

**Feasibility Study of Utilising Electronic
Nose to Detect BSR Disease in Oil Palm
Plantation**

MARNI AZIRA MARKOM

UNIVERSITI MALAYSIA PERLIS
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**Feasibility Study of Utilising Electronic
Nose to Detect BSR Disease in Oil Palm
Plantation**

by

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TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	ACKNOWLEDGEMENTS	ii
	TABLE OF CONTENTS	iii
	LIST OF FIGURES	x
	LIST OF TABLES	xiv
	LIST OF ABBREVIATIONS	xvi
	ABSTRACT	xix
	ABSTRAK	xx
CHAPTER 1	INTRODUCTION	
1.0	Background	1
1.1	Problem Statements	3
1.2	Research Objectives	6
1.3	Research Scopes	6
1.4	Thesis Outlines	7
CHAPTER 2	LITERATURE REVIEW	
2.0	The Sense of Smell and Machine Olfaction	9
2.1	The Electronic Nose Concept	11
2.1.1	Electronic Nose Sensors	13
2.1.1.1	Metal Oxide Semiconductor (MOS)	15

2.1.1.2	Conducting Polymer (CP)	18
2.1.2	Odour Delivery System	19
2.2	Data Processing	21
2.2.1	Dimension Reduction	22
2.2.2	Principle Component Analysis	23
2.2.3	Normalisation	24
2.3	Pattern Recognition	26
2.3.1	The Artificial Neural Networks	27
2.3.2	The Multilayer Perceptron	30
2.3.3	Radial Basis Function	31
2.3.4	Training Algorithm	33
2.4	Electronic Nose Applications in Agricultural Research	35
2.5	Ganoderma Boninense	36
2.5.1	Current Method for Ganoderma Boninense Detection	38
2.5.2.1	DNA probes	38
2.5.2.2	Polymerase Chain Reaction	38
2.5.2.3	Enzyme-Linked Immunosorbent Assay (ELISA)	39
2.6	Production of Fungi Volatiles	40
2.7	Summary	41

**CHAPTER 3 UTILISING COMMERCIAL ELECTRONIC NOSE AND
ARTIFICIAL INTELLIGENCE**

3.1	The Cyranose 320	42
3.1.1	Cyranose 320 Pattern Recognition	46
3.1.2	Identification	47
3.1.3	Experimental Setup	48
3.2	Sensor Data Pre-processing	50
3.2.1	Data Analysis	50
3.2.2	Dimension Reduction	51
3.2.3	Normalisation	57
3.3	Artificial Neural Networks (ANN)	58
3.3.1	ANN Data	59
3.3.2	ANN Size	60
3.3.3	Activation Function	61
3.3.4	ANN Training and Validation	62
3.3.5	ANN Testing	64
3.3.6	ANN Platform	67
3.4	Evaluation of Embedded Cyranose Pattern Recognition Compared to ANN	67
3.4.1	Methodology	68
3.4.2	Data Profile Results	70
3.4.3	Embedded C-320 Pattern Recognition Results	71
3.4.4	Principle Component Analysis (PCA) Results	73
3.4.5	ANN Pattern Recognition Results	75

**CHAPTER 4 FEASIBILITY OF USING ELECTRONIC NOSE AND ANN TO
DETECT THE PRESENCE OF GANODERMA**

4.1	<i>Ganoderma boninense</i> Fruiting Bodies and Ambient Discrimination Using ANN with Laboratory Data	81
4.1.1	Sample Preparation and Data collection	81
4.1.2	Data Profile	82
4.1.3	Data Consistency	83
4.1.4	ANN Training and Testing	85
4.1.5	ANN Training and Testing Results	86
4.2	Data Collection for the ANN Testing / Detection of the Presence of <i>Ganoderma</i> Odour using a Few Types of Parameters	87
4.3	The ANN Models of <i>Ganoderma boninense</i> and Ambient Testing Using Different Types of Parameters to Verify the Presence of <i>Ganoderma boninense</i> Odour	89
4.3.1	The ANN Testing / Detection Results	90
4.4	<i>Ganoderma boninense</i> Fruiting Bodies and the Air Surrounding Healthy Trunk Odour Discrimination Using ANN with On-site Data	91
4.4.1	Data Profile	92
4.4.2	Data Consistency	92

4.4.3	ANN Training and Testing Results	93
4.4.4	The ANN models testing using different types of parameters to verify the presence of <i>Ganoderma boninense</i> odour	95
4.4.4.1	The Testing / detection Results	96
4.5	Summary	97

CHAPTER 5 PLANT DISEASE DETECTION USING ELECTRONIC NOSE AND ANN

5.1	Investigation of Infected Oil Palm Tree Discrimination using On-site Data	100
5.2	On-site Odour Recording and Sample Collection Procedures	101
5.3	Laboratory Data Collection	104
5.4	ANN Training and Testing	104
5.5	Results and Discussions	106
5.5.1	The Consistency and Data Profile	106
5.5.2	The Comparison between Odours Captured On-site and in the Laboratory	109
5.5.3	Principle Component Analysis Results	111
5.5.4	ANN Training Results	112
5.5.5	The System Testing Results	114
5.6	Summary	116

CHAPTER 6 DEVELOPMENT OF IN-HOUSE ELECTRONIC NOSE

6.1	Commercial Electronic nose and Low Cost Alternative	119
6.1.1	The Electronic Nose Design Considerations	121
6.1.2	The Basic Operation of the In-house Electronic Nose	123
6.2	The System Description	125
6.2.1	The Sensor Array	125
6.2.2	The Odour Capturing Module	126
6.2.3	The Microprocessor	127
6.2.4	Pattern Recognition	129
6.3	Hardware Development	129
6.4	Software Development	130
6.5	Prototype and Odour Capturing Module Development and Fabrication	132
6.6	Graphic User Interface	134
6.7	System Integration and Testing	136
6.8	The Laboratory Testing Results	138
6.8.1	Data Consistency	138
6.8.2	Data Profile	139
6.8.3	ANN Training Results	140
6.8.4	The Detection Results	141
6.9	The On-site Testing Results	142
6.10	Summary	144

CHAPTER 7 CONCLUSIONS

7.1 Odour Detection Issues 150

7.2 Future Works 151

REFERENCES

152

APPENDIX A

The Parameter Setup for Cyranose 320

Experimental Procedure When Using the Cyranose 320

1. The Data Collection General Procedure
2. The C-320 Training Pattern Recognition Procedure
3. The C-320 Identify Procedure

APPENDIX B

The In-house E-nose Circuit Layout

APPENDIX C

The In-house E-nose Program Flow Chart

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LIST OF FIGURES

FIGURES	TITLE	PAGE
Figure 2.1	The analogy between biological and artificial noses	12
Figure 2.2	The basic electronic nose block diagram	13
Figure 2.3	Model of inter-grain potential barrier A (in the absence of gases)	16
Figure 2.4	Model of inter-grain potential barrier B (in the presence of gases)	17
Figure 2.5	A representation of the composite sensor material responding during the analyte exposure	19
Figure 2.6	The sample flow system	20
Figure 2.7	Electronic nose data processing block diagram	21
Figure 2.8	A basic neuron model	29
Figure 2.9	Activation functions	30
Figure 2.10	Architecture of MLP	31
Figure 2.11	The Radial Basis Function ANN	32
Figure 2.12	The <i>Ganoderma boninense</i> fruiting body	37
Figure 3.1	Cyranose 320	43
Figure 3.2	The schematic of the purge cycle	45
Figure 3.3	The schematic of sample cycle	45
Figure 3.4	Cyranose 320 setup for lab data collection	49
Figure 3.5	Cyranose 320 setup for on-site data collection	50
Figure 3.6	The steps to get the dimension reduction value	56

Figure 3.7	The flow of neural network training process	63
Figure 3.8	The flow of testing and identification process	65
Figure 3.9	Vial used in this experiment	68
Figure 3.10	Profile of essence samples	70
Figure 3.11	CDA results	71
Figure 3.12	The PCA result	73
Figure 3.13	The ANN training result using eight hidden nodes	76
Figure 4.1	Ganoderma in a glass beaker	82
Figure 4.2	The ambient and <i>Ganoderma boninense</i> data profiles	83
Figure 4.3	Data consistency of <i>Ganoderma boninense</i> and ambient odour	84
Figure 4.4	The bored trunk	88
Figure 4.5	<i>Ganoderma boninense</i> at the oil palm trunk	89
Figure 4.6	<i>Ganoderma boninense</i> and air surrounding healthy trunk odour profile	92
Figure 4.7	Data consistency of the on-site data of <i>Ganoderma boninense</i> and air surrounding the healthy trunk	93
Figure 4.8	ANN training results	94
Figure 5.1	The research areas in oil palm plantation	101
Figure 5.2	Data collection point for an oil palm tree	102
Figure 5.3	The air around the tree trunk data and sample collection	103
Figure 5.4	The plots of the sensors response for the different points / trees of the same classification for on-site data collection	107

Figure 5.5	The plots of the sensors response for the different points / trees of the same classification for laboratory data collection	108
Figure 5.6	(a) profile of healthy and infected data for odour surrounding the trunk. (b) profile of healthy and infected for odour of bored trunk. (c) profile of healthy and infected for odour of soil	109
Figure 5.7	The comparison between on-site and laboratory odour profiles	110
Figure 5.8	PCA result	111
Figure 5.9	ANN training result for odour surrounding the trunk	114
Figure 6.1	FOX 2000 from Alpha MOS	120
Figure 6.2	Sensors' chamber	122
Figure 6.3	(a) The data collection operation (b) The ANN training operation (c) The detection/recognition operation	124
Figure 6.4	The odour capturing module	127
Figure 6.5	The in-house electronic nose block diagram	128
Figure 6.6	The Sensor Circuit for TGS 825	130
Figure 6.7	The CAD drawing of the electronic nose showing the internal components	133
Figure 6.8	The completed in-house electronic nose	133
Figure 6.9	The main GUI window	135
Figure 6.10	The sensor response window	135
Figure 6.11	Sample in beaker	137

Figure 6.12	(a) The consistency of control condition data.	139
	(b) The consistency of ganoderma data	
Figure 6.13	Profile data of control condition and ganoderma odour	139
Figure 6.14	(a) The ANN training result. (b) The plot of SSE conducted at the end of every epoch during the ANN training	141
Figure 6.15	The data consistency (tree1 to tree 7)	143

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LIST OF TABLES

TABLES	TITLE	PAGE
Table 2.1	Typical materials used as sensors	14
Table 3.1	Identification rating descriptions	47
Table 3.2	Classification designation for the two outputs for two samples	60
Table 3.3	Classification designation for the four outputs for four samples	61
Table 3.4	Number of training, validation and testing data for each sample	69
Table 3.5	The Identification result using Cyranose 320	72
Table 3.6	PCA output for dimension reduction	74
Table 3.7	The percentage of accuracy for testing using eight hidden nodes	77
Table 4.1	Number of training, validation and testing for each sample	85
Table 4.2	Target used in the ANN training	85
Table 4.3	The ANN training results	86
Table 4.4	The ANN testing results with percentage of accuracy	87
Table 4.5	Number of data for each parameter	90
Table 4.6	The detection of the presence of <i>Ganoderma boninense</i> based on parameters	90
Table 4.7	Number of data for each parameter	91

Table 4.8	The ANN testing results with percentage of accuracy	95
Table 4.9	The detection results for the ANN model with hidden node 16 and 20	96
Table 5.1	The number of training, validation and testing data for each parameters	105
Table 5.2	Target used in the ANN training	105
Table 5.3	PCA coefficient	112
Table 5.4	The percentage of accuracy using testing data set	115
Table 5.5	The percentage of accuracy / recognition of testing that using the new data set	116
Table 6.1	Sensor and its characteristics	125
Table 6.2	Button descriptions	136
Table 6.3	The ANN testing result	141
Table 6.4	The detection result	142

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LIST OF ABBREVIATIONS

2D	=	2 Dimensions
3D	=	3 Dimensions
ADC	=	Analog to Digital Converter
ANN	=	Artificial Neural Networks
BP	=	Backpropagation
BSR	=	Basal Stem Rots
C-320	=	Cyranose 320
CA	=	Cluster Analysis
CAD	=	Computer-aided Design
CDA	=	Canonical Discriminant Analysis
CNS	=	Central Nervous System
COM	=	Communications Port
CP	=	Conducting Polymer
DAS	=	Dimension Auto-scaling
DC	=	Data Collection
DNA	=	Deoxyribonucleic Acid
EEPROM	=	Electrically Erasable Programmable ROM
ELISA	=	Enzyme Linked Immunosorbant Assay
E-nose	=	Electronic Nose
FELDA	=	Federal Land Development Authority
FIS	=	Fuzzy Intereference System
GC	=	Gas Chromathography
GC-MS	=	Gas Chromathography – Mass Spectrometry

GUI	=	Graphic User Interface
HPLC	=	High-performance Liquid Chromatography
HPTLC	=	High-performance Thin Layer Chromatography
KNN	=	K-nearest Neighbour
LC-MS	=	Liquid Chromatography Mass Spectrometry
LCD	=	Liquid Crystal Display
LDA	=	Linear Discriminant Analysis
MLP	=	Multilayer Perceptron
ml	=	millilitre
MOS	=	Metal Oxide Sensor
MSE	=	Mean of Squared Error
OCM	=	Odour Capturing Module
PARC	=	Pattern Recognition
PC	=	Personal Computer
PC1	=	Principle Component 1
PC2	=	Principle Component 2
PCA	=	Principle Component Analysis
PCB	=	Printed Circuit Board
PCR	=	Polymerase Chain Reaction
PLS	=	Partial Least Squares
POD	=	Proper Orthogonal Decomposition
Ps	=	Power Comsumptions
QCM	=	Quartz Crystal Microbalance
RBF	=	Radial Basis Function
R _L	=	Load Resistor

RS232	=	Recommended Standard 232
rRNA	=	Ribosomal RNA
SAW	=	Surface Acoustic Wave
SOM	=	Self-organising Map
sp.	=	Species
SSE	=	Sum of Squared Error
VAS	=	Vector Auto-scaling
VB	=	Visual Basic
VNORM	=	Vector Normalisation

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ABSTRAK

Kajian Kebolehlaksanaan Menggunakan Hidung Elektronik Untuk Mengesan Penyakit BSR di Ladang Kelapa Sawit

Industri pertanian telah lama bergantung kepada kepakaran manusia untuk mengesan penyakit pokok. Walau bagaimanapun, manusia mengambil masa yang lama untuk menjadi seorang pakar, tidak konsisten dan mempunyai kelemahan. Kerja yang dibentangkan ini adalah kerja yang dilakukan menggunakan hidung elektronik menggabungkan kepintaran buatan untuk mengesan penyakit pokok, khususnya, penyakit pangkal batang reput yang diakibatkan oleh *Ganoderma boninense*, sejenis kulat yang mengancam ladang kelapa sawit di Asia Tenggara. Hidung elektronik komersial, Cyranose 320, digunakan sebagai pengesan hadapan manakala rangkaian neural buatan yang dilatih dengan algoritma Levenberg-Marquadt diguna untuk membuat keputusan. Untuk peringkat pertama, satu pembelajaran tentang pengelasan corak terbenam pada Cyranose 320 dan rangkaian neural buatan telah dijalankan menggunakan beberapa jenis bauan. Peringkat ini akhirnya mengenalpasti bahawa ANNs lebih baik dari pengelasan corak terbenam dari segi ketepatan dan ia patut digunakan untuk eksperimen yang akan datang. Peringkat kedua melibatkan pengesanan kulat *Ganoderma boninense* di dalam makmal dan di ladang kelapa sawit. Peringkat ini membuktikan bahawa bau kulat ini boleh dikesan selepas diuji dengan menggunakan beberapa jenis parameter bau. Peringkat seterusnya ialah untuk mendiskriminasi pokok kelapa sawit yang sihat dengan berpenyakit di dalam ladang. Kerja yang dijalankan telah menunjukkan bahawa penggabungan antara hidung elektronik dengan ANNs mempunyai kebarangkalian-boleh untuk mendiskriminasi pokok berpenyakit di ladang. Hasil kajian ini juga digunakan untuk membangunkan hidung elektronik sendiri untuk kajian asas dan menyediakan hidung elektronik yang berkos rendah. Kesimpulannya, kerja yang menggunakan hidung elektronik and ANNs ini berkeupayaan untuk mengesan dan mendiskriminasi penyakit BSR di dalam makmal dan ladang.

ABSTRACT

Feasibility Study of Utilising Electronic Nose to Detect BSR Disease in Oil Palm Plantation

*The agricultural industry has been, for a long time, dependent upon human expertise to detect plant disease. However, human experts may take years of training and can be inconsistent, as well as prone to fatigue. Presented in this thesis is the work conducted on utilising electronic nose incorporating artificial intelligence to detect plant malaise, specifically, basal stem rot (BSR) disease that is caused by *Ganoderma boninense*, a type of fungi affecting oil palm plantations in South East Asia. A commercial electronic nose, Cyranose 320, was used as the front-end sensors with artificial neural networks trained using Levenberg-Marquardt algorithm employed for decision making. For the first stage, a study on Cyranose 320 embedded pattern recognitions and artificial neural networks (ANNs) was conducted using a few types of essences. This stage confirmed that the ANNs is better than the embedded pattern recognitions in terms of accuracy and hence should be used for the next experiments. The second stage involved the *Ganoderma boninense* fruiting bodies detection in laboratory and oil palm plantation. This stage proved that the fungi odour can be detected after being tested using a few types of odour parameter. The next stage is to discriminate the healthy and non-healthy oil palm trunk in the plantation. The conducted work indicates that the combination of the electronic nose and ANNs has the ability to discriminate the infected trunk. The findings of the work were also used to develop an in-house low cost electronic nose to support further fundamental study and implementations. As a conclusion, this work confirms that it is feasible to utilise the electronic nose and ANNs to detect and discriminate the BSR disease both in the laboratory and in the plantation.*

CHAPTER 1

INTRODUCTION

1.0 Background

Odour is a distinctive smell, a lingering quality or impression (Soanes, C. et al, 2005). It functions to signal pleasure, avoidance, sexual attraction and many others. Odours are also called smells, which can refer to both pleasant and unpleasant odours. The terms fragrance, scent, or aroma are used primarily by the food and cosmetic industry to describe a pleasant odour, and are sometimes used to refer to perfumes. In contrast, stench, reek, and stink are used specifically to describe unpleasant odour.

Odours and volatile compounds have been widely used in a variety of studies. For example, 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. The odour was used to determine the stage of fruit ripeness as well as the state of health of crops (Brezman, et. al, 2005; G´omez, et. al, 2006; Keller, et. al, 1995; Marrazzo, 1999; Md Salim, et. al, 2005).

Odour analysis traditionally involves the use of a panel of human sensory analyst (Shafiqul Islam, 2006). The former uses qualitative analysis, where the difference in odours detected, even complex combinations of volatiles, is

discriminated by perception and feels based on experience, and not quantitative analysis. The use of human panellists is not, however, without disadvantages. Human panellists are prone to fatigue, inconsistencies as well as costly, in addition to requiring long training periods. Also, the decisions made by human panellists may be subjective, and not suitable for certain types of analyses such as those involving toxic organic molecules.

The second method is to use advance analytical instruments in the laboratories (Shafiqul Islam, 2006). These techniques can give very detailed information about the precise contents of the odour. These classical analytical techniques involve gas chromatography (GC-MS), liquid chromatography mass spectrometry (LC-MS), high-performance liquid chromatography (HPLC), high-performance thin layer chromatography (HPTLC) and etc. Since odour is usually composed of complex mixture of volatiles, such techniques are too cumbersome for practical everyday applications and costly to set-up. Also, many volatile chemicals are of very minute quantity and beyond their detection limit. Moreover, the relationship between the physical and chemical properties of the odourant molecules and their sensory impact is still unclear, in spite of a number of research efforts.

In addressing these problems and limitations, a device that mimics the mammalian olfactory system commonly referred to as electronic nose (e-nose) has been developed. This device consists of headspace sampling, gas sensor array and pattern recognition modules to generate signal pattern that are used to characterise odours, and achieved through qualitative analysis (Keller, 1995).

To some extent, e-nose provides rapid odour analysis and addresses the issue of subjectivity of the human sensory technique. The applications of these devices are wide ranging, from agricultural applications to solving environmental issues (Brezman, et. al, 2005; G´omez, et. al, 2006; Keller, et. al, 1995; Laszlo, 2005; Marrazzo, 1999; Masila, 1998; Md Salim, et. al, 2005).

The agricultural industry can benefit tremendously from the use of such systems as the e-nose. It provides the flexibility and rapid training of qualitative analysis of a variety of odours. Hence the use of this system may replace traditional methods that are labour intensive, inconsistent, sometimes impractical and time consuming (Md Salim, et. al, 2005). Among the applications of the e-nose for the agricultural industry are to assist product quality monitoring, fruit ripeness determination, inspection of fish as well as other post-harvest activities (Brezman, et. al, 2005; G´omez, et. al, 2006; Keller, et. al, 1995; Marrazzo, 1999; Md Salim, et. al, 2005).

1.1 Problem Statements

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 (Adom, A.H. et al, 2007). In Malaysia, the production of palm oil has exceeded that of natural rubber, and its importance has been further boosted by the introduction of bio-diesel (Singh, H. et al, 2006).