



UNIVERSITI PUTRA MALAYSIA

***OIL PALM MATURITY CLASSIFIER USING SPECTROMETER AND
MACHINE LEARNING***

GOH JIA QUAN

FK 2022 11



**OIL PALM MATURITY CLASSIFIER USING SPECTROMETER AND
MACHINE LEARNING**

By

GOH JIA QUAN

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

November 2021

All material contained within the thesis, including without limitation text, logos, icons, photographs and all other artwork, is copyright material of Universiti Putra Malaysia unless otherwise stated. Use may be made of any material contained within the thesis for non-commercial purposes from the copyright holder. Commercial use of material may only be made with the express, prior, written permission of Universiti Putra Malaysia.

Copyright © Universiti Putra Malaysia



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in
fulfilment of the requirement for the degree of Master of Science

OIL PALM MATURITY CLASSIFIER USING SPECTROMETER AND MACHINE LEARNING

By

GOH JIA QUAN

November 2021

**Chair : Prof. Sr. Gs. Abdul Rashid Bin Mohamed Shariff C. Eng,
PhD**
Faculty : Engineering

The quality of palm oil depends on fresh fruit bunch (FFB) ripeness level. Ripe bunch has higher oil quantity compared to unripe bunch. It also has less free fatty acid (FFA) compared to overripe bunch which reduces the quality of palm oil to become poor. Therefore, classification and grading of FFB into correct categories and process them separately is an important step to avoid loss in quality of the extracted palm oil. Traditionally, the grading of FFB bunches is performed by well-trained graders according to different parameters such as mesocarp color, number of loose fruits on the ground and number of empty sockets on the bunches. This method depends heavily on human eyes which can be subjective and lead to different outcomes of grading between graders. Thus, non-destructive method is another option for tasks of FFB ripeness level classification. In this research, a spectrometer with a wavelength range of 180 to 1100 nm was applied to collect the reflectance data of FFB from unripe, ripe, and overripe classes. The three objectives in this study are (1) to determine the most suitable part of FFB for classifying oil palm ripeness level, (2) to identify the ideal vegetation index as prediction model for FFB classification and (3) To assess the classification accuracies and validate the selected prediction model. Each bunch was scanned at its different parts including apical, front equatorial, front basil, back equatorial and back basil. The reflectance data from these five parts was analyzed using statistical method and machine learning algorithm. Front equatorial was found to have significant difference between the three classes of ripeness, and an overall 92.7% of accuracy in differentiating between the maturity classes. Next, specific bands were extracted to compute vegetation indices for prediction model. Normalized Difference Vegetation Index (NDVI) is selected as the best prediction model with 93.8% classification accuracy. The accuracy assessment showed that NDVI has precision of 0.938, recall of 0.939

and F1-Score of 0.937. This shows a promising result of the NDVI as vegetation index to classify FFB ripeness level. The trained NDVI model was exported as prediction model that can assist in predicting ripeness level of FFB which can be applied by researcher and graders from the industry. The model was validated by predicting ripeness level for another FFB reflectance dataset. The prediction was able to produce 100% accuracies by using Linear and Weighted KNN as classification testing algorithm. An application was built by using the NDVI prediction model. It allows users to enter red and NIR reflectance values of FFB for the prediction of FFB ripeness level. Furthermore, the average accuracies of each classifier were compared. Fine KNN had the highest average accuracy of 68.6% whereas Coarse KNN had the lowest average accuracies of 36.0%. These findings provide valuable information to future researchers in this field to develop automatic oil palm FFB classifier.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Master Sains

KLASIFIER KEMATANGAN KELAPA SAWIT MENGGUNAKAN SPEKTROMETER DAN PEMBELAJARAN MESIN

Oleh

GOH JIA QUAN

November 2021

**Pengerusi : Prof. Sr. Gs. Abdul Rashid Bin Mohamed Shariff C. Eng,
PhD**
Fakulti : Kejuruteraan

Kualiti minyak sawit bergantung pada tahap kematangan buah segar (FFB). Tandan masak mempunyai kuantiti minyak yang lebih tinggi berbanding dengan tandan yang belum masak. Ia juga mempunyai kurang free fatty acid (FFA) dibandingkan dengan tandan yang terlalu banyak yang mengurangkan kualiti minyak sawit menjadi kurang. Oleh itu, pengelasan dan penggredan FFB menjadi kategori yang betul dan memprosesnya secara berasingan adalah langkah penting. Secara tradisinya, penggredan tandan FFB dilakukan oleh pekerja yang terlatih mengikut parameter yang berbeza seperti warna mesocarp, jumlah buah yang jatuh di tanah dan jumlah soket kosong pada tandan. Kaedah ini sangat bergantung pada mata manusia yang boleh menjadi subjektif dan membawa kepada hasil penilaian yang berbeza antara kelas. Oleh itu, kaedah tidak merosakkan adalah pilihan lain untuk tugas pengelasan tahap kematangan FFB. Dalam penyelidikan ini, spektrometer dengan jarak 180 hingga 1100 nm digunakan untuk mengumpulkan pantulan FFB dari kelas belum masak, matang, dan terlalu masak. Tiga objektif dalam kajian ini ialah (1) untuk menentukan bahagian FFB yang paling sesuai untuk mengklasifikasikan tahap kematangan kelapa sawit, (2) untuk mengenal pasti indeks tumbuh-tumbuhan yang ideal sebagai model ramalan untuk pengelasan FFB dan (3) Untuk menilai ketepatan klasifikasi dan mengesahkan model ramalan yang dipilih. Setiap kumpulan diimbas pada bahagian yang berlainan termasuk apikal, khatulistiwa depan, basil depan, khatulistiwa belakang dan basil belakang. Data pantulan dari lima bahagian ini dianalisis menggunakan kaedah statistik dan algoritma pembelajaran mesin. Khatulistiwa depan (front equatorial) didapati mempunyai perbezaan yang signifikan antara ketiga kelas kematangan, dan keseluruhan ketepatan 92.7% dalam membezakan antara kelas kematangan. Seterusnya, jalur tertentu diekstrak untuk menghitung vegetation index untuk model ramalan. Normalized Difference Vegetation Index (NDVI) dipilih sebagai model ramalan terbaik dengan ketepatan klasifikasi 93.8%. Penilaian ketepatan menunjukkan

NDVI mempunyai precision 0.938, recall 0.939 dan F1-Score 0.937. Ini menunjukkan hasil yang menjanjikan dari NDVI sebagai indeks vegetasi untuk mengklasifikasikan tahap kematangan FFB. Model NDVI yang terlatih dieksport sebagai model ramalan yang dapat membantu dalam meramalkan tahap kematangan FFB yang dapat diterapkan oleh penyelidik dan graduan dari industri. Model ini disahkan dengan meramalkan tahap kematangan untuk set data pantulan FFB yang lain. Ramalan tersebut dapat menghasilkan 100% ketepatan dengan menggunakan Linear dan Weighted KNN sebagai algoritma pengujian klasifikasi. Aplikasi dibina dengan menggunakan model ramalan NDVI. Ia membolehkan pengguna memasukkan nilai pantulan merah dan NIR FFB untuk ramalan tahap kematangan FFB. Selanjutnya, ketepatan purata setiap pengelasan dibandingkan. Fine KNN mempunyai ketepatan purata tertinggi 68.6% sedangkan Coarse KNN mempunyai ketepatan purata terendah 36.0%. Penemuan ini memberikan maklumat yang berharga kepada penyelidik masa depan dalam bidang ini untuk mengembangkan pengelasan FFB kelapa sawit automatik.

ACKNOWLEDGEMENTS

I would like to thank my supervisor, Professor Dr. Abdul Rashid, who accepted me as his master student and giving me the opportunity to further my study in the agricultural engineering field. His kindness and insightful opinion always push me to work joyful and think outside of the boxes to improve my research performance. Many thank also to Prof Rashid for encouraging me to participate in many workshops and international conferences to add more valuable experience to my life and also my resume.

I would also like to thank my co-supervisor, Associate Professor Dr. Nazmi for agreeing to be a member of my supervisory committee. I was given valuable advices during every progress presentation. My papers were also read carefully and commented by him in a detailed way. His opinion provided me the right direction to correct my mistakes.

In addition, I would like to express my gratitude to the staff from Hakuto Singapore Pte. Ltd., Mr Kelvin Tee, Mr. Gregory Quek and Mr. Chong Swee Yean from Hakuto Malaysia Sdn. Bhd. for providing me the SE Series Spectrometer for my data collection. Also thanks to them for guiding me how to use the spectrometer correctly during operating the device.

Also thank you Mr. Ahmad Syazmin from East Oil Mill, Sime Darby Sdn. Bhd. for allowing me to visit several times to the mill to collect data. The staffs at the mill also gave warm welcome and helped me a lot during my experiment there.

Besides, I would particularly like to appreciate my friends, Mr. Thum Guan Wei and Ms. Tee Say Jin for accompanying me to visit the oil palm mill during the data collection. Their selfless acts really helped me to finish my field work efficiently. Without their helps, I would not have the ability to complete this study.

Furthermore, I would like to thank my parents and family members for their wise counsel and encouragement. There are always there to support me for every big decision in my life. They also support me from financial so that I can focus fully on my study.

Last but not least, I would like to thank all my favorite singers, musician and artists that make wonderful music. These music help me to gain courage and

fight boredom. Although they do not know me, I am grateful to have such wonderful people and music that pushed me all the way for the past three years.



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

Abdul Rashid bin Mohamed Shariff, PhD

Professor. Sr. Gs. Dr. C.Eng
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Nazmi bin Mat Nawi, PhD

Associate Professor.
Faculty of Engineering
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD

Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 14 April 2022

Declaration by graduate student

I hereby confirm that:

- this thesis is my original work;
- quotations, illustrations and citations have been duly referenced;
- this thesis has not been submitted previously or concurrently for any other degree at any other institutions;
- intellectual property from the thesis and copyright of thesis are fully-owned by Universiti Putra Malaysia, as according to the Universiti Putra Malaysia (Research) Rules 2012;
- written permission must be obtained from supervisor and the office of Deputy Vice-Chancellor (Research and Innovation) before thesis is published (in the form of written, printed or in electronic form) including books, journals, modules, proceedings, popular writings, seminar papers, manuscripts, posters, reports, lecture notes, learning modules or any other materials as stated in the Universiti Putra Malaysia (Research) Rules 2012;
- there is no plagiarism or data falsification/fabrication in the thesis, and scholarly integrity is upheld as according to the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) and the Universiti Putra Malaysia (Research) Rules 2012. The thesis has undergone plagiarism detection software.

Signature: _____ Date: _____

Name and Matric No.: _____

Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

Signature: _____

Name of Chairman
of Supervisory
Committee: _____

Signature: _____

Name of Member of
Supervisory
Committee: _____

TABLE OF CONTENTS

	Page
ABSTRACT	i
ABSTRAK	iii
ACKNOWLEDGEMENTS	v
APPROVAL	vii
DECLARATION	ix
LIST OF TABLES	xiv
LIST OF FIGURES	xvi
LIST OF ABBREVIATIONS	xix
CHAPTER	
1 INTRODUCTION	1
1.1 General introduction to oil palm industry in Malaysia	1
1.2 Research motivation and problem statement	4
1.3 Research Objectives	5
1.4 Scope of the research	5
1.5 Hypothesis and research gap	6
2 LITERATURE REVIEW	6
2.1 Introduction	7
2.3 Agronomy of oil palm	8
2.4 Oil Palm production in Malaysia	9
2.5 Ripeness classification of fruit ripeness level using wavelength reflectance data	11
2.6 Oil Palm Ripeness Grading Research	12
2.7 Machine learning	27
2.7.1 Support Vector Machine	27
2.7.2 K nearest neighbors	29
2.7.3 Discriminant Analysis	31
2.7.4 Review of LDA, SVM and KNN	32
2.7.5 Limitations of machine learning	34
2.8 Statistical Analysis	34
2.8.1 Boxplot	35
2.8.2 Principal component analysis	36
2.8.3 Levene's Test	37
2.8.4 ANOVA Test	38
2.9 Statistical analysis and machine learning software	38
2.10 Summary	39
3 METHODOLOGY	40
3.1 Introduction	40
3.2 Study area	40
3.3 Research Workflow	41
3.4 Data collection and experimental setup	42
3.5 Data preprocessing	44
3.6 Data analysis	45

3.6.1	Preliminary testing	45
3.6.2	Classifications	46
3.6.3	Vegetation Indices	47
3.7	Assessment of analysis	50
3.7.1	Receiver operating characteristic curve and area under the curve	51
3.7.2	Kappa coefficient	52
3.7.3	Precision, recall and F1-Score	53
4	RESULTS AND DISCUSSION	54
4.1	Introduction	54
4.2	Principal Components Analysis	54
4.3	Boxplots	55
4.4	Test of homogeneity	56
4.5	Means comparisons of ripeness level	58
4.6	Classifications	66
4.6.1	Front equatorial	66
4.6.2	Front basil	67
4.6.3	Back equatorial	68
4.6.4	Back basil	69
4.6.5	Apical	70
4.6.6	PCA comparisons	72
4.7	Prediction Models	72
4.8	Validation of the prediction model	77
4.9	Assessment	78
4.9.1	ROC and AUC	78
4.9.2	Confusion matrix	80
4.9.3	Kappa coefficient	85
4.9.4	Precision and recall	86
4.10	Comparison between classifiers	87
4.11	Application for harvesting decision	90
4.12	Comparison with manual grading method	92
4.13	Summary	92
5	CONCLUSION AND RECOMMENDATIONS	94
5.1	Conclusion	94
5.2	Recommendations for future work	95
	REFERENCES	97
	APPENDICES	105
	BIODATA OF STUDENT	120
	PUBLICATION	121

LIST OF TABLES

Table		Page
1.1	Grading standard of oil palm fresh fruit bunch (Murad, 1995)	3
2.1	CPO production in Malaysia	10
2.2	Reflectance percentage and intensity range	12
2.3	OPRiD sensors	14
2.4	OPRiD LED modules	14
2.5	Summary of oil palm ripeness classification	24
2.6	SVM with different kernels	29
2.7	KNN with different distance metric or number of neighbors	31
3.1	SE Series Spectrometer specifications	44
4.1	PCA results	55
4.2	Amount of samples in PC after removal of outliers	55
4.3	Levene's test for front equatorial	56
4.4	Levene's test for front basil	57
4.5	Levene's test for back equatorial	57
4.6	Levene's test for back basil	57
4.7	Levene's test for apical	57
4.8	Welch test for front equatorial	58
4.9	Games-Howell test for front equatorial	58
4.10	ANOVA test for front basil	59
4.11	ANOVA test for back equatorial	60
4.12	Tukey HSD test for back equatorial	61
4.13	ANOVA test for back basil	62

4.14	Tukey HSD test for back basil	63
4.15	ANOVA test for apical	64
4.16	Tukey HSD test for apical	65
4.17	Classification accuracies of front equatorial	67
4.18	Classification accuracies of front basil	68
4.19	Classification accuracies of back equatorial	69
4.20	Classification accuracies of back basil	70
4.21	Classification accuracies of apical	71
4.22	Top three accuracies of each part of FFB	71
4.23	PC classification results	72
4.24	Vegetation indices (chlorophyll-based) models accuracies	73
4.25	Vegetation indices (based on carotenoids) models' accuracies	75
4.26	Classification accuracy for predicted NDVI	77
4.27	Front equatorial's AUC	79
4.28	NDVI AUC	79
4.29	Kappa coefficient	85
4.30	Precision	86
4.31	Recall	87
4.32	F1-Score	87

LIST OF FIGURES

Figure		Page
1.1	dirty bunch and rotten bunch	6
2.1	Electromagnetic spectrum	7
2.2	concealed and non-concealed part of FFB	9
2.3	Malaysia Palm Oil Exports by Year (Source: United States Department of Agriculture)	10
2.4	Main interface of grading system	13
2.5	Fuzzy rule examples	18
2.6	Spectral reflectance of virescens type FFB. A chlorophyll absorption hole was found around 650nm.	19
2.7	Experimental setup of fruit battery	21
2.8	Schematic diagram of fruit battery circuit with charging concept	21
2.9	Charging terminals	22
2.10	A typical machine learning approach	27
2.11	A decision boundary or hyperplane is used to classify two different groups	28
2.12	A simple example of k-nearest neighbors' classification	31
2.13	Difference between PCA and LDA	32
2.14	A boxplot with all elements labeled	35
2.15	Example of boxplot with outliers	36
3.1	Study area location	40
3.2	Research workflow	41
3.3	Division of FFB into basil, equatorial and apical. Kasim et al. (2014)	42
3.4	Division of FFB into front and back side. Hafiz et al. (2011)	42

3.5	Experimental setup	43
3.6	SpectraSmart software interface	44
3.7	Confusion matrix example	51
4.1	Front equatorial	56
4.2	Scatter plot of NDVI model trained by Weighted KNN. (Blue dots represent unripe, red dots represent ripe, yellow dots represent overripe)	74
4.3	Scatter plot of NDVI model trained by Fine KNN. (Blue dots represent unripe, red dots represent ripe, yellow dots represent overripe)	76
4.4	Scatter plot of CRI 550 model trained by Weighted KNN. (Blue dots represent unripe, red dots represent ripe, yellow dots represent overripe)	76
4.5	Confusion matrix of evaluated model using Fine KNN	78
4.6	ROC of front equatorial with all bands as inputs	79
4.7	ROC of front equatorial with UV region as input	79
4.8	Confusion matrix with PC as input	80
4.9	Confusion matrix with all band as input	81
4.10	Confusion matrix with UV bands as input	81
4.11	Confusion matrix with blue bands as input	82
4.12	Confusion matrix with green bands as input	83
4.13	Confusion matrix with red bands as input	83
4.14	Confusion matrix with NIR bands as input	84
4.15	Confusion matrix with NDVI as input	85
4.16	The average classification accuracies of FFB ripeness levels using different classifiers	89
4.17	Component library in MATLAB apps designer	90
4.18	Application for ripeness level prediction and decision making for harvesting	91
4.19	Examples of the outcomes produced by the application	92

8.1	Front basil PC 1	105
8.2	Front basil PC 2	105
8.3	Front basil PC 3	106
8.4	Front basil PC 4	106
8.5	Front basil PC 5	106
8.6	Back equatorial PC 1	107
8.7	Back equatorial PC 2	107
8.8	Back equatorial PC 3	107
8.9	Back equatorial PC 4	108
8.10	Back equatorial PC 5	108
8.11	Back basil PC 1	108
8.12	Back basil PC 2	109
8.13	Back basil PC 3	109
8.14	Back basil PC 4	109
8.15	Back basil PC 5	110
8.16	Apical PC 1	110
8.17	Apical PC 2	111
8.18	Apical PC 3	111
8.19	Apical PC 4	112
8.20	Apical PC 5	112

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ANOVA	Analysis Of Variance
AUC	Area Under The Curve
CARI	Carotenoid Index
CPO	Crude Palm Oil
CRI	Carotenoid Reflectance Index
FFA	Free Fatty Acid
FFB	Fresh Fruit Bunch
FN	False Negative
FP	False Positive
CAR _{green}	Green Carotenoid Index
GDP	Gross Domestic Product
HSI	Hue, Saturation and Intensity
IPVI	Infrared Percentage Vegetation Index
IR	Infrared
KNN	K-Nearest Neighbors
LAI	Leaf Area Index
LDA	Linear Discriminant Analysis

ML	Machine Learning
MLC	Maximum Likelihood Classifier
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MTVI1	Modified Triangular Vegetation Index 1
NDM	Non-Destructive Methods
NDVI	Normalized Difference Vegetation Index
NGRDI	Normalized Green Red Difference Index
NIR	Near Infrared
NLI	Non-Linear Index
NPCI	Normalized Pigment Chlorophyll Index
PC	Principal Components
PCA	Principal Component Analysis
PLS	Partial Least Squares
PRI	Photochemical Reflectance Index
QDA	Quadratic Discriminant Analysis
RBF	Radial Basis Function
RGB	Red, Green, Blue
ROC	Receiver Operating Characteristic
CAR _{red edge}	Red Edge Carotenoid Index

RVI	Ratio Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
SVM	Support Vector Machine
TCARI	Transformed Chlorophyll Absorption Reflectance Index
TN	True Negative
TP	True Positive
UV	Ultraviolet
VI	Vegetation Indices

CHAPTER 1

INTRODUCTION

1.1 General Introduction to Oil Palm Industry in Malaysia

Agriculture and agro-based industry have been the foundation of the Malaysian economy. Although this industry had been the “sunset industry” since former Prime Minister, Tun Dr. Mahathir Mohammed decided that Malaysia developed towards an industrialized country in early 1980’s; agriculture continues to have a significant role in the national economy. The successor of Tun. Dr. Mahathir, Tun Abdullah Badawi prioritised agricultural development, relying mostly on domestic food production to offset imports. (Bakar, 2009). In 2019, the agricultural sector provided RM89.5 million to the total Malaysian Gross Domestic Product (GDP), and the oil palm sector alone accounted for 37.9% of the agricultural GDP (DOSM, 2020). Malaysian exports of oil palm products totaled 27.86 million tonnes in 2019, up 12.0% from the previous year's figure of 24.88 million tonnes.

Oil palm tree (*Elaeis guineensis jacq.*) comes from West Africa and was brought to Malaya by the British in the early 1870’s. During the early period, it was planted as an ornamental plant. Nicholas Joseph Jacquin, who identified *Elaeis guineensis*, also known as African oil palm, in 1763, formally brought the genus *Elaeis* of the monocotyledonous palm family *Arecaceae* into botanical classification (Corley and Tinker, 2003).

Later, this crop was introduced into commercial planting and became foundation of palm oil industry in Malaysia. Oil palm output exploded in the early 1960s as part of the agriculture expansion policy of the government, which aimed to diminish the country's reliance on rubber and tin for economic survival (MPOC, n.d). Ever since, the oil palm business has evolved into one of the country's most vital sources of revenue. Oil palm is a blessing to thousands of people in tropical rural areas, providing much-needed money to fast developing countries. (Sayer et.al., 2012).

Being the most productive oil crop, oil palm can meet the world's vast and expanding need for vegetable oils, which is predicted to reach 240 million tonnes by 2050. Oil palm trees produce three to eight times more oil than other oil crop (Barcelos et al., 2015). Fresh palm fruits are collected and crushed separately to obtain the oil from the kernel and the fruit flesh. The oil from the kernel is mostly

utilised in soap, industrial applications, and processed foods, whereas the oil from the fruit is used in food preparation. (Meijaard et. al., 2018).

After 30 months of field planting, the oil palm tree will begin bearing fruits and will remain productive for the next 20 to 30 years, assuring a steady supply of oils. Each ripe bunch is commonly known as Fresh Fruit Bunch (FFB) (MPOC, n.d). There are several research that proved the maturity level of FFB has a high influence on the oil quality. Mohanaraj et. al. (2016) stated that oil content in each fruitlet is maximized during the ripening process. The abscission process then kicks off, forcing them to separate from the bunch. However, as the level of free fatty acids (FFA) in the oil rises, the quality of the oil begins to decrease in the abscised fruit. (Mohanara et. al., 2016). The amount of FFA in the soil effects the price and quality of crude palm oil (CPO) produced, as well as the manner of production, storage, and marketing of CPO. (Azeman et. al., 2015).

The commercial worth of FFBs is determined by the appearance of the bunch as well as the quantity and quality of oil extracted from it. Ripe bunches are preferred because they contain more oil than unripe ones and have lower FFA than overripe bunches. (Makky et. al., 2014). Therefore, FFBs ripeness grading is an important task in a mill to ensure the extracted oil fulfill the standard. Traditionally, this task is done by human graders according to color and number of empty sockets on the bunch. Malaysia Palm Oil Board had set a standard to guide the graders to classify FFBs into different classes. Table 1.1 gives description of FFB classification.

Throughout the years, different researchers from the world have developed different approaches to assess fruit maturity level. Some have been utilised for on-tree fruit quality inspection, while others are better suited for laboratory uses. These included destructive test method and non-destructive method. Chauhan et. al. (2017) stated that non-destructive methods (NDM) are more effective than conventional method since they are based on physical features that correspond well with certain crop quality parameters. (Chauhan et al., 2017). Besides, NDM do not rupture the fruit tissue, can be used to assess internal variable of fruits. These included applications of LiDAR scanning (Zuhaira et al., 2018), optical-based sensors (Utom et al., 2018), computer and camera vision system (Makky, 2016), laser-based imaging system (Shiddiq et al.,2017), handheld optical spectrometer (Dayaf, 2017), LED optical sensor (Setiawan et al., 2019), thermal imaging technique (Zolfagharnassab et al., 2017) and resonant frequency technique (Mison et al., 2017).

Table 1.1: Grading standard of oil palm fresh fruit bunch (Murad, 1995)

Bunch Classifications	Description
Ripe	reddish orange color fruits, at the time of examination at the mill, the fruit had at least 10 sockets of detached fruitlets and more than fifty percent (50%) of the fruit was still connected to the bunch
Underripe	reddish orange color fruits and has at least 10 sockets of detached fruitlets at the time of inspection at the mill.
Unripe	purplish black color fruits and without any socket of detached fruitlets at the time of inspection at the mill.
Overripe	darkish red color fruits and has more than fifty percent (50%) of detached fruitlets but with at least ten percent (10%) of the fruits still attached to the bunch at the time of inspection at the mill.
Empty	Bunch which has more than ninety percent (90%) of detached fruitlets at the time of inspection at the mill.
Rotten	Bunch partly or wholly, including its loose fruits, has turned blackish in color, rotten and mouldy.
Long stalk	Bunch which has s stalk of more than 5cm in length (measured from the lowest level of the bunch stalk).
Unfresh/ Old	Bunch which has been harvested and left in the field for more than 48 hours before being sent to the mill. The whole fruit or part of it together with its stalk has dried out. Normally, this type of bunch is dry and blackish in color.
Dirty	Bunch with more than half of its surface covered with mud, sand, other dirt particles and mixed with stone or foreign matter.
Small	Bunch which has small fruits and weighs less than 2.3kg.
Pest damaged	Bunch with more than thirty percent (30%) of its fruits damaged by pest attack such as rat etc.
Diseased	Bunch which has more than fifty percent (50%) parthenocarpic fruits and is not normal in terms of its size of its density.
Dura	Shell thickness 2-8mm, Ratio of shell to fruit 25-50%, Ratio of mesocarp to fruit 20-60%, Ratio of kernel to fruit 4-20%,
Loose fruit	Fruit detached from a fresh bunch because of ripeness and reddish orange in color.
Wet	Consignment of FFB which has excessive free water.

1.2 Research motivation and problem statement

The FFB fruit starts to ripe from outer and top of the bunch. However, the word 'ripe' is subjective, and can be interpreted from the view of oil content, changes in the color of the surface and number of loose fruits. Only the color changes and number of loose fruits can be observed before harvest. The color change is not sensitive sufficiently. In fact, the oil formation and fruit abscission processes are quite separate processes (Corley, 2005). Junkwon et al. (2009) and Hafiz et al. (2011) also investigated the color properties of different part of FFB. Makky and Soni (2013) stated that the color of the fruitlets on a FFB is not uniform within the whole bunch. However, these previous researches did not quantify the differences between front and back of FFB, which is front equatorial, front basil, back equatorial, back basil and apical. In our present study, these five parts will be studied, compared and classified to identify the most suitable part for ripeness level identification.

Traditional methods to grade FFBs are conducted through manually. Trained graders will inspect the quality and ripeness of FFBs. However, this method is subjective and inaccurate. Even for a skilled grader, manually classifying oil palm FFB into ripeness categories is a tough and time-consuming operation. Furthermore, human perceptions of color are frequently erratic, influenced by physical and psychological factors (Makky, 2016). The low grade of oil extraction is due to overripe and unripe FFB at the mills. Because of these flaws, optimal crude oil production is impossible; as a result, some operating expenditures become a loss and burden for manufacturers (Kassim et al., 2014). Saeed et al. (2011) proposed few vegetation indices for classification of FFB ripeness level. They proved that VI can produce high accuracies. However, this method was not tested in a prediction process. Therefore, we proposed some vegetation indices to act as the prediction models.

ML is an interesting technique that can discover hidden patterns and information lies within the huge amount of dataset. It can be used to classify and predict the categories of data. However, high accuracy of classification does not ensure the model can serve as a good prediction model. The model needs to be validated with the ground truth data to check for its ability in predicting the classes of them. In the third objective, we will validate the selected prediction model from the second objective outcome. Lastly, we will carry out classification accuracies assessment by using precision, recall and F1-score.

Another problem focus on is that NDM to assess the FFBs ripeness appear to require further laboratory analysis of collected data to achieve the objective of grading ripeness level of FFBs. This will increase the time-cost in the grading process. Therefore, a fast and accurate method to classify FFBs ripeness is needed.

1.3 Research Objectives

There are several specific objectives in this study which are:

1. To determine the most suitable part of FFB for classifying oil palm ripeness level.
2. To identify the ideal vegetation index as prediction model for FFB classification.
3. To assess the classification accuracies and validate the selected prediction model.

1.4 Scope of the research

This research explores the use of different bands across the light spectrum to investigate the ability of each band to classify FFBs into unripe, ripe and overripe. These three categories are critical, as there is a pressing need to avoid the harvesting of unripe fruits to avoid low oil yield. The other categories graded by MPOB were not studied in this research as they are easily identified by human eyes. For example, Figure 1.1 showed the images of dirty bunch and rotten bunch. Dirty bunch was covered by sand and mud whereas rotten bunch showed rotten fruitlets that were attached by pest especially mouse. The graders at the mill can easily eliminate these bunches from the process line. Meanwhile, as mentioned in the problem statement, unripe, ripe and overripe bunches cannot be easily differentiated from each other by using human eyes. Hence, we focused on them. The images of the other categories that were not studied were attached in the Appendix section for reference.

An optical spectrometer is presented as a device to collect reflectance of FFBs from 180nm to 1100nm. FFBs from three classes of maturity level were scanned using spectrometer. Different vegetation indices were applied by selecting specific features from the reflectance of FFBs to create a secondary parameter to test whether VI can improve the accuracy of FFB ripeness classification and used as a prediction model for ripeness levels. Machine learning algorithms were applied for the classification accuracy testing.

This scope is relevant to our main research topic and objectives where we investigate the applicability of digital agriculture to the oil palm industry. We are trying to combine the effectiveness of NDM and ML to provide an accurate prediction method to the industry.



Figure 1.1: dirty bunch and rotten bunch

1.5 Hypothesis and research gap

Reflectance of different bands is a popular technique in the study of FFB ripeness level classification. However, FFB is large in size and its growth condition on the tree leads to different exposure of sunlight to each part of it. Some parts faced the tree and even covered by leaves. The other part faced towards the sunlight and obtained different amount of sunlight for photosynthesis. This situation caused the different parts of FFB to have different colors. Previous research may have focused on comparison between parts that were covered by leaves and not covered by leaves. In this research, the research gap is further filled by dividing FFB into five different parts which were apical, front equatorial, front basil, back equatorial and back basil for analysis. Each of them from every FFB were scanned and compared to discover the best part of FFB for ripeness classification. We assumed that the front parts that faced towards the sunlight are more accurate than the back parts of FFB.

REFERENCES

- Alfatni, M. S. M., Shariff, A. R. M., Abdullah, M. Z., Marhaban, M. H., Shafie, S. B., Bamiruddin, M. D., & Saaed, O. M. B. (2014, June). Oil palm fresh fruit bunch ripeness classification based on rule-based expert system of ROI image processing technique results. In IOP Conference Series: Earth and Environmental Science (Vol. 20, No. 1, p. 012018). IOP Publishing.
- Alfatni, M. S. M., Shariff, A. R. M., Saaed, O. M. B., Albhah, A. M., & Mustapha, A. (2020, July). Colour feature extraction techniques for real time system of oil palm fresh fruit bunch maturity grading. In IOP Conference Series: Earth and Environmental Science (Vol. 540, No. 1, p. 012092). IOP Publishing.
- Alhadi, D, A. A. H. Ben. (2017). Oil Palm Fresh Fruit Bunches Maturity Classification and Oil Analysis Correlation. (Doctoral dissertation thesis). Universiti Putra Malaysia, Selangor, Malaysia.
- Ali, A., Alrubei, M., Hassan, L. F. M., Al-Ja'afari, M., & Abdulwahed, S. (2019). Diabetes classification based on KNN. IIUM Engineering Journal, 21(1), 175–181. <https://doi.org/10.31436/iiumej.v21i1.1206>
- Ali, M. M., Hashim, N., & Hamid, A. S. A. (2020). Combination of laser-light backscattering imaging and computer vision for rapid determination of oil palm fresh fruit bunches maturity. Computers and Electronics in Agriculture, 169, 105235.
- Andre, Y. (2020). Linear Discriminant Analysis, Explained in Under 4 Minutes. Retrieved from: <https://medium.com/analytics-vidhya/linear-discriminant-analysis-explained-in-under-4-minutes-e558e962c877>
- Azeman, N. H., Yusof, N. A., & Othman, A. I. (2015). Detection of free fatty acid in crude palm oil. Asian Journal of Chemistry, 27(5), 1569–1573. <https://doi.org/10.14233/ajchem.2015.17810>
- Bakar, B. B. (2009). The Malaysian Agriculture Landscapes. The Malaysian Agricultural Industry in the New Millennium – Issues and Challenges, (c), 337–356.
- Barcelos, E., De Almeida Rios, S., Cunha, R. N. V., Lopes, R., Motoike, S. Y., Babychuk, E., ... Kushnir, S. (2015). Oil palm natural diversity and the potential for yield improvement. Frontiers in Plant Science, 6(MAR), 1–16. <https://doi.org/10.3389/fpls.2015.00190>
- Bensaeed, O. M., Shariff, A. M., Mahmud, A. B., Shafri, H., & Alfatni, M. (2014). Oil palm fruit grading using a hyperspectral device and machine learning algorithm. IOP Conference Series: Earth and Environmental Science, 20(1). <https://doi.org/10.1088/1755-1315/20/1/012017>
- Brownlee, J. (2016). Linear Discriminant Analysis for Machine Learning. Retrieved from: <https://machinelearningmastery.com/linear-discriminant-analysis-for-machine-learning/>

- Castillo, E. G., Rodríguez C, L. F., & Páez, A. F. (2017). Evaluation of two harvesting procedures for oil palm (*Elaeis guineensis* Jacq.) fruits. A case study. *Agronomía Colombiana*, 35(1), 92-99.
- Chauhan, O. P., Lakshmi, S., Pandey, A. K., Ravi, N., Gopalan, N., & Sharma, R. K. (2017). Non-destructive Quality Monitoring of Fresh Fruits and Vegetables. *Defence Life Science Journal*, 2(2), 103. <https://doi.org/10.14429/dlsj.2.11379>
- Cherie, D., Herodian, S., Ahmad, U., Mandang, T., & Makky, M. (2015). Optical characteristics of oil palm fresh fruits bunch (FFB) under three spectrum regions influence for harvest decision. *J Adv Sci Eng Inform Technol*, 5(3), e104-112.
- Chung, C. L., Huang, K. J., Chen, S. Y., Lai, M. H., Chen, Y. C., & Kuo, Y. F. (2016). Detecting Bakanae disease in rice seedlings by machine vision. *Computers and electronics in agriculture*, 121, 404-411.
- Corley, R.H.V, Tinker, P.B. (2003). *The Oil Palm: Fourth Edition*. Blackwell Science Ltd.
- Cunningham, P., & Delany, S. J. (2007). K -Nearest Neighbour Classifiers. *Multiple Classifier Systems*, (April 2007), 1–17.
- DOSM. (Nov, 2020). Selected Agricultural Indicators, Malaysia, 2020. Retrieved January 12, 2021, from https://www.dosm.gov.my/v1/index.php?r=column/cthemeByCat&cat=72&bul_id=RXVKUVJ5TitHM0cwYWxIOHcxU3dKdz09&menu_id=Z0VTZGU1UHBUT1VJMFpaXRRR0xpdz09
- FAO. 1977. *The Oil Palm*. Issues 3-24 of FAO economic and social development series. Food and Agriculture Organization of the United Nations
- Farizawani, A. G., Puteh, M., Marina, Y., & Rivaie, A. (2020). A review of artificial neural network learning rule based on multiple variant of conjugate gradient approaches. *Journal of Physics: Conference Series*, 1529(2). <https://doi.org/10.1088/1742-6596/1529/2/022040>
- Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems, 1(1), 1–8.
- Gitelson, A. A., Merzlyak, M. N., Zur, Y., Stark, R., & Gritz, U. (2001). Non-destructive and remote sensing techniques for estimation of vegetation status.
- Gitelson, A. A., Keydan, G. P., & Merzlyak, M. N. (2006). Three-band model for noninvasive estimation of chlorophyll, carotenoids, and anthocyanin contents in higher plant leaves. *Geophysical research letters*, 33(11).
- Goel, N. S., & Qin, W. (1994). Influences of canopy architecture on relationships between various vegetation indices and LAI and FPAR: A computer simulation. *Remote Sensing Reviews*, 10(4), 309-347.
- Haboudane, D., Miller, J. R., Pattey, E., Zarco-Tejada, P. J., & Strachan, I. B.

- (2004). Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: Modeling and validation in the context of precision agriculture. *Remote sensing of environment*, 90(3), 337-352.
- Hafiz, Mohd, & Shariff, A. R. M. (2011). Oil palm physical and optical characteristics from two different: Planting materials. *Research Journal of Applied Sciences, Engineering and Technology*, 3(9), 953–962.
- Hafiz, M. H. M., Shariff, A. R. M., Amiruddin, M. D., Ramli, A. R., & Saripan, M. I. (2012). Oil palm bunch ripeness classification using fluorescence technique. *Journal of food engineering*, 113(4), 534-540.
- Hafiz, M. H. M., Shariff, A. R. M., & Amiruddin, M. D. (2012). Determination of oil palm fresh fruit bunch ripeness—Based on flavonoids and anthocyanin content. *Industrial Crops and products*, 36(1), 466-475. content. *Industrial Crops and products*, 36(1), 466-475.
- Ikemefuna, J., & Adamson, I. (1984). Chlorophyll and carotenoid changes in ripening palm fruit, *Elaeis guineensis*. *Phytochemistry*, 23(7), 1413-1415.
- Ivan, R., 2017. What is Machine Learning?. Retrieved October 5, 2020 from <https://www.cognizantsoftvision.com/>
- Jaadi, Z. (2019). A Step-By-Step Explanation Of Principal Component Analysis. Retrieved from: <https://builtin.com/data-science/step-step-explanation-principal-component-analysis>
- Jain, A. K., Mao, J., & Mohiuddin, K. M. (1996). Artificial neural networks: A tutorial. *Computer*, 29(3), 31–44. <https://doi.org/10.1109/2.485891>
- Jamil, N., Mohamed, A., & Abdullah, S. (2009). Automated grading of palm oil fresh fruit bunches (FFB) using neuro-fuzzy technique. In 2009 International Conference of Soft Computing and Pattern Recognition (pp. 245-249). IEEE.
- Jordan, C. F. (1969). Derivation of leaf-area index from quality of light on the forest floor. *Ecology*, 50(4), 663-666.
- Junkwon, P., Takigawa, T., Okamoto, H., Hasegawa, H., Koike, M., Sakai, K., ... Bahalayodhin, B. (2009). Hyperspectral imaging for nondestructive determination of internal qualities for oil palm (*Elaeis guineensis* Jacq. var. *tenera*). *Agricultural Information Research*, 18(3), 130–141. <https://doi.org/10.3173/air.18.130>
- Junkwon, P., Takigawa, T., Okamoto, H., Hasegawa, H., Koike, M., Sakai, K., ... Bahalayodhin, B. (2009). Potential Application of Color and Hyperspectral Images for Estimation of Weight and Ripeness of Oil Palm (*Elaeis guineensis* Jacq. var. *tenera*). *Agricultural Information Research*, 18(2), 72–81. <https://doi.org/10.3173/air.18.72>
- Kassim, M. S. M., Ismail, W. I. W., & Teik, L. H. (2014). Oil palm fruit classifications by using near infrared images. *Research Journal of Applied Sciences, Engineering and Technology*, 7(11), 2200–2207.

<https://doi.org/10.19026/rjaset.7.517>

- Khalid, K., & Abbas, Z. (1992). A microstrip sensor for determination of harvesting time for oil palm fruits (Tenera: *Elaeis Guineensis*). *Journal of microwave power and electromagnetic energy*, 27(1), 3-10.
- Khodabakhshian, R., & Emadi, B. (2017). Application of Vis/SNIR hyperspectral imaging in ripeness classification of pear. *International journal of food properties*, 20(sup3), S3149-S3163.
- Kufflinski, Y. (2020). Machine Learning in Agriculture: What it can do now and in the future. Retrieved from: <https://www.iflexion.com/blog/machine-learning-agriculture>
- Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
- Liu, C., Liu, W., Lu, X., Ma, F., Chen, W., Yang, J., & Zheng, L. (2014). Application of multispectral imaging to determine quality attributes and ripeness stage in strawberry fruit. *PloS one*, 9(2), e87818.
- Lu, H., Wang, F., Liu, X., & Wu, Y. (2017). Rapid assessment of tomato ripeness using visible/near-infrared spectroscopy and machine vision. *Food Analytical Methods*, 10(6), 1721-1726.
- Makky, M. (2016). A Portable Low-cost Non-destructive Ripeness Inspection for Oil Palm FFB. *Agriculture and Agricultural Science Procedia*, 9, 230–240. <https://doi.org/10.1016/j.aaspro.2016.02.139>
- Makky, M., Soni, P., & Salokhe, V. M. (2014). Automatic non-destructive quality inspection system for oil palm fruits. *International Agrophysics*, 28(3), 319–329. <https://doi.org/10.2478/intag-2014-0022>
- Maluin, F. N., Hussein, M. Z., & Idris, A. S. (2020). An overview of the oil palm industry: Challenges and some emerging opportunities for nanotechnology development. *Agronomy*, 10(3), 356.
- May, Z., & Amaran, M. H. (2011). Automated oil palm fruit grading system using artificial intelligence. *Int. J. Eng. Sci*, 11(21), 30-35.
- Meftah, A. & shariff, rashid & Shafri, Helmi & Saaed, Mafaz & Eshanta, Omar. (2008). Oil Palm Fruit Bunch Grading System Using Red, Green and Blue Digital Number. *Journal of Applied Sciences*. 8. 10.3923/jas.2008.1444.1452.
- Meijaard, E., Garcia-Ulloa, J., Sheil, D., Wich, S.A., Carlson, K.M., Juffe-Bignoli, D., and Brooks, T. M. (2018). Oil palm and biodiversity: a situation analysis by the IUCN Oil Palm Task Force. *Oil palm and biodiversity: a situation analysis by the IUCN Oil Palm Task Force*. <https://doi.org/10.2305/iucn.ch.2018.11.en>
- Minakata, K., Tashiro, K., Wakiwaka, H., Kobayashi, K., Misrom, N., Aliteh, N. A., & Nagata, H. (2018, December). Proposal of fruit battery method for estimating oil palm ripeness. In 2018 12th International Conference on

Sensing Technology (ICST) (pp. 399-402). IEEE.

- Mison, N., Aliteh, N. A., Harun, N. H., Tashiro, K., Sato, T., & Wakiwaka, H. (2017). Relative estimation of water content for flat-type inductive-based oil palm fruit maturity sensor. *Sensors (Switzerland)*, 17(1), 1–10. <https://doi.org/10.3390/s17010052>
- Mison, N., Azhar, N. S. K., Hamidon, M. N., Aris, I., Tashiro, K., & Nagata, H. (2020). Fruit battery with charging concept for oil palm maturity sensor. *Sensors (Switzerland)*, 20(1). <https://doi.org/10.3390/s20010226>
- Mison, N., Ibrahim, N. A., Azhar, N. S. K., Saini, L. M., Vaithilingam, C. A., Tashiro, K., & Nagata, H. (2021). Implementation of Four Terminal Fruit Battery With Charge Switching. *IEEE Access*, 9, 128157-128165.
- Mohanaraj, S. N., & Donough, C. R. (2016). Harvesting practices for maximum yield in oil palm: results from a re-assessment at IJM plantations, Sabah. *Oil Palm Bulletin* 72, 72(May), i.
- Murad, A.J. (1995). Grading of FFB for Palm Oil Mills In Malaysia. Retrieved from <http://palmoilis.mpob.gov.my/POEB/index.php/2020/03/29/grading-of-ffb-for-palm-oil-mills-in-malaysia/>
- MPOC. (n.d). The Oil Palm Tree. Retrieved 10 December 2020 from <http://mpoc.org.my/the-oil-palm-tree/>
- Nabilah, A.N.A, et al. 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.
- National Aeronautics and Space Administration, 2013. The Electromagnetic Spectrum. Retrieved: October 5, 2020 from <https://imagine.gsfc.nasa.gov/science/toolbox/emspectrum1.html>
- NCSS Statistical Software. (n.d). Discriminant Analysis. Chapter 440. Retrieved from: https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/NCSS/Discriminant_Analysis.pdf
- Nooni, I. K., Duker, A. A., Van Duren, I., Addae-Wireko, L., & Osei Jnr, E. M. (2014). Support vector machine to map oil palm in a heterogeneous environment. *International journal of remote sensing*, 35(13), 4778-4794.
- Novianty, I., K B Seminar, Irzaman, I W Budiastira. (2020). Improving the accuracy of near-infrared (NIR) spectroscopy method to predict the oil content of oil palm fresh fruits. *IOP Conf. Series: Earth and Environmental Science*, Vol. 460.
- Penuelas, J., Gamon, J. A., Griffin, K. L., & Field, C. B. (1993). Assessing community type, plant biomass, pigment composition, and photosynthetic efficiency of aquatic vegetation from spectral reflectance. *Remote Sensing of Environment*, 46(2), 110-118.
- Penuelas, J., Filella, I., & Gamon, J. A. (1995). Assessment of photosynthetic radiation-use efficiency with spectral reflectance. *New Phytologist*, 131(3),

291-296.

- Pinto, J., Chacon, H. F. R., & Fuentes, H. A. (2019). Classification of Hass avocado (*persea americana* mill) in terms of its ripening via hyperspectral images. *Tecnológicas*, 22(45), 109-128.
- Raj, T., Hashim, F. H., Huddin, A. B., Hussain, A., Ibrahim, M. F., & Abdul, P. M. (2021). Classification of oil palm fresh fruit maturity based on carotene content from Raman spectra. *Scientific Reports*, 11(1), 1-11.
- Ramos, P. J., Prieto, F. A., Montoya, E. C., & Oliveros, C. E. (2017). Automatic fruit count on coffee branches using computer vision. *Computers and Electronics in Agriculture*, 137, 9-22.
- Ray. S. (2017). Commonly used Machine Learning Algorithms (with Python and R Codes). Retrieved from <https://www.analyticsvidhya.com/blog/2017/09/common-machine-learning-algorithms/>
- Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote sensing of environment*, 55(2), 95-107.
- Rouse, J. W., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA special publication*, 351(1974), 309.
- Savas, C., & Dervis, F. (2019). The impact of different kernel functions on the performance of scintillation detection based on support vector machines. *Sensors*, 19(23), 5219.
- Sayer, J., Ghazoul, J., Nelson, P., & Klintuni Boedhihartono, A. (2012). Oil palm expansion transforms tropical landscapes and livelihoods. *Global Food Security*, 1(2), 114–119. <https://doi.org/10.1016/j.gfs.2012.10.003>
- Saeed, O. M. B., Sankaran, S., Shariff, A. R. M., Shafri, H. Z. M., Ehsani, R., Alfatni, M. S., & Hazir, M. H. M. (2012). Classification of oil palm fresh fruit bunches based on their maturity using portable four-band sensor system. *Computers and electronics in agriculture*, 82, 55-60.
- Sengupta, S., & Lee, W. S. (2014). Identification and determination of the number of immature green citrus fruit in a canopy under different ambient light conditions. *Biosystems Engineering*, 117, 51-61.
- Setiawan, A. W., & Prasetya, O. E. (2020, February). Palm oil fresh fruit bunch grading system using multispectral image analysis in HSV. In *2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT)* (pp. 85-88). IEEE.
- Silalahi, D. D., Reaño, C. E., Lansigan, F. P., Panopio, R. G., & Bantayan, N. C. Linear Discriminant Analysis vs. Genetic Algorithm Neural Network with Principal Component Analysis for Hyperdimensional Data Analysis: A study on Ripeness Grading of Oil Palm (*Elaeis guineensis* Jacq.) Fresh Fruit. *Philippine Statistician*.

- Sivakumar, S. S., Qiao, J., Wang, N., Gariépy, Y., Raghavan, G. S. V., & McGill, J. (2006). Detecting maturity parameters of mango using hyperspectral imaging technique. In 2006 ASAE Annual Meeting (p. 1). American Society of Agricultural and Biological Engineers.
- Schott, M. (2019). K-nearest Neighbors (KNN) Algorithm for Machine Learning. Retrieved from: <https://medium.com/capital-one-tech/k-nearest-neighbors-knn-algorithm-for-machine-learning-e883219c8f26>
- Setiawan, A. W., Mengko, R., Putri, A. P. H., Danudirdjo, D., & Ananda, A. R. (2019). Classification of palm oil fresh fruit bunch using multiband optical sensors. *International Journal of Electrical and Computer Engineering*, 9(4), 2386–2393. <https://doi.org/10.11591/ijece.v9i4.pp2386-2393>
- Shabdin, M. K., Shariff, A. R. M., Johari, M. N. A., Saat, N. K., & Abbas, Z. (2016). A study on the oil palm fresh fruit bunch (FFB) ripeness detection by using Hue, Saturation and Intensity (HSI) approach. *IOP Conference Series: Earth and Environmental Science*, 37(1). <https://doi.org/10.1088/1755-1315/37/1/012039>
- Shiddiq, M., Fitmawati, Anjasmara, R., Sari, N., & Hefniati. (2017). Ripeness detection simulation of oil palm fruit bunches using laser-based imaging system. *AIP Conference Proceedings*, 1801. <https://doi.org/10.1063/1.4973101>
- Software, N. S. (2006). *Discriminant Analysis*, Chapter 44(2), 1–12.
- Tuerxun, A., Shariff, A. R. M., Janius, R., Abbas, Z., & Mahdiraji, G. A. (2020, July). Oil palm fresh fruit bunches maturity prediction by using optical spectrometer. In *IOP Conference Series: Earth and Environmental Science* (Vol. 540, No. 1, p. 012085). IOP Publishing.
- United States Department of Agriculture, & Wahab, A. G. (2021, July). Oilseeds and Products Update. https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Oilseeds%20and%20Products%20Update_Kuala%20Lumpur_Malaysia_07-01-2021.pdf
- Utom, S. L., Elmy Johana Mohamad, H. L. M., Ameran, Kadir, H. A., Muji, S. Z. M., Abdul, R., ... Puspanathan, J. (2018). Non-Destructive Oil Palm Fresh Fruit Bunch (FFB) Grading Technique Using Optical Sensor.pdf.
- Vitola, J., Pozo, F., Tibaduiza, D. A., & Anaya, M. (2017). A sensor data fusion system based on k-nearest neighbor pattern classification for structural health monitoring applications. *Sensors*, 17(2), 417.
- Yusuf, B., He, Y. (2011). Application of hyperspectral imaging sensor to differentiate between the moisture and reflectance of health and infected tobacco leaves. *African Journal of Agricultural Research* Vol. 6(29), pp. 6267-6280, 5 December, 2011.
- Zarco-Tejada, P. J., Miller, J. R., Noland, T. L., Mohammed, G. H., & Sampson, P. H. (2001). Scaling-up and model inversion methods with narrowband optical indices for chlorophyll content estimation in closed forest canopies

with hyperspectral data. *IEEE Transactions on Geoscience and Remote Sensing*, 39(7), 1491-1507.

Zolfagharnassab, S., Mohamed Shariff, A. R., & Ehsani, R. (2017). Emissivity determination of oil palm fresh fruit ripeness using a thermal imaging technique. *Acta Horticulturae*, 1152, 189–193. <https://doi.org/10.17660/ActaHortic.2017.1152.26>

Zolfagharnassab, Shahrzad. (2019). Application of thermal imaging technique to quantify the oil palm fresh fruit maturity, oil content and oil quality parameters. (Doctoral dissertation thesis). Universiti Putra Malaysia, Selangor, Malaysia.

Zhou, X., Huang, W., Kong, W., Ye, H., Dong, Y., & Casa, R. (2017). Assessment of leaf carotenoids content with a new carotenoid index: Development and validation on experimental and model data. *International journal of applied earth observation and geoinformation*, 57, 24-35.

Zuhaira Mohd Zulkifli, Fazida Hanim Hashim, Thinal Raj, A. B. H. (2018). A Rapid and Non-Destructive Technique in Determining The Ripeness of Oil Palm Fresh Fruit Bunch (FFB). *Jurnal Kejuruteraan*, 30(1), 93–101. [https://doi.org/10.17576/jkukm-2018-30\(1\)-12](https://doi.org/10.17576/jkukm-2018-30(1)-12)