Agarwood Chips Grading Using Neural Network

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Abstract
This paper presents the use of image processing and artificial neural network to determine the grade of the agarwood chips and thus provide an automated approach of the agarwood grading system. A backpropagation multilayer feedforward neural network has been used in this study with the inputs taken from the texture measurements and density. The relationship between texture properties and the price of agarwood was analyzed in order to select suitable input parameter to the neural network model. As a result, neural network architecture with three input parameters taken from textural properties and one input parameter taken from density, one hidden layer, seven number of neurons in hidden layer and three output layers has been developed. Neural network with algorithm of traincgp and transfer function of purelin and tansig give the best result of prediction with the percentage of accuracy of 60.58%.

Keywords: image processing, neural network, agarwood grading;

1. Introduction

Agarwood is produced from genus *Aquilaria* and has been known for its usefulness as incense, aromatherapy, perfume and even traditional medicine. At least fifteen species of *Aquilaria* trees are known to produce the agarwood especially *Aquilaria malaccensis*. These trees can be found in the forest of South and Southeast Asia, from the foothills of the Himalayas to the rainforests of Papua New Guinea. The tree first has to be infected by a certain group of fungi (Angela B. et al., 2000) to allow the formation of an aromatic resinous in the tree. This means that uninfected trees from the species are not valuable. Since the tree has become very rare due to continuous harvesting, certain organizations in Southeast Asia have done research to develop methods to cultivate agarwood**.**

Before the trees are traded, it will go through a grading process. Different country uses different methods to grade the wood. Basically it is determined based on the type, density of resin and the intensity of the aroma it produces. For example, in the past, Japan grading system is influenced by the Chinese methods. The wood is graded by theconcentration of oleoresin and the buoyancy in water. But now, since different people have different preferences to fragrance, they started to grade the wood differently. In Indonesia, the wood is burnt to generate

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fragrant and six different grades were created. The highest grade would be Kyara, followed by Rakoku, Manka, Manaban, Sumotara and Sasora.Mostly, the grading was done by individual who got expertise in this area. However, visual inspection and 'sinking grade' method is not necessarily accurate. Sometimes the color of the resin didn't exactly describe its quality and even sinking wood wouldn't produce enough oil. Grading is a time consuming process and recruiting an expert will take an even longer time.

A few researches have created better method in grading agarwood. (Azma. A et al., 2007) used image processing technique to relate the price of the wood. However, they found that the system is only suitable for the lower grade of agarwood because the accuracy of the test for grade A was below 50%. Mahirah. (2007) used image processing and density to grade agarwood. It has been found that the difference between means value of specific gravity for density group is closed to each other and the range are overlapping. The difference between means value of gray for each group is also closed to each other. Then, there is also another research by Khairuddin (2007) dealing with RGB color model. The correlation between the price of agarwood and pixel intensity at each band has been analyzed. The result showed that the gray value of agarwood chips gives quadratic correlation to its price. However, the disadvantage of this approach is the sensitivity of the RGB colour space to the light sources which are fairly difficult to control. This leads to less accurate result.

In this study, information from texture and density of the wood will be used as the input in the process of grading the chip. Texture is the term used to characterize the surface of a given object or phenomenon and it is one of the main features used in image processing and pattern recognition. Grey Level Co-occurrence Matrix is one of the earliest texture analyzers which are still being used in many studies. This technique has been introduced by Haralick et al. (1973). It estimates image properties related to second order statistics (C.H. Chen et al., 1998). Sadiq. C et al. (2008) tries to compare three different approaches to solve the problem of texture analysis; Laws Energy Measures, Gabor filter and Gray Level Co-occurrence matrix. From the experiments, they found that GLCM gave the best performance. M. Khalid et al. (2008) developed a wood species classification system based on the extracting textural wood features using GLCM approach. Juha K. and Matti P. (2000) found that the performance of color based wood inspection systems can be improved by combining color and texture features.

Artificial neural network were inspired by biological findings relating to the behavior of the brain as a network or units called neurons (M. Larry, 1994). It has gained widespread acceptance for classification and identification of tasks. This new technology has capable to solve complex task in many different fields. For example, it's widely acceptance has been used in agriculture. R. Pydipati et el. (2005) has conduct experiments to find a suitable network architecture to detect citrus leaf disease. He determined that two hidden layers network with 10 neurons per layer performed significantly better than any option. Kurdthongmee (2008) proposed automatic approach based on a combination of an image processing technique and an artificial neural network. One model based on the back propagation-trained multi layer perceptron has been built to train a wood data acquired in the Database Module (M. Khalid et al., 2008). The system shows a high rate of accuracy of more than 95% recognition success of 20 different tropical wood species. In this study, image processing and artificial neural network approach will be used to determine the quality of the agarwood chips and provide a standard method to the grading system.

2. Materials and Methods

Data

The data used in this study were taken from the previous study by M. Jahari (2007). There are seven grades of agarwood available i.e RM 250, RM 350, RM 800, RM 900, RM 1000, RM 2500 and RM 3500. The wood samples has been grades and classified by an expert from Malaysian Institute for Nuclear Technology Research (MINT). Agarwood images were captured by using Nikon Coolpix 5600 5.1 Megapixel CCD camera in a room with a control lighting condition and a fixed distance between camera and samples of agarwood. In order to eliminate the shadow, the position of the camera has been fixed into 90°. Another input parameter used in this study is density. The data of density is also taken from previous study by M. Jahari (2007).

Image Feature Extraction

The relationship between eight statistical texture parameters taken from the GLCM and the price of agarwood will be analyzed. The parameters used were mean, homogeneity, contrast, correlation, dissimilarity, entropy, variance and second moment. Therefore, the process of finding the texture statistics will be done as follow; first, the value of texture statistics in every agarwood images will be extracted by using the ENVI software. The average value of every property will be calculated by dividing the total value of properties in each grade by the total number of sample. The standard deviation of the result is then calculated. Only texture properties with smallest standard deviation will be used as the input parameter in a neural network.

Neural Network Model

Once image features are identified, the next step is to classify the price of agarwood based on its texture statistic. Numerical techniques for the task would be artificial neural network. Neural networks have proven themselves as proficient classifiers and are particularly well suited for addressing non-linear problems. Given the non-linear nature of real world phenomena, like wood classification, neural networks is certainly a good candidate for solving the problem.

While there are numerous different (artificial) neural network architectures that have been studied by researchers, multilayer feed forward networks are the most successful applications in data mining. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range -1 to +1.

In the networks there is an input layer consisting of nodes that simply accept the input values and successive layers of nodes that are neurons. The outputs of neurons in a layer are inputs to neurons in the next layer. The last layer is called the output layer. Layers between the input and output layers are known as hidden layers. There is no clear theory to be used as a guide on choosing the number of nodes in each hidden layer or indeed the number of layers. The common practice is to use a trial and error approach. Figure 1 shows the architecture of back propagation neural network. First, a training input pattern is presented to the network input layer. The network propagates the input pattern from layer to layer until the output pattern is generated by the output layer. If this pattern is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated.

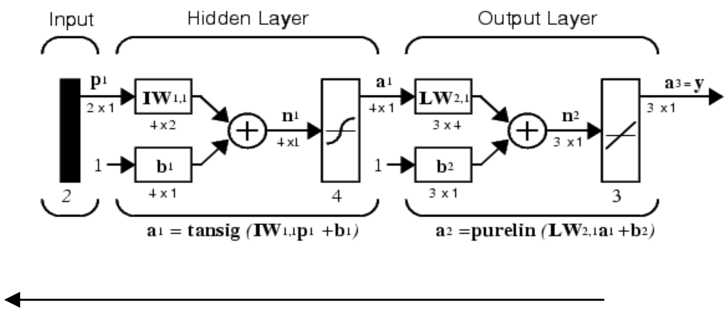


Figure 1: The example of an algorithm with transfer function of tansig and purelin

There are three different combinations of basic components to be used to develop the best neural network model. There are the number of neurons, types of training function and types of transfer function. An artificial neural network consists of a number of neurons which are connected by weighted links passing signal from one neuron to another. The number of neurons that is chosen to train and test the network is based on Fibonacci number, i.e. 1, 2, 3, 5, 8, 13 and 21.

In this study, there are three types of transfer function will be used in the hidden and output layer; logsig, tansig, and purelin. The logsig is a log sigmoid transfer function that generates outputs between 0 and 1 as the neuron's network input goes from negative to positive infinity. Tansig is a tan-sigmoid transfer function that generates output between +1 to -1. The purelin is a linear transfer function and it ropvides an output equal to the neuron weighted input. Each of the transfer functions can be called to calculate its own derivative.

Back propagation can train multilayer feed-forward networks with differentiable training algorithm to perform function approximation, pattern association, and pattern classification. There are several different back propagation training algorithms. They have a variety of different computation and storage requirements, and none of the algorithm is best suited to all situations. The training algorithms used in this study are tabulated in Table 1.

Table 1: List of network training function used to train the neural network

Acronym	Algorithm	
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiére Conjugate Gradient
OSS	trainoss	One Step Secant
GDX	traingdx	Variable Learning Rate Backpropagation

3. Result and Discussion

Data

The data of density is tabulated into graph as shown in Figure 2 below. Theoretically, when the price gets higher, the density of the agarwood increases. From the graph it can be seen that the value of density for RM 250 and RM 350 is lower compared to the value of density for RM 3500. However, the graph does not clearly differentiate the grades of agarwood because most of the data were overlapped with each other. This means that the agarwood grades couldn't be differentiated only based on its density.

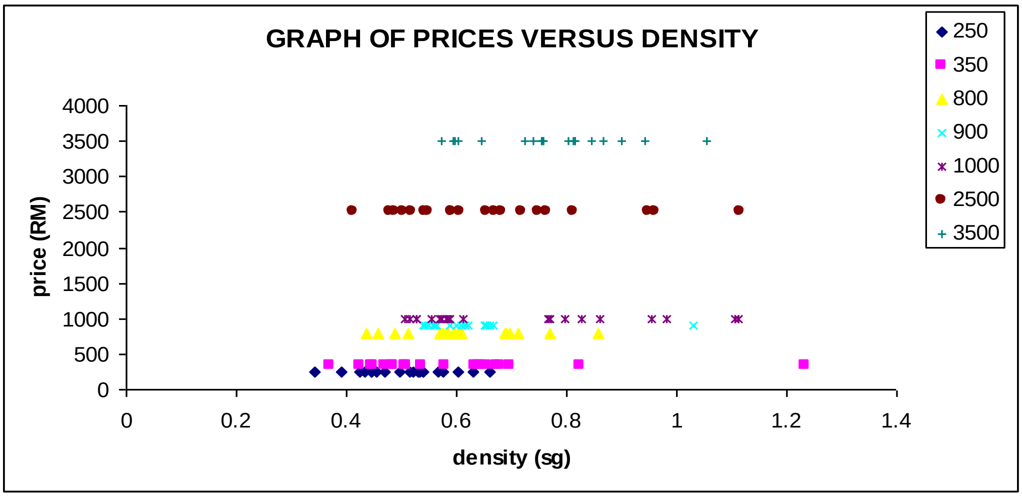
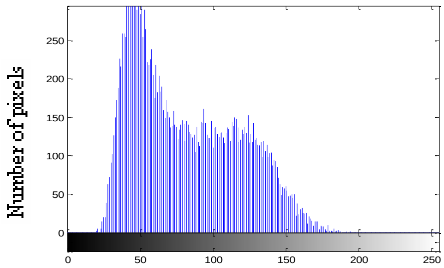


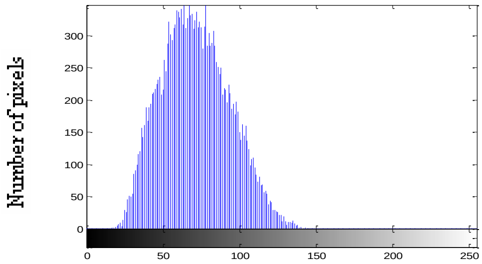
Figure 2: Graph of price versus density of agarwood

Image feature extraction

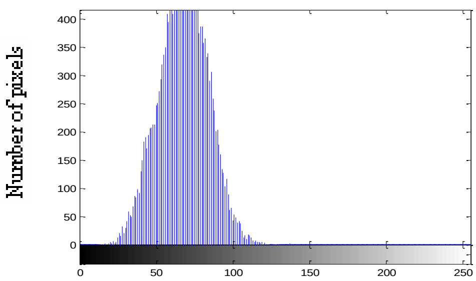
Image of agarwood chip sample in RGB format is converted into grayscale. Grayscale is an image in which the value of each pixel is a single signal, that is, it carries only luminous intensity information in [0,1] with 0=black and 1=white. It is usually the preferred format for image processing. Figure 3 shows the histogram of agarwood image in seven different prices. From this figure it can be shown that the pixels were not distributed in all range of histogram. Furthermore, the patterns in all prices are almost the same.



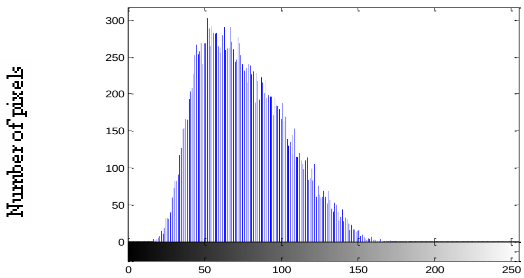
(a)



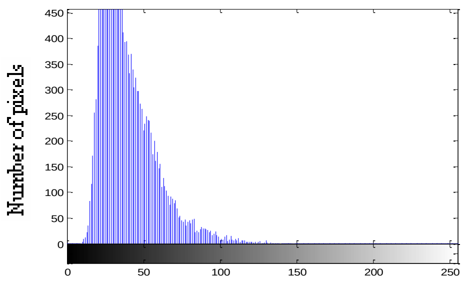
(b)



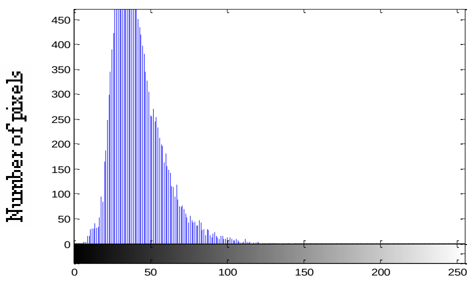
(c)



(d)

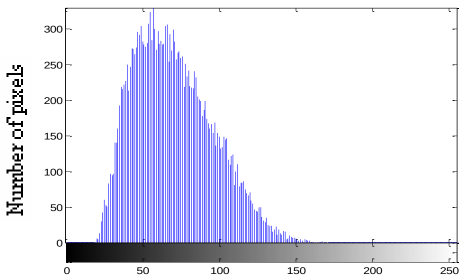


(e)



(f)

Pixels val



(g)

Figure 3: Histogram of agarwood sample in greyscale images taken from seven different prices.

(a) RM 250 (Sample no. 001) (b) RM 350 (Sample no. 041)
(c) RM 800 (Sample no. 081) (d) RM 900 (Sample no. 121)
(e) RM 1000 (Sample no. 161) (f) RM 2500 (Sample no. 201)
(g) RM 3500 (Sample no 241)

Therefore, an image enhancement technique has been performed to the images in order to get images with high contrast. Image enhancement does not increase the inherent information content of the data. It increases the dynamic range of the chosen features so that they can be detected easily. Histogram stretching and Histogram equalization has been applied to the images to enhance the images. The histogram stretch adjusts the range of brightness values so that the entire available range is used. Thus the lowest brightness is mapped to black and the highest brightness mapped to white. All levels in between are mapped proportionally. Figure 4 shows result of the histogram stretching for sample of agarwood in four different prices. From this figure, it can be seen that the histogram stretching still couldn't distinguished one price to the others. The pattern of the histogram is almost the same for each price.

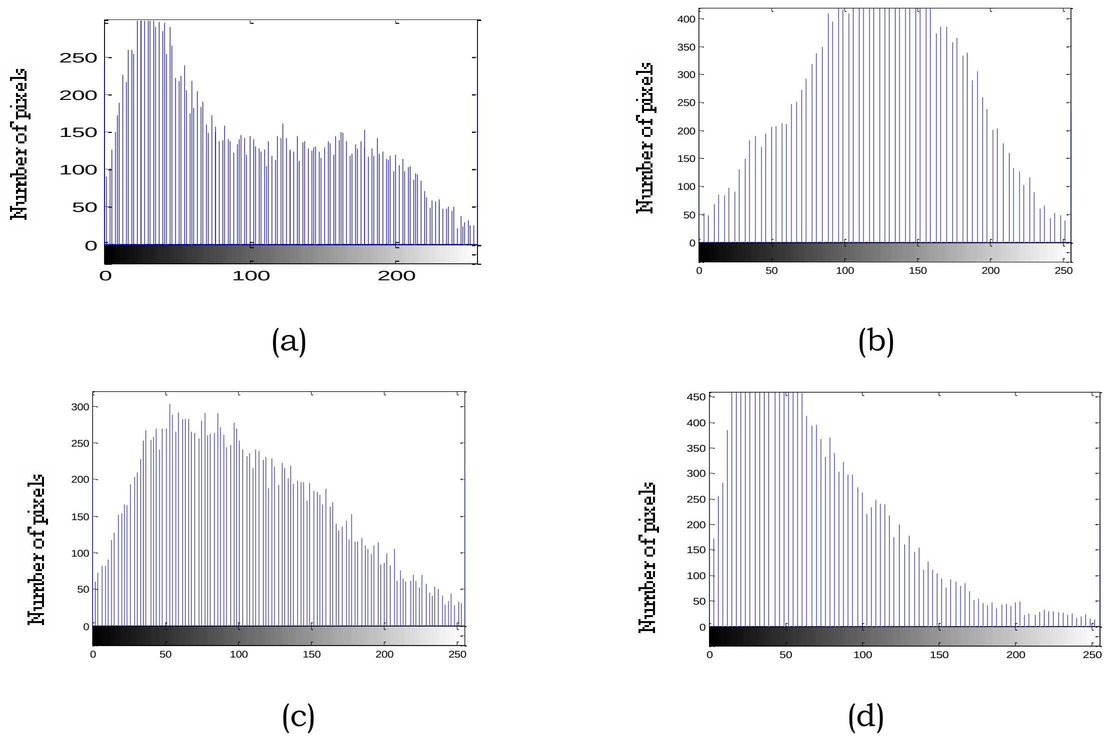
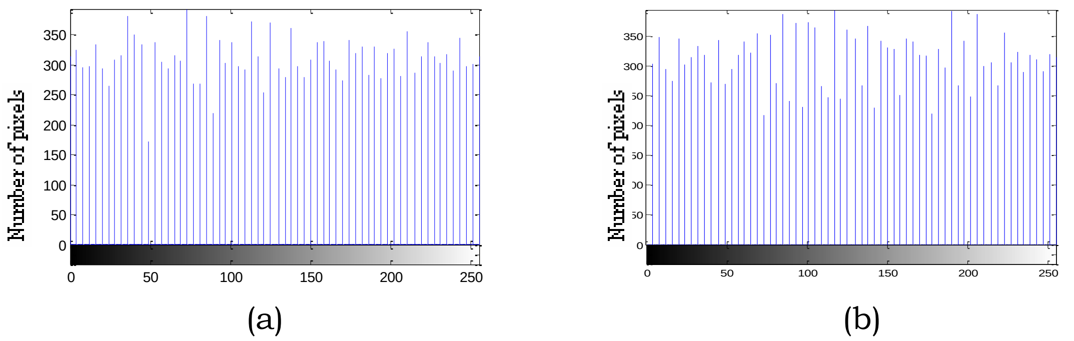
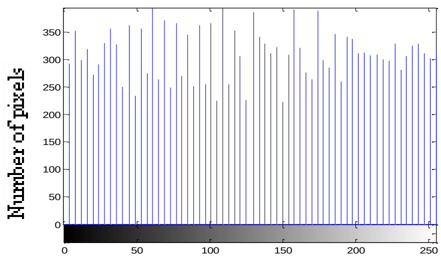


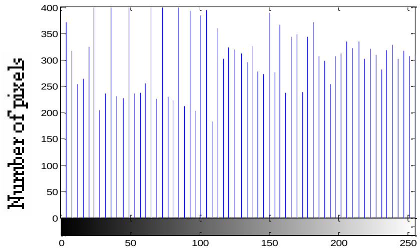
Figure 4: Histogram stretch of agarwood sample in greyscale images taken from four different prices.
(a) RM 50 (Sample no. 001) (b) RM 800 (Sample no. 081)
(c) RM 900 (Sample no. 121) (d) RM 1000 (Sample no. 161)

The histogram equalization has been done to the agarwood images to evenly distribute the occurrence of pixel intensities so that the entire range of intensities is used more fully. Figure 5 show result of the histogram equalization in seven prices of agarwood. The result is still the same. None of the histogram could show the difference between each price.





(c)

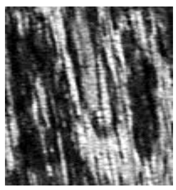
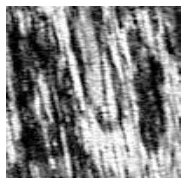


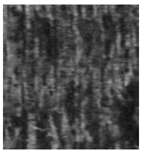
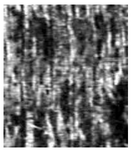
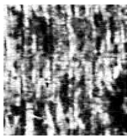
(d)

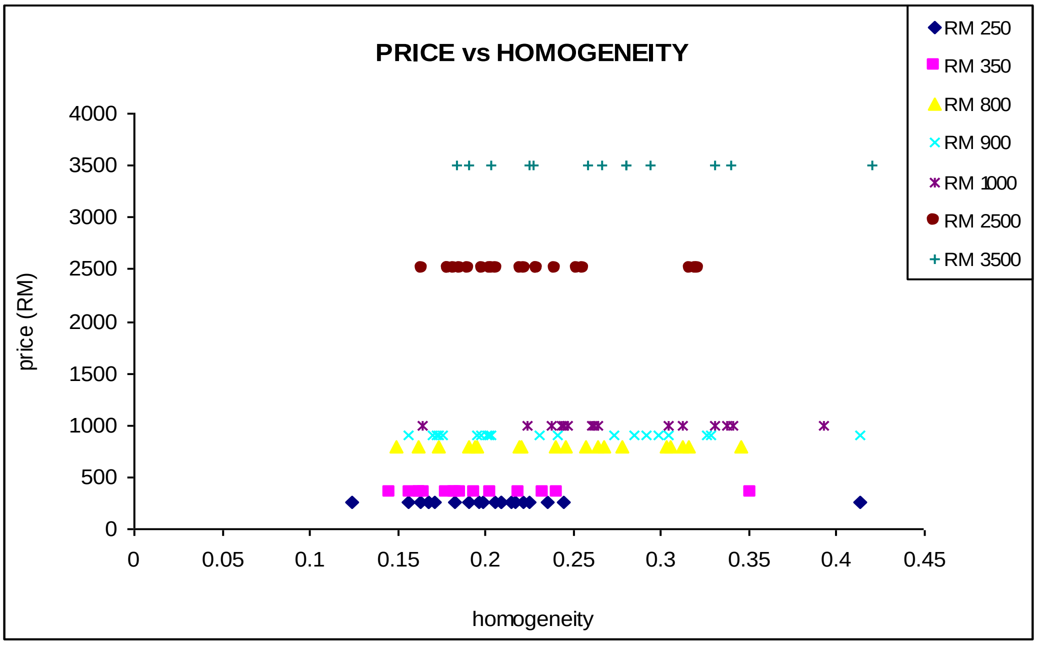
Figure 5: Histogram equalization of agarwood images taken from four different prices.
(a) RM 250 (Sample no. 001) (b) RM 350 (Sample no. 041)
(c) RM 1000 (Sample no. 161) (d) RM 2500 (Sample no. 201)

Table 2 shows the images of the greyscale, histogram stretch and histogram equalization of agarwood chips taken from three different prices. From this figure, it clearly shown that the histogram stretching and histogram equalization can improve the contrast of the images. This contrast can help different price of agarwood images be differentiated better. However, one sample of agarwood image did not give a true representation of the price. Therefore, the relationship between texture properties in different images need to be analyzed in order to find which method would give better result of prediction based on its texture properties.

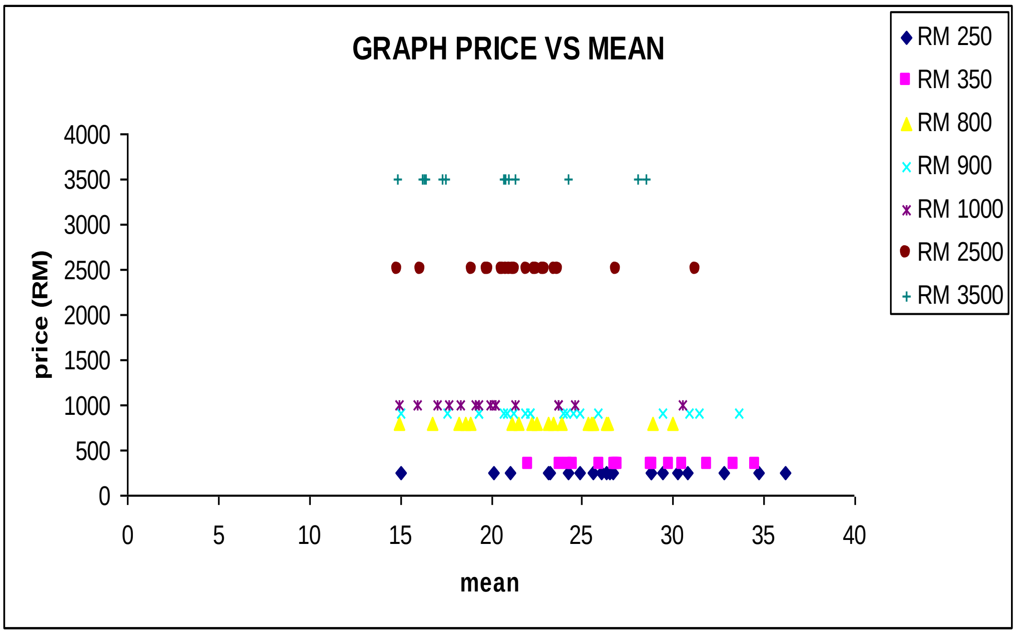
Table 2: Different prices of agarwood images in greyscale, after histogram stretch and after histogram equalization

PRICE	NO. OF SPECIMEN	ORIGINAL IMAGE (GRAYSCALE)	IMAGE AFTER HISTOGRAM STRETCH	IMAGE AFTER HISTOGRAM EQUALIZATION
RM 250	001			
RM 350	041			

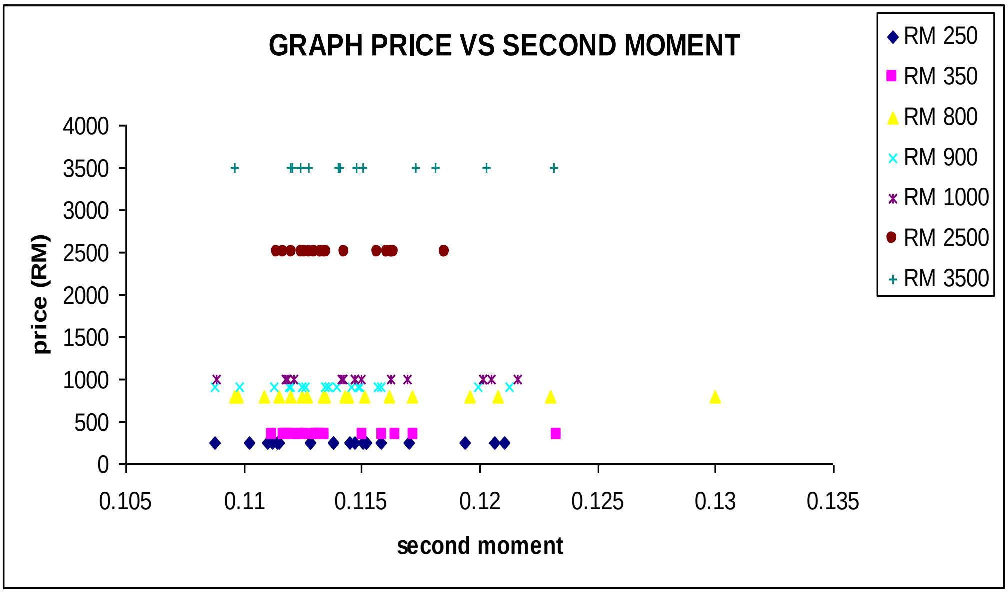
RM 3500	241			



(a)



(b)



(c)

Figure 6: Graph of price versus selected texture properties in different sample of images.

(a) Graph price versus homogeneity for greyscale images
(b) Graph price versus mean for stretching histogram images
(c) Graph of price versus entropy for equalization histogram images

Grey-Level Co-occurrence Matrix texture measurements have been used to process image texture since they were proposed by Haralick et al. (1973). There are three groups of texture measures in GLCM. The first were contrast group (contrast, dissimilarity and homogeneity). The second group is orderliness (second moment and entropy) and the last group would be statistic group (mean, variance, correlation).

The relationship between all texture properties and the price of agarwood were then be analyzed. Result of the experiment has shown that all of the properties did not show any significant relationship with the price of agarwood. The texture properties extracted from original images (greyscale), stretched images and equalization images were overlapped from one price to the others. From figure 6(a) it could be seen that the price of RM 250 and RM 350 gave the value of homogeneity between 0.15 to 0.25. However, almost half of these values were overlapped with the data taken from RM 800, RM 900 and RM 1000. When the histogram of the image is stretched, it produced almost the same graph as the graph of greyscale image. From figure 6(b), the price group of RM 250 and RM 350 could be differentiate from price of RM 1000. Graph of the data taken from the histogram equalization are almost similar. From figure 6(c) it could be seen that it is difficult to differentiate the prices of agarwood because the data is overlapped with each other. Therefore, we conclude that the image enhancement did not give any significant improvement in dealing with the price determination with the texture properties. The original image will be used in the next analysis.

3.3 Suitable input parameter

The selection of suitable parameter for the input of neural network is done by selecting texture properties with the low value of standard deviation. First, the mean of each property will be calculated. The average (mean) will describe the central location of the data, and the standard deviation describes the spread. A low standard deviation indicates that the data points tend to be very close to the mean, whereas high standard deviation indicates that the data are spread out over a large range of values. This means that data with low standard deviation is more consistent than data with high standard deviation. Since the data for original image, histogram stretch and histogram equalization is almost the same, only data from original image is going to be considered. From Table 3, it has been shown that contrast (12.98-17.38) and correlation (23.32-38.23) give the highest range of standard deviation. While second moment (0.006-0.013), entropy (0.03-0.06) and homogeneity (0.057-0.067) were among the lowest standard deviation. As a result, only these three parameters are going to be used as an input to the neural network training.

Table 3: Mean, standard deviation and R^2 of textural properties in every prices of agarwood.

Texture Measurement	Price	Mean	Standard Deviation	R^2
Mean	RM 250	24.936065	4.468321	0.42
	RM 350	24.462700	4.712115	
	RM 800	18.687373	4.387024	
	RM 900	19.387638	5.549253	
	RM 1000	18.298752	3.840048	
	RM 2500	19.047222	3.222297	
	RM 3500	17.675737	4.071845	
Homogeneity	RM 250	0.2055799	0.0572479	0.29
	RM 350	0.1977333	0.0979834	
	RM 800	0.2440581	0.0573292	
	RM 900	0.2418539	0.0694103	
	RM 1000	0.2777280	0.0577152	
	RM 2500	0.2251196	0.0477218	
	RM 3500	0.2693290	0.0669377	
Correlation	RM 250	-64.661636	29.599610	0.30
	RM 350	-60.882734	27.487026	
	RM 800	-53.765488	28.110255	
	RM 900	-51.240828	23.328213	
	RM 1000	-60.366823	26.561656	
	RM 2500	-45.040234	23.462491	
	RM 3500	-55.206955	38.234288	

Dissimilarity	RM 250	4.6982140	1.0714976	0.15
	RM 350	4.8014635	1.0921415	
	RM 800	3.8283188	1.0804288	
	RM 900	3.8531444	1.1878948	
	RM 1000	3.2703861	0.7456889	
	RM 2500	4.3523882	1.0498034	
	RM 3500	3.5713827	1.0141027	
Contrast	RM 250	31.403235	17.032712	0.01
	RM 350	44.356534	17.385874	
	RM 800	26.701692	13.459327	
	RM 900	29.697450	15.671875	
	RM 1000	23.614170	11.067609	
	RM 2500	39.927513	16.388227	
	RM 3500	27.530107	12.989690	
Entropy	RM 250	2.028779	0.059044	0.31
	RM 350	2.037326	0.040724	
	RM 800	2.006178	0.042105	
	RM 900	2.004075	0.058671	
	RM 1000	1.967115	0.052024	
	RM 2500	2.007845	0.035162	
	RM 3500	1.976891	0.065378	
Variance	RM 250	23.6305404	8.6934515	0.37
	RM 350	21.0795893	7.5668167	
	RM 800	16.1172885	8.3606614	
	RM 900	16.2494389	8.8630765	
	RM 1000	12.3854285	5.0434697	
	RM 2500	19.6146257	8.2135477	
	RM 3500	9.5596173	6.8181084	
Second Moment	RM 250	0.1186032	0.0120813	0.13
	RM 350	0.1169140	0.0078550	
	RM 800	0.1225774	0.0079778	
	RM 900	0.1230180	0.0113176	
	RM 1000	0.1300859	0.0102193	
	RM 2500	0.1222545	0.0066646	
	RM 3500	0.1283726	0.0136226	

3.4 Training and Testing Neural Network

Three parameters from texture analysis and density will act as inputs to a neural network and the grade of the wood will act as the output (target). Given an input, which constitutes the three observed values from the texture analysis of a chip and density, the neural network is expected to classify the chip into group 1(RM250 and RM350), group 2 (RM800 and RM900) andgroup 3 (RM1000, RM2500 and RM3500). This is achieved by presenting previously recorded inputs to a neural network and then tuning it to produce the desired target outputs. This process is called neural network training. The neural network will learn to identify the grade of the wood chips. The target will be classified into three groups as described above. Total images being used in this study is 210 images. During the process the network pick randomly about 60%-70% of the data to be trained and 30%-40% to be tested.

Table 5 shows the fixed parameter that has been used during a training process. When the neural network is being trained and testing with different combination of number of neurons, types of transfer function and training function, this parameter will stay the same.

Table 5: Fixed parameter in neural network testing and training

Parameter	Limit
Number of epochs between showing the progress	20
Maximum number of epochs	1000
Performance goal	0.1
Learning rate	0.2
Learning rate increase multiplier	1.05
Learning rate increase multiplier	0.7
Momentum constant	0.9

The neural network model has been run by using different combination of training algorithm, transfer function in hidden and output layer and also different number of neuron. These combinations has been developed from nine training algorithm, three transfer function in hidden layer, three transfer function in output layer and seven different number of neurons. Each combination will be run five times. That would make the total number of the network being run to get the lowest error is 2835 times. Table 6 shows the percentage of error after the one of the test is done. The number of error in each group is calculated to give the total percentage. The test set provides a completely independent measure of network accuracy. After training and testing of the data with different set of network training function and transfer function, the result with lowest average of total error is 39.42% as shown in Table 7. This means that the best training function would be *traincgp* with *purelin* and *tansig* as transfer function with two neurons.

Table 6: Percentage of error on each group after one of the network being run

	No. of error	% of error
Agarwood-group1 recognition error:	3	12.50
Agarwood-group2 recognition error:	9	40.91
Agarwood-group3 recognition error:	14	45.16
Total Agarwood chip recognition error:		33.77

Table 7: The percentage of error after the network is trained with different combination of neurons and activation function

Neurons	Network Training Functions	Transfer Function 1	Transfer Function 2	Average Error (%)
1	trainscg	purelin	purelin	42.39
2	**traincgp**	**purelin**	**tansig**	**39.42**
3	trainlm	purelin	purelin	40.83
5	traincgb	logsig	logsig	45.66
8	trainscg	purelin	logsig	41.82
13	traincgp	logsig	tansig	43.19
21	traincgb	purelin	tansig	42.05

4. Conclusion and Recommendation

The relationship between all texture properties and the price of agarwood has been tabulated into graph and analyzed for its difference between grades. From the graph, it can be seen that the lower price of the wood, that is grade 1 (RM 250 and RM 350) does show a significant different than other grade. Some of grade 2 data is overlapped with grade 1. However data for grade 3 is totally overlapped with other data. This makes it quite difficult to determine grade 3 of the wood. Therefore the input parameter from texture measurement has been chosen by comparing its standard deviation. The parameters with lowest standard deviation were homogeneity, entropy and second moment. This parameter has been used as the inputs in the neural network.

Deciding the right architecture before using backpropagation algorithm has proved to be time consuming and complex procedure. The practical way to decide is by doing several trial and error runs on several architectures. This has proved to be the most useful in deciding the right activation function for the network. With the accuracy of 60.58%, the use of textural properties in predicting the price of agarwood is promising. However, the model needs to be improved for more practical usage. Since the price of agarwood is naturally graded by considering their color, density and odour properties, therefore all of these elements might be added to improve the prediction. Other color models such as HSI, HSV, YUV, YCbCr, CIELAB, CIELUV and etc might also be used to prevent the shortcomings from RGB color space. This is because RGB color space has high correlation between its component and it is device dependant.

Previous research by Azma. A et al. (2007) also produces the same result. Only price from lower grade could be predicted. The accuracy of the result for grade A is below 50%. In this study the image dimension is quite small, therefore the statistic information from the image is not enough to describe its characteristic based on each grade. Better sample of agarwood images might improve the prediction for higher grade of agarwood chips.

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