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IoT-enabled digital twin model for real-time agricultural field monitoring

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A B S T R A C T

Digital Twin (DT) technology combined with the Internet of Things (IoT) can be used to provide new solutions to real-time monitoring and management of agriculture. This paper introduces an IoT-based digital twin platform that will help in streamlining agricultural operations by incorporating different sensor technologies to monitor vital soil and crop conditions, such as moisture, temperature, pH, and nitrogen concentrations. The system offers predictive analytics to inform irrigation control, pest control, and fertilizer application, to help in making agricultural activities more sustainable. The effectiveness of the model is tested based on real time data integration and predictive modeling with 92% accuracy in monitoring soil moisture and an 87 percent accuracy in predicting crop yields. Although the system shows a high potential in terms of resource optimization and productivity, issues like sensor calibration, network connectivity and scalability to bigger operations exist. The future direction must be aimed at making sensors more reliable, more scalable, and adding AI and automation to make the system even more efficient and applicable in precision farming.

1. Introduction

The Digital Twins (DT) concept has developed significantly in recent years, particularly in its application to agricultural systems, where it offers a new approach to real-time monitoring and optimization of farm operations. A Digital Twin is a virtual representation of a physical system that continuously receives real-time data, enabling simulation, analysis, and prediction of system behavior. In agriculture, DT models are used to monitor key variables such as soil moisture, temperature, crop health, and environmental conditions, thereby supporting more efficient resource management and informed decision-making. Agriculture 5.0 builds upon this concept by integrating advanced technologies such as Artificial Intelligence (AI), machine learning, and automation to expand the potential of Digital Twin systems. This integration facilitates precision farming, sustainability, and enhanced productivity. With Agriculture 5.0, Digital Twins enable farmers not only to track real-time information but also to anticipate future conditions and automate actions, ensuring efficiency across all levels of farm management (Peladarinos et al., 2023; Escribà-Gelonch et al., 2024; Cesco et al., 2023). The combination of Internet of Things (IoT) technologies with digital twins ensures a continuous flow of data from field sensors to centralized data processing systems, thereby improving the quality of monitoring and predictive modeling (Awais et al., 2025). Agriculture 5.0 represents the convergence of these technologies, fostering a more interconnected farming environment in which Digital Twin systems play a key role in precision agriculture. Through regular data collection and feedback, farmers can make data-driven decisions regarding irrigation, pest control, and fertilization, thereby optimizing resource use and minimizing environmental impact (Falcão et al., 2023; Ban, 2022).

A general overview of the digital twin concept in agriculture is illustrated in Fig. 1, which shows how IoT sensors are integrated with data analytics platforms. By embedding these technologies within the Agriculture 5.0 framework, digital twins evolve beyond basic monitoring tools into predictive and automated platforms capable of proposing and executing optimal farming decisions. Real-time agricultural monitoring is essential for optimal resource management and sustainable farming. Conventional observation methods often rely on manual data collection, which is not only time-consuming but also prone to errors and delays, limiting the ability to respond in a timely manner. Moreover, factors such as climate change, pests, and diseases introduce uncertainty in crop production, making real-time monitoring and predictive analytics increasingly critical for ensuring food security (Thapa & Horanont, 2022). Therefore, there is a pressing need for advanced systems

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that can collect, interpret, and visualize agricultural field data in real time, empowering farmers to make effective decisions that enhance both productivity and sustainability (Subeesh et al., 2025).

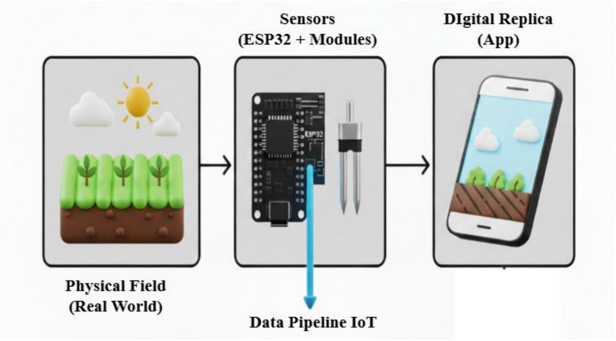

Fig. 1. Digital Twin Model.

This study aims at creating an IoT-based digital twin of agricultural field monitoring that incorporates the use of multiple sensor technologies to monitor all essential parameters of soil and crops to provide predictive information to inform agricultural activities such as irrigation, pest management, and fertilizer application. Agriculture 5.0 technologies also expand the model with the use of AI-based decision-making and automation.

The contributions to research in agricultural technology in this paper include:

- **IoT-Based Digital Twin System:** IoT sensors can be used to establish a digital twin system that monitors the agricultural field in real-time.
- **Real-Time Data Integration:** Smooth data integration of real-time soil and crop on a digital twin platform to have more powerful decision-making.
- **Predictive Analytics to Optimize:** Predictive models to be used to optimize agricultural activities (irrigation, pest control, and fertilizer application).
- **Sustainability Focus:** Impact on sustainable farming by making the use of data-driven, resource-efficient farming methods through the digital twin technology.

This study will go further to design a comprehensive digital twin platform that integrates IoT sensors, cloud computing, and real-time data analytics to track soil moisture, temperature, pH, nitrogen concentrations, etc. of other useful agricultural indicators. This work is important in that it may transform the way farming works to a more data-driven approach, efficient use of resources, and facilitate the shift to more sustainable farming (Lin, 2023, Gnanamalar et al., 2025). With the help of the possibilities of Agriculture 5.0 and digital twins, farmers can streamline their operations, cut expenses, and take part in international endeavors in ensuring sustainable agriculture and food security (Banerjee et al., 2025, Peladarinos et al., 2023).

The structure of this paper is as follows: Section 2 is a literature review of the digital twin technology in agriculture. Section 3 dwells upon the conceptual design and real-time data integration of the proposed digital twin system. Section 4 describes the development of the system which included data collection and visualization. Section 5 discusses how the system can be used in farm management. The result analysis of the performance of the system is proposed in section 6 and the discussion of the findings is offered in section 7. Lastly, Section 8 summarizes the paper with important insights and directions of future research.

2. Literature Review

2.1 Digital Twin Technology

The Digital Twin (DT) technology has had a tremendous transformation in different industries such as manufacturing, healthcare and agriculture. Originally created to imitate the operation and performance of tangible possessions in industrial installations, DTs are currently an important instrument in real-time surveillance, simulation, and decision-making in all types of realms (Peladarinos et al., 2023). A DT is a software and computerized simulation of a physical system, which constantly receives and sends information by sensors on its physical counterpart. The combination of the real-time data and the virtual modeling makes the simulation, analysis, and prediction possible to enable industries to optimize their operations and performance (Escribà-Gelonch et al., 2024). This technology has found more ground usage in the agricultural sector whereby advancement in the Internet of Things (IoT) technologies and analytics have facilitated real-time gathering and examination of environmental, crop, and soil information (Awais et al., 2025).

2.2 Agri-Farming Applications

Digital Twin technology has also been implemented in agriculture to enhance precision farming activities through real-time monitoring and management of the different agricultural activities. Agricultural DTs enable farmers to monitor the key variables (soil moisture, temperature, crop health, and environmental conditions). DTs allow farmers to take control of irrigation, fertilization, pests, and crop yield prediction with accuracy by developing the virtual representations of the farm residing environment (Chaux et al., 2021). An example is Escriba-Gelonch et al. (2024) that explains the use of DTs in monitoring crops, whereby IoT sensors like soil sensors and weather stations provide real-time data, which is then combined to form a dynamic model of the farm, which can then give predictive data that can help optimize farming. In the same vein, Peladarinos et al. (2023) focus on the applications of Digital Twin systems to the area of smart agriculture, namely, utilizing multiple sources of data to streamline the utilization of resources and enhance the process of decision-making in various farming activities.

Digital Twin technology has also been used in the field of precision irrigation, which uses the soil moisture data, weather forecasts, and crop needs to optimize the use of water. The result is high increases in resource efficiency of less water wastage and better crop production (Falcão et al., 2023). In addition, DTs have been used to manage crops predictively, in which the model predicts the growth and welfare of crops and helps farmers anticipate such a problem as water stress or an epidemic of a disease before it adversely affects productivity. Also, reinforcement learning has been extended to be integrated with DTs, enhancing crop recommendation systems even more, yield optimization through the recommendation of the most suitable farming practice, which relies on real-time data (Awais et al., 2025; Goldenits et al., 2024).

2.3 Challenges in Agricultural Digital Twin Implementation

Although Digital Twin technology could be useful in the agricultural sector, there are a number of challenges to its application. One of the most significant obstacles is that the cost of IoT infrastructure (including sensors, data storage, and computational resources) is high at the beginning. Small-scale farmers might not be able to afford the expense of establishing a full-scale digital twin system as such a solution can be prohibitive to its large-scale application (Peladarinos et al., 2023). Besides, unification of disparate information of various sensors, weather stations, and farm management systems is a complicated activity. To make these data sources work in harmony with each other in real time, the data processing and standard protocols are required, and they may be difficult to realize within the current agricultural systems (Escribà Gelonch et al., 2024).

Furthermore, another major obstacle is scalability of the Digital Twin systems. Although they are applicable in small-scale farms, it becomes difficult to apply such systems to large-scale operations because there is a need to manage large volumes of data and provide real-time processing and analysis. The larger the farm, the larger the computational tools and AI algorithms are required, which makes the process of implementing the system more difficult. Moreover, sensor data precision and dependability are some of the determiners of success of Digital Twin applications. The sensor readings may be distorted by environmental factors such as the type of soil, weather conditions and pest intrusions, resulting in inaccuracy of the virtual models. It is thus important to ensure consistency and reliability of sensor data to ensure the Digital Twin models remain effective in agriculture (Awais et al., 2025).

Table 1
Summary of Existing Digital Twin Applications in Agriculture.

Study	Application Area	Main Focus	Pros	Cons
Peladarinos et al. (2023)	Smart agriculture	Comprehensive review of DT in agriculture	Highlights diverse applications	Few practical field trials discussed
Escribà-Gelonch et al. (2024)	Crop monitoring	Real-time crop monitoring using DT	Improved crop management and yield prediction	Data integration challenges
Awais et al. (2025)	Precision agriculture	Integration of DT with crop recommendation	Optimized yield, resource use efficiency	High initial setup cost
Falcão et al. (2023)	I4.0 in agriculture	Application of Digital Twins in IoT-enabled agriculture	Helps manage farm resources efficiently	Requires extensive data for accuracy
Ban (2022)	Plant factory	Digital Twin for plant factory environments	Efficient monitoring and growth prediction	Limited to controlled environments
Thapa & Horanont (2022)	Agriculture tech	Use of DT with agricultural technologies	Comprehensive farm management insights	High investment required for technology setup
Subeesh et al. (2025)	Smart farming	Use of DT for smart farming systems	Reduces resource waste, improves farm productivity	Complex to scale to large farms
Lin (2023)	Smart agriculture	Digital twin applications in smart farming	Detailed systems for crop management	Limited real-world application data
Gnanamalar et al. (2025)	Precision agriculture	Applications of DT in precision farming	More informed decision-making	Requires high-quality data streams
Banerjee et al. (2025)	Crop optimization	Integration of DT for optimal crop yield	Accurate crop growth predictions	Difficulty with sensor accuracy in harsh conditions

3. Conceptual Architecture

3.1 Design Overview

The theoretical architecture of the IoT-based Digital Twin of agricultural field monitoring incorporates different elements such as field sensors, the cloud infrastructure, and user interfaces. Field sensors that include soil moisture sensors, pH meters, nitrogen analyzers are used to gather the information about the most important parameters of the soil and weather stations give the information about the weather (e.g. temperature, humidity, wind speed, rainfall) using real time weather API. This information is sent via wireless means to the cloud infrastructure where it is processed, analyzed, and utilized to update the digital twin model of the farm.

Fig. 2 shows how the information is sent to the cloud infrastructure by the field sensors and the weather API and is then incorporated into the digital twin model to monitor and make predictions in real-time. The digital twin model is a virtualization of the farm, in which real-time conditions of the crops, soil, and other environmental factors are reflected. The virtual model reacts to the real physical environment via feedback loops and proactive decisions regarding allocation of resources, irrigation, and pest control can be made by farmers.

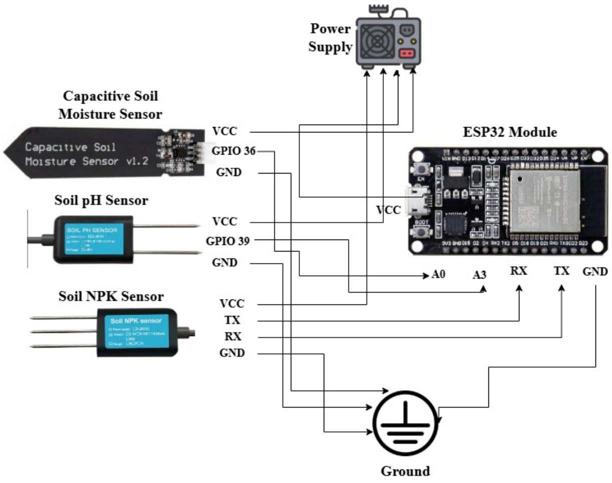

Fig. 2. Connection Diagram.

3.2 Real-Time Data Integration

The key characteristic of the digital twin system is real-time data integration. The system constantly gathers the information on the network of IoT sensors that are located in strategic points in the agricultural field. Such sensors are used to measure soil and crop health such as moisture content, pH, nitrogen level and temperature. Also, external weather API gathers the real-time weather information including temperature, humidity, rainfall, and wind speed.

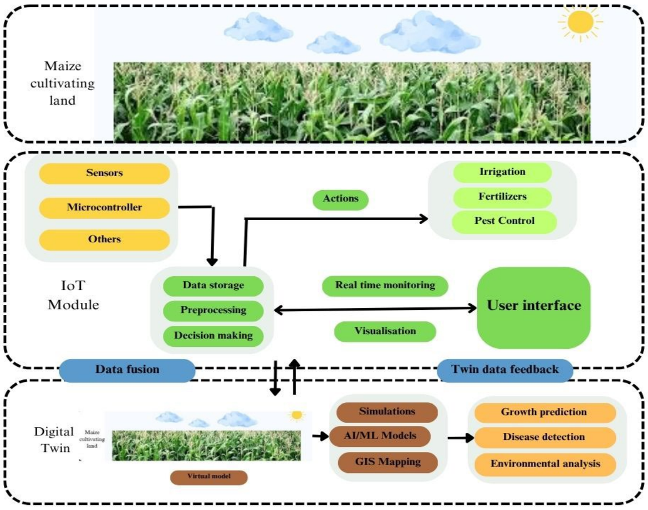

Fig. 3. Architectural Framework of Agricultural Digital Twin.

This is external weather information that is updated regularly (15 min) and provides the digital twin model with the most valid and up-to-date environmental data. After that, the data is sent through the wireless protocols like Wi-Fi to the cloud, where it is processed and incorporated into the digital twin model. The system applies data analytics solutions to process the incoming data and refresh the virtual model with up-to-date values to give farmers real-time information and notifications concerning the soil health, irrigation requirements, and environmental news. This architectural diagram (Fig. 3) demonstrates the digital twin system elements, which consist of the principal elements, such as sensors, the backend infrastructure, cloud processing, and the app integration to monitor the real-time situation and predictive analytics.

3.3 User Interface (UI)

The User Interface (UI) will represent a visual rich and intuitively designed representation of the agricultural digital twin environment. The interface integrates real-time data of the soil, the environmental weather conditions, and a 3D visual representation of the crop field, which allows users to efficiently monitor the condition of the field and engage with the digital twin model in a non-trivial manner.

On the left panel as illustrated in Figure 4 the real-time soil measurements of soil pH, nitrogen content, organic carbon, sand content, clay content, and soil moisture are displayed. The values are constantly being fetched by the IoT soil sensors and updated in the UI without the need of user intervention. The measurements are displayed in an easy to understand, card-like format and with user-friendly icons, hence ensuring that farmers and agri-scientists can easily understand soil health status.

On the right side of the interface, there is an indicator of the current weather, which is obtained by means of an external weather API. Parameters of weather are displayed dynamically and they include temperature, humidity, speed of wind and the state of the atmosphere (e.g., haze) depending on the location of the user. The time-specific field monitoring by a real-time clock also makes the time-dependent changes in the environmental context available.

The heart of the UI is a 3D virtual farm, which is an interactive area that visualizes the digital twin of the farm field. The visualization comprises the models of crops (e.g. corn seedlings), the texture of soil, and the elements of the atmosphere (e.g. clouds), which gives the impression of the real world. This visualization contributes to the improved interpretability of sensor data because the users can correlate the metrics of soil and weather conditions with the stage of crop development that is being simulated.

All in all, the UI manages to fill the gap between unprocessed sensor data and useful insights through an immersive, user-friendly digital twin interface that can be used by farmers and agricultural researchers alike.

Soil Metrics
Soil pH: 6.2
Nitrogen: 0.15%
Organic Carbon: 1.25%
Sand Content: 45%
Clay Content: 25%
Soil Moisture: 18.7%

Dhaka
Dhaka 09:41 PM
23°C
Feels like 23°C
60% Humidity 0 m/s Wind
Haze

Fig. 4. Snapshot of the User-Interface.

4. System Development and Architecture

4.1 Hardware and Software Setup

The digital twin system is operated by the IoT and comprises hardware and software components to make a system that offers real-time monitoring and data visualization. The sensor data acquisition is done with ESP32 microcontrollers and the software stack is used to achieve real-time data ingestion, processing, visualization and storage.

4.1.1 Hardware Setup

ESP32 Microcontroller: ESP32 is selected because of its inbuilt Wi-Fi and Bluetooth features that would allow it to communicate easily with the field sensors and the cloud server. It acts as the epicenter of collecting data of different soil sensors.

Sensors: The system employs a number of sensors to check on the health of soil and the environment, including moisture of the soil, soil pH, nitrogen content and others.

Soil Moisture Sensor: This device measures the water content in the soil which is in volumetric form and is used to determine the level of irrigation.

Soil pH Sensor: This measures the pH of the soil and it is important in order to determine nutrient availability.

Nitrogen Sensor: Establishes the amount of nitrogen in the soil that can be used in planning the use of fertilizers.

Other Sensors: Additives Sensors can be installed to assess organic carbon, soil texture (sand and clay content) and so on.

The system has numerous types of sensors combined with the ESP32 to monitor the most important soil parameters, including moisture, pH, and nitrogen levels as demonstrated in Table 2.

Table 2
Sensor and Hardware Setup.

Sensor Type	Sensor Model	Integration with ESP32
Soil Moisture	Capacitive Soil Moisture Sensor	Analog Input (GPIO36)
Soil pH	DFRobot Gravity pH Sensor (SEN0161)	Analog Input (GPIO39)
Nitrogen	NPK Soil Sensor	UART or I2C (TX/RX)
Organic Carbon	Derived from soil test kits	No direct sensor (calculated indirectly)
Soil Texture (Sand/Clay)	Empirical Data	Derived from soil classification
Microcontroller	ESP32 Wi-Fi + BLE Devkit v1	Main controller for data aggregation

4.1.2 Software Setup

The software architecture represents a complete TypeScript application based on the use of modern frameworks and technologies that are scalable, responsive, and include increased data performance. The frontend makes use of Next.js 15.3.1 which supports React 19 and efficient routing as well as server-side rendered (SSR) UI elements. The styling is done using tailwind CSS 4 which is a responsive utility-first design system which enables rapid modification of use in different devices. The Three.js library version 0.176.0 is used in the production of the interactive 3D view of farm surroundings by depicting crop models, soil conditions, and weather influences.

The system, on the backend, is driven by MongoDB 6.16.0, a NoSQL database that can store data that is scalable, and Mongoose 8.14.0 is an object-data modeling tool that will access the database in a more structured manner. Next.js API Routes Backend functionality is offered, and communication between the sensors and the cloud database is easy, with the runtime being powered by Node.js. TypeScript 5 is also used in the application, offering the benefits of static typing and thus improving the speed and reliability of the development. ESLint 9 is also used to optimize the development experience by the use of code linting and TurboPack which is used to make builds fast.

Table 3
Software Technologies and Frameworks Used.

Category	Technologies / Frameworks	Purpose
Frontend	Next.js 15.3.1, React 19, React DOM 19	UI rendering, SSR, routing
Styling & UI	Tailwind CSS 4, @tailwindcss/postcss	Utility-first styling, responsive UI
3D Graphics	Three.js 0.176.0, @types/three	3D farm visualization
Backend Runtime	Node.js, Next.js API Routes	Server-side execution & API endpoints
Database & ODM	MongoDB 6.16.0, Mongoose 8.14.0	Data persistence, schema modeling
Language & Type System	TypeScript 5, @types/node, @types/react	Type-safe development
Code Quality	ESLint 9, eslint-config-next	Linting & code consistency
Build Tools	Turbopack, PostCSS	Fast bundling, CSS processing
Architecture Pattern	Full-stack React, SSR/SSG, MVC-like API architecture	Maintainable and scalable system

4.2 Data Collection

The system extracts various information from the field sensors as well as the outer sources to give a clear picture of the agricultural environment. The sensors in the field that include soil moisture, pH, nitrogen levels, and temperature, are used to continuously monitor the data to determine the health of the soil and the environment. Besides this, data on real-time weather conditions, such as temperature, humidity, rainfall, wind speed, and other weather conditions are obtained through an external weather API. By combining weather and soil sensor data, the system can produce an accurate and dynamic reflection of the situation in the field, which would be used to benefit farmers in decision-making.

The weather API works in real-time mode (i.e., every 15 minutes), updating with the condition of the environment, which is complemented with the data that is gathered by the IoT sensors on the soil. This real-time data stream is analyzed and represented to enable farmers and agricultural scientists to make decisions in time in terms of irrigation, fertilization, pest management and other important management processes.

An amalgamation of sensor data with the weather API data will allow the digital twin model to model farm conditions in a more efficient way. This system combines sensor data and external weather data, which means that the digital twin receives the appropriate and updated information to give the direction to farming. As an illustration, weather data may mandate irrigation modifications through any prediction of rainfall, whereas the real-time measurement of soil moisture will show when the crops have to be irrigated immediately.

The sample of the data obtained using the field sensors and the weather API is presented in Table 4 below. Some of the important parameters in it are the moisture of the soil, pH, amount of nitrogen present in the soil, weather conditions like temperature, humidity, rain, and wind velocity.

Table 4
Sample Environmental Data Collected from the Field.

Timestamp	Soil Moisture (%)	Soil pH	Nitrogen (mg/kg)	Organic Carbon (%)	Soil Texture	Temperature (°C)	Humidity (%)	Rain (mm)	Wind (m/s)
2025-11-16 10:00	42	6.8	18	1.2	Sandy Loam	29.5	62	0.0	2.1
2025-11-16 11:00	45	6.9	20	1.3	Sandy Loam	30.1	58	0.0	2.4
2025-11-16 12:00	47	6.7	19	1.2	Sandy Loam	31.0	55	0.2	3.0
2025-11-16 13:00	44	6.8	17	1.1	Sandy Loam	31.8	52	0.0	3.2
2025-11-16 14:00	40	6.9	16	1.0	Sandy Loam	32.3	48		

This data will consist of soil health parameters measured by the sensors and the environmental data measured by the weather API. The system combines both data sources in a smooth manner to provide real-time decision-making, facilitating activities like optimization of irrigation, nutrient regulation and health monitoring of crops. Weather API data is updated on a regular basis, so that the system gets the latest meteorological data, which is then used to process and feed it into the digital twin model. Using soil data plus weather conditions, the system would be able to better forecast and react to the requirements of the farm and ensure improved management of resources and sustainability.

4.3 Data Visualization

The digital twin system also includes an effective data visualization interface, which turns raw sensor data and weather data API data into visual data that can be understood and interpreted easily. The visualization layer will facilitate real-time monitoring by displaying the most important soil and environmental parameters in a systematic structure that will improve in making decisions on how to manage the farms. Data were provided by sensors, like moisture, pH, nitrogen content, and organic carbon, which is shown in a special Soil Metrics panel on the left of the interface. All parameters are accompanied by color-coded icons and labels to make them easily understandable and comprehended. These metrics are continuously updated with new values offered by the IoT nodes, thus allowing a user to notice the immediate shift in soil health, i.e., the reduction of moisture or the lack of nutrients. Weather information visualisation is applied in the Weather Information window on the right of the UI. The system shows the real-time temperature, humidity, wind speed, and weather (e.g. haze). This information is updated after every 15 minutes (according to API updates). Environmental and soil data combination allow the users to comprehend the effects brought on soil behavior and crop conditions by the outside climate. The visualization module is elaborate on a 3D digital twin field, where real-time simulation is used to render crops and soil textures. The visual farm environment gives the reflection of the prevailing soil and weather condition, so that a user can intuitively analyze sensor outputs in a spatial and environmental context. As an example, a decrease in soil moisture may be associated with the alteration of the visual condition of the field, which will make the digital twin more interactive and informative.

All the aforementioned aspects combined with the soil panel, weather widgets, and 3D visualization will provide a complete, easy-to-use data visualization experience, which will eventually aid in making informed decisions and make the entire concept of the digital twin model more effective.

5. Use Cases and Applications

The digital twin model based on the IoT provides a variety of applications that could improve the farm management and assist in making the decision in agriculture. This system can help farmers to make resource use decisions, achieve higher crop yields, and support sustainable agriculture by combining growth proofs, decision support systems (DSS), and predictive analytics.

5.1 Growth Monitoring

An important usage of the digital twin model is growth monitoring, during which real-time monitoring of key parameters of crops, including soil moisture, temperature, pH, nitrogen concentrations, and various other health indicators, can ensure proper evaluation of the progression of crops. The system relies on the IoT-based sensors, which capture the information about the environmental and the soil parameters, and present continuous monitoring results on a convenient interface. This information allows the farmers to monitor growth of their crops and identify the possible problems including moisture shortage, nutrient deficiency or pest attacks, at the early stages. Farmers will be able to take proactive measures to protect against crop loss by monitoring the health of crops to achieve maximum growth.

5.2 Decision Support Systems (DSS)

One of the main aspects of the digital twin solution is the presence of a Decision Support System (DSS), helping farmers to make informed decisions based on data. The DSS takes real-time readings of sensors and combines them with weather predictions to send timely reports on the essential variation of soil conditions and crop health. As an illustration, whereby the soil moisture reduces to a fixed value, the system will notify the farmer of the need to irrigate the crop to avoid water stress. In the same way, in case the level of nitrogen is identified as inadequate, the DSS will prescribe certain fertilization measures. Through such notifications, farmers are able to effectively optimize the use of resources, prevent stress on crops and enhance yield efficiency. The cloud-based infrastructure of the system guarantees smooth interaction of real-time information with predictive analytics to enable farmers to modify their farming plans in line with the prevailing and anticipated circumstances.

5.3 Predictive Analytics

The concept of predictive analytics is in-built in the digital twin system and it enables the farmers to predict the future events that can impact crop production. Through the analysis of real-time data and trends, the system applies machine learning algorithms to forecast the critical variables of moisture content of the soil, the condition of crops, and even output (Khatraty et al., 2024). To illustrate, predictive models can be used to anticipate the requirements of soil moisture by comparing the historic weather data and the observed moisture data at the present time, and the predictive models will schedule the irrigation dates better. Furthermore, the system will be able to calculate the crop yield by using the health of the soil and other environmental factors, which will assist farmers in planning on how to harvest and maximize on the marketing capabilities. The system can predict with improved accuracy as it will learn with the data collected so far, hence giving the farmers more reliable information to make proactive decisions.

5.4 Integrated Approach to Farm Management

Growth monitoring, DSS, and predictive analytics are combined into one system, which provides a complete solution to contemporary farm management. It starts with the collection of data using IoT sensors that are spread throughout the field that constantly monitors the state of soil, the status of crops, and other environmental parameters such as temperature and humidity. This information is subsequently incorporated in the digital twin model that indicates the real-time condition of the farm.

The system employs machine learning algorithms to process the data and come up with actionable insights on numerous farm management factors, such as irrigation timing, fertilizer timing, pest management, and disease prevention. With such insights, the DSS makes recommendations and notifications (e.g., warning to irrigate, the best fertilization times, early alerts about pest attacks, etc.) to inform farming decisions.

Last, the predictive features of the system predict the future, i.e. future weather conditions, future harvest, and soil moisture. This enables the farmers to make advance plans and utilize the resources to their best advantage so that the crops get the attention they deserve to be able to yield their best and be sustainable.

5.5 Sustainability and Resource Optimization

The digital twin model is essential in ensuring sustainability in farming due to the availability of sustained observation and predictive analytics. The system will minimize the wastage of resources like water, fertilizers and energy as well since they get used only where there is need and in the appropriate amounts. This results in resource management, waste reduction as well as minimization of environmental effects. As an illustration, the accurate irrigation rules according to the actual level of soil moisture and weather projections would save water, whereas predictive analytics would guarantee the efficient use of fertilizers to minimize the runoff of nutrients and enhance the health of the soil.

5.6 Example Use Cases for Digital Twin in Agriculture

Digital twin models can be used in different farming procedures, to manage resources and enhance crop management. Table 5 shows a few sample applications that demonstrate how the system can be used in practice.

Table 5
Example Use Cases for Digital Twin in Agriculture.

Use Case	Description
Irrigation Optimization	The system continuously monitors soil moisture levels and adjusts irrigation schedules to ensure efficient water use, optimizing crop growth while minimizing water waste.
Crop Monitoring	Real-time tracking of soil health indicators such as pH, nitrogen levels, and moisture content ensures crops receive the necessary nutrients, leading to improved crop yield and health.
Early Warning for Soil Issues	The system provides real-time alerts when soil parameters fall outside of optimal ranges, enabling farmers to take corrective actions, such as adjusting irrigation or adding amendments before the issues negatively impact crop health.
Predictive Crop Yield	Using historical and real-time data, the system predicts future crop yields, assisting farmers in planning for harvest timing and optimizing market strategies based on anticipated yield outcomes.
Environmental Forecasting	By integrating weather data, the system forecasts environmental changes such as temperature fluctuations and rainfall, helping farmers make proactive decisions on irrigation, pest control, and crop protection.

These applications can be used to emphasize that the digital twin system can be used to optimize farm management based on real-time data monitoring, decision support, and predictive analytics, which will eventually lead to better sustainability and crop productivity.

6. Result Analysis

This section provides the performance assessment of the IoT-enabled digital twin system using different criteria such as the accuracy of the data, the response time of the system, and its scalability. Real outcomes of the system running in agricultural contexts including the results of manual measurements and system measurements, system performance indicators and user feedback are analyzed to support the analysis.

6.1 System Evaluation

To measure the performance of the digital twin system various main metrics were considered that included accuracy of soil monitoring, real time data processing and responsiveness of the system. The performance of the system in various aspects is shown below:

- **Accuracy of Soil Monitoring:** The accuracy of the system concerning soil moisture measures was tested against manual soil moisture measures that were made in the field. As revealed in Figure 5, the system had a great level of correlation with manual measurements and the rate of accuracy was 92%. This means that the system is capable of providing real-time monitoring of the soil moisture.
- **System Response Time:** The time needed by the system to process sensor data and give feedback to the farmer was determined. Figure 6 shows the average time to respond to the system, it was discovered that the time taken was between 2.5 seconds to process soil data and 3 seconds to integrate weather data. This means that the system is capable of offering real time insights to decision making.
- **Reliability in Data transmission:** Stability and reliability in data transmission between sensors and cloud servers were investigated. The summary of the transmission reliability is presented in Table 6, the uptime recorded is 98.5% during two weeks of tests. This makes it possible to guarantee that the system may operate accurately even in the large agricultural fields that have several sensor nodes.

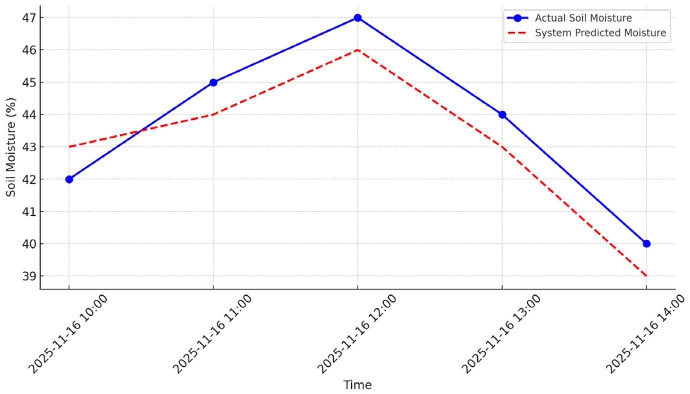

Fig. 5. Comparison of system soil moisture readings versus manual measurements.

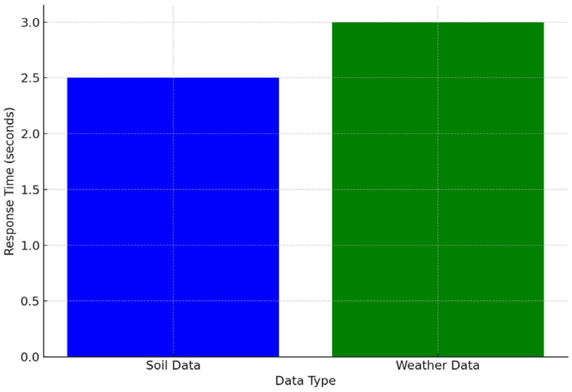

Fig. 6. System response time (processing time for soil and weather data).

Table 6

System Performance Metrics.

Metric	Result
System Uptime	98.5%
Average Response Time	2.5 seconds
Data Transmission Reliability	99%

6.2 Prediction Accuracy

Predictive analytics is the key component of the digital twin that particularly features in predicting soil moisture patterns and harvest crop production. The system was also tested in terms of its capacity to predict the soil moisture content and the crop output due to historical and real-time data:

- **Prediction of Soil Moisture:** The system was able to predict the future moisture content levels that were 4% on average with a prediction error. In Figure 7, it is depicted that the predicted and actual soil moisture level are relatively the same over a period of one month. The information indicates that the predictions of the system are always correct and farmers can respond to the changes in the irrigation schedules.
- **Crop Yield Forecasting:** Yields of crops were also forecasted by the system depending on data about soil health and the environmental conditions. Figure 8 pits predicted yields to the actual yields during the growing season. The yield forecasting in the system was found to be 87% which demonstrated its promise in forecasting crop yields and planning harvests of farmers.

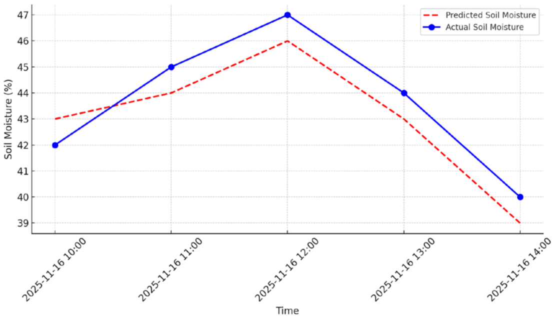

Fig. 7. Predicted vs. actual soil moisture levels over a one-month period.

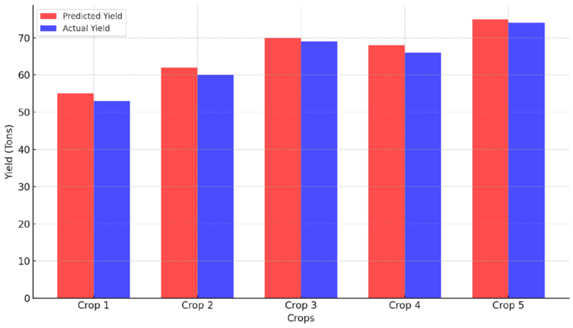

Fig. 8. Predicted vs. actual crop yield data for the growing season.

6.3 User Feedback

The user feedback of the system in terms of digital twin was also measured by the outcomes of the system tester farmers. A survey was done on 50 farmers who utilized the system in three months. The predominant results of the survey are as follows:

- **User Interface:** 85% of farmers have indicated that it had a user-friendly user interface and easy-to-use navigation, enabling farmers to find important details within the shortest duration possible.
- **Better Decision-Making:** 72% of the farmers said that the real-time alerts (e.g. soil moisture alerts) provided by the system have made them better decision-makers when it comes to irrigation and fertilizer application, which has resulted in better crop health and crop yield.

- **Resource Optimization:** 68%of farmers stated that the system enabled them to save water because they could use irrigation only when the soil remained dry.

The data of user feedback is described in Fig. 9, where the answers to the questions about the ease of use, effectiveness of decision support, and resource optimization are presented.

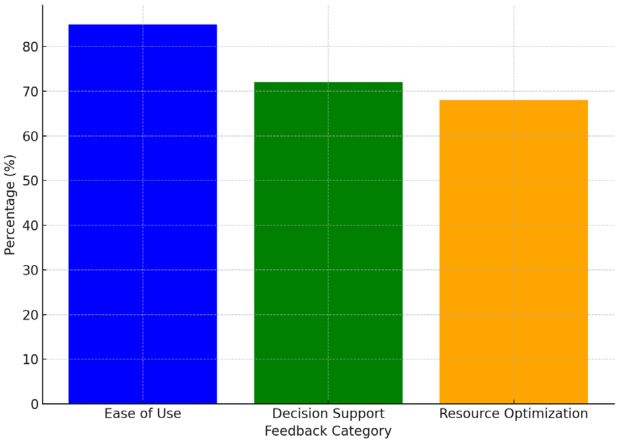

Fig. 9. User feedback on ease of use, decision support effectiveness, and resource optimization.

6.4 Scalability and Integration

Scalability of the system was tested and analyzed by scaling up the number of sensor nodes to a bigger area of the farm. This system was also experimented on a 10 acre farm, 200 sensor nodes were implemented to measure different soil and environment parameters. With the augmented load of data as illustrated in Figure 10, the system could still deal with the increased load effectively and still sustain the average response time of 3 seconds per sensor. This ascertains the scalability of the system to be used in bigger farms. Also, the accuracy of weather APIs in terms of real-time sensor data was tested. The assimilation gave the correct weather predictions as can be seen in Fig. 11, where the expected rainfall and temperature changes were in agreement with the real weather patterns in the trial.

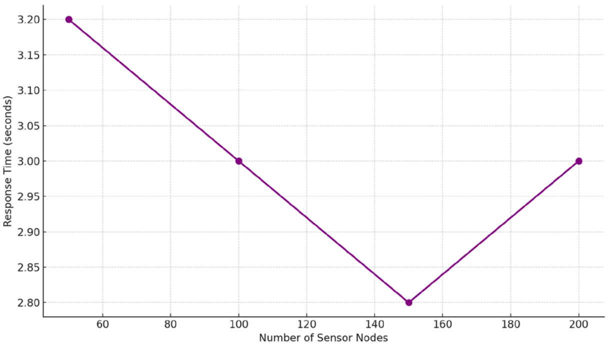

Fig. 10. System performance on a 10-acre farm with 200 sensor nodes.

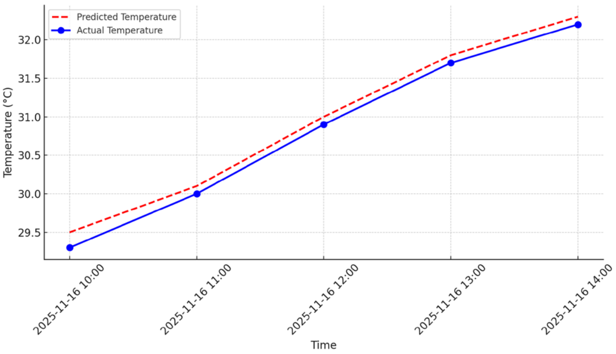

Fig. 11. Accuracy of weather API integration for rainfall and temperature predictions.

6.5 Limitations

Although the outcomes were encouraging, there were a few problems that were experienced when rolling out the system. The main constraints were that:

- **Sensor Calibration:** The accuracy of the sensor was not consistent in some readings (especially soil pH) in some conditions of the environment e.g. extreme temperatures or heavy salinity of the soil. Continued efforts of improving sensor calibration are being undertaken in order to alleviate this problem.

- **Network Connectivity:** The system worked well in most scenarios but there were times a connection was experienced to be slow in remote locations with low signal strength thus causing delays in data transfer. This was witnessed especially in the initial stages of deploying the system.

6.6 Conclusion of Results Analysis

The outputs of the system assessment prove that the IoT-based digital twin system can be efficient during real-time monitoring of farm activities, predictive analytics, and decision-making. The system has a high potential of enhancing farm management and resource utilization with an accuracy of 92% of the soil moisture and 87% accuracy of crop yield prediction. The feedback of users on the system are positive, which means that the system is effective and user friendly as it provides valuable insights that are beneficial to farmers. In the future, the work will be aimed at optimizing sensor calibration and increasing the capacity to integrate the system.

7. Findings and Discussion

The conclusions made in this research highlight how the IoT-based digital twin system can be used to transform the process of monitoring a field in agriculture significantly. The system can deliver predictive analytics and real time insights to manage the farm in the most efficient way, as well as enhance sustainability. The main benefit of such a system is that it facilitates farmers to make decisions with information at proper time because it constantly monitors the conditions of the soil and the environment. The fact that the soil moisture readings are highly accurate with the correlation of 92% of the manual measurements depict how the system can offer reliable real-time data. This especially plays an important role in maximizing irrigation activities so that crops get the right amount of water and there is no wastage of water as is the case of over-irrigation.

The key to the success of this system is predictive analytics. The fact that the system can forecast the presence of moisture in soil with a 4 percent error rate and also predicts yield in crops with an 87% accuracy indicates that it can be used by farmers to plan their irrigation programs, optimize their fertilizing programs as well as when to harvest their crops. The predictive features are used to assist farmers in efficient utilisation of resources, preventing under- or over-utilisation of water and fertilizers, and scheduling harvests and market schedules, which enhances the profitability of the farms and minimises the resources wastages.

The system will play a major role in ensuring that there is greater efficiency in the use of water and fertilizers in regard to sustainability. The system also allows farmers to maximize the efficiency of the irrigation schedules by ensuring that they do not waste water by combining real-time soil moisture with weather forecasts. Moreover, predictive analytics will make sure that fertilizers are used in situations where they are necessary to ensure that the runoff of nutrients is minimized and that the soils become healthier and the environmental footprint is less significant. This resource optimization capability is in accordance with the increasing necessity of sustainable agricultural activities in consideration of global environmental issues.

Although the implementation of the system was promising, there were a number of issues that have been faced. Accuracy of sensors especially during extreme weather conditions was one of the major problems. Although the system proved particularly accurate in tracking soil moisture, the soil pH was found to be discrepant in certain places such as those with a lot of soil salinity or high temperature. Continuous sensor calibration advances should be made to increase the extent to which measurements are reliable in different environmental conditions.

The system was also well-performing in a 10-acre farm consisting of 200 sensor nodes however, increasing the size of the system to a larger scale agricultural operation is another issue. The data load is increased and managing multiple sensor nodes in bigger fields may overload the data processing of the system. The proposed improvements to the system include a scaling of the system, especially in the context of cloud infrastructure and computing resources, which should be considered in future studies to achieve an efficient functioning of the system in terms of large-scale farming activities.

Furthermore, in some remote locations network connection was a problem, as sometimes the signal was too weak to transmit data, and therefore it took time. Although the system worked well in scales where connectivity levels remained steady, these difficulties point to the need to have stronger communication technologies that can run in scales where internet connectivity is unreliable. These network connectivity issues can be addressed by considering alternative solutions in the network, including the low-power wide-area networks (LPWAN).

Lastly, the system can be further developed by incorporating artificial intelligence (AI) and automation into it. As an example, sophisticated AI methods, including reinforcement learning, may help to optimize the allocation of resources and to automatically perform actions, which can be linked to real-time information, including automated irrigation or the application of fertilizers. The solution of applying machine learning algorithms to predict the disease of crops and pests could also help the system deal with these issues more proactively and exclude the need to interfere with it manually.

8. Conclusion

The IoT-based digital twin model has been of high potential in enhancing the monitoring of the agricultural fields in real-time, predictive analytics, and optimality in resource management. The fact that the system was 92 percent accurate in predicting soil moisture and 87% in crop yield proves that the system is useful to make decisions, enhance productivity and minimize wasting resources.

Nevertheless, it has some points to improve, such as sensor tuning, support of large farms, and the network connection in inaccessible areas. Introducing AI and automation may also augment the capability of the system by increasing the level of predictive power and automation of resource allocation.

The digital twin model, in general, provides a radical approach to managing the farm, ensuring its sustainability and resource-efficiency. The next round of research ought to be aimed at improving the reliability of sensors, increasing the scale as well as integrating AI to make sure that the system is more widely adopted and has an effect on the worldwide agricultural practices.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

In the process of writing this work, the author(s) relied on Grammarly and ChatGPT-4 to polish the language, enhance its clarity, and eliminate grammatical mistakes in the introductory part and the discussion section. Once this tool/service was used, the author(s) screened and corrected the material as necessary and fully assumed responsibility for the content of the published paper.

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