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MACHINE-LEARNING APPROACH USING THERMAL AND SYNTHETIC APERTURE RADAR DATA FOR CLASSIFICATION OF OIL PALM TREES WITH BASAL STEM ROT DISEASE

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By

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

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Chairman : Prof. Sr. Gs. Abdul Rashid Mohamed Shariff, C.Eng
Faculty : Engineering

The fast growth of oil palm has resulted in its development as a strategic global commodity. Oil palm creates export revenues and strengthens the economies of numerous nations, especially Indonesia and Malaysia. However, oil palms are susceptible to basal stem rot (BSR) caused by *Ganoderma boninense* (*G. boninense*), the most dangerous oil palm disease. This disease has been a cause for concern as it has caused significant tree mortality in several plantations in Malaysia. Given that there is currently no effective cure for this disease, the only viable solution is to prolong the life of oil palm trees. This study explored the early detection of the BSR using thermal images and an ALOS PALSAR-2 image with dual-polarization, Horizontal transmit and Vertical receive (HV), and Horizontal transmit and Horizontal receive (HH). The study was conducted in Seberang Perak, part of Felcra Seberang Perak 10, and is located in Perak, Malaysia. Initially, an experiment was carried out to (1) identify the potential temperature variables; (2) identify the potential backscatter variables; (3) utilize the imbalance data approach like Random under-sampling (RUS), Random oversampling (ROS), Synthetic Minority Oversampling (SMOTE) and AdaBoost; and (4) evaluate the performance of machine learning (ML) classifiers Naïve Bayes (NB), Multilayer Perceptron (MLP), as well as Random Forest (RF) in classifying the stages and severity levels of *G. boninense*. The sample size was comprised of 55 non-infected trees and 37 infected trees. During the field experiments, oil palm tree samples of non-infected (T0), mild infected (T1), moderate infected (T2), and severe infected (T3) were measured using the FLIR T620 IR infrared thermal imaging camera to obtain the temperature of the oil palm trees. The temperature variation for each thermal image was examined using FLIR ResearchIR Max, the camera manufacturer's software,

and feature extraction for each thermal image was extracted using FLIR Tools in the FLIR ResearcherIR environment software. The backscattering value of each tree was then extracted from the ALOS PALSAR-2 image. Using the Extract Multi Values tool in ArcGIS, the backscattering value for each oil palm point was derived from the processed ALOS PALSAR-2 image. As the ALOS PALSAR-2 image was evaluated with dual-polarization (HH and HV), each digitized point has two distinct backscatter data with four severity levels (T0 to T3). The machine learning algorithm consistently performs well when presented with a well-balanced dataset. In an imbalanced dataset, one of the two classes contains fewer total samples than the other class. The sampling-based method, also known as the data level method, is used to deal with this problem. In this study, the resampling method and ensemble procedure relied entirely on the Waikato Environment for Knowledge Analysis (WEKA) version 3.8.5 software. The classification is performed using the derived features from the thermal images and the backscatter features. The extracted features serve as predictors and the status of oil palm as a response. To identify non-infected and BSR-infected trees, the WEKA tool version 3.8.5 was used for classification. The classifiers evaluated in this study were Nave Bayes (NB), Multilayer Perceptron (MLP), and Random Forest (RF). Two datasets, for training and testing, were both classified. We divided the dataset into a training dataset of 70% and a test dataset of 30%. The classification was done with 10-fold cross-validation to avoid overfitting and get unbiased prediction error estimates. This was the recommended validation method for the small dataset. This study, therefore, detailed the description of the confusion matrix as an alternative in terms of the rate of success of the non-infected and BSR-infected tree together with the balanced classification rate (BCR) or balanced accuracy, the precision-recall curve (PRC), and receiver operating characteristics (ROC) curve region (AUC) to evaluate different classifier and imbalanced approaches and measure their performance. The study found that the T_{max}, T_{min} feature is the most beneficial concerning other temperature characteristics for classifying non-infected or infected BSR trees. In the meantime, the HV feature is most advantageous for classifying non-infected or infected BSR trees compared to other backscatters. Compared with a single approach and other approximate imbalance data approaches, the ROS approach improves BCR, AUC, and PRC data results in datasets. Next, all classifier models were employed in classifying the BSR disease severity using the combination of the best features of temperature (T_{max}, T_{min}), backscatter features (HV), and significant ground-based data (DbH and soil moisture) with a single and ROS approach. In conclusion, all three ML methods can classify the oil palm with severe BSR disease with an outstanding result using the ROS approach. Meanwhile, the MLP was found to be the ideal model with a BCR value of 0.964, AUC and PRC having the same value of 1.000, model accuracy of 96.43%, and a Kappa coefficient of 0.95. The MLP classifier model also had a high success rate, whereby it correctly classified 85.71% (T0-healthy), 100% (T1-mild infected), 100% (T2-moderate infected), and 100% (T3-severe infected). This study concluded that for the early detection of BSR, a significant degree of accuracy was obtained. Infected palms are asymptomatic throughout the disease's early stages, making disease detection challenging. The survival of affected trees must detect BSR at the mild infected (T1) stage. A meaningful conclusion of this study is that the ROS technique can differentiate the severity of mild infection (T1) compared to a single approach that is incapable of doing so. The main benefit of this study is the development of an appropriate model for early identification and severity classification of BSR disease in oil palms via remote sensing and data mining approaches rapidly and cost-effectively.

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

PENDEKATAN PEMBELAJARAN MESIN MENGGUNAKAN DATA TERMA DAN RADAR BUKAAN SINTETIK UNTUK PENGELASAN POKOK KELAPA SAWIT DENGAN PENYAKIT REPUT PANGKAL BATANG

Oleh

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Pertumbuhan pesat kelapa sawit telah menghasilkan pembangunannya sebagai komoditi global yang strategik. Kelapa sawit menyediakan hasil eksport dan mengukuhkan ekonomi banyak negara, terutamanya Indonesia dan Malaysia. Bagaimanapun, kelapa sawit mudah terdedah kepada penyakit reput pangkal batang (RPB), yang disebabkan oleh kulat *Ganoderma boninense* (*G. boninense*) dan merupakan penyakit kelapa sawit yang paling berbahaya. Penyakit ini telah menimbulkan kebimbangan, kerana ia telah menyebabkan kematian pokok yang ketara di beberapa ladang di Malaysia. Memandangkan pada masa ini tiada rawatan yang berkesan untuk penyakit ini, satu-satunya penyelesaian yang berdaya maju ialah memanjangkan hayat pokok kelapa sawit. Kajian ini meneroka pengesanan awal RPB menggunakan gabungan imej termal dan imej ALOS PALSAR-2 dengan polarisasi dwi, transmisi *Horizontal* dan penerima *Horizontal* (HH) dan transmisi *Horizontal* dan penerima *Vertical* (HV). Kajian telah dijalankan di Seberang Perak yang merupakan sebahagian daripada Felcra Seberang Perak 10 dan terletak di Perak, Malaysia. Kajian ini telah dijalankan untuk (1) mengenalpasti potensi pembolehubah suhu; (2) mengenalpasti potensi pembolehubah nilai daya hamburan gelombang radar; (3) menggunakan pendekatan data ketidakseimbangan seperti *Random oversampling* (ROS), *Random under-sampling* (RUS), *Synthetic Minority Oversampling* (SMOTE) dan *AdaBoost*; dan (4) mengkaji prestasi pengkelasan pembelajaran mesin (ML) *Naïve Bayes* (NB), *Multilayer Perceptron* (MLP) dan *Random Forest* (RF) dalam mengklasifikasikan peringkat dan tahap keparahan *G. boninense*. Saiz sampel terdiri daripada 55 pokok tidak dijangkiti serta 37 pokok yang dijangkiti. Semasa eksperimen

di lapangan, sampel pokok kelapa sawit tidak dijangkiti (T0), dijangkiti ringan (T1), dijangkiti sederhana (T2) dan dijangkiti teruk (T3) diukur menggunakan kamera pengimejan termal inframerah *FLIR T620 IR* untuk mendapatkan suhu pokok kelapa sawit. Variasi suhu bagi setiap imej termal telah diperiksa menggunakan *FLIR ResearchIR Max*, perisian pengeluar kamera, dan pengekstrakan ciri untuk setiap imej terma telah diekstrak menggunakan *FLIR Tools* dalam perisian persekitaran *FLIR ResearcherIR*. Nilai daya hamburan gelombang radar setiap pokok kemudiannya diekstrak daripada imej ALOS PALSAR-2. Menggunakan fungsi *Extract Multi Values* dalam ArcGIS, nilai daya hamburan gelombang radar bagi setiap titik kelapa sawit diperoleh daripada imej ALOS PALSAR-2 yang diproses. Memandangkan imej ALOS PALSAR-2 dinilai dengan polarisasi dwi (HH dan HV), setiap titik didigitalkan mempunyai dua nilai daya hamburan gelombang radar yang berbeza dengan empat tahap keterukan (T0 hingga T3). Apabila mempunyai dengan set data yang seimbang, algoritma pembelajaran mesin secara konsisten menunjukkan prestasi yang baik. Dalam set data yang tidak seimbang, salah satu daripada dua kelas mengandungi jumlah sampel yang lebih sedikit daripada kelas yang lain. Untuk menangani masalah ini, kaedah berasaskan persampelan, juga dikenali sebagai kaedah tahap data, digunakan. Dalam kajian ini, kaedah pensampelan semula dan prosedur *ensemble* telah menggunakan perisian Waikato Environment for Knowledge Analysis (WEKA) versi 3.8.5. Pengelasan dilakukan menggunakan ciri yang diekstrak daripada imej termal dan daya hamburan gelombang radar. Ciri yang diekstrak berfungsi sebagai peramal dan status kelapa sawit sebagai tindak balas. Untuk mengenal pasti pokok yang tidak dijangkiti dan dijangkiti RPB, perisian WEKA versi 3.8.5 telah digunakan untuk pengelasan. Pengelas yang dinilai dalam kajian ini ialah NB, MLP, dan RF. Dua set data, latihan dan ujian, kedua-duanya dikelaskan. Untuk tujuan ujian, kami membahagikan set data kepada set data latihan sebanyak 70% dan set data ujian sebanyak 30%. Pengelasan telah dilakukan menggunakan pengesahan silang 10 kali ganda untuk mengelakkan *overfitting* dan mendapatkan anggaran ralat ramalan yang tidak berat sebelah, kerana ini adalah teknik pengesahan yang disyorkan untuk dataset kecil. Kajian ini mengemukakan penerangan mengenai matriks kekeliruan sebagai alternatif dari segi kadar kejayaan pokok yang tidak dijangkiti dan yang dijangkiti RPB bersama dengan kadar klasifikasi yang seimbang atau ketepatan yang seimbang (BCR), rantau lengkung (AUC) ciri operasi penerima (ROC), dan keluk penarikan semula ketepatan (PRC) bagi menilai pendekatan pengkelasan dan ketidakseimbangan yang berbeza dan mengukur prestasinya. Kajian mendapati bahawa ciri T_{max}, T_{min} adalah ciri yang paling bermanfaat berbanding dengan ciri suhu lain untuk klasifikasi pokok yang tidak dijangkiti atau dijangkiti RPB. Sementara itu, ciri HV paling berkelebihan berbanding dengan nilai daya hamburan gelombang radar lain untuk mengklasifikasikan pokok yang tidak dijangkiti atau dijangkiti RPB. Berbanding dengan pendekatan tunggal dan pendekatan data ketidakseimbangan yang lain, pendekatan ROS meningkatkan data BCR, AUC dan PRC dalam set data. Seterusnya, semua model pengklasifikasian digunakan bagi mengklasifikasikan keparahan penyakit RPB menggunakan kombinasi ciri suhu terbaik (T_{max}, T_{min}), nilai daya hamburan gelombang radar (HV) dan data asas yang signifikan (diameter pada paras dada dan

kelembapan tanah) dengan pendekatan tunggal dan ROS. Kesimpulannya, ketiga-tiga kaedah mesin pembelajaran dapat mengklasifikasikan tahap keparahan pokok kelapa sawit dengan penyakit BSR dengan hasil yang luar biasa menggunakan pendekatan ROS. Sementara itu, MLP dikenal pasti sebagai model terbaik dengan nilai BCR 0.964, AUC dan PRC mempunyai nilai yang sama 1.000, ketepatan model 96.43%, dan pekali Kappa 0.95. Model pengkelasan MLP juga mempunyai kadar kejayaan yang kuat, dapat mengkelaskan 85.71% (T0-sihat), 100% (T1-jangkitan ringan), 100% (T2-jangkitan sederhana) dan 100% (T3-jangkitan teruk) dengan betul. Kajian ini merumuskan bahawa untuk pengesanan awal RPB, tahap ketepatan yang ketara telah diperolehi. Pokok yang dijangkiti adalah tanpa gejala pada peringkat awal penyakit, menjadikan pengesanan awal penyakit mencabar. Adalah penting untuk mengesan RPB pada peringkat jangkitan ringan (T1) bagi pokok yang terjejas. Kesimpulan yang perlu diberi perhatian dalam kajian ini ialah teknik ROS boleh membezakan keterukan pada peringkat jangkitan ringan (T1) berbanding pendekatan tunggal yang tidak mampu berbuat demikian. Faedah utama kajian ini ialah pembangunan model yang sesuai untuk pengesanan awal dan klasifikasi keparahan penyakit RPB dalam kelapa sawit melalui pendekatan penderiaan jauh dan data perlombongan dengan cara dan kos yang efektif.

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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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Declaration by Members of Supervisory Committee

This is to confirm that:

- the research and the writing of this thesis were done under our supervision;
- supervisory responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2015-2016) are adhered to.

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LIST OF ABBREVIATIONS

EU	European Union
MSPO	Malaysian Sustainable Palm Oil
PFR	Permanent Forest Reserve
MPOB	Malaysia Palm Oil Board
BSR	Basal Stem Rot
GSM	*Ganoderma* Selective Medium
DNA	Deoxyribonucleic Acid
PCR	Polymerase Chain Reaction
SAR	Synthetic Aperture Radar
ML	Machine Learning
ROS	Random Oversampling
RUS	Random Under-sampling
SMOTE	Synthetic Minority Oversampling
NB	Naïve Bayes
MLP	Multilayer Perceptron
RF	Random Forest
HS-SPME	Headspace Solid-Phase Microextraction
GC–MS	Gas Chromatography-Mass Spectrometry
ELISA-PAb	Enzyme-Linked Immunosorbent Assay-Polyclonal Antibody
RS	Remote Sensing
ASW	Average Silhouette Width
TLC	Total Leaf Chlorophyll
GER	Geophysical And Environmental Research
ANN	Artificial Neural Network
FR-IR	Fourier Transform Infrared
LDA	Linear Discriminant Analysis
QDA	Quadratic Discriminant Analysis
kNN	K-Nearest Neighbour
PCA	Principal Component Analysis

SVM	Support-Vector Machines
NIR	Near Infrared
AISA	Airborne Imaging Spectroradiometer for Applications
DGPS	Differential Global Positioning System
MNF	Minimum Noise Fraction
NDVI	Normalized Difference Vegetation Index
VOGI	Vogelmann Red Edge Index
MSR	Modified Simple Ratio
SRI	Simple Ratio Index
SAM	Spectral Angle Mapper
VI	Vegetation Indices
REP	Red Edge Position
CR	Continuum Removal
DSI	Disease Severity Index
BDNA	Band Depth Normalized to Area
ARVI	Atmospherically Resistant Vegetation Index
GBNDVI	Green Blue Normalized Difference Vegetation Index
SAVI	Soil Adjusted Vegetation Index
CART	Regression Tree
ORF	Oblique Random Forest
PLS	Partial Least Squares
Rferns	Random Ferns
PRF	Parallel Random Forest
RLB	RF Rule-Based
DT	Decision Tree
UAV	Unmanned Aerial Vehicles
MLD	Maximum Likelihood
MD	Mahalanobis Distance
NN	Neutral Net
OBIA	Object-Based Image Analysis
FLS	Full-Lambda Schedule
RGB	Red, Green, Blue

R	Red
G	Green
B	Blue
LiDAR	Light Detection and Ranging
DBH	Diameter at Breast Height
TLS	Terrestrial laser scanning
CWSI	Crop Water Stress Index
RADAR	RAdio Detection and Ranging
HH	Horizontal - Transmit and Horizontal – Receive
HV	Horizontal - Transmit and Vertical – Receive
VV	Vertical - Transmit and Vertical – Receive
SNAP	Sentinel Application Platform
KNB	Kernel Naïve Bayes
PC	Principal Components
TP	True Positive
FP	False Positive
FN	False Negative
TN	True Negative
BCR	Balanced Accuracy
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve
PRC	Precision-Recall Curve
GIS	Geographical Information System
JAXA	Japan Aerospace Exploration Agency
ALOS	Advanced Land Observation Satellite
PALSAR	Phased Array L-type Synthetic Aperture Radar
AGC	Automatic Gain Control
PE	Plateau Equalization
ROI	Region of Interest
ENL	Equivalent Number of Looks
SMPI	Speckle Suppression and Mean Preservation Index
dB	Decibel

DN	Digital Number
T_{max}	Maximum Temperature of Oil Palm Trunk
T_{min}	Minimum Temperature of Oil Palm Trunk
T_{center}	Center Temperature of Oil Palm Trunk
T_{mean}	Mean Temperature of Oil Palm Trunk
T_{sd}	Standard Deviation Temperature of Oil Palm Trunk
ANOVA	Analysis of Variance
WEKA	Waikato Environment for Knowledge Analysis

CHAPTER 1

INTRODUCTION

1.1 Research Background

Palm oil is an important raw material for food and non-food industries. Over the recent years, Malaysia faced the implications of the European Union's (EU) anti-palm oil campaign on the palm oil industry due to concerns that oil palm cultivation accelerates global warming and deforestation. Nevertheless, Malaysia is committed to developing the country's palm oil industry sustainably through various initiatives (Ishak, 2020). Among them are the mandatory implementation of the Malaysian Sustainable Palm Oil Certification Scheme (MSPO) from 1 January 2020, strengthening policies in maintaining the country's oil palm cultivation activities such as limiting the area of oil palm cultivation throughout the country with a target of 6.5 million hectares. These include a ban on the cultivation of new oil palm in new peatland areas, a ban on the conversion of Permanent Forest Reserve (PFR) land use for oil palm or other agricultural cultivation activities, and the preparation of an official map of oil palm areas for community access. Malaysia accounts for 18.5 million tonnes representing 34.15% of the global palm oil production (Malaysian Palm Oil Council, 2019). Being among the largest producers and exporters of palm oil and palm-based products, Malaysia plays a vital role in meeting the increasing demand worldwide for sustainable oils and fats. In 2021, the export revenue from palm oil and palm-based products was expected to increase by 2.4% to RM74 billion versus RM72.30 billion recorded in 2020 (Bernama, 2021a). In Malaysia, 2.5 million people are dependent on oil palms (A. Ibrahim, 2015). Growing palm oil cultivation each year implies that it is preferred for farming and a significant source of income for the rural community (A. Ahmad, Osman, Omar, Rahman, & Ishak, 2020). Hence, the role of the palm in the nation's economic and socioeconomic development is crucial.

Palm oil is one of the leading vegetable oils in various industries, especially the food industry, and plays an essential economic role, especially in major producer countries. The oil extracted through the oil palm kernel is used in numerous processed food production and cooking oils. It is employed to manufacture cosmetics, soap, shampoos, and detergents with its derivatives. It can also be used as a biofuel (Ghazali, Yusof, & Ahmad, 2006).

Based on Malaysia Palm Oil Board (MPOB), palm oil production and export have rapidly increased in Malaysia between the year 2012 to 2013 (Bejo & Vong, 2014). However, in Malaysia, a common soil-borne fungus known as *Ganoderma*, which can infect palm trees, is becoming a growing concern for oil palm plantations. *Ganoderma* has the potential to reduce yields long before it kills an oil palm significantly, and its spores can travel rapidly through wind and water over ever-increasing portions of a plantation once introduced. In 1930, *Ganoderma* infection, which is a severe plant root system disease, was first reported by discrimination on *Ganoderma lucidum* pathogens in oil palm plantations in Malaysia (Ariffin, Idris, & Marzuki, 1996) and it was termed as the Basal Stem Rot (BSR) infection (Haniff, Ismail, & Idris, 2005; Utomo, Werner, Niepold, & Deising, 2005) Many studies in Malaysia and Indonesia's oil palm plantations indicate that BSR infection is predominantly brought about by a single pathogen called *Ganoderma boninense (G.boninense)* (Ho & Nawawi, 1985). A severe plant root system disease causes BSR infection (Haniff et al., 2005; Utomo et al., 2005; Idris et al., 2002). Therefore, to ensure that palm oil management is sustainable, these types of fungal diseases must be controlled to increase high-quality palm oil production.

In the BSR infection, fungal pathogens infect and kill the roots and the basal stem. Even in oil palm nurseries, the disease is infectious (Naher, Yusuf, Tan, & Ismail, 2013; Wong, Bong, & Idris, 2012). The contaminated internal tissues and palm roots become very dry, soft, and powdery. The cortical tissue color gets altered quickly into brown color and the fragments and the stale color to black (Singh, 1991). There are a number of particular symptoms indicating a strong prevalence likelihood of those diseases in oil palms, which includes wilting and hanging down green fronds (Kandan, Bhaskaran, & Samiyappan, 2010; Singh, 1991), changing frond color from green to yellow (Kandan, et al., 2010; Singh, 1991), decreased frond production leading to smaller canopy size (Naher et al., 2013) and eventually, basidiomata which occur on the trunks (Kandan, et al., 2010; Ariffin, Idris, & Singh, 2000) It is possible for the oil palms that are infected to rupture and collapse should they remain in the plantation areas (Idris et al., 2002). BSR is considered a silent disease as it shows no apparent symptoms until the infection severity level in the plant roots is around 8% (Naher, Tan, Yusuf, Ho, & Siddiquee, 2012). Young palms that are infected will usually die within six months to two years of the prevalence of these symptoms, while mature palms generally take two to three years (Ariffin et al., 2000). (Naher, Ho, Tan, Yusuf, & Abdullah, 2011) found that the chitinase gene is more significant in the root tissues of infected oil palms than the leaf tissues. When BSR foliar symptoms emerge, young oil palms die much faster than mature ones. When foliar signs occur, the fungus has already infected fifty percent of the plant's tissue (Arrifin et al., 2000). Relevant studies show that palm oil growth and metabolism initially decrease in BSR infection and its production.

Many scientific experiments have been carried out to determine a practical approach to detect BSR earlier, including the minor scale laboratory-based technique. A small number of biochemical approaches can be used to distinguish between BSR infections such as the first method is culture-based, like *Ganoderma* Selective Medium (GSM) (Ariffin et al., 1996) and the second technique uses Deoxyribonucleic Acid (DNA) molecules such as Polymerase Chain Reaction (PCR) (Kandan et al., 2009; Utomo & Niepold, 2000). In the disease detection method in PCR, it is found that the DNA of a microorganism causes a particular disease to be extracted and purified, accompanied by amplification. Disease-triggering organisms are confirmed using gel electrophoresis (Sankaran, Mishra, Ehsani, & Davis, 2010). There are several advantages and disadvantages to the techniques of detecting molecular-based disease. It can be considered a robust reference method to detect specific plant diseases earlier. However, as it requires stem collection and laboratory work that is expensive, time-consuming, elaborate, and laborious, it can not be used as a preparatory experiment method on a large scale (Sankaran et al., 2010). For BSR infection's early detection, the GSM-based method can also be used (Ariffin & Idris, 1991). It is capable of isolating the pathogen selectively from the infected tissue. Therefore, except for *Ganoderma*, growing fungi and bacteria are excepted in this method (Ariffin & Idris, 1991). However, because it is labor-intensive and time-consuming, it is not applicable on a large scale.

Therefore, to monitor such a dangerous plant disease in a comfortable, rapid, accurate and widespread way, it is crucial for identifying well-organized, non-invasive and non-destructive techniques. Geospatial technologies and remotely sensed sensors have been placed as practical as well as applicable methods for the classification and detection of BSR contingent on the recent research (Azmi et al., 2020; Bejo, Abdol Lajis, Abd Aziz, Seman, & Ahamed, 2018; Husin et al., 2020a; Izzuddin, Hamzah, Nisfariza, & Idris, 2020; Izzuddin et al., 2018; Khaled et al., 2020; Santoso, Tani, Wang, Prasetyo, & Sonobe, 2019; Toh, Izzuddin, Ewe, & Idris, 2019; Wiratmoko, Jatmiko, Yusuf, Farrasati, & Prasetyo, 2020). These reports have shown that the techniques can identify BSR early and differentiate between healthy and BSR-infected trees. Nevertheless, a part of the approaches still was limited to further classifying the level of severity of the BSR infection.

Thermal imaging uses an image to represent infrared radiation and thus the heat of an object. All objects having a temperature higher than absolute zero (-273 ° C) emit infrared radiation, but humans' vision is limited to electromagnetic visible spectrum radiation. Thermal imaging extends the limited vision of humans to view infrared radiation beyond the boundary. Over the recent years, developments in the thermal imaging field have been rapid. The current availability of commercial systems has made it possible to apply thermal imaging methods to a wide array of agricultural, veterinary, soil moisture studies, medical and military, and industrial thermal imaging is used commonly (Vadivambal & Jayas, 2011). In many operations involving in agriculture, there are various potential applications for thermal imaging, which includes estimating soil water status, assessing the viability of seedlings, estimating the crop water stress, planning irrigation, determining the pathogen and disease affected plants, estimating the fruit yield as well as evaluating fruit and vegetable maturity. Based on the literature, we can conclude that thermal imaging could analyze plant water stress and disease detection. Since the water transport of oil palm was affected by BSR infection, the BSR-infected tree's water stress would differ from healthy trees. There is, therefore, a potential thermal imaging use in the detection of infection with BSR.

As an active remote sensing technology, microwave remote sensing can generate its own radiation and provide imagery regardless of weather or daylight conditions. The device resolves the cloud cover issue associated with optical remote sensing, common in the tropics, where most oil palms are grown. This information is derived from the ground surface's backscattered energy. The microwave's wavelength is longer, which allows for a higher penetrating power. Measurement of the pixels in the same row and column as the illuminated target also collects texture information. Using this information, you can tell if a surface is smooth, like water or rugged trees (Daliman, Rahman, & Busu, 2014). Since the L-band (at 30–15 cm wavelength) is the most effective in mapping forested vegetation and oil palms, the L-band is considered the most effective at determining the structure of the sub-canopy levels (Ottinger & Kuenzer, 2020; Teng et al., 2015). Microwave remote sensing has been used in the oil palm classification because of these valuable characteristics and the capacity to identify different crop types and monitor crop growth (K. L. Chong, Kanniah, Pohl, & Tan, 2017; Descals et al., 2019; Silva, Rudorff, Formaggio, Paradella, & Mura, 2012). Besides, there is still a lack of microwave wavelength monitoring of oil palm trees' health to date. Thus, it is possible to assess SAR data's potential in identifying *G. boninense* disease by its disease stage.

1.2 Problem Statement

Identifying the plant's health condition is the first essential step in controlling diseases, just as it is in all other crop production procedures. One of the significant challenges in detecting BSR is that the foliar symptoms appear in an advanced stage of the disease. One only way to detect the fruiting body visually is around the oil palm trunk. Due to the disease's difficulties in being diagnosed early, it spreads rapidly during the field's earliest stages of oil palm production. Generally, detecting and controlling BSR in its early phases is ineffectual and inaccurate (Chong, Dayou, and Alexander, 2017; Fowotade et al., 2019). Early identification is difficult because of the absence of visible symptoms, which has become a significant impediment to controlling BSR disease (Siddiqui, Surendran, Paterson, Ali, & Ahmad, 2021). While BSR is incurable, having an early identification tool for infected palms is crucial for economically maintaining the condition.

The BSR disease detection in oil palm trees has been done through various studies and approaches, including manual visual inspection, laboratory analysis, and remote sensing. However, these techniques' abilities to detect BSR in oil palm trees have some limitations regarding the issues of labor, price, and time detecting BSR in oil palm trees. Due to these limitations, developing cost-effective and environmentally safe alternative methods is an essential solution and a critical approach to controlling BSR. Additionally, BSR infection is challenging to be detected in the early stages of the disease.

Disease-specific and rapid techniques deemed fitting for the early disease detection were created due to increased demand for automated non-destructive methods. Plant diseases and stress monitoring could be carried out with remote sensing techniques (Ennouri & Kallel, 2019; Gerhards, Schlerf, Mallick, & Udelhoven, 2019; Gogoi, Deka, & Bora, 2018; Yang, 2020; J. Zhang et al., 2019; N. Zhang et al., 2020). Studies in the recent times have attempted to formulate this technology to identify and measure plant diseases as well as stress in large-scale and real-time trials in the field (Bock, Barbedo, Del Ponte, Bohnenkamp, & Mahlein, 2020; Donatelli et al., 2017; Singh, Ganapathysubramanian, Sarkar, & Singh, 2018; Wu et al., 2019). Additionally, remote sensing methods can be formulated to identify BSR infections at a sufficient scale in oil palm plantation areas. This method provides fast, accurate, and real-time monitoring concerning control and management.

The use of thermal imaging in agricultural applications has aided in detecting disease and determining the amount of water stress. Studies show that the capability to track the spatial and temporal trends of crop diseases throughout numerous disease growth stages is possible using thermal remote sensing (Hashim et al., 2020; Hernández-Clemente et al., 2019; Khanal, Fulton, & Shearer, 2017; Mahlein, 2016). There has been a minimal exploration of thermal imaging in a palm oil plantation to detect an infected BSR tree.

Due to cloud penetration and capability in all-weather environments, the promising remote sensing method is the microwave sensors. Besides, unlike optical sensors that rely on the supply of energy from sunlight, microwave sensors rely on their own energy source. The capability of Synthetic Aperture Radar (SAR) data to track plant conditions and follow biophysical parameters has been depicted in numerous researches (Harfenmeister, Itzerott, Weltzien, & Spengler, 2021; Mandal et al., 2020; Sivasankar, Kumar, Srivastava, & Patel, 2018). According to several studies, the SAR backscattering sensitivity to plant conditions is associated with the SAR sensor parameters (polarization, incident angle, and wavelength) (El Hajj, Baghdadi, Bazzi, & Zribi, 2019; Harfenmeister, Spengler, & Weltzien, 2019; Mandal et al., 2020; Nasirzadehdizaji et al., 2019). In addition, the use of microwave wavelengths to monitor the health of oil palm plants is currently insufficient.

The machine learning (ML) algorithm may be useful for identifying oil palm trees that are non-infected and BSR-infected. ML algorithms rely on a computation method to locate data directly from the data without using any predefined equations (C. W. Chang, Lee, & Liu, 2018). Over the last decade, land cover analysis, forest monitoring, and farm monitoring have used ML algorithms in different applications. ML has been expanded to applications such as classifying remote sensing data and plant diseases to date. Despite this, a majority class often gains from a high degree of accuracy thru the class imbalance compared to the minority class; thus, the class imbalance of the data poses a challenge to the ML classifiers. Data-level approaches are commonly employed to alleviate class imbalance problems. The most widely used data-level methods to solve the imbalance problem include RUS, ROS, and SMOTE (Fernández, del Río, Chawla, & Herrera, 2017; Leevy, Khoshgoftaar, Bauder, & Seliya, 2018; Tyagi & Mittal, 2020; Wah, Aryani, Rahman, He, & Bulgiba, 2016).

Several studies have demonstrated the utility of thermal and SAR data for crop monitoring. However, health monitoring of oil palm plants using thermal and microwave wavelengths has not been implemented. Therefore, it is possible to evaluate the applicability of thermal and SAR data in differentiating non-infected and infected oil palm trees by *G. boninense*. This study's major initiative and contribution are evaluating the class imbalance and the performance of the associated classifier. This is not thoroughly investigated in agriculture. Despite the fact that many individuals are aware that class imbalance produces problems, there have been no in-depth studies of its precise effects.

Therefore, this research will provide a new benchmark in evaluating ground-based thermal imaging and SAR to diffrentiate oil palm trees that are both non-infected and BSR-infected using ML algorithm with an imbalanced approach since these techniques are still mostly unexplored for oil palm research.

1.3 Research Objectives

The primary aim of this research is to establish a rapid and reliable method to detect BSR disease. Remote sensing may provide an opportunity to achieve this aim, and it has already been used in a few agricultural practices. There are several specific objectives to achieve our desired goal:

1) To evaluate the potential of extracted thermal features to differentiate oil palm trees based on the various stages of BSR disease.

2) To evaluate the potential of extracted SAR features to differentiate oil palm trees based on the various stages of BSR disease.

3) To explore the potential of machine-learning algorithms with an imbalanced approach in classifying oil palm trees based on the various stage levels of BSR disease.

4) To compare the potential of machine-learning algorithms and imbalanced data approach in classifying stages and severity levels of BSR disease.

1.4 Research Framework

This research explores the early detection of the BSR by combining thermal images and a dual-polarized ALOS PALSAR-2 image. The study was conducted in Felcra Seberang Perak 10, which is situated in the Perak Tengah District in the Malaysian state of Perak. Figure 1.1 provides a concise narrative explanation of the overall methodology employed in this study. The primary objective of this study was to evaluate the applicability of temperature variables and backscatter variables in categorizing phases and severity levels of *G. boninense* disease using machine-learning algorithms and an imbalanced data method. The number of non-infected (T0), mildly infected (T1), moderately infected (T2), and severely infected (T3) oil palm tree samples is 55, 11, 15, and 11, respectively. FLIR ResearchIR Max was utilised to analyze the temperature variation of each thermal image. The value of each tree's backscattering was then derived from the ALOS PALSAR-2 image. The resampling approach and ensemble procedure were utilized to address the issue of class imbalance. NB, MLP, and RF were assessed in this study as classifiers. The dataset was separated into a 70 per cent training dataset and a 30 per cent test dataset for testing reasons. The classification was performed using 10-fold cross-validation to prevent overfitting and obtain objective prediction error estimates. Lastly, this study described the confusion matrix as an alternative in terms of the success rate of the non-infected and BSR-infected tree and the BCR, the PRC, and the AUC to evaluate different imbalanced approaches and classifiers and measure performance in enhancing the early detection of *Ganoderma* infection.

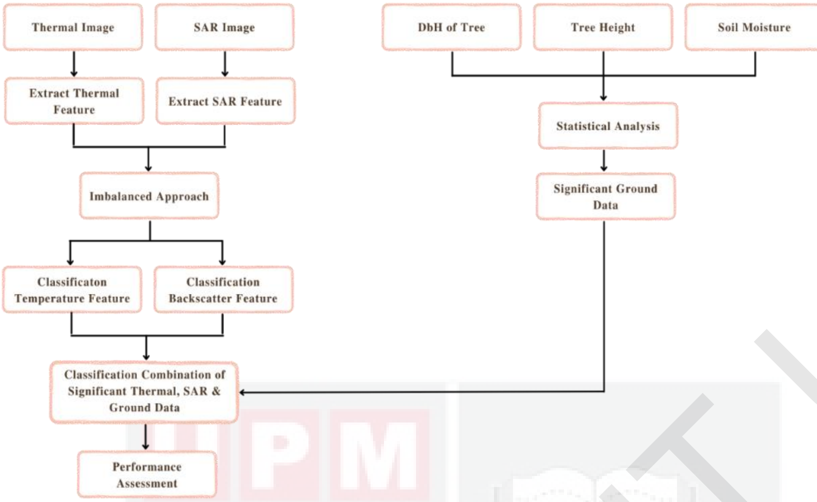

Figure 1.1: Research framework

1.5 Scope of the Study

The present research explores the potential of using thermal imaging and SAR data in detecting *G. boninense* disease in oil palm plantations. This study emphasized only the classification of non-infected and infected *G. boninense* of matured oil palm trees (13 years old). The number of samples of the oil palm tree used in this study was 92. An expert from the Malaysian Palm Oil Board (MPOB) ascertained the trees' health status. Hence, the tree condition variations are presumed to be due to the *G. boninense* infection rather than any other causes. This research focused on analyzing the trees' thermal temperature variation and SAR backscattering. The classification methods used were NB, MLP, and RF, and imbalanced data approaches like RUS, ROS, AdaBoost, and SMOTE were considered in this study.

1.6 Key Findings

The most prominent issue with oil palm plantations is BSR, for which there is no impressive treatment that works. One approach to tackle BSR in oil palm plantations is early detection (Hushiarian, Yusof, & Dutse, 2013), where the disease can be detected quickly and at a low cost. By incorporating machine learning techniques, remote sensing can increase detection precision. This study's findings are intended to enhance detection methods for early-stage *G. boninense* disease in oil palm plantations. The following are the key findings of this study:

1) A technique for detecting BSR based on individual oil palm trees using thermal images.

2) A technique to extract backscatter value for detecting BSR based on individual oil palm trees using the SAR image.

3) Classification of non-infected and BSR’s severity in oil palm plantation using machine learning and imbalanced approach.

1.7 Thesis Organization

This thesis is divided into five chapters. Chapter One consists of a general overview, problem statement, research objectives, research scopes, and the thesis outline. The rest of this thesis is organized as follows:

Chapter two focuses on the review of some related studies and work which is helpful in the detection as well as monitoring of *G. boninense* infection in oil palm plantations. The various applications of geospatial technology efficiency over the last decade are presented. Imbalanced data approach, classification models, and accuracy assessment-related in this study also are reviewed.

Chapter 3 presents an overview of the research methodology used in this research. The research method consists of four different processes. This process refers to the field data collection, image processing for thermal and ALOS PALSAR 2 data, statistical analysis of data, and finally, the classification used to classify non-infected and *G. boninense* infected trees.

Based on the methodology presented in the previous chapter, Chapter Four focuses on the results and discussion.

Lastly, chapter five provides the study's overall conclusion and recommendations for further studies.

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