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# COLOUR GRADING OF STRAWBERRY USING COMPUTER VISION AND BACKPROPAGATION ARTIFICIAL NEURAL NETWORK

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## ABSTRACT

Colour is often used as an indication of quality, ripeness and freshness for agricultural products including strawberry fruits. A laboratory computer vision system was established for colour grading of strawberry (*Fragaria* × *ananassa*) based on its ripeness stage. Colour features extracted from an image contained the brightness values of each pixel in the image; therefore these features represent the appearance of the fruits and strongly reflect ripening stage and firmness of the fruits. Colour of each fruit in the image was expressed using the average value of three channels (red 'R', green 'G' and blue 'B') of all pixels representing fruit in the image. In addition, to obviate illumination differences and to facilitate differentiation between tested fruits, the RGB components were also transformed to normalized RGB (r, g and b) and to CIE L*a*b* colour space. The most significant colour features were selected based on the analysis of variance (ANOVA) tests experienced on all samples. A backpropagation artificial neural network (BPANN) model was applied as a pattern recognition tool for classification purposes and for fruit firmness prediction using only the selected significant colour features. The efficiency of BPANN model in classifying fruits to six ripeness stages was 92.88%. Furthermore, firmness of strawberry fruits was predicted with correlation coefficients of 0.91 % and 0.89 % for training and validation sets, respectively.

**Keywords**: Strawberry, Computer Vision, Artificial Neural Network (ANN), Firmness, Quality Evaluation, Ripeness.

## INTRODUCTION

The Egyptian production from fruits and vegetables is 24.1 million tons and this represents 1.74 % from overall world production (FAO, 2004). Strawberry is considered one of the strategic horticultural crops produced in Ismailia governorate, Egypt. The net production of strawberry in Ismailia governorate is 27201 tons which represents 38.5 % from Egypt's total production (MALR, 2004). Products only keep their high quality when handled gently and appropriately. In order to offer inexpensive high-quality products, the procedure chain during harvest, storage and marketing has to be optimized using modern measuring and control systems.

The necessity to be responsive to market needs places a greater emphasis on quality assessment resulting in the greater need for improved and more accurate grading and sorting practices. A good sorting system could be beneficial for the whole handling chain from farmer to consumer (Xing and De Baerdemaeker, 2005). Generally, vegetables and fruits are graded and sorted on the basis of shape, colour, weight and size (Lammertyn *et al*., 1998; Du and Sun, 2006). Unfortunately, most of the quality evaluation processes in Egypt still heavily depend on manual inspection. Efforts to develop more capable, efficient and accurate automated fruit classification systems continue as industry priorities, since manual fruit grading has some drawbacks such as subjectivity, tediousness, cost, unavailability, and inconsistency. Technical advancements, especially in the areas of computer vision gave a good motive and helped in the movement toward automated grading of fruits according to shape, size, colour, and recently, blemishes (Kavdir and Guyer, 2002; Li *et al.*, 2002; Du and Sun, 2004). Also, the postharvest physico-mechanical properties data of fruits and vegetables are important in adoption and design of various handling, packaging, storage and transportation systems (Singh and Reddy, 2006).

Computer vision technology is becoming an integral part of the industry to move grading and sorting operations toward automation. In essence, a simple definition of computer vision is the analysis of picture elements by computer. Image processing and image analysis are the core of computer vision involving mathematics, computer science and software programming. Imaging technique is generally non-destructive, reliable, and rapid, depending on the specific technique used (Mehl *et al*., 2004). This non-destructive method of inspection has found applications in the agricultural and food industry, including the inspection and grading of fruits and vegetables. Also, computer vision has shown to be a viable means of meeting increased requirements for fruits and vegetable industry. The system offers the potential to automate manual grading practices thus standardizing techniques and eliminating tedious human inspection tasks (Lu and Sun, 2000 and Brosnan and Sun, 2002). Therefore, many researchers have devoted considerable effort towards the development of computer vision systems for different aspects of quality evaluation and sorting of agricultural products. Computer vision systems are being used increasingly in the food industry for quality assurance purposes from routine inspection to complex vision-guided robotic controls. Currently, computer vision systems are being developed as an integral part of food processing plants for on-line, real-time quality evaluation and quality control (Gunasekaran, 1996). The development of automatic technologies has enabled new methods for evaluating various quality factors on agricultural products. The high cost of their implementation is still a considerable drawback (Carlomagno *et al*., 2004).

Recently, numerous pattern recognition methods and algorithms conjugated in computer vision systems have been developed and tested for their capability to extract surface features of fruits for grading purposes. Despite mathematical differences, artificial neural networks (ANNs) have shown strength over the other methods in identifying and classifying agricultural produces (Jayas *et al*., 2000). Neural network is presented with an input pattern together with the target output for that pattern. The target output is supposed to be the correct corresponding outcome for the input pattern. In response to this paired data, the neural network adjusts the values of its weights. This procedure is called neural network training. If the training is successful, the trained neural networks can produce the correct answer in response to each input pattern (Kondo *et al*., 2000). For instance, an ANN was applied to classify apples into three blemish output categories with an average classification accuracy of 96.6% (Yang, 1993). Also, Nakano (1997) applied two neural network models to the colour grading of apples with accuracy of more than 95% and Kondo *et al*. (2000) evaluated quality of oranges with a great success for predicting pH and sugar content. Barreiro *et al*. (1997) tested different neural network approaches for bruise prediction in apple, pear and peach. Kavdir and Guyer (2004) developed a backpropagation neural network (PBNN) with the texture features extracted from spatial distribution of colour/gray levels to detect defects in apples.

The objective of this study was to investigate the feasibility of using computer vision and backpropagation artificial neural network (BPANN) techniques for the purpose of colour grading, identifying ripeness stage and firmness prediction of strawberry as the first step in developing a computerized grading and sorting systems.

## MATERIALS AND METHODS

### Strawberry Samples

Strawberry (*Fragaria* × *ananassa*) selected for this experiment was hand harvested from a local farm in Ismailia governorate, Egypt. A total of 281 strawberries representing the whole ripeness range from unripe to full-ripe stages were harvested from different plants based on their colour uniformity. In this study, strawberries were graded first by an expert to six colour quality grades based on their ripening stage. Moreover, all fruits suffering from injuries, defects or diseases were completely discarded. Each fruit was individually numbered and then all fruits were transferred to the lab for image acquisition and firmness determination. Fruits were randomly divided into two equal groups for calibrating/training and validating the neural network model. It was essential for both groups to contain fruits of all ripening stages as shown in Fig. (1). Calyx was entirely excised from each fruit and then weighed and put in the imaging chamber for image acquisition.

**Fig. 1: Strawberries of six ripening stages used in the experiment.**

### Image Acquisition Unit

The procedure for estimating ripening stage of a strawberry by measuring its colour using image analysis is done by placing the fruit on an illumination chamber and an RGB image was acquired. A digital colour image with a full resolution of 2272×1704 pixels was acquired for each individual fruit using the image acquisition unit shown in Fig. (2).

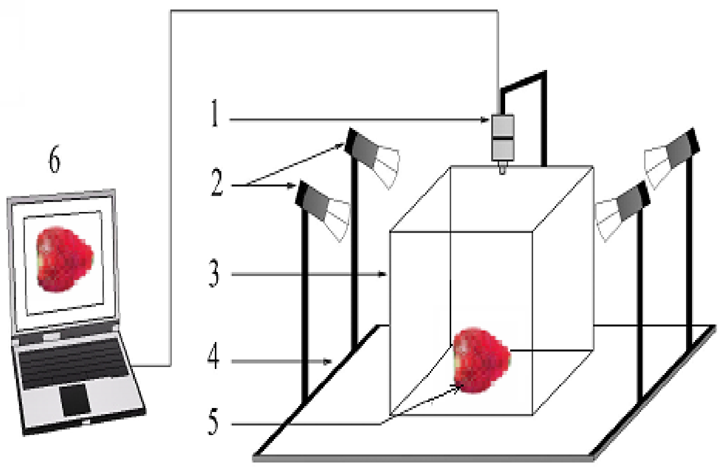


**Fig. 2: Image acquisition unit.**

*1) Digital camera, 2) Illumination units, 3) White nylon box, 4) Base, 5) A sample, and 6) Computer.*

The unit consists of (1) digital colour camera, PowerShot A580 model (Canon Co., USA) located vertically over the background at a distance of 35 cm., (2) illumination unit consisting of four 50W halogen lamps adjusted at angle of 45º to illuminate the camera's field of view, (3) white nylon tent to equally disperse and distribute the light over samples, (4) a base covered with a black velvet for holding the sample (5) to act as background and (6) a computer to record images acquired by the camera. A program written in Matlab7.1 (Release 14, The MathWorks Inc., MA, USA) was developed for controlling the unit, processing images, and for extracting colour parameters from each image.

**Extraction of Colour Parameters from Images**

Colour of each fruit in the image was expressed by the average value of red (R), green (G) and blue (B) for all pixels in the image. In addition, to facilitate differentiation between tested fruits, the RGB components were also converted to L*a*b* colour space. The digital colour image (called RGB image) consists of pixels at red, green and blue channels in the range of 0–255 and stored using eight bits per colour component. These three intensity images (R, G and B) are thus electronically combined in various ways to reproduce broad combinations of primary colours in the digital colour image. Fig. (3) shows the procedure used to extract colour parameters of each fruit in the image. The acquired colour images were first resized to smaller size of 800×600 pixels to hasten computational time of their processing and then converted to grayscale images called intensity images. The intensity images were segmented by choosing a suitable threshold to separate the sample from the black background to obtain binary images. A binary image consists only of black and white pixels representing background and the fruit, respectively. The R, G and B colour components were then calculated only from the white pixel representing the fruit. Also, the normalized colour components (r, g and b) were calculated using the following formulas:

$$r = R/(R+G+B) \quad (1)$$
$$g = G/(R+G+B) \quad (2)$$
$$b = B/(R+G+B) \quad (3)$$

Finally, all colour images were also transformed into CIE L*a*b* colour space format. The L*a*b* colour space is an international standard for colour measurement developed by the Commission Internationale d'Eclairage (CIE) in 1976. The L*a*b* colour space is device independent coordinates which provide consistent colours regardless of the input or output device. The L*a*b* values are often used in food research studies (Yam and Papadakis, 2004). Where the 'L*' (black-white component, luminosity) stands for colour lightness which varies from 255 for perfect white to zero for black, the 'a*' defines the colour degree between red and green (0 indicates green while 255 indicates red), and the 'b*' indicates the colour degree between yellow and blue (0 indicates blue and 255 indicates yellow). Moreover, some additional colour parameters such as r/g, hue angle (h), chroma (C) were calculated. The 'h' and 'C' were calculated using the following formulas (Nunes *et al.*, 2006):

$$h = \text{arctangent}\ (b^*/a^*) \quad (4)$$
$$C = (a^{*2}+b^{*2})^{1/2} \quad (5)$$

All image analysis routines were carried out by scripts developed using Matlab 7.1 and its image processing toolbox (Release 14, The MathWorks Inc., MA, USA).

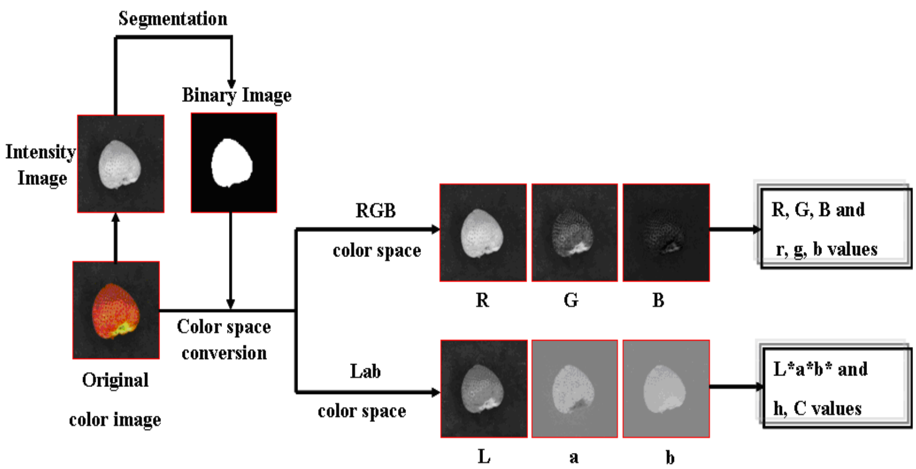


**Fig. 3: Schematic diagram for image analysis to extract colour parameters.**

**Firmness Measurement**

After acquiring an image for each fruit, firmness was determined by Effigi penetrometer (Model FT 011, Alfonsine, Italy) with a plunger diameter of 11.1 mm for depth of 7.9 mm on both sides of each fruit and then both readings were averaged to obtain one firmness value for each fruit expressed as kg/cm$^2$.

**Designing Feedforward Back-propagation Neural Network (BPANN) Model**

The developed BPANN model consisted of three layers: the input layer, the output layer and the hidden layer. The input layer consisted of 5 neurons representing the data of most important colour parameters chosen from analysis of variance (ANOVA) experienced on all tested samples. The number of neurons in the hidden middle layer was gradually changed from two to five to find the most suitable number. Only one hidden layer with 3 neurons was found to be efficient. Six neurons in the output layer were selected to correspond to the number of classes under investigation (six ripening stages). A sigmoid function was used as a transfer function between input and hidden layer and a linear transfer function was used between hidden and output layer, and over-fitting was avoided by using Bayesian regularization training algorithm. The network model was trained for at least 5000 epochs or until the error measurement approached 0.001. In this study, a multilayer neural network that uses a backpropagation learning rule was used to differentiate between strawberries of different ripening stage. The architecture of the designed multilayer backpropagation artificial neural network (BPANN) is depicted in Fig. (4). The data extracted from fruits of training group were used for training the BPANN model; meanwhile the data extracted from the other group were used to validate the model.

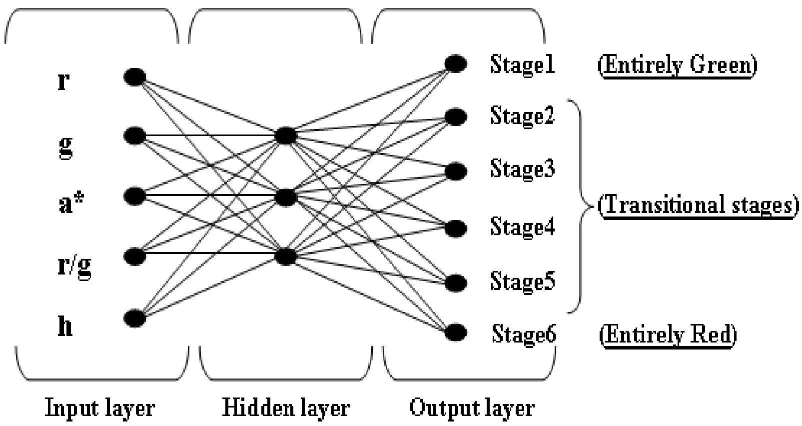


**Fig. (4): Schematic representation of the structural design of backpropagation artificial neural network (BPANN) for identifying ripeness stage.**

Another BPANN model with the same features but with only one neuron in the output layer was also implemented to predict fruit firmness. Only 181 fruits were chosen to develop BPANN model for firmness prediction. The 181 fruits were randomly divided into two groups: the first group consisting of 120 fruits (2/3 of the fruits) was used as a learning/training set for developing this neural network model; meanwhile the other group consisting of 61 fruits (1/3 of the fruits) was used as a validation set. It was essential for both sets to contain fruits of all ripening stages as shown in Fig. (1) to guarantee having all firmness range. The quality of this BPANN model was evaluated by the standard error of calibration (SEC), standard error of prediction (SEP) and the correlation coefficient (r) between the predicted and measured value of fruit firmness. A good model should have a low SEC, a low SEP, a high correlation coefficient, and a small difference between SEC and SEP. These criteria are defined as follows:

$$SEC = \sqrt{\frac{1}{I_C - 1}\sum_{i=1}^{I_C}\left(\hat{y}_i - y_i\right)^2} \qquad (6)$$

$$SEP = \sqrt{\frac{1}{I_p - 1}\sum_{i=1}^{I_p}\left(\hat{y}_i - y_i - bias\right)^2} \qquad (7)$$

Where $\hat{y}_i$ is the predicted value of firmness of fruit number i; $y_i$ is the measured value of firmness of fruit number i; $I_C$ is the number of fruits in the calibration set (120) and $I_p$ is the number of fruits in the validation set (61).

## RESULTS AND DISCUSSION

### 1. Relationship between Colour Parameters and Ripening Stages

Strawberry is non-climacteric fruit which generally ripens on plant; therefore fruits are varying remarkably in size, colour and shape depending on mother plant status, irrigation and fertilization programs. There is no relationship between ripening and size or shape because it is possible to find a small full-ripe fruit and a big unripe fruit. In case of colour, ripening development makes strawberry fruits to be converted from green to red colour due to degradation of chlorophyll commensurate with synthesis of carotenoids and anthocyanins. Fig. (5) shows the relationships between the normalized colour components (r, g and b). It is clear that the normalized colour components only could not perfectly differentiate between the six ripening stages. The classification efficiency using any pairs of these components (r-g, r-b or g-b) was 84.7%. To augment this efficiency, additional information could be achieved by adding other colour parameters or by using nonlinear models for better discrimination. However, this discriminatory power of the colour parameters extracted from fruit image pose a highly promising trend to build such a model. Therefore, with the computer vision system it is possible to assess the overall colour change during ripening, similar to human perception. These results are in agreement with those of O'Sullivan *et. al.* (2003) who concluded that taking a picture of the entire surface of a sample provided a more representative realistic colour profile than the spot measurements of traditional colorimeters.

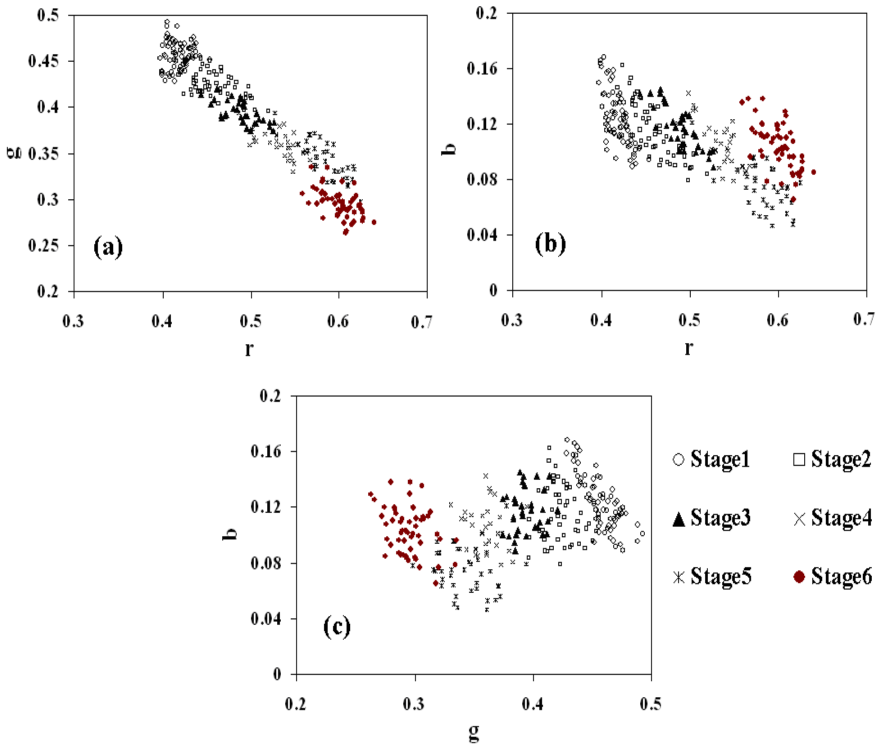


**Fig. (5): Relationships between average values of normalized colour components (r, g and b) of strawberry at different ripeness stages.**

As shown in Fig. (5a) which represents the relationship between the normalized value of red (r) and green (g) components of the colour, it is evident to conclude that there is a very simple trend due to ripeness variation among the six stages. The variation among ripening stages can be characterized more by the 'r' and 'g' values while the 'b' component doesn't change significantly. The trend in ripeness change can be described by a straight line which starts at high green values and low red values in the first ripening stage and ended at low green values and high red values in the sixth ripeness stage. Felföldi and Szepes, (2002) stated that the 'r' and 'g' colour parameters calculated from the average RGB parameters of the unripe side of the samples was found to be suitable to characterize the ripeness of the apricot sample. It can be used for ripeness evaluation of the samples in a given stage and to follow the post-ripening process as well. However, this finding should be confirmed by analysis of variance test. Also, as depicted in Fig. (5b) and Fig. (5c), there is a difficulty to entirely discriminate among ripeness stages using blue-red components or blue-green components. This is due to the little contribution of the blue components throughout fruit ripening.

**Selection of Important Colour Parameters**

To choose the most significant colour parameters among those extracted from the images of the fruits of different ripening stages, analysis of variance (ANOVA) tests were experienced on the data using individual colour parameter each time. The colour parameters having the ability in differentiation between ripening stages significantly (*P < 0.05*) would be chosen for establishing the BPANN nonlinear model. Table (1) shows the results of ANOVA tests for each parameter.

**Table 1: Analysis of variance (ANOVA) for selecting important colour parameters. Values explained are mean ± standard deviation.**

| Parameter | Stage1 | Stage2 | Stage3 | Stage4 | Stage5 | Stage6 |
|---|---|---|---|---|---|---|
| r | 0.42**a**±0.012 | 0.46**b**±0.024 | 0.49**c**±0.020 | 0.54**d**±0.020 | 0.58**e**±0.025 | 0.60**f**±0.019 |
| g | 0.46**a**±0.014 | 0.42**b**±0.014 | 0.39**c**±0.012 | 0.36**d**±0.013 | 0.34**e**±0.021 | 0.30**f**±0.015 |
| b | 0.12**a**±0.020 | 0.11**ab**±0.021 | 0.12**a**±0.015 | 0.10**b**±0.016 | 0.07**c**±0.016 | 0.10**b**±0.017 |
| L* | 204.86**a**±12.1 | 195.11**b**±12.7 | 194.77**b**±9.3 | 177.07**c**±8.4 | 157.67**d**±8.0 | 135.78**e**±9.7 |
| a* | 108.48**a**±3.9 | 123.91**b**±6.4 | 136.05**c**±5.7 | 150.60**d**±4.8 | 157.91**e**±6.6 | 165.05**f**±3.17 |
| b* | 194.51**a**±2.9 | 193.66**a**±2.0 | 193.48**a**±2.4 | 191.20**b**±2.5 | 190.01**b**±3.0 | 179.79**c**±4.4 |
| r/g | 0.92**a**±0.038 | 1.09**b**±0.081 | 1.24**c**±0.082 | 1.49**d**±0.098 | 1.71**e**±0.165 | 2.04**f**±0.148 |
| h | 1.06**a**±0.020 | 1.00**b**±0.025 | 0.96**c**±0.022 | 0.90**d**±0.018 | 0.88**e**±0.022 | 0.83**f**±0.015 |
| C | 222.75**a**±2.0 | 229.98**b**±3.3 | 236.58**c**±3.5 | 243.43**d**±3.2 | 247.12**e**±4.8 | 244.09**d**±3.9 |

**Values having the same letter in the same row are not significantly different (P < 0.05).**

As declared in Table (1), it is evident to observe that the parameters r, g, a*, r/g and h are the most efficient parameters for discrimination between ripening stages. In the same colour space there is a collinearity between colour parameters as obviously seen in ‘r’ and ‘g’ colour parameters because the fruit having low value of red ‘r’ component (first stage of ripening) should exhibit high value of green ‘g’ colour component. Therefore, it is possible to remove one of them before building the nonlinear prediction model. Stepwise discriminant analysis could also be implemented to exclude these parameters. Also, correlation coefficient chart could be used for this kind of parameter(s) selection. However, in this study it was decided to keep all important colour parameters in the prediction model. According to the results shown in Table 1, the r, g, a*, r/g or h values seem to be suitable characteristics to describe the ripeness stage of a given strawberry. The result of the analysis of variance of these parameters on ripeness classes reveled that there is a significant difference ($P < 0.05$) between the ripeness classes even between the neighboring classes.

**Classification of Fruits Using BPANN Model**

The performance of BPANN model for classifying fruits into six ripening classes (stages) is shown in Table (2). When using a neural network to perform fruit classification, some representative features must be selected to form an input pattern for the neural network to learn and to classify. Careful selection of features generally leads to a good performance of the neural network classifier (**Yang, 1993**). The most important colour parameters (r, g, a*, r/g and h) were the inputs of this model, meanwhile, the outputs were the ripening stages. Only one hidden layer with 3 neurons was found to be very useful for obtaining high classification accuracy. In this model the 281 fruits were divided into two groups for learning/training and validation processes.

**Table 2: Classification matrix from 5-3-6 BPANN model using the important colour parameters (r, g, a*, r/g and h)**

| Maturity satge | Stage1 | Stage2 | Stage3 | Stage4 | Stage5 | Stage6 | Total | %, Correct |
|---|---|---|---|---|---|---|---|---|
| Stage1 | 70 | 1 | 0 | 0 | 0 | 0 | 71 | 98.59 |
| Stage2 | 1 | 46 | 4 | 0 | 0 | 0 | 51 | 90.20 |
| Stage3 | 0 | 4 | 27 | 4 | 0 | 0 | 35 | 77.14 |
| Stage4 | 0 | 0 | 1 | 31 | 1 | 0 | 33 | 93.94 |
| Stage5 | 0 | 0 | 0 | 2 | 35 | 0 | 37 | 94.60 |
| Stage6 | 0 | 0 | 0 | 0 | 2 | 52 | 54 | 96.30 |
| Total | 71 | 51 | 32 | 37 | 38 | 52 | 281 | 92.88 |

It is evident from Table (2) that the developed BPANN with described architecture has a high capability in classifying fruits into six ripening classes with an overall accuracy of 92.88%. The first stage (entirely green stage) and the last stage (entirely red stage) were distinguished clearly with a high accuracy of 98.59 and 96.30 %, respectively. The performance of BPANN model for classifying transitional stages (from stage 2 to stage 5) was lower but it is still acceptable. However, the accuracy of identifying third stage of maturity was the lowest (77.14%) among the other maturity stages. In general, the selected important parameters (r, g, a*, r/g and h) combined in one nonlinear model such as BPANN are very practical solution for classification purposes especially when expeditious grading is required. If these six stages were compacted to only three or four classes the classification accuracy will definitely be augmented.

**Linear Relationship between Colour Parameter and Fruit Firmness**

For predicting fruit firmness, only 181 fruits have been used for this purpose as mentioned before. The abilities of each individual colour parameter (r, g, a*, r/g or h) for predicting fruit firmness are shown in Fig. (6).

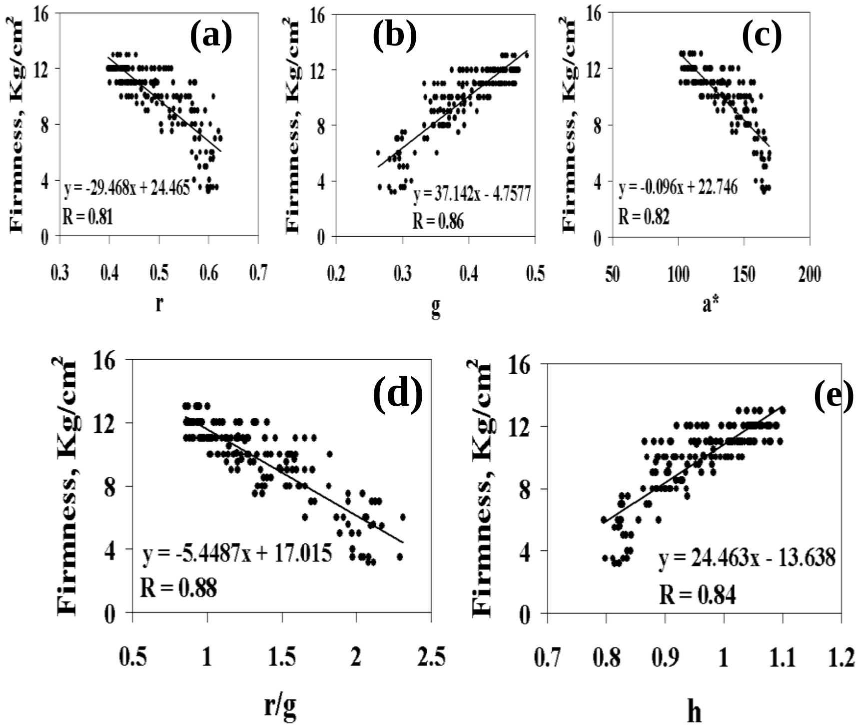


**Fig. (6): Linear relationship between colour parameters and fruit firmness.**

Green component 'g' has the highest correlation (0.86) with fruit firmness compared with the other individual colour components. Fruits having high values of green 'g' component possess the highest firmness as shown in Fig. (6b), and this is found in fruits of the first ripening stage. When fruits proceed in ripening they lost their green colour due to degradation of chlorophyll and then become softer with rather low firmness values. Although the red 'r' colour component correlated with fruit firmness by 0.81, the correlation increased when red 'r' component was combined with the green 'g' component in one parameter (r/g) as shown in Fig. (6d). The correlation coefficient between 'r/g' values and fruit firmness was quite high (0.88) indicating good ability of this parameter for nondestructive prediction of fruit firmness. It is necessary to mention that the other colour components showed a weak correlation with fruit firmness in comparison with 'r/g' parameter.

### Firmness Prediction by BPANN Model

For firmness prediction by BPANN, the most important colour parameters (r, g, a*, r/g and h) extracted from training group (120 fruits) were used as the inputs in the training/learning step. The same features were tested again in the validation group (61 fruits) to examine the ability of these colour features in firmness estimation. The accuracy of BPANN model for firmness prediction in both training and validation sets are shown in Fig. (7). The results revealed that the selected colour features are sufficient to give a reasonable prediction accuracy of fruit firmness.

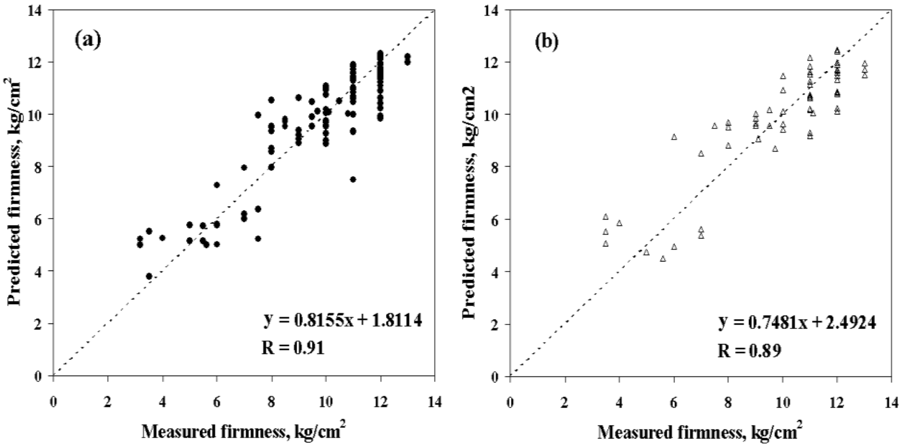


**Fig. (7): Firmness prediction by 5-3-1 BPANN model using only r, g, a*, r/g and h as input parameters in (a) training set and (b) validation set.**

The BPANN model performed well in predicting fruit firmness with standard error of calibration (SEC) of 0.99 Kg/cm$^2$ in the training set (120 fruits) with correlation coefficient of 0.91. In the validation set (61 fruits), the model also achieved high success for predicting fruit firmness with standard error of prediction (SEP) of 1.18 Kg/cm$^2$ and correlation coefficient of 0.89. The high correlation coefficients in both sets as well as the small difference between SEC and SEP are signs of high performance of the proposed BPANN model in predicting fruit firmness. Strictly speaking, the performance of this nonlinear BPANN model in firmness prediction was much better than that obtained when only one colour parameter was used in a linear model.

### Conclusion

In this study it has been demonstrated that the proposed computer vision system supported with neural network approach is feasible for colour grading of strawberry into six ripening stages with reasonable classification accuracy. The input features to the network model should be carefully picked to guarantee high performance. With these features, it was found that the three layered 5-3-6 network was computationally more efficient and offered the best classification accuracy of 92.88%. The same colour parameters were also utilized in another three layered 5-3-1 network for predicting fruit firmness. The performance of this nonlinear BPANN model in firmness prediction was much better than that obtained when only one colour parameter was used in a linear model. Generally, the modern grading mechanisms in most packinghouses should be expeditious, nondestructive, easily operated and accurate. These requirements could only be fulfilled when a reliable system utilizing computer vision is employed. By this way, growers, processors, traders and consumers will benefit not only during fruit monitoring, product development, quality control but also in all inspection and quality evaluation processes.

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# التدريج اللوني لثمار الفراولة باستخدام الحاسب الآلي والشبكة العصبية الصناعية

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يعتبر اللون أحد المؤشرات الهامة التي تستخدم لتحديد جودة ودرجة نضج الكثير من المنتجات الزراعية مثل الفراولة. وعلي هذا فقد تم في هذه الدراسة بناء نظام معالجة للصور يعمل بالحاسب الآلي وذلك بغرض التدريج اللوني لثمار الفراولة الي ستة درجات. وحيث أن الصفات اللونية المستخرجة من الصورة تحتوي علي درجة اللون في كل عنصر من عناصر الصورة Pixels فإنه يمكن استخدام هذه الصفات اللونية لتعكس مرحلة نضج الثمار وبالتالي تدريجها لونيا الي أقسام مختلفة تبعا لمرحلة نضجها. ولقد تم التعبير عن لون الثمرة في الصورة باستخراج العديد من الصفات اللونية من الصورة مثل متوسط الألوان الرئيسية وهي الأحمر R ، الأخضر G والأزرق B و القيم النسبية لهذه الألوان r ، g ، b والقيم المعيارية *L* ، a* ، b وقيم أخري مثل الهيو h والكروما C. وقد تم اختيار أفضل هذه الصفات اللونية للتمييز بين ثمار الفراولة وذلك بإجراء اختبارات تحليل التباين ANOVA باستخدام صفة لونية واحدة في كل اختبار ، حيث تم تحديد الصفات اللونية الهامة فقط والتي يكون عندها فروق معنوية بين درجات النضج المختلفة.
وباستخدام جميع الصفات اللونية الهامة فقد تم بناء نموذج شبكة عصبية صناعية Artificial Neural Network model لتدريج ٢٨١ ثمرة فراولة الي ستة درجات مختلفة تبعا لدرجة نضجها ، وكانت كفاءة هذا النموذج هي ٩٢,٨٨ %. وحيث أن اللون هو دليل لمدي صلابة الثمرة لذا فقد تم بناء نموذج شبكة عصبية آخر باستخدام نفس الصفات اللونية الهامة فقط للتنبؤ بصلابة ١٨١ ثمرة فراولة ، ونجح هذا النموذج في التنبؤ بمقدار صلابة الثمار بمعامل ارتباط ٠,٩١ لمجموعة ثمار اختبارية (١٢٠ ثمرة) وبمعامل ارتباط ٠,٨٩ لمجموعة ثمار أخري تأكيدية (٦١ ثمرة).