Automatic Differentiating of Postharvest Banana Fruits with High Traits Using Imagery Data
Candra Dewi 1,2,*, Wayan Firdaus Mahmudy 2, Solimun 3 and Endang Arisoesilaningsih 1)
1) Department of Biology, Faculty of Mathematics and Natural Sciences, Universitas Brawijaya, Malang, East Java, Indonesia
2) Department of Informatics Engineering, Faculty of Computer Science, Universitas Brawijaya, Malang, East Java, Indonesia
3) Department of Statistics, Faculty of Mathematics and Science, Universitas Brawijaya, Malang, East Java, Indonesia

ARTICLE INFO
Keywords: Banana Finger Classification High Similarity Shape Feature Texture Feature

ABSTRACT
Visually differentiating banana cultivar with high similarity in shape, color and peel texture requires skill and experience during harvesting to reduce mistake on identifying cultivar. This study aims to identify automatically some similar banana cultivars using banana finger imagery and computer vision. The identification process was carried out to distinguish two groups of bananas with high similarities, namely group 1 (Ambon, Hijau, Goroho) and group 2 (Barlin, Mas). The test was conducted on the pair of datasets of unripe Ambon-Hijau-Goroho, ripe Hijau-Goroho, ripe and unripe Barlin-Mas. Testing was done to determine the performance of identification and to find out the most effective characteristics that could be used as cultivar identification. Results of classification using extreme learning machine (ELM) showed that texture features extracted from local binary pattern (LBP) could accurately distinguish unripe Ambon-Goroho, unripe Goroho-Hijau, ripe Goroho-Hijau with 100% accuracy. While unripe Ambon-Hijau, unripe Barlin-Mas and ripe Barlin-Mas could be optimally distinguished using a combination of shape and peel texture features with accuracy of 93.39%, 89.68%, 99.31% respectively. This result indicated that the proposed method could be used as an alternative of automatic banana sortation during post-harvest. The use of shape and peel texture features had shown effectively differentiating these high similarity banana cultivars.

INTRODUCTION
Bananas are well known fruits and widely consumed for reasons of their essential ingredients of vitamins and minerals (Ekasa, Mirroir, Blomme, Van Den Bergh, & Davey, 2013; Okorie, Eleazu, & Nwosu, 2015). Banana cultivars have high economic value and currently more widely cultivated by farmers (Punwadaria, 2006) in monoculture system or in mixed agroforest. The existing cultivars today are derived from the hybridization of two banana species, namely Musa acuminata (Genome A) and M. balbisiana (Genome B) (Simmonds, 1966; Simmonds & Shepherd, 1955). However, among the two hundred identified banana cultivars in Indonesia, some cultivars are not be easily distinguished because they have a very similar shape, peel color and peel texture (Dwivany, 2018). Some cultivars that show a high similarity include Ambon, Hijau and Goroho. The others such as Barlin and Mas. Ambon, Hijau and Goroho bananas have a similar shape, color and peel texture when they are unripe. Hijau and Goroho bananas also have similar characteristics even though the fruit has ripened, and the peel color remains green. While Barlin and Mas bananas have

ISSN: 0126-0537 Accredited First Grade by Ministry of Research, Technology and Higher Education of The Republic of Indonesia, Decree No: 30/E/KPT/2018

Cite this as: Dewi, C., Mahmudy, W. F., Solimun and Arisoesilaningsih, E. (2022). Automatic differentiating of postharvest banana fruits with high traits using imagery data. AGRIVITA Journal of Agricultural Science, 44(2), 276-289. http://doi.org/10.17503/agrivita.v44i2.3648
almost similar shape, peel color and texture when both unripe and ripe.

Based on the direct observations of banana gardens in Malang and Kesamben Blitar, mostly banana plants were grown as mixed cultivars gardens where more than one banana cultivars planted. In addition, farmers usually obtain banana seedlings from shoots that have not been clearly identified. Neither farmers could not receive the sufficient information of cultivars origin. Therefore, it provides a great difficulty to identify the planted cultivars.

After harvesting, each cultivar usually has a different price in the market. Based on information obtained from the website of www.hargabulanini.com and www.wartasolo.com, the price of Ambon is higher than Hijau. As well as Mas bananas are more expensive than Barlin. Thus, cultivar identification is required in addition to fruit quality in the post-harvest processing to reduce mistakes in marketing.

A technique that has been used for a long time to determine the diversity of bananas is the morphological approach, namely by visually observing the characteristics of the banana plant (Hapsari, Lestari, & Masrum, 2015; Simmonds, 1966; Simmonds & Shepherd, 1955). With the large number of characters from each part of the banana plant, the identification and characterization processes using morphological features are quite difficult. The processes spend a long time and often involve subjectivity from researchers (Fauziah, Trimanto, & Hapsari, 2017). For this purposes, a fast and accurate method is needed to assist farmers in identifying banana cultivars in the post-harvest period before delivering the fruits to the market. A visual rapid identification can also help farmers to determine the prices based on cultivar information.

Currently, the development of computer vision-based technology makes it possible to identify objects using image data. Various studies show that image data can be used optimally to identify plants based on leaf characteristics (Dewi, Mahmudy, Arifando, Arbawa, & Ahmadie, 2020; Pahikkala et al., 2015; Zhang, Weckler, Wang, Xiao, & Chai, 2016). The previous studies also proved that image data can be used to determine quality, maturity and type of fruit effectively (Begum & Hazarika, 2022; Huang, 2012; Li, Lee, & Wang, 2014; Mohd Ali, Hashim, Abd Aziz, & Lasekan, 2022; Mohi-Alden, Omid, Firouz, & Nasiri, 2022; Zhang, Wang, Ji, & Phillips, 2014).

Since each ripeness level of bananas contains different vitamins and minerals, research on banana using fruit imagery was more widely applied to identify the level of banana ripeness (Bora, Lin, Bhattacharya, Bali, & Pathak, 2015; Hou, Hu, Hou, Guo, & Satake, 2015; Santoyo-Mora, Sancen-Plaza, Espinosa-Calderon, Barranco-Gutierrez, & Prado-Olivarez, 2019; Srividhya, Sujatha, & Ponmagal, 2016; Zulkifli, Hashim, Abdan, & Hanafi, 2019). The other studies with banana tiers imagery have been done, but they focused on identifying the quality of bananas based on reject categories or not for industrial purposes (Le, Lin, & Piedad, 2019; Piedad, Larada, Pojas, & Ferrer, 2018). While research related to the identification of banana cultivars utilizing shape feature was conducted by Dittakan et al. (2017). Then, Iklima, Nasir, & Hidayat (2017), Sanjaya & Wijaya (2020), and Yana & Nafi’iyah (2021) performed identification of banana cultivar using color, shape and texture features. Nevertheless, the banana cultivars identified on their studies have very different shapes, colors and textures that making it easier in the identification process. The example cultivars were cavendish, lady finger dan pisang awak (Dittakan et al., 2017). These three cultivars really have different sizes and shapes. Iklima, Nasir, & Hidayat (2017), Sanjaya & Wijaya (2020), and Yana & Nafi’iyah (2021) identified some local Indonesian cultivars such as ambon, raja, kapok, mas, susu, and tanduk. These cultivars also have very different sizes, shapes and peel textures. These studies also do not mention whether the identification was done on unripe or ripe bananas. Most cultivars showed different peel colors when they are unripe and ripe, so this condition really needs to be considered in the identification process using imagery. Therefore, Dewi, Arisoesilaningsih, Mahmudy, & Solimun (2022) identified unripe ambon and hijau bananas which had high traits and obtained good results. However, the model still needs to be improved and further tested for the other cultivars than Ambon and Hijau.

To improve the previous research, this study was added the other cultivars such as goroho, barlin and mas. Consequently, more detailed analysis of extracted shapes and textures characteristics was conducted to obtain precisely distinguishing characters in the identification process. In addition, testing was also carried out on unripe and ripe banana to ensure the difference in these two conditions. This study applied extreme leaning machine (ELM) classification as recognition technique. ELM has been proven to have advantages in terms of training process and accuracy over other neural network methods (Ding, Xu, & Nie, 2014; Huang, Zhu, & Siew, 2004) and SVM (Chorowski, Wang, & Zurada, 2014; Huang, Zhu, & Siew, 2006).
MATERIALS AND METHODS

Modeling and simulations carried out in this study were to obtain optimal models in identifying banana cultivars with high characteristics similarity. The study was conducted from March to September 2021.

Materials

The banana tiers used in the study was obtained from a traditional market in Malang (Ambon, Hijau, Barlin, Mas) and ordered from banana farmers in Wonosobo (Goroho). The banana fingers of each cultivar were then separated from its tier.

Banana finger imagery was taken using the main camera of mobile phone with specification of 13 MP, f/2.2, 1/3.1inch sensor, 1.12µm, Phase Detection Autofocus and single-LED flash. The camera position above the fruit and a distance of 20-25 cm. The banana fingers were placed on white paper and the photo shoot was taken in a room with fairly bright solar lighting between 8 a.m. and 3 p.m.

An example of a banana finger image of each cultivar is shown in Fig. 1.

Methods

The cultivar recognition process involves of two main stages namely the pre-process and the identification (Fig. 2). The pre-process stage consists of imagery resizing and feature extraction. Image resizes was used to reduce the image resolution from the original size (4160x3120 pixels) to 20% of the original image size (832x624 pixels). The smaller image size can speed up the computational process without reducing the accuracy of the identification. The feature extraction process was used to obtain the shape and peel texture characteristics from the image. The two feature extraction approaches used were shape/morphological features and texture feature extractions.

The shape features were extracted using morphological descriptors (Singh, Gupta, & Gupta, 2010) and convex hulls (Wang, Du, & Zhang, 2005). The total of shape features was 13 that consist of five basic features (diameter, physiological length, physiological width, area and perimeter), six derivative features (form factor, aspect ratio, rectangularity, perimeter and diameter ratio, narrow factor, perimeter ratio with physiological length and physiological width) and two convex hull features (convexity and solidity).

Texture features were extracted using the local binary pattern (LBP). This method proved to be resilient enough to get information on the difference in surface of the image and not be affected by image rotation (Ojala, Pietikäinen, & Harwood, 1996). The spatial patterns and contrast values of the image were calculated through the thresholding of gray level imagery using a certain distance of determination and texture descriptor was expressed using a histogram.

A neighborhood distance used in this study was two and the number of bin histograms was 26 to form 26 optimal texture features. The result of the preprocess stage was a features dataset.

The identification phase of the study used the ELM architecture that was introduced by Huang, Zhu, & Siew (2004). The network consists of a single hidden layers with a number of nodes and feedforward learning running on a single epoch. The performance of the classification was then measured by calculated confusion matrix to obtain the value of accuracy, precision and recall (Deng, Liu, Deng, & Mahadevan, 2016).

RESULTS AND DISCUSSION

To determine the performance of the developed model, a program was created using Python simulated each identification stage as shown in Fig. 2. In the program implementation, several libraries were used, namely opencv-python library for image resizing and extraction of shape/ morphology features, Python.scikit-image library for local binary pattern texture feature extraction and Python Extreme Learning Machine library for ELM classification.

To find out the optimal cultivar identification, the test was conducted on two groups of cultivars that have a high similarity, namely the Ambon-Goroho-Hijau banana group (group 1) and the Barlin-Mas banana group (group 2). Tests were done separately in each group to find out how resilient the proposed method on recognizing banana cultivars.

In each group three testing scenario were also conducted to find out the optimal features in recognizing cultivars, namely 1) testing using only shape features, 2) testing using only texture features and 3) testing using a combination of shape and texture features. The entire test was conducted using k-fold cross validation with a value of k = 3, which means the two-thirds part of the dataset was used as training data and one-third part was used as test data. Sampling of training and testing data on k-fold was done randomly stratified. Each test was conducted five times to find out the stability of test result with different training and test data. The
Candra Dewi et al.: Differentiating High Traits Banana Fruits

average value of accuracy, precision and recall of the
fifth test were then calculated to obtain the final result
of performance.

The total amount of image data used in the
test were 368 that composed by 43 unripe Ambon,
33 unripe Hijau, 28 unripe Goroho, 59 unripe Barlin,
67 unripe Mas, 33 ripe Hijau, 36 ripe Goroho, 37 ripe
Barlin, and 50 ripe Mas. The total amount of features
was 39 that consist of 13 shape features and 26
texture features.

Feature Dataset of Image

This study used all the features both in shape
and texture feature as input in the identification
process. The value of the extracted features varies
from fractions under one, tens, hundreds and even
hundreds of thousands. The greatest variation of
feature values was found in shape features where
some derived morphological features are worth less
than zero, while area feature in basic morphology
run into the tens of thousands. Therefore, the
normalization was done to uniform the range of
values between zero and one.

The significant difference in the mean values
of the thirteen shape features in the unripe Ambon-
Goroho-Hijau banana was the Goroho with Ambon
and Goroho with Hijau (Fig. 3). Exceptions were
found in the ratio of perimeter with physiological
length and physiological width (ratio of PLPW)

Fig. 1. The studied banana finger images: (a) unripe Ambon, (b) unripe Hijau, (c) ripe Hijau, (d) ripe Goroho,
(e) unripe Barlin, (f) ripe Barlin, (g) unripe Mas, (h) ripe Mas

Fig. 2. Flow diagram of high traits banana cultivar identification
Fig. 3. Normalized of mean value of shape features (Error bars represent standard error of mean)
Fig. 4. Principal component analysis of shape features for cultivar group of unripe Ambon-Goroho-Hijau (a), ripe Goroho-Hijau (b), unripe Barlin-Mas (c) and ripe Barlin-Mas (d)
feature where in Goroho and Hijau bananas have almost the same value and convexity feature which has a very small value. Based on the feature values in the graph, it can be known that the differences in the features of unripe Ambon-Goroho and the unripe Goroho-Hijau were more clearly seen than the unripe Ambon-Hijau.

Significant differences in the ripe Goroho-Hijau group were found in the perimeter ratio with physiological length and physiological width (ratio of PLPW), convexity, solidity and area features. While the width and diameter ratio features have almost the same average value.

Based on the graph, it can also be seen that most of the features in the unripe Barlin-Mas and ripe Barlin-Mas groups have insignificant differences values. The ratio of PLPW and convexity features (Ripe Barlin-Mas) and form factor (unripe Barlin-Mas) even had almost the same values. Significant differences were found in the features of convexity, narrow factor, solidity and diameter ratio (unripe Barlin-Mas).

The correlation of each feature to the cultivar can be observed using the principal component analysis (PCA) shown in Fig. 4. In the unripe Ambon-Goroho-Hijau group, the two main components (PC1 and PC2) have a total variance percentage of 80.72%. Goroho cultivar was separated from Ambon and Hijau based on PC1. Goroho cultivar correlated with most features, Ambon correlated with convexity, narrow factor and rectangularity features, while Hijau correlated with ratio of diameter features.

Two main components (PC1 and PC2) of ripe Goroho-Hijau group have a total variance percentage of 78.52%. Using the PC1 component it was known that the cultivars of ripe Goroho and Hijau were separated quite well where most features were correlated with Goroho and some features such as ratio of diameter, convexity, rectangularity and narrow factor were correlated with Green.

For unripe Barlin-Mas cultivar group, the main components of PC1 and PC2 had a total variance percentage of 89.19%. In this group, the PC1 can separate Barlin and Mas cultivars quite well. From the graph it was seen that the ratio of perimeter with physiological length and physiological width (PLPW), ratio of diameter, narrow factor, rectangularity and convexity were correlated with Barlin cultivars, while the remaining features were correlated with Mas.

Ripe Barlin-Mas cultivar group had a total variance percentage of 74.48% for the two main components of PC1 and PC2. The PC1 in this group can clearly separate Barlin and Mas cultivars. The narrow factor, convexity, rectangularity and ratio of diameter features were correlated with Mas cultivars, while other form features were correlated with Barlin.

A total of 26 extracted texture features represents the value of the bin histogram of the LBP image. The lowest bin stores the frequency of image pixel values that are close to black while the highest bins store the frequency of image pixel values that are close to white. The graph of normalized texture feature average values is shown in Fig. 5.

In unripe Ambon-Goroho-Hijau, the significant difference of features from the three bananas was found in the LBP1, LBP5, LBP6, LBP8, LBP19, LBP20 and LBP21. While the LBP2 and LBP26 features have almost the same values. Fig. 5 showed that most of unripe Goroho's features differ significantly compared to unripe Ambon and Hijau. While in unripe Ambon and Hijau, it can be seen that some features have almost the same values, although most of the features have different value. Based on this value the unripe Ambon-Goroho and unripe Goroho-Hijau have more different features value than unripe Ambon-Hijau. Ripe Goroho and Hijau have a fairly clear difference in almost all features except LBP3, LBP17 and LBP20. Significant differences were found in the features of LBP5, LBP6, LBP7, LBP9, LBP11 and LBP22.

Most of the features in the unripe Barlin-Mas did not show significant differences (LBP2, LBP8, LBP20 and LBP25) and only the LBP4 features have almost the same values. While the ripe Barlin-Mas has a significant difference in values in almost all features, except on LBP9 feature. Based on these features values, it can be seen that ripe Barlin-Mas have more clear different feature values when compared to unripe Barlin-Mas.

The PCA of the texture feature against the four cultivar subgroups was presented in Fig. 6. The main components of PC1 and PC2 of unripe Ambon-Goroho-Hijau had a total variance percentage of 85.49%. Based on PC1, the Hijau cultivar was separated from Goroho significantly, while Ambon cultivar was almost flanked by a positive axis of PC1. Nevertheless, these three cultivars look separated and each was correlated with different features.

In the ripe Goroho-Hijau group, the main components of PC1 and PC2 have a fairly high total variance percentage of 88.92%. The two cultivars are clearly separated on PC1 and each of them was
Fig. 5. Normalized mean value of texture features (Error bars represent standard error of mean)
Fig. 6. Principal component analysis of texture features for cultivar groups of unripe Ambon-Goro-Hijau (a), ripe Goro-Hijau (b), unripe Barlin-Mas (c), and ripe Barlin-Mas (d).
correlated with a different feature but the number of correlated features was almost the same in each cultivar.

In the group cultivar of unripe Barlin-Mas and ripe Barlin-Mas, the labels of two cultivars were positioned at the meeting point of the PC1 and PC2 axes. This means most features were correlated the same in both cultivars. The total correlation percentage of the main components (PC1 and PC2) in unripe Barlin-Mas was relatively low of 69.09%, while ripe Barlin-Mas had high value at 87.64%.

Test Results on Ambon-Goroho-Hijau Banana Group

Ambon (A), Goroho (G) and Hijau (H) bananas have almost similar fruit colors, shapes and textures thus, making them difficult to be distinguished. When the fruit became ripe, however, Ambon banana peel becomes yellow while the banana peel of Hijau and Goroho remains green so it is easier to distinguish Ambon bananas from Hijau and Goroho. Therefore, testing for these three cultivars was done when the fruit was still unripe and additional testing was carried out on Hijau and Goroho bananas on the ripe stage. In total there were five test sub-group, namely unripe Ambon-Goroho-Hijau, unripe Ambon- Hijau, unripe Ambon-Goroho, unripe Goroho-Hijau, and ripe Goroho-Hijau.

Each sub-group was tested with three combinations of features: shape/morphology, texture, and a combination of shape and texture features. The classification performance test results in the form of accuracy, precision and recall values of all sub-group and features combinations are presented in Table 1.

Testing result on each feature combination and sub-group showed that accuracy, precision and recall had almost the same value (the range below 1%). It means that the accuracy has a high level of consistency because the misidentification in the form of false positive and false negative were quite similar with the misclassification on accuracy.

Table 1 showed that the best recognition results using the shape feature were found at the unripe Ambon-Goroho sub-group with the accuracy at 97.74%, followed by ripe Goroho-Hijau and unripe Goroho-Hijau with an accuracy of 97.68% and 94.11% respectively. The lowest recognition accuracy was found in unripe Ambon-Hijau, which was 85.56%.

Using the texture feature, the highest accuracy was 100% for unripe Ambon-Goroho, unripe Goroho- Hijau and ripe Goroho-Hijau sub-group. The lowest recognition result was the unripe Ambon-Hijau with an accuracy of 91.30%. While the use of combination of shape and texture features obtained the best accuracy of 98.55% at ripe Goroho-Hijau and the lowest accuracy was 93.39% at unripe Ambon-Hijau. Based on these results the use of shape features produces the lowest recognition accuracy for all sub-group.

Based on the result, it can clearly be known the best features that can be effectively used in identifying differences on unripe Ambon-Goroho- Hijau, unripe Ambon-Goroho, unripe Goroho-Hijau and ripe Goroho-Hijau were texture features. While the best feature that can be used to distinguish unripe Ambon-Hijau was a combination of shape and texture features. The test result showed that unripe Ambon and Hijau banana has a very similar shape and texture so it was more difficult to be distinguished.

### Table 1. Classification test performance on Ambon (A), Goroho (G) and Hijau (H) banana group

| Performance Measurement | Unripe AGH | Unripe AH | Unripe AG | Unripe GH | Ripe GH |
|-------------------------|------------|-----------|-----------|-----------|---------|
| **Shape Feature**       |            |           |           |           |         |
| Accuracy                | 87.88      | 85.56     | 97.74     | 94.11     | 97.68   |
| Precision               | 88.58      | 85.88     | 98.06     | 94.33     | 97.95   |
| Recall                  | 88.95      | 86.67     | 97.11     | 94.38     | 97.55   |
| **Texture Feature**     |            |           |           |           |         |
| Accuracy                | 96.92      | 91.30     | 100.00    | 100.00    | 100.00  |
| Precision               | 96.80      | 91.14     | 100.00    | 100.00    | 100.00  |
| Recall                  | 97.50      | 92.19     | 100.00    | 100.00    | 100.00  |
| **Shape+Texture Feature** |         |           |           |           |         |
| Accuracy                | 94.24      | 93.39     | 98.32     | 97.71     | 98.55   |
| Precision               | 94.94      | 93.34     | 98.08     | 98.00     | 98.54   |
| Recall                  | 94.89      | 93.54     | 98.24     | 97.29     | 98.64   |
The best identification results were obtained when distinguishing Ambon from Goroho and Hijau with Goroho in unripe conditions (unripe A-G, unripe G-H) and ripe (ripe G-H) using texture features. The highest accuracy obtained was 100%. The use of shape and the combination of shape and texture features also provides high accuracy even though it does not reach maximum values which was between 97% to 98%, unless on the recognition of Goroho-Hijau with shape features. This accuracy result was higher compared to the recognition of Ambon and Hijau. This also shows that Goroho was more easily distinguished from Ambon and Hijau. Although produces the lowest accuracy compared to the use of texture features, the results of recognition using the shape feature still had quite high accuracy which can reach 97.74% (unripe Ambon-Goroho).

In general, the offered method can satisfactorily distinguish Ambon-Goroho-Hijau. Goroho can be distinguished from Ambon and Hijau bananas with a very high accuracy that reaches 100%. Pattern and the hue of fruit imagery extracted with LBP were proven to be able to systematically extract differences in fruit peel of each cultivar. This is in line with research conducted by Kaewchote, Janyong, & Limprasert (2018), Kaplan, Kaya, Kuncan, & Ertunç (2020), and Mahale, Ali, Yannawar, & Gaikwad (2017), where the use of LBP produces texture features that prove optimal as input in the classification process. The results of recognition using the shape feature although produces the lowest accuracy compared to the use of texture features, the results of recognition using the shape feature still had quite high accuracy which can reach 97.74% (unripe Ambon-Goroho).

Ambon and Hijau bananas have a smoother peel texture compared to Goroho, therefore it was easier to distinguish. Although the texture of Ambon and Hijau was almost the same, the surface of Ambon banana peel is smoother and brighter than Hijau bananas. Unripe Ambon and Hijau can be distinguished, but the highest accuracy only reached 93.39%. The use of texture features extracted with LBP and ELM classifiers was shown to be outperform from the previous works (Iklima, Nasir, & Hidayat, 2017). The model also could differentiate the ambon, hijau and goroho cultivar very well, indicated by an increase in accuracy compared to the previous study (Dewi, Arisoesilaningsih, Mahmudy, & Solimun, 2022).

Test Results on the Barlin and Mas Banana Group
Barlin (B) and Mas (M) banana have a small fruit size. Both have almost the same shape, color and peel texture although Mas fruit sometimes appears larger in diameter. They have green peel color when unripe and yellow when ripe. Although the green and yellow peel colors of these cultivar look different at first glance due to environmental influences and planting locations, but the difference can only be identified by people who have often interacted with these two cultivars. Therefore, the testing on this group of bananas was conducted on unripe Barlin-Mas and ripe Barlin-Mas. The testing was also carried out on combinations of features to find out the best features in the identification process. The result of identification for the Barlin-Mas group is presented in Table 2.

Table 2. Classification results of test on the Barlin (B) and Mas (M) banana group

| Performance Measurement | Performance of Cultivar Sub-group (%) |
|-------------------------|---------------------------------------|
|                        | Unripe BM  | Ripe BM   |
| **Shape Feature**      |           |           |
| Accuracy                | 83.33      | 85.75     |
| Precision               | 85.18      | 85.53     |
| Recall                  | 82.96      | 85.14     |
| **Texture Feature**     |           |           |
| Accuracy                | 87.94      | 99.54     |
| Precision               | 88.03      | 99.54     |
| Recall                  | 87.85      | 99.57     |
| **Shape+Texture Feature** |          |           |
| Accuracy                | 89.68      | 99.31     |
| Precision               | 90.27      | 99.32     |
| Recall                  | 89.82      | 99.27     |
The calculation of the confusion matrix for the shape, texture and combination of shape-texture features shows that the accuracy, precision and recall produced have almost the same values (the range below 2%). The accuracy obtained was quite consistent because the misidentification in the form of false positive and false negative were almost same.

The test results showed that the use of shape features was only able to produce the highest recognition accuracy of 85.75% on unripe Barlin-Mas. In the use of texture features, there was an increase in accuracy both on unripe Barlin-Mas (87.94%) and on ripe Barlin-Mas (99.54%) compared to the use of shape features. While the combined use of shape and texture features showed an increase in accuracy for unripe Balin-Mas by 1.74% and a decrease of 0.23% for ripe Barlin-Mas when compared to the use of texture features.

Based on the value of accuracy, precision and recall it can be derived the best features that can be used in identifying unripe Barlin-Mas were the combination of shape and texture features. While for ripe Barlin-Mas was the texture feature. This result also showed that the difference between Barin and Mas bananas was easily recognized when the fruits are ripe, especially based on the texture of the fruit peel.

Based on the results, the best identification of ripe Barlin-Mas banana group reached 99.5% using texture features. While the combined use of shape and texture features resulted an accuracy of 99.31%, which is only a very small difference from the use of texture features. But the use of fewer features can speed up computation. Although the accuracy of recognition in unripe bananas is lower than in ripe bananas, the accuracy was quite high at 89.68% (with a combination of features of shape and texture) and 87.94% (with texture features).

Although the identification results of the Barlin-Mas group were lower than the Ambon-Goroho-Hijau group, overall the results had the highest accuracy at 99.54%. In this group, shape and texture features were also proven to be able to differentiate the Barlin-Mas cultivar. The lowest accuracy in the recognition of unripe Barlin-Mas was 83.33%. In general, the use of shape features extracted by morphological descriptors and convex hull results has higher accuracy than that reported by Dittakan et al. (2017) and only recognition of unripe Barlin-Mas has lower accuracy compared to respected report.

In addition, our study performed identification of banana cultivars with high similarity characteristics, which is different from previous studies that identifying bananas with very different shapes or low similarities (Dittakan et al., 2017; Iklima, Nasir, & Hidayat, 2017; Sanjaya & Wijaya, 2020; Yana & Nafi‘iyah, 2021). The model developed in this study proved to outperform previous studies when viewed from the obtained high accuracy. The use of texture features extracted with LBP can recognize the difference in patterns on banana peels quite well. The angle of the fruit that cannot be detected with shape features, can also be recognized through changes in the hue of the banana peel image.

CONCLUSION

Several banana cultivars with high similarities were identified in this study by using shapes and textures features extracted with morphology descriptors, convex hulls and local binary patterns. The results of the classification with ELM showed that the proposed method effectively distinguished Ambon-Goroho-Hijau and Balin-Mas with the highest achieved accuracy close to 100%. Further testing is needed to identify other cultivars with high similarities to prove the effectiveness of the proposed model.

ACKNOWLEDGEMENT

We would like to thank to Faculty of Computer Science, University of Brawijaya for the funding of this research.

REFERENCES

Begum, N., & Hazarika, M. K. (2022). Maturity detection of tomatoes using transfer learning. Measurement: Food, 7, 100038. https://doi.org/10.1016/j.meafoo.2022.100038

Bora, G. C., Lin, D., Bhattacharya, P., Bali, S. K., & Pathak, R. (2015). Application of bio-image analysis for classification of different ripening stages of banana. Journal of Agricultural Science, 7(2), 152-160. https://doi.org/10.5539/jas.v7n2p152

Chorowski, J., Wang, J., & Zurada, J. M. (2014). Review and performance comparison of SVM- and ELM-based classifiers. Neurocomputing, 128, 507–516. https://doi.org/10.1016/j.neucom.2013.08.009

Deng, X., Liu, Q., Deng, Y., & Mahadevan, S. (2016). An improved method to construct basic probability assignment based on the confusion matrix for classification problem. Information Sciences,
Candra Dewi et al.: Differentiating High Traits Banana Fruits

Dewi, C., Ariosesilaningsih, E., Mahmudy, W. F., & Solimun. (2022). Identifying of unripe Ambon and Hijau banana fruits using computer vision and extreme learning machine classifier. *IOP Conference Series: Earth and Environmental Science*, 951(1), 012031. https://doi.org/10.1088/1755-1315/951/1/012031

Dewi, C., Mahmudy, W. F., Arfando, R., Arbawa, Y. K., & Ahmadie, B. L. (2020). Improve performance of extreme learning machine in classification of patchouli varieties with imbalanced class. Paper presented at *SIET '20: Proceedings of the 5th International Conference on Sustainable Information Engineering and Technology*, November 2020 (pp. 16-22). New York: Association for Computing Machinery. https://doi.org/10.1145/3427423.3427424

Ding, S., Xu, X., & Nie, R. (2014). Extreme learning machine and its applications. *Neural Computing and Applications*, 25(3-4), 549–556. https://doi.org/10.1007/s00521-013-1522-8

Dittakan, K., Theera-Ampornpunt, N., Witthayarat, W., Hinnoy, S., Klaiwan, S., & Pratheep, T. (2017). Banana cultivar classification using scale invariant shape analysis. Paper presented at *Proceeding of 2017 2nd International Conference on Information Technology, INCIT 2017* (pp. 1–6). Nakhonpathom, Thailand: IEEE. https://doi.org/10.1109/INCIT.2017.8257854

Dwivany, F. (2018). *Pentingnya data pisang Indonesia*. https://doi.org/10.31227/osf.io/m9rg4

Ekesa, B., Mirroir, C., Blomme, G., Van Den Bergh, I., & Davey, M. W. (2013). Retention of provitamin a carotenoids during postharvest ripening and processing of three popular musa cultivars in South-Western Uganda. *Acta Horticulturae*, 986, 319–330. https://doi.org/10.17660/ActaHortic.2013.986.34

Fauziah, Trimanto, & Hapsari, L. (2017). Morphology and molecular identification of local cultivars of pisang raja (Musa spp.) from Yogyakarta, Central Java and East Java, Indonesia. Paper presented at *Prosiding International Conference Celebrating Bicentenary of Bogor Botanic Gardens and the Golden Year of LIPI*, 18-20 May 2017, Lembaga Ilmu Pengetahuan Indonesia. Retrieved from http://lipi.go.id/publikasi/morphology-and-molecular-identification-of-local-cultivars-of-pisang-raja-musa-spp-from-yogyakarta-central-java-and-east-java-indonesia/29774

Hapsari, L., Lestari, D. A., & Masrum, A. (2015). *Album koleksi pisang Kebun Raya Purwodadi seri 1*: 2010-2015. Unit Pelaksana Teknis Balai Konservasi Tumbuhan Kebun Raya Purwodadi-LIPI. Retrieved from https://www.researchgate.net/publication/292881817_ALbum_Koleksi_ Pisang_Kebun_Raya_Purwodadi_Seri_1_2010-_2015

Hou, J. C., Hu, Y. H., Hou, L. X., Guo, K. Q., & Satake, T. (2015). Classification of ripening stages of bananas based on support vector machine. *International Journal of Agricultural and Biological Engineering*, 8(6), 99–103. https://doi.org/10.3966/j.jabe.20150806.1275

Huang, G.-B., Zhu, Q.-Y., & Siew, C.-K. (2004). Extreme learning machine: A new learning scheme of feedforward neural networks. Paper presented at *2004 IEEE International Joint Conference on Neural Networks* (IEEE Cat. No.04CH37541) (pp. 985–990). Budapest, Hungary: IEEE. https://doi.org/10.1109/IJCNN.2004.1380068

Huang, G.-B., Zhu, Q.-Y., & Siew, C.-K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, 70(1–3), 489–501. https://doi.org/10.1016/j.neucom.2005.12.126

Huang, K.-Y. (2012). Detection and classification of areca nuts with machine vision. *Computers and Mathematics with Applications*, 64(5), 739–746. https://doi.org/10.1016/j.camwa.2011.11.041

Iklima, C. P., Nasir, M., & Hidayat, H. T. (2017). Klasiﬁkasi jenis pisang menggunakan metode K-Nearest Neighbor (KNN). *Jurnal Teknologi Rekayasa Informasi dan Komputer*, 1(1), 11–14. Retrieved from http://e-jurnal.pnli.ac.id/TRIK/article/view/1854

Kaewchote, J., Janyong, S., & Limprasert, W. (2018). Image recognition method using Local Binary Pattern and the Random forest classiﬁer to count post larva shrimp. *Agriculture and Natural Resources*, 52(4), 371–376. https://doi.org/10.1016/j.anres.2018.10.007

Kaplan, K., Kaya, Y., Kuncan, M., & Ertunç, H. M. (2020). Brain tumor classiﬁcation using modiﬁed local binary patterns (LBP) feature extraction methods. *Medical Hypotheses*, 139, 109696. https://doi.org/10.1016/j.mehy.2020.109696

Le, T.-T., Lin, C.-Y., & Piedad, E. Jr. (2019). Deep learning for noninvasive classiﬁcation of clustered horticultural crops – A case for banana fruit tiers. *Postharvest Biology and Technology*, 156, 110922. https://doi.org/10.1016/j.postharvbio.2019.05.023

Li, H., Lee, W. S., & Wang, K. (2014). Identifying blueberry fruit of different growth stages using natural outdoor color images. *Computers and Electronics in Agriculture*, 106, 91–101. https://doi.org/10.1016/j.compag.2014.05.015

Mahale, V. H., Ali, M. M. H., Yannawar, P. L., & Gaikwad, A. T. (2017). Image inconsistency detection using...
Local Binary Pattern (LBP). Procedia Computer Science, 115, 501–506. https://doi.org/10.1016/j.
procs.2017.09.097

Mohd Ali, M., Hashim, N., Abd Aziz, S., & Lasekan, O. (2022). Quality prediction of different pineapple (Ananas comosus) varieties during storage using infrared thermal imaging technique. Food Control, 138, 108988. https://doi.org/10.1016/j.
foodcont.2022.108988

Mohi-Alden, K., Omid, M., Firouz, M. S., & Nasiri, A. (2022). A machine vision-intelligent modelling based technique for in-line bell pepper sorting. Information Processing in Agriculture, In Press. https://doi.org/10.1016/j.inpa.2022.05.003

Ojala, T., Pietikäinen, M., & Harwood, D. (1996). A comparative study of texture measures with classification based on featured distributions. Pattern Recognition, 29(1), 51–59. https://doi.
org/10.1016/0031-3203(95)00067-4

Okorie, D. O., Eleazu, C. O., & Nwosu, P. (2015). Nutrient and heavy metal composition of plantain (Musa paradisiaca) and banana (Musa paradisiaca) peels. Journal of Nutrition & Food Sciences, 5(3), 1–4. https://doi.org/10.4172/2155-9600.1000370

Pahikkala, T., Kari, K., Mattila, H., Lepistö, A., Teuhola, J., Nevalainen, O. S., & Tyystjärvi, E. (2015). Comparative study of texture measures with classification based on overlapping leaves. Computers and Electronics in Agriculture, 118, 186–192. https://doi.
org/10.1016/j.compag.2015.08.004

Piedad, E. Jr, Larada, A. I., Pojas, G. J., & Ferrer, L. V. V. (2018). Postharvest classification of banana (Musa acuminata) using tier-based machine learning. Postharvest Biology and Technology, 145, 93–100. https://doi.org/10.1016/j.postharvbio.2018.06.004

Purwadaria, H. K. (2006). Issues and solutions of fresh fruit export in Indonesia. Paper presented at International Seminar on Enhancing Competitiveness of Asian Fruits, Bangkok, Thailand, 18-19 May 2006 (pp. 24–33). Retrieved from https://un-csam.org/sites/default/files/2021-01/issues%20and%20solutions%20of%20Fresh%20Fruit%20Export%20in%20Indonesia.pdf

Sanjaya, H. K., & Wijaya, N. (2020). Klasifikasi jenis pisang menggunakan Support Vector Machine dengan fitur GLCM dan HOG. Indonesian Journal of Computer Science, 9(2), 129–143. Retrieved from https://docplayer.info/20875857-Klasifikasi-jenis-pisang-menggunakan-support-vector-machine-dengan-fitur-glcmand-hog.html

Santoyo-Mora, M., Sancen-Plaza, A., Espinos-Calderon, A., Barranco-Gutierrez, A. I., & Prado-Olivarez, J. (2019). Nondestructive quantification of the ripening process in banana (Musa AAB Simmonds) using multispectral imaging. Journal of Sensors, 2019, 6742896. https://doi.
org/10.1155/2019/6742896

Simmonds, N. W. (1966). Bananas. London: Longmans. Retrieved from https://books.google.co.id/books/about/Bananas.html?id=GgA2AAAMAAJ&redir_esc=y

Simmonds, N. W., & Shepherd, K. (1955). The taxonomy and origins of the cultivated bananas. Botanical Journal of the Linnean Society, 55(359), 302–312. https://doi.org/10.1111/j.1095-8339.1955.
tb00015.x

Singh, K., Gupta, I., & Gupta, S. (2010). SVM-BDT PNN and fourier moment technique for classification of leaf shape. International Journal of Signal Processing Image Processing and Pattern Recognition, 3(4), 67–78. Retrieved from https://www.researchgate.net/publication/284831182__SVM-BDT_PNN_and_fourier_moment_
technique_for_classification_of_leaf_shape

Srividhya, V., Sujatha, K., & Ponmagal, R. S. (2016). Ethylene gas measurement for ripening of fruits using image processing. Indian Journal of Science and Technology, 9(31), 1–7. https://doi.
org/10.17485/ijst/2016/v9i31/93838

Wang, X.-F., Du, J.-X., & Zhang, G.-J. (2005). Recognition of leaf images based on shape features using a hypersphere classifier. In D. S. Huang, X. P. Zhang, G. B. Huang (Eds.), Advances in Intelligent Computing (ICIC 2005), Lecture Notes in Computer Science, 3644(PART I), 87–96. https://doi.
org/10.1007/11538059_10

Yana, Y. E., & Nafi’iyah, N. (2021). Klasifikasi jenis pisang berdasarkan fitur warna, tekstur, bentuk citra menggunakan SVM dan KNN. RESEARCH : Journal of Computer, Information System & Technology Management, 4(1), 28. https://doi.
org/10.25273/research.v4i1.6687

Zhang, L., Weckler, P., Wang, N., Xiao, D., & Chai, X. (2016). Individual leaf identification from horticultural crop images based on the leaf skeleton. Computers and Electronics in Agriculture, 127, 184–196. https://doi.org/10.1016/j.compag.2016.06.017

Zhang, Y., Wang, S., Ji, G., & Phillips, P. (2014). Fruit classification using computer vision and feedforward neural network. Journal of Food Engineering, 143, 167–177. https://doi.
org/10.1016/j.jfoodeng.2014.07.001

Zulkifli, N., Hashim, N., Abdan, K., & Hanafi, M. (2019). Application of laser-induced backscattering imaging for predicting and classifying ripening stages of “Berangan” bananas. Computers and Electronics in Agriculture, 160, 100–107. https://doi.
org/10.1016/j.compag.2019.02.031