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Realtime Forecasting for Smart Agriculture System using Simple Moving Average Method

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Abstract

This study proposes a real-time smart agriculture monitoring system that integrates Internet of Things (IoT) technology with a SMA forecasting method. The system utilizes soil moisture, temperature–humidity, and light intensity sensors connected to an ESP32 microcontroller to monitor environmental conditions in agricultural fields. Sensor data are transmitted to a cloud database and visualized through a mobile application to support remote monitoring. This study obtains reliable environmental measurements during field testing in a rice field environment. The system harvests temperature values ranging from 27.5 °C to 35.6 °C, relative humidity between 48.1% and 69.4%, and light intensity values between 21,580 and 54,612 lux, while soil moisture measurements consistently reflect variations between dry and wet soil conditions. This study also implements a lightweight forecasting module using the Simple Moving Average method with a bounded trend adjustment to provide short-term environmental predictions. We obtain stable prediction performance using a moving window of ten observations, which effectively smooths sensor noise while maintaining responsiveness to environmental changes. Forecasting evaluation using the MAPE indicates low prediction error values, demonstrating the reliability of the proposed prediction mechanism. By executing the forecasting module externally from the embedded ESP32 device, the system maintains efficient real-time monitoring while still delivering predictive insights to support early agricultural decision-making. These findings confirm that the proposed IoT monitoring system provides reliable environmental measurements while offering additional advantages.

Keywords:
Smart Farming, Forecasting, Field Monitoring, Simple Moving Average

1. Introduction

The rapid development of information technology and the Internet of Things (IoT) significantly transforms modern agricultural practices. Traditional agriculture often relies on manual observation and periodic measurement of environmental parameters, which limits the ability of farmers to respond quickly to changing conditions in the field. Real-time monitoring systems provide a more effective approach by enabling continuous observation of environmental parameters such as soil moisture, temperature, light intensity, and humidity. IoT-based monitoring systems allow sensors to collect environmental data and transmit it directly to cloud or mobile platforms for analysis. Several studies demonstrate that IoT technologies can improve agricultural productivity by providing accurate environmental information and supporting timely decision-making. However, many agricultural monitoring systems still lack reliable data processing mechanisms to filter sensor noise and provide stable real-time measurements, which becomes an important challenge in smart agriculture development [1], [4], [18].

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Environmental monitoring plays a critical role in maintaining optimal plant growth conditions. Agricultural environments are highly dynamic, and parameters such as soil moisture, temperature, and pH levels can change rapidly due to weather conditions and irrigation activities. Researchers have developed various sensor-based monitoring systems to measure these parameters in real time. These systems commonly integrate soil moisture sensors, temperature sensors, and light sensors with microcontroller platforms to provide continuous environmental data. Although these systems can collect large volumes of data, many existing implementations simply display raw sensor readings without applying data smoothing or filtering techniques. Raw sensor data often contains fluctuations and noise that reduce measurement reliability. Therefore, efficient data processing methods are required to stabilize sensor outputs and provide more accurate environmental monitoring results in smart farming applications [2], [3], [13].

Smart agriculture systems also rely heavily on wireless communication technologies to enable remote monitoring and control. IoT-based systems allow sensor nodes deployed in agricultural fields to transmit data to cloud platforms or mobile applications through wireless networks such as Wi-Fi, LoRa, or cellular communication. These technologies enable farmers to monitor environmental conditions without being physically present in the field. Several studies highlight that remote monitoring systems improve efficiency and reduce labor requirements in agricultural management. Nevertheless, large volumes of sensor data generated continuously in IoT environments can create challenges related to data reliability, bandwidth usage, and real-time processing. Without proper data management techniques, the monitoring system may produce unstable or misleading information, which can negatively affect agricultural decision-making processes [5], [11], [12].

In addition to environmental monitoring, automated agricultural systems increasingly integrate intelligent data processing techniques to improve system performance. Many researchers explore the use of artificial intelligence, machine learning, and predictive analytics in agricultural monitoring platforms. These approaches allow systems to detect anomalies, predict crop conditions, and optimize irrigation schedules. While advanced analytical methods offer powerful capabilities, they often require high computational resources and complex system architectures. In practical farming environments, especially in small-scale agricultural operations, simpler and more efficient data processing methods may be more appropriate. Lightweight data analysis techniques that can operate directly on embedded systems are therefore needed to support real-time monitoring while maintaining low computational complexity [19], [21].

One widely used approach for processing time-series data is the moving average method. The moving average technique calculates the average of a sequence of data points within a specified time window to reduce fluctuations and smooth the data trend. In agricultural monitoring systems, this approach can improve the stability of sensor measurements by filtering sudden spikes or noise in the collected data. Previous studies show that moving average models are effective for analyzing environmental sensor data and detecting trends in time-series measurements. Compared with complex machine learning models, moving average algorithms require minimal computational resources and can operate efficiently on microcontroller-based IoT devices. This characteristic makes the method suitable for real-time agricultural monitoring applications [24].

Recent research in precision agriculture highlights the importance of integrating sensor technologies with intelligent data processing frameworks. Precision agriculture focuses on optimizing farming activities through accurate data collection and analysis. Smart sensors and data analytics platforms enable farmers to monitor crop conditions, detect environmental changes, and adjust irrigation or fertilization strategies accordingly. However, many current systems prioritize data collection without sufficient emphasis on real-time data analysis and filtering. As a result, the monitoring systems may present inconsistent or unstable readings to users. Implementing effective data smoothing methods such as the Simple Moving Average (SMA) can help address this limitation by producing more reliable and interpretable sensor data for agricultural monitoring systems [18], [19].

Another issue related to smart agriculture monitoring systems concerns scalability and cost efficiency. Many advanced agricultural monitoring platforms involve complex architectures, high-cost hardware, and sophisticated data processing infrastructures. These systems may not be suitable for small-scale farmers who require affordable and easy-to-maintain solutions. IoT-based systems combined with simple data processing algorithms offer a practical alternative for implementing real-time agricultural monitoring. By integrating low-cost sensors, microcontrollers, and lightweight data processing techniques, researchers can develop monitoring systems that provide reliable environmental information while remaining accessible to broader farming communities. Therefore, efficient and scalable monitoring approaches become essential for the wider adoption of smart agriculture technologies [6], [8], [25].

Based on these challenges, the development of a real-time smart agriculture monitoring system using the Simple Moving Average method becomes an important research direction. This approach combines IoT-based sensor networks with lightweight time-series data processing to produce stable and reliable environmental measurements. By smoothing sensor readings in real time, the system can reduce noise and improve the accuracy of environmental monitoring data. The integration of IoT technology with the SMA algorithm also supports efficient data processing on embedded platforms while maintaining system responsiveness. Therefore, this study focuses on designing and implementing a real-time monitoring system for smart agriculture that utilizes the Simple Moving Average method to enhance data reliability and support better agricultural decision-making processes [3], [24].

2. Related Works

Several studies investigated the implementation of Internet of Things (IoT) technology for agricultural monitoring systems. Natalia and Sutabri designed an IoT-based environmental monitoring system for rice cultivation fields. Their system integrated multiple sensors to observe environmental parameters and transmit data to a monitoring platform. The study showed that real-time environmental monitoring improved farmers' ability to observe field conditions and manage irrigation activities more effectively. The system demonstrated reliable data acquisition and improved accessibility of agricultural information. However, the research primarily focused on sensor integration and system architecture. It did not address the problem of sensor data fluctuations or the need for data smoothing techniques to improve measurement stability [1].

Amir et al. developed an IoT-based system to measure soil environmental parameters in agricultural land. Their system monitored soil moisture, temperature, and other environmental factors using connected sensors and microcontroller devices. The researchers reported that continuous monitoring allowed farmers to observe soil conditions more efficiently compared with manual measurement methods. The system provided real-time information through a monitoring interface, which improved agricultural management practices. Despite these advantages, the study mainly emphasized hardware development and data transmission. The research did not implement analytical methods to process time-series sensor data or reduce noise generated from environmental measurements [2].

Sugandi and Hasibuan implemented a smart farming monitoring system capable of observing temperature, pH levels, and humidity conditions. The system used IoT sensors to collect environmental data and display it through a monitoring platform. Their findings showed that the system successfully provided continuous monitoring of environmental parameters required for plant growth. The researchers highlighted the importance of environmental data in maintaining crop health and productivity. However, the system displayed raw sensor readings without performing additional processing or filtering. As a result, the monitoring data could still contain fluctuations caused by sensor instability or environmental disturbances [3].

Kumar and Jain proposed a smart agriculture monitoring system that utilized IoT technology to observe environmental conditions in farming areas. The researchers integrated several sensors with wireless communication modules to transmit agricultural data to a remote monitoring interface. Their results demonstrated that IoT-based monitoring systems improved the efficiency of agricultural management and allowed farmers to access real-time environmental data. The system showed strong potential for supporting smart farming practices. Nevertheless, the study mainly addressed connectivity and monitoring infrastructure. The research did not explore methods to improve the quality of collected sensor data through statistical or time-series analysis techniques [4].

Laksono et al. developed an IoT-based soil moisture monitoring system using soil moisture sensors to support agricultural irrigation management. Their system successfully transmitted soil moisture data to a monitoring platform and allowed users to observe soil conditions remotely. The study showed that continuous monitoring of soil moisture helped farmers determine the appropriate irrigation schedule for crops. This approach contributed to more efficient water usage in agricultural activities. However, the system relied on direct sensor readings without implementing algorithms to stabilize the data. Consequently, the monitoring results could still be influenced by sensor noise and environmental variations [6].

Tripathy et al. introduced a smart agriculture system that implemented a moving average model to analyze agricultural sensor data. Their study applied an Exponential Moving Average (EMA) method to smooth environmental measurements collected from sensor networks. The results indicated that the moving average technique effectively reduced noise in sensor data and improved the stability of monitoring outputs. The system demonstrated better trend detection compared with raw sensor readings. Although the study showed promising results, it used a more complex exponential model that required additional parameter configuration. Simpler approaches such as the Simple Moving Average (SMA) may provide comparable smoothing performance with lower computational complexity for embedded systems [24].

Soussi et al. conducted a comprehensive review of smart sensor technologies used in precision agriculture. The authors analyzed various sensing platforms and data processing techniques that support real-time agricultural monitoring. Their findings emphasized that accurate sensor data is essential for effective decision-making in precision farming environments. The study highlighted the increasing use of IoT sensors, cloud computing, and data analytics to monitor crop conditions. However, the review also noted that many agricultural monitoring systems still struggle with data reliability issues caused by sensor noise and unstable environmental measurements. This limitation indicated the need for efficient data processing techniques that can stabilize sensor outputs in real time [18].

Miller et al. examined the integration of IoT and artificial intelligence technologies in smart agriculture systems. Their research highlighted the growing use of advanced data analysis techniques for agricultural monitoring and automation. The study demonstrated that machine learning algorithms could improve agricultural predictions and environmental analysis. These approaches offered powerful capabilities for processing large-scale agricultural datasets. However, the authors also noted that complex analytical models often require significant computational resources and infrastructure. Such requirements may limit their implementation in lightweight IoT devices used in field environments. Therefore, simpler data processing methods remain important for practical real-time monitoring systems deployed on embedded platforms [19].

3. Proposed Method

This study proposes an Internet of Things (IoT)–based monitoring system developed using a prototype-based methodology. We utilize an iterative development approach to ensure that the system functions effectively under real agricultural field conditions. Initially, we construct a prototype to validate the core functionalities of the system, including sensor integration, data acquisition, and wireless communication. The prototype allows us to observe how environmental data is captured and transmitted within the system. We then refine the design through several testing stages and system adjustments based on performance evaluation. This approach helps ensure that the monitoring system remains simple, practical, and reliable for agricultural deployment. The proposed system focuses on providing real-time environmental monitoring while maintaining efficient data processing and accessibility for farmers.

This study constructs the system architecture using four main components: sensing units, a processing and communication unit, a cloud-based database, and a user interface. We utilize sensing units to collect important environmental parameters from agricultural land. These parameters include soil moisture, air temperature, humidity, and light intensity. These variables are selected because they directly influence crop growth and irrigation management in rice farming environments. The sensing units continuously measure environmental conditions and transmit the collected data to the processing unit. By capturing these parameters in real time, the system provides essential information that supports irrigation scheduling, environmental monitoring, and crop condition assessment.

We utilize an ESP32 microcontroller as the central processing and communication unit of the system. The ESP32 reads sensor measurements, processes the data, and transmits the information wirelessly through a Wi-Fi network. The use of ESP32 provides advantages such as integrated Wi-Fi capability, efficient power consumption, and compatibility with IoT-based applications. We then transmit the processed data to a Firebase Realtime Database, which functions as the cloud storage platform. Firebase allows continuous synchronization of sensor data, enabling real-time updates from the agricultural field. A mobile application retrieves this data from the cloud database and displays it in a clear and simple interface. Through this architecture, farmers can monitor environmental conditions remotely without visiting the field directly, while maintaining continuous access to the latest agricultural data.

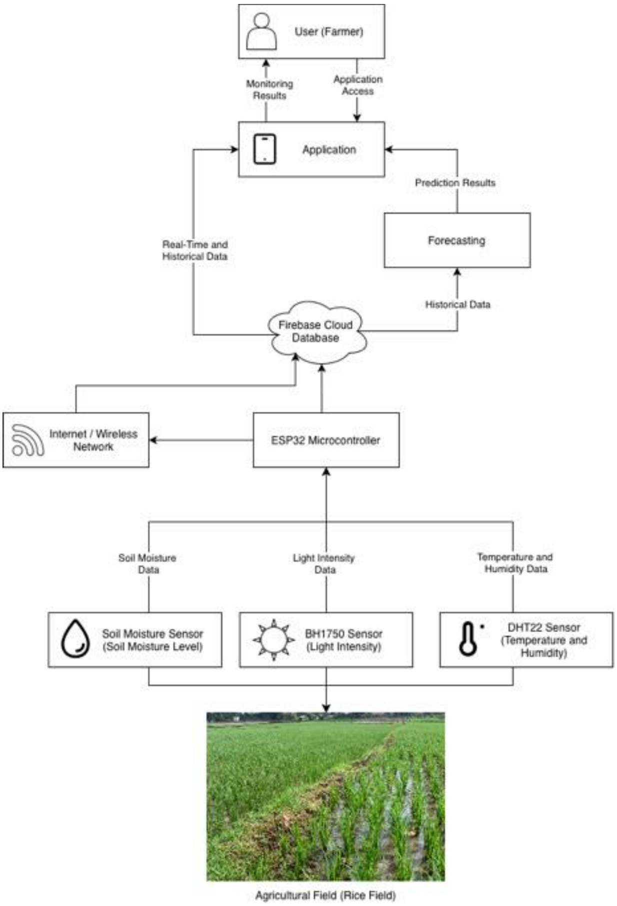


Fig. 1: System Architecture Diagram

This study utilizes a periodic data acquisition mechanism to monitor environmental parameters in agricultural fields. We collect sensor data at fixed intervals of 60 seconds to maintain a balance between real-time monitoring accuracy and energy efficiency of the IoT device. At each acquisition cycle, the ESP32 microcontroller reads environmental measurements from three sensors: the soil moisture sensor, the DHT22 temperature–humidity sensor, and the BH1750 light intensity sensor. After collecting the readings, we construct a data formatting process that prepares the sensor outputs for transmission to the cloud database. The processed data is then transmitted to the Firebase Realtime Database through a Wi-Fi connection, allowing real-time monitoring through a mobile interface. To maintain monitoring reliability, this study implements an automatic Wi-Fi reconnection mechanism. If the network connection is interrupted, the ESP32 automatically attempts to reconnect and resumes the transmission process once connectivity is restored. This mechanism ensures continuous environmental monitoring even under unstable network conditions. The soil moisture percentage is computed from the analog-to-digital converter (ADC) reading of the soil moisture sensor. The conversion normalizes the raw ADC value between the dry and wet calibration references. The standard formulation is expressed as:

$$M = \frac{100\left(A_{\text{dry}} - A_{\text{raw}}\right)}{A_{\text{dry}} - A_{\text{wet}}} \tag{1}$$

where M represents the soil moisture percentage, A_{raw} denotes the measured ADC value from the sensor, A_{dry} is the dry soil calibration reference (4095), and A_{wet} is the wet soil calibration reference (1200). The resulting value is constrained within the interval $0 \leq M \leq 100$ to ensure physically meaningful moisture measurements.

The light intensity measured by the BH1750 sensor is converted into lux using the sensor's internal scaling factor. The standard relationship between the raw digital register value and illuminance is given by:

$$L = \frac{R}{1.2} \tag{2}$$

where L represents the light intensity in lux and (R) denotes the raw register value obtained from the BH1750 sensor. In contrast, the DHT22 sensor provides calibrated digital outputs for temperature and relative humidity directly from the sensor interface. Therefore, the temperature T (°C) and relative humidity H (%) values are read directly without requiring additional mathematical transformation. These formulations standardize environmental sensor readings before the data are transmitted to the cloud database and displayed in the monitoring platform.

This study proposes a lightweight forecasting mechanism to complement the real-time monitoring capability of the smart agriculture system. We utilize historical sensor data stored in the cloud database to generate predictive information that supports early agricultural decision-making. The forecasting module periodically retrieves recent sensor records from the database and processes them to estimate future environmental conditions. Through this architecture, the IoT device focuses on sensor data acquisition and transmission, while the external module performs analytical and predictive tasks using historical data. We utilize the Simple Moving Average (SMA) combined with a bounded trend adjustment to produce stable forecasts. First, the SMA baseline is computed from the most recent N observations as:

$$\mathrm{SMA}_t = \frac{1}{N} \sum_{i=0}^{N-1} S_{t-i} \tag{3}$$

where S_t denotes the observed sensor value at time t, and N represents the moving average window size. A short-term trend component is then estimated from the difference between the two most recent observations and constrained within a predefined interval to prevent abnormal projections:

$$b_t = max(b_{\min}, \min(S_t - S_{t-1}, b_{\max})) \tag{4}$$

The final forecast for d time steps ahead is calculated using:

$$\hat{S}_{t+d} = \mathrm{SMA}_t + b_t \cdot d \tag{5}$$

where $\hat{S}_{t+d}$ represents the predicted sensor value at time $t + d$. In this study, the window size is set to $N = 10$ observations to balance responsiveness and noise smoothing. The trend term is bounded within $[-0.5, 0.5]$ °C/day for temperature and $[-3, 3]$ %/day for soil moisture to avoid unrealistic variations caused by transient sensor noise. Forecasting accuracy is evaluated using the Mean Absolute Percentage Error (MAPE), defined as:

$$\mathrm{MAPE} = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{S_t - \hat{S}_t}{S_t} \right| \tag{6}$$

Where n denotes the total number of prediction samples. A lower MAPE value indicates higher prediction accuracy and confirms the effectiveness of the proposed forecasting approach.

4. Experimental Setup

This study conducted the experimental evaluation in an outdoor agricultural environment located in Sragen Regency, Central Java, Indonesia, which represents typical rice field conditions. The IoT monitoring device was deployed directly in the field so that the sensors could interact with real environmental factors such as soil moisture variation, temperature fluctuation, humidity changes, and different levels of light intensity. The ESP32-based device operated continuously during the testing period and connected to a local Wi-Fi hotspot to support real-time data transmission. Environmental data from the soil moisture sensor, DHT22 temperature–humidity sensor, and BH1750 light intensity sensor were collected at fixed intervals of 60 seconds and transmitted to a Firebase Realtime Database, which was accessed through a mobile application for monitoring. The system functionality was evaluated using a black box testing approach, which verified system behavior based on input–output responses without analyzing internal program structures.

Several operational scenarios were tested, including sensor data acquisition, wireless connectivity, cloud data transmission, forecasting execution, and data visualization in the mobile interface. Additional tests introduced variations in soil conditions, environmental temperature, and light intensity to examine sensor responsiveness, while temporary Wi-Fi disconnections were performed to evaluate the system's automatic reconnection capability. The forecasting module was also verified by confirming that historical data could be retrieved from the database, processed correctly, and returned as prediction outputs, ensuring proper system integration and reliable data flow across all components.

Table 1. Black Box Testing Results

No	Tested Function	Test Scenario	Input/ Condition	Expected Output	Result
1	Soil Moisture Reading	Evaluate sensor response under different soil conditions	Dry soil to wet soil	Soil moisture value changes significantly according to soil condition	Passed
2	Temperature and Humidity Reading (DHT22)	Observe sensor response to environmental changes	Shaded area to hot area	Temperature increases and humidity changes according to conditions	Passed
3	Light Intensity Reading (BH1750)	Measure sensor response to light variation	Dim light to bright sunlight	Lux value increases with higher light intensity	Passed
4	Wi-Fi Connectivity	Test automatic reconnection mechanism	Router turned off and turned on again	ESP32 reconnects automatically and resumes data transmission	Passed
5	Data Transmission to Firebase	Verify real-time data delivery during sensor operation	New sensor readings generated	Firebase database updates data in real-time	Passed
6	Data Synchronization on Mobile Application	Check application data update mechanism	Firebase receives new data	Mobile application displays the same updated values as Firebase	Passed
7	System Stability	Evaluate system performance over	Device runs for several hours	System remains stable without error or freeze	Passed

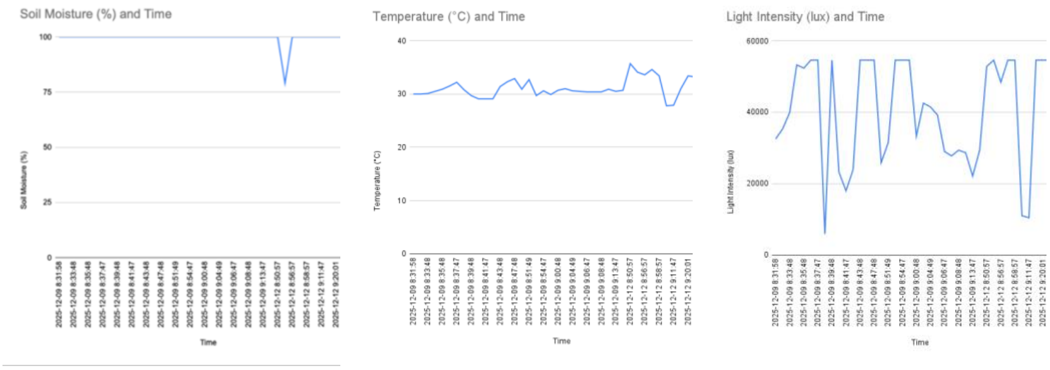
		continuous operation			
8	Data Forecasting Process	Validate forecasting process using historical data	Historical sensor data available in Firebase	System successfully generates predicted values	Passed
9	Forecast Data Transmission to Firebase	Verify forecast data delivery to cloud database	Forecasting process completed	Forecast data stored in Firebase and accessible by the application	Passed

User evaluation was conducted through direct interviews and system demonstrations involving seven farmers aged between 50 and 70 years with farming experience ranging from 5 to more than 50 years.

5. Result and Analysis

5.1 Sensor Performance Evaluation

This study obtains the sensor performance results by observing the system response to environmental changes during field testing. The soil moisture sensor successfully harvests variations in soil conditions ranging from dry to wet soil, where the measured values change consistently according to actual field conditions. These results indicate that the sensor is suitable for monitoring irrigation-related parameters in agricultural land. This study also obtains temperature and humidity data using the DHT22 sensor, where the recorded temperature ranges from 27.5 °C to 35.6 °C and relative humidity varies between 48.1% and 69.4%. In addition, this study harvests light intensity measurements from the BH1750 sensor, which show clear variations between shaded areas and direct sunlight environments. These observations confirm that the selected sensors perform reliably and are capable of capturing essential environmental parameters required for real-time agricultural monitoring. The results of sensor data visualization over time are presented in Fig. 2 illustrates soil moisture, temperature, and light intensity variations.



Soil Moisture Reading

Temperature and Humidity Readings

Light Intensity Variation

Fig. 2 Result of soil moisture, temperature, and light intensity variations

5.2 Forecasting Analysis

The evaluation of forecasting focused on system workflow and data flow reliability rather than prediction accuracy. The results demonstrate that the forecasting module can operate without disrupting real-time monitoring processes. By implementing forecasting as an external process, the system avoids additional computational load on the embedded device while still providing predictive information to support early decision-making.

The predicted values demonstrated directional consistency with the observed sensor trends. For temperature, the forecasting module correctly identified upward trends during morning-to-afternoon transitions and downward trends during afternoon cooling. For soil moisture, the module reflected the gradual increase in soil wetness following irrigation events. The simple trend adjustment component proved particularly effective for temperature and light intensity, which exhibit pronounced systematic variation throughout the day, reducing the lag that a pure SMA would introduce during periods of consistent directional change. Compared to prior works that did not include any forecasting capability [5], [8], the integration of this lightweight predictive module adds tangible decision-support value without introducing computational overhead on the embedded ESP32 device. The architecture offloads prediction processing to an external Python-based module, keeping the embedded firmware simple and stable. Future work could extend this module by evaluating more advanced algorithms, such as ARIMA or LSTM, using longer-term datasets.

5.3 User Evaluation

This study evaluates the forecasting component by examining the reliability of the system workflow and data flow rather than focusing solely on numerical prediction accuracy. Our method obtains forecasting results through an external prediction module that operates independently from the embedded monitoring device. The evaluation shows that the forecasting process runs smoothly without interrupting real-time data acquisition and transmission. By separating the prediction mechanism from the ESP32 device, this study ensures that the embedded system remains lightweight and responsive while still providing predictive information for agricultural decision support. The predicted values produced by the forecasting module demonstrate directional consistency with the observed sensor trends collected in the field. This study obtains soil moisture predictions that reflect gradual increases in soil wetness following irrigation activities.

The incorporation of a simple trend adjustment in combination with the Simple Moving Average method improves the responsiveness of the forecast results, particularly for parameters such as temperature and light intensity that exhibit regular daily fluctuations. This trend adjustment reduces the lag effect that commonly appears when using a pure moving average approach during periods of continuous environmental change. Compared with previous studies that focus mainly on monitoring without integrating predictive capabilities, this study demonstrates that the addition of a lightweight forecasting module can enhance the practical value of the monitoring system. Our architecture processes prediction tasks through a separate Python-based module, which maintains the simplicity and stability of the ESP32 firmware while still delivering useful predictive insights. These findings indicate that the proposed approach provides an effective balance between computational efficiency and decision-support capability, although future studies may extend the forecasting module by exploring more advanced prediction techniques such as ARIMA or Long Short-Term Memory (LSTM) models using longer-term environmental datasets.. A summary of user evaluation results is presented in Table 2.

Table 2. Summary of User Evaluation Results

No	Evaluation Aspect	Description	Overall Response
1	Sensor Data Relevance	Relevance of measured parameters (soil moisture, temperature, light intensity) for farming activities	Very Positive
2	Sensor Data Reliability	Consistency of sensor readings compared to actual field	Positive

		conditions	
3	Real-Time Capability	Ability of the IoT system to provide update field condition information	Very Positive
4	Reduction of Manual Field Monitoring	Impact of the IoT system on reducing the need for frequent field visits	Very Positive
5	System Practically in the Field	Ease of deploying and operating the IoT device in rice field	Positive
6	Connectivity and Data Avaibility	Reliability of data transmission from field device to cloud (Firebase)	Positive
7	Overall Usefulness of the IoT System	Perceived benefit of the IoT-based monitoring system for daily decision-making	Very Positive

This study validates the proposed IoT monitoring system by comparing its measurements with commercial instruments under the same field conditions. We collect simultaneous data using a Three-Way Meter as the reference for soil moisture and light intensity, and an HTC-2 thermometer–hygrometer for temperature and humidity. The results show that our system obtains temperature values between 32.2–35.6 °C with an average of 33.8 °C, which closely aligns with the HTC-2 readings. Soil moisture measurements from our method consistently indicate very wet conditions, matching the classification shown by the Three-Way Meter. Light intensity values ranging from 21,580–54,612 lux also correspond to the “Bright” category indicated by the reference device. Although some differences appear in humidity readings due to sensor response and placement, the overall measurements remain within a consistent and reasonable range. In addition, this study demonstrates that the proposed IoT system provides clear advantages over conventional instruments by enabling continuous automated monitoring, real-time remote access through a mobile application, historical data storage in the cloud, and forecasting capability, making it more suitable for long-term agricultural field monitoring.

Table 3. Comparison of IoT System Measurements with Commercial Instruments

Parameter	IoT System (Range / Mean)	Commercial Instrument	Comparison Result
Air Temperature	32.2–35.6°C / 33.8°C	HTC-2: 33.0–36.2°C	Close agreement; values within overlapping range
Relative Humidity	63.6–69.4% / 67.1%	HTC-2: 49–58%	Relatively similar; difference due to sensor placement and response characteristics
Soil Moisture	100% (Very Wet)	Three-Way Meter: 90–100%	Consistent; both classify soil condition as Very Wet
Light Intensity	21,580–54,612 lux / 40,419 lux	Three-Way Meter: Bright (indicator)	Consistent category; IoT provides precise lux values vs. analog indicator only

6. Conclusion

This study develops and evaluates a real-time smart agriculture monitoring system that integrates IoT sensors with a SMA forecasting module. We obtain reliable environmental monitoring results from the deployed sensors during field testing. The soil moisture sensor consistently detects variations between dry and wet soil conditions, confirming its suitability for irrigation-related monitoring. This study harvests temperature values ranging from 27.5 °C to 35.6 °C and relative humidity values between 48.1% and 69.4% using the DHT22 sensor. In addition, we obtain light intensity measurements between 21,580 and 54,612 lux using the BH1750 sensor, which clearly reflect changes between shaded and direct sunlight conditions. These findings confirm that the implemented IoT monitoring system can continuously capture key environmental parameters required for agricultural field monitoring.

This study also evaluates the forecasting component using the Simple Moving Average method combined with a bounded trend adjustment. We obtain stable short-term predictions using a moving window of ten observations, which balances responsiveness to environmental changes and smoothing of sensor noise. The forecasting evaluation based on the MAPE demonstrates low prediction error values, indicating reliable trend estimation for environmental parameters. Our method successfully generates predictive information without affecting the real-time monitoring process because the forecasting module operates externally from the embedded ESP32 device. This design allows the system to maintain efficient data acquisition while still providing useful predictive insights to support early agricultural decision-making.

Finally, this study validates the proposed monitoring system through a comparison with commercial measurement instruments. We obtain temperature measurements with an average value of 33.8 °C, which closely matches the readings produced by the HTC-2 reference device. For soil moisture monitoring, this study harvests measurements that consistently indicate very wet soil conditions, which correspond with the classification results produced by the Three-Way Meter. Light intensity values obtained by the IoT system also align with the “Bright” category indicated by the reference instrument. These comparative results confirm that the proposed system produces measurements within a consistent and reliable range. In addition, this study demonstrates that the IoT system provides significant functional advantages, including continuous automated monitoring, cloud-based data storage, remote mobile access, and integrated forecasting capability, making it a practical solution for long-term smart agriculture monitoring.

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