



UNIVERSITI PUTRA MALAYSIA

***INTERNET OF THINGS-BASED SOIL SENSING PLATFORM FOR
Ganoderma boninense INFECTION DETECTION IN OIL PALM
SEEDLINGS USING MACHINE LEARNING***

MOHD HAMIM BIN ABDUL AZIZ

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By

MOHD HAMIM BIN ABDUL AZIZ

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

April 2021

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DEDICATION

This thesis is dedicated to

My lovely family, wife, and kids:

With love, respect, and a bunch of memories
Indeed, we belong to Allah and indeed to Him we will return.



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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MOHD HAMIM BIN ABDUL AZIZ

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Chairman : Associate Professor Siti Khairunniza binti Bejo, PhD
Faculty : Engineering

Basal stem rot (BSR), caused by a white-rot fungus *Ganoderma boninense* is a destructive disease that causes tremendous losses in the oil palm industry. The primary route of the disease infection is through root that has contact with *Ganoderma boninense* inoculum in the soil. The use of planting materials (seedlings) that are resistant to *Ganoderma boninense* could prevent the spread of BSR disease in the plantation. A manual census is used commonly by nurseries to monitor the progress of the disease development associated with various treatments. This common nursery practice is usually conducted every two to four weeks. An irregular monitoring leads to delays in detecting the disease occurrence. This study, therefore, is focused on the use of a sensor network to obtain soil data to diagnose the *Ganoderma boninense* infection using the internet of things (IoT) platform. This approach could lead to a possible early infection detection methodology since rapid monitoring can avoid missing data. The objectives of the research include studying the potential use of soil properties as the indicators for BSR disease, analyzing temporal changes of infected seedlings, and developing the *Ganoderma boninense* disease detection model using soil properties. A total of 40 oil palm seedlings aged five months old were used in the study. They consisted of 20 healthy and 20 infected seedlings. The infected seedlings were prepared by artificially inoculating the tree roots with the *Ganoderma boninense* rubber woodblock. The seedlings were placed in the greenhouse with controlled environmental temperature and humidity. Three soil sensors were buried at 8 cm depth in each seedling's growth medium to measure the amount of soil moisture content (MC) in volumetric water content (in %), soil electrical conductivity (EC) (in $\mu\text{S}/\text{cm}$), and soil temperature (T) (in $^{\circ}\text{C}$). The soil parameters data was collected every hour daily for 24 weeks (six months). These data were stored in the cloud (ThingSpeak) and available for real-time monitoring and data extraction for further analysis. The results of soil analysis revealed that more than 80% of monitored weeks in all parameters yielded

significant differences ($P\text{-value} < 0.05$) between healthy and infected seedlings when tested using a t-test at 5% significance level. Detail analysis was later conducted to check on how soon these changes can be observed by analyzing its temporal data based on a daily, weekly, and monthly basis. The temporal data collected showed the same fluctuation pattern of healthy and infected seedlings, however, among all the parameters, only EC responded to the fertilizer application activities in both categories. In general, based on the daily and weekly monitoring basis, the values of MC, EC, and T for healthy seedlings are higher than infected seedlings in the whole 24 weeks and the first 15 weeks, respectively. For the monthly monitoring basis, the values of MC and EC gave the same trend, while the values of T for infected seedlings were higher than healthy seedlings in the last two months of the six months monitoring period. Detection models were developed using seven classifiers of machine learning algorithms. The optimization process was conducted by analyzing the possibility of reducing the number of soil parameters and reducing the number of temporal data. In general, the results showed that the use of all soil parameters performed better in all weeks compared to the reduced soil parameters and PC data. The results also showed that the model with 6 hours of input data collected every three days at 2 – 7 am gave the most accurate results with an average accuracy of 98.3%. The Fine k-Nearest Neighbors (Fine kNN) algorithm was identified as the best classifier to differentiate between healthy and infected seedlings. Among 414 models developed using reduced data, 269 (65%) of the models with the highest accuracy obtained using Fine kNN. It can be concluded that the major contribution of the study is on the development of the machine learning model suitable for detection of *Ganoderma boninense* infection in an oil palm seedling as early as 12th weeks after infection using the rapid soil sensing data through the IoT platform. The proposed method, hopefully, can help in better management of the disease and thus, increase the oil palm yield.

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

**PLATFORM PENGINDERAAN TANAH BERDASARKAN INTERNET
PELBAGAI BENDA UNTUK PENGESANAN JANGKITAN *Ganoderma
boninense* DI DALAM ANAK POKOK KELAPA SAWIT MENGGUNAKAN
PEMBELAJARAN MESIN**

Oleh

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Reput pangkal batang (RPB) yang disebabkan oleh kulat reput putih *Ganoderma boninense* adalah penyakit yang merosakkan yang menyebabkan kerugian besar dalam industri kelapa sawit. Laluan utama jangkitan penyakit ini adalah melalui akar yang mempunyai sentuhan dengan inokulum *Ganoderma boninense* di dalam tanah. Penggunaan bahan tanaman (anak pokok) yang rintang terhadap *Ganoderma boninense* mampu mengekang penularan RPB di dalam ladang. Bancian secara manual biasanya dipraktikkan di tapak semaian untuk memantau perkembangan pembentukan penyakit yang terkait dengan pelbagai rawatan. Amalan bancian di tapak semaian ini kebiasaannya dilakukan setiap dua ke empat minggu. Pemantauan yang tidak berkala membawa kepada kelewatan dalam mengesan kejadian penyakit. Oleh itu, kajian ini berfokus kepada penggunaan jaringan penderia bagi mendapatkan data tanah untuk mendiagnos jangkitan *Ganoderma boninense* menggunakan platform internet pelbagai benda (IPB). Pendekatan ini memungkinkan kaedah pengesanan awal jangkitan kerana pemantauan secara pantas dapat mengelakkan kehilangan data. Objektif-objektif kajian termasuk untuk mengkaji potensi penggunaan sifat tanah sebagai petunjuk penyakit RPB, untuk menganalisis perubahan berkala yang berlaku pada pokok yang telah dijangkiti dan untuk membina model pengesanan penyakit menggunakan sifat-sifat tanah. Sebanyak 40 anak pokok yang berusia lima bulan digunakan dalam kajian. Ianya terdiri daripada 20 anak pokok sihat dan 20 anak pokok yang dijangkiti. Teknik inokulasi buatan digunakan bagi menyediakan sampel anak pokok yang dijangkiti. Teknik ini dilakukan dengan melekatkan akar anak pokok dengan blok kayu getah *Ganoderma boninense*. Anak pokok tersebut diletakkan di dalam rumah hijau yang dikawal suhu dan kelembapan persekitarannya. Tiga penderia tanah diletakkan dalam medium pertumbuhan anak pokok sawit pada kedalaman 8 cm untuk mengukur jumlah kandungan kelembapan (KK) tanah dalam unit isipadu

kandungan air (dalam %), konduktiviti elektrik (KE) tanah (dalam $\mu\text{S/cm}$), dan suhu (S) tanah (dalam $^{\circ}\text{C}$). Pengambilan data tanah dilakukan setiap jam setiap hari selama 24 minggu (6 bulan). Data-data ini disimpan di dalam awan (ThingSpeak) dan sedia ada untuk pemantauan waktu sebenar dan pengekstrakan data bagi tujuan analisis lanjut. Keputusan analisis tanah telah menunjukkan bahawa lebih 80% daripada minggu pemantauan dalam semua parameter telah memberikan perbezaan yang signifikan (nilai- $P < 0.05$) antara anak pokok yang sihat dan yang dijangkiti apabila diuji dengan menggunakan ujian-t pada tahap signifikan 5%. Analisis lanjut kemudiannya dilakukan untuk mengesan bilakah perubahan ini boleh dilihat dengan menganalisis data berkala secara harian, mingguan dan bulanan. Walaupun anak pokok yang sihat dan yang dijangkiti memberikan pola turun-naik yang sama, namun, antara kesemua parameter, hanya KE yang memberikan maklumbalas terhadap aktiviti pembajaan dalam kedua-dua kelas. Secara umumnya, berdasarkan kepada pemantauan secara harian dan mingguan, nilai KT dan KE; dan S untuk anak pokok sihat adalah lebih tinggi berbanding anak pokok yang dijangkiti masing-masing disepanjang 24 minggu dan 15 minggu yang pertama. Bagi pemantauan secara bulanan, Nilai KK dan KE memberikan pola yang sama, manakala nilai S bagi pokok yang dijangkiti adalah lebih tinggi pada dua bulan yang terakhir daripada enam bulan pemantauan. Model pengesanan telah dibangunkan dengan menggunakan tujuh algoritma pengelasan Pembelajaran Mesin. Proses pengoptimuman telah dilakukan dengan mengurangkan bilangan parameter dan mengurangkan bilangan data berkala. Secara umumnya, keputusan menunjukkan bahawa penggunaan semua parameter tanah memberikan keputusan yang lebih baik dalam semua minggu dibandingkan dengan parameter tanah yang dikurangkan dan data KP. Keputusan juga menunjukkan model yang dibina dengan input data 6 jam yang diambil setiap hari tiga hari pada pukul 2 - 7 pagi telah memberikan keputusan yang paling tepat dengan purata ketepatan adalah 98.3%. Model k-Jiran-jiran Terdekat halus (kJD halus) dikenalpasti sebagai pengelas terbaik untuk membezakan antara anak pokok sihat dan anak pokok sakit. Antara 414 model-model yang dibina menggunakan data yang dikurangkan, 269 (65%) daripada model-model tersebut diperolehi dengan menggunakan kJD halus. Ianya dapat disimpulkan bahawa sumbangan utama kajian adalah pada pembangunan model pembelajaran mesin yang sesuai untuk pengesanan jangkitan *Ganoderma boninense* pada anak pokok sawit seawal 12 minggu selepas jangkitan menggunakan penderian tanah yang pantas melalui platform IPB. Kaedah yang dicadangkan diharap dapat membantu dalam pengurusan penyakit yang lebih baik seterusnya mampu meningkatkan hasil kelapa sawit.

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LIST OF ABBREVIATIONS

AISA	Airborne Imaging Spectrometer for Applications
ANOVA	Analysis of Variance
ARVI	Atmospherically Resistant Vegetation Index
BSR	Basal Stem Rot
CRI	Continuum Removal Indices
CS	continuous significant hours
CV	coefficient of variation
D	Discriminant
DA	Discriminant Analysis
DOSM	Department of Statistic Malaysia
DT	Decision Tree
E	Ensemble
EC	electrical conductivity
EDTA	ethylenediaminetetraacetic acid
EH	even hours
ELISA	Enzyme-linked immunosorbent assay
ENVI	Environment for Visualizing Images
GBNDVI	Green Blue Normalized Difference Vegetation Index
GDP	Gross Domestic Product
GRWB	<i>Ganoderma</i> rubber wood block
HS	healthy seedling
IoT	Internet of Things
IS	infected seedling

ITAFoS	Institute of Tropical Agriculture and Food Security
KNB	Kernel Naïve Bayes
kNN	k-Nearest Neighbors
LDA	Linear Discriminant Analysis
MC	moisture content
MPOC	Malaysian Palm Oil Council
MS	most significant hours
NB	Naïve Bayes
NDVI	Normalized Difference Vegetation Index
NN	Neural Networks
NPK	Nitrogen, Phosphorous, K for Potassium
PABs	polyclonal antibodies
PC	principal component
PCA	principal component analysis
PCR	Polymerase chain reaction
PLSR	Partial Least Square Regression
QDA	Quadratic Discriminant Analysis
r	correlation coefficient
R ²	coefficient of determination
RCBD	Randomized Complete Block Design
RF	Random Forest
RWB	rubber wood block without <i>Ganoderma</i>
SD	standard deviation
SVM	Support Vector Machine
T	temperature

TEM	Transmission Electron Microscopy
UART	Universal Asynchronous Receiver/Transmitter
UPM	Universiti Putra Malaysia
USA	United States of America
V_{air}	volume of air
V_{soil}	volume of soil
V_{water}	volume of water
VWC	volumetric water content

CHAPTER 1

INTRODUCTION

1.1 Research background

Oil palm (*Elaeis guineensis*) is the most planted commodity crop in Malaysia that yielded millions of tons of crude palm oil per year. Malaysia is the second-largest palm oil producer and exporter in the world (after Indonesia), with approximately 18 million tons exported per year. The United States, the European Union, China, India, and Pakistan are among the major importers of Malaysian palm oil (May, 2012).

The oil palm production in Malaysia is threatened by Basal Stem Rot (BSR) disease caused by the wood-rotting fungus named *Ganoderma boninense*, which reduces oil palm production (Idris et al., 2000). According to Chong et al. (2017), yearly losses in Malaysia due to this disease can be up to RM 1.5 billion. The disease is considered to be the biggest threat to the palm oil industry in Malaysia (Idris et al., 2000).

Infected oil palm trees mostly recognizable by visual inspection on the trees' foliar, stem, and trunk i.e., the presence of unopened spear leaves, yellowish fronds, fronds hanging downward, small canopy size, rot at the basal part of the stem, and the existence of fruiting bodies on the trunks (Gurmit, 1991; Ariffin et al., 2000; Kandan et al., 2010). The infection causes damage to the internal tissue of trees, which consequently disrupts the water and nutrient uptake to the trees (Rees et al., 2009). It could also affect the ability of the trees to perform normal photosynthesis due to water deficiencies and foliar symptoms (Haniiff et al., 2005).

The disease can attack oil palm trees at nurseries and plantations. *Ganoderma boninense* is a soil-borne fungus that survived in the soil before invading its host. The primary route of infection appears to be through root contact with inoculum sources in the soil (Rees et al. 2009). It was proven through studies in oil palm seedling. The infection of the disease in oil palm seedlings through root contact with *Ganoderma* inoculum was also confirmed by Alexander et al. (2017). High incidences of infection were recorded in locales where many old oil palm trees were felled and the stumps left to rot on the ground. Thus, creating a friendly environment for fungi to grow on a wounded host in the soil. Subsequently, the disease spreads from a plant to another either by roots or spores (Paterson, 2007). When the fungi invaded the roots (Rees et al, 2009), it damaged the structure of the roots (Alexander et al., 2017) and as a result disturbed the operational function of water and nutrient uptake by roots (Fitter, 1991).

Generally, the survival of a soil-borne fungal is significantly related to soil moisture content (Eastburn and Butler, 1991; Garret, 1938; Gill et al., 2001; Chang, 2003), nutrient content (Yadav et al., 2011; Rashid et al., 2016) and temperature (Nawawi and Ho, 1990; Saremi and Burgess, 2000; Rees et al., 2007), either directly or indirectly (Liddell, 1992). The high moisture content of coastal soils invigorates *Ganoderma boninense* to grow (Gurmit, 1991). The BSR disease favors soils with poor drainage and high water retention capacity. However, this report contradicted the report by Chang (2003) that suggested flooding the infected area as a way to control the spread of the disease. This is based on the notion that the high soil moisture content makes it harder for *Ganoderma boninense* to survive. This condition was tested based on laboratory conditions. Therefore, we can conclude that perhaps there exists a certain range of soil moisture content that favors the occurrence of *Ganoderma boninense* disease, but not due to a high or low value of soil moisture content. Under laboratory conditions, Nawawi and Ho (1990) reported that *Ganoderma boninense* were found to grow at an optimum soil temperature between 27-30°C. Gurmit (1991) reported that high salinity appeared to suppress the disease's spread. Soil electrical is a measure of the amount of salt in the soil. It is an important indicator of soil health.

The proliferation of internet usages in the wide spectrum of industries and the innovation of the Internet of Things or IoT have also positively impacted agriculture practices. A wide range of applications was developed to assist the agricultural industry and amongst them is plant disease detection and prediction. Foughali et al. (2018) used the IoT platform to monitor the environmental temperature and humidity to predict the potential attack of the fungal infection in potatoes. Based on the environmental data, the risk of the disease occurrence was measured and predicted by a parameter called "Blight units". When the defined threshold of Blight units reached favorable values for the disease occurrence i.e., humidity > 90% for a day and average temperature at 15 – 21 °C, the system notifies the farmers via SMS to begin treatment. A similar approach was adopted by Patil and Thorat (2016), Truong et al. (2017), and Materne and Inoue (2018) to predict the occurrence of disease due to fungal attacks in various types of plants. While Sarangdhar and Pawar (2017), Nandhini et al. (2018), Mathana and Nagarajan (2020), Pan and Wang (2021), Sowmyalakshmi et al. (2021), and Devi et al. (2021) used IoT platform and images to detect the disease occurrence in various types of plants. As a conclusion, along with the environmental conditions and/or leaves images monitoring, some research deployed soil sensors to measure soil moisture content, electrical conductivity, and temperature as additional data.

1.2 Problem statement

The impact of diseases in plants can be reduced through proper management of cultural practices, agronomic, and phytosanitary. However, it should be implemented with the use of planting materials (seedlings) which are resistant to *Ganoderma boninense* (Turnbull et al., 2014) to prevent the spread of BSR

disease in the plantation and eventually economic losses (Idris, 2009; Turnbull et al., 2014). A comprehensive study to determine the level of resistance or susceptibility of the planting materials to disease is an important aspect to be looked at before any development of a successful breeding program and for the sustainability of this crop, particularly in Southeast Asia (Breton et al., 2009). Breeding programs to develop planting materials resistant to *Ganoderma boninense* involves long-term studies if it only involves field trials. This is because the environmental conditions and other extraneous variables in the field are much difficult to control than the glasshouse or nursery due to the spatial variability in the field. These uncontrollable environmental conditions can affect the optimum growth of the plants (Rebitanim et al., 2020). Distinguishing plants' different levels of susceptibility and resistance to the disease is of utmost importance hence, it is crucial to conduct an artificial inoculation of the pathogen at the nursery level to create an early screening test (Breton et al., 2009).

In common nursery practices, a manual census used to monitor the progress of the disease development associated with various treatments (Parker et al., 2007; Chung, 2012) was done by a human. It is normally conducted every two to four weeks. This irregular monitoring leads to delays in detecting the disease occurrence. Furthermore, human inspection relied heavily on the visible symptoms of the disease. It is prone to error due to a lack of experience and subjective judgements. Laboratory-based methods provide high accuracy of detection, however, it is time-consuming, complicated, labour intensive, and costly (Naher et al., 2013). Researchers had proposed various types of remote sensing approaches with different levels of detection accuracies. However, none of them provide a regular and rapid monitoring approach which can cause delays in detecting the disease occurrence.

Based on the literature, there is conclusive evidence that regular and rapid monitoring of disease development in a plant using an IoT platform could lead to early detection as possible missing of useful data could be avoided. The approach used in this study shows the potential use of rapid monitoring for soil-borne disease detection due to *Ganoderma boninense* infection. Furthermore, an intensive study can be performed to understand the *Ganoderma boninense* infection in oil palm seedlings associated with soil properties.

1.3 Objectives

The general objective of this thesis is to study the capability of a soil sensing network to detect the changes of the soil properties due to the *Ganoderma boninense* infection in oil palm seedlings. The specific objectives of this thesis are:

1. To determine the relationships between soil moisture content, soil electrical conductivity, and soil temperature in oil palm seedlings.
2. To identify the optimum interval of monitoring time for BSR disease detection by analysing temporal changes of soil moisture content, soil electrical conductivity, and soil temperature in relation to *Ganoderma boninense* infection.
3. To develop a model for *Ganoderma boninense* infection detection using an optimal dataset and machine learning approach.

1.4 Scope and limitation

The study was conducted at a transgenic greenhouse under the management of the Institute of Tropical Agriculture and Food Security (ITAFoS), Universiti Putra Malaysia. The seedlings were grown in a greenhouse under controlled environmental temperature and humidity. A suitable environmental temperature and humidity are important for the optimum growth of the seedlings in the greenhouse. It is difficult to control the environmental condition if the seedlings are grown in an open area in the plantation or estate. Oil palm seedlings used in this study are from the *tenera* (*dura* x *pisifera*) variety. A drip irrigation system was used to supply water to the seedlings. A fertilizer with NPK ratio of 15:15:15 was used to grow the seedlings. Soil properties parameters measured in this study were soil moisture content measured as a percentage of volumetric water content (%), soil temperature ($^{\circ}\text{C}$) and, salinity measured as electrical conductivity in units of micro Siemens per centimetre ($\mu\text{S}/\text{cm}$). The monitoring period was six months or 24 weeks. The eminence penetration or invasion of *Ganoderma boninense* into the roots or bowl system of the seedlings was verified through laboratory analysis using the PCR (Polymerase chain reaction) method by taking two random samples of seedlings after two months of inoculation. If the PCR test analysis on all inoculated seedlings shows positive results then those seedlings were assumed to be infected by *Ganoderma boninense* inoculum.

1.5 Structure of the thesis

Chapter 2 presents a literature review that covers topics like oil palm growth, economic value, BSR disease that affects the production of the oil palm, soil properties associated with the soil-borne fungi growth and control, and the available methods used for the disease detection. The application of the Internet of Things in agriculture and a review on temporal monitoring applied in oil palm seedling for monitoring the artificial inoculation progress was also described. This chapter also covers a review of the technique of the machine learning application employed for BSR and other various diseases in agriculture.

Chapter 3 presents a proposed method used for the *Ganoderma boninense* disease detection in oil palm seedlings. The chapter gives a brief overview of the study area and the facilities available in the greenhouse. It is followed by a brief explanation of the method of inoculating artificial *Ganoderma boninense* to the plants and the experimental design of the fieldwork. A standard lab-based method used to confirm the infection of the *Ganoderma boninense* is discussed. Then this chapter gives a detailed explanation of the system sets up – a sensing network used to collect data and store it in the cloud for online monitoring. It includes hardware and software integration to develop the system. Statistical analysis then used to find the relationship between each parameter and pattern of its temporal changes over time were also presented. Finally, it presented the technique of machine learning used to classify the seedlings.

Chapter 4 presents the results and discusses the findings of the study. The result of the study presents the significance of soil properties to be used to detect the *Ganoderma boninense* infection. This chapter also cites the results of soil properties' relationship with each other concerning the *Ganoderma boninense* infection. Then, the chapter divulges details of temporal analysis of the soil parameters reading in monthly, weekly, daily, and hourly. Results of the multi-temporal analysis were then used to select the more significant data as input data for the classification model development. The last subtopic in this chapter analysed and discussed the development of the classification model using machine learning. The models developed using different types and selection of data were compared to get the best model.

Finally, the conclusions of the study were presented in Chapter 5. This chapter describes the main contributions of the study and some suggestions on the future work to be undertaken.

REFERENCES

- Abdullah, R., & Wahid, M. B. (2010). World palm oil supply, demand, price and prospects: focus on Malaysian and Indonesian palm oil industry. *Malaysian Palm Oil Board Press, Malaysia*.
- Abercrombie, M., Hickman, C. J., & Johnson, M. L. (1954). A Dictionary of Biology, 2nd ed. Harmondsworth : Penguin.
- Ahmadi, P., Muharam, F. M., Ahmad, K., Mansor, S., & Abu Seman, I. (2017). Early detection of Ganoderma basal stem rot of oil palms using artificial neural network spectral analysis. *Plant disease*, 101(6): 1009-1016.
- Al Tamie, M. S. (2014). Effect of salinity on the fungal occurrence in Al-Shega Area at Al-Qassim, Saudi Arabia. *Res J Microbiol*, 9, 287.
- Alexander, A., Dayou, J., Abdullah, S., & Phin, C. K. (2019). Differential Expression and Profile of Oil Palm Root-sterols Composition Related to Ganoderma boninense Infection. *ASM Sci. J.*, 12(3), 40-47.
- Alexander, A., Sipaut, C. S., Dayou, J., & Chong, K. P. (2017). Oil palm roots colonisation by Ganoderma boninense: An insight study using scanning electron microscopy. *J Oil Palm Res*. 2017b, 29, 262-66.
- Alexandra C. M., Sassan S. S., Yadvinder M., Nicholas J. B., Lindsay B., David B., Reuben N., & Robert C. O., (2011). Estimating Aboveground Biomass In Forest And Oil Palm Plantation In Sabah, Malaysian Borneo Using ALOS PALSAR Data. *Forest Ecology and Management* 262, 1786–1798.
- Ali, H., Lali, M. I., Nawaz, M. Z., Sharif, M., & Saleem, B. A. (2017). Symptom based automated detection of citrus diseases using color histogram and textural descriptors. *Computers and Electronics in agriculture*, 138, 92-104.
- Amir, I., Raghavan, G. S. V., McKyes, E., & Broughton, R. S. (1976). Soil compaction as a function of contact pressure and soil moisture content. *Can. Agric. Eng*, 18(1), 54-57.
- Arango, M., Martínez, G., & Torres, G. (2016). Advances in the interpretation of tomographic images as an early detection method of oil palm affected by basal stem rot in Colombia. *Plant Disease*, 100(8): 1559-1563.
- Ariffin D, Idris A, & Singh G. (2000). Ganoderma diseases of perennial crops. CABI Publishing: Wallingford; p. 49-267.

- Ariffin, D., Idris A. S., & Marzuki A. (1996). Spread of *Ganoderma boninense* and vegetative compatibility studies of a single field palm isolates. In *Proceedings of the 1996 PORIM International Palm Oil Congress (Agriculture)*.
- Ariffin, D., & Idris, S. (1993). A selective medium for the isolation of *Ganoderma* from disease tissues. In *PORIM International Palm Oil Conference. Progress, Prospects Challenges Towards the 21st Century. (Agriculture) September 9-14 Kuala Lumpur, Malaysia* (No. L-0218). PORIM.
- As'wad, A. M., Sariah, M., Paterson, R. R. M., Abidin, M. Z., & Lima, N. (2011). Ergosterol analyses of oil palm seedlings and plants infected with *Ganoderma*. *Crop Protection*, 30(11), 1438-1442.
- Asuero, A. G., Sayago, A., & Gonzalez, A. G. (2006). The correlation coefficient: An overview. *Critical reviews in analytical chemistry*, 36(1), 41-59.
- Aziz, M. H. A., Bejo, S. K., Hashim, F., Ramli, N. H., & Ahmad, D. (2019). Evaluations of Soil Resistivity in Relation to Basal Stem Rot Incidences Using Soil Moisture Sensor. *Pertanika J. Sci. & Technol.* 27 (S1): 225 – 234.
- Azmi, A. N. N., Bejo, S. K., Jahari, M., Muharam, F. M., Yule, I., & Husin, N. A. (2020). Early Detection of *Ganoderma boninense* in Oil Palm Seedlings Using Support Vector Machines. *Remote Sensing*, 12(23), 3920.
- Azuan, N. H., Khairunniza-Bejo, S., Abdullah, A. F., Kassim, M. S. M., & Ahmad, D. (2019). Analysis of Changes in Oil Palm Canopy Architecture From Basal Stem Rot Using Terrestrial Laser Scanner. *Plant disease*, 103(12), 3218-3225.
- Bejo, S., Abdol-Lajis, G., Abd-Aziz, S., Abu-Seman, I., & Ahamed, T. (2018). Detecting Basal Stem Rot (BSR) disease at oil palm tree using thermal imaging technique. *Proceedings of the 14th International Conference on Precision Agriculture*, International Society of Precision Agriculture: Monticello, Illinois, U.S.A.
- Benesty, J., Chen, J., Huang, Y., & Cohen, I. (2009). Pearson correlation coefficient. In *Noise reduction in speech processing* (pp. 1-4). Springer, Berlin, Heidelberg.
- Bouillet, J. P., Laclau, J. P., Arnaud, M., M'Bou, A. T., Saint-André, L., & Jourdan, C. (2002). Changes with age in the spatial distribution of roots of *Eucalyptus* clone in Congo: impact on water and nutrient uptake. *Forest Ecology and Management*, 171(1-2), 43-57.
- Breiman, L., & Friedman, J. H. (1985). Estimating optimal transformations for multiple regression and correlation. *Journal of the American statistical Association*, 80(391), 580-598.

- Breton, F., Hasan, Y., Lubis, Z., & De Franqueville, H. (2005a). Characterization of parameters for the development of an early screening test for basal stem rot tolerance in oil palm progenies. *Journal of Oil Palm Research* (Special issue, April 2006), 24–36.
- Breton, F., Hasan, Y., Lubis, Z., & De Franqueville, H. (2005b). Rhizotron: a demonstrative tool for monitoring in vivo the infection process of oil palm seedling by *Ganoderma boninense*. In *Agriculture, biotechnology & sustainability conference, PIPOC International Palm Oil Congress*, 971 (Eds Malaysian Palm Oil Board). Kuala Lumpur.
- Breton, F., Miranti, R., Lubis, Z., Hayun, Z., Setiawati, U., Flori, A., & De Franqueville, H. (2009). Implementation of an early artificial inoculation test to screen oil palm progenies for their level of resistance and hypothesis on natural infection: *Ganoderma* disease of the oil palm.
- Bruehl, G. W. (1987). *Soilborne plant pathogens*. Macmillan publishing company..
- Chang, T. (2003). Effect of soil moisture content on the survival of *Ganoderma* species and other wood-inhabiting fungi. *Plant disease*, 87(10), 1201-1204.
- Chong, K. P., Markus, A., & Rossall, S. (2012). The susceptibility of different varieties of oil palm seedlings to *Ganoderma boninense* infection. *Pak. J. Bot*, 44(6), 2001-2004.
- Chong, K. P., Dayou, J., & Alexander, A. (2017). Pathogenic nature of *Ganoderma boninense* and basal stem rot disease. In *Detection and Control of Ganoderma boninense in Oil Palm Crop* (pp. 5-12). Springer, Cham.
- Chung, G. F. (2012). Effect of pests and diseases on oil palm yield. In *Palm Oil* (pp. 163-210). AOCS Press.
- Cooper, R. M., Flood, J., & Rees, R. W. (2011). *Ganoderma boninense* in oil palm plantations: current thinking on epidemiology, resistance and pathology. *Planter*, 87(1024), 515-526.
- Corwin, D. L., & Yemoto, K. (2020). Salinity: Electrical conductivity and total dissolved solids. *Soil Science Society of America Journal*, 84(5), 1442-1461.
- Coe, R. (1996). Sample size determination in farmer surveys. *Lecture notes, World Agroforestry Centre, Nairobi, Kenya*.
- Dane, J. H., & Hopmans, J. W. (2009). Volumetric water content—Matric potential relationship. *Groundwater-Volume II*, 232.

- Danisman, Y., Yilmaz, M. F., Ozkaya, A., & Comlekçiler, I. (2014). A comparison of eigenvalue methods for principal component analysis. *Appl. and Comput. Math*, 13, 316-331.
- Darmono, T. W. (1999). Detection of basal stem rot disease of oil palm using polyclonal antibody. *Menara Perkebunan*, 67(1): 32-39.
- Department Of Statistic Malaysia (2020). Selected agricultural indicators, Malaysia, 2020. Retrieved from <https://www.dosm.gov.my>.
- Devi, R. D., Nandhini, S. A., Hemalatha, R., & Radha, S. (2019). IoT enabled efficient detection and classification of plant diseases for agricultural applications. In *2019 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET)* (pp. 447-451). IEEE.
- Durand-Gasselin, T., Asmady, H., Flori, A., Jacquemard, J. C., Hayun, Z., Breton, F., & De Franqueville, H. (2005). Possible sources of genetic resistance in oil palm (*Elaeis guineensis* Jacq.) to basal stem rot caused by *Ganoderma boninense*—prospects for future breeding. *Mycopathologia*, 159(1), 93-100.
- Eastburn, D. M., & Butler, E. E. (1991). Effects of soil moisture and temperature on the saprophytic ability of *Trichoderma harzianum*. *Mycologia*, 83(3), 257-263.
- Falcon, M. F., Fox, R. L., & Trujillo, E. E. (1984). Interactions of soil pH, nutrients and moisture on *Phytophthora* root rot of avocado. *Plant and soil*, 81(2), 165-176.
- Fitter, A. H. (1991). Characteristics and functions of root systems. *Plant roots: the hidden half*, 2, 1-29. New York, NY, USA
- Foughali, K., Fathallah, K., & Frihida, A. (2018). Using Cloud IOT for disease prevention in precision agriculture. *Procedia computer science*, 130, 575-582.
- Franqueville, H. D., Asmady, H., Jacquemard, J. C., Hayun, Z., & Durand-Gasselin, T. (2001). Indications on sources of oil palm (*Elaeis guineensis* Jacq.) genetic resistance and susceptibility to *Ganoderma* sp., the cause of basal stem rot. In *Cutting-edge technologies for sustained competitiveness: Proceedings of the 2001 PIPOC International Palm Oil Congress, Agriculture Conference, Kuala Lumpur, Malaysia, 20-22 August 2001* (pp. 420-431). Malaysian Palm Oil Board (MPOB).
- Friedman, S. P. (2005). Soil properties influencing apparent electrical conductivity: a review. *Computers and electronics in agriculture*, 46(1-3), 45-70.

- Gao, S., Pan, W. L., & Koenig, R. T. (1998). Integrated root system age in relation to plant nutrient uptake activity. *Agronomy Journal*, 90(4), 505-510.
- Garrett, S. D. (1938). Soil conditions and the root- infecting fungi. *Biological Reviews*, 13(2), 159-184.
- Gill, J. S., Sivasithamparam, K., & Smettem, K. R. J. (2001). Effect of soil moisture at different temperatures on Rhizoctonia root rot of wheat seedlings. *Plant and Soil*, 231(1), 91–96. <https://doi.org/10.1023/A:1010394119522>.
- Goh, Y. K., Choon, K. L., Cheng, C. R., Tan, S. Y., Cheah, L. W., Ah Tung, P. G., & Goh, K. J. (2017). Effects of chemical properties of different soils on ganoderma disease in oil palm (*Elaeis guineensis*). *Oil Palm Bulletin*, 75, 17-26.
- Gorea, E. A., Godwin, I. D., & Mudge, A. M. (2020). Ganoderma infection of oil palm—a persistent problem in Papua New Guinea and Solomon Islands. *Australasian Plant Pathology*, 49(1), 69-77.
- Govender, N. T., Mahmood, M., Seman, I. A., & Wong, M. Y. (2017). The phenylpropanoid pathway and lignin in defense against Ganoderma boninense colonized root tissues in oil palm (*Elaeis guineensis* Jacq.). *Frontiers in Plant Science*, 8, 1395.
- Griffin, D. M. (1972). *Ecology of soil fungi*. Syracuse University Press.
- Gulhane, V. A., & Gurjar, A. A. (2011). Detection of diseases on cotton leaves and its possible diagnosis. *International Journal of Image Processing (IJIP)*, 5(5): 590-598.
- Guo, G., Wang, H., Bell, D., Bi, Y., & Greer, K. (2003). KNN model-based approach in classification. In *OTM Confederated International Conferences" On the Move to Meaningful Internet Systems"* (pp. 986-996). Springer, Berlin, Heidelberg.
- Gurmit, S. (1991). Ganoderma-the scourge of oil palm in the coastal area. In *Proceedings of Ganoderma workshop, Bangi, Selangor, Malaysia, 11 September 1990*. (pp. 7-35). Palm Oil Research Institute of Malaysia.
- Haniff, M. H., Ismail, S., & Idris, A. S. (2005). Gas exchange responses of oil palm to Ganoderma boninense infection. *Asian Journal of Plant Sciences*, 4(4), 438-444.
- Hasan, Y., & Turner, P. D. (1998). The comparative importance of different oil palm tissues as infection sources for basal stem rot in replantings. *Planter*, 74(864): 119-135.

- Hashim, C.I., Rashid, M.S.A., Bejo, S.K., Muharam, F.M. & Ahmad, K. (2018) Severity of *Ganoderma boninense* disease classification using SAR data. In: *39th Asian Conference on Remote Sensing (ACRS 2018)*, 15-19 Oct. 2018, Renaissance Kuala Lumpur Hotel, Malaysia. (pp. 2492-2499).
- Husin, N. A., Khairunniza-Bejo, S., Abdullah, A. F., Kassim, M. S. M., & Ahmad, D. (2020a). Study of the oil palm crown characteristics associated with Basal Stem Rot (BSR) disease using stratification method of point cloud data. *Computers and Electronics in Agriculture*, 178, 105810.
- Husin, N. A., Khairunniza-Bejo, S., Abdullah, A. F., Kassim, M. S., Ahmad, D., & Azmi, A. N. (2020b). Application of Ground-Based LiDAR for Analysing oil palm canopy properties on the occurrence of Basal Stem Rot (BSR) Disease. *Scientific reports*, 10(1), 1-16.
- Husin, N. A., Khairunniza-Bejo, S., Abdullah, A. F., Kassim, M. S., Ahmad, D., & Aziz, M. H. (2020c). Classification of Basal Stem Rot Disease in Oil Palm Plantations Using Terrestrial Laser Scanning Data and Machine Learning. *Agronomy*, 10(11), 1624.
- Idayu, I., & Supriyanto, E. (2014). Oil palm plantations management effects on productivity Fresh Fruit Bunch (FFB). *APCBEE procedia*, 8, 282-286.
- Idris, S., Arifin, D., Swinburne, R., & Watt, A. A. (2000). The Identity of *Ganoderma* Species Responsible for BSR Disease of Oil Palm in Malaysia Morphological Characteristics. *Malaysian Palm Oil Board*, 102, 77a.
- Idris, A., Kushairi, A., Ismail, S., & Ariffin, D. (2004). Selection for partial resistance in oil palm progenies to *Ganoderma* basal stem rot. *J Oil Palm Res*, 16(2), 12-18.
- Idris, A. S., Kushairi, D., Ariffin, D., & Basri, M. W. (2006). Technique for inoculation of oil palm germinated seeds with *Ganoderma*. *MPOB Inf Ser*, 314, 1-4.
- Idris, A. S., & Rafidah, R. (2008). Enzyme linked immunosorbent assay-polyclonal antibody (ELISA-PAb). *MPOB Information Series*, 430, 1-4.
- Idris, A. S. (2009). Basal Stem Rot in Malaysia-Biology, economic importance, epidemiology, detection and control. In *International workshop on awareness, detection and control of oil palm devastating diseases* (Vol. 6).
- Intara, Y. I., Nusantara, A. D., Supanjani, S., Caniago, Z., & Ekawita, R. (2018). Oil palm roots architecture in response to soil humidity. *International journal of oil palm*, 1(2), 79-89.

- Jiang, H., Zhang, C., He, Y., Chen, X., Liu, F., & Liu, Y. (2016). Wavelength selection for detection of slight bruises on pears based on hyperspectral imaging. *Applied Sciences*, 6(12), 450.
- Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2065), 20150202.
- Kacira, M., & Ling, P. P. (2001). Design and development of an automated and Non-contact sensing system for continuous monitoring of plant health and growth. *Transactions of the ASAE*, 44(4), 989.
- Kandan, A., Bhaskaran, R., & Samiyappan, R. (2010). Ganoderma—a basal stem rot disease of coconut palm in south Asia and Asia pacific regions. *Archives of Phytopathology and Plant Protection*, 43(15), 1445-1449.
- Khairunniza-Bejo, S. & Vong, C. N. (2014). Detection of basal stem rot (BSR) infected oil palm tree using laser scanning data. *Agriculture and Agricultural Science Procedia*, 2: 156–164.
- Khairunniza-Bejo, S., Yusoff, Y., Yusoff, N. S. N., Seman, I. A., & Anuar, M. I. (2015) Identification of healthy and BSR-infected oil palm trees using color indices. *International Journal of Agricultural and Biosystem Engineering*, 9: 785-788.
- Khaled, A. Y., Aziz, S. A., Bejo, S. K., Nawi, N. M., & Seman, I. A. (2018a). Spectral features selection and classification of oil palm leaves infected by Basal stem rot (BSR) disease using dielectric spectroscopy. *Computers and Electronics in Agriculture*, 144: 297-309.
- Khaled, A. Y., Abd Aziz, S., Bejo, S. K., Nawi, N. M., Seman, I. A., & Izzuddin, M. A. (2018b). Dielectric constant and chlorophyll content measurements for basal stem rot (BSR) disease detection. In *2018 International Conference on Signals and Systems (ICSigSys)* (pp. 69-72). IEEE.
- Khaled, A. Y., Abd Aziz, S., Bejo, S. K., Nawi, N. M., Jamaludin, D., & Ibrahim, N. U. A. (2020). A comparative study on dimensionality reduction of dielectric spectral data for the classification of basal stem rot (BSR) disease in oil palm. *Computers and Electronics in Agriculture*, 170, 105288.
- Khattab, A., Habib, S. E., Ismail, H., Zayan, S., Fahmy, Y., & Khairy, M. M. (2019). An IoT-based cognitive monitoring system for early plant disease forecast. *Computers and Electronics in Agriculture*, 166, 105028.

- Kouziokas, G. N. (2016). Technology-based management of environmental organizations using an Environmental Management Information System (EMIS): Design and development. *Environmental Technology & Innovation*, 5, 106-116.
- Kresnawaty, I., Mulyatni, A. S., Eris, D. D., Prakoso, H. T., Triyana, K., & Widiastuti, H. (2020). Electronic nose for early detection of basal stem rot caused by *Ganoderma* in oil palm. *E&ES*, 468(1), 012029.
- Kurale, N. G., & Vaidya, M. V. (2018, July). Classification of Leaf Disease Using Texture Feature and Neural Network Classifier. In *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)* (pp. 1-6). IEEE.
- Laila, N., Chai-Ling, H., Soon, G. T., Umi Kalsom, Y., & Faridah, A (2011). Cloning of Transcripts Encoding Chitinases from *Elaeis Guineensis* Jacq. and Their Expression Profiles in Response to Fungal Infections. *Physiological and Molecular Plant Pathology*, 76: 96-103.
- Lakshmi, V., Jackson, T. J., & Zehrhuhs, D. (2003). Soil moisture–temperature relationships: results from two field experiments. *Hydrological processes*, 17(15), 3041-3057.
- Larsen, J., Jaramillo-López, P., Nájera-Rincon, M., & González-Esquivel, C. E. (2015). Biotic interactions in the rhizosphere in relation to plant and soil nutrient dynamics. *Journal of soil science and plant nutrition*, 15(2), 449-463.
- Lelong, C. C., Roger, J. M., Brégand, S., Dubertret, F., Lanore, M., Sitorus, N. A., & Caliman, J. P. (2010). Evaluation of oil-palm fungal disease infestation with canopy hyperspectral reflectance data. *Sensors*, 10(1): 734-747.
- Liaghat, S., Mansor, S., Ehsani, R., Shafri, H. Z. M., Meon, S., & Sankaran, S. (2014). Mid-infrared spectroscopy for early detection of basal stem rot disease in oil palm. *Computers and electronics in agriculture*, 101, 48-54.
- Liddell, C. M. (1992). Measurement and Control of Soil Temperature and Water Potential In: "Methods for Research on Soilborne Phytopathogenic Fungi", (Eds.) Singleton, Mihail, SD, and Ruch, CM. *The American Phytopathological Society*. St. Paul, Minnesota, 187-203.
- Lim TK, Chung G F, Ko W H, 1992. Basal stem rot of oil palm caused by *Ganoderma boninense*. *Plant Pathology Bulletin* 1, 147–52.
- Lussenhop, J. (1992). Mechanisms of microarthropod-microbial interactions in soil. In *Advances in ecological research* (Vol. 23, pp. 1-33). Academic Press.

- Madiah, A. Z., Idris, A. S., & Rafidah, A. R. (2014). Polyclonal antibodies of *Ganoderma boninense* isolated from Malaysian oil palm for detection of basal stem rot disease. *African Journal of Biotechnology*, 13(34): 3455-3463.
- Markom, M. A., Shakaff, A. M., Adom, A. H., Ahmad, M. N., Hidayat, W., Abdullah, A. H., & Fikri, N. A. (2009). Intelligent electronic nose system for basal stem rot disease detection. *Computers and Electronics in Agriculture*, 66(2), 140-146.
- Materne, N., & Inoue, M. (2018). Potential of IoT System and Cloud Services for Predicting Agricultural Pests and Diseases. In *2018 IEEE Region Ten Symposium (Tensymp)* (pp. 298-299). IEEE.
- Mathana, J. M., & Nagarajan, T. S. (2020). Secured IoT Based Smart Greenhouse System with Image Inspection. In *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)* (pp. 1080-1082). IEEE.
- Markopoulos, P. P., Kundu, S., Chamadia, S., & Pados, D. A. (2017). Efficient L1-norm principal-component analysis via bit flipping. *IEEE Transactions on Signal Processing*, 65(16), 4252-4264.
- May, C. Y. (2012). Malaysia: economic transformation advances oil palm industry. *American Oil Chemists' Society*.
- Mazliham, M. S., Pierre, L., & Idris, A. S. (2008). Towards Automatic Recognition and Grading of *Ganoderma* Infection Pattern Using Fuzzy Systems, *World Academy of Science, Engineering and Technology* 25.
- Mielke, T. (2020). Oil World annual. ISTA Mielke GmbH, Hamburg. Retrieved from <https://www.oilworld.biz/t/publications/annual>.
- Moalemiyan, M., Vikram, A. C. K. A., Kushalappa, A. C., & Yaylayan, V. (2006). Volatile metabolite profiling to detect and discriminate stem- end rot and anthracnose diseases of mango fruits. *Plant pathology*, 55(6): 792-802.
- MPOC (2020). Palm oil. Retrieved from <http://mpoc.org.my/palm-oil-trade-statistics-2020/>
- Mukaka, M. M. (2012). A guide to appropriate use of correlation coefficient in medical research. *Malawi medical journal*, 24(3), 69-71.
- Naher, L., Yusuf, U. K., Ismail, A., Tan, S. G., & Mondal, M. M. A. (2013). Ecological status of '*Ganoderma*' and basal stem rot disease of oil palms ('*Elaeis guineensis*' Jacq.). *Australian Journal of Crop Science*, 7(11): 1723.

- Nandhini, S. A., Hemalatha, R., Radha, S., & Indumathi, K. (2018). Web enabled plant disease detection system for agricultural applications using WMSN. *Wireless Personal Communications*, 102(2), 725-740.
- Navaratnam, S. J., & Chee, K. L. (1965). Root inoculation of oil palm seedlings with *Ganoderma* sp. *Plant Dis*, 49, 1011-1012.
- Nawawi, A., & Ho, Y. W. (1990). Effect of temperature and pH on growth pattern of *Ganoderma boninense* from oil palm in Peninsular Malaysia. *Pertanika*, 13(3), 303-307.
- Nicholas, D. J. D. (1965). Utilization of inorganic nitrogen compounds and amino acids by fungi. *The fungi*, 1, 349-376.
- Nisfariza, M.N., Shafri, Z.H., Idris, A., Steven, M., Boyd, D., & Mior, M. (2010). Hyperspectral sensing possibilities using continuum removal index in early detection of *Ganoderma* in oil palm plantation. In: *World Engineering Congress 2010, Conference on Geomatics and Geographical Information Science*, Kuching, Malaysia (pp. 233-239).
- Nurnadiah, E., Aimrun, W., Amin, M. S. M., & Idris, A. S. (2014). Preliminary study on detection of basal stem rot (BSR) disease at oil palm tree using electrical resistance. *Agriculture and Agricultural Science Procedia*, 2, 90-94.
- Nur Sabrina, A. A., Sariah, M., & Zaharah, A. R. (2012). Suppression of Basal Stem Rot Disease Progress in Oil Palm (*Elaeis guineensis*) after Copper and Calcium Supplementation. *Pertanika Journal of Tropical Agricultural Science*, 35.
- Ommelna, B. G., Jennifer, A. N., & Chong, K. P. (2012). The potential of chitosan in suppressing *Ganoderma boninense* infection in oil-palm seedlings. *J Sustain Sci Manage*, 7(2), 186-192.
- Orzali, L., Corsi, B., Forni, C., & Riccioni, L. (2017). Chitosan in agriculture: a new challenge for managing plant disease. *Biological activities and application of marine polysaccharides*, 17-36.
- Pan, A., & Wang, N. (2021). Design and Implementation of Crop Automatic Diagnosis and Treatment System Based on Internet of Things. In *Journal of Physics: Conference Series*. Vol. 1883, No. 1, p. 012062
- Panigrahi, N. (2014). Computing in geographic information systems. CRC Press.
- Parker, I. M., & Gilbert, G. S. (2007). When there is no escape: the effects of natural enemies on native, invasive, and noninvasive plants. *Ecology*, 88(5), 1210-1224.

- Parthiban, K., Vanitah, R., Jusoff, K., Nordiana, A. A., Anuar, A. R., Wahid, O., & Hamdan, A. B. (2016). GIS mapping of basal stem rot disease in relation to soil series among oil palm smallholders. *Am. J. Agric. Biol. Sci.*, 11, 2-12.
- Paterson, R. R. M. (2007). Ganoderma disease of oil palm—A white rot perspective necessary for integrated control. *Crop protection*, 26(9): 1369-1376.
- Patil, S. S., & Thorat, S. A. (2016). Early detection of grapes diseases using machine learning and IoT. In *2016 second international conference on Cognitive Computing and Information Processing (CCIP)* (pp. 1-5). IEEE.
- Rashid, M. I., Mujawar, L. H., Shahzad, T., Almeelbi, T., Ismail, I. M., & Oves, M. (2016). Bacteria and fungi can contribute to nutrients bioavailability and aggregate formation in degraded soils. *Microbiological Research*, 183, 26-41.
- Ratner, B. (2009). The correlation coefficient: Its values range between+ 1/- 1, or do they?. *Journal of targeting, measurement and analysis for marketing*, 17(2), 139-142.
- Rebitanim, N. A., Hanafi, M. M., Idris, A. S., Abdullah, S. N. A., Mohidin, H., & Rebitanim, N. Z. (2020). GanoCare® Improves Oil Palm Growth and Resistance against Ganoderma Basal Stem Rot Disease in Nursery and Field Trials. *BioMed Research International*, 2020. <https://doi.org/10.1155/2020/3063710>
- Rees, R. W., Flood, J., Hasan, Y., & Cooper, R. M. (2007). Effects of inoculum potential, shading and soil temperature on root infection of oil palm seedlings by the basal stem rot pathogen *Ganoderma boninense*. *Plant Pathology*, 56(5), 862-870.
- Rees, R. W., Flood, J., Hasan, Y., Potter, U., & Cooper, R. M. (2009). Basal stem rot of oil palm (*Elaeis guineensis*); mode of root infection and lower stem invasion by *Ganoderma boninense*. *Plant pathology*, 58(5), 982-989.
- Rhoades, J. D. (1996). Salinity: Electrical conductivity and total dissolved solids. *Methods of Soil Analysis: Part 3 Chemical Methods*, 5, 417-435.
- Rivera, N. V., Gómez-Sanchis, J., Chanona-Pérez, J., Carrasco, J. J., Millán-Giraldo, M., Lorente, D., & Blasco, J. (2014). Early detection of mechanical damage in mango using NIR hyperspectral images and machine learning. *Biosystems Engineering*, 122, 91-98.
- Roslan, A., & Idris, A. S. (2012). Economic impact of Ganoderma incidence on Malaysian oil palm plantation—a case study in Johor. *Oil Palm Industry Economic Journal*, 12(1): 24-30.

- Rossel, R. V., Adamchuk, V. I., Sudduth, K. A., McKenzie, N. J., & Lobsey, C. (2011). Proximal soil sensing: an effective approach for soil measurements in space and time. In *Advances in agronomy* (Vol. 113, pp. 243-291). Academic Press.
- Rumy, S. S. H., Hossain, M. I. A., Jahan, F., & Tanvin, T. (2021). An IoT based System with Edge Intelligence for Rice Leaf Disease Detection using Machine Learning. In *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, pp. 1-6.
- Saharan, B. S., & Nehra, V. (2011). Plant growth promoting rhizobacteria: a critical review. *Life Sci Med Res*, 21(1), 30.
- Sanderson, F. R. (2005). An insight into spore dispersal of *Ganoderma boninense* on oil palm. *Mycopathologia*, 159(1), 139-141.
- Santoso, H., Gunawan, T., Jatmiko, R. H., Darmosarkoro, W., Minasny, B. (2011). Mapping and identifying basal stem rot disease in oil palms in North Sumatra with QuickBird imagery. *Precision Agriculture*, 12(2): 233-248.
- Santoso, H., Tani, H., & Wang, X. (2017). Random Forest classification model of basal stem rot disease caused by *Ganoderma boninense* in oil palm plantations. *International Journal of Remote Sensing*, 38(16): 4683-4699.
- Sarangdhar, A. A., & Pawar, V. R. (2017, April). Machine learning regression technique for cotton leaf disease detection and controlling using IoT. In *2017 International conference of Electronics, Communication and Aerospace Technology (ICECA)* (Vol. 2, pp. 449-454). IEEE.
- Saremi, H., & Burgess, L. W. (2000). Effect of soil temperature on distribution and population dynamics of *Fusarium* species.
- Sariah, M., Hussin, M. Z., Miller, R. N. G., & Holderness, M. (1994). Pathogenicity of *Ganoderma boninense* tested by inoculation of oil palm seedlings. *Plant Pathology*, 43(3), 507-510.
- Shafri, H. Z., & Hamdan, N. (2009). Hyperspectral imagery for mapping disease infection in oil palm plantation using vegetation indices and red edge techniques. *American Journal of Applied Sciences*, 6(6), 1031.
- Shahid, S. A., Zaman, M., & Heng, L. (2018). Introduction to soil salinity, sodicity and diagnostics techniques. In *Guideline for salinity assessment, mitigation and adaptation using nuclear and related techniques* (pp. 1-42). Springer, Cham.

- Sowmyalakshmi, R., Jayasankar, T., Pillai, V. A., Subramaniyan, K., Pustokhina, I., Pustokhin, D. A., & Shankar, K. (2021). An Optimal Classification Model for Rice Plant Disease Detection. *CMC-COMPUTERS MATERIALS & CONTINUA*, 68(2), 1751-1767.
- Steppe, K., Saveyn, A., Vermeulen, K., & Lemeur, R. (2006). A comprehensive model for simulating stem diameter fluctuations and radial stem growth. In *III International Symposium on Models for Plant Growth, Environmental Control and Farm Management in Protected Cultivation* 718 (pp. 35-42).
- Tachibana, Y., & Ohta, Y. (1983). Root surface area, as a parameter in relation to water and nutrient uptake by cucumber plant. *Soil Science and Plant Nutrition*, 29(3), 387-392.
- Tajudin, N. S., Musa, M. H., SEMAN, I. A., AINI, C. N., & AMRI, C. (2020). QUANTIFYING SPATIAL VARIABILITY OF SOIL AND LEAF NITROGEN, PHOSPHOROUS AND POTASSIUM OF BASAL STEM ROT INFECTED OIL PALMS USING GEOSPATIAL INFORMATION SYSTEM. *Journal of Oil Palm Research*, 32(3), 427-438.
- Talbot, B., Pierzchała, M., & Astrup, R. (2017). Applications of remote and proximal sensing for improved precision in forest operations. *Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering*, 38(2), 327-336.
- Talley, P. J., & Blank, L. M. (1942). Some factors influencing the utilization of inorganic nitrogen by the root rot fungus. *Plant Physiology*, 17(1), 52.
- Truong, T., Dinh, A., & Wahid, K. (2017). An IoT environmental data collection system for fungal detection in crop fields. In *2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)* (pp. 1-4). IEEE.
- Turnbull, N., de Franqueville, H., Breton, F., Jeyen, S., Syahoutra, I., Cochard, B., & Durand-Gassellin, T. (2014). Breeding methodology to select oil palm planting material partially resistant to *Ganoderma boninense*. In *5th quadrennial international oil palm conference, Bali Nusa Dua Convention Center, Indonesia* (pp. 17-19).
- Turner, P. D., & Gillbanks, R. A. (1974). Oil palm cultivation and management. Kuala Lumpur: Incorporated Society of Planters; 1974. p. 672.
- Turner P.D. (1981). Oil Palm Diseases and Disorder. Kuala Lumpur, Malaysia. The Incorporated Society of Planters.
- Utomo C, & Niepold F. (2000.) The development of diagnostic tools of *Ganoderma* in oil palm. *Phytopathol.* 148:507-514.

- Vetterlein, D., & Doussan, C. (2016). Root age distribution: how does it matter in plant processes? A focus on water uptake. *Plant and Soil*, 407(1-2), 145-160.
- Warcup, J. H. (1951). The ecology of soil fungi. *Transactions of the British Mycological Society*, 34(3), 376–399.
- Wong, L., Bong, C. F. J., & Idris, A. S. (2012). Ganoderma species associated with basal stem rot disease of oil palm. *American Journal of Applied Sciences*, 9(6), 879-885.
- Yadav, J., Verma, J. P., Yadav, S. K., & Tiwari, K. N. (2011). Effect of salt concentration and pH on soil inhabiting fungus *Penicillium citrinum* Thom. for solubilization of tricalcium phosphate. *Microbiol J*, 1(1), 25-32.
- Yang, X., & Guo, T. (2017). Machine learning in plant disease research. *European Journal of BioMedical Research*, 3(1), 6-9.
- Zhang, T., & Yang, B. (2016). Big data dimension reduction using PCA. In *2016 IEEE international conference on smart cloud (SmartCloud)* (pp. 152-157). IEEE.
- Zhang, S., Wu, X., You, Z., & Zhang, L. (2017). Leaf image-based cucumber disease recognition using sparse representation classification. *Computers and Electronics in Agriculture*, 134: 135-141.