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The Feasibility Study of Utilising Electronic Nose and ANN for Plant Malaise Detection

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Abstract – The agricultural industry has been, for a long time, dependent upon human expertise in using odour for classification, grading, differentiating and discriminating different types of produce. Odour was also used to determine the state of health of crops, although this is not favourable when dealing with detecting plant malaise that may pose health threats to human beings. In addition to these, human experts may take years of training and can be inconsistent, as well as prone to fatigue. This paper presents a work conducted on utilising an electronic nose incorporating artificial intelligence to detect plant malaise, specifically basal stem rot (BSR) disease that is caused by ganoderma boninense fungus affecting oil palm plantations. This study used a commercially available electronic nose, Cyranose 320 as the front end sensors and artificial neural networks for pattern recognition. The odour samples were captured on site at Besout oil palm plantation, and the classification performed on a PC. The results showed that the system was able to differentiate healthy and infected oil palm tree using different odour parameters with a high rate of accuracy. This proved the feasibility of using enose with artificial intelligence to an discriminate healthy and infected plants.

Keywords: Commercial electronic nose, ANN, Basal Stem Rot disease, Ganoderma boninense.

I. INTRODUCTION

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In recent years, the development of innovative devices such as electronic nose has been investigated and implemented by many researchers. The electronic nose (enose) is often referred as an intelligent device, able to mimic the human olfaction and may be used for detection, recognition and classification of volatile compounds and odours. This type of electronic olfactory system was introduced in 1982 by Dodd and Persaud from The Warwick Olfaction Research Group, UK [1]. Basically, an enose consists of sensing elements (an array of sensors), signal collecting unit(s) and suitable automated pattern recognition system [2]. The applications of these devices are wide ranging, from the agricultural applications to solving environmental issue [2]-[7].

The agricultural industry can benefit tremendously from the use of enose. An enose may provide rapid, automatic as well as real time classification and detection. Also, it can be easily re-trained to detect a variety of odours.

In this study, neural networks have been used as the pattern recognition tool. It has been used extensively to perform pattern recognition, and has been reported to produce good performance for the classification of food stuff such as coffee and wine [2].

This paper presents the feasibility study of using an enose incorporating artificial neural networks to detect a type of fungus that causes basal stem rots (BSR) disease. The disease is a threat to the oil palm industry, causing large amount of losses in profits [5]-[9].

II. OIL PALM TREE AND BASAL STEM ROT (BSR) DISEASE

The oil palm (Elaeis guineensis Jacq.) tree is a leading source of edible vegetable oil production in the world, with production figures of more than 32 million tonnes of oil in 2003. In Malaysia, the hierarchy of palm oil as a leading cash crop has exceeded that of natural rubber, and its importance has been further boosted by the recent introduction of bio-diesel [7]-[8].

Its cultivation, in much of South-East Asia, is threatened by the BSR caused by Ganoderma boninense, where losses can reach as much as 80% after repeated planting cycles. BSR has been causing serious damage to the oil palm plantations in Malaysia for more than 50 years and is currently the most important disease of economical importance causing large amount of losses in revenue [5]-[8]. Under severe infestation situations, more than 50% of oil palm stand can be lost to the malady. The FELDA plantations, for example, recorded high incidence of the disease in the Peninsular Malaysia, ranging to about 50%, from 1994 to 2005. The disease does not show indication of early infection whereby it progresses through the palm from the base without any observable symptoms, leading to eventual death of the palm. It causes root and stem rot in many tropical perennial crops, including coconut, betel palm, rubber, tea, coffee, cocoa and forest trees [8].

The causal agent, ganoderma boninense, a white-rot basidiomycete, is a saprophyte or weak parasite that can infect a living palm if there is a massive inoculum. Ganoderma *sp.* produces enzymes that will degrade the palm tissue. As the fungus destroys the internal palm tissues, it will affect the palm xylem, thus causing serious problems to the distribution of water and other nutrients to the top of the palm tree, which eventually, leads to the death of the oil palm [9].



Figure 1: Ganoderma boninense fruiting body

It has been demonstrated that Ganoderma sp. can set in as early as 12 to 24 months after planting but more usually when the oil palm is 4 to 5 years old, particularly in replanted areas. The incidence increases rapidly to the extent that by the time the palms were 15 years old, the disease levels can reach between 40 to 50 per cent of the palm. In severe cases, up to 85 per cent of the standing palms succumb to BSR by the time the palms are 25 years old.

Until today, a few methods based on biochemistry process are used to detect ganoderma infection, which can be divided into two categories; 1. Culture, such as Ganoderma Selective Medium (GSM) 2. Molecular DNA, such as a polymerase chain reaction (PCR) [9]. However, these methods require the stem collection for further tests in the laboratories. There has yet to be a method which is able to give results in real time or directly on-site [9].

It is estimated that if only 2.5% of the total acreage of the oil palm plantation in Malaysia is affected by BSR, the industry would lose about RM80 million each year [5]. This amount could be turned into profit if there is an early detection system in the form electronic nose for the Ganoderma *sp*.

III. SYSTEM DESCRIPTIONS

This section will describe the system used in this study which consists of the commercial enose, Cyranose 320, and artificial neural networks.

The Cyranose 320 is a handheld enose instrument that made by Cyrano Sciences Inc (USA). It is widely used in quality control, process measurement, hazardous material identification and biomedical sample discrimination [10]. The main components of Cyranose 320 included sampling, sensory and signal processing components as well as pattern recognition.



Figure 2: Cyranose 320

The sensing component consists of an array of sensor with 32 elements. All sensors are polymer conducting based and each sensors have different response specificity to a broad range of compounds. Therefore, this kind of enose is able to produce a number of output signals, which is referred to as the signal pattern or fingerprint [10].

Artificial neural networks (ANN) is the most commonly artificial intelligence used in enose systems for pattern recognition. It is an interconnected group of artificial neurons that uses a mathematical or computational model for data processing. In practical terms, neural networks are non-linear statistical data modelling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data [3]. In this study, the Multi-Layer Perceptron (MLP) which was trained using the Levenberg-Marquardt algorithm was employed.

IV. METHODOLOGY

The work conducted was divided into three main stages which involved sample data collection, neural network training as well as testing. These stages will be discussed thoroughly in this section.

The ganoderma odour data collection was performed at FELDA Besout 7, Sungkai, Perak, Malaysia oil palm plantation. The area of interest in the plantation was divided into two parts; the first part would be the healthy plant area while the second was the infected area.

This stage involved three types of odour, namely odour of the air surrounding the tree, odour of bored tree trunk and as well as odour of soil surrounding the base of the tree trunk. Three trees were chosen randomly from each of the healthy as well as the infected areas. For each tree, three points were marked as the data collection points as shown in Figure 3.

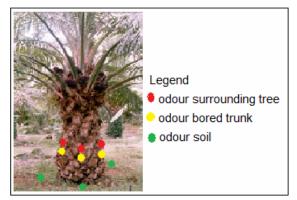


Figure 3: Data collection points around the oil palm tree

The general procedures for this stage are as follows:

- 1. The odours of the different parts of the tree were collected using C-320 on site.
- 2. The samples from which the odour readings were taken (air around the tree trunk base, bored tree trunk and soil around the tree trunk) were also collected and taken back to laboratory. The odour data of these samples were also collected in the laboratory. This will allow the comparison of the odour readings taken on site and at the laboratory. This is to verify if any physiological changes of the samples will change its odour profile.
- 3. The comparison of on site and laboratory odour data ware performed by plotting the raw sensor readings versus number of sensors.
- 4. Odour profile analyses were performed to verify the consistency of the data recorded regardless of the point from which the readings were performed.
- 5. ANN training was performed in MATLAB software.
- 6. The NN models were saved and used in testing stage.

The collected data are divided into two sets, one for training and the other for testing. The data were normalised to ensure no dominance of any specific sensor to the ANN output. Normalisation adopted here changes the data mean to zero and variance of one.

Different network sizes were tested, with the number of inputs and outputs set to 32 and one respectively. This is because the number inputs and outputs of the system are determined by the implementation. Since there are 32 sensors used for the enose, the network has the same number of inputs. Also, since the sample implementation only involve determining the existence of ganoderma, only a single output is sufficient. That means, output of 1 will indicate the positive recognition while 0 being negative. Table 1 shows the output target of the ANN.

Table 1: Target used in the ANN training

Parameter	Target	
	Healthy	Infected
Odour of surrounding tree	0	1
Odour of bored trunk	0	1
Odour of soil	0	1

The ANN uses sigmoidal function, and thus limiting its output range from zero to one. Thresholding is implemented: if the output is less than 0.4, then it will be defined as zero. If the output of the ANN is greater than 0.6, then, it will be defined as 1 to indicate the presence of the fungus. Else, the output will be unclassified.

At the beginning of the training, all the weights were arbitrarily chosen. Through learning iteration of the network, the weights are updated until they generate the desired output by comparing the output with the desired target. This process determines a neural model. The training uses iterative weight update approach, and the network validated after every epoch. The sum of squared error (SSE) observed during this validation are used to determine the convergence of the network.

The final stage was the network testing. The testing was performed using the testing data set. This data will give some indication of the accuracy of the ANN model obtained from the training phase. In other words, the testing will show the ability of the NN model to recognise and classify the sample correctly. This result is presented in percentage of accuracy.

V. RESULTS AND DISCUSSIONS

The comparison of the results show that the laboratory and on site data produced different odour profiles as shown in table 2. This means that there are some physiological changes to the samples during transit and caused different profile to be recorded by the sensors of the enose. Hence, only the data samples recorded on site are used.

The odour profile analysis showed that the on site data taken from one tree by C-320 are consistent regardless of the location of the points. Table 3 showed that T1, T2 and T3 which is represented tree 1, tree 2 and tree 3 have the same sensor responses. In other word, the collected data of tree 2 and tree 3 can perform the same data as well as the collected data of tree 1. This proved that the collected data of all trees are consistent and can be used in ANN training.

The training of the ANN showed that the enose was able to discriminate healthy and infected tree trunk samples as shown in Table 4. The blue line represents the output of the network while the red line represents the target. After the completion of the network training phase, 100 data of each sample were tested using the resulting ANN model with 100% accuracy.

Table 2: Onsite and laboratory data sample comparison results.			
Parameter	Results based on sensor readings		
Odour of	5 × 10 ⁻¹² Trunk Healthy Tree 1		
surrounding tree	$\mathbf{r} = \begin{pmatrix} \mathbf{r} \\ \mathbf{r} $		
	$10 \xrightarrow{\times 10^{12}} 10^{12} \xrightarrow{\text{Trunk Infected Tree 1}} 10 \xrightarrow{\times 10^{12}} 0^{12} \xrightarrow{\text{Trunk Infected Tree 1}} 10^{12} \xrightarrow{\text{In lab data}} 0^{12} \xrightarrow{\text{In lab data}} 0^{12} \xrightarrow{\text{In lab data}} 0^{12} \xrightarrow{\text{In lab data}} 10^{12} \text{In lab d$		
Odour of	v 10 ⁻¹² Duct Inforted Tree 1		
bored trunk	et posiciemular and a consideration of the second s		
	20 5 10 15 20 25 30 35 Sensors 20 25 30 35 2 x 10 ⁻¹² Dust Infected Tree 1		
	to the second se		
	-20 5 10 15 20 25 30 35		
Odour of soil			
	The second secon		
	z 10 ⁻¹² 30cm East Soil Infected Tree		
	Image: Second		
	-4 Sensors		

Table 2: Onsite and laboratory data sample comparison results.

Parameter	Healthy	Infected	
Odour of	Odour of surrounding healthy tree	Odour of surrounding infected tree	
surrounding			
tree	16	16	
	14	14 -	
	12 -	12 -	
	- 01 01 02 01 02 01 02 01 02 01 02 02 01 02 02 01 02 02 02 02 02 02 02 02 02 02 02 02 02		
	6	6-	
		4	
	2	2	
	0 50 100 150 200 250 300		
Odour of	T1 T2 T3	T1 T2 T3	
bored trunk	Odour of bored healthy tree	Odour of bored infected tree	
bored truik	16	16	
	14	14	
	12	12	
		01 0 00 00 00 00 00 00 00 00 00 00 00 00	
	6	6	
	4	4	
	2	2	
		0 50 100 150 200 250 300	
	Т1 Т2 Т3	T1 T2 T3	
Odour of soil	Odour of soil healthy tree	Odour of soil infected tree	
	16	16	
	14	14	
	12 - 8	12- 8	
		so o 10	
	6	6	
	4	4	
	2	2	
	0 50 100 150 200 250 300 T1 T2 T3	0 50 100 150 200 250 300 T1 T2 T3	

Table 3: The consistency data from tree 1 to tree 3

 Table 4: The ANN training result

 Parameter
 Result

 Odour of surrounding tree
 Image: Color of surrounding tree

 Odour of bored trunk
 Image: Color of surrounding tree

 Odour of surrounding tree
 Image: Color of surrounding tree

 Odour of surrounding tree
 Image: Color of surrounding tree

 Odour of bored trunk
 Image: Color of surrounding tree

 Odour of soil
 Image: Color of soil

VI. CONCLUSIONS

The electronic nose used, Cyranose 320, has been proved to be useful as front-end sensors for odour discrimination. The odour profiles recorded are consistent for each tree. The 32 different sensors in Cyranose 320 were able to give different odour fingerprints of healthy and infected trees. ANN analysis conducted showed that the collected data were successfully used in the training and testing phase. This proved that the enose incorporating ANN was able to detect and discriminate healthy and ganoderma infected oil palm trees.

This result is valuable as it proved the feasibility of using an enose with artificial intelligence to discriminate healthy and infected plants. This approach holds promise for a better plant disease monitoring, and may also be extended to other plant malaise.

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