



UNIVERSITI PUTRA MALAYSIA

***ASSESSMENT OF NEAR-INFRARED AND MID-INFRARED
SPECTROSCOPY FOR EARLY DETECTION OF BASAL
STEM ROT DISEASE IN OIL PALM PLANTATION***

SHOHREH LIAGHAT

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ASSESSMENT OF NEAR-INFRARED AND MID-INFRARED
SPECTROSCOPY FOR EARLY DETECTION OF BASAL STEM ROT
DISEASE IN OIL PALM PLANTATION

By

SHOHREH LIAGHAT

Thesis Submitted to the School of Graduate Studies, Universiti
Putra Malaysia, in Fulfilment of the Requirement for the Degree of
Doctor of Philosophy

October 2013

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DEDICATION

Dedicated with Love to

My Kind Father, Mahmood and My Beloved Mother, Zohreh

For Their Endless Love, Support and Sacrifices



Abstract of thesis presented to the Senate of Universiti Putra Malaysia
in fulfilment of the requirement for the degree of Doctor of Philosophy

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SPECTROSCOPY FOR EARLY DETECTION OF BASAL STEM ROT
DISEASE IN OIL PALM PLANTATION

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SHOHREH LIAGHAT

October 2013

Chair: Prof. Shattri Bin Mansor, PhD

Faculty: Engineering

Basal stem rot (BSR) is a fatal fungal (*Ganoderma*) disease in oil palm plantations which has a significant impact on palm oil production in Malaysia. Since there is no effective treatment to control this disease, early detection of BSR is vital for sustainable disease management. Current method of detection includes periodic visual inspection based on the symptoms of the disease which often shows up at the later stage of the disease infection and consequent laboratory analysis for confirmation. The limitations of current detection technique have led to an interest in developing alternative field-based methods that can be used for rapid diagnosis of this disease.

The ultimate goal of this study was to develop an appropriate spectroscopic technique that can be used for an early and accurate detection and differentiation of *Ganoderma* disease with different severities. The short term goal was to evaluate the possibility of using visible (VIS) and near-infrared (NIR), and mid-infrared (MIR) spectroscopy as possible techniques for the above mentioned ultimate goal. Reflectance spectroscopy analysis ranging from visible to near-infrared region (325-1075 nm) and mid-infrared region (2.55-25.05 μm /3921-399 cm^{-1}) was used to analyze oil palm leaf and trunk samples of healthy (G0), mildly-infected (G1), moderately-infected (G2) and heavily-infected (G3) trees in order to detect and quantify *Ganoderma* disease at different infection levels. Reflectance spectra were pre-processed and principal component analysis (PCA) was performed to obtain PC scores as input features used in different pattern recognition algorithms in order to select the best learning model of *Ganoderma* discrimination. Linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), k-nearest neighbor (kNN), Naïve-Bayes (NB), artificial neural networks (ANNs) and support vector machines (SVMs) classification techniques, were tested to classify the leaf and trunk samples into four levels of disease severity. The applicability of using band combinations extracted from mid-infrared spectroscopy (2.55-25.05 μm) for the detection of BSR disease in oil palm leaves was investigated using

optimum index factor (OIF) and analysis of variance (ANOVA). The results indicated that LDA-based model resulted in high average overall classification accuracies of 92% (leaf samples) and 94% (trunk samples) when mid-infrared absorbance spectra were analyzed. The analysis of VIS-NIR leaf reflectance spectra, in both field and laboratory conditions, showed that kNN-based model predicted the disease with high overall average classification accuracies of 99% and 90%, respectively. Comparing the results achieved from analyzing the reflectance spectra (VIS-NIR and MIR) of leaf and trunk samples with SVM and NN classifiers demonstrated that mid-infrared absorbance data of trunk samples with the average overall classification accuracies of 97% (standard deviation = 1%) for SVM and 97% (standard deviation = 3%) for NN resulted in better performance in classifying four classes of *Ganoderma* infestation. Moreover, among different ratio indices resulted from band combinations method, A13.10/A9.90 could differentiate between four different classes of healthiness more accurately. Results confirmed the usefulness and efficiency of spectra-based classification approach for fast screening of BSR.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENILAIAN SPEKTROSKOPI INFRA-MERAH HAMPIR DAN INFRA-MERAH PERTENGAHAN UNTUK PENGESANAN AWAL PENYAKIT REPUT BATANG DI LADANG KELAPA SAWIT

Oleh

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Reput pangkal batang (BSR) ialah sejenis penyakit kulat (Ganoderma) dalam perladangan kelapa sawit yang mempunyai kesan ketara terhadap pengeluaran minyak sawit di Malaysia. Biarpun tiada rawatan berkesan untuk mengawal penyakit ini, pengesanan awal BSR adalah mustahak untuk membendung penularan penyakit ini. Kaedah semasa pengesanan termasuk pemeriksaan gambaran berkala berdasarkan gejala-gejala penyakit itu bagaimanapun kerap kali menunjukkan peringkat terkemudian jangkitan penyakit dimana memerlukan analisis makmal secara berterusan untuk pengesahannya. Keterbatasan dalam kaedah pengesanan semasa telah mewujudkan kecenderungan dalam

membangunkan kaedah-kaedah alternatif berasaskan ladang dimana boleh digunakan untuk pengesanan secara pantas penyakit ini.

Kemuncak matlamat kajian ini adalah untuk membangunkan satu teknik berkesan inframerah dekat dan inframerah pertengahan yang boleh digunakan untuk pengesanan awal dan tepat serta dapat membezakan penyakit *Ganoderma* dengan tahap permasalahan yang berbeza. Matlamat jangka pendek adalah untuk menilai kemungkinan penggunaan spektroskopi inframerah tampak (VIS), inframerah dekat (NIR), dan inframerah tengah (MIR) sebagai suatu teknik yang berkemungkinan dalam menepati matlamat akhir yang telah disebutkan diatas. Analisis spektroskopi pantulan berjulat daripada kawasan tampak kepada rantau inframerah dekat (325-1075 nm) dan rantau inframerah tengah (2.55-25.05 μm / 3921-399 cm^{-1}) digunakan untuk menganalisa daun kelapa sawit dan sampel batang pokok yang sihat (G0), sedikit dijangkiti (G1), sederhana dijangkiti (G2) dan teruk dijangkiti (G3) daripada pokok-pokok sebagai langkah untuk mengesan dan menganggarkan penyakit *Ganoderma* di setiap peringkat jangkitan berbeza. Spektrum pantulan merupakan pemprosesan awal juga sebagai komponen analisis utama (PCA) telah dilaksanakan untuk memperolehi kiraan PC sebagai nilai ciri-ciri kemasukan yang digunakan dalam algoritma pengenalanpastian sebagai syarat untuk

memilih model pembelajaran terbaik dalam mendiskriminasikan *Ganoderma*. Analisis diskriminasi linear (LDA), analisis diskriminasi kuadratik (QDA), jiran terdekat k (kNN), Naive-Bayes (NB), jaringan saraf tiruan (ANNs) dan teknik pengkelasan mesin sokongan vektor (SVMs), telah diuji terhadap lebih daripada ratusan daun dan sampel batang pokok untuk mengkelaskan ia kepada empat peringkat kemudahan penyakit. Kebolegunaan dalam menggunakan jalur gabungan yang diambil dari spektroskopi inframerah tengah (2.55-25.05 μm) untuk pengesanan penyakit BSR dalam daun-daun sawit telah dikaji menggunakan faktor indeks optimum (OIF) dan analisis varians (ANOVA). Keputusan menunjukkan bahawa model berasaskan LDA berhasil di dalam klasifikasi keseluruhan tinggi purata berketepatan 92% (sampel daun) dan 94% (sampel batang pokok) apabila serapan inframerah tengah dianalisis. Analisis spektrum pantulan daun VIS-NIR, dalam kedua-dua ladang dan makmal, menunjukkan bahawa model berasaskan kNN meramalkan penyakit itu dengan pengelasan sederhana tinggi keseluruhan yang berketepatan 99% dan 90%, masing-masing. Dengan membandingkan keputusan yang diperolehi daripada penganalisan spektrum pantulan (VIS-NIR and MIR) sampel daun dan batang pokok menggunakan pengkelas SVM and NN telah menunjukkan bahawa data serapan inframerah tengah sampel batang pokok dengan klasifikasi keseluruhan berketepatan 97%

(sisihan piawai = 1%) untuk SVM dan 97% (sisihan piawai = 3%) untuk NN menghasilkan keadaan lebih baik dalam mengklasifikasikan empat kelas wabak *Ganderma*. Tambahan pula, diantara nisbah indeks berbeza yang terhasil dari gabungan kaedah jalur, A13.10 / A9.90 dapat membezakan diantara empat kelas kesihatan dengan lebih tepat. Keputusan-keputusan yang diperolehi telah mengesahkan kegunaan dan kesesuaian pengelasan berasaskan spektrum sebagai pendekatan kepada pemeriksaan pantas BSR.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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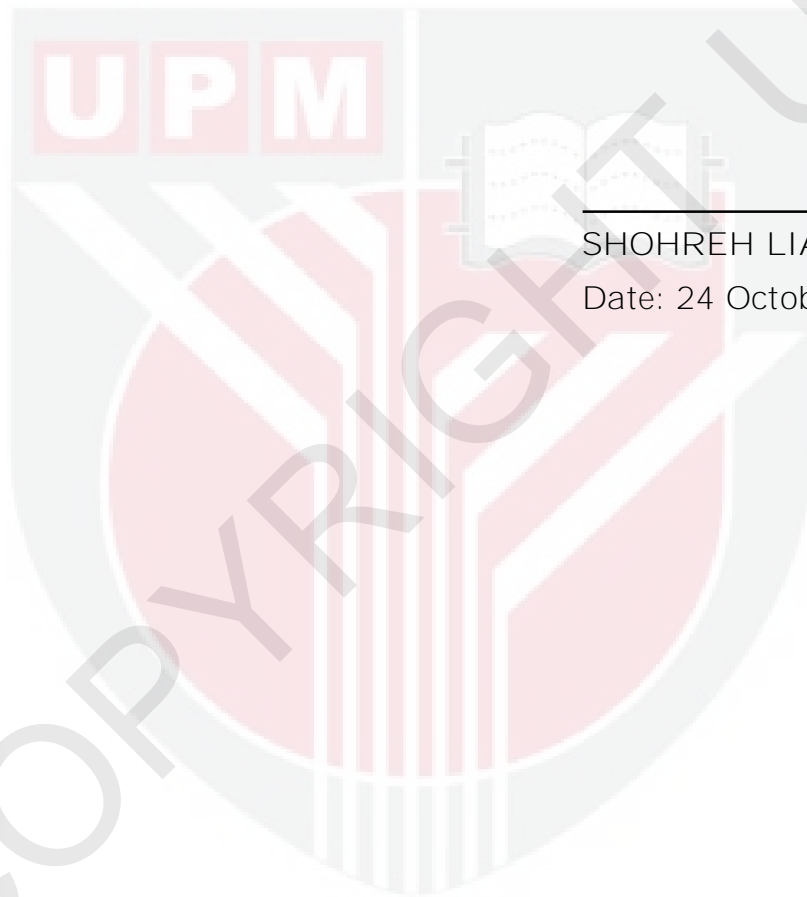
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DECLARATION

I declare that the thesis is my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously, and is not concurrently, submitted for any other degree at Universiti Putra Malaysia or at any other institutions.



SHOHREH LIAGHAT

Date: 24 October 2013



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LIST OF ABBREVIATIONS

ANN	Artificial neural network
ANOVA	Analysis of variance
ARD	Average reflectance data
ATR	Attenuated total reflection
BP	Back-propagation
BSR	Basal stem rot
CVC	Citrus variegated chlorosis
d.f.	Degrees of freedom
EMR	Electromagnetic radiation
FLDA	Fisher linear discriminant analysis
FOV	Field of view
FT-IR	Fourier transform infrared
HLB	Huanglongbing
IR	Infrared
IRE	Internal reflection element
KNN	k-nearest neighbor
LDA	Linear discriminant analysis
LIF	Laser Induced Fluorescence
LS-SVM	Least square-support vector machine
LVO	Learning vector quantization
MC	Moisture content
MIR	Mid-infrared
MSE	Mean squared error
MSR	Modified Simple Ratio
MSR	Multiple stepwise regression
NB	Naïve-Bayes

NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared
OIF	Optimum index factor
PC	Principal component
PCA	Principal component analysis
PCR	Polymerase chain reaction
pH	Potential hydrogen
PLS	Partial least square
PLSR	Partial least square regression
QDA	Quadratic discriminant analysis
RBF	Radial basis function
RMSE	Root mean square error
SAD	Spectral angle data
SD	Standard deviation
SID	Spectral index data
SIMCA	Soft independent modeling of classification analogies
SMLR	Stepwise multi-linear regression
SOFM	Self-organizing Feature Maps
SPA	Successive projections algorithm
SVC	Support vector classification
SVM	Support vector machine
TR	Transmission Reflection
TSS	Total soluble solids
UVE	Uninformative variable elimination
VIS	Visible

CHAPTER 1

INTRODUCTION

Malaysia, with more than five million hectares of land under oil palm cultivation, produces up to 18 million tons of palm oil each year. Palm oil is the widely used vegetable oil. About 12% and 27% of the world's total productions and exports of oils and fats is provided through Malaysian palm oil industry. Malaysia is considered as the world second largest grower of oil palm by producing about 40% of the world's palm oil and the most exporter of palm oil by exporting more than 50% of their palm oil. Recently there is an increasing interest in producing bio-diesel from palm oil as a source of renewable energy (Shuit et al., 2009; Sumathi et al., 2008). Over the past few years, there has been a stagnation in palm oil production for Malaysia due to various factors (FAPRI, 2010) such as disease and concern over healthiness of palm oil in daily diets. Basal stem rot (BSR) or *Ganoderma* fungal infection caused by *Ganoderma boninense* is serious disease in oil palm plantations that makes irreparable damage to palm oil industry in Malaysia each year with yield losses up to 80% in the infected area. This disease also is one of the major causes for increasing the use of chemicals and consequently production costs.

Ganoderma is known as the most destructive disease of oil palm plantations in Southeast Asia especially in Malaysia and North Sumatra (Flood et al., 2000).

Ganoderma can affect the trunk xylem tissue by producing enzymes to degrade lignin into carbon dioxide (CO₂) and water which are consumed by the fungus (Paterson et al., 2000). Lignin is a water impermeable seal across cell walls, and acts as a wall against microbial attack. Lignin strengthens the xylem tissues of plants (Paterson, 2007). As the fungal activity affects the vascular circulation, it restricts the nutrient and water consumption resulting in appearance of specific foliar symptoms (Figure 1.1a-d) such as one sided yellowing or mottling of the lower fronds followed by necrosis, shorter leaves and unopened spears, pale appearance with retarded growth, small canopy and skirt-like shape of crown (due to leaves declination) as well as reducing the oil palm production (Paterson, 2007). This disease can significantly reduce the leaf stomatal conductance, transpiration rate, intercellular CO₂ concentration and chlorophyll content that affect photosynthesis (Haniff et al., 2005). *Ganoderma* has great economic impact on palm oil industries (Sumathi et al., 2008) especially in Malaysia, with millions of hectares of oil palm cultivation (Shuit et al., 2009). This disease can infect oil palm trees in all growth stages, although the incidence of this

disease increases with the tree age and usually does not affect young trees (Ariffin et al., 2000). The spores that grow in non-living tissues such as oil palm residues (Khalid et al., 2000) probably spread root to root (Sanderson, 2005) or by wind when airborne spores can enter trees through wounds caused by shedding of branches, etc. (Paterson et al., 2000). Once infected, light-brown lesion filled in with swollen hyphal cells and cavities will appear and consecutively oil palm trees develop typical symptoms. With disease progressing, trunk will become hollow and in advanced cases, the infected tree may collapse (Paterson, 2007). Usually, the foliar symptoms will appear in advanced stages of infection. It is reported that at least one-half of the basal stem tissue has been killed by fungus when the foliar symptoms appeared (Paterson, 2007; Idris et al., 2000). Young palms usually die within 6-24 months of the first symptoms but mature palms can survive a little bit longer (2-3 years) (Paterson, 2007).

Different methods have been used to control *Ganoderma* infection such as fungicide treatment (George et al., 1996; Sheephard et al., 1986), biological control (Zaiton et al., 2006; Wijeskera et al., 1996), removal of infected palms and soil mounding, or combination of these methods (Ariffin and Idris, 2002). Unfortunately, in advanced infections, none of

these methods are entirely satisfactory in reducing the disease effects on the yield (Singh, 1990).

Currently, the most commonly used method for detection of infected trees is visually finding *Ganoderma* specific symptoms such as foliar symptoms and fungus fruiting bodies (Basidiomycota mushroom) on the infected trunks or primary roots near soil level by the scouting crew (Figure 1.1e). Following the identification, the infected trunk samples are extracted by drilling for the isolation, growth and identification of the fungus in the laboratory (Lim and Fong, 2005) and polymerase chain reaction (PCR) analysis is performed to confirm the presence of fungus. Such diagnostics process is often difficult and expensive (As'wad et al., 2010; Idris et al., 2003). Now *Ganoderma* disease is mostly managed by applying fungicides (George et al., 1996) and biological agents (Sapak et al., 2008; Azevedo et al., 2000) but removing the infected trees is the only effective way to prevent the spread of this disease (Ariffin and Idris, 2002).



Figure 1.1: ***Ganoderma*** specific symptoms on oil palm trees in Banting, Selangor, Malaysia: (a) healthy tree (b) and (c) infected trees with retarded growth and skirt-like shape of the crown (d) yellowing and necrosis leaves (e) fungus fruiting bodies (Basidiomycota mushroom) on the infected trunk.

One of the major challenges in identifying foliar symptoms of *Ganoderma* disease is that the symptoms appear only in the advanced stages of the infection. Thus, there is a need for an efficient sensing technique for early detection of *Ganoderma* in oil palm plantations. Some works done using different techniques for early detection of *Ganoderma* but the results were not quite satisfactory. For example classification algorithms applied by Shafri et al. (2011) and Lelong et al. (2010) were able to identify only the severely infected samples with acceptable accuracy using visible and near-infrared (VIS-NIR) spectral data. Moreover, the significant bands selected from VIS-NIR spectral data of healthy and *Ganoderma*-infected palms by Shafri et al. (2009) and Shafri and Anuar (2008), were not be able to discriminant between healthy and mildly-infected leaf samples with high efficiency. Also, the airborne hyperspectral imagery used by Shafri and Ezzat (2009), Shafri and Hamdan (2009) and Shafri et al. (2012) to detect BSR disease, was costly technique which resulted in moderate classification accuracy.

Results demonstrated that despite great efforts, BSR early detection is still quite challenging. The current detecting method of this disease is time consuming and labor intensive. Application of spectroscopic technique along with development of robust statistical models of discrimination could provide more efficient and timely management of

the disease. This work evaluates the applicability of spectroscopic technique for BSR detection in oil palm. The long term goal of this study was to develop a cost effective method for detecting *Ganoderma* disease. The short term goal was to develop a NIR and MIR technique for detecting *Ganoderma* disease at early symptomless stage and find the best classification algorithm to classify the infected trees from healthy trees.

The research problem of this study was to seek a sensing technique for early detection of basal stem rot (BSR) in oil palm plantations caused by the fatal fungal (*Ganoderma*) disease. The hypothesis was, if spectroscopic technique can be used at BSR asymptomatic stage then great losses in palm oil production and high use of fungicide chemicals can be prevented.

Objectives:

The general objective of this research was to detect *Ganoderma* at early asymptomatic stages. Thus, with special focus on early detection of oil palm *Ganoderma* disease, the specific objectives were:

1. To explore the applicability of middle infrared spectroscopy for early detection of *Ganoderma* infected oil palm trees and to discover the limit of disease detection by conducting tests at different stages of disease infection.
2. To study the potential application of visible and near-infrared reflectance spectral data for early detection of *Ganoderma* infected trees at different levels of severity under laboratory and field conditions.
3. To evaluate the accuracy of six different discrimination models (LDA, QDA, kNN, NB, SVM and ANN) for detecting oil palm *Ganoderma* infected trees at different stages of infection and selecting the best model.

REFERENCES

- Ali Akcayol, M. and Cinar, C. 2005. Artificial neural network based modeling of heated catalytic converter performance. *Applied Thermal Engineering* 25: 2341-2350.
- Alvarez, R. 2009. Predicting average regional yield and production of wheat in the Argentine Pampas by an artificial neural network approach. *European Journal of Agronomy* 30: 70-77.
- Arbain, M.A. and Chong, T.C. 2009. Field application of *Trichoderma* and *Arbuscular mycorrhizal* fungi for the control of *Ganoderma* basal stem rot of oil palm. In Proc. of the PIPOC 2009 International Palm Oil Congress (Agriculture, Biotechnology & Sustainability), pp. 439-449. November 9-12, Kuala Lumpur, Malaysia.
- Ariffin, D. and Idris, A.S. 2002. Progress and research on *Ganoderma* basal stem rot of oil palm. Seminar Recent Progress in the Management of Peat and *Ganoderma*, p. 50. May 6-7, MPOB, Bangi, Malaysia.
- Ariffin, D., Idris, A.S. and Singh, G. 2000. Status of *Ganoderma* in oil palm. *Ganoderma Diseases of Perennial Crops*, ed. J., Flood, P.D., Bridge, and M. Holderness, pp. 49-68. Wallingford, UK: CABI Publishing.
- Asraf, H.M., Nooritawati, M.T. and Shah Rizam, M.S.B. 2012. A comparative study in kernel-based support vector machine of oil palm leaves nutrient disease. *Procedia Engineering* 41: 1353-1359.
- As'wad, A. W., M., Pasari, R.R.M., Abidin, M.A.Z. and Lima, N. 2011. Ergosterol analyses of oil palm seedlings and plants infected with *Ganoderma* *Crop Protection* 30: 1438-1442.
- Ausmus, B.S. and Hilty, J.W. 1971. Reflectance studies of healthy, maize dwarf mosaic virus-infected, and *Helminthosporium maydis*-infected corn leaves. *Remote Sensing of Environment* 2: 77-81.
- Azevedo, J.L., Maccheroni Jr., W., Pereira, J.O. and Araújo, W.L. 2000. Endophytic microorganisms: a review on insect control and recent

advances on tropical plants. *Electronic Journal of Biotechnology* 3: 40-65.

Balasundram, D., Burks, T.F., Bulanon, D.M., Schubert, T. and Lee, W.S. 2009. Spectral reflectance characteristics of citrus canker and other peel conditions of grapefruit. *Postharvest Biology and Technology* 51: 220-226.

Bas, D. and Boyaci, I.H. 2007. Modeling and optimization II: comparison of estimation capabilities of response surface methodology with artificial neural networks in a biochemical reaction. *Journal of Food Engineering* 78: 846-854.

Bauriegel, E., Giebel, A., Geyer, M., Schmidt, U. and Herppich, W.B. 2011. Early detection of Fusarium infection in wheat using hyperspectral imaging. *Computers and Electronics in Agriculture* 75: 304-312.

Belasque, L., Gasparoto, M.C.G. and Marcassa, L.G. 2008. Detection of mechanical and disease stresses in citrus plants by fluorescence spectroscopy. *Applied Optics* 47: 1922-1926.

Bing, C., Shao-kun, L., Ke-ru, W., Jing, W., Fang-yong, W., Chun-hua, X., Jun-chen, L. and Na, W. 2008. Spectrum characteristics of cotton canopy infected with verticillium wilt and applications. *Agricultural Sciences in China* 7: 561-569.

Bishop, C.M. 1995. Neural networks for pattern recognition. Oxford, UK: Clarendon Press.

Blackard, J.A. and Dean, D.J. 1999. Comparative accuracies of artificial neural networks and discriminate analysis in predicting forest cover types from cartographic variables. *Computers and Electronics in Agriculture* 24: 131-151.

Boggs, G.S. 2010. Assessment of SPOT 5 and QuickBird remotely sensed imagery for mapping tree cover in savannas. *International Journal of Applied Earth Observation and Geoinformation* 12: 217-224.

Boyd, S. and Vanderberghe, L. 2004. Convex Optimization, Seventh ed. Cambridge University Press, Cambridge, UK.

- Bravo, C., Moshou, D., West, J., McCartney, A. and Ramon, H. 2003. Early disease detection in wheat fields using spectral reflectance. *Biosystems Engineering* 84: 137-145.
- Burges, C.J.C. 1998. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery* 2: 955-974.
- Bunaciu, A.A., Aboul-Enein, H.Y. and Fleschi, S. 2011. Recent application of fourier transform infrared spectrophotometry in herbal medicine analysis. *Applied Spectroscopy Reviews* 46: 251-260.
- Cardinali, M.C.B., Boas, P.R.V., Milori, D.M.B.P., Ferreira, E.J., Silva, M.F., Machado, M.A., Bellete, B.S. and Silva, M.F.G.F. 2012. Infrared spectroscopy: A potential tool in huanglongbing and citrus variegated chlorosis diagnosis. *Talanta* 91: 1-6.
- Carter, G.A. 1994. Ratios of leaf reflectance in narrow wavebands as indicators of plant stress. *International Journal of Remote Sensing* 15: 697-703.
- Chavez, P.S., Guphill, S.C. and Howell, J.A. 1984. Image processing techniques for thematic mapper data. Technical Papers, 50th Annual Meeting of the American Society Photographers. 2: 728-742.
- Chen, B., Li, S., Wang, K., Wang, J. Wang, F., Xiao, C., Lai, J. and Wang, N. 2008. Spectrum characteristics of cotton canopy infected with Verticillium Wilt and applications. *Agricultural Sciences in China* 7: 561-569.
- Chen, X., Ma, J., Qiao, H., Cheng, D., Xu, Y. and Zhao, Y. 2007. Detecting infestation of take-all disease in wheat using Landsat Thematic Mapper imagery. *International Journal of Remote Sensing* 28: 5183-5189.
- Cortes, C. and Vapnik, N.V. 1995. Support-vector networks. *Machine Learning* 20: 273-297.
- Dai, X., Huo, Z. and Wang, H. 2011. Simulation for response of crop yield to soil moisture and salinity with artificial neural network. *Field Crops Research* 121: 441-449.

- Delalieux, S., Somers, B., Verstraeten, W.W., van Aardt, A.N.J., Keulemans, W. and Coppin, P. 2009. Hyperspectral indices to diagnose leaf biotic stress of apple plants, considering leaf phenology. *International Journal of Remote Sensing* 30: 1887-1912.
- Delalieux, S., van Aardt, J., Keulemans, W., Schrevens, E. and Coppin, P. 2007. Detection of biotic stress (*Venturia inaequalis*) in apple trees using hyperspectral data: Non-parametric statistical approaches and physiological implications. *European Journal of Agronomy* 27: 130-143.
- Delwiche, S.R. and Kim, M.S. 2000. Hyperspectral imaging for detection of scab in wheat. In Proc. of SPIE, Biological Quality and Precision Agriculture II, Boston, MA 4203: 13-20.
- Di, W., Cao, F., Zhang, H., Sun, G.M., Feng, L. and He, Y. 2009. Study on disease level classification of rice panicle blast based on visible and near infrared spectroscopy. *Spectroscopy and Spectral Analysis* 29: 3295-3299.
- EIMasry, G., Wang, N., EISayed, A. and Ngadi, M. 2007. Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. *Journal of Food Engineering* 81: 98-107.
- EIMasry, G., Wang, N., Vigneault, C., Qiao, J. and EISayed, A. 2008. Early detection of apple bruises on different background colors using hyperspectral imaging. *LWT* 41: 337-345.
- FAPRI, 2010. Food and Agricultural Policy Research Institute.
- Flood, J., Huan, Y., Turner, P., Dreda and O' of *Ganoderma* from infective sources in the field and its implications for management of the disease in oil palm. *Ganoderma Diseases of Perennial Crops*, ed. J., Flood, P.D., Bridge, and M. Holderness, pp. 101-112. Wallingford, UK: CABI Publishing.
- Forato, L.A., Bernardes-Filho, R. and Colnago, L.A. 1998. Protein structure in KBr pellets by infrared spectroscopy. *Analytical Biochemistry* 259: 136-141.
- George, S.T., Chung, G.F. and Zakaria, K. 1996. Updated results (1990-1995) on trunk injection of fungicides for the control of

Ganoderma basal stem rot. In: Proc. of the 1996 PORIM International Palm Oil Congress-Agriculture Conference, pp. 508-515. September 23-28, Kuala Lumpur, Malaysia.

Graeff, S., Link, J. and Claupein, W. 2006. Identification of powdery mildew (*Erysiphe graminis* sp. *tritici*) and take-all disease (*Gaeumannomyces graminis* sp. *tritici*) in wheat (*Triticum aestivum* L.) by means of leaf reflectance measurements. *Central European Journal of Biology* 1: 275-288.

Gutierrez, P.A., Lopez-Granados, F., Pena-Barragan, J.M., Jurado-Exposito, M., Gomez-Casero, M.T. and Hervas-Martinez, C. 2006. Mapping sunflower yield as affected by *Ridolfia segetum* patches and elevation by applying evolutionary product unit neural networks to remote sensed data. *Computers and Electronics in Agriculture* 60: 122-132.

Haniff, M.H., Ismail, S. and Idris, A.S. 2005. Gas exchange responses of oil palm to *Ganoderma boninense* infection. *Asian Journal of Plant Science* 4: 438-444.

Hatfield, J.L., Gitelson, A.A., Schepers, J.S. and Walthall, C.L. 2008. Application of spectral remote sensing for agronomic decisions. *Agronomy Journal* 100: 117-131.

Hawkins, S.A., Park, B., Poole, G.H., Gottwald, T., Windham, W.R. and Lawrence, K.C. 2010. Detection of citrus Huanglongbing by Fourier transform infrared-attenuated total reflection spectroscopy. *Journal of Applied Spectroscopy* 64: 100-103.

Higdon, T. 2010. *FT-IR Spectroscopy Technology, Market Evaluation and Future Strategies of Bruker Optics Inc.*, Master Thesis, Massachusetts Institute of Technology.

Hochberg, E.J. and Atkinson, M.J. 2000. Spectral discrimination of coral reef benthic communities. *Coral Reefs* 19: 164-171.

Hsu, C.W., Chang, C.C. and Lin, C.J. 2008. A practical guide to support vector classification. In: Technical Report, Department of Computer Science, National Taiwan University.

<http://botit.botany.wisc.edu/>

- Huang, K.Y. 2007. Application of artificial neural network for detecting Phalaenopsis seedling diseases using color and texture features. *Computers and Electronics in Agriculture* 57: 3-11.
- Hubert, M. and Deriessen, K.V. 2004. Fast and robust discriminant analysis. *Computational Statistics and Data Analysis* 45: 301-320.
- Idris, A.S., Ariffin, D., Swinburne, T.R. and Watt, T.A. 2000. The identity of *Ganoderma* species responsible for BSR disease of oil palm in Malaysia-Morphological characteristics. MPOB Information Series No. 77a, pp. 1-4.
- Idris, A.S., Yamaoka, M., Hayakawa, S., Basri, M.W., Noorhasimah, I. and Ariffin, D. 2003. PCR Technique for detection of *Ganoderma*. MPOB Information Series No.188, p. 4.
- Jamain, A. and Hand, D.J. 2005. The naive bayes mystery: a classification detective story. *Pattern Recognition Letters* 26: 1752-1760.
- Jiang, J.B., Chen, Y.H. and Huang, W.J. 2007. Study on hyperspectral estimation of pigment contents in canopy leaves of winter wheat under disease stress. *Spectroscopy and Spectral Analysis* 27:1363-1367.
- Jiang, X. and Siew Wah, A.H.K. 2003. Constructing and training feed-forward neural networks for pattern classification. *Pattern Recognition* 36: 853-867.
- Jiménez, D., Cock, J., Satizábal, H.F., Barreto S.M.A., Pérez-Urbe, A., Jarvis, A. and Damme, P.V. 2009. Analysis of Andean blackberry (*Rubus glaucus*) production models obtained by means of artificial neural networks exploiting information collected by small-scale growers in Colombia and publicly available meteorological data. *Computers and Electronics in Agriculture* 69: 198-208.
- Jones, C.D., Jones, J.B. and Lee, W.S. 2010. Diagnosis of bacterial spot of tomato using spectral signatures. *Computers and Electronics in Agriculture* 74: 329-335.
- Kacurakova, M. and Wilson, R.H. 2001. Developments in mid-infrared FT-IR spectroscopy of selected carbohydrates. *Carbohydrate Polymers* 44: 291-303.

- Karimi, Y., Prasher, S.O., Patel, R.M. and Kim, S.H. 2006. Application of support vector machine technology for weed and nitrogen stress detection in corn. *Computers and Electronics in Agriculture* 51: 99-109.
- Kaul, M., Hill, R.L. and Walthall, C. 2005. Artificial neural networks for corn and soybean yield prediction. *Agricultural Systems* 85: 1-18.
- Khalid, H., Zin, Z.Z. and Anderson, J.M. 2000. Decomposition processes and nutrient release patterns of oil palm residues. *Journal of Oil Palm Research* 12: 46-63.
- Knipling, E.B. 1970. Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. *Remote Sensing of Environment* 1: 155-159.
- Kobayashi, T., Kanda, E., Kitada, K., Ishiguro, K. and Torigoe, Y. 2001. Detection of rice panicle blast with multispectral radiometer and the potential of using airborne multispectral scanners. *Phytopathology* 91: 316-323.
- Kos, G., Krska, R., Lohninger, H. and Griffiths, P.R. 2004. A comparative study of mid-infrared diffuse reflection (DR) and attenuated total reflection (ATR) spectroscopy for the detection of fungal infection on RWA2-corn. *Analytical and Bioanalytical Chemistry* 378: 159-166.
- Kose, E. 2008. Modelling of colour perception of different age groups using artificial neural networks. *Expert Systems with Applications* 34: 2129-2139.
- Lasch, P. 2012. Spectral pre-processing for biomedical vibrational spectroscopy and microspectroscopic imaging. *Chemometrics and Intelligent Laboratory Systems* 117: 100-114.
- Lelong, C.C.D., Pinet, P.C. and Poilve, H. 1998. Hyperspectral imaging and stress mapping in agriculture: A case study on wheat in Beauce (France). *Remote Sensing of Environment* 66: 179-191.
- Lelong, C.C.D., Roger, J.M., Brégrand, S., Dubertret, F., Lanore, M., Sitorus, N.A., Raharjo, D.A. and Caliman, J.P. 2010. Evaluation of Oil-Palm fungal disease infestation with canopy hyperspectral reflectance data. *Sensors* 10: 734-747.

- Li, X., Lee, W.S., Li, M., Ehsani, R., Mishra, A.R., Yang, C. and Mangan, R.L. 2012. Spectral difference analysis and airborne imaging classification for citrus greening infected trees. *Computers and Electronics in Agriculture* 83: 32-46.
- Li, S.K., Suo, X.M., Bai, Z.Y., Qi, Z.L., Liu, X.H., Gao, S.J. and Zhao, S.N. 2002. The machine recognition for population feature of wheat images based on BP neural network. *Agricultural Sciences in China*, 8: 885-889.
- Li, Y. and Tang, X.C. 2009. Improved performance of fault detection based on selection of the optimal number of principal components. *Acta Automatica Sinica* 35: 1550-1557.
- Libnua, F.O., Kvalheim, O.M., Christy, A.A. and Toft, J. 1994. Spectra of water in the near- and mid-infrared region. *Vibrational Spectroscopy* 7: 243-254.
- Lim, H.P. and Fong, Y.K. 2005. Research on basal stem rot (BSR) of ornamental palms caused by basidiospores from *Ganoderma boninense*. *Mycopathologia* 159: 171-179.
- Lin, H.T. and Lin, C.J. 2003. A study on sigmoid kernels for SVM and the training of non-PSD kernels by SMO-type methods. In: Technical report, Department of Computer Science, National Taiwan University.
- Liu, Z.Y., Huang, J.F., Shi, J.J., Tao, R.X., Zhou, W. and Zhang, L.L. 2007. Characterizing and estimating rice brown spot disease severity using stepwise regression, principal component regression and partial least-square regression. *Journal of Zhejiang University Science B* 10:738-744.
- Liu, Z.Y., Huang, J.F. and Tao, R.X. 2008. Characterizing and estimating fungal disease severity of rice brown spot with hyperspectral reflectance data. *Rice Science* 15: 232-242.
- Liu, Z.Y., Wang, D.C., Li, B. and Huang, J.F. 2009. Discrimination of lodged rice based on visible/near infrared (VIS/NIR) spectroscopy. *Journal of Infrared and Millimeter Waves* 28: 321-324.
- Liu, Z.Y., Wu, H.F. and Huang, J.F. 2010. Application of neural networks to discriminate fungal infection levels in rice panicles

using hyperspectral reflectance and principal components analysis. *Computers and Electronics in Agriculture* 72: 99-106.

Lopez, M.M., Bertolini, E., Olmos, A., Caruso, P., Gorris, M.T., Llop, P., Penyalver, R. and Cambra, M. 2003. Innovative tools for detection of plant pathogenic viruses and bacteria. *International Microbiology* 6: 233-243.

Lorenzen, B. and Jensen, A. 1989. Changes in leaf spectral properties induced in barley by cereal powdery mildew. *Remote Sensing of Environment* 27: 201-209.

Luther, J.E. and Carroll, A.L. 1999. Development of an index of Balsam Fir vigor by foliar reflectance spectra. *Remote Sensing of Environment* 69: 241-252.

Malthus, T.J. and Madeira, A.C. 1993. High resolution spectroradiometry: Spectral reflectance of field bean leaves infected by *Botrytis fabae*. *Remote Sensing of Environment* 45: 107-116.

Manjunath, B.G., Frick, M. and Reiss, R.D. 2012. Some notes on extremal discriminant analysis. *Journal of Multivariate Analysis* 103: 107-115.

Mascarenhas, M., Dighton, J. and Arbuckle, G.A. 2000. Characterization of plant carbohydrates and changes in leaf carbohydrate chemistry due to chemical and enzymatic degradation measured by microscopic ATR FT-IR Spectroscopy. *Applied Spectroscopy* 54: 681-686.

Mehl, P.M., Chen, Y.R., Kim, M.S. and Chan, D.E. 2004. Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations. *Journal of Food Engineering* 61: 67-81.

Mirik, M., Michels Jr., G.J., Kassymzhanova-Mirik, S., Elliott, N.C., Catana, V., Jones, D.B. and Bowling, R. 2006. Using digital image analysis and spectral reflectance data to quantify damage by greenbug (Hemiptera: Aphididae) in winter wheat. *Computers and Electronics in Agriculture* 51: 86-98.

- Mishra, A., Karimi, D., Ehsani, R. and Albrigo, L.G. 2011. Evaluation of an active optical sensor for detection of Huanglongbing (HLB) disease. *Biosystems engineering* 110: 302-309.
- Moshou, D., Bravo, C., Oberti, R., West, J.S., Bodria, L., McCartney, A. and Ramon, H. 2005. Plant disease detection based on data fusion of hyper spectral and multi-spectral fluorescence imaging using Kohonen maps. *Real-Time Imaging* 11: 75-83.
- Moshou, D., Bravo, C., Oberti, R., West, J.S., Ramon, H., Vougioukas, S. and Bochtis, D. 2011. Intelligent multi-sensor system for the detection and treatment of fungal diseases in arable crops. *Biosystem Engineering* 108: 311-321.
- Moshou, D., Bravo, C., West, J., Wahlen, S., McCartney, A. and Ramon H. 2004. Automatic detection of reflectance measurements and neural networks. *Computers and Electronics in Agriculture* 44: 173-188.
- Muhammed, H.H. 2005. Hyperspectral crop reflectance data for characterizing and estimating fungal disease severity in wheat. *Biosystems Engineering* 91: 9-20.
- Naidu, R.A., Perry, E.M., Pierce, F.J. and Mekuria, T. 2009. The potential of spectral reflectance technique for the detection of Grapevine leafroll-associated virus-3 in two red-berried wine grape cultivars. *Computers and Electronics in Agriculture* 66: 38-45.
- Nanyam, Y., Choudhary, R, Gupta, L. and Paliwal, J. 2012. A decision fusion strategy for fruit quality inspection using hyperspectral imaging. *Biosystem Engineering* 111: 118-125.
- Nocedal, J. and Wright, S.J. 2006. Numerical optimization, second edition, ed. T.V. Mikosch, S.I. Resnick, and S.M. Robinson, pp. 258-261. New York: Springer.
- Okamoto, H. and Lee, W.S. 2009. Green citrus detection using hyperspectral imaging. *Computers and Electronics in Agriculture* 66: 201-208.
- Pacumbaba Jr., R.O. and Beyl, C.A. 2011. Changes in hyperspectral reflectance signatures of lettuce leaves in response to

- macronutrient deficiencies. *Advances in Space Research* 48: 32-42.
- Pahlavan, R., Omid, M. and Akram, A. 2012. Energy input-output analysis and application of artificial neural networks for predicting greenhouse basil production. *Energy* 37: 171-176.
- Paterson, R.R.M. 2007. *Ganoderma* disease of oil palm—A white rot perspective necessary for integrated control. *Crop Protection* 26: 1369-1376.
- Paterson, R.R.M., Holderness, M., Kelley, J. , Miller, R. and O' 2000. In vitro diodegradation of oil-palm stem using macroscopic fungi from South East Asia: a preliminary investigation. *Ganoderma* Diseases of Perennial Crops, ed. J. Flood, P.D. Bridge, and M. Holderness, pp. 129-138. Wallingford, UK: CABI Publishing.
- Peñuelas, J. and Filella, I. 1998. Visible and near-infrared reflectance techniques for diagnosing plant physiological status. *Trends in Plant Science* 3: 151-156.
- Prabhakar, M., Prasad, Y.G., Thirupathi, M., Sreedevi, G., Dharajothi, B. and Venkateswarlu, B. 2011. Use of ground based hyperspectral remote sensing for detection of stress in cotton caused by leafhopper (Hemiptera: Cicadellidae). *Computers and Electronics in Agriculture* 79: 189-198.
- Qin, J., Burks, T.F., Kim, M.S., Chao, K. and Ritenour, M.A. 2008. Citrus canker detection using hyperspectral reflectance imaging and PCA-based image classification method. *Sensing and Instrumentation for Food Quality and Safety* 2: 168-177.
- Qin, J., Burks, T.F., Ritenour, M.A. and Bonn, W.G. 2009. Detection of citrus canker using hyperspectral reflectance imaging with spectral information divergence. *Journal of Food Engineering* 93: 183-191.
- Qin, Z. and Zhang, M. 2005. Detection of rice sheath blight for in-season disease management using multispectral remote sensing. *International Journal of Applied Earth Observation and Geoinformation* 7: 115-128.

- Rahman, M.M. and Bala, B.K. 2010. Modelling of jute production using artificial neural networks. *Biosystems Engineering* 105: 350-356.
- Rockafellar, R.T. 1993. Lagrange multipliers and optimality. *SIAM Review* 35: 183-238.
- Romer, C., Burling, K. Hunsche, M., Rompf, T., Noga, G. and Plumer, L. 2011. Robust fitting of fluorescence spectra for pre-symptomatic wheat leaf rust detection with Support Vector Machines. *Computers and Electronics in Agriculture* 79: 180-188.
- Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W., Plümer, L. 2010. Early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance. *Computers and Electronics in Agriculture* 74: 91-99.
- Sanderson, F.R. 2005. An insight into dispersal of *Ganoderma boninense* on oil palm. *Mycopathologia* 159: 139-141.
- Sankaran, S. and Ehsani, R. 2011. Visible-near infrared spectroscopy based citrus greening detection: Evaluation of spectral feature extraction techniques. *Crop Protection* 30: 1508-1513.
- Sankaran, S. and Ehsani, R. 2012. Detection of Huanglongbing infected citrus leaves using statistical models with a fluorescence sensor. *Applied Spectroscopy* 67: 463-469.
- Sankaran, S., Ehsani, R. and Etxeberria, E. 2010a. Mid-infrared spectroscopy for detection of Huanglongbing (greening) in citrus leaves. *Talanta* 83: 574-81.
- Sankaran, S., Mishra, A., Ehsani, R. and Davis, C. 2010b. A review of advanced techniques for detecting plant diseases. *Computers and Electronics in Agriculture* 72: 1-13.
- Sankaran, S., Mishra, A., Maja, J.M. and Ehsani, R. 2011. Visible-near infrared spectroscopy for detection of Huanglongbing in citrus orchards. *Computer and Electronics in Agriculture* 77: 127-134.
- Santoso, H., Gunawan, T., Jatmiko, R.H., Daromosarkoro, W. and Minasny, B. 2011. Mapping and identifying basal stem rot disease in oil palms in North Sumatra with QuickBird imagery. *Precision Agriculture* 12: 233-248.

- Sapak, Z, Meon, S. and Ahmed, Z.A.M. 2008. Effect of endophytic bacteria on growth and suppression of *Ganoderma* infection in oil palm. *International Journal of Agriculture and Biology* 10: 127-132.
- Savitzky, A. and Golay, M.J.E 1964. Smoothing and differentiation of data by simplified least-squares procedures. *Analytical Chemistry* 36: 1627-1639.
- Schölkopf, B. and Smola, A. 2002. Learning with kernels – support vector machines, regularization and beyond. Cambridge: MIT Press.
- Shafri, H.Z.M. 2009. Trends and issues in noise reduction for hyperspectral vegetation reflectance spectra. *European Journal of Scientific Research* 29: 404-410.
- Shafri, H.Z.M. and Anuar, M.I. 2008. Hyperspectral signal analysis for detecting disease infection in oil palms. In: Proc. of International Conference on Computer and Electrical Engineering, pp. 312-316. December 20-22, Phuket, Thailand.
- Shafri, H.Z.M., Anuar, M.I. and Saripan, M.I. 2009. Modified vegetation indices for *Ganoderma* disease detection in oil palm from field spectroradiometer data. *Journal of Applied Remote Sensing* 3: 1-23.
- Shafri, H.Z.M., Anuar, M.I., Seman, I.A. and Noor, N.M. 2011. Spectral discrimination of healthy and *Ganoderma*-infected oil palms from hyperspectral data. *International Journal of Remote Sensing* 32: 7111-7129.
- Shafri, H.Z.M. and Ezzat, M.S. 2009. Quantitative performance of spectral indices in large scale plant health analysis. *American Journal of Agriculture and Biological Sciences* 4: 187-191.
- Shafri, H.Z.M. and Hamdan, N. 2009. Hyperspectral imagery for mapping disease infection in oil palm plantation using vegetation indices and red edge techniques. *American Journal of Applied Science* 6: 1031-1035.
- Shafri, H.Z.M., Hamdan, N. and Anuar, M.I. 2012. Detection of stressed oil palms from an airborne sensor using optimized spectral indices. *International Journal of Remote Sensing* 33: 4293-4311.

- Sheephard, M.C., Noon, R.A., Worthington, P.A., McClellan, W.D. and Lever, B.G. 1986. Hexaconazole: a novel triazole fungicide. In: Proc. of Brighton Crop Protection Conference-Pests and Diseases, pp. 19-26. November 17-20, Brighton, Metropole, England.
- Shuit, S.H., Tan, K.T., Lee, K.T. and Kamaruddin, A.H. 2009. Oil palm biomass as a sustainable energy source: A Malaysian case study. *Energy* 34: 1225-1235.
- Sighicelli, M., Colao, F., Lai, A. and Patsaeva, S. 2009. Monitoring postharvest orange fruit disease by fluorescence and reflectance hyperspectral imaging. In: Proc. of First International Symposium on Horticulture in Europe, ISHS Acta Horticulturae 817: 277-284.
- Singh, G. 1990. *Ganoderma* the scourge of oil palms in the coastal areas. Procedure of *Ganoderma* Workshop, pp. 130-135. PORIM, Bangi, Malaysia.
- Spinelli, F., Noferini, M. and Costa, G. 2006. Near infrared spectroscopy (NIRs): perspective of fire blight detection in asymptomatic plant material. In: Proc. of 10th International Workshop on Fire Blight, ISHS Acta Horticulture 704: 87-90.
- Steddom, K., Heidel, G., Gones, D. and Rush, C.M. 2003. Remote detection of *Rhizomania* in sugar beets. *Phytopathology* 93: 720-726.
- Sumathi, S., Chai, S.P. and Mohamed, A.R. 2008. Utilization of oil palm as a source of renewable energy in Malaysia. *Renewable and Sustainable Energy Reviews* 12: 2404-2421.
- Suo, X., Jiang, Y., Yang, M., Li, S., Wang, K. and Wang, C. 2010. Artificial neural network to predict leaf population chlorophyll content from cotton plant images. *Agricultural Sciences in China* 9: 38-45.
- Taillieze, B. and Koffi, C.B. 1992. A method for measuring oil palm leaf area. *Oléagineux* 47: 537-545.
- Vapnik, V. 1979. Estimation of dependences based on empirical data. Nauka, Moscow, pp. 5165- 5184, 27 (in Russian) (English translation: Springer Verlag, New York, 1982).

- Wang, H.W. 1999. Partial least squares method and applications. pp. 197-201. Beijing, China: National Defense Industry Press.
- Wang, W., Thai, C., Li, C., Gitaitis, R., Tollner, E.W. and Yoon, S.C. 2009. Detecting of sour skin diseases in *Vidalia* sweet onions using near-infrared hyperspectral imaging. ASABE Annual International Meeting, Reno, NV, Paper No. 096364.
- Wang, X., Zhang, M., Zhu, J. and Geng, S. 2008. Spectral prediction of *Phytophthora infestans* infection on tomatoes using artificial neural network (ANN). *International Journal of Remote Sensing* 29: 1693-1706.
- West, J.S., Bravo, C., Oberti, R., Lemaire, D., Moshou, D. and McCartney, H.A. 2003. The potential of optical canopy measurement for targeted control of field crop disease. *Annual Review of Phytopathology* 41: 593-614.
- Wijeskerera, H.T.R., Wijesundera, R.L.C. and Rajapakse, C.N.K. 1996. Hypal interactions between *Trichoderma viride* and *Ganoderma boninense* Pat. the cause of coconut root and bole rot. *Journal of National Science Seri Lanka* 24: 217-219.
- Wu, D., Feng, L., Zhang, C. and He, Y. 2008a. Early detection of *Botrytis cinerea* on eggplant leaves based on visible and near-infrared spectroscopy. Transactions of the ASABE 51: 1133-1139.
- Wu, X., Kumar, V., Quinlan, R.J., Ghosh, Joydeep, Y.Q., Motoda, H., McLachlan, J., Geofirey, N.A., Liu, B., Yu, S.P., Zhou, Z.H., Steinbach, M., Hand, J.D. and Steinberg, D. 2008b. Top 10 algorithms in data mining. *Knowledge and Information Systems* 14: 1-37.
- Wu, C., Niu, Z., Tang, Q. and Huang, W. 2008c. Estimating chlorophyll content from hyperspectral vegetation indices: Modeling and validation. *Agricultural and Forest Meteorology* 148: 1230-1241.
- Xu, H.R., Ying, Y.B., Fu, X.P. and Zhu, S.P. 2007. Near-infrared spectroscopy in detecting leaf miner damage on tomato leaf. *Biosystems Engineering* 96: 447-454.
- Yang, C.M. and Cheng, C.H. 2001. Spectral characteristics of rice plants infested by brown planthoppers. In Proc. of the National Science Council, Republic of China. Part B, Life Sciences 25: 180-186.

- Yang, C.M., Cheng, C.H. and Chen, R.K. 2007. Changes in spectral characteristics of rice canopy infested with brown planthopper and leafhopper. *Crop Science* 47: 329-335.
- Yang, Z., Rao, M.N., Elliott, N.C., Kindler, S.D. and Popham, T.W. 2009. Differentiating stress induced by greenbugs and Russian wheat aphids in wheat using remote sensing. *Computers and Electronics in Agriculture* 67: 64-70.
- Yang, K., Xue, Z., Li, H., Jia, T. and Cui, Y. 2011. New methodology of hyperspectral information extraction and accuracy assessment based on a neural network. *Mathematical and Computer Modelling*, In Press, Corrected Proof. doi:10.1016/j.mcm.2011.10.037
- Zaiton, S., Sariah, M. and Zainalabidin, M.A. 2006. Isolation and characterization of microbial endophytes from oil palm roots: implication as bio control agents against *Ganoderma*. *The Planter* 82: 587-597.
- Zangeneh, M., Omid, M. and Akram, A. 2011. A comparative study between parametric and artificial neural network approaches for economical assessment of potato production. *African Journal of Agricultural Research* 6: 3061-3070.
- Zhang, H., Hu, H., Zhang, X., Zhu, L., Zheng, K., Jin, Q. and Zeng, F. 2011. Estimation of rice neck blights severity using spectral reflectance based on BP-neural network. *Acta Physiologiae Plantarum* 33: 2461-2466.
- Zhang, M. and Meng, Q. 2011. Automatic citrus canker detection from leaf images captured in field. *Pattern Recognition Letters* 32: 2036-2046.
- Zhang, J., Pu, R., Huang, W., Yuan, L., Luo, J. and Wang, J. 2012a. Using in-situ hyperspectral data for detecting and discriminating yellow rust disease from nutrient stresses. *Field Crops Research* 134: 165-174.
- Zhang, J., Pu, R., Wang, J., Huang, W., Yuan, L. and Luo, J. 2012b. Detecting powdery mildew of winter wheat using leaf level hyperspectral measurements. *Computers and Electronics in Agriculture* 85: 13-23.

Zhang, M., Qin, Z., Liu, X. and Ustin, S.L. 2003. Detection of stress in tomatoes induced by late blight disease in California, USA, using hyperspectral remote sensing. *International Journal of Applied Earth Observation and Geoinformation* 4: 295-310.

Zhu, G. and Blumberg, D.G. 2002. Classification using ASTER data and SVM algorithms; The case study of Beer Sheva, Israel. *Remote Sensing of Environment* 80: 233-240.

