JOIV : Int. J. Inform. Visualization, 8(3-2): IT for Global Goals: Building a Sustainable Tomorrow - November 2024 1749-1754

INTERNATIONAL JOURNAL
ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

MobileNet Backbone Based Approach for Quality Classification of Straw Mushrooms *(Volvariella volvacea)* Using Convolutional Neural Networks (CNN)

Bayu Priyatna [a,b], Titik Khawa Abdul Rahman [b], April Lia Hananto [a], Agustia Hananto [a], Aviv Yuniar Rahman [c]

[a] *Information System, University of Buana Perjuangan Karawang, Karawang, West Java, Indonesia*
[b] *ICT, Asia e University, Subang Jaya, Selangor, Malaysia*
[c] *Information Technology, University of Widyagama, Lowokwaru, Malang, Indonesia*
*Corresponding author: *bayu.priyatna@ubpkarawang.ac.id*

***Abstract*—Straw mushrooms (*Volvariella volvacea*) are a crucial commodity in Indonesia, with consumption on the rise due to their nutritional value and increasing demand for healthy food options. Despite this growth, farmers often struggle with accurately assessing the post-harvest quality of mushrooms according to market standards, which can diminish their economic value. Manual classification, which relies on human judgment and estimation, is frequently inefficient and susceptible to errors such as inconsistencies in quality assessment and limitations in detecting subtle variations. This study aims to automate the classification of straw mushrooms based on quality using deep learning, specifically by employing MobileNetv3 as the backbone for classifying mushrooms based on their shape and color by the Indonesian National Standards (SNI). The MobileNet-CNN Backbone model implemented in this study demonstrated exceptional performance, achieving a classification accuracy of 99%, thus proving its effectiveness and reliability in replacing traditional manual methods. The results of this research indicate significant potential for applying deep learning models to enhance the efficiency and precision of mushroom quality assessment. However, there remain challenges that require further development, including adding more diverse background data, improving image resolution, and refining data augmentation techniques. Addressing these challenges is essential for achieving optimal results in varying environmental conditions, ensuring the model can be broadly implemented in the agricultural industry. Such advancements could lead to more consistent and accurate quality assessments, benefiting producers and consumers in the mushroom market.**

***Keywords*— Straw mushroom; quality classification; deep learning, MobileNetv3; image processing; smart agriculture.**

Manuscript received 8 Jun. 2024; revised 14 Aug. 2024; accepted 19 Oct. 2024. Date of publication 30 Nov. 2024.
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I. Introduction

Mushrooms have become important for Indonesians, especially with the increasingly popular healthy lifestyle trend. The popularity of mushrooms continues to increase because of their delicious taste, enjoyment when consumed, and high nutritional content. Research conducted by the Food Security Agency [1] shows that public interest in straw mushrooms continues to grow, with average consumption growth increasing from 8.7% in 2014 to 17.7% in 2018 .

Mushrooms are often processed into pepes, soup, stir-fry, pizza, sate, and mushroom spaghetti. In addition, mushrooms have also developed into various processed packaged products such as chips, nuggets, and shredded meat. Straw mushroom (*Volvariella volvacea*) is a widely cultivated mushroom species in Indonesia [2]. The advantage of mushrooms compared to other foodstuffs is their high nutritional content. The protein in mushrooms is comparable to meat protein, while the carbohydrate content is higher than that in potatoes [3].

Mushrooms are vegetables that can be produced sustainably and do not require large land areas to cultivate [4]. Straw mushrooms are one of the products that have good prospects for development in the future [5]. After harvesting, mushroom farmers in Indonesia often face obstacles due to a lack of knowledge on assessing the quality of mushrooms by market demand, which have high economic value. This inability usually causes losses for farmers, especially if the mushrooms produced do not meet the specifications expected by consumers, making them difficult to sell or can only be sold at a price lower than the market price. [6]. This price risk arises because farmers have no control over market prices. Frequent price fluctuations in agricultural products affect the level of risk that farmers must face, ultimately impacting their production and income [7].

Post-harvest marketing of straw mushrooms (*Volvariella volvacea*) in Indonesia is divided into classes: 1 for modern and 2 for traditional markets [8]. In Indonesia, the quality standards for straw mushrooms have been set in the Indonesian National Standard (SNI) with the number SNI: 01-6945-2003 [9]. Straw mushrooms are declared uniform if all fresh mushrooms in one lot have the same characteristics in terms of size, shape, and skin color [9]. This general standard is similar to the ASEAN Standard for Oyster Mushrooms (ASEAN STAN 35: 2014) and the United Standard FFV-24, which generally have similarities in determining the quality and class of mushrooms.

In Indonesia, mushroom quality and class assessment are done manually by human eye observation based on national standards. However, this manual inspection is often less effective and efficient, which can cause losses for farmers[10]. In the context of agriculture, it should be noted that if the quality inspection system based on visual and manual equipment (such as vernier, calipers, and scales) is replaced by a computer vision system at a commercial level, this can be a faster, more efficient, and more accurate evaluation system [11].

Previous studies have shown that mushroom farming automation, especially in the classification of poisonous mushrooms, can be optimized through the application of machine learning with ensemble models combining several classifiers such as Decision Tree, K-Nearest Neighbors, and Support Vector Machine, achieving good accuracy [12]. In addition, another study used the YoLov5 algorithm for mushroom classification with an F1 score of 76.5% and a late growth stage detection accuracy of up to 70% [13]. Another approach combined YoLov5 and PSP-Net for real-time object detection and image segmentation, with MobileNetv3 as the backbone, resulting in 92.1% precision in mushroom size classification [14].

Overall, deep learning-based computer vision approaches have proven effective in classification tasks, offering solutions that can match or even exceed human performance in some cognitive tasks, so in this study, deep learning was used with the MobileNetv3 model approach as the backbone in classifying the quality of straw mushrooms based on their class which refers to the Indonesian National Standard (SNI) number SNI: 01-6945-2003 with the criteria as parameters being the shape and color of straw mushrooms..

II. Materials and Method

This section presents a comprehensive insight into the materials and methods applied in this study. We describe the dataset used, the preprocessing steps applied, and the implementation of the classification using the MobileNetv3 architecture as a CNN backbone specifically tailored for the straw mushroom dataset. Figure 1 is included to illustrate the general workflow visually, the proposed method, and its stages.

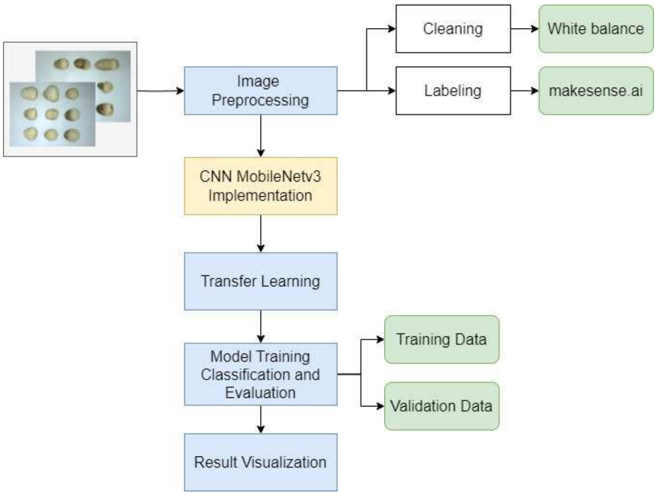

Fig. 1 Workflow of the proposed method

A. Datasets

The data set used in this study was obtained from straw mushroom cultivators consisting of two locations with 15 mushroom houses. In contrast, the data collected consisted of 150 data samples of 1350 data objects grouped into 3 main criteria: Class 1, Class 2 Black Spots, and Class 3 Oval. These classes represent all existing Mushroom Houses. Image data collection was carried out with a uniform size with dimensions of 800x600 pixels. The straw mushroom data set is a strong basis for training and emitting a straw mushroom quality classification model. The data taken is based on a harvest duration of 7 days, with differences in harvest time expected to obtain variations in the quality of straw mushrooms so that the data increases the accuracy and adaptability of the straw mushroom quality classification model.

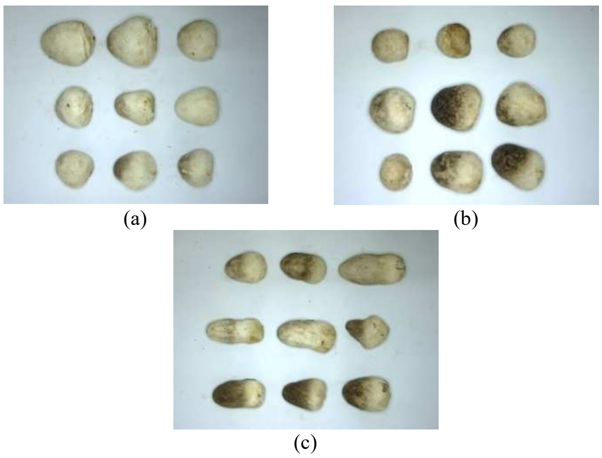

Fig. 2 Image classes in the straw mushroom dataset: (a) average of Class 1; (b) average of Class 2 Black Spot; (c) average of Class 2 Oval [9],[15].

B. Image Preprocessing

This research carries out several stages in the preprocessing process, including the following processes:

1) Cleaning is the initial step to clean the image: in this study, white balance ensures consistent and accurate colors before the next process is carried out[16]. White balance is an important technique in image processing used to correct colors so that images appear more natural in various lighting conditions [17],[18]. Soft White Spread through HSV Value Manipulation. This method effectively brightens images in a smoother and more controlled way, resulting in pictures with more even lighting and detail.

Converting an image from BGR to HSV color space:

$$HSV\_Img = Conv(BGR\_Image, BGR\ to\ HSV) \quad (1)$$

Adds a fixed value to an HSV image value (V) channel to increase brightness:

$$V_{new}(x,y) = V(x,y) + \Delta V \quad (2)$$

2) Labeling: after the image is cleaned using white balance, the next step is labelling the image. This process is carried out to mark the criteria of mushrooms based on their quality, including labelling the straw mushroom object with the following planting:

0 = Class 1
1 = Class 2 Black Spot
2 = Class 2 Oval

The software for labelling straw mushroom data is makesense.ai, which allows tagging objects in images for model training purposes.

C. CNN MobileNetv3 Implementation

After preprocessing, the straw mushroom image is ready to implement the MobileNetv3 architecture[19]. MobileNetv3 is a Convolutional Neural Network (CNN) architecture used as a backbone to extract features from mushroom images [20]. MobileNetV3 consists of several consecutive layers as follows:

- Input Layer:
- Initial Convolutional Layer
- Inverted Residual Blocks
- Output from Backbone

After several Inverted Residual blocks, the last convolution layer produces a tensor feature ready to be used by the head model for classification [20].

$$Z_{out} = Conv_{1x1}(Z_{lost}, W_{Out}) \quad (3)$$

This Tensor feature can be used in fully connected layers to generate output classification. Overall Formulation of MobileNetV3 Backbone [21].

$$\begin{aligned} Backbone\ (X) &= Z_{Out} \\ &= Conv_{1x1}\ (IRB_n\ (\ldots IRB_1\ (Conv_{3x3}(X)))\end{aligned} \quad (4)$$

D. Transfer Learning

In this stage, the Transfer Learning method is applied to utilize previously trained models, thereby speeding up the training process and increasing model accuracy[22]. Models with initial knowledge from similar datasets are used as a starting point for further training [23].

E. Model Training, Classification, and Evaluation

At this stage, the model is trained using labelled data. Training Data is used to train the model [24]. The validation Data is used for model performance and hyper model parameter settings to achieve optimal results [25]. The data used for the classification process is divided into a training set (80%), a validation set (20%), and a detection set for evaluation.

F. Result Visualization

The final stage of this process is the visualization of the results. After the model is trained and evaluated [26], the classification results are displayed in graphs or matrix [27], which describe the model's performance in classifying mushroom quality. Confusion matrix is one of the important tools in machine learning that explains the performance of the classification model [28],[29]. To provide an overview of how the MobileNetv3 model classifies existing classes by displaying the number of correct and incorrect predictions compared to the actual value [20]. The following is the formula in the confusion matrix:

1) Accuracy: Accuracy measures the proportion of correct predictions (both positive and negative) out of all predictions.

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \quad (5)$$

2) Precision: The proportion of correct positive predictions out of all positive predictions made by the model [30].

$$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$

3) Recall (Sensitivity, True Positive Rate): The proportion of positive cases that the model truly detects out of all positive cases [31].

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

4) F1 Score: The harmonic mean of precision and recall this is more useful when you need to balance between precision and recall. [26].

$$\text{F1 Score} = 2\ x \frac{Precision\ x\ Recall}{Precision + Recall} \quad (8)$$

*5) Specificity (True Negative Rate):*The proportion of negative cases that the model detects out of all negative cases. [32].

$$\text{Specificity} = \frac{TP}{TN+FP} \quad (9)$$

G. Experimental Setup

The measurements performed on the hardware and software setup in this study are as follows: Digital Microscope Camera; (Cooling Technology) Sensor: high-performance chip; Main control chip: dedicated master 24Bit DSP, Photo or video: software control, Light source: 8 white LED lights, Statistical resolution: SD 800 x 600; HD 1200x1600; ultra-clear 2592x1944 pixels, Digital zoom: 5X. opera system, Dell Inc. System Model: Latitude E7450 Bios: A03 Processor: Intel ® Core ™ I7-5600u CPU @2.60 GHz Memory: 8192 Mb RAM DirectX Version: DirectX® 12 Windows 11 ® Professional 64-bit Operating System. Google Colab Software with Python Programming Language. Our experimental setup is designed to cover the essential steps that align with the specified methodology [33]. Initially, all input images are uniformly resized to 800x600 pixels due to RGB channels. The data collection is then partitioned into a training set (80%) and a validation set (20%) to facilitate detection and evaluation. As explained in the previous steps.

III. Results and Discussion

A. *Application of White Balance Using the Soft White Spread HSV Value Manipulation method*

Significant improvements in the consistency and color accuracy of the straw mushroom image have been shown. The corrected straw mushroom image shows better brightness and color balance, contributing to more reliable analysis results. This process is important because the quality of the initial image greatly affects the results of subsequent analysis. In conditions where lighting is not optimal, white balance can reduce color distortion to make the resulting data more representative and reliable for subsequent analysis stages. Figure 3 shows the results of white balance pre-processing with the Soft White Spread HSV Value Manipulation method.

(a) (b)

Fig. 3 Image Processing Data of Straw Mushroom (a) Normal Mushroom Image Data; (b) White Balanced Pre-processing Mushroom Data

B. *Proses Labeling*

After going through the cleaning stage with the application of white balance to ensure the consistency and accuracy of the image colour, the next step is the labelling process. The results of the labelling process show that the distribution of labels in the dataset is quite even, with an adequate number of images in each category. This is important to ensure that the deep learning model to be built has representative data for each category of straw mushroom quality. The following are the results of the labelling process shown in Figure 4.

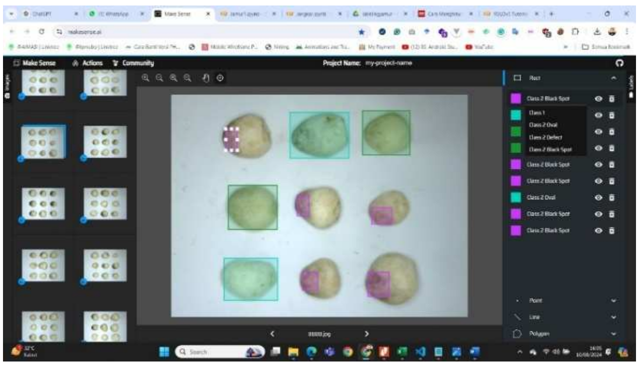

Fig. 4 Labeling Straw Mushroom Data based on criteria

C. *Training and Validation of Straw Mushroom Quality with MobileNet-CNN Model*

Training and validating pre-processed straw mushroom image datasets and applying them to the Backbone MobileNet-CNN model produces high accuracy. The following is the implementation of Backbone in the form of a Script.

```
# CNN backbone with MobileNetV3
   backbone:
   # [from, number, module, args]
      [
      [-1, 1, Conv, [32, 3, 2]], # 0-P1/2
      [-1, 1, Conv, [64, 3, 2]], # 1-P2/4
      [-1, 1, Models.MobileNet_v3, [True]],

   #2-P3/8,   use   MobileNetV2   with   pretrained
   weights:

      [-1, 1, Conv, [128, 3, 2]], # 3-P4/16
      [-1, 1, Conv, [256, 3, 2]], # 4-P5/32
      ]
```

The results of the evaluation of the performance of the Backbone MobileNet-CNN model for detecting straw mushroom-quality objects are shown in Figure 5. F1-Confidence.

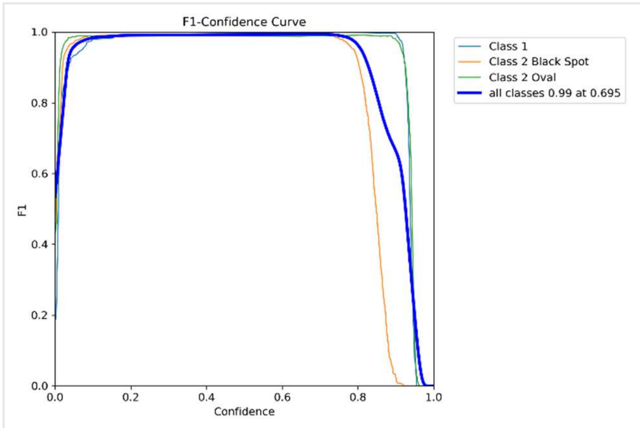

Fig. 5 Performance of MobileNet-CNN Backbone model in F1-Confidence.

This graph shows that the drilled model performs well overall, with an optimal confidence of around 0.695 to achieve the highest F1 score. However, there are differences in model performance across classes, especially in Class 2 Black Spot, which may require further attention or model tuning to improve precision or recall in that class.

The results of evaluating the relationship between the confidence value used for prediction and the precision of the Backbone MobileNet-CNN model in classification are shown in Figure 6 Precision-Confidence Curve.

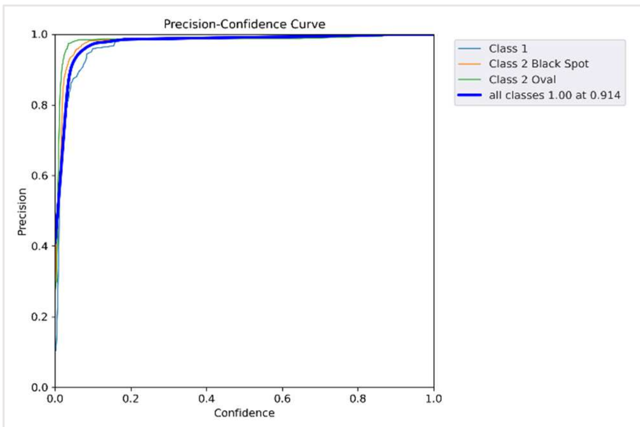

Fig. 6 Performance of MobileNet-CNN Backbone Model in Precision-Confidence Curve.

This Precision-Confidence Curve shows that the model performs very well, especially at confidence values above 0.914, where precision reaches its maximum value (1.00). This means that when the model is very confident (high confidence), there are almost no false positive predictions. Precision-Recall Curve is an important evaluation in the MobileNet-CNN Backbone model for classification, especially in imbalanced contexts or when the focus is on the model performance of the minority class. Here is Figure 7. The resulting Precision-Recall Curve.

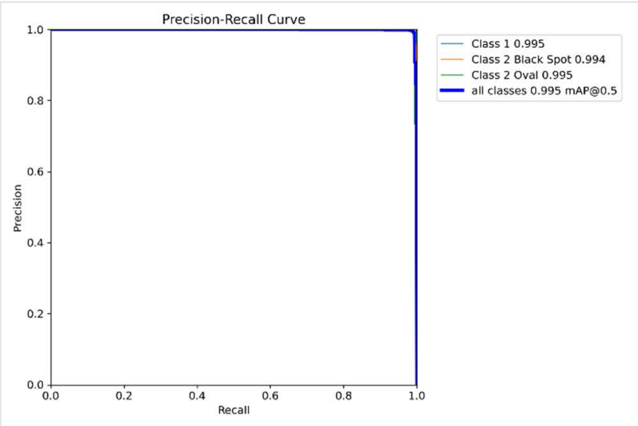

Fig. 7 Performance of MobileNet-CNN Backbone Model in Precision-Confidence Curve.

This figure shows that the model balances precision and recall for all classes with a nearly perfect mAP@0.5 (0.995). This means the model is very effective in correctly identifying objects without making mistakes (false positives) and not missing many relevant objects (false negatives). Recall-Confidence Curve shows how the recall value changes as the Confidence Threshold value increases for the MobileNet-CNN Backbone model prediction. The following is the Recall-Confidence Curve shown in Figure 8.

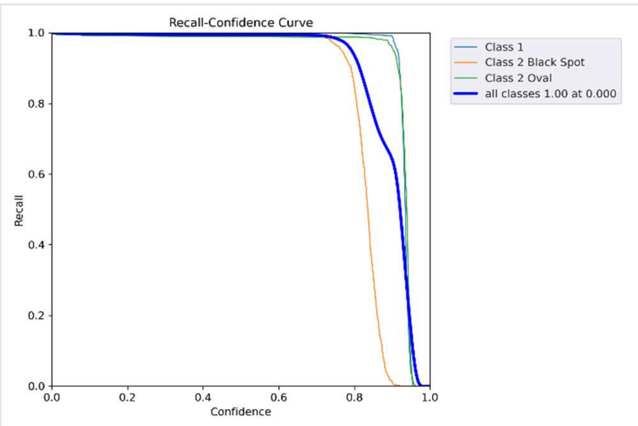

Fig. 8 Performance of MobileNet-CNN Backbone Model in Recall-Confidence Curve.

This graph shows the model has good recall at low to medium confidence values for Class 1 and Class 2 Oval. This means the model effectively finds all positive examples for these classes when it is not too selective (low confidence). The confusion matrix shows the number of predictions the Backbone MobileNet-CNN model made and how they correspond to the actual labels. The following is a screenshot of the straw mushroom quality classification shown in Figure 9. Confusion matrix.

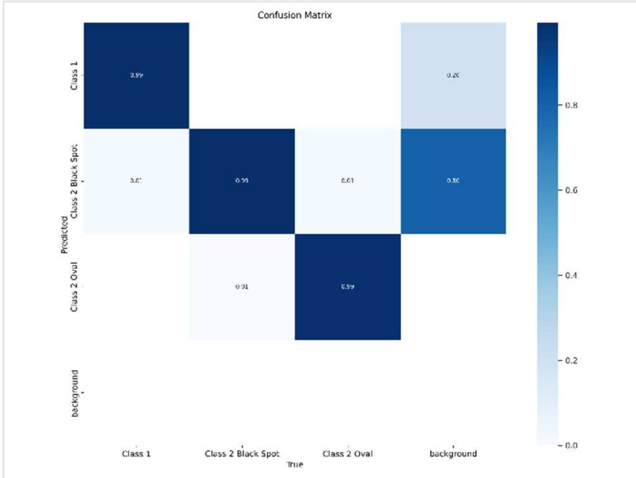

Fig. 9 Confusion matrix of Straw Mushroom Quality Classification of MobileNet-CNN Backbone model.

The model performs well for Class 1 and Class 2 Ovals with 99% accuracy. However, there are significant challenges in distinguishing Class 2 Black Spots from the background, which leads to the background being misclassified as Class 2 Black Spots. The results of removing the background of the straw mushroom image object from the classification designation in Table I below:

TABLE I
ACCURACY AFTER BACKGROUND REMOVAL

	Class 1	Class 2 Black Spot	Class 2 Oval
Class 1	0.99		0.20
Class 2 Black Spot	0.01	0.99	0.01
Class 2 Oval		0.01	0.99

IV. CONCLUSION

In this study, a deep learning model has been developed and evaluated for image classification tasks, specifically to detect and classify various quality classes of straw mushrooms. Based on the analysis using multiple evaluation metrics, such as Precision-Recall Curve, F1-Confidence Curve, and Confusion Matrix, it can be concluded that the resulting model has very good performance in detecting Class 1 and Class 2 Oval with high accuracy.

However, this study also revealed several challenges, especially in detecting Class 2 Black Spots and distinguishing them from the image background. Although the model showed high overall precision and recall, the Confusion Matrix showed that the background prediction was misclassified as Class 2 Black Spot, indicating that the model still has limitations in distinguishing certain features from the background and target classes.

Therefore, steps for improvement, such as adding more varied background data and improving data augmentation techniques, can be considered for further research. Overall, this study has successfully demonstrated the great potential of using the Backbone MobileNet-CNN deep learning model for straw mushroom quality classification, with several areas still requiring further development to achieve optimal results.

Acknowledgment

The authors thank all parties who have provided support in the development and deep learning models used in this study. We want to thank BIMA Kemdikbudristek for providing the facilities and resources needed for this study. This study was also supported by some colleagues at University of Buana Perjuangan Karawang for providing us guidance, input, and research direction during this research process. The support of the Research Team is invaluable in helping the authors understand and overcome the challenges faced, especially in developing a straw mushroom quality classification model. We also thank the Research Team, who have provided technical support, ideas, and constructive discussions. The collaboration and team spirit greatly assisted in completing various technical aspects of this study.

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