*Biji-Kopi Hitam*	*Biji-Kopi Berlubang*
Original Images	97.59	98.43	99.45	90.96
CLAHE + USM	97.50	98.83	100	94.44
Rel. Improv. (%)	-0.09	0.41	0.55	3.83

Table 4 shows that the *Biji-Kopi Normal* class experienced a slight performance decrease of approximately –0.9% at AP50 when using the CLAHE and USM dataset. This decline may be attributed to the effect of USM, which sharpens object edges and makes contours appear somewhat coarse and rigid, potentially leading the model to misclassify, as illustrated in **Table 2**. The performance of other classes, however, remained comparable or improved: the *Biji-Kopi Pecah* class increased by 0.41%, the *Biji-Kopi Hitam* class by 0.55%, and the highest improvement at AP50 was achieved by the *Biji-Kopi Berlubang* class, with an increase of 3.83%.

Table 5. Comparison of each class at AP75

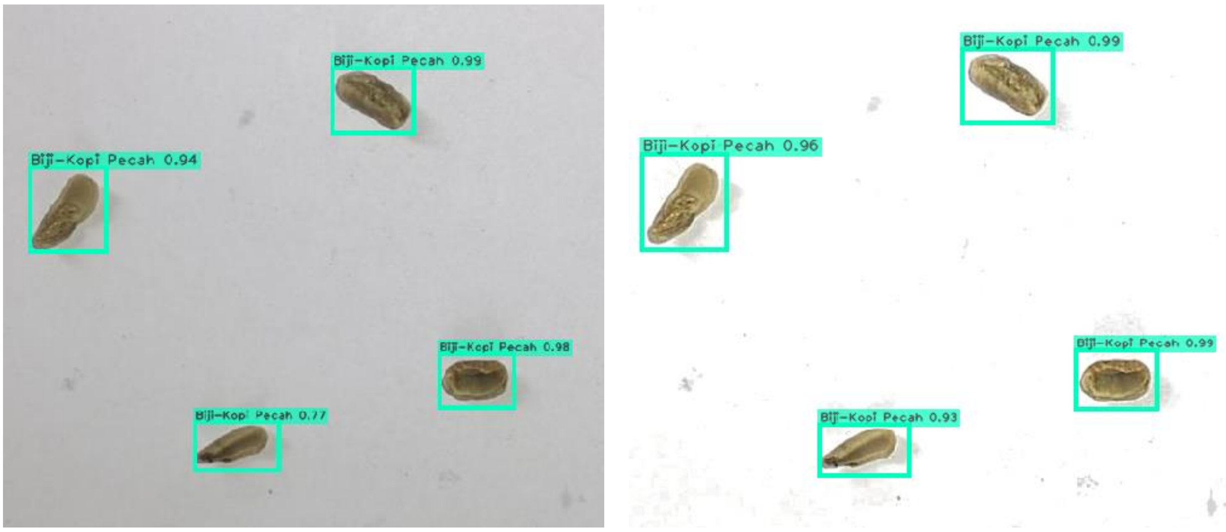
AP75	*Biji-Kopi Normal*	*Biji-Kopi Pecah*	*Biji-Kopi Hitam*	*Biji-Kopi Berlubang*
Original Images	80.37	37.21	67.11	54.92
CLAHE + USM	85.98	40.59	79.71	58.65
Rel. Improv. (%)	6.98	9.08	18.77	6.79

AP75 measures the accuracy of detection performance when the model is evaluated at a threshold greater than or equal to 75. As shown in **Table 5**, the CLAHE and USM dataset outperforms the Original Images across all classes. *Biji-Kopi Normal* class improved by 6.98%, the *Biji-Kopi Pecah* class by 9.08%, the *Biji-Kopi Berlubang* class by 6.79%, and the most substantial improvement was observed in the *Biji-Kopi Hitam*class, with an increase of 18.77%. The detection performance for the *Biji-Kopi Hitam* class shows a particularly significant enhancement. This improvement can be attributed to the application of CLAHE, which reduces shadow effects in the original images, thereby producing a more uniform illumination distribution. Subsequently, the USM method sharpens the distinction between object edges and the background, enabling the detection model to better recognize the shape and contour of the coffee beans, as illustrated in **Table 2**.

Table 6. Comparison of each class at AP95

AP95	*Biji-Kopi Normal*	*Biji-Kopi Pecah*	*Biji-Kopi Hitam*	*Biji-Kopi Berlubang*
Original Images	0.04	0	0.01	0
CLAHE + USM	0.05	0	0.01	0
Rel. Improv. (%)	25	0	0	0

AP50 reflects general or lenient detection performance, AP75 represents a moderate detection level, and AP95 measures a very high detection standard. At AP95, a detection is considered correct only if the overlap between the predicted bounding box and the ground truth bounding box is greater than or equal to 95. In other words, the model must achieve very high precision in localizing objects. As shown in Table 6, CLAHE and USM did not yield significant improvements for the *Biji-Kopi Pecah*, *Biji-Kopi Hitam*, and *Biji-Kopi Berlubang* classes. However, the *Biji-Kopi Normal* class exhibited a relative improvement of 25%, increasing from 0.04 to 0.05.



(a) (b)

Figure 6. Performance Visualization Using Test Image

Figure 6 illustrates the testing of images using both the Original Images and the CLAHE and USM enhanced images. The application of CLAHE improves and balances the contrast across the image without negatively affecting the contrast of the objects. Meanwhile, USM enhances the image by strengthening the contours and edges of the objects, making it easier for the model to learn and extract features from the dataset. As observed, the confidence scores for predictions on CLAHE and USM images are higher compared to those obtained from the Original Images.

Conclusion

The application of CLAHE has been shown to enhance contrast distribution without adversely affecting the original color of the objects, thereby preserving essential color characteristics, which are critical for object identification. Compared to [35], which used SVM with CLAHE and achieved 95.95% AP50, and [36], which combined SMOTE with CLAHE and obtained 88.1% on EfficientNETV2B2 and 86.4% on DenseNET169 for cassava leaf disease classification, our approach integrates CLAHE and USM to provide improved image quality enhancement, leading to better visual clarity for the classification task, especially for agriculture classification. Furthermore, the application of USM contributes to the enhancement of spatial features, particularly object contours and edges, making the boundaries between objects and the background more distinct. Histogram analysis demonstrates that CLAHE and USM outperforms other metrics across all categories, including mean, variance, standard deviation, skewness, and kurtosis. Consequently, the combination of CLAHE and USM not only improves the visual quality of the images but also strengthens the features relevant for object detection by the model. In YOLOv4-Tiny model training, the Precision mAP of CLAHE and USM increased by 4.8%, from 56.248 to 58.953. At AP50, CLAHE and USM improved by 1.13%, from 96.61 to 97.70, at AP75, it increased by 10.58%, from 59.91 to 66.24, and at AP95, no significant change in detection performance was observed. One limitation of this study is the use of Unsharp Masking (USM), which enhances edge sharpness but may produce overly rigid contours, potentially increasing the risk of misclassification. The uniform sharpening mechanism does not adequately distinguish between noise and meaningful edges, which can affect feature representation. Therefore, future work should explore edge-aware enhancement methods that apply adaptive sharpening only to important edges while preserving smooth regions, with the aim of improving visual quality and model robustness. Overall, CLAHE and USM has been proven, through analysis and detection testing, to enhance the accuracy of coffee beans detection.

References

[1] V. Voora, S. Bermudez, C. Larrea, and S. Balino, "Global Market Report: Coffee." International Institute for Sustainable Development, 2019. [Online]. Available: https://www.iisd.org/system/files/2022-09/2022-global-market-report-coffee.pdf

[2] P. T. S. Soares, E. R. Tavares Filho, M. M. Pagani, E. T. Mársico, A. G. Cruz, and E. A. Esmerino, "Coffee quality: Insights of Brazilian consumers from different sociodemographic levels combining modified Word Association and Maximum Difference Scaling (MaxDiff)," *Journal of Sensory Studies*, vol. 38, no. 5, p. e12856, 2023, doi: 10.1111/joss.12856.

[3] K. Zuiderveld, "Contrast limited adaptive histogram equalization," in *Graphics gems IV*, USA: Academic Press Professional, Inc., 1994, pp. 474–485. doi: https://doi.org/10.1016/B978-0-12-336156-1.50061-6.

[4] B. HatiPoğlu, Prof. Dr. İ. Karagöz, and M. İNal, "Threshold Based Image Enhancement Method for Low Contrast X-Ray Images Using CLAHE," *IJERAD*, Dec. 2022, doi: https://doi.org/10.29137/umagd.1203617.

[5] "Adaptive Clip Limit Tile Size Histogram Equalization for Non-Homogenized Intensity Images", doi: https://doi.org/10.1109/ACCESS.2021.3134170.

[6] K. Kumar and B. T. Chakkaravarthy, "Contrast Enhancement and Noise Reduction Through Synthesizing Gaussian Filter, CLAHE and HE Algorithm for Image Preprocessing," in *2025 International Conference on Emerging Technologies in Engineering Applications (ICETEA)*, Jun. 2025, pp. 1–5. doi: 10.1109/ICETEA64585.2025.11100055.

[7] X. Liang, Y. Tian, S. Yan, K. Wang, C. Guo, and B. Du, "A real-time infrared image enhancement algorithm based on improved CLAHE," in *2018 International Conference on Image and Video Processing, and Artificial Intelligence*, SPIE, Oct. 2018, pp. 130–138. doi: 10.1117/12.2514629.

[8] K. Lucknavalai and J. P. Schulze, "Real-Time Contrast Enhancement for 3D Medical Images Using Histogram Equalization," in *Advances in Visual Computing*, G. Bebis, Z. Yin, E. Kim, J. Bender, K. Subr, B. C. Kwon, J. Zhao, D. Kalkofen, and G. Baciu, Eds., Cham: Springer International Publishing, 2020, pp. 224–235. doi: 10.1007/978-3-030-64556-4_18.

[9] T. P. H. Nguyen, Z. Cai, K. Nguyen, S. Keth, N. Shen, and M. Park, "Pre-processing Image using Brightening, CLAHE and RETINEX," Mar. 22, 2020, *arXiv*: arXiv:2003.10822. doi: 10.48550/arXiv.2003.10822.

[10] M. J. Kobra, A. M. Nakib, P. Mweetwa, and M. O. Rahman, "Effectiveness of Fourier, Wiener, Bilateral, and CLAHE Denoising Methods for CT Scan Image Noise Reduction," *Scientific Journal of Engineering Research*, vol. 1, no. 3, pp. 96–108, Jun. 2025, doi: 10.64539/sjer.v1i3.2025.27.

[11] J.-H. Kim, K.-H. Lee, J.-W. Lee, and K.-S. Kim, "Image Enhancement by Unsharp Mask Filtering Based on Detrending Method," *International Journal of Engineering & Technology*, vol. 7, pp. 26–29, Dec. 2018, doi: 10.14419/ijet.v7i4.39.23693.

[12] W. Ye and K.-K. Ma, "Blurriness-guided unsharp masking," in *2017 IEEE International Conference on Image Processing (ICIP)*, Sep. 2017, pp. 3770–3774. doi: 10.1109/ICIP.2017.8296987.

[13] J. Joseph and R. Periyasamy, “Nonlinear sharpening of MR images using a locally adaptive sharpness gain and a noise reduction parameter,” *Pattern Anal Applic*, vol. 22, no. 1, pp. 273–283, Feb. 2019, doi: 10.1007/s10044-018-0763-7.

[14] I. Majid Mohammed and N. Ashidi Mat Isa, “Contrast Limited Adaptive Local Histogram Equalization Method for Poor Contrast Image Enhancement,” *IEEE Access*, vol. 13, pp. 62600–62632, 2025, doi: 10.1109/ACCESS.2025.3558506.

[15] O. G. S, S. V.V, and Bekbolatov, “Application of the Clahe Method Contrast Enhancement of X-Ray Images,” *ternational Journal of Advanced Computer Science and Applications*, vol. 13, no. 5, pp. 412–420, 2022, doi: https://dx.doi.org/10.14569/IJACSA.2022.0130549.

[16] X. Liu, M. Pedersen, and R. Wang, “Survey of natural image enhancement techniques: Classification, evaluation, challenges, and perspectives,” *Digital Signal Processing*, vol. 127, p. 103547, Jul. 2022, doi: 10.1016/j.dsp.2022.103547.

[17] X. Chen *et al.*, “Histogram analysis in predicting the grade and histological subtype of meningiomas based on diffusion kurtosis imaging,” *Acta Radiol*, vol. 61, no. 9, pp. 1228–1239, Sep. 2020, doi: 10.1177/0284185119898656.

[18] L. Jiang *et al.*, “Machine Learning Based on Diffusion Kurtosis Imaging Histogram Parameters for Glioma Grading,” *J Clin Med*, vol. 11, no. 9, p. 2310, Apr. 2022, doi: 10.3390/jcm11092310.

[19] J. Ren, Y. Yuan, and X. Tao, “Histogram analysis of diffusion-weighted imaging and dynamic contrast-enhanced MRI for predicting occult lymph node metastasis in early-stage oral tongue squamous cell carcinoma,” *Eur Radiol*, vol. 32, no. 4, pp. 2739–2747, Apr. 2022, doi: 10.1007/s00330-021-08310-0.

[20] Y. Chen *et al.*, “Histogram analysis of MR quantitative parameters: are they correlated with prognostic factors in prostate cancer?,” *Abdom Radiol*, vol. 49, no. 5, pp. 1534–1544, May 2024, doi: 10.1007/s00261-024-04227-6.

[21] H. Yang, X. Liu, J. Jiang, and J. Zhou, “Apparent diffusion coefficient histogram analysis to preoperative evaluate intracranial solitary fibrous tumor: Relationship to Ki-67 proliferation index,” *Clinical Neurology and Neurosurgery*, vol. 220, p. 107364, Sep. 2022, doi: 10.1016/j.clineuro.2022.107364.

[22] O. Holub and S. T. Ferreira, “Quantitative histogram analysis of images,” *Computer Physics Communications*, vol. 175, no. 9, pp. 620–623, Nov. 2006, doi: 10.1016/j.cpc.2006.06.014.

[23] G. Yuan *et al.*, “Noninvasive assessment of renal function and fibrosis in CKD patients using histogram analysis based on diffusion kurtosis imaging,” *Jpn J Radiol*, vol. 41, no. 2, pp. 180–193, Feb. 2023, doi: 10.1007/s11604-022-01346-2.

[24] M. A. Rasel, S. A. Kareem, and U. Obaidellah, “Integrating color histogram analysis and convolutional neural networks for skin lesion classification,” *Computers in Biology and Medicine*, vol. 183, p. 109250, Dec. 2024, doi: 10.1016/j.compbiomed.2024.109250.

[25] X. Mingjin *et al.*, “Research on Fast Multi-Threshold Image Segmentation Technique Using Histogram Analysis,” *https://www.mdpi.com/journal/electronics*, 2023, doi: https://doi.org/10.3390/electronics12214446.

[26] W. Wang and Y. Yang, “A histogram equalization model for color image contrast enhancement,” *SIViP*, vol. 18, no. 2, pp. 1725–1732, Mar. 2024, doi: 10.1007/s11760-023-02881-9.

[27] E. Onyedinma, I. Onyenwe, and H. Inyiama, “Performance Evaluation of Histogram Equalization and Fuzzy image Enhancement Techniques on Low Contrast Images,” Sep. 01, 2019, *arXiv*: arXiv:1909.03957. doi: 10.48550/arXiv.1909.03957.

[28] X. Zhu, X. Xiao, T. Tjahjadi, Z. Wu, and J. Tang, “Image Enhancement using Fuzzy Intensity Measure and Adaptive Clipping Histogram Equalization,” Jan. 15, 2021, *arXiv*: arXiv:2101.05922. doi: 10.48550/arXiv.2101.05922.

[29] J. Lee, S. R. Pant, and H.-S. Lee, "An Adaptive Histogram Equalization Based Local Technique for Contrast Preserving Image Enhancement," *International Journal of Fuzzy Logic and Intelligent Systems*, vol. 15, no. 1, pp. 35–44, Mar. 2015, doi: 10.5391/IJFIS.2015.15.1.35.

[30] Y. Chang, C. Jung, P. Ke, H. Song, and J. Hwang, "Automatic Contrast-Limited Adaptive Histogram Equalization With Dual Gamma Correction," *IEEE Access*, vol. PP, pp. 1–1, Jan. 2018, doi: 10.1109/ACCESS.2018.2797872.

[31] Y. Miao *et al.*, "Application of the CLAHE Algorithm Based on Optimized Bilinear Interpolation in Near Infrared Vein Image Enhancement," in *Proceedings of the 2nd International Conference on Computer Science and Application Engineering*, in CSAE '18. New York, NY, USA: Association for Computing Machinery, Oct. 2018, pp. 1–6. doi: 10.1145/3207677.3277957.

[32] I. Lazarevich, M. Grimaldi, R. Kumar, S. Mitra, S. Khan, and S. Sah, "YOLOBench: Benchmarking Efficient Object Detectors on Embedded Systems," Aug. 21, 2023, *arXiv*: arXiv:2307.13901. doi: 10.48550/arXiv.2307.13901.

[33] N. T. Allo, Indrabayu, and Z. Zainuddin, "A Novel Approach of Hybrid Bounding Box Regression Mechanism to Improve Convergency Rate and Accuracy," *IJIES*, vol. 17, no. 2, pp. 715–727, Apr. 2024, doi: 10.22266/ijies2024.0430.57.

[34] Z. Zainuddin and N. T. Allo, "More Focused Remote Sensing Object Detection Based on Improved Bounding Box Regression Loss," *IJIES*, vol. 17, no. 6, pp. 230–247, Dec. 2024, doi: 10.22266/ijies2024.1231.19.

[35] V. Ayumi, "Klasifikasi Penyakit Tanaman Berdasarkan Analisis Citra Daun Padi Menggunakan Metode SVM Dan CLAHE," vol. 7, no. 3, 2024, doi: 10.36085.

[36] H. Tribiakto, A. Sunyoto, and E. Pramono, "Enhancing Deep Learning-based Classification of Cassava Leaf Diseases using CLAHE and SMOTE," *Sistemasi: Jurnal Sistem Informasi*, vol. 14, no. 6, pp. 2698–2706, Nov. 2025, doi: 10.32520/stmsi.v14i6.5530.

Supplementary Material

Supplementary material that may be helpful in the review process should be prepared and provided as a separate electronic file. That file can then be transformed into PDF format and submitted along with the manuscript and graphic files to the appropriate editorial office.