Multilayer Perceptron (MLP) tuned Kernel Parameter in Support Vector Machine (SVM) for Agarwood Oil Compounds Quality Classification

Mohammad Nur Faisal bin Ariffin[1*], Nurlaila Ismail[1], Nor Azah Mohd Ali[2], Mohd Hezri Fazalul Rahiman[1], Saiful Nizam Tajuddin[3] and Mohd Nasir Taib[1]

[1]*Faculty of Electrical Engineering, Universiti Teknologi Mara Shah Alam, 40000 Shah Alam, Selangor*

[2]*Natural Product Program, Forest Research Institute of Malaysia (FRIM), 52109 Kepong, Selangor*

[3]*Bio Aromatic Research Centre of Excellent, Universiti Malaysia Pahang, 26300 Gambang, Pahang*

**Email:* nrk_my@yahoo.com

Abstract

Agarwood or gaharu is one of the expensive woods in the earth. The wood is valuable in many cultures due to its extraordinary fragrance and extensively used as perfume ingredient, medicine and incense. The agarwood oil is highly demanded especially in the countries of Saudi Arabia, UAE, China and Japan. As one of the researches in classified the quality of agarwood oil, the implementation of Multilayer Perceptron (MLP) tuned kernel parameter in Support Vector Machine (SVM) are presented in this research especially to classify agarwood oil compounds to the different quality. The works involved of the data taken from previous researcher consist of agarwood oil samples from low and high qualities. The input for agarwood oil was the abundances (%) of compounds and the agarwood oil quality was the output which is low or high. The input and output data of agarwood oil were preprocessed by normalizing, randomizing and splitting the data to training and testing dataset. The training dataset were fed to Support Vector Machine (SVM) for network development model. After that, the testing dataset were used to test on model performance. All the analytical works were performed automatically using MATLAB software version R2015a. The result showed that the Support Vector Machine (SVM) model with Multilayer Perceptron (MLP) tuned kernel parameter that passes all the performance measures; confusion matrix, accuracy, sensitivity, specificity and precision. The finding in this research was benefit the future works of agarwood oil research area especially to the oil quality classifications.

Keywords: SVM, MLP, Agarwood Oil, Classification, Oil Quality.

**corresponding author: musab@usim.edu.my*

1. Introduction

Agarwood or *gaharu* is from the *Thymelaeaceae* family which has an aromatic and hugely treasured wood found in *Aquilaria* species. The immune feedback of tree to the fungi infection is the result the wood is formed. Agarwood is complex and gratifying with few or no identical natural analogues based on its odour. Other names of agarwood are eaglewood, aloeswood and *gaharu* just for the fragrant, resinous and hugely profitable heartwood founded in *Aquilaria Malaccensis* that typically used as ingredient to make perfumes, traditional medicinal preparations and incense for religious ceremony [1, 2]. The dark and heavy wood from the richness of agarwood's names reflects its boundless and diverse benefit over thousands of years [3].

Aquilaria is a giant evergreen tree that grows up with height of 40 meter, its diameter about 60 centimeter and also consists of white flowers [4]. The agarwood have adapted to live in assorted habitats, as well as sandy, rocky, well drained ridges or slopes and also land nearby marsh. They commonly mature between altitudes of 0 – 850 meter and the average daily temperature of 20 – 22 degree in celsius (°C) in locations [5].

The quality of agarwood oil which is high and low is traded in the country such as Japan. The high quality oil is more expensive than low quality. The normal price for a high quality oils is traded at the price USD126 to USD633 per tola (12 ml) [6]. Furthermore, agarwood oil prices can range between USD19 per kg for low qualities and up to USD100, 000 per kg for eminent quality [7]. Meanwhile, the high quality can be sold at premium price which consists of oil with dark color and durable odour [8].

The identification of the agarwood oil have been done by a lots of researcher to classify its qualities [9]. Usually, agarwood oil is grading by trained human graders (sensory panels). Nonetheless, there are drawbacks in the method which is objectivity and repeatability terminology. In supplementary, human nose cannot accept various samples since the fatigues speedily with expanding number of samples [6].

The Support Vector Machine was introduced by Vladimir Vapnik as binary classifier by building a separating hyperplane using various kernel functions that discriminates between two cases [10]. SVM is a computer algorithm that is trained to recognize and classify objects through a process based on supervised machine learning method. As a part of pattern recognition solving methods, the data is mapped and maximum separating hyperplane is generating in a higher dimensional input space [11].

SVM also consists of two groups which divided into linear and nonlinear SVM that has the different structure between them. It stated that linear SVM using hyperplane to divide the data into two groups while for nonlinear SVM, hyperplane cannot be used to separate the data [12, 13].

MLP is also known as sigmoid kernel [14] with a sigmoid kernel function curve as shown in Figure 1. The weight,v and bias,c are the Multilayer Perceptron (MLP) tuning parameter. In MATLAB, the parameters are expressed as P1 for the slope or weight and P2 for the intercept constant or bias. It is stated in MATLAB that P1>0 and P2<0. By delinquency, the value is set at 1 and -1, appropriately.

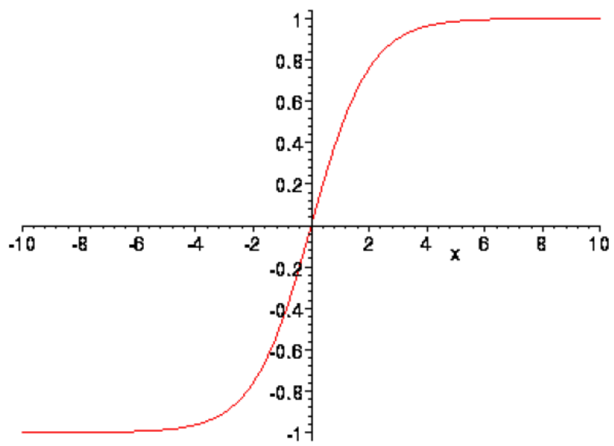

Figure 1 Multilayer Perceptron Curve [15]

The equation of Multilayer Perceptron kernel function defined as below that derives from artificial neural network.

$$K(x, y) = \tanh\,(v(x, y) + c) \qquad (1)$$

2. Theoretical Work

A. Support Vector Machine (SVM)

Support Vector Machine was introduced by Vladimir Vapnik as the machine learning method based on the process of statistical learning theory [16, 17]. At the beginning, SVM were evolved by Vladimir Vapnik and his colleagues as a binary classification method called Support Vector Classification (SVC) [18]. In the mid 1990, they enlarged it to regression problems named Support Vector Regression (SVR) [18]. SVM have been successfully practiced to the binary classification and regression problems and usually producing improved results compared to other machine learning techniques [18].

Nevertheless, the main benefit of Support Vector Machine (SVM) which they can handle with nonlinear by applying a "kernel trick" [16]. The kernel trick is an uncomplicated and general principle to convert the original space into a high-dimensional space named feature space. The feature space transforms by using a mathematical function called kernel function. With this function, it determines the possibility to show nonlinear relationships in a linear form. Regrettably, Support Vector Machine (SVM) faced some drawbacks like fewer attractive for practical problems.

A Support Vector Machine is a discriminative classifier between two cases that represented by using a separating hyperplane [19]. Particularly, an optimal hyperplanes can categorizes new examples by given the labeled training data likes *supervised learning* the algorithm outputs. For the linear SVM, it was introduced by hard margin and soft margin while nonlinear SVM have to tune the kernel function. In the Figure 2 and 3, it illustrates the linear and nonlinear SVM.

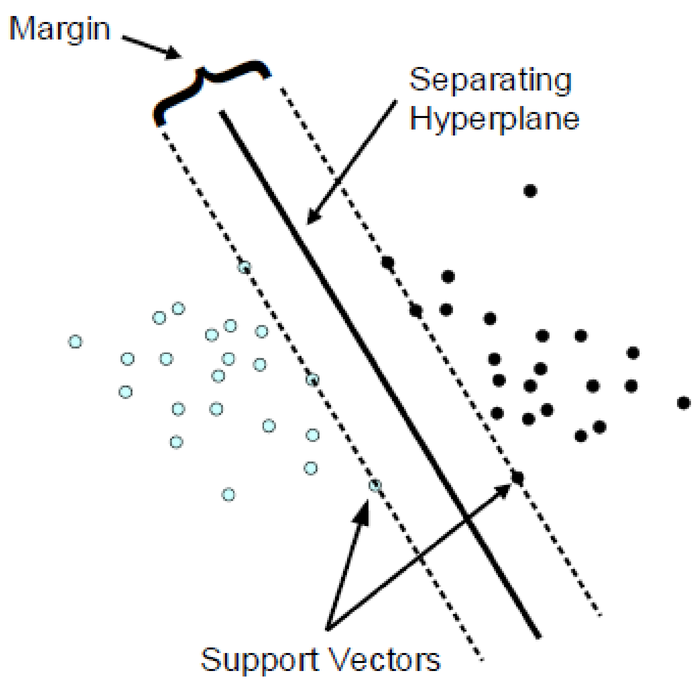

Figure 2 Linear Support Vector Machine [19]

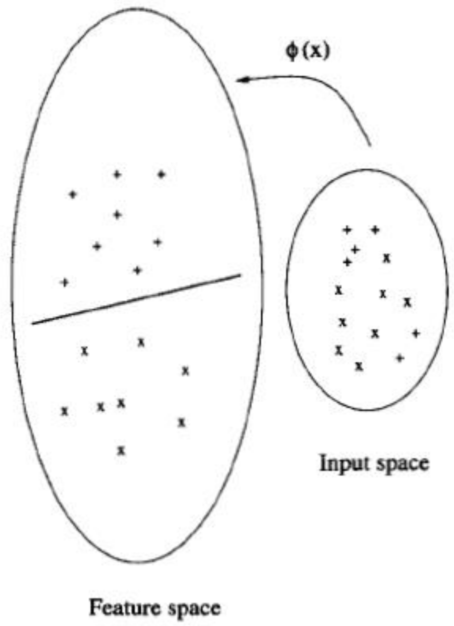

Figure 3 Nonlinear Support Vector Machine [20]

B. Multilayer Perceptron (MLP)

Multilayer Perceptron (MLP) is current dynamic methods that commonly used in function fitting and recognition problems by using the supervised learning technique called error back propagation during network training to perform work [21, 22].

A basic neuron with n_o input is show in equation below. The input (x) is weighted with a relevant w. The input from the total of the weighted inputs (v) and the bias (b) shows a part of the activation function v(t) output. Besides, the positive activation is produce when the receiving weighted activity is higher than negative bias weight. As for the mathematical equation, it is defined as below:

$$V(t) = w_{n_0} + b \tag{2}$$

The structure for Multilayer Perceptron (MLP) typically consists of three of more layers [12]. First is the input layer which will accept the inputs from dataset while the output layer will present the output of the Multilayer Perceptron (MLP) to the outside. The task of the hidden layer is to learn the relationship of input/output through a process. Figure 4, shows the example of Multilayer Perceptron (MLP).

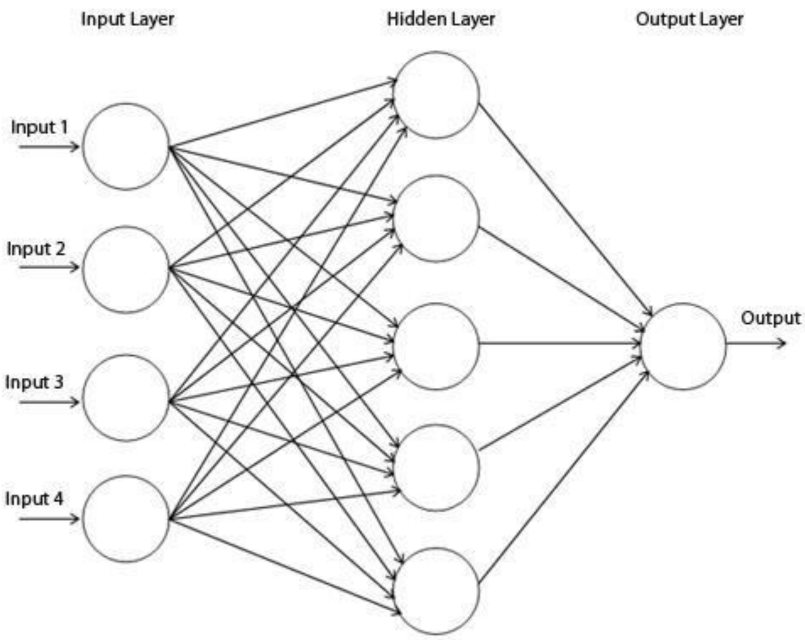

Figure 4 Example of Multilayer Perceptron (MLP) [12]

There are two phase training process in the hidden layer that was undergo. The first phase is called forward phase which the inputs are conferred to the network at first layer (input layer) and it passed to the output layer through hidden layer. Then, it will make the network output. The second phase is called backward phase which the network error is calculated based on difference predicted output and actual output.

For the activation function used in Multilayer Perceptron (MLP), there are two of most common. The first activation function is the tangent-sigmoid (tansig). Tangent-sigmoid is used in the hidden layer and consists of an input active range between -1 and +1. Any values outside from this range will put down to within these limits. The formula for tansig as below [23]:

$$tansig\ (v(t)) = \frac{e^{v(t)} - e^{-v(t)}}{e^{v(t)} + e^{-v(t)}} \tag{3}$$

where e is error.

The second activation function is the pure linear (purelin) which used in the output layer. It also has an input active range between -1 and +1 but it has no squashing effect compared to tansig activation function due to the output is linear. The formula for purelin as below [23]:

$$purelin\ (v(t)) = v(t) \tag{4}$$

C. The Performance Measures

The performance measure used in the research is the confusion matrix. The confusion matrix divide into the matrix row which denotes the actual class and matrix column shows the predicted class [24]. There are four elements that involved in this measurement which is the true positive (*tp*), true negative (*tn*), false positive (*fp*) and false negative (*tn*). The four elements as shown in the Table I below:

Table I Confusion Matrix [24]

Data class	Classified as positive	Classified as negative
Positive	True positive (*tp*)	False negative (*fn*)
Negative	False positive (*fp*)	True negative (*tn*)

or it is indicated in matrix form as $\begin{bmatrix} tp & fn \\ fp & tn \end{bmatrix}$ where,

- tp is the number of correctly classified to the class examples
- tn is the number of correctly identified to the not class examples
- fp is the number of incorrectly identified to the class examples
- fn is the number of incorrectly identified to the not class examples

The accuracy is the overall effectiveness of a classifier. The formula is define by [25]:

$$ACC = \frac{tp+tn}{tp+fn+fp+tn} \quad (5)$$

The sensitivity is the effectiveness of a classifier to identify positive labels. The formula is define as [25]:

$$SENS = \frac{tp}{tp+fn} \quad (6)$$

The specificity is how effective a classifier identifies negative labels. As for the formula, it is describe by [25]:

$$SPEC = \frac{tn}{fp+tn} \tag{7}$$

The precision is the class agreement of the data labels with positive labels given by the classifier. The formula is describe by [25]:

$$PREC = \frac{tp}{tp+fp} \tag{8}$$

3. Methodology

A. Block Diagram of Experiment Set-Up

The 96 samples of agarwood oil founded in *Aquilaria Malaccensis* species were collected from Forest Research Institute Malaysia (FRIM), Selangor, Malaysia and Bio Aromatic Research Centre of Excellent (BARC), Universiti Malaysia Pahang (UMP). Then, the agarwood oil compounds identification was done by using Support Vector Machine (SVM). The sample preparation and compounds evaluation were done by the previous researcher [26]. Next, the data was pre-processed. Lastly, Multilayer Perceptron (MLP) tuned kernel parameter were used as classifier to classify the agarwood oil according to its grade. The Multilayer Perceptron (MLP) tuned kernel parameter was developed by using the Support Vector Machine (SVM).

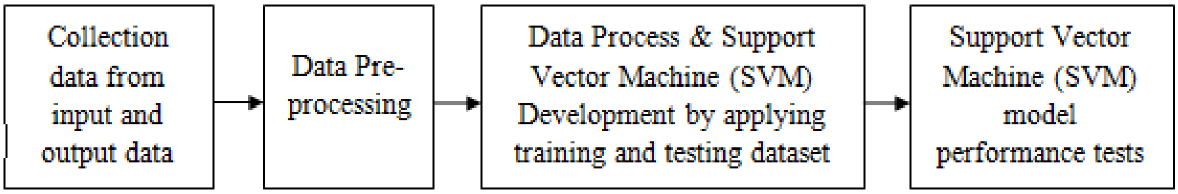

Figure 5 Block Diagram of Experiment Set-Up

B. Flow Chart of Experiment Set-Up

Figure 6 shows the flow chart of experimental set-up achieved in this research. It consists of data collection of agarwood oil which were done by previous researcher [26]. It also included the scope for this project that is limited to data pre-processing, data process using Support Vector Machine (SVM) by applying the Multilayer Perceptron (MLP) tuned kernel parameter with training and testing dataset of SVM model built. Then, the process continues with the data pre-processed. The process were normalized the data, randomized it and finally split the data into 2 groups which is train and test using the ratio of 80%:20%, respectively. The next process is the data were test the trained Support Vector Machine (SVM) model built. If the model is passed, the model is accepted. But if not, it will go to either two processes as seen in the Figure 6. The criteria that the model needed for it to be passed are the confusion matrix, accuracy, sensitivity, specificity and precision.

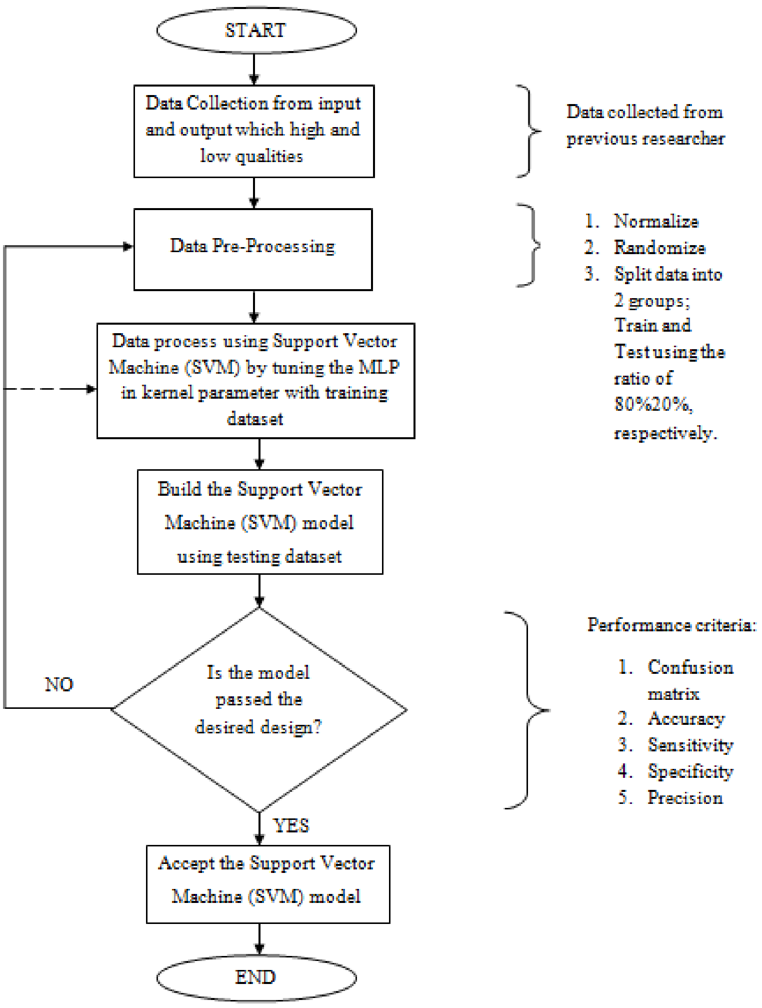

Figure 6 Flow Chart of Experiment Set-Up

4. Result and Discussion

The data obtained from 96 samples of agarwood oil which is low and high quality used to build the SVM model by applying Multilayer Perceptron (MLP) kernel function. SVM model was build using training dataset. By applying this kernel trick, the 18 support vectors were achieved as in Table II.

Table II 18 Support Vectors for seven compounds which are C1 to C7

Vectors	C1	C2	C3	C4	C5	C6	C7
1	-0.74	-0.76	-0.03	-1.38	-0.27	-0.38	-0.37
2	-0.74	-0.76	-1.23	-0.69	3.41	3.37	3.34
3	-0.74	-0.76	-0.59	0.32	-0.31	-0.38	-0.37
4	-0.74	-0.76	0.67	-1.38	-0.31	-0.38	-0.37
5	-0.55	-0.76	-0.99	-1.04	-0.31	-0.38	-0.37
6	-0.27	-0.76	0.69	0.28	-0.31	-0.38	-0.37
7	-0.55	-0.72	-0.99	-1.04	-0.3	-0.32	-0.33
8	-0.41	-0.73	0.7	0.27	-0.3	-0.17	-0.34
9	-0.72	-0.75	0.67	-1.38	-0.3	-0.27	-0.33
10	-0.54	-0.75	-1	-1.04	-0.29	-0.38	-0.37
11	-0.72	-0.73	0.67	-1.37	-0.28	-0.27	-0.36
12	1.08	1.61	0.56	0.99	-0.27	-0.3	-0.35
13	-0.54	-0.71	-1	-1.03	-0.29	-0.36	-0.37
14	-0.72	-0.72	-0.02	-1.37	-0.3	-0.31	-0.37
15	-0.66	-0.6	0.66	-1.36	-0.26	-0.21	-0.36
16	-0.55	-0.75	-1	-1.02	-0.31	-0.36	-0.37
17	-0.7	-0.75	-0.02	-1.36	-0.27	-0.34	-0.34
18	-0.74	-0.61	0.66	-1.35	-0.3	-0.21	-0.35

Table II shows the support vector from seven compounds which are C1 to C7. From the point of view, it shows that C1 has the minimum and maximum vector which is -0.74 and 1.08 at vector 12. For C2, the minimum vector is -0.76 and maximum vector is 1.61 at vector 12. C3 has the minimum vector of -1.23 at vector 2 and maximum vector is 0.70 at vector 8. For C4, -1.38 is the minimum vector while maximum vector is 0.99 at vector 12. The minimum vector for C5 is -0.31 while maximum vector is 3.41 at vector 2. C6 consists of minimum and maximum vector which are -0.38 and 3.37 at vector 2. Lastly, C7 has the minimum and maximum vector are -0.37 and 3.34 at vector 2.

Table III Test Output Target, Predicted Test Output, Error Test Output and Mean Square Error

Number of Samples	Test Output Target	Predicted Test Output	Error Test Output	Mean Square Error
1	2	2	0	
2	1	1	0	
3	2	1	1	
4	2	2	0	
5	1	1	0	
6	2	2	0	
7	2	2	0	
8	2	2	0	(MSE)
9	2	2	0	
10	1	1	0	0.11
11	2	2	0	
12	2	2	0	
13	2	2	0	
14	2	2	0	
15	1	1	0	
16	2	2	0	
17	2	2	0	
18	2	2	0	
19	2	1	1	

Table III shows the 19 samples from the testing dataset that were split from the 96 agarwood oil sample of data collection. From the test output target, Group 1 is the low quality and Group 2 is the high quality. As an outcome, the classification has two error test outputs of the test output target which is at sample number 3 and 19. So, the overall data predicted that MSE has 0.11 error result.

Table IV Testing Data for MLP tuned kernel parameter

Data Class	Classified as Positive	Classified as Negative
Positive	4	0
Negative	2	13

Table IV explains about performance measure used in the research that is the confusion matrix. It shows the result of Multilayer Perceptron (MLP) in confusion matrix. The value of true positive in MLP is 4 and the value of false negative which is 0. The false positive of the result is 2 while true negative is 13. The result shows that 19 numbers of samples has strongly predicted the four numbers to Group 1, low quality and the 13 numbers to Group 2, high quality. The other two numbers was incorrectly classified as the low quality.

Table V Performance Measures for MLP tuned Kernel Parameter

Performance Measures	MLP Kernel Parameter
Accuracy (%)	89.47
Sensitivity (%)	100
Specificity (%)	86.67
Precision (%)	66.67
Error Test	10.53
MSE Test	0.11

By observation in Table V, it is clearly showed that sensitivity dataset achieve 100%. It was followed by training and testing datasets when the accuracy for MLP is 89.47 was obtained. In other hand, it was found that the specificity for MLP is 86.67. The result for MLP's precision is 66.67. Overall, the result shows the best performance and agarwood oil classification system using SVM was proven as a good classifier. The graphical observations for these performance measures were shown in Figure 7 for better understanding.

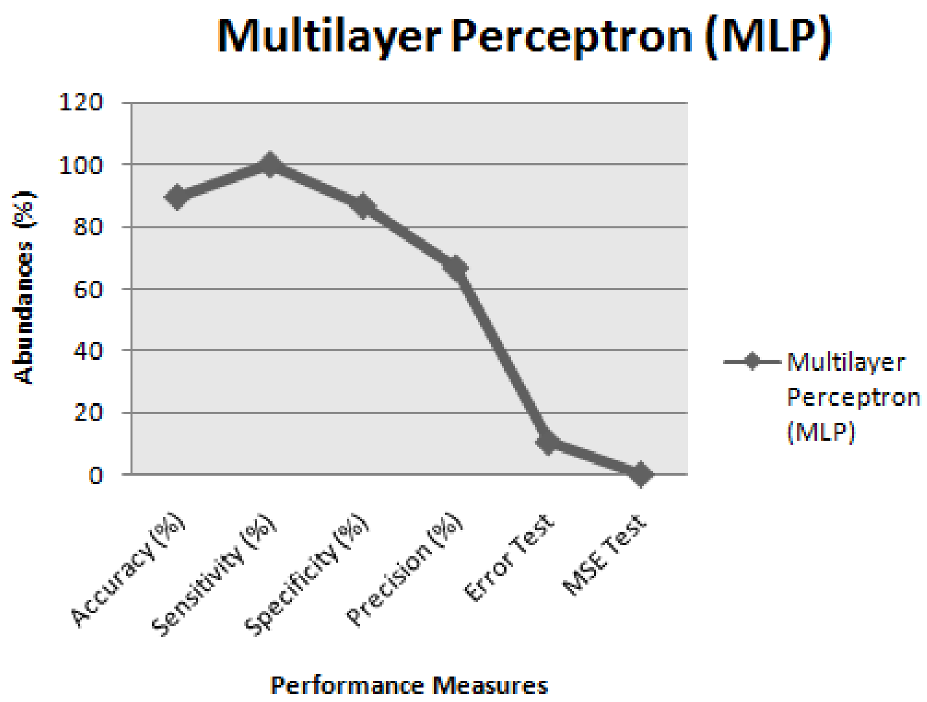

Figure 7 Graphical of Performance Measures

5. Conclusion

The study in this research has successfully evaluated the agarwood oil quality to high and low using Multilayer Perceptron (MLP). The technique was chosen because it was one of the most ideal techniques for classification system of agarwood oil by implementing the abundances of significant chemical compound as the input and agarwood oil quality as output. The data was extracted by the use of Support Vector Machine (SVM).

From the result, it showed that the researchshould comes out with a model that can differentiate the agarwood oil quality which is high or low. It will implemented by the network development using Support Vector Machine (SVM) and applying Multilayer Perceptron (MLP) tuned kernel parameter. The finding in this research was significance thus it will benefit other future work especially in agarwood oil classification system.

Acknowledgment

The authors wish to thank Universiti Teknologi MARA, Shah Alam, Selangor for providing financial supports under BESTARI Grant (600-IRMI/DANA 5/3 BESTARI (054/2017)) awarded to Nurlaila binti Ismail

References

[1] S. Akter, M. T. Islam, M. Zulkefeli, and S. I. Khan, "Agarwood production-a multidisciplinary field to be explored in Bangladesh," *International Journal of Pharmaceutical and Life Sciences*, vol. 2, pp. 22-32, 2013.

[2] M. S. Najib, M. N. Taib, N. A. M. Ali, M. N. M. Arip, and A. M. Jalil, "Classification of Agarwood grades using ANN," in *Electrical, Control and Computer Engineering (INECCE), 2011 International Conference on*, 2011, pp. 367-372.

[3] N. A. B. Sidik, "Comparison of Gaharu (Aquilaria Malaccensis) Essential Oil Composition Between Each Country," UMP, 2008.

[4] S. Subasinghe and D. Hettiarachchi, "Agarwood resin production and resin quality of Gyrinops walla Gaertn," *Int. J. Agric. Sci*, vol. 3, pp. 357-362, 2013.

[5] S. N. F. Jusoh, "Identification of Chemical Constituents of Agarwood (aquilaria Malaccencis) Oil Extracted by Supercritical Fluid and Hydrodistillation Method," UMP, 2014.

[6] J. Mailina, N. Azah, and M. Nasir, "Profiles of selected supreme agarwood oils from Malaysia," in *Proceedings of the Seminar on Medicinal and Aromatic Plants (MAPS 2008)*, 2009.

[7] R. Naef, "The volatile and semi-volatile constituents of agarwood, the infected heartwood of Aquilaria species: a review," *Flavour and Fragrance Journal*, vol. 26, pp. 73-87, 2011.

[8] M. Nor Azah, Y. Chang, J. Mailina, S. Saidatul Husni, H. Nor Hasnida, and Y. Nik Yasmin, "Comparison of chemical profiles of selected gaharu oils from Peninsular Malaysia," *Malaysian Journal of Analytical Sciences*, vol. 12, pp. 338-340, 2008.

[9] M. Ishihara, T. Tsuneya, M. Shiga, and K. Uneyama, "Three sesquiterpenes from agarwood," *Phytochemistry*, vol. 30, pp. 563-566, 1991.

[10] H. Jantan, I. M. Yassin, A. Zabidi, N. Ismail, and M. S. A. M. Ali, "Differentiation of Agarwood oil quality using Support Vector Machine (SVM)," *Journal of Engineering and Applied Sciences*, vol. 12, pp. 3810-3812, 2017.

[11] W. Hidayat, A. Y. M. Shakaff, M. N. Ahmad, and A. H. Adom, "Classification of agarwood oil using an electronic nose," *Sensors*, vol. 10, pp. 4675-4685, 2010.

[12] N. Zubir, M. Abas, N. Ismail, N. A. M. Ali, M. Rahiman, N. Mun, *et al.*, "Analysis of algorithms variation in Multilayer Perceptron Neural Network for agarwood oil qualities classification," in *Control and System Graduate Research Colloquium (ICSGRC), 2017 IEEE 8th*, 2017, pp. 122-126.

[13] R. Mohamed and S. Y. Lee, "Keeping Up Appearances: Agarwood Grades and Quality," in *Agarwood*, ed: Springer, 2016, pp. 149-167.

[14] C.-Y. Liou and W.-C. Cheng, "Implementation of the MLP Kernel," in *International Conference on Neural Information Processing*, 2008, pp. 378-385.

[15] A. Radzol, K. Y. Lee, W. Mansor, and I. Omar, "PCA criterion for SVM (MLP) classifier for flavivirus biomarker from salivary SERS spectra at febrile stage," in *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the*, 2016, pp. 6206-6209.

[16] B. Ustun, *Support vector machines: facilitating the interpretation and application*: [Sl: sn], 2009.

[17] A. J. Smola and B. Schölkopf, "A tutorial on support vector regression," *Statistics and computing*, vol. 14, pp. 199-222, 2004.

[18] S. R. Gunn, "Support vector machines for classification and regression," *ISIS technical report*, vol. 14, pp. 85-86, 1998.

[19] D. Meyer and F. T. Wien, "Support vector machines," *R News*, vol. 1, pp. 23-26, 2001.

[20] J. A. Suykens, "Nonlinear modelling and support vector machines," in *Instrumentation and Measurement Technology Conference, 2001. IMTC 2001. Proceedings of the 18th IEEE*, 2001, pp. 287-294.

[21] A. Zabidi, L. Y. Khuan, W. Mansor, I. M. Yassin, and R. Sahak, "Classification of infant cries with asphyxia using multilayer perceptron neural network," in *Computer Engineering and Applications (ICCEA), 2010 Second International Conference on*, 2010, pp. 204-208.

[22] S. Mishra, R. Prusty, and P. K. Hota, "Analysis of Levenberg-Marquardt and Scaled Conjugate gradient training algorithms for artificial neural network based LS and MMSE estimated channel equalizers," in *Man and Machine Interfacing (MAMI), 2015 International Conference on*, 2015, pp. 1-7.

[23] M. Beale, M. T. Hagan, and H. B. Demuth, "Neural network toolbox," *Neural Network Toolbox, The Math Works,* vol. 5, p. 25, 1992.

[24] J. Parker, "Rank and response combination from confusion matrix data," *Information fusion,* vol. 2, pp. 113-120, 2001.

[25] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing & Management,* vol. 45, pp. 427-437, 2009.

[26] N. Ismail, "ANN modelling of agarwood oil significant chemical compounds for quality discrimination," 2015.