AUTOMATED RIPENESS ASSESSMENT SYSTEM OF TOMATOES USING PCA AND SVM TECHNIQUES

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Chapter 6
Automated Ripeness Assessment System of Tomatoes Using PCA and SVM Techniques

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ABSTRACT

One of the prime factors in ensuring a consistent marketing of crops is product quality, and the process of determining ripeness stages is a very important issue in the industry of (fruits and vegetables) production, since ripeness is the main quality indicator from the customers' perspective. To ensure optimum yield of high quality products, an objective and accurate ripeness assessment of agricultural crops is important. This chapter discusses the problem of determining different ripeness stages of tomato and presents a content-based image classification approach to automate the ripeness assessment process of tomato via examining and classifying the different ripeness stages as a solution for this problem. It introduces a survey about resent research work related to monitoring and classification of maturity stages for fruits/vegetables and provides the core concepts of color features, SVM, and PCA algorithms. Then it describes the proposed approach for solving the problem of determining different ripeness stages of tomatoes. The proposed approach consists of three phases, namely pre-processing, feature extraction, and classification phase. The classification process depends totally on color features (colored histogram and color moments), since the surface color of a tomato is the most important characteristic to observe ripeness. This approach uses Principal Components Analysis (PCA) and Support Vector Machine (SVM) algorithms for feature extraction and classification, respectively.

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INTRODUCTION

Fruits and vegetables development is characterized by a short period of cell division followed by a longer period of cell elongation by water uptake. The final fruit size mainly depends on initial cell number, rather than cell size(Cowan, Cripps, Richings, & Taylor, 2001). Fruit ripening on the other hand is characterized by the development of color, flavor, texture and aroma. The actual time from anthesis until full maturity can vary tremendously among species/cultivars due to genetic and environmental differences. Even between fruit on the same plant, fruit development and ripening can take more or less time depending on local microclimate conditions and differences in sink/source relations within the plant. In addition, when a fruit is harvested, the time of anthesis of a particular fruit is generally unknown, as is its full history.

Monitoring and controlling produce (fruits and vegetables) ripeness has become a very important issue in the crops industry, since ripeness is perceived by customers as the main quality indicator. Also, the product's appearance is one of the most worrying issues for producers as it has a high influence on product's quality and consumer preferences. However, up to this day, optimal harvest dates and prediction of storage life are still mainly based on subjective interpretation and practical experience.

Hence, automation of this process is a big gain at agriculture and industry fields. For agriculture, it may be used to develop automatic harvest systems and saving crops from damages caused by environmental changes. On the other hand, for industry, it is used to develop automatic sorting system or checking the quality of fruits to increase customer satisfaction level[(Brezmes, Llobet, Vilanova, Saiz, & Correig, 2000),(Elhariri, El-Bendary, Fouad, Plato, Hassanien, & Hussein, 2014)]. So, an objective and accurate ripeness assessment of agricultural crops is important in ensuring optimum yield of high quality products. Moreover, identifying physiological and harvest maturity of agricultural crops correctly, will ensure timely harvest to avoid cutting of either under- and over-ripe agricultural crops[(Elhariri, El-Bendary, Fouad, Plato, Hassanien, & Hussein, 2014),(May & Amaran, 2011)].

Every fruit shows one or more apparent signs when it reaches physiological maturity or ripeness. Tomatoes, with their continuously prevailing daily nutrition and dietary value, are taking a dominant place among the vegetables all over the world. In Tomatoes, over maturity or over ripening is the stage when the fruit softens and loses part of its characteristic taste and flavor(Camelo, 2004). At this point, it is necessary to differentiate between two types of fruits: climacteric and non-climacteric. Tomato belongs to the group of climacteric agricultural products, which means that it is capable of generating ethylene, the hormone required for ripening even when detached from the mother plant and they reach full red color even when harvested green(Camelo, 2004).On the other hand, bell pepper for example, belongs to the group of non-climacteric agricultural products, which means that ripeness (full red color) is only obtained while fruit is attached to the plant and slight changes in color take place after harvest [(Camelo, 2004), (Coates & Johnson, 1997)].

Tomato maturity has been related to quantifiable parameters that reflect the biochemical changes during ripening. Color is used as a major method in determining maturity of tomato. However, skin color of tomato varies from cultivar to another cultivar even at the same maturity stage [(Molyneux, Lister, & Savage, 2004), (Zhang & McCarthy, 2011)]. During ripening, tomatoes go through a series of highly ordered physiological and biochemical changes, such as chlorophyll degradation and increased activity of cell wall-degrading enzymes, bring on changes in color, firmness, and development of aromas and flavors (Prasanna, Prabha, & Tharanathan, 2007). For tomatoes, ripeness issue is often handled via classifying harvested produce according to discrete color classes going from immature green to mature red, as stated in some recent researches that have classified tomatoes in different maturity stages based on measurements of color [(Hahn, 2002), (Aranda-Sanchez, Baltazar, & Gonzlez-Aguilar, 2009)]. Different tomato products have distinct requirements for maturity to achieve quality standards; hence, tomato maturity is one of the most important factors associated with the quality of processed tomato products.

Recently, utilizing computer vision in food products has become very wide spread, especially for products where measuring color or other spectral features enables estimating the ripeness stage (Rodrguez-Pulido, Gordillo, Gonzlez-Miret, & Heredia, 2013).

This chapter presents a multi-class content-based image classification system to automate the ripeness assessment process of tomato via investigating and classifying the different maturity/ripeness stages based on the color features. The dataset used for experiments were constructed based on real sample images for tomato at different stages, which were collected from different farms in Minya city, Upper Egypt.

Dataset of total 250 images was used for both training and testing datasets with 10-fold cross-validation. Training dataset is divided into 5 classes representing the different stages of tomato ripeness. The proposed approach consists of three phases; namely pre-processing, feature extraction}, and classification phases. During pre-processing phase, the proposed approach resizes images to 250x250 pixels, in order to reduce their color index, and the background of each image will be removed using background subtraction technique. Also, each image is converted from RGB to HSV color space. For feature extraction phase, Principal Component Analysis (PCA) algorithm is applied in order to generate a feature vector for each image in the dataset. Finally, for classification phase, the proposed approach applied Support Vector Machine (SVM) algorithm classification of ripeness stages.

The rest of this chapter is organized as follows. Section 2 introduces a survey about resent research work related to monitoring and classification of maturity stages for fruits/vegetables. Section 3 presents the core concepts of color features, SVM and PCA algorithms. Section 4 describes the different phases of the proposed content-based classification system; namely pre-processing, feature extraction, and classification phases. Section 5 discusses the tested image dataset and presented the obtained experimental results. Finally, Section 6 presents conclusions.

BACKGROUND

This section reviews a survey about current approaches which tackling the ripeness assessment and classification problem of tomatoes and other fruits/vegetables.

(Zhang & McCarthy, 2011)offered tomato maturity evaluation approach using magnetic resonance imaging (MRI). The tomatoes used for this approach were collected from the field at different maturity stages. Firstly, MR images were captured, then for each of the MR images, the mean and histogram features of the voxel intensities in the region of interest (RoI) were calculated. Finally, partial least square discriminant analysis (PLS-DA) was applied using both the calculated features and maturity classes variables in order to deduce a maturity classification model and shows that different maturity stages are embedded in MR images signal intensity.

Also, (Baltazar, Aranda, & Gonzalez-Aguilar, 2008)used total of 128 tomatoes samples that were harvested and preliminarily sorted with colorimeter choosing only those with roughly breaker color, which represents the ripeness stage where there is a definite break in color from green to tannish-yellow. So, they firstly applied data fusion to nondestructive image of fresh intact tomatoes by assessing both of colorimeter and nondestructive firmness measurements for the samples at the selected testing days using two sensors placed at different points. Then, the measurements data were normalized. Finally, a three-class Bayesian classifier was applied and the results showed that multi-sensorial data fusion is better than single sensor data and considerably reduces the classification error.

Moreover, (Polder, Heijden, & Young, 2002) proposed an approach based on spectral images analysis to measure the ripeness of tomatoes for automatic sorting. The proposed approach compared hyper-spectral images with standard RGB images for classification of tomatoes ripeness stages. That depends on individual pixels and includes gray reference in each image for obtaining automatic compensation of different light sources. The proposed approach applied the linear discriminant analysis (LDA) as a classification technique depending on pixels values and proved that spectral images are better than standard RGB images for measuring ripeness stages of tomatoes via offering more discriminating power.

In (Ghazali, Samad, Arshad, & Karim, 2009), an approach for automatic grading of oil palm fruits has been presented. The proposed approach based on image processing. Firstly, samples of oil palm fruits were collected at three different ripeness stages(ripe, under ripe, and over ripe), then RGB images were captured using digital camera. The proposed approach removed background pixels, then R,G and B component were analyzed and mean value for each component was computed. After the analysis step a threshold of red components was set. Finally a neural network application was applied for ripeness checking. this approach gave 100% correct classification for ripe stage, but the under ripe and unripe stages have some errors with 20% and 25% respectively.

Also, (May & Amaran, 2011) offered an automated ripeness assessment approach for oil palm fruit in order to assess oil palm ripeness and overcome the problem of subjectivity and inconsistency of manual human grading techniques based on experience to ensure optimum yield of high quality oil.Depending on color intensity palm fruit can be classified into three ripeness stages(under ripe, ripe and overripe).The proposed approach used RGB with fuzzy logic technique to assess the ripeness. Firstly, image is captured and preprocessed, and then RGB features were extracted. Finally fuzzy logic model was applied for the classification purpose. This approach achieved an efficiency of 88.74%.

On the other hand,(Jaffar, Jaafar, Jamil, Low, & Abdullah, 2009) applied a photogrammetric methodology in order to depict a relationship between the color of the palm oil fruits and their ripeness and sort them out physically depending on this relationship. The proposed methodology works as follow, firstly, image were preprocessed for noise removal. Then image segmentation using K-means clustering with the L*a*b* Color Space was applied to images because palm fruit imagesare fused with dirt and branches, this resulting in a difficulty of using the average color digital number values at RGB color space for evaluating ripeness, so the proposed approach applied, after segmentation step color digital numbers calculations were performed. Then, to differentiate ripe FFB from unripe fruits, the calculated color value to R/G and R/B ratios of the digital number of the segmented images was used. This methodology considered the first automation of palm oil grading system.

(Fadilah, Mohamad-Saleh, Halim, Ibrahim, & Ali, 2012)presented an approach for ripeness classification of oil palm fresh fruit bunch. the proposed approach based on image processing, ANN and PCA techniques. Firstly, FFBs were collected at different ripeness stages, then FFBs were classified into four ripeness (unripe, underripe, ripe and overripe). Then for each FFB, four images were captured at different areas of the bunch, after that, images were segmented into two regions fruits area and spikes. Then color features were extracted for fruits part. Finally, an ANN model was applied using two method. the first one used all features as the input parameters of ANN, whereas the other, Firstly it applied PCA for features reduction, then it used the resulting features as the input parameters of ANN. this approach achieved 91.67% accuracy for the first method and 93.33% for the second one.

Furthermore,(Paulraj, Hema, R. Pranesh, & Siti Sofiah, 2009) designed a neural network with image processing approach for color recognition for the problem of identifying the ripe of banana fruit . The proposed approachbased on RGB color components of banana images. It used four sets of bananas used with different type of sizes and ripeness. Each image of the banana is captured in four different positions and the images are captured daily until all bananas turn to be rotten. The images of banana is captured and resized. Later, the image is extracted into the RGB color components and each pixel of the color component is rescaled using a simple heuristic method. As a result, histograms are obtained and used as the feature vector in determining the ripeness of the banana. Then a supervised Neural Network model with utilizing the error back propagation model was applied as a classification technique. It achieved an identification accuracy of 96%.

Also,(Shah Rizam, Farah Yasmin, Ahmad Ihsan, & Shazana, 2009) designed an artificial neural network with image processing approach for measuring and determining the ripeness and quality of watermelon. the proposed approach depends on watermelon colors in YCbCr Color Space. Firstly, the colour in watermelon images is segmented into three regions. Then from each region watermelon was classified into ripe depending on the amount of pixels at each region. Then CbCr colour feature was extracted. Finally, an ANN model was applied for determining ripeness stages. This approach achieved an accuracy of 86.51%.

(Effendi, Ramli, & Ghani, 2010)presented a back propagation neural network approach for the identification of Jatropha curcas fruit maturity. Firstly, Jatropha curcas fruits were collected at three different maturity stages(raw, ripe and overripe) and images were captured using digital camera. Then, the Jatropha fruits were separated from background and segmented to 100 X 100 Pixels. Then features were extracted by classifying Each pixel of a Jatropha curcas fruit image into one of 256 categories, represented by an integer in the range from 0 (black)-255 (white). Finally, Back propagation neural network approach was applied for the identification process of maturity stages. This approach achieved 95% accuracy.

Also, (Syal, Mehta, & Darshni, 2013) proposed a fruit sorting and grading approach based on image processing techniques and fuzzy logics for. The proposed approach depends on three basic features: RGB color components, shape, and size of the fruit object. Jatropha fruit can be classified into three grades(A, B, C) depending on selected features values. In this approach authors Firstly extracted features using image processing techniques, then a fuzzy system is applied to classify the grade of the fruit (A, B or C). it achieves an very promising and accurate results.

Also, (Dadwal & Banga, 2012) proposed an approach based on color image segmentation and fuzzy logic technique to classify the ripeness stages of Apple fruit. Apple fruit can be classified into three stages ripe, under ripe and overripe stages. The proposed approach depends on RGB color components, where Firstly four images are captured from different directions for each fruit. Then a segmentation approach is applied to these images to get region of interest, Then the mean value for each color component (R, G and B) is calculated for the area of interest. Finally the fuzzy logic system is applied to decide the ripeness stages of apple depending on mean values of Red, Green and Blue color components. This system can be applied at many applications.

Furthermore, (balestani, Moghaddam, motlaq, & Dolaty, 2012) designed an approach based on image processing for cherry sorting and grading. it depend on RGB color components of the captured images of cherry. Cherry samples at four different ripeness stages were collected with an interval of 5 days. The proposed sorting system of cherries used color criteria and the TTS(Total Soluble Solids) in fruit to classify it to the right ripeness stage.The reflected light in image was removed in order to minimize the error rate in calculating the average color components.This system achieved 92% accuracy in sorting cherries according to their ripeness.

Also, (Damiri & Slamet, 2012) proposed an approach based on image processing and Artificial Neural Networks for lime maturity and ripeness identification. Lime samples from three levels of maturity and ripeness were collected and used as dataset for this approach. Theproposed approach depends on area, shape factor, RGB color index and texture features of lime to identify its ripeness stages. These features are sent to ANN using back propagation method as inputs for training to perform the classification. Thisapproach achieved 100% accuracy in classifying the maturity and ripeness of lime.

This chapter presents a multi-class content-based image classification system to automate the ripeness assessment process of tomato via investigating and classifying the different maturity/ripeness stages based on the color features. The datasets used for experiments were constructed based on real sample images for tomato at different stages, which were collected from different farms in Minya city, Upper Egypt. Colors features were computed firstly, and thenPrincipal Component Analysis (PCA) algorithm is applied for features extraction in order to generate a feature vector for each image in the dataset. Then, Support Vector Machine (SVM) algorithms were applied for classification of ripeness stages.

PRELIMINARIES

This section presents a brief idea concerning the core concepts of PCA and SVM algorithms that have been utilized for feature extraction and classification, respectively.

Principal Component Analysis (PCA)

Principal component analysis is a statistical common technique, which is widely used in image recognition and compression for a dimensionality reduction, data representation and features extraction tool as it ensures better classification[(Suganthy & Ramamoorthy, 2012),(Xiao, 2010)(El-Bendary, Zawbaa, Hassanien, & Snasel, 2011),(Ada & RajneetKaur, 2012). It basically reduces the dimensionality by avoiding redundant information, and reducing samples features space to features sub-space (smaller space which contains all independent variables which are needed to describe the data) by discarding all un-effective minor components. So, it's necessary to perform various pre-processing steps in order to utilize the PCA method for feature extraction. Steps of PCA algorithm are shown in algorithm (1).

Color Features

A widely used feature in image retrieval and image classification problems is the color, which is as well an important feature for image representation (El-Bendary, Zawbaa, Hassanien, & Snasel, 2011). In this research two color descriptors will be used; namely color moments and color histogram.

Color Moments

The first three color moments, which are mean, standard deviation, and skewness(Shahbahrami, Borodin, & Juurlink, 2008),(Soman, Ghorpade, Sonone, & Chavan, 2012), have been proved to be efficient and effective way for representing

Algorithm 1. Principal component analysis (PCA) algorithm

Step 1: Calculate the sample mean $\overline{\mu}$

$$\overline{\mu} = \frac{\sum_{i=1}^{n} X_i}{n}$$

Step 2: Subtract sample mean from each observation X_i

$$\overline{Z}_i = X_i - \overline{\mu}$$

Step 3: Calculate the covariance matrix C

$$C = \sum_{i=1}^{n} Z_i . Z_i^t$$

Step 4: Calculate the eigenvectors and eigenvalues of the covariance matrix C
Step 5:Rearrange the eigenvectors and eigenvalues and select a subset as basis vectors
Step 6:Project the data

color distribution in any image. Mean, standard deviation, and skewness for a colored image of size N X M pixels are defined by Equations (1), (2), and (3).

$$\overline{x}_i = \frac{\sum_{j=1}^{M.N} x_{ij}}{M.N} \tag{1}$$

$$\partial_i = \sqrt{\left(\frac{1}{M.N}\sum_{j=1}^{M.N}\left(x_{ij} - \overline{x}_1\right)^2\right)} \tag{2}$$

$$S_i = \sqrt[3]{\left(\frac{1}{M.N}\sum_{j=1}^{M.N}\left(x_{ij} - \overline{x}_1\right)^3\right)} \tag{3}$$

where x_{ij} is the value of image pixel j of color channel i (e.g RGB, HSV and etc..), $\overline{x}_1$. is the mean for each channel i=(H,S and V), ∂_i is the standard deviation and S_i is the skewness for each channel(Shahbahrami, Borodin, & Juurlink, 2008),(Soman, Ghorpade, Sonone, & Chavan, 2012). HSV channels can be computed for RGB channels using Equations (4), (5), and (6), where R, G and B are color component of RGB color space (Singh & Hemachandra, 2012).

$$H = \cos^{-1}\frac{\frac{1}{2}\left[\left(R-G\right)+\left(R-B\right)\right]}{\sqrt{\left(R-G\right)^2+\left(R-B\right)\left(G-B\right)}} \tag{4}$$

$$S = 1 - \frac{3\left[\min\left(R,\ G,\ B\right)\right]}{R+G+B} \tag{5}$$

$$V = \left(\frac{R+G+B}{3}\right) \tag{6}$$

where R, G and B are color component of RGB color space.

Color Histogram

Color histogram is a color descriptor that shows representation of the distribution of colors in an image. It represents the number of pixels that have colors in each range of colors (El-Bendary, Zawbaa, Hassanien, & Snasel, 2011). Color histogram can be calculated for many color spaces (e.g. RGB, HSV, etc). It is often used with 3-dimensional spaces like as RGB and HSV color spaces. color histogram is invariant with rotation, translation, and scale (Meskaldji, Boucherkha, & Chikhi, 2009).

Support Vector Machine

One of the most used algorithms at classification problems is the Support Vector Machine. it is a machine learning algorithm which is applied for classification and regression problem of high dimensional datasets with excellent results. [(Wu & Zhou, 2006),(Zawbaa, El-Bendary, Hassanien, & Abraham, SVM-based Soccer Video Summarization System, 2011),(Zawbaa, El-Bendary, Hassanien, & Kim, Machine Learning-Based Soccer Video Summarization System, 2011)].

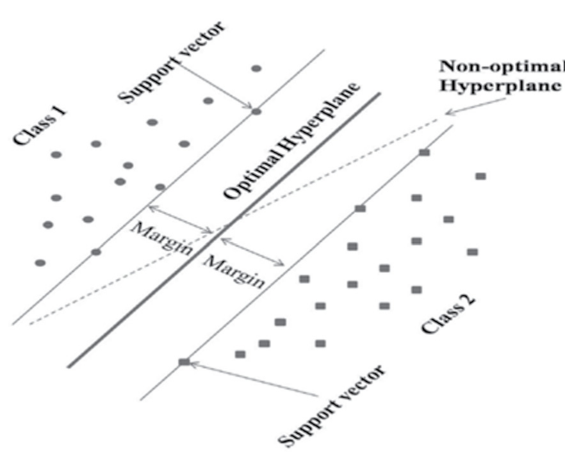
SVM solves the classification problem via trying to find an optimal separating hyperplane between classes. it depends on the training cases which are placed on the edge of class descriptor this is called support vectors, any other cases are discarded as shown at Figure 1[(A. Tzotsos, 2006),(Zhang, Xie, & Cheng, 2010),(Suralkar, Karode, & Pawad, 2012)].Theoretically, for linearly separable data, there is an infinite number of hyperplanes. thesehyperplanes can classify training data correctly, SVM algorithm seeks to maximize the margin around a hyperplane that separates a positive class from a negative class. [(Wu & Zhou, 2006),(Zawbaa, El-Bendary, Hassanien, & Abraham, SVM-based Soccer Video Summarization System, 2011),(Zawbaa, El-Bendary, Hassanien, & Kim, Machine Learning-Based Soccer Video Summarization System, 2011)]. Given a training dataset are represented by { x_i , y_i }, i=1,2,3,....., N, where N is the number of training samples, x_i is a features vector and $y_i \in$ {-1,+1} is the target label, y=+1 for samples belong to class C_1 and y=-1 for samples belong to class C_2 . Classes C_1, C_2 are linearly separable classes. [(Wu & Zhou, 2006),(Zawbaa, El-Bendary, Hassanien, & Abraham, SVM-based Soccer Video Summarization System, 2011),(Zawbaa, El-Bendary, Hassanien, & Kim, Machine Learning-Based Soccer Video Summarization System, 2011)]. Geometrically, the SVM modeling algorithm finds an optimal hyperplane with the maximal margin to separate two classes, which requires to solve the optimization problem, as shown in Equations (7) and (8).

$$\text{maximize}\sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j . K\left(x_i, x_j\right) \quad (7)$$

$$Subject - to : \sum_{i=1}^{n}\alpha_i y_i , 0 \le \alpha_i \le C \quad (8)$$

where, $\pm_i$ is the weight assigned to the training sample x_i . If $\pm_i > 0$, x_i is called a support vector. C is a regulation parameter used to trade-off the training accuracy and the model complexity so that a superior generalization capability can be achieved. K is a kernel function, which is used to measure the similarity between two samples.

Figure 1. SVM procedure



There are many different kernel functions have been applied in the past. Linear, multi-layer perceptron MLP, polynomial and the Gaussian radial basis function (RBF) are the most popular kernel functions[(Boolchandani & Sahula, 2011),(Vanschoenwinkel & Manderick, 2005)].

These kernel functions can be defined by the following Equations(9,10, 11 and 12:

Linear Kernel Function:

$$K\left(X_i,\ X_j\right) = X_i^T X_j \tag{9}$$

RBF Kernel Function:

$$K\left(X_i,\ X_j\right) = e^{\left(-\frac{X_i - X_j^{\,2}}{2\tilde{A}^2}\right)} \tag{10}$$

MLP Kernel Function:

$$K\left(X_i,\ X_j\right) = \tanh\left({}^{2}{}_{0} X_i^T X_j + {}^{2}{}_{1}\right) \tag{11}$$

Polynomial, Order P Kernel Function:

$$K\left(X_i,\ X_j\right) = \left(1 + X_i^T X_j\right)^P \tag{12}$$

N-Class Support Vector Machine

SVM is a binary class classification method and our problem is an N-class classification problem. Therefore, in this article, the SVM algorithm is applied to a multi-class problem [(Liu & Zheng, 2005), (Anthony, Gregg, & Tshilidzi, 2007)] and two different approaches have been applied in order to do that; namely one-against-all (OAA) and one-against-one (OAO) approaches.

The first approach, one-against-all (OAA), worked according to Algorithm (2)

In the second approach, one-against-one (OAO), a SVM classifier was created for each pair of classes (for N-class problem) resulting in $N\left(N-1\right)/2$ classifiers. The OAO approach worked according to Algorithm (3).

THE PROPOSED APPROACH FOR THE AUTOMATED PROCESS OF RIPENESS ASSESSMENT

The proposed approach for the automated process of ripeness assessment for tomato consists of three phases; namely pre-processing, feature extraction, and classification. Figure 2 describes the general structure of the proposed approach.

The datasets used at this research were prepared from real samples for tomato at different stages, which were collected from different farms at Al-Minya city,which is located approximately 245 km (152 mi) south of Cairo on the western bank of the Nile River. Figure 3 shows some farms.

Tomato fruits can be classified into six different ripeness stages as shown at Figure 4. The ripeness stages are green, breaker, turning, pink, light red and red stages.For green stage, green represents the ripeness stage where fruit surface is completely green, For breaker stage, breaker represents the ripeness stage where there is a definite break in color from green to tannish-yellow, pink or red on not more than 10% of the surface. For turning

Algorithm 2. One-against-all (OAA)

Step 1: Construct N binary SVM. Step 2: Each SVM separates one class from the rest classes. Step 3: Train the i^{th} SVM with all training samples of the i^{ti} class with positive labels, and training samples of other classes with negative labels.

Algorithm 3. One-against-one (OAO)

Step 1: Create $N(N-1)/2$ binary SVMs Step 2: Train $N(N-1)/2$ binary SVMs as follow $(1,2),\ (1,3),\ \ldots\ldots\ldots\ldots,\ (1,\ k),\ \ (2,3),\ (2,4),\ldots\ldots.,\ \ (k1,\ k).$

Figure 2. Architecture of the proposed ripeness classification approach

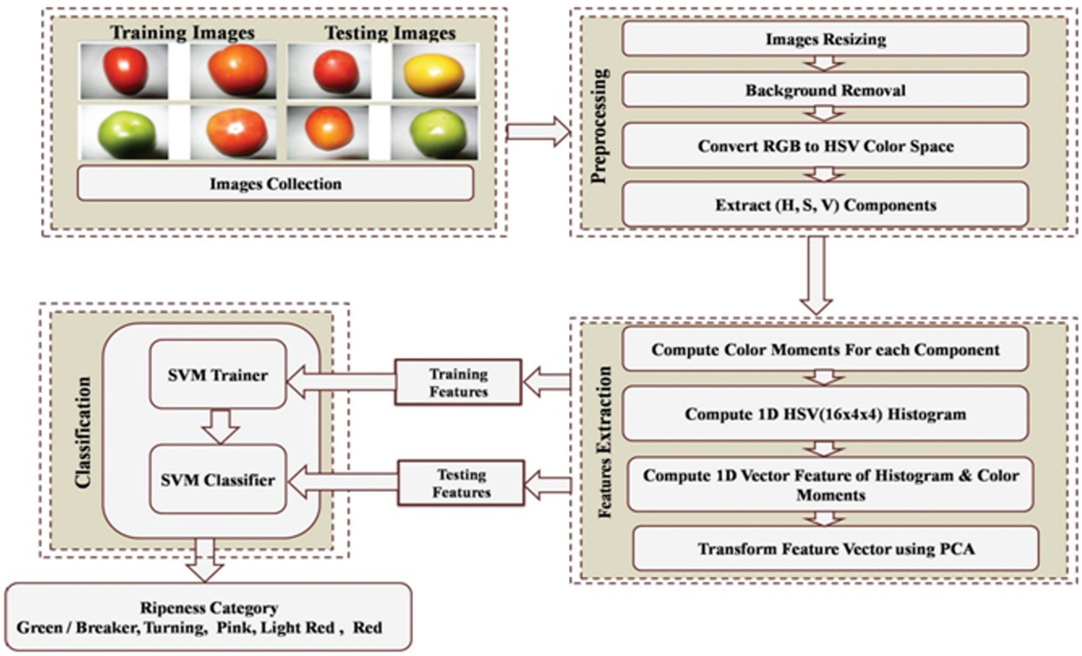
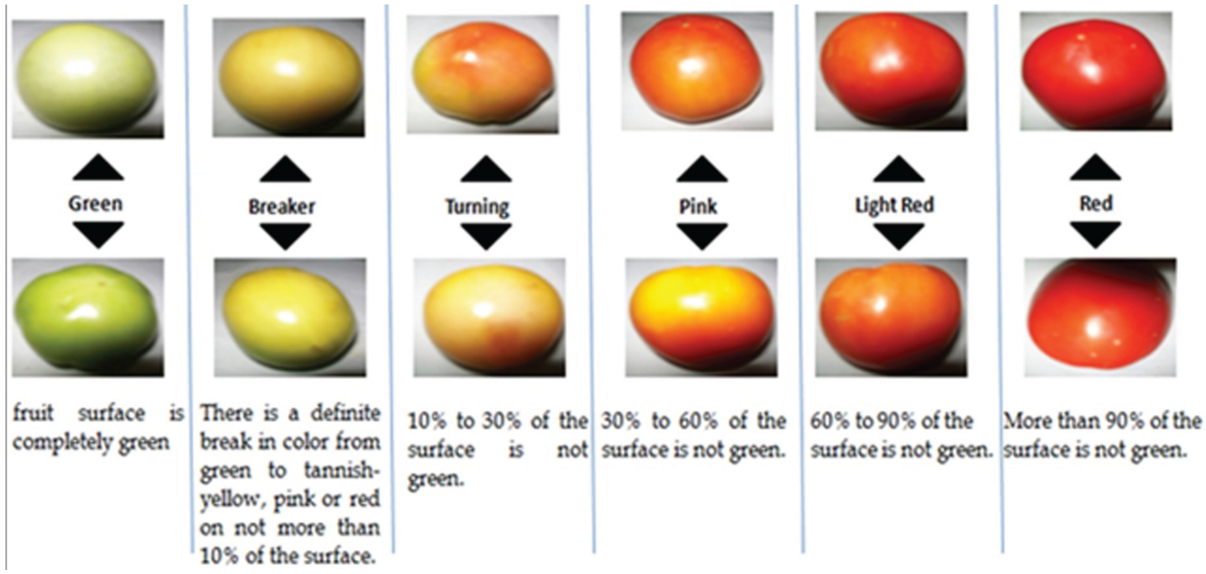


Figure 3. Farms at Al-Minya City

Figure 4. Tomato ripeness stages



stage, 10% to 30% of the surface is not green. For pink stage, 30% to 60% of the surface is not green. For light red stage, 60% to 90% of the surface is not green. Finally, for red stage, more than 90% of the surface is not green(U.S.D.A., 1991).

Pre-Processing Phase

During pre-processing phase, the proposed approach aimed to preprocess each image for the features extraction phase to get only fruit part. The proposed approach resizes images to 250x250 pixels, in order to reduce their color index, and the background of each image is removed using background subtraction technique. Figure 5 show preprocessing procedure flowchart and Figure 6 shows an example of background removal algorithm. Also, each image is converted from RGB to HSV color space, as it is widely used in the field of color vision and close to the categories of human color perception (Yu, Li, Zhang, & Feng, 2002). Then H,S and V components were extracted individually.

Feature Extraction Phase

As previously stated, since tomato surface color is the most important characteristic to asset the ripeness of tomato, this system uses HSV color

Figure 5. Preprocessing procedure

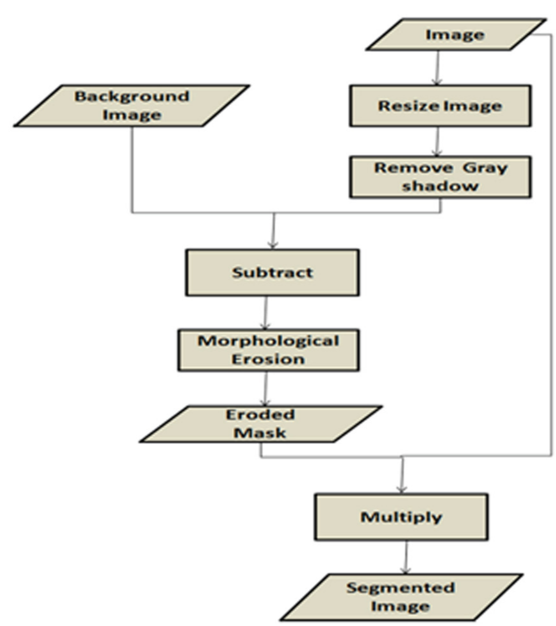
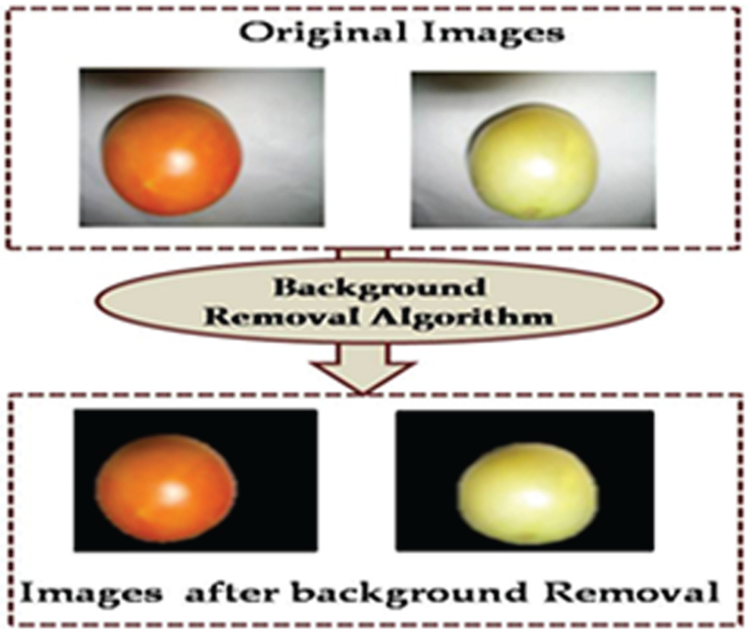


Figure 6. Samples of background removal



histogram and color moments for ripeness stages classification.

For feature extraction phase, PCA algorithm is applied as features extraction technique in order to generate a feature vector for each image in the dataset.

The proposed approach transforms the input space into sub-spaces for dimensionality reduction. After completing the previous 1D 16x4x4 HSV histogram, 16 levels for hue and 4 levels for each of saturation and value are resulted in 1X256 feature vector. In addition, nine color moments, three for each channel (H, S and V channels) (mean, standard deviation, and skewness), were computed. Then, a 1X265 feature vector was formed as a combination of HSV 1D histogram and the nine color moments.

Classification Phase

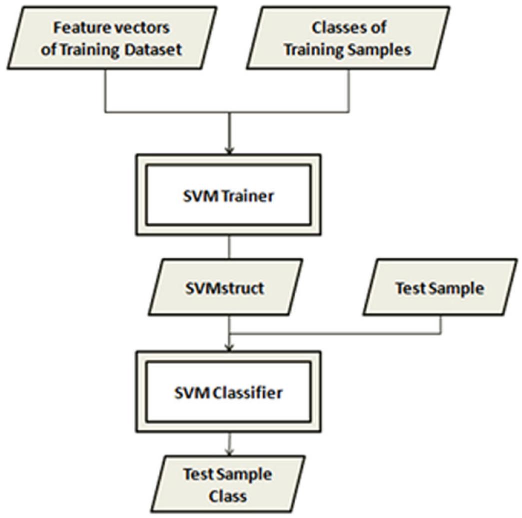
Finally, for classification phase, the proposed approach applied SVM algorithm for classification of ripeness stages. The inputs are training dataset feature vectors and their corresponding classes, whereas the outputs are the ripeness stage of each image in the testing dataset. Figure 7 shows a block diagram of classification procedure.

In this phase, the classification approach, previously proposed in (Elhariri, El-Bendary, Fouad, Plato, Hassanien, & Hussein, 2014), has been utilized along with the one-against-one (OAO) approach with 10-fold cross validation for multi-class SVM problems.

EXPERIMENTAL RESULTS

Simulation experiments in this article are done on a PC with Intel Core i7 Q720 @ 1.60 GHZ CPU and 6GB memory. The proposed approach is designed with Matlab running on Windows 7. The datasets used for experiments were constructed based on real sample images for tomato at different ripeness stages, which were collected from different farms in Minya city. The collected datasets contained colored JPEG images of resolution 3664 X 2748

Figure 7. Block diagram for classification procedure



pixels that were captured using Kodak C1013 digital camera of 10.3 megapixels resolution. The dataset is of total 250 images were used for both training and testing datasets with 10-fold cross-validation. Training dataset is divided into 5 classes representing the different stages of tomato ripeness. The classes are Green & Breaker, Turning, Pink, Light Red, and Red stages.

The proposed approach has been implemented considering two scenarios; namely

- **Scenario 1:** One-against-One multi-class SVM system using10-fold cross validation
- **Scenario 2:** One-against-All multi-class SVM system using10-fold cross validation

Scenario 1: One-Against-One Multi-Class SVM System Using10-Fold Cross Validation

The first scenario presents implementing One-against-One multi-class SVM system using10-fold cross-validation and a total of 250 images for both of training and testing datasets. The used features for classification are a combination of color HSV histogram and color moments and PCA algorithm was applied for features extraction. Moreover, SVM algorithm was employed with different kernel functions that are: Linear kernel, radial basis function (RBF) kernel, and Multi-Layer Perceptron (MLP) kernel and Polynomial kernel for ripeness stage classification. Figure 8 shows classification accuracy obtained via applying each kernel function.

Figures 9 to 16 show 5-class receiver operating characteristic (ROC) curve and area under curve (AUC) for the first two best features resulting from different kernel functions using one-against one multi-class SVM approach with 10-fold cross-validation and total of 250 images (used for both of training and testing). The ROC curve separates each class from other classes.

Figure 9, showing the ROC curve for the best feature using linear kernel function for OAO multi class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 1.

Figure 10, showing the ROC curve for the second best feature using linear kernel function for OAO multi class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 2.

Figure 11, showing ROC curve for the best feature using MLP kernel function for OAO

Figure 8. Results for different kernel functions using one-against-one multi-class approach and 10-fold cross-validation

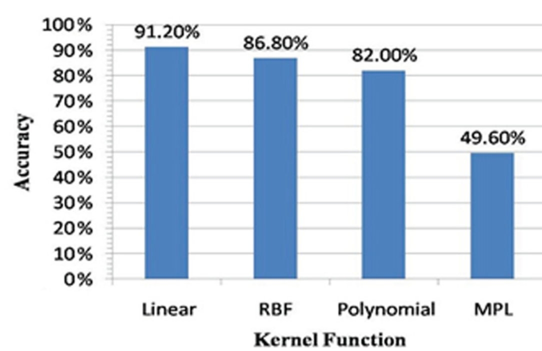


Figure 9. Curve for the best feature using linear kernel function (OAO multi-class SVM with cross-validation), AUC=0.8340

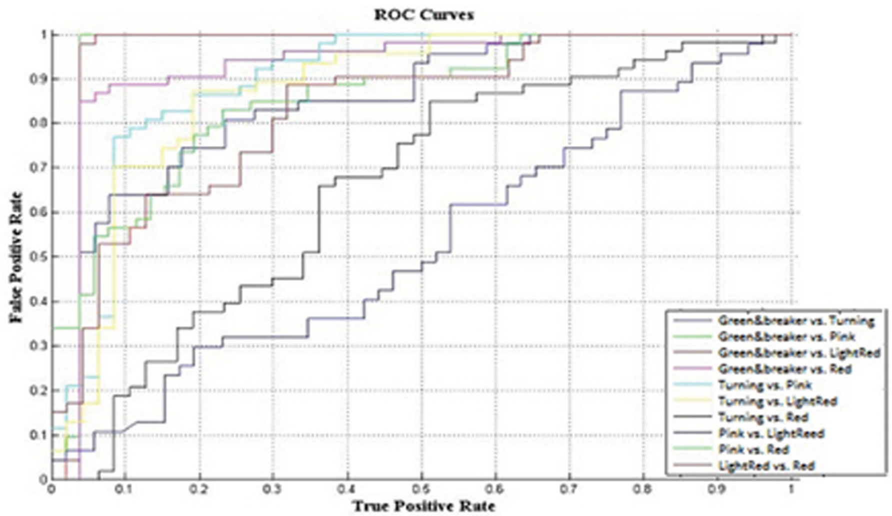


Table 1. AUCs of OAO multiclass-SVM using Linear kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8469	0.9627	0.9612	0.9264
Turning	0.8469	-	0.8969	0.9612	0.9264
Pink	0.9627	0.8969	-	0.5264	0.8592
Light Red	0.9612	0.9612	0.5264	-	0.8298
Red	0.9264	0.9264	0.8592	0.8298	-

Figure 10. Curve for the second best feature using linear kernel function (OAO multi-class SVM with cross-validation), AUC=0.8233

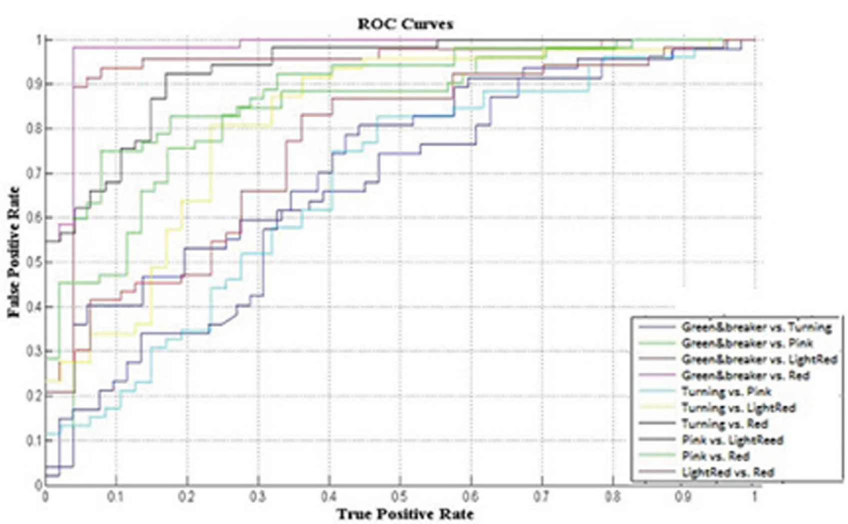
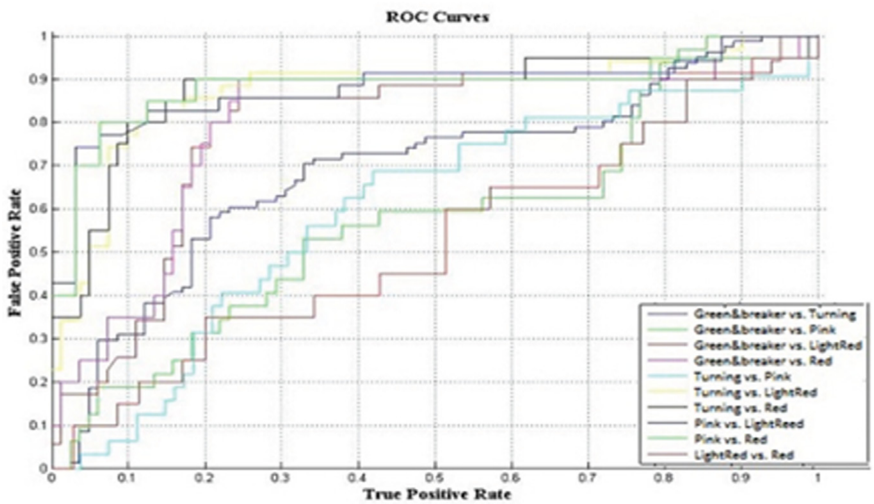


Table 2. AUCs of OAO multiclass-SVM using Linear kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.7050	0.8650	0.9424	0.9785
Turning	0.7050	-	0.6759	0.8180	0.9322
Pink	0.8650	0.6759	-	0.6901	0.8639
Light Red	0.9424	0.8180	0.6901	-	0.7615
Red	0.9785	0.9322	0.8639	0.7615	-

Figure 11. Curve for the best feature using MLP kernel function (OAO multi-class SVM with cross-validation), AUC=0.7484



multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 3.

Figure 12, showing ROC curve for the second best feature using MLP kernel function for OAO multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 4.

Figure 13, showing ROC curve for the best feature using RBF kernel function for OAO multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 5.

From Figure 14, showing ROC curve for the second best feature using RBF kernel function for OAO multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 6.

Figure 15, showing ROC curve for the best feature using Polynomial kernel function for OAO multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 7.

Figure 16, showing ROC curve for the second best feature using Polynomial kernel function for OAO multi-class SVM with cross-validation, the

Table 3. AUCs of OAO multiclass-SVM using MLP kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.6923	0.5774	0.7834	0.7976
Turning	0.6923	-	0.6015	0.8737	0.8741
Pink	0.5774	0.6015	-	0.8799	0.8797
Light Red	0.7834	0.8737	0.8799	-	0.5243
Red	0.7976	0.8741	0.8797	0.5243	-

Figure 12. Curve for the second best feature using MLP kernel function (OAO multi-class SVM with cross-validation), AUC=0.7263

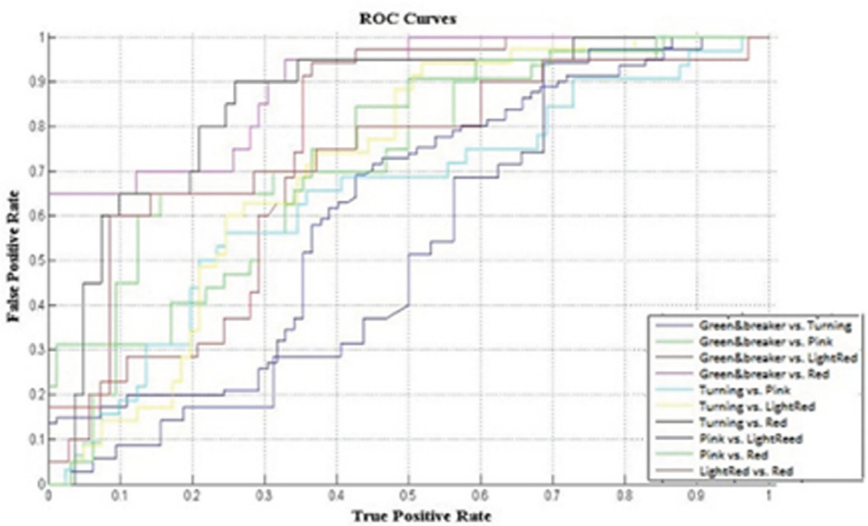


Table 4. AUCs of OAO multiclass-SVM using MLP kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.6188	0.7355	0.7549	0.8957
Turning	0.6188	-	0.6431	0.7122	0.8543
Pink	0.7355	0.6431	-	0.5201	0.7469
Light Red	0.7549	0.7122	0.5201	-	0.7543
Red	0.8957	0.8543	0.7469	0.7543	-

Figure 13. ROC curve for the best feature using RBF kernel function (OAO multi-class SVM with cross-validation), AUC=0.8313

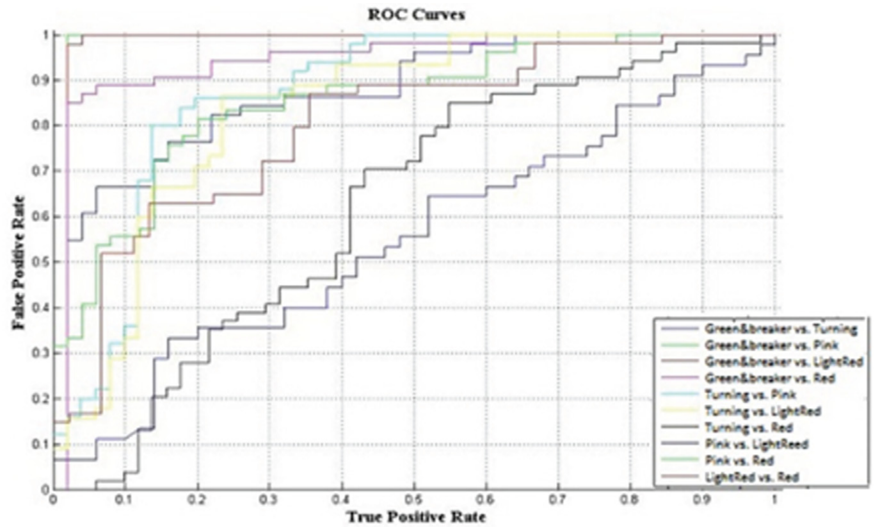


Table 5. AUCs of OAO multiclass-SVM using RBF kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8729	0.9800	0.9796	0.9456
Turning	0.8729	-	0.8678	0.8375	0.6220
Pink	0.9800	0.8678	-	0.5509	0.8552
Light Red	0.9796	0.8375	0.5509	-	0.8012
Red	0.9456	0.6220	0.8552	0.8012	-

applied approach separated each class from each one of the rest classes by AUCs shown at Table 8.

Scenario II: One-Against-All Multi-Class SVM System Using 10-Fold Cross Validation

In the second scenario, the proposed One-against-All multi-class SVM approach was also tested using the previously stated specifications of One-against-One multi-class SVM approach for ripeness stages classification. Figure 17 shows classification accuracy obtained via applying each kernel function.

Figures from 18 to 25 show 5-class receiver operating characteristic (ROC) curve and area under curve (AUC) for the first two best feature for different kernel function using one-against-all multi-class SVM approach with 10-fold cross-validation and total of 250 images (used for both of training and testing).

Figure 18, showing ROC curve for the best feature using linear kernel function for OAA multi class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 9.

Figure 19, showing ROC curve for the second best feature using linear kernel function for OAA multi class SVM with cross-validation, the applied

Figure 14. ROC curve for the second best feature using RBF kernel function (OAO multi-class SVM with cross-validation), AUC=0.8197

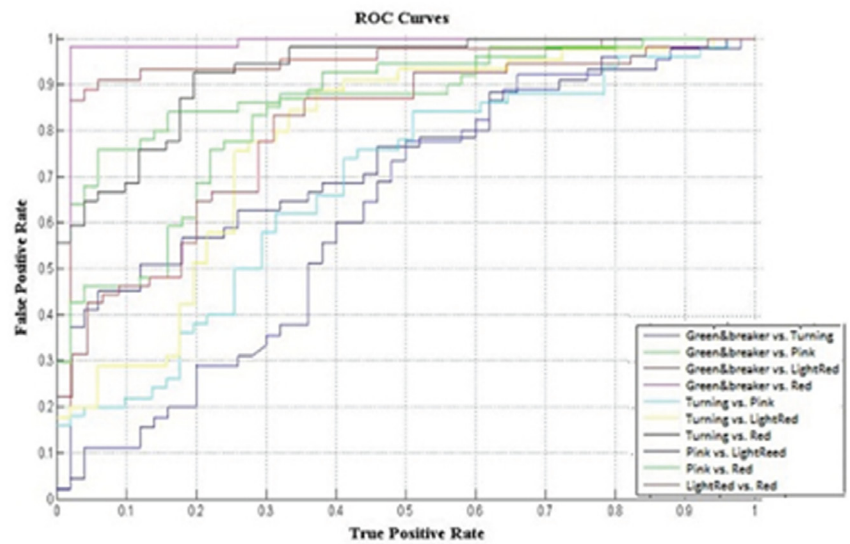


Table 6. AUCs of OAO multiclass-SVM using RBF kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.7373	0.8840	0.9467	0.9867
Turning	0.7373	-	0.6808	0.7782	0.9274
Pink	0.8840	0.6808	-	0.6131	0.8422
Light Red	0.9467	0.7782	0.6131	-	0.8008
Red	0.9867	0.9274	0.8422	0.8008	-

Figure 15. ROC curve for the best feature using Polynomial kernel function (OAO multi- class SVM with cross-validation), AUC=0.8223

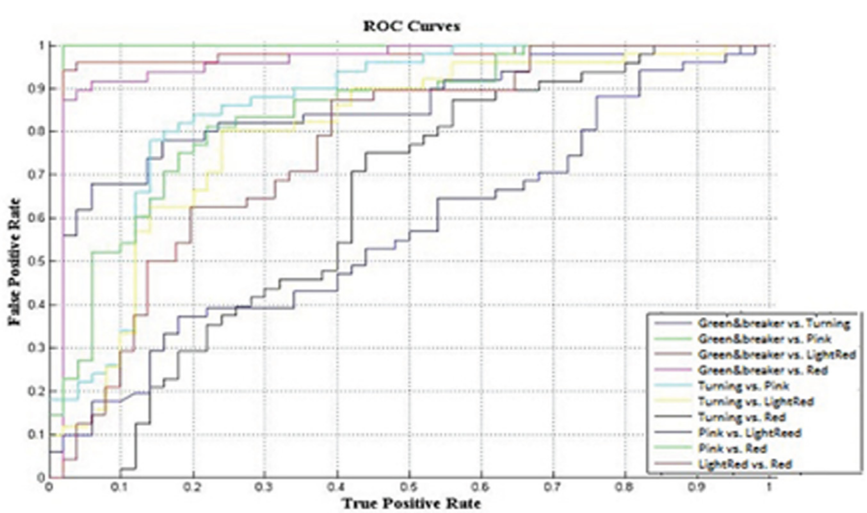


Table 7. AUCs of OAO multiclass-SVM using Polynomial kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8510	0.9804	0.9635	0.9567
Turning	0.8510	-	0.8580	0.8000	0.6338
Pink	0.9804	0.8580	-	0.5724	0.8438
Light Red	0.9635	0.8000	0.5724	-	0.7635
Red	0.9567	0.6338	0.8438	0.7635	-

Figure 16. ROC curve for the second best feature using Polynomial kernel function (OAO multi- class SVM with cross-validation), AUC=0.8205

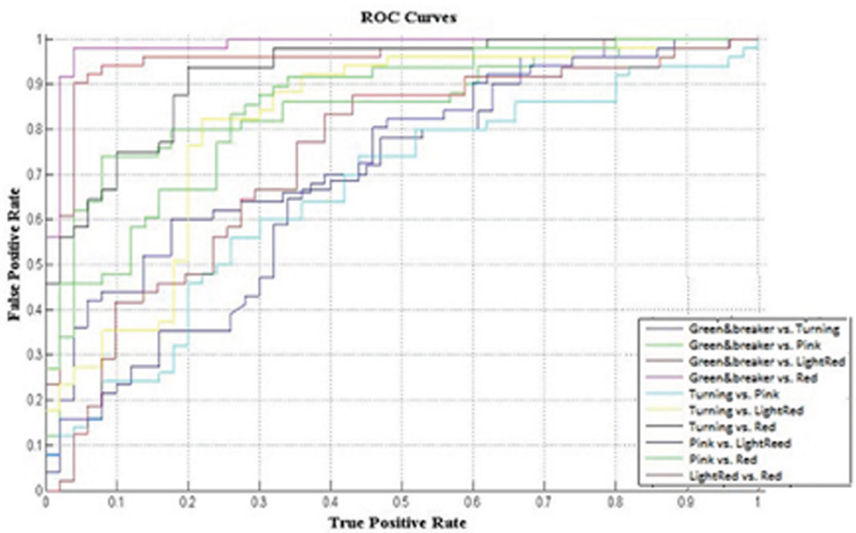
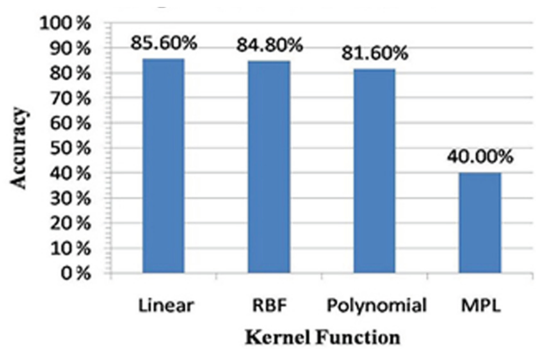


Table 8. AUCs of OAO multiclass-SVM using Polynomial kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.7451	0.8502	0.9512	0.9853
Turning	0.7451	-	0.6616	0.8157	0.9225
Pink	0.8502	0.6616	-	0.6845	0.8508
Light Red	0.9512	0.8157	0.6845	-	0.7377
Red	0.9853	0.9225	0.8508	0.7377	-

Figure 17. Results for different kernel functions using one-against-all multi-class approach and 10-fold cross-validation



approach separated each class from each one of the rest classes by AUCs shown at Table 10.

Figure 20, showing ROC curve for the best feature using MLP kernel function for OAA multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 11.

Figure 21, showing ROC curve for the second best feature using MLP kernel function for OAA multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 12.

Figure 18. ROC curve for the best feature using linear kernel function(OAA multi-class SVM with cross-validation), AUC=0.8233

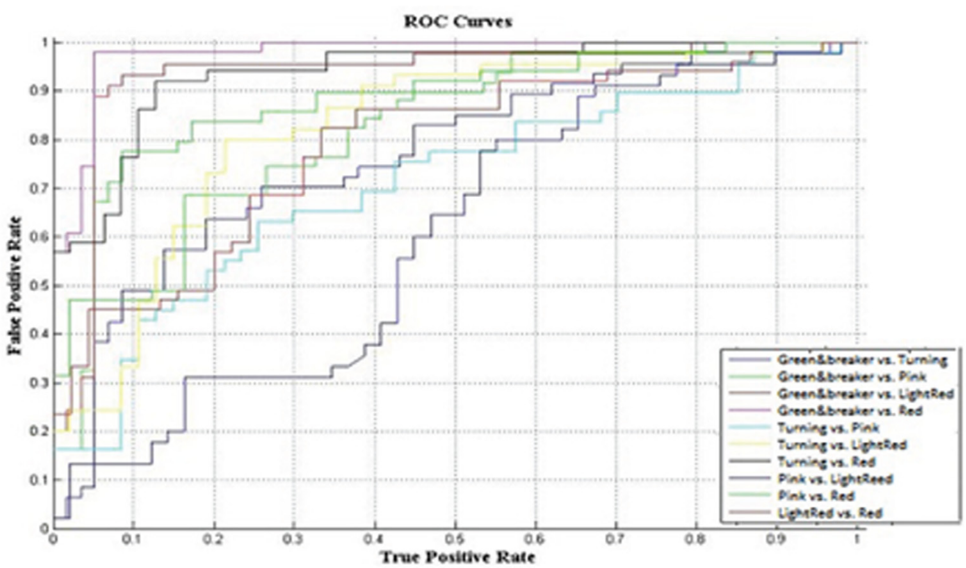


Table 9. AUCs of OAA multiclass-SVM using linear kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.7663	0.8776	0.9330	0.9773
Turning	0.7663	-	0.7086	0.8217	0.9378
Pink	0.8776	0.7086	-	0.5998	0.8247
Light Red	0.9330	0.8217	0.5998	-	0.7856
Red	0.9773	0.9378	0.8247	0.7856	-

Figure 19. ROC curve for the second best feature using linear kernel function(OAA multi-class SVM with cross-validation), AUC=0.7882

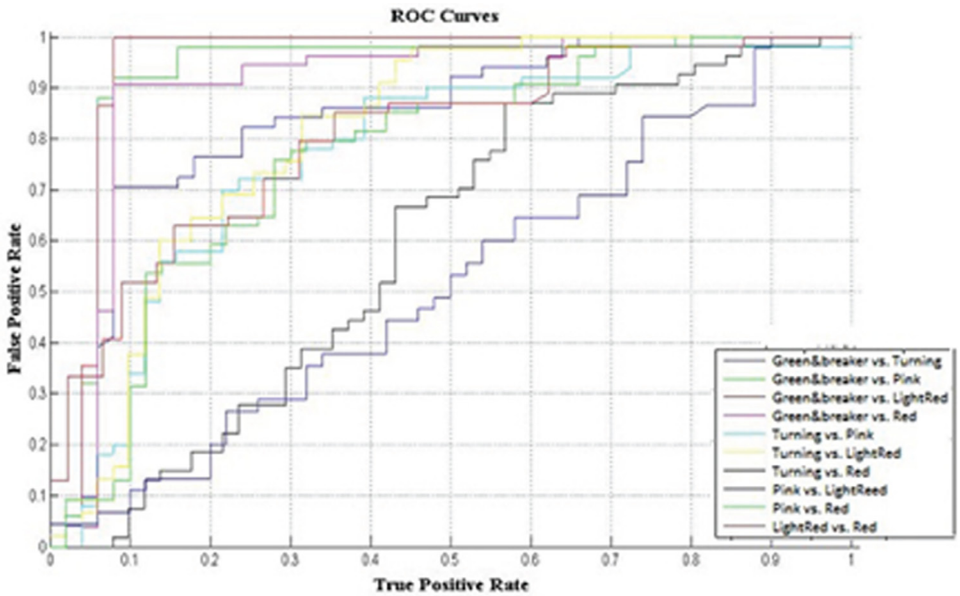


Table 10. AUCs of OAA multiclass-SVM using linear kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8402	0.9264	0.9453	0.9022
Turning	0.8402	-	0.7727	0.8105	0.5951
Pink	0.9264	0.7727	-	0.5176	0.7678
Light Red	0.9453	0.8105	0.5176	-	0.8043
Red	0.9022	0.5951	0.7678	0.8043	-

Figure 22, showing ROC curve for the best feature using RBF kernel function for OAA multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 13.

Figure 23, showing ROC curve for the second best feature using RBF kernel function for OAA multi-class SVM with cross-validation, the applied approach separated each class from each one of the rest classes by AUCs shown at Table 14.

Figure 24, showing ROC curve for the best feature using Polynomialkernel function for OAA multi-class SVM with cross-validation, the appliedapproach separated each class from each one of the rest classes by AUCs shown at Table 15.

Figure 25, showing ROC curve for the second best feature using Polynomial kernel function for OAA multi-class SVM with cross-validation, the appliedapproach separated each class from each one of the rest classes by AUCs shown at Table 16.

From the previously depicted experimental results, we found out that the One-against-One multi-class SVM approach is better than the One-against- All multi-class SVM approach, when applied for ripeness stage classification.

Figure 20. ROC curve for the best feature using MLP kernel function (OAA multi-class SVM with cross-validation), AUC=0.7390

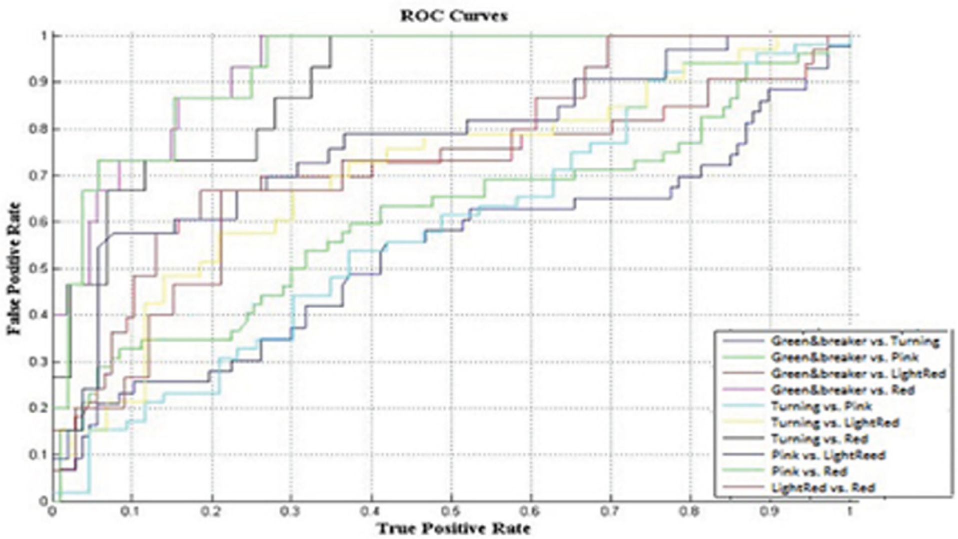


Table 11. AUCs of OAA multiclass-SVM using MLP kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.5310	0.6094	0.7133	0.9302
Turning	0.5310	-	0.5814	0.7047	0.8930
Pink	0.6094	0.5814	-	0.7713	0.9282
Light Red	0.7133	0.7047	0.7713	-	0.7273
Red	0.9302	0.8930	0.9282	0.7273	-

Figure 21. ROC curve for the second best feature using MLP kernel function (OAA multi-class SVM with cross-validation), AUC=0.7827

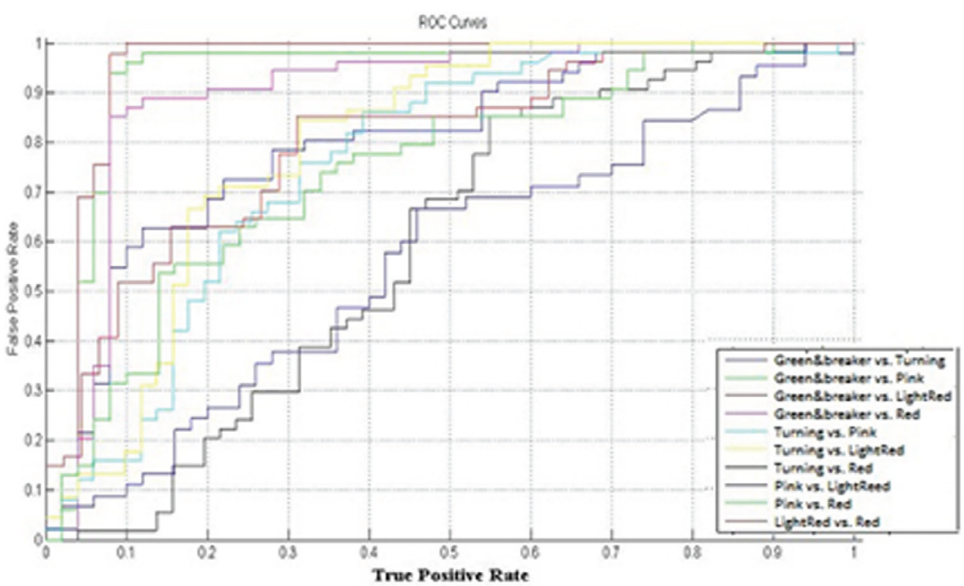


Table 12. AUCs of OAA multiclass-SVM using MLP kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.7961	0.9300	0.9498	0.8967
Turning	0.7961	-	0.7575	0.7969	0.5904
Pink	0.9300	0.7575	-	0.5656	0.7437
Light Red	0.9498	0.7969	0.5656	-	0.8004
Red	0.8967	0.5904	0.7437	0.8004	-

Figure 22. ROC curve for the best feature using RBF kernel function(OAA multi-class SVM with cross-validation), AUC=0.8355

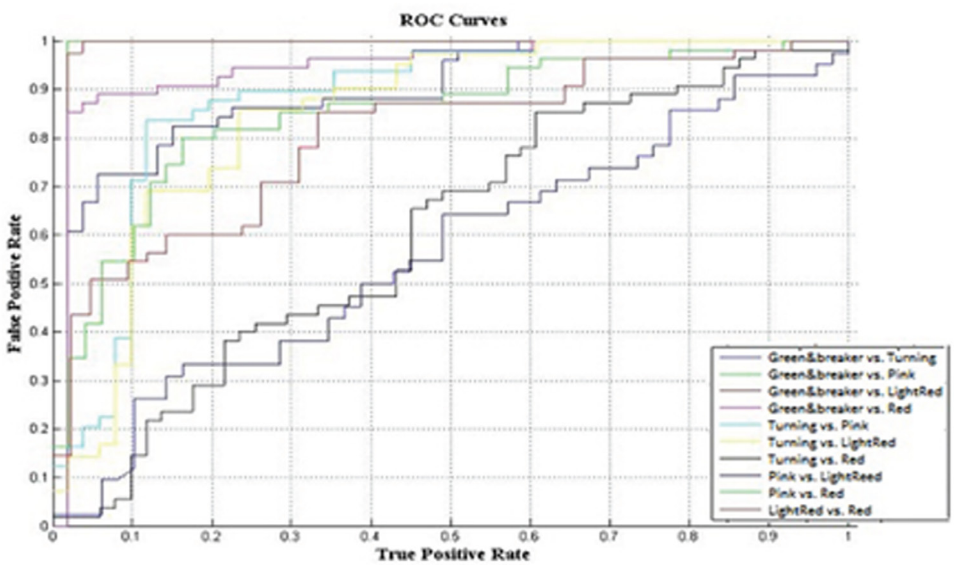


Table 13. AUCs of OAA multiclass-SVM using RBF kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8942	0.9811	0.9807	0.9468
Turning	0.8942	-	0.8796	0.8487	0.6068
Pink	0.9811	0.8796	-	0.5624	0.8505
Light Red	0.9807	0.8487	0.5624	-	0.8043
Red	0.9468	0.6068	0.8505	0.8043	-

Figure 23. ROC curve for the second best feature using RBF kernel function(OAA multi-class SVM with cross-validation), AUC=0.7917

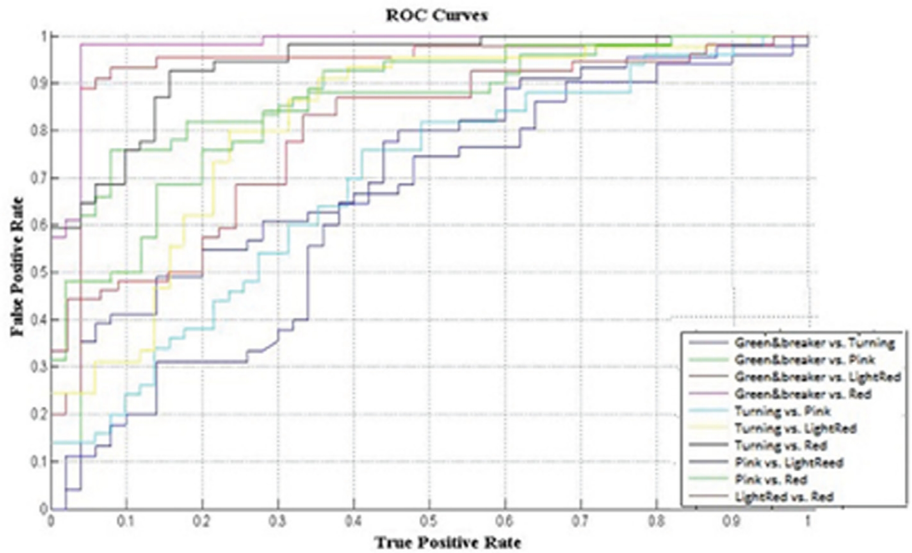


Table 14. AUCs of OAA multiclass-SVM using RBF kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8388	0.9472	0.9609	0.9252
Turning	0.8388	-	0.7982	0.8074	0.5846
Pink	0.9472	0.7982	-	0.5118	0.7641
Light Red	0.9609	0.8074	0.5118	-	0.7790
Red	0.9252	0.5846	0.7641	0.7790	-

Figure 24. ROC curve for the best feature using Polynomial kernel function (OAA multi-class SVM with Cross-validation), AUC=0.8136

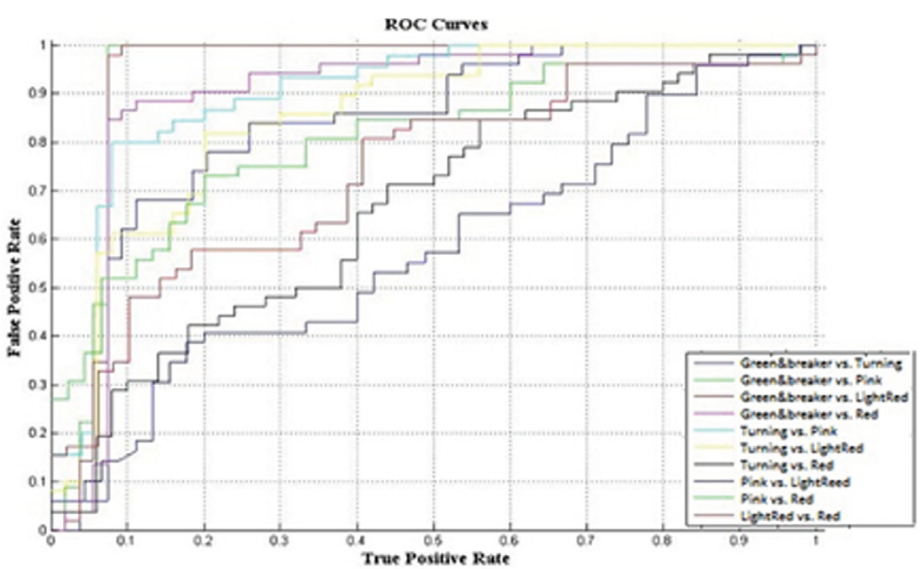


Table 15. AUCs of OAA multiclass-SVM using Polynomial kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.8285	0.9403	0.9350	0.8957
Turning	0.8285	-	0.8996	0.8518	0.6627
Pink	0.9403	0.8996	-	0.5785	0.8056
Light Red	0.9350	0.8518	0.5785	-	0.7382
Red	0.8957	0.6627	0.8056	0.7382	-

Figure 26 shows a comparison between accuracies obtained by each of the two approaches.

The accuracy measure is calculated as shown in Equation (9).

$$\text{Accuracy} = \frac{\text{number of correctly classified images}}{\text{total number of testing images}}$$

FUTURE RESEARCH DIRECTIONS

There are many problem related to this topic. These problems suggest a variety of research directions. One such direction would be to use this system for other crops or apply it to different applications. another direction is to utilize this system for the whole automation process of harvest. Another direction is to work at the trend of crops diseases and develop automated system for diseases detection and classification.

CONCLUSION

In this chapter, a system for classifying the ripeness stages of tomato has been developed. The proposed system has three main stages; pre-processing, feature extraction and ripeness classification. The proposed classification approach was implemented by applying resizing, background removal,

Figure 25. ROC curve for the second best feature using Polynomial kernel function(OAA multi-class SVM with cross-validation), AUC=0.7937

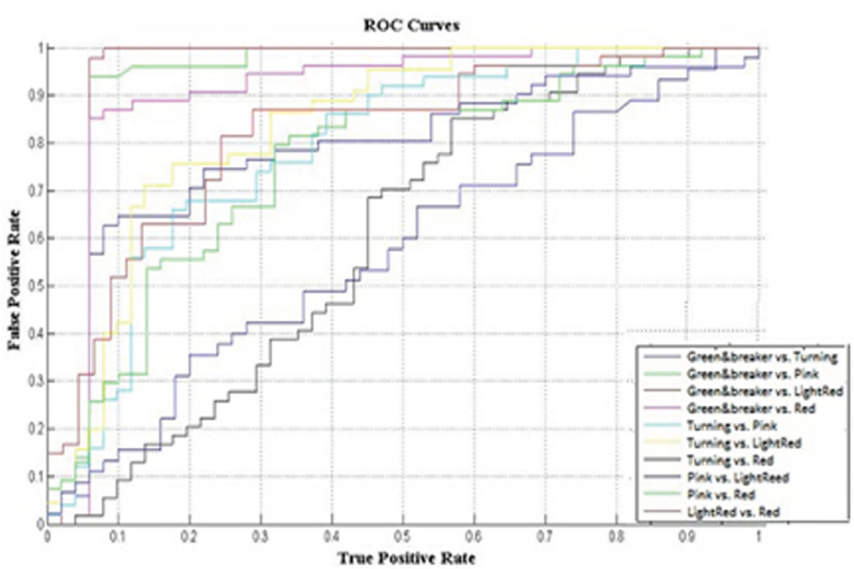
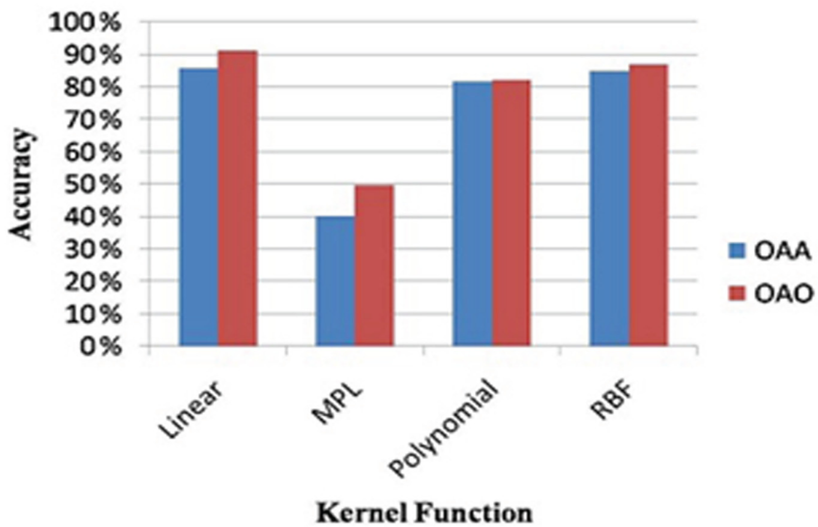


Table 16. AUCs of OAA multiclass-SVM using Polynomial kernel functions & 10-fold cross validation

	Green & Breaker	Turning	Pink	Light Red	Red
Green & Breaker	-	0.7835	0.9338	0.9440	0.9030
Turning	0.7835	-	0.7878	0.8362	0.5984
Pink	0.9338	0.7878	-	0.5758	0.7559
Light Red	0.9440	0.8362	0.5758	-	0.8189
Red	0.9030	0.5984	0.7559	0.8189	-

Figure 26. Comparison between the classification accuracy of OAA and OAO multi-class SVM approaches



and extracting color components for each image. Then, feature extraction was applied to each pre-processed image, HSV histogram and color moments are obtained as a feature vector, and used as a PCA inputs for transformation.

Finally, SVM model is developed for ripeness stage classification. The proposed approach has been implemented considering two scenarios via applying One-against-One multi-class SVM system using10-fold cross-validation and One-against-All multi-class SVM system using10-fold cross-validation. Based on the obtained the experimental results, the highest ripeness classification accuracies of 91.20% and 85.60% have been achieved by the first scenario and the second scenarios, respectively, using linear kernel function. Thus, it can be concluded that the ripeness classification accuracy obtained by the OAO multi-class SVM approach is better than ripeness classification accuracy obtained by the OAA multi-class SVM approach.

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KEY TERMS AND DEFINITIONS

Climacteric Fruits: Fruits which can continue ripening after being picked from the mother plant.

Image Classification: The process of analyzing the properties of images features then organizing these images into categories/classes in according to its visual content.

Non-Climacteric Fruits: Fruits which can ripen only when it is attached to the mother plant.

Principal Component Analysis (PCA): PCA is a statistical technique, widely used in recognition, compression for dimensionality reduction, data representation and features extraction.

Ripeness: Ripeness is a process that causes fruits to become more palatable. Simply, a fruit becomes sweeter, less green, and softer as it ripens.

Ripeness Assessment: The process of determining and evaluating ripeness stage of fruits.

Support Vector Machine (SVM): SVM is one of the most used machine learning algorithms for classification and regression problems.