Fruit-Based Tomato Grading System Using Features Fusion and Support Vector Machine

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Abstract. Machine learning and computer vision techniques have applied for evaluating food quality as well as crops grading. In this paper, a new classification system has been proposed to classify infected/uninfected tomato fruits according to its external surface. The system is based on feature fusion method with color and texture features. Color moments, GLCM, and Wavelets energy and entropy have been used in the proposed system. Principle Component Analysis (PCA) technique has been used to reduce the feature vector obtained after fusion to avoid dimensionality problem and save time and cost. Support vector machine (SVM) was used to classify tomato images into 2 classes; infected/uninfected using Min-Max and Z-Score normalization methods. The dataset used in this research contains 177 tomato fruits each was captured from four faces (Top, Side1, Side2, and End). Using 70% of the total images for training phase and 30% for testing, our proposed system achieved accuracy 92%.

Keywords: food quality, feature fusion, Color moments, GLCM, Wavelets, Tomato, PCA, SVM.

1 Introduction

The need of intelligent systems that serve the industry is increasing every day. Vegetables, fruits and crops sorting isone of the most important biological processes in crops production. This process is still done manually in most countries, including Egypt. According to (FAOSTAT Database, 2011)[1], tomato is the 8th most important vegetable crop next to wheat. World production was about 159 million tons fresh fruit produced in 2011 with income about 582 trillion Dollars. Tomato production has been reported for 144 countries. Egypt is the 5^{th} major country after China, India, United States and Turkey in both income of harvested production $(2,995,413\$1000)$and weight of fruit produced (8,105,263 Mt) [1]. Computer-based fruit sorting has great attention by Computer Vision and AI researchers [2–7]. Although the great importance of Tomato production

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as mentioned before, there are very few works in the literatures concerns with tomato grading especially with diseases detection. The great concern with quality control due to new market restrictions in recent years has become so important that it has demanded a technology of process geared toward more reliable tests and new methods of monitoring product quality [4]. The aim of this work is to help in grading systems before manufacturing or to be a basic block in computer vision based expert systems.

The objective of this study is to propose an automatic tomato grading system dedicated for Egyptian tomato most disorders. It's known that most crops disorders appear in the plant root, stem, leaves and fruits according to the type and causes of injury. In this paper, only fruit images are used for detection purpose. Twelve different disorders have been captured. The image acquisition procedure we have used to collect the dataset, insures the examination of whole fruit surface. The rest of the paper is organized as follows. Section (2) presents the proposed fruit-based tomato grading system in details. System results are presented in section (3). Finally, Section (4) concludes the paper.

2 The Proposed Grading System

This work has been divided into three basic stages. Dataset preparation, Features Extraction and Classification which will be discussed in details in this section. The dataset used by the proposed system has been collected randomly from fresh vegetables and fruits market in Menofia city, Egypt. Exactly, 177 samples out of 200 collected ones have been included in this study. As there were 13 samples have been eliminated due to transportation damages and 10 have been excluded due to their immaturity. The samples varied between un-defected and defected ones.

First, the stem green part in each sample has been removed. Each sample has been cleaned. A special studio has been prepared for imaging purpose. The studio was constructed from a white box, CCD camera (Sony DCR-SR46 with 40x optical zoom) and a Day-Light florescent lamp (Toshiba FL2019 D/19 Daylight). The camera has been set in a perpendicular angle with the box on the same surface plan. The light has been set in the same angle and distance of the camera. The resolution of the captured photos is 640×480. All photos are decoded by JPEG standard coding technique. Most of the previous works assume imaging the injured face directly. For best defect detection results, the fruits have been imaged from 4 sides (Top, End, Side1 and Side2) to cover the whole fruit surface.

2.1 Dataset Preparation Phase

In this stage of work, segmentation has been made using ground truth. The white background has been replaced by completely white color ($r = 255, g = 255, b = 255$) using Photoshop image editing tool. The dataset images has been annotated by three experts to define the type of defect based on the visual symptoms appeared on the fruit only. Table (1) shows the number of samples for each disorder. The collected disorders varied between physiological, fungal and insects effect diseases. There are some samples faced different reasons to be defected. In this stage of our system, we care about automatic classification between defected and un-defected fruit whatever the type of defect. After the samples being ready for processing, features have been extracted.

Table 1. Summary of collected dataset

defect	**no. samples**
radial cracks	13
concentric cracks	1
blossom end rot	11
early blight	28
anthracnose	15
sun scald	37
worms	6
mite spider	14
blotchy ripeness	10
normal	27
tomato spots	8
yellow shoulders	7
total	177

2.2 Feature Extraction Phase

Preprocessing Stage. Preceding feature extraction procedure, white background has been detected and neglected to calculate the features of the fruit part only using Algorithm(1):

Algorithm 1. Background Removal Algorithm

1: Given RGB Image Img of Tomato and White Mask $Mask$ both of size 640×480
2: Convert RGB image to GrayScale one $GrayImg$
3: Calculate the difference $Diff$ between Img and $GrayImg$
4: Perform morphological opening on $Diff$
5: Perform holes filling on $Diff$
6: Perform morphological erosion by 5×5 structure element on $Diff$
7: Multiply Img by $Diff$
8: Output is segmented RGB Image of size 640×480

Color Features. One of the most well used features is the color information in the image. Color information can be retrieved either from intensity channel, chromaticity channels or both. Many researchers prefer using intensity information to recognize wither the fruit is defected or not. Color models play very important role in features extraction when the target is to extract the chrominance information. Many color models can be used for this purpose like RGB, YCbCr, HSV, and YIQetc. Color features include statistical features like as mean, variance, and standard deviation and color moments. First, the images have been converted to HSV color model. Four moments have been calculated for the fruit part in 7 channels; $Intensity(I)$, $Red(R)$, $Green(G)$, $Blue(B)$, $Hue(H)$, $Saturation(S)$ and $Value(V)$. So, a total of 28 statistical features has been extracted for each face. Color moments(Mean, Variance, Skewness and Kurtosis) have been calculated by the equations (2-5):

$$\bar{X} = \frac{\sum_{k=1}^{N} P_k}{N} \tag{1}$$

$$Variance = \frac{1}{N} \sum_{k=1}^{N} (P_k - \bar{X})^2 \tag{2}$$

$$Skewness = \frac{\frac{1}{N} \sum_{k=1}^{N} (P_k - \bar{X})^3}{\sigma^3} \tag{3}$$

$$Kurtosis = \frac{\frac{1}{N} \sum_{k=1}^{N} (P_k - \bar{X})^4}{\sigma^4} \tag{4}$$

Where p is a pixel in the fruit part in the image, and N is the total number of pixels in the fruit part.

Texture Features. Texture features have been used for defect recognition purpose in many works in literature. One of the most well-known methods to get texture features is the Gray Level Co-occurrence Matrix (GLCM).In this method, the relative frequencies of gray level pairs of pixels separated by a distance d in the direction θ combined to form a relative displacement vector (d, θ), which is computed and stored in a matrix referred to as gray level co-occurrence matrix (GLCM). This matrix is used to extract second-order statistical texture features. Haralick in [11] suggests 14 features describing the two-dimensional probability density function P. Nine of the most popular commonly used are ASM (Energy/Angular Second Moment), Con (Contrast), Cor(Correlation), Ent (Entropy), Var (Variance), Sent (Sum of Entropy), Shd (Cluster Shade), Prom (Prominance) and Hom (Homoginity). The features from (6-12) have been selected from[12], while features (13 -14) have been selected from[9]and [13]respectively:

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (P_{ij})^2 \tag{5}$$

$$Con = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-j)^2 P_{ij} \tag{6}$$

$$Cor = \frac{1}{\sigma_x \sigma_y} \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} [(ij)P_{ij} - \mu_x \mu_y] \tag{7}$$

$$Ent = -\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P_{ij} log P_{ij} \tag{8}$$

$$Var = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-\pi)^2 P_{ij} \tag{9}$$

$$Hom = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{(i-j)^2} P_{ij} \tag{10}$$

$$Sent = -\sum_{i=2}^{2G-2} P_{x+y}(i) log P_{x+y}(i) \tag{11}$$

$$Shd = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i+j-\mu_x-\mu_y)^3 P_{ij} \tag{12}$$

$$Prom = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i+j-\mu_x-\mu)^4 P_{ij} \tag{13}$$

Where μ_x, μ_y, σ_x, and σ_y are the means and the standard deviations of the corresponding distributions; and G is the number of gray levels. The GLCM features are obtained based on distance d=1 and angles $\theta = \{0^o, 45^o, 90^o, 135^o\}$, leading to a total of 36 GLCM features per face. Two other texture features was extracted in our proposed system; the entropy and the energy of wavelets decomposition coefficients of the image [14]. The entropy gives a positive criterion for analyzing and comparing probability distribution. It provides a measure of the information of any distribution. We define the total Wavelets Entropy (WPy) as:

$$WPy = WPy(P) = -\sum_{j<0} P_j \cdot ln P_j \tag{14}$$

Where resolution level$j = 1, \ldots, D$. Wavelet energy appears as a measure of the degree of order/disorder of the signal, so it can provide useful information about the underlying dynamical process associated with the signal[14]. The energy of wavelet coefficient is varying over different scales. To calculate the energy of wavelets sub-bands, consider the four sub-bands of decomposition LL, LH, HL and HH. The Wavelet Energy (WGy) for D decomposition levels are extracted using the equation:

$$WGy_j = \sum_k \frac{|C_j(k)|^2}{N_k} \tag{15}$$

Where j is the decomposition level, $C(k)$ is the coefficient at subband k and N_k is the number of coefficients in subband k. The energy at each sampled time k will be:

$$E(k) = \sum_{j=1}^{D} \frac{|C_j(k)|^2}{N_k} \tag{16}$$

In consequence, the total energy can be obtained by using the following equation:

$$WGy = \sum_{j} E_j \tag{17}$$

Feature Fusion. Fusion in feature level may improve the performance of the systems. Fusion of features achieved through concatenating two or more different feature vectors into one vector. Assume $f_1 = x_1 \ldots .x_r$, $f_2 = y_1, \ldots ,y_s$, and $f_3 = z_1, \ldots ,z_t$ are three feature vectors with three different sizes r, s, and t respectively. $f_{new} = x_1, \ldots, x_r, y_1, \ldots, y_s, z_1, \ldots, z_t$, can represent the concatenation of the three feature vectors f_1, f_2 and f_3[20]. One of the problems of combining features is the compatibility of different features. Thus, normalization techniques are used to solve this problem before concatenation [16]. In our experiments we used Z_{score}. It is the most common method. This method maps the input scores to distribution with mean of zero and standard deviation of 1 as follows:

$$\acute{f_i} = \frac{f_i - \mu_i}{\sigma_i} \tag{18}$$

Where f_i is the i^{th} feature vector, μ_i and σ_i are the mean and standard deviation of the i^{th} vector, respectively, $\acute{f_i}$ is the i^{th} normalized feature vector. Another normalization technique used is Min-Max normalization. It is the simplest normalization technique. This method maps the input scores to the [0,1] range as follows:

$$\acute{f_i} = \frac{f_i - min}{max - min} \tag{19}$$

Where f_i, $i = 1, 2, 3, \ldots, n$ represents the set of matching scores,$\acute{f_i}$, $i = 1, 2, 3, \ldots, n$ represents the set of normalized matching scores, max represents maximum score value, and min is the minimum score value. This method is not robust because min and max values are sensitive to outliers. The fusion of all features is occurred through concatenate the normalized feature vectors as:

$$f_{new} = [\acute{f_1}\acute{f_2}\acute{f_3}] = [x_1, \ldots, x_{p1}, \ldots, y_1, \ldots, y_{p2}, z_1, \ldots, z_{p3}] \tag{20}$$

Where f_{new} is the combined feature with (r+s+t dimension) [17]. Concatenation results increased the dimension of the feature, and leads to high computation time and storage. Thus, dimensionality reduction technique such as PCA (Principal Component Analysis) is used to reduce a largest set of features. PCA is the most commonly used techniques in feature reduction techniques [18]. PCA is a linear subspace method used to transform the data into another space that reduce the dimension. In our experiment we used PCA to select the effective features from GLCM, Color moment, and wavelet features as follows:

$$f_{PCA} = [f_1, \ldots, f_p], p < (r + s + t) \tag{21}$$

2.3 Classification Phase

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 problems of high dimensional datasets with excellent results [19]. SVM tries to evaluate a linear hyperplane between two classes. Theoretically, for linearly separable data, there is an infinite number of hyperplanes. These hyperplanes can classify training data correctly, but SVM seeks to find out the optimal hyperplane separating 2-classes [20]. Given a training dataset are represented by $\{x_i, y_i\}$, i=1,2,..., 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. Geometrically, the SVM modeling algorithm finds an optimal hyperplane with the maximal margin to separate two classes, which requires solving the optimization problem, as shown in equations:

$$\begin{gathered} maximize \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j . K(x_i, x_j) \\ \text{subject to:} \sum_{i=1}^{n} \alpha_i y_i, 0 \leq \alpha_i \leq C \end{gathered} \tag{22}$$

where α_i is the weight assigned to the training sample x_i. If $\alpha_i > 0$, 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. There are many different kernel functions have been applied in the past. Linear, multi-layer perception MLP, polynomial and the Gaussian radial basis function (RBF) are the most popular kernel functions [20].

3 Experimental Results

The system has been implemented on a 4GB RAM, Intel Core i5-2400 CPU 3.5 GHz PC using Matlab R2012b release. New feature vector after combining GLCM, Color, and texture features has been classified with SVM classifier. In our experiment, we have tested SVM with 4 kernels; Linear, Quadratic, RBF and MLP using two normalization methods; Min-Max and Z-Score. Using, 70% of samples have been used for training and 30% for testing; the maximum accuracy obtained by the system is 92%.

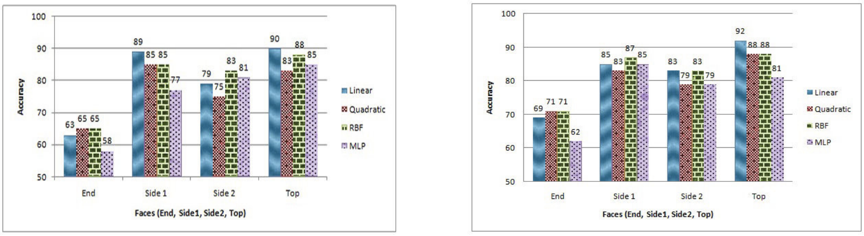
Tables (2-3) present the accuracy results of testing 30% of samples with Min-Max and Z-Score normalization methods respectively. Figure (1a and 1b) show

Table 2. Accuracy using different classifiers (training size (70%)) - using Min-Max score normalization

	End	**Side1**	**Side2**	**Top**
Linear	63%	89%	79%	90%
Quadratic	65%	85%	75%	83%
RBF	65%	85%	83%	88%
MLP	58%	77%	81%	85%

Table 3. Accuracy using different classifiers (training size (70%)) - using Z_{score} score normalization

	End	**Side1**	**Side2**	**Top**
Linear	69%	85%	83%	92%
Quadratic	71%	83%	79%	88%
RBF	71%	87%	83%	88%
MLP	62%	85%	79%	81%



(a) Using Min-Max normalization (b) Using Z_{score} normalization

Fig. 1. Accuracy using different classifiers (training size (70%))

the graph of these results. As shown in Tables (2-3) and Figure (1) we observe that SVM using Linear kernel archived best accuracy in case of Top and Side1 sides images. While RBF kernel achieved the best accuracy when using End and Side2 sides. On the other hand, MLP and Quadratic kernels achieved results that are relatively lower than the other two kernels (Linear and RBF) as well as Linear and RBF kernels in SVM classifier achieved better results than using the other two kernels (MLP and Qaudratic). Also, Z_{score} normalization achieved accuracy better than using Min-Max normalization. Finally, using SVM with Linear and RBF kernels and Z_{score} normalization achieved the best results and detection accuracy reached 92%.

4 Conclusion

In this paper, we have proposed a system for grading tomato fruits based on surface defects. The system has three main phases; preprocessing, feature extraction and fusion, and classification. Color moments for both RGB and HSV channels have been used for color information while GLCM statistics and Wavelets textures features have been fused for texture features in Intensity level. An evaluation of using Linear, Quadratic, RPF and MLP kernels for SVM has measured after using PCA for features dimensionality reduction. Z_{score} and Min-Max normalization methods were compared with 70% training and 30% testing samples. Linear and RBF kernels with Z_{score} normalization achieved the best results. Our system succeeded to detect the defected tomatoes and achieve suitable accuracy reached 92%.

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