American Journal of Applied Sciences 7 (3): 390-394, 2010
ISSN 1546-9239

A Back Propagation Neural Networks for Grading *Jatropha curcas* Fruits Maturity

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Abstract: Problem statement: *Jatropha curcas* has the potential to become one of the world's key energy crops. Crude vegetable oil, extracted from the seeds of the *Jatropha* plant, can be refined into high quality biodiesel. Traditional identification of *Jatropha curcas* fruits is performed by human experts. The *Jatropha curcas* fruit quality depends on type and size of defects as well as skin color and fruit size. **Approach:** This research develops a back propagation neural networks to identify the *Jatropha curcas* fruit maturity and grade the fruit into relevant quality category. The system is divided into two stages: The first stage is a training stage that is to extract the characteristics from the pattern. The second stages is to recognize the pattern by using the characteristics derived from the first task. Back propagation diagnosis model is used to recognition the *Jatropha curcas* fruits. It is ascertained for the developed system is used in recognizing the maturity of *Jatropha curcas* fruits. This study presents a pattern recognition system of *Jatropha curcas* using back propagation. **Results:** By using back propagation, 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. **Conclusion:** The training data set for back propagation had 4 levels of grading i.e., raw, fruit-aged, ripe and over ripe with twenty-seven images of *Jatropha curcas* fruits. 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 back propagation was satisfactory when incorporated with the software tool, since there were number of errors arising in categorizing.

Key words: *Jatropha curcas* fruit, back propagation, maturity, grading, neural networks

INTRODUCTION

Jatropha grows in tropical and subtropical regions in a band around the earth between latitudes 30° north and south of the Equator. *Jatropha* is hardy and relatively drought resistant. Trees have a lifespan of up to 30 years. *Jatropha* grows on a wide range of land types, including non-arable, marginal and waste land and need not compete with vital food crops for good agricultural land. As *Jatropha curcas* seeds and green leaves are poisonous that works as a very effective barrier. Long qualified as an interesting but "underutilized" crop, it is now being increasingly used in reforestation programs in tropical countries because it thrives on poor soils and on land that is suffering under erosion (Giovanni, 2007). The good news for the world which is facing significant reduction in fossil fuel availability as main source of energy because from *Jatropha curcas* fruits, a biofuel can be extracted. The use of fossil fuel also polluting the environment with Carbon dioxide (CO_2) which in turn causing global warming. Therefore seed oil from *Jatropha curcas* offers an excellent alternative for the source of energy (Jatropha World, 2007). Here one of the most important tasks in the overall domain known as Image Processing (IP) is the task of image classification (Gonzalez and Woods, 2002). Color grading is an important process for the *Jatropha curcas* fruit that often used to determine quality. Color image processing based systems have more recently been used in color grading. Color grading applications are implemented by using color image processing (Blasco *et al*., 2003). Since food products can be graded by their color, color grading for apples (Devrim and Barnard, 2004; 2007; Nakano, 1997), strawberry (Nagata *et al*., 1997), tomato (Choi *et al*., 1995) and other fruits have been developed (Njoroge *et al*., 2002). Two main characteristics that are decisive for visual inspection and classification of fruits are color and shape. For *Jatropha curcas* fruit, the estimation of quality cannot be done just by its shape

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because a fruit may have a different shape but the same level of quality (Jain and Vailaya, 1996).

The classification of *Jatropha curcas* fruit is used for the purpose of identifying the class labels for *Jatropha curcas* fruit on a set of target features. The classification of *Jatropha curcas* fruit can be represented by external appearance such as color. For example, *Jatropha curcas* fruit with green, yellow and black color that represent raw, ripe and overripe can analyze surface color of the *Jatropha curcas* fruit from their images. Learning classifiers from pre-classified *Jatropha curcas* fruit are used in a pattern recognition system. Neural network have proven to be a promising paradigm for intelligent systems. Neural network have been trained to perform complex functions in various fields of application including pattern recognition, identification and classification (Johnson and Picton, 1995).

Pattern recognition is the human ability to see regularities in observations. From the early development of computers, scientist and engineers tried to imitate this ability by mechanical means, either partially or in its entirety. The four best approaches for pattern recognition are template matching, statistical classification, syntactic or structural recognition and artificial neural networks (Theodoridis and Koutroumbas, 1998; Bishop, 2000; Ripley, 1996; Fukunaga, 1990; Friedman and Kandel, 1999). The latter approach 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, neural network has the fastest speed and best accuracy for classification work (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 (Schurmann, 1996; Kohonen, 1997; Fausett, 1994). 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/ 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 neural networks can be as accurate as procedural model (Deck *et al*., 1995; Timmermans and Hulzebosch, 1996). For example, the accuracy of classification of potted plants can be greater than 99% (Timmermans and Hulzebosch, 1996), apples can be graded by color with an accuracy of 95% (Nakano, 1997), the classification of logs for defects using computed tomography imagery can be 95% accurate (Schmoldt *et al*., 1997) and the accuracy for the classification of wheat kernels by color can be 98% or more (Wang *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 *et al*., 1997a; 1997b).

In this study, we present a development of pattern recognition system of *Jatropha curcas* fruit using neural networks that focused on the *Jatropha curcas* fruit classification problem. All features are extracted from digital data of *Jatropha curcas* fruits. We adopt back propagation algorithm neural network for its fast speed and simple structure. The whole algorithm is easy to implement, using common approaches (McClelland *et al*., 1987). The back propagation algorithm is used in layered feed-forward neural network. This means that the artificial neurons are organized in layers and send their signal “forward” and then 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.

MATERIALS AND METHODS

This research was initially planned to be completed in two stages. The first stage is to extract the characteristics from the pattern being studied. The second stages is to recognize the pattern by using some characteristics derived from the first task. A neural network diagnosis model is used to recognition the *Jatropha curcas* fruits. The flow diagram of pattern recognition system is shown in Fig. 1.

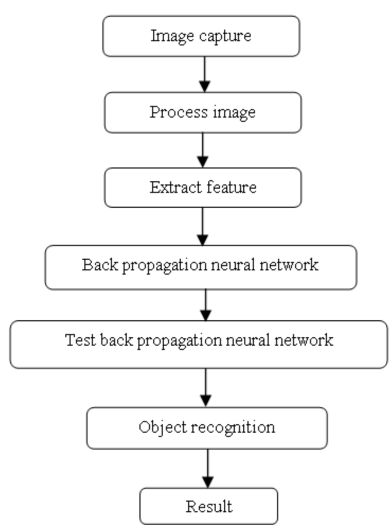

Fig. 1: Flow diagram processing

Fig. 2: Background purification (top: Original image; bellow: After background purification)

Stage 1: Training Stage: A digital camera is used to capture *Jatropha curcas* fruit images from the *Jatropha curcas* plants in University Kebangsaan Malaysia (UKM). The *Jatropha curcas* fruit images are transfered to a personal computer and were converted from jpeg to bitmap format (BMP). The image size *Jatropha curcas* fruit images was 756×504 pixel. These *Jatropha curcas* images is cropped to a size of 100×100 pixels. The *Jatropha curcas* fruit images separated from the background. The result is shown in Fig. 2.

Later the images are segmented to 100×100 pixel so that it can be used as a training data set. The size of 100×100 pixel was to make sure that back propagation neural networks was kept to the smallest possible size in order to achieve easier training. Each pixel of a *Jatropha curcas* fruit image is classified into one of 256 categories, represented by an integer in the range from 0 (black)-255 (white). Each assigned color indices the only inputs used in this study, others features, such as shape, are expected to be taken into account by neural networks since information about them is implicit in the relationships between the pixel colors.

Back propagation neural networks architecture developed is chosen as it was a simple and one of the most commonly used neural networks (Demuth *et al*., 2009). Another reason to chose back propagation due to it's ability to perform pattern classification on data where the input and the output had no linear relationship, as in the case of this application (Rao, 1996). The back propagation neural networks is as represented weighted sum:

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

Where:

$A_j(\bar{x},\bar{\omega})$ = Back propagation
x_i = Input
w_{ji} = Weights

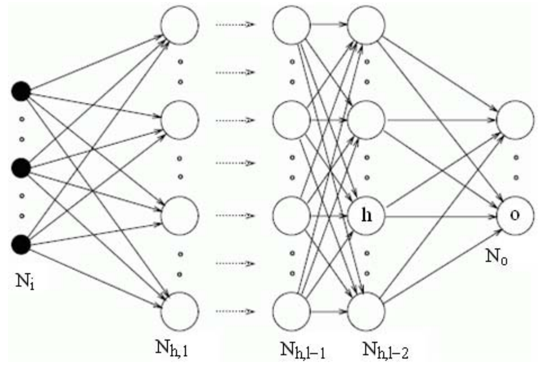

Fig. 3: Back propagation neural network structure

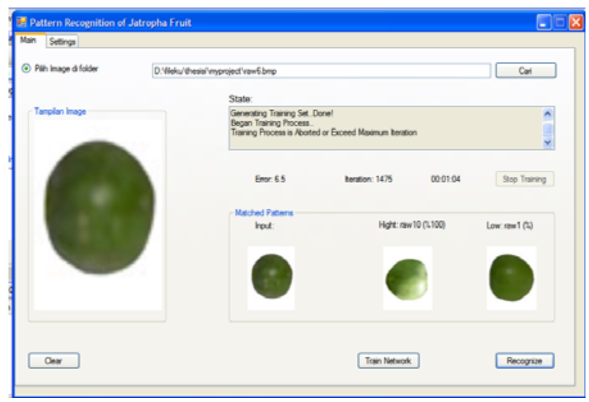

Fig. 4: Display GUI of trained process

In the training process, the network obtain 45 essential training data parameters. The weights of 45 node-layer altered and then the parameters are passed to the hidden layer respectively. Figure 3 shows the back propagation neural network structure.

Stage 2: Analyzing *Jatropha curcas* fruits: In the second stage an analyzing process is carried out software tool. In this process has been developed incorporating the back propagation that was trained, which display the *Jatropha curcas* fruit image to the user in a Graphical User Interface (GUI). Figure 4 show the GUI that has been developed

The result of the GUI analysis window is displayed after analyzing the *Jatropha curcas* fruit image. The *Jatropha curcas* fruit image segments with the grading (raw, ripe and over ripe) are shown on the analysis window.

RESULTS

Our database consists of twenty-seven images. A set of fifteen images were used for training the network and twelve were used for testing the performance.

Table 1: Result matched pattern of object recognition

Matched pattern	Validation (%)	Iteration	Timing
Raw	95.41	2008	0:02:10
Ripe	97.98	1975	0:01:29
Fruit-aged	98.33	1962	0:01:11
Over ripe	98.99	1452	0:00:59
Raw	96.80	1413	0:00:56
Fruit aged	95.55	2014	0:02:32
Raw	96.78	1968	0:01:18
Ripe	97.35	1322	0:00:52
Over ripe	95.00	2153	0:02:55
Over ripe	98.65	1970	0:01:25
Raw	97.18	1952	0:01:22
Raw	95.45	1389	0:00:58

Parameters selected for the classification of images as raw, fruit-aged, ripe and over ripe are, color and shape. These parameters were extracted for the images shown in Fig. 2. The preliminary results of the four classifiers are shown in Table 1.

Raw, fruit-aged, ripe and over ripe status images were used in the training. In the back propagation neural network, it gave an accuracy of about 95%, based on our samples used of the twenty-seven images. For the self-organizing network, it gave almost perfect results but because of the small sample size used, confirmation can only be given with further testing. The results produced by neural network were found to be more accurate due to its capability to distinguished complex decision regions.

DISCUSSION

The system captures the images of various *Jatropha curcas* samples for analyzing those samples using color matching technique to provide a pixel color value more precisely and reliably. It also finds a suitable match from the previously created image database. Grading will be done based on color. Others feature such as shape was expected to be taken into account by neural networks since information about them is implicit in the relationships between the pixel colors Color image is analyzed using RGB (Red, Green, and Blue) model because human perception is closely matched with this classification system. A suitable color-matching algorithm with soft computing technique has been utilized to determine the nearest match from this image database.

CONCLUSION

The training data set for back propagation neural networks had 4 level of grading (raw, fruit-aged, ripe, over ripe) with twenty-seven images of *Jatropha curcas* fruits. At the end training the neural network achieved its performance function but the time taken to achieve it was significantly high. When tested with a selected set of different image other than that used for training the back propagation neural network was able to categorize it accordingly.

When incorporated into the software tool the performance of the back propagation neural network was satisfactory as there were not substantial number of errors in categorizing. This was expected as the back propagation neural networks had not been trained with data directly from the tool. Training with live data from the tool itself is the next goal and the use of different learning algorithms and learning rates with learning optimization techniques are yet to be undertaken.

ACKNOWLEDGEMENT

The researchers would like to Government of Malaysia and University Kebangsaan Malaysia for their financial support under UKM-GUP-BTT-07-25-025 Grant.

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