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The Development of Machine Vision System for Sorting Passion Fruit using Multi-Class Support Vector Machine

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Abstract

This research aims to develop a machine vision system for sorting passion fruit based on the classification of the ripeness level. For years in the food processing industry, the sorting process has been done manually which is time-consuming and produces unreliable classification. To cope with this problem, this research proposed a machine that can sort passion fruit according to the ripeness level automatically. The system is equipped with a pneumatic drive, gripper collector, camera and bowl selector. Passion fruit is taken by the gripper collector and rotates 360° in front of the camera so that all the passion fruit surfaces can be captured. The camera feeds the images for the sorting process in three categories, i.e., ripe, nearly ripe and unripe using a computer vision-based intelligent system. The used computer vision method is K-Means Clustering as feature extraction and Multi-Class Support Vector Machine (MSVM) for classification of passion fruit ripeness level. The results show that Fruit Passion Sorting Machine can achieve 93.3% accuracy with an average time to sort each fruit is 0.94128 seconds with RBF kernel function parameters C = 25 and γ = 1e-5.

Keywords: Passion Fruit, Ripeness Level, Pneumatic, Gripper Collector, Bowl Selector.

1. Introduction

Passion fruit is one of the top export commodities from the province of South Sulawesi, Indonesia. According to the Online Tribune East Tabloid (2018), South Sulawesi Regional Government has signed a cooperation with Singaporean companies to market passion fruit products abroad because the demand for passion fruit in Singapore is quite high [1].

To supply this high demand, post-harvest quality of the passion fruit must be kept high. One process in the post-harvest is to differentiate the ripeness level of the fruit. The ripeness level of passion fruit influences the quality of passion fruit extract and juice. At present, the process of sorting passion fruit based on the ripeness is done manually. Therefore, the process is very time consuming, and the result is not uniform which leads to the lower quality of the fruit used in the food industry.

To cope with this problem, it is necessary to have a machine that can sort passion fruit according to the ripeness level automatically and accurately. The two main advantages of using this automatic system are to cut processing time and to produce a high level of uniformity. In related research, Reddy et al. developed a robot sorting objects passing on conveyor belts in the form of hand robot that detect the presence of objects using infrared sensors, AT89S52 microcontrollers and display on Liquid Crystal Display (LCD) to make it easier to use [2].

Another research in sorting and detecting the ripeness level of lime fruit was carried out by Afrisal et al. by applying computer vision to recognize the color change of lime fruit based on the HSV method (Hue, Saturation, and Value). It then classified the fruit with ROI (Region of Interest) where the average error estimated at around 6.88%. This research used a servo motor with a mechanical concept following the LEGO toy equipped with the Logitech C920 webcam [3]. Perez et al. conducted similar research on apples. Perez at al. suggested that to achieve higher accuracy in the sorting process; it is necessary to take at least four pictures of the apples rotated 90°. Perez's study introduced the model of fruit sorting segmentation using IELab color space method, chroma (C*) and color angle (h*) while identifying the three stages of apple ripeness namely; ripe stage, unripe stage, and senescent stage. To analyze the ripeness level of fruit, the researchers used the Multivariate discriminant analysis method and achieved 95% accuracy rate [4]. In different research to identify different fruits, Tho et al. used high-resolution cameras placed on top of the conveyor belt to identify fruit objects (tomatoes and passion fruit). The method used is the Adaptive Neuro-Fuzzy Inference System with coordinate sorting error of 0.234 mm for tomatoes and 0.036 mm for passion fruit [5].

Pise et. al had using machine vision systems for grading of harvested mangoes quality and maturity. The system considered RGB values size and shape of mangoes and to detect the maturity of mangoes used Naïve Byes and Support Vector Machine (SVM). Naïve Byes had taken time faster than SVM in grading mango images around 600 ms [6]. On another hand, Chandini et.al applied Gray Level Co-occurrence Matrix (GLCM) and MSVM for classified a quality of apple by obtained 86,54% accuracy [7]. Jana et.

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al. proposed an automatic fruit recognition from natural images using color and texture features. The methods that used are also GLCM and SVM for identifying variety fruit (i.e apple, asian pear, cucumber, mango, orange, pineaple, pomegranate, and strawberry), with achieved the highest accuracy 91,67% on the validation set [8].

Whereas Mhaski et al. made a complete and flexible fruit sorting system equipped with modular conveyor consisting of Raspberry Pi Model B+, conveyor belt system, sorting store and Pi camera [9]. Raspberry Pi Model B + is a processor that manages all information of the motor and Pi camera, adjusts the speed of the conveyor belt and continuously updates the tomato sorting process to three categories using the K-Means Clustering method. The time required for the K-mean Clustering process is 0.89 seconds. Sidehabi et al. used K-Means Clustering with Neural Network feed forward to classify the ripeness level of passion fruit into ripe, nearly ripe and unripe stages. They are adopted RGB and a* color features with the result of 90 % accuracy rate [10]. While using MSVM, the research had an accuracy of 96.67 % [11].

Based on the previous mentioned researches and description above, this research aims to develop an automatic sorting process for passion fruit based on the ripeness level by using a webcam combined with a computer vision application to perform passion fruit sorting tasks. The proposed computer vision method is the K-Means Cluster algorithm as feature extraction, with Multi-class Support Vector Machine for sorting the ripeness level of passion fruit in three categories, i.e., ripe, nearly ripe and unripe with input data in the form 6 sides of passion fruit.

The rest of the paper is organized as follows: Section 2 discusses the materials and methods involved: the description of a machine vision system for sorting passion fruit, K-Means Clustering for feature extraction, various type of kernel function in SVM, and performance evaluation with an analysis of receiver operating characteristics (ROC). Section 3 details the results of a machine vision system for sorting passion fruit by the implemented algorithm and parameter optimization on kernel functions with the grid-search method. Section 4 explains the result of this research. Finally, section 5 presents the main conclusion of this research.

2. Methodology

This research developed a fruit sorting machine, which is also a form of post-harvest technology in the passion fruit processing industry. Figure 1 below shows the overall system design of the machine.

Figure 1 shows the process from getting the individual fruit into the system all the way to the final step of the process which is the validation. The purpose of this study is to ease the sorting process because at present the sorting of passion fruit is still done manually. This greatly affects the classification of the fruit due to the inconsistency of the individual worker in sorting the fruit. On the other hand, the proposed automatic sorting machine serves as a substitute for the human eyes in sorting the passion fruit for further process.

In order to achieve uniformity in classifying the fruit, the process is carried out in the following order:

1. First, the passion fruit is entered into the sorting machine, and then it will be lifted using the Gripper Collector which is detected by the camera through the image processing process. This research used a total of 120 passion fruit, with 90 pieces for data training and 30 data testing. The training data consists of 30 passion fruit for each stage: ripe, nearly ripe, and unripe stages. The testing data used ten pieces each for a different stage of ripeness level.
2. The pre-processing stage is where the data preparation takes place before entering the feature extraction process [12]. Data obtained from the camera will be forwarded to the enhancement image process. The image quality is improved during this enhancement process. The process starts with the level of clarity, brightness level and video filter partitioned into image form by tracking objects that will be used as a process of object detection and classified object as the passion fruit. Furthermore, image preprocessing is to obtain the desired and noise-free image. It is performed feature extraction using the method namely K-Means Clustering to produce RGBa* features.

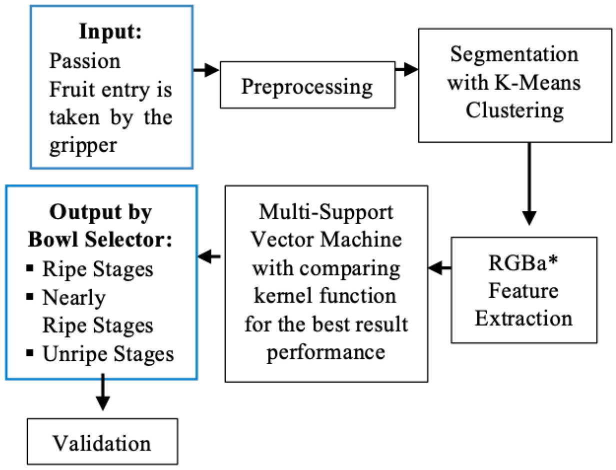

Fig. 1. System Design

Dubey et al. point out that the image segmentation using the k-means algorithm is quite useful for the image analysis. An important goal of image segmentation is to separate the object from the background clearly regardless of the blurry boundary of the image [13]. Furthermore, Racmawati et al. stated that k-means clustering could be utilized to classify a pixel taken from the fruit image. The removal of the redundant color pixel, noise removal (the background color pixel and the effect of illumination), identification of the appropriate cluster centroid and determination of threshold for refining cluster from outliners, are processes that were performed during the generation on fruit color palette [14].

K-Means groups object into K clusters. This method will look for cluster centers and cluster boundaries through an iterative process. The closeness or similarity of an object to another object or the cluster center is calculated by using the distance function. In general, K-means uses Euclidean distance to calculate the similarity. The first step of the K-Means method is to determine the initialization of some K center clusters. Iteratively, the center of the cluster will be fixed so that it represents the centers of the K cluster [15].

The stages of the K-Means algorithm are as follows [16]:

a. Inilization: specify the K value as the desired number of clusters and the desired metrics (distance). If necessary, set the objective function change threshold and the threshold for changing the position of the centroid.

b. Select K data from the X data set as a centroid.
c. Allocate all data to the nearest centroid with the specified distance metric (updating the cluster ID for each data).
d. Recalculate centroid C based on the data that follows each cluster. To get the centroid point C, it is obtained by calculating the average of each feature of all data incorporated in each cluster. The average of a feature of all data in a cluster is expressed by the following equation:

$$c_j = \frac{1}{N_k}\sum_{i=1}^{N_k} x_{ji} \qquad (1)$$

Nk is the amount of data that integrated into a cluster

e. Repeat steps 3 and 4 until the convergent conditions are achieved, namely (a) the change in the objective function is already below the desired threshold; (b) there is no data that moves clusters, or (c) the change in position of the centroid is below the specified threshold.

In this research, the pre-processing stages used for the real-time implementation are capture and resize video frame, limit working windows of the image using Region Of Interest by square cropping (passion fruit) and convert color channel image into L*a*b. Then the K-Means Clustering method is used to separate between foreground (passion fruit) and background (non-object). The detailed process of segmentation system of K-Means clustering in this study can be seen in Figure 2.

In this research has conducted two methods of segmetation feature by comparing fuzzy Cmeans and K-Means. Fortunately, K-Means is better than FCM to segment the feature of passion fruits.

3. The last stage is classifying passion fruit objects based on their ripeness level by using computer vision method, namely Multi-class Support Vector Machine (MSVM). According to Xu et al. [17] that the classification based on the SVM method is the most commonly used because of its ease of use and it gets more accurate results. SVM is one of the supervised learning class. According to Nurtanio et al., as a machine after supervised learning is more efficient than humans in performing classifications with the help of computers [18]. The basic concept of SVM is to maximize the hyperplane limit, where the hyperplane with the maximum margin will give a better generalization to the classification method. Hyperplane (decision limit) the best separator between the two classes can be found by measuring the margin of the hyperplane and finding its maximum point. The margin is the distance between the hyperplane and the closest data from each class. The closest data is called support vector [19].

SVM is a linear hyperplane that only works on data that can be linearly separated. For data whose class distribution is not linear, the kernel approach is used. The kernel is defined as a function that maps data features from the initial (low) dimensions to new features with relatively higher dimensions (even much higher). This approach is different from the general classification method which reduces the initial dimensions to simplify the computational process and provide better prediction accuracy. The kernel illustration used to map the initial dimensions (lower) data sets to new dimensions (which are relatively high) is shown in Figure 3 [18].

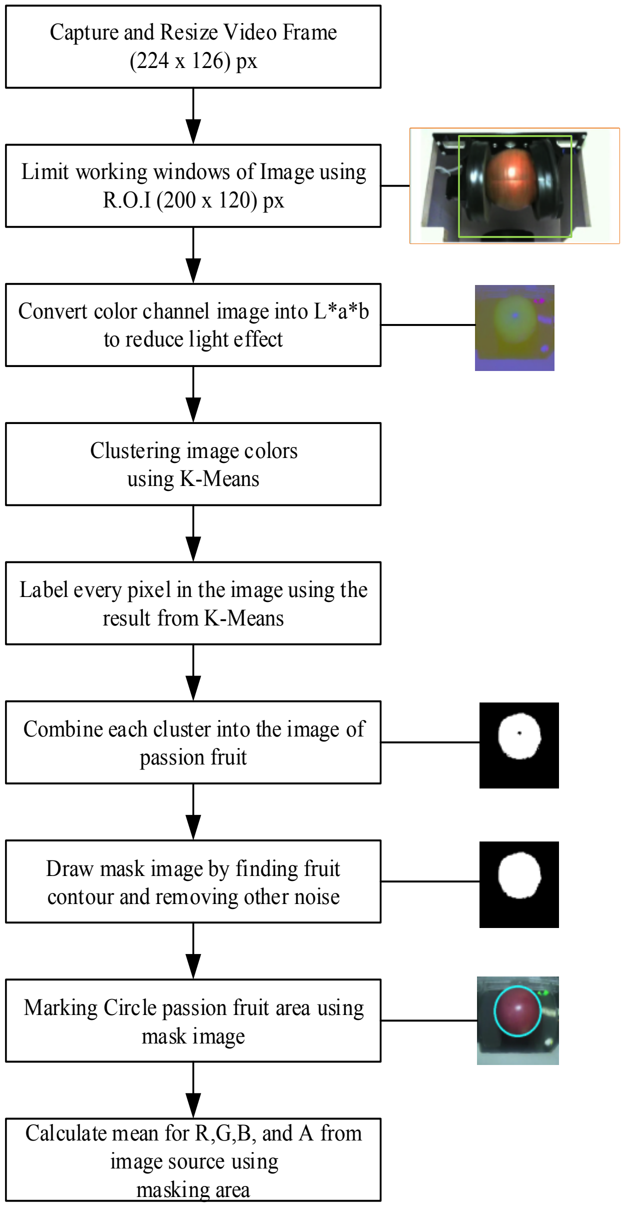

Fig. 2. The Process of K-Means Clustering Segmentation System

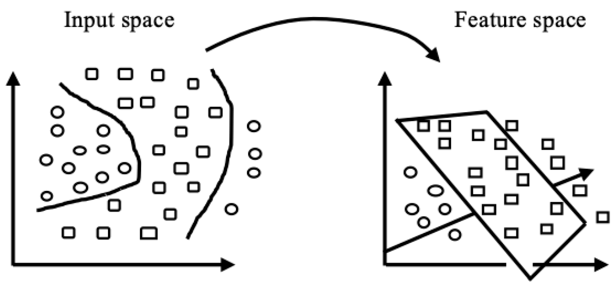

Fig. 3. SVMs allow mapping of the data from the input space to a high dimensional feature space by using Kernel Function

As a consequence, the transformation function with the product point ϕ (x) as written in equation 2 and the hyperplane function can be written in equation 3 as follows [19]:

$$K(x_n, x_i) = \emptyset(x_n)\emptyset(x_1) \qquad (2)$$

$$f(x_i) = \sum_{n=1}^{n} \propto_n y_n K(x_n, x_i) + b \quad (3)$$

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

Nanda et al. in their research compared four kernels that function on SVM algorithms, particularly, Linear, Radial Basis Function (RBF), Sigmoid and Polynomial which are shown in Table 1. Each kernel function has special parameters that can be optimized to get the best performance results [19].

Table 1. Kernel Function

No	Kernel Function	Formula	Optimization Parameter
1	Linear	$K(x_n, x_i) = (x_n, x_i)$	C and γ
2	RBF	$K(x_n, x_i) = \exp(-\gamma \lvert\lvert x_n - x_i \rvert\rvert^2 + C)$	C and γ
3	Sigmoid	$K(x_n, x_i) = \tanh(\gamma((x_n, x_i) + r)$	C, γ and r
4	Polynomial	$K(x_n, x_i) = (\gamma((x_n, x_i) + r)^d$	C, γ,r and d

Explanation, C: cost; γ: gamma;r: coefficient; d: degree

To get the optimal value from the kernel function, the search method is performed on the parameters C, γ, r, and d. Therefore, data that is not known can be accurately predicted by its classification. This method is called a grid search. It is a complete search method based on a subset of hyperspace parameters [20]. The hyperparameter is determined using a minimum value (lower limit), the maximum value (upper limit) and several steps. This research found that the best performance results can be obtained on the kernel Radial Basis Function (RBF) function.

After getting the best kernel value, it is then referenced to classify the ripeness level of passion fruit through training data. From the gripper collector, passion fruit is graded based on ripeness, divided by three lines. That is path 1 for fruit that is high value with the ripe category, line 2 for quality second-grade passion fruit with nearly ripe level and line 3 for passion fruit with the unripe condition. Sorting standards were obtained from interviews with Aurora Passion Fruit Syrup owners and passion fruit-producing farmers in the District of Rumbai Jeneponto listed on table 2.

Table 2. Classification of ripeness levels of passion fruit

No.	Category	Detailed Information	Level of Ripeness
1	Ripe	Purple or Purple with slightly green	
2	Nearly Ripe	Faded in green towards yellow (there is a change in color) and there is a slight purple color.	
3	Unripe	Green Color	

The system validation is then conducted by comparing the sorting results of the passion fruit based on its level of ripeness between the sorting machine and human vision. This accuracy value is used to see whether the passion fruit sorting system has gone well.

The design and manufacturing of Passion Fruit Sorting Machine based on the ripeness level by computer vision include hardware and software. The working principle of this passion fruit sorting system can be seen in Figure 4.

Controller for this machine is done by Raspberry Pi 3 Model B Plus which is installed on the side of the passion fruit sorting line. Data are retrieved by using a Logitech C270 webcam with data results based on a real-time video. The resolution of the camera is 1280 x 720 pixels. The placement of the camera located in the middle based on the direction of passion fruit walking through a pneumatic path at a certain height. It will be considered the angle of the camera to get the maximum tilting to the integrality of passion fruit which can be detected and covered according to the need for the ripeness sorting process of passion fruit.

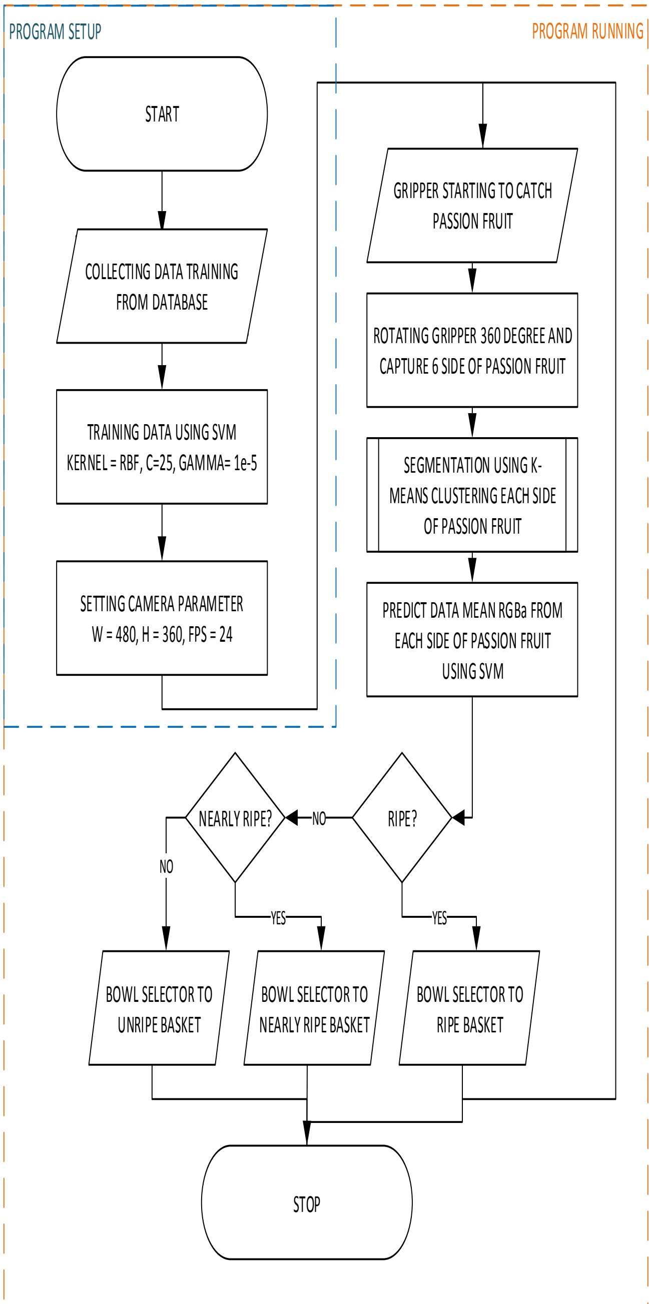

Fig. 4. Working Principles of Passion Fruit Sorting System

Implementation of Passion Fruit Sorting Machine by using Multi-Class Support Vector Machines has several main parts as shown in Figure 5 below.

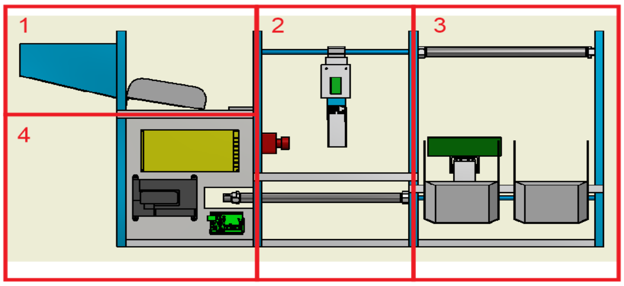

Fig. 5. Passion Fruit Sorting Machine Parts

- Part 1 is the fruit input section, in this section the fruit is directed one by one.
- Part 2 is the computer vision section, in this section passion fruit is taken by the Gripper Collector which is directed to the front of the camera to take a video of the fruit. The Gripper Collector be equipped with three type TowerPro MG995 motor servo.
- Part 3 is the sorting output section. In this section, a selector bowl with one type TowerPro MG995 motor servo and actuators will direct the fruit to the output according to the quality of each ripeness level.
- Section 4 is the control and electronic circuit. In this section, there is a power supply, Raspberry Pi 3 Model B Plus with software Python 3.35 and driver. This section is the control center of this passion fruit sorting machine.

The size of a Machine Vision System for Sorting Passion Fruit's hardware can be seen in Figures 6, 7 and 8.

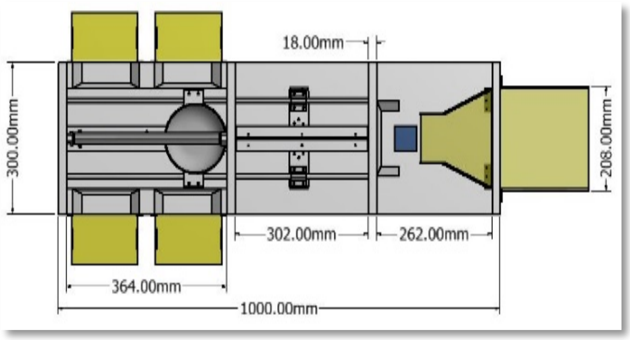

Fig. 6. Dimensions of Passion Fruit Sorting Machine Parts

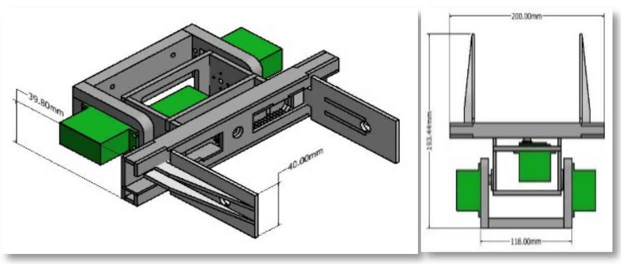

Fig. 7. Dimensions of the Gripper Collector

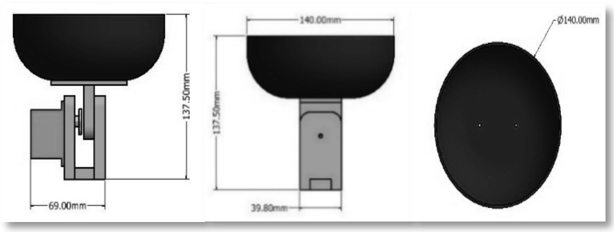

Fig. 8. Dimensions of the Bowl Selector

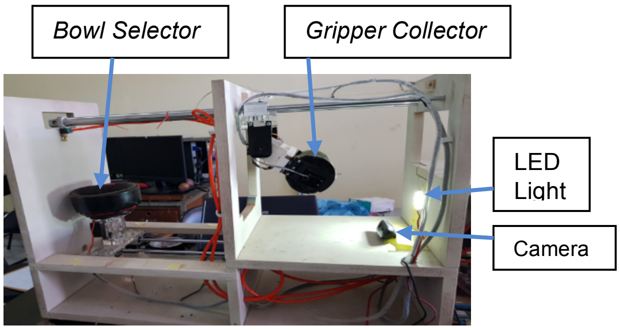

Fig. 9. Display all of Passion Fruit Sorting Machine

Before predicting the ripeness level of passion fruit between ripe, nearly ripe and unripe, it is necessary to train the characteristics of the data so that they match the experimental sample of the known class [16]. In this study, the data collection evaluated the performance of the model for the classification process using the Receiver Operating Characteristics (ROC) curve method [15]. The ROC curve describes the trade-offs between sensitivity or true positive rate (TPrate) as the coordinate y value and 1-specificity or the false positive rate (FP rate) as the x coordinate; it is useful in assigning the best cut-off for classification. The area expresses the most common quantitative index to describe accuracy is the area under the ROC curve (AUC), which provides useful parameters for assessing and comparing classifications. AUC calculations include the results of f(xi) for training data sets with different kernel functions in equation 3. Furthermore, AUC can be determined in equation 4, accuracy in equation 5 and table 3 is summarized the accuracy of the rating system in the form of AUC.

$$AUC = \frac{1 + TP_{rate} - FP_{rate}}{2} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Table 3. The accuracy of the ROC Curve Assessment System with the AUC Equation

AUC Value	Classified as
0.90 – 1.00	Excellent
0.80 – 0.90	Good
0.70 – 0.80	Fair
0.60 – 0.70	Poor
0.50 – 0.60	Failed

3. Experiments and Results

In the process of performing the search grid, the best classification training in kernel functions, namely the RBF kernel function with parameters C = 25 and γ = 1e-5, has 100% training accuracy and AUC = 0.993643 with 90 passion fruit seen in table 4.

Table 4. Optimal parameters for each Kernel function

NO	Kernel Function	Optimum Parameter				Training Accuracy
		C	γ	r	d	
1	Linear	10	0.01	n/a	n/a	98,9%
2	RBF	25	1e-5	n/a	n/a	100%
3	Sigmoid	0.001	1e-05	0.001	n/a	51,1%
4	Polynomial	0.001	0.01	0.001	3	98,9%

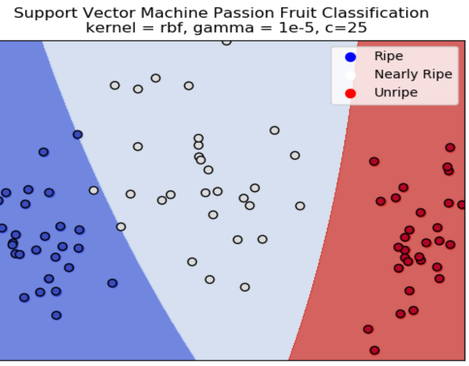

Fig. 10. Graph ROC of SVM Multi-class with RBF kernel function

In the graph, it is shown that the ROC RBF value of 0.993643 is classified as the best, as expressed in Figure 10 and for the distribution of training data can also be seen in Figure 11.

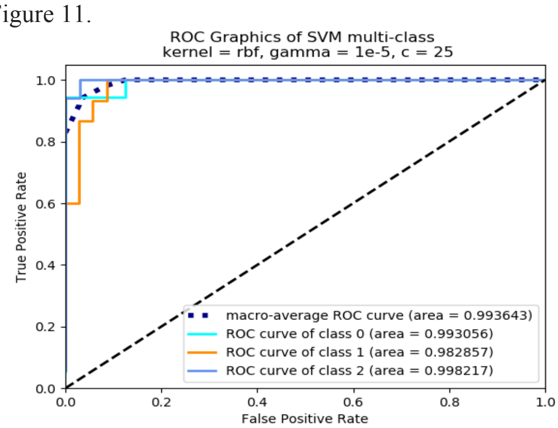

Fig. 11. The Distribution Data Training of SVM Multi-class with RBF kernel function

In this research is held testing with 30 pieces of passion fruits, with error occurs in fruits 16 and 25 as shown in Table 5.

Table 5. Results of MSVM Classification with RBF Kernel

Number Of Fruit	Real Classification	MSVM	Time Sorting [Seconds]
1	Ripe	Ripe	1.790489
2	Ripe	Ripe	0.974004
3	Ripe	Ripe	0.903842
4	Ripe	Ripe	0.930118
5	Ripe	Ripe	0.968065
6	Ripe	Ripe	0.956415
7	Ripe	Ripe	0.881524
8	Ripe	Ripe	0.927947
9	Ripe	Ripe	0.913292
10	Ripe	Ripe	0.902584
11	Nearly Ripe	Nearly Ripe	0.950637
12	Nearly Ripe	Nearly Ripe	0.952747
13	Nearly Ripe	Nearly Ripe	0.960679
14	Nearly Ripe	Nearly Ripe	0.877133
15	Nearly Ripe	Nearly Ripe	0.913125
16	Nearly Ripe	Unripe	0.919048
17	Nearly Ripe	Nearly Ripe	0.870493
18	Nearly Ripe	Nearly Ripe	0.932813
19	Nearly Ripe	Nearly Ripe	0.906753
20	Nearly Ripe	Nearly Ripe	0.873023
21	Unripe	Unripe	0.89383
22	Unripe	Unripe	0.880268
23	Unripe	Unripe	0.922199
24	Unripe	Unripe	0.897569
25	Unripe	Nearly Ripe	0.895744
26	Unripe	Unripe	0.878541
27	Unripe	Unripe	0.876992
28	Unripe	Unripe	0.880982
29	Unripe	Unripe	0.877201
30	Unripe	Unripe	0.930514
The Total Time To Sort 30 Passion Fruit Is 28.2386 Seconds		The Average Time To Sort 30 Passion Fruit Is 0.94128 Seconds	

4. Discussion

The error that occurs in the 16th and 25th fruit samples is caused by the effect of light that causes the 16th fruit sample looks dominant in bright green color. So it is categorized as unripe by the passion fruit sorting machine, with the actual classification is nearly ripe. On the other hand, for 25th fruit sample has to be unripe level, but it is wrongly classified as a nearly ripe by this sorting machine. It is more clearly seen in Figures 11 and 12

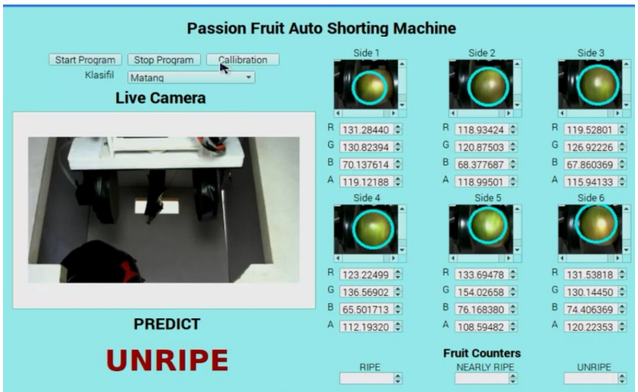

Fig. 11. The 16th fruit sample that is misclassified as an unripe category

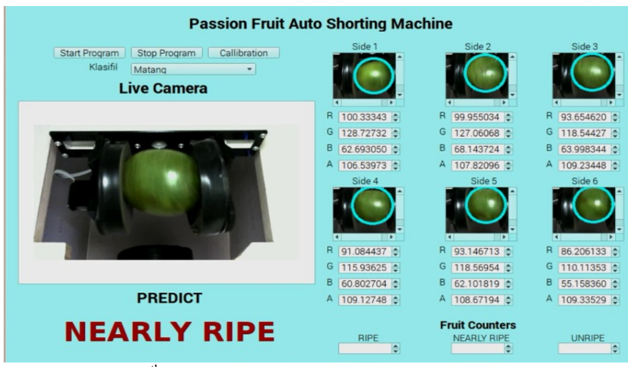

Fig. 12. The 25th fruit sample that is misclassified as a nearly ripe category

In this research, a comparison was made between the machine vision system for sorting passion fruit based on its ripeness level by using Multi-Class Support Vector Machine and the manual processing. For the manual processing, the visual inspection of each fruit sample was done with three experienced workers from Industrial Aurora Syrup Of Passion Fruit.

The testing is used the same of 30 pieces of passion fruits that applied at the sorting machine. Table 6 shows the comparison between the result of the sorting machine versus visual inspection.

Table 6. The Comparison of Sorting Machines with human vision.

Ripeness Level	Sorting Machine	Worker 1	Worker 2	Worker 3
Ripe	100%	80%	90%	90%
Nearly Ripe	90%	80%	100%	90%
Unripe	90%	100%	100%	80%
Total Accuracy (%)	93.3%	86.6%	96.6%	86.6%
Total Time (Seconds)	28.2386	28.15	30	27

From table 6 implied that the machine vision system for sorting passion fruit is qualified enough compared to three workers. The comparison time happened in the afternoon when humans begin to feel sleepy and tired also the passion fruits are mixed randomly. In the ripe level; the sorting machine is preferable than human vision because it get 100 % accuracy and the lowest percent is 80% by worker 1. Respectively, in the nearly ripe and unripe level, the sorting machine get 90% accuracy. It is not quite the lowest, compared to human vision 1 and worker 2. Moreover, for total time for sorting, the sorting machine is faster than worker 2.

5. Conclusion

This system can be applied for assisting for the automation process in sorting passion fruit based on the ripeness level. The passion fruit sorting machine yields an accuracy of 93.3% with an average time of 0.94128 seconds. This was completed using Raspberry Pi 3 Plus for the control system and by implementing K-Means Clustering as a method of segmentation and Multi-class Support Vector Machine (MSVM) as a classification method, with the kernel function best RBF parameters C = 25 and γ = 1e-5.

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