*ICIC Express Letters*
Volume **15**, Number **9**, September **2021**

ICIC International ©2021 ISSN 1881-803X
pp. 1013–1020

# CLASSIFICATION OF AMBARELLA FRUIT RIPENESS BASED ON COLOR FEATURE EXTRACTION

Raymond Erz Saragih, Dessy Gloria and Albertus Joko Santoso*

Department of Informatics
Universitas Atma Jaya Yogyakarta
Jl. Babarsari No. 43, Janti, Caturtunggal, Depok, Sleman, Daerah Istimewa
Yogyakarta 55281, Indonesia
{ raymonde.saragih; dessypalijama70 }@gmail.com
*Corresponding author: albjoko@staff.uajy.ac.id

Received December 2020; accepted March 2021

Abstract. *In the food industry, determining fruit maturity is very important to obtain fruit of good quality. The ripeness of some fruits can be determined by the color of the skin. Like several other types of fruit, the skin color can be used to determine the ripeness of Ambarella fruit. However, determining the ripeness of Ambarella fruit is still done manually by human labor, which is considered time-consuming, tiring, requires a lot of workers, and can cause inconsistencies. The development of technology such as computer vision allows the determination of fruit ripeness to be carried out automatically, accurately, and relatively quickly. This study aims to classify the ripeness of the Ambarella fruit based on its color feature with the use of machine learning. The color features used are RGB, HSV, and L*a*b*, with Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) as the classifiers. Segmentation was done using the Otsu method. Google Colab, OpenCV, and scikit-learn are utilized in carrying out the experiments. The performance result shows that the highest accuracy, precision, recall, and f-measure were achieved by using SVM on the L*a*b* color feature.*

**Keywords:** Fruit ripeness, Computer vision, Color feature, Machine learning

1. **Introduction.** Indonesia is one of the countries whose economy relies on agriculture [1]. Agriculture is one of the main sectors in the category of economic activity in Indonesia [2]. Indonesia produces various agricultural products, and one of them is fruits, such as oranges, mangoes, and salak [3]. One of the fruits produced in Indonesia is the Ambarella fruit. Ambarella (Spondias cytherea or Spondias dulcis) is a type of plant originating from the family of Anacardiaceae, which is the family of several types of tropical fruit plants, such as mangoes [4]. In Indonesia, people generally consume Ambarella fruit for salad food or made as salted fruit [5]. The Ambarella plant offers various efficacies, including as medicine for hemorrhoids, indigestion, diabetes mellitus treatment, and blood purifier [4-6].

In the food industry, determining fruit maturity is very important to obtain the fruit of good quality [7]. Several ways can be done to determine the ripeness of the fruit, one of which is the color of the skin, such as mangoes, tomatoes, and apples [8]. Like several other types of fruit, the skin color can be used to determine the ripeness of Ambarella fruit [4]. Determining the ripeness of Ambarella fruit is still done manually by human labor. Determining the ripeness of fruit manually is considered time-consuming, tiring, requires a lot of workers, and can cause inconsistencies [2,7,9,10]. Therefore, a way to determine the ripeness of Ambarella fruit automatically and quickly is needed.

The development of technology is rapid and has developed technology such as computer vision. Computer vision has been used for various things, one of which is to determine

DOI: 10.24507/icicel.15.09.1013

the ripeness of fruit [8]. Computer vision allows the determination of fruit ripeness to be carried out automatically, accurately, and relatively quickly [3]. In computer vision, the use of the color feature and machine learning can classify the ripeness of fruit [3,7]. Therefore, the use of technology can automate the classification process.

Based on the above-stated problem, this study aims to classify Ambarella fruit. The contribution of this paper proposes a method to classify the ripeness of the Ambarella fruit with different ripening stages, such as unripe, mid-ripe, ripe, and overripe, using machine learning based on its color feature. The color features are RGB, HSV, and L*a*b*. Supervised machine learning techniques were applied to classifying the ripeness of the Ambarella fruit based on the extracted features. The classifiers used in this study are SVM and KNN. Both classifiers have been used for various supervised learning problems, one of which is the case of classifying fruit ripeness [2,3,7], and shown satisfying result; therefore, in this study, SVM and KNN are used to classify the ripeness of Ambarella fruit. Several image processing techniques are applied before the classifying process, such as cropping, resizing, segmentation, and extracting features. The Otsu method was used for segmentation. The experiment was done using Google Colab and utilized several libraries, such as OpenCV and scikit-learn.

2. **Literature Review.** Pardede et al. [3] in their study classified the ripeness of various types of fruit. The types of fruit used were apples, mangoes, oranges, and tomatoes. Four color features were used, namely RGB, HSV, HSL, and L*a*b*. The color feature was used as inputs for the Support Vector Machine (SVM) to classify the ripeness. The experimental results indicate that the use of different color features affects the accuracy obtained by the classifier. The use of different degrees of the polynomial kernel was tested to determine the influence on accuracy. The test results show that the highest accuracy was successfully obtained using the HSV color feature and with a 6th-degree polynomial kernel.

Suban et al. [2] conducted a study to classify the ripeness of Carica papaya fruit using K-Nearest Neighbor (KNN). The types of ripeness that are classified are ripe and unripe. The RGB value is used as an input feature for the KNN. The researcher managed to obtain 100% accuracy. Castro et al. [7] conducted a study to classify the ripeness of Cape Gooseberry fruit. There are different classifiers used, such as SVM, Artificial Neural Network (ANN), decision tree, and KNN. The color features used are RGB, HSV, L*a*b*. Besides, researchers used PCA to combine the three color features. The results show that the L*a*b* color feature and SVM produce the highest f-measure, and using PCA, the model performance can be improved.

Mazen and Nashat [11] proposed a system to classify the ripeness of banana fruit using several models, such as ANN, SVM, Naïve Bayes, KNN, decision tree, and discriminant analysis. There were several steps taken in the study, including image pre-processing, removing brown spots on bananas, extracting features, and classifying using different models. Researchers used the Tamura texture feature and new features to define the ripeness factor of bananas, which are used for the input to each classifier. After being tested, the highest level of accuracy was obtained using ANN, which shows up to 100% for the green and overripen classes, and 97.75% for the mid-ripen and yellowish-green classes.

Septiarini et al. [12] conducted a study to classify the ripeness of oil palm fruit. Researchers used SVM as a classifier. The Otsu method was used to segment the oil palm fruit in the image. There are eight features used, namely the average intensity value and the standard deviation of the colors Red, Green, Blue, and gray. Different $k$ parameters for the KNN were used, which were 2, 4, 10, and 20, to compare the accuracy obtained by the classifier. The highest accuracy obtained was 92.50%, when using 20 neighbors.

Previous studies have utilized color features and machine learning to classify the ripeness of fruit and have shown satisfying results. Based on the method used in the previous studies, this study aims to classify Ambarella fruit using two machine learning methods, support vector machine and k-nearest neighbor, and the color features. The color features are RGB, HSV, and L*a*b*.

3. **Materials and Methods.** In this study, the experiment was done through several steps. The steps are shown in Figure 1.


Figure 1. The steps in conducting the experiment

As shown in Figure 1, the steps taken for the experiment are image acquisition, image preprocessing, segmentation, color feature extraction, and Ambarella fruit classification. The details of these steps are described below.

3.1. **Acquisition of Ambarella fruit images.** In this study, a total of 100 Ambarella fruit images were collected. The images are in RGB color images with a white background. The images were taken using a smartphone camera with $3120 \times 4160$ pixels and stored in jpg format. The Ambarella fruit images are divided into four classes, unripe, mid-ripe, ripe, and overripe, and each class consists of 25 images. Figure 2 shows image samples of the Ambarella fruit with different ripeness, which are unripe, mid-ripe, ripe, and overripe.


Figure 2. Image samples of Ambarella fruit with different ripeness

The images taken as shown in Figure 2 have various illumination and contain shadows of the Ambarella fruit. Before extracting the color feature, image preprocessing and segmentation must be done.

3.2. **Image preprocessing.** Several image preprocessing steps were done to the images. First, the original images are cropped to the shape of a square. Cropping is done to remove excess and unused white background surrounding the fruit. Lastly, after cropping the images, resizing was done to reduce the size of the images and reduce the computation process. Images were resized to the size of $320 \times 320$ pixels. Figure 3 shows samples of the cropped and resized images.

As shown in Figure 3, the excess background has been reduced. The purpose of resizing the image is to reduce the file size, therefore speeding up the computation in later processes.

FIGURE 3. Samples of the cropped and resized images

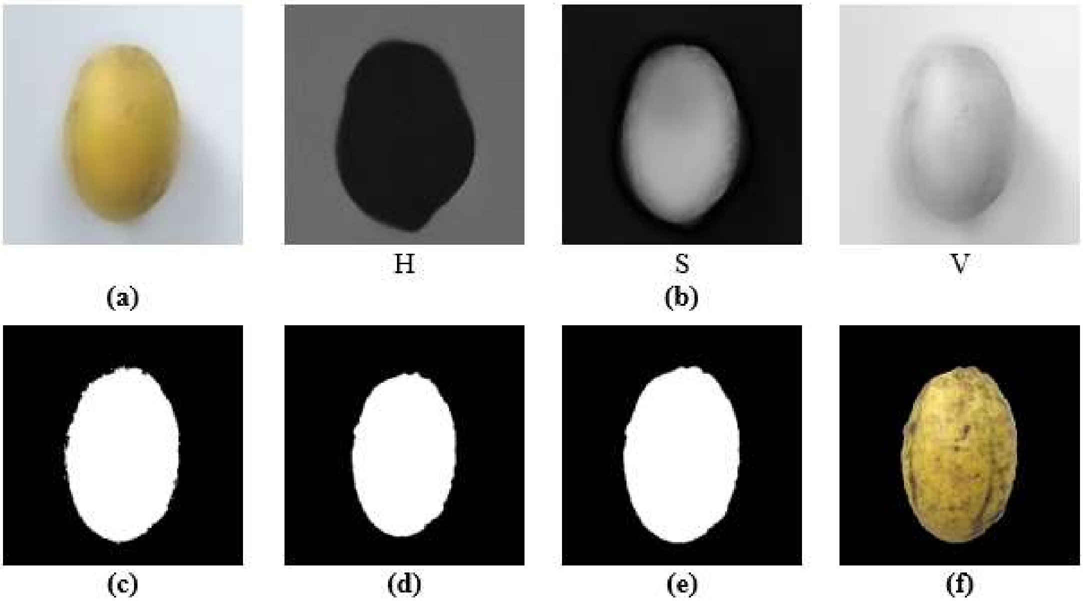


FIGURE 4. Segmentation of Ambarella fruit

3.3. **Segmentation.** The resized images are processed for segmentation. The purpose of segmentation is to remove the background from the main object in the image [7]. There are several steps conducted in segmenting the Ambarella fruit, such as shown in Figure 4.

The preliminary step is applying a bilateral filter to the image. A bilateral filter is one of the filters used to remove noise from an image but still preserving the edges [13]. The trial was done using other filters, such as the Average filter and Gaussian filter, but the fruit edge was blurred. The bilateral filter shows a better result than the other filters; therefore, it is used. The result is shown in Figure 4(a). After applying the bilateral filter, the next step is converting the RGB image to HSV color space. As shown in the sample images above, the image has various luminance. The HSV color spaces can separate color and luminance from the image [11]; therefore, it is used. The resulting HSV image is then split into its 3-individual color space, which are H, S, and V, as shown in Figure 4(b). Based on observation, the image on the S color space produces a gray image and it clearly shows the difference between the object and the background, while the H color space shows changes in the fruit shape and the V color space does not clearly show the difference between the fruit and the background.

The next step is segmenting the Ambarella fruit from the white background. The method used to segment the object is the Otsu method, which was used on [8,11,12]. The Otsu method generates a binary image, where the white part has a luminance below the threshold value, while the part that has a luminance above the threshold value is converted to black. In this case, the Ambarella fruit is converted to white, and the white background is converted to black. The resulting binary image from the Otsu method is shown in Figure 4(c).

The binary image generated by the Otsu method still needs further processing, as there are parts of the background that are included because it has dark color as a result of the shadow of the Ambarella fruit, or there are gaps in the fruit. To overcome this, morphological operations, namely erosion, and dilation, were applied using a disk-shaped structural element. The erosion operation is used to reduce the structure of the image; therefore, some parts of the background that are included can be reduced. The result of the erosion operation in Figure 4(d) shows that the fruit object area shrinks, enlarging, or even producing gaps in the fruit. To overcome this problem, the next step is applying a dilation operation to filling in the gaps in the fruit and slightly enlarging the fruit object area. The binary image resulted from the dilation operation shown in Figure 4(e) is used as a mask that is applied to the original image, resulting in the segmentation of the Ambarella fruit shown in Figure 4(f).

3.4. **Color feature extraction.** The ripeness of the fruit can be determined through color [12]. Similar to several other types of fruit, the ripeness of the Ambarella fruit can be determined from the color of the skin [4]. Therefore, in this study, the color feature is used to determine the fruit maturity of Ambarella. The color features were extracted from the fruit segmentation of Ambarella. Average values of the RGB, HSV, and L*a*b* color spaces were used, similar to [7]. The OpenCV was used to acquire the color features. The average values, that are obtained from each fruit in each class, are stored for later use in training and testing the machine learning models.

3.5. **Ambarella fruit ripeness classification.** Classification is carried out using three values obtained from calculating the average value in each color space, the RGB, HSV, and L*a*b* color space. Two supervised machine learning methods are used, the support vector machine and k-nearest neighbors. SVM and KNN have been used for various supervised learning problems, such as predicting diseases [14,15], and classification, of which is the case of classifying fruit ripeness.

Support Vector Machine (SVM) is one of the supervised learning that can be used for both classification and regression purposes. SVM applications for classification purposes can either be used for binary classification or multi-class classification [14]. The SVM classifier constructs an optimal hyperplane or decision boundary for binary classification, or multiple hyperplanes for multi-class classification, in the dimensional space that separates the classes [7]. This work uses the SVM because based on previous work, the SVM has been able to successfully classify fruit ripeness.

Aside from SVM, another classifier that has been successfully used for various cases of classification is the K-Nearest Neighbor (KNN). KNN is supervised learning. KNN classifies new data based on the neighbors that have the closest distance to the data. The $k$ specifies the number of neighbors in the training [16]. KNN is one of the simplest methods used in supervised learning [2]. Although the KNN is simple, it is proved to be successful in various cases of classification. A simplified depiction of SVM and KNN is shown in Figure 5 [17]. In this work, the KNN is used and the performance will be compared with the SVM classifier. In this work, the SVM and KNN provided by scikit-learn are used to create the classifier.

The last step is evaluating the performance of each model through the use of a confusion matrix to measure the accuracy, precision, recall, and f-measure [7,18]. Equations (1)-(4) were used to calculate the accuracy, precision, recall, and f-measure, respectively [11].

$$\text{Accuracy} = (\text{TP} + \text{FN})/(\text{TP} + \text{FP} + \text{FN} + \text{TN}) \tag{1}$$

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \tag{2}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \tag{3}$$

$$\text{F-measure} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall}) \tag{4}$$

In the above equations, TP, TN, FP, and FN represent the number of True Positive, True Negative, False Positive, and False Negative [11]. The confusion matrix and the calculation results of accuracy, precision, recall, and f-measure were generated automatically using sklearn.

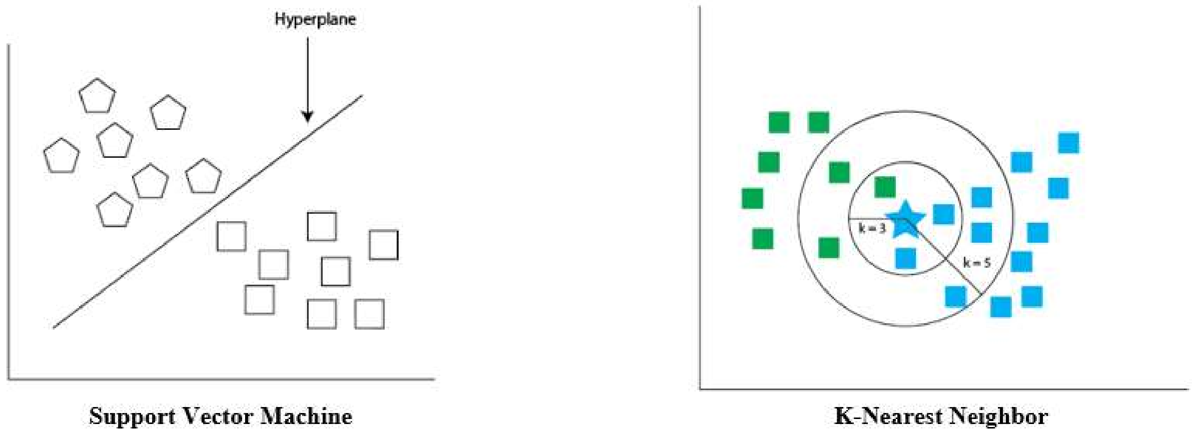


FIGURE 5. Simplified depiction of SVM and KNN

4. **Result and Discussion.** In this study, two machine learning techniques, SVM and KNN, were used to classify the ripeness of Ambarella fruit based on the extracted color features which are RGB, HSV, and L*a*b*. Each color space contains 3 values from 100 images of Ambarella fruits. The dataset was divided into 70% for training and 30% for testing. The SVM model was created by using the linear kernel [7] and it gives the best result. For the KNN, four different $k$ neighbor parameters were used, which are 1, 3, 5, and 7, to compare the result. Based on [15], the KNN will randomly select the class used as output if the $k$ parameter is an even number. Therefore, to prevent it, odd numbers were used.

Table 1 shows the accuracy, precision, recall, and f-measure of the SVM and KNN classifier on the RGB color feature. The macro average values of precision, recall, and f-measure were used.

TABLE 1. Performance of the SVM and KNN on RGB color feature

| Classifiers | RGB color feature | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F-measure |
| SVM | 93.33% | 93.75% | 94.10% | 93.29% |
| KNN ($k = 1$) | 70.00% | 76.25% | 73.16% | 70.18% |
| KNN ($k = 3$) | 56.67% | 64.04% | 61.36% | 54.77% |
| KNN ($k = 5$) | 53.33% | 64.29% | 56.40% | 53.99% |
| KNN ($k = 7$) | 46.67% | 58.96% | 50.50% | 45.71% |

Based on the result of using SVM and KNN classifiers on RGB color feature, the highest accuracy, precision, recall, and f-measure were achieved by using SVM, which are 93.33%, 93.75%, 94.10%, and 93.29% respectively. The KNN, on the other hand, was only capable of achieving the highest accuracy of 70% with $k$ equal to 1. KNN with $k$ equal to 1 achieves the highest precision, recall, and f-measure, which are 76.25%, 73.16%, and 70.18% respectively. The lowest performance achieved with $k$ equal to 7. The experiment using the RGB color feature shows that SVM performs much better than KNN. The following experiment is using the HSV color feature. Table 2 shows the performance of the SVM and KNN classifier on the HSV color feature.

Table 2. Performance of the SVM and KNN on HSV color feature

| Classifiers | HSV color feature | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F-measure |
| SVM | 76.67% | 83.75% | 77.23% | 74.65% |
| KNN ($k = 1$) | 63.33% | 70.83% | 67.01% | 61.30% |
| KNN ($k = 3$) | 56.67% | 63.45% | 60.76% | 54.46% |
| KNN ($k = 5$) | 53.33% | 65.60% | 57.19% | 52.12% |
| KNN ($k = 7$) | 53.33% | 52.78% | 56.50% | 51.15% |

The highest accuracy, precision, and recall were achieved by using SVM. The SVM achieves 76.67% on accuracy, 83.75% on precision, 77.23% on recall, and 74.65% on f-measure. However, the performance of SVM on the HSV color feature is lower than that on the RGB color feature. The KNN similarly performs lower on the HSV color feature than on the RGB color feature. The KNN with $k$ equal to 1 was able to obtain the highest performance, with an accuracy of 63.33%, 70.83% on precision, 67.01% on recall, and 61.30% on f-measure. The SVM once again performs better than the KNN on the HSV color feature. The last experiment was done by using the L*a*b* color feature with both classifiers. Table 3 shows the performance result of each classifier.

Table 3. Performance of the SVM and KNN on L*a*b* color feature

| Classifiers | L*a*b* color feature | | | |
|---|---|---|---|---|
| | Accuracy | Precision | Recall | F-measure |
| SVM | 96.67% | 96.43% | 96.88% | 96.41% |
| KNN ($k = 1$) | 70.00% | 77.08% | 72.82% | 70.00% |
| KNN ($k = 3$) | 66.67% | 72.39% | 70.39% | 66.06% |
| KNN ($k = 5$) | 66.67% | 72.02% | 69.59% | 67.09% |
| KNN ($k = 7$) | 56.67% | 70.42% | 61.01% | 54.57% |

The results of using SVM and KNN classifiers on the L*a*b* color feature show that the highest accuracy, precision, recall, and f-measure were achieved by using SVM, which are 96.67%, 96.43%, 96.88%, and 96.41% respectively. The KNN with $k$ equal to 1 could achieve 70.00% on accuracy, 77.08% on precision, 72.82% on recall, and 70.00% on f-measure, outperforming KNN with $k$ equal to 3, 5, and 7. In terms of precision, the KNN achieves higher on L*a*b* color feature than on RGB and HSV color features.

The results comparison between SVM and KNN shows that SVM performs better than KNN. For KNN, the $k$ neighbors parameter affects the performance. The KNN performs the best with $k$ equal to 1. Increasing the number of $k$ neighbors on the contrary lowers the performance. The use of color features also affects the performance. The lowest performance was achieved on the HSV color feature, and better performance was achieved on the RGB and the L*a*b* color features. However, comparing all the results, it can be concluded that the SVM achieved the highest performance based on the L*a*b* color feature, while in terms of accuracy, KNN performs the same on L*a*b* color feature and RGB color feature.

5. **Conclusions.** In this study, the ripeness classification of the Ambarella fruit has been conducted. Four ripeness stages are used, which are unripe, mid-ripe, ripe, and overripe. The experiment was done through several steps such as acquiring fruit images, image processing techniques, feature extraction, and lastly classification using the SVM and KNN. The color features used are RGB, HSV, and L*a*b*. The total images used are 100 images, 70 images for training, and 30 images used for testing. The results show that using SVM with the L*a*b* color feature achieved the highest accuracy, precision, recall,

and f-measure, with a value of 96.67%, 96.43%, 96.88%, and 96.41% respectively. In the future, the aim is to use the deep learning method, such as CNN to classify the ripeness of the Ambarella fruit and object detection to automatically detect and crop the fruit image.

**Acknowledgment.** We would like to convey our gratitude to Universitas Atma Jaya Yogyakarta, Indonesia, for funding this research.

## REFERENCES

[1] A. Bashir, S. Suhel, A. Azwardi, D. P. Atiyatna, I. Hamidi and N. Adnan, The causality between agriculture, industry, and economic growth: Evidence from Indonesia, *Etikonomi*, vol.18, no.2, pp.155-168, 2019.

[2] I. B. Suban, A. Paramartha, M. Fortwonatus and A. J. Santoso, Identification the maturity level of carica papaya using the k-nearest neighbor, *J. Phys. Conf. Ser.*, vol.1577, no.1, 2020.

[3] J. Pardede, M. G. Husada, A. N. Hermana and S. A. Rumapea, Fruit ripeness based on RGB, HSV, HSL, L*a*b* color feature using SVM, *2019 Int. Conf. Comput. Sci. Inf. Technol. (ICoS-NIKOM2019)*, 2019.

[4] M. Mohammed, S. H. Ahmad, R. A. Bakar and T. L. Abdullah, Golden apple (*Spondias dulcis* Forst. syn. *Spondias cytherea* Sonn.), in *Woodhead Publishing Series in Food Science, Technology and Nutrition, Postharvest Biology and Technology of Tropical and Subtropical Fruits*, E. M. Yahia (ed.), Woodhead Publishing, 2011.

[5] R. Rakhmawati and Y. Yunianta, Effects of proportion fruit: Water and heating time on antioxidant activity of hogplum juice, *J. Pangan dan Agroindustri*, vol.3, no.4, pp.1682-1693, 2015.

[6] S. D. Ismanto, I. D. Rahmi and A. Febrian, The influence of drying temperature on chemical components of herbal tea leaves (Spondias Dulcis, Soland), *Int. Conf. Sustain. Agric. Food Energy (SAFE2016)*, pp.1-8, 2016.

[7] W. Castro, J. Oblitas, M. De-La-Torre, C. Cotrina, K. Bazan and H. Avila-George, Classification of cape gooseberry fruit according to its level of ripeness using machine learning techniques and different color spaces, *IEEE Access*, vol.7, pp.27389-27400, 2019.

[8] V. Mohammadi, K. Kheiralipour and M. Ghasemi-Varnamkhasti, Detecting maturity of persimmon fruit based on image processing technique, *Sci. Hortic. (Amsterdam)*, vol.184, pp.123-128, 2015.

[9] M. P. Arakeri and Lakshmana, Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry, *Procedia Comput. Sci.*, vol.79, pp.426-433, 2016.

[10] A. Wajid, N. K. Singh, P. Junjun and M. A. Mughal, Recognition of ripe, unripe and scaled condition of orange citrus based on decision tree classification, *Proc. of 2018 Int. Conf. Comput. Math. Eng. Technol. Inven. Innov. Integr. Socioecon. Dev. (iCoMET2018)*, vol.1, pp.1-4, 2018.

[11] F. M. A. Mazen and A. A. Nashat, Ripeness classification of bananas using an artificial neural network, *Arab. J. Sci. Eng.*, vol.44, no.8, pp.6901-6910, 2019.

[12] A. Septiarini, H. Hamdani, H. R. Hatta and A. A. Kasim, Image-based processing for ripeness classification of oil palm fruit, *Proc. of 2019 5th Int. Conf. Sci. Inf. Technol. Embrac. Ind. 4.0 Towar. Innov. Cyber Phys. Syst. (ICSITech2019)*, pp.23-26, 2019.

[13] D. Zhang, J. Kang, L. Xun and Y. Huang, Hyperspectral image classification using spatial and edge features based on deep learning, *Int. J. Pattern Recognit. Artif. Intell.*, vol.33, no.9, 2019.

[14] A. K. Dwivedi, Performance evaluation of different machine learning techniques for prediction of heart disease, *Neural Comput. Appl.*, vol.29, no.10, pp.685-693, 2018.

[15] J. Qin, L. Chen, Y. Liu, C. Liu, C. Feng and B. Chen, A machine learning methodology for diagnosing chronic kidney disease, *IEEE Access*, vol.8, pp.20991-21002, 2020.

[16] A. C. Muller and S. Guido, *Introduction to Machine Learning with Python*, O'Reilly Media, Inc., Sebastopol, 2016.

[17] S. Uddin, A. Khan, M. E. Hossain and M. A. Moni, Comparing different supervised machine learning algorithms for disease prediction, *BMC Med. Inform. Decis. Mak.*, vol.19, no.1, pp.1-16, 2019.

[18] M. Murata, K. Orikane and R. Akae, Automatic selection and analysis of verb and adjective synonyms from Japanese sentences using machine learning, *International Journal of Innovative Computing, Information and Control*, vol.15, no.6, pp.2135-2147, 2019.