OIL PALM FEMALE INFLORESCENCES ANTHESIS STAGES IDENTIFICATION USING SELECTED EMISSIVITIES THROUGH THERMAL IMAGING AND MACHINE LEARNING

By

YOUSEFIDASHLIBOROUN MAMEHGOL

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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April 2022

Chair : Azmin Shakrine bin Mohd Rafie, PhD
Faculty : Engineering

Oil palm industry seeks for a reduction of cost and environmental impact, promote sustainability and to maximize crop production and quality. In the oil palm production process, pollination is one of the main factors contributing to yield. However, oil palm pollination is facing issues with fruit formation and filling due to poor natural pollination. Alternatively, assisted/artificial pollination and Wireless Sensor Network (WSN) systems have been introduced to determine pollination readiness of the oil palms, break the reproduction cycle, and producing new breeding material. To perform these methods, several factors are taken into account such as the number of inflorescences to be pollinated per hectare and if these inflorescences require the opening of bracts. These tasks are labor-intensive and subjective to the availability of experts. All these methods depend on manual monitoring and visual inspection with ever decreasing labor, making farming economically inefficient and unstable. Therefore, it’s necessary to identify the pollination stages to ensure successful assisted/artificial pollination operation. To achieve this in digital agriculture, useful data about the different stages of oil palms inflorescences pollination is necessary to deliver better decision-making systems. This research studies different Machine Learning (ML) classification and ensemble techniques for the assessment of the four pollination stages consist of pre-anthesis I, pre-anthesis II, pre-anthesis III, and anthesis using thermal imaging. Different ML algorithms such as Random Forest (RF), *k* Nearest Neighbor (*k*NN), Support Vector Machine (SVM), Artificial Neural Network (ANN) as well as an ensemble method are used on data extracted from thermal images collected during infield oil palms pollination stages monitoring. Thermal images are captured with a selected emissivity values of 0.96, 0.97, and 0.98 and evaluated to determine the best model performance. To apply the above-mentioned models, there are two feature sets are utilized consisting of endogenous features from thermal images taken with three emissivity values and exogenous features including meteorological variables. These models' performance is validated statistically and empirically considering the average accuracy, recall, precision, and F-measure in classifying the present datasets. The ensemble method on endogenous and endogenous+exogenous feature sets from emissivity of 0.96 achieved F-measure scores of 92.68% and 93.42% respectively and with emissivity of 0.97 resulted in 87.06% and 89.73% respectively. However, the ensemble method on emissivity of 0.98 using endogenous and endogenous+exogenous feature sets resulted in F-measure score of 57.81% and 86.63%, respectively lower than that of the latter. Ultimately, the results suggest that the proposed ML method can be utilized effectively to accurately estimate the four pollination stages in plantations, becoming a reliable and accurate tool in automated assisted/artificial pollination decision making systems. The proposed detection system capable of rapid and accurate screening and identification of oil palms inflorescences can be applied.

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

PERINGKAT PERINGKAT WANITA KELAPA SAWIT MEKAR PENGENALAN MENGGUNAKAN EMISIVITI TERPILIH MELALUI PENGIMEJIAN TERMA DAN PEMBELAJARAN MESIN

Oleh

YOUSEFIDASHLIBOROUN MAMEHGOL

April 2022

Pengerusi : Azmin Shakrine Mohd bin Rafie, PhD
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Industri kelapa sawit sentiasa berusaha untuk berusaha untuk pengurangan kos dan impak terhadap alam sekitar, mempromosikan kelestarian dan memaksimumkan pengeluaran dan kualiti tanaman. Dalam proses pengeluaran kelapa sawit, pendebungaan adalah salah satu faktor utama yang menyumbang kepada hasil. Walau bagaimanapun, pendebungaan kelapa sawit menghadapi masalah dengan isu pembentukan dan pengisian buah disebabkan oleh penyebaran pendebungaan semula jadi yang lemah. Sebagai alternatif, sistem pendebungaan terbantu/tiruan dan Sistem Rangkaian Penderiaan Tanpa Wayar (WSN) telah diperkenalkan untuk menentukan kesediaan pendebungaan kelapa sawit, memutuskan kitaran pembiakan, dan menghasilkan bahan pembiakan baru. Untuk melaksanakan kaedah ini, beberapa faktor yang perlu diambil kira adalah jumlah pendebungaan yang akan didebungakan per hektar dan juga sama ada pendebungaan ini memerlukan pembukaan braktea yang akau menjurus kepada pergantuagan kepada teuaga buruh yang intensif tenaga pakar. Semua kaedah ini bergantung pada pemantauan secara manual dan pemeriksaan visual yang memerlukan tenaga kerja yang sememangnya berkurangan, menjadikan ketidakcekapan dan ketidakstabilan ekonomi pertanian. Oleh itu, adalah sangat diperlukan untuk mengenal pasti peringkat pendebungaan bagi memastikan operasi pendebungaan terbantu/tiruan yang berjaya. Untuk mencapai keadaan ini dalam pertanian digital, data yang berguna mengenai pelbagai peringkat pendebungaan perbungaan betina kelapa sawit amat diperlukan untuk menghasilkan sistem pembuat keputusan yang lebih baik. Tesis ini menyiasat kemampuan Pembelajaran Mesin (ML) dan ensemble tekniques empat peringkat pendebungaan yang utama iaitu terdiri daripada pramekar I, pra-mekar II, pra-mekar III, dan mekar mengguuakan pengimejan termal. Algoritma Pembelajaran Mesin (ML) yang berbeza seperti Pengkelasan Hutan Rawak (RF), Jiran Terdekat *k* (*k*NN), Mesin Vektor Sokongan (SVM), dan

Rangkaian Neural Buatan (ANN) dan satu kaedah ensemble akan digunakan pada data dari pengimejan terma yang diambil di ladang kepala sawit semasa pemantauan peringkat pendebungaan kelapa sawit. Imej termal tersebut diambil menggumakan kepancaran terpilih iaitu 0.96, 0.97 dan 0.98 dinilai untuk menentukan model yang memberikan prestasi yang terbaik. Bagi mengaplikasika algoritma ML di atas, dua set ciri telah dipilih iaitu ciri endogenus dari imej termal dengan tiga nilai kepancaran dan ciri eksogenus yang meliputi data-data meteorologi. Prestasi model ini disahkan secara statistik dan empirik dengan mengambil kira purata ketepatan, penarika balik, kejituan, dan ukuran F dalam mengklasifikasikan set data yang diperolehi. Kaedah ensemble pada set ciri endogenus + eksogenus dan endogenus dari emisiviti 0.96 mencapai skor ukuran-F masing-masing 92.68% dan 93.42% manakala dengan emisiviti 0.97 masing-masing menghasilkan 87.06% dan 89.73%. Walau bagaimanapun, model ensemble pada emisiviti 0.98 yang menggunakan set ciri endogenus dan endogenus + eksogenus memberi keputusan skor ukuran-F 57.81% dan 86.63%, masing-masing lebih rendah berbanding kepancaran terpilih lain.

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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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I hereby confirm that:

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LIST OF ABBREVIATIONS

UPM	Universiti Putra Malaysia
AI	Artificial Intelligence
ANN	Artificial Neural Network
AUC	Area Under Curve
ADOPSY	Artificial Domestic Pollination System
BBCH	Bundesanstalt, Bundessortenamt and Chemical
DL	Deep Learning
DCT	Discrete Cosine Transform
DT	Decision Tree
DWT	Discrete Wavelet Transform
EK	Elaeidobius Kamerunicus
ERT	Extremely Randomized Trees
FFB	Fresh Fruit Bunch
FNN	Feedforward Neural Network
GDP	Gross Domestic Product
GNDVI	Green Normalized Difference Vegetation Index
IoT	Internet of Things
*k*NN	*k* Nearest Neighbor
LIDAR	Light Detection and Ranging
LR	Logistic Regression
MAE	Mean Absolute Error
MPOB	Malaysian Palm Oil Board
ML	Machine Learning
MP	Multilayer Perceptron
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
MSC	Multi-Scale Classifier
NB	Naïve Bayesian
NDVI	Normalized Difference Vegetation Index
NREI	Normalized Red Edge Index
PNG	Papua New Guinea

RBKF	Radial Basis Kernel Function
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machine
SVR	Support Vector Regression
UAV	Unmanned Aerial Vehicle
WSN	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

1.1 Background

Oil palm is the most efficient commercial crop with the potential to fulfil the growing global demand for vegetable oil consumption. It contributes to the economy of several countries such as Malaysia, Indonesia, Nigeria, Congo, West Africa, Brazil, Colombia, Costa Rica, Ecuador, and other south and central American countries (Vijay et al., 2016). Today the world oil palm production has stagnated around 73.49 Mt (Woittiez et al., 2017), yet the demand will increase to 250 Mt by 2050 (Corley and Tinker, 2008). With the acceleration of global growth and demand for palm oil, its production is concerned. In accordance, there are four production levels: the potential, water-limited, nutrient-limited, and the actual yield are distinguished. The pollination determines the production over a plantation lifetime, incoming Photosynthetically Active Radiation (PAR), temperature, atmospheric CO2 concentration, planting material, planting density, canopy management, and harvesting. Water-limited yield can be less than one-third of the potential product with water deficits greater than 400 mm year-1 depending on other factors such as temperature, wind speed, soil texture, and soil depth. Nutrient-limited yields have been associated with a lack of nitrogen or potassium. Lastly, actual yield losses are affected by improper ground vegetation, pests, diseases, and worse in case of severe infestations (Woittiez et al., 2017).

Naturally, oil palms are cross-pollinated by EKs visiting both male and female flowers from 65-70 months onwards. Therefore, before this age and where EK is absent, assisted pollination has been given in plantations to improve production and enhance breeding materials normally performed by workers (Verheye, 2010; Vera et al., 1996; Li et al., 2019). Assisted pollination is performed based on a controlled application of pollens on female inflorescences at the anthesis stage. However, this practice is labor-intensive, costly, not applicable for large scale plantations, time-consuming, and short-term solution (Abrol and Shankar, 2012; Melendez and Ponce, 2016; Teo, 2015). Inflorescences identification is the most crucial part of assisted /artificial pollination operations. Hence, to identify the oil palm inflorescence pollination readiness, Wireless Sensor Network (WSN) system was tested using several sensors, including temperature (Kassim and Harun, 2015). During the plants' developmental stages, the temperature is one of the highly correlated factors across all plant species (Hatfield and Prueger, 2015). While for every plant's observable growth boundary, a rate of minimum and maximum temperatures has been defined. Oil palm reproductive developmental stages with reported thermogenic behavior will provide new features to simulate a pollination detection system. Specifically, various changes occur during the oil palm flowering period, such as fragrance release, temperature elevation, pollen dispersal, etc.

Also, an anise-like scent known as estragole is mainly produced attracts EK during the anthesis stage (Ervik et al., 1999). Oil palm female inflorescences pollination phenology stages changes can be associated with thermal changes (Combres et al., 2013). The temperature changes could be related to pollen dispersal through lowering atmospheric humidity and drying out of female inflorescences (Turner and Gillbanks, 1982). Also, oil palm inflorescences thermogenic behaviour (Knudsen et al., 2001) induces the volatilization of a strong floral scent (in this case, estragole) that attract natural pollinators (Ervik et al., 1999). Besides, the bracts covering the inflorescences start tearing when the flower bud begins to grow that could cause temperature and scent production. It’s evident from various outlooks that effective methods should be implemented to improve oil palm assisted pollination (Tuo et al., 2011). Therefore, thermal imaging technology can offer great potential to automate plant developmental stages identification. The variability of electromagnetic radiation in oil palms female inflorescences anthesis stages allows samples to be collected and analyzed. These radiations emitted from inflorescences are discernible by infrared thermal detectors at any temperature consists of a wide range of frequencies. Hence, infrared thermal imaging, applied to the quantitative analysis of pollination stages in oil palms, is a well-known secondary procedure for simplicity of operation, throughput, objectivity, and accuracy.

With the advancement of non-invasive imaging and computing technologies, it’s feasible to transform large data from plantations into sensible patterns and information. Artificial Intelligence (AI) has revolutionized a broad array of industries focusing on data at its core. Machine Learning (ML), as a subset of AI, provided highly versatile methods able to generate knowledge and outputs with higher speed and accuracy in agricultural engineering (Huang et al., 2010). Thus, the combination of a non-invasive imaging technique and AI need to be scrutinized to fulfil the intelligent pollination systems. The present research aims to determine oil palm female inflorescence pollination stages consisting of pre-anthesis (I, II, III) and the anthesis with the combination of ML algorithms and thermal imaging technologies. The infrared thermal imaging technique is a non-invasive, simple, and effective tool to obtain features from the targeted objects in controlled and infield environments. Remote sensing adaptation in agriculture and other domains led to the collection of significant volumes of data. The amount of the data is continuously increasing, and it’s beyond human ability to personally analyze, integrate and make the best-informed decisions. ML is an emerging technology that can help to find patterns and rules in any data type. Crop pollination growth and development prediction are considered an important research area in precision agriculture. Therefore, issues associated with current assisted pollination techniques such as field staff dependency, late decision-making, and pollination stages can be improved while eliminating the need for sensor nodes.

Yet with the explosion of remotely sensed data in many domains, discovering optimal solutions to explore the data for modelling approaches is becoming a challenge. Recognition of ML algorithms for the agricultural application provides working solutions quickly, specifically with data from outdoor environments. One of the main advantages of ML methods is their capability to perform pattern recognition from various datasets. Specifically, the classification techniques have been employed to make efficient, quick, and unified decisions to initiate immediate and appropriate actions among a large number of plants for many environmental and agricultural applications using a wide array of data (Kar, 2016). According to Lu and Weng (2007), the right choice of classification method affects the quality of results, not only the imagery appropriateness. In accordance, many classification algorithms have been proposed in the form of a decision tree or a set of rules to predict the target outputs from new feature samples (Cunningham and Holmes, 1999). These methods range from classical algorithms such as Random Forest (RF) (Liu et al., 2013), *k* Nearest Neighbor (*k*NN) (Guo et al., 2018), and Support Vector Machine (SVM), and Artificial Neural Network (ANN) (Rumpf et al., 2010).

Over the past decade, non-parametric classifiers (ML-based algorithms) increasingly being acknowledged for multi-source data classification. According to a study performed to evaluate the performance of 176 classifiers to solve real-world problems, the RF was selected as the best model (Fernandez-Delgado et al., 2014). The RF classifier represents a modern approach, which has proven to be a reliable method for crop yield and phenology predictions for its high accuracy, speed, and simple implementation process (Jeong et al., 2016). Several studies have adopted *k*NN to perform land and crop classification; however, finding the best value of k and high computational cost limited its application (Naidoo et al., 2012). The SVM classification method has been applied to identify the main agricultural system classes based on phenological metrics (Lebrini et al., 2019).

Similarly, both RF and SVM are insensitive to noise or over-fitting, which shows their ability in dealing with unbalanced data. Another popular method, ANNs capable of performing both classification and regression are increasingly applied in remote sensing applications. One of the main benefits offered by ANNs is that they can handle large amount of data currently being generated and perform more accurately on data with various statistical distribution (Atkinson and Tatnall, 1997). A precision pollination detection model is one of the recent potential techniques to make an efficient, quick, and unified decision from the available data if it exists. The comparison of accuracy statistics of several algorithms represented non-parametric classifiers RF, SVM, *k*NN, and ANN which can handle training data of various distributions favored among other models (Shao and Lunetta, 2012; Bargiel, 2017).

Using thermal imaging and modelling approaches, the presented study introduces a new approach to identify oil palm inflorescences pollination stages. The most established ML algorithms such as RF, *k*NN, SVM, and ANN are constructed and evaluated using three datasets (from three emissivity values) based on two feature sets: 1) endogenous and 2) endogenous in combination with exogenous features (meteorological parameters). The endogenous feature set comprise features extracted from the recorded thermal images such as (T_{max}, T_{min}, and T_{avg}). The exogenous features studied here are Relative Humidity (RH) and air temperature T_{air}. In addition to individual algorithms investigation, an ensemble method is applied to assess whether it can predict the stages better than single learners. The ensemble method utilizes combination (i.e., single learners) to attain a strong generalization ability rather than selecting the best single learner. It also reduces the computational variance and bias commonly related to single learners (Zhou, 2019). These methods are applied to predict the pollination stages in response to two feature sets.

This new approach ensures full implementation of certain features of oil palms' pollination phenology into a classification approach for future improvement of artificial pollination systems.

1.2 Motivation of Study

Ongoing worldwide population growth demands vegetable oils; oil palm produces much more oil per area than any other crops (Meijaard et al., 2018). But, in plantations, lower yield rates are reported with poor pollination and EKs decline (Woittiez et al., 2017). Consequently, this results in more significant land needs and deforestation. Such factors of reduced pollination and declining yields urge scientists and decision-makers to discover detailed information about the pollination phenology of oil palms in plantations. Thus, monitoring oil palm female inflorescences anthesis stages will enable researchers to improve and automate pollination detection systems. In this research, new possibilities to identify oil palm pollination readiness using modelling approaches are proposed to overcome the issues related to the current assisted pollination methods. For this purpose, infrared thermal imaging and ML technologies provide new insights into the autonomous identification of oil palm pollination phases. It also enables the planters to facilitate the inter-operation and decision-making process.

Assisted pollination in plantations requires a more significant number of workers to identify the anthesis stages and perform pollen transfer to every single inflorescence through manual works (Ruiz-Alvarez et al., 2021) that are not feasible on a large scale. Thus, a reliable and accurate stages identification system determines oil palm success towards efficient pollination. Thermal imaging and ML classification techniques have proven to be more accurate than traditional methods. The classification stochastic approaches process the obtained data and predict the probability of stages under different conditions.

This model can identify the patterns using random variables and make accurate predictions on future events (adaptable). Pollination is necessary to guarantee commercially usable palm oil; hence, new technologies should be adopted to overcome the challenges related to pollination stages identification complementing assisted and artificial pollination. The research is motivated to automate the identification process of pollination stages by developing a classification model with thermal images and meteorological features inputs.

While the pollination requirements of many crops appear to be small, but their impacts are enormous. Assisted pollination consists of the controlled application of pollen on female inflorescences in anthesis is necessary to guarantee the successful formation of FFB. The absence of natural pollinators (Kevan and Phillips, 2001) necessitates the employment of alternative artificial practices to boost oil palm yield (Melendez and Ponce, 2016). Nevertheless, assisted/artificial pollination and WSN systems (Kassim and Harun, 2015) have been adopted, their application requires two labour forces 1) to inspect and detect inflorescence anthesis stages and 2) to transfer the pollen. In addition, three times more workers are employed in artificial pollination than in assisted pollination due to the need to apply regulator Naphthaleneacetic Acid (NAA). Thus, these methods are inconsistent, labour intensive, time-consuming, expensive, and impractical (Abrol and Shankar, 2012).

Alternatively, WSN-based pollination prediction included temperature and humidity sensor nodes placed in bagged inflorescences and soil elements, is shown to be impractical considering large quantities of oil palms on an enormous scale of plantations. Deployment of WSN involves several challenges as follows: 1) the necessity to install a large number of sensor nodes on crops using workers makes it impractical, 2) sensor nodes are non-biodegradable and can cause destructive effects on the crops and the ecosystem, and 3) power requirement, cost per node, and required infrastructure prevents this method deployment in natural environment (Lloret et al., 2009). Therefore, it’s evident that oil palm pollination demands a knowledge-based automated solution to overcome the summarized challenges with the sophisticated and power-consuming WSN sensors.

1.3 Problem Statement

Human-assisted pollination methods in commercial plantations have been developed and are practiced despite their high economic costs due to increased labour requirements. With the increasing interest in this domain and emergence of new technologies, it’s important to study the specific features and data-based learning methods to predict oil palm female inflorescence pollination stages. Within this context the research questions addressed are:

1. How do the thermal imagery and meteorological features contribute to oil palm female inflorescences pollination stages identification?

2. How precisely does an optimal data-driven technique automate the pollination stages process?

Therefore, splitting the research questions elucidates the need for an efficient feature acquisition system that encounters the current manual inspection, sensor nodes need and provides efficient inputs to experiment data-based models. This thesis aimed to propose an automated mechanism to predict the oil palm female inflorescences pollination stages. It presents models designed using ML classification techniques that assist the decision making of planters and pollination workers. Further, various domain-specific thermal and meteorological features are evaluated to find the most contributing features and the best model. This study develops predictive algorithms such as RF, *k*NN, SVM, ANN, and ensemble. Then, the results of these models are validated by comparing the ensemble method against RF, *k*NN, SVM, and ANN. The algorithm's generalization performance is evaluated with two feature sets of thermal images (endogenous) from three selected emissivity values (0.96, 0.97, and 0.98) and in combination with meteorological features (exogenous). The performance evaluation metrics such as average accuracy, recall, precision, and F-measure are calculated to further verify the algorithms in classifying the present samples.

1.4 Research Objectives

The issues mentioned above lead this thesis to research the combination of non-destructive imaging and ML modelling technologies and processes that will help address the related problems. The first part of this research quantifies the relationship between oil palms pollination stages and thermal images. Then, evaluated and tested the performance of individual ML models whether a single model would outperform the rest. Finally, an ensemble method is constructed to examine if it can better predict the stages than the single models. The classification method is used to relate the quantified thermal features to pollination stages consists of pre-anthesis I, II, III, and anthesis. In addition, meteorological variables named exogenous features are utilized to improve the models' performance and provide more insights for pollination stage identification. It also compared the performance of three sets of thermal image features from emissivities of 0.96, 0.97, and 0.98, used on the same samples. As such, the performance of models is evaluated and compared through empirical and statistical methods. The project outcome aims to shift the current assisted/artificial pollination from an input-intensive to a knowledge-intensive industry. It also enhances monitoring using a non-invasive technique with a better detection power, eliminates the need for human manual intervention, and provides distinctive features. Hence, the number of objectives is summarized as below:

1. To evaluate selected emissivity and exogenous features to determine the best model's performance
2. To study the relationship between features obtained from thermal images in respect to pollination stages

1.5 Scopes of Study

Whilst the application of assisted/artificial pollination and WSN have been investigated in oil palm plantations where natural pollinators don't exist or are low in numbers, the identification of the pollination stages with non-destructive and automated solutions are not explored. This thesis aims to identify the oil palms female inflorescences four pollination stages using a combination of non-destructive thermal imaging and ML techniques.

The scope of this study is limited to a total number of 180 female inflorescences samples consisted of four stages (pre-anthesis I, II, III, and anthesis) from *Dura* x *Pisifera* (DxP) cultivar. After samples identification and tagging, thermal imagery was performed using a hand-held FLIR E60 camera. For any particular wavelength and temperature, the amount of thermal radiation emitted depends on the emissivity of the object's surface. Henceforth, for this specific study focusing on vegetation, the emissivity ranges between 0.96 to 0.98 are examined due to the restrictions to measure the inflorescences emissivity on trees (Messina and Modica, 2020). Therefore, three sets of thermal images were obtained with three emissivities on the same samples. This approach is taken to gain domain-specific features from the inflorescences at pollination stages and not detect the inflorescences' exact temperature.

Thermal images provide important thermal features of surface energy fluxes, which are integral to distinguish major phenological stages for potential agricultural automation. Hence, three sets of endogenous features were extracted from each collection of thermal images with three different emissivities and built the related datasets. Predominately, thermal features are used to quantify and identify the different pollination stages. In addition, other exogenous features (meteorological variables) are used to improve the models' performance and provide more insights into pollination identification in the field environment. This research focuses on discovering new features and methods to predict the pollination stages of oil palms.

Five ML methods, namely RF, *k*NN, SVM, ANN, and ensemble, were applied and evaluated to achieve stages identification automation. These models can be used to the same dataset, and each method makes specific assumptions about an underlying model and tries to learn within that framework. The ensemble method is proven to improve pattern recognition and finding better fits within that model.

The models' performance was evaluated empirically and statistically using a set of quantitative metrics (overall accuracy, precision, recall, and F-measure). Ultimately, the method with high generalization performance and feature selection capability can be used to automate the pollination stages detection process and demonstrate the features' effectiveness. The developed model will then be utilized to design assisted/artificial pollination systems for future plantations.

Proven that oil palm pollination is in danger, there is a pressing need for more data about its reproductive stages to enable a data-based automated pollination system. With further refinement in analytical techniques and models, thermal data from thermal imaging techniques could be beneficial for parameterizing oil palm pollination stages and developing better artificial pollination systems.

1.6 Research Contribution

The study contributions are outlined as follows:

- ML models provided an essential contribution for efficient oil palm pollination stages identification with reasonable accuracy. In the absence of a comprehensive set of empirical tests to determine a single best learning algorithm to apply on a collected dataset, we find it most effective to use several modelling schemes.

- Collecting and creating site-specific datasets for pollination stages classification. Since this is, to the best of our knowledge, the first work that attempts to solve the most critical problems in oil palm artificial/assisted pollination using ML and thermal imaging techniques, the pollination stages identification model and the dataset will be used as a baseline for future research.

- Evaluating the effectiveness of designed models with thermal features (endogenous) and meteorological (exogenous) feature sets about the four main pollination stages

- Integration of thermal imaging and modeling can potentially enable artificial pollination management, improving the monitoring of a large number of palms in plantations by only scanning and algorithm-based prediction compared to manual monitoring using human sources and sensors in WSNs

- Thermal imaging allows fast monitoring of oil palm pollination status, with the potential of cost-effective and non-invasive data acquisition technique replacing sensor nodes in WSN

- Ensemble method applied to endogenous features individually and in combination with exogenous are capable of developing a method for the evaluation of oil palms pollination stages

1.7 Organization of the Thesis

This thesis is included five chapters. The first chapter is Introduction, and the following chapters are organized as follows:

Chapter 2 provides background knowledge of oil palm pollination effectiveness with natural pollinators and conventional methods of assisted pollination in oil palm plantations. Moreover, the application of thermal imaging techniques and the principles of the ML algorithms for agricultural tasks are reviewed and justified.

Chapter 3 illustrates the methodology of the sample's selection, data collection and the model design and implementation procedure. The models' principles and methods are elaborated in this chapter. Lastly, the evaluation metrics used to evaluate the models' prediction performance are elaborated.

Chapter 4 discusses the models' prediction results from three datasets consist of the thermal images features (endogenous) individually and in combination with meteorological features (exogenous). Further, the performance metrics such as average accuracy, recall, precision, and F-measure are calculated and used to validate the algorithms' performance in classifying the present datasets. Simultaneously, the designed model prediction performance is analyzed empirically and statistically.

Chapter 5 covers the conclusion of the presented research and points out some gaps and issues which can be investigated in future studies.

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