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Ứng dụng Raspberry và PLC Mitsubishi trong thiết kế hệ thống tự động phân loại cà chua

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TÓM TẮT

Bài viết này trình bày về việc ứng dụng Raspberry và PLC Mitsubishi để thiết kế hệ thống tự động phân loại cà chua. Trong bài báo này, thuật toán KNN (K-Nearest Neighbors) và thuật toán xác định màu sắc quả được sử dụng để phân loại cà chua theo mức độ chín, hình dạng và kích thước. Các thuật toán này được nhúng vào Raspberry để xử lý hình ảnh. Sau khi xử lý, các tín hiệu điện từ Raspberry được truyền đến PLC Mitsubishi để điều khiển các cơ cấu phân loại của hệ thống. Thêm vào đó, tác giả cũng xây dựng hệ thống SCADA (Supervisory, Control and Data Acquisition) để điều khiển, giám sát và thu thập dữ liệu của hệ thống phân loại. Các kết quả thu được từ thực nghiệm cho thấy hệ thống phân loại cà chua hoạt động ổn định, độ chính xác khá cao và năng suất lao động cao.

Từ khóa: *PLC, SCADA, cà chua, hình dạng, thuật toán KNN.*

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Application of Raspberry and PLC Mitsubishi to the design of tomato classified system automatically

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ABSTRACT

This article illustrates the application of Raspberry and PLC Mitsubishi to the design of a tomato classifying system automatically. In this paper, the KNN (K-Nearest Neighbors) algorithm is used in conjunction with the fruit color determination algorithm to determine the level of ripeness, shape and size of tomatoes. These algorithms are embedded into the Raspberry to perform image processing. After processing, the electrical signals from the Raspberry are transmitted to the PLC Mitsubishi to control the actuators of the sorting system. In addition, the authors also establish a SCADA (Supervisory, Control And Data Acquisition) system to control, monitor and collect data of the classification system. The experimental results point out that the tomato grading system is stable, with relatively high accuracy and high labor productivity.

Keywords: *PLC, SCADA, tomato, shape, KNN algorithm.*

1. INTRODUCTION

In Vietnam, agricultural products after harvest are often not classified or visually classified, leading to low productivity, high labor costs and low accuracy. This issue greatly affects the competitiveness of Vietnamese agricultural products with other countries in the world.

Along with agricultural production in accordance with VietGAP and GlobalGAP standards, the classification and packaging of products that meet export criteria is also one of the important factors to help improve the competitiveness of Vietnamese agricultural products. In recent years, there have been several great developments in the field of science and engineering such as robotics,[1-3] artificial intelligence (AI)[4,5] and machine learning.[3,6] We can make use of these achievements of science and technology to build labor-saving, high-precision, high-productivity agricultural product sorting systems.

Our country has many types of agricultural products that need to be classified and packaged for export such as tomatoes, mangoes, green-skinned pomelos, litchi, dragon fruit, etc. In this article, agricultural products need to be classified as tomatoes after is harvested. The classification criteria are the degree of ripeness of the fruit, the size of the fruit and the shape of the fruit.

Today, there have been many studies on the use of image processing technology to classify tomato products after harvest, but most of them only study the classification of tomatoes based on one or a few classification criteria

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such as classification of tomatoes based on fruit color,[7,8] classification based on fruit shape criter-ion,[9] or classification of fruit based on 2 criteria of shape and color[10] without giving a complete classification system. This paper applies and updates existing scientific achievements in desig-ning an automatic tomato sorting system based on all 3 criteria of fruit shape, fruit size and fruit ripeness in order to replace for manual classifica-tion in Vietnam.

In this paper, image processing techniques are embedded in Raspberry for image processing. The color identification algorithm[13,14] would be used in combination with the K-Nearest Neighbors (K-Nearest Neighbors) algorithm[6,11,12] to classify tomatoes according to the following criteria: fruit ripeness, size fruit and fruit shape (fruit distortion). Then, the processing signals from the Raspberry are transmitted to the PLC (Programmable Logic Controller) to perform the classification stage. Contents related to the design of the control, monitoring and data acquisition (SCADA) system of the classification are also presented in the paper.

KNN algorithm is an algorithm used in machine learning.[3,6] Despite a simple algorithm, it has a relatively high accuracy[15] and a fast processing time.[6] These characteristics allow it to be embedded in an embedded computer (Raspberry) easily.

The image processing signals from the Raspberry would be transmitted to the Mitsubishi PLC (FX2N 128MR), and then the PLC controls the actuators to perform the classification. Besides, aiming to build a convenient, intuitive and modern classification system, the authors also built a control, monitoring and data acquisition system (SCADA) for the classifica-tion system.

2. CLASSIFICATION PROCESS

2.1. Classification algorithm

2.1.1. Determining fruit shape and size

In image processing techniques, there are many algorithms to determine shape and size in tomato classification such as: KNN,[6,11,12] Naive Bayes,[12] SVM,[6,11] etc. KNN has the advantages such as fast processing time, simple algorithm easily embedded in the Raspberry embedded computer and highly accurate, therefore, this algorithm is chosen to determine the shape and size of the fruit in this paper.

The KNN algorithm consists of two stages: the training phase and the classification phase.[16] In the training phase, the training samples are vectors (each vector has a label). In this stage, the feature vectors and labels of the training samples are stored. In the classification phase, the input query point or feature vector is compared with the reference vector library, and the query point is labeled.

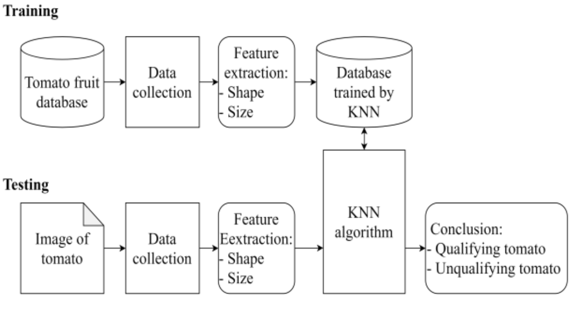

Figure 1. KNN algorithm

The process of classifying tomato shape and size is shown in Figure 1. The first step is to create a data library. This gallery includes images of 2500 tomatoes selected based on fruit shape and size characteristics. These samples are then labeled and put into a classification system for identification. Then the constant K is determined. K is the number of sample data points with the closest distance (nearest neighbor) to the data point of the unclassified tomato. The empirical method is used to determine the coefficient K in the KNN algorithm. Specifically, 300 tomato sample data were included in the identification, showing that when K > 5, the accuracy of the classification system does not seem to change, but the time to classify a tomato product increases proportionally to the magnitude of K. This means the system's productivity would decrease as K is larger. Therefore, K = 5 is chosen.

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The distance between feature vectors of the object to be classified with all training data is determined by Euclidean formula.[17] Suppose that we have two given data matrices with 1 row and n columns as follows: $X = [x_1, x_2,\ldots, x_n]$ and $Y = [y_1, y_2,\ldots, y_n]$ then the distance between the vectors x and y is calculated as Euclidean formula (1).

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (1)$$

Then, this calculation result is sorted in ascending order and the K closest neighbors to the data of the tomato to be classified are determined and finally concluded.

2.1.2. Determining the color of the fruit

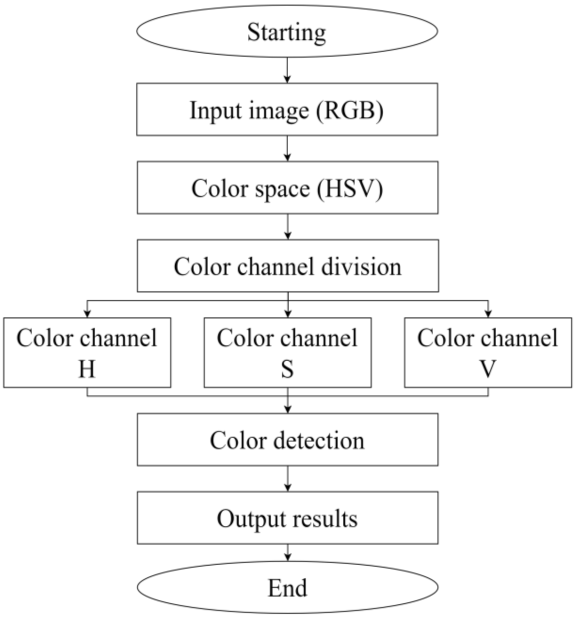


Figure 2. Algorithm to detect color (ripeness) of fruit.

The process of detecting the color (ripeness) of the fruit is shown in Figure 2.

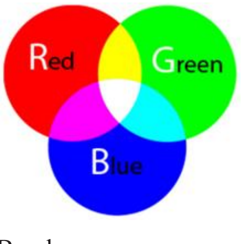


Figure 3. RGB color space.

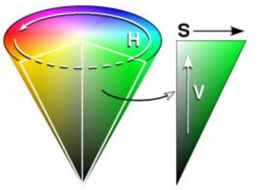


Figure 4. HSV color space.

The process of detecting the color (ripeness) of the fruit is shown in Figure 2.

To determine the color (ripeness) of the tomato, the system relies on images taken from the camera. At this point, the tomato image belonging to the RGB color space (Figure 3) would be converted to the HSV color space (Figure 4).

To convert from RGB color space to HSV color space, formula 2 [18,19,20] is used.

$$\begin{cases} H = \arccos\left(\dfrac{\frac{1}{2}(2R - G - B)}{\sqrt{(R-G)^2 - (R-G)(G-B)}}\right) \\ S = \dfrac{\max(R,B,G) - \min(R,B,G)}{\max(R,B,G)} \\ V = \dfrac{\max(R,B,G)}{255} \end{cases} \qquad (2)$$

Once the value of the color channels is calculated, the number of pixels in the tomato image to be classified, the number of pixels of white and the number of pixels of black are determined. Based on that, the degree of ripeness of the fruit is found.

2.2. Building experimental system

Figure 5 is a general block diagram of the classification system. The equipment used in the experimental model is shown in Figure 6. In it, the camera block is used to collect and transmit image data of the tomato to the Raspberry. The sensor block is used to send an electrical signal to the Raspberry when the tomato reaches the camera position. The processing block consists of Raspberry and PLC (Programmable Logic Controller). In it, Raspberry receives image data from the camera, executes image processing, and sends the processing results in the form of electrical signals to the PLC so that the PLC controls the actuators (motors, pneumatic cylinders,…). The display block is used to display the results of tomato image processing.

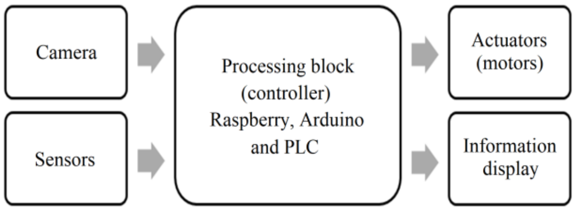


Figure 5. Image of blocks in the classification system.

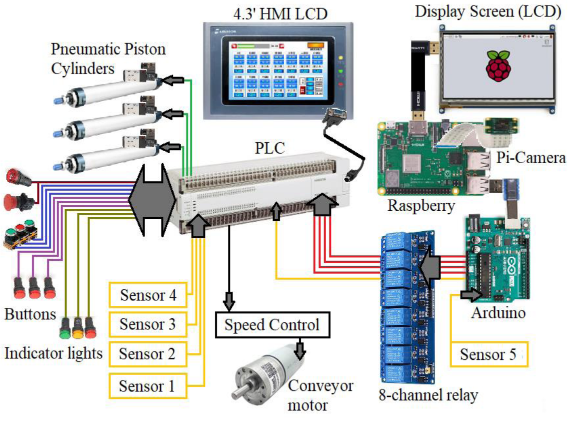


Figure 6. Images of devices in the experimental model.

The working process of the classification system is shown in Figure 7.

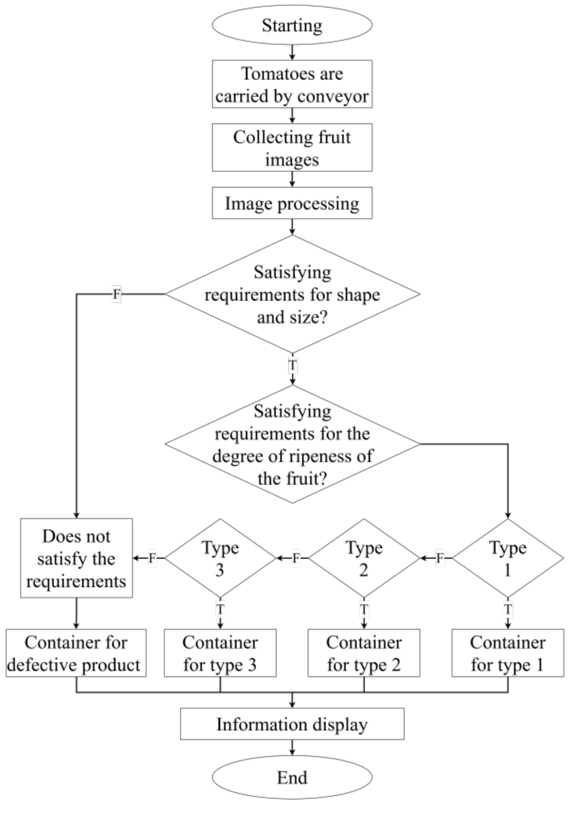


Figure 7. The working process of the classification system.

Figure 8. Experimental model of the classification system.

Figure 8 is an experimental model image of the automatic tomato classifying system.

The operating process of the system is as follows: When starting the system, the cylinder pushes the tomatoes into the conveyor, the tomatoes would be brought to the camera position. When the sensor detects the fruit has reached the camera position, a picture of the tomato is taken. Raspberry would take the image signal of the object and process the image.

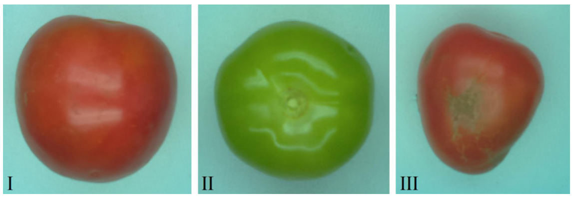


Figure 9. The images collected from the camera.

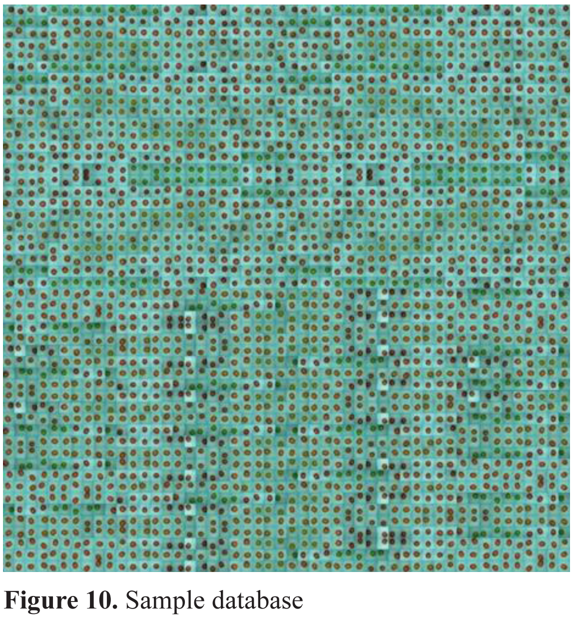


Figure 10. Sample database

The shape and size of the tomatoes that need to be classified were compared with a library of 2500 sample tomatoes for classification. A library of 2500 sample tomatoes is shown in Figure 10.

Figure 11 shows the result of the tomato sorting process displayed on the system notification screen. As seen, the images of fruit I and fruit II are satisfactory in terms of fruit size and fruit shape, while fruit III is unsatisfactory in shape (distorted fruit).

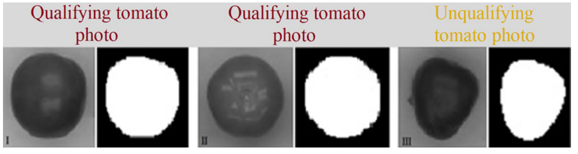


Figure 11. Classification results based on the criteria of fruit size and fruit shape (fruit distortion).

If any fruit does not meet the standard in shape and size, Raspberry would send a signal to PLC Mitsubishi to proceed to put the fruit into the container of the defective product.

The fruits that meet the standards in shape and size would be further classified by the system according to the degree of ripeness of the fruit based on the color classification algorithm mentioned in Subsection 2.1.2. Figure 12 is the result of the level of ripeness grading of the fruit displayed on the notification screen. For fruits with different degrees of ripeness, the PLC sends signals to the actuators to put them in the corresponding containers. Finally, the sorting results would be displayed on the LCD screen for the operator to easily monitor the sorting process. In this step, information about the ripeness, shape and size of the fruit (satisfy or not) is displayed on the screen (see Figure 13).

Figure 12. Classification of fruit ripeness.

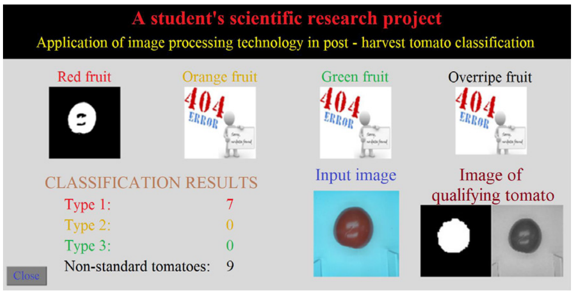


Figure 13. Screen showing classification result information.

SCADA system for automatic tomato sorting system was also built by the authors. The operator can control the system, monitor its operation and collect system data on the Samkoon HMI screen (see Figures 14 and 15). In which, Figure 14 is the system control interface.

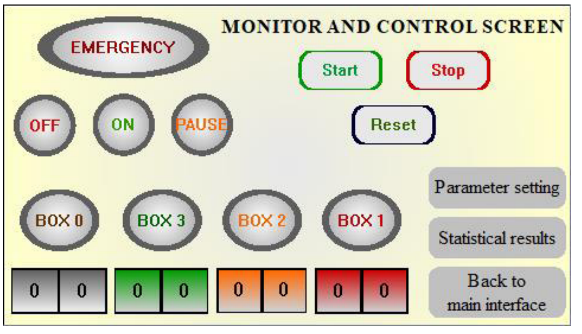
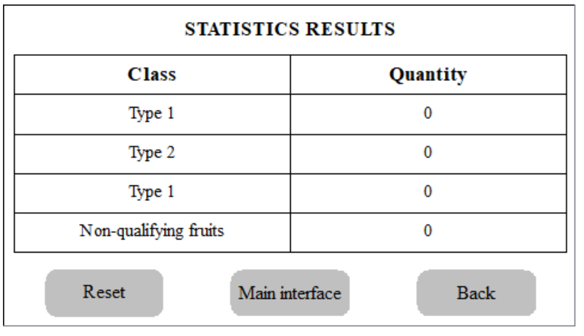


Figure 14. The HMI screen shows the monitoring – control interface of the classification system.

Figure 15 is the screen to monitor the number of tomatoes that meet the standards of classes I, II, III and those that do not meet the requirements.



STATISTICS RESULTS

Class	Quantity
Type 1	0
Type 2	0
Type 1	0
Non-qualifying fruits	0

Figure 15. The screen monitoring the number of tomatoes that meet the standards of classes I, II, III and those that do not meet the requirements.

2.3. Experimental results

The author carried out the experimental process on 300 tomato samples. Figure 16 shows

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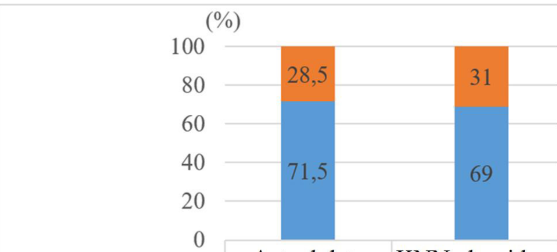
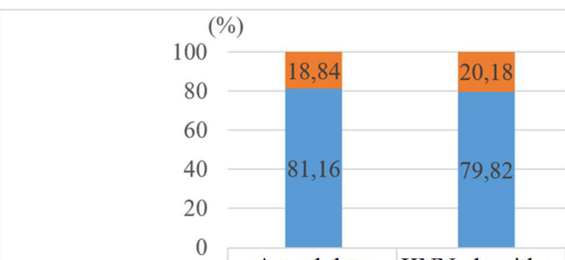
the accuracy of the system when classifying according to the standard of fruit distortion. Of the 300 tested fruits, 71.5% of the fruits did not meet the shape criterion, labeled as failing, and 28.5% of the fruits met the shape criterion, labeled as meeting the requirement. The result of the system's classification revealed that 69% of the tested fruits were unsatisfactory and 31% satisfactory. Therefore, the accuracy of the system in classification according to the criterion of shape (distortion) of fruit is 95.87%.

The process of evaluating the accuracy of the system according to the criteria of fruit size and fruit color was also done similarly. Figure 17 demonstrates the result of the system's classification according to fruit size criteria. The system could classify according to this criterion with an accuracy of 95.87%.



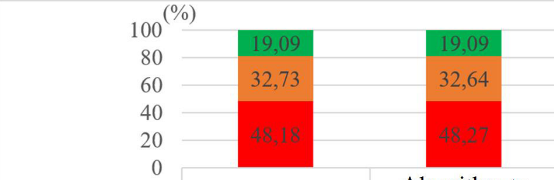
	Actual data	KNN algorithm
Quantity of quality tomatoes (%)	28,5	31
Quantity of unqualified tomatoes (%)	71,5	69

Figure 16. Classification results according to the criteria of fruit shape.



	Actual data	KNN algorithm
Quantity of quality tomatoes (size) (%)	29,71	32,61
Quantity of unqualified tomatoes (size) (%)	70,29	67,39

Figure 17. Results of classification according to fruit size criteria.



	Actual data	Algorithm to determine fruit color
Unripe fruit (%)	19,09	19,09
Orange fruit (%)	32,73	32,64
Ripe fruit (%)	48,18	48,27

Figure 18. Classification results according to the degree of ripeness of the fruit (fruit color).

As can be seen from Figure 18 which shows the result of the system's classification according to fruit color criteria (ripeness), the system had an accuracy of approximately 99%.

The reason for errors in the product classification of the system is due to the resolution of the captured images and the location of the camera installation. When the shooting angle is different, it is more or less affects the results of the fruit's shape and size classification. The resolution of the image affects the fruit's ripeness classification results. The higher the resolution of the image, the better the accuracy of the classification process. However, too high image resolution affects the recognition speed and reduces the classification performance of the system.

Besides, the experimental results also show that the time to classify a tomato product from the time of image collection to the time when the classification process results are displayed was small, approximately 1.2 seconds.

3. CONCLUSION

In this paper, the author used Mitsubishi PLC (FX2N 128MR) and Raspberry embedded computer to design a tomato grading system. Besides, the author has also successfully design a monitoring, control and data collection system for an automatic tomato classification system. The experimental results show that the system had high stability and fast sorting speed (1.2 seconds for 1 tomato product). Experiment with 300 samples gave accurate results of 95.87% in terms of shape and size standards and 99% in terms of maturity standards. This system can be applied in practice.

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