ICIC Express Letters
Part B: Applications
Volume **15**, Number **5**, May **2024**

ICIC International ©2024 ISSN 2185-2766
pp. 525–533

REAL-TIME CLASSIFICATION ALGORITHM FOR RIPENESS EVALUATION OF CAYENNE PEPPER BASED ON ENHANCED IMAGE PROCESSING

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Received September 2023; accepted December 2023

Abstract. *Developing video processing models in classification systems requires appropriate adaptation to maximize accuracy. The object of this research is a Cayenne Pepper fruit image taken using a conveyor with recording parameters and technical aspects tailored to the needs of the processing industry. How to develop an image processing model on real-time data to classify the quality of Cayenne Pepper adaptively with conveyor devices is a problem for the industry. The concept of identification using the image processing system developed in this research uses a segmentation system that converts RGB (Red, Green, Blue) to HSV (Hue, Saturation, and Value), image masking by producing a binary image combined with the results of edge detection using the Canny operator, and then morphological operations for object edge scraping. The segmentation system model makes a strong contribution to improving the accuracy of the identification and classification system of the quality of Cayenne Pepper divided into four categories: immature, half-ripe, ripe, and rotten, using a specially designed conveyor device. In addition, the RGB average approach of the object is a new development from previous research to minimize detection errors from adjacent objects. The classification model uses the SVM method with the best parameter values on the Radial Basis Function (RBF) kernel, Cost (C) = 100 and gamma (γ) = 0.2 obtained from Grid Search, and multi-class OAA (One Against All). The approach with the segmentation system developed by the Support Vector Machine (SVM) gave the best classification result of 95.92%.*
Keywords: Real-time classification, Cayenne Pepper, Quality control, Conveyor system

1. **Introduction.** Previous research has focused on using image segmentation and classification algorithms for video processing research [1]. In agriculture, particularly with Cayenne Pepper, automation is essential due to its perishable nature and economic importance. These peppers have a short shelf life and are used fresh and in processed products. To address this, an automated system with a conveyor and camera is needed for quality classification, but it faces challenges due to varying object shapes, colors, and conditions, including overlap [2]. In this study, the method used to see changes in the color of chili peppers using image processing with an adaptation of the preprocessing process assembled into a unit to maximize the object detection process. Chili peppers in the system will be classified into 4 class categories: immature, half-ripe, ripe, and rotten chilies. This research can potentially optimize the image processing process in real time by developing

DOI: 10.24507/icicelb.15.05.525

an adaptive segmentation model connected to the designed conveyor system. This research aims to develop an innovative approach to the sorting and quality classification of Cayenne Pepper by integrating computer vision technology and image processing. Analyses of blob object areas and shapes during detection are the contributions made in this paper. This approach localizes subsequent detection areas, ensuring enhanced accuracy by focusing on bounding boxing and cropping objects within specified pixel parameters, enabling effective contour search and extraction for individual object identification in each frame. This method will enable automatic and accurate prediction of Cayenne Pepper ripeness, and this research is within the current to revolutionize Cayenne Pepper sorting and quality classification by merging computer vision and image processing, focusing on precise detection through blob object analysis for improved accuracy despite varying conditions.

2. **Related Works.** Research on fruit classification in videos has been extensively conducted, including for peppers, where a specialized machine-learning concept named iPepper has been designed to categorize chili grades [3]. This research distinguishes itself by emphasizing precise detection techniques using image processing and computer vision technologies to enhance accuracy in Cayenne Pepper classification compared to the previous focus on machine learning-based grading systems like iPepper in fruit video classification studies. The application of conveyor systems in downstream fruit processing, as this study by Sidehabi et al., resulted in an object detection concept using K-Means Clustering for feature extraction and Multi-Class Support Vector Machine (MSVM) with an accuracy of 93.3% [4]. Another study focused on tomato quality assessment based on color, achieving an accuracy of 95.55% using Grid Search SVM [5] so that this research can be a reference for using the used SVM parameters. In a different case, the research examined strawberry ripeness classification using a multi-class SVM algorithm, achieving a high accuracy of 90.31% [6]. However, a similar approach applied to larger-sized Ambon fruits using RGB color space transformation only reached an accuracy of 85% [7]. Studies related to chili quality assessment involved image data from chili plants under varying conditions, with accuracy ranging from 97% to 100%. Using YOLOv3 outperformed Mask Region-Based Convolutional Neural Network (Mask-RCNN) in thermal imaging [8]. The research identifies the quality of chili directly on the plantation tree. It is quite different from the research conducted but with the development of a computer vision system similar to the research conducted. In another study, comparing Fuzzy logic and Artificial Neural Networks resulted in 100% and 88% accuracy, respectively. This study differed by employing a five-angle image capture system for data collection [9]. This image capture technique becomes a reference in modeling the image capture system in the designed conveyor system.

3. **Data Preparation.** The data used in this study are images and videos of Cayenne Pepper objects. The camera used is a Logitech Webcam C922 Pro camera. The video was recorded with the camera position on the box facing straight down, the distance between the camera and the color of the belt used, and the object's background is white. When the Cayenne Pepper is put into the funnel, the Cayenne Pepper will pass through the funnel assembled to regulate the release of the Cayenne Pepper using Arduino UNO and Tower Pro MG995 servo motor. The circuit is paired with a cover that is set to move up and down from an angle of 90° to an angle of 180° with a time delay of 10 seconds. Cayenne Peppers will come out towards the conveyor belt line. The conveyor belt moves to carry Cayenne Peppers with a motor gearbox speed of 40 rpm to the position of the camera mounted on the box. The video recording results are saved in (.MP4) format with a frame rate of 15 fps and a resolution of 1920 × 1080. Video data is separated for training and testing data.

4. **System Design.** The system design aims to provide an overview of the system design that will be built and developed and to understand the flow of processes in the system. The flowchart of the system design is shown in Figure 1.

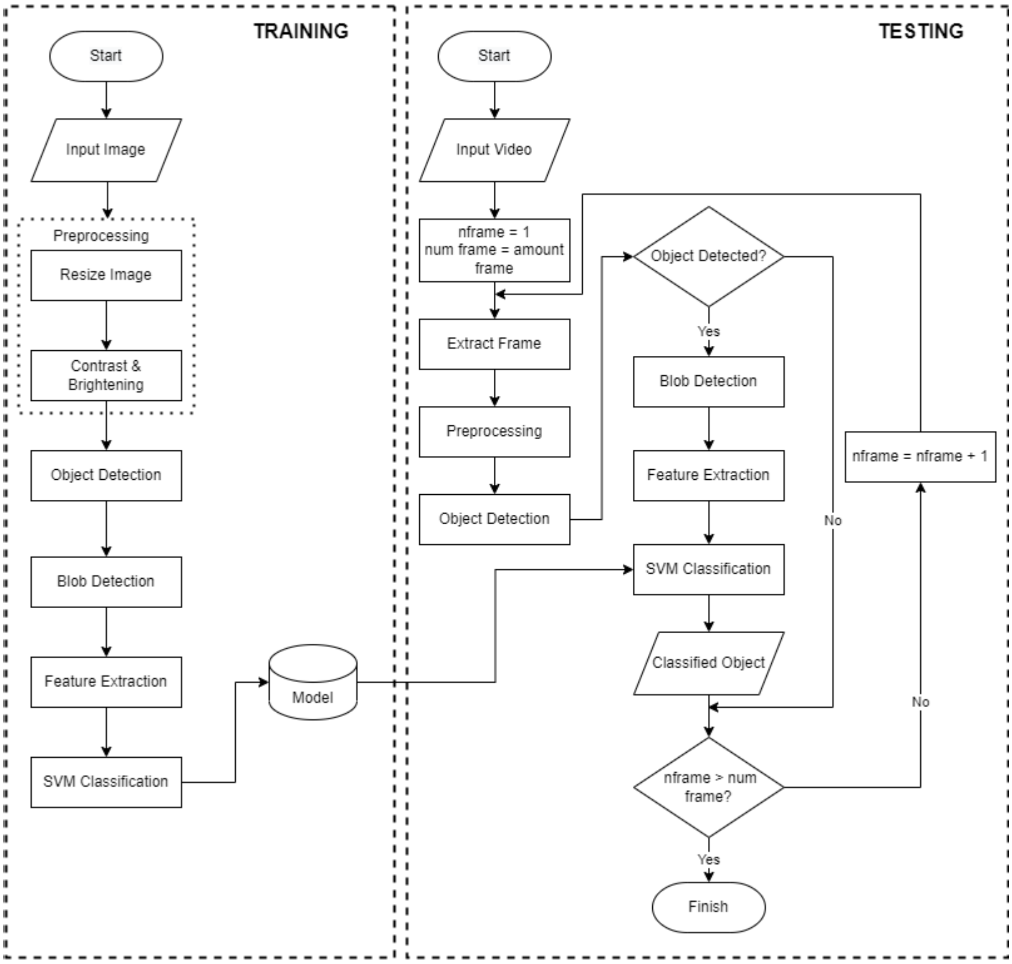


FIGURE 1. Flowchart of system design

4.1. **Training phase.** This training data is taken from video frames in each quality category of Cayenne Pepper, namely immature (BM), half-ripe (SM), ripe (M), and rotten (B). Each category consists of 35 Cayenne Peppers recorded for video training. The video that has been stored is first extracted into the form of image data frames and processed one by one until the last frame in the video. The output generated from this input is an RGB frame. The frame or image data is then selected as the best so that not all images will be used in the training process. The best frame is a frame that has a Cayenne Pepper object completely from the top side. The frame is not used if an object is not comprehensive or cut. The results of the best frame selection are saved into a folder based on the category class and are automatically used as labels for each class. The amount of training data used was 324 images. Figure 2 shows an example of a Cayenne Pepper frame in the training data.

The preprocessing phase aims to decrease the image's dimensions or file size while maintaining its quality. It starts with resizing the image, altering its dimensions from the original 1920 × 1080 pixels to 960 × 540 pixels. Additionally, it involves enhancing the image's brightness by computing contrast and brightness using with formula:

$$C = (R, G, B) \times \alpha + \beta \qquad (1)$$

The value of α represents contrast, and β represents brightness. The values of α and β are determined based on trial and error, so the optimal values used are 1.2 and 0, respectively.

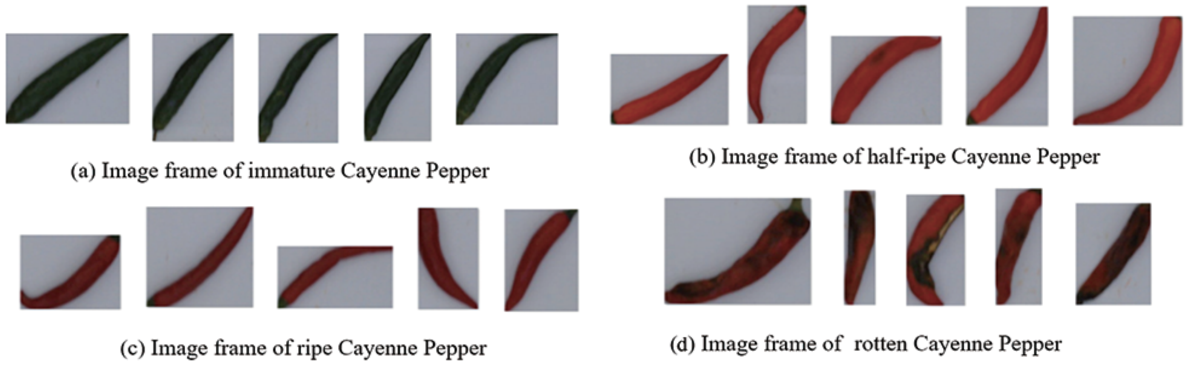


FIGURE 2. System design Cayenne Pepper frame in the training stage

Object detection is done by blurring the image, converting the image from RGB color to HSV color, masking the image, and morphological operations. In comparison, blob detection is done by analyzing the area of the object and the shape of the blob object from an image, which will be the focus area of detection for the bounding box and image crop. Feature extraction at this stage is carried out to take characteristics or features of the Cayenne Pepper object. Feature extraction is based on color features that refer to the characteristics of the maturity of Cayenne Peppers. SVM classification is the final part of the process carried out for classification. This study uses the RBF kernel because the data used is non-linear, so it requires a kernel to map the feature vector into a high-dimensional space. The Grid Search method is used for the training process to find the optimal value for the parameters used in SVM. The resulting function for the SVM classification process is the following formula.

$$f(x_i) = \sum_{i=1}^{n} a_i y_i K(x_i, x_j) + b \tag{2}$$

where $K(x_i, x_j) = \left(-\gamma \|x - x'\|^2\right) \cdot \gamma$, x = feature data, y_i = target of the support vector, $i = \alpha$ optimal obtained from *Quadratic Programming*, n = amount of data, and b = bias.

4.2. **Testing phase.** In this testing process, the input used is a video consisting of 40 Cayenne Peppers, each category of which has 10 immature Cayenne Pepperes (BM), 10 half-ripe Cayenne Peppers (SM), 12 ripe Cayenne Peppers (M), and 8 rotten Cayenne Peppers (B). The Cayenne Pepper class will be recorded randomly or mixed on the conveyor belt from each category. The video input specifications at this stage use a resolution of 1920×1080 pixels, with a frame rate of 15 fps, in a duration of 53 seconds. Preprocessing at this stage is done by adding processes to obtain good object segmentation results. Starting from ROI segmentation, this step limits the area that only wants to be processed to optimize the detection of chili objects at the focal point of detection for each frame. Pixel coordinate points that will cover areas that are not the focus of detection (Non-ROI). The specified pixel coordinate points are $(220, 0)$, $(730, 0)$, $(220, 540)$, $(730, 540)$. Next, RGB to grayscale conversion and edge detection. Object edges characterize the boundaries of objects and are useful for segmentation and identification processes in the image. The purpose of edge detection is to improve the appearance of the boundary lines of a region or object in the image. To detect edges in this image, the Canny operator is used [10]. The following are the results of each preprocessing stage shown in Figure 3.

Gaussian Blur is used next as a filter for reducing noise in the image and getting better image quality than before so that the image obtained becomes smoother. The image that has previously gone through the Gaussian blur process will then be converted from RGB to HSV. Color segmentation using HSV is done by taking pixels as a color reference and analyzing the color value of each image pixel to get the desired segment or feature with a tolerance value in each HSV color dimension. The HSV image is converted to a binary

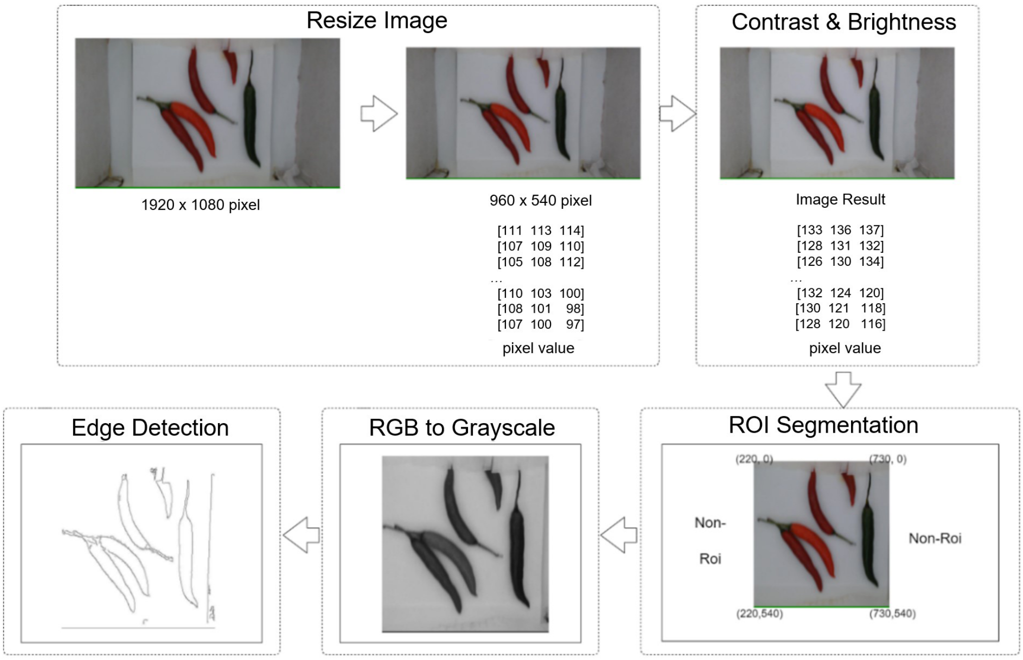


FIGURE 3. The result flow of the preprocessing stage

image at this stage through masking. The result of the masking process has two pixel values, namely 0 and 255. Pixel value 255 is marked white as the foreground area, while pixel value 0 is marked black as the background. To convert to a binary image, it is necessary to determine the desired range or color threshold value. The color threshold value to be taken is based on the lower and upper values.

Lower and upper are threshold values for background and foreground separation in HSV images, where lower is the lower threshold value and upper is the upper threshold value in the HSV color model to be selected. HSV color threshold values are obtained from a simple process by finding the value based on random values with hue (H) values between 0-179, saturation (S) between 0-255, and value (V) between 0-255. This threshold value is based on trial and error to obtain the optimum threshold value. Segmentation with HSV detection is done by analyzing the color value of each image pixel according to the desired features with a tolerance value (threshold) in each HSV color dimension. Then, the masking result from converting HSV to the binary image is combined with the binary image result from the edge detection process using the Canny operator. This process aims to separate the pixel values of the binary image incorporated in the binary image conversion process from the HSV color image. Thus, the edge line with a pixel value 0 will become the background. The following is an example of a Cayenne Pepper frame in the masking process shown in Figure 4(a).

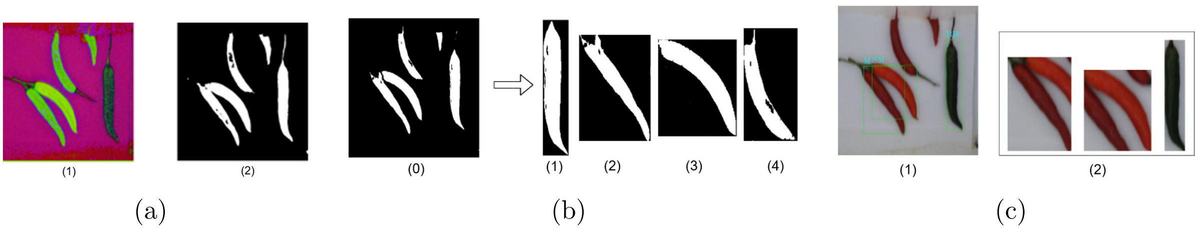


FIGURE 4. Blob detection

4.3. **Enhanced blob detection.** This process analyzes the area and shape of the blob object from an image that is the focus of detection. This process is important to localize the next detection area for better accuracy [11]. In this process, the detection focus area is the object that will be bounding box and crop. The area parameter value used is between 1,000 and 13,500 pixels. This is based on the observation of the area of each Cayenne Pepper object. So, if the area in question is between the specified area values, the area is considered foreground. In this process, it can be seen in Figure 5 that several objects are detected in one frame, so it is necessary to take one object at a time to be used in the next feature extraction stage. What needs to be done is contour search. This contour search is useful for modifying the image and finding the number of coordinates that show the contours on the white object (foreground) from the black background (background). Then, this contour search finds four foreground areas, so contour sorting is carried out based on the area where the contour with the largest size will be taken first, as shown in Figure 4(b), and the following blob detection and bounding box results are shown in Figure 4(c).

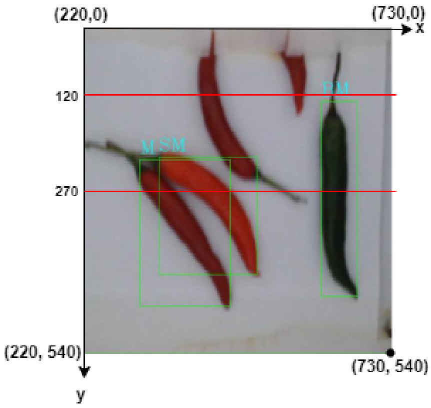
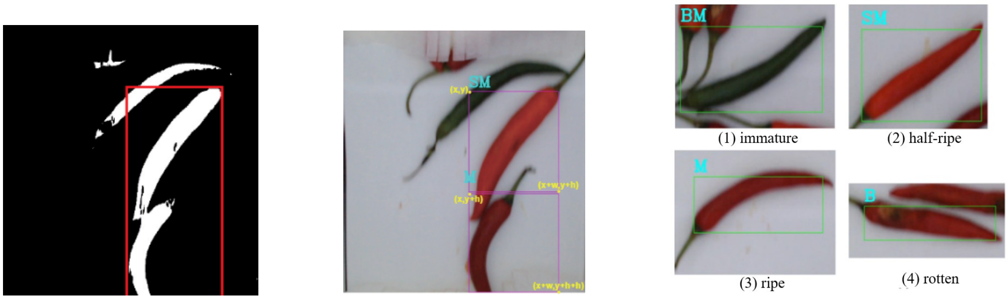


FIGURE 5. Limitation of detecting objects

It can be seen in Figure 4(c) that the bounding box and crop results only take three areas. This is due to the limitation of the y-coordinate point, where objects within the range of the y-coordinate point $(120, 270)$ will only be detected and classified. Providing coordinate point restrictions is the optimal y-coordinate point in detecting objects. Figure 5 shows an example of the y-coordinate point.

The segmentation process has been completed in this blob detection, but there are conditions where objects are close together and considered one area. The following example frame can be shown in Figure 6(a). This condition shows that the area in Figure 6(a) is outside the boundaries of the predetermined area. So, check the height of the bounding box. Determination of bounding box height limits based on observations where, in general, the bounding box on Cayenne Pepper is in the range h $(50, 360)$. So, when the height h exceeds the 360 limits, it is considered that there are objects that are close together. The following example of solving this condition is shown in Figure 6(b). To separate these adjacent objects, a process is carried out where objects within the bounding box will be divided by 2. Therefore, the position of the bounding box coordinates is set with the first bounding box starting point (x, y) and endpoint $(x + w, y + h)$, then for the second bounding box starting point $(x, y + h)$ and endpoint $(x + w, y + h + h)$. The value of h is taken from the value of h divided by two. The results of the SVM classification consist of immature red chilies (BM), half-ripe (SM), ripe (M), and rotten (B). The following is an example of the classification results on the test data shown in Figure 6(c).

5. **System Testing Results and Discussion.** In this research, system testing was carried out by taking test data in the form of video recorded by a Logitech Webcam



(a) (b) (c)

Figure 6. Enhanced image processing

C922 Pro camera inside the conveyor box belt box with a speed of 40 rpm, same as scenario, data type, and resolution of training dataset model. The video for this testing data takes 53 seconds with a frame rate of 15 fps. The test scenario is done by randomly entering or mixing as many as 40 pieces, where each category consists of 10 pieces of immature Cayenne Pepper (BM), 10 pieces of half-ripe (SM), and 12 pieces of ripe (M). The test data used is 22%, so the ratio between training and test data is 78% and 22%, respectively. As a contribution to the research, the color segmentation process uses HSV to separate the Cayenne Pepper objects close to each other. Separate Cayenne Pepper objects that are close to each other. Furthermore, the classification process is carried out with the Support Vector Machine (SVM) algorithm. The parameters used are kernel RBF kernel, Cost (C) = 100, and gamma (γ) = 0.2 obtained from Grid Search and multi-class OAA (One Against All). The following describes the classification results for immature, half-ripe, ripe, and rotten categories, shown in Table 1.

Table 1. System accuracy results with SVM algorithm

		Prediction				Total	Accuracy (%)	Total accuracy (%)
		BM	SM	M	B			
Actual	BM	86	0	0	0	86	100	95.92
	SM	0	89	5	0	94	94.68	
	M	0	0	120	3	123	97.56	
	B	2	1	3	64	70	91.43	

Table 1 shows that the highest accuracy is in the immature class with 100% accuracy, while the lowest accuracy result is in the rotten class with 91.43% accuracy based on the number of accuracy results for each class divided by the total number of classes, and the total accuracy in this system is 95.92%. The total frames that detect Cayenne Peppers in the immature class category are 86, with the correct classification. The half-ripe class category has 94 frames, with 89 correctly and five incorrectly classified frames. Cayenne Peppers detected in the ripe class category have 123 frames, with 120 correctly and 3 incorrectly classified frames. Cayenne Peppers detected in the rotten class category have 70 frames, with 64 frames correctly and 6 incorrectly classified. Detection errors occur due to errors in the segmentation stage. Segmentation errors will affect the final classification results because the extracted feature values also change or do not match the supposed feature values. The segmentation error results from the color distribution in each category of the Cayenne Pepper class, which is almost the same and falls within the lower and upper HSV threshold values, making the adjacent Cayenne Pepper object area considered one area or one blob even though the edge detection process and morphological operations have been carried out.

Based on the results of system accuracy with the SVM algorithm shown in Table 1, it is known that the data distribution strongly influences the parameter value because the value of parameter C affects the hyperplane model formed during the training process. In addition to the parameters used in the SVM algorithm, other parameters that affect the accuracy value of the system are the lower and upper HSV values, the average value of each RGB channel in the image, the light intensity used, and the segmentation process on Cayenne Pepper. The lower and upper values are obtained from the results of trials conducted on objects. They are useful for precisely separating the foreground from the background, even though the colors in the four class categories differ. The average value for color feature extraction is useful for showing the average size of each class category. Light intensity also greatly affects the results of object detection and classification in controlling light. The segmentation process is useful for separating if objects are close together.

This approach is different from previous research conducted by Sidehabi et al. [4], which only performed classification with conveyor systems and SVM classification systems. Likewise, in the identification of tomato maturity, in [5], the Grid Search SVM adopted also contributed to the research, but with the addition of an image processing approach with blob analysis able to provide better accuracy. The case study shown in the related research has a difference in the object's shape in Cayenne Pepper, where the opportunity for two objects to overlap and be read as one greatly reduces accuracy. However, with a blob analysis approach as the inspiration adopted in [11], it succeeded in reducing the misclassification of two objects that were previously classified as one object.

6. Conclusions.

Based on the results of research that has been carried out on the quality classification system of Cayenne Pepper, it can be concluded that the quality classification system of Cayenne Pepper can produce maximum accuracy with a blob detection analysis approach, including the RGB average approach from the results of object feature extraction which has not been done in previous studies. The segmentation process carried out in the study sequentially by converting RGB to HSV, masking the image, and then combining it with the results of edge detection and morphology using erosion or scraping operations gave maximum results with an accuracy of 95.92%. The classification uses the Support Vector Machine algorithm with RBF kernel parameters, Cost (C) = 100 and gamma (γ) = 0.2 obtained from Grid Search, and multi-class OAA (One Against All). Further development of this research can be done by utilizing other features, such as texture and shape, to improve the accuracy of the fruit quality classification system.

Acknowledgment. This work is supported by the Ministry of Education, Culture, Research and Technology (Grant. 124/E5/PG.02.00.PL/2023).

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