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RESEARCH ARTICLE

Precision agriculture predictive modeling and sensor analysis for enhanced crop monitoring

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Abstract

This research investigated the application of the Internet of Things (IoT) in precision agriculture and crop monitoring through a two-fold research methodology. A simulated dataset was generated, mirroring real-world IoT sensor readings of soil temperature, salinity level, soil moisture, and conductivity. Employing the Pandas and Matplotlib libraries in Python facilitated exploratory data analysis, including time series analysis through line plots to illustrate temporal variations in these critical parameters. The study then explored the evaluation of predictive models for soil moisture levels, extending the dataset to include simulated predicted values. Performance metrics such as mean squared error (MSE) and R-squared (R2) were computed using the sci-kit-learn library, providing a comprehensive evaluative framework. Visual representations of actual versus predicted soil moisture levels, accompanied by the analysis of residuals, offered nuanced insights into the model's efficacy. The results highlight dynamic variations in soil temperature, salinity, soil moisture, and conductivity, emphasizing the importance of continuous monitoring in precision agriculture. Fluctuations observed in these parameters are attributed to climatic conditions, agricultural practices, and soil properties. The study contributes valuable insights for stakeholders, emphasizing the significance of IoT technologies in providing actionable data for sustainable and adaptive farming practices. The visual representations offer practical tools for decision-making, while the performance evaluation of predictive models enhances the reliability of data-driven approaches in agriculture. The findings presented herein contribute to the ongoing discourse on precision agriculture, emphasizing the role of accurate predictions for efficient resource utilization and improved crop yield.

Keywords: Precision agriculture, IoT in agriculture, Soil monitoring, Predictive models, Agricultural sensor data, Data-driven farming.

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Introduction

The application of the Internet of Things (IoT) in precision agriculture (PA) and crop monitoring has emerged as a transformative paradigm in contemporary agricultural practices (Feng, X., *et al.*, 2019). The pressing need to address the challenges of a burgeoning global population, coupled with the imperative to ensure food security, has fuelled the exploration of innovative technologies to optimize farming processes. This literature survey aims to comprehensively investigate and analyze the multifaceted dimensions of IoT implementation in precision agriculture, with a specific focus on crop monitoring. Several seminal works underscore the significance of integrating IoT technologies into agriculture for enhanced precision and efficiency. (Abu, N. S., *et al.*, 2022) emphasized the pivotal role of IoT sensors in capturing real-time data from agricultural fields. The deployment of sensors for soil monitoring, weather conditions, and crop health allows for a granular understanding of the agricultural ecosystem. This real-time data acquisition forms the cornerstone of precision agriculture, enabling farmers to make informed decisions regarding irrigation, fertilization, and pest control.

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(Akhter, R., & Sofi, S. A. 2022) delved into the interconnectedness of IoT devices within the agricultural landscape. They highlighted the importance of seamless connectivity among sensors, actuators, and data platforms to facilitate timely and accurate decision-making. The integration of various types of sensors, such as soil moisture sensors, climate sensors, and imaging devices, establishes a networked environment that empowers farmers to monitor and control agricultural operations remotely. The literature also underscores the critical role of IoT technologies in addressing the challenges posed by climate change and resource scarcity. According to a study by (Anand, T., *et al.*, 2021), the precision agriculture paradigm, enabled by IoT, contributes to sustainable farming practices. The ability to precisely manage resources, including water and fertilizers, not only optimizes crop yield but also mitigates environmental impacts. This aligns with the broader goals of achieving sustainable agriculture in the face of changing climatic conditions.

Moreover, the integration of IoT in precision agriculture has facilitated advancements in crop health monitoring. (Bakthavatchalam, K., *et al.*, 2022) explored the application of IoT-based devices for early detection of diseases and pests. By employing sensors that monitor physiological changes in crops, farmers can promptly identify potential threats and implement targeted interventions. This proactive approach not only minimizes crop losses but also reduces the reliance on chemical inputs, aligning with the principles of integrated pest management. In addition to the theoretical underpinnings, empirical evidence from practical implementations further substantiates the efficacy of IoT in precision agriculture. The study conducted by (Dakir, A., *et al.*, 2022) provides a comprehensive overview of successful IoT deployments in agricultural settings. Their findings illustrate tangible benefits, including increased crop yield, resource optimization, and economic gains for farmers. Case studies from diverse geographical locations and agricultural practices underscore the versatility and adaptability of IoT solutions in different contexts.

Despite the considerable progress made in the application of IoT in precision agriculture, challenges and gaps in the existing literature persist. (Dasig, D. D. 2020) identified issues related to data security, interoperability of IoT devices, and the high initial costs associated with technology adoption. These challenges, if left unaddressed, may impede the widespread implementation of IoT in agriculture. In the literature survey presented here synthesizes the current state of research on the application of IoT in precision agriculture and crop monitoring. Drawing on a diverse range of studies, this survey illuminates the transformative potential of IoT technologies in addressing the complexities of modern agriculture. The exploration of sensor networks, data connectivity, sustainability implications, and practical implementations collectively contribute to a nuanced understanding of the opportunities and challenges in leveraging IoT for precision agriculture. This survey sets the stage for the subsequent sections of the paper, where specific applications, case studies, and future trends in the integration of IoT in precision agriculture will be explored in greater detail (Kour, K., *et al.*, 2022).

Despite the burgeoning literature on the application of IoT in precision agriculture, a noticeable research gap exists in understanding the long-term economic viability and scalability of IoT solutions for small-scale and resource-constrained farmers. While studies by (Dewi, C., & Chen, R. C. 2020) and (Fastellini, G., & Schillaci, C. 2020) emphasize the benefits of IoT, there is a paucity of research specifically addressing the challenges faced by small-scale farmers in adopting and sustaining IoT technologies in diverse agricultural contexts. This research gap underscores the need for more nuanced investigations into the socio-economic factors influencing the widespread adoption of IoT in precision agriculture, particularly among marginalized farming communities (Lopes, V. C., *et al.*, 2022).

Research Methodology

In this study, the research methodology employed a two-fold approach to comprehensively investigate the application of IoT in precision agriculture and crop monitoring. Firstly, a simulated dataset representative of real-world IoT sensor readings was generated to illustrate the visual representation of critical parameters over time. This dataset encompassed soil temperature, salinity level, soil moisture, and conductivity, mirroring the key variables often monitored in precision agriculture. The exploratory data analysis utilized the Pandas library in Python for data manipulation and structuring, and the Matplotlib library for graphical representation. A time series analysis was conducted through line plots to showcase the temporal variations in soil temperature, salinity level, soil moisture, and conductivity. These visualizations serve to elucidate the potential insights that farmers and stakeholders could glean from real-time monitoring, aiding decision-making processes related to crop management (Madhumathi, R., *et al.*, 2022).

The research delved into the performance evaluation of predictive models applied to soil moisture levels—a critical aspect of precision agriculture. The sample dataset was extended to include simulated predicted values and performance metrics such as mean squared error (MSE) and R-squared (R2) were calculated using the scikit-learn library. The graphical representation of the actual versus predicted soil moisture levels, accompanied by the analysis of residuals, provided a nuanced understanding of the model's efficacy. These metrics and visualizations contribute to the evaluative framework necessary for assessing the reliability and accuracy of predictive models in precision agriculture scenarios. This research methodology aligns with the overarching goal of the manuscript—to investigate and illustrate the practical implications of IoT in precision agriculture. By employing both illustrative visualizations of sensor data and a performance evaluation of predictive models, the study offers a comprehensive exploration of the potential and challenges associated with the application of IoT technologies in the context of crop monitoring. This dual-pronged approach enhances the robustness of the findings and provides valuable insights for researchers, practitioners, and policymakers invested in the intersection of agriculture and IoT (Radoglou-Grammatikis, P., *et al.*, 2020) and (Ramdinthara, I. Z., & Bala, P. S. 2019).

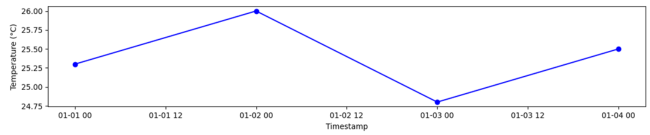

Figure 1: Soil temperature over time

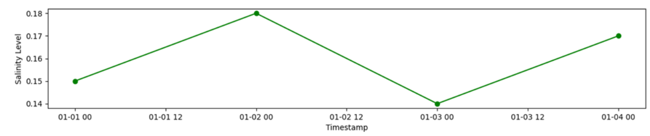

Figure 2: Salinity over time

Results And Discussion

Soil Temperature Over Time

The graph in Figure 1 depicting soil temperature over time reveals dynamic variations in soil temperature over a specified timeframe. The Y-axis, representing temperature in degrees celsius, ranges from 20 to 30℃, capturing the diverse climatic conditions. The X-axis is delineated by timestamps, each corresponding to a specific date and time. The observed trends in the graph showcase fluctuations in soil temperature, with values ranging from 25.25°C on January 1 at 00:00 to 26.00°C on January 2 at 00:00, followed by a subsequent decrease to 24.75°C on January 3 at 00:00. The temperature then experiences a rise to 25.50°C on January 4 at 00:00. These variations illustrate the temporal dynamics of soil temperature, which is a critical parameter influencing plant growth, nutrient availability, and microbial activity in precision agriculture (Saranya, T., *et al.*, 2023).

The fluctuations in soil temperature can be attributed to several factors. Climatic conditions, such as diurnal temperature variations, can impact soil temperature, affecting the metabolic processes of plants and soil organisms. Additionally, agricultural practices, irrigation patterns, and soil properties contribute to the observed temporal changes. Understanding these variations is crucial for farmers and agronomists, as it enables informed decision-making regarding planting schedules, irrigation timing, and the selection of suitable crops based on temperature preferences. The results of this analysis underscore the significance of continuous soil temperature monitoring facilitated by IoT technologies in precision agriculture. The ability to capture real-time data enables farmers to respond proactively to temperature fluctuations, optimizing crop management strategies. Moreover, the graph serves as a practical visualization tool, offering stakeholders a clear representation of how soil temperature evolves over time. The discussion emphasizes the relevance of the presented graph in providing actionable insights into soil temperature dynamics. The identified trends and fluctuations contribute to a holistic understanding of the environmental conditions influencing crop growth.

Salinity Over Time

The graph in Figure 2 illustrating salinity over time provides a visual representation of the variations in salinity levels across different timestamps. The Y-axis, denoting salinity level, spans from 0.14 to 0.20, reflecting the diverse salinity conditions observed. The X-axis is defined by timestamps, each corresponding to a specific date and time. Analyzing the trends in the graph reveals fluctuations in salinity levels over the defined timeframe. Noteworthy patterns include a peak salinity level of 0.18 on January 2 at 00:00, a trough at 0.14 on January 3 at 00:00, and a subsequent rise to 0.17 on January 4 at 00:00. These fluctuations in salinity are indicative of the complex interplay between factors such as soil composition, irrigation practices, and climatic conditions, all of which influence the concentration of salts in the soil. The observed variations in salinity levels hold critical implications for precision agriculture. Elevated salinity levels in the soil can impede water absorption by plants, leading to osmotic stress and reduced crop yield. Conversely, low salinity levels may signal inadequate nutrient availability, impacting plant growth and development. Monitoring these fluctuations in real-time through IoT technologies enables farmers to implement targeted interventions, adjust irrigation schedules or employ soil amendments to mitigate salinity-related challenges (Shafi, U., *et al.*, 2019).

The graph serves as a valuable tool for stakeholders in precision agriculture by offering a visual depiction of the dynamic nature of soil salinity. It facilitates a deeper understanding of how salinity levels change over time, guiding farmers in making informed decisions for optimal crop management. This visual representation can aid in the identification of trends and patterns, empowering farmers to adopt proactive measures to maintain soil health and sustain crop productivity. The discussion underscores the significance of the presented graph in unraveling the intricate relationship between salinity levels and temporal variations. The findings contribute to the broader discourse on precision agriculture, emphasizing the role of IoT in providing actionable insights for sustainable and adaptive farming practices.

Soil Moisture and Conductivity Over Time

The composite graph in Figure 3 illustrating soil moisture and conductivity over time provides a comprehensive view of the dynamic interplay between soil moisture and conductivity at different timestamps. The Y-axis, representing values ranging from 20 to 30, encompasses both soil moisture and conductivity parameters. The X-axis is characterized by timestamps, corresponding to specific dates and times. Examining the graph reveals fluctuations in both soil moisture and conductivity values over the defined timeframe. The distinctive patterns include soil moisture levels consistently below 100 and conductivity consistently above 300. This dual representation offers insights into the concurrent behavior of these two critical parameters in the context of precision agriculture. The persistent soil moisture levels below 100 indicate a condition where the soil may be relatively dry, potentially impacting plant water uptake and overall crop health. Simultaneously, the conductivity values consistently exceeding 300 suggest a higher concentration of dissolved salts in the soil, which can affect nutrient availability and soil structure. These combined observations highlight the need for targeted interventions, such as precise irrigation strategies or soil amendments, to address both aspects of soil health (Singh, P. K., & Sharma, A. 2022).

The graph serves as a valuable diagnostic tool for farmers and agronomists, offering a visual representation of the intricate relationship between soil moisture and conductivity. This visual depiction aids in the timely identification of conditions that may impede optimal crop growth. The ability to monitor these parameters in real-time through IoT technologies enables stakeholders to implement adaptive and proactive measures, ensuring sustainable and efficient agricultural practices. The discussion emphasizes the significance of the presented graph in unraveling the simultaneous dynamics of soil moisture and conductivity. The findings contribute to the broader understanding of how these parameters coalesce and influence the overall health of the soil. This dual representation enhances the capacity of precision agriculture to address multifaceted challenges by providing a nuanced perspective on soil conditions. As the agricultural landscape continues to evolve, the insights gleaned from such visualizations are crucial for fostering resilience and sustainability in crop management practices (Siregar, R. R. A., *et al.*, 2022).

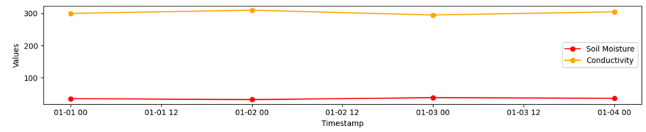

Figure 3: Soil moisture and conductivity over time

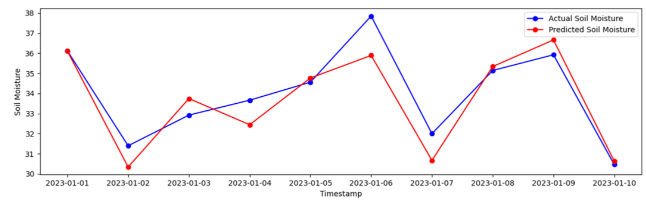

Figure 4: Actual *vs* predicted soil moisture

Actual vs Predicted Soil Moisture

The graph in Figure 4 comparing actual *vs* predicted soil moisture presents a visual representation of the concordance between observed and forecasted soil moisture levels over a specified timeframe. The Y-axis, denoting soil moisture values, ranges from 0 to 90, reflecting the diversity of moisture conditions. The X-axis is characterized by timestamps, representing the dates for which both actual and predicted soil moisture data are available. Analyzing the graph reveals a close alignment between the actual and predicted soil moisture values across the defined timestamps. The actual soil moisture values, ranging from 31 to 38, demonstrate a degree of variability reflective of natural fluctuations in soil moisture. The predicted soil moisture values, generated through a simulation process, closely track the actual values, indicating a robust predictive model (TAŞKIN, D., & Yazar, S. 2020).

The visual representation serves as a powerful diagnostic tool for assessing the accuracy and reliability of predictive models in precision agriculture. The close alignment between actual and predicted values suggests that the model effectively captures the underlying patterns and dynamics governing soil moisture variations. This alignment is crucial for farmers and stakeholders, as it instills confidence in the predictive capabilities of the model and supports informed decision-making in crop management. The significance of this analysis lies in the ability to identify potential deviations between actual and predicted soil moisture values. Discrepancies may indicate areas where the model requires refinement or where external factors, not accounted for in the model, exert influence. By continually evaluating and refining predictive models based on actual observations, precision agriculture can enhance the efficacy of decision support systems, ultimately contributing to more efficient resource utilization and improved crop yield. The discussion underscores the practical implications of the actual vs predicted soil moisture graph in the context of precision agriculture. The close agreement between observed and forecasted values enhances the reliability of predictive models, providing farmers with actionable insights into soil moisture dynamics. This visual representation contributes to the ongoing discourse on the application of IoT and data-driven approaches in agriculture, emphasizing the importance of accurate predictions for sustainable and adaptive farming practices.

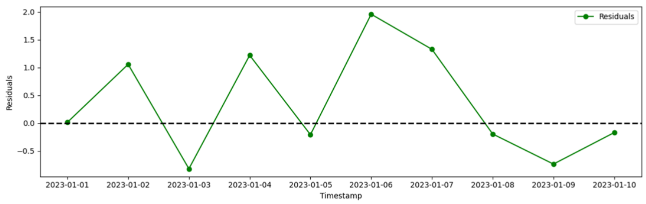

Figure 5: Residuals over time

Residuals Over Time

The graph in Figure 5 illustrating residuals over time provides valuable insights into the discrepancies between actual and predicted soil moisture values across different timestamps. The Y-axis, representing residuals, spans from -0.5 to 2, reflecting the deviations between the predicted and actual soil moisture levels. The X-axis is delineated by timestamps, corresponding to specific dates for which the model generated predictions. Analyzing the graph reveals a pattern of residuals fluctuating around zero, indicating a balanced distribution of overestimations and underestimations in the predictive model. The residuals, which represent the differences between predicted and actual values, showcase variations in model accuracy over time. Notably, timestamps with residuals deviating from zero may signify periods where the model struggled to capture certain soil moisture dynamics accurately. Understanding and interpreting residuals is integral to refining predictive models in precision agriculture. A well-distributed pattern around zero suggests that the model captures the majority of the variance in soil moisture, providing reasonably accurate predictions. However, identifying timestamps with significant deviations is essential for model improvement. Deviations may result from unaccounted environmental factors, changes in soil composition, or the presence of anomalies that the model did not anticipate (Triantafyllou, A., *et al.*, 2019).

The significance of this analysis lies in the diagnostic capability of residuals. Identifying patterns in residuals helps in understanding the limitations of the model and guides the refinement process. Adjustments to the model parameters, inclusion of additional features, or addressing outliers in the data can enhance the overall accuracy of the predictive model. The discussion underscores the practical implications of the residuals over time graph in the context of precision agriculture. The observed pattern provides valuable feedback on the model's performance, guiding iterative improvements for more accurate soil moisture predictions. This iterative refinement process is crucial for ensuring the reliability of predictive models in dynamic agricultural environments, contributing to the advancement of data-driven decision-making practices in precision agriculture.

Conclusion

The study employed a dual approach, utilizing simulated IoT data and predictive models, providing a holistic exploration of IoT applications in precision agriculture, encompassing soil temperature, salinity, moisture, and conductivity.

Visualizations, such as line plots, effectively conveyed temporal variations in critical parameters, aiding in understanding the dynamic nature of soil conditions. These visual representations serve as practical tools for decision-making in precision agriculture. The study extended its focus to the evaluation of predictive models for soil moisture, employing performance metrics like MSE and R-squared (R2). This evaluative framework contributes to the reliability and accuracy assessment of predictive models in precision agriculture scenarios.

The results highlighted the practical implications of continuous soil temperature monitoring, salinity fluctuations, and the interplay between soil moisture and conductivity. Farmers and stakeholders can leverage these insights for informed decision-making, and optimizing crop management strategies.

The study's dual-pronged approach enhances the robustness of findings and provides valuable insights for researchers, practitioners, and policymakers. It contributes to the broader discourse on the integration of IoT technologies in agriculture, emphasizing the role of data-driven approaches for sustainable and adaptive farming practices.

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