ICIC Express Letters
Part B: Applications
Volume **9**, Number **10**, October **2018**

ICIC International ©2018 ISSN 2185-2766
pp. 991–998

GRADING FOR RIPENESS OF PASSION FRUIT USING MULTI-CLASS SUPPORT VECTOR MACHINE

Sitti Wetenriajeng Sidehabi[1], Ansar Suyuti[1], Intan Sari Areni[1] and Ingrid Nurtanio[2]

[1]Department of Electrical Engineering
[2]Department of Informatics Engineering
Universitas Hasanuddin
Gowa, South Sulawesi, Indonesia
tenri@atim.ac.id; asuyuti06@yahoo.com; { intan; ingrid }@unhas.ac.id

Received May 2018; accepted August 2018

Abstract. *Assurance for a high standard of food quality is imperative in the agrofood industry. Processed passion fruit (Passiflora Edulis) is one of the main products of the agrofood industry in Makassar, Indonesia. The passion fruit is processed into sweet toffee (dodol), juice and passion fruit extract. The ripeness level of the fruit greatly affects the quality of its finished products. Hence, the need for a practical, automated and precise mechanism to determine the grading of the ripeness level for the passion fruit is needed by using image processing techniques on the computer vision. This paper describes the use of K-means clustering method to segment the passion fruits and the Multi-class Support Vector Machine (MSVM) process to classify their ripeness using 120 fruit pieces (90 pieces for training, and 30 pieces for data testing). The accuracy obtained using this method is 96.67%.*

Keywords: Passion fruit, K-means clustering, MSVM, Ripeness

1. **Introduction.** In the agrofood industry, the standard quality of materials for food processing supplies must be guaranteed. The materials must meet the prevailing standards of quality system or food management system and product certification. Processed passion fruit (Passiflora Edulis) is one of the main products of the agrofood industry in Makassar, Indonesia. The passion fruit is processed into sweet toffee (dodol), juice and passion fruit extract. Hariyadi stated that the fruit and vegetable processing industry wants uniformity in size, colour and age as well as ease of handling and processing [1]. The existing process of manually sorting the fruits is prone to inconsistencies and resulting in longer processing time. Switching from the manual process to automation process is one solution to this problem. The automation process using computer vision application yields a high level of uniformity, shorter processing time, and bigger processing capacity which can be tailored to the need of end user. Hartato mentioned, the application of automation technology in the form of artificial intelligence in the production line will improve efficiency because it can identify when certain raw materials enter the plant, what the next process is and how much raw materials it needs [2].

Research on grading apples, Asian pears, cucumbers, mangoes, oranges, pineapples, pomegranates, and strawberries has been conducted by Jana et al. using Gray-Level Co-occurrence Matrix (GLCM), statistical colour and Support Vector Machine (SVM) algorithms with an average accuracy of 83.33% [3]. As for the classification 5 level of the bell pepper ripeness researched by Elhariri et al., the accuracy obtained is 93.89% using Principal Component Analysis (PCA) and Support Vector Machine (SVM) methods [4]. To detect the damaged guava, Hasan and Monir used an independent analysis conversion

DOI: 10.24507/icicelb.09.10.991

and Support Vector Machine (SVM) resulting in 94.5% accuracy [5]. Raj and Vinod applied the Fuzzy C-Means (FCM), Histogram of Oriented Gradients (HOG) and Multi-class Support Vector Machine (MSVM) methods for grading apples into damaged apples, slightly damaged apples, and good apples. The research obtained accuracy is 94.66% [6].

Grading the ripeness level of passion fruit into ripe, nearly ripe, and unripe using K-means segmentation method and Neural Network (NN) classification of feedforward network has conducted by Sidehabi et al. [7]. This research used RGB color features and a* with an accuracy rate of 90%. This slightly lower margin of error occurs because of the high colour resemblance between the nearly ripe and unripe passion fruits which is very difficult to differentiate. To obtain the higher level of accuracy, this paper applies K-means clustering and Multi-class Support Vector Machine (MSVM) by utilizing input data in the form of six sides of passion fruit. The remaining paper is organized as follows. Section 2 reviews the proposed method, algorithms used and design implementation. Section 3 describes the results obtained from this research. The last Section 4 concludes this research's approach and gives some suggestions for further research.

2. **Proposed Methods.** The proposed system design in this study is shown in Figure 1.

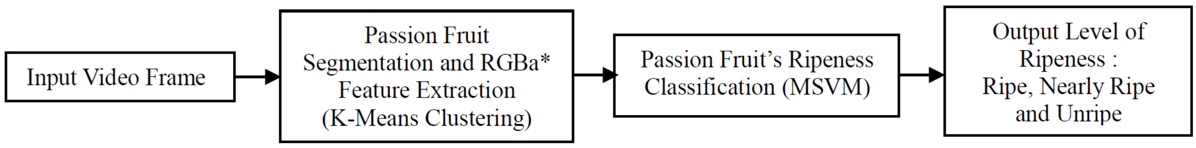

FIGURE 1. Framework for grading the passion fruit system

The first stage of the research system is to input data in the form of passion fruit video. For this purpose, the research used a total of 120 videos of passion fruits in various ripening stages, 40 ripe videos, 40 fruit nearly ripe videos, and 40 unripe videos. Each video is 5-second long with the quality of 60 frames-per-second (fps) capturing the image of one passion fruit, and then extracted in the form of 384×216 pixel frame. 30 videos on each level of ripeness are used for training purpose and the remaining ten videos of each level of ripeness are entered into the testing phase. The passion fruits segmentation is accomplished using K-means clustering to get RGBa* feature value. The final step is to grade the ripeness level using Multi-class Support Vector Machine (MSVM) in order to classify whether the individual fruit is ripe, nearly ripe or unripe.

According to the survey result in Aurora Passion Fruit Syrup Industry it is stated that ripe passion fruit is characterized by its purple or purple with slight green colour, the nearly ripe fruit has green with yellowish and purplish tint, while the unripe fruit is green.

2.1. **Segmentation and RGBa* feature extraction.** This research utilizes the segmentation process on the video frames to separate background and foreground so that passion fruit features can be extracted. This process applies the K-means clustering method based on the a*b* feature value of each frame. Before segmentation, space color of each frame was converted from RGB to L*a*b*. The significant difference of a*b* value range between the passion fruit and the background becomes the success parameter of the segmentation process.

The segmentation stage uses K-means clustering method with the following algorithm [8].

1) Determining the number of clusters.

2) Determining the value of the centroid.
In determining the centroid value for the initial iteration, the initial value of the centroid is randomized. In order to determine the value of the centroid, the used formula is as follows:
$$\overline{V_{ij}} = \frac{1}{N_i} \sum_{k=0}^{N_i} X_{kj} \tag{1}$$
where:
V_{ij} is the centroid of the i-th cluster for the j-variable.
N_i is the amount of data that belongs to the i-th cluster.
i, k are the indexes of the cluster.
j is the index of the variable.
X_{kj} is the value of the k-th data present in the cluster for the j-th variable.
3) Calculating the distance between the centroid points and the point of each object.
To calculate the distance, Euclidean distance (D_e) formula is used as follows.
$$D_e = \sqrt{(x_i - s_i)^2 + (y_i - t_i)^2} \tag{2}$$
where i is the number of objects, (x, y) is the object coordinate and (s, t) is the coordinate of the centroid.
4) Grouping objects.
To determine cluster members, the research takes account of the minimum distance of the object. The value obtained in the membership of the data at the distance matrix is 0 or 1. The value 1 for the data is allocated to the cluster and the value 0 for the data allocated to the other cluster.
5) Return to stage 2), do the looping until the centroid value is fixed and the cluster member does not move to another cluster.

2.2. **Multi-class support vector machine.** The next stage of this research employs the classification of multi-class support vector machine. According to Xu et al. [9], the classification by SVM method is most commonly used today because it is easy to use and get more accurate results. The basic concept of SVM is to maximize hyperplane boundaries. Hyperplane with maximum margins will give better generalization to the classification method. Hyperplane (boundary) from the best separator between the two classes can be found by measuring the hyperplane's margins and looking for the maximum point. The margin is the distance between the hyperplane and the closest data from each class. The closest data is called support vector [10].

When the input data are divided into more than two classes, the multi-class SVM approach consists of One-Against-All (OAA), One-Against-One (OAO), and Error Correcting Output Code (ECOC). For any number of class labels in the data set denote $Y = \{y_1, y_2, \ldots, y_K\}$. The OAA decomposes the multi-classes problem into a binary K problem. For each $y_i \in Y$, a binary problem created in which all vectors belonging to the class y_i are viewed as positive samples, while others viewed as negative samples. The binary SVM classification of K is then formed to separate the class vector y_1 from the other.

One of the constraints in the classification process is the dissemination of data that tends to vary, so it will be difficult to separate linearly [11,12]. In this case, SVM introduces a kernel function that converts the original data space into a new space with a higher dimension [13], and this process is including the transformation function with the product point $\phi(x)$ as written in Equation (3). The goal is to easily separate the data which has been changed into a higher dimension. Thus, the hyperplane function can be written in Equation (4) as follows:
$$K(x_n, x_i) = \phi(x_n)\phi(x_1) \tag{3}$$

$$f(x_i) = \sum_{n=1}^{n} \propto_n y_n K(x_n, x_i) + b \tag{4}$$

where x_n is the data support vector, $\propto_n$ is the Lagrange multiplier, and y_n is the membership of class label $(+1, -1)$ with $n = 1, 2, 3, \ldots, N$.

This study applies more than two classes, i.e., ripe, nearly ripe and unripe. The type of MSVM used in this study is OAA and Gaussian Radial Basis Function kernel (RBF) with Box Constraint (C) and RBF Sigma (γ) values. Each kernel function has a custom parameter that must be optimized to get the best performance results [14]. Determination of kernel functions used will significantly affect the results of classification, the following of kernel radial basis function formula, notably:

$$K(X_n, X_i) = \exp\left(-\gamma||X_n - X_i||^2 + C\right) \tag{5}$$

The training process will carry out some testing to get the highest accuracy value by changing the values of C and γ in accordance with training data. It is called grid-search methods [15].

A classification system is expected to get the correct classification results against all data sets. Therefore, a classification system should also be measured for performance by using the confusion matrix. Table 1 shows the confusion matrix for recording the results of classification [10].

Table 1. The confusion matrix

f_{ij}		Prediction Class	
		Positive	**Negative**
Actual Class	**Positive**	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Accuracy can be obtained from the confusion matrix for each level of ripeness for passion fruits by using Equation (6) below:

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} * 100\% \tag{6}$$

3. **Results & Discussion.** This research used 2 clusters: cluster 1 for background and cluster 2 for foreground (passion fruit), and then K-means clustering will find for two centroid values between a*b* values of each inputted frame. Afterward, each pixel will be calculated to have a distance to each centroid as a cluster determination parameter. If the distance to centroid 1 is smaller than the distance to centroid 2, then the pixel will be segmented as background. Whereas, if the distance to centroid 2 is lower than the distance to centroid 1, then the pixel will be segmented as passion fruit. The process further extracts the RGB and a* values of the segmented segmentation features that are in size of 56×56 pixels as seen in Figure 2.

To grade the ripeness level, each passion fruit has an RGBa* feature of 6 sides. So the total number of feature is 24 features for each passion fruit. This method is used

Figure 2. Extracting image by K-means clustering

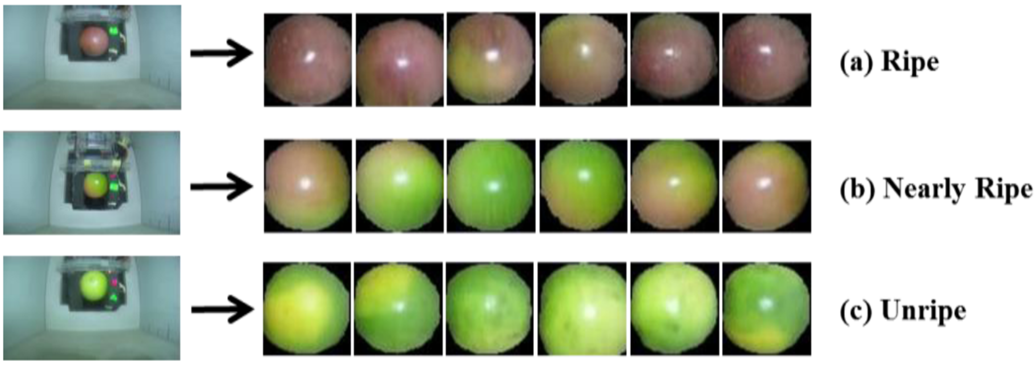

Figure 3. Display of 6 sides of passion fruit segmentation results

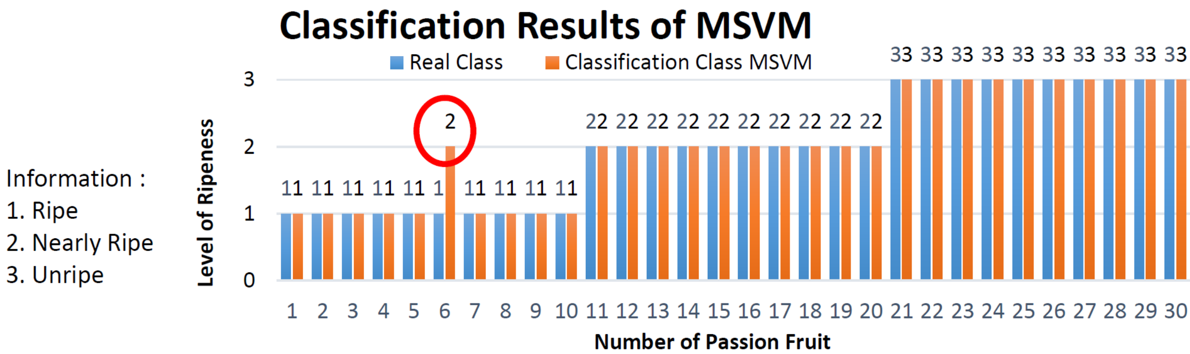

Figure 4. (color online) Graph classification results of MSVM

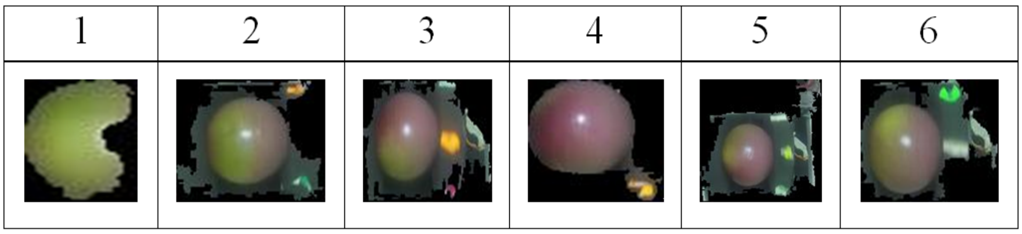

Figure 5. Display of six sides of the sixth passion fruit

because the classification system employs the color feature. Since the spread of color on the surface of each passion fruit side is not always homogenous, particularly for fruits with ripe and nearly ripe category according to paramater of Aurora Passion Fruit Syrup Industry. Figure 3 shows an example of a six side view of segmented passion fruit.

Figure 4 shows that MSVM made one classification error on the 6th passion fruit data. It should be classified as ripe, but it was misclassified to be nearly ripe. This is shown with a red circle in the graph. In this graph, the passion fruit ripeness level for grade 1 is ripe, grade 2 is nearly ripe, and grade 3 is unripe.

The research then explored the reason for the misclassification. Figure 5 shows that the sixth passion fruit data is classified incorrectly by MSVM as a nearly ripe level of passion fruit. When it is observed from the spread of the surface color of the six sides, the first and second sides show a green dominant color, while the rest of the sides are purplish red. The parameter stated that a passion fruit is classified as ripe when most of its sides are purplish red and slightly green. However, the research notes that on the 4th, 5th and 6th sides, the segmentation results are not optimal, reducing the accuracy of the RGBa* value obtained. This has resulted in MSVM's misclassification of the fruit.

The training process in MSVM is conducted using grid-search methods for the parameter optimization in each kernel function by setting parameter of C and γ. Figures 6 and 7 show the process of grid-search algorithm of MSVM for training and testing.

Figure 8 is attained by using Equation (5). It produces the smallest error 0.033 with value $C = 1$ and $\gamma = 2.5$. When $C = 1$, $\gamma = 1$, the classification error is 0.27.

The confusion matrix on passion fruit for grading ripeness can be seen in Table 2, and the accuracy for each level of grading passion fruit is seen in Table 3.

From the confusion matrix, on the nearly ripe and unripe levels, get 100% accuracy value, which means that each data used is relevant and appropriate, and the system is running properly. As for the ripe level, the accuracy is achieved at 90% which means that there is one data that should be relevant but not readable in the system. The average of this accuracy is 96.67%.

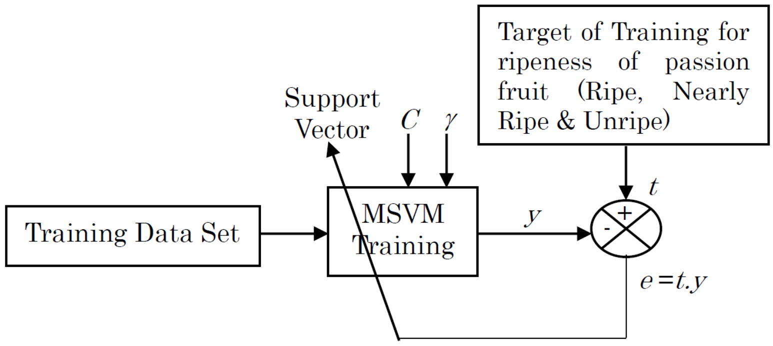

FIGURE 6. Training process for finding C and γ

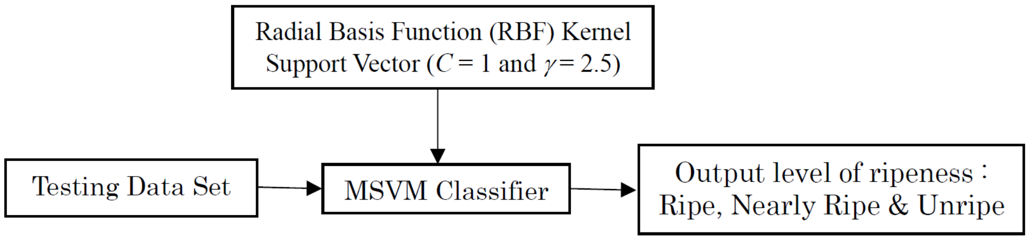

FIGURE 7. Testing MSVM

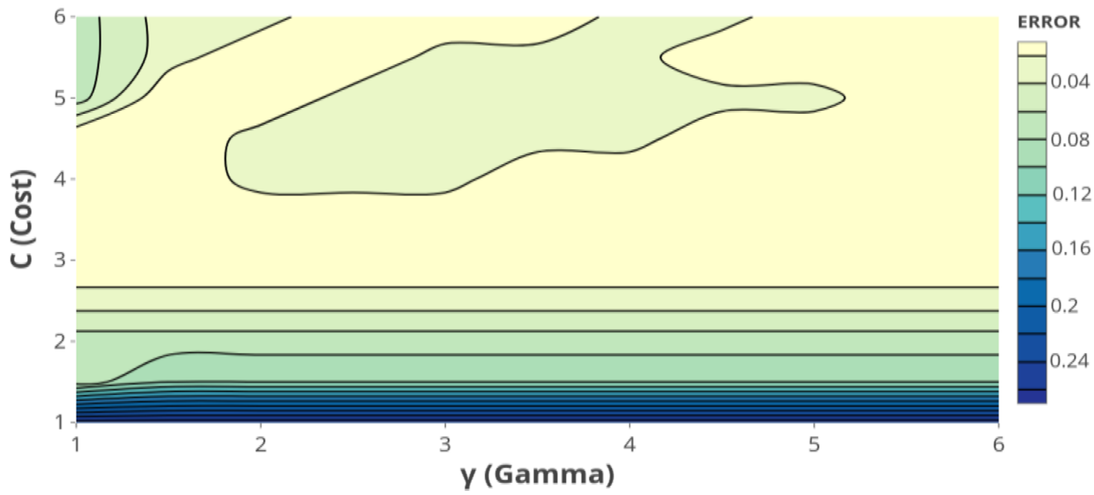

FIGURE 8. Grid-search on Radial Basis Function (RBF) kernel function for finding the optimum C and γ

Table 2. The confusion matrix of grading passion fruit

f_{ij}		Classification		
		Ripe	**Nearly Ripe**	**Unripe**
Actual Class	**Ripe**	9	1	0
	Nearly Ripe	0	10	0
	Unripe	0	0	10

Table 3. The accuracy of grading passion fruit

Level of Grading Passion Fruit	**Accuracy (%)**
Ripe	90
Nearly Ripe	100
Unripe	100
Average	**96.67**

4. **Conclusions.** This research used K-means clustering as a method of segmentation and Multi-class Support Vector Machine (MSVM) as a classification method. The average accuracy is 96.67%, with the ripe, nearly ripe and unripe category, yielding 90%, 100%, 100% accuracy, respectively. These results indicate that this system can be applied to assisting in the automation of the grading process of the ripeness of passion fruits. This can lead to improved productivity and efficiency in agrofood industry. The future work is to implement this method to the hardware sytem of grading for passion fruit's ripeness.

REFERENCES

[1] P. Hariyadi and N. Aini, *Basics of Postharvest Handling of Fruits and Vegetables*, 1st Edition, Penerbit ALFABETA, Bandung, 2015.

[2] A. Hartato, Ready to apply industry 4.0, *The Official Portal of the Ministry of Industry*, no.1, pp.7-9, 2018.

[3] S. Jana, S. Basak and R. Parekh, Automatic fruit recognition from natural images using color and texture features, *Devices for Integrated Circuits (DevIC)*, pp.620-624, 2017.

[4] E. Elhariri, N. El-Bendary, A. E. Hassanien, A. Badr, A. M. Hussein and V. Snášel, Random forests based classification for crops ripeness stages, *Proc. of the 5th International Conference on Innovations in Bio-Inspired Computing and Applications*, pp.205-215, 2014.

[5] R. Hasan and S. M. G. Monir, Viable vestige segregation by support vectors: An implementation for background, shadow and unnecessary fragment amputation of Guava, *Tencon IEEE Region 10 Conference*, pp.2226-2230, 2017.

[6] S. Raj and D. S. Vinod, Automatic defect identification and grading system for 'Jonagold' apples, *The 2nd International Conference on Cognitive Computing and Information Processing (CCIP)*, pp.1-5, 2016.

[7] S. W. Sidehabi, A. Suyuti, I. S. Areni and I. Nurtanio, Classification on passion fruit's ripeness using K-means clustering and artificial neural network, *International Conference on Information & Communications Technology*, pp.305-310, 2018.

[8] N. Wakhidah, K-means algorithm clustering, *Journal of Transformation*, vol.8, no.1, pp.33-39, 2010.

[9] K. Xu, X. Chen, S. Jing, Y. Liu and C. Kang, A real time hand gesture recognition method based on the multi-class SVM, *ICIC Express Letters, Part B: Applications*, vol.8, no.5, pp.851-857, 2017.

[10] E. Prasetyo, *Data Mining Processing Data into Information Using MATLAB*, 1st Edition, CV. ANDI OFFSET, Yogyakarta, 2014.

[11] S. Wang, P. Phillips, A. Liu and S. Du, Tea category identification using computer vision and generalized eigenvalue proximal SVM, *Fundamenta Informaticae*, vol.151, nos.1-4, pp.325-339, 2017.

[12] Y. Zhang, Z. Dong, S. Wang, G. Ji and J. Yang, Preclinical diagnosis of magnetic resonance (MR) brain images via discrete wavelet packet transform with tsallis entropy and generalized eigenvalue proximal support vector machine (GEPSVM), *Entropy*, vol.17, no.4, pp.1795-1813, 2015.

[13] D. Wilk-Kolodziejczyk, K. Regulski and G. Gumienny, Comparative analysis of the properties of the nodular cast iron with carbides and the austempered ductile iron with use of the machine learning and

the support vector machine, *International Journal of Advanced Manufacturing Technology*, vol.87, nos.1-4, pp.1077-1093, 2016.

[14] M. A. Nanda, K. B. Seminar, D. Nandika and A. Maddu, A comparison study of kernel functions in the support vector machine and its application for termite detection, *Information*, vol.9, no.1, p.5, 2018.

[15] R. Diani, U. N. Wisesty and A. Aditsania, Analysis of the effect of kernel support vector machine (SVM) on microarray data classification for cancer detection, *Indonesia Journal on Computing*, vol.2, no.1, pp.109-118, 2017.