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OPTIMISATION OF IMAGE DATA PREPARATION USING HYBRID WHITE BALANCE METHOD FOR CLASSIFICATION OF STRAW MUSHROOM IMAGE QUALITY

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ABSTRACT

This study aims to enhance the quality of straw mushroom images by applying a Hybrid White Balance (HWB) preprocessing method to improve classification accuracy. Variations in illumination often introduce color distortion, which negatively affects feature extraction and reduces the performance of machine learning models. Therefore, robust preprocessing techniques are required to handle lighting inconsistencies and improve image quality. In this study, the HWB method is combined with normalization and histogram equalization to produce more consistent visual representations. Straw mushroom images were collected under varying lighting conditions from different agricultural environments. The preprocessing stage includes color correction using HWB followed by normalization to reduce variability. The processed images were then classified using a Convolutional Neural Network (CNN). The results show that preprocessing significantly affects classification performance. The model without preprocessing achieved an mAP@0.5 of approximately 0.927, while Standard White Balance improved performance to around 0.978 in terms of precision, recall, and F1-score. The best results were obtained using HWB, achieving precision of approximately 0.996, mAP of about 0.994, and F1-score around 0.9395, indicating more accurate and robust classification. Additionally, image quality evaluation shows that HWB reduces Mean Squared Error (MSE) and increases Peak Signal-to-Noise Ratio (PSNR) and Signal-to-Noise Ratio (SNR), outperforming standard preprocessing methods. In conclusion, HWB-based preprocessing effectively enhances both image quality and classification performance. This method has strong potential as a reliable preprocessing approach for agricultural image analysis, particularly under varying illumination conditions, and can support the development of more robust and adaptive classification systems.

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1. INTRODUCTION

Straw mushrooms (*Volvariella Volvacea*) in Indonesia are marketed as Class 1 (for modern markets) and Class 2 (for traditional markets) after the harvest [1]. In Indonesia, the straw Mushroom Quality Standard SNI:01-6945-2003 has been established as the official quality standard for straw mushrooms. According to this standard, straw mushrooms are deemed uniform if they share the same cultivar characteristics in terms of size, shape, flesh color, and skin color among fresh straw mushroom cultivars in one lot [2].

The classification of straw mushroom images in agricultural applications faces considerable challenges due to image quality degradation caused by varying illumination conditions. Unstable or suboptimal lighting may introduce visual inconsistencies, which hinder accurate feature extraction and ultimately reduce classification performance. Image pre-processing techniques such as normalization, noise reduction, and color correction are therefore essential to enhance visual quality and information richness, leading to improved classification outcomes [3], [4].

White balance plays a critical role in compensating for color distortions generated during image acquisition. Accurate color representation directly affects the reliability of feature extraction and classification accuracy. Techniques including histogram equalization have been utilized to improve white balance, ensuring straw mushroom images are represented faithfully and support more robust classification performance [5], [4]. Recent findings indicate that integrating color correction with pre-processing approaches can significantly improve classification accuracy [6], [7].

However, environmental variability in agricultural imaging remains a major obstacle. Straw mushrooms are often photographed under natural or semi controlled conditions with inconsistent background settings, different harvesting environments, and diverse coloration across maturity stages. These factors generate substantial intra class variation and can lead to misclassification or degraded predictive reliability, particularly for automated quality inspection systems [7], [8]. Therefore, enhanced pre-processing pipelines capable of stabilizing visual attributes are urgently needed to support real-time classification deployment in the field.

Despite existing advancements, many traditional white balance algorithms remain limited in their capability to handle uneven or extreme illumination conditions. To address this issue, hybrid strategies that combine conventional white balance approaches with advanced techniques such as Convolutional Neural Networks (CNN) and multi resolution wavelet filters have been proposed to achieve superior illumination adaptation and enhance classification effectiveness [9], [10], [11]. Hybrid approaches are expected to deliver improved contrast normalization, noise suppression, and feature structure preservation, which are essential to strengthen classification robustness.

In addition, the effectiveness of image classification systems is highly dependent on the quality and consistency of the training data. In agricultural contexts, limited control over image acquisition conditions often results in datasets with significant illumination bias and color inconsistency [12]. Without appropriate pre-processing, such imperfections can propagate through the learning process and reduce the generalization capability of classification models. Therefore, robust pre-processing strategies are not only beneficial for improving visual appearance but also play a fundamental role in enhancing the stability and reliability of machine learning-based classification systems [13].

This study aims to investigate the role of image pre-processing and white balance enhancement in improving straw mushroom image classification. By integrating a Hybrid White Balance approach into the pre-processing stage, this research seeks to overcome illumination discrepancies, refine image quality, and support more accurate classification of mushroom quality categories. The contributions of this work align with the ongoing development of intelligent agricultural systems, where high quality visual data are vital to enable reliable decision making in real world production, harvesting, and quality monitoring environments. In addition, the application of artificial intelligence based image classification systems in the agricultural sector has significant potential to improve the efficiency and consistency of automated quality assessment. With the support of optimal image pre-processing, classification systems can reduce reliance on manual inspections that are subjective and time consuming. This enables the quality evaluation of straw mushrooms to be conducted more rapidly, objectively, and in a standardized manner, thereby supporting improvements in product quality and enhancing the competitiveness of agricultural products in both modern and traditional markets.

2. RESEARCH METHODS

2.1 Research Period and Location

This study is conducted from 2024 to 2025 in the Computer Vision and Image Processing Research Laboratory at Universitas Buana Perjuangan Karawang. The dataset consists of 105 straw mushroom (*Volvariella Volvacea*) images, collected using a specially designed image acquisition box equipped with controlled lighting. The mushrooms are placed inside the box during image capture to ensure consistent object positioning and lighting quality. The collected images are subsequently processed for image quality classification tasks.

2.2 Method Overview

The methodological approach applied in this study focuses on optimizing image pre-processing through the implementation of the Hybrid White Balance (HWB) method to enhance the quality of straw mushroom images used in classification. The HWB method combines multiple white balance algorithms to correct color distortion, which may negatively affect classification accuracy The use of HWB is considered essential for reducing illumination distortions caused by diverse light sources This technique also aims to overcome lighting variations that may impact classification outcomes and improve the performance of image classification algorithms in agricultural environments, particularly for assessing straw mushroom quality [14], [15], [16].

The methodological approach applied in this study focuses on optimizing image pre-processing through the implementation of the Hybrid White Balance (HWB) method to enhance the quality of straw mushroom images used in classification. The HWB method combines multiple white balance and image enhancement processes in a structured pipeline to correct color distortion, normalize illumination, and preserve important visual information that may negatively affect classification accuracy [17], [18]. Specifically, the method begins with color correction through RGB channel balancing and gain adjustment to reduce color dominance, followed by brightness enhancement on the HSV color space, particularly the Value (V) channel, to improve visibility in poorly illuminated regions. After that, segmentation is performed using thresholding and contour detection to separate the mushroom object from the background. The resulting mask is refined through smoothing and then used in an inpainting process (TELEA algorithm) to reconstruct missing or corrupted background regions. Finally, image sharpening is applied to enhance edge definition and texture details, which are important for improving feature extraction in CNN-based classification. The use of HWB is considered essential for reducing illumination distortions caused by diverse light sources [19], [20]. This technique also aims to overcome lighting variations that may impact classification outcomes and improve the performance of image classification algorithms in agricultural environments, particularly for assessing straw mushroom quality [14], [15], [16].

2.3 Research Process Stages

This study was conducted through six main stages, beginning with problem identification and data collection, where relevant straw mushroom images were gathered and analyzed to define the scope and requirements of the research, followed by data preprocessing, which included cleaning, resizing, and standardizing the images to minimize noise and inconsistencies. The next stage involved the implementation of the Hybrid White Balance (HWB) method to enhance color consistency and correct illumination variations, followed by model testing and result analysis using metrics such as Mean Square Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Signal-to-Noise Ratio (SNR) to evaluate image quality and the effectiveness of the method. The results were then compared to identify the best-performing dataset, which was used for image classification, demonstrating that preprocessing and image enhancement directly affect the accuracy and reliability of the classification model.

Furthermore, this methodological framework was designed to ensure that each stage contributes to improving the overall robustness and reliability of the system. The integration of preprocessing, image enhancement, and classification forms a structured pipeline that effectively addresses variations in image quality, particularly those caused by inconsistent lighting conditions. Therefore, the proposed approach not only improves visual quality but also enhances the performance and stability of the classification model in handling straw mushroom image datasets. The overall workflow of the proposed method is illustrated in Fig. 1.

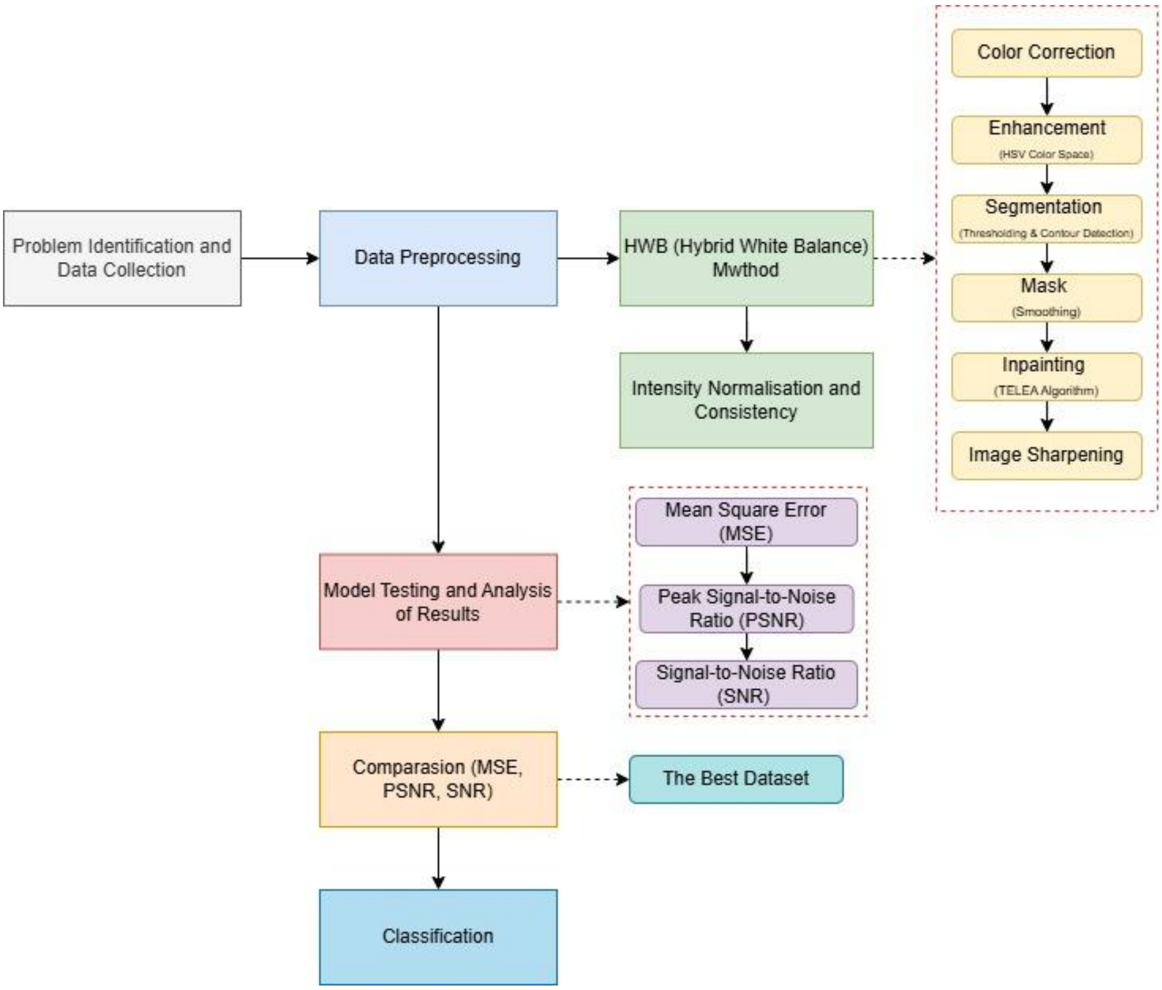


Figure 1. Propose Method

Fig. 1 shows that the proposed method in this study was developed to address color distortion in straw mushroom images caused by inconsistent lighting conditions. The research process begins with problem identification, followed by the collection of image data from various agricultural locations. The acquired images are then processed using the Hybrid White Balance (HWB) preprocessing method to correct color imbalance [21], followed by normalization techniques to reduce image variability [9], [16].

Next, intensity normalization and consistency techniques are applied to enhance visual quality and support feature extraction [17], [22]. A CNN-based image classification model is then used to classify image quality based on color and texture features. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The evaluation results are analyzed to assess the model performance.

Finally, quantitative analysis is conducted to identify model limitations and to explore potential improvements through more adaptive HWB techniques [23], [24].

3. RESULTS AND DISCUSSION

3.1 Hybrid Data Pre-processing

In this study, the initial and essential stage involves enhancing the visual quality of straw mushroom images through a pre-processing procedure designed to address uneven lighting conditions. The Hybrid White Balance (HWB) method is applied to balance the color distribution within the images, ensuring more uniform and illumination consistent color representation. This method is considered crucial, as inconsistent lighting may cause color distortion, which negatively affects feature extraction and image classification performance.

The following is the mathematical formulation used in the Hybrid Image Restoration process (White Balance Method):

1. White Balance Correction

$$I = f(x, y) = [R(x, y), G(x, y), B(x, y)], \tag{1}$$

$$I_{WB}(x, y) = \mathrm{WB}\big(I(x, y)\big) = \left[\frac{R(x,y)}{\mu R}, \frac{G(x,y)}{\mu G}, \frac{B(x,y)}{\mu B}\right]. \tag{2}$$

2. Brightness Enhancement
   a. Conversion to HSV space:

$$I_{HSV} = RGB\ to\ HVS\ (I_{WB}). \tag{3}$$

   b. Value channel adjustment (brightness):

$$V^{I}(x, y) = \min(V(x, y) + \Delta V, 255). \tag{4}$$

   c. Return to BGR room:

$$I_{bright}(x, y) = HVS\ to\ RGB\ (H, S, V^{I}). \tag{5}$$

3. Segmentation
   a. Conversion to grayscale:

$$I_{gray}(x, y) = 0.299R + 0.587G + 0.114B. \tag{6}$$

   b. Thresholding biner:

$$M_{bin}(x, y) = \begin{cases} 1, & I_{gray}(x, y) > T \\ 0, & \text{Other} \end{cases}. \tag{7}$$

   c. Contour detection:

$$C = Contours\ (M_{bin}). \tag{8}$$

   d. Create a binary mask from the contour:

$$M_{obj}(x, y) = DrawContour\ (C_{max}). \tag{9}$$

4. Mask Smoothing

$$M_{smooth}(x, y) = G_{\sigma} * M_{obj}(x, y). \tag{10}$$

5. Inpainting (TELEA Method)

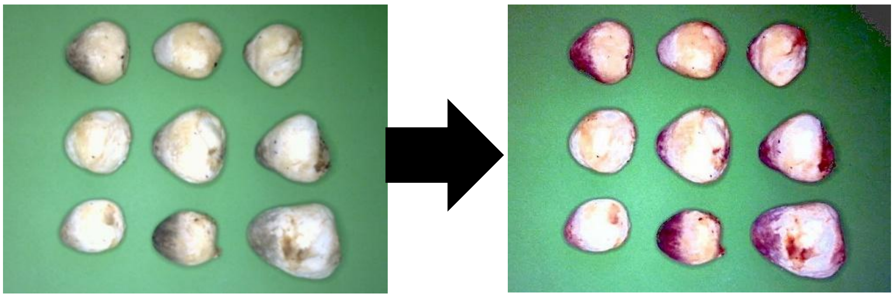
$$I_{inpain}(x, y) = Inpaint_{TELEA}\left(I_{bright,}\ \neg M_{smooth}\right). \tag{11}$$

6. Sharpening (Enhance Details)

$$I_{sharp}(x, y) = I_{inpaint}(x, y) * K_{sharp}, \tag{12}$$

$$I_{final}(x, y) = I_{sharp}(x, y). \tag{13}$$

To demonstrate the effectiveness of the HWB method in improving image quality, a visual comparison was performed between the original images and those processed using the proposed technique. Fig. 2 illustrates the image restoration results using the Hybrid White Balance method.



(a) Original Image (b) Hybrid White Balance

Figure 2. Image Restoration Using the Hybrid White Balance Method

The figure presents a visual comparison between the original straw mushroom image (a) and the image processed using the Hybrid White Balance method (b). In the original image, variations in illumination can be observed, leading to noticeable color distortion and reduced clarity of surface texture details. These issues negatively affect visual feature extraction, particularly in color and texture-based image classification tasks.

After applying the Hybrid White Balance method, the processed image exhibits significant improvements in both color consistency and visual clarity. The mushroom surface appears more contrasted and sharper, with illumination distributed more uniformly across the image. This enhancement indicates that the method successfully corrects color imbalance caused by uneven lighting conditions while clarifying relevant visual characteristics.

These findings support the hypothesis that color correction techniques, such as Hybrid White Balance, play a critical role in improving image data quality, thereby increasing the likelihood of success in subsequent stages such as segmentation, feature extraction, and classification. Therefore, this pre-processing technique has proven effective in enhancing the visual representation of objects within images, which is essential for artificial intelligence-based image processing systems.

3.2 Evaluation of the Hybrid Data Preprocessing

Table 1 presents the evaluation results obtained using the MSE, PSNR, and SNR metrics to assess the image restoration performance of the Hybrid White Balance method, with the condition that the data used is a straw mushroom dataset previously acquired through a data acquisition process.

Table 1. Evaluation Results of Restoration Using the Hybrid Balance Method

No	File Name	MSE	PSNR	SNR
1	Mushroom_001.jpg	648,67	20,01	15,47
2	Mushroom_002.jpg	533,3	20,86	16,31
3	Mushroom_003.jpg	488,43	21,24	16,75
4	Mushroom_004.jpg	545,33	20,76	16,14
5	Mushroom_005.jpg	549,7	20,73	16,42
…	…	…	…	…
104	Mushroom_104.jpg	463,61	21,47	16,71
105	Mushroom_105.jpg	623,19	20,18	15,64
	Average	543,32	20,8	16,19
	Minimum	463,55	20,01	15,47
	Maximum	648,67	21,47	16,79

The data based on Table 1, the evaluation results using MSE evaluation are visualized in a graph as shown in Fig. 3:

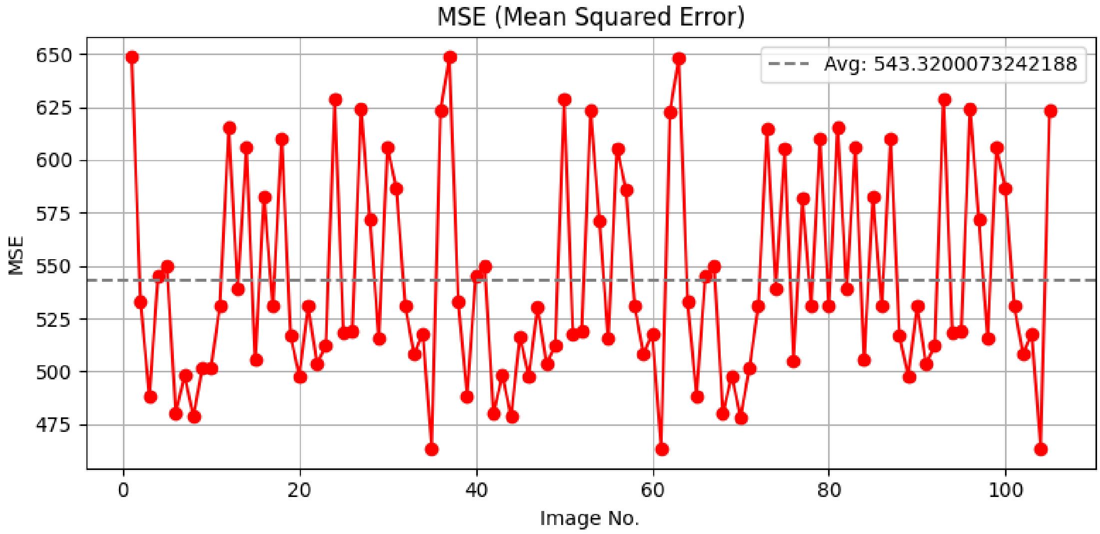


Figure 3. MSE (Mean Squared Error) Evaluation of the Hybrid White Balance Method

Fig. 3 illustrates the distribution graph of Mean Squared Error (MSE) values for 105 straw mushroom images that have undergone a restoration process using the specified method. Each point in the graph represents a single image, showing varying MSE values across the dataset. The average MSE value of 543.32 is indicated by a horizontal dashed line. The fluctuations observed in the graph suggest that the restoration quality differs for each image, depending on their individual characteristics. Notably, the highest MSE value is observed in *Mushroom_001*, indicating a larger deviation between the restored image and the reference image. This condition is likely caused by uneven or extreme illumination during image acquisition, which introduces significant color distortion and increases the difficulty of accurate restoration. Previous studies have reported that non-uniform illumination and multi-illuminant conditions remain challenging for white balance algorithms, potentially leading to higher reconstruction errors and reduced restoration performance [21],[23]. Lower MSE values indicate smaller differences between the restored and reference images, meaning that the restoration results are more accurate.

The data based on Table 1, containing the evaluation results using PSNR, are visualized in graphical form as shown in Fig. 4:

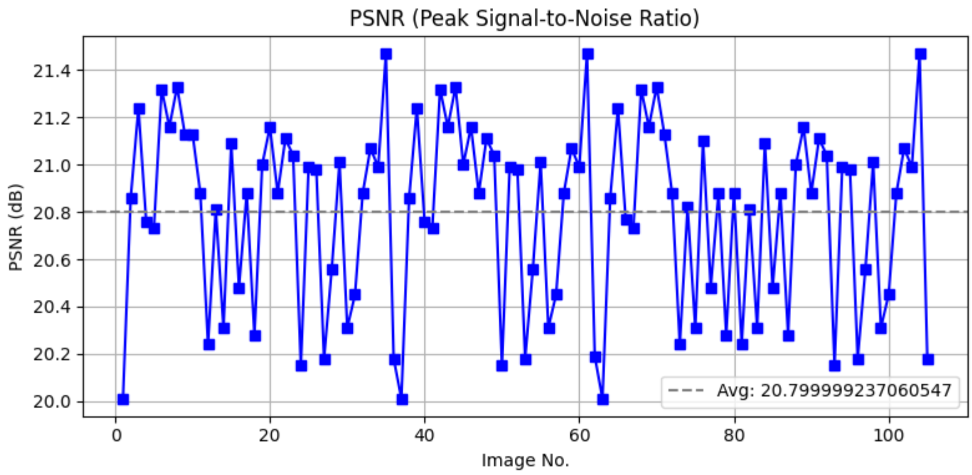


Figure 4. PSNR (Peak Signal-to-Noise Ratio) Evaluation Standard White Balance Method

The graph presented in Fig. 4 displays the distribution of Peak Signal to Noise Ratio (PSNR) values for 105 straw mushroom images that have undergone the restoration process. Each point in the graph represents the individual PSNR value of a corresponding image, measured in decibels (dB). PSNR is used to describe the visual quality of the restored image by indicating the ratio between the maximum signal and the noise level. A horizontal dashed line marks the average PSNR value of 20.78 dB. The fluctuations in the graph reflect variations in the clarity and sharpness of the restoration results across the images. Higher PSNR values indicate better visual quality, which corresponds to a lower level of noise.

The data based on Table 1, containing the evaluation results using SNR (Signal to Noise Ratio), are visualized in graphical form as shown in Fig. 5:

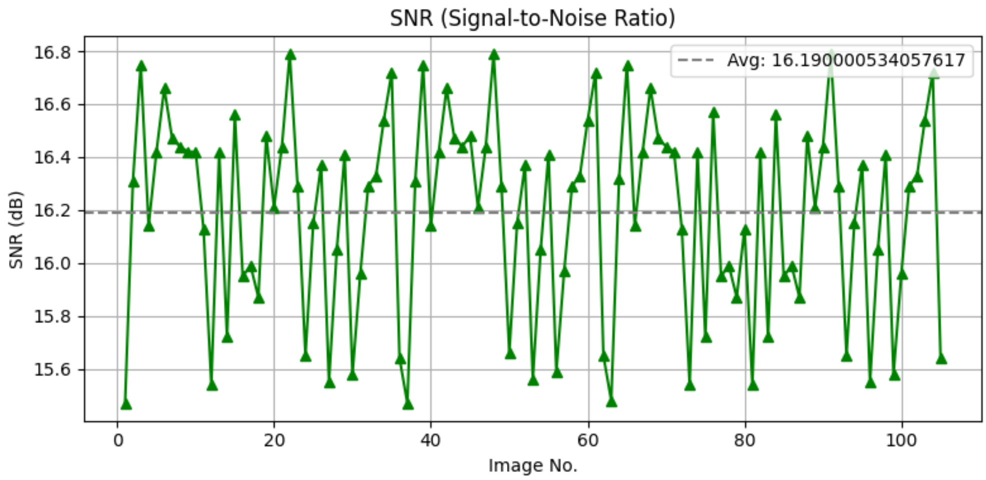


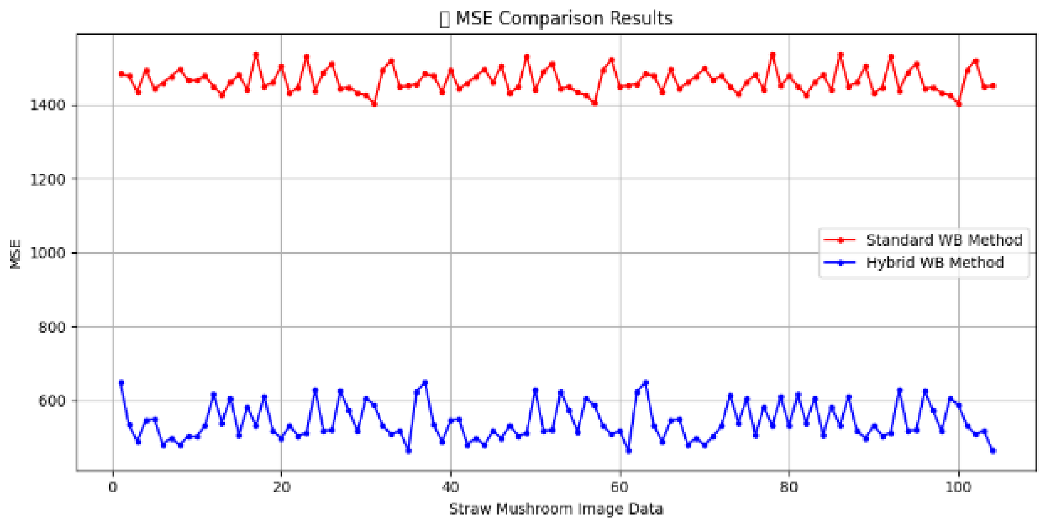
Figure 5. SNR (Signal to Noise Ratio) Evaluation Standard White Balance Method

Fig. 5 presents the distribution graph of Signal to Noise Ratio (SNR) values for 105 straw mushroom images that have undergone the restoration process. SNR is measured in decibels (dB) and indicates the comparison between the strength of the image signal and the existing noise or interference. Each point in the graph represents the SNR value of a single image, while the horizontal dashed line indicates the overall average value recorded at 16.19 dB. The fluctuations shown in the graph signify variations in the clarity of the images after restoration. Higher SNR values indicate better image quality, as they represent a stronger dominance of visual information compared to noise.

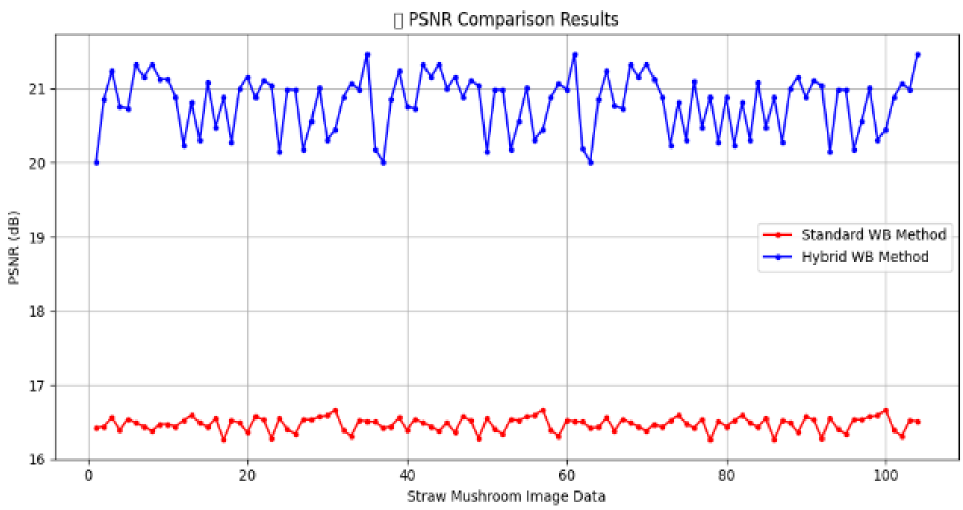
3.3 Comparison Result Evaluation

To evaluate the effectiveness of the Hybrid White Balance (HWB) method in improving the quality of straw mushroom images, a quantitative analysis was conducted using three primary evaluation metrics: Root

Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), and Signal to Noise Ratio (SNR). These metrics were employed to assess the extent to which visual clarity, color reproduction accuracy, and the ratio of signal to noise in the images could be improved by the HWB method. The evaluation results are presented in comparative graphical form between the HWB method and the Standard White Balance method, allowing for an objective and measurable performance analysis of both approaches.



(a) MSE



(b) PSNR

(c) SNR

Figure 6. Comparison Results of Standard and Hybrid Method in White Balance Preparation

The three graphs attached in Fig. 6 present a comparison of image evaluation metrics, namely RMSE (Root Mean Square Error), PSNR, and SNR, between the Standard White Balance and Hybrid White Balance methods applied to straw mushroom images. Graph (a) shows that the RMSE values for the Hybrid White Balance method (depicted in blue) are consistently lower than those of the standard method (red), indicating smaller pixel level errors and better color correction quality. Graph (b) demonstrates an opposite trend for PSNR, where the Hybrid White Balance method produces higher and more stable PSNR values, reflecting improved image clarity and sharpness. These findings are further supported by graph (c), in which the SNR values for the Hybrid method are consistently higher, indicating that the image signal visual information is more dominant than the noise following the application of the method.

Overall, the three graphs show a consistent pattern, confirming that the Hybrid White Balance method significantly outperforms the standard method in enhancing image visual quality based on all three-evaluation metrics. These results provide empirical evidence that the Hybrid White Balance approach can generate cleaner, more accurate, and more representative images for further analysis, such as feature extraction and image classification.

However, this study has several limitations, including the use of a dataset that is still limited to straw mushroom images, so the generalizability of the method to other objects cannot yet be fully ensured. In addition, the evaluation is still focused on objective metrics such as RMSE, PSNR, and SNR without involving subjective assessment, and it does not fully cover more complex variations in real-world lighting conditions.

3.4 Classification

In the straw mushroom quality classification stage, three experimental scenarios were conducted. The first experiment used a dataset without any preprocessing. The second experiment used a dataset that had been preprocessed using the Standard White Balance (WB) method. Meanwhile, the third experiment used a dataset processed using the Hybrid White Balance (HWB) method. These three scenarios were designed to compare the effect of each preprocessing method on the performance of straw mushroom quality classification. The classification method employed the GoogLeNet CNN model.

The results of these three experiments are then presented in the form of evaluation diagrams, including precision, recall, and F1-score metrics.

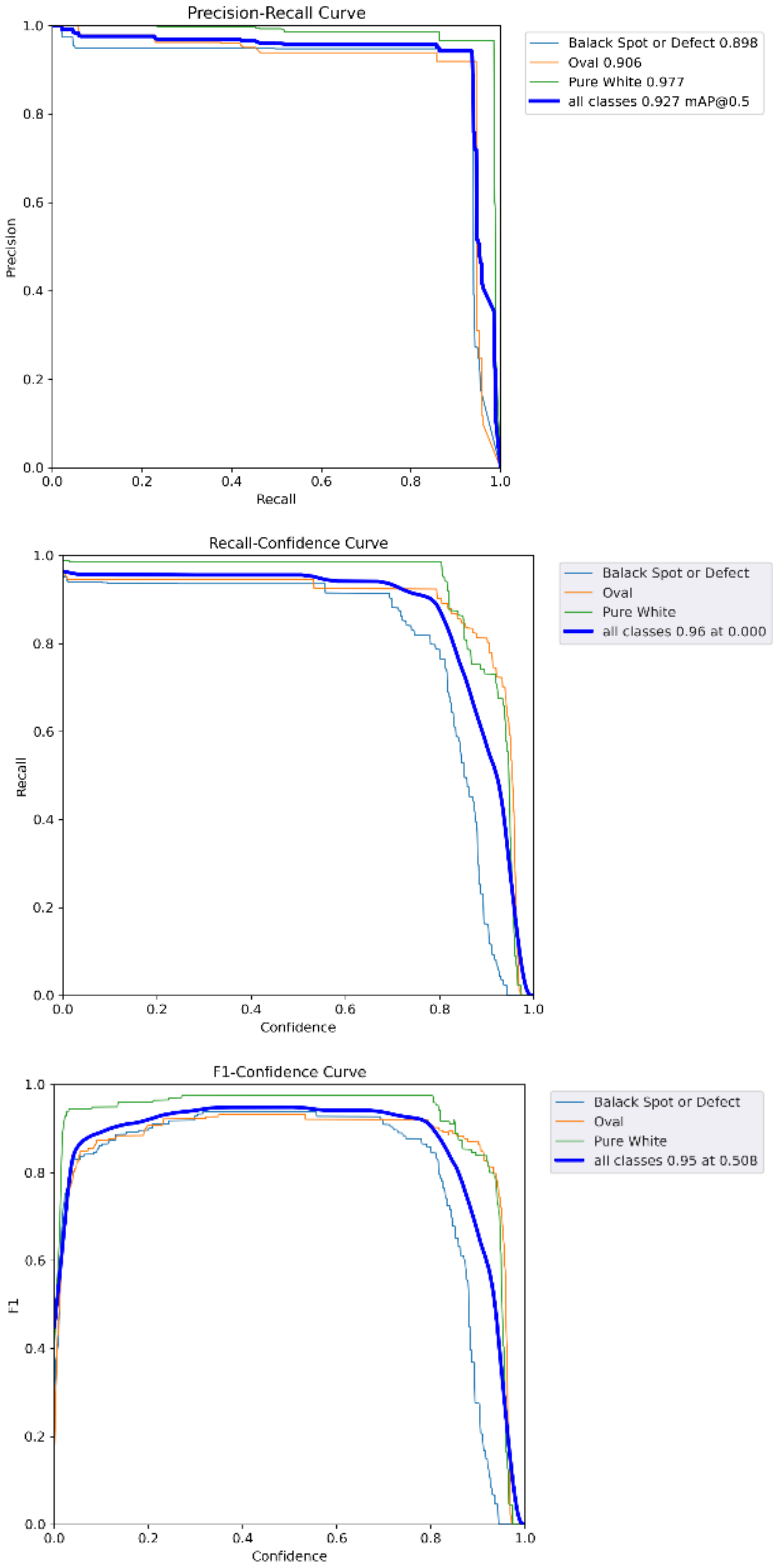


Figure 7. Evaluation of Straw Mushroom Classification Using Precision, Recall, and F1-Score (No Preprocessing Applied)

Based on Fig. 7, the model without preprocessing demonstrates relatively good performance, with an mAP@0.5 of approximately 0.927. Precision and recall across all classes are fairly high, although recall decreases at higher confidence levels. The optimal F1-score is around 0.95 at a confidence threshold of approximately 0.508, indicating a reasonably balanced trade-off between precision and recall.

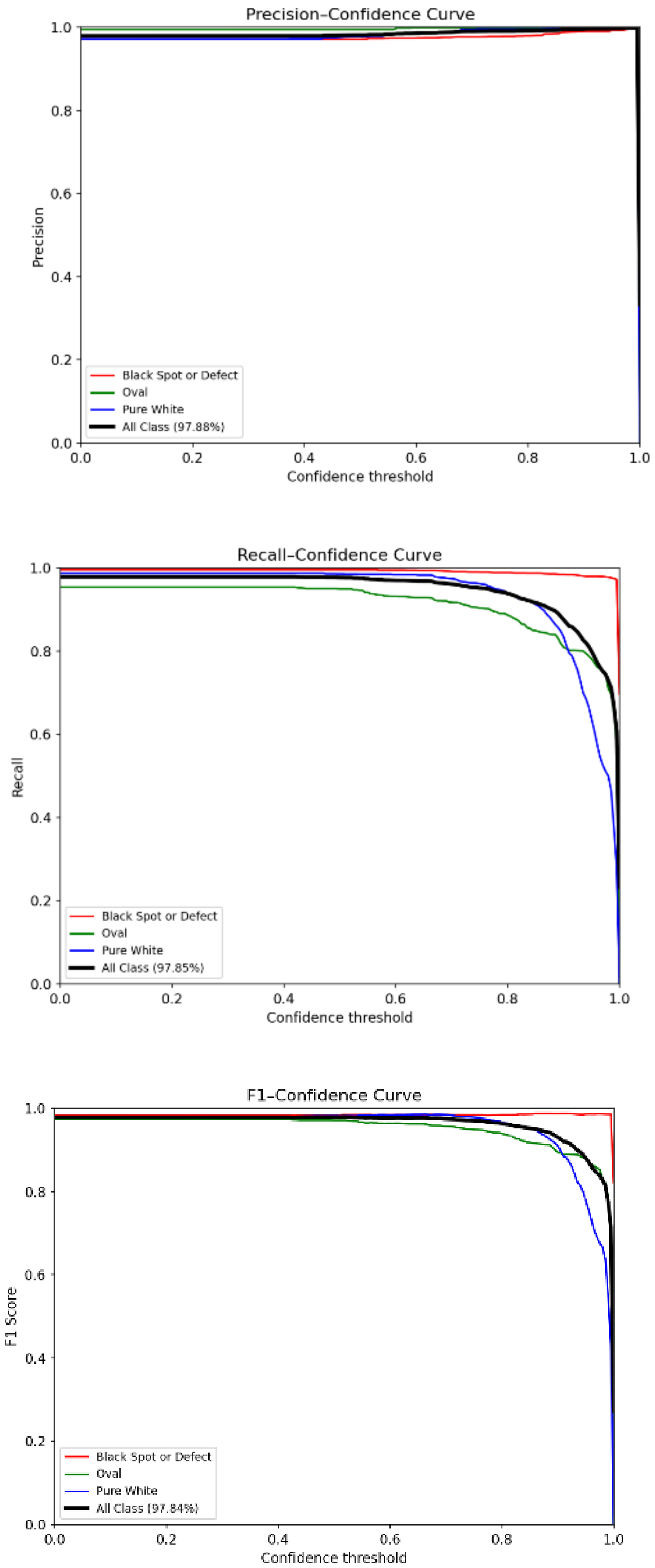


Figure 8. Evaluation of Straw Mushroom Classification Using Precision, Recall, and F1-Score (Standard White Balance (WB) Applied)

Based on Fig. 8, the model with Standard White Balance (WB) preprocessing shows good performance, with precision, recall, and F1-score values around 0.978. Recall slightly decreases at higher confidence levels, with the optimal F1-score of approximately 0.978 achieved at a threshold of 0.95–0.97, indicating a good balance between precision and recall.

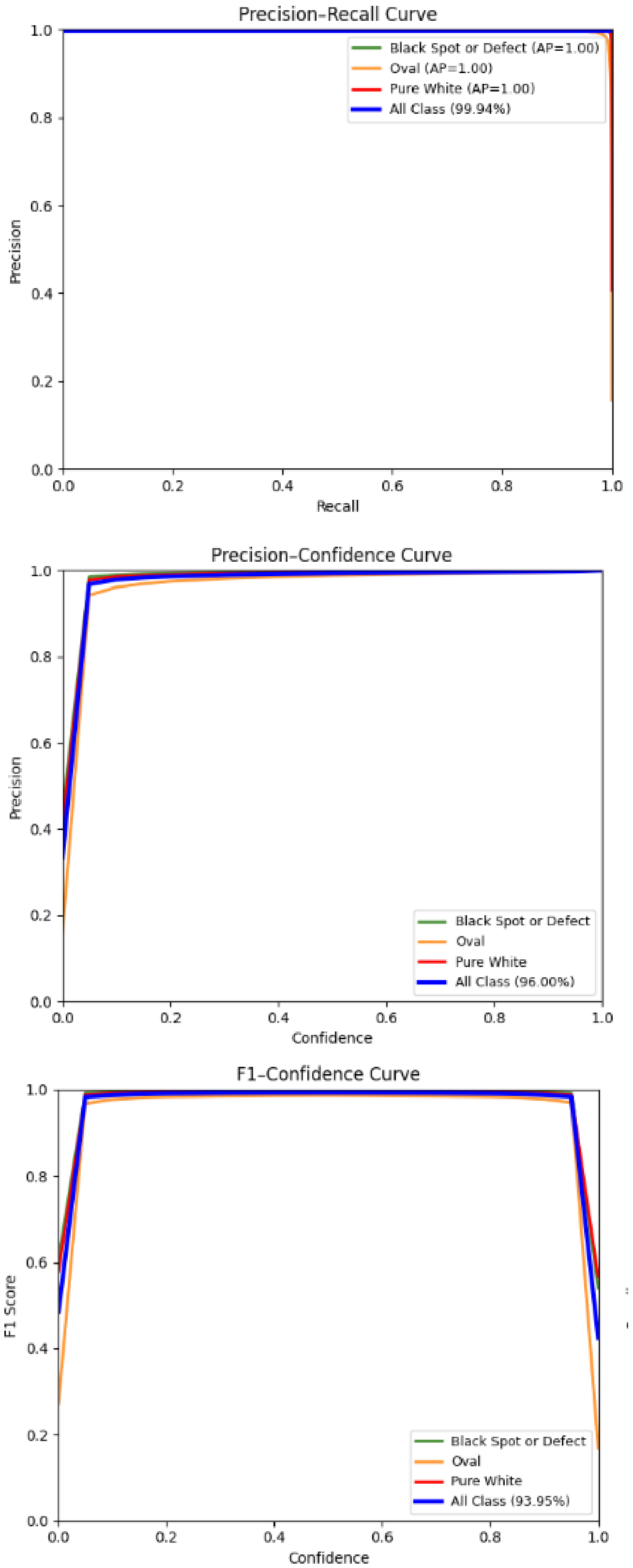


Figure 9. Evaluation of Straw Mushroom Classification Using Precision, Recall, and F1-Score (Hybrid White Balance Applied)

Based on Fig. 9, the model with Hybrid White Balance (HWB) preprocessing demonstrates very high performance, with precision approaching 0.996 and an F1-score of approximately 0.9395. The precision-recall curve indicates an AP of 1.00 for each class, resulting in an overall mAP of around 0.994. However, the F1-score slightly decreases at very high confidence levels. The optimal F1-score is achieved within a mid-range confidence threshold (around 0.1–0.9), indicating an excellent balance between precision and recall.

4. CONCLUSION

The proposed Hybrid White Balance (HWB) method is effective in improving the visual quality of straw mushroom images by enhancing color consistency and performing illumination correction during the preprocessing stage.

Experimental results evaluated using MSE, PSNR, and SNR metrics demonstrate that the HWB method consistently outperforms the standard White Balance approach, as indicated by lower MSE values and higher PSNR and SNR values, which reflect reduced reconstruction errors and improved image clarity and signal quality.

Comparative analysis confirms that improved image quality contributes to more reliable visual representations, which are essential for downstream tasks such as segmentation, feature extraction, and classification.

In classification performance, the model without preprocessing achieved an mAP@0.5 of approximately 0.927, while the use of Standard White Balance improved performance to around 0.978 in terms of precision, recall, and F1-score. The best results were obtained using the Hybrid White Balance method, which achieved near-perfect precision (≈0.996), an mAP of approximately 0.994, and strong F1-score performance, indicating a more robust and accurate classification capability.

Despite its strong performance, this study has limitations, including the use of a dataset restricted to straw mushroom images and the absence of subjective visual quality evaluation.

Future work is expected to address these limitations by applying the proposed method to more diverse datasets, incorporating perceptual evaluation metrics, and exploring adaptive or deep learning-based enhancement techniques to further improve robustness and generalization performance.

Author Contributions

Bayu Priyatna: Formal analysis, Data curation, Resources, Writing - Original Draft. Titik Khawa Abdurahman: Methodology, Investigation. April Lia Hananto: Funding Acquisition. Aviv Yuniar Rahman: Visualization, Writing – Original Draft. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Declaration of Generative AI and AI-assisted technologies

ChatGPT was utilized only to improve the readability and grammatical structure of the manuscript. No AI tool was used to generate or alter the research data, methodology, results, or interpretations. All content was verified by the authors for accuracy and consistency with the study.

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