Part IV Research Project

Project Report

Developing AI-powered Image Processing Web Application for Smart Farm

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DEVELOPING AI-POWERED IMAGE PROCESSING WEB APPLICATION FOR SMART FARM

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ABSTRACT

The growing global food demand, coupled with climate change and resource scarcity, necessitates innovative solutions for efficient farmland management. This paper proposes a smart agriculture system utilising an AI-powered image processing web application to enhance crop management and reduce labour. Our system integrates computer vision AI models to monitor plant growth, including size, ripeness, and disease detection, alongside a web interface displaying plant status. This allows for informed decision-making by collecting, processing, and displaying real-time data on plant growth and environmental conditions. A user survey was conducted to evaluate the usability and performance of the system, and very positive feedback was found, with an average satisfaction of 4.7 out of 5 on key indicators. Users found the interface easy to navigate, beneficial, and visually attractive. These results demonstrate the ease of use and high performance of our system. By combining sensing technology and artificial intelligence, we show the potential of comprehensive crop monitoring solutions that improve agricultural productivity and sustainability. This approach leads to more efficient and data-driven agricultural practices, which can demonstrate excellent efficiency in the agricultural sector.

DECLARATION

Student

I hereby declare that:

1. This report is the result of the final year project work carried out by my project partner (see cover page) and I under the guidance of our supervisor (see cover page) in the 2024 academic year at the Department of Electrical, Computer and Software Engineering, Faculty of Engineering, University of Auckland.
2. This report is not the outcome of work done previously.
3. This report is not the outcome of work done in collaboration, except that with a potential project sponsor (if any) as stated in the text.
4. This report is not the same as any report, thesis, conference article or journal paper, or any other publication or unpublished work in any format.

In the case of a continuing project, please state clearly what has been developed during the project and what was available from previous year(s):

Signature:

Date: 13/10/24

Table of Contents

Acknowledgements

I would like to express my sincere gratitude to several individuals who contributed significantly to the development of this plant monitoring system and the completion of this report.

First and foremost, I would like to thank my supervisor, Ho Seok Ahn, for their invaluable guidance, support, and encouragement throughout this project. Their insightful advice and expertise were instrumental in overcoming challenges and ensuring the successful completion of this work.

I also extend my thanks to JongYoon Lim for providing constructive feedback and advice during the course of this project. Their input greatly enhanced the quality and clarity of this report.

Finally, I would like to acknowledge my research partner, Kim Zuo, for their hard work, collaboration, and dedication. Working together on this project was a rewarding experience, and their contributions were essential to our success.

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List of Figures

1. Introduction

The agricultural industry currently faces significant challenges due to climate change, continued population growth, and declining resources, which require a 70% increase in food production by 2050. This situation necessitates a shift toward more productive and sustainable agricultural practices [1]. In this current situation, Artificial Intelligence (AI) and integrated web platforms leveraging it emerge as promising solutions to these challenges, providing a way to improve crop management and optimize agricultural practices [2].

Our research proposes a cutting-edge smart farming system that can improve crop management, simplify plant monitoring, and integrate data on the plant's environment by leveraging AI. Our system aims to provide farmers and agricultural professionals with tools to make more informed decisions by collecting, analyzing, and providing real-time data on plant growth and environmental conditions [3]. We also aim to make it easier for agricultural professionals and farmers to monitor plant growth. Ultimately, we aim to enable farmers to estimate when to harvest their plants [4].

The key contributions of our research include:

1. AI-driven Monitoring System: We present an integrated solution that combines environmental variable detection, multi-model AI processing for tomato size and ripeness measurement, and real-time data collection and visualization.
2. Smart Farm Web Platform: We developed a web application using Flask and created an intuitive React-based interface, facilitating efficient data transfer and user-friendly access to environmental variables and analyzed information.
3. Real-world Testing: We conducted trials in an actual tomato greenhouse, providing valuable insights into the system's effectiveness and identifying areas for future refinement. We also incorporated user feedback on usability to guide future improvements.
4. Open Source Implementation: Our code is publicly available, contributing to the open-source community and encouraging further development and adaptation in smart agriculture. [1]

By integrating sensing and detection technologies with artificial intelligence, our system aims to provide a comprehensive plant monitoring solution that can lead to more efficient, productive, and data-driven agricultural practices. It also provides an efficient plant monitoring solution by making these data easily accessible to users through an efficient back-end server and a user-friendly web platform. This research is consistent with the broader goal of improving agricultural productivity and sustainability through technology and addresses the need for innovative solutions in modern agriculture [5].

We collected real data from a tomato greenhouse, as shown in Figure 1, to address implementation challenges and verify the effectiveness of the system. This process allowed us to explore the feasibility of the technology and pinpoint areas for future improvements. Our research contributes to the growing knowledge of smart farming applications and provides insight into the practical challenges and opportunities in implementing AI-based crop monitoring solutions. [6].

[1] https://github.com/dkwo575/P4P-61-Webpage

Figure 1 Indoor tomato farm.

User experience is crucial for the successful adoption of such systems [7]. A user survey was conducted to evaluate the usability and performance of the web interface, and the results were overwhelmingly positive. The interface received an average score of 4.7 out of 5, indicating high user satisfaction across a range of dimensions, including ease of navigation, clarity of data visualization, and intuitive design. These results highlight the potential of AI-based approaches and excellent web interfaces to improve agricultural management efficiency [8].

With the goal of developing an integrated crop monitoring system for farmers and agricultural professionals, my partner focused on the camera system, image data processing, and AI model parts, while my research focus was on collecting and analyzing crop environmental variable data, developing a backend server, and web platform. And my partner helped me develop a web platform, and I helped my partner with the AI model processing part. Our research methods and results were summarized and submitted to ACRA 2024 under the title "Developing AI-powered Image Processing Web Application for Plant Monitoring in Smart Farm".

In this paper, we describe related work about the AI-powered Web platform, Plant Growth Monitoring system and Environment Monitoring System in Section 2. In Section 3, we explain our plant growth monitoring system with research methods and experiments. Section 4 presents our results. Section 5 presents a discussion about our project and system, and Section 6 concludes the paper.

2. Related Works

2.1 AI-powered Web Platform for Smart Farm

Smart farming is a concept that uses the latest technologies, such as the Internet of Things and artificial intelligence, to improve agricultural productivity [9]. Smart farming relies heavily on AI-based integrated web platforms that seamlessly integrate data collection, storage, analysis, and visualization [10]. These systems typically incorporate backend databases, AI algorithms, APIs, and user-friendly interfaces, allowing farmers and agriculture professionals to easily access and interpret complex agricultural information [11].

One such example is the iFarm system, a web-based platform for cultivation and cost management. This system, created by Murakami's research team, utilizes smartphones, cloud servers, and web browsers to improve agricultural efficiency [12]. The iFarm system allows farmers and managers to monitor farm data and upload work schedules to the server via a website or mobile app. It also allows easy data sharing between managers through cloud-based storage, improving the work efficiency of farm workers [13].

Another example is the CLUeFARM system, an integrated web service platform that aims to improve the quality of products grown on farms and support business development in the agricultural sector. This system benefits from cloud computing, focusing on flexibility, availability, and security, and can be accessed anytime, anywhere, as long as there is an Internet connection [11]. The system can also access humidity, temperature, soil moisture, and soil temperature sensors and display the data in real-time. Their system is more focused on creating a social network for farmers rather than focusing on crop monitoring. Their system makes it easier to share agricultural data with other farmers [14].

Researchers have underscored the significance of big data in smart agriculture, focusing on its applications in the field. They advocate for combining big data analysis with extensive data collection and storage, AI, and predictive analytics [15]. The integration of big data and AI in agriculture has the potential to address numerous challenges facing the industry, significantly boosting both the quality and quantity of agricultural output [16]. Furthermore, AI and big data can be utilized to forecast soil quality, predict disease and pest outbreaks, and determine optimal crop harvesting times [15].

Previous studies have developed extended web platforms that focus more on social networks for smart farms or web platforms that are configured only for monitoring environmental variables for crop growth. However, our research focused more on crop monitoring functions that are essential for farmers today rather than adding excessive functions such as social networking. In addition, our system can display results using AI as well as environmental variable data by grafting AI onto the web platform.

2.2 AI-based Plant Growth Monitoring System

Data analysis using Artificial Intelligence (AI) is greatly helping to analyze the large amount of image data generated by cameras in smart farming environments [17]. In particular, the integration of machine learning and computer vision has become a mainstay of smart farming, with applications in various aspects of crop management, including plant disease detection, harvest estimation, and decision-making processes [18].

In one study, an AI-based system for early detection of plant diseases was developed using image analysis. The system trained a large dataset of normal and diseased leaf images using a deep-learning model. It was then used to detect plant diseases that appeared on leaves

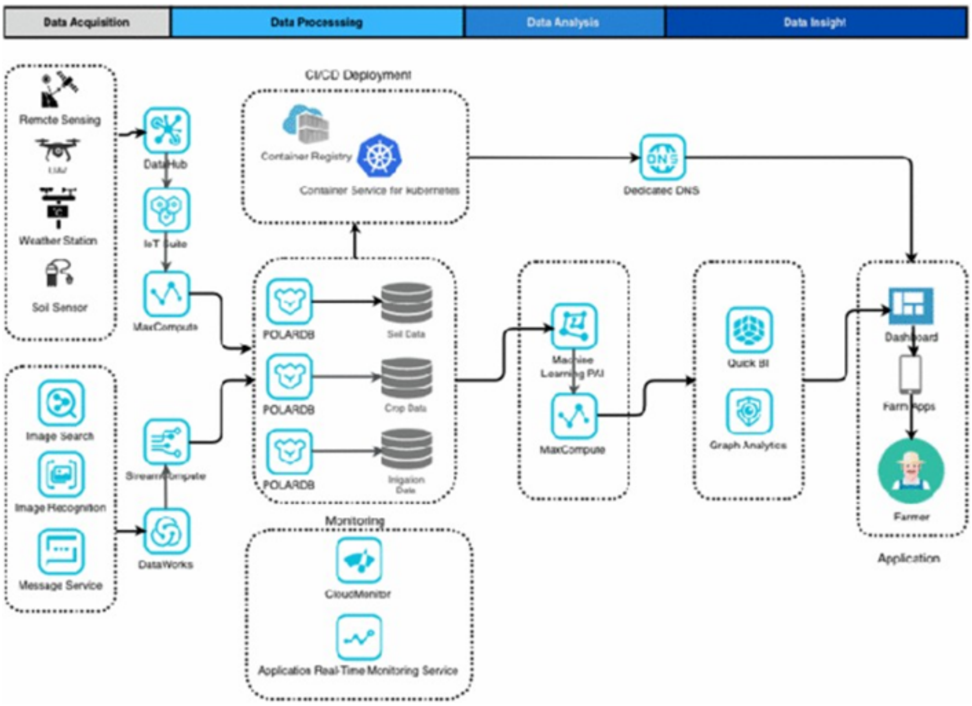


Figure 2 Big data cloud-based system architecture from literature

early, and the deep learning model achieved 95% accuracy in identifying common crop diseases. The system demonstrated the potential for rapid and automated disease detection, which could reduce crop losses [19].

Another research project designed an intelligent diagnosis system to help non-expert farmers detect plant diseases or nutritional deficiencies. This system, based on Artificial Neural Networks (ANNs), made expert-level diagnosis accessible to non-skilled farmers by providing visual symptoms through images. The system analyzed crop symptoms in five categories (overall, root, leaf, fruit, and crop factors) to make a diagnosis. Field verification showed an error rate of less than 8%, making it user-friendly for non-expert farmers [20].

In this study, we developed a method to count coffee cherries using computer vision and AI to determine and estimate coffee harvest. The system classified coffee cherries into ripe, unharvestable, and intermediate and estimated their weight and maturity rate. The trained AI model recognized the coffee cherries, matched the images, and classified the maturity rate into three categories, then used the number of coffee cherries to measure the weight. The approach aimed to provide production data for better resource allocation, machine preparation, and maximizing economic benefits for coffee growers [21].

In this research, the researchers also highlighted the application of machine learning to agricultural production. Machine learning is an evolving field of computational algorithms designed to mimic human intelligence by learning from data and experience without explicit programming [22]. Machine learning can be used for tasks such as harvest prediction, weed detection, disease identification, and crop quality assessment [23]. These tasks often involve applying machine learning to sensor data and computer vision to transform farm management systems into practical AI systems that can manage crops more efficiently while maximizing productivity and economic benefits [18].

Unlike previous studies, our study not only analyzes image data using AI models and derives results but also displays them on a web interface, making it easy for farmers to access this data.

2.3 Environment Monitoring System

Sensor systems that measure environmental variables have now become an essential component of smart agriculture, and Internet of Things (IoT) technologies are widely adopted in most smart agriculture environments [24]. IoT sensor systems enable real-time collection and monitoring of environmental variable data [25]. These systems typically consist of a network of sensors that measure various environmental conditions such as humidity and temperature, soil properties such as soil moisture and soil temperature, and plant health indicators [26].

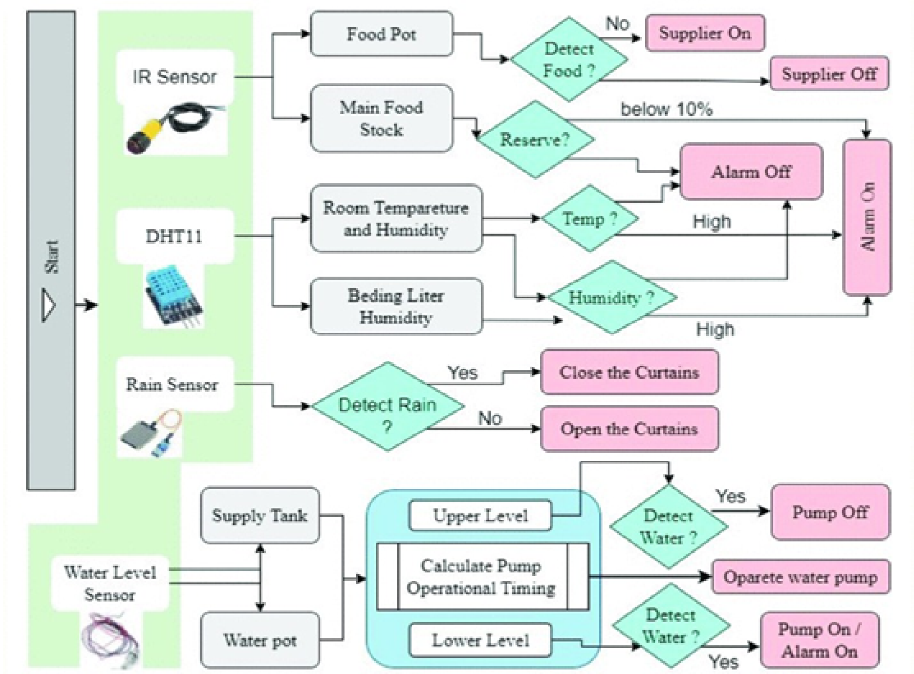


Figure 3 System Overview of IoT-based Automated Farm from literature

This research has shown that using IoT technologies in agriculture can increase efficiency, reduce costs, and improve the economic viability of farming [27]. IoT technology is a technology that integrates all devices into a common infrastructure called the Internet to control and report the status of objects around them [28]. Using IoT technologies in agriculture can effectively save time and financial resources by reducing manual work and increasing automation, making farms smarter, more efficient, and more productive [27]. Environmental monitoring using this technology is a critical component of smart farming, using various sensors to track important environmental factors such as temperature, humidity, and soil moisture [29].

Studies have emphasized that IoT technology can increase agricultural sophistication without significant capital investment. Low-cost sensors for humidity, temperature, light, and soil moisture can help farmers easily monitor environmental variables and achieve high results with minimal capital expenditure [30]. These sensors provide farmers with crucial data to optimize irrigation, pest control, and overall crop management [25].

Another research introduced a tomato indoor farming technology utilizing IoT, similar to our research. By developing a variety of sensor and actuator-based systems, users can access information related to crop growth, climate, and irrigation settings using environmental data from sensors to improve crop quality. Users can easily access this sensor data through a web-based decision-making system [31]. As a result, IoT system technology can be used to easily monitor crops, reduce resource usage, and increase productivity [32].

3. Research Method and Experiments

3.1 System Architecture

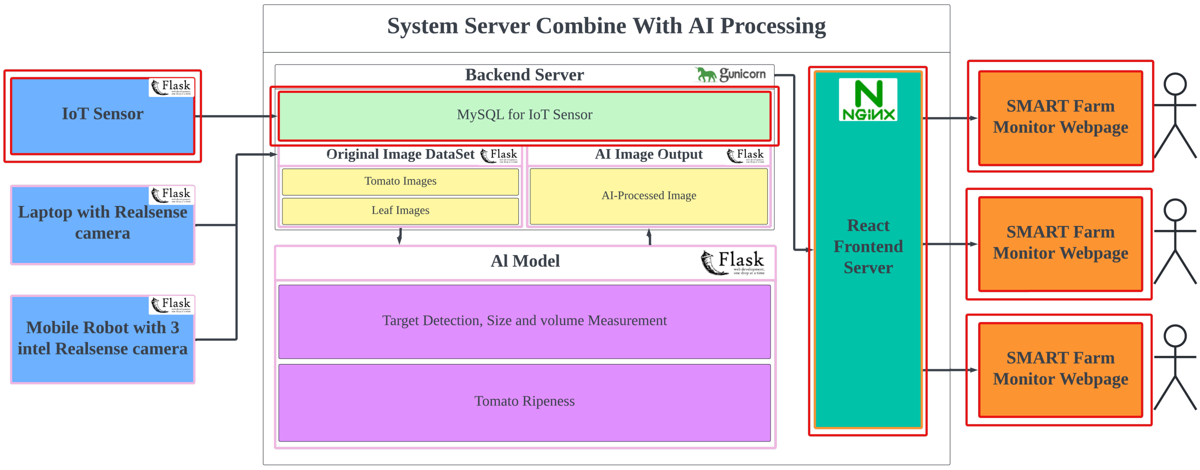


Figure 4 Overall System Architecture showing IoT sensors, AI server, and user web interface

Figure 4 illustrates our overall Plant Growing Monitoring System Architecture. The red squares in the figure are the parts I studied, and the rest are the parts that my partner studied or studied together.

Our plant monitoring system consists of three main components:

1. Input devices: Located on the left section of the figure 4. It includes IoT sensors that collect environmental data, a stationary laptop with RealSense cameras, and a mobile robot equipped with three RealSense cameras for dynamic image collection.

2. AI server: Located on the center section of the figure 4. This central component houses the backend server and the AI model. The backend server includes a MySQL database server for IoT sensor data. It also includes a backend application for the web interface, a repository for original plant images, and code to output processed AI images. The AI model performs several functions, such as target detection, size and volume measurement, and tomato ripeness analysis.

3. Web interface: Located on the right section of the figure 4. The web-based SMART Farm Monitor interface that runs on top of the frontend server allows multiple users to access the system simultaneously.

The system operates by collecting various data from various environmental variable sensors and RealSense cameras. Environmental variable sensors continuously collect environmental data necessary for plant growth, such as temperature, humidity, and light. Realsense cameras mounted on robots or attached to laptops collect image data and depth data. These devices become the eyes and ears of our system and collect various data.

At the heart of this system is an AI server that integrates a backend server and AI models. This AI server manages, analyzes, and processes all data. Data collected from external input devices is transmitted to the AI server, and the AI server processes and analyzes the data. The server stores the environmental variable data in a MySQL database and manages the environmental data through a Flask application using the HTTP protocol. Image data and depth data are also uploaded through the Flask application using the HTTP protocol. These uploaded data are stored in a location prepared for AI processing.

A web interface developed using React provides real-time access to processed data, environmental variables, crop status, and AI-generated data. This integrated architecture provides an efficient smart agricultural system, including crop monitoring, that can be used on farms of various sizes.

3.2 Environment Monitoring System

The environmental variable monitoring system is an essential part of the plant growth monitoring system. The system is designed to collect, transmit, store and visualize data on key environmental factors that affect plant growth, such as temperature and humidity. The system leverages IoT and sensor technologies to provide real-time data for comprehensive plant growth analysis and management.

Our initial consideration when building the environmental variable monitoring system was the hardware. The hardware needed to be installed across various locations to collect environmental data from multiple points, so cost and size were key considerations. So we purchased KeyeStudio's smartfarm Kit, which includes all of this hardware. This kit includes an ESP32 development board that can control the sensor and various sensors that can collect environmental variable data. Figure 5 is a prototype of the completed smartfarm sensor kit.

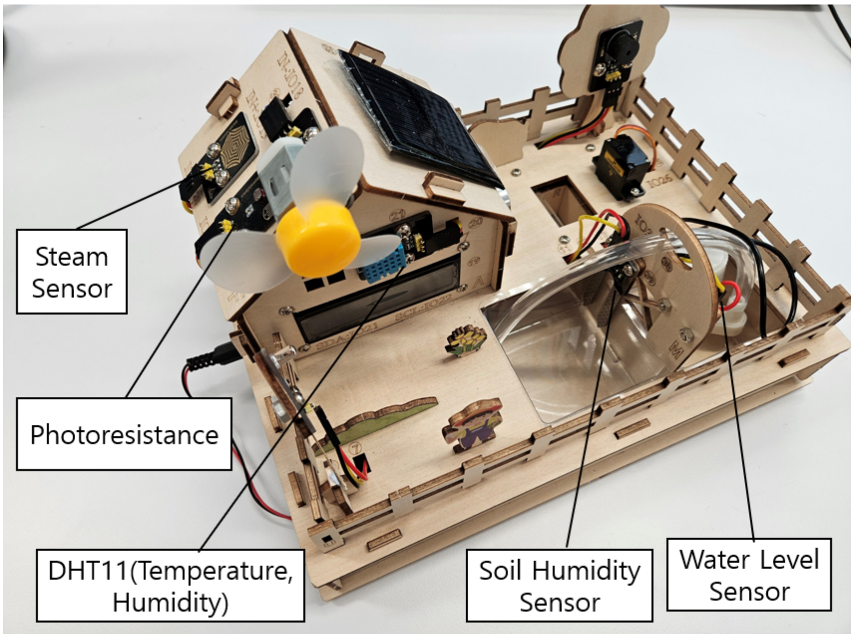


Figure 5 Prototype of Environment Monitoring System with sensors

The core of the hardware used in the environmental variable monitoring system is the ESP32 development board. The ESP32 development board is a board that has low power consumption, a built-in WiFi function, and the ability to easily interface with various sensors. The excellent processing power of this Microcontroller Unit (MCU) enables real-time data collection, processing, and wireless transmission to a database server. In addition, the built-in WiFi module facilitates data transmission to the database server.

The sensors used in this system are a temperature and humidity sensor (DHT11) that can measure temperature and humidity, a photoresistor for measuring illuminance, a steam sensor, a water level sensor, and a soil humidity sensor. Using Arduino code and MCU, the data values of six environmental parameters measured by the sensors, temperature, humidity, illumination, steam, soil humidity, and water level, can be controlled by the MCU. For regular data collection, the MCU is programmed to collect data at 30-second intervals.

Then, to store the sensor data, we looked for a suitable database and decided to use MySQL. MySQL is a relational database, and since data is stored in the form of a table consisting of rows and columns, it is easy to organize the data and see it at a glance. MySQL is also highly reliable and has fast data classification, sorting, and search speed [33]. In particular, when storing the data of these sensors, the data values of all sensors must be recorded every 30 seconds, so we decided to use MySQL.

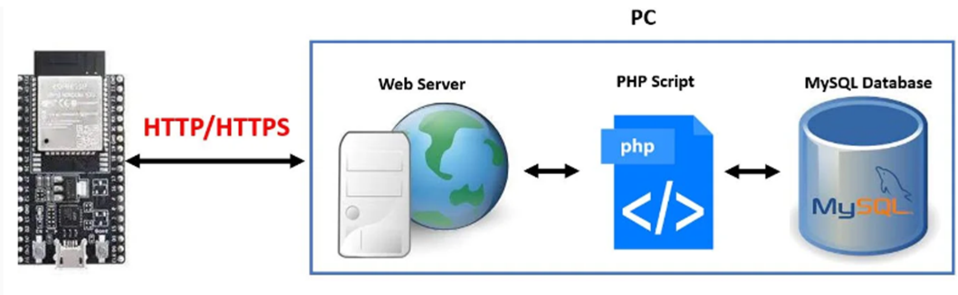


Figure 6 Sensor Workflow

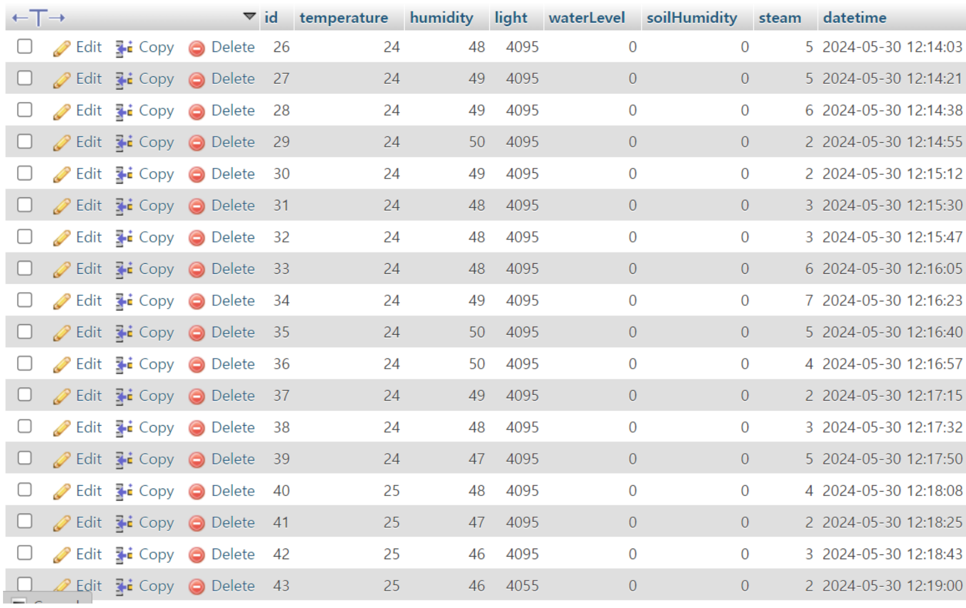
Figure 6 illustrates how data collected from the sensor is stored in a MySQL database server through the ESP32. The ESP32 collects data from sensors and transmits it via WiFi to a local web server using HTTP POST requests. A PHP script on the server then stores this data in a MySQL database, with each entry timestamped for temporal analysis.

To facilitate data analysis and monitoring, we developed a web-based interface using React.js, TypeScript, and Flask. This interface uses HTTP GET requests to request MySQL data to the Flask backend. The Flask backend then requests data from the MySQL server using the SQLalchemy library, and this data is displayed on the web interface. The system presents environmental variables in real-time, allowing users to view data in table or menu formats. Users can select specific dates for analysis and monitor environmental variables remotely using mobile devices and computers, enhancing the system's accessibility and utility for agricultural management.

Figure 7a shows the data stored in the MySQL database server. As shown in the figure, the data obtained through the sensor is updated in real-time in the MySQL server. Figure 7b shows the sensor data displayed in the web interface.

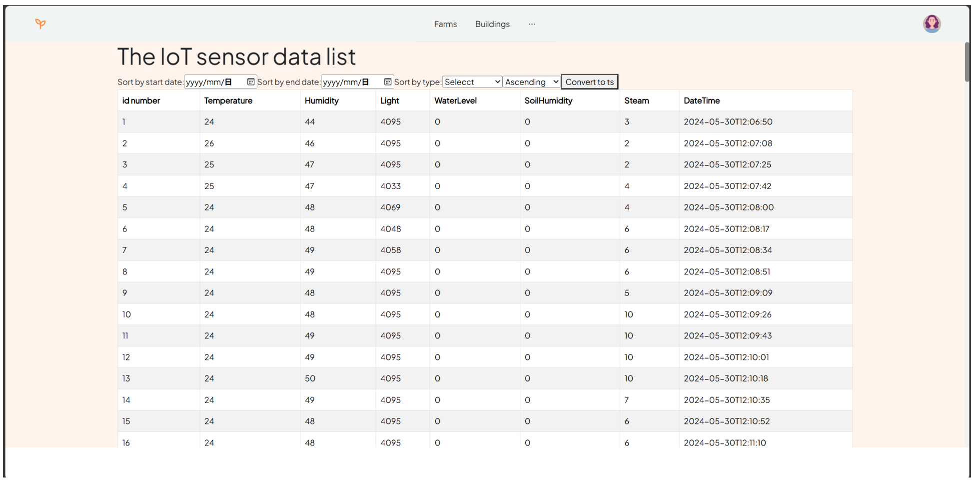
3.3 Web Interface

The web interface consists of a front-end built with React.js and TypeScript and a back-end built with Flask. The front-end handles everything that users see and interact with on the web interface, such as the layout, fonts, colours, and menus. The back-end stores and manages data and handles interactions between users on the front-end, such as page navigation or button clicks. The front-end and back-end of the web interface communicate



				id	temperature	humidity	light	waterLevel	soilHumidity	steam	datetime
☐	Edit	Copy	Delete	26	24	48	4095	0	0	5	2024-05-30 12:14:03
☐	Edit	Copy	Delete	27	24	49	4095	0	0	5	2024-05-30 12:14:21
☐	Edit	Copy	Delete	28	24	49	4095	0	0	6	2024-05-30 12:14:38
☐	Edit	Copy	Delete	29	24	50	4095	0	0	2	2024-05-30 12:14:55
☐	Edit	Copy	Delete	30	24	49	4095	0	0	2	2024-05-30 12:15:12
☐	Edit	Copy	Delete	31	24	48	4095	0	0	3	2024-05-30 12:15:30
☐	Edit	Copy	Delete	32	24	48	4095	0	0	3	2024-05-30 12:15:47
☐	Edit	Copy	Delete	33	24	48	4095	0	0	6	2024-05-30 12:16:05
☐	Edit	Copy	Delete	34	24	49	4095	0	0	7	2024-05-30 12:16:23
☐	Edit	Copy	Delete	35	24	50	4095	0	0	5	2024-05-30 12:16:40
☐	Edit	Copy	Delete	36	24	50	4095	0	0	4	2024-05-30 12:16:57
☐	Edit	Copy	Delete	37	24	49	4095	0	0	2	2024-05-30 12:17:15
☐	Edit	Copy	Delete	38	24	48	4095	0	0	3	2024-05-30 12:17:32
☐	Edit	Copy	Delete	39	24	47	4095	0	0	5	2024-05-30 12:17:50
☐	Edit	Copy	Delete	40	25	48	4095	0	0	4	2024-05-30 12:18:08
☐	Edit	Copy	Delete	41	25	47	4095	0	0	2	2024-05-30 12:18:25
☐	Edit	Copy	Delete	42	25	46	4095	0	0	3	2024-05-30 12:18:43
☐	Edit	Copy	Delete	43	25	46	4055	0	0	2	2024-05-30 12:19:00

(a) MySQL Database on server



id number	Temperature	Humidity	Light	WaterLevel	SoilHumidity	Steam	DateTime
1	24	44	4095	0	0	3	2024-05-30T12:06:50
2	26	46	4095	0	0	2	2024-05-30T12:07:08
3	25	47	4095	0	0	2	2024-05-30T12:07:25
4	25	47	4033	0	0	4	2024-05-30T12:07:42
5	24	48	4069	0	0	4	2024-05-30T12:08:00
6	24	48	4048	0	0	6	2024-05-30T12:08:17
7	24	49	4058	0	0	6	2024-05-30T12:08:34
8	24	49	4095	0	0	6	2024-05-30T12:08:51
9	24	48	4095	0	0	5	2024-05-30T12:09:09
10	24	48	4095	0	0	10	2024-05-30T12:09:26
11	24	49	4095	0	0	10	2024-05-30T12:09:43
12	24	49	4095	0	0	10	2024-05-30T12:10:01
13	24	50	4095	0	0	10	2024-05-30T12:10:18
14	24	49	4095	0	0	7	2024-05-30T12:10:35
15	24	48	4095	0	0	6	2024-05-30T12:10:52
16	24	48	4095	0	0	6	2024-05-30T12:11:10

(b) MySQL Database on Web Interface

Figure 7 MySQL Database

via the HTTP protocol using the Axios library. The front-end web interface consists of several main pages, each designed to provide specific functionality and data visualization. The most notable pages are:

1. Building Page and Plant Page: These pages share a similar layout and focus on providing recent farm environmental data. They display information retrieved from the MySQL database using widgets, charts, and user-friendly cartoon-style UI icons. All environmental data is displayed with the date and time, and when the user taps on the date and time, they can view the temperature, humidity, light, steam, water level, and soil humidity data for that date. This approach provides an intuitive and visually appealing way to monitor the current farm conditions. Our system is also scalable, allowing additional sensors to be added to obtain data on a variety of environmental variables depending on the farm environment. Therefore, after adding a new sensor in the environmental variable monitoring system section, you only need to change the settings in the MySQL Database, and the newly added environmental variable will be displayed on this page.

2. IoTData Page: This page is designed for efficient data analysis and comparison. The top of this page has a sorting feature that allows users to quickly identify peak values for various environmental factors on a given date. Users can select environmental parameters and sort the data in ascending or descending order to make visualization and trend identification easier. Users can also download the data as a JSON formatted file at the press of a button.

3. Image Page: This page is designed for image comparison and analysis. This page is divided into two columns, each of which has a drop-down menu to select different clients based on client_id. Client_id is the id assigned to the device connected to Realsense, and Original and Result images differ depending on Client_id. This page accesses images stored in the server directory, which consists of two main folder types: Original and Result. On this page, users can view Original and Result images of the fruit. The result image is divided into a Ripeness image that can determine the ripeness of the fruit and a Size measurement image that can show the size of the fruit.

3.4 Server Architecture and deployment

After creating the backend and front-end of the web interface and connecting them, the last thing to do is to distribute this web interface so that others can use it. Figure 8 briefly shows our server deployment structure. To distribute the web interface, we used Nginx and Gunicorn. Nginx is a lightweight and high-performance web server program that can process dynamic sites. If you distribute the web server using Nginx, others can access the web server from outside. Gunicorn is a type of Web Server Gateway Interface (WSGI) and is an interface for the Flask backend application to communicate with the web server. When Gunicorn receives a server-side request from the web server (Nginx), it forwards it to the server application (Flask) through Gunicorn. Once we start deploying on a Linux server machine via Gunicorn and Nginx, multiple users will be able to access our web service via URL or IP address.

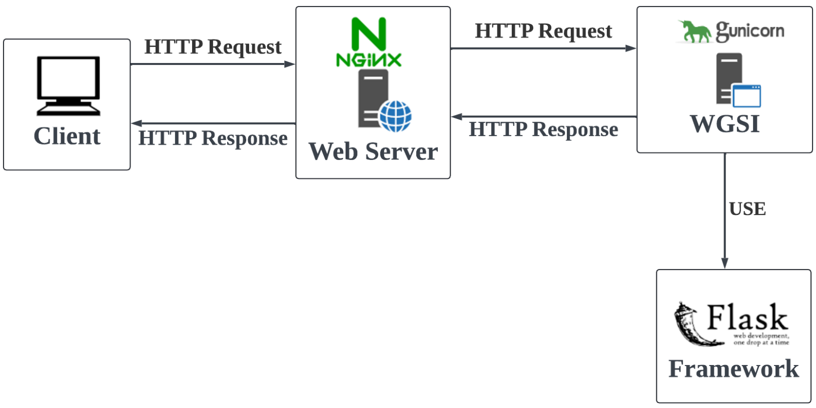
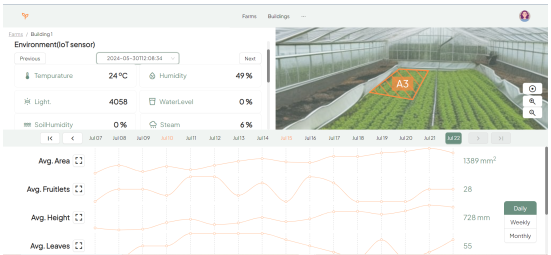


Figure 8 Server Deployment Architecture

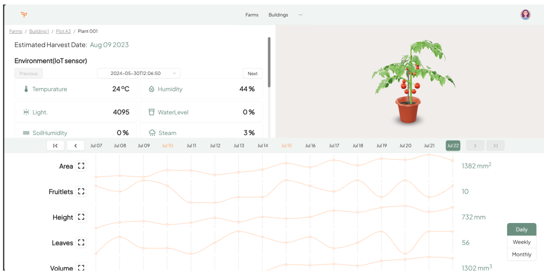
4. Result

4.1 Integrated Web Interface

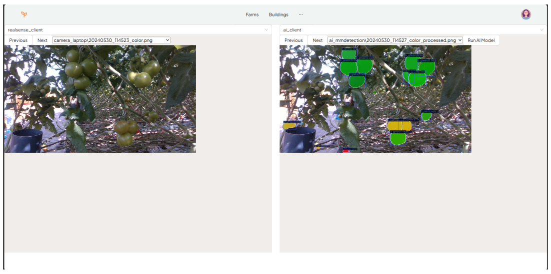
Figure 9 shows the results for the main pages of our web interface. Figure 9a is the Region select page, where users can select a desired region on the farm and view six types of



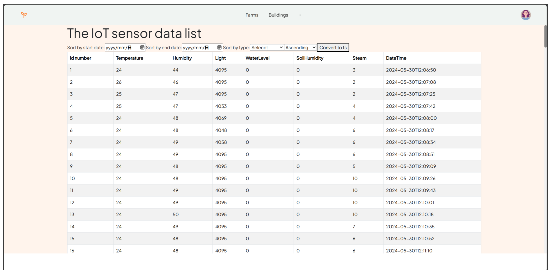
(a) Region Select page. Users can select buildings and areas to inspect.



(b) Plant Page. Users can view the environmental data of the plant.



(c) Image Page. Users can view the plant ripeness results.



(d) MySQL Database displayed in the Web Interface.

Figure 9 Overview of the Frontend Pages

sensor data, such as temperature, humidity, and illuminance, according to date and time. Figure 9b is the plant page, where users can view 3D images of specific plants. Figure 9c is the image page, where users can view the Original image captured using RealSense and the Ripeness measurement image or Size Measurement image processed using AI. Users can select the desired original image and processed image and compare the two images to predict the crop's harvest time. Figure 9d is the IoT page, where users can view all environmental variable data for the region selected on the previous page in a table format at once and download the data as a JSON format file.

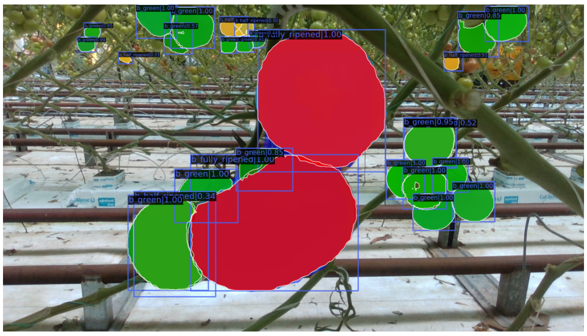
Figure 10b and Figure 10c are the ripeness measurement and size measurement result images, which can be viewed on our web interface Image page.

4.2 Evaluation Result

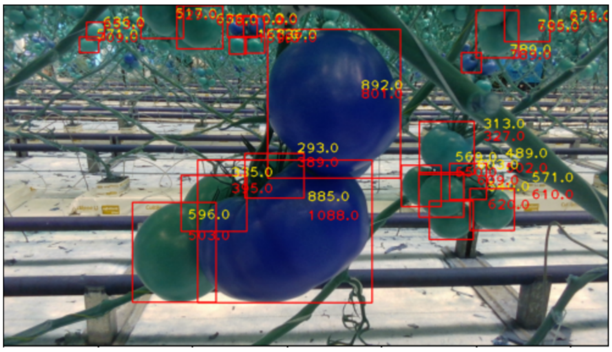
Using the integrated plant monitoring system that my partner and I created, we evaluated this system based on data obtained from a real farm environment. We visited an indoor tomato farm and collected image data and Detph using the RealSense Camera, and collected environmental variable data using sensors. We took close-up photos of tomatoes, and because it was an indoor farm, the angle and intensity of light were adjusted consistently. As a result, the data collected using the environmental variable monitoring system were very similar to the actual farm environment. The farm manager said that the temperature and humidity should be constant in an actual farm. According to the data collection results, the average temperature in the farm was 24°C and the humidity was 40-50%, which was very similar to the information provided by the farm manager. Also, because it was a greenhouse farm, the illuminance value was maintained at a constant value. Also, since it was not raining indoors, the steam value was relatively constant at an average of about 5. The sensor data is very similar to reality and has excellent accuracy.

We also conducted a user survey to evaluate our system on the usability and performance aspects of the web interface. The user survey was conducted via Google Forms and due

(a) Original Image



(b) Ripeness Measurement Result



(c) Size Measurement Result

Figure 10 Size and Ripeness Measurement Result

to time constraints, we conducted the survey with approximately 10 people. The survey responses included evaluations of various aspects of the web interface such as ease of navigation, finding the information needed, clarity of data visualization tools, visual appeal, and intuitiveness. All evaluations were given on a scale of 1 to 5, with 5 being the highest score. The results were very positive feedback with an average satisfaction score of 4.7 out of 5 for the core indicators. Users found the interface easy to navigate, informative, and visually appealing.

5. Discussion

The results of the integrated web interface and plant monitoring system suggest that the system is functional and effective in a real farm environment. This section analyzes the results from two perspectives: the technical accuracy and reliability of the system and the usability of the web interface based on user feedback.

5.1 Technical Performance and Accuracy

The environmental data collected from the indoor farm using the sensors closely matched the actual conditions reported by the farm manager. The average temperature in the farm was recorded as 24°C, and the humidity level was between 40% and 50%. This consistency, which is in line with the farm manager's expectations, demonstrates the reliability of the system in maintaining accurate environmental monitoring. The steam value remained constant at an average of 5 due to the absence of external factors such as rain and the controlled indoor environment of the greenhouse, and the illuminance value also remained stable. The accuracy of these sensor readings is crucial for real-time farm monitoring, and further validates the accuracy of the sensor-based monitoring system. The evaluation data collected from the tomato farm demonstrates that the environmental sensors that track temperature, humidity, and other key variables performed with impressive accuracy. Furthermore, these results indicate that the system has the potential for real-time monitoring and can be applied to similar farm settings. These results can measure whether our system provides significant performance improvements compared to existing commercial solutions for farm monitoring. However, it is difficult to measure accurately compared to existing commercial solutions due to many variables that need to be considered. Future research will explore this by comparing accuracy and stability with similar monitoring systems.

5.2 Usability of the Web Interface

The user survey results show positive feedback on the usability and effectiveness of the web interface. With an average satisfaction score of 4.7 out of 5, users found the system easy to navigate, visually appealing, and informative. This high score suggests that the interface is intuitive, allowing users to easily access and interpret the data collected from the farm sensors and image processing. In particular, the high average score of 4.7 out of 5 in key areas, such as ease of navigation and visual appeal, indicates that the web interface is intuitive and user-friendly, even for individuals without extensive technical expertise. While technical functionality is important, ease of use is crucial, as it determines how often and effectively the system will be used in a real farm environment.

Users also valued the ability to view multiple types of data, such as environmental variables and images, in a single interface. By integrating the original images with AI-processed ripeness and size measurements, users can easily compare the degree of crop variation and more accurately predict harvests, providing a more interactive and intuitive experience. This functionality indicates that the system can not only support data collection, processing, and viewing but also aid in decision-making for farm crops.

Despite the positive feedback, the evaluation has its limitations. Due to time constraints, the user survey was conducted with a relatively small sample size. These results may not comprehensively represent the experiences of a wider user base.

While the results are promising, a larger and more diverse sample would allow for a more accurate evaluation of the usability of the interface and a clearer picture of the strengths and weaknesses of the web interface. In addition, future surveys should include participants from a wider range of user groups, such as farm managers, agricultural scientists, and novice users, to gather a broader perspective on the functionality and usability of the system.

5.3 Achieving research goals

Reflecting the goals of this project, the Integrated Plant Monitoring System successfully achieved its goal of developing an effective and user-friendly web interface and integrated system for monitoring and managing crop health. The system effectively collected and displayed environmental data with high accuracy, and the web interface made it easy to navigate and interpret this data. By integrating AI models for ripeness and size measurements and image processing, we addressed the need for a more interactive and predictive crop management tool, enabling harvest timing predictions and better decision-making.

5.4 Limitations and Future Work

One limitation of the study is that the system was tested only in a controlled indoor farm environment. While the system performed well under these conditions, it is unclear how it would perform in outdoor environments where weather conditions, light levels, and other factors vary significantly. Future steps should include evaluating and measuring the system in a variety of environments.

Another limitation is the relatively small sample size used in the user evaluation. Expanding the survey to a larger and more diverse group of users would provide more comprehensive insights into the usability and user experience of the system. Additionally, conducting a long-term study in a real farm environment would help assess the stability and consistency of the system over time.

6. Conclusion

The integrated plant monitoring system we developed in this project aims to monitor environmental variables and crop conditions on the farm in real-time to predict the harvest time of the crop. In addition, through the web interface, farmers or agricultural experts can easily monitor the condition of the plant and the farm environment from anywhere and manage crop growth more precisely and effectively to reduce labour costs and optimize harvest timing.

Combining sensor data collection and processing, image collection, and AI-based image processing, the system provides accurate real-time insights into key agricultural conditions such as temperature, humidity, and crop maturity. These features not only match the goals of the project but also support the need for a smarter farm management solution. We enhanced the decision-making process for users by providing real-time plant information via a web interface. In addition, our system is highly scalable, allowing us to collect and analyze additional data as needed by adding sensors or cameras.

Our system has shown its potential as an effective tool for monitoring plant conditions through environmental variable monitoring and AI-based image processing in indoor tomato farms. Sensors and data collection and analysis technologies were used for environmental variable monitoring. React.js, Flask, MySQL, and TypeScript were used to create the overall system architecture for the web interface.

My main research contributions in this project are as follows:

1. Developed a reliable sensor-based environmental variable monitoring system for monitoring farm environments.
2. Integrating AI models for crop maturity and size measurement into a web interface.
3. Created a user-friendly web interface and supporting server that enables effective data visualization and decision-making for farm management.
4. Conducted an initial user evaluation that gave positive feedback on the usability of the system.

Future research directions are as follows:

1. Testing in various environments: Since our current system focuses on tomato crops, we will expand the functionality to test it in the future by monitoring outdoor farms with various environmental conditions and various crop types.

2. Advanced prediction models: In the future, we will integrate more diverse machine learning algorithms and AI models to improve the prediction function for crop growth and harvest time.

3. Large-scale user evaluation: Since the current system conducted a user survey with a small sample group, we will conduct a more extensive user survey with various user groups in the future to conduct a more in-depth evaluation of the usability and performance of the system.

By addressing these areas, the system has the potential to become a more comprehensive tool for smart agriculture, enabling more efficient and data-driven farm management in various environments.

References

[1] Food and Agriculture Organization, *The future of food and agriculture*. Rome, Italy: Food & Agriculture Organization of the United Nations (FAO), Jun. 2017.

[2] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors*, vol. 18, no. 8, 2018. [Online]. Available: https://www.mdpi.com/1424-8220/18/8/2674

[3] S. Wolfert, L. Ge, C. Verdouw, and M.-J. Bogaardt, "Big data in smart farming â a review," *Agricultural Systems*, vol. 153, pp. 69–80, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0308521X16303754

[4] N. T. Anderson, K. B. Walsh, and D. Wulfsohn, "Technologies for forecasting tree fruit load and harvest timingâfrom ground, sky and time," *Agronomy*, vol. 11, no. 7, 2021. [Online]. Available: https://www.mdpi.com/2073-4395/11/7/1409

[5] A. Walter, R. Finger, R. Huber, and N. Buchmann, "Smart farming is key to developing sustainable agriculture," *Proceedings of the National Academy of Sciences*, vol. 114, no. 24, pp. 6148–6150, 2017. [Online]. Available: https://www.pnas.org/doi/abs/10.1073/pnas.1707462114

[6] M. Bacco, A. Berton, E. Ferro, C. Gennaro, A. Gotta, S. Matteoli, F. Paonessa, M. Ruggeri, G. Virone, and A. Zanella, "Smart farming: Opportunities, challenges and technology enablers," in *2018 IoT Vertical and Topical Summit on Agriculture - Tuscany (IOT Tuscany)*, 2018, pp. 1–6.

[7] H. M. Hassan and G. H. Galal-Edeen, "From usability to user experience," in *2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*, 2017, pp. 216–222.

[8] V. R. Khawale, H. A. Fidvi, M. D. Shamout, G. F. Nama, N. Anute, and N. Limbore, "Examining the usability and security features of smart farm iot systems," in *2023 International Conference on Power Energy, Environment Intelligent Control (PEEIC)*, 2023, pp. 1687–1691.

[9] M. Amiri-Zarandi, M. Hazrati Fard, S. Yousefinaghani, M. Kaviani, and R. Dara, "A platform approach to smart farm information processing," *Agriculture*, vol. 12, no. 6, 2022. [Online]. Available: https://www.mdpi.com/2077-0472/12/6/838

[10] A. Faid, M. Sadik, and E. Sabir, “An agile ai and iot-augmented smart farming: a cost-effective cognitive weather station,” *Agriculture*, vol. 12, no. 1, p. 35, 2021.

[11] M. Colezea, G. Musat, F. Pop, C. Negru, A. Dumitrascu, and M. Mocanu, “Cluefarm: Integrated web-service platform for smart farms,” *Computers and Electronics in Agriculture*, vol. 154, pp. 134–154, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169917305112

[12] Y. Murakami, “ifarm: Development of web-based system of cultivation and cost management for agriculture,” in *2014 Eighth International Conference on Complex, Intelligent and Software Intensive Systems*, 2014, pp. 624–627.

[13] M. J. O’Grady and G. M. O’Hare, “Modelling the smart farm,” *Information processing in agriculture*, vol. 4, no. 3, pp. 179–187, 2017.

[14] K. Spanaki, E. Karafili, and S. Despoudi, “Ai applications of data sharing in agriculture 4.0: A framework for role-based data access control,” *International Journal of Information Management*, vol. 59, p. 102350, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0268401221000438

[15] S. A. Bhat and N.-F. Huang, “Big data and ai revolution in precision agriculture: Survey and challenges,” *IEEE Access*, vol. 9, pp. 110 209–110 222, 2021.

[16] S. A. Osinga, D. Paudel, S. A. Mouzakitis, and I. N. Athanasiadis, “Big data in agriculture: Between opportunity and solution,” *Agricultural Systems*, vol. 195, p. 103298, 2022.

[17] N. C. Eli-Chukwu, “Applications of artificial intelligence in agriculture: A review.” *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, 2019.

[18] H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, “Computer vision technology in agricultural automationâa review,” *Information Processing in Agriculture*, vol. 7, no. 1, pp. 1–19, 2020.

[19] J. Jung, M. Maeda, A. Chang, M. Bhandari, A. Ashapure, and J. Landivar-Bowles, “The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems,” *Current Opinion in Biotechnology*, vol. 70, pp. 15–22, 2021, food Biotechnology.Plant Biotechnology. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0958166920301257

[20] H. Song and Y. He, “Crop nutrition diagnosis expert system based on artificial neural networks,” in *Third International Conference on Information Technology and Applications (ICITA’05)*, vol. 1, 2005, pp. 357–362 vol.1.

[21] P. Ramos, F. Prieto, E. Montoya, and C. Oliveros, “Automatic fruit count on coffee branches using computer vision,” *Computers and Electronics in Agriculture*, vol. 137, pp. 9–22, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S016816991630922X

[22] I. El Naqa and M. J. Murphy, *What is machine learning?* Springer, 2015.

[23] K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, “Machine learning in agriculture: A review,” *Sensors*, vol. 18, no. 8, 2018. [Online]. Available: https://www.mdpi.com/1424-8220/18/8/2674

[24] R. Dagar, S. Som, and S. K. Khatri, "Smart farming–iot in agriculture," in *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*. IEEE, 2018, pp. 1052–1056.

[25] G. Sushanth and S. Sujatha, "Iot based smart agriculture system," in *2018 international conference on wireless communications, signal processing and networking (WiSPNET)*. IEEE, 2018, pp. 1–4.

[26] S. Jaiganesh, K. Gunaseelan, and V. Ellappan, "Iot agriculture to improve food and farming technology," in *2017 Conference on Emerging Devices and Smart Systems (ICEDSS)*, 2017, pp. 260–266.

[27] M. Rahman, M. S. R. Kohinoor, and A. A. Sami, "Enhancing poultry farm productivity using iot-based smart farming automation system," in *2023 26th International Conference on Computer and Information Technology (ICCIT)*, 2023, pp. 1–6.

[28] F. Wortmann and K. Flüchter, "Internet of things: technology and value added," *Business & information systems engineering*, vol. 57, pp. 221–224, 2015.

[29] O. M. Mico, P. B. M. Santos, and R. B. Caldo, "Web-based smart farm data monitoring system: A prototype," *J. Eng. Comput. Stud.*, vol. 3, no. 3, 2016.

[30] R. Dolci, "Iot solutions for precision farming and food manufacturing: Artificial intelligence applications in digital food," in *2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC)*, vol. 2, 2017, pp. 384–385.

[31] J. Jung, J. Lee, and H. Noh, "Web-based data analysis service for smart farms," *KIPS Transactions on Software and Data Engineering*, vol. 11, no. 9, pp. 355–362, 2022.

[32] S. Wolfert and G. Isakhanyan, "Sustainable agriculture by the internet of things â a practitionerâs approach to monitor sustainability progress," *Computers and Electronics in Agriculture*, vol. 200, p. 107226, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169922005403

[33] J. L. Harrington, *Relational database design and implementation*. Morgan Kaufmann, 2016.