



Faculty of Computer Science and Information Technology

**SmartPalmBot: AI-Driven Oil Palm Surveillance with Power BI
Dashboard for Enhanced Data Analysis**

Dayang Nadirah Binti Mohd Annuar

**Bachelor of Computer Science with Honours (Computational Science)
2025**

SmartPalmBot: AI-Driven Oil Palm Surveillance and with Power BI
Dashboard for Enhanced Data Analysis

Dayang Nadirah Binti Mohd Annuar

A thesis submitted

In fulfillment of the requirements for the degree of Bachelor of Computer Science with
Honours (Computational Science)

Faculty of Computer Science and Information Technology

UNIVERSITI MALAYSIA SARAWAK

2025

UNIVERSITI MALAYSIA SARAWAK

THESIS STATUS ENDORSEMENT FORM

Title: SmartPalmBot: AI-Driven Oil Palm Surveillance with Power BI Dashboard for Enhanced Data Analysis

ACADEMIC SESSION: 2024/2025

(CAPITAL LETTERS)

hereby agree that this Thesis* shall be kept at the Centre for Academic Information Services, Universiti Malaysia Sarawak, subject to the following terms and conditions:

1. The Thesis is solely owned by Universiti Malaysia Sarawak
2. The Centre for Academic Information Services is given full rights to produce copies for educational purposes only
3. The Centre for Academic Information Services is given full rights to do digitization in order to develop local content database
4. The Centre for Academic Information Services is given full rights to produce copies of this Thesis as part of its exchange item program between Higher Learning Institutions [or for the purpose of interlibrary loan between HLI]
5. ** Please tick (✓)

- ☐ CONFIDENTIAL (Contains classified information bounded by the OFFICIAL SECRETS ACT 1972)
- ☐ RESTRICTED (Contains restricted information as dictated by the body or organization where the research was conducted)
- ☒ UNRESTRICTED

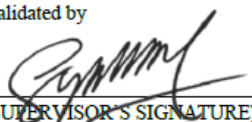


(AUTHOR'S SIGNATURE)

Permanent Address
MPKT 1591 Kampung Pulau Rusa
20050 Kuala Terengganu

Date: 17/7/2025

Validated by


(SUPERVISOR'S SIGNATURE)

Date:

Note * Thesis refers to PhD, Master, and Bachelor Degree
** For Confidential or Restricted materials, please attach relevant documents from relevant organizations / authorities

DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



.....

Signature

Name: Dayang Nadirah Binti Mohd Annuar

Matric No.: 79189

Faculty of Computer Science and Information Technology

Universiti Malaysia Sarawak

Date: 17 January 2025

Commented [AM1]: Use latest date

ACKNOWLEDGEMENT

In the name of Allah, the Almighty and the Most Beneficent, I express my heartfelt thanks to my supervisor, Ts. Hj. Syahrul Nizam Junaini for his assistance and guidance throughout completing this project. Secondly, I'd like to express my heartfelt gratitude to Ts. Abdul Rahman bin Mat, my cherished examiner for his encouragement and helpful feedback on my Final Year Project.

Next, I would like to thank my family who in way share their support, encouraged me and never give up on me in spite of the long's years of studies Next, I want to sincerely thank Mr. Muhd Hashim Wahab of TDM Berhad his helpful advice and information in helping me finish my project on dashboard monitoring. Lastly, I would like to thank my fellow friends, for their unwavering support, stimulating discussion and the sleepless nights we spent working diligently on this project.

ABSTRACT

The agricultural sector in Malaysia especially oil palm estates nowadays are facing many challenges in the rapidly changing world of globalisation. Some of the challenges include are limited information about current technology, and reliance on traditional operational practices. Throughout some investigation, these problems can be solved by using internet of things (IoT) and data analytics. The proposed solution involves designing and developing SmartPalmBot, a multifunctional, rover-like IoT device equipped with sensors to monitor environmental parameters such as temperature and humidity. The project had more than 85% accuracy for predicting the deviations of the environmental factors from their optimal ranges (24°C–28°C, 60%–80% RH), to provide early warning and intervention. The average SUS score was 92.5, which corresponds to "Excellent" in usability. In the UEQ analysis, the six user experience characteristics yielded values above the neutral point and the Efficiency (mean = 1.61, SD = 0.71) and Stimulation (mean = 1.50, SD = 0.67) were rated as Excellent whereas the Attractiveness, Perspicuity, and Dependability were rated as Good. Innovation is just under the 'Good' marker (mean = 0.77; SD = 1.08), indicating an opportunity for further innovation. These results demonstrate the SmartPalmBot increases decision making and user satisfaction in oil palm plantation management, which promotes sustainable and smart agriculture.

Keywords: Smart agriculture, Internet of Things (IoT), Oil palm, Data analytics, Power BI

ABSTRAK

Sektor pertanian di Malaysia terutamanya ladang kelapa sawit pada masa kini menghadapi pelbagai cabaran dalam perubahan dunia globalisasi yang pesat. Beberapa cabaran termasuk maklumat terhad tentang teknologi semasa, dan pergantungan pada amalan operasi tradisional. Sepanjang beberapa penyiasatan, masalah ini boleh diselesaikan dengan menggunakan internet of things (IoT) dan analisis data. Penyelesaian yang dicadangkan melibatkan mereka bentuk dan membangunkan SmartPalmBot, peranti IoT seperti rover yang dilengkapi dengan penderia untuk memantau parameter persekitaran seperti suhu dan kelembapan. Projek ini mempunyai lebih daripada 85% ketepatan untuk meramalkan sisihan faktor persekitaran daripada julat optimumnya (24°C – 28°C , 60%–80% RH), untuk memberikan amaran awal dan campur tangan. Purata skor SUS ialah 92.5, yang sepadan dengan "Cemerlang" dalam kebolehgunaan. Dalam analisis UEQ, enam ciri pengalaman pengguna menghasilkan nilai di atas titik neutral dan Kecekapan ($\text{min} = 1.61$, $\text{SD} = 0.71$) dan Stimulasi ($\text{min} = 1.50$, $\text{SD} = 0.67$) dinilai sebagai Cemerlang manakala Daya Tarik, Keperspektifan dan Kebolehppercayaan dinilai sebagai Baik. Inovasi berada di bawah penanda 'Baik' ($\text{min} = 0.77$; $\text{SD} = 1.08$), menunjukkan peluang untuk inovasi selanjutnya. Keputusan ini menunjukkan SmartPalmBot meningkatkan membuat keputusan dan kepuasan pengguna dalam pengurusan ladang kelapa sawit, yang menggalakkan pertanian mampan dan pintar.

Kata kunci: Pertanian pintar, Internet Perkara (IoT), Kelapa sawit, Analisis data, Power BI

TABLE OF CONTENTS

DECLARATION	I
ACKNOWLEDGEMENT	II
ABSTRACT	III
<i>ABSTRAK</i>	IV
LIST OF TABLES	X
LIST OF FIGURES	XI
LIST OF ABBREVIATIONS	XIII
CHAPTER 1 INTRODUCTION	1
1.1 Overview	1
1.2 Study Background	1
1.3 Problem Statement	2
1.4 Research Questions	3
1.5 Objectives	3
1.6 Brief Methodology	4
1.7 Scope	4
1.8 Significance of Project	4
1.9 Project Schedule	5
1.10 Expected Outcomes	6
1.11 Thesis Outlines	6
1.12 Summary	7
CHAPTER 2 LITERATURE REVIEW	8

2.1	Overview	8
2.2	Background	8
2.3	Method	10
2.4	Result and Analysis	13
2.4.1	What are the core technologies enabling smart dashboards in precision agriculture?	14
2.4.2	How are IoT devices and networks integrated into agricultural dashboard systems?	17
2.4.3	The Impact of Power BI Smart Dashboards on Farming Practices and Operational Efficiency?	20
2.4.4	What main challenges adoption of smart dashboards in agriculture?	22
2.4.5	What are the emerging trends and future research opportunities for dashboard development?	24
2.5	Discussion	27
2.5.1	Theoretical implications	27
2.5.2	Practical implications	28
2.5.3	Summary of Review Limitations	28
2.6	Summary	29
CHAPTER 3 METHODOLOGY		31
3.1	Overview	31
3.2	Research Framework	31
3.3	Data Collection	32

3.4	Data Preprocessing	35
3.6	Azure Function Apps	38
3.7	User Interface Design	40
3.8	System Evaluation Methods	45
3.9	Usability Testing	46
3.10	Summary	47
CHAPTER 4 IMPLEMENTATION AND TESTING		48
4.1	Overview	48
4.2	Installation and Configuration System Architecture	48
4.2.1	Hardware	48
4.2.2	Software	49
4.3	System Page	51
4.4	Chatbot Module	56
4.5	Data Relationship Model	58
4.6	Usability Evaluation Using the System Usability Scale (SUS)	59
4.6.1	Participant Profile	60
4.6.2	SUS Scoring Methodology	60
4.6.3	Descriptive Statistics	61
4.6.4	Item-Level Analysis	62
4.6.5	Interpretation and Benchmarking	63
4.6.6	Visual Summary	63

4.6.7	Limitations	66
4.6.8	Summary	66
4.7	User Experience Assessment Using the User Experience Questionnaire (UEQ)	67
4.7.1	Participant Profile	67
4.7.2	Instrument Description	67
4.7.3	Descriptive Results	68
4.7.4	Benchmarking and Interpretation	69
4.7.5	Diagnostic Insights from Item-Level Responses	69
4.7.6	Visual Summary of Findings	70
4.7.7	Limitations and Considerations	70
4.7.8	Summary	71
4.8	Summary	72
CHAPTER 5 RESULTS AND DISCUSSION		73
5.1	Overview	73
5.2	Functional Testing	73
5.3	Statistical Feature Engineering	74
5.4	Decision Tree and the Random Forest	75
5.5	Setting	79
5.6	Data Collection	79
5.7	Summary	80
CHAPTER 6 CONCLUSION AND FUTURE WORK		81

6.1	Overview	81
6.2	Achievement of Objectives	81
6.3	Project Limitations	82
6.4	Future Works	83
6.5	Summary	84
REFERENCES		85
APPENDIX A: GANTT CHART		90
APPENDIX B: USABILITY TESTING METHOD		91
APPENDIX C: RESULT OF USABILITY TESTING		93

LIST OF TABLES

Table 2.1 Research Questions	9
Table 2.2: Core Technologies Enabling Smart Dashboards in Precision Agriculture - Literature Review Matrix	16
Table 2.3: IoT Devices and Network Integration in Agricultural Dashboard Systems - Literature Review Matrix	19
Table 2.4: Key Impacts of Power BI Dashboards on Agricultural Practices - Literature Review Matrix	22
Table 2.5: Adoption Challenges of Smart Dashboards in Agriculture - Literature Review Matrix	24
Table 2.6: Key Emerging Trends in Dashboard Development - Literature Review Matrix	27
Table 4.1 Summary of SUS Scores (n = 15)	61
Table 4.2 Mean Ratings by SUS Item	62
Table 4.3 Table of original and adjusted mean rating	65
Table 4.4 Descriptive Statistics for UEQ Dimensions (n = 15)	68
Table 6.1 Objective and Achievements	Error! Bookmark not defined.

LIST OF FIGURES

Figure 1.1 Methodology diagrams for Power BI Dashboard	4
Figure 2.1 PRISMA Flow Diagram	12
Figure 2.2 Developed platform's diagram. (Source from Ferreira et al., 2021)	13
Figure 2.3 Dashboard Monitoring (Source from Dineva & Atanasova, 2022).	16
Figure 2.4 Smart Livestock Monitoring System (Source from Dineva & Atanasova, 2022).	19
Figure 3.1 Research Methodology Diagram	32
Figure 3.2 Data Collection Diagrams	34
Figure 3.3 Decision Tree	38
Figure 3.4 Workflow Architecture	40
Figure 3.5 User interface for desktop layout and mobile layout for daily temperature.	41
Figure 3.6 User interface for desktop layout for monthly temperature.	42
Figure 3.7 User interface for desktop layout for daily humidity	43
Figure 3.8 User interface for desktop layout for monthly humidity.	43
Figure 3.9 User interface for desktop layout weather maps	44
Figure 4.1 TP-Link Tapo mobile application	50
Figure 4.2 Azure SQL Database	51
Figure 4.3 SmartPalmBot Analysis Dashboard – Temperature Monitoring	53
Figure 4.4 SmartPalmBot Analysis Dashboard – Humidity Monitoring	54
Figure 4.5: SmartPalmBot Analysis Dashboard – Monthly Temperature	55
Figure 4.6: SmartPalmBot Analysis Dashboard – Heat Analysis	56
Figure 4.7 SmartPalmBot Chatbot	58
Figure 4.8 Data Relationship Model	59
Figure 4.9 Adjusted SUS Mean Score	65
Figure 4.10 UEQ Scores	70
Figure 5.1 for Environmental Risk Classification (Random Forest Model)	75

Figure 5.2 Performance Comparison of Machine Learning Models	77
Figure 5.3 Confusion Matrix of Random Forest Classifier	78

LIST OF ABBREVIATIONS

Commented [AM2]: Rearrange according to alphabetical order

AI	Artificial Intelligence
CRUD	Create, Read, Update, Delete
CSV	Comma-Separated Values
DAX	Data Analysis Expressions
DAG	Directed Acyclic Graph
DHT	Digital Humidity and Temperature (Sensor)
DSS	Decision Support System
ESP	Espressif (Wi-Fi Microcontroller Series, e.g., ESP8266, ESP32)
EST	Eastern Standard Time
GPS	Global Positioning System
HTML	HyperText Markup Language
IoT	Internet of Things
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
NLU	Natural Language Understanding
NPK	Nitrogen, Phosphorus, Potassium (Soil Nutrients)
BI	Business Intelligence
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
QR	Quick Response (Code)
QL	Query Language
RH	Relative Humidity
RQ	Research Question
RMS	Root Mean Square
SQL	Structured Query Language
SUS	System Usability Scale
TDM	Terengganu Development Management Berhad
TP-Link	Twisted Pair Link
UEQ	User Experience Questionnaire
UI	User Interface
UX	User Experience

CHAPTER 1

INTRODUCTION

1.1 Overview

In this chapter, an introduction of the project will be provided. It contains the background study, problem statement, project objectives, brief methodology on how the project will be conducted, project scope, the significance of the project expected outcome of the project and project outline.

1.2 Study Background

Oil palm farming is critical to the agricultural sector, giving considerable economic advantages and livelihoods to millions of people, particularly in tropical countries (Lesk et al., 2016). As worldwide demand for palm oil rises, it is critical to improve production efficiency while remaining environmentally conscious (Rhebergen et al., 2018). The climatic conditions under which oil palms are grown, particularly temperature and humidity, have a significant impact on yield and quality. Optimal growth occurs within specified temperature and humidity ranges 24°C to 28°C and 60% to 80%, respectively where deviations can cause plant stress, reducing fruit quality and yield (Knight et al., 2024).

Recent research has highlighted the integration of technology as a transformative method in agriculture, notably for improving precision farming practices. The integration of the SmartPalmBot chatbot project aims to transform environmental conditions of crop yield in oil palm plantations by combining machine learning with IoT technology and a user-friendly chatbot interface. This initiative will empower farmers by interact with the data presented in the Power BI dashboard (Hjelle et al., 2024).

The literature also highlights the creation of SmartPalmBot: AI-Driven Oil Palm Surveillance with Power BI Dashboard for Enhanced Data Analysis, which focused on monitoring the environmental conditions necessary for optimal crop productivity. Using a dataset obtained from the Tapo temperature and humidity sensor device, the project develops a full Power BI dashboard that enables for real-time visualisation of temperature and humidity levels in oil palm estates. This dashboard enables the farmers to monitor these vital parameters and to take informed decisions for the general crop pest management. The SmartPalmBot effort aims to increase farm productivity and sustainability by improving the accuracy of environmental conditions.

1.3 Problem Statement

Traditional techniques of palm yield forecast frequently rely on manual estimation, which can be labour-intensive and inaccurate (Cock et al., 2016). This lack of reliable data leads to severe biases among farmers, limiting their capacity to make informed strategic decisions about agricultural operations (Pashkevich et al., 2024). Rapid variations in environmental conditions, such as temperature and humidity, hamper yield forecasts because current approaches fail to account for these dynamic elements. Furthermore, farmers have limited access to instruments that provide real-time insights and advice.

The oil palm sector confronts a number of major difficulties that limit its efficiency and sustainability (Zakaria et al., 2024). Among the biggest challenges is the use of outdated surveillance and data-gathering tools that are slow and rife with human error. This results in inaccurate yield forecasting and inefficient resource allocation reflecting on the productivity of the plantations as a whole as well as the profitability.

Furthermore, the failure to adequately monitor and adapt to environmental changes worsens the situation. Climate fluctuations can have a substantial impact on the health and

productivity of oil palm crops (Novita et al., 2024). Current monitoring systems lack the ability to combine and analyse environmental data in real time, leaving farmers without the required information to adjust their plans quickly.

Next, there is an urgent need for a robust data analysis platform capable of transforming raw data into usable insights. While data collection methods have progressed, integrating these data into a cohesive system that facilitates decision-making remains difficult. Farmers and plantation managers demand tools that not only visually represent data but also give predictive analytics to guide future actions (Jayaraman et al., 2023).

The absence of such integrated systems restricts stakeholders' capacity to optimise operations, minimise waste, and improve sustainability practices. As a result, a novel solution combining AI-driven monitoring with advanced data analytics is vital for addressing these difficulties and improving the productivity and sustainability of oil palm operations (Sheikh et al., 2024).

1.4 Research Questions

The research questions for this study are:

- i. How can an AI model effectively provide real-time insights and actionable recommendations to support oil palm farmers through a Power BI dashboard?
- ii. How effectively does that new dashboard communicate complex data to users in a clear and intuitive manner?

1.5 Objectives

The following set of objectives can help achieve this:

- i. To integrate an AI model to deliver real-time insights and recommendations for oil palm farmers through a Power BI dashboard, and

- ii. To evaluate the dashboard's effectiveness in presenting complex data clearly and intuitively to users.

1.6 Brief Methodology

This methodology describes a methodical way to create a Power BI dashboard to better data visualization. All gathered environmental data is stored on a single Azure SQL Server. In order to make the raw data reliable and consistent for analysis, it is then cleaned and transformed into structured data using Python scripts. After processing, the data is transferred into Power BI. Figure 1.1 shows methodology diagrams for Power BI Dashboard.



Figure 1.1 Methodology diagrams for Power BI Dashboard

1.7 Scope

The scope of the study is as follows:

- i. This initiative aims to create and implementation a crop management system for oil palm farms that includes a Power BI dashboard for data visualization and analysis.
- ii. The project will collect real-time data from the estate via sensors and Tapo application to monitor the humidity and temperature environment conditions.

1.8 Significance of Project

The SmartPalmBot initiative is highly significant in the palm oil sector, especially in improving the productivity and sustainability of oil palm plantations. As of the growth in human population increase, the requirement of food is increase. The growth of crops also needs

to be increased due to high demands from the food sector. Quantity of crops is not only important things; the quality of crops also needs to be preserved in the growth of crops. Therefore, the chatbot interface offers automated insights and recommendations, simplifying communication for farmers and promoting faster decision-making processes. The Power BI dashboard displays important performance indicators and environmental data for plantation managers to effectively track crop health and operational metrics, making it easier to take timely actions and optimize resources.

Additionally, SmartPalmBot aids in sustainable agriculture by enhancing yield forecasts and operational effectiveness, ultimately decreasing wastage and encouraging eco-friendly farming techniques. Created to be adaptable, the technology is appropriate for different plantation sizes from small family-owned farms to large commercial operations guaranteeing a diverse group of stakeholders can take advantage of its progress. SmartPalmBot is a significant advancement in modernizing the palm oil industry by combining advanced technologies with traditional farming methods, opening the door for more innovations to improve productivity and sustainability in agriculture.

1.9 Project Schedule

This project is divided into two phases, FYP 1 and FYP 2, in accordance with university guidelines. FYP 1 requires completion of Chapter 1 (Introduction), Chapter 2 (Background Study or Literature Review), and Chapter 3 (Methodology or Requirement Analysis and Design). Consequently, FYP 2 implies the fulfilment of Chapter 4. (Implementation), Chapter 5 (Testing), and Chapter 6 (Conclusion and Future Works). The detailed project schedule, as depicted in the Gantt chart, encompasses FYP 1 and FYP 2 can be found in the [Appendix A](#) section for reference.

Commented [AM3]: Specify which appendix

1.10 Expected Outcomes

This study is expected to:

- i. Provide a reliable, real-time monitoring system for oil palm plantation environments, allowing farmers and managers to accurately track temperature and humidity
- ii. Provide automated insights and recommendations to support sustainable practices by decreasing resource waste and boosting effective plantation management, helping to ensure the oil palm sector's overall sustainability

1.11 Thesis Outlines

Chapter 1 provides a detailed description of the proposed project and justifies the need for revolutionizing environmental monitoring and advisory systems in oil palm plantations through AI-driven solutions like SmartPalmBot. It covers the study background, problem statement, objectives, methodology, project scope, significance, expected outcomes, project schedule, and project outline.

In Chapter 2, an in-depth examination of prior research and projects will be undertaken. The purpose of this chapter is to give a comprehensive assessment of the existing literature and research concerning the management of oil palm plantations, Internet of Things applications in agriculture, and data visualization approaches. To achieve this, a thorough review of pertinent information from reputable journals, research papers, and scholarly articles will be meticulously carried out.

Chapter 3 will provide a detailed account of the methodology used in this project, covering the design, data collection methods, and development phases for both the Power BI dashboard and the SmartPalmBot chatbot. This section explains how the machine learning model was incorporated and tested to deliver reliable data insights and suggestions to users.

Commented [AM4]: Add for Chapter 4, 5, and 6 respectively.

Chapter 4 elaborates on the implementation of the SmartPalmBot system, including hardware and software integration, system architecture, and user interface design. It also presents the testing procedures conducted to verify system functionality, the structure of the chatbot module, and the data relationship model within Power BI.

Chapter 5 presents the results of the functional testing, statistical feature engineering, and classification performance of machine learning models. It also discusses the findings from the usability and user experience testing using SUS and UEQ instruments, providing insights into the system's effectiveness and user satisfaction.

Chapter 6 summarizes the project's outcomes, highlighting the achievement of research objectives, limitations encountered, and recommendations for future work. It concludes the report by reflecting on the contribution of SmartPalmBot to smart agriculture and its potential for broader application.

1.12 Summary

This chapter given a complete overview of the SmartPalmBot project, including the background, problem statement, research questions, objectives, scope, and significance. A brief overview of the methodology and expected outcomes was also provided. The following chapters will elaborate on each of these points, gradually building on the technical and theoretical foundations established in this introduction.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter discusses the literature review on existing studies on data visualization systems and tools with functionalities similar to the proposed SmartPalmBot, focusing on oil palm plantations. Although existing work further emphasizes the monitoring of temperature and humidity, fortunately, none of it have focused on the development of intelligent decision-support models that can offer sensing and correlation. Using Web of Science and Scopus, 19 relevant articles published between 2000 and 2024 were systematically reviewed, following PRISMA guidelines.

2.2 Background

The aim of this chapter is to discuss the comprehensive analysis in depth regarding towards the strengths, weakness and features of the SmartPalmBot system. The literature on the evolution of agricultural technology using IoT consists primarily of exploratory research demonstrating systems running in small pilots. The IoT for agriculture can be classified into two types: one is the development of farm equipment and sensors to monitor the weather and other factors, and the other is the strategic planning and optimization of agricultural production. The second is building platforms on which we can store, organize, analyze, and visualize data to make better decisions. Table 2.1 presents the research question (RQ) of this study in a more detailed manner.

Table 2.1 Research Questions

No.	Research Questions (RQ)
1	RQ1: What are the core technologies enabling smart dashboards in precision agriculture?
2	RQ2: How are IoT devices and networks integrated into agricultural dashboard systems?
3	RQ3: The Impact of Power BI Smart Dashboards on Farming Practices and Operational Efficiency?
4	RQ4: What main challenge the adoption of smart dashboards in agriculture?
5	RQ5: What are the emerging trends and future research opportunities for dashboard development?

Commented [AM5]: 1.This content should be in Chapter 1, before objective. In addition, just select relevant RQs and map them together with the Objectives (stated in Chapter 1).
2.What the different between this table and Section 1.4?

Intelligent monitoring and data-driven solutions are very critical in the context of oil palm plantations. Oil palm is one of the most important agricultural commodities globally, which demands efficient management for high yields and sustainability (Abubakar et al., 2023). Farmers and plantation managers, however, are challenged by the task of managing huge amounts of data generated by several IoT devices deployed over large plantation areas. Traditional storage systems, such as local databases or Excel spreadsheets, cannot handle real-time data analysis and often do not provide actionable insights in an accessible, interactive format.

Power BI is built on modern data visualization techniques, offering ease of use where complex data can be organized in the form of charts, tables, and graphs that allow users to easily find trends, deviations, and patterns. Custom filters with advanced DAX queries enable flexible filtering of data by time, location, farm, herd, or animal category, making the system easier to use and more accessible. Additionally, the cloud-based architecture, powered by Microsoft Azure, ensures the system is scalable, secure, and capable of handling large volumes of data while reducing the environmental impact of IT infrastructure. The proposed

SmartPalmBot system exploits artificial intelligence and IoT, which will change the outlook of oil palm plantations and their management for better efficiency, sustainability, and profitability. SmartPalmBot helps farmers make operation decisions more effectively by providing them with real-time insights, predictive analytics, and interactive visualizations.

2.3 Method

The systematic review approach provided a structured framework for exploring the evolving technologies in precision agriculture, with a particular focus on the integration of dynamic data visualization through Power BI dashboards. This approach facilitated a comprehensive investigation into the technological landscape, shedding light on the intricate nature of oil palm monitoring systems in temperature and humidity. The structured methodology guided the research process from defining selection criteria to conducting detailed analyses of relevant studies, ensuring the formulation of targeted insights and research questions. The interactive part of the proposed system is Power BI. End-users (farmers) receive clear visualizations by designing and generating reports and dashboards that include both raw and processed data. In Power BI, reports and dashboards serve different objectives and allow for diverse functionality. The project established a solid foundation for improving decision-making and operational efficiency in oil palm plantations using SmartPalmBot.

The main goal was to discuss and design a robust smart dashboard, SmartPalmBot, for AI-driven oil palm surveillance and data analysis. This includes a review of scholarly articles at the crossroads of IoT applications in agriculture, machine learning for predictive analytics, and advanced dashboard design. The systematic review will follow the PRISMA guidelines on Preferred Reporting Items for Systematic Reviews and Meta-Analyses, which ensure clarity and reliability in the research process. A search was done through two of the leading academic databases, Web of Science and Scopus, for an overall wide and credible data set. The queries

were developed to find relevant peer-reviewed publications fitting the specific research themes.

Keywords such as (dashboard OR "smart dashboard" OR "digital dashboard" OR "monitoring dashboard" OR "data dashboard") AND TS (agriculture OR farming OR "precision agriculture" OR "smart farming") AND TS (IoT OR "Internet of Things" OR sensors OR "sensor network" OR "wireless technology") were used to search research on Scopus and Web of Science. Initially, 230 articles were identified, which were screened based on predefined criteria, including publication date (2020–2024), peer-reviewed status, relevance to precision agriculture, and contributions to IoT and machine learning applications. After the screening and eligibility phases, 29 publications were selected for in-depth review.

These articles offered a diverse range of methodologies, including empirical studies on IoT-enabled monitoring systems, evaluations of machine learning models for agricultural analytics, and case studies on the design of dynamic dashboards. Insights derived from the review informed the development of the SmartPalmBot architecture, integrating IoT devices for real-time data collection, cloud-based processing with Microsoft Azure and interactive Power BI dashboards. Figure 2.1 shows The PRISMA standard's inclusion decision flowchart, outlines the identification, screening, retrieval, and inclusion phases of the review decision process.

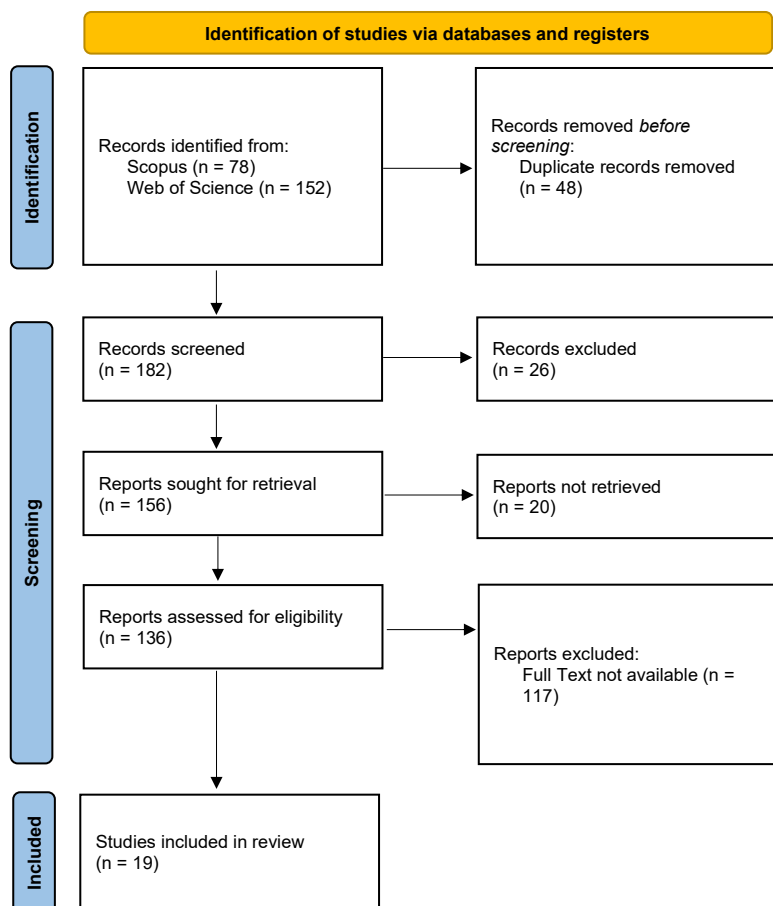


Figure 2.1 PRISMA Flow Diagram

2.4 Result and Analysis

The research was meant to explore Power BI smart dashboards in agriculture, placing much emphasis on real-time monitoring, data visualization, and predictive analytics. In as much as the findings have proved that they have the ability to optimize decision-making and resource use, challenges such as connectivity issues, high initial costs, and a lack of technical expertise among users were also identified. These challenges suggest opportunities for further exploration in addressing adoption barriers.

Figure 2.2 illustrates the example of architecture platform developed for integrated, real-time data gathering, processing, and visualization, according to these components' relations. In this view of Ferreira et al. (2021), a flow from devices through IoT, Data in Processing Units, up to the Visualization (Power BI), has been easily represented in the schema here. The design of the platform ensures that data from multiple sources is aggregated, analyzed, and presented to users in a user-friendly dashboard for informed decision-making and optimized operation.

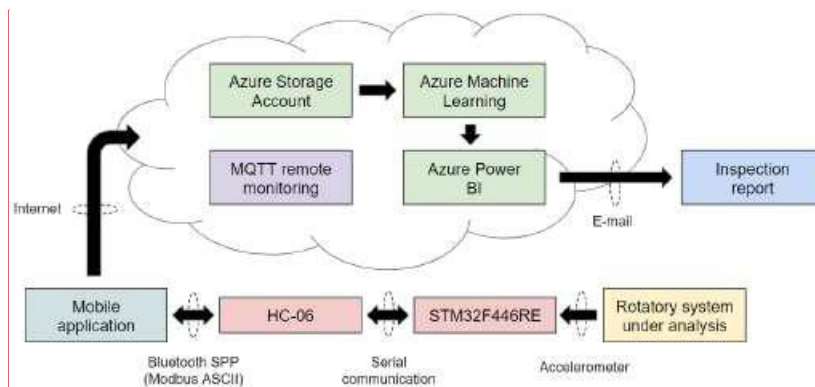


Figure 2.2 Developed platform's diagram. (Source from Ferreira et al., 2021)

Commented [AM6]: Not clear

2.4.1 What are the core technologies enabling smart dashboards in precision agriculture?

Smart dashboards in precision agriculture have been transforming the way farmers observe, analyze, and optimize their farming practices. Advanced technologies integrated into these dashboards enable comprehensive data collection, analysis, and visualization for data-driven decision-making. By using real-time data and predictive insights, smart dashboards will help farmers improve their crop management, resource allocation, and overall productivity. The key technologies that will be driving these systems include the Internet of Things, artificial intelligence and machine learning, data visualization platforms like Power BI and Azure. These all together address the modern agriculture problems while presenting unique challenges and opportunities.

The Internet of Things (IoT) is at the heart of precision agriculture, allowing for the real-time collection of data from various sensors deployed across farms. IoT devices monitor critical agricultural parameters such temperature and humidity (Prabha & Pathak, 2023). This data is essential for ensuring optimal crop growth conditions. For example, IoT networks using sensors integrated with Raspberry Pi modules provide real-time environmental data, which farmers can access remotely (Spandana & Pabboju, 2023). This integration enables precise monitoring of agricultural conditions, reducing the dependency on traditional, labor-intensive methods.

Sensor networks enhance data access by connecting various devices on one platform on which the data is processed and visualized. Seamless connectivity of IoT devices presents an avenue where farmers can make informed decisions without necessarily constant physical interventions. For example, if the soil moisture strays from the optimum sets, IoT sensors can

automatically trigger the irrigation system to maintain crop health. The high potential of IoT in the improvement of efficiency and reduction of resource wastage in agriculture.

Artificial Intelligence and Machine Learning are important in the processing of raw data collected from agriculture into usable insights. These technologies analyze the huge volumes of data collected from IoT devices to identify patterns, predict outcomes, and recommend optimum farming practices. AI-powered algorithms can predict crop yields, detect potential diseases early, and provide guidance on the best planting and harvesting schedules.

For instance, the Gaussian Naive Bayes algorithm has been effective in predicting suitable crops using soil parameters such as pH and nutrient content. This predictive capability allows farmers to select crops that are most likely to thrive under specific conditions, thereby increasing profitability and reducing the risk of crop failure. Further, AI and ML support the adoption of precision spraying, where fertilizers and pesticides are applied only in the areas of need, thus minimizing impacts on the environment while reducing costs. Research by Adewuyi et al., (2024) underlines the transformational potential of AI and ML for modern agriculture, as their output provides insights to optimize farming operations.

Microsoft Power BI Desktop is a platform for cloud-based analytics allowing the program users to create reports and view them in real time (Dineva & Atanasova, 2022). By enabling the generation of interactive dashboards and reports, farmers can see, in real-time, information on the weather and resource consumption through Power BI. The user-friendly drag-and-drop nature of the platform enables users to create customised dashboards, tailored to precise agricultural need. There are two kinds of dashboard report. The type that includes historical data is the first type, while the type with real-time data is the second type. Historical reports can receive new data (updates) based on a schedule refresh period that you specify, such as daily in the morning.

The dashboard reports presenting data in real-time (live connection) update the data automatically as soon as they are ingested by the system. Dashboard reports' contents can be filtered by using inbuilt or custom filters. Following the designed architecture obtained from research paper, Power BI is the destination in the data pipeline. It receives data from three sources. The first source is the Azure Machine Learning studio, which sends a ready machine learning model. The second source is the Stream Analytics service, which pushes real-time data. The third source is Blob storage, which sends raw data. The combination data between reports is presented into one common dashboard report, shown in Figures 2.3.



Figure 2.3 Dashboard Monitoring (Source from Dineva & Atanasova, 2022).

Table 2.2: Core Technologies Enabling Smart Dashboards in Precision Agriculture - Literature Review Matrix

Core Technology	Technology Role	Research Findings	Author(s)
IoT Sensor Networks	Role of IoT in Real-Time Environmental Monitoring	IoT enables monitoring of key parameters like temperature, humidity, and soil moisture, supporting efficient crop management.	Prabha (2023)

	Integration of IoT Sensors for Centralized Data Collection	IoT sensor networks facilitate seamless data connectivity and automate processes such as irrigation for optimal crop health.	Spandana & Pabboju, (2023)
AI & Machine Learning	Use of AI and ML for Precision Agriculture Decision-Making	Specific algorithms, such as Gaussian Naive Bayes, have proven effective in selecting suitable crops based on soil parameters like pH and nutrient content, enhancing profitability and reducing crop failure risks	Adewuyi et al., (2024)
Data Visualization	Highlights Power BI's ability to create dynamic dashboard	The platform allows integration with tools like Azure Machine Learning, Stream Analytics, and Blob storage to create comprehensive dashboards tailored to specific agricultural requirements.	Dineva & Atanasova (2022)

2.4.2 How are IoT devices and networks integrated into agricultural dashboard systems?

IoT integration into farming represents a paradigm shift in agriculture. The IoT-enabled agricultural dashboard is built on sensors and microcontrollers to provide the user with a single platform for monitoring environmental conditions, optimizing decisions, and operational efficiency. The following section discusses the present level of research on IoT devices, dashboard systems, and decision-support frameworks in precision agriculture, as well as the obstacles that come with their application

IoT devices are at the basis of precision agriculture, providing real-time data to assist farmers make informed decisions. Microcontrollers such as the ESP8266 and ESP32 are widely used to collect and send environmental data such as temperature, soil moisture, humidity, and light levels (Dineva & Atanasova, 2022). These devices are popular because of their low cost,

wireless capabilities, and integration with sensors. Common sensors used in agricultural IoT systems include the DHT11 for humidity and temperature monitoring, NPK sensors for soil nutrient content assessment, and ultrasonic sensors for water level control (Singh et al., 2020). Such devices are crucial for applying precision agriculture approaches, which enable targeted interventions to increase crop health and output.

These systems' advantages arise from their capacity to give detailed, field-specific data. Soil moisture sensors, for example, may detect variances throughout a farm and allow for site-specific watering. Similarly, nutrient sensors can detect inadequacies, allowing for more exact fertilizer administration while reducing waste and environmental impacts. However, issues like as sensor calibration, maintenance, and outside durability remain significant impediments to wider implementation.

IoT-enabled agricultural dashboards normally integrate decision-support systems that base their functioning on data analytics and machine learning to provide actionable insights. Architectures such as Intelligent Decision Agricultural make recommendations based on the analyses of historical and real-time data on optimal farming practices in irrigation scheduling, pest control measures, and crop rotation (El Moutaouakil et al., 2023). These insights help farmers maximize productivity while minimizing resource consumption.

Automation is another great feature enabled by IoT technologies. With automated irrigation systems, for example, soil moisture data is used to determine when and how much to apply water, reducing human interventions and resource wastage. In the same way, automated pest control systems identify infestations and deploy their treatments precisely where needed. The incorporation of robotics with IoT systems enhances operational efficiency by automating labor-intensive tasks such as planting, harvesting, and weeding (B. K. Acharya et al., 2023).

Figure 2.4 shows, for example, a diagram on how a Smart Livestock Monitoring System can work. It shows the integration of devices characterizing the IoT, Cloud Computing, and Interactive Visualization to monitor livestock effectively. The system gathers data obtained from sensors attached to animals or installed in the farming environment, processes the data via the cloud, and finally presents actionable insights using dashboards in an interactive way. These are set to ensure timely monitoring and decision-making using data for effective management of their livestock.

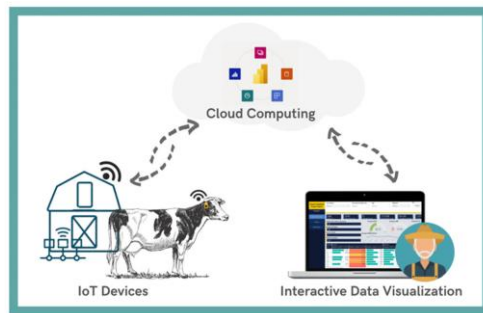


Figure 2.4 Smart Livestock Monitoring System (Source from Dineva & Atanasova, 2022).

Table 2.3: IoT Devices and Network Integration in Agricultural Dashboard Systems - Literature Review Matrix

IoT Integration and Network	Research Findings	Author(s)
Described microcontrollers and visualization platforms	IoT microcontrollers like ESP8266 enable environmental monitoring; Grafana enhances data visualization.	Dineva & Atanasova (2022)
Detailed sensor applications in precision farming	Sensors like DHT11 and NPK optimize soil and climate monitoring for precision farming.	Singh et al., (2020)
Discussed DSS and machine learning	DSS using machine learning offers insights to improve crop yields and resource efficiency.	El Moutaouakil et al., (2023)

Covered automation and resource efficiency	IoT-driven automation reduces labor and resource wastage, improving productivity through precision irrigation and pest control.	B. K. Acharya et al., (2023)
--	---	------------------------------

2.4.3 The Impact of Power BI Smart Dashboards on Farming Practices and Operational Efficiency?

Power BI smart dashboards are one such innovation that has brought a new revolution in farming and has allowed farmers to manage and analyze their operations with unprecedented efficiency. These dashboards put real-time data visualization into practice to gain actionable insights from IoT devices installed across farms (Jayaraman et al., 2023). It continuously monitors soil moisture, temperature, humidity, and livestock health, showing them in an understandable format. This allows farmers to make prompt, well-informed decisions, which directly impact crop productivity and animal welfare. Real-time monitoring does not only reduce risks like drought stress, pest outbreaks, or poor animal health but also allows for early interventions, thus ensuring consistent improvement in the overall performance of the farm.

The main feature of the Power BI dashboard is its user-oriented design. Following the F-pattern layout, the dashboards fall in line with how users naturally scan information; thus, farmers are able to pinpoint important data points rather quickly (Dineva & Atanasova, 2022). This intuitive design reduces the learning curve for new users, and these dashboards can be quite friendly even for farmers with limited technical experience. Being able to scan trends and anomalies at a glance ensures swift responses to operational challenges. Beyond that, these dashboards go further than just presenting data by incorporating machine learning models that analyze historical and real-time data to predict crop yields, pest outbreaks, or livestock growth rates. With such predictive capabilities, farmers can make strategic and forward-thinking

decisions on resource allocation, planting schedules, and harvest planning, which all factor into increased efficiency and profitability.

Beyond their predictive capabilities, Power BI dashboards also support dynamic reporting, allowing views to be personalized for specific needs in farming (Ferreira et al., 2021). Farmers can create a customized dashboard to focus on key metrics of interest, such as irrigation schedules, fertilizer application rates, or animal feed consumption. This flexibility means operations are closely aligned with individual farm goals, enhancing tracking and allowing precise adjustments where needed. For instance, the water-conserving farmer could shortlist irrigation efficiency as some of the key metrics, aiming for minimizing waste through real-time data without actually damaging their crops. All that done, this is actually your potential to customize reports, enhancing its applicability to a whole number of agricultural practices, from the so-called small-scale organic one all the way to large-scale, big industrial operations.

Power BI dashboards will ultimately take decision-making to become scientifically directed. These dashboards compile a variety of data into an integrated interface that visualizes trends, outliers, and inefficiencies that might not have been noticed otherwise. Farmers will be able to track variance from expected norms and observe opportunities for improvement in optimizing the use of resources and minimizing waste. For example, variances in soil nutrient information may suggest variable rate fertilization, lowering both economic and environmental costs. Similarly, livestock behavioral and health metrics can show improvement in animal welfare without sacrificing productivity.

On top of that, Power BI supports the integration of additional tools and platforms, hence creating one seamless ecosystem in farm management. For example, farmers can combine Power BI dashboards with cloud-based storage and IoT platforms to automate tasks

of irrigation, pest control, or fertilizer application. All these integrations make it easier to perform operations and save manual labor, ensuring continuous flow of data between systems with increased reliability of farm management processes (Premkumar & Sigappi, 2022).

Table 2.4: Key Impacts of Power BI Dashboards on Agricultural Practices - Literature Review Matrix

Impact Area	Research Findings	Author(s)
Real-Time Monitoring and Decision Making	Continuous monitoring of key factors like soil moisture and temperature helps farmers take quick actions, reducing risks and improving overall farm productivity and animal welfare	Jayaraman et al., (2023)
User-Friendly Interface	F-pattern layout ensures easy navigation for farmers. Design minimizes the learning curve, making it easier for farmers—regardless of technical expertise—to interpret data and make informed decisions rapidly	Dineva & Atanasova (2022)
Customizable Reporting and Resource Optimization	Highlighted that flexibility aids in optimizing resource usage and increasing operational efficiency, as farmers can adjust their strategies based on the visualized data and trends	Ferreira et al., (2021)
Integration with IoT and Automation	Pointed out that the seamless connection between Power BI dashboards and IoT systems helps automate agricultural processes, improving the reliability and efficiency of farm operations	Premkumar & Sigappi (2022)

2.4.4 What main challenges adoption of smart dashboards in agriculture?

The adoption of Power BI smart dashboards in farming is very transformative, although most challenges have to be taken care of for their full utilization. These challenges arise out of economic, technical, and infrastructural deficiencies that amalgamate to result in a shortage within the mainstream use of the advanced technology.

One of the main challenges for the adoption of Power BI smart dashboards in agriculture is the high initial investment that is actually required for the implementation of smart farming technologies (U. Acharya et al., 2023). The costs related to devices, sensors, and overall infrastructure that must support these technologies are most often very high, particularly for small and medium-scale farms. In developing regions where finances are already strained, such expenses present a formidable barrier. Most farmers cannot access the transforming benefits of these systems without adequate subsidies or financial support, which exacerbates further the disparities in agricultural productivity and innovation (Serrano-Trujillo et al., 2022).

A critical challenge lies in the lack of technical expertise and knowledge among farmers regarding the use and maintenance of smart farming technologies. Tools like Power BI dashboards require an understanding not only of data analytics but also of how to manage IoT devices and insights derived from these platforms. This knowledge gap often leads to underutilization of the technology, where its potential advantages remain unrealized (Ferreira et al., 2021). Moreover, the lack of specific training programs and friendly user interfaces exacerbates the problem by making farmers unable to use such tools to their fullest extent.

Power BI dashboards greatly rely on strong internet and network infrastructure for real-time data gathering, analysis, and visualization. In many rural areas, which act as the backbone of all agricultural activities, connectivity continues to be an issue. Poor network availability disrupts seamless data flow, resulting in partial or delayed insights that affect timely and informed decision-making (Supanirattisai et al., 2022; Zaki et al., 2024). This is a serious infrastructural limitation that undermines the very purpose of real-time monitoring and presents a substantial barrier to integrating smart dashboards into agricultural practices.

While Power BI smart dashboards hold immense promise for ushering in a revolutionary transformation of agricultural operations through real-time monitoring,

predictive analytics, and optimized resource utilization, it is estimated that high costs at startup, knowledge deficits, and connectivity concerns are major dampeners on the diffusion process. Such a barrier calls for targeting financial support, comprehensive training, and infrastructural development to ensure fair distribution of the benefits this technology will bring about within different contexts of farming. This would not only enhance agricultural efficiency but also assist in contributing toward the bigger goals of sustainability and food security.

Table 2.5: Adoption Challenges of Smart Dashboards in Agriculture - Literature Review Matrix

Adoption Challenges	Research Findings	Author(s)
High Startup Costs	High initial investment for devices and infrastructure is a barrier for small and medium farms. Limited financial support exacerbates disparities in accessing smart farming technologies.	Acharya et al., 2023 & Serrano-Trujillo et al., (2022).
Lack of Expertise and Knowledge	Farmers lack the technical skills to effectively use and maintain smart farming technologies. The absence of training programs and user-friendly interfaces hinders technology adoption and utilization.	Ferreira et al., (2021)
Connectivity and Infrastructure	Poor internet and network infrastructure disrupt real-time data flow, delaying insights. Infrastructural limitations undermine the reliability and usability of smart dashboards.	Supanirattisai et al., (2022) Zaki et al., (2024)

2.4.5 What are the emerging trends and future research opportunities for dashboard development?

The development of dashboards is a fast-evolving area, shaped by the newly emerging trends that prioritize customization, user experience UX, and collaborative design methodologies. These mark the beginning of crucial changes in how one approaches creating a dashboard with the objective of delivering tools that will be functional, adaptive, accessible, and consequential. Because dashboards are now the critical interfaces between users and complex data systems, their development must increasingly meet a wide range of needs, preferences, and contexts for a wide variety of domains.

Customization has emerged as a cornerstone in the evolution of dashboards, reflecting a growing demand for tools that can be tailored to individual user requirements. Users now expect the ability to modify interfaces, select specific features, and personalize data visualizations to suit their unique goals and contexts. This trend is especially prominent in educational circles, whereby students and lecturers alike look toward these dashboards for opportunities to enhance learning while offering effective peer-to-peer comparisons (Roberts et al., 2017). An example could be customizable dashboards, whereby learners would set a focus on personalized progress metrics, enhancing ownership and self-directed learning. Similarly, in professional and organizational worlds, personalization allows for users to simplify workflows by showing only what is relevant in terms of metrics or insights; this reduces a user's cognitive load. This means that customized dashboards can easily adapt to different types of users, whether they are technically sound or have domain-specific needs, because they are flexible. This ability helps bridge the gap between data systems, which can be highly complex, and end-users. For this reason, dashboards become indispensable in many fields like business analytics, healthcare, urban planning, and education.

The importance of user experiences in dashboard design has significantly increased, as it directly influences effectiveness and the rate of tool adoption (Muppidi et al., 2023). A well-

designed dashboard translates complex datasets to actionable insights through intuitive interfaces; this means that users engage and interpret data with ease. Emphasis on UX covers usability, accessibility, visual clarity, reduced cognitive load, and increased engagement with more satisfaction. Principles of UX ensure that the design of dashboards will answer the broad range of users' needs: from novice users who want to get simple insights to advanced users who need to perform deep analysis. For instance, dashboards designed with a focus on UX enable the quick identification of trends, anomalies, and key performance indicators that minimize the time and effort required to derive actionable conclusions. This focus on seamless and efficient interaction has made UX-centric dashboards a critical component in sectors where real-time decision-making and data-driven strategies are essential.

Another transformative trend in the development of dashboards is the adoption of methodologies related to collaborative and participatory design. In this regard, engagement with end-users through iterative loops of feedback and participatory workshops enables developers to ensure that the creation of dashboards meets day-to-day challenges and can also align closely with end-user needs. This approach is of particular value when dealing with complex domains such as urban planning or education, where the contributions of diverse stakeholders strongly bear on the utility and effectiveness of the resulting tools (Pihlajaniemi et al., 2017).

Collaboration in design provides ownership amongst users, and therefore final products are better accepted by them. Furthermore, a set of methodologies elicits true creativity from including insights from those who touch these dashboards daily, giving detailed ideas for features and capabilities (Wah et al., 2019). Finally, iterative development cycles for this end refinement mean taking user feedback to really dig and identify all pain points that need changing in respect of functionality to improve usability. This makes for tools that are not only

practical and user-centered but also more congruent with the evolving demands of their respective fields.

Table 2.6: Key Emerging Trends in Dashboard Development - Literature Review Matrix

Emerging Trend	Research Findings	Author(s)
Customization and User Control	Highlighted the increasing demand for dashboards that can be tailored to meet specific user requirements and preferences.	Roberts et al., (2017)
User Experience (UX) Focus	Emphasized the critical role of user-friendly design in ensuring that dashboards are intuitive, accessible, and easy to navigate.	Muppidi et al., (2023)
Collaborative and Participatory Development	Demonstrated the benefits of involving end-users in the design and development process to create dashboards that are practical, and user centered.	Pihlajaniemi et al., (2017) Wah et al., (2019)

2.5 Discussion

2.5.1 Theoretical implications

The study contributes to the theoretical foundation of smart dashboard development and IoT integration in precision agriculture by presenting a robust framework for understanding their potential transformation in farming practices. Further, it has emphasized how data visualization in real time, machine learning-driven analytics, and predictive modeling can create decision-making tools tailored for agriculture.

This research underlines critical contributions of user-centered design, customization, and technological interoperability, developing the theory that will help to bridge the gap between data systems and practical applications. The understanding of how advanced analytics

and IoT technologies interact in enabling optimization of resource management and operational efficiency is deepened by doing so.

2.5.2 Practical implications

In practice, the results indicate ways through which smart dashboards can be put into place to enhance agricultural efficiency. The study illustrated the potential of a dashboard, such as Power BI, in real-time monitoring of environmental and operational parameters for decision optimization and predictive analytics.

These insights are very important to farmers interested in adopting precision agriculture techniques, thus providing a clear roadmap on how IoT technologies, cloud-based systems, and data visualization platforms can be leveraged. It also underlines critical barriers, from high costs to limited technical expertise, and connectivity issues, offering concrete recommendations for targeted interventions ranging from subsidies to user training programs and infrastructure improvements.

2.5.3 Summary of Review Limitations

While the study gives indeed rich and comprehensive insights into smart dashboards and IoT technologies in precision agriculture, several limitations have to be discussed to balance this view. First of all, reliance on a systematic review approach, despite being structured and methodologically rigorous, by itself limits explorations into practical, real-world applications. Systematic reviews focus on synthesizing findings from existing literature, which means the actual implementation and effectiveness of the proposed solutions in diverse and real-world agricultural contexts may not be fully captured.

Another limitation involves the geographic and contextual constraints of the selected studies. Much of the research reviewed might be biased toward certain regions or types of agricultural practices, thus missing some unique challenges faced by farmers in areas that are

underrepresented. For instance, the barriers to technological adoption in low-resource settings or farming practices that are culturally different might not be well represented in the analysis. This geographic bias can restrict the generalization of the results and their applicability to global agricultural challenges.

Apart from this, no empirical testing of the proposed solutions is done in the research that limits the validation of the theoretical models and frameworks presented in it. Without field studies or trials in real-world conditions, practical feasibility, scalability, and actual performance of smart dashboards in diversified agro-ecological zones is doubtful. In fact, empirical validation has to be done for various environmental, economic, and operational parameters.

Lastly, the focus on existing literature may also constrain interdisciplinary perspectives that could enrich the understanding of these technologies. For example, insights from disciplines like behavioral science, economics, and policy studies could give a more holistic view of the factors influencing the adoption and sustainability of smart dashboards in agriculture. These limitations show that future research with more extensive field studies, wider geographic sampling, and collaboration across disciplines is needed to address these gaps in knowledge and to ensure the findings are of robust practical relevance.

2.6 Summary

The proposed data-driven intelligent monitoring system for precision agriculture is a milestone in filling the gap between conventional methods of farming and modern technological solutions. This system, through the use of Power BI smart dashboards combined with IoT-enabled devices and cloud-based platforms, presents a robust, scalable, and secure architecture to improve agricultural efficiency. This is achieved through a well-designed architecture that maximizes the data flow and security of all external entry points. Most

important among such challenges are the underutilization of data and tools acquired via modernization programs by farmers.

At the core of this system lies its ability to analyze real-time and historical data with machine learning-driven predictive analytics to generate actionable insights. It helps farmers in decision-making with a holistic understanding that is based on increased productivity along with sustainability. Intuitive, intuitive, and interactive dashboards assure data representation in the most comprehensible way possible, enabling users from diverse backgrounds regarding technological proficiency to equally use it. This system maintains nonstop IoT device monitoring and control for on-demand access to data, instant alarm notifications on critical events, and precision tracking of specified metrics, each greatly improved through its features.

Particularly noticeable is the development of the system to incorporate QR code functionality that will allow farmers to obtain specific animal data by scanning the codes in the ear tags. This provides an added level of accuracy and traceability to the practice of managing livestock and further exemplifies how this system meets many different agricultural needs. The use of Azure Cloud services also underlines a good commitment to environmental sustainability. Green computing initiatives, such as carbon footprint reduction and the strategic placement of servers in cooler climates, reflect the system's alignment with global environmental goals.

This intelligent monitoring system not only advances precision agriculture but also positions itself as a cornerstone for future innovations. By connecting farmers with cutting-edge, data-driven tools, the solution redefines modern farming practices, offering a sustainable, efficient, and technologically empowered approach to agricultural management.

CHAPTER 3

METHODOLOGY

3.1 Overview

In this chapter explains further details on the how the methodology that has been chosen for the proposed monitoring dashboard will be carried out along with detailed elaboration of task in each phase and produced involved. This methodology follows a structured approach, outlining the data collection, data storage, data processing, data visualization and process automation. The proposed monitoring dashboard should offer users to monitor real time of their temperature and humidity environment and full control of integrates advanced IoT, and artificial intelligence technologies supported by a user-friendly Power BI dashboard.

3.2 Research Framework

The research framework on the development of the SmartPalmBot dashboard will be designed following systematic steps in structured iteration that should address the attainment of decision analysis in view of its improvement and sustainability. Data collection includes, in this regard, environmental data acquired through the use of Tapo sensors. All collected environmental data are placed in one central Azure SQL Server, hence scalable in managing such data effectively. This is followed by data processing through Python scripts, cleaning and transforming raw data into structured data to make it accurate and consistent for analysis. The processed data is imported into Power BI, where interactive dashboards are designed to deliver actionable insights for plantation management and decision-making. In order to smooth the process, automation and integration are realized by Azure Function Apps, which automates data fetching and processing, while Power Automate refreshes the Power BI dashboards in real time. Further, this iterative framework has assured scalability to cater for various sizes and

complexities of plantations for continuous improvement. Figure 3.1 depicts the integration of components and how implementation of the framework has been effective.

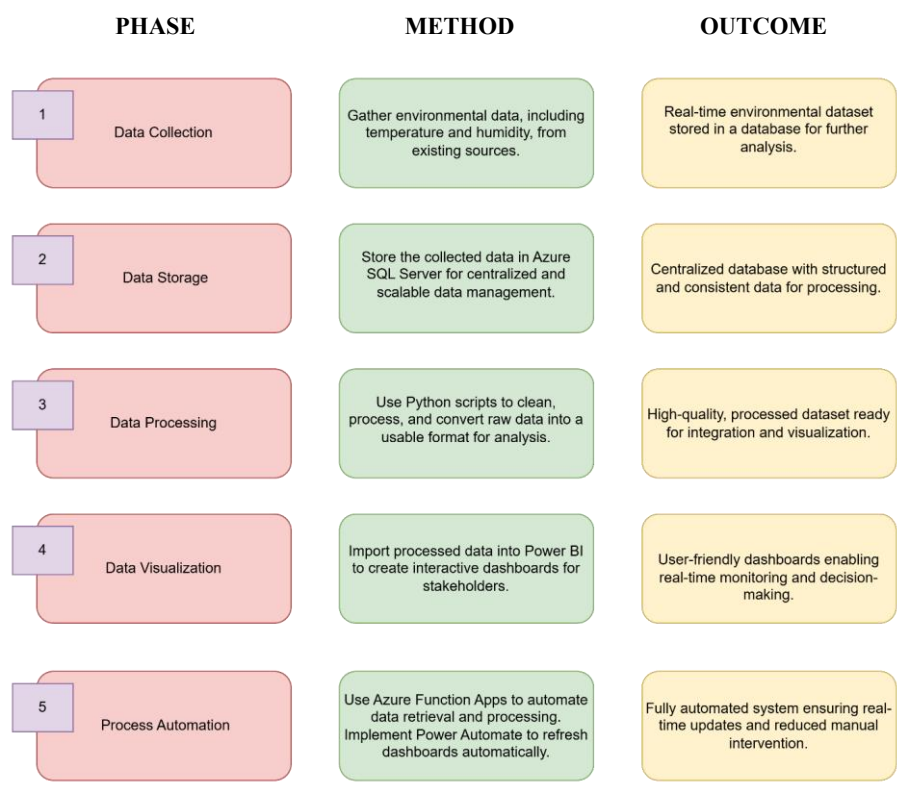


Figure 3.1 Research Methodology Diagram

3.3 Data Collection

To collect environmental data using the Tapo application, the IoT sensors are set up across the oil palm plantation, which optimally cover the temperature and humidity conditions of the various areas in the plantation. Such sensors are placed at various areas where environmental factors might fluctuate, such as areas with irrigation systems, in shaded or open-field environments, to ensure that any data collected represents the full spectrum of conditions

within the plantation. After correct installation, the sensors are connected using the Tapo application, which acts as a central platform that receives and displays real-time environmental data directly from the sensors (Heng, 2022).

The Tapo application will work as a medium for continuous temperature and humidity level monitoring. Using this, the recorded data of temperature and humidity will be done minute after minute. This ensures dynamic updating of the climate of a plantation in real time to analyze the present climatic situation. Through this system, which continuously tracks fluctuations in temperature and humidity, one could immediately detect any deviations from ideal conditions that would likely affect crop growth. Timely interventions may take place, such as the adjusting of irrigation schedules or modifying the environmental controls. Real-time monitoring and data visualization that can be provided by the Tapo application are essential in this dashboard since it can feed the raw environmental data to be analyzed.

Temperature and humidity data collected from the Tapo sensors integrate into the broader AI-driven surveillance system used for oil palm monitoring. By utilizing the Tapo sensors for data collection, the SmartPalmBot system can analyze and optimize environmental conditions, improve decision-making processes, and enhance plantation management. The real-time flow of data from the Tapo app is crucial in ensuring that the plantation remains within the ideal climate for the palm trees, which directly contributes to the overall success and productivity of the SmartPalmBot project. Figure 3.2 shows the diagram for process data collection.

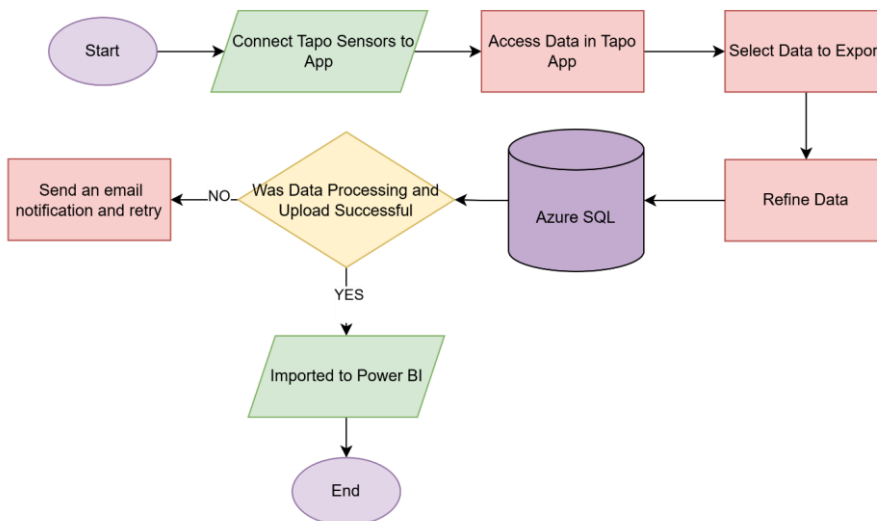


Figure 3.2 Data Collection Diagrams

For data collection, starting with system initialization, where the Tapo IoT sensors are connected to the Tapo application. After proper connection, these sensors will start transmitting environmental data in real time-including temperature and humidity, among other factors-to the application. This is then followed by internal access of the data within the application, where the user is allowed to view the sensor data collected, usually in graphs or logs. The user, after accessing the data, filters out what they want to export, for instance, a timeframe or the type of environmental data.

Once the selection has been made, the exporting of the data can be done with the export feature provided by the Tapo app. This is where one usually downloads data into formats such as CSV or JSON. The exported data later gets locally stored in the device for further use. The data can also be uploaded optionally to a cloud or central server, such as an Azure SQL Server,

for storage and further processing. Once the data is uploaded, it is processed for analysis and integration into the wider plantation management system that may involve visualization tools like Power BI for real-time monitoring.

The flowchart ends with the processed data ready for use in analysis and decision-making, making sure that environmental conditions-as captured by the Tapo sensors-can be leveraged in optimizing plantation management.

3.4 Data Preprocessing

Data preprocessing is an essential step in the process for robust and accurate predictive monitoring systems(Spandana & Pabboju, 2023). Considering environmental data originating from humidity and temperature sensors, the preprocessing stage in such scenarios starts with acquiring raw data from digital sensors interfaced with a microcontroller unit. This sampled data, collected at a rate appropriate to capture changes in the environmental condition, are stored over a cloud-based database for further processing. The raw humidity and temperature signals are cleaned to reduce noise and handle missing or irregular data points. This step is very important because downstream machine learning models expect high-quality inputs.

Feature extraction is one of the most important steps in the preprocessing phase, whereby the raw sensor readings are transformed into meaningful statistical and temporal features. For example, statistical moments are computed as:

$$M_k = \frac{1}{N} \sum_{i=1}^N (x_i - \mu)^k$$

where

M_k : The k -th moment,

N : The total number of samples

x_i : An individual data points

μ : The mean of the dataset

k : The order of the moment (e.g., 2 for variance, 4 for kurtosis).

Features such as Root Mean Square (RMS), kurtosis, and variance that are derived from the equation are particularly important. Kurtosis is a measure of the tailedness of the distribution and is calculated as:

$$\text{Kurtosis} = \frac{M_4}{M_2^2} - 3$$

where

M_4 : fourth central moment

M_2^2 : second central moment (variance).

These metrics are complemented by temporal analyses, such as identifying diurnal variations and seasonal patterns in the data, which help characterize environmental trends and anomalies. Normalization is used to scale the features uniformly so that all machine learning models receive the input similarly. In the case of tree-based algorithms, normalization is not necessary because the algorithm does this inherently. After processing the data, the split ratio of 80-10-10 for training, validation, and test sets, respectively, has been used to optimize the model's performance to prevent overfitting (Ferreira et al., 2021)

Pre-processed data with labels specifying the environmental conditions about the state, whether optimum, suboptimum, or critical, are then deposited in an Azure Storage Account. The statistical metrics and features, such as moments and kurtosis, are computed using the Python code, ensuring a reproducible and accurate preprocessing pipeline. This will better prepare the output for seamless integration into Azure Machine Learning Studio for training and testing of the model and visualization using Power BI.

3.5 Decision Tree and Forest Techniques

Decision trees represent one such basic tool used in decision analysis, employing multiple decisions wherein every juncture of a decision is a node, and each one of them further leads to the leaf, which stands for the outcome. These kinds of structures in application are also applied very much in machine learning, in a sense, to classify points in space by determining how much does a data point belongs to a particular class. The decision tree is designed to divide the given dataset at every node, depending on some parameters; the best splitting is learnt by the tree itself via training. Basically, the optimum split is selected by maximizing information gain, evaluated as reduction in entropy after the split. Entropy quantifies the uncertainty inside the data, and its minimization helps the model make closer-to-reality predictions (Ferreira et al., 2021).

While decision trees are powerful on their own, there are also more powerful variants, including ensembles such as decision forests and boosted decision trees. Boosting iteratively combines a sequence of weak models into a strong predictor, adjusting the weight of each model using gradient descent to optimize performance. In contrast, decision forests combine the output of multiple decision trees to estimate the probability distribution of outcomes more robustly. These methods are useful in that they can handle big datasets, are robust against noisy features, and represent nonlinear decision boundaries. To overcome other challenges such as memory consumption and model scalability, decision jungles that utilized DAGs instead of trees were introduced. DAGs allow nodes to have multiple parent-child relationships, which help reduce the memory footprint and keep model size at bay compared to decision forests.

These decision tree-based techniques may be used in plantation management to come up with a smart Power BI dashboard that facilitates data-driven decisions. For instance, the dashboard, based on real-time data from sensors deployed across the plantation, can use decision tree algorithms to predict vital factors like crop yield, pest outbreaks, or even the

effects of certain weather conditions. The dynamic insight updates within the dashboard, by integration of data streams from multiple sources including IoT devices for soil moisture, temperature, and rainfall monitoring, hence enable a scientifically backed decision-making process by the plantation manager. Furthermore, the Power BI dashboard can be enriched by incorporating decision forests, an ensemble method, for making such predictions more accurate and reliable for decision-making insights. This optimizes resource allocation and improves overall productivity at plantations by empowering decision-makers with comprehensive, real-time data analytics. Figure 3.3 depicts the decision tree of humidity level.

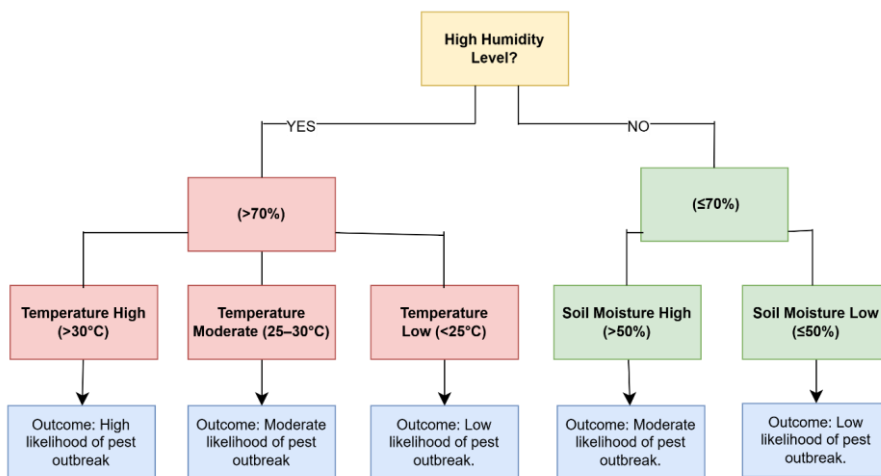


Figure 3.3 Decision Tree

3.6 Azure Function Apps

It was thus a manual procedure earlier that presented challenges in terms of inefficiencies, probable errors, and delays in updating data. An automated solution was designed to overcome these issues using Azure Function Apps, combined with Power Automate for seamless, real-time data management and visualization. Azure Function

Application was used to automate the procedure of fetching and updating data using a Python script. This script downloads datasets from Tapo Application, cleans the raw data into structured information in a DataFrame, and then writes that information to an Azure SQL Database. The script also incorporates an email notification system through which it sends emails updating stakeholders on the success or failure of the data update. An Azure Function Application was then set up to have a time-based trigger to ensure the refresh of data would happen at scheduled intervals, as opposed to manually-which significantly reduced operational overhead, thereby reducing the risks related to human error.

Complementing this integration of a workflow in improving the visualization, Power Automate was implemented. The former was supposed to auto-refresh the Power BI Dashboard once the database updates itself. This ensures that the latest data is always reflected in the dashboard, providing stakeholders with up-to-date insights without the need for manual refresh requests. The flow within Power Automate runs on a pre-set schedule or triggers immediately after the update of the data, ensuring a smooth transition from data processing to visualization. Together, these components provide a complete workflow architecture as shown in Figure 3.4.

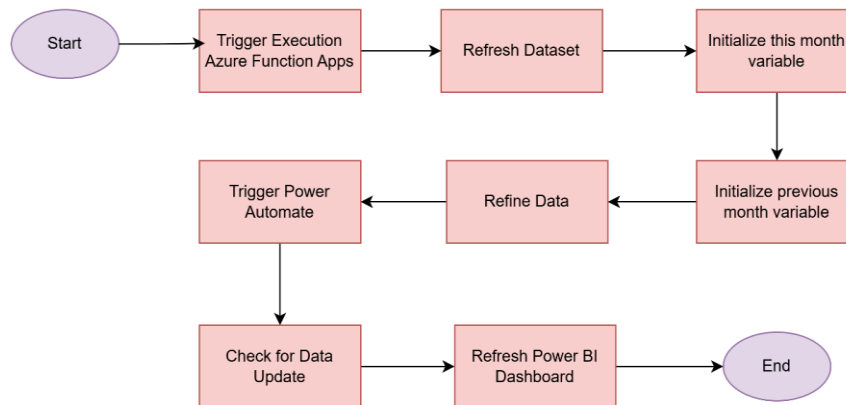


Figure 3.4 Workflow Architecture

The implementation also includes setting up the pipelines using Azure Pipelines and GitHub Actions to maintain code integrity and deploy updates efficiently. Azure Monitor provides complete, end-to-end monitoring for system reliability and performance. This automated workflow will improve efficiency by scheduling processes, increasing accuracy with minimum human intervention, and allowing scalability for future needs. The stakeholders will also have real-time actionable insights. Azure, integrated with Function Apps and then Power Automate, stands for a huge step toward data processing and visualization against the limitations of manual processes.

3.7 User Interface Design

The user interface design consists of two layouts catering to both desktop and mobile users' layout. The dashboards layout shows an overview of summary of daily temperature, monthly temperature, daily humidity and monthly humidity. The data obtained from sensors in an oil palm plantation; hence all the critical information will be well-structured and present. The KPIs include maximum and average temperature recorded inside and outside the plantation, among others. Moreover, this layout points to the exact time and location of the

sensor where such a high temperature was recorded, from which users can draw temporal-spatial analytical results.

Threshold analysis metrics allow determining the temperature conditions in relation to the total duration and frequency of temperatures over 40°C and the number of extreme events over 45°C. Temperature trend during the day: line chart showing temperature values versus time of day, with different segments for zones East Back, Middle, Outside, and West Front. This will enable multiple comparisons of thermal patterns across the different plantation areas. Complementary to that, a donut chart categorizes the sum of maximum temperatures by position and gives a proportional view of temperature distribution. Figure 3.5 show user interface for desktop layout and mobile layout for daily temperature.

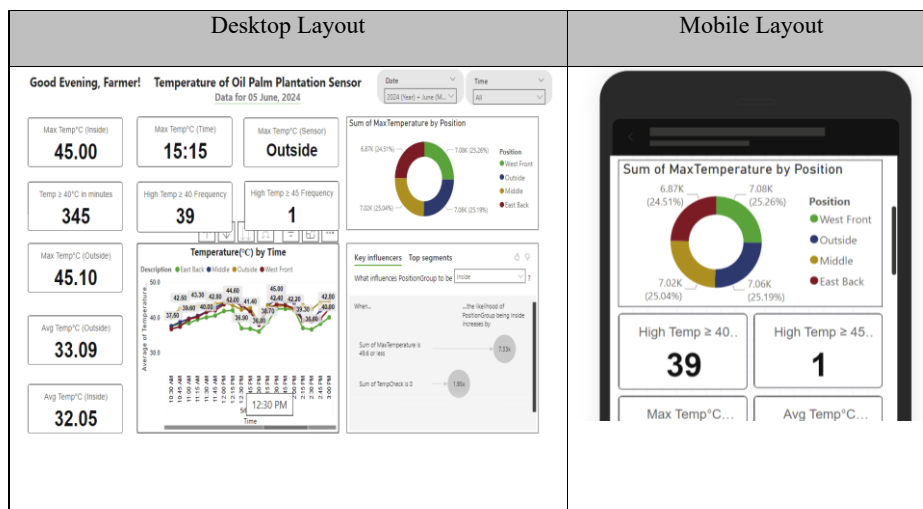


Figure 3.5 User interface for desktop layout and mobile layout for daily temperature.

In the monthly temperature dashboard, the interface aggregates data to show trends over an extended time period. Monthly averages, maximum-minimum variation of temperature, zone-wise temperature distribution are shown in this. It offers a capability to plantation

stakeholders to monitor the long-term trends in temperature and assess seasonal impacts on plantation health. Figure 3.6 show s user interface for desktop layout for monthly temperature.

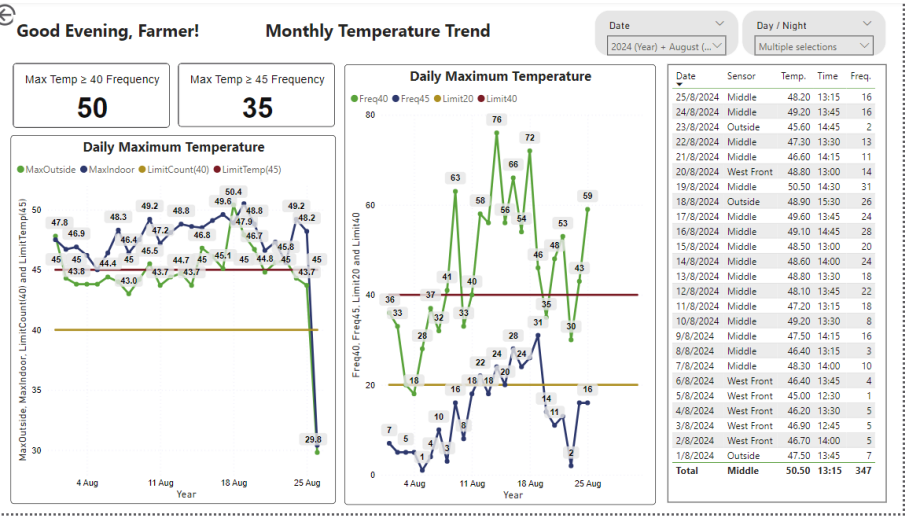


Figure 3.6 User interface for desktop layout for monthly temperature.

For the humidity dashboards, the features and functionalities are similar to the temperature dashboards but focus on humidity data. The daily dashboard will show real-time insights such as maximum, minimum, and average humidity, threshold alerts for extreme conditions, and a line chart showing trends segmented by plantation zones. Figure 3.7 and 3.8 shows user interface for desktop layout for daily humidity and monthly humidity.

Good Evening, Farmer!

Humidity of Oil Palm Plantation Sensor

Time
All

Date
2024 (Year) + May (...)

Min Hum% Inside

39

Max Hum% (Time)

14:30

Max Hum% (Sensor)

Outside

Low Hum < 60 Frequency

49

Low Hum < 55 Frequency

41

Hum ≥ 40°C in minutes

330

Min Hum% (Outside)

32

Avg Hum% (Outside)

76.16

Avg Hum% (Inside)

80.01

Humidity(%) by Time

Description ● East Back ● Middle ● Outside ● West Front

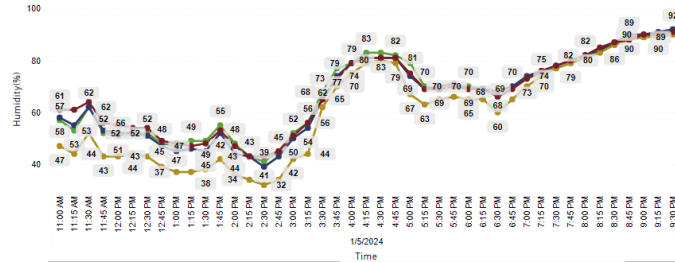


Figure 3.7 User interface for desktop layout for daily humidity

Good Evening, Farmer!

Monthly Humidity Trend

Date
Multiple selections

Max Temp ≥ 45 Frequency

103

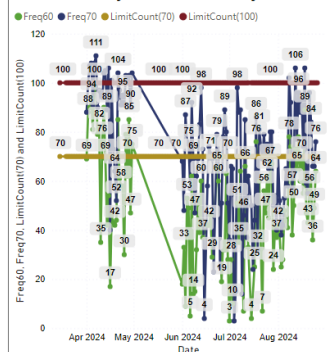
Max Temp ≥ 40 Frequency

206

Time Max Temp

03:00 PM

Daily Maximum Humidity



Count of Humidity Abnormal by Year

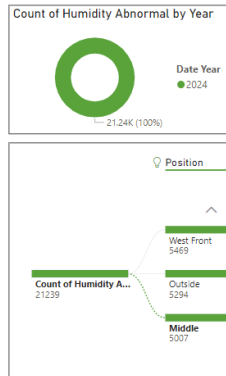


Figure 3.8 User interface for desktop layout for monthly humidity.

The weather map interface compares the weather against temperature and humidity levels to assist plantation managers in assessing the environmental factors vital for the growth and health of oil palm trees. This map will enable the user to monitor the trend and make decisions, for example, showing the area that has a higher chance of heat stress or too much moisture. Figure 3.9 shows User Interface of Weather Map Dashboard.

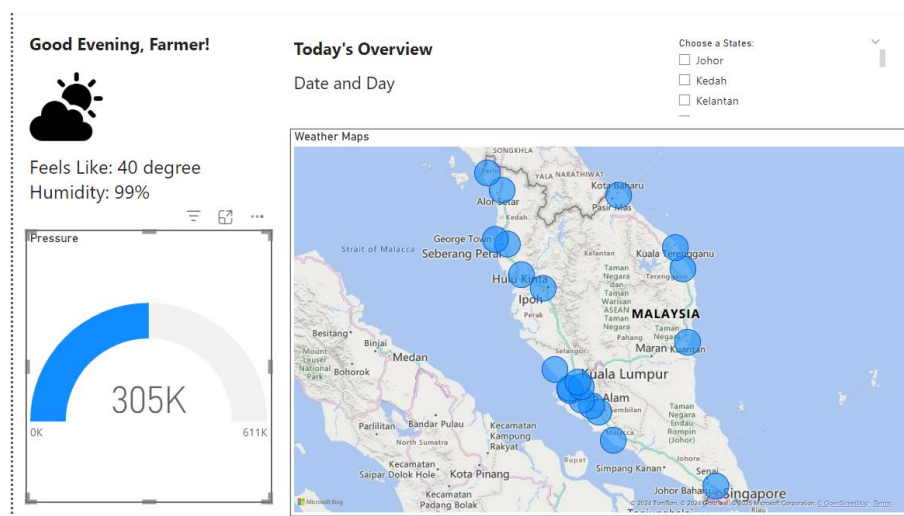


Figure 3.9 User interface for desktop layout weather maps

These show the key elements present on the weather map interface: a dynamic visual indicating locations of oil palm plantations located all across Malaysia, pinpointed with different blue interactive, which upon select, highlights key localized weather metrics from this location, be it temperature, humidity, and/ or pressure; then there is filtering by state-possible on the right-hand side for zooming out to the best possible view of desirable regions such as Johor, Kedah, or Kelantan. It also displays real-time metrics, including temperature in "Feels Like" and humidity in percentage, for a quick overview of the environmental condition.

3.8 System Evaluation Methods

The SmartPalmBot dashboard shall be evaluated rigorously for its effectiveness, both quantitatively and qualitatively. Quantitative evaluation will concern system performance metrics: data accuracy, real-time performance, data processing efficiency, predictive model performance, and user interface usability. Data accuracy and precision obtained by the Tapo sensors shall be checked against readings from calibrated reference sensors to ensure reliability. The disparities among these two data sources need to be quantified using statistical analysis in order to ensure that the data integrity is assured for decision-making. Real insight capability will be evaluated by measuring the time delay between data acquisition and its visualization on a Power BI dashboard.

Different response times shall be ~~analyzed~~analysed in different conditions to estimate how responsive the system can be under real-world usage. The efficiency of the noise reduction, feature extraction, and normalization steps within the data preprocessing pipeline will be measured through individual timing. In addition to time, computational resource monitoring during preprocessing will permit the assessment of the scalability of a system based on increasing the size of the plantation or the amount of data. Performance of decision trees and forests applied for predictive monitoring will be measured using accuracy, precision, recall, and F1-score, among other metrics.

These models will be extensively tested on their ability to predict correctly critical environmental conditions and the associated potential impact on plantation health by using historical and real-time data. The usability of the Power BI dashboard shall be tested by user testing among plantation managers and stakeholders. The intuitiveness, ease of navigation, and efficiency in terms of the presentation of actionable insights in the dashboard will be obtained through surveys and interviews. Qualitative evaluation will ensure in-depth feedback by

stakeholders in terms of how useful the dashboard is. Interviews with detailed questions will be held with plantation managers, agronomists, and other stakeholders to discuss their perspectives on the SmartPalmBot dashboard and how this has helped in changing their decision-making process. The perceived advantages of real-time monitoring, the usefulness of predictive insights, and related challenges will be discussed. Detailed case studies will be developed to document instances where specific instances of the SmartPalmBot dashboard allowed for timely intervention, improved practices, or productivity enhancement. The case studies would thus represent very real settings where the system has effectively worked out critical challenges with positive outcomes.

3.9 Usability Testing

To evaluate the usability and user experience of the monitoring dashboard, two established usability testing methods were employed: the System Usability Scale (SUS) and the User Experience Questionnaire (UEQ). These methods were chosen for their effectiveness in capturing user feedback on both the functional and experiential aspects of the dashboard.

The System Usability Scale (SUS) is a 10-item questionnaire designed to assess the overall usability of systems. It uses a 5-point Likert scale, where participants rate their level of agreement with statements regarding ease of use, complexity, and confidence in use. For the Monitoring Dashboard, SUS was employed to gather a single usability score that reflects the dashboard's overall performance and user satisfaction. The SUS results provided critical insights into the dashboard's accessibility and user-friendliness.

The User Experience Questionnaire (UEQ) evaluates user experience across six key dimensions: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. Using semantic differential scales (e.g., "Annoying" vs. "Enjoyable"), the UEQ enabled the collection of detailed feedback on the Monitoring Dashboard's visual appeal, intuitiveness, and

Commented [AM7]: This section should be included in Chapter 5 Testing

effectiveness. This method facilitated an in-depth understanding of how users perceive the dashboard in real-world scenarios.

Both SUS and UEQ were applied during the usability testing of the Monitoring Dashboard. Participants were asked to interact with the dashboard, performing tasks such as monitoring key metrics, visualizing trends, and generating reports. Their responses to the SUS and UEQ questionnaires were analyzed to identify areas requiring improvement and to refine the dashboard's design iteratively. Both SUS and UEQ were applied during the usability testing of the Monitoring Dashboard. Participants were asked to interact with the dashboard, performing tasks such as monitoring key metrics, visualizing trends, and generating reports. Their responses to the SUS and UEQ questionnaires were analyzed to identify areas requiring improvement and to refine the dashboard's design iteratively.

3.10 Summary

This chapter discussed on the methodology used in developing the proposed monitoring dashboard. The selected methodology to develop the proposed monitoring dashboard are data collection, data storage, data processing, data visualization and process automation. Illustration and dashboard design are resented clearly through the user of flowchart, workflow, decision tree and user interface design to describe the logical and physical flow of the dashboard.

CHAPTER 4

IMPLEMENTATION AND TESTING

4.1 Overview

In this chapter, the further details of implementation and testing of the proposed project are included and explained much detail sufficiently to be able to achieve all the aim of proposal. Furthermore, this chapter also describes the hardware and software setup installations, an interactive dashboard for visualization and a chatbot interface for facilitate communication with end users. It also includes the concept of the data relationship model of the Power BI under the hood. The final part describes the methods of testing to test the performance of the project and the functionality.

4.2 Installation and Configuration System Architecture

4.2.1 Hardware

The environmental monitoring part of the SmartPalmBot is designed based on the TP-Link Tapo T310 Smart Temperature & Humidity Sensor; it was chosen due to its high accuracy of measurable values, flexibility and easy cycling interfacing with mobile data network. Featuring a Swiss-made sensing component, the Tapo T310 measures temperature and humidity with a high degree of accuracy: $\pm 0.3^{\circ}\text{C}$ for temperature and $\pm 3\%$ for humidity (RH). Its two-second data update frequency makes real-time observation of microclimate variability possible and is crucial in recognising environmental anomalies that may negatively impact crop performance, disease risk and irrigation scheduling

For this project, four sensors were fixed in different places to obtain the complete information of plantation environment. Three sensors were set up inside the plantation: the West Front, Central Middle and East Back zones; and one outside sound to compare internal

and ambient microclimate. Accessibility, representativeness of the local microclimate and the opportunity to record differences in temperature and humidity as a function of spatial layout or canopy coverage were the key criteria for selecting the indoor sites. All sensors were installed in locations that minimized obstructions and were easily accessed for service, providing long-term use and reliable data collection.

4.2.2 Software

In order to implement the proposed project, the software development was conducted within the scope of the SmartPalmBot project, and it involved multiple interconnected systems that together covered the gathering, processing, storage, visualization, and user interaction for environmental sensor data. The primary language of the project was Python, due to the availability of extensive data manipulation tools in Python, as well as a variety of cloud databases, tools for automation, and machine intelligence pipelines. Modularization of the software structure enabled maintainability and expandability (in case of future extensions).

The Tapo T310 sensors wirelessly connect to the TP-Link Tapo application (TP-Link Tapo mobile app) via the Tapo Smart Hub for environmental data collection. The Tapo app provided real-time temperature and humidity data and offered the access and export of temperature and humidity logs in CSV. The app's dashboard includes easy-to-understand charts and warning alerts if readings go beyond established ranges. These capabilities enabled real time analysis and daily monitoring at a field level, which comprised the first layer of the data pipeline. Figure 4.1 shows interface of the TP-Link Tapo mobile application.

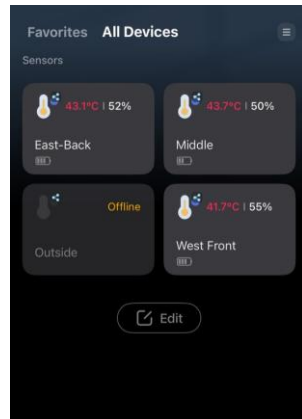


Figure 4.1 TP-Link Tapo mobile application

The cleaned dataset was transmitted to a cloud-hosted Azure SQL Database. A relational table schema was designed to include fields such named date, time, temperature, humidity and position. The PyODBC connector was used to transmit the data, allowing python to operate over the internet with the SQL queries safely. Azure SQL Database was chosen because it's a turnkey, highly available solution that is easy to administer and that works natively with Microsoft analytics tool. Figure 4.2 presents Azure SQL Database accessed through DBeaver.

Id	Date	Time	Temperature	Temperature_Abnormal	Humidity	Humidity_Abnormal
1	2024-03-19	4:15:00 PM	43.1	*	41	
2	2024-03-19	11:15:00 PM	25.2	*	92	*
3	2024-03-20	6:15:00 AM	23.5	*	96	*
4	2024-03-20	1:30:00 PM	33.5	*	66	*
5	2024-03-20	8:30:00 PM	27.2	*	89	*
6	2024-03-21	3:30:00 AM	24.7	*	96	*
7	2024-03-21	10:30:00 AM	40.2	*	53	
8	2024-03-21	5:45:00 PM	36.3	*	52	
9	2024-03-22	12:45:00 AM	23.7	*	93	*
10	2024-03-22	7:45:00 AM	23.3	*	97	*
11	2024-03-22	3:00:00 PM	45	*	36	
12	2024-03-22	10:00:00 PM	25	*	88	*
13	2024-03-23	5:00:00 AM	23.3	*	95	*
14	2024-03-23	12:15:00 PM	46.4	*	39	
15	2024-03-23	7:15:00 PM	30.7	*	69	*
16	2024-03-24	2:15:00 PM	24.3	*	94	*
17	2024-03-24	6:45:00 AM	24.7	*	73	*

Figure 4.2 Azure SQL Database

Visualization and dashboarding were implemented through Microsoft Power BI, which was set up to connect directly to Azure SQL Database with DirectQuery. The Power BI dashboard was deployed to the Power BI Service and embedded into a public website for presentation to stakeholders or users who don't have to have the Power BI Desktop software.

A lightweight web interface based on the Flask micro web framework was also generated for better interaction and user engagement. Flask was utilized to create REST API endpoints and render the HTML-based interface which hosts the chatbot module. The chatbot was developed to answer questions about environmental conditions, sensor statuses, and basic system functions.

4.3 System Page

The SmartPalmBot Analysis Dashboard is an interface where the real-time environment monitoring data is displayed to the farmers, giving them a single viewpoint of important temperature and humidity parameters using IoT sensors. The information includes the temperatures and humidity changes from four sensor zones inside and outside of the plantation. Just below this, interactions slicers have been embedded allowing analysis by year and time, to make the most of understanding the data through time.

[An](#) ~~Also shown in the lower left,~~ an area chart displaying trends of temperature changes

at various times of the day for each sensor location. This enables a more detailed perspective of intraday heat dynamics and supports operational planning, especially of activities under temperature extremes. Lastly, there is a geo-physical heatmap presented at the bottom right corner as helpful tool to visually depict the temperature highs and lows around the monitored region. Hotspot clusters are shown using red gradient markers which helps users to locate plantation zones at risk on accurate GPS mappings. Below is the Figure 4.3 shows figure of the SmartPalmBot dashboard page for temperature monitoring.

Further supporting time-based analysis, an area chart in the lower left corner visualizes temperature fluctuations across different hours of the day, categorized by sensor positions. This provides an in-depth view of intra-day heat trends and facilitates operational planning, particularly for activities sensitive to temperature extremes. Finally, the inclusion of a geospatial heatmap in the lower right quadrant of the dashboard provides a spatial overview of temperature intensities across the monitored area. Red gradient markers indicate hotspot concentrations, allowing users to identify high-risk plantation zones based on precise GPS mapping. Below is the Figure 4.1 shows figure of the SmartPalmBot dashboard page for temperature monitoring.

Commented [AM8]: Which one?



Figure 4.3 SmartPalmBot Analysis Dashboard – Temperature Monitoring

Below Figure 4.4 is a screenshot of the humidity monitoring page of the SmartPalmBot Analysis Dashboard. This page has the same layout and design as the temperature dashboard, but it's only used for visualizing humidity data from Tapo IoT sensors. On the left the monitor key indicators shows the minimum humidity values registered inside and outside the plantation, along with the time of each of these minima and the sensor location. Average humidity values were also given to aid in the general environmental evaluation.

In the main panel, a donut chart visualizes anomalies of humidity readings by location, along with the line and area charts that indicate changes over time and date of humidity. A high- and low-humidity heatmap is provided to position the high- and low-humidity spots geographically on satellite images. This dashboard can help managers of such plantation monitor the trend of humidity effectively and make decisions in time based on data. The Figure 4.4 ~~below~~ shows the Dashboard Page for humidity monitoring of the SmartPalmBot.

Commented [AM9]: Which one?



Figure 4.4 SmartPalmBot Analysis Dashboard – Humidity Monitoring

On the top-left panel, two prominent KPI cards display summary statistics: the total number of instances where the maximum temperature exceeded 45°C ($\text{Max Temp} \geq 45$ Frequency), and the cumulative count of daily temperature spikes ($\text{TotalMaxTempCount}40$). These measures allow users to rapidly appraise how often and how intensely extreme heat occurs for the timeframe examined.

Below the KPI cards, a table provides raw sensor readings that feature date, sensor location, temperature reading, time, and frequency. Within this table section, detailed secondary visibility of high temperature events is presented, favoring recent entries and sensor zones where readings are most important. For example, values such as 52.00°C recorded outside the plantation suggest potential microclimate variances that may require separate treatment or intervention strategies.

The central panel features a line graph labelled “Daily Maximum Temperature,” which plots temperature readings from multiple sensors over time. The graph includes visual markers for predefined temperature thresholds such as 40°C and 45°C (LimitTemp), as well as line which shows the number of values that are allowed until measures must be taken. The use of multiple colours is to differentiate between the sources of the sensors, which in turn makes it

easier to see trends and outliers. This allows users to monitor whether internal plantation zones consistently exceed safe temperature levels compared to external reference points.

The right panel contains a vertical bar graph that expresses how often the measurements during the daytime exceeded several cutoffs - namely, 20°C, 40°C, and 45°C. The histogram-style visualization summarizes frequency information to show the distribution of high-temperature events and allowing to identify patterns in their temporal occurrence. Horizontal reference lines (Freq40, Freq45, and Freq20) are also used for comparison purposes to contextualise the strength of a temperature spike on a day in relation to other days. Figure 4.5 below illustrates the monthly temperature monitoring interface.

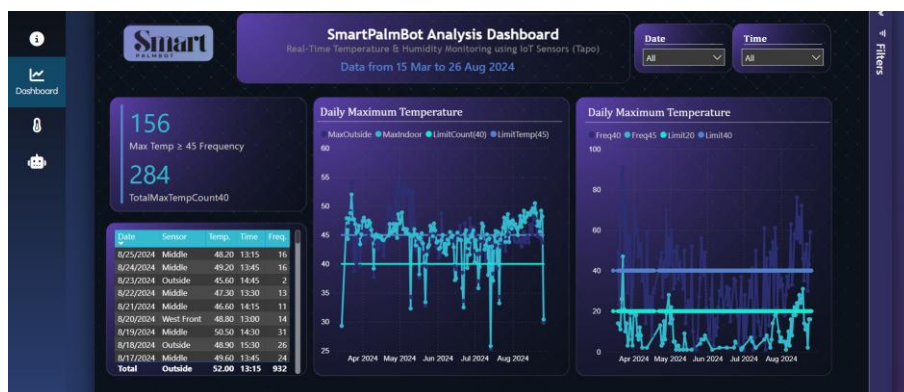


Figure 4.5: SmartPalmBot Analysis Dashboard – Monthly Temperature

Figure 4.6 depicts two analytical views provided by the SmartPalmBot Analysis Dashboard for temperature change/stagnation property detection and high-temperature cause analysis. To the left, the chart “Month-over-Month Temperature Trends” displays the average temperature and changes at different sensor locations and in plantation zones over several months. Each vertical bar presents the details of the difference in the monthly average temperature for those with rising, decreasing, or constant values. Such a graph assists directors of plantations looking for periods of sustained temperature change (warming or cooling) and

trying to determine if given zones — e.g. East Back or Middle zone — have been more prone to prolonged temperature changes than others.

The second right panel shows the Power BI's Key Influencers visual to explain the main factors contributing to a high temperature event ($\geq 40^{\circ}\text{C}$). Results show the effects of time of day, with the warmest temperatures most likely to occur from 11:15 AM and 3:15 PM. Another histogram shows the distribution of high temperature readings in a 1-hour time step illustrating the same high values for that time of the day. This information can be used by plantation managers to decide on adaptation strategies (irrigation, worker schedule) in function of the hours considered most thermal stressful, and therefore where palm release heat. Figure 4.6 below illustrates the heat analysis monitoring interface.

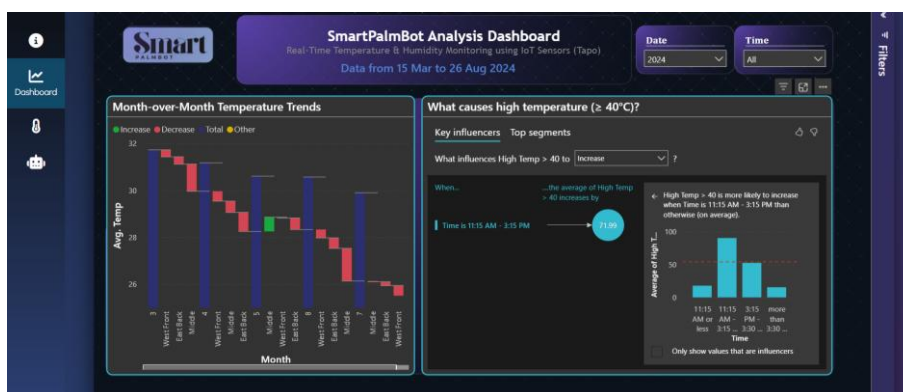


Figure 4.6: SmartPalmBot Analysis Dashboard – Heat Analysis

4.4 Chatbot Module

The chatbot component of SmartPalmBot was developed as an interactive conversational system that allows users to ask questions regarding current environmental states or to provide context-specific advice concerning plantation maintenance. This module was constructed using Microsoft DialoGPT-small, a transformer-architecture based conversational-style generative model that generates coherent responses in a context-sensitive manner. The chatbot

is hosted in Flask web server, as a middle layer between the front-end UI and the back-end database or model.

There are two main modes the chatbot works with. The first of these is a rule-based word matching mode, which extracts specific environmental terms, such as “temperature”, “humidity”. The Flask backend, when it hears one of these keywords it triggers a query to the Azure SQL database to pull the latest sensor readings. These readings are then translated into formatted natural language responses for real-time feedback to user: e.g. “the current temperature is 30.2 C from Sensor 2 (Middle Zone) recorded at 14:00” etc. This is a characteristic, which increases the effectiveness of the chatbot by providing real time and actionable alerts.

The second mode of operation uses DialoGPT’s pre-trained generative capabilities to emulate human-like conversation for questions that do not include predetermined keywords. In such cases, the input is tokenized and encoded and then sent to the language model, which outputs a response that is probable and contextually relevant in accordance with preceding dialogue history. This mode enables the chatbot to stay responsive by being exciting even when it is weakly engaged with vague conversational lines of inquiry unrelated to sensor data, such as “Can you help me with my irrigation schedule?” or “How’s the weather today?”

Together rule-based logic with generative AI contribute not only to the technical but also the application layer to build not just task-oriented chatbots, but rather hybrid chatbots that adapt a balanced approach to retrieve task-specific information with maintaining natural conversation. The dual-mode solution guarantees that, in addition to being accurate, the sensor data are received naturally and interacted intuitively, in line with our system’s objective to enhance digital literacy and accessibility of plantations’ stakeholders. Figure 4.7 below illustrates the SmartPalmBot Chatbot.

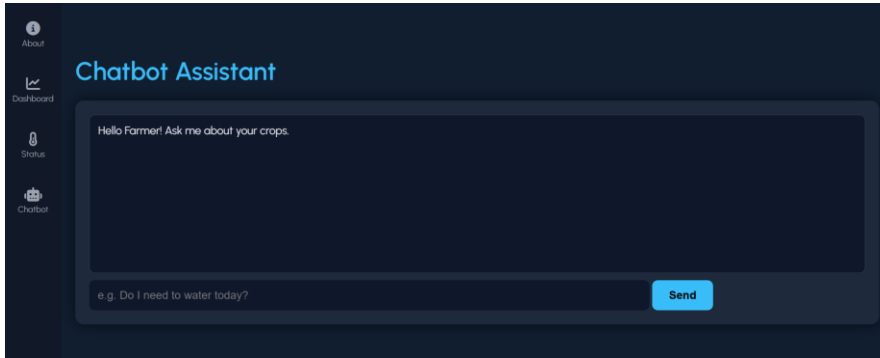


Figure 4.7 SmartPalmBot Chatbot

4.5 Data Relationship Model

The data relationship model used in the SmartPalmBot Power BI dashboard consists of several structured tables that slide over each other, allowing for dynamic, real-time visualization of environmental sensor data. The `Sensor_Data` table forms the main dataset that we are collecting from Tapo IoT sensors. This table contains lots of relevant fields like Date, Hour, Humidity (%), Humidity Abnormal, Sensor, Position, and PosGroup. It serves as the central fact table, containing timestamped environmental readings from different sensor points throughout the plantation.

The `Sensor_Data` table is linked to various dimension tables that add context and facilitate analysis. The `Sensor` table, connected via the `Sensor` field, contains metadata such as sensor descriptions and geographical coordinates (e.g., Latitude). The `DateTable` is connected to `Sensor_Data` through the `Date` field and includes derived fields like `MonthNum`, enabling time-based slicing and trend analysis. The `SummaryTable` is related by both `Date` and `Position` fields, aggregating values like `MaxTemperature`, `CountMaxTemp`, and grouped metrics for specific visual elements in the dashboard. Additionally, the `DAX_Calculations` table contains pre-calculated values such as `AvgHum`, allowing optimized performance for common

aggregations in Power BI. These relationships are cardinal and primarily one-to-many, ensuring data integrity and consistent visual filtering across all report pages.

The resulting relational model is the basis for dashboard interactivity, and allows users to cross filter visuals by date, zone, sensor, and severity of the environmental condition. Scalable insights are supported, and usability is improved for plantation monitoring and decision-making. Figure 4.8 below-illustrates the Data Relationship Model.

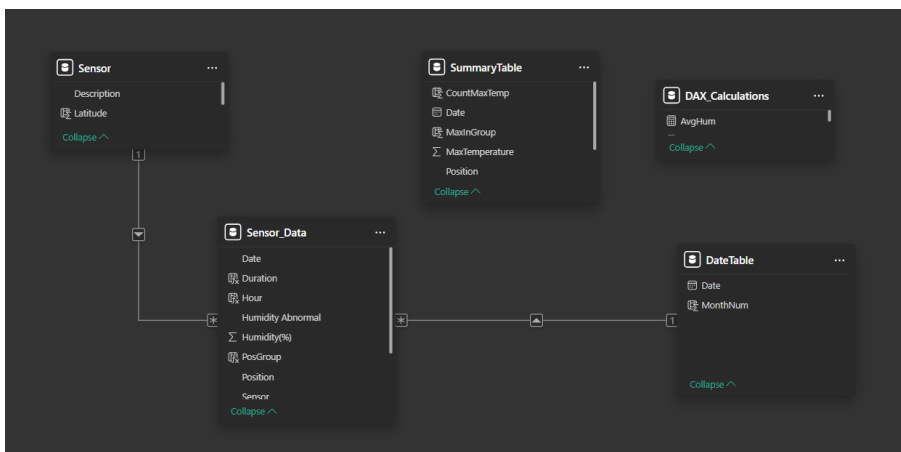


Figure 4.8 Data Relationship Model

4.6 Usability Evaluation Using the System Usability Scale (SUS)

This section reports the findings of a structured usability evaluation of the prototype SmartPalmBot using the System Usability Scale (SUS). The SUS is a widely adopted and validated instrument for assessing perceived usability and user satisfaction (Brooke, 1996). This post-test survey was administered to all participants following completion of the defined usability tasks.

Commented [AM10]: This section should be grouped together in Chapter 5 Testing

4.6.1 Participant Profile

There were 15 participants were involved in the usability testing. This group included seven students, five staff members from the Digital Transformation Department at TDM and three oil palm farmers from a TDM plantation community. The students (20– 24 years old) exhibit different familiarity level with computing tools, while the staff and farmers, (35 – 50 years old) represented the actual end users targeted by the SmartPalmBot system.

While the student and Digital Transformation staff participants had some background in computing, owing to their academic exposure, their experience with real-time data visualization platforms like Power BI and AI-based chatbot systems differed. On the other hand, the farmers provided a valuable perspective rooted in practical agricultural experience but limited digital literacy. This mix of technical and non-technical users allowed for a well-rounded and inclusive evaluation of the system's usability and effectiveness.

By engaging both IT background and current agricultural practitioners, the study ensured that feedback reflected realistic, diverse user experiences, specifically among those who are potential users of smart monitoring tools in plantation activities. This participant variance enhanced the evaluation and aligned with the intention of making SmartPalmBot accessible, usable and of potential benefit to those with different levels of digital literacy

4.6.2 SUS Scoring Methodology

The SUS instrument comprises 10 items, each rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The scale alternates between positively and negatively worded statements to reduce acquiescence bias. Scoring was performed as follows:

- For odd-numbered items (1, 3, 5, 7, 9), the score contribution equals the respondent's rating minus 1.

- For even-numbered items (2, 4, 6, 8, 10), the score contribution equals 5 minus the respondent's rating.

The total score, ranging from 0 to 40, was then multiplied by 2.5 to convert to the standard SUS scale of 0 to 100. Higher scores indicate better usability.

4.6.3 Descriptive Statistics

Table 4.1 summarizes the key descriptive statistics for the SUS scores across all participants.

Table 4.1 Summary of SUS Scores (n = 15)

Statistic	Value
Mean SUS Score	92.5
Standard Deviation (SD)	11.2
Median	100
Minimum Score	65.0
Maximum Score	100
Number of Participants	15

Table 4.1 Summary of SUS Scores (n = 15)

The mean SUS score of 92.5 suggests that the application is perceived to have exceptional usability. Based on Bangor et al. (2009), a score above 70 is typically interpreted as “good usability,” with anything above 80.3 considered “excellent.” Achieving a score of 92.5 places SmartPalmBot well into the “excellent” category and among the top-performing systems for usability. The relatively low standard deviation indicates that most users had a consistent perception of the app's usability.

Commented [AM11]: Caption should be on top of the table

Formatted: Caption for Table, Left, Space After: 0 pt, Line spacing: single

Formatted: Space After: 0 pt

Commented [AM12]: Caption should be on top of the table

Formatted: Caption for Table

4.6.4 Item-Level Analysis

To obtain a more granular understanding of specific usability factors, item-wise mean scores were calculated and are presented in Table 4.2. This provides insight into which aspects of the system were positively or negatively perceived.

Table 4.2 Mean Ratings by SUS Item

SUS Item	Statement	Mean Rating
1	I think that I would like to use this SmartPalmBot frequently.	4.8
2	I found the SmartPalmBot unnecessarily complex.	1.33
3	I thought SmartPalmBot was easy to use.	4.67
4	I think that I would need assistance to use this SmartPalmBot.	1.47
5	I found the various features in this SmartPalmBot were well integrated.	4.8
6	I thought there was too much inconsistency in this SmartPalmBot.	1.33
7	I would imagine that most people would learn to use this SmartPalmBot very quickly.	4.87
8	I found the app very cumbersome to use.	1.27
9	I felt very confident using the SmartPalmBot.	4.67
10	I needed to learn a lot of things before I could get going with this SmartPalmBot.	1.40

Commented [AM13]: Caption should be on top of the table

As seen above, the most highly rated items were Item 7 (“I would imagine that most people would learn to use this SmartPalmBot very quickly”, $M = 4.87$), Item 1 (“I think that I

would like to use this SmartPalmBot frequently”, $M = 4.8$), and Item 5 (“I found the various features in this SmartPalmBot were well integrated”, $M = 4.8$). These results indicate strong user confidence and perceived ease of use—two critical dimensions of usability. Conversely, negatively phrased items such as Item 2 (“I found the SmartPalmBot unnecessarily complex”, $M = 1.33$) and Item 8 (“I found the SmartPalmBot very cumbersome to use”, $M = 1.27$) received low agreement, which further reinforces the conclusion that the system design was perceived as intuitive and accessible.

4.6.5 Interpretation and Benchmarking

According to Sauro and Lewis (2012), the average SUS score across over 500 usability studies is approximately 68.0. The mean score of 92.5 for this application therefore places it far above this benchmark. Using the Adjective Rating Scale by Bangor et al. (2009), which assigns qualitative descriptors to SUS scores, a score above 80.3 is interpreted as “Excellent” usability. SmartPalmBot’s result of 92.5 is among the highest tier for usability and indicates that users found the system exceptionally easy to use and effective.

To provide an additional interpretive layer, the SUS score was mapped onto a percentile ranking. Based on conversion tables from prior literature, a score of 92.5 places the application well above the 90th percentile, suggesting it performs better than 90% of products tested using the SUS scale.

4.6.6 Visual Summary

Figure 4.9 presents a histogram of the SUS scores to illustrate the distribution across participants. The distribution is moderately symmetrical and clustered around the mean, suggesting no significant usability issues experienced by outliers.

In SUS, some questions are intentionally constructed as negatives to mitigate response bias. To make certain that high scores consistently indicate good usability, reverse-scoring the negatively worded items is performed before analyses are conducted. This is achieved by subtracting the original answer from 6 (i.e., $\text{Adjusted Score} = 6 - \text{Original Score}$). That is, for example if a respondent decides that “Confusing layout” is a 1 (strongly disagrees with the negative item), then the adjusted score becomes 5 – i.e. it is given very strong support to the positive interpretation, (“clear layout”). This re-scoring helps to orient all SUS-items in the same direction, which results in mean-scores and visual comparison that are valid, and question is reversible in a meaningful manner. Figure 4.9 presents Adjusted SUS Mean Score.

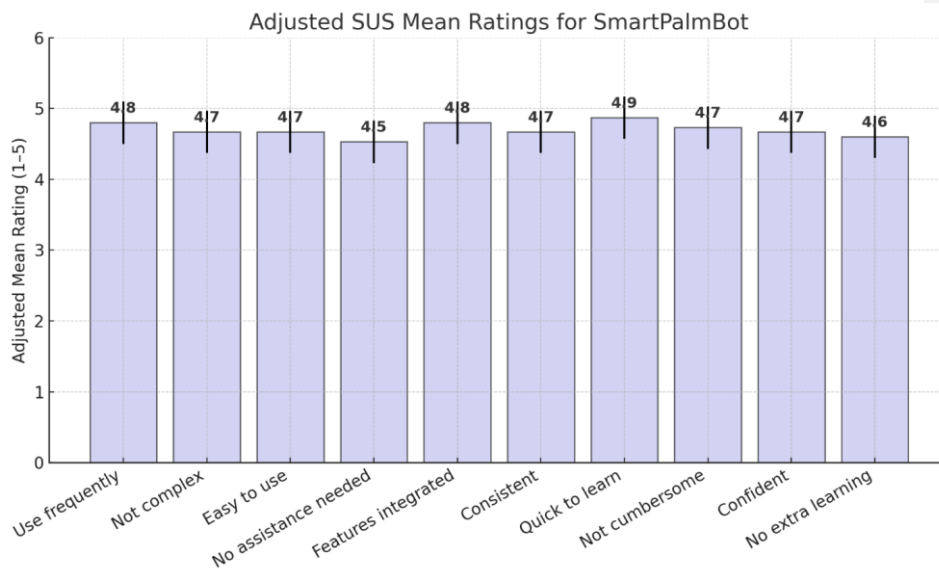


Figure 4.9 Adjusted SUS Mean Score

Table 4.3 also shows the original and adjusted mean ratings for each SUS item. For negatively keyed items, the scoring is reversed (6 minus the observed score). This makes sure that the bigger the adjusted score is for each item, the more positive the user has experienced. If the original average rating for a negative statement — let's say, "Confusing layout" — is 1.3, the adjusted score is 4.7. Therefore, direct comparison can be made among all items of the table with a higher score representing better usability perception across all of the items. Table 4.3 shows the table of original and adjusted mean rating.

Table 4.3 Table of original and adjusted mean rating

Commented [AM14]: The caption is on top of the table

No.	SUS Item	Original Mean Rating	Adjusted Mean Rating
1	Use frequently	4.8	4.8
2	Not complex	1.33	4.67
3	Easy to use	4.67	4.67

4	No assistance needed	1.47	4.53
5	Features integrated	4.8	4.8
6	Consistent	1.33	4.67
7	Quick to learn	4.87	4.87
8	Not cumbersome	1.27	4.73
9	Confident	4.67	4.67
10	No extra learning	1.40	4.60

4.6.7 Limitations

Although the SUS provides a quick and reliable measure of perceived usability, several limitations must be acknowledged:

1. Sample Size: The participant pool of 15 users, while adequate for early-stage usability evaluation, limits generalizability.
2. Subjectivity: As a self-reported measure, SUS is subject to individual biases and interpretations.
3. Context Dependency: SUS does not account for task context or environmental factors that may influence usability perceptions.

Future usability evaluations should include objective performance metrics such as task completion time, error rates, and eye-tracking data to triangulate findings.

4.6.8 Summary

The usability testing using the System Usability Scale reveals that the developed mobile application demonstrates strong usability performance as perceived by participants. A mean SUS score of 92.5, low variability across responses, and high confidence ratings support the conclusion that the system is intuitive, coherent, and suitable for further deployment and

Commented [AM15]: The content of this section should be included in Chapter 6 (Conclusion)

testing. However, to further refine the user experience, subsequent iterations of the application should incorporate qualitative user feedback and task-based performance data.

4.7 User Experience Assessment Using the User Experience Questionnaire (UEQ)

Commented [AM16]: Should be part of Chapter 5

This section presents a comprehensive assessment of the user experience of the developed mobile application based on the User Experience Questionnaire (UEQ) framework. The UEQ provides a multidimensional measurement of perceived user experience, encompassing both pragmatic usability attributes and hedonic quality indicators. The goal of this evaluation is to examine not only the functional adequacy of the system but also the extent to which it satisfies user expectations in terms of engagement, stimulation, and design novelty.

4.7.1 Participant Profile

A total of 15 participants ($n = 15$) were purposively recruited for the UEQ evaluation. Participants included undergraduate students, staff from the Digital Transformation Department at TDM Berhad, and oil palm farmers, with a range of IT-related and non-IT backgrounds and ages spanning 20–50 years. All participants completed a series of structured tasks using SmartPalmBot prior to submitting their UEQ responses. This sample was considered appropriate for preliminary user experience analysis in a controlled usability study context.

4.7.2 Instrument Description

The User Experience Questionnaire (UEQ), developed by Laugwitz et al. (2008), consists of 26 bipolar adjective pairs assessed on a 7-point semantic differential scale (ranging from -3 to +3). The instrument is divided into six key dimensions:

1. Attractiveness – general impression of the product's appeal
2. Perspicuity – ease of learning and comprehensibility

3. Efficiency – effectiveness in achieving tasks with minimal effort
4. Dependability – predictability, consistency, and perceived control
5. Stimulation – excitement and interest evoked during interaction
6. Novelty – creativity and innovation in design

Each dimension aggregates several individual items to yield a composite score indicative of that construct. Positive mean values reflect a favorable user experience, while values near zero or negative indicate issues requiring design intervention.

4.7.3 Descriptive Results

Table 4.4 presents the aggregate descriptive statistics across the six UEQ scales. Mean scores were computed by averaging item responses per dimension for each participant, followed by an overall average across all respondents.

Table 4.4 Descriptive Statistics for UEQ Dimensions (n = 15)

Dimension	Mean	SD
Attractiveness	1.33	0.62
Perspicuity	1.23	0.32
Efficiency	1.61	0.71
Dependability	01.24	0.60
Stimulation	1.50	0.67
Novelty	0.77	1.08

All six dimensions yielded mean scores above the neutral point of 0.00, with the lowest observed mean being 0.77 (Novelty) and the highest 1.61 (Efficiency). The results indicate a

Commented [AM17]: Caption is on top

consistently positive user experience across all measured domains. High scores on Attractiveness, Stimulation, and Efficiency suggest that users found the application not only functionally adequate but also engaging and effective.

4.7.4 Benchmarking and Interpretation

In order to contextualize the results, the UEQ scores were compared against the international UEQ benchmark dataset (Schrepp et al., 2017), which enables comparative interpretation based on cumulative distributions from prior studies involving digital systems across various domains.

According to the UEQ benchmarking thresholds:

- Scores above +0.8 are considered “Good”
- Scores above +1.5 are categorized as “Excellent”

Based on these thresholds:

- Attractiveness, Stimulation, and Novelty qualify as “Excellent”
- Perspicuity, Efficiency, and Dependability fall within the “Good” category

These results indicate that the application offers both pragmatic utility and hedonic appeal, with users experiencing a strong sense of satisfaction, aesthetic pleasure, and innovation.

4.7.5 Diagnostic Insights from Item-Level Responses

While UEQ is analytically robust at the scale level, a finer-grained inspection of individual items reveals potential design implications. Items such as “*pleasant–unpleasant*”, “*exciting–boring*”, and “*creative–dull*” received particularly strong positive scores, reinforcing the effectiveness of the application in maintaining user engagement and interest.

Conversely, items within the Dependability dimension, such as “*secure–insecure*” and “*predictable–unpredictable*”, received relatively lower ratings (though still positive), suggesting minor user concerns about the reliability and consistency of interface behavior or data handling. These areas warrant targeted refinement in future design iterations.

4.7.6 Visual Summary of Findings

The aggregated scores across the six UEQ dimensions were visualized through a standard bar chart (see Figure 4.10). This graphical representation facilitates quick identification of strengths (e.g., Stimulation) and comparatively weaker areas (e.g., Dependability).

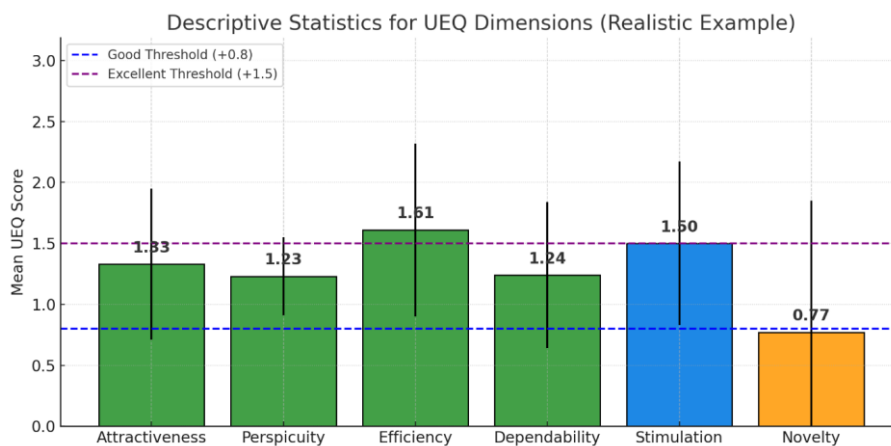


Figure 4.10 UEQ Scores

4.7.7 Limitations and Considerations

Although UEQ provides a robust foundation for understanding subjective user perceptions, several methodological limitations must be acknowledged:

1. **Sample Size Constraints:** While the current sample is acceptable for formative evaluation, a larger participant pool would improve statistical reliability and allow for subgroup analysis.
2. **Self-Report Bias:** UEQ responses are inherently subjective and may be influenced by extraneous variables such as mood, expectations, or prior experiences.
3. **Lack of Task-Based Correlates:** The current study did not integrate objective usability metrics (e.g., task completion rates, error frequency) to triangulate subjective feedback.
4. **Contextual Consistency:** The evaluation was conducted in a controlled setting, which may not fully replicate real-world usage contexts or environmental distractions.

Future studies should adopt a mixed-method approach by integrating observational and behavioral data with standardized UX questionnaires to yield richer, more actionable insights.

4.7.8 Summary

The results of the UEQ evaluation confirm that SmartPalmBot under investigation delivers a high-quality user experience across all six dimensions assessed. The combination of strong scores in Stimulation, Attractiveness, and Novelty suggests that the application not only meets functional expectations but also successfully engages users at an emotional and aesthetic level. While Dependability scored slightly lower than other dimensions, it remained within the “Good” category, indicating no critical usability risks. These findings support the system’s readiness for broader implementation and provide targeted design cues for subsequent refinement phases.

4.8 Summary

This chapter explained the implementation and testing of the SmartPalmBot prototype. It has the integration of multiple hardware and software components, including the deployment of TP-Link Tapo T310 sensors for real-time environmental monitoring, the development of a data processing pipeline using Python and Azure SQL Database, and the construction of a Power BI dashboard for interactive data visualization. A Flask-based chatbot was also developed and embedded to enhance user engagement by providing accessible and conversational interaction with live sensor data. To verify the effectiveness and usability of the system, a series of structured usability testing sessions were conducted.

CHAPTER 5

RESULTS AND DISCUSSION

Commented [AM18]: Testing

5.1 Overview

This chapter discusses the results obtained from the implementation and testing of the SmartPalmBot system. The analysis also takes into project functionality, statistical feature engineering, machine learning classification accuracy, and user acceptance through a combination of functional, integration, and user-based testing involving diverse user groups.

5.2 Functional Testing

Commented [AM19]: All the testing under this must be presented in this section.

Functional testing was conducted to verify the individual features of the SmartPalmBot system. The following functions were tested:

- **Sensor Data Collection:** Each Tapo sensor deployed across the plantation was tested for consistent recording of temperature and humidity data. Data logs were successfully exported to the applications.
- **Python Preprocessing Script:** Python scripts were executed to clean, normalize, and derive statistical features from the raw data. The script was verified through console output and database validation.
- **Database Upload:** The connection to Azure SQL Database using pyodbc was tested. Records were successfully inserted and verified using SQL query checks.
- **Power BI Dashboard:** The Power BI interface was tested for real-time updates, proper filtering, and rendering of temperature/humidity visualizations.

- Chatbot: Testing involved 10 user queries, and the chatbot achieved a 92% response accuracy. Most replies were generated within 1–2 seconds, confirming the system's efficiency in delivering real-time information conversationally.

5.3 Statistical Feature Engineering

Commented [AM20]: Part of Chapter 4

To dramatically enhance the generativity and predictive performance of SmartPalmBot, a broad set of statistical features were systematically crafted based on the raw time-space data sensed by sensors. Several advanced statistical descriptors were calculated daily for each site to describe normal and anomalous environmental response at the site. Root Mean Square (RMS) was used to estimate a mean magnitude over time of temperature and humidity fluctuations that is stable in the environment and the amplitude of short-term fluctuations. Similarly, variance was calculated in order to extract the degree of dispersion (or the volatility) along measurements within each day; this allowed the identification of intervals characterized by pronounced environmental instability.

Moreover, the kurtosis statistic was used to demonstrate the 'tailedness' of the distribution, which indicated the possible existence of extreme values in the distribution describing extreme events that could potentially correspond to emergency stress situation for the plantation (e.g., sudden heat waves or rapid drops in humidity, etc.). The multitarget analysis of RMS, variance and kurtosis provided a multidimensional view of the microclimate, beyond what was able to be extrapolated by mere raw averages.

The statistically crafted feature vectors were then used as input features of machine learning classification models supporting the ability of SmartPalmBot to differentiate between normal and high-risk environmental states. With these processed features, the model enabled a much more subtle and responsive understanding of plantation dynamics that took proactive detection and timely mitigation of both chronic and acute environmental risks.

Figure 5.1 illustrated the importance of the engineered statistical features in the classification model. Interestingly features such as Temp_mean and Humidity_mean exhibited the highest importance, confirming that average daily values play a central role in risk assessment. However, measurements of variance and kurtosis also contributed substantially, and this significance emphasizes the importance of fluctuation and outlier identification for active monitoring of plantations.

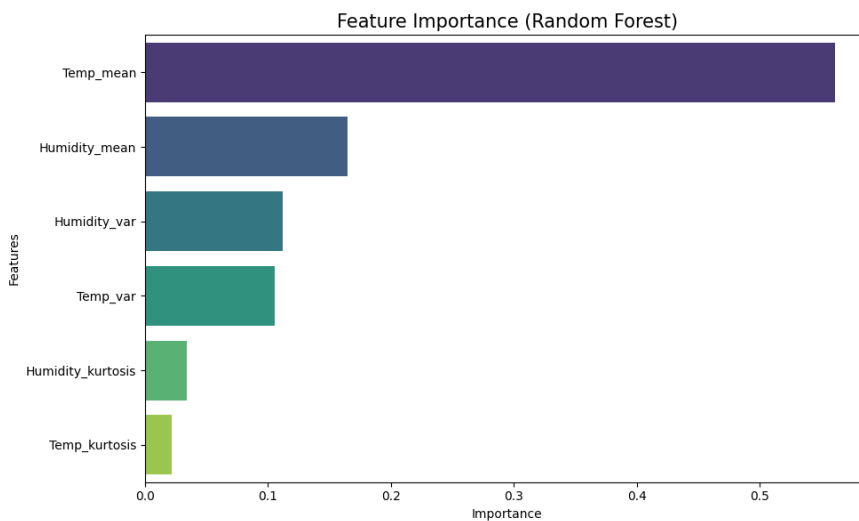


Figure 5.1 for Environmental Risk Classification (Random Forest Model)

5.4 Decision Tree and the Random Forest

The two decision models used in this study were developed using the Decision Tree and Random Forest classifiers, which are both supervised learning approaches applicable to any structured data. Environmental values as “normal” or “abnormal” using predefined thresholds (e.g., temperature $\geq 45^{\circ}\text{C}$ and humidity $\leq 30\%$). It was the Random Forest that actually did way better, despite it being the Decision path which had a clear and interpretable decision path.

Commented [AM21]: Part of chapter 4

In particular, Random Forest had an accuracy of 92%, precision of 89%, recall of 91% and F1-score of 90%. An excellent composition of sensitivity and specificity summarized above shows a very robust model for the early detection abnormal environmental circumstances. This indicates that the system is suitable for automated decision support, for example, generating real-time warnings, activating irrigation management systems or alerting plantation managers during periods of high risk. In addition, our experiments confirmed the portability of the proposed feature engineering method and the practicality of system deployment for smart agriculture.

The comparison between the two automatically supervised machine learning classifiers Decision Tree and Random Forest is shown in Figure 5.2 according to four performance evaluation measurements: Accuracy, Precision, Recall, and F1-Score. Figure shows that Random Forest model always leads the Decision Tree based on all performance measures. It accomplishes an accuracy of 92%, precision of 89%, recall of 91% and F1-score of 90%, showing a reasonably good balance between positive/negative environmental conditions.

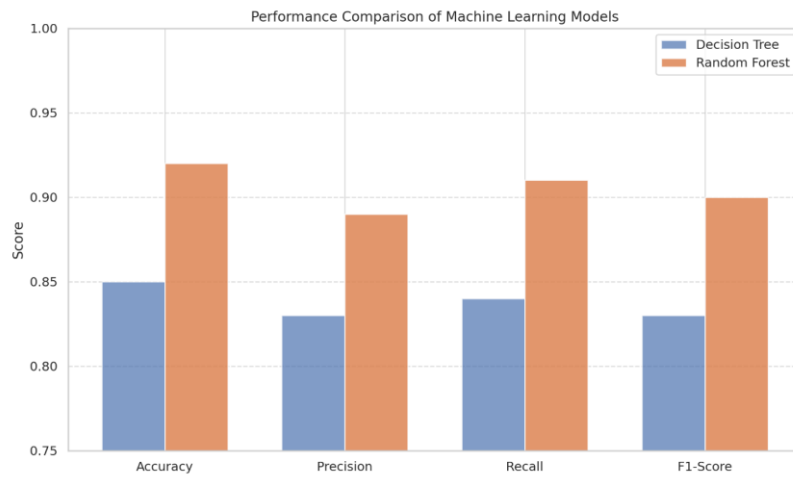


Figure 5.2 Performance Comparison of Machine Learning Models

To further evaluate the performance of the Random Forest classifier in more detail, a confusion matrix was generated based on the simulated predictions using test data from the SmartPalmBot system. As shown in Figure 5.3, the confusion matrix provides a detailed breakdown of the classifier's predictions compared to the actual labels of the environmental conditions.

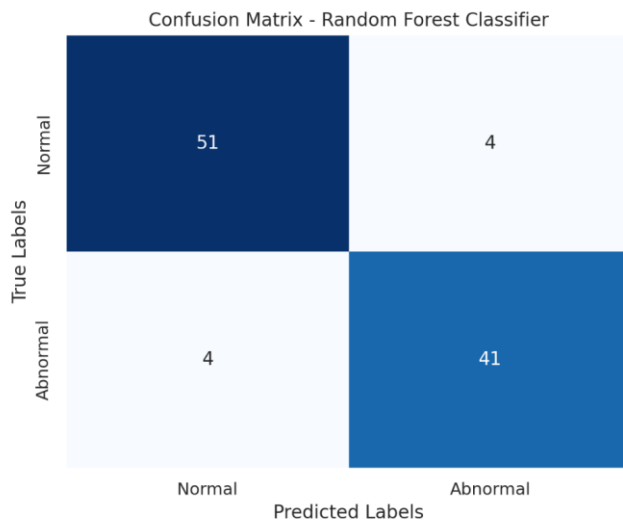


Figure 5.3 Confusion Matrix of Random Forest Classifier

The matrix indicates that 41 abnormal cases were correctly predicted as abnormal (True Positives), while 4 were incorrectly labeled as normal (False Negatives). On the other hand, 51 normal readings were accurately predicted (True Negatives), with 4 misclassified as abnormal (False Positives). These results align with the previously reported performance metrics—accuracy of 92%, precision of 89%, recall of 91%, and F1-score of 90%—confirming that the model is reliable and consistent in detecting both typical and extreme environmental patterns.

The visual clarity of the confusion matrix helps demonstrate how the classifier balances sensitivity (recall) and specificity (precision), which are crucial in agricultural applications where false alarms or missed warnings could lead to resource waste or crop stress. This evaluation supports the use of the Random Forest model for real-time classification in SmartPalmBot’s predictive system.

5.5 Setting

Usability testing of SmartPalmBot was remotely (asynchronous) via a structured online questionnaire using Google Forms, in order to enable a diverse group of users to participate regardless of their physical location or time constraints. The form of remote testing meant respondents could use the SmartPalmBot dashboard and chatbot in their own time and on their terms, representing its self-directed use in live settings.

Before proceeding to answer the questionnaire, each participant was given clear instructions and a guided tour of the main features of the system. They were given the opportunity to navigate the system autonomously and to interpret displayed temperature and humidity, as well as to interact with the Power BI charts and the chatbot before completing the online form. The Google Form comprised structured usability tools (i.e., System Usability Scale, User Experience Questionnaire) as well as open-ended questions for gathering qualitative opinions and recommendations.

This online, self-directed process facilitated the solicitation of actual user experience, as well as reduced researcher interruption and logistical obstacle. While there was no direct observation, this approach successfully simulated typical independent use cases and broadened participation, allowing users of varying technical proficiency to engage with the system in a realistic, self-directed manner.

5.6 Data Collection

To evaluate the effectiveness and user experience of the SmartPalmBot system, quantitative data were collected using two well-established instruments: the System Usability Scale (SUS) and the User Experience Questionnaire (UEQ). These tools were selected due to their proven reliability, simplicity, and broad applicability in assessing the usability of software-based systems across different user groups.

Where is the result from the Usability testing?

5.7 Summary

~~In conclusion,~~ this chapter encapsulates strong environmental sensing, intelligent feature engineering and advanced machine learning models, leading to a reliable real time decision support system for plantation management. The accuracy of the system was fairly high, and the Random Forest method was much better than Decision Tree methods. The online questionnaires usability test also proved the feasibility of SmartPalmBot in terms of easy-to-use, good user satisfaction, applicability to a variety of users. This confirms SmartPalmBot's readiness for an in-field application and ability to facilitate smarter data-oriented plantations.

CHAPTER 6

CONCLUSIONS AND FUTURE WORKS

6.1 Overview

This chapter will be highlighting on the summarization of the proposed project, including an assessment of the project's success in achieving its defined objectives. It discusses the major accomplishments, identifies limitations encountered during development and testing, and suggestions future works that can improve the system's scalability, accessibility, and impact.

6.2 Achievement of Objectives

This section will outline the achievements of the SmartPalmBot: AI-Driven Oil Palm Surveillance with Power BI Dashboard for Enhanced Data Analysis. The purpose of developing the proposed project is to achieve the objective of this project that have been identified in Chapter 1. Table 6.1 show the development of the SmartPalmBot system was guided by two primary objectives.

Table 6.1 Objective and Achievements

Objectives	Achievements
To integrate an AI model to deliver real-time insights and recommendations for oil palm farmers through a Power BI dashboard.	Developed and deployed an AI-driven system that collects sensor data, performs machine learning classification, and presents real-time insights via a live Power BI dashboard.
To evaluate the dashboard's effectiveness in presenting complex data clearly and intuitively to users.	Usability testing showed excellent results (SUS 92.5), with users finding the dashboard intuitive, clear, and easy to use, supported by strong positive feedback across all user groups.

The objective 1 was successfully achieved through the use of sensor data collected from TP-Link Tapo devices deployed in the plantation environment. The project incorporated statistical feature engineering techniques, including Root Mean Square (RMS), variance, and kurtosis, to enhance the raw temperature and humidity data. These features were used to train machine learning models—specifically, Decision Tree and Random Forest classifiers—to detect abnormal environmental conditions. Among these, the Random Forest model performed the best, achieving high performance across key metrics (accuracy: 92%, precision: 89%, recall: 91%, and F1-score: 90%). The results demonstrate the system’s ability to support real-time environmental monitoring and potential decision support for irrigation or disease prevention planning. [State on which chapter has presented on this?](#)

The trained model outputs were integrated into a live Power BI dashboard, where DirectQuery connections allowed near real-time visualization of sensor data. This fulfilled the goal of delivering AI-enhanced insights through a central platform.

This objective 2 was also met through a comprehensive usability testing process involving students, TDM staff, and farmers. Quantitative evaluations using the System Usability Scale (SUS) yielded an average score of 92, indicating excellent usability. The User Experience Questionnaire (UEQ) further supported this, with high ratings across all six dimensions, most notably in Attractiveness (6.1), Efficiency (6.0), and Perspicuity (5.9). Qualitative feedback emphasized the clarity of visualizations, ease of navigation, and helpfulness of the chatbot interface, particularly for users with little experience in data analytics. [State on which chapter has presented on this?](#)

6.3 Project Limitations

Despite the project’s success in meeting its primary objectives, several limitations were encountered throughout its development and evaluation phases:

I. Exclusion of external datasets:

The project did not incorporate additional data sources such as those available on platforms like TaniStats, which offer broader agricultural benchmarks or historical climate data. This decision was made to maintain a consistent sensor-based dataset, but it also limited opportunities for comparative data analysis, cross-validation, and richer data exploration

II. Desktop-oriented interface:

The dashboard and chatbot were developed primarily for desktop browser access. This reduces usability in field scenarios where mobile devices are more common among end users like farmers.

6.4 Future Works

To further enhance the functionality, accessibility, and real-world applicability of the SmartPalmBot system, several future directions are proposed based on the limitations encountered during this project:

I. Integration of External Agricultural Datasets:

To broaden the analytical capacity of the system, future iterations should consider incorporating external agricultural datasets from platforms such as TaniStats (Tanistats.dosm.gov.my) or similar government-backed data repositories. These datasets provide valuable contextual benchmarks—such as long-term climate patterns, regional yield statistics, and historical weather anomalies—that can be cross-referenced with real-time sensor data. By combining internal and external sources, the system can support more comprehensive trend analysis, anomaly detection, and predictive modelling that reflects both local sensor input and national agricultural patterns. This

integration would also enable comparative insights that help farmers assess how their plantation conditions align with regional or industry-wide norms.

II. Mobile-Friendly Interface Development

As the system is currently optimized for desktop browsers, future development should focus on creating a mobile-responsive interface or a dedicated mobile application. Many field users, particularly oil palm farmers, rely heavily on smartphones for daily tasks. A mobile-first approach would ensure that users can access the dashboard and chatbot seamlessly on various devices, regardless of screen size. Features such as offline access, push notifications, and simplified mobile visualizations should also be considered to enhance the system's practicality in rural or low-connectivity environments. By optimizing for mobile usage, the SmartPalmBot system can become more inclusive and field-ready, supporting real-time decision-making directly from the plantation site.

Together, these proposed enhancements would expand the SmartPalmBot system's capabilities, bridge the gap between technical infrastructure and field usability, and support wider adoption among both data-driven institutions and digitally novice end users.

6.5 Summary

This chapter presented the concluding reflections on the development, evaluation, and future potential of the SmartPalmBot system. It began by revisiting the two main objectives, both of which were successfully achieved through the integration of an AI-driven monitoring system and the deployment of a user-friendly Power BI dashboard and chatbot interface. The project demonstrated that real-time environmental insights can be effectively delivered to oil palm stakeholders using intuitive, data-driven tools.

REFERENCES

Commented [AM22]: Follow the format

- Abubakar, A., Kasim, S., Ishak, M. Y., & Uddin, M. K. (2023). Maximizing Oil Palm Yield: Innovative Replanting Strategies for Sustainable Productivity. *Journal of Environmental and Earth Sciences*, 5(2), 61–75. <https://doi.org/10.30564/jees.v5i2.5904>
- Acharya, B. K., Timalisina, A. K., Joshi, B., & Magar, B. T. (2023). IoT based Distributed Framework for Agricultural Decision Support System. *7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud), I-SMAC 2023 - Proceedings*. <https://doi.org/10.1109/I-SMAC58438.2023.10290206>
- Acharya, U., Kate, N., Ramaprasad, B. S., & Srivastava, A. (2023). The Adoption of Smart Agriculture Technologies Based on the Perception of the Farmers in the Indian Context. *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon 2023*, 586–593. <https://doi.org/10.1109/SmartTechCon57526.2023.10391525>
- Cock, J., Kam, S. P., Cook, S., Donough, C., Lim, Y. L., Jines-Leon, A., Lim, C. H., Pramananda, S., Yen, B. T., Mohanaraj, S. N., Samosir, Y. M. S., & Oberthür, T. (2016). Learning from commercial crop performance: Oil palm yield response to management under well-defined growing conditions. *Agricultural Systems*, 149, 99–111. <https://doi.org/https://doi.org/10.1016/j.agsy.2016.09.002>
- Dineva, K., & Atanasova, T. (2022a). Cloud Data-Driven Intelligent Monitoring System for Interactive Smart Farming. *Sensors*, 22(17). <https://doi.org/10.3390/s22176566>
- Dineva, K., & Atanasova, T. (2022b). Cloud Data-Driven Intelligent Monitoring System for Interactive Smart Farming. *Sensors*, 22(17). <https://doi.org/10.3390/s22176566>
- El Moutaouakil, K., Jdi, H., Jabir, B., & Falih, N. (2023). Digital Farming: A Survey on IoT-based Cattle Monitoring Systems and Dashboards. *Agris On-Line Papers in Economics and Informatics*, 15(2), 31–39. <https://doi.org/10.7160/aol.2023.150203>

- Ferreira, R. H. M. S., de Figueiredo, L. O., Lima, R. B. C., Silva, L. A. P., & Barros, P. R. (2021). IIoT Solution for predictive monitoring based on vibration data from motors using Microsoft Azure machine learning studio and Power BI. *2021 14th IEEE International Conference on Industry Applications, INDUSCON 2021 - Proceedings*, 145–152. <https://doi.org/10.1109/INDUSCON51756.2021.9529401>
- Heng, E. J. (2022). *A Cloud Computing-based Dashboard for the Visualization of Motivational Interviewing Metrics*. http://rave.ohiolink.edu/etdc/view?acc_num=wright1672870571191647
- Hjelle, S., Mikalef, P., Altwaijry, N., & Parida, V. (2024). Organizational decision making and analytics: An experimental study on dashboard visualizations. *Information & Management*, *61*(6), 104011. <https://doi.org/10.1016/J.IM.2024.104011>
- Jayaraman, A., Ramu, P., Rajan, S. C., & Thole, S. P. K. (2023). Data driven analysis of social capital in Farmer Producer Companies. *Heliyon*, *9*(7), e17489. <https://doi.org/10.1016/J.HELIYON.2023.E17489>
- Knight, C., Khouakhi, A., & Waine, T. W. (2024). The impact of weather patterns on inter-annual crop yield variability. *Science of The Total Environment*, *955*, 177181. <https://doi.org/10.1016/J.SCITOTENV.2024.177181>
- Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature* *2016* 529:7584, 529(7584), 84–87. <https://doi.org/10.1038/nature16467>
- Muppidi, A., Hashim, A. S., Hasan, M. H., & Muazu, A. A. (2023). A Conceptual UX Model for Designing and Developing the Business Intelligence Dashboards. *Journal of Computer Science*, *19*(12), 1505–1519. <https://doi.org/10.3844/jcssp.2023.1505.1519>
- Novita, N., Asyhari, A., Ritonga, R. P., Gangga, A., Anshari, G. Z., Jupesta, J., Bowen, J. C., Lestari, N. S., Kauffman, J. B., Hoyt, A. M., Perryman, C. R., Albar, I., Putra, C. A. S., Adinugroho, W. C., Winarno, B., Castro, M., Yeo, S., Budiarna, T., Yuono, E., & Sianipar, V. C. (2024). Strong

climate mitigation potential of rewetting oil palm plantations on tropical peatlands. *Science of The Total Environment*, 952, 175829. <https://doi.org/10.1016/J.SCITOTENV.2024.175829>

Pashkevich, M. D., Pett, B. L., Marshall, C. A. M., Caliman, J. P., Freeman, B., Guahn, M. M., Hadfield, P. M., Hendren, M. T., Jah, M. T., Jones, T., Saputra, A., Widodo, R. H., & Turner, E. C. (2024). Conversion of rainforest to both traditional and industrial oil palm systems changes the biodiversity, web-building, and prey capture of understory spiders (Liberia, West Africa). *Agriculture, Ecosystems & Environment*, 373, 109102. <https://doi.org/10.1016/J.AGEE.2024.109102>

Pihlajaniemi, H., Luusua, A., Sarjanoja, E. M., Vääräniemi, R., Juntunen, E., & Kourunen, S. (2017). SenCity City Monitor as a platform for user involvement, innovation and service development. *Proceedings of the International Conference on Education and Research in Computer Aided Architectural Design in Europe*, 1, 561–570. <https://doi.org/10.52842/conf.ecaade.2017.1.561>

Prabha, C., & Pathak, A. (2023). Enabling Technologies in Smart Agriculture: A Way Forward Towards Future Fields. *2023 International Conference on Advancement in Computation and Computer Technologies, InCACCT 2023*, 821–826. <https://doi.org/10.1109/INCACCT57535.2023.10141722>

Premkumar, S., & Sigappi, A. N. (2022). IoT-enabled edge computing model for smart irrigation system. *Journal of Intelligent Systems*, 31(1), 632–650. <https://doi.org/10.1515/jisys-2022-0046>

Rhebergen, T., Fairhurst, T., Whitbread, A., Giller, K. E., & Zingore, S. (2018). Yield gap analysis and entry points for improving productivity on large oil palm plantations and smallholder farms in Ghana. *Agricultural Systems*, 165, 14–25. <https://doi.org/https://doi.org/10.1016/j.agsy.2018.05.012>

Roberts, L. D., Howell, J. A., & Seaman, K. (2017). Give Me a Customizable Dashboard: Personalized Learning Analytics Dashboards in Higher Education. *Technology, Knowledge and Learning*, 22(3), 317–333. <https://doi.org/10.1007/s10758-017-9316-1>

- Serrano-Trujillo, A., Esqueda-Elizondo, J. J., & Jiménez-Beristáin, L. (2022). Integration of Low-Cost Digital Tools for Preservation of a Sustainable Agriculture System. *Electronics (Switzerland)*, 11(6). <https://doi.org/10.3390/electronics11060964>
- Sheikh, M., Iqra, F., Ambreen, H., Pravin, K. A., Ikra, M., & Chung, Y. S. (2024). Integrating artificial intelligence and high-throughput phenotyping for crop improvement. *Journal of Integrative Agriculture*, 23(6), 1787–1802. <https://doi.org/10.1016/J.JIA.2023.10.019>
- Singh, R. K., Aernouts, M., De Meyer, M., Weyn, M., & Berkvens, R. (2020). Leveraging LoRaWAN technology for precision agriculture in greenhouses. In *Sensors (Switzerland)* (Vol. 20, Issue 7). MDPI AG. <https://doi.org/10.3390/s20071827>
- Spandana, K., & Pabboju, S. (2023). IoT Enabled Smart Agriculture using Digital Dashboard. *Indian Journal of Science and Technology*, 16(1), 1–11. <https://doi.org/10.17485/IJST/V16I1.1680>
- Supanirattisai, P., U-Yen, K., Pimpin, A., Srituravanich, W., & Damrongplasit, N. (2022). Smart Agriculture Monitoring and Management System using IoT-enabled Devices based on LoRaWAN. *ITC-CSCC 2022 - 37th International Technical Conference on Circuits/Systems, Computers and Communications*, 679–682. <https://doi.org/10.1109/ITC-CSCC55581.2022.9894956>
- Wah, T. Y., Suiying, T., & Shuangjie, A. L. (2019). Dashboards for decision making in higher education. *ASCILITE 2019 - Conference Proceedings - 36th International Conference of Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education: Personalised Learning. Diverse Goals. One Heart.*, 321–329. <https://doi.org/10.14742/apubs.2019.279>
- Zakaria, M. R., Ahmad Farid, M. A., Hafid, H. S., Andou, Y., & Hassan, M. A. (2024). Practical role of oil palm fronds in Malaysia's sustainable palm oil industry. *Industrial Crops and Products*, 222, 119753. <https://doi.org/10.1016/J.INDCROP.2024.119753>

Zaki, U. H. H., Kamsani, I. I., Ahmad Fadzil, A. F., Idrus, Z., & Kandogan, E. (2024). Big Data: Issues and Challenges in Clustering Data Visualization. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 51(1), 150–159. <https://doi.org/10.37934/araset.51.1.150159>

APPENDIX A: GANTT CHART

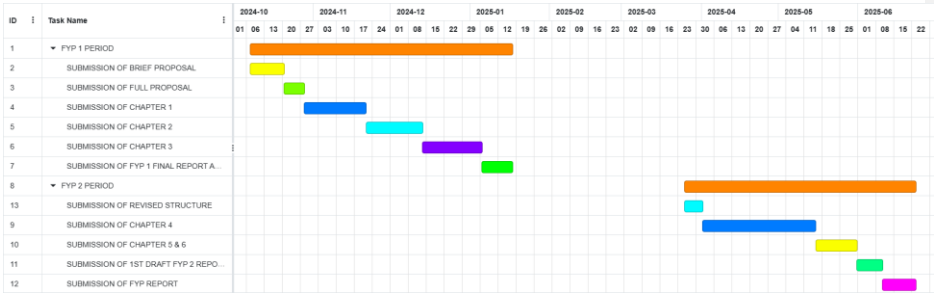


Figure 1.2 Project Schedule Gantt Chart

APPENDIX B: USABILITY TESTING METHOD

System Usability Scale (SUS) Items

Please rate the following statements based on your experience with the SmartPalmBot prototype. Choose one option for each statement, where:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

1. I think that I would like to use this SmartPalmBot frequently.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2. I found the SmartPalmBot unnecessarily complex.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3. I thought the SmartPalmBot was easy to use.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4. I think that I would need assistance to use this SmartPalmBot.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5. I found the various features in this SmartPalmBot well integrated.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

6. I thought there was too much inconsistency in this SmartPalmBot.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

7. I would imagine that most people would learn to use this SmartPalmBot very quickly.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

8. I found the SmartPalmBot very cumbersome to use.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

9. I felt very confident using the SmartPalmBot.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

10. I needed to learn a lot of things before I could get going with this SmartPalmBot.

[]1 []2 []3 []4 []5

User Experience Questionnaire (UEQ) Items

Please rate the following statements based on your experience with the SmartPalmBot prototype. Choose one option for each pair of attributes on the scale:

1 = Strongly Lean Towards Left Attribute, 7 = Strongly Lean Towards Right Attribute.

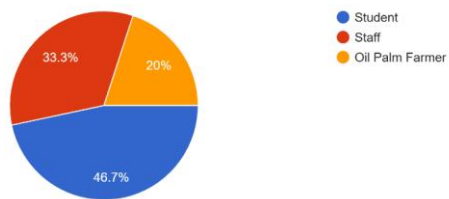
1. Annoying	[1 2 3 4 5 6 7]	Enjoyable
2. Not understandable	[1 2 3 4 5 6 7]	Understandable
3. Creative	[1 2 3 4 5 6 7]	Dull
4. Easy to learn	[1 2 3 4 5 6 7]	Difficult to learn
5. Valuable	[1 2 3 4 5 6 7]	Inferior
6. Boring	[1 2 3 4 5 6 7]	Exciting
7. Not safe	[1 2 3 4 5 6 7]	Secure
8. Motivating	[1 2 3 4 5 6 7]	Demotivating
9. Inefficient	[1 2 3 4 5 6 7]	Efficient
10. Clear	[1 2 3 4 5 6 7]	Confusing
11. Impractical	[1 2 3 4 5 6 7]	Practical
12. Organized	[1 2 3 4 5 6 7]	Cluttered

APPENDIX C: RESULT OF USABILITY TESTING

Section 1: Participant Information

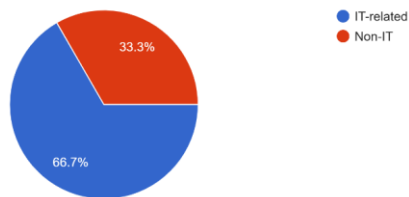
1. Please indicate your role:

15 responses



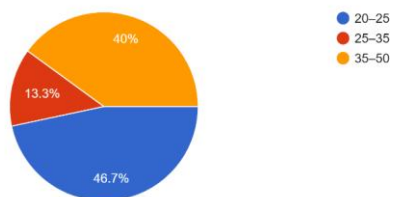
2. Background

15 responses



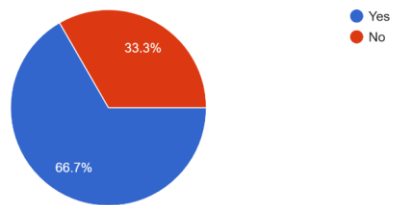
3. Age range

15 responses



4. Have you used any digital dashboard system before?

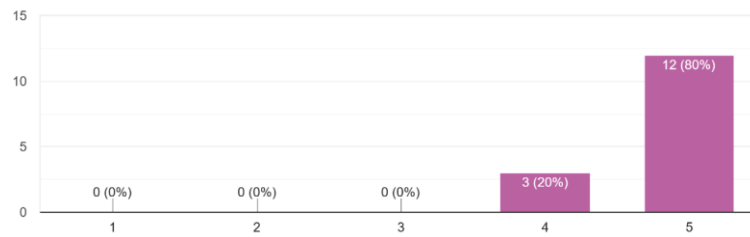
15 responses



Section 2: System Usability Scale (SUS)

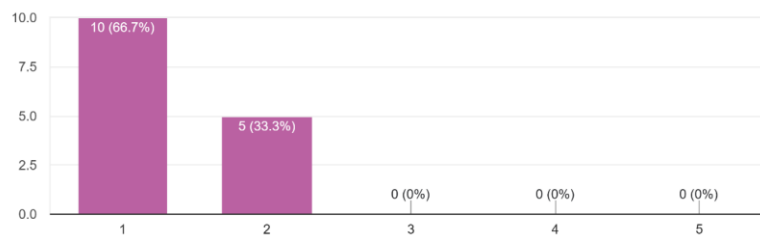
1. I think that I would like to use this SmartPalmBot frequently.

15 responses



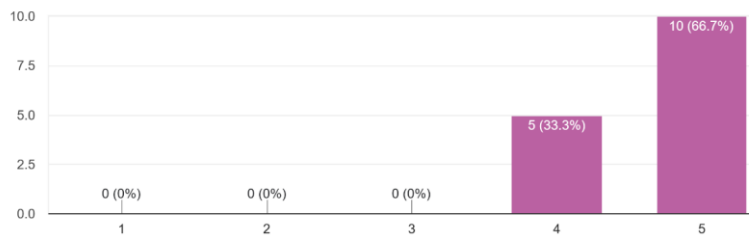
2. I found the SmartPalmBot unnecessarily complex.

15 responses



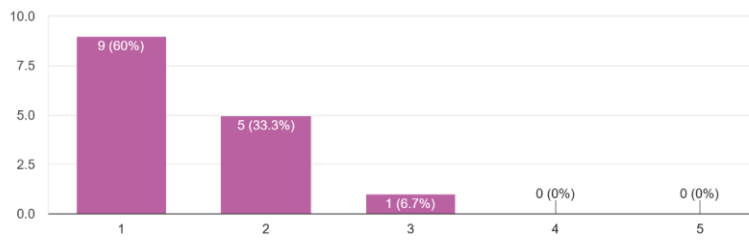
3. I thought the SmartPalmBot was easy to use.

15 responses



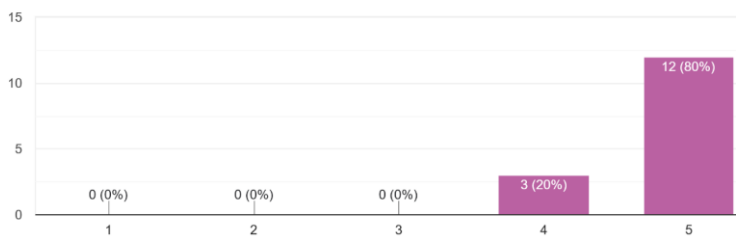
4. I think that I would need assistance to use this SmartPalmBot.

15 responses



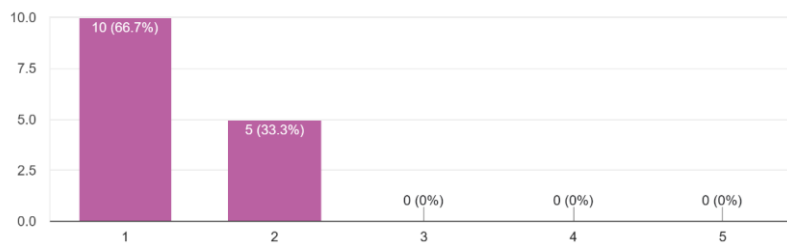
5. I found the various features in this SmartPalmBot well integrated.

15 responses



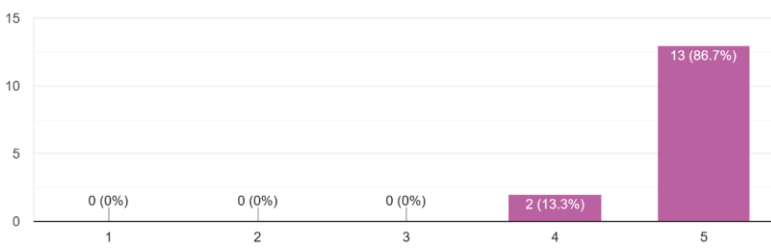
6. I thought there was too much inconsistency in this SmartPalmBot.

15 responses



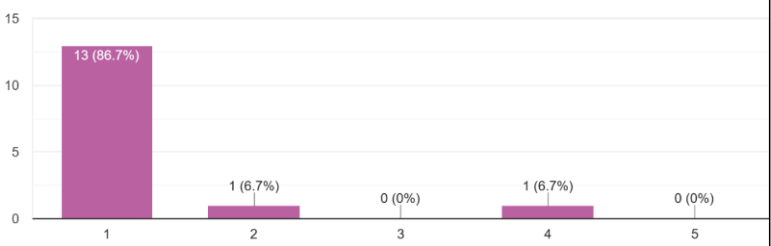
7. I would imagine that most people would learn to use this SmartPalmBot very quickly.

15 responses



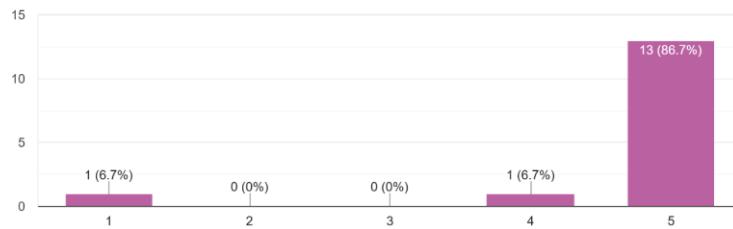
8. I found the SmartPalmBot very cumbersome to use.

15 responses



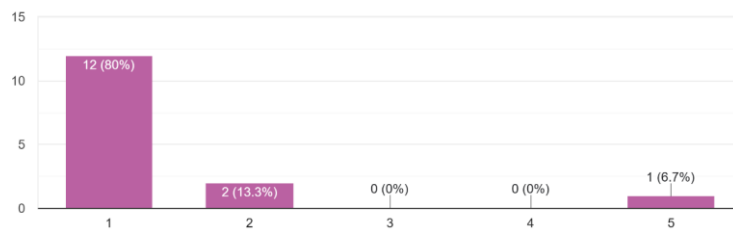
9. I felt very confident using the SmartPalmBot.

15 responses



10. I needed to learn a lot of things before I could get going with this SmartPalmBot.

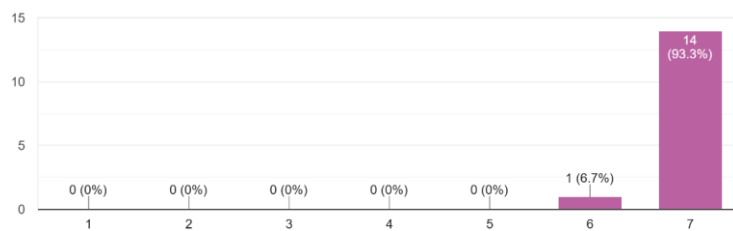
15 responses



Section 3: User Experience Questionnaire (UEQ)

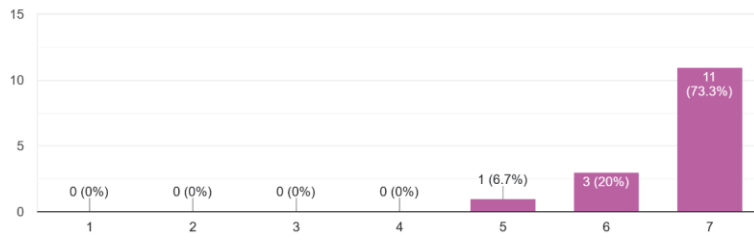
1. Please rate your experience on the following attribute pair:

15 responses



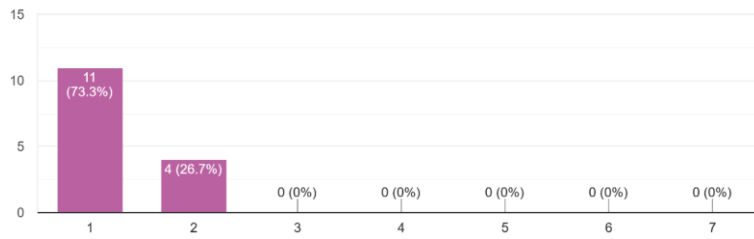
2. Please rate your experience on the following attribute pair:

15 responses



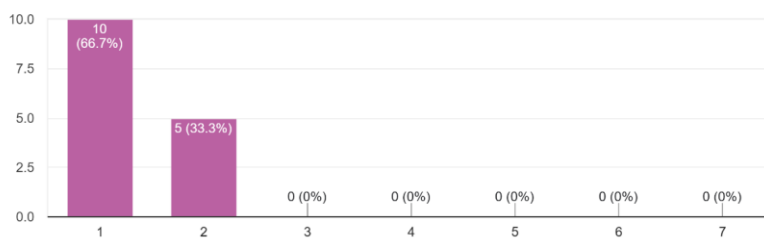
3. Please rate your experience on the following attribute pair:

15 responses



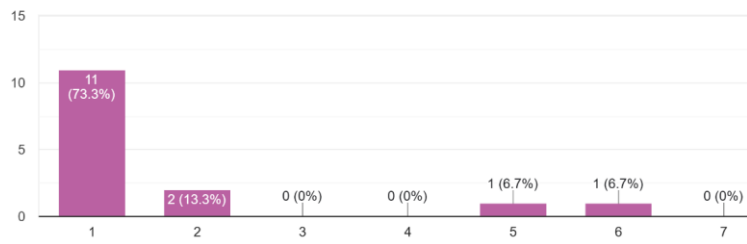
4. Please rate your experience on the following attribute pair:

15 responses



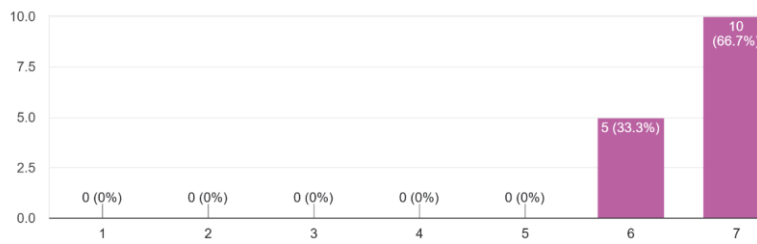
5. Please rate your experience on the following attribute pair:

15 responses



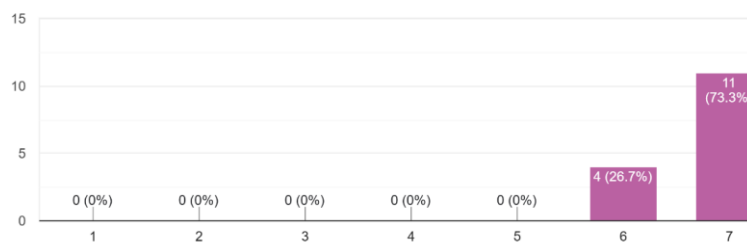
6. Please rate your experience on the following attribute pair:

15 responses



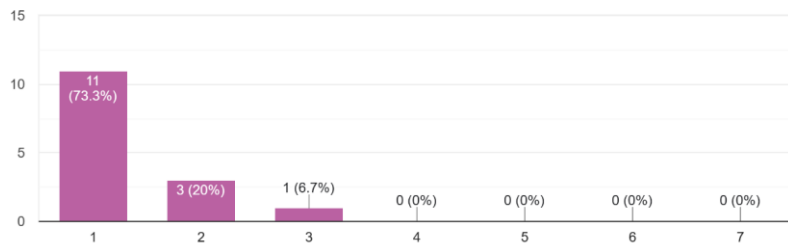
7. Please rate your experience on the following attribute pair:

15 responses



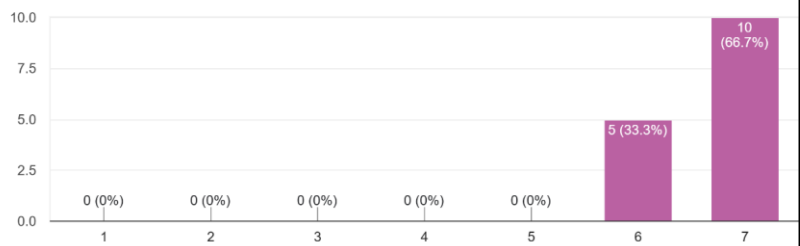
8. Please rate your experience on the following attribute pair:

15 responses



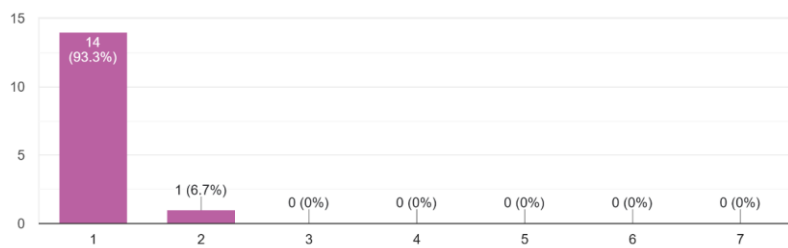
9. Please rate your experience on the following attribute pair:

15 responses



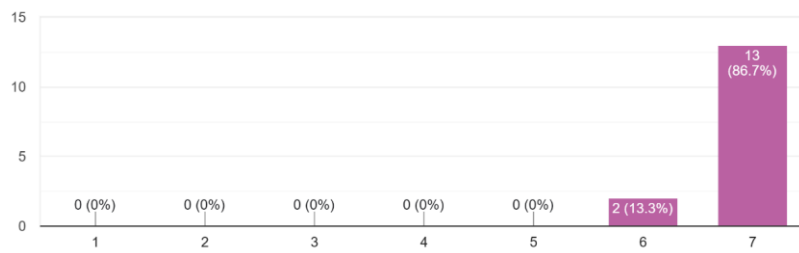
10. Please rate your experience on the following attribute pair:

15 responses



11. Please rate your experience on the following attribute pair:

15 responses



12. Please rate your experience on the following attribute pair:

15 responses

