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Application of Back Propagation Diagnostic Model for Fruit Maturity Classification: Case Jatropha Curcas

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Abstract: Recently, studies on biodiesel alternative have attracted researchers to find another agricultural solution for bio energy. One of the alternatives is biodiesel from *Jatropha curcas* fruits. The quality of the fruit is largely depends on type of defects, skin color and size of the fruit. In this research, we develop an image recognition system to identify the level of maturity of *Jatropha curcas* fruit and classify them into various categories. A back propagation diagnosis model(BPDM) is adopted to recognize the image of the matured fruits. Color indices associated with image pixels are used as input. As a result, the developed BPMD can give 95% accuracy based on samples of twenty-seven images. It can be ascertained that our proposed BPDM can achieved its performance function.

Key words: Neural Network, Back Propagation Diagnostic Model, Image Recognition, Maturity

INTRODUCTION

Recently, since the world is facing significant reduction in fossil fuel as its main source energy, researchers are searching other alternative solutions for biodiesel resource. One of the alternative fuel is the *Jatropha curcas* oil, which is widely planted in many subtropical and semi-arid regions. Since biofuel can be extracted from its fruit, the seed oil from *Jatropha curcas* offers an excellent alternative for the source of energy. In order to determine the maturity level of a fruit, color grading plays an important role which is often used. Studies show that most of the color grading applications are implemented by color image processing, which is (D. Unay *et al.* 2007; D. Unay *et al* 2004; J. Blasco. 2003; JB Njoroge *et al.* 2002; K. Nakano. 1997; KH Choi *et al.* 1995; Nagata M *et al*, 1997). Two main characteristics that are essential for image processing of fruits are the color and shape. However it the case of *Jatropha curcas*, the estimation of level of maturity cannot be done just by its shape because a fruit may have *Jatropha curcas* different shape but have the same level of maturity (Jain, A.K *et al.* 1996).

The four best approaches for image recognition are template matching, statistical classification, syntactic or structural recognition, and artificial neural networks (ANN) (Bishop C M. 2000; Ripley B. 1996; Friedman M *et al.* 1999; Fukunaga K. 1990; Jeffry Johnson *et al.* 1995). ANN attempts to use some organizational principles as learning, generalization, adaptively, fault tolerance and distributed representation and computation in order to achieve the recognition. Among all approaches, ANN has the fastest speed and best accuracy for work classification (J. Du *et al.* 2005). The main characteristics of neural network are that they have ability to learn complex nonlinear input-output relationships, use sequential training procedures and adapt themselves to data. Some popular modules of neural network have been shown to be capable of associative memory and learning (Fausett L. 1994; Kohonen T. 1997; Schurmann J. 1996)

The learning process involves updating the network architecture and modifying the weights between the neurons so that the network can efficiently perform a specific classification and clustering task. There have been many application of neural networks reported for interpretation of image in the agri-food industry. Studies have shown that for the interpretation of image, the neural networks can be as accurate as procedural model (Deck, S. H *et al.* 1995; Timmermans *et al.* 1996). For example, the accuracy of classification of potted plants can be greater than 99%, apples can be graded by color with an accuracy of 95%, the classification of logs for defects using computed tomography imagery can be 95% accurate, and the accuracy for the classification of wheat kernels by color can be 98% or more (Wang, D *et al.* 1999). Generally, neural networks can efficiently model various input and output relationships with the advantage of requiring less execution time than a procedural model (Yang, C.-C *et al.* 1997a; Yang, C.-C *et al.* 1997b).

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In this paper, we present the application of our developed back propagation diagnostic model (BPDM) that adopts a image recognition system to classify the level of maturity of *Jatropha curcas*. The BPDM have been proved as a promising paradigm for intelligent systems because it can be trained to perform complex functions in various fields of application including pattern recognition, identification and classification. The developed BPDM consists of a layered feed-forward neural network in which the artificial neurons are organized in layers, and their signals are sent to forward and errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by neurons on an output layer.

2. Methodology:

We conducted the research by fractionalizing into the image recognition into two stages. The first stage is a preprocessing stage, which is to purify and improve the image from the image acquisition . The second stage is the classification process where the image recognition is performed by using some characteristics that are derived from the first stage. The BPDM is used for analyzing the level of maturity of *Jatropha curcas*. The algorithm and procedure of the image recognition process by BPDM as shown Figure 1 and Figure 2:

2.1. Stage 1: Preprocessing Stage:

The samples of *Jatropha curcas* fruit images are captured from the plant at Universiti Kebangsaan Malaysia (UKM), Bangi. As a pre-processing, the image size is reduced from 756x504 pixels to 100x100 pixels so that the iteration time can be shorten. The images are purified from the background as shown in Figure 3. The images are segmented to 100x100 pixels to be used as training data set. Each pixel of the *Jatropha curcas* fruit image is classified into one of 256 categories, represented by an integer in the range from 0 to 255. The input of each assigned color indices and shapes are expected to be taken into account by neural networks since the information is implicated in the relationships between the pixel colors.

2. 2. Stage 2: Analyzing and Classification Process:

In the second stage, we analyzed the characteristics of the trained images by using a developed system. This tool is developed by using the trained BPDM, which displays the *Jatropha curcas* image to the user in a graphical user interface (GUI) which is shown in Figure 4. The result of the GUI analysis window is displayed after analyzing process of the image. The *Jatropha curcas* image is segmented with the grading level whether it is raw, ripe and over ripe that are shown in the analysis window.

In this stage, we used the BPMD to analysis the image color of Jatropha curcas. The BPDM is used because of its less complex architecture and the most commonly used neural networks (Howard Demuth *et al.* 1998). In addition, the BPDM can perform image classification on data where there is no linear relation between the input and the output (Valluru B Rao *et al.* 1996). The BPDM is represented as weighted sum

$$A_j(\bar{x}, \varpi) = \sum_{i=0}^{n} x_i w_{ji} \tag{1}$$

where, $A_j(\bar{x}, \varpi)$ is back propagation, x_i is input and w_{ji} is weights. The output unit is calculated the actual output x_j by using some function of the total weighted input. Typically we use the sigmoid function.

$$x_j = \frac{1}{1+e^{-A_j}} \tag{2}$$

Once the activities of all output units have been determined, the network computes the error *E*, which is defined by the expression

$$E = \frac{1}{2}\sum_f (x_j - d_f)^2 \tag{3}$$

where d_t is the desired output.

In the training process of BPDM, 45 essential training data parameters can be obtained. The weights of 45 node-layer altered, and then the parameters are passed to the hidden layer respectively. Figure 2 shows the structure of BPDM.

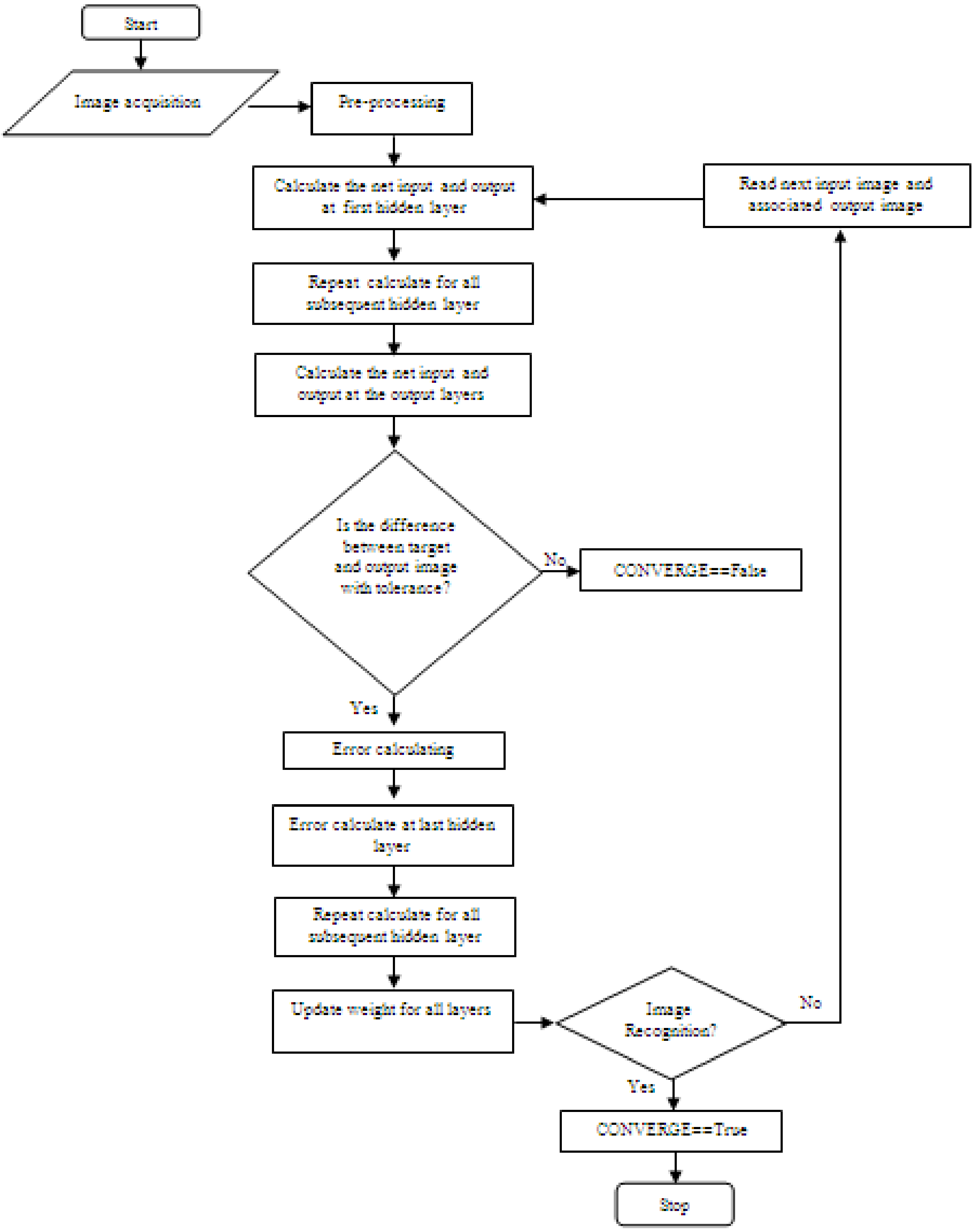

Fig. 1: The algorithm of image recognition

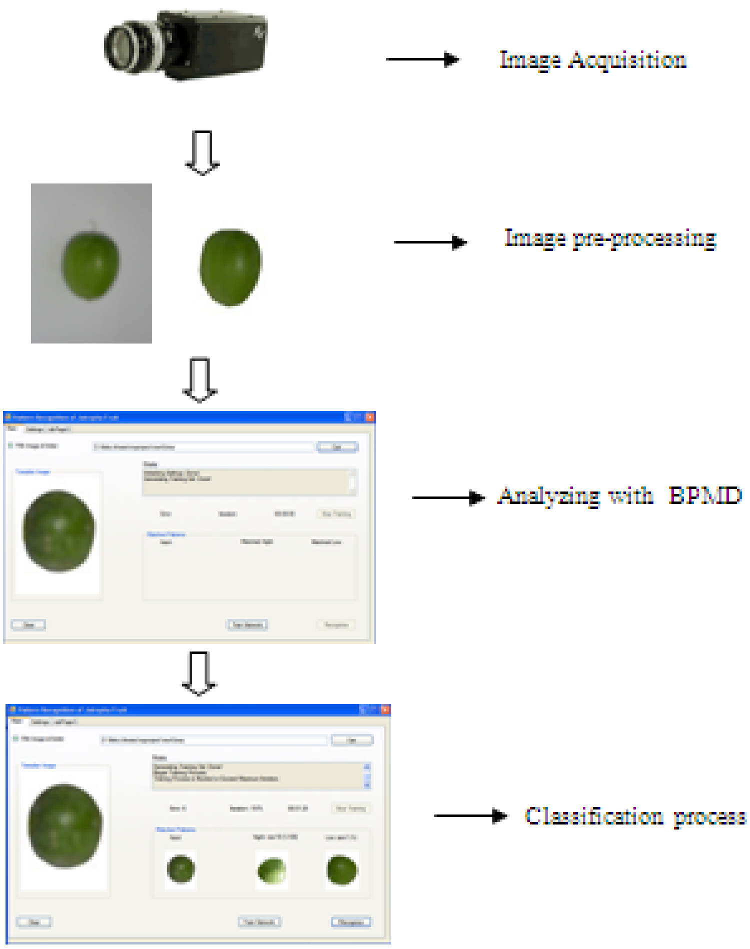

Fig. 2: The procedure of image recognition.

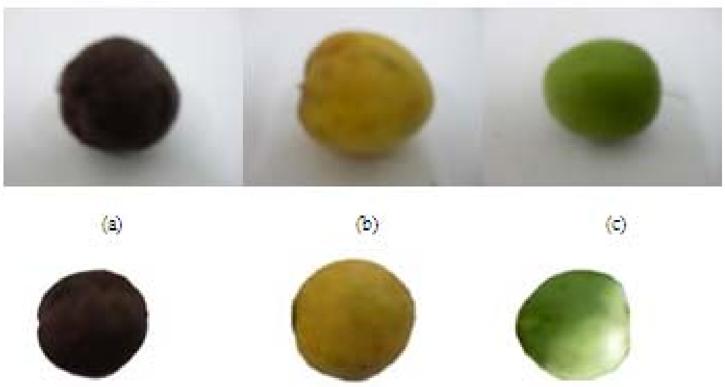

Fig. 3: Purification of image background (a), (b), (c) originally captured images of over ripe, ripe and raw. (d), (e), (f) are purified images

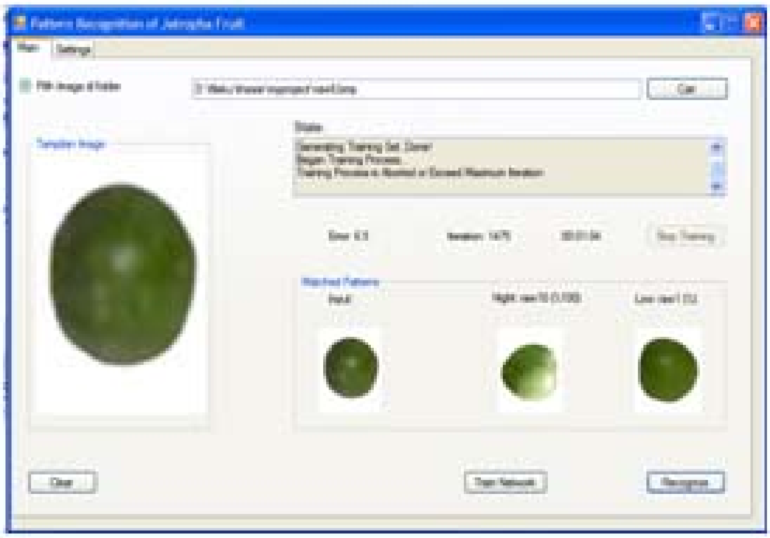

Fig. 4: Developed GUI for Jatropha curcas

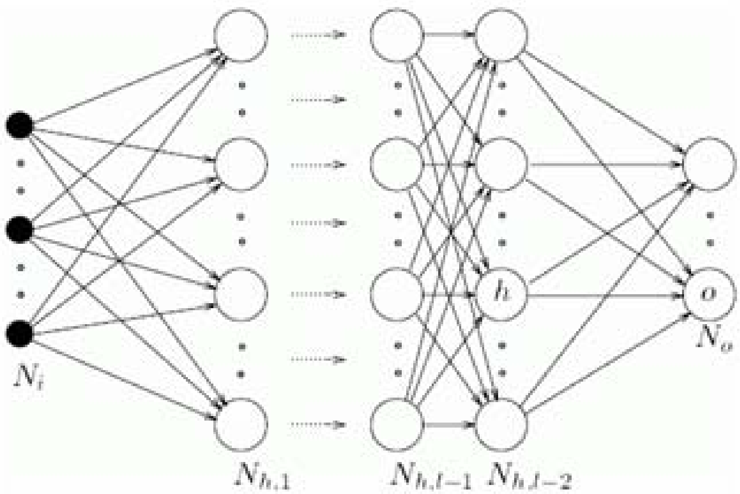

Fig. 3: BPDM structure.

RESULT AND DISCUSSION

The images used in this study were obtained with a standard digital camera. The resolution used to take the photos are 756x504 pixels, in jpg format. In the experiment, we used sampling database consists of twenty-seven images. A set of fifteen images were used for the training of the network and twelve were used for the testing of the performance. Parameters selected for the classification of images are raw, ripe and over ripe. These parameters were extracted for the images that have been captured in the training stage. The results of the three classifiers are shown in Table 1.

Then the raw, ripe and over ripe status images were used in the training. By using BPDM, it gave an accuracy of about 95 % based on our samples which used the twenty-seven images. The results produced by neural network were found to be more accurate due to its capability to distinguished complex decision regions.

Table 1: Result matched pattern of object recognition

No. Images	Matched Pattern	Validation (%)	Iteration	Timing
1	Raw	96.41	2008	0:02:10
2	Ripe	97.98	1975	0:01:29
3	Ripe	98.33	1962	0:01:11
4	Over ripe	95.99	1452	0:00:59
5	Raw	96.8	1413	0:00:56
6	Raw	95.55	2014	0:02:32
7	Raw	95.78	1968	0:01:18
8	Ripe	97.35	1322	0:00:52
9	Over ripe	96	2153	0:02:55
10	Over ripe	96.65	1970	0:01:25
11	Raw	96.18	1952	0:01:22
12	Raw	97.45	1389	0:00:58

Conclusions:

The method proposed in this paper for fruit maturity classification of *Jatropha curcas* using image recognition of BPDM. The training data set for BPDM had 3 levels of grading i.e. raw, ripe and over ripe with twenty-seven images of *Jatropha curcas*. At the end of the training, the neural network achieved its performance function by testing with a selected set of different images. The performance of the BPDM was satisfactory when incorporated with the software tool, since there were number of errors arising in categorizing. It was expected since the BPDM was trained with the data from the tool directly. Training with real data from the tool itself is the next goal to be achieved by using different learning algorithms, rates, and optimization techniques. It can be ascertained that our developed system is able to categorize the images accordingly.

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