Journal of Applied Data Sciences
Vol. 7, No. 2, May 2026, pp. 967-982

Improved Hybrid GoogLeNet-Based Deep Learning Optimization for Standardized Straw Mushroom Quality Classification in Indonesia

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(Received: October 10, 2025; Revised: December 10, 2025; Accepted: February 27, 2026; Available online: March 17, 2026)

Abstract

Deep learning plays a crucial role in modern computer vision due to its ability to automatically extract hierarchical features from large-scale image data. Among various architectures, Convolutional Neural Networks (CNNs) have been extensively utilized for image pattern interpretation, including in agricultural product inspection. Straw mushrooms (Volvariella volvacea) are important agro-industrial commodities in Indonesia, however, their quality assessment still relies on subjective manual evaluation based on the Indonesian National Standard (SNI:01-6945-2003), leading to inconsistency in grading results. To address this limitation, this research proposes an Improved Hybrid GoogLeNet model integrated with a YOLO-based detection framework and hybrid preprocessing to enhance feature clarity and classification robustness. The proposed system applies a hybrid image preprocessing pipeline consisting of colour distortion reduction, white balance correction, and intensity normalisation to enhance feature clarity under varying illumination. The system is capable of conducting object detection, 3-class morphological quality classification (Pure White, Oval, and Black Spot/Defect), and automatic diameter measurement using calibrated pixel-to-centimeter conversion. Performance evaluation is carried out by benchmarking the proposed model against several popular deep learning architectures including YOLOv5, LeNet, AlexNet, VGGNet, and ResNet. Experimental results demonstrate that the Improved Hybrid GoogLeNet achieves the highest performance with precision of 97.99%, recall of 96.07%, and F1-score of 96.98%, along with low misclassification rates across all classes. These results indicate that the proposed method provides accurate, reliable, and efficient quality assessment that supports standardized automated grading in industrial applications. Therefore, this study contributes to the advancement of intelligent computer vision solutions for digital transformation in the Indonesian mushroom agro-industry.

Keywords: Deep Learning, Straw Mushroom, Improved Hybrid GoogLeNet, CNN, YOLOv5, Quality Classification, Computer Vision, SNI Standards.

1. Introduction

Deep learning is a subfield of machine learning that employs multi-layered neural network algorithms to automatically learn and extract information from large amounts of data. This technology has demonstrated outstanding capabilities in various domains such as facial recognition, speech recognition, natural language processing, and image pattern analysis [1]. Among the most widely adopted deep learning architectures for image interpretation tasks is the Convolutional Neural Network. CNNs possess the ability to extract hierarchical visual features automatically, shifting the paradigm of image processing from manual feature engineering toward fully data-driven learning approaches [2].

In addition to classification-oriented CNNs, object detection frameworks such as You Only Look Once have gained significant popularity due to their ability to detect multiple objects from a single image in real time without relying on region proposal mechanisms [3]. Deep learning has emerged as the dominant computational approach in computer vision applications due to its effectiveness in analyzing large-scale datasets and achieving human-level performance in several complex cognitive tasks [4]. Among these deep learning architectures, GoogLeNet has exhibited high

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DOI: https://doi.org/10.47738/jads.v7i2.1206

recognition accuracy with efficient parameter usage through its Inception structure, which extracts multi-scale features while maintaining lower computational cost. Its success in various agricultural and food-quality inspection tasks provides a strong foundation for further adaptation and improvement.

Straw mushrooms (Volvariella volvacea) are one of the most widely consumed edible mushrooms in Indonesia due to their high nutritional value, desirable taste, and increasing use in various culinary and processed food industries, including snacks and ready-to-cook products [5]. This mushroom species contains protein comparable to meat and higher carbohydrate content than potatoes, while also having the advantage of sustainable cultivation with limited land resources [6], [7], [8], [9]. With strong market demand and economic potential, straw mushrooms have become a promising agro-industry commodity in Indonesia [10].

However, determining the quality grade of straw mushrooms remains challenging for local farmers, especially in post-harvest handling. Insufficient knowledge regarding standardized quality grading often leads to misclassification, causing difficulties in distribution and price reductions that impact farmers' income [11], [12]. The Indonesian National Standard SNI:01-6945-2003 regulates quality classification based on weight, size uniformity, shape, flesh color, and skin color (BSNI, 2013). In this work, the standard is operationalised by aligning each grading parameter with measurable visual cues and system outputs: colour-related criteria are supported through colour distortion reduction, white balance correction, and intensity normalisation, shape and morphological conformity are learned via class prediction within the detected region of interest, and size-related requirements are represented by automatic cap-diameter measurement using calibrated pixel-to-centimetre conversion. Visible nonconformities related to cleanliness and defects are captured as surface irregularities and spot patterns in the localized mushroom region. Yet, the quality inspection process is still performed manually through visual observation, which is highly subjective, inefficient, and inconsistent, particularly under commercial-scale production, [12], [13]. Therefore, automated computer vision-based inspection is required to improve accuracy, consistency, and operational efficiency [14].

Several studies have attempted to support mushroom quality and safety evaluation through computer vision. YOLOv5 combined with PS-Net has been employed for real-time measurement of mushroom size, reducing human subjectivity [15], [16]. Ensemble machine learning techniques have been adopted to classify poisonous mushrooms [17], while fungal growth detection using YOLOv5 achieved recognition accuracy up to 76.5 percent [18], [19]. Nevertheless, research specifically addressing automated quality classification of straw mushrooms based on the Indonesian National Standard remains limited. Furthermore, no existing study has focused on optimizing the GoogLeNet architecture for this targeted classification scenario [20], [21].

Although GoogLeNet has demonstrated strong recognition performance with efficient parameter usage, existing GoogLeNet variants remain insufficient for standardized straw mushroom grading under real post harvest conditions. Most implementations rely on whole image classification, making the model sensitive to background clutter, illumination changes, and the presence of multiple mushrooms or non-target objects in a single frame. Moreover, the Indonesian National Standard requires assessment of fine-grained and object specific attributes such as size uniformity, shape, and subtle color cues on the mushroom surface, which are easily diluted when the target region is not explicitly localized. Consequently, a purely classification-based GoogLeNet pipeline may yield unstable feature representations and increased confusion between adjacent quality grades. These limitations motivate a hybrid approach that first isolates the mushroom region and then performs refined classification on the standardized region of interest, enabling clearer feature extraction and improved robustness to real-world variability.

To address this research gap, this study proposes an Improved Hybrid GoogLeNet architecture for standardized straw mushroom quality classification. The proposed model enhances the structural layers of the original GoogLeNet while incorporating a hybrid preprocessing pipeline designed to improve feature clarity and reduce the risk of overfitting [22], [23], [14]. Performance evaluation will be conducted by benchmarking the proposed model against several widely used deep learning architectures in computer vision including You Only Look Once, LeNet, standard GoogLeNet, AlexNet, VGGNet, and ResNet to validate overall improvements in both accuracy and computational efficiency [24], [25], [26].

ISSN 2723-6471

This research is expected to contribute to automated mushroom quality assessment aligned with the Indonesian National Standard and support digital transformation efforts in the national agro-industry sector through intelligent computer vision technologies.

2. Literature Review

The classification workflow begins with the utilization of a ready-to-use dataset that is fed into the classification pipeline. In the GoogLeNet, the fully connected (classifier head) layer is replaced to adapt the network to the three target quality classes. YOLO-based object detection is employed to extract Regions of Interest (ROI) from mushroom images prior to the classification process. In addition, diameter measurement is performed as an auxiliary feature to support physical quality assessment. The same dataset is also used to evaluate and compare the performance of other models, including LeNet, AlexNet, VGG [22], ResNet, and YOLO. Training and validation processes are conducted to ensure that the models produce reliable and accurate classification outputs. The classification stage follows a structured workflow using various CNN models, as illustrated in figure 1.

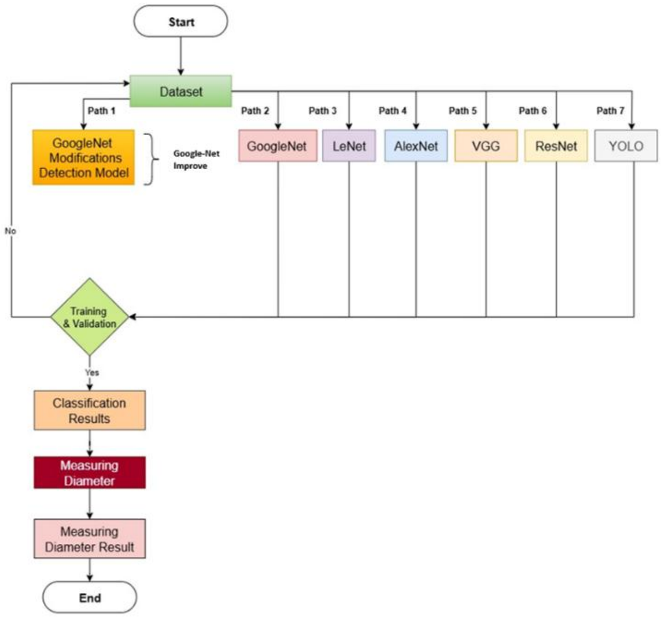


Figure 1. Stages of straw mushroom quality classification

Figure 1 the process in the flowchart begins with the preparation of a dataset that is ready to be classified. The first path involves the improvment of the GoogleNet Modification Detection Model to improve classification accuracy, followed by the improvment of GoogleNet itself. From here, the process splits into six paths, each using a different CNN model, namely GoogleNet, LeNet, AlexNet, VGG, ResNet, and YOLO. After selecting the model, the next step is Training & Validation to ensure valid classification results. Then, the classification results are evaluated, followed by an additional step to measure the diameter of the straw mushroom objects. The process ends with the collection of the classification results and the obtained diameter measurements. This diagram provides a structured approach to comparing the performance of various CNN models in classifying straw mushrooms with varying accuracy. This process ends with classification results that show the best performance of each model tested.

In the analysis section, classifying straw mushrooms with the CNN model involves two main activities: data training and data validation. In data training, models such as the improved GoogleNet and standard models such as LeNet, AlexNet, VGG, ResNet, and YOLO are trained using the dataset to recognize straw mushroom patterns and optimize model parameters. After that, data validation is carried out to test the model's performance on new data that has not been seen, using metrics such as accuracy, precision, and recall to ensure that the model is not overfitting and can generalize well. This stage aims to produce an accurate and reliable classification model according to quality standards.

Figure 2 illustrates the flowchart of the improvement of the GoogLeNet and hybrid models with YOLOv5, as well as the detector adjustments using ROI in the comparison models, including LeNet, AlexNet, VGG, and ResNet.

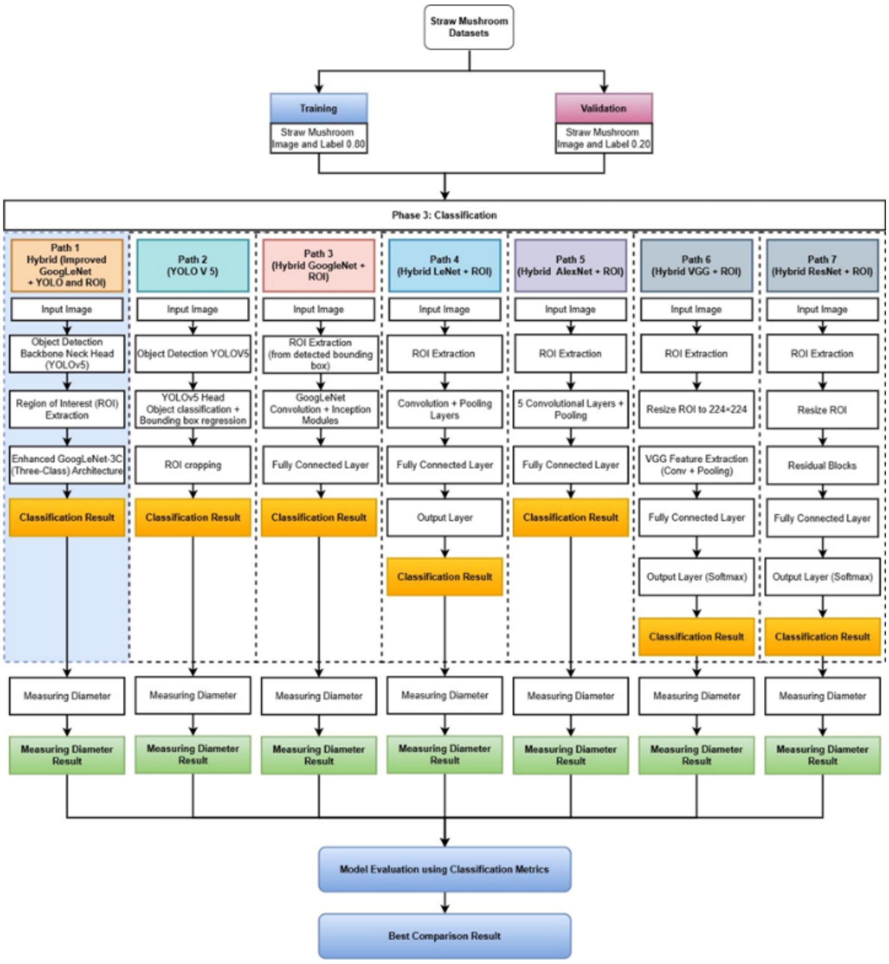


Figure 2. Straw Mushroom Classification Workflow

Figure 2 in this study, a total of 1350 images were used, corresponding to 12150 straw mushroom objects extracted from the image dataset. The collected dataset was then divided into two subsets, with 80% (9720 objects) allocated for training and 20% (2430 objects) for validation. This split was determined during the dataset preparation stage to ensure a consistent evaluation process. The validation dataset was not involved in the training phase and was used solely to assess the performance of the proposed model, ensuring that the evaluation reflects the model's generalization ability on previously unseen data.

All images were acquired using a digital camera with a resolution of 800 × 600 pixels under controlled lighting conditions, utilizing white LED lights at 121 lux in an enclosed room, and captured from a fixed top-down viewpoint. These lighting conditions produced a Mean Pixel Intensity (MPI) of 128.4, which served as a reference for lighting quality during dataset acquisition, ensuring consistent illumination and minimizing lighting variations that could affect detection and classification processes.

To clarify the integration strategy between object detection and classification, the proposed system employs a sequential processing pipeline as described below, in which YOLOv5 and GoogLeNet operate as independent modules without parameter sharing or end-to-end joint training. YOLOv5 is executed first to perform object localization and generate bounding box coordinates, which are then used to extract regions of interest (ROI). The extracted ROIs are subsequently processed and classified exclusively by the modified GoogLeNet classifier head, with no feedback or gradient propagation from the classification stage back to the detection model.

Each pathway in the straw mushroom classification workflow begins with input images obtained from the training and validation datasets. The first pathway applies an improved GoogLeNet classifier head (3-Class) combined with YOLO-based detection and region-of-interest (ROI) extraction, in which YOLO functions as an object localization module to generate ROIs, while the classification process is entirely performed by the modified GoogLeNet classifier head. This pathway differs from the GoogLeNet+ROI approach in that the classifier head is specifically modified and fine-tuned for the target classes, whereas the GoogLeNet+ROI model employs the standard GoogLeNet architecture applied to the extracted ROIs without additional modification to the classifier head. The second pathway utilizes the full YOLOv5 pipeline for both detection and classification. Pathways three through seven adopt an ROI-first extraction approach, followed by classification using various CNN architectures, namely Hybrid GoogLeNet+ROI, Hybrid LeNet+ROI, Hybrid AlexNet+ROI, Hybrid VGGNet+ROI, and Hybrid ResNet+ROI. After the classification stage is completed, all pathways proceed to the diameter measurement process to obtain physical size information of the mushrooms. The diameter measurement results are then evaluated together with classification performance metrics to determine the most effective model in terms of object detection, quality classification, and straw mushroom size measurement.

2.1. Classification Result

Following the training and validation processes, the classification outcomes are analyzed to assess the effectiveness of each model in classifying straw mushrooms according to the given dataset. In the subsequent evaluation stage, performance metrics such as accuracy, precision, recall, F1-score, and expert agreement are utilized to compare each model quantitatively [27], [28]. This assessment identifies the most reliable model with minimal misclassification rates and determines its suitability for real-world application in agricultural and industrial fields.

2.2. Diameter Measurement Process

The diameter measurement stage is carried out after the classification results are obtained, aiming to extract physical dimension information as an indicator of product quality and suitability. The system retrieves the coordinates or region of the detected mushroom object, followed by a segmentation process to isolate the relevant area. The diameter is then calculated using bounding-box geometry or other appropriate geometric methods. The following equation represents the pixel-per-centimeter calculation.

$$pixels\_per\_cm = \frac{pixel\_size}{actual\_size(cm)} \quad (1)$$

To ensure accurate physical dimension representation, a calibration step is implemented using the pixels-per centimeter (px/cm) value, which converts pixel-based size measurements into real-world units in centimeters.

2.3. Diameter Measurement Result

The resulting diameter values are expressed in centimeters based on the calibration scale used in the imaging system. These measurements can be visualized in tables or graphs to observe dimensional patterns and variations across different samples. Such information provides valuable insights for automated sorting, quality control, and further applications in agricultural and industrial sectors related to straw mushroom production and processing.

3. Methodology

The optimized GoogleNet model served as the primary classifier, accompanied by performance comparisons with LeNet, AlexNet, VGG, ResNet, and YOLO to evaluate the strengths and weaknesses of each architecture in detecting mushroom objects. The analysis process was conducted through training and validation using a standardized dataset to ensure the model's ability to recognize each class with high accuracy according to the required quality standards. In addition to classification, the diameter of the detected objects was also measured as supplementary information related to the dimensions of the mushrooms.

The visualization of the annotated dataset distribution in figure 3 illustrated the variations of straw mushroom objects used in the model development, categorized into three main quality classes, thereby supporting a comprehensive analysis of classification performance.

ISSN 2723-6471

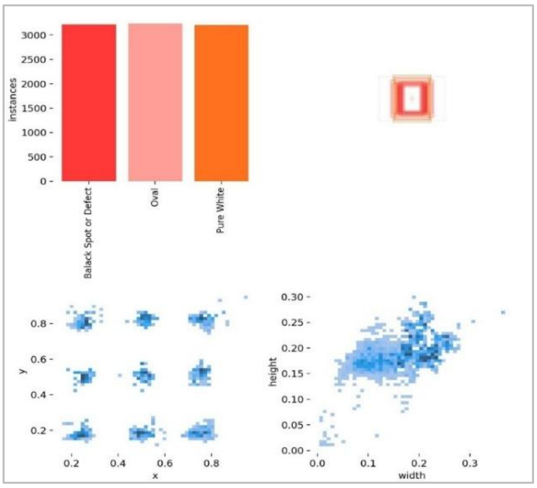


Figure 3. Category Distribution of Annotated Straw Mushroom Images

Figure 3 presented a balanced distribution of straw mushroom image datasets across three main categories Black Spot or Defect, Oval, and Pure White each consisting of approximately 3240 samples after the annotation and preprocessing stages. This balanced dataset minimized class imbalance and ensured that model training was conducted without bias toward any specific category. The analysis also confirmed that the dataset met the required representativeness criteria and was ready to be used in the subsequent detection and classification training stages. Figure 4 Workflow of Path 1 Using the Improved Hybrid GoogleNet Model for 3-Class Classification

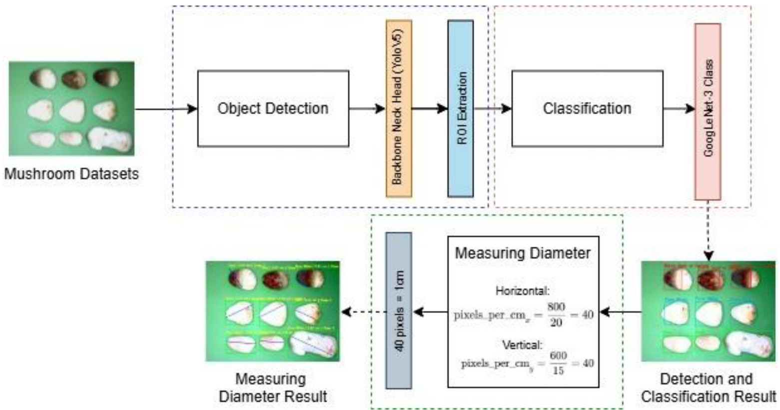


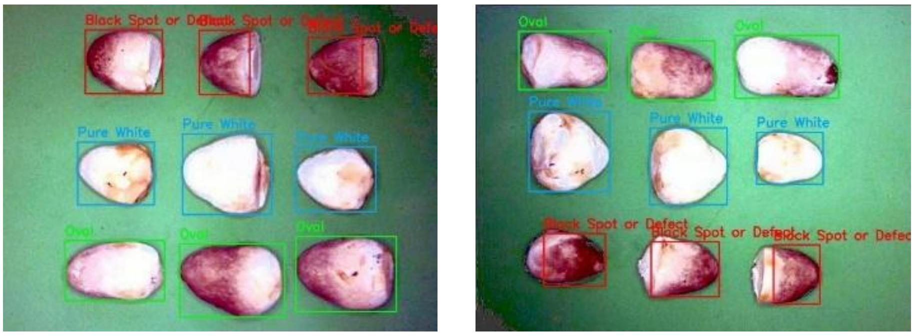
Figure 4. Workflow of the Improved Hybrid GoogleNet Model for 3-Class

Figure 4 presents the workflow of the proposed straw mushroom classification system. Input images from the dataset are first processed using YOLO-based object detection to localize straw mushroom objects and extract regions of interest (ROIs). The extracted ROIs are then classified using GoogLeNet with a modified classifier head tailored to three target quality classes. The classification results are visualized through bounding boxes and corresponding class labels. In addition, the ROIs are used to measure mushroom diameter based on pixel-to-length conversion, providing physical size information. The final outputs include detection results, quality classification, and diameter measurements, demonstrating the effectiveness of the proposed approach in integrating object detection, classification, and physical attribute assessment.

3.1. Object Detection Backbone Neck Head YOLOv5

At this stage, the object detection process was conducted using the pretrained YOLOv5 architecture, which internally consists of three main components: Backbone, Neck, and Head. These components were employed in their standard configuration without any additional fine-tuning. The Backbone automatically extracts visual features from straw mushroom images, including shape, color distribution, and cap surface characteristics. The extracted features are then processed by the Neck to integrate multi-scale representations, enabling robust object localization across variations in mushroom size and orientation. Subsequently, the Head generates detection outputs in the form of bounding box coordinates and corresponding class labels, which are used exclusively for object localization and region-of-interest (ROI) extraction prior to the classification stage.

The detection results are presented in figure 5, which illustrates examples of YOLOv5 outputs in localizing straw mushroom objects and assigning preliminary labels corresponding to quality-related categories, namely Black Spot or Defect, Oval, and Pure White.



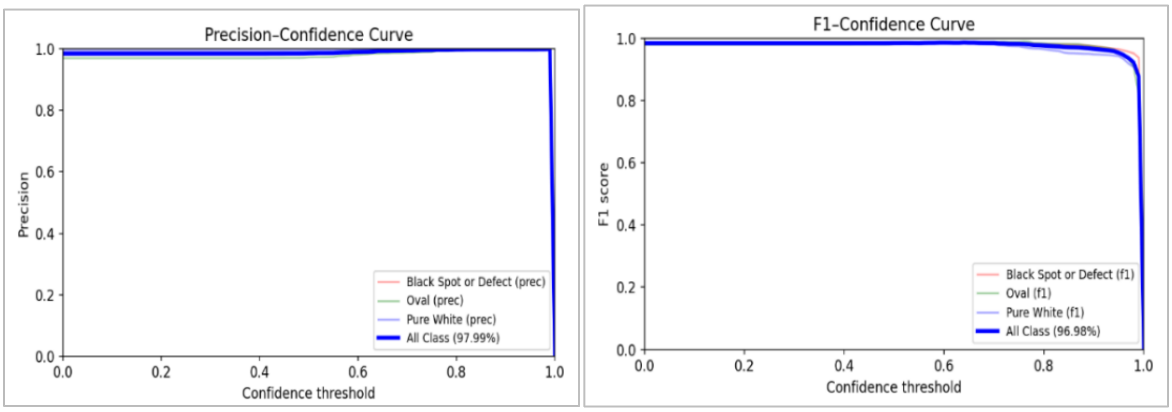
(a) Smple Mushroom 1.jpg (b) Smple Mushroom 2.jpg

Figure 5. Straw Mushroom Object Detection Results Using YOLOv5 Based

Figure 5 presents examples of detection and quality classification results for straw mushrooms produced by the proposed system. Each detected mushroom object is indicated by a colored bounding box and an associated quality class label, namely Black Spot or Defect, Pure White, and Oval. The different bounding box colors represent distinct quality categories, facilitating clear visual interpretation of the classification outcomes. The results demonstrate that the system is capable of simultaneously detecting and classifying multiple mushroom objects within a single image with a high level of consistency across various shapes and surface conditions. Mushrooms exhibiting dark spots or surface defects are correctly classified as Black Spot or Defect, while mushrooms with clean and bright surfaces are identified as Pure White, and those with elongated shapes are categorized as Oval. This visualization highlights the effectiveness of integrating YOLO-based object detection with GoogLeNet-based classification using a modified classifier head for comprehensive straw mushroom quality assessment.

3.2. Classification of Straw Mushroom Using Improved GoogLeNet-3C

The model's performance was evaluated using precision, recall, and F1-score on a per-class and macro-average basis to comprehensively assess its classification capability. The Enhanced GoogLeNet-3C model demonstrated high accuracy in detecting the Pure White and Oval classes, while performance variations occurred in the Black Spot or Defect class due to the complexity of spot patterns. Visualizations through the confusion matrix and Precision-Recall curves confirmed the model's ability to recognize essential features of the mushroom cap, as illustrated in figure 6.



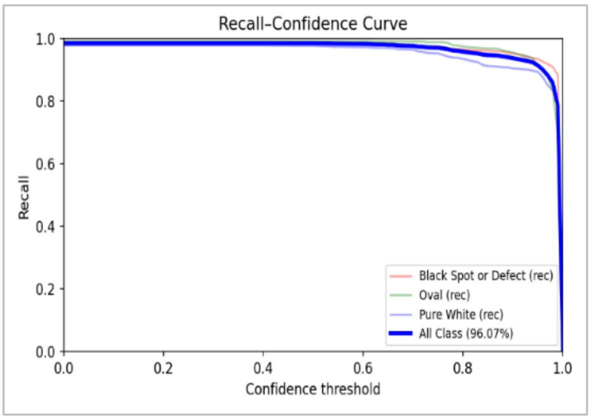


Figure 6. Performance Evaluation of the Image Detection Model Based on Precision, Recall, and Confidence Metrics

Figure 6 the detection model performance was evaluated using the Precision-Confidence, F1-Confidence, and Recall-Confidence curves, all of which showed consistently high values close to 1.0 across the confidence threshold range. The model achieved an overall precision of 97.99%, an F1-score of 96.98%, and a recall of 96.07%, indicating accurate, balanced, and reliable detection across all mushroom classes. Although confidence intervals were not explicitly calculated, the proposed model shows consistent performance across all classes as reflected in the confusion matrix and confidence-based evaluation curves, indicating stable classification behavior. These results confirmed that the model was highly stable in distinguishing the three categories, as also supported by the confusion matrix presented in figure 7.

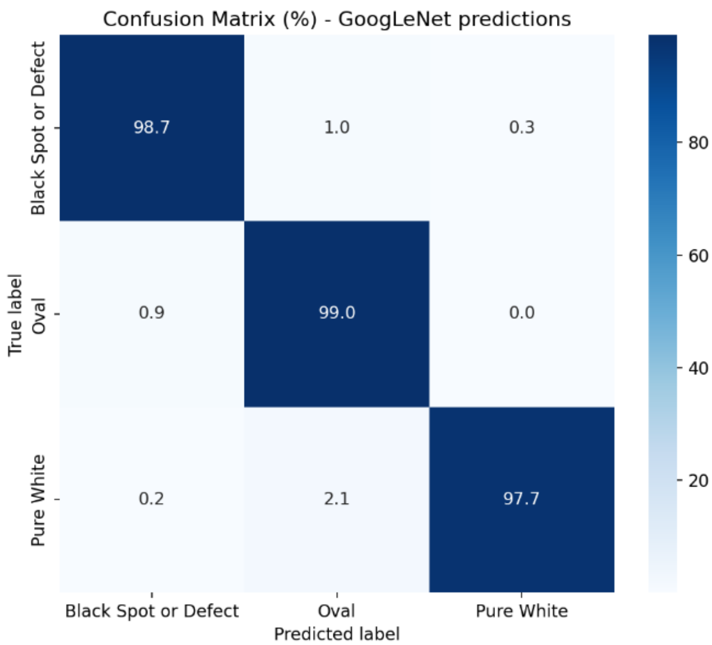
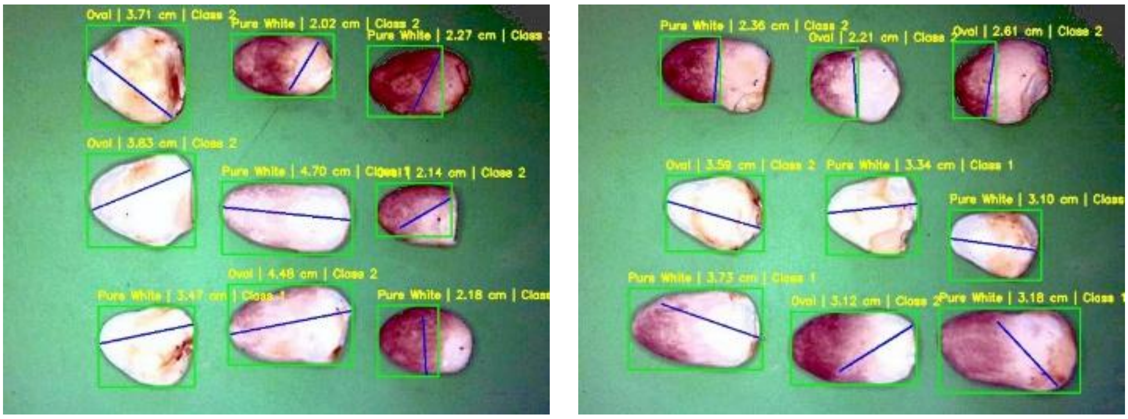


Figure 7. Classification Performance Confusion Matrix Improved GoogleNet (3 Classes)

Figure 7 the confusion matrix in figure 7 demonstrated high classification accuracy for all three classes-98.7% for Black Spot or Defect, 99.0% for Oval, and 97.7% for Pure White-indicating that the model provided excellent stability and reliability with minimal misclassification.

3.3. Measuring Diameter Straw Mushroom

The diameter of the straw mushrooms was measured automatically using YOLOv5 object detection and image processing to obtain accurate and consistent diameter values without manual measurement, with a calibration factor of pixels_per_cm = 40. The obtained diameter values were then integrated with the morphological classification results (color and shape) generated by the Improved Hybrid GoogLeNet model to determine the quality categories of the straw mushrooms. Mushrooms classified as Pure White with diameters ranging from 3 to 5 cm were categorized as Class 1, while those outside this range were categorized as Class 2. Figure 8 presented the integrated results of diameter measurement and morphological classification.



(a) Smple_Mushroom_206.jpg (b) Smple_Mushroom_252.jpg

Figure 8. Integrated Results of Diameter Measurement and Morphological Classification of Straw Mushrooms Using the Impuved Hybrid GoogLeNet Model

Figure 8 all measurement data were stored in tabular format and visualized using a strip plot to illustrate the diameter distribution according to morphological criteria and quality class. Hence, this system not only identifies the visual characteristics of straw mushrooms but also performs automatic, accurate, and standardized quantitative diameter measur-ement. Table 1 shows the results of the diameter measurements of straw mushrooms.

Table 1. Results of Straw Mushroom Diameter Measurement and Quality Classification

No	Filename	Object	Mushroom Diameter (cm)	Criteria	Quality
1	Sample(1).jpg	1	3.45	Oval	Class 2
2	Sample(1).jpg	2	4.31	Pure White	Class 1
3	Sample(1).jpg	3	5.14	Pure White	Class 2
4	Sample(1).jpg	4	3.52	Pure White	Class 1
5	Sample(1).jpg	5	3.01	Black Spot or Defect	Class 2
6	Sample(1).jpg	6	4.32	Oval	Class 2
7	Sample(1).jpg	7	2.55	Black Spot or Defect	Class 2
8	Sample(1).jpg	8	3.8	Oval	Class 2
9	Sample(1).jpg	9	2.62	Black Spot or Defect	Class 2
…	…	...			
9712	Sample(999).jpg	1	3.25	Pure White	Class 1
9713	Sample(999).jpg	2	2.52	Oval	Class 2
9714	Sample(999).jpg	3	5.35	Pure White	Class 2
9715	Sample(999).jpg	4	2.96	Oval	Class 2
9716	Sample(999).jpg	5	3.96	Oval	Class 2
9717	Sample(999).jpg	6	3.8	Pure White	Class 1
9718	Sample(999).jpg	7	4.47	Black Spot or Defect	Class 2
9719	Sample(999).jpg	8	4.93	Black Spot or Defect	Class 2
9720	Sample(999).jpg	9	3.35	Black Spot or Defect	Class 2

Based on the table 1, each image contains multiple detected mushroom objects with varying diameters. Mushroom quality is classified into Class 1 and Class 2, where the Pure White criterion is generally categorized as Class 1, while Oval and Black Spot or Defect criteria are classified as Class 2, indicating that quality assessment is influenced not only by diameter but also by visual characteristics. Figure 9 presents the diameter distribution according to the morphological criteria and quality classification of straw mushrooms.

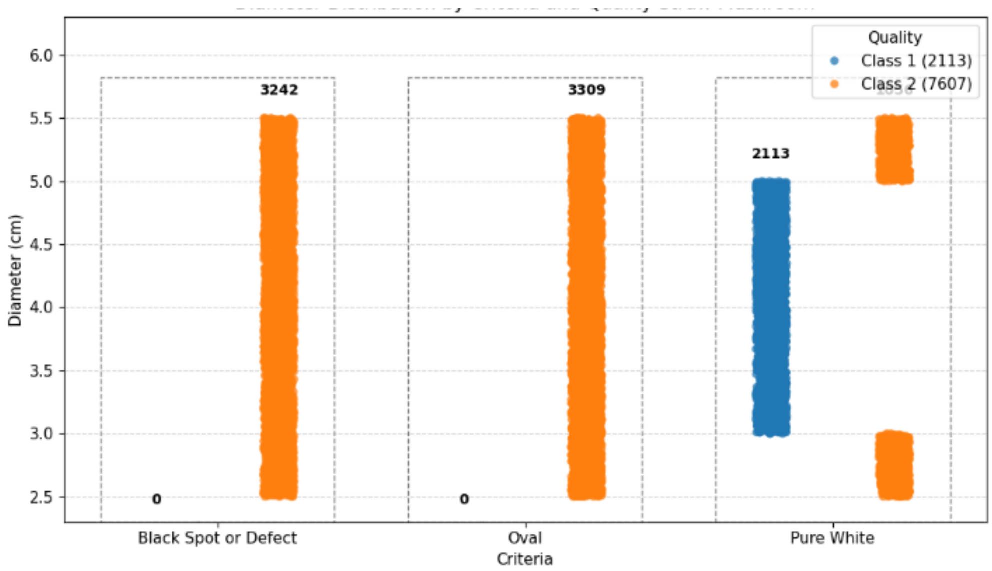


Figure 9. Diameter Distribution of Straw Mushrooms Based on Morphological Criteria and Quality

Figure 9 presents the results obtained from the Improved Hybrid GoogLeNet classification model and the diameter measurements of the straw mushrooms. The figure shows that the Pure White category is predominantly composed of Class 1 mushrooms, totaling 2113 samples, with diameters mostly ranging from 3 to 5 cm, indicating superior quality and consistent morphological characteristics. In contrast, the Black Spot or Defect and Oval categories are dominated by Class 2 mushrooms, comprising 3242 and 3309 samples, respectively, which display surface defects or irregular shapes that reduce their quality. Overall, the dataset consists of 9720 samples, with 2113 (21.7%) classified as Class 1 and 7607 (78.3%) classified as Class 2.

These results demonstrate that mushroom quality is strongly correlated with morphological characteristics and diameter size, confirming the accuracy and reliability of the hybrid Improved Hybrid GoogLeNet model in differentiating the quality grades.

3.4. Comparasion of Results

A comprehensive evaluation was conducted on the precision, recall, and F1-score values of all tested classification models, including Improved Hybrid GoogLeNet-3C, YOLOv5, GoogLeNet + ROI, LeNet+ ROI, AlexNet + ROI, VGGNet + ROI, and ResNet + ROI, to provide a clearer overview of their performance in accurate and balanced class identification. A confusion matrix analysis was also performed to observe prediction-error patterns and assess each architecture's ability to distinguish visually similar classes. The comparative performance results of all models were presented in table 2.

Table 2. Precision, Recall, and F1-Score Comparison Across Models

Model	**All**			
	Precision	**Recall**	**F1-Score**	**Average**
Improved Hybrid GoogLeNet 3-C	97.99%	96.07%	96.98%	97,01%
YOLOv5	92.07%	96.00%	95.00%	94,36%
Hybrid GoogLeNet+ROI	95.00%	95.49%	94.98%	95,16%
Hybrid LeNet+ROI	96.00%	95.72%	93.95%	95,22%
Hybrid AlexNet+ROI	90.16%	90.04%	90.07%	90,09%
Hybrid VGGNet+ROI	91.37%	91.07%	91.07%	91,17%
Hybrid ResNet+ROI	98.33%	94.07%	94.27%	95,56%

Based on the table 2, evaluation results, the Improved Hybrid GoogLeNet 3-C stands out as the best-performing model with an average of 97.01%, supported by a high precision of 97.99% and an F1-score of 96.98%, demonstrating balanced performance in accurate class identification. YOLOv5 shows a high recall of 96.00%, but its lower precision of 92.07% indicates a tendency for false positive predictions. Hybrid GoogLeNet+ROI and Hybrid LeNet+ROI exhibit balanced performance with averages of 95.16% and 95.22%, although the F1-score of LeNet+ROI is slightly lower (93.95%), reflecting some imbalance between precision and recall for certain classes. Hybrid AlexNet+ROI has the lowest performance (average 90.09%), suggesting difficulty in distinguishing visually similar classes, while Hybrid VGGNet+ROI performs slightly better (average 91.17%). Interestingly, Hybrid ResNet+ROI achieves very high precision (98.33%) but lower recall (94.07%), resulting in an F1-score of 94.27%, indicating high selectivity but some missed samples. Overall, the Improved Hybrid GoogLeNet 3-Class excels as the most balanced model, whereas the other models show specific strengths but remain limited in overall performance. The following is the model ranking result as shown in figure 10 based on Precision, Recall, and F1 Score.

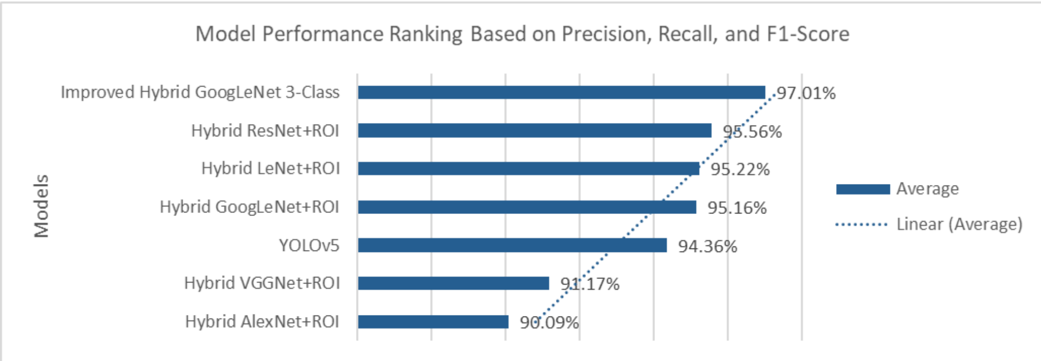
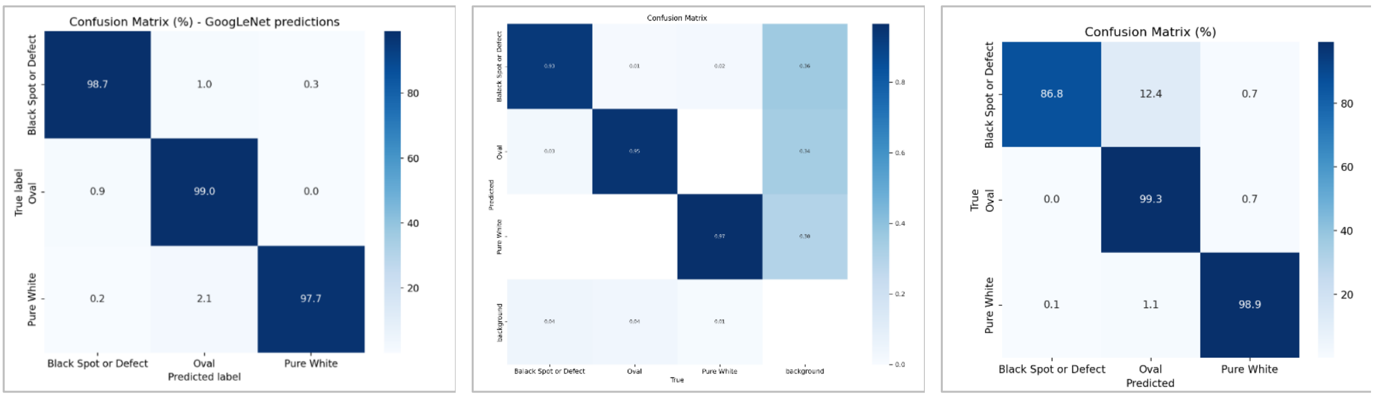


Figure 10. Performance Ranking of Models Based on Precision, Recall, and F1 Score

Based on the figure 10 average values (mean of precision, recall, and F1-score), Improved Hybrid GoogLeNet 3-C ranks the highest with an average of 97.01%, indicating the most consistent and superior performance compared to the other models. It is followed by Hybrid ResNet+ROI, Hybrid LeNet+ROI, and Hybrid GoogLeNet+ROI, which achieve averages in the 95% range, reflecting high and relatively stable performance. YOLOv5 performs slightly lower at 94.36%, while Hybrid VGGNet+ROI and Hybrid AlexNet+ROI record the lowest averages at approximately 91.17% and 90.09%, respectively. Overall, the average trend demonstrates that the Improved Hybrid GoogLeNet 3-C model delivers the best performance among all evaluated models.

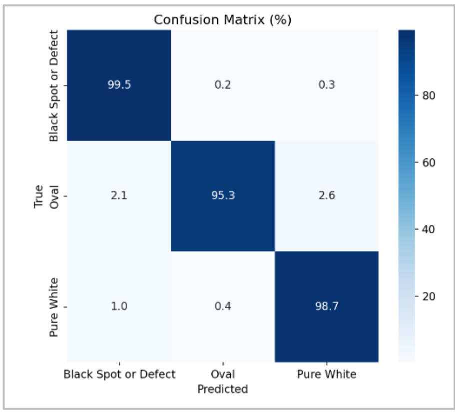
To further analyze class-level performance and classification error behavior, confusion matrices were generated for all evaluated models. These confusion matrices present results in both percentages and raw values (estimates), allowing for a clearer interpretation of model performance while accounting for the potential influence of class distribution. Figure 11 shows the Classification Performance Confusion Matrix of all models.



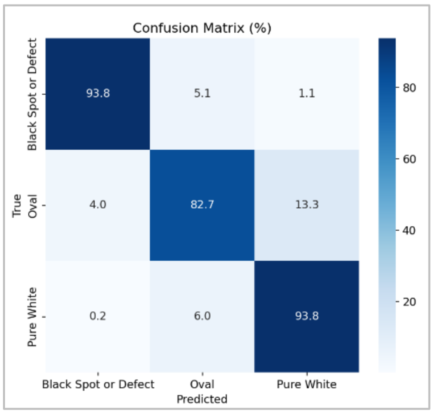
(a) Confusion Matrix of Improved Hybrid GoogLeNet-3Class

(b) Confusion Matrix of YOLOv5

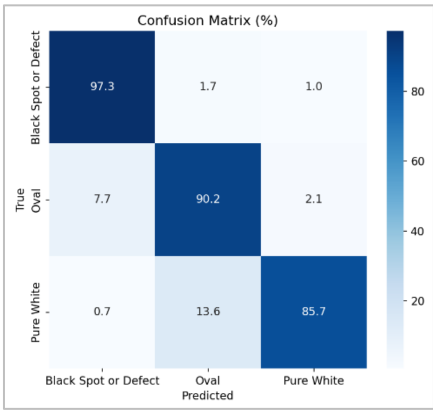
(c) Confusion Matrix of Hybrid GoogLeNet+ROI



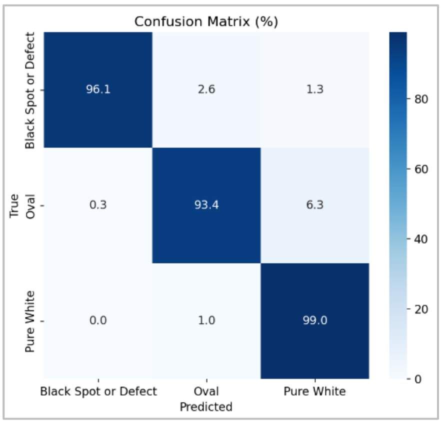
(d) Confusion Matrix of Hybrid LeNet+ROI



(e) Confusion Matrix of Hybrid AlexNet+ROI



(f) Confusion Matrix of Hybrid VGGNet+ROI



(g) Confusion Matrix of Hybrid ResNet+ROI

Figure 11. Classification Performance Confusion Matrix of the All Models

From the comparison of all models presented in figure 11, an overall view of the performance of all evaluated models can be obtained. To provide more detailed information on the performance of each class, table 3 presents the confusion matrices of all evaluated models.

Table 3. Confusion Matrix and Performance Analysis for Models

Model	Black Spot or Defect	Oval	Pure White	Average
Improved Hybrid GoogLeNet-3Class	98.7%	99.0%	97.7%	98,47%
YOLOv5	93%	95%	97%	95,00%
Hybrid GoogLeNet+ROI	86.8%	99.3%	98.9%	95,00%
Hybrid LeNet+ROI	99.5%	95.3%	98.7%	97,83%
Hybrid AlexNet+ROI	93.8%	82.7%	93.8%	90,10%
Hybrid VGGNet+ROI	97.3%	90.2%	85.7%	91,07%
Hybrid ResNet+ROI	96.1%	93.4%	99.0%	96,17%

Based on table 3, a comparative analysis of the confusion matrices and class-wise accuracies of all evaluated models, the Improved Hybrid GoogLeNet-3C consistently demonstrated the most balanced and stable performance in classifying the three morphological categories of straw mushrooms. The model achieved high classification accuracy across all classes, attaining 98.7% for the Black Spot or Defect class, 99.0% for the Oval class, and 97.7% for the Pure White class, resulting in the highest average accuracy of 98.47%. In contrast, other models exhibited strong performance only in specific categories but lacked consistency across all classes. For example, the Hybrid LeNet+ROI model achieved the highest accuracy for the Black Spot or Defect class (99.5%) but showed reduced performance for the Oval class (95.3%). Similarly, the Hybrid ResNet+ROI model achieved excellent accuracy for the Pure White class (99.0%) while demonstrating lower accuracy in the remaining categories. The Hybrid AlexNet+ROI and Hybrid VGGNet+ROI models experienced notable difficulty in distinguishing between the Oval and Pure White categories, as reflected by their lower average accuracies of 90.10% and 91.07%, respectively.

The consistently high class-wise accuracy achieved by the Improved Hybrid GoogLeNet-3C model, combined with its low inter-class misclassification rate and the highest overall average performance among all evaluated approaches, indicated strong generalization capability and robustness in capturing discriminative visual features. Therefore, the Improved Hybrid GoogLeNet-3C model was concluded to be the most optimal approach and was highly suitable for implementation in an image-based quality evaluation system for straw mushrooms, as it delivered accurate, stable, and reliable classification performance.

Although the Improved Hybrid GoogLeNet-3C model demonstrated high overall performance, an error analysis was conducted based on the confusion matrix to identify the remaining misclassification patterns. The complete results of the error analysis and the most frequently confused class pairs are presented in table 4 as a basis for further evaluation of the model's limitations.

Table 4. Dominant Misclassification Patterns Based on Confusion Matrix Analysis

Model	Dominant Misclassification	Error Rate (%)
Improved Hybrid GoogLeNet-3C	Pure White → Oval	2.1
YOLOv5	Pure White → non-target / background	~2–3
Hybrid GoogLeNet+ROI	Black Spot/Defect → Oval	12.4
Hybrid LeNet+ROI	Oval → Pure White	2.6
Hybrid AlexNet+ROI	Oval → Pure White	13.3
Hybrid VGGNet+ROI	Pure White → Oval	13.6
Hybrid ResNet+ROI	Oval → Pure White	6.3

Table 4 the results indicated that the most dominant errors occurred between the Oval and Pure White classes, where brightly colored Oval mushrooms were often misclassified as Pure White, and vice versa when slight shape elongation or illumination effects altered the perceived morphology. The second prominent error pattern occurred between the Black Spot or Defect and Oval classes, particularly for mushrooms with small or low-contrast spots that were difficult to distinguish from normal surface characteristics. Compared with other models, the Improved Hybrid GoogLeNet-3C exhibited significantly lower error rates across all class pairs, indicating that the combination of the modified GoogLeNet architecture and ROI-based localization was more effective in preserving discriminative morphological and textural features.

4. Conclusion

This study proposed and evaluated an Improved Hybrid GoogLeNet model integrated with YOLO-based object detection and an automatic diameter measurement module for standardized straw mushroom quality classification in accordance with the Indonesian National Quality Standard. The experimental results demonstrated that the proposed approach achieved the most balanced overall performance among all evaluated models, reflecting its strong capability to extract discriminative morphological features, reduce misclassification, and support consistent automated grading. The integration of visual classification and physical measurement also enhanced the practical relevance of the system, as it enabled both visual and dimensional quality assessment within a single unified processing pipeline. Furthermore, the error analysis revealed that the remaining misclassifications were mainly concentrated between visually similar categories, particularly between the Oval and Pure White classes, indicating that most errors occurred under subtle shape variations and illumination effects rather than random failures.

Although the proposed system showed strong potential for application in post-harvest sorting and agro-industrial quality control, several limitations were identified. The current implementation required relatively high computational resources, particularly during the detection stage, which could pose challenges for deployment on low-cost devices. In addition, the dataset was collected under controlled conditions; therefore, the model's generalization capability in more complex real-world environments had not yet been fully validated, including its scalability in terms of industrial throughput, long-term stability, and maintenance cost. Consequently, future research should focus on developing lightweight models, hardware-oriented optimization, and large-scale real-world validation to further enhance the robustness, scalability, and industrial readiness of the proposed system for intelligent and standardized straw mushroom quality assessment.

5. Declarations

5.1. Author Contributions

Conceptualization: B.P., T.K.A., M.F.M., A.L.H., A.H., and A.Y.R.; Methodology: B.P., T.K.A., and M.F.M.; Software: B.P. and A.Y.R.; Validation: B.P., M.F.M., and A.L.H.; Formal Analysis: B.P., M.F.M., and A.H.; Investigation: B.P. and A.Y.R.; Resources: T.K.A. and A.H.; Data Curation: T.K.A., A.L.H., and A.Y.R.; Writing Original Draft Preparation: B.P., M.F.M., and A.L.H.; Writing Review and Editing: T.K.A., B.P., M.F.M., A.H., and A.Y.R.; Visualization: B.P. and A.Y.R.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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