International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:3, No:2, 2009

Non-destructive Watermelon Ripeness Determination Using Image Processing and Artificial Neural Network (ANN)

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***Abstract*—**Agriculture products are being more demanding in market today. To increase its productivity, automation to produce these products will be very helpful. The purpose of this work is to measure and determine the ripeness and quality of watermelon. The textures on watermelon skin will be captured using digital camera. These images will be filtered using image processing technique. All these information gathered will be trained using ANN to determine the watermelon ripeness accuracy. Initial results showed that the best model has produced percentage accuracy of 86.51%, when measured at 32 hidden units with a balanced percentage rate of training dataset.

***Keywords*—**Artificial Neural Network (ANN), Digital Image Processing, YCbCr Colour Space, Watermelon Ripeness.

I. INTRODUCTION

AGRICULTURE products are being more demanding in market today. In order to increase its productivity, automation to produce these products will be very helpful [1]. External appearance, such as colour, is one of the major factors that affect consumer perception of the quality of the fruit. In the case of watermelons, for example, the consumers are attracted by the colour tone distribution on the skin of the watermelon [2].

One of the main factors in ensuring the consistent marketing of watermelon is the quality of the product. Therefore, it is important to monitor and control the fruit ripeness since it has become a major issue in fruit production. Traditional methods for assessing fruit ripeness are destructive, thus cannot be so readily applied, particularly in mass production [3, 4].

This paper presents a non-destructive method for determining the ripeness of watermelons based on its colour. An Artificial Neural Network (ANN) model has been used to determine the quality of the watermelon.

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The objective of this work is to classify between the ripeness indexes of the watermelon based on ANN from sample images. The significant of this study is to determine the ripeness stages with the mean value that obtained from the image by using colour space of the watermelon. ANN is used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques.

II. THEORETICAL BACKGROUND

A. YCbCr Colour Space

The YCbCr colour space is used in this project as the colour space for image representation and processing. The YCbCr colour space has three components that store luminance and chrominance information separately. The Y component stores the luminance information, while the Cb and Cr component stores the chrominance information. The Cb component represents the difference between the blue component and a reference value. Cr represents the difference between the red component and a reference value [5].

YCbCr signals are created from the corresponding a gamma adjusted RGB (red, green, blue) source as follows:

$$Y = 0.299 * R' + 0.587 * G' + 0.114 * B' \quad (1)$$

$$Cb = -0.168736 * R' - 0.331264 * G' + 0.5 * B' \quad (2)$$

$$Cr = 0.5 * R' - 0.418688 * G' - 0.081312 * B' \quad (3)$$

where R’, G’ and B’ are nonlinear (gamma-adjusted) red, green and blue components. Each of the components has a nominal range from 0 to 1, with 0 representing the minimum intensity and 1 the maximum. The resulting luminance (Y) value will then have a nominal range from 0 to 1, and the chrominance (Cb and Cr) values will have a nominal range from -0.5 to +0.5. The reverse conversion process can be readily derived by inverting the above equations [6].

B. ANN Model

Artificial Neural Networks (ANN) is a problem-solving tool that has become an alternative modeling method to some physical and non-physical systems with scientific or mathematical basis. It mimics the brain in two aspects, the ANN acquires knowledge from its environment through a learning process, and synaptic weight connections are used to store the acquired knowledge [7].

The common type of ANN is called the multi-layer perceptron (MLP). It consists of three layers of units as depicted in Figure 1. A layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units [6]. Fig 1 shows an example of three layer MLP architecture.

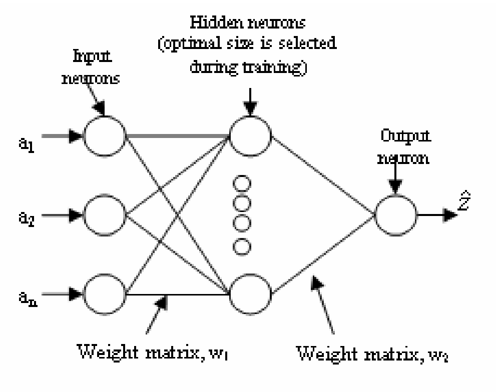


Fig. 1 A three-layer MLP

III. Methodology

The process to determine the ripeness of watermelons involved five steps namely data collection, image acquisition, pre-processing, feature extraction, recognition and classification. The flowchart in Fig. 2 summarized the steps taken.

A. Data Collection

The watermelon samples were obtained from Melon Master Sdn. Bhd., Selayang. The samples were divided into three categories that is ripe, under ripe and over ripe. 90 samples were collected, where 45 samples were used as the training set, 15 samples were used as the validation set, and 30 samples were used as the testing set.

Since the data set is too small for ANN training, based on Duda & Stock [8], one can generate virtual or surrogate training patterns and use them as if they were normal training patterns sampled from the source distributions. A natural assumption is that such arrogate patterns should be made by adding d-dimensional Gaussian noise to true training points.

Thus, the data set is added by adding noise to the original data set that gave all the data set 360 all together. The noise is added by using the MATLAB programming where 5% value from the original data set is added to generate new data set. The data set is divided to 215 samples for training, 35 samples for validation and 110 samples for testing. Hence the ANN will be trained using this new data set.

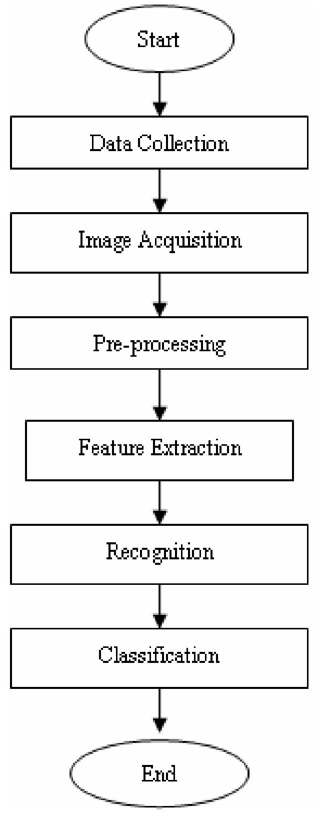


Fig. 2 Flowchart of the watermelon classification

B. Image Acquisition

Watermelon colour images were acquired using a FinePix 6900 Zoom (FujiFilm) digital camera. The images were obtained with a resolution of 1280x960 pixels and saved using the Joint Pictures Expert Group (JPEG) format.

The image capturing process had been done under standard and controlled environment in the Image Capturing Studio Room (ICS Room) at the Advanced Signal Processing (ASP) Research Lab, Faculty of Electrical Engineering, Universiti Teknologi MARA, Shah Alam.

(a) (b)

Fig. 3 The setting of capturing devices (a) camera placement, data logger and light meter placement (b) spotlight and table placement

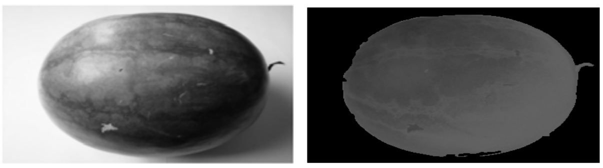
International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:3, No:2, 2009

Fig. 3(a) and 3(b) shows the equipment setup for image acquisition. The camera was placed at a distance of one foot directly above the watermelon samples. The lighting used for capturing image was the Digicolor K-250C spotlight. The light intensity was controlled by using a Heavy Duty Light Meter (Model 407026) and a Heavy Duty Data Logger (Model 380340) having a mean brightness of 1276.93 $\pm$ 25.818 Lux.

C. Pre-processing

The captured images were analyzed using MATLAB software. The colour in watermelon is segmented into 3-dimensional colour map of RGB [1]. Then, it was converted into YCbCr colour space. From the segmented image, the watermelon is classified into the ripe index based on the amount of pixel in each of the segmented region. The data collected is stored in one database. Then it used to train the ANN which performs the pattern recognition function [9]

In this research, the Y component is eliminated since the Y component represents brightness where, by eliminated this component, the colour of the image will not be affected by the brightness of the surroundings. Therefore, the image consists only component colour specifically Cb and Cr. Fig. 4(a) shows an example of the original image whilst Fig. 4(b) illustrated the image after pre-processing.



(a) (b)

Fig. 4 Image obtained before and after pre-processing

D. Feature Extraction

The CbCr colour feature was extracted after completing the pre processing stage. The sum of each colour chrominance (Cb and Cr) was computed for every pixel area to determine the mean value. The background of the image that contributed the pixel value of 0 (black) was not included in the summation since the concerned part is only on the CbCr components of the watermelon's rind.

E. Artificial Neural Network (ANN) Model

This research employed supervised learning where the target values for the output are presented to the network, in order for the network to update its weights. Supervised learning attempts to match the output of the network to values that have already been defined. After training network verification is applied in which only the input values are presented to the network so that the success of the training can be established. The input for the ANN model will be the mean value of the two color components namely Cb and Cr. The output will be the ripeness stage of the watermelon.

Further, the Levenberg-Marquardt algorithm is chosen and designed to approach second-order training speed without having to compute the Hessian matrix. This algorithm appears to be the fastest method for training moderate-sized feed forward neural networks. It also has a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB setting [10].

IV. Result and Discussion

Fig. 5 shows the performance accuracy employing different numbers of hidden units. From the graph, it can be realized that the best hidden unit with higher accuracy is at 32 hidden units.

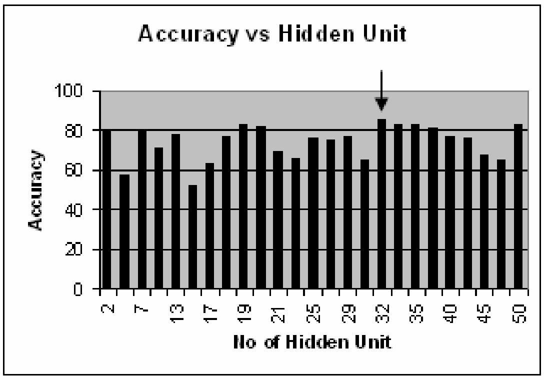


Fig. 5 Accuracy of the performance from different hidden units

Next, the mean square error (MSE) for each of the hidden units is depicted in Fig. 6. From this figure, small error existed for every hidden unit.

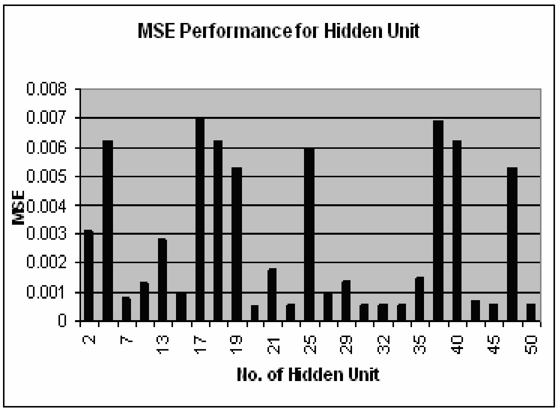
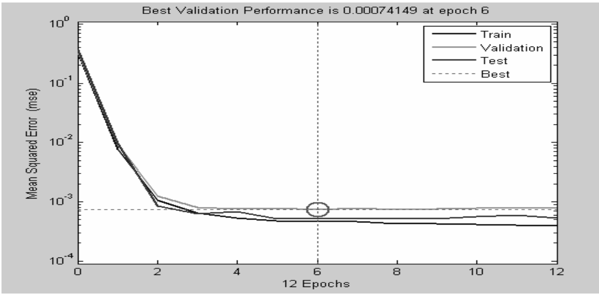
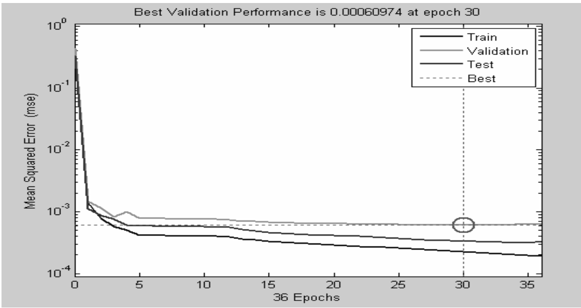


Fig. 6 Mean Square Error (MSE) vs. number of hidden units

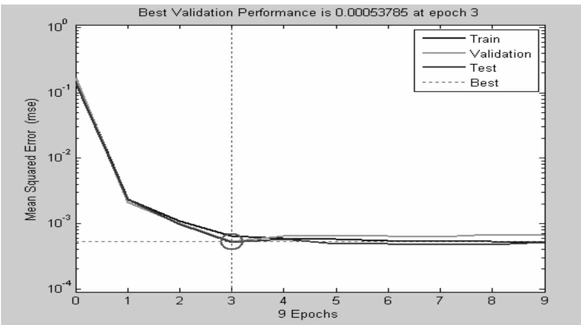
Additionally, Figure 7 shows the training result with different hidden units from the training data set. The respective MSE are observed to be converging before it approaches to 300 epochs. This is due to utilization of the early stopping in order to obtain optimum ANN generalization performance. Thus, implying that training of the model is successful for the experiment. The accuracy of the training is 80% for 7 hidden units, 86.51% for 32 hidden units, 83.72% for 35 hidden units and 83.72% for 50 hidden units. In these figures, the plots are showed for the training, validating and testing set. It is observed that the MSE is decrease when the hidden units increased.



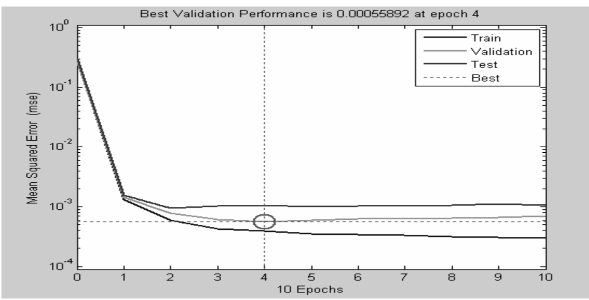
(a)



(b)



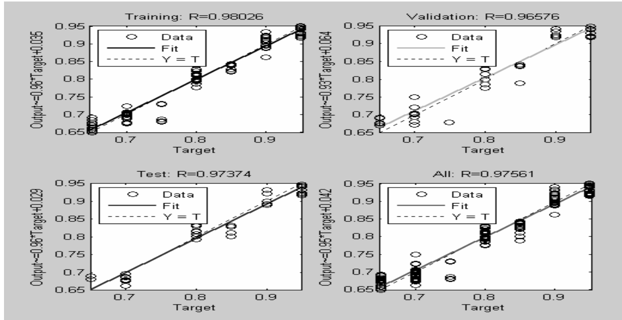
(c)



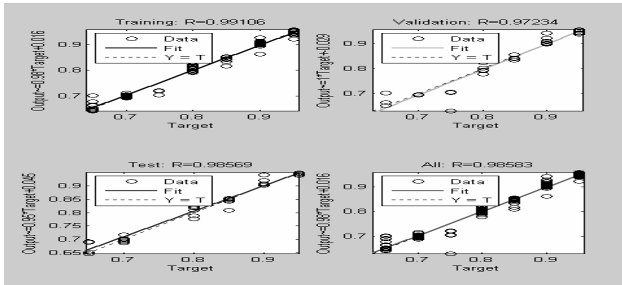
(d)

Fig. 7 Epoch performance with respect to the hidden layer size where (a) 7 hidden units, (b) 32 hidden units, (c) 35 hidden units, (d) 50 hidden units

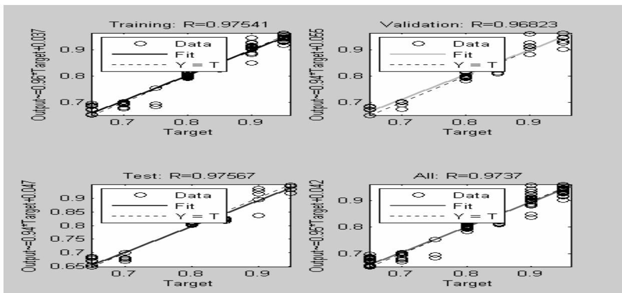
Next, Figure 8 depicted the regression plots of the different hidden units. The outputs seem to track the targets reasonably well and the R-values are around 0.9. The correlation coefficient (R-value) between the outputs and targets is to measure of how well the variation in the output is explained by the targets. If this number is equal to 1, then there is perfect correlation between targets and outputs. In the experiment, the number is very close to 1, which indicates a good fit.



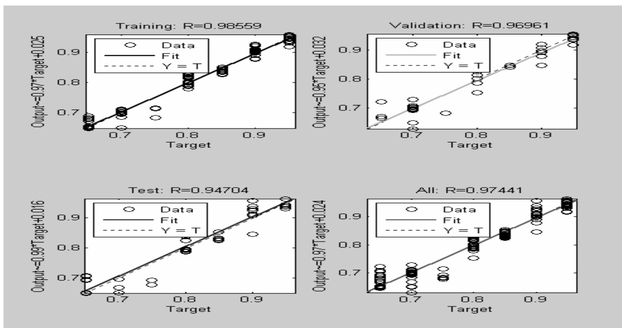
(a) 7 hidden units



(b) 32 hidden units



(c) 35 hidden units



(d) 50 hidden units

Fig. 8 Regression plots for training, validation, testing and all data set

Subsequently, Table I tabulated the comparison of the accuracy performance for testing data set based on 32 hidden units since from the experiment it is the best hidden unit compared to others. The testing data set is compared between the ANN results as compared to the human experts' classification that is based on the percentage of the ripeness of the watermelon. It can be seen that only a small percentage of errors occurred when compared to the ANN results.

TABLE I
PERCENTAGE ERROR COMPARISON BETWEEN ANN CLASSIFICATION AND HUMAN EXPERTS

Sample testing	Human experts	ANN	Error %
1	0.65	0.646	0.62
2	0.7	0.702	0.29
3	0.75	0.742	1.07
4	0.8	0.807	0.88
5	0.85	0.842	0.94
6	0.9	0.909	1.00
7	0.95	0.954	0.42

V. CONCLUSION

In conclusion, from the analysis through the performance indicator, it is proven that the image processing techniques can be utilized to determine the watermelon ripeness. This is based on different mean value attained from each image for every different stages of ripeness. Results showed that the best model with excellent abilities was at 32 hidden units since it obtained the highest accuracy percentage with 86.51% at training dataset rate of 60:10:30. From this study, it can be concluded that the best model is the 32 hidden units applied to ANN, with error percentage for the ripeness of watermelon between 0.29 to 1.07 percents.

ACKNOWLEDGMENT

We would like to thank Mr. M. Kaliyannan, the owner of Melon Master Sdn Bhd for his valuable information on watermelon.

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