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HORTICULTURE SMART FARMING FOR ENHANCED EFFICIENCY IN INDUSTRY 4.0 PERFORMANCE

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Abstract

Chili peppers and papayas are important horticultural commodities in Indonesia with high economic value. To enhance productivity and efficiency in cultivating these crops, the application of Smart Farming technology is crucial. This study evaluates the use of image processing and artificial intelligence in the pre-harvest and post-harvest processes for chili peppers and papayas. For the pre-harvest process, data from 50 images of ripe chili peppers on the plant were used. The counting of ripe chilies was performed using HSV color segmentation with two masking processes, resulting in an average accuracy of 82.58%. In the post-harvest phase, 30 images of papayas, consisting of 10 images for each ripeness category—unripe, half-ripe, and ripe—were used. Papaya ripeness classification was carried out using the Support Vector Machine (SVM) algorithm with a Radial Basis Function (RBF) kernel and parameters C = 10 and $\gamma = 10^{-3}$*, achieving perfect classification accuracy of 100% for all categories. This study underscores the significant potential of Industry 4.0 technologies in enhancing agricultural practices and efficiency in the horticultural sector, providing important contributions to optimizing chili pepper and papaya production.*

Keywords: Classification, Counting, Horticulture, Industry 4.0, Smart Agriculture,

PERTANIAN CERDAS TANAMAN HOLTIKULTURA UNTUK PENINGKATAN EFISIENSI KINERJA INDUSTRI 4.0

Abstrak

Cabai dan pepaya adalah komoditas hortikultura penting di Indonesia dengan nilai ekonomi tinggi. Untuk meningkatkan produktivitas dan efisiensi budidaya tanaman ini, penerapan teknologi Smart Farming sangat penting. Penelitian ini mengevaluasi penerapan pengolahan citra dan kecerdasan buatan dalam proses pra dan pasca panen cabai dan pepaya. Pada proses pra-panen, digunakan data sebanyak 50 citra cabai matang pada pohon. Penghitungan cabai matang dilakukan melalui segmentasi warna HSV dengan dua kali proses masking, menghasilkan akurasi rata-rata 82,58%. Dalam fase pasca panen, digunakan 30 citra pepaya yang terdiri dari 10 citra untuk masing-masing kategori kematangan: belum matang, setengah matang, dan matang. Klasifikasi kematangan pepaya dilakukan menggunakan algoritma Support Vector Machine (SVM) dengan kernel Radial Basis Function (RBF) dan parameter C = 10 and $\gamma = 10^{-3}$, menghasilkan akurasi klasifikasi sempurna 100% untuk semua kategori. Hasil penelitian ini menegaskan potensi signifikan teknologi Industri 4.0 dalam meningkatkan praktik pertanian dan efisiensi sektor hortikultura, serta memberikan kontribusi penting bagi optimalisasi produksi cabai dan pepaya.

Kata kunci: Industry 4.0, Klasifikasi, Perhitungan Cabai, Pertanian Pintar.

1. INTRODUCTION

Industry 4.0 is driving the automation of systems across various fields, including the development of Smart Agriculture. The application of technologies that implement image processing and artificial intelligence continues to evolve to support Smart Agriculture, as it can enhance efficiency, productivity, and quality from upstream to downstream sectors of agricultural and plantation commodity products [1]. One of the leading agricultural commodities is horticultural plants. Horticultural plants with potential for development in Indonesia include chili and papaya [2]. Chili and papaya are popular horticultural crops widely cultivated in

Indonesia. These two plants have high economic value and are important commodities in the agricultural industry [3].

To maximize productivity and efficiency in farmers' performance in cultivating horticultural plants, particularly chili, the use of Smart Farming technology during the pre-harvest process is essential. The condition of chili production, which varies with each harvest, significantly impacts farmers. It is crucial for farmers to understand chili production to determine sales methods. Besides knowing the sales volume, farmers can also estimate when and how much chili will be harvested. However, farmers still face difficulties in predicting chili production as they rely solely on visual inspection, which is time-consuming.

Improvements in productivity and efficiency in the horticultural industry, particularly for papaya, can be achieved through the use of technology in the post-harvest process. The increasing demand for papaya, both for direct market sales and industrial processing, makes it crucial to sort papayas using technology to select high-quality fruit that meets consumer needs. In industrial papaya processing, especially for sorting the ripeness of papayas, the process is generally still performed manually by employees. The drawback of this method is that employees have physical limitations, such as quick fatigue and other physical issues. Additionally, differing perceptions among employees in assessing the ripeness of papayas result in inconsistent ripeness classification. This causes employee performance to be less effective and efficient. Moreover, processing papaya for added value on an industrial scale requires significant labor and time due to the large scale of operations. Therefore, consistent classification of papaya ripeness is crucial, as it impacts consumer satisfaction with the quality of papayas or processed products.

There have been numerous previous studies that perform automatic calculation and classification of fruit ripeness using different objects and methods by leveraging image processing technology[4]-[6]. This helps minimize errors in the calculation and sorting of fruit ripeness when done conventionally. Research conducted by Indrabayu et al. used image processing with Blob analysis to detect and count ripe chili peppers, achieving an accuracy of 89.7%. This study has limitations in detecting overlapping chili peppers [7]. Hasanah et al. conducted research on the detection process of ripe oranges using the Hue, Saturation, and Chrominance-Red color space. The counting of detected ripe oranges was performed using the watershed algorithm, resulting in an accuracy of 82.14%. This method was limited to a single fruit type without applying double masking segmentation to improve accuracy [8]. Pandey et al. conducted automatic estimation of chili yield using image processing, achieving an accuracy of 99.64% [9]. Although highly accurate, this approach did not consider HSV color segmentation with double masking, which has been proven more accurate in other studies.

In addition to research related to object measurement, for the case of classifying fruit ripeness levels, an algorithm that performs well and has been used by several researchers is the Support Vector Machine. This algorithm is used to classify fruit ripeness levels and has been proven to achieve good accuracy. J. Pardede et al. classified fruit ripeness for mango, tomato, orange, and apple using an SVM algorithm with a 6th-degree polynomial kernel. The model, utilizing HSV color features, achieved an accuracy of 0.76, precision of 0.80, recall of 0.76, and F-Measure of 0.78 [10]. However, this study used a polynomial kernel rather than an RBF kernel, which has been shown to achieve better accuracy results. J. A. M. Galindo et al. classified cocoa ripeness using acoustic sensing technology. The device generates an acoustic signal from the cocoa pods, which is then recorded for acoustic signal analysis. A cepstral-based technique was used for feature extraction, and the Support Vector Machine (SVM) algorithm model, tested using nested cross-validation, achieved a mean test score of 94% [11]. Although it has high accuracy, it has various limitations, such as the fact that the sound produced by the cocoa pods can be influenced by environmental conditions, which can affect the accuracy of the measurements. B. Maulana Alfaruq et al. performed tomato ripeness classification using the SVM algorithm based on GLCM features, achieving an accuracy of 91.1% [12]. A. Hamzah et al. performed avocado ripeness classification using SVM with an accuracy of 86.67% [13]. Furthermore, other researchers have compared the performance of the SVM algorithm with other algorithms. The comparison results show that the SVM algorithm achieves excellent accuracy, with an average of over 95% [14][15].

Based on the literature review conducted, image processing can address the challenges of calculating and classifying fruit ripeness. Therefore, In the pre-harvest phase, this study aims to enhance the accuracy of determining chili pepper ripeness using HSV (Hue, Saturation, Value) color segmentation combined with double masking. This technique is designed to differentiate ripe chili peppers from unripe ones based on their color characteristics, with double masking helping to reduce noise and improve detection accuracy. By implementing this approach, the goal is to achieve more precise detection of ripe chilies, aiding farmers in determining the optimal harvest time and improving the quality of their yield. In the post-harvest phase, the focus shifts to classifying papaya ripeness into three categories: ripe, semi-ripe, and unripe. This is achieved using HSV color features extracted from papaya images to automatically distinguish between different ripeness levels. Accurate classification aims to sort papayas according to their ripeness, thereby enhancing product quality and extending shelf life. Overall, this research seeks to boost productivity and efficiency in horticulture by applying image processing technology and contributes significantly to the advancement of Smart Agriculture in the Industry 4.0 era.

2. RESEARCH METHOD

There are two stages in the Smart Agriculture process for horticultural crops: pre-harvest and post-harvest. In the pre-harvest stage, HSV segmentation is used to count the number of chilies on the plant. This method is chosen for its ability to separate colors based on Hue, Saturation, and Value, which is highly effective in identifying objects like chilies that have striking colors. HSV segmentation provides accurate results in separating the objects from the background, thus making it easier to automatically count the number of chilies. In the post-harvest stage, the ripeness of papaya fruit is classified using the SVM algorithm. SVM is selected for its accuracy and efficiency in classification. It effectively separates data into distinct categories with clear margins, allowing papayas to be grouped into ripe, semi-ripe, and unripe categories. Additionally, SVM has strong generalization capabilities, making the model applicable to new data. Therefore, SVM is used in classifying papaya ripeness, supporting the Smart Agriculture system to achieve better efficiency and productivity. By utilizing these methods, the productivity and efficiency in managing horticultural plants are expected to improve, fostering smarter and more sustainable agriculture.

2.1 Counting chili ripeness

The stages of the method for calculating ripe chili peppers on the plant are shown in Figure 1 below:

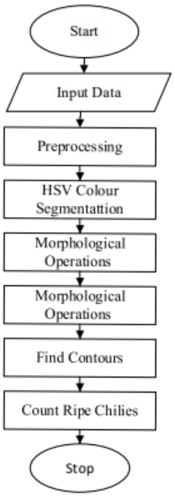

Figure 1. The stages for counting chilies

Input Data: Input chili images for processing. A total of 50 ripe chili images are used. The example of chili images used is shown in Figure 2 below.

Figure 2. Sample data for chili ripeness

Prepocessing: The next step is to perform preprocessing by resizing the images to 200 x 300 pixels. This resizing helps save memory usage and reduce the program's execution time.

HSV color segmentation: Next, color segmentation is performed using HSV. Color segmentation is the process of separating or identifying areas or objects in an image based on their color characteristics. The goal of this segmentation is to distinguish objects or areas with a specific color from the background or other objects in the image. This can be achieved using a specific color model, such as the RGB (Red, Green, Blue) color model or the HSV (Hue, Saturation, Value) color model. The HSV model consists of three main components: Hue, Saturation, and Value (also known as brightness). Segmentation with HSV detection is performed by analyzing the color values of each pixel in the image according to the desired features with tolerance values in each HSV color dimension. The HSV color space includes 3 components: H represents the type of color (such as red, blue, or yellow) or the hue, which indicates where the color falls within the color spectrum. S represents the level of color dominance, or the degree of purity of the color. V represents the level of brightness, or the amount of light coming from the color [14].

Conversion process from RGB to HSV as follows:

RGB Value: RGB value is a representation of color in the Red, Green, and Blue color model. Below are examples of RGB values shown in Table 1.

Table 1. RGB Value

Red	Green	Blue
255	125	100

Normalize RGB Values: Normalization is performed to scale the RGB values to a range between 0 and 1. This process helps in standardizing the input values, making it easier to apply mathematical operations and algorithms, such as conversion to other color models or image processing techniques. The normalization process that is performed is shown with the following formula:

$$R_{norm} = \frac{R}{255} \quad (1)$$

$$G_{norm} = \frac{G}{255} \quad (2)$$

$$B_{norm} = \frac{B}{255} \quad (3)$$

The result of normalizing RGB values is :

$$R_{norm} = \frac{255}{255} = 1$$

$$G_{norm} = \frac{125}{255} = 0.49$$

$$B_{norm} = \frac{100}{255} = 0.39$$

Calculate the Minimum and Maximum Values:

$$C_{max} = \max(R_{norm}, G_{norm}, B_{norm})$$

$$C_{max} = \max(1, 0.49, 0.39)$$

$$C_{max} = 1$$

$$C_{min} = \min(R_{norm}, G_{norm}, B_{norm})$$

$$C_{min} = \min(1, 0.49, 0.39)$$

$$C_{min} = 0{,}39$$

To calculate the HSV (Hue, Saturation, Value) from the normalized RGB values, we'll use the following formulas:

$$Hue\ (H) = 60°\ x\ \frac{G-B}{C_{max}-C_{min}} \quad \text{if} \quad C_{max} = R \quad (4)$$

$$Saturation\ (S) = \frac{C_{max}-C_{min}}{C_{max}} \quad (5)$$

$$Value\ (V) = C_{max} \quad (6)$$

Given Calculations:

$$Hue\ (H) = 9.84°$$

$$Saturation\ (S) = 0.61$$

$$Value\ (V) = 1$$

Masking Image: After the image is converted to the HSV color space, the next step is to define the color range that represents ripe chili peppers. After the image is converted to the HSV color space, masking is performed twice because red chili peppers can appear in two different color ranges within the HSV color space. The masking process involves creating two binary masks: The masking process involves creating two binary masks, as shown in Table 2:

Table 2. HSV Value Ranges for Binary Masks

Mask	LowerHSV	UpperHSV
Mask1	[0, 0.2, 0.2]	[0.03, 1, 1]
Mask2	[0.67, 0.2, 0.2]	[0.71, 1, 1]

Morphological Operations to Remove Noise: Next, morphological operations enhance the quality of the mask. Erosion removes small noise and unwanted elements, while dilation expands the remaining areas and fills gaps. These steps make the mask cleaner and more accurate, improving the overall detection of the target objects.

Find Contours: The cleaned binary mask is used to detect contours, which represent the boundaries of the ripe chili peppers in the image.

Count Ripe Chilies: After all the processes are completed, the number of ripe chilies detected can be counted.

2.2 Classification of papaya Maturity

The stages of the papaya ripeness classification process consist of two processes: the training process and the testing process, which are shown in Figure 3 below:

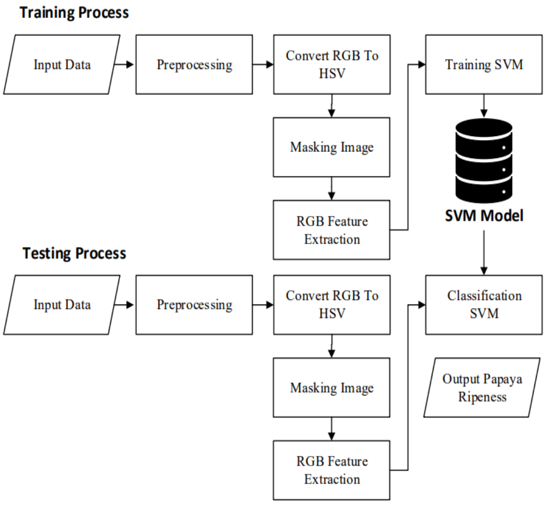

Figure 3. The stages for classification papaya ripeness

The following are the stages of papaya ripeness classification using the SVM algorithm, as shown in Figure 3:

Training Process: At this stage, the process of training papaya image data is carried out to obtain the best model from the algorithm used. The stages of the feature extraction process in the training phase are as follows:

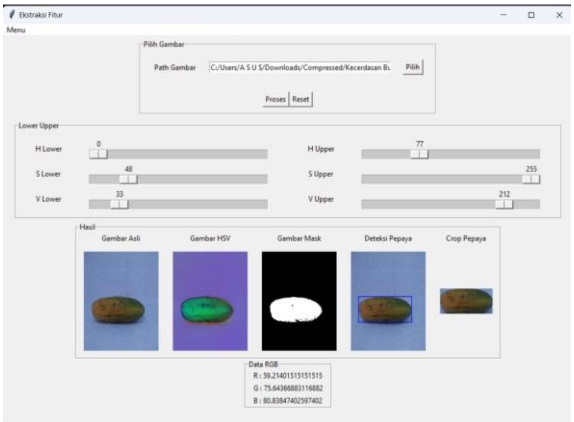

Figure 4. Feature extraction process

Input Data: Input the papaya images for processing. The data set used consists of 90 images, with 30 images for each class: unripe, half-ripe, and ripe.

Preprocessing: Resize the images to save memory usage and reduce execution time.

Convert RGB To HSV: The next step is to convert the RGB values to HSV. The segmentation process using HSV color features is carried out by analyzing the color values of each image pixel according to the desired features, with tolerance values applied to each dimension of the HSV color space. The range of HSV values used is shown in Table 3 below [indrabayu].

Tabel 3. The range of HSV values

	Lower	Upper
H	0	77
S	48	255
V	33	212

Masking Image: After that, the HSV image is converted to a black-and-white image through a masking process. The next step is to analyze the object's area to apply a bounding box. Blob detection will analyze the area and shape of the blob object in the image that is the focus of detection. Once detected, the object will be cropped and processed in the feature extraction stage.

RGB Feature Extraction: Extract RGB color features from the image to differentiate between objects and assign labels into 3 categories: 1 for unripe, 2 for half-ripe, and 3 for ripe.

Training SVM Model: In the training process, the SVM algorithm is used because it can handle the classification of both linear and non-linear data[15]. The output of this training process is a model that includes alpha (α) values and a bias value, which are used in the testing process.

Testing Process: At this stage, the model developed in the training phase is tested. The data used consists of new images that do not have class labels, and the process stages are almost the same as those in the training data. The test data used comprises 30 images, with 10 images for each ripeness category. The example classification results are shown in the following Figure 5.

Figure 5. Example Classification Results

3. RESULT

The results from counting 50 chilies yielded an average accuracy of 82.58%. This indicates that the method used has a fairly good success rate in detecting and counting the number of ripe chilies, although there is still room for improvement in reducing detection errors and increasing overall accuracy.

The results of the papaya ripeness classification study using 30 images, with 10 images for each category (unripe, half-ripe, and ripe), employed an SVM algorithm with an RBF kernel and parameter values of C = 10 and $\gamma = 10^{-3}$. The results of the testing are shown in the following Table 3.

Table 3. Papaya Image Testing Results

Actual Class	**Prediction**			**Accuracy**
	Unripe	Half-Ripe	Ripe	
Unripe	**10**	0	0	100%
Half-Ripe	0	**10**	0	100%
Ripe	0	0	**10**	100%
Total Akurasi				**100%**

The classification results, shown in Table 3, indicate that the SVM algorithm achieved perfect accuracy in classifying all images. Each category unripe, half-ripe, and ripe reached an accuracy of 100%, demonstrating that all images were correctly identified according to the class. Overall, the total classification accuracy was 100%, indicating that the SVM model with the selected parameters was highly effective in distinguishing between unripe, half-ripe, and ripe papayas. These results highlight the strength of the SVM algorithm and the quality of the feature extraction and classification processes used in this study. The following example of classification results from test data based on the average values of R, G, and B is shown in Table 4 below.

Table 4. Test results of tomato images

Actual	R	G	B	Prediction
Unripe	53.7060	95.0806	69.1349	Unripe
Unripe	55.6543	88.3506	75.2375	Unripe
Unripe	62.8987	95.4940	81.7265	Unripe
Unripe	64.6451	95.7528	83.2873	Unripe
Unripe	60.2528	90.7957	77.7597	Unripe
Half-Ripe	49.4864	107.1261	84.8051	Half-Ripe
Half-Ripe	55.0255	108.1397	103.0505	Half-Ripe
Half-Ripe	53.7366	109.4856	104.5159	Half-Ripe
Half-Ripe	55.5517	110.7160	104.0557	Half-Ripe
Half-Ripe	52.1753	106.5452	100.7937	Half-Ripe
Ripe	57.5842	120.2573	155.1369	Ripe
Ripe	71.8967	162.9759	201.0654	Ripe
Ripe	65.4599	142.3049	179.5103	Ripe
Ripe	59.2134	99.0821	153.9112	Ripe
Ripe	71.7093	83.0692	100.7336	Ripe

4. DISCUSSION

The results of this study reveal a significant difference in detection accuracy between the two types of objects tested: chilies and papayas. For counting ripe chilies, the method used achieved an average accuracy of 82.58%. This accuracy indicates that the method is quite effective in detecting and counting the number of ripe chilies. However, there is still potential for further improvement. The detection errors that occurred were caused by various factors, such as variations in lighting, overlapping chilies, leaves covering the chilies, and other conditions that affect the object recognition process.

On the other hand, the study on papaya ripeness classification showed much better results, with an accuracy reaching 100% using the Support Vector Machine (SVM) algorithm with a Radial Basis Function (RBF) kernel and parameters C = 10 and $\gamma = 10^{-3}$. This high level of accuracy can be attributed to several factors. Firstly, papaya ripeness classification is easier to differentiate based on clearer visual characteristics, such as significant changes in color and texture between the categories of unripe, half-ripe, and ripe. In this study, the SVM model was able to learn more effectively in a simpler feature space, resulting in optimal outcomes.

The difference in accuracy between chili detection and papaya classification is also due to the different characteristics of the datasets and the complexity of the tasks. Detecting and counting chilies requires more detailed and varied object identification within a single image, while classifying papaya ripeness focuses more on recognizing patterns in images with predefined categories. The SVM model with an RBF kernel is well-suited for classification where the data can be non-linearly separated in the feature space, and in the case of papayas, the chosen parameters seem highly effective.

Additionally, the success of papaya ripeness classification also indicates that the dataset used was sufficiently representative of all ripeness categories, allowing the model to learn the distinctions more effectively. This underscores the importance of a good dataset, not just in terms of quantity but also in terms of variation and proper category representation. Conversely, the chili dataset faced challenges such as overlapping objects, less significant color variations, and inconsistencies in lighting, all of which affected accuracy.

In this context, to improve the accuracy of chili detection, several steps can be considered, including adding more representative training data, using better preprocessing methods, or applying algorithms capable of handling overlapping objects. In conclusion, the papaya classification method showed optimal results with the parameters and model used, while chili counting still requires further optimization. Future research should focus on improving methodologies and data quality to overcome these challenges and achieve better results.

The comparison between this study and the previous research conducted by A. Fatah and R. Rahmadew lies in the different objects used. Their study focused on identifying the ripeness of lemons using HSV features and multi-level thresholding with threshold values of T1 = 140 and T2 = 198, achieving an accuracy of 75%. Although both studies utilized HSV color segmentation, this study employed different HSV threshold values, using a lower HSV range of [0, 48, 33] and an upper HSV range of [77, 255, 212], resulting in an accuracy of 100%. From the research conducted by Saputra, Joni et al., the classification of the ripeness level of avocado butter was done using the K-Nearest Neighbor (KNN) method, resulting in an average accuracy of 77.45%. Meanwhile, this study used a different method, namely the Support Vector Machine (SVM) algorithm, and focused on papaya as the research object, achieving a maximum accuracy of up to 100%. This comparison underscores the importance of selecting appropriate thresholding and classification methods based on the characteristics of the objects being studied. While both KNN and HSV segmentation proved effective in their respective applications, the use of SVM with RBF kernel in this study provided significantly better results, demonstrating its strength in handling high-dimensional data and generalizing effectively across different ripeness levels. Thus, the findings suggest that SVM is a more suitable choice for tasks requiring precise classification of visually complex categories, such as fruit ripeness.

Meanwhile, a comparison of studies focusing on fruit counting is also illustrated in the research conducted by Elva Amalia, who counted the number of oranges using the Hough Transformation method with an accuracy of 95.4%. On the other hand, this study, which counts chili peppers on the plant using HSV masking twice, only achieved an accuracy of 82.58%. This difference is due to the complexity involved in counting chili peppers directly on the plant, which is more challenging compared to counting oranges against a black background. This complexity may arise from factors such as the presence of leaves and stems that interfere with the segmentation process, variations in lighting, and the color difference between the chili peppers and their surroundings, which may not be as distinct as the color difference between oranges and a black background.

Additionally, chili peppers often grow in clusters and can overlap with one another, making it harder to isolate individual fruits compared to oranges, which are more uniformly distributed and easier to detect. The variation in the size and shape of chili peppers also adds to the complexity, as these factors can affect the segmentation and counting process. Furthermore, the irregularities in lighting conditions in outdoor environments where the chili plants grow can introduce noise and shadows, complicating the detection process even further.

Therefore, the method used in this study faces greater challenges in accurately detecting and counting the number of chili peppers. Future research should focus on refining methods such as improving the preprocessing techniques to handle overlapping objects, incorporating advanced machine learning models that can learn to detect peppers in more complex environments, and using better lighting normalization techniques to reduce the impact of external factors. Enhancing the quality and diversity of the dataset by including more representative samples in various conditions could also help improve accuracy in chili pepper detection and counting.

5. CONCLUSION

The results of this study reveal a significant difference in detection accuracy between the two types of objects tested: chili peppers and papayas. Counting 50 chilies yielded an average accuracy of 82.58%, indicating that the method used is fairly effective in detecting and counting the number of ripe chilies. However, there is still potential for improvement in reducing detection errors and increasing overall accuracy.

On the other hand, the study on papaya ripeness classification using 30 images and the Support Vector Machine (SVM) algorithm with a Radial Basis Function (RBF) kernel and parameters $C = 10$ and $\gamma = 10^{-3}$, achieved perfect accuracy of 100%. This indicates that the SVM model was highly effective in distinguishing between unripe, half-ripe, and ripe papayas. The quality of the dataset used was also sufficiently representative, allowing the model to learn effectively.

The difference in accuracy between chili detection and papaya classification can be largely attributed to the differing characteristics of the datasets and the complexity of the tasks involved. Detecting and counting chilies requires more detailed and varied object identification within a single image, while classifying papaya ripeness focuses more on recognizing patterns in images with predefined categories.

To improve the accuracy of chili detection, several steps should be considered, including adding more representative training data, utilizing better preprocessing methods, and applying algorithms capable of handling overlapping objects. Future research should focus on refining methodologies and enhancing data quality to overcome these challenges and achieve better results.

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