Ripeness Classification of Bananas Using an Artificial Neural Network

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Ripeness Classification of Bananas Using an Artificial Neural Network

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Abstract

The quality of fresh banana fruit is a main concern for consumers and fruit industrial companies. The effectiveness and fast classification of banana's maturity stage are the most decisive factors in determining its quality. It is necessary to design and implement image processing tools for correct ripening stage classification of the different fresh incoming banana bunches. Ripeness in banana fruit generally affects the eating quality and the market price of the fruit. In this paper, an automatic computer vision system is proposed to identify the ripening stages of bananas. First, a four-class homemade database is prepared. Second, an artificial neural network-based framework which uses color, development of brown spots, and Tamura statistical texture features is employed to classify and grade banana fruit ripening stage. Results and the performance of the proposed system are compared with various techniques such as the SVM, the naive Bayes, the KNN, the decision tree, and discriminant analysis classifiers. Results reveal that the proposed system has the highest overall recognition rate, which is 97.75%, among other techniques.

Keywords Image segmentation · Features extraction · Ripening of bananas · Fruit maturity detection · Computer vision · Artificial neural network

1 Introduction

Banana is one of the most consumed fruits globally. It contributes about 16% of the world's fruit production according to FAO. Maturity stage of fresh banana fruit is a principal factor that affects the fruit quality during ripening and marketability after ripening. The ability to identify maturity of fresh banana fruit will boost farmers to optimize harvesting phase which helps to avoid harvesting either over-matured or under-matured banana. Early in the ripening process, the banana fruit synthesizes compounds such as alkaloids and tannins. These fight infections and cause the under-ripe banana fruit to taste bitter and astringent. As banana fruit continues to grow, its storage cells expand, engorging it with water, sugars, starches, organic acids, vitamins, and minerals, and its skin turns from green to yellow with brown spots. Starch and acid contents decrease, while sugar content increases, and alkaloids and tannins disappear. Aromas develop as the acid and protein composition changes, and the fruit's texture softens as the substances that hold up its cell walls begin to break down. All these changes make the banana fruit ripe and ready to eat. Ripening treatment of banana is accomplished globally with controlled humidity, suitable temperature, time, air flow, and using ethylene gas.

To ensure the productivity, competitivity, quality standards, and reliability of banana fruit products, automatic image processing tools based upon intelligent techniques are paramount over visual features methods. Such machine vision system has the advantage in making decisions at a very fast rate. This paper is intended first to generate a database for the Egyptian banana species with different ripening levels such as unripe, ripe, and overripe. Then, new efficient ripening level determination algorithms are presented. The proposed techniques are based on HSV color, development of brown spots, and texture analysis of the banana fruit.

2 Related Research

In the literature, a lot of methods, which depend on shape, size, color, and texture features, have been developed for banana fruit ripening classification. First of these are the color moments and the color histogram [1,2]. The mean and

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the variance of the RGB, the HSV, and the CIELAB color spaces of the banana fruit intensity histograms are extracted and analyzed. The system was able to correctly predict with more than 94% the seven ripening stages of the banana bunch. The seven ripening stages are the green, the green with traces of yellow, more green than yellow, more yellow than green, green tip and yellow, all yellow, and yellow flecked with brown. Secondly, the third and the fourth statistical moments [3] can be used to classify the under-mature, mature, and over-mature banana fruit classes. The classification accuracy of this technique for the three classes reaches 99.1%.

The accuracy of the banana fruit ripening classification class depends upon the used preprocessing segmentation algorithm. Segmentation is a vital step for many computer vision tasks. The technology of image segmentation is widely used in medical image processing, fruit industry, face recognition, pedestrian detection, etc. Discrete wavelet transform (DWT) and wavelet packet transform (WPT) have proven to be effective in image compression, de-noising, segmentation, and classification [4–6]. They span many disciplines. It is demonstrated that DWT and WPT could be used for 2D images surface segmentation and 3D images volume segmentation [7–11].

Two-dimensional DWT is used as a multi-resolution analysis tool for segmenting and classifying healthy and damaged fruits while they are moving in a conveyor belt [9,11]. It has demonstrated that DWT distinguishes the healthy green olive fruits from the damaged fruits with accuracy of 90% [9], while the recognizer can identify the healthy brown, light or deep, or the healthy black olive fruits with accuracy of about 78% [9]. Texture homogeneity measuring technique, which is based on measuring the degree of homogeneity of adjacent pixels, and the special image convolution algorithm, which uses special kernels or masks to perform image convolution, are another 2D texture feature algorithms for detecting, classifying, and calculating automatically the external defects of fruits and its area [12]. It is shown that [12] the classification accuracy of these algorithms is higher than the 2D fuzzy C-means algorithm by 7%, for the healthy olives, whereas it is higher by 9% for defected olives.

Additionally, it is illustrated that 3D DWT and WPT could be used for medical 3D images volume segmentation and for tumor quantification and measurement and thus radio therapy planning and cancer diagnosis [7,8]. Three-dimensional volume segmentation aims at partitioning the voxels into 3D objects (sub-volumes) which represent meaningful physical entities. The 3D wavelet domain detected the objects with better accuracy and reduces the percentage error by several percent more than the traditional 2D segmentation techniques [8]. Besides the 3D DWT volume segmentation, unsupervised 3D fuzzy C-means clustering algorithm to extract region of interest, ROI, for objects in 3D volumes reveals that the algorithm detects accurately the ROI [13].

Besides DWT, independent component analysis (ICA) is another feature extraction technique for detection and classification [14]. ICA maximizes the absolute value of the normalized kurtosis. It aims at capturing the statistical structure in images that is beyond second-order information, by exploiting higher-order statistical structure in data. It has proven a useful tool for finding structure and changes in fruit's images. ICA seeks basis vectors that best fit the variance of the fruit's images. In contrast, local binary pattern (LBP) is considered as a high-performance texture features technique [15]. It transforms an image into an array or image of integer labels describing small-scale textures of the image. LBP and its variants produce long histograms, which slow down the recognition speed. Local gradient code (LGC), which is based on the relationship of neighboring pixels, is proved to be more stable to local intensity variation, less influenced by local color variation, and more distinctive than LBP [16]. The LGC is able to capture the locally changing gradient information, while LBP is globally invariant, since it only compares the central pixel value with the neighboring pixel value.

On the other hand, learning-/trained-based classifiers require an intensive training phase of the classifier parameters, and hence a higher recognition rate is obtained. Examples are the support vector machine [17] (SVM), the hidden Markov model [16] (HMM), and the artificial neural network [18–22] (ANN).

As an application of the supervised classification techniques, it was demonstrated that laser light backscattering imaging (LLBI) with five laser diodes emitting at wavelengths 532, 660, 785, 830, and 1060 nm could be employed for predicting quality attributes of banana fruit [23,24]. The predicted attributes were chlorophyll, elasticity, and soluble solids content (SSC). A correct classification accuracy of 92.5% and 95.5% was claimed using the ANN model and the SVM model, respectively. In [19,20], a computer vision system that uses gray-level co-occurrence matrix (GLCM) texture features is proposed to train an artificial neural network. The system can be used to sort banana at an accuracy of 98.8%.

SVMs, HMMs, and ANNs are used for supervised learning tasks and classification. However, deep learning models can be trained in an unsupervised manner for unsupervised learning tasks. Convolutional neural network [18] (CNN) is a class of deep learning neural networks and has acquired a broad application in image classification. It is a powerful visual model that yields hierarchies of features. It is demonstrated that CNN architecture of 17,312 images of bananas produces a classification accuracy of 94.4% [18].

In this paper, we propose a novel ANN adapted to fine-grained feature-based representation for classifying ripening stages of the Egyptian banana's species. To show the power of the proposed classification system, we create a database,[1] comprising of 300 Egyptian banana images, with different ripening levels such as unripe (green banana), yellowish green, mid-ripe, and overripe. The proposed scheme makes use of the Tamura's contrast, coarseness, and the direction visual perceptual texture features to correct labeling the data [25,26]. The rest of the paper is organized as follows: Sect. 3 illustrates the basic principles of the proposed system for classifying the different banana's ripening stages. In Sect. 4, the proposed classification system is tested and compared against other supervised classification algorithms, such as SVM, naive Bayes, KNN, decision tree, and discriminant analysis classifiers. Finally, Sect. 5 offers the conclusion.

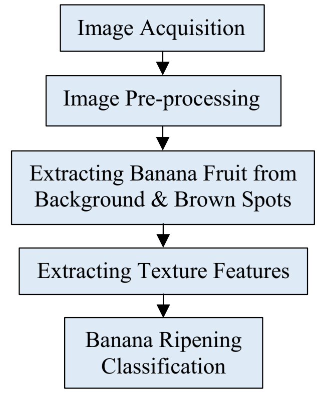

Fig. 1 Steps of the proposed algorithm

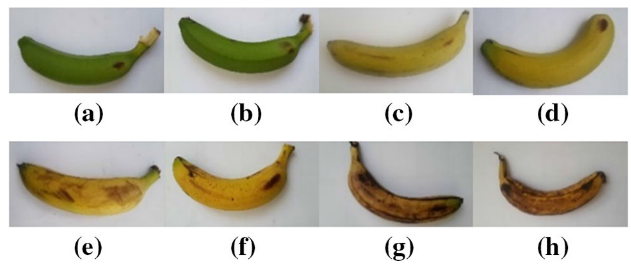

Fig. 2 Samples of different banana fruits. **a**, **b** Are for the green bananas, **c**, **d** are for the yellowish green bananas, **e**, **f** are for the mid-ripe bananas, **g**, **h** are for the overripe bananas

3 The Proposed Banana's Ripening Classification System

The determination of the ripeness state of banana fruits is an essential element in the agriculture research field. This is because ripeness is related to quality and it can affect the commercialization of the product. Manual approach is often used in product grading and quality control, but this leads to uneven products, higher time expense, and fatigue by the human operators. Therefore, we propose in this article, a ripening identification system that performs the visual perception of the human operator in making decisions at a very fast rate. A computer vision system for ripening classification of banana fruits is realized generally based on several processes. Figure 1 underlines the major signal processing steps. The algorithm begins with image acquisition. Then, these images go through preprocessing operations to be ready for analysis. The main module for computer vision machines is the image segmentation followed by image classification. An artificial neural network is then used for ripening classification decision, which depends upon color and Tamura statistical texture features. Details of the proposed algorithm stages are presented in Fig. 1.

1. *Samples Collections and Images Acquisition* A database of Egyptian banana species with different ripening levels is created. The database is comprised of 300 banana images, with different ripening levels such as unripe (green banana), yellowish green, mid-ripe, and overripe. All these samples are collected by a digital Samsung Note 3 color camera. The camera is a HD format with 4128 (h) × 3096 (v) pixels and a 30 frames/s with full resolution. Figure 2 shows samples of banana fruits of different ripening levels. The dataset has 104 green bananas, 57 yellowish bananas, 97 mid-ripen bananas, and 42 overripen bananas.
2. *Image Preprocessing* The database goes through some preprocessing steps before training and testing the artificial neural network. First, a guided filter is applied to perform edge preserving and smoothing on the banana image. Second, the RGB banana image is then converted to HSV color space. The HSV model describes colors similarly to how the human eye tends to perceive color. The HSV, also, is used to separate image luminance from color information. In RGB, color information cannot be separated from luminance. Third, morphological filtering is used to enhance the image. These operations include dilation, which fills gaps between pixels of edges and erosion, which suppresses structures in the background.
3. *Banana Fruit Segmentation* This module has two phases. It, first, extracts banana fruit from the background. This is done by assigning a global threshold using Otsu's method. Pixels in the input image with luminance greater than the threshold are replaced with the value 0 (black), and all other pixels are replaced with the value 1 (white). Figure 3 shows the mask that is used for segmentation. A function is, then, implemented to restore the original input banana fruit image. This is done by reading the constructed binary mask image pixel by pixel. A pixel is recognized as a background, if its level value is zero.

[1] https://drive.google.com/drive/folders/1nRWBYAHNRqmL4R0SLrs6dbGQFSWGVY8V?usp=sharing.

Fig. 3 Segmentation of the four classes of banana fruits and extraction of brown spots. The first column is the input image, the second column is the segmentation mask, the third column is the segmented banana fruit, and the fourth column is the segmented banana fruit without brown spots

Otherwise, equate the level value of that pixel with the original one. The segmented banana fruit images for the four classes are shown in the third column of Fig. 3.
The second phase of this module is to calculate the ripeness factor of the banana fruit. The ripeness factor (RF) of the banana fruit is defined as:

$$\text{Banana's Ripeness Factor (RF)} = \frac{\text{Total Area of the Brown Spots}}{\text{Total Area of the Banana}}, \quad (1)$$

where the total area of the banana is given by the total number of white pixels of the banana fruit segmentation mask. To calculate the total area of the brown spots, a new color mask is performed on the segmented image to detect the brown spots on the banana peel. The brown color is characterized by having $H = 30°$ or 8.33%, $66.7\% \leq S \leq 67.6\%$, and $4.7\% \leq V \leq 60\%$. The white segments in the fourth column of Fig. 3 represent the brown regions of the banana peel. The total area of the brown spots in the banana fruit is given by the total number of white pixels within the segmented banana peel.

4. *Extracting Texture Features* Besides the color-based analysis method for ripeness index calculation, texture-based techniques help in surface, shape, and banana class determination. Statistical texture analysis is the most popular method used for image recognition. Tamura contrast, coarseness, and direction features are three quantitative second-order statistical texture measures for image classification. They are based on psychological studies of human perception. Contrast, defined by Eq. 2, measures the way in which gray levels vary in the image and between neighboring pixels and to what extent their distribution is biased to black or white.

$$\text{Contrast} = \frac{\sigma}{(\alpha_4)^{0.25}}, \text{ and } \alpha_4 = \frac{\mu_4}{\sigma^4}, \quad (2)$$

where μ_4 is the fourth moment about the mean and σ^2 is the variance. On the other hand, coarseness, defined in [25], basically relates to distances of notable spatial variations of gray levels, which is implicitly related to the number and the size of primitive elements forming the texture. It has the direct relationship to scale and repetition rates. It is expected that coarseness of the four banana fruit classes to be within the same range, since the peel of banana fruits of the four classes is characterized by having many small primitives, with a high degree of local variations of gray levels. In consequence, the coarseness feature is excluded from the input of the proposed artificial neural network. Another very important characteristic of the texture image is the distributing trait of texture directions. This feature refers the shape of texture primitives and their placement rule. The directionality [25] is obtained by examining the sharp degree of a histogram which is constructed from the gradient vectors of all the image pixels. The banana ripeness classification algorithm is as follows:

- Compute the texture feature vector, F, for each training banana image.

$$F = [\text{Contrast Directivity HSV RF}]. \quad (3)$$

The thresholds of the HSV color space for the four classes of banana fruits are obtained based upon analogy between HTML color codes and various natural colors of banana peels of different classes under an outstanding illumination. The green banana fruits are featured as having $72° \leq H \leq 78°$, $85\% \leq S \leq 100\%$, and $27\% \leq V \leq 50\%$. Light green bananas are picked and cured before they have ripened. At the beginning of the ripening cycle, the chlorophyll in the peel breaks down and the starch within the fruit is converted into simple sugars. As a result, the peel turns yellow hue with brown spots and the fruit softens up and becomes sweet. The yellow banana fruits are featured as having $50° \leq H \leq 72°$, $70\% \leq S \leq 100\%$, and $79\% \leq V \leq 100\%$. The ethylene gas emitted by the fruit causes the yellow pigments in bananas to decay into golden yellow with more brown spots in a process called enzymatic browning. The golden yellow or mid-ripen banana is characterized by $39° \leq H \leq 50°$, $69\% \leq S \leq 96\%$, and $75\% \leq V \leq 100\%$. The last phase of the ripening cycle of the banana is the yellowish brown or overripen banana. The banana peel looks deep brown with dark streaks.

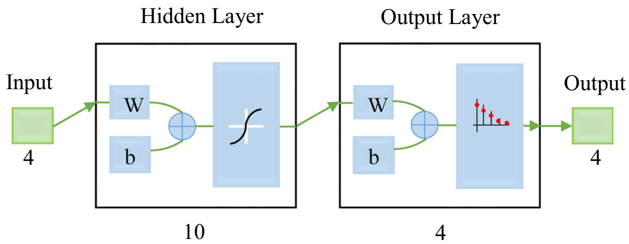

Fig. 4 Architecture of the proposed artificial neural network

- A different measure value of the vector F is obtained for each banana ripening class.

5. *Banana Ripening Classification* Figure 4 shows a block diagram for the proposed classifier.
The Levenberg–Marquardt backpropagation optimization algorithm is used for training the suggested artificial neural network. The input layer of the model is made up of four neurons. These are the quality indices of the vector F, defined by Eq. 3. The model has ten hidden layers. The sigmoid function is used as the activation function because of its simplicity in derivative and its soft switching capability. The number of neurons of the output layer is four, which represents the four ripening levels. The output layer produces the actual output of the neural network which is then subtracted from the desired output (target) to produce the error. The mean squared error is used as a performance function and is sent back into the network hidden layers to update the weighted sum of the input and bias of each neuron.
In this work, the training dataset is 70% of the total dataset, while the testing dataset carried the remaining percentage. Therefore, out of 300 images as the actual dataset, 74 (green bananas), 40 (yellowish bananas), 67 (mid-ripen bananas), and 30 (overripen bananas) are used as the training set, while the remaining 30 (green bananas), 17 (yellowish bananas), 30 (mid-ripen bananas), and 12 (overripen bananas) are used as the testing set. Figure 5 shows the flowchart of our proposed neural network system for training and testing banana fruits.

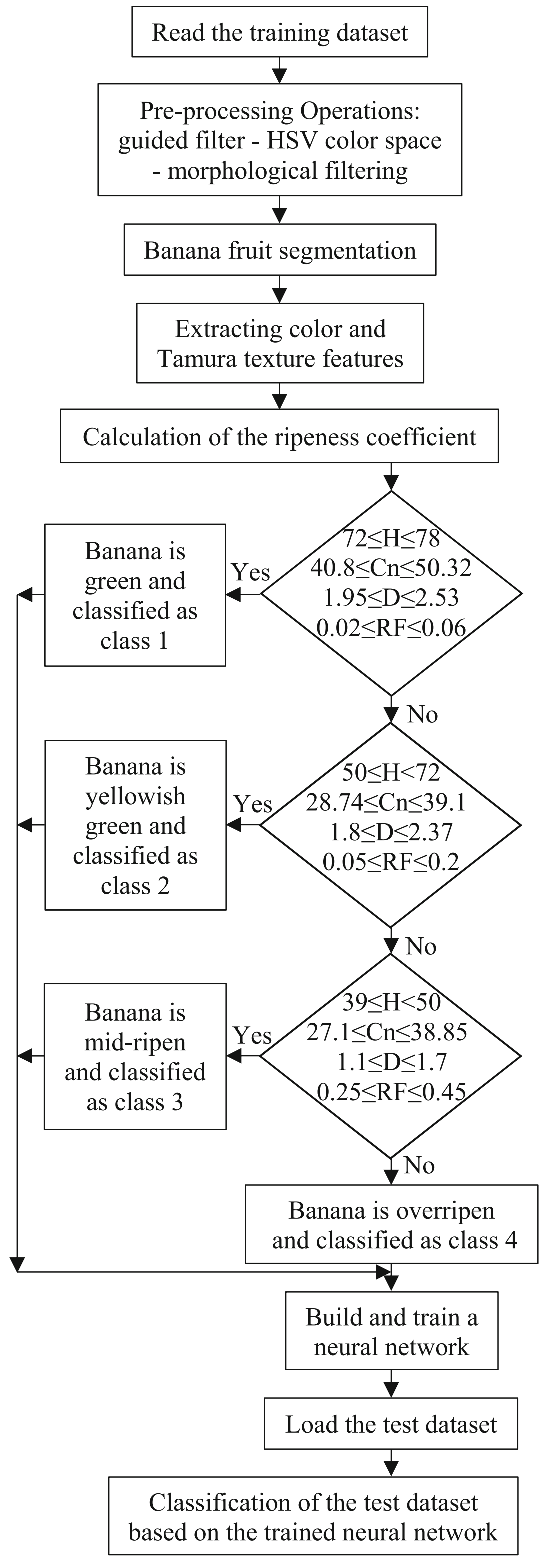

Fig. 5 Flowchart of the proposed classification neural network model

4 Experiment Results and Discussion

To test the performance of the banana's ripening classification system, 89 banana fruits of assorted colors and shapes are selected for testing. Table 1 shows results of the texture feature vector (F), described by Eq. 3, for the 211 trained banana fruits. As expected, the coarseness of the four banana fruit classes is about the same. In consequence, it will be excluded from the feature vector (F) and from the input of the proposed artificial neural network. Table 1, also, distinguishes between the four classes of banana fruits in terms of

Table 1 Texture features of the 211 training banana fruits for different classes

Texture features	Class 1 Green	Class 2 Yellowish green	Class 3 Mid-ripen	Class 4 Overripen
Coarseness (Cr)	$57.84 \leq \mathrm{Cr} \leq 58.44$	$57.56 \leq \mathrm{Cr} \leq 58.85$	$57.51 \leq \mathrm{Cr} \leq 58.87$	$57.48 \leq \mathrm{Cr} \leq 58.52$
Contrast (Cn)	$40.8 \leq \mathrm{Cn} \leq 50.32$	$28.74 \leq \mathrm{Cn} \leq 39.1$	$27.1 \leq \mathrm{Cn} \leq 38.85$	$41.7 \leq \mathrm{Cn} \leq 50.42$
Directivity (D)	$1.95 \leq D \leq 2.53$	$1.8 \leq D \leq 2.37$	$1.1 \leq D \leq 1.7$	$1.29 \leq D \leq 1.9$
Hue color space (H)	$72 \leq H \leq 78$	$50 \leq H < 72$	$39 \leq H < 50$	$39 \leq H < 50$
RF	$0.02 \leq \mathrm{RF} \leq 0.06$	$0.05 \leq \mathrm{RF} \leq 0.2$	$0.25 \leq \mathrm{RF} \leq 0.45$	$\mathrm{RF} \geq 0.7$

Table 2 Texture features that differentiate banana fruits classes

	Class 1 Green	Class 2 Yellowish green	Class 3 Mid-ripen	Class 4 Overripen
Class 1	–	Hue color space & RF & contrast	Hue color space & RF & contrast	Hue color space & RF & directivity
Class 2	Hue color space & RF & contrast	–	Hue color space & RF & directivity	Hue color space & RF & contrast
Class 3	Hue color space & RF & contrast	Hue color space & RF & directivity	–	Contrast & RF
Class 4	Hue color space & RF & directivity	Hue color space & RF & contrast	Contrast & RF	–

the contrast, the directivity, the hue color space values, and the RF values. Each class is discriminated from the other one utilizing only three features out of the four, while each class is distinguished from the others using all features.

Table 2 shows the used texture features that discriminate the four banana classes. It is seen that values of the hue color space, the RF, and Tamura's contrast features are used to discriminate class 1 and class 2 bananas, and similarly class 1 and class 3 bananas as well as class 2 and class 4 bananas. However, class 1 and class 4 are differentiated according to the values of the hue color space, the RF, and Tamura's directivity, and likewise class 2 and class 3 bananas, whereas class 3 and class 4 bananas are separated according to values of the contrast and the RF only.

Table 3 shows the confusion matrix for the proposed banana fruits classification model using the artificial neural network. The model achieves a 97.75% overall correctness or recognition rate. Tables 4, 5, 6, 7, and 8 show the confusion matrices for some other supervised classification algorithms. In this work, the performance of the SVM, the naive Bayes, the k-nearest-neighbors, the decision tree, and the discriminant analysis classifiers is compared with the ANN classifier. Simulation results show that the overall correctness or the model classification accuracy and the class sensitivity of the SVM, the naive Bayes, the KNN, and the discriminant analysis classifiers are less than the proposed artificial neural classification system and the decision tree classifier. Accordingly, these classifiers are excluded from analogy and not discussed further in this work.

Sensitivity and precision are two statistical performance measures for classification tests. Sensitivity is defined as the ability of the prediction model to select the instance of a certain class from the dataset. It is the proportion of the actual positive classes which are correctly identified. On the other hand, precision is defined as the proportion of the predicted positive classes which are correctly identified. They are given by:

$$\text{Sensitivity} = \frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FN})}, \text{ and} \tag{4}$$

$$\text{Precision} = \frac{\mathrm{TP}}{(\mathrm{TP}+\mathrm{FP})}, \text{ where} \tag{5}$$

TP, FP, and FN are the numbers of the true positive, the false positive, and the false negative predictions for the considered class, respectively. Both the neural network and the decision tree classifiers have a sensitivity of 100% for classes 1, 2, and 4. However, the sensitivity of the third class dropped to 93.3% for both classifiers. This is because two mid-ripen banana fruits are misclassified as yellow banana fruits for the ANN and misclassified as overripen banana fruits for the decision tree classifier. Additionally, simulation results show that the ANN-predicted classes are more precise than that of the decision tree classifier.

Specificity and overall class prediction accuracy are other useful statistical measures that describe the performance of a classifier. They are used for binary classifiers. Specificity is defined as the proportion of actual negative classes (all except the positive class) which are correctly identified, while

Table 3 Confusion matrix for the proposed artificial neural network

Actual class	Predicted class				Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	
Class 1	30	0	0	0	100
Class 2	0	17	0	0	100
Class 3	0	2	28	0	93.3
Class 4	0	0	0	12	100
Class precision %	100	89.5	100	100	Overall correctness = 97.75%

Table 4 Confusion matrix for the SVM classifier

Actual class	Predicted class				Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	
Class 1	30	0	0	0	100
Class 2	0	14	3	0	82.4
Class 3	0	0	30	0	100
Class 4	0	0	0	12	100
Class precision %	100	100	90.9	100	Overall correctness = 96.6%

Table 5 Confusion matrix for the naive Bayes classifier

Actual class	Predicted class				Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	
Class 1	30	0	0	0	100
Class 2	0	17	0	0	100
Class 3	0	4	26	0	86.6
Class 4	0	0	0	12	100
Class precision %	100	81	100	100	Overall correctness = 95.5%

Table 6 Confusion matrix for the KNN classifier

Actual class	Predicted class				Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	
Class 1	30	0	0	0	100
Class 2	0	17	0	0	100
Class 3	0	4	26	0	86.6
Class 4	0	0	0	12	100
Class precision %	100	81	100	100	Overall correctness = 95.5%

Table 7 Confusion matrix for the decision tree classifier

Actual class	Predicted class				Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	
Class 1	30	0	0	0	100
Class 2	0	17	0	0	100
Class 3	0	0	28	2	93.3
Class 4	0	0	0	12	100
Class precision %	100	100	100	85.7	Overall correctness = 97.75%

Table 8 Confusion matrix for the discriminant analysis classifier

Actual class	Predicted class				Class sensitivity %
	Class 1	Class 2	Class 3	Class 4	
Class 1	30	0	0	0	100
Class 2	0	15	2	0	88.2
Class 3	0	0	30	0	100
Class 4	0	0	0	12	100
Class precision %	100	100	93.75	100	Overall correctness = 97.75%

Table 9 Binary confusion matrix for the proposed artificial neural network

Actual class	Predicted class		
	Class 1	Not class 1	
Class 1	TP = 30	FN = 0	Sensitivity = 100%
Not class 1	FP = 0	TN = 59	Specificity = 100%
	Precision = 100%	Negative predictive value = 100%	Overall prediction accuracy = 100%
	Class 2	Not class 2	
Class 2	TP = 17	FN = 0	Sensitivity = 100%
Not class 2	FP = 2	TN = 70	Specificity = 97.2%
	Precision = 89.5%	Negative predictive value = 100%	Overall prediction accuracy = 97.75%
	Class 3	Not class 3	
Class 3	TP = 28	FN = 2	Sensitivity = 93.3%
Not class 3	FP = 0	TN = 59	Specificity = 100%
	Precision = 100%	Negative predictive value = 96.7%	Overall prediction accuracy = 97.75%
	Class 4	Not class 4	
Class 4	TP = 12	FN = 0	Sensitivity = 100%
Not class 4	FP = 0	TN = 77	Specificity = 100%
	Precision = 100%	Negative predictive value = 100%	Overall prediction accuracy = 100%

TP, TN, FN, and FP stand for true positive events, true negative events, false negative events, and false positive events

overall class prediction accuracy is defined as the proportion of the total number of predictions that were correct. They are given by:

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN} + \text{FP})}. \tag{6}$$

$$\text{Overall Prediction Accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}. \tag{7}$$

To demonstrate the performance of the proposed ANN classification model and the supervised decision tree classifier, the (4 × 4) confusion matrices, shown in Tables 3 and 7, are transformed to four (2 × 2) confusion matrices. Tables 9 and 10 show the four binary confusion matrices, each for a different banana fruits class, for the ANN and the decision tree classifiers, respectively. Results show that specificity for the two models is about the same. Three classes out of four have 100% specificity. The remaining class has 97.2% specificity for the ANN classifier, while it is 97.4% for the decision tree classifier. Hence, the two classifiers have the ability to correctly distinguish a banana fruit not from the right class. Tables 9 and 10, also, show that the overall class prediction accuracy for the proposed ANN and decision tree classification models is the same. Accordingly, the classification of the banana fruits is highly correct and true and the misclassification rate, which is the complement of the prediction accuracy, is minimum.

Figures 6 and 7 show the receiver operating characteristic (ROC) curves for the proposed ANN and the decision tree classifiers. ROC is a metric used to check the quality of the classifier. It is the TP rate or the sensitivity against the FP rate or (1-specificity), which is the probability of false alarm, for the different possible cut-points of the test dataset. The proposed ANN classifier is perfectly accurate for classes 1, 2,

Table 10 Binary confusion matrix for the decision tree classifier

Actual class	Predicted class		
	Class 1	Not class 1	
Class 1	TP = 30	FN = 0	Sensitivity = 100%
Not class 1	FP = 0	TN = 59	Specificity = 100%
	Precision = 100%	Negative predictive value = 100%	Overall prediction accuracy = 100%
	Class 2	Not class 2	
Class 2	TP = 17	FN = 0	Sensitivity = 100%
Not class 2	FP = 0	TN = 72	Specificity = 100%
	Precision = 100%	Negative predictive value = 100%	Overall prediction accuracy = 100%
	Class 3	Not class 3	
Class 3	TP = 28	FN = 2	Sensitivity = 93.3%
Not class 3	FP = 0	TN = 59	Specificity = 100%
	Precision = 100%	Negative predictive value = 96.7%	Overall prediction accuracy = 97.75%
	Class 4	Not class 4	
Class 4	TP = 12	FN = 0	Sensitivity = 100%
Not class 4	FP = 2	TN = 75	Specificity = 97.4%
	Precision = 85.7%	Negative predictive value = 100%	Overall prediction accuracy = 97.75%

TP, TN, FN, and FP stand for true positive events, true negative events, false negative events, and false positive events

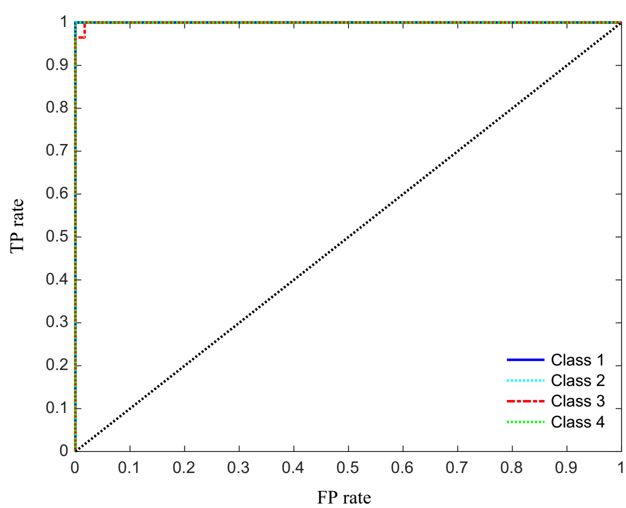

Fig. 6 ROC of the proposed ANN classification model

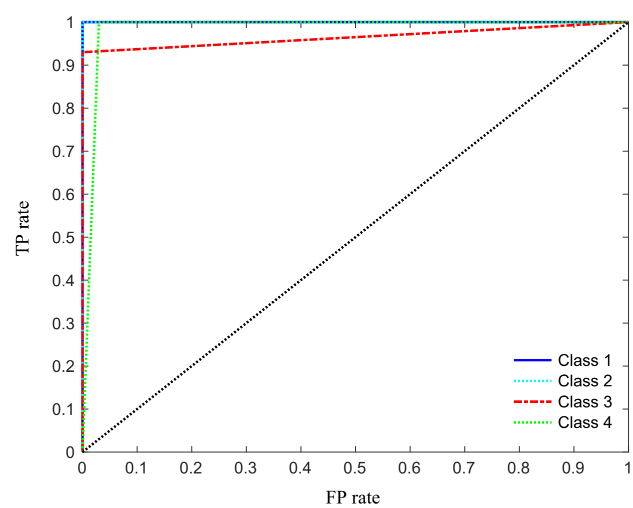

Fig. 7 ROC of the decision tree classification model

and 4, since the area under the ROC curve equals to one. However, the area under the curve for the third class is 0.99, which is very close to one. On the other hand, the decision tree classifier is perfectly accurate for classes 1 and 2, since the area under the curve is one. However, it is less accurate than the ANN classifier for the other classes, since the area under the curve for the third class is 0.965 and 0.985 for the fourth class. Hence, the ANN model is better than the decision tree classifier in distinguishing between the right class and not the right class. The ANN model has a perfect measure of separability between classes than the other supervised classification algorithms.

5 Conclusion

An artificial neural network-based system for the classification of ripeness state of banana fruits has been discussed. The proposed model uses Tamura's texture features and a new feature defined as ripening factor to properly discriminate between the four banana fruits classes. The system has optimal performance as compared with other supervised classification algorithms as the SVM, the naive Bayes, the KNN, the decision tree, and the discriminant analysis classifiers. The overall class recognition accuracy of 100% is obtained for the green and overripen classes, while it is 97.75% for the yellowish green and mid-ripen classes. The simplicity, the high recognition rate, and the speed of the classification model, 18 s for the 89 test bananas, make it appropriate for implementing a productive and profitable computer vision machine for the food processing industry.

Future directions will focus on applying 3D volume segmentation techniques, transfer learning, and deep learning methods to supervised/semi-supervised machine learning algorithms to enhance the classification rate and to minimize the training and the testing run time for banana fruits classification application.

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