



## DETECTING ARTIFICIAL AND NATURAL MANGO RIPENING USING COLOUR IMAGE PROCESSING

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### Abstract

This work proposes a novel image based method to determine the artificial and natural ripening methods used to ripen the mangoes. Monitoring the quality of ripening is a herculean task because the variation cannot be easily identified by manual vision judgement. Hence an automated method using image processing and Artificial Neural Networks (ANN) is proposed here. Features are extracted from the images of the mangoes after pre-processing is done. This feature set is used to train the Multi-Layered Perceptron (MLP) model. Initially, the conventional rule called the Gradient steepest Descent Rule (GDR) is used for training the MLP. Since, satisfactory performance is not achieved; a hybrid model of the MLP with Black Widow Optimization (BWO) is used to identify the naturally and artificially ripened mangoes effectively.

**Keywords:** Artificial ripening, Natural ripening, Multi-Layered Perceptron, feature extraction and Black Widow Optimization.

### 1. Introduction

It is important to promote health and fitness in humans during consumption of fruits and vegetables that provide a variety of key nutrients for the body. Fruits go through a process known as ripening during which they experience a more substantial phase that makes them more edible, sweeter, softer, biologically, and commercially. The fruits do, however, establish a suitable phase, weight, texture, color, perfume, and flavor during the developmental stage. Numerous metabolic processes are accelerated during the ripening process, which ultimately produces enzymatically controlled and catalyzing mechanisms. According to reports, the yearly global production of fruits is estimated to be in the neighborhood of 370 million metric tons, or 8% of the world's total fruit production. When compared to other fruits, India produces the most bananas and mangoes in the world, ranking second overall. Singh, J.M., and Dhawan (2015)

Ethylene (C<sub>2</sub>H<sub>4</sub>), a gaseous plant hormone, plays a major role in controlling the ripening process. The phyto-hormone ethylene has been shown to control the expression of genes involved in fruit ripening. Therefore, controlling the activity of several enzymes involved in the ripening process (see figure 1.1). The enzymes soften the fruit's peel as they work to break down complex polysaccharides into simple sugars. The growing points of roots, flowers,

injured tissue, and ripening fruit are typically where ethylene is emitted. Fruits are divided into climacteric and non-climacteric categories according on how they ripen.

## **2. Review and Literature Survey**

In this study, our main goal has been to identify ripe fruit using image processing and then evaluate with artificial intelligence. This planned developments in prior for diagnosing the quality for ripening of fruits, followed by a variety of techniques employed during their quality assessment.

### **2.1 Quality Assessment for fruit**

Fruit commercialisation and grade categorization depend heavily on automatic fruit quality detection. The employment of effective tools to evaluate fruit quality is currently being emphasized by the food industry. As a result, prospective research has been carried out to create a fully and partially automated technique to guarantee the safety and quality of fruits ingested by the general public (Weyrich et al., 2012; Rahman et al., 2014). Due to a number of factors, such as the ones listed below, automation is widely favoured in the food and agricultural industries.

- (i) By a rise in the demand from consumers for high-quality produce (Aleixos et al., 2002)
- (ii) According to Deck et al. (1995) and Njoroge et al. (2002), machines are used more frequently than people
- (iii) Lack of labor in industrialized nations (Walsh, 2005)
- (iv) To lower labor expenses (Bato et al., 2000)

It is anticipated that multiple authors will highlight the key advancements in this sector during the past few years. According to Butz et al. (2005) and Nicolai et al. (2006), many technologies have been compared to describe the interior quality of fruits and vegetables. As a result, there are numerous techniques for classifying fruits in order to assess the quality (Swarnalakshmi and Kanchanadevi 2014). Fruit quality sensors that are non-destructive have been discussed in another peer reviewed article (Ramos et al. 2005). The Color Co-occurrence Technique (CCT) and statistical classification algorithms were used to identify the immature fruits (Pydipati et al. 2005). The creation of a mechanism to determine the maturity of oranges based on color grading is another option in image processing that has been suggested. The CCD camera in this system is used to take the images, and the classifier produces the output (Sirisathikul et al. 2006). Using image processing and artificial neural network, a multilayer network has been utilized to assess the color changes, solid gain, and water loss from the kiwi fruits (Fathi et al. 2011).

The color hues that were taken from the photos were used for stimulation in fruit flaws which could be detected. This has been done by segmenting the regions using unsupervised clustering methods (Indira Gandhi et al. 2015). Any fruit's quality is evaluated by looking at its outward appearance, which includes its color, shape, size, and surface conditions. When assessing the production of fruit, the analysis of color is especially important. The study combined image processing with Artificial Neural Network (ANN) technology in such a way that it would be a cost-effective way to forecast cherry and strawberry color parameters (Kranti Raut and Vibha Bora 2016).

### **2.2 Electronic Strategies used for assessing fruit quality**

Electronic devices have been created for a long time in an effort to mimic human sensory characteristics, and they are successfully employed in fruit quality assessment. Electronic

instruments have been employed in the grading of fruits since the 1980s. The development of the color sorting system application was made possible in the early stages of detection by the employment of photocells and microprocessors. One of the most crucial characteristics that can help us identify ripening fruit is color. In order to sort produce according to shape and color, machine vision-based systems that utilise charge coupled device (CCD) cameras and PC frame grabbers are used. To detect the ripening fruit linked to increasingly complex algorithms (neural networks, fuzzy logics, etc.), machines based on image processing were introduced to the market in the middle of the 1990s. The agri-food industry uses non-invasive image technology in addition to medical applications (Süsstrunk and Fredembach, 2010). As a result, additional methods emerged, including electrical impedance, gas sensors, and biosensors. These advancements have led to a more thorough and precise rating of fruit quality.

For the purpose of removing noise from corrupted digital photos, a different approach known as a partition-based fuzzy median filter has been put forth (Lin et al. 2014). The proposed filter was created, the current pixel value was weighted, and the median filter's output was used. Fuzzy logic is deployed to determine the quantity of noise in the pixel so as to set the weight values. To divide the observation vector, a neural network model with a new weight function was built. Each observation vector was transferred to one of the 'M' blocks that make up the observation vector space in this framework. To determine the ideal weight for each block, the Least Mean Square (LMS) technique was used.

Currently, a fuzzy inference method is applied in the traditional switching median filter to create fuzzy switching median filters. When compared to other studies, the outcomes were better (Pradeep Kumar et al. 2015).

### **3. Research gap in fruit ripening process**

There are advantages and disadvantages to the current climacteric fruit ripening techniques. However, there are now a lot of methods available for more precise ripening. However, various fruits need varied amounts of time to ripen and become edible. Therefore, a reliable approach is required to distinguish ripe fruit from unripe or decaying fruit. During the ripening process, each fruit changes in color and texture.

They include

- When a mango is allowed to ripen inside a rice container with airtight lid. Despite not being relevant on a wide scale, this is a natural process of ripening.
- The use of machine learning algorithms to improve fruit classification accuracy while reducing training and testing times.
- There are numerous classifiers available to examine the ripening process, one of which was utilized to support the ripening.
- One other important aspect of online ripening quality monitoring is the estimation of ethylene  $C_2H_4$  and  $CO_2$  gas using intelligent image processing technique, which results in an instantaneous dynamic adjustment of  $C_2H_4$  flow rate to ensure an active ripening process.

Acetylene gas is released when calcium carbide, a highly reactive substance, comes into contact with water. For artificially ripening fruits like mangoes, calcium carbide has gained popularity recently.

In fields like mining and metal working, calcium carbide is a chemical substance that is frequently employed for welding and cutting processes. Acetylene gas is released when calcium carbide combines with water.

Recently, calcium carbide has gained popularity for artificially ripening fruits like mangoes. The substance, which is applied to the fruit during transportation, is intended to fasten the ripening process by releasing acetylene gas. However, using calcium carbide to ripen mangoes is extremely risky and may have detrimental effects on one's health.

Additionally, the FSSAI has issued a warning that using calcium carbide to ripen mangoes may result in the creation of harmful compounds including arsenic and phosphorus. These compounds have the potential to build up in the body and result in long-term health issues.

There are a number of secure and efficient alternatives to calcium carbide for ripening mangoes. One such technique is the use of ethylene gas, a naturally occurring plant hormone produced by ripening fruits. Mangoes can be hastened to ripen by being exposed to ethylene gas without endangering human health.

Ripening chambers are a different option; they are specially created spaces that mimic the way fruit naturally ripens. Without the use of dangerous chemicals, the fruit ripens naturally in these chambers using a combination of temperature, humidity, and ethylene gas. A safe ripening agent at concentrations upto 100 ppm from sources like ethephon, ethephal, etc., depending on the crop, type, and maturity, according to FSSAI produces quality ripening.

By using these alternatives, the organic ripening of mangoes can be facilitated preserving the fruit's quality and flavor. This is crucial because it guarantees that mangoes continue to be a high-quality and healthful fruit for customers while also generating income for growers.

When a mango is chemically ripe, it has green spots on it and is easy for identification. The shape of the mangoes will reveal whether it has been chemically ripened. Mangoes that have been artificially ripened are often tiny and are juicy. Apart from that, the mangoes have a white or blue mark that should never be purchased. This will enable the recognition of mangoes that have been artificially ripened. Mangoes that are ripened naturally have brown spots, whilst those that have been chemically ripened will have pale or white spots.

#### **4. Materials and Methods**

##### ***4.1. Black Widow Optimization***

BWO (Black widow optimization) was developed using the theory of the black widow spider. The black widow spider is primarily nocturnal; during the day, the female is blind, but at night, she constructs her web. Additionally, the female one lives the majority of her life within the same web as the male one. Typically, the female spider initiates mating. Through a constant process of doing this, the female sprays specific locations in the net with a liquid called a pheromone to attract the male spiders. The strange thing about this situation is that after mating, the female spider consumes the male spider and saves the egg for the egg sack. In addition, there is a possibility of child cannibalism, in which the child consumes its mother if it is not physically fit, after the egg hatches and the young ones have been created and are suitable for sibling cannibalism.

The first is sexual cannibalism, in which a woman consumes her husband after mating in consideration of the fitness value. The second type of cannibalism involves stronger siblings being eaten by the stronger spider. The idea is applied in accordance with the rate of cannibalism. The population only retains the most physically fit young people, discarding others. Sibling cannibalism is the term for this. The third is child cannibalism, in which the child eats its mother when the values are weaker.

After eleven days of gestation, the female spider lays her eggs in socks, and by the time her young are ready for sibling cannibalism, they have developed and are ready for development. This involves the young, strong spider eating the younger, weaker spider. Sibling cannibalism has been frequent this time around as the Black widow spiders cohabit for seven days for the mother web. The size of the population is determined by density-dependent cannibalism; this is particularly important in colonies of black widow spiders, as the mother even quickly consumes the baby spiders. The baby spiders that are still alive are regarded as the healthiest. Thus, the Black Widow Optimization (BWO) is achieved based on the black spider notion.

#### 4.2. Mathematical evaluation

The black widow optimization process has begun using the random initial population of black widows. For the purpose of creating offspring, this kind of randomly generated population includes both male and female black widows. The black widow's initial population is defined as in Equation 1.

$$X_{N,d} = [x_{1,1}x_{1,2}x_{1,3} \dots \dots x_{1,d}] \quad (1)$$

Where the number of the decision variable is  $d$ , the population of the black widow is  $X_{N,d}$ , then the upper bound population is 'ub' and the population number is 'N'.

The ( $X_{N,d}$ ) is useful in minimizing or maximizing the core function and is denoted by effective solution population as follows,

$$\text{Objective Function} = f(X_{N,d}) \quad (2)$$

In the proposed BWO model, various predefined parameters are specified such as  $Q_{pt}$ ,  $Q_e$ ,  $R_p$ ,  $R_E$ ,  $\Omega_{ts}$ ,  $\Omega_{es}$ ,  $\Omega_{er}$ ,  $\Omega_{sr}$  which are defined in the previous sections. These parameters are used to indicate the upper and lower bounds of  $P_e$  and  $P_s$ .

Upper bound of  $P_e$  is  $P_{e \max}$ , lower bound of  $P_e$  is  $\frac{Q_E - P_{pt}\Omega_{ts}}{\Omega_{es}}$ , upper bound of  $P_s$  is  $\frac{Q_P - P_{e.\max}\Omega_{er}}{\Omega_{es}}$ , upper bound of  $P_s$  is  $\frac{Q_P - (Q_E - P_{pt}\Omega_{ts})\Omega_{er}/\Omega_{es}}{\Omega_{sr}}$  and the lower bound of  $P_s$  is  $\frac{Q_P - P_{e.\max}\Omega_{er}}{\Omega_{sr}}$ ,

The following phase in black widow optimization is mutation, where the selection of juvenile spiders is based on the mutation rate. The mutation process for a chosen baby spider is a small random value.

Smaller random produced values are combined with a chosen young sibling spider for the mutation process.

$$Z_{k,d} = Y_{k,d} + \alpha \quad (3)$$

Where  $Z_{k,d}$  is the mutated population of black widows, Here, the randomly generated muted value ' $\alpha$ ', then the randomly selected number is ' $k$ ' and the younger spider which is selected randomly,  $Y_{k,d}$ .

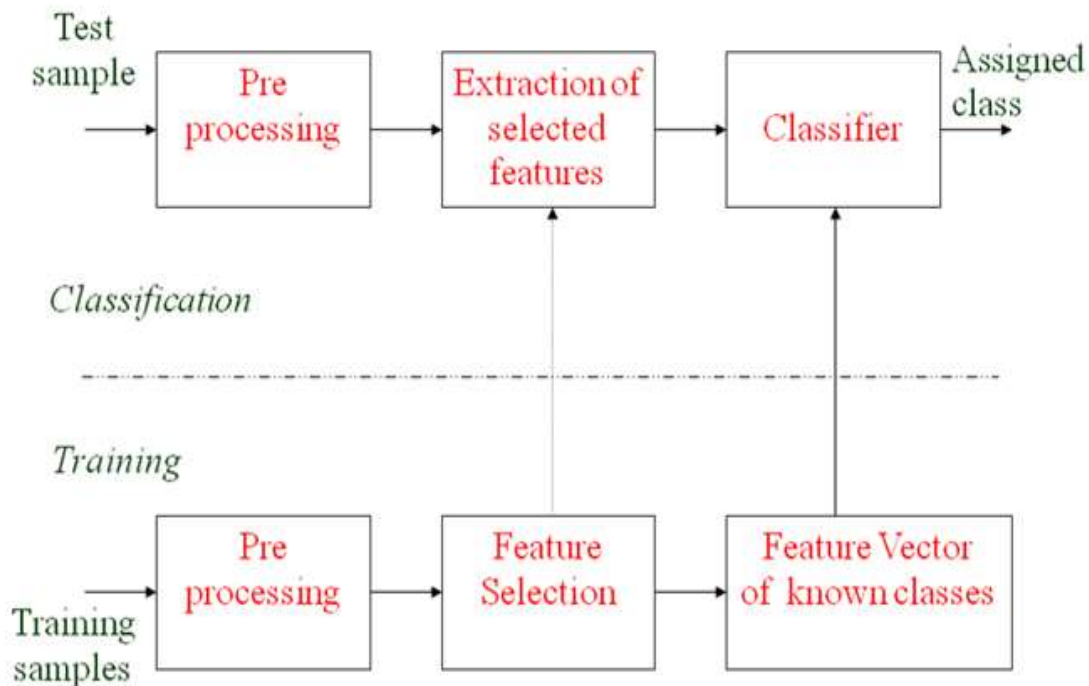
### 5. Methodology

The techniques for using image processing and artificial intelligence to analyze the fruit

ripening process are briefly described. Initial fruit maturity, temperature, air velocity, air humidity, ethylene, and carbon dioxide (CO<sub>2</sub>) in the ripening store room are all significant challenges that affect the ripening process. However, rotten fruits and vegetables may result if carbon dioxide emissions reach excess levels of 5%. An infrared camera will record the change in color as the fruit ripens, which is a step-by-step process that first turns it from green to yellow. Additionally, the movie is split into frames, and features are then retrieved from the images. Ethylene and CO<sub>2</sub> gas estimate uses these properties. Therefore, the following methods are suggested as an efficient way to measure the gaseous emissions of carbon dioxide from the color of fruits.

1. A servo motor system was employed with the camera's image sensor.
2. The control room has a careful monitoring setup in place.
3. Streaming video from a CRT monitor to a PC
4. The laptop is loaded with VTD image processing software.
5. A frame grabber that divides the video file into frames
6. Image analysis software to examine the elements of the photographs.
7. A plan to use an intelligent control system to monitor and gauge the ripening process.
8. Verifying the developed algorithms

The technique and estimation for the ripening process utilizing image processing is shown in Figure 1, along with a schematic representation of the main processes in the proposed ripening quality monitoring system.



**Figure 1. Methodology and estimation for ripening process using image processing**

### 5.1. Pre-processing

The pre-processing phase after that involves edge detection and dithering filtering. Filtering reduces noise so that the photos with no noise can be used for additional analysis. The region of interest is extracted using the edge detection procedure, and this controls which features

should be extracted. Image approximation is carried out as a follow-up procedure in the pre-processing stage to lessen the number of colors in an image, producing the final image. The loss of some colors makes the original image poorer, nevertheless.

Dithering is used to make the output image more colorful while simultaneously altering the colors of the pixels in each neighborhood so that the average color in each neighborhood closely resembles the original RGB color.

### **5.2. RGB to gray conversion**

RGB to gray conversion is a low level preprocessing, and there are primarily two ways utilized. They are both extremely straightforward methods that take the average of R, G, and B (Dameshwari Sahu and Ravindra Manohar Potdar 2017).

### **5.3. Noise reduction**

Using the average filter, unwanted noise is eliminated (Misigo Ronald, Miriti Evans 2016). In order to reduce noise, the split and merge technique is employed (Yoshio Makino, Kenjiro Goto, et al. 2016).

### **5.4. Feature extraction**

Measured data are used to determine the features of the images through feature extraction. Shape, size, texture, and color are the most common features used. However, many characteristics were taken from the fruits. According to Ghulam Muhammad (2014) and EmnyHarnaYossya, Jhonny Pranataa at El (2014), erosion and dilations are morphological operations used to remove tiny items.

### **5.5. Classification**

Numerous classifiers of various kinds are employed for the classification of fruits. These characteristics are utilized to create the training set, and a classification method is then used to extract the knowledge base that determines the outcome of the given case. There are many different ways utilized in computer vision systems; however we have chosen the MLP for estimating the amount of ethylene gas. This method is made possible by employing the Back Propagation Algorithm to train the MLP.

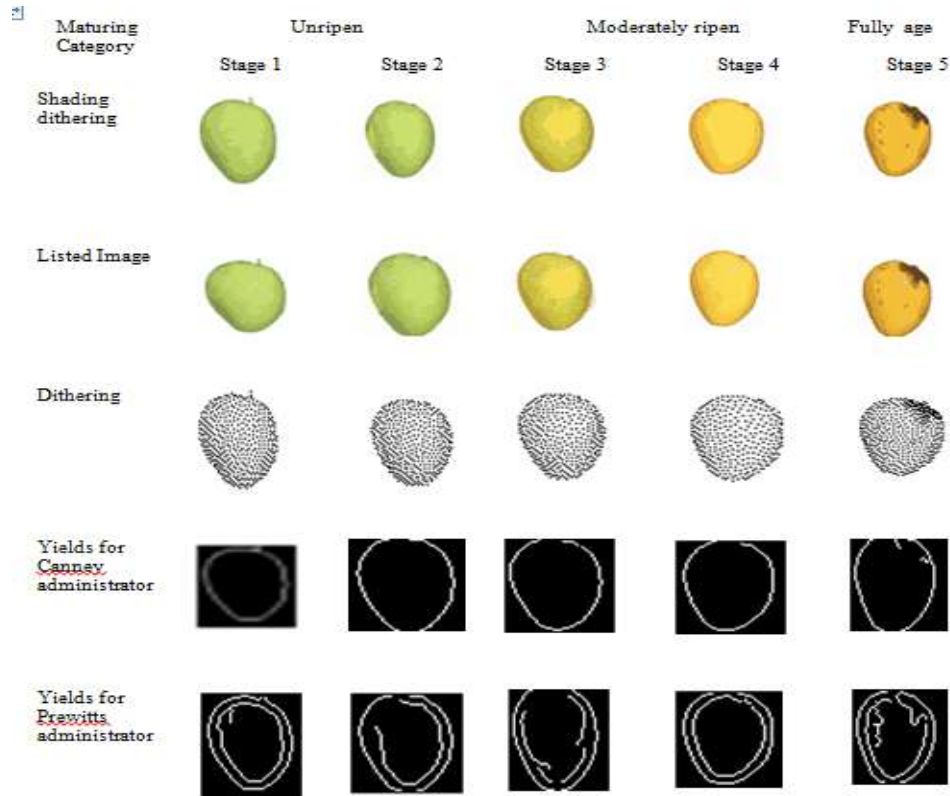
There are 'H' hidden layers, 1 output layer, and 1 input layer in a feed-forward neural network. Every unit (or neuron) in a given layer is fully associated with every unit in the layer above it. This means that each layer is made up of units. The graphic representation can be mathematically described as a configuration of matrix multiplication and stimulation functions. The stimulation function typically exhibits nonlinearity and simulates the firing of an artificial neuron. According to theory, the network can learn any function approximation because of this non-linear activation function.

## **6. Results and Discussion**

The infrared camera records photos of the fruits as they are rotated and oriented differently. The pre-processed photos were also categorized and subjected to characteristic mining. Additional edge revealing is done to extract the area of interest during processing, which also involves fickle filtering to remove noise. These pictures are deciding which features should be extracted (Sujatha K, Pappa N 2011, and Sujatha K 2014). According to Figure 2, filtering increases the amount of colors in the pixels pertaining to the region under scrutiny and the standard color in each region comes close to the original RGB color.

These are aided by the Feed Forward Neural Network (FFNN), which is used to calculate the amount of ethylene gas. The evaluation of ethylene gas for the ripening process is identified

using an FFNN structure that has been trained with BPA. As the fruits are being de-greened, this procedure helps to keep them from spoiling. One output variable and seven input variables are constructed in the suggested work. The final goal, however, is the value of the ethylene concentration. In this situation, normalization for each value of the feature divided by the maximum value of that feature is employed as the formula to reduce the computational burden. Using the inputs of four features and ultimate weights learned from training, the proposed testing algorithm determines the ripening state and ethylene concentration from the fruit image to enable feed-forward control of ethylene gas concentration.

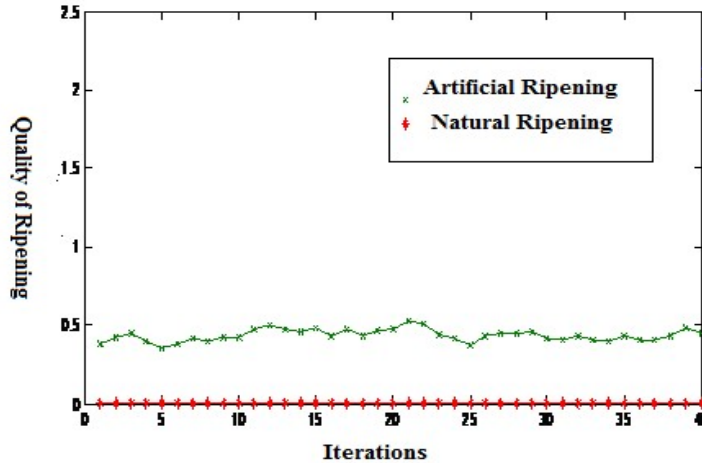


**Table 1. Highlighted Feature Extraction for Mango**

S. No	Mean	Std Dev	Mode	Median
1.	201.9	48.4	255	182
2.	195.8	47.6	255	177
3.	197.3	46.8	255	181
4.	205.2	40.9	255	187
5.	188.6	54.9	255	169

By utilizing desired target ethylene (C<sub>2</sub>H<sub>4</sub>) gas during preparation, the definitive weights are obtained. With definitive weights collected after preparing to complete feed forward control C<sub>2</sub>H<sub>4</sub> gas focus, the estimated calculation to gather the aging state and C<sub>2</sub>H<sub>4</sub> gas concentration fixation from the organic product image is tested. Figure 2, displays the results for training the FFNN with BPA and BWO. As a result, the FFNN was ready and worked out as previously mentioned. Table 2 denotes the classification efficiency.





**Figure 2. Simulation result for MLP trained with BPA and BWO**

**Table 2. Classification Efficiency**

S. No	Network Architecture/Algorithm	% Classification
1.	MLP with BPA	92
2.	MLP with BPA & BWO	93

### 7. Conclusion

Complete set of 132 images from the ripening chamber were used in this study (81 images for training and 51 for assessment). Features are retrieved once images have been pre-processed. The pre-processing comprises morphological closing, filtering, histogram analysis, and dithering. The FFNN may be trained using BPA with BWO (Black widow optimization) and the extracted features. To achieve a fully effective ripening process, control measures can be employed to raise or reduce the C<sub>2</sub>H<sub>4</sub> gas supply depending on the quality of the ripening process. In order to expand the work, it is possible to explore estimating the supply of C<sub>2</sub>H<sub>4</sub> gas using artificial intelligence techniques.

In this study, 102 photos from the ripening room were gathered (51 for training and 51 for assessment). Features are taken from the pre-processed pictures. To produce the final result, 51 photos from classes 1, 2, and 3 are used in the training of the FFNN using BPA with BWO. The greatest classification performance is attained, according to the testing and validation. It was believed that classification performance could enhance the initial picture pre-processing. In order to ensure a fully effective ripening process, the C<sub>2</sub>H<sub>4</sub> gas supply must be increased or decreased depending on the quality of ripening and in accordance with the color of the fruit pictures. By effectively monitoring, an intellectual system would always aid in the process of ripening. This has been demonstrated by our output, where the efficiency rate has greatly increased.

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