AVOCADO RIPENESS CLASSIFICATION USING A CONVOLUTIONAL NEURAL NETWORK (CNN)

[1]*Nur'aini Mufaidhah Tangahu,* [2*]*Mohamad Ilyas Abas,* [3]*Widya Eka Pranata,* [4]*Rizal Lamusu,* [5]*Syahrial,* [6]*Irawan Ibrahim*
[1,2,3,4,5,6]*Program Studi Ilmu Komputer Universitas Muhammadiyah Gorontalo*
Coresponding: ilyasabas@umgo.ac.id*
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ABSTRACT

The determination of avocado ripeness plays a crucial role in post-harvest handling and quality The determination of avocado ripeness plays a crucial role in post-harvest handling and quality control within the agricultural sector; however, conventional assessment methods based on visual inspection and human experience are often subjective and inconsistent, potentially leading to classification errors and economic losses. To address this issue, this study proposes an automated avocado ripeness classification system using a Convolutional Neural Network (CNN) based on digital image analysis. The model employs a transfer learning approach using the MobileNet architecture implemented through the Teachable Machine platform. The dataset utilized in this research was obtained from Mendeley Data and consists of avocado images categorized into four ripeness levels: underripe, breaking, ripe, and overripe. Prior to model training, the images underwent preprocessing and data augmentation to improve model robustness and generalization. Model evaluation was conducted using 1,200 test images, with 300 samples per class. Experimental results show that the proposed model achieved an overall accuracy of 91.42%, indicating strong and stable classification performance. Analysis using a confusion matrix reveals that most predictions were correctly classified, while misclassifications primarily occurred between ripeness stages with visually similar characteristics. Among all classes, the underripe category demonstrated the highest performance with minimal classification errors. These findings indicate that the proposed CNN-based approach is effective and reliable, and it has significant potential to be further developed as an automated system for avocado ripeness classification and post-harvest quality assessment.

Keywords: Avocado Ripeness; Convolutional Neural Network; Transfer Learning; MobileNet; Computer vision; Image Classification

1. INTRODUCTION

The advancement of information technology enables the identification of fruit based on color characteristics with the aid of computers. This computational method is conducted through indirect visual observation, using a camera to process images which are then analyzed with computer software. Digital image processing techniques are utilized to simplify and expedite the maturity level testing proces [1].

Avocado is a highly valued fruit crop in tropical and subtropical regions around the world [2]. Determining the ripeness level of avocado fruit is one of the factors. The ripening process of avocados is influenced by various factors, including climate, growing conditions, and storage. Traditionally, ripeness is assessed subjectively through inspection of organoleptic characteristics or objectively through analysis of physical parameters [3]. However, the process of assessing avocado ripeness has largely remained conventional, relying on visual observation and human experience. This method is subjective and prone to error, leading to inconsistencies in post harvest sorting and distribution. Consequently, the ripeness levels of avocados available in the market vary widely.

This often poses a challenge for consumers in selecting avocados to purchase according to their desired ripeness level [4] [5]. Therefore, a more objective and reliable approach is needed. The implementation of automated technology based on computer vision and deep learning presents a potential solution to support the process of identifying fruit ripeness levels accurately and efficiently.

Image classification is the process of grouping all pixels in an image into clusters so that they can be interpreted as specific properties. The existence of digital image classification has spurred numerous studies utilizing various algorithms. However, research on algorithm optimization, particularly in testing, remains limited. Objects that

have nearly identical test values have not yet been specifically identified. Algorithm optimization is therefore essential, especially for test data objects with highly similar values.[6]

2. METHOD

This research aims to classify the ripeness level of avocado fruit using the Convolutional Neural Network (CNN) method. The research flowchart has been included.

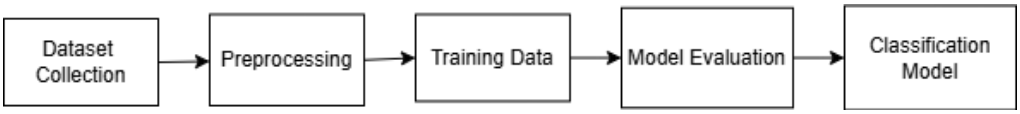


Figure 1. research diagram

2.1 Dataset Collection

The dataset used in this study consists of avocado fruit images obtained from Mendeley Data at the address https://data.mendeley.com/datasets/3xd9n945v8/. This dataset contains avocado images at several ripeness stages, namely underripe, ripe, breaking, and overripe. These image data are used as training and testing data to build and evaluate the classification model.

2.2 preprocessing

Before the model training process is conducted, the avocado image data undergoes a preprocessing stage. The preprocessing steps performed include Resizing, which involves determining the resolution change of the images [7]. from the original size of 800 x 800 pixels to 224 x 224 pixels, This step ensures that the CNN can process images efficiently [8][9]. Additionally, the dataset is automatically split into training and testing data by the Teachable Machine platform.

2.3 Clasificasion Method

CNN have been the most significant advancement in the study of artificial intelligence and computer vision because of their origins in biology, mathematics, and computer science (AI) [10].The classification method used in this study is Convolutional Neural Network (CNN) with a transfer learning approach. The CNN model is based on the MobileNet architecture, a model that has been pre-trained on a large-scale dataset. Through transfer learning, the MobileNet model is utilized as a base model to extract visual features from images, then adapted in the final layers to specifically classify avocado ripeness levels. Compared to other neural network architectures of a similar type, CNN has significantly fewer parameters and connections, making it more efficient in terms of training time and computational resources while still achieving excellent performance in image classification tasks [11]. This efficiency allows CNN to effectively capture spatial and hierarchical features from images, which is crucial for visual-based classification problems. Furthermore, MobileNet is a class of lightweight deep convolutional neural networks designed to be smaller in size and faster in performance compared to many popular deep learning models. Its lightweight architecture enables efficient computation without sacrificing accuracy, making MobileNet particularly suitable for real-time applications and systems with limited computational resources, while maintaining strong performance in feature extraction and classification [12].

2.4 Model Training Process

The model training process is conducted using the Teachable Machine platform. In this stage, the preprocessed avocado images are used to train the MobileNet model using a transfer learning approach, Teachable Machine is a web-based interface that allows people to train their own ML classification models [13][14]. The training parameters used in this study are Number of epochs 80 and Learning rate 0.0001 [15]. As noted in [16],

a learning rate of 0.0001 is ideal for CNNs at both the training and testing levels.Training is performed until the model achieves optimal performance based on the provided training data.

2.5 Model Evaluation

Training is performed until the model achieves optimal performance based on the provided training data. Model evaluation is conducted to assess the system's performance in classifying avocado ripeness levels. The evaluation methods used include per-class accuracy calculation and analysis using a confusion matrix. A confusion matrix is a table that presents the classification results, showing the number of correctly and incorrectly classified test data points [17]. This method is appropriate for classification tasks where each sample is assigned to a single class, enabling accuracy to be measured based on the number of correctly identified pixels or instances [18]. Through this evaluation, the study aims to identify the model's success rate and examine patterns of misclassification, especially among classes with similar visual characteristics. An illustration of the confusion matrix is presented in Table 1 below.

Table 1. Results of Driver Drowsiness Detection Experiments

Prediction	Actual	
	True	False
True	TP (True Positive)	FP (False Positive)
False	TN (True Negative)	FN (False Negative)

a. TP (True Positive) refers to data that is actually positive and is correctly predicted as positive.
b. TN (True Negative) refers to data that is actually negative and is correctly predicted as negative.
c. FP (False Positive) is an error condition where data that is actually negative is incorrectly predicted as positive
d. FN (False Negative) is an error condition where data that is actually positive is incorrectly predicted as negative.

This confusion matrix measurement tool can also be used to calculate the values of accuracy, precision, recall, and F1-Score [19].

a. Accuracy, which quantifies the ratio of correct predictions (true positives and true negatives) to the total number of data points, thereby reflecting the overall correctness of the classification model [20]. this metric is employed to provide an initial and general overview of the model's predictive capability, particularly in evaluating how well the model performs across all classes collectively [21]. The accuracy calculation formula is presented in Equation 1 below.

$$Accuracy = \frac{TP\ total}{total\ sample} \quad (1)$$

b. Precision, is the comparison between the number of true positive predictions and the total predictions classified as positive [22]. Precision indicates how well the model's predicted results align with the requested accurate data [23]. The formula for calculating precision can be seen in Equation 2 below.

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

c. Recall, measures the proportion of true positives among all instances predicted as positive. It reflects the model's ability to avoid false positive [24]. Additionally, Recall does not fully capture the full information on the accuracy of the classification with regard to the positive cases [25]. The precision calculation formula is shown in Equation 2 below.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

d. F1-Score, is the harmonic mean of Precision and Recall [26]. The F1-Score serves to determine the balance between Precision and Recall [27]. The formula for calculating the F1-Score can be seen in Equation 4 below.

$$F1 - Score = 2\,X\,\frac{precision\ x\ recall}{precision + recall} \quad (4)$$

3. RESULT AND DISCUSSION

3.1 Experimental Results

Based on the experimental results conducted using 300 image samples per class that had undergone data augmentation, the avocado fruit ripeness classification model demonstrated excellent performance. The total test data used in this evaluation amounted to 1,200 images, consisting of four ripeness level classes: breaking, overripe, ripe, and underripe.

The evaluation results show that the model was able to achieve an overall accuracy of 91.42%, indicating that the model possesses high and stable classification capability. Performance distribution across classes was also relatively even, with each class achieving a good level of accuracy. The training process was conducted over 80 epochs with a learning rate of 0.0001 using the MobileNet architecture implemented through the Teachable Machine platform. The training results show a stable trend of increasing accuracy and decreasing loss.

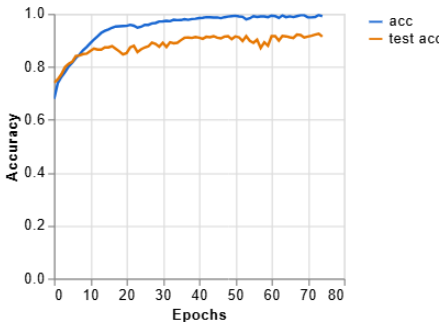


Figure 2. Accuracy graph

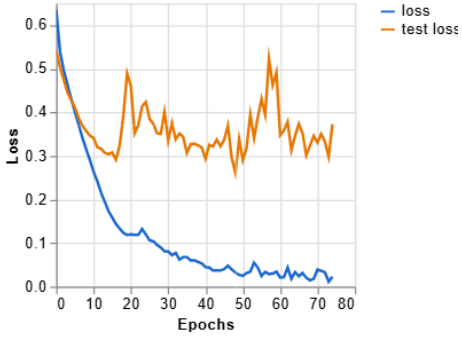


Figure 3. Loss graph

Based on both graphs, it can be observed that the model achieved a final test accuracy of 91.42% with a test loss value below 0.2 after the 50th epoch. The small gap between the training and testing curves indicates that the model did not experience overfitting and has good generalization capability. The stability of the loss curve also suggests that the learning process converged well.

3.2 Confussion Matrix

In a Confusion Matrix each column represents the instances ina predicted class, while each row represents the instances in anactual class. The confusion matrix shows the ways in which theclassification model is “confused” when it makes predictions. It cangive insight not only into the errors being made by a classifier, butmore importantly the type of the resulting error [28]. A confusion matrix is used as an objective measure of accurate quality [29]. A confusion matrix is a visual representation of the performance of a classification model used to analyze the model's test results [30]. confusion matrix approach as a performance measure to execute the most outstanding algorithm that detects the true corner points for all tested characters [31]. There are four avocado ripeness levels: breaking (beginning to ripen), overripe (overripe), ripe (ripe), and underripe (unripe). This matrix is used to assess the extent to which the model's predictions match the true labels in the test data.

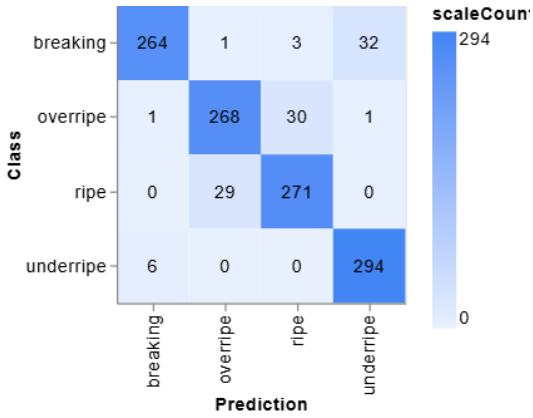


Figure 2. Confussion Matrix

The breaking, overripe, and ripe classes each have a high number of correct predictions, although misclassification still occurs between classes with similar ripeness levels, such as between breaking and underripe, and ripe and overripe. The underripe class shows the most optimal performance with the highest number of correct predictions and very low error rates, indicating that the features of this class are more easily recognized by the model.

Overall, the confusion matrix shows that the model has good classification ability, with relatively low error rates, and most errors occur among classes that share similar visual characteristics. This result indicates that the model can effectively recognize fruit ripeness patterns, although there remains room for improving accuracy among classes with closely adjacent ripeness level.

3.3 Classification Metric Evaluation

Based on the confusion matrix, the evaluation metric values of precision, recall, and F1-score were obtained for each class. The underripe class has a precision of 0.97, recall of 0.88, and F1-score of 0.92. The breaking class achieved a precision of 0.89, recall of 0.98, and F1-score of 0.93. Meanwhile, the ripe and overripe classes each show a precision and F1-score of 0.89, with a recall of 0.90 for the ripe class and 0.89 for the overripe class.

Table 2. Results of Driver Drowsiness Detection Experiments

Metric	Class			
	Underripe	Breaking	Ripe	Overripe
Presicion	0.97	0.89	0.89	0.89
Recall	0.88	0.98	0.90	0.89
F1-Score	0.92	0.93	0.89	0.89
Total Accuracy	91.42			

These values indicate a good balance between the model's ability to correctly detect positive data (recall) and the accuracy of its predictions for a specific class (precision). With a total accuracy of 91.42%, it can be concluded that the developed CNN model has an effective and reliable performance in classifying the ripeness level of avocado fruit based on digital images.

4. CONCLUSION

Based on the conducted research, it can be concluded that the Convolutional Neural Network (CNN) method with a transfer learning approach using the MobileNet architecture, implemented via the Teachable Machine platform, is capable of effectively classifying avocado ripeness levels based on digital images. The model was trained using a public dataset from Mendeley Data that underwent preprocessing and augmentation stages, with a total of 1,200 test images divided into four ripeness classes: underripe, breaking, ripe, and overripe. The evaluation results indicate that the model achieved an overall accuracy of 91.42%, signifying high and stable classification performance. Analysis of the confusion matrix and evaluation metrics precision, recall, and F1-score demonstrates that the majority of data was correctly classified. The underripe class achieved the best performance with a very low error rate, while misclassification generally occurred among classes with visually adjacent ripeness levels, such as between breaking and underripe, as well as ripe and overripe. Nevertheless, the occurring error rate is relatively low; thus, the developed model is considered reliable and effective for use as an automated support system in identifying avocado ripeness levels. Looking ahead, this model still holds potential for further development, particularly in enhancing its discrimination capability among classes with similar visual characteristics.

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