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PIYANUN RUANGURAI[1]
NATTABUT TANASANSURAPONG[1]
SIRAKUPT PRASITSANHA[1]
REWAT BUNCHAN[1]
WIPUT TUVAYANOND[3]
THANA CHOTCHUANGCHUTCHAVAL[1,2]
CHAIYAPORN SILAWATCHANANAI[4]

[1]College of Industrial Technology, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

[2]Center of Sustainable Energy and Engineering Materials (SEEM), King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

[3]Industry Agricultural Engineering, Rajamangala University of Technology Thanyaburi, Pathum Thani, Thailand

[4]Department of Teacher Training in Mechanical Engineering, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

SCIENTIFIC PAPER

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UTILIZING MACHINE VISION AND ARTIFICIAL NEURAL NETWORKS FOR DRIED GRAPE SORTING DURING PRODUCTION

Article Highlights

- The five significant characteristics of grapes observed by image processing during the drying process
- An ANN approach is developed to classify completely dried grapes and partially dried grapes
- The ANN model achieved a level of accuracy performance of 78%
- The entirety of the grapes trends into raisins; the dehydration machine will cease operation

Abstract

This study introduces a machine vision technique that utilizes an artificial neural network (ANN) to develop a predictive model for classifying dried grapes during the drying process. The primary objective of this model is to mitigate the burden placed on the operator and minimize the occurrence of over-dried items. The present study involves the development of a model that is constructed using the characteristics of grape color and shape. There exist two distinct categories of labels for grapes: fully desiccated grapes, commonly referred to as raisins, and grapes that have undergone partial drying. Image processing is utilized to collect and observe five significant characteristics of grapes during the drying process. The findings indicate a significant decrease in the levels of red, green, and blue colors (RGB) during the initial 15-hour drying period. The predictive model extracts properties such as RGB color, roundness, and shrinkage from the image while it undergoes the drying process. The artificial neural network (ANN) model achieved a level of accuracy performance of 78%. In this work, the dehydration apparatus will cease operation in an automated manner whenever the entirety of the grapes situated on the tray has been projected to transform raisins.

Keywords: machine vision; grape drying process; artificial neural network; embedded systems.

The contemporary lifestyle of individuals in the present period acknowledges the significant influence of food consumption on human well-being. Fiber-rich foods are particularly recommended, especially for the senior population, as outlined in the dietary guidelines represented by the food pyramid [1]. Fruits and vegetables are rich sources of dietary fiber, essential vitamins, and minerals. Nevertheless, the availability of fruits is restricted to their respective natural seasons for harvesting. The utilization of preservation techniques aids in prolonging the durability of fruit-based products. Dehydration is a fundamental method employed in fruit preservation to decrease the moisture content of fruits.

Correspondence: C. Silawatchananai, Department of Teacher Training in Mechanical Engineering, King Mongkut's University of Technology North Bangkok, Bangkok, 10800, Thailand.
E-mail: chaiyaporn.s@fte.kmutnb.ac.th
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The primary advantage of dehydration is the extension of a product's shelf life. An additional aspect to consider is the convenience of portability and transportation. The dehydration technique is well recognized and utilized in both industrial and home environments. In recent years, there have been notable advancements in dehydration technology, resulting in enhancements in the quality, color, texture, and nutritional composition of dehydrated products. Hence, the utilization of dehydrated food effectively meets the requirements of consumers. Dehydrated items are commonly observed in several food categories such as breakfast cereals, bakeries, snacks, desserts, and convenience meals [2].

Enhancing the quality of dehydrated fruit has become a critical area of investigation. A multitude of scholarly investigations have been conducted to examine the control algorithms employed in dehydrator machines. To regulate the temperature within the chamber, the researchers employed a proportional-integral-derivative (PID) controller that was calibrated using fictitious reference iterative tuning (FRIT) based on Particle Swarm Optimization (PSO) [3]. Another investigation was conducted to regulate the ultimate moisture content (MC) level of the grain. The application of the genetically optimized fuzzy immune proportional integral derivative controller (GOFIP) was utilized to manage grain dryer machines [4].

Numerous research investigations have commenced by investigating the morphological changes that occur in fruit during the drying process under various environmental conditions. For example, in a study conducted by Karaaslan *et al.* (2017), microwave oven drying was employed to examine the impact of moisture ratio on grape drying by utilizing various power levels [5]. Carter *et al.* (2005) conducted a study to investigate the correlation between the moisture content (MC) of grapes and the power level of microwave hoover technology [6]. The research examples aimed to gain comprehension of the impact of power levels and moisture content of grapes, followed by the implementation of mathematical models. In their study, Ojediran *et al.* (2020) presented a novel approach utilizing an Artificial Neural Network (ANN) that incorporates the Takagi-Sugeno fuzzy inference system. This approach, known as the Adaptive Neuro-Fuzzy Inference System, was employed to accurately forecast the residual moisture content of yam slices under convective conditions. The input parameters comprised time, temperature, air velocity, and thickness [7].

Numerous researchers have endeavored to enhance the quality of dehydrated items by the integration of machine vision technology inside their systems. Machine vision is a commonly employed technique for the surveillance and analysis of objects' chromatic properties, geometric characteristics, and surface qualities. One instance was the utilization of machine vision in a far-infrared drying system to monitor many attributes of ginger, including its properties, moisture ratio, drying rate, browning index, and color difference. The three-stage fuzzy logic control system received two parameters, specifically the browning index and the color difference, as its inputs. The required temperature of the chamber is indicated by the output [8]. Furthermore, the color difference, browning index, perimeter, area, intensity, and diameter of banana slices were observed and recorded throughout the hot air-drying procedure [9].

Over the past decade, ANN has been prominent in the field of dehydration systems. The researchers developed several models for determining the moisture content of grapes by employing ANN and machine vision techniques [10]. Furthermore, ANN was employed to forecast the drying kinetics of paddy, encompassing the moisture ratio and drying rate [11]. Another use of machine learning involves the utilization of categorization models for predictive purposes. The classification of freeze-dried apples with red flesh, such as 'Lex Red', 'Trinity', '314', and '602 Red', was conducted by analyzing image textures and color [12]. For example, the classification of two sultana genotypes, Kecimen and Bensni, was conducted using various textural parameters including area, perimeter, main axis length, minor axis length, eccentricity, convex area, and extent [13]. In their study, Krzysztof *et al.* (2020) employed acoustic signals, comprising frequency and sound level, in conjunction with the ANN Multi-Layer Perceptron, to effectively categorize the dried strawberry as either ripe or overripe [14]. In their study, Masumeh *et al.* (2021) utilized ANN to forecast the moisture content of banana slices and microwave power density throughout the microwave drying procedure [15].

The enhancement of the quality of dehydration products is of considerable importance to researchers, as indicated by much-existing literature. Consequently, numerous promising strategies have emerged in this field. Nevertheless, there are still some areas that require further enhancement, one of which includes the development of cost-effective automatic control systems. During small-scale production, grape dryness is typically assessed by specialists by the observation of color, shrinkage, and texture alterations. In contrast, in industrial settings, the drying process typically terminates once the moisture level of the grapes reaches 13% [16]. This study proposes the implementation of machine vision technology for monitoring the dryness of grapes, providing an alternative to conventional approaches that rely on expert evaluation or measuring moisture content. Thus, the primary focus of this study is to develop an ANN model to classify fully dried grapes (commonly known as raisins) and grapes that have undergone partial dehydration. This classification task is achieved through the utilization of machine vision data. The proposed approach involves employing machine vision techniques to monitor and gather data on the visual characteristics of the material, including color and form. These data serve as input parameters for predicting the classification of grapes during the drying process. Additionally, the embedded code operates on a Raspberry Pi, a cost-efficient device that utilizes cost-effective technologies.

MATERIAL AND METHODS

Materials

Throughout, a domestic food dehydrator machine was modified to be used as a drying system. The Raspberry Pi connected to the Raspberry Pi Camera module was attached to the top of the chamber to capture images, as shown in Figure 1. The Open-source computer vision library (OpenCV) was integrated with Python to determine grapes' characteristics and classify grapes' labels.

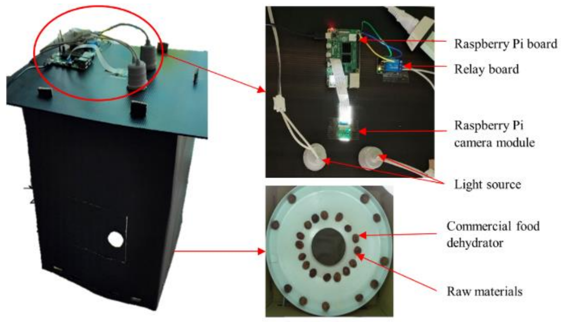

Figure 1. Drying chamber.

The utilization of a domestic food dehydrator machine was adapted to serve as a drying system. The Raspberry Pi, which was connected to the Raspberry Pi Camera module, was affixed to the upper portion of the chamber to take photographs, as depicted in Figure 1. The integration of the Open-source computer vision library (OpenCV) with Python was utilized to determine the features of grapes and classify the labels associated with them.

Preparation of grape samples

Before the drying process, it was necessary to prepare fresh grapes (Ralli Red Seedless) by cleaning and extracting grape seeds. Initially, grapes samples were sensed and cleansed with fresh water. Subsequently, immerse the samples in hot water for 30 seconds. Subsequently, proceed to rinse the washed grapes under a steady stream of cool water without delay. Subsequently, proceed to perforate minuscule apertures in the grapes and desiccate the unprocessed constituents by positioning them above a sanitary surface for approximately 10 minutes.

Drying protocol

Once the preparation of the raw materials was completed, proceed to position them onto a tray situated within the chamber. It was imperative to exercise control over the drying conditions in the experiment. It was crucial to position the grapes distinct from one another to extract the individual characteristics of each grape. The second need entails establishing the temperature at 56 °C. During the drying phase, several photos were recorded and transmitted to the Raspberry Pi controller. Moreover, an image-processing approach was utilized to analyze the characteristics of each grape, including color, roundness, and shrinkage. The ANN technique was employed to classify the properties of both fully dried grapes (raisins) and partially dried grapes drying at regular intervals of twenty minutes. The input in the ANN procedure consisted of the features of the grapes. Upon the completion of the drying process, Raspberry Pi issued a command to activate a relay mechanism, so terminating the power supply to the drying apparatus. Additionally, the system implemented a graphical user interface (GUI) on top of the MQTT protocol in a real-time system.

The drying system's procedure commences with the preparation of images. During this procedure, a grayscale image of the region of interest (ROI) was acquired without any distortion. In the second stage of the image processing procedure, the attributes of grapes, including color, shrinkage, and roundness, were extracted after the preprocessing of the image. The third procedure involved the ANN technique. At this Juncture, the system categorized the grape data into two distinct labels: fully-dried grapes and partially-dried grapes. The dataset was divided into three distinct subsets, namely training, validation, and testing. During the training phase, the model for dried grapes was trained by establishing a mapping relationship between the model parameter and the desired output. Once the construction of the model was completed, the trained model was subsequently sent to the Raspberry Pi controller to conduct an analysis and classification of many attributes of dried grapes. In this instance, the image obtained from the camera within the chamber was categorized into two distinct labels. If the model's prediction indicates complete dehydration of all grapes, the relay circuit was responsible for deactivating the heat source of the dehydrator machine. The comprehensive understanding of each component of the process was listed as follows.

Process1: Image preprocessing

The first protocol to categorize the quality of the dried grapes was performed via the image preprocessing method. The process commenced with the acquisition of RGB images. Subsequently, the undistort function, implemented by OpenCV, was employed to mitigate the distortion present in the image. To track any possible change during the drying process at a fast pace, the dimensions of the unaltered image were decreased from 1280 x 1024 pixels to 640 × 512 pixels. Subsequently, the RGB color image was inputted into a grayscale transformation. The binary mask was utilized to apply the ROI and selectively choose the pixels of interest while excluding undesired pixels. During this particular stage, the undesired pixels were substituted with an intensity value of 127. The sample outcome is depicted in Figure 2.

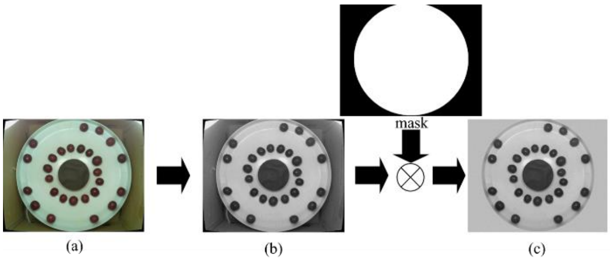

Figure 2. Sample result of preprocessing: (a) Result of undistorting and downscaling; (b) Result of converting RGB to grayscale; (c) Result of selecting ROI and changing intensity of background.

Process2: Image feature extraction

During this phase, the essential discernible characteristics of each grape, including RGB color, roundness, and shrinkage, were retrieved. The aforementioned attributes were utilized as input for training and making predictions. At this stage, the input consisted of the preprocessed image." Subsequently, median filters were implemented to diminish the presence of noise in the image. Afterward, adaptive thresholding was employed to distinguish foreground areas from the background, improving segmentation and significantly reducing glare effects compared to traditional thresholding techniques. In addition, a closing operator was utilized to examine each image for its geometric characteristics, specifically its shape, to enhance image segmentation. Consequently, the revised picture was applied to occupy any empty spaces. The morphological technique was successful in rectifying segmentation mistakes resulting from glare or shade. Additionally, the grapes were subjected to filtration based on their constituent components, followed by the delineation of the contour of interest. Ultimately, the essential characteristics of each grape were thoroughly isolated. The general procedure is depicted in Figure 3. Furthermore, it was necessary to monitor the location of each grape during the various stages of processing, as the drying process introduced a degree of uncertainty regarding the position of each grape. The Euclidean distance formula was used to compute the displacement between the previous and present positions of each grape. If the calculated distance is minimal, it is assumed that the location remains unchanged for the same grape.

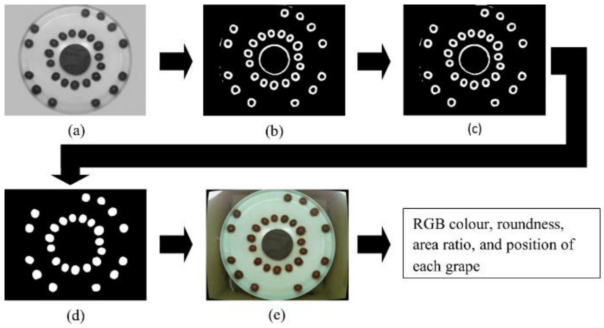

Figure 3. Sample result of feature extraction in the initial image from Figure 2c: (a) Result of filtering; (b) Result of applying adaptive thresholding; (c) Result of performing morphological process; (d) Result of filling holes; (f) Result of drawing grapes' contour.

The measurement of grape shrinkage during the drying process is based on the two-dimensional area ratio. This method is simpler and more practical than direct volume measurement, as outlined in Eq. (1) [10].

$$S(t) = \frac{A(t)}{A(0)} \tag{1}$$

where *S(t)* is the shrinkage at instantaneous time *t*. *A(t)* stands for the sample's surface area in pixels at a time *t*. *A(0)* is the sample's surface area in pixels at the initial time.

In similia fashion, roundness was equated via Eq. (2):

$$R(t) = \frac{A(t)}{\pi (r(t))^2} \tag{2}$$

where *R(t)* is the roundness and the instantaneous radius of the grape *r(t)*, measured in pixels, is defined as the radius of the smallest circle that completely encloses the grape.

Process3: ANN classification

The objective of the artificial neural network (ANN) was to distinguish between two classifications: slightly desiccated grapes and fully desiccated grapes. The experiment observed alterations in the hue, circularity, and shrinkage of each grape as they underwent the process of dehydration at a temperature of 56 °C. The model was fed with inputs that encompassed the following characteristics: RGB color, roundness, and shrinkage, which were monitored during the drying process, as depicted in Figure 4.

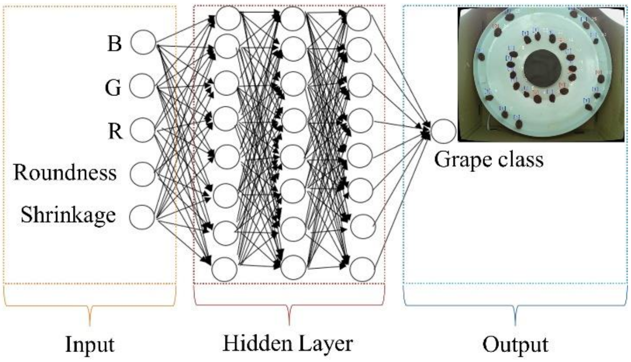

Figure 4. Architecture of the ANN.

The data was partitioned into three sets using a random allocation method. Specifically, 64% of the data was assigned for training purposes, while 18% was allocated for validation and another 18% for testing. During the training data phase, the model's predictions were based solely on the training and validation data. Additionally, early stopping was employed to mitigate the issue of overfitting. The ANN performs intricate computations to analyze intricate patterns, such as the correlation between the characteristics of grapes and the corresponding output label, to classify raisins. The Multi-Layer Perceptron, a feedforward neural network, is utilized in this study, consisting of three hidden layers. Each hidden layer was comprised of eight nodes. Here, the rectified linear unit (ReLU) function was utilized in the hidden layers to perform the transfer of the weighted sum between layers. Additionally, the Rectified Linear Unit (ReLu) activation function was employed as a means of mitigating the issue of vanishing gradients [8]. It was noted that the Rectified Linear Unit (ReLU) originated from a mathematical function that was commonly used in artificial neural networks as shown in Eq. (3):

$$f(z) = max(0, z) = \begin{cases} 0\, for\, z \leq 0 \\ z\, for\, z > 0 \end{cases} \tag{3}$$

where f is the function of ReLu and z is the weighted sum of a neuron.

The sigmoid function was commonly used as an activation function in two-class classification tasks. It was applied to the weighted sum of inputs to turn it into a probability score. The output of the sigmoid function was binary, with values of either 0 or 1. In this experiment, 0 and 1 stand for partially dried and fully dried grapes respectively. Mathematically, the sigmoid function was formally defined via Eq. (4):

$$\sigma(z) = \frac{1}{\left(1 + e^{-z}\right)} \tag{4}$$

where σ is the function of sigmoid and z is the weighted sum of a neuron.

Process4: AC source controlling

The final step involved regulating the AC power supply of the dehydration machine by the act of activating or deactivating it. The Raspberry Pi transmitted a command to a magnetic relay to regulate the power supply inside this system. The alternating current (AC) supply would be deactivated by the relay once the ANN model ascertained that all grapes had reached the desired level of dryness.

RESULTS AND DISCUSSION

To commence the experiment, an examination was conducted to study the drying characteristics of grapes at a temperature of 56 °C. The ANN model for classifying grapes into two distinct labels: partially dried grapes, and fully dried grapes utilizes five significant feature parameters: RGB color, roundness, and shrinkage. These parameters were employed as input during the training process of the model. The dataset was partitioned into three distinct sections. The training dataset consisted of 1,347 samples, which were utilized for training the model. Subsequently, a validation dataset including 380 samples was employed to assess the model's performance during the training process. The final set employed for testing purposes consisted of 370 instances, which were utilized to assess the performance of the model.

Drying protocol

The study focused on examining the physical phenomena of color and shape to evaluate the traits and properties of grapes during the drying process at a temperature of 56 °C.

Initially, an examination was conducted on 27 grapes to ascertain the average intensity change within each RGB color channel. The photographs were captured at intervals of 20 minutes. The average color characteristic is shown as follows Figure 5a. In accordance with the given prompt, the following response will address the academic nature of the user's text without adding any additional information: At the onset of the experiment, it was observed that the red color exhibited the highest intensity, followed by green and blue, respectively. Throughout the process of drying, it was evident that the red color exhibited the greatest degree of variation, indicating a high level of sensitivity. Notably, there was a significant decline in the red color intensity for 15 hours, after which it reached a state of stability. The patterns for the intensity of green and blue colors were comparable. Initially, there was a minuscule increase. Subsequently, the intensity values underwent a rapid decrease and subsequently stabilized after 15 hours. In comparison to green and blue, it was worth noting that red exhibits the highest level of sensitivity.

The shape of the grapes, taking into account factors such as roundness and shrinkage, represented the second attribute that could be observed. The roundness and shrinkage behavior of grapes exhibited similar patterns, as depicted in Figure 5b and Figure 5c, respectively. The form had a rapid decline for approximately 12 hours and afterward reached a state of stability, remaining unaltered. The sample grapes undergoing dehydration at a temperature of 56 °C are shown in Figure 6.

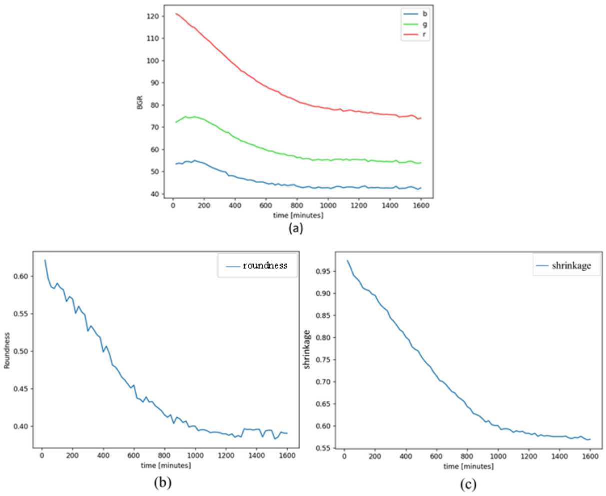

Figure 5. Grape characteristics during the drying process at 56 °C: (a) Result of RGB color; (b) Result of roundness; (c) Result of shrinkage.

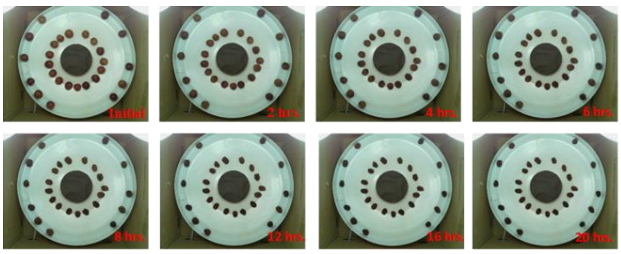

Figure 6. The grapes undergo dehydration at a temperature of 56 °C.

This experiment utilized a small sample size to demonstrate the effects of dehydration on grapes. The color and shape changes seen during the dehydration process remained similar across the entire bin. The grapes underwent dehydration, resulting in browning and shrinkage. The only significant differences seen were in their initial color and form. This indicates that the data is sufficient to accurately depict the characteristics of grape dryness throughout the dehydration process.

Classification

The classification label was divided into two distinct categories: fully dried grapes and partially dried. The ANN algorithm was applied across five batches of experiments, involving a total of 135 grapes. As a result, the dataset encompassed a total of 2,097 cases. The loss and accuracy curves of the training and validation were determined by the size of the training data set. Figure 7 displays the graphical representation of the performance of the model in terms of loss and accuracy. The utilization of the early stopping function resulted in training and validation accuracies of 0.78 and 0.85, respectively. The performance of the training and validation loss functions was satisfactory, as indicated by the respective losses of 0.50 and 0.42.

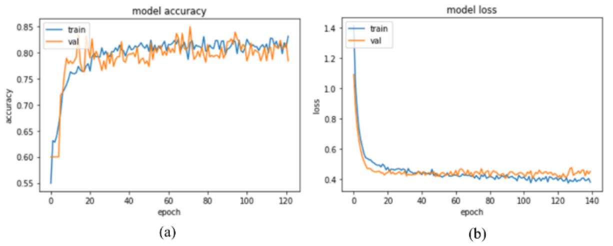

Figure 7. Train and validate learning curves of the ANN model: (a)Model loss; (b) Model accuracy.

Following the prediction of the ANN model, a total of 370 instances were utilized to test the proposed model. The classification outcome is presented in Table 1, wherein two distinct classes are identified: class 1 represents fully dried grapes, while class 0 represents partially dried grapes.

Table 1. Confusion matrix for raisin classification in ANN model.

		Actual	
		Class 1	Class 0
Predicted	Class 1 (fully dried)	95	63
	Class 0 (partially dried)	18	194

The section discussed the categorization of performance. Performance could be defined as the execution or accomplishment of a task, activity, or function, typically measured against predetermined criteria or standards. The precision of each class was quantified based on Eq. (5).

$$P_j = \frac{TP_j}{\left(TP_j + FP_j\right)} \quad (5)$$

where P is the precision for class j. TP stands for true-positive and FP stands for false-positive for class j.

Furthermore, the recall in each class (Rj) was defined as,

$$R_j = \frac{TP_j}{\left(TP_j + FN_j\right)} \tag{6}$$

where FN stands for false-negative for class j.

In addition, F1-score in each class (Fj) was defined as,

$$F_j = \frac{2 \times P_j \times R_j}{\left(P_j + R_j\right)} \tag{7}$$

The accuracy parameter A was defined as follows:

$$A = \frac{TP + TN}{\left(TP + TN + FP + FN\right)} \tag{8}$$

where FP stands for false-positive.

The findings indicate that the classification model achieved an accuracy of 78%, with a f1-score of 70%, and 83% for class 1 and class 0, respectively. Furthermore, the performance for class 1 and class 0 was determined to be Table 2.

Table 2. Overall classification performance measurement results.

Class	Precision	Recall	f1-score	Accuracy
Class 1 (fully dried)	60%	84%	70%	78%
Class 0 (partially dried)	92%	75%	83%	78%

The occurrence of inaccurate categorizations in grape drying processes predominantly arises when grapes were only partially dried, yet erroneously identified as fully dried grapes. The scenario of the minority instance arises when the grapes underwent complete dehydration, yet were erroneously classified as partially dried grapes.

Historically, the categorization of dehydrated grape grades has been conducted by specialists. This study presents an alternative approach that utilizes a machine vision-based Artificial Neural Network (ANN) algorithm. The primary advantage of an artificial neural network (ANN) based system is a significant reduction in the burden of specialists. Nevertheless, there is a limitation in evaluating the quality of raisins due to the absence of grape moisture content analysis in the current model, which is an essential aspect in determining raisin quality. Subsequent improvements to the model will strive to address this constraint.

The process is completed by the machine automatically turning off when the system recognizes that all grapes have completely dried out and become raisins (100% dry). Nevertheless, this setpoint has a disadvantage: it has the potential to cause certain samples to become excessively dry. To alleviate this issue, the setpoint should be established by considering the grapes that have fully dried out in the majority. Therefore, additional tests are required to observe and determine the most favorable value for the ultimate dehydration time under real-life circumstances.

In addition, the primary objective of this experiment was to investigate the feasibility of employing a Raspberry Pi, a cost-effective microcontroller, for classification purposes, as opposed to the conventional utilization of personal computers (PCs) or laptops, which was prevalent in most research endeavors. The cost of a Raspberry Pi, when purchased with a camera module, was approximately $100. Therefore, it was highly affordable to many small-scale manufacturing businesses. To compromise, the average accuracy of the model was 78%. At this juncture, the acceptability of the situation could be acknowledged; yet, when examining the precision of class 1, it is observed to be merely 60%. Therefore, it is imperative to enhance the accuracy by using more grape attributes, such as the L*a*b* color model. In addition, the inclusion of additional data significantly contributes to the model's ability to attain favorable outcomes. Another aspect to consider is the potential for enhancing accuracy through the utilization of more sophisticated artificial neural network (ANN) methods, such as the deep neural network (DNN) algorithm. Moreover, deep neural networks (DNNs) can yield more accurate outcomes; nonetheless, they still encounter a challenge while processing large volumes of data. In subsequent research endeavors, the proposed model will evaluate the algorithm's performance in real-world scenarios, specifically involving the placement of intact grapes within the tray. The ultimate objective of the future work is to achieve a fully automated system.

CONCLUSION

In this research, a machine vision system was employed to monitor dried grapes during the drying process. The ANN algorithm is applied to create the model for classifying grapes' class labels as completely dried and partially dried grapes. The model's input parameters include color (RGB color) and shape (roundness and shrinkage). The model's performance in classification shows a satisfactory result with an accuracy of 78%. When the system determines that all grapes are raisins, the AC power of the dehydration machine will automatically turn off. Then, the proposed system is aimed at reducing over-dried products and the workload of the operator.

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PIYANUN RUANGURAI[1]
NATTABUT TANASANSURAPONG[1]
SIRAKUPT PRASITSANHA[1]
REWAT BUNCHAN[1]
WIPUT TUVAYANOND[3]
THANA CHOTCHUANGCHUTCHAVAL[1,2]
CHAIYAPORN SILAWATCHANANAI[4]

[1]College of Industrial Technology, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

[2]Center of Sustainable Energy and Engineering Materials (SEEM), King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

[3]Industry Agricultural Engineering, Rajamangala University of Technology Thanyaburi, Pathum Thani, Thailand

[4]Department of Teacher Training in Mechanical Engineering, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

NAUČNI RAD

KORIŠĆENJE OBRADE SLIKE I VEŠTAČKIH NEURALNIH MREŽA ZA SORTIRANJE SUŠENOG GROŽĐA TOKOM PROIZVODNJE

Ovaj rad uvodi tehniku obrade slike koja koristi veštačku neuronsku mrežu (ANN) za razvoj prediktivnog modela za klasifikaciju suvog grožđa tokom procesa sušenja. Primarni cilj ovog modela je da se ublaži teret koji se stavlja na operatera i minimizira pojavu previše osušenih grozdova. Ova studija podrazumeva razvoj modela koji se konstruiše korišćenjem karakteristika boje i oblika grožđa. Postoje dve različite kategorije za grožđe: potpuno isušeno grožđe, koje se obično naziva suvo grožđe, i grožđe koje je podvrgnuto delimičnom sušenju. Obrada slike se koristi za prikupljanje i posmatranje pet značajnih karakteristika grožđa tokom procesa sušenja. Nalazi ukazuju na značajno smanjenje nivoa crvene, zelene i plave boje (RGB) tokom početnog perioda sušenja od 15 sati. Prediktivni model izdvaja svojstva, kao što su RGB boja, zaobljenost i skupljanje iz slike, dok se grožđe podvrgava procesu sušenja. Model veštačke neuronske mreže (ANN) postigao je nivo tačnosti od 78%. U ovom radu, aparat za dehidraciju će automatski prestati sa radom kad god se planira da celokupno grožđe na tacni preobrazi u suvo grožđe.

Ključne reči: obrada slike; proces sušenja grožđa; veštačka neuronska mreža; ugrađeni sistemi.