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Classification of RRIM clone series using artificial neural network

Faridatul Ama Ismail, Nina Korlina Madzhi, Noor Ezan Abdullah, Hadzli Hashim
Centre of System Engineering Studies (CSES), Fakulti Kejuruteraan Elektrik, Universiti Teknologi MARA Malaysia, 40450 Shah Alam, Selangor, Malaysia

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ABSTRACT

This paper presents comparative investigation on the classification of rubber latex clone series using Artificial Neural Network (ANN) based on optical sensing technique. Rubber Research Institute of Malaysia (RRIM) introduced the rubber breeding program known as RRIM clone series in order to increase the yield of latex production and the rubber wood to meet the requirement for export and import in upstream sector. Due to the large numbers of clones launched with different characteristics and properties, this bring difficulty such as lack of information regarding to the identification on cloning. Therefore, this work developed an optical based sensing system for classification of the selected RRIM 2000 and 3000 clone series based. Near Infrared Sensors was used as sensing element in order to measure the latex from the top surface and photodiode which received the reflected light from the sensor via reflectance index in term of voltage. The raw obtained data was then used as input parameter for ANN tool which supervised by scaled gradient back propagation and the performance was optimized at 25 neurons with 74.4% accuracy. By using ANN the sensitivity, specificity and accuracy for each clones are measured. RRIM 3001 shows the highest sensitivity, 94.1% while RRIM 2002 shows the highest specificity of 99.1% accuracy, 93.1%. As a result, the system could differentiate RRIM 2002 more compare to other clones.

Corresponding Author:

Nina Korlina Madzhi,
Centre of System Engineering Studies(CSES),
Fakulti Kejuruteraan Elektrik,
Universiti Teknologi MARA Malaysia,
40450 Shah Alam,Selangor, Malaysia.
Email: nina6875@yahoo.com

1. INTRODUCTION

In year 1877, the rubber tree was introduced in Malaysia and started planted at Kuala Kangsar, Perak [1-2]. Since then, the rubber product be the most significant sector that influence the Malaysia economy [1]. The rubber sector can be divided into three sector which are upstream, midstream and downstream [3]. Each rubber sectors will carries different activity. For example, upstream sector it more focuses on the cultivation and breeding program and also handle the raw material supplier which is natural rubber latex [1, 3].

In Malaysia, Rubber Research Institute of Malaysia (RRIM) is the one of research institute that implemented the breeding program [4]. The systematic selection of rubber breeding program have been introduced by them in 1982 in order to produce the high yielding latex clone that comply to the market needs [5-7]. Based on the rubber breeding program been held, there are a several of RRIM clone series have been introduced such as RRIM 600, RRIM 900, RRIM 2000, RRIM 3000 clone series and etc. [5, 7]. By having a lots of number of existing clones, its bring difficulty for farmer or unskilled person to recognize the type of clone series. The lack of the information in books and other research paper also cannot help the recognition process. The recognition of the clones was usually done by expertise such as the people who handle the tree clone for more than 10 years [8]. But basically, the expertise can recognize the clone based on the feature characteristics not in latex.

By referring to the problem occurred, there are numbers of research were studied and investigated in determination on rubber content such as standard laboratory method (SLM) [9-10], microwave [11], annular photoelectric [12] capacitive transducer [9, 13], differential scanning calorimetry (DSC) [9, 14], FTIR spectroscopy and TGA technique [9], rotational flow [15], Mooney viscometer [4, 16-17], titration method [9] and etc. Though, the determination is to find the rubber content, but still its help to give the clue for classification of the clone series.Since NIR is more often used in medical diagnosis [18-19] compare to the agricultural field, this give an opportunity for this research to discover classification on cloning by applying NIR using reflectance technique.

ANN has been used widely due to its capability for classification/ prediction such as energy management prediction [20], voltage instability [21] particularly agriculture [22-25] since agriculture is considered the most vulnerable sector to yearly climate change and variability which have greatest impact on agricultural production such as crop yields [26]. The advantages of identification system such as ANN farmers and other decision makers in agriculture can require precise crop yield prediction methods such as in deciding on seasonal crop planning and scheduling [27], as well as determining the possible future outcome of an event.

This paper present the measurement of the latex of selected rubber clone using NIR and classification of the clone series using ANN system and vision system to overcome the problem of clone recognition specifically for in-situ measurement.

2. RESEARCH METHOD

The research method starts with collection of latex samples, samples measurement using optical sensing system and identification system using Artificial Neural Network (ANN).

2.1. Latex sampling

Latex samples were collected at Field 4 and 17 of rubber field in Permatang Station located at RRIM Kota Tinggi, Johor. Figure 1 shows the specimen case used which filled with 20ml latex collected for the NIR experiment. Based on the recommendation from RRIM clones RRIM 2002, RRIM 2007, RRIM 2008, RRIM 2014 and RRIM 3001 were selected due to the productivity of the clone. 1000 samples were collected from all those clones with 200 samples per clone. Each of the selected tree goes through the same tapping procedure where tapping were done at 6.00 a.m. in the morning and the latex collected around 9.00 to 11.00 a.m. The collection was done in medium yielding period begins from end of June to mid of July in 2014.

Figure 1. Collected latex samples

2.2. Optical sensing measurement

Samples collected were measured using NIR sensing indicator based on reflection technique via voltage. The developed indicator consists of NIR led, photodiode and signal conditioning. The experiment was done in a month and setup at Dry Rubber Content Laboratory located at RRIM Kota Tinggi, Johor. The experiment started at 11.00 a.m. until 5.00 p.m. every slot session as the same day as the samples being collected. The finalized raw data used in this research are 1000 samples from five different clones (200 samples each).

Figure 2 shows the illustration of the NIR reflection rays that applied in this research. Near Infrared (NIR) led 950nm wavelength was used in the development of the reflectance indicator paired with the 900-950nm photodiode and signal conditioning. The reflectance technique was used to obtain reflectance index via voltage from the latex surface in order to find the differentiation between the selected clones. The NIR will emit the rays to the latex surface; the photodiode then will collect the reflected ray from the surface. By referring to the illustration, the barrier is use to avoid the photodiode receiving the rays by side and to make sure the rays reflect directly to the opposite object.Each alphabet of Label A to G shows the fixed parameters used in the experiment;
A: barrier to photodiode length: 1.5cm,
B: barrier to Near-IR led length: 1.5cm,
C: thickness of barrier: 0.3cm,
D: height of barrier 1.6cm,
E: specimen case diameter: 6.3cm.
F: specimen case height: 2.5cm.
G: filled specimen case of latex height: 1.2cm.

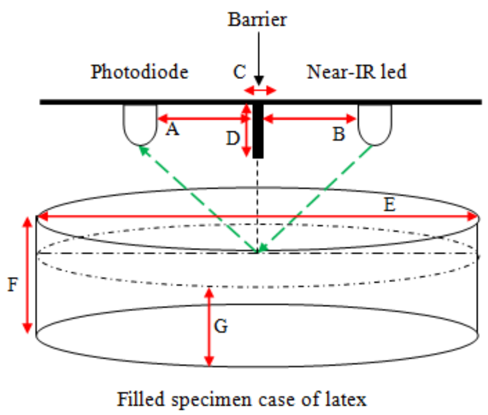

Figure 2. The illustration of Near-IR led rays reflection

2.3. Identification system using artifical neural network (ANN)

The identification system starts with the analysis using the entire raw data of 1000 samples. All samples will go through the basic analysis such as normality test, error bar plot and the one-way ANOVA. The ANN system is used to differentiate between each clone based on the reflectance index via voltage of the latex. The data were trained using ANN toolbox supervised by scaled gradient backpropagation. In ANN, the optimized model was decided using a confusion matrix [19]. The confusion matrix is the two-class classifier of matrix which consists of diagnosis and predicted classification information as tabulate in Table 1.

Table 2 shows the division data of training, validation and testing (70:10:20) for ANN toolbox which used in this research. The output of the ANN system is classification of RRIM 2002, RRIM 2007, RRIM 2008 and RRIM 3001 and defined as 1000, 0100, 0010 and 0001.

Table 1. The classification of diagnosis and predicted

		Diagnosis Case	
		D+	D-
PREDICTED CASE	T+	TP	FP
	T-	FN	TN

Table 2. The ANN toolbox data division for training, validation and testing

Case	Training: 70%	Validation: 10%	Testing: 20%	Output
RRIM 2002	560	80	160	1000
RRIM 2007	560	80	160	0100
RRIM 2008	560	80	160	0010
RRIM 3001	560	80	160	0001

3. RESULTS AND ANALYSIS

This section, explained the results obtained and categorized intro reflectance measurement, classification using ANN and vision system.

3.1. Reflectance measurement

Figure 3 shows the bar chart of the mean for five selected clone. Based on the figure, it can be observed that every clone have the specific value that be differentiate. A part of that, the bar chart also showed RRIM 2014 has the higher voltage value amongst other clones. The second higher value followed by RRIM 2008, RRIM 2007, RRIM 3001 and the lowest value was RRIM 2002. Based on the Figure 3, this finding can be relate to the previous research [12] which said, there is a proportional relationship between the latex and the voltage; when the rubber content in the latex the increase voltage also increase. This can be conclude that RRIM 2014 shows the highest rubber content amongst other while RRIM 2002 will be the lowest of the rubber content in the latex.

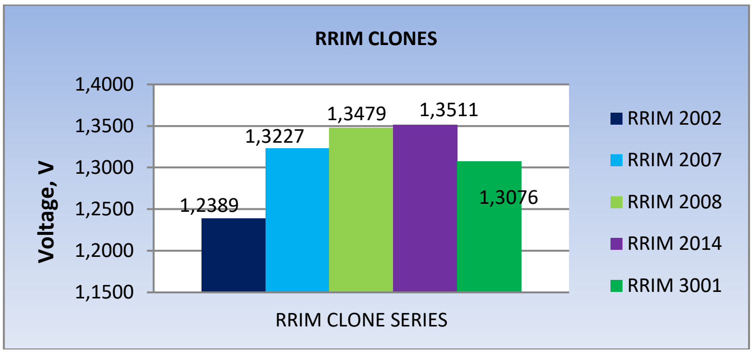

Figure 3. Bar chart of RRIM clone series

3.2. Classification using ANN

The data have been used in the classification part was the obtained result from the final analysis [20] that proved only four clone can be decided used for next application since there are significant different between them. The clones of RRIM 2002, RRIM 2007, RRIM 2008 and RRIM 3001 then were trained using ANN toolbox with ±0.5 fixed threshold. The data was trained using 10 different hidden layer sizes which are 3, 7, 15, 18, 21, 25, 32, 35, 47, and 50 neurons. Each of the hidden layers was trained seven times in order to get the best optimized accuracy as shown in Figure 4. Figure 4 shows the best optimized accuracy which obtained from each hidden layer size as stated before. Based on the line graph, the highest accuracy belongs to the hidden layer of 25 neurons with 74.4% and will be used in development of vision system. The ranking then followed by 21 neurons for 73.8%, 18 neurons for 72.5%, 7 neurons for 71.9%, 32 and 35 neurons for 71.3%, 50 neurons for 70.9%, 15 neurons for 70.0%, 47 neurons for 69.4% and the lowest is 3 neurons with 68.1%.

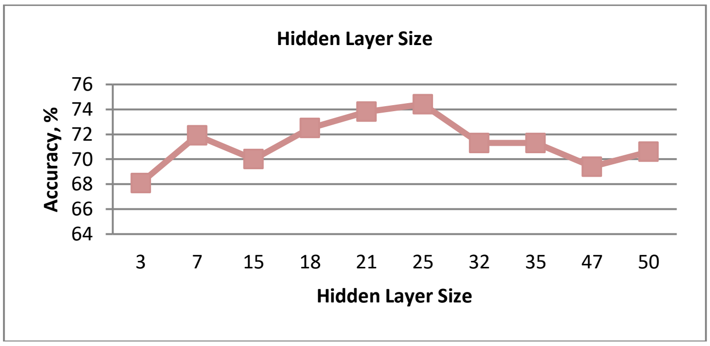

Figure 4. The line graph of selected hidden layer size

Each hidden layer size will produced their owned confusion matrix and the accuracy will depends to a data set. In this research, the confusion matrix for the best hidden layer obtained was shown in Figure 5. From the confusion matrix, the percentage accuracy can be found directly or it also can be calculated from the information within it. As shown in the table of confusion matrix, the percentage accuracy of hidden layer size of 25 neurons was 74.4%.

Table 3 is the summarization of the confusion matrix information by calculation for each clone. The table also described the performance of the four selected clones consists of sensitivity, specificity and accuracy. By referring to the table, RRIM 3001 shows the highest sensitivity, 94.1% while the highest specificity, 99.1% is belongs to the RRIM 2002 same goes to the accuracy, 93.1%. However, based on the three term of performance, the most needed to be focused and considered is percentage accuracy. As a result, the system could more differentiate RRIM 2002 compare to other clones.

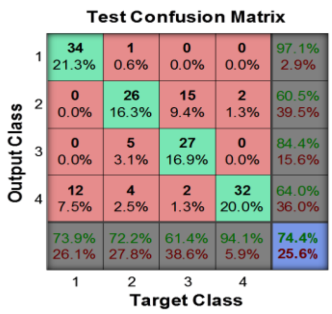

Figure 5. Confusion matrix table for the best optimized testing accuracy with hidden layer of 25 neurons

Table 3. The performance of four selected clones

Model performance indicator: threshold ±0.5 Model: scaled conjugate gradient backpropagation ANN (Input: Output: Hidden Layer): 01: 04: 25				
Clones:	RRIM 2002	RRIM 2007	RRIM 2008	RRIM 3001
Sensitivity (%)	73.9	72.2	61.4	94.1
Specificity (%)	99.1	86.3	95.7	85.7
Accuracy (%)	93.1	83.1	86.25	87.5

Receiver operating characteristic (ROC) is used to described the true positive rate (TPR) versus the false positive rate (FPR) across the multiples thresholds. Figure 6 shows the ROC curve for hidden layer of 25 neurons at the fixed threshold ±0.5 which consists of blue line (RRIM 2002), green line (RRIM 2007), moss-green line (RRIM 2008) and red line (RRIM 3001). Based on the curve, the blue and red line shows the nearest line to the ideal point (0, 1) which means the highest point of the sensitivity and specificity for classification of the clone as shown by orange arrow.

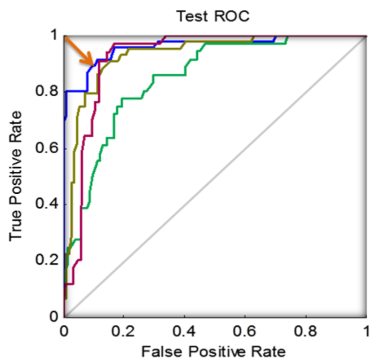

Figure 6. Receiver operating characteristic curve

3.3. Vision system using GUI tool

Vision system were developed to show the classification using ANN system. Thee performance accuracy by ANN toolbox was used and the complete system then was tested for 120 voltages value measured which carries 30 values each. The testing was done in order to validate the system. Figure 7 shows the main page of the developed vision system while Figure 8 shows the second page for classification system where used to display the result. Figure 8 also shows the one of obtained result for validation.

Table 4 described the summarization of vision system validation for four clones; RRIM 2002, RRIM 2007, RRIM 2008 and RRIM 3001. Based on the validation results, RRIM 3001 shows the highest accuracy amongst others. The rest followed by RRIM 2002, RRIM 2008 and the lowest shows RRIM 2007. In can be concluded, this vision system was perform well since the validation performance almost similar to the obtained performance using ANN system.

Figure 7. The vision system main page

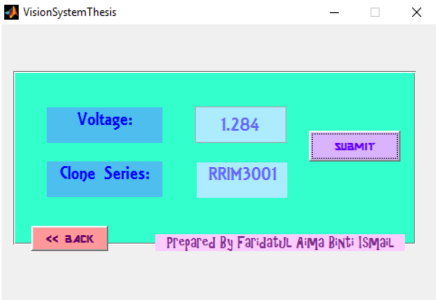

Figure 8. The classification display window

Table 4. Table of summarization for vision system validation

Clones	YES, % (Accuracy)	NO, %		Total NO, %
		Other Clone, %	Unknown, %	
RRIM 2002	73.33	16.67	10	26.67
RRIM 2007	20	43.33	36.67	80
RRIM 2008	63.34	3.33	33.33	36.66
RRIM 3001	76.67	20.00	3.33	23.33

4. CONCLUSION

The finding obtained in this research demonstrates the value of the artificial neural network in classification of rubber latex clones by using NIR sensing techniques. The obtained result shows the best optimized hidden layer of 25 neurons produced percentage accuracy of 74.4%. From four clones (RRIM 2002, RRIM 2007, RRIM 2008 and RRIM 3001) have been used, only two clones showed the best performance in classification which are RRIM 2002 and RRIM 3001. The validation results of the developed vision system also shows the similarity of the performance where RRIM 2002 and RRIM 3001 could be classified more than other clone by this system. The specificity and accuracy level of the prediction obtained between these two clones with RRIM 3001 shows the highest sensitivity of 94.1% while RRIM 2002 shows the highest specificity of 99.1% and accuracy of 93.1%.

The issues of identifying clone series by depending on the color, texture and other more now can be solve after several analysis have been done to. The significant information have been gathered from the result had almost successfully answer the objective of this research.

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BIOGRAPHIES OF AUTHORS

Faridatul Aima is a M.Sc. by research student at Fakulti Kejuruteraan Elektrik, UiTM Shah Alam. Her research interest includes Instrumentation and Measurement and Signal Processing.

Ir Dr. Nina Korlina Madzhi is a member of Fakulti Kejuruteraan Elektrik, UiTM Shah Alam. and was a Head of Department for Centre of System Engineering Studies for the Electronics Engineering Degree Programme, UiTM Shah Alam. She has more than 18 years experience in circuit and system design in both the industry and academic sectors.Currently, she is actively researching new techniques in Agriculture application and Engineering Education.