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IMAGE CLASSIFICATION OF SPICES BASIC INGREDIENTS FOR MAKING BUMBU BALI BASE GENEP BASED ON DEEP LEARNING

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Abstract

One of Indonesia's abundant natural wealth is spices and seasonings. Base Genep is a basic spice in making traditional Balinese culinary preparations. Base Genep uses many spices and seasonings, including turmeric, ginger, galangal, galangal, candlenuts, nutmeg, pepper, shallots, garlic, coriander, lemongrass, and cloves. From the variety of spices and seasonings that exist in Indonesia, it turns out that the knowledge of the Indonesian people is still low regarding spices and seasonings, especially among the younger generation. This is because these spices/seasonings have characteristics, shapes, and skin colors that are almost similar at first glance, making them difficult to differentiate. Based on these problems, this research was carried out with the aim of helping the public, especially the younger generation, recognize and differentiate types of spices and seasonings. Therefore, in this research, a model based on Deep Learning technology was created. The general objective of this research is to classify spices/seasonings which are often used as basic ingredients in the manufacture of Bumbu Bali Base Genep such as ginger, aromatic ginger, turmeric, and galangal using the YOLOv8 model. The data used in this study were obtained with a smartphone. The data consists of 1200 images consisting of 4 classes. The data is divided into several parts, namely training data, validation and testing data. The resulting dataset is divided into 4 dataset schemes in conducting model training. The highest score for the model in this study was obtained in dataset scheme number 4.

Keywords: Classification, Spices, Base Genep, Deep Learning, YOLOv8.

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INTRODUCTION

Indonesia is known as a country that produces a lot of natural wealth. One of the products of abundant natural wealth in Indonesia is spices. The large diversity of spices in Indonesia provides its own uniqueness that is rarely found in other countries. Spices are widely used as ingredients for cooking in Indonesia. Not only that, spices are also widely used for the needs of the pharmaceutical, food, and other industries[1], [2]. One of the Indonesian culinary preparations that uses a lot of spices as the main seasoning ingredient is traditional Balinese cuisine, one of which is Bumbu/Base Genep. Base genep is the basic seasoning used in making traditional Balinese culinary delights[3]. Genep Base consists of turmeric, ginger, galangal, galangal, candlenut, nutmeg, pepper, shallots, garlic, chili, coriander, lemongrass, shrimp paste, cloves, and salt[4].

Of the various spices and seasonings that exist in Indonesia, it turns out that the knowledge of the Indonesian people is still low regarding these spices/seasonings. Many people still feel confused about differentiating the names of spices/seasonings. This causes many people and even farmers to have difficulty recognizing types of spices and seasonings, especially among the younger generation[5]. Differentiating between one spice/seasoning and another is a challenge for the younger generation. Several types of spices/seasonings at first glance have similarities if we don't know their respective characteristics.

In this study, 4 types of spices/seasonings were taken that were difficult to differentiate, including ginger, turmeric, and galangal. These spices/seasonings have almost similar characteristics, shape, and skin color so they are difficult to differentiate[6]. The introduction of spices to the younger generation is still minimally taught by educational institutions.

This is proven based on research that has been done before at SMKN 9 Bandung[7]. At the time of implementing the Indonesian Food Processing subject, there were 47% of students who still did not know about the herbs and spices that would be used during processing. But now there is a lot of learning that leads to Culinary. Examples include the Vocational Education and Culinary Arts Study Program (PVSK) at the Ganesha University of Education (Undiksha) as well as on tourism campuses that lead to culinary learning.

To help the public, especially the younger generation, recognize the characteristics of existing spices and seasonings, several studies discussing the classification of types of spices/seasonings have been developed. Many studies use machine learning algorithm methods such as K-NN, Naïve Bayes, Support Vector Machine (SVM), and other algorithms[6], [8]–[11]. For example, in research conducted by Suastika Yulia Riska and Lia Farokhah[9]. This research proposes the use of the K-Nearest Neighbors (KNN) method in classifying Indonesian kitchen spices from images. This study used as many as 800 image data of spices by utilizing the RGB color extraction feature in the preprocessing phase. This research divides the dataset into 3 parts with values K=1, K=3, and K=5. The percentage distribution of training data and testing data with a percentage of 90%:10% has the highest accuracy. From the results of this study, the results obtained accuracy with the highest average with a score of 73% with a value of K = 1.

Several other studies have also raised issues related to spices[12]–[15] and the difficulty of distinguishing spices that have almost the same color and shape. This research uses Deep Learning-based technology such as the Convolutional Neural Network (CNN) in carrying out the spice classification phases[5], [16]–[23]]. Such as the research conducted by Evan Tanuwijaya and Angelica Roseanne who proposed using the CNN method by modifying the VGG16 architectural model for the classification of digital spice images in Indonesia [5]. To create this research model, we used the library from Tensorflow. The author modified the VGG16 model by modifying several layers, namely reducing the number of layers and parameters. This research used a dataset from Kaggle of 100 train data and 25 test data. Then the image segmentation preprocessing phase is carried out to increase the image data. This research has an accuracy result of 0.857 with a loss value of 0.376 which was tested using a dataset from Kaggle.

Based on the problems that have been described as well as several previous related studies, this research will classify the images of spices/seasonings used in the manufacture of Genep Base Kitchen Seasonings based on Deep Learning. This research aims to help the community, especially the younger generation, in recognizing and differentiating the types of spices used as ingredients in making Base Genep. Classification is done using the YOLOv8 algorithm which is the latest version of the YOLO algorithm. YOLOv8 supports various vision tasks such as object detection, segmentation, pose estimation, tracking, and classification. This study will use a dataset created by the researcher himself which consists of image data of turmeric, ginger, aromatic ginger, and galangal spices. The dataset is divided into 4 schemes, of the four schemes we will look for which dataset scheme produces the most accurate results in classifying spices.

MATERIAL AND METHOD

The material used in this study is a picture of spices, namely ginger, turmeric, aromatic ginger, and galangal. These spices are the basic ingredients used in making Bumbu Bali Base Genep. Image data was obtained by photographing it directly using a Xiaomi Poco F3 type smartphone digital camera with the jpeg data format and the resulting image size is 3000*3000. The shooting process is carried out in an open area. The time to take pictures was when there was still sunlight. To be precise, it is during the day towards the afternoon so that it gets lots of light support so that the image looks clearer. The shooting scheme is carried out by photographing spice objects placed on a cutting board. This is done so that the resulting image is more natural. In this research, the background for the image used is a cutting board, because cutting boards are a tool that is often used in the kitchen area. For example, it is used in making cooking spices, one of which is making Base Genep seasoning. Then all image data is then resized to the size 512*512. A total of 1200 image data were collected. The data consists of 4 groups, namely ginger with 300 images, 300 images of aromatic ginger, 300 images of turmeric, and 300 images of galangal. The dataset is then divided into 3 parts: training data, validation data, and testing data. The sample of the image dataset is shown in Table 1. The augmentation process was also carried out in this research to create variation and diversity in the image data. So, this process is expected to improve the quality and performance of the model. By applying image data augmentation to the model, the model becomes more robust to various situations and environmental conditions from the image. Such as translation, rotation, light shifts, and other problems in the image. Dataset labeling is done by annotating images using a bounding box which can be done manually or with tools like Roboflow. The labeled dataset will be trained to produce a model that will be used in the testing process. The model that is formed is a model that already has a pattern whose results are in the form of weights. This weight will be used in the testing process.

Table 1. Descriptions of Dataset

Class Name	Quantization	Image Sample
Ginger	300	
Aromatic Ginger	300	
Turmeric	300	
Galangal	300	

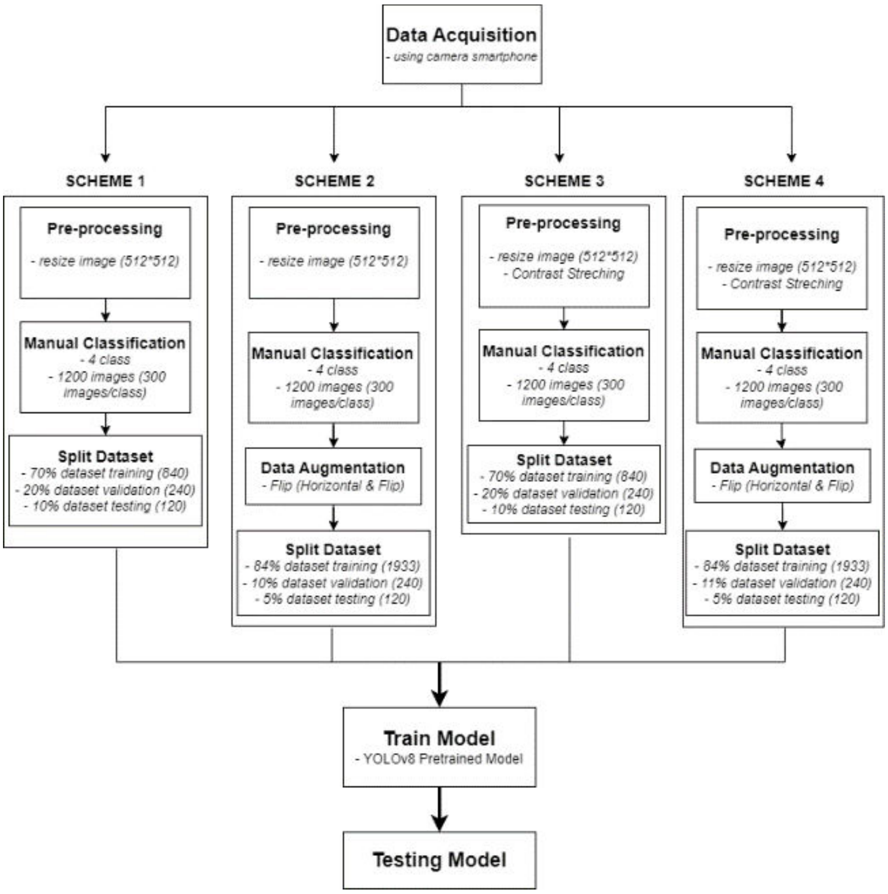

Figure 1. Research Method

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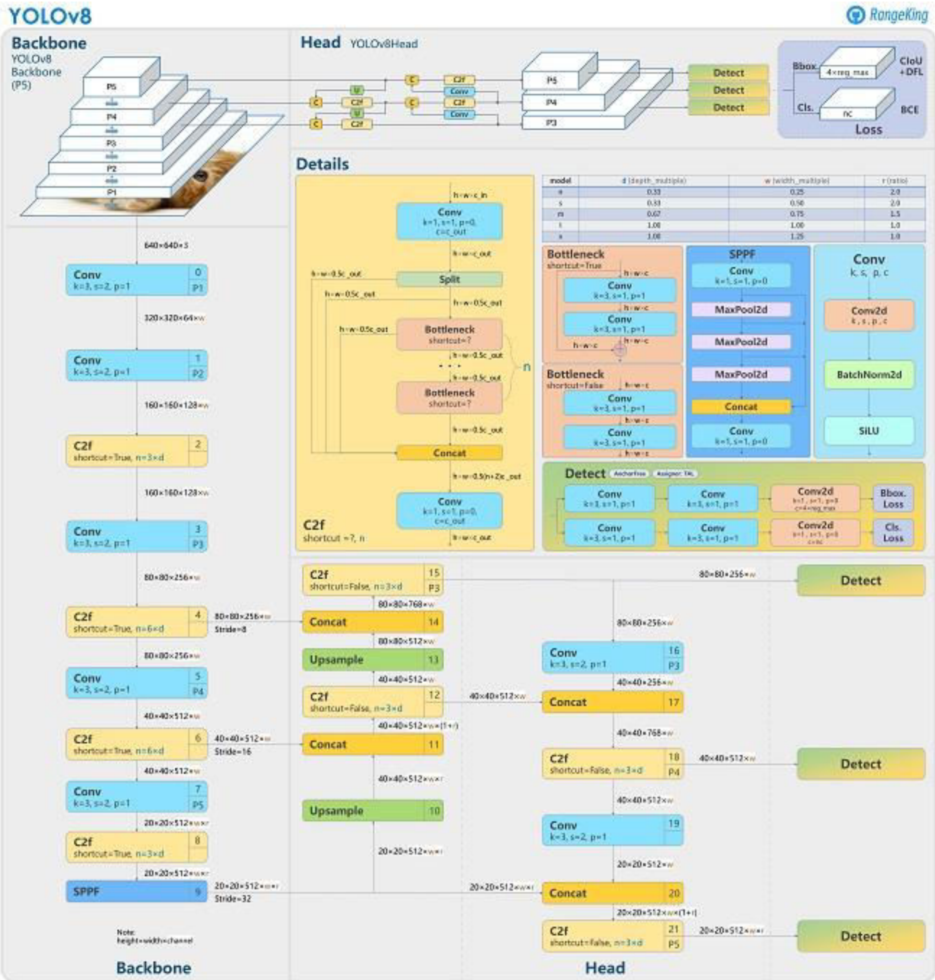

Figure 2. YOLOv8 Architecture

The YOLO collection of algorithms has gained interest in the field of computer vision. YOLO's popularity is a result of its high level of accuracy while maintaining a small model size. Since YOLO models can be trained on a single GPU, a wide range of developers can use them. Machine learning specialists can install it affordably on edge hardware or in the cloud. Applications like object detection, image categorization, and segmentation could all benefit from using the most latest and cutting-edge YOLO method, YOLOv8. Yolo v8 was created by Ultralytics, the same company that created the influential YOLOv5 model that shaped the sector. The architecture of YOLOv8 has been updated and improved over YOLOv5[24].

In this paper, a YOLOv8-based approach for Image Classification of Balinese Seasoning Base Genep (Ginger, Aromatic Ginger, Turmeric, Galangal) is proposed. Figure 2 is the architecture of the YOLOv8 model. There are five different models (YOLOv8n (nano), YOLOv8s (small), YOLOv8m (medium), YOLOv8l (large), and YOLOv8x (extra large)) available for identification, segmentation, and classification. In this research using the YOLOv8n model. The fastest of them all is YOLOv8n, which is smaller and faster than YOLOv8x, which is the most accurate but also the slowest of them all[25].

Model training In this step, the YOLOv8n model is trained on the labeled dataset prepared in the previous step. The training model involves teaching a deep learning model to recognize the characteristics of the spices ginger, aromatic ginger, turmeric, and galangal. YOLOv8n models are trained using deep learning frameworks such as TensorFlow or PyTorch, which provide the necessary tools and libraries to build and train neural networks.

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Figure 3. Examples of Training And Validation Datasets

Figure 4. Examples of Testing Datasets

The testing phase is carried out using the training dataset. Testing using a training dataset is a testing phase for the model produced in the previous training phase. In this phase, 120 images are used to serve as the test dataset. An example of the Testing dataset is shown in Figure 4.

Table 2. YOLOv8n Configuration Parameters

Parameters	Values
Epoch	50
Optimizer	SGD
Learning Rate	0.01
Image Size	512
Batch Size	16
Number of Images	Scheme 1 (1200), Scheme 2 (2293), Scheme 3 (1200), Scheme 4 (2281)
Layers	225
Parameters	3,011,628

Measurements made in the testing process use the multi-class confusion matrix shown in Figure 5. A multi-class confusion matrix, created to assess the performance of classification models with more than two classes, builds on a straightforward binary confusion matrix. An n x n table, where n is the number of classes in the issue, is a multi-class confusion matrix. The instances of the actual class are represented by the rows of the matrix, while the instances of the predicted class are represented by the columns. Confusion Matrix presents a matrix that presents the predicted results of the system and its actual conditions.

		PREDICTED classification				
	Classes	a	b	c	d	Total
ACTUAL classification	a	6	0	1	2	9
	b	3	9	1	1	14
	c	1	0	10	2	13
	d	1	2	1	12	16
	Total	11	11	13	17	52

Figure 5. Example of Multi-Class Confusion Matrix

The FM score is the weighted average of the mean recall percentage and precision percentage. FM Score, one of the evaluation metrics frequently used to gauge the effectiveness of classification models, is typically referred to as FM score or F-Measure (F1-Score). As a result, this score detects erroneous positives while misrepresenting negatives. The F1-Score is more widely used than precision, yet accuracy is not always simple to comprehend. Accuracy performs well when the costs of false positives and false negatives are equivalent. If there are differences in the costs of false positives and false negatives, recall factors as well as accuracy are favored. Precision is the ratio of accurately anticipated observations to all predicted positive findings in terms of positive findings. Recall is the proportion of actual positive predictions overall positive actual predictions. This can be calculated as in Eq. (1). Precision is the proportion of true positive predictions overall predicted positive predictions. This can be calculated as in Eq. (2)

$$Recall = \frac{TP}{TP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$F1-Score = 2 * \frac{Recall\ x\ Precision}{Recall+Precision} \quad (3)$$

Where TP stands for True Positive. FP stands for False Positive, TN stands for True Negative, and FN stands for False Negative. Precision and recovery are considered when calculating the F1-Score, the F1-Score formula as calculated in Eq. (3).

RESULT AND DISCUSSION

This section will explain the results and discussion in the form of performance metrics and model performance evaluation. The results of data acquisition and distribution of Training, Validation, and Testing data are shown in Figure 3 and Figure 4. After the Training, Validation, and Testing datasets are formed. Then training is carried out on the Training dataset. The training uses the YOLOv8 Architecture in Table 2.

Variations in the dataset schemes carried out in this study use the 4 schemes shown in Figure 1. Scheme 1 uses the original dataset without augmenting it. Scheme 2 uses data augmentation in the form of vertical and horizontal flips in the image. Scheme 3 by doing additional preprocessing in the form of contrast stretching without doing Data Augmentation. Scheme 4 by preprocessing contrast stretching and augmenting vertical and horizontal flip data on images. The proposed model has been implemented, trained, and validated on Google Colab using the GPU platform. A snippet of Training Results is shown in Figure 6. By using graphs, we can show patterns of training results. Figure 7-10 shows the overall results of the model using the proposed 4 dataset schemes including loss, precision, and recall. Figure 11 a, b, c, and d show the prediction results of the model.

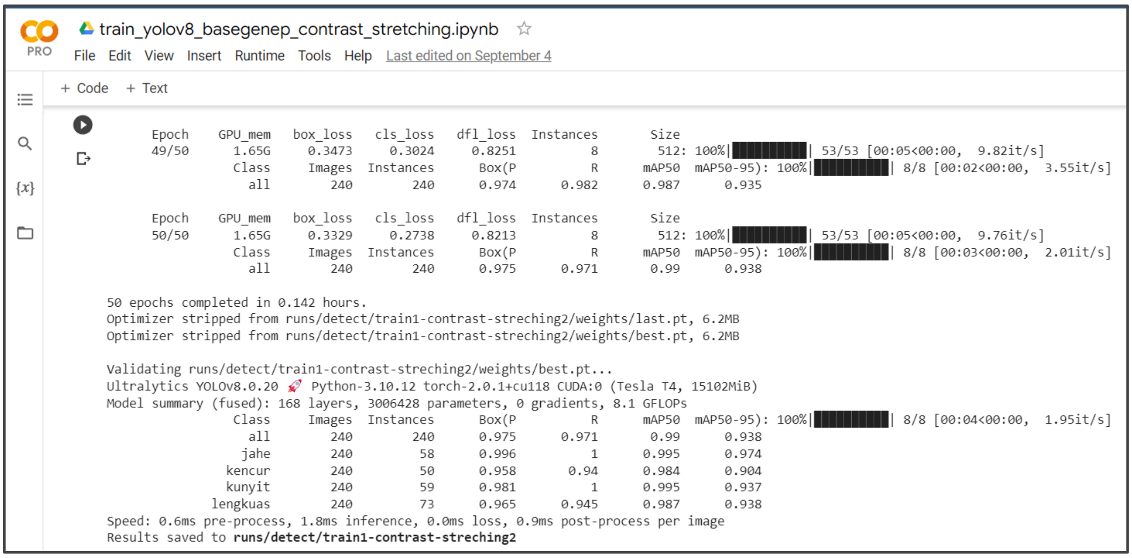

Figure 6. Snippets of Training Process & Results.

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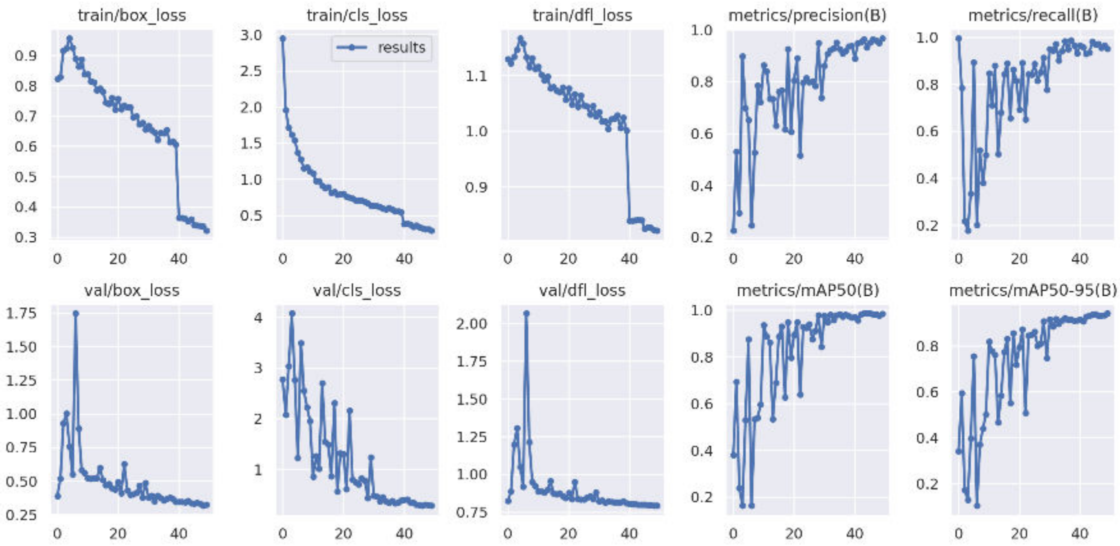

Figure 7. The results of the model use Scheme 1.

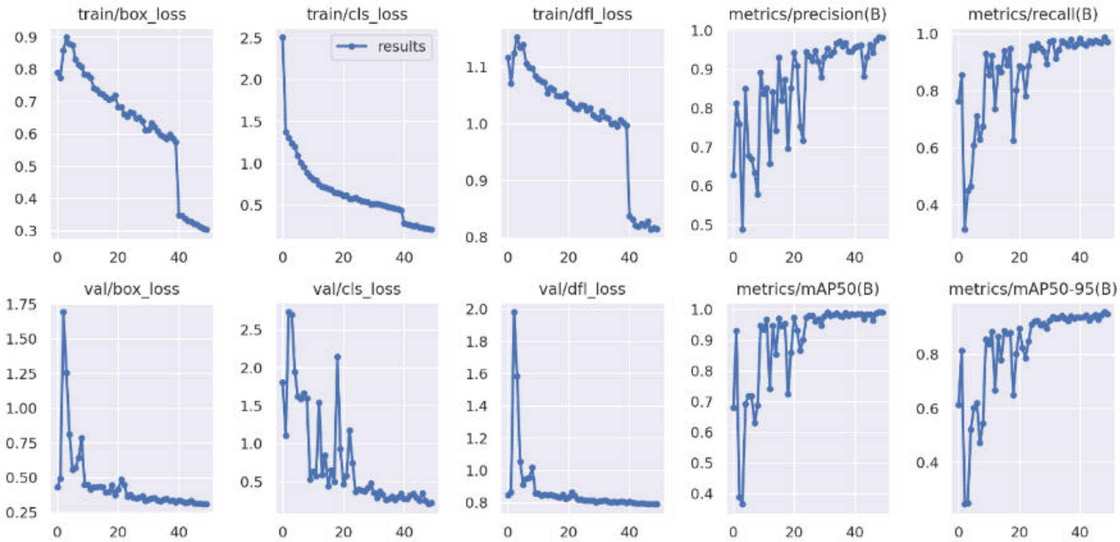

Figure 8. The results of the model use Scheme 2.

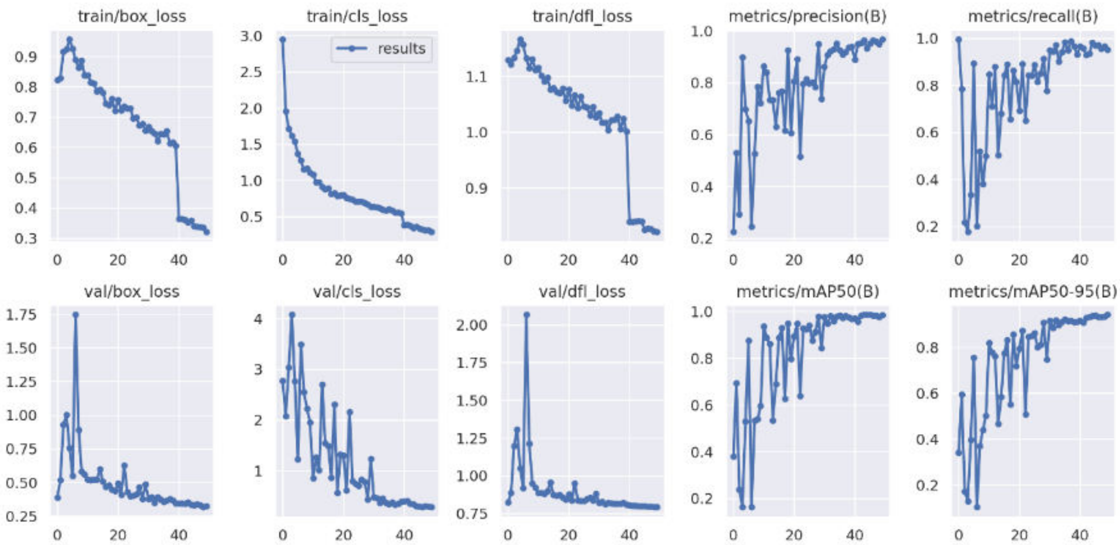

Figure 9. The results of the model use Scheme 3.

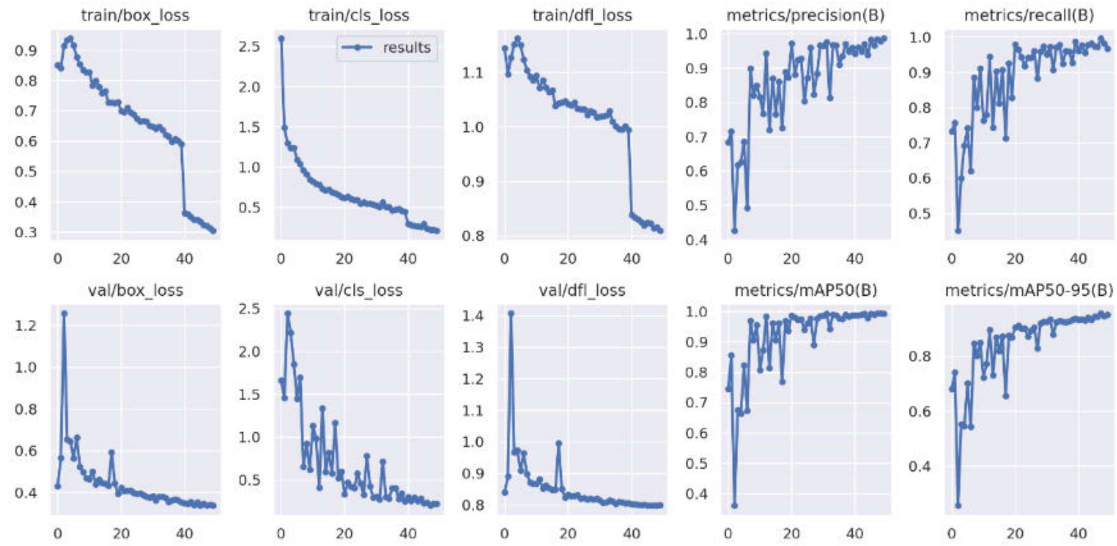

Figure 10. The results of the model use Scheme 4.

Figure 11. The results of testing the spice classification model. (a)Scheme 1, (b)Scheme 2, (c)Scheme 3, (d)Scheme 4.

In Figure 7 and Figure 11a, the researchers present the training and testing results of the model trained using the original dataset (Scheme 1) without data augmentation or additional preprocessing. These training results reflect the model's performance when faced with an image dataset that has not experienced any changes or improvements in quality. This model can classify images in the context of four main classes: ginger, turmeric, galangal, and galangal. Although this model was able to produce acceptable results in several evaluation metrics such as precision, recall, and F1-Score, its performance could possibly be improved. When the model is tested with data containing images with significant contrast variations, it may have difficulty correctly identifying and classifying them. This indicates that this model has a limited level of sharpness in recognizing features and differences in images with low levels of contrast.

In Figure 8 and Figure 11b, researchers show the results of model training and testing trained with a dataset that has gone through a data augmentation process (Scheme 2). These results show an improvement in the model's performance in terms of its ability to recognize and classify images in the dataset. The additional variation of the data introduced through data augmentation has helped the model to better cope with variations in the dataset. These results reflect the positive impact of data augmentation on model performance. This can be seen in the increase in evaluation metric results such as precision, recall, and F1-Score. The model with the Scheme 2 dataset gets higher results compared to the first model which uses the Scheme 1 dataset.

Figure 9 and Figure 11c show the results of model training and testing using contrast stretching preprocessing techniques on the dataset (Scheme 3). This model can produce better results in recognizing image features and significant differences, especially in images with less clear contrast. The model with the Scheme 3 dataset shows an increase in the model's ability to deal with images that require contrast improvement as shown in the evaluation metrics. The model with the Scheme 3 dataset gets higher results compared to the model using the Scheme 1 dataset or the original dataset. However, the evaluation metric results obtained by the model with the Scheme 3 dataset are lower than those with the Scheme 2 dataset. This shows that contrast stretching preprocessing may be less effective in improving model performance compared to the addition of significant data variations carried out in the data augmentation process. These results show that in the context of this dataset and classification task, data augmentation in models with the Scheme2 dataset seems to have a greater positive impact compared to preprocessing contrast stretching in models with the Scheme 3 dataset. Therefore, this experiment allows researchers to assess that in situations where image variation or low contrast is an obstacle, data augmentation may be a superior option in improving model performance.

Figure 10 and Figure 11d depict the superior training and testing results in all previous experiments. This model uses contrast stretching techniques to clarify images, as well as data augmentation to enrich the training dataset. These results show improvements in model performance in terms of precision, recall, and F1-Score compared to the previous 3 models. The combination of these two techniques helps the model to be sharper at recognizing and classifying images, as well as providing diversity in the training data which is very useful. Based on the test results, the model with the Scheme 4 dataset is a highly recommended choice, as it provides superior results in relevant evaluation metrics. These results confirm that the combined strategy of contrast stretching preprocessing and data augmentation, as applied in dataset scheme 4, has produced a model with the best results in improving model performance in this image classification task.

The vertical axis in a YOLO (You Only Look Once) metric or training graph will represent the loss value. Loss is a measure of how well a model performs during training. Lower loss values indicate better model performance, while higher values indicate worse performance. The goal during training is to minimize the loss value.

In the YOLOv8 context, there are the terms "box_loss", "cls_loss", and "dfl_loss". Box_loss is a bounding box regression loss, which measures the error in the prediction of bounding box coordinates and dimensions compared to the ground truth. Lower box_loss means more accurate bounding box predictions. Cls_Loss is the classification loss, which measures the error in the predicted class probability for each object in the image compared to the ground truth. A lower cls_loss means the model predicts the object class more accurately.

Dfl_loss is a deformable convolution layer loss, a new addition to the YOLO architecture in YOLOv8. This loss measures the error in the deformable convolution layer, which is designed to improve the model's ability to detect objects with varying scales and aspect ratios. A lower dfl_loss indicates that the model is better at handling object deformation and appearance variations.

Table 3 Model Comparison Table With 4 Dataset Schemas

Model	Scheme Dataset	Precision	Recall	F1-Score
YOLOv8n	1	97%	94.8%	95.8%
	2	98.2%	98.8%	98.4%
	3	97.5%	97.1%	97.2%
	4	98.4%	99.7%	99.04%

The overall loss value is usually a weighted sum of the individual losses. The specific units of the vertical axis will depend on the implementation, but in general, they represent the magnitude of the error or difference between the predicted value and the ground truth value.

The following is a comparison table of the results of model testing using 4 dataset schemes in the spice classification. The table of calculation results for each dataset scheme is shown in Table 4. A comparison of the calculation results of model testing in schemes 1, 2, 3, and 4 shows that the highest precision value is in Scheme 4, namely 97%. Then the highest Recall value was obtained in scheme 4, namely 99.7%. Then for the F1-Score value in scheme 4, it is 99.04%. Dataset 4 scheme obtained the highest score of all the schemes tested.

CONCLUSION

This research proposes a Deep Learning method to classify several spices which are the basic ingredients for making Bumbu Bali Base Genep (Ginger, Aromatic Ginger, Turmeric, and Galangal). The Deep Learning method proposed in this research is YOLOv8 which is one of the popular methods in the field of computer vision. Several stages of the research method proposed in this research are Data Acquisition, Preprocessing, Dataset Labeling, Data Augmentation, Manual Classification, and division of 3 datasets (training, validation, and testing data). The dataset produced in this research proposes 4 dataset schemes to carry out the model training process. Then the testing phase was carried out for the 4 schemes to find out the comparison of the values of each model. So it can be seen which dataset scheme can produce a model with the highest score, both precision, recall, and F1-Score. The number of images used for model testing for all schemes is 120 images that have been prepared on the testing dataset. Based on the results of comparative calculations on schemes 1, 2, 3, and 4, scheme 4 was obtained with the highest precision value of 98.4%, Recall of 99.7%, and F1-Score of 99.04%. From these results, it can be concluded that scheme 4 is the best model of all the models tested in this research. The model with the Scheme 4 dataset confirms that the combination of contrast stretching preprocessing and data augmentation strategies has produced the model with the best results in improving model performance in this image classification task.

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