A STUDY ON COLOR SORTING OF TOMATOES MATURITY USING MACHINE VISION AND ARTIFICIAL NEURAL NETWORKS

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Abstract

Tomatoes are commercial commodies that play a major role in Egyptian economy. They are considered one of the major vegetable crops in Egypt because of its nutritional, consumption, processing and export value. They may be harvested at different maturity stages and each maturity stage has its characteristics of quality. On the other hand, acceptance of tomato for eating depends on many factors such as variety, texture, maturity, size, shape etc. In this study, a simple machine vision system was developed for sorting three maturity classes of tomatoes grown in Egypt. For the sorting analysis, three color features L*,a* and b* were extracted from each tomatoes class images. Nine different color features are calculated from the three color features. An artificial neural network classifier with Backpropagation method was tested. The input layer consists of twelve color features, the hidden layer consists of twelve nodes and the output layer consists of three nodes representing three tomatoes classes (green, pink and red). The best sorting accuracies in testing data set are 100%, 92.9% and 100% for green, pink and red classes, respectively. The overall sorting accuracy is 97.9%. Finally, based on the obtained results, a tomato sorting machine can be designed to categorize 3 colors of tomatoes decreasing human labor and to reducing sorting time.

INTRODUCTION

Tomato is one of the most widely grown vegetable crops, highly popular due to its high nutritive value, taste and versatile use. It is a good source of vitamins (A and C) and minerals (Hobson and Davies; 1971, Kalloo, 1991). In Egypt, tomato is widely grown in different areas with different varieties. It is grown in four main periods during year with total production of 9.2 million ton (FAO, 2008). Stages of tomato maturity are classified as mature green: fruits are mature and entirely light to dark green, breaker: yellow or pink color appearance first but not more than 10%, turning: yellow or pink color is between 10 to 30%, pink: pink or red color ranges between 30 to 60% and red: red color is more than 60% but less than 90% (Yamaguchi, 1983). Sorting of tomatoes is accomplished based on appearance, texture, shape and sizes. Manual sorting is based on traditional visual quality inspection performed by human operators, which is tedious, time-consuming, slow and non-consistent (Raji and Alamutu, 2005). In absence of tomatoes defects, the surface color of tomatoes is considered as important factor to assess the quality of tomatoes after harvesting (Bittner and Norris 1968; Thai *et. al.;* 1990, Thai and Shewfelt, 1991, and Tijskens, 1994). Color of tomatoes is one of the main attribute for selecting them for eating. However, some people prefer tomatoes pink, light red or red maturity stages. They are never select tomato in mature-green for eating. In the field, the traditional job of sorting tomatoes is done based on its color manually and this method is not rapid, economic nor consistent.

Egypt has very successful and lucrative stations for sorting and packing fruits and vegetables for local consumption and export. Manual sorting in fruits and vegetables industry continues to be the most prevalent method used (El-Sheikha *et. al.,* 2012a and 2012b). Problems inherent in this system include high labor costs, worker fatigue, inconsistency, variability, and scarcity of trained labor. The paucity of available labor and increasing employment costs during the peak harvesting seasons have been identified as the important factors driving the demand for automation of the industry (Jarimopas and Jaisin, 2008). On the other hand, with recent advances in computer technology, modern food and fruits and vegetables manufacturers have turned their attention to machine-vision inspection systems. The advantages of computer vision include precise descriptive data generation, quick and objective, reduction of human involvement, consistency, efficiency and cost effectiveness, automation, non-destructive sample handling, easiness, robustness, permanent record, and allowing further analysis later (Thottam, *et. al.,* 2001, and Brosnan and Sun, 2002). Also, neural network-based computer color vision is good inspection systems for tomatoes (De Grano and Pabico, 2007).

Shibata *et. al.* (1996) developed a method for evaluating tomato ripeness, utilizing its surface color using a machine vision system with color image processing capability and a multi layered neural network-based software system. The tomato ripeness was classified into four categories, unripe, half ripe, full ripe and over ripe according to the standard commercial classification for manual sorting. The total processing time from the image capturing to the final output for a single fruit was 0.45 second. The recognition rate for the ripeness classification using this method was as high as 93 %.

Polder *et. al.* (2002) studied a spectral image analysis technique for measuring ripeness of tomatoes. Spectral images of five ripeness stages of tomatoes were recorded and analyzed. Linear discriminant analysis was used for analyzing the preprocessed images. Results showed that spectral images offered more discriminating power than standard RGB images for measuring ripeness stages of tomatoes.

Nagata *et. al.* (2004) used CIE, L*,a* and b* color model to classify tomato maturities and the average classification success rates of 60.0 % was obtained using linear discriminant analysis and they reported that this model was better than RGB model in classification tomatoes maturity. The evaluation of the maturity stages of the tested tomatoes was based on skin color.

Iraji and Tosinia (2011) proposed an efficient and accurate method for tomatoes sorting. They extracted features from tomato images. Accurate and appropriate decision on classification tomatoes using adaptive fuzzy neural network method was tested. The results showed that the proposed system had less error and the system worked more accurate and appropriative than prior methods.

Fojlaley *et. al.* (2012) developed an automatic control of analysing tomato quality based on using three different techniques. Images were captured by a digital camera and then denoising and contrast improvement operations were performed on them. The extracted features include: degree of redness and yellowness, greenness degree, first moment, second moment, third moment, average of these three moments, roundness value and surface area. The obtained features were given to three different classifiers and the final results were compared and evaluated. The results suggested that support vector machines had a better performance compared to two alternative methods (learning vector quantization and artificial neural network classifiers).

Rokunuzzaman and Jayasuriya (2013) developed a low cost machine vision system for sorting tomatoes. The system utilized webcams and image processing algorithms for defect detection and sorting of tomatoes. Two methods, rule based and neural network approaches, were developed for decision based sorting. The overall accuracy of defect detection attained by the rule based approach and the neural network method were 84 and 87.5%, respectively.

Ukirade (2014) designed a system to perform classification of tomato maturity based on color. Image processing techniques including image acquisition, image enhancement and feature extraction were implemented in the system. To improve image quality, the collected images were converted to color space format (HSV). A Backpropagation neural network used Matlab software and its image processing toolbox used in the analysis. The result of this work indicated that the proposed method can process, analyze and recognize the tomato based on color features.

The recent study aims to build a simple low costs and maturity purposes machine vision system for capture images of tomatoes for sorting purposes. The sorting process is based on color surface and maturity stages of tomatoes. Artificial neural networks classifier is applied.

MATERIALS AND METHODS

Tomatoe samples

The experiments of this study were conducted at Department of Agricultural and Biosgntens Engineering, Faculty of Agriculture, Alexandria University, Egypt. One variety of tomatoes (Baladi variety) was harvested manually from open filed at Educo, El- Beheira Governorate. Three maturity stages of these tomatoes were harvested by inspection them by their color. These maturity stages were green, pink and red. Different samples of each maturity were harvested and they were transferred to the laboratory for analysis. In laboratory, the samples were washed with tape water and labeled with number.

Machine vision system

Tomatoe samples were illuminated by four lighting 26 W fluorescent lamps as light source (lumen = 1250 +/-20%). All lamps (13 cm long) were situated 15 cm above the tomatoes sample and at an angle of 90º with the sample. A color digital camera, model BenQ DCL1020 with 10.0 Mega Pixels was located vertically over the background at a distance of 30 cm. The angle between the camera lens and the lighting source axis was approximately 90°. The camera was fixed on the top of the lighting chamber (dimensions of lighting chamber are 30×30×30 cm constructed from wood) as shown in Fig. 1.

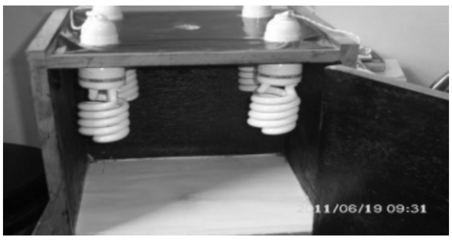

Fig. 1. Simple vision system.

Samples images were taken on a white background and manual mode, no zoom, no flash were used by the camera. Images are stored in JPEG format. The camera was connected to the USB port of a PC (Pentium 4, Intel, 2.8 GHZ, 512MB RAM, 60 GB hard disk) provided with a control software version 1.0.1 of Windows for image acquisition by BenQ to visualize and acquire the digitalized images directly from the computer. Measurements of surface color were made at four positions on the surface of each tomato. Average data for the four positions were used in the analysis.

Color features

Hunter Lab system is one type of measuring color systems. It has proven valuable in describing visual color deterioration and providing useful information for quality control in various fruits and vegetables. The color parameters are expressed as L (lightness), a (redness/greenness) and b (yellowness/blueness). The Hunter "L" value represents the lightness or darkness of a sample on a scale of 0 to 100 (100 being white and 0 being black). Hunter "a" value represents the greenness or redness of the sample (-50 being green and +50 being red). Hunter "b" value is also rated on a scale of -50 to +50, with -50 representing blue and +50 representing yellow. The color was analyzed quantitatively using Photoshop software (Adobe Systems, 2002).

The Histogram Window of the Photoshop was used to determine the color distributions along the x-axis and y-axis (Fig. 2). In Fig. 3, the Histogram Window displays the statistics (mean, standard deviation, median, percentage, and so on) of the color value L. The Histogram Window can also display the statistics for two other color values (a and b), which is done by selecting a and b under the Channel drop-down menu. Hence, the mean color of tomatoes samples can be obtained easily using the Histogram Window. The Lightness, a and b in the Histogram Window are not standard color values. However, they can be converted to L*, a* and b* values using the following formulas (Yam and Papadakis, 2004):

$$L^* = \frac{Lightness}{255} \times 100 \quad (1)$$

$$a^* = \frac{240a}{255} - 120 \quad (2)$$

$$b^* = \frac{240b}{255} - 120 \quad (3)$$

Also, *L*, a* and b** scales could be normalized between 0 and 1 to facilitate comparison. The normalized values are obtained using the following equations (Papadakis *et. al.,* 2000):

$$Normalized\,L^* = \frac{L^*}{100} \quad (4)$$

$$Normalized\;a^* = \frac{a^*+120}{240} \quad (5)$$

$$Normalized\;b^* = \frac{b^*+120}{240} \quad (6)$$

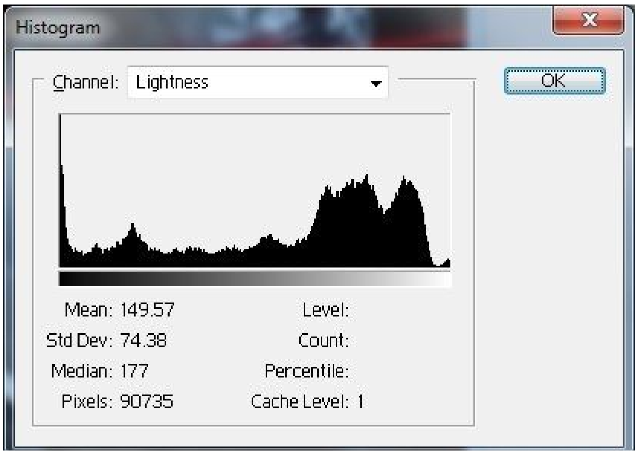

Fig. 2. Histogram Window of Photoshop software.

Another different color features could be calculated according to the following equations (López Camelo and Gómez, 2004):

- Hue= $H°= \tan^{-1} (b^*/a^*)^2$ .... (7)

When $a^* < 0$, $H°= 180+ \tan^{-1} (b^*/a^*)$.. (8)

Hue or true color is the angle between the color vector and the a+ axis,

- Chroma= $(a^{*2} + b^{*2})^{0.5}$ .... (9)

Chroma (purity or saturation) is the distance between the color locus and the mid-point.

- Color index = $(2000 \, x \, a^*)/(L^* \, x \, (a^{*2}+b^{*2})^{0.5})$ (López Camelo *et. al.,* 1995) .... (10)
- Ratio I= a^*/b^* .... (11)
- Ratio II = $(a^*/b^*)^2$ .... (12)
- Color difference with true red (DE) = $[(L^*-50)^2 + (a^*-60)^2 +b^{*2}]^{0.5}$ .... (13)

The maximum and minimum values of the used color features in the developed artificial neural network classifier in training set are shown in Table (1).

Development of artificial neural network (ANN) classifier

ANN consists of simple processing elements or 'neurons' linked with each other in a particular configuration. The basic working mechanism of a neuron is shown in Fig. 3, where the neuron receives a series of inputs, each carrying a specific synaptic weight. The result is filtered by an activation function that generates an output signal with certain intensity, which serves as the stimulus for the next neuron (Haykin, 1999). 'Training' of the network consists of the adjustment of the weight coefficients of input neuron signals.

Table 1. The maximum and minimum values of the input features in artificial neural network classifiers in training set.

Color features	Minimum value	Maximum value
Mean L*	28.41	51.80
Mean a*	-19.20	78.79
Mean b*	-7.24	34.25
Hue (°)	2.27	123.48
Chroma	13.23	80.33
Color index	-28.97	59.29
Ratio I	-1.53	5.03
Ratio II	0.00	25.26
Normalized mean a* (Na*)	0.42	0.83
Normalized mean b* (Nb*)	0.47	0.64
Normalized mean L*(NL*)	0.28	0.52
Color difference with true red (DE)	29.75	86.11

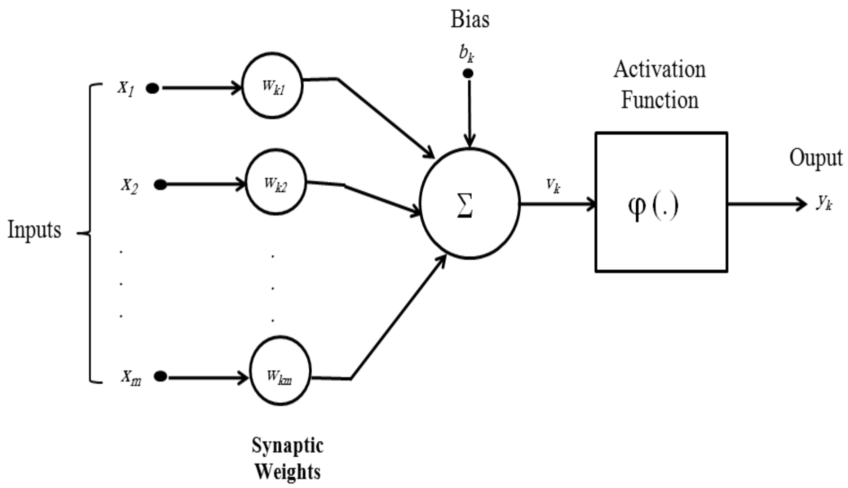

Fig. 3. A single neuron model (Haykin, 1999).

There are many types of ANN structures and training algorithm. In many network types, a feed forward neural network with back propagation algorithm is used in agricultural applications such as the study conducted by (Ghamari *et. al.,* 2010). The basis of feed forward neural network with back propagation algorithm is that the signals coming from the previous layer are processed and then the output is transmitted to the next layer (Ozbek and Fidan, 2009).

Feed forward multilayer perceptron model with Backpropagation learning rule which is based on supervised learning was used. The output vectors (maturity classes) are represented by using the numbers 0 and 1. The value 1 indicates whether the feature data set is the member of that class. Moreover, if the value of the column is 1, the feature data set is the member of the class. If the value of the column vector is 0, it indicates that the feature data set is not the member of the class.

In order to design ANN classifier, commercial Neural Network software of QNET 2000 for WINDOWS (Vesta Services, 2000) was used. The ANN classifier used in this study was a standard Backpropagation neural network with three layers: an input layer, a hidden layer and an output layer. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function which associates input vectors with specific output vectors.

The color features and corresponding tomatoes maturity stages were randomized and divided randomly into two data sets: a training data set and a test data set. The training data set was 80% and test set was 20% according to (Aycheh, 2008). The 80% makes 190 observations and 20% makes 47 observations.

Before training, a certain pre-processing steps on the network inputs and targets to make more efficient neural network training was performed. The range of input and targets values was from 0 to 1, i.e., normalizing the inputs and target values according to:

$$X_{norm} = (X - X_{min})/(X_{max} - X_{min}) \quad \text{.........} \quad (14)$$

The inputs to the ANN classifier in this study were 12 color features. The outputs of the ANN classifier were the tomato maturity classes. The randomized data were used in training. The test points provide an independent measure of how well the network can be expected to perform on data not used to train it. Take 190 of the data for the training and 47 points for the test set. Various layers ANN structures were investigated, including different number of neurons in the hidden layer, different values of the learning coefficient, different values of the momentum and different transfer functions. Training a given neural network was achieved. Its performance was evaluated using the selected testing points. The best ANN structure and optimum values of network parameters were obtained on the basis of the lowest error on training set by trial and error.

The training data set was used to develop the classification model, while the test data set was used to evaluate performance of the classifier. The training data set consisted of 190 patterns (73 for green maturity, 62 for pink maturity and 55 for red maturity), and the test data set consisted of 47 patterns (18 for green maturity, 14 for pink maturity and 15 for red maturity). A three-layer (1 input, 1 hidden and 1 output layers) network was used. The hidden layer consisted of twelve nodes. The activation function of the hidden layer was sigmoid transfer function. In the output layer, sigmoid transfer function was selected because its output (0 to 1) was fit for the classification. The network was trained to output 1 in the correct class of the output vector and to fill the rest of the output vector with 0.

During training, the connection weights of the neural network were initialized with some random values. The classifier outcome was compared with the known visual grade, and performance of the classifier was judged based on accuracy of prediction. According to Shahine *et. al.* (2002), sorting accuracy can be calculated as following:

$$Sorting\ Accuracy\ (\%) = 100 \times \frac{number\ of\ correct\ predictions}{total\ number\ of\ tomatoes} \quad (15)$$

RESULTS AND DISCUSSION

1-Color features of tomatoes

Table (2) illustrates statistical distribution parameters (mean, standard deviation, kurtosis and skewness) for color parameters (L*, a* and b*) at different studied tomatoes maturity stages. Fig. 4. illustrates the effect of ripening stages of tomatoes on color parameters (L*, a* and b*).

Table 2. Statistical distribution parameters (mean, standard deviation, kurtosis and skewness) for color parameters at different studied tomatoes maturity stages.

Statistical parameters	Green			Pink			Red		
	L*	a*	b*	L*	a*	b*	L*	a*	b*
Mean	44.96	-16.70	28.59	39.54	7.27	23.17	35.65	19.62	18.06
Standard deviation	2.97	1.01	2.36	4.77	11.24	4.38	3.86	7.64	2.71
Kurtosis	-0.07	-0.54	-0.64	-0.62	-1.29	30.91	3.17	53.95	-0.54
Skewness	0.04	-0.17	0.20	0.26	-0.19	-4.45	1.32	6.90	0.22
Count	91	91	91	76	76	76	70	70	70

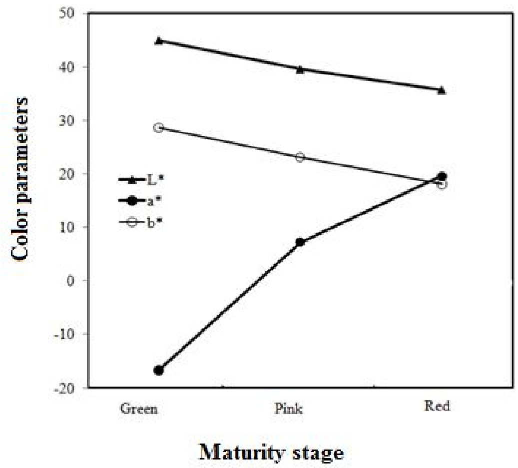

Fig. 4. Effect of maturity stages of tomatoes on color parameters (means of L*,a* and b*).

From Table (2), the means of L*,a* and b* for green maturity are 44.96,-16.70 and 28.59, respectively. Also, the means of L*,a* and b* for pink maturity are 39.54,7.27 and 23.17, respectively. Moreover, the values of the means of L*,a* and b* for red maturity are 35.65, 19.62 and 18.06, respectively. The a* component showed the most obvious change, Fig. 4. From Fig. 4, there was a sharp increase between stages (green to red) with a* changing from negative (green color) to positive (red color) values, as a consequence of both, chlorophyll degradation and lycopene synthesis. Also, decreasing L* value indicated the darkening of the red color (from pink to red) as illustrated in Fig. 5. b* values changed between stages 1 and 3 (green to red) from 28.59 to 18.06. This is may be due to the changing in concentration of some elements of tomatoes like ζ-carotenes (pale-yellow color), lycopene (red color) and β-carotene (orange color) (Lopez Camelo and Gomez, 2004).

Tables (3 and 4) illustrate the average values of color features used in sorting tomatoes maturity. From Table (3) as chroma is calculated by squaring a* and b* values it makes positive the negative a* values (green color) masking its influence. The lower values of chroma tend to turning stage. Color index and Ratio I increased with percentage of red color. Analysis of calculated ripening indexes indicated that hue, color index, color difference (DE) and Ratio I were essentially expressing the same (Tables 3 and 4). In all these cases, differences between visual ripening stages were clear, showing hue a higher range of values and, like color difference (DE), a negative trend. The noramlized color parameters (L*) decrease from green stage to red stage and the noramlized color parameter a* and b*increases from green stage to red stage as shown in Table (4). Howevere, color changes during tomato ripening were the result of changes in the values of L*, a* and b*, although the more important ones were along the a* axis, related to chlorophyll degradation and lycopene synthesis (Lopez Camelo and Gomez, 2004).

Table 3. Mean values of L*, a*, b*, Hue, Color index, Chroma and Ratio I at three maturity stages.

Mean			Hue °	Color index	Chroma	Ratio I	Maturity stage
L*	a*	b*					
44.96	-16.70	28.59	120.34	-22.59	33.12	-0.59	Green
39.54	7.27	23.17	78.10	14.32	26.81	0.31	Pink
35.65	19.62	18.06	42.29	41.08	26.87	1.10	Red

Table 4. Mean values of Ratio II, normalized mean L*, a*and b* and DE at three maturity stages.

Ratio II	Normalized mean			Color difference (DE)	Maturity stage
	L*	a*	b*		
0.34	0.45	0.43	0.62	82.09	Green
0.37	0.40	0.53	0.60	59.09	Pink
1.44	0.36	0.58	0.58	47.26	Red

2-ANN classificatiom method performance

Table (5) shows the confusion matrix that indicates the correct classification and misclassification of 47 instances of the testing data. As indicated in Table (5), the summary result of ANN classifier using all color features together showed that from the total test examples of 47 instances, 46 were correctly classified and 1 was misclassified. The percentage of correctly classified instances for each class was shown in the last row of Table (5). Overall classification accuracy was 97.9%. The result of ANN classifier using all color features together showed that the classification accuracy of green, pink and red tomatoes classes were 100, 92.9 and 100, respectively (in percent).

Table 5. Summary results of ANN classifier of the testing data.

Actual class / Predicted class	Green	Pink	Red
Green	18	0	0
Pink	0	13	1
Red	0	0	15
Total	18	13	16
Percent correct	100	92.9	100

CONCLUSION

A computerized image analysis technique to quantify standard color using L*, a* and b* color spaces was implemented and analyzed with simple method to use it in sorting three ripping stages of tomatoes. Nine color features were extracted from L*, a* and b* color spaces for ripping stages. A Feedforward neural network with Backpropagation training method was used as a classifier. The best sorting accuracy was obtained when all color features were used together as inputs to artificial neural network classifier. The three tomatoes classes, green, pink and red, were identified with the sorting accuracy of 100%, 92.9% and 100%, respectively with overall performance of 97.9%.

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دراسة على التدريج اللوني لنضج الطماطم مستخدما الرؤية الآلية والشبكات العصبية الاصطناعية

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تعتبر الطماطم متنوعة الاستخدام لقيمتها الغذائية العالية، وهي مثل السلع التجارية والزراعية الأخرى تلعب دورا رئيسيا في الاقتصاد المصري، لذا يجب الاهتمام بالأبحاث عليها. علاوة على ذلك، قد يتم حصاد الطماطم في مراحل نضج مختلفة، وكل مرحلة نضج لها خصائصها النوعية. من ناحية أخرى، يعتمد قبول الأفراد على تناول الطماطم على عوامل كثيرة متنوعة مثل الملمس والحجم ودرجة النضج والمظهر العام، أما لون الطماطم فيعتبر واحد من أهم تلك العوامل لاختيار الطماطم للاستهلاك. ودرجات نضج الطماطم تستند بصفة أساسية إلى درجة التلون على سطحها. لذا فإن تحديد درجة النضج للطماطم لابد أن يكون بطريقة متناسقة. وتمشيا مع هذا ، نجد أن تقنيات الرؤية الآلية التي تم تطبيقها في المنتجات الزراعية لفحصها، تمييزها، تصنيفها، تدريجها،...الخ أعطت نتائج جيدة ومتنوعة عند استخدامها مع أحد تقنيات التصنيف مثل مصنفات الشبكات العصبية الاصطناعية. تم في هذه الدراسة استخدام تقنيات تحليل الصور البسيطة ونموذج تصنيف يعتمد على الشبكات العصبية الاصطناعية في تدريج ثلاث مراحل لنضج الطماطم المنزرعة في مصر. من تقنية تحليل الصور البسيطة وكاميرا رقمية ذات دقة مناسبة تم الحصول على عناصر اللون الأساسية لصور الطماطم الملتقطة. هذه العناصر هي L*, a* and b* ومنها تم الحصول على معايير إضافية مثل كثافة اللون وشدة اللون ودليل اللون... الخ. وأظهرت النتائج التجريبية أن استخدام سمات اللون معا (١٢ سمة) أعطى دقة تدريج مقبولة للثلاث مراحل لنضج الطماطم تحت الدراسة عند استخدام مصنف الشبكة العصبية الاصطناعية ذو الثلاث طبقات، مما يدل على أهمية ميزة اللون في تمييز درجات نضج من الطماطم. وبشكل عام، يمكن تدريج مراحل نضج زراعة الطماطم في مناطق مختلفة من مصر عن طريق استخدام الرؤية الآلية. وقد تم تدريج درجات نضج للطماطم (الأخضر والوردي والأحمر)، مع دقة تدريج ١٠٠٪، ٩٢.٩ ٪ و ١٠٠ ٪ على التوالي عن طريق استخدام مصنف الشبكة العصبية الاصطناعية مع دقة تدريج كلية ٩٧.٩ ٪.