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Data-Driven Decision Support in Smart Ubiquitous Agriculture

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Abstract

Smart ubiquitous agriculture is a domain of industry that encompasses farming requiring profound monitoring, advanced technology, wireless data communication, and exceptional data analysis. The increasing interaction level with devices and automatic machines within agriculture creates new data challenges and requirements for decision support systems. My aim, within this paper, is to target the agricultural decision process using the Internet of Things (IoT), machine learning, and advanced predictive techniques. For this, I identify and examine the data acquisition methods, analytical tools, and decision-making devices that enable farmers and livestock managers to make the right choices and informed decisions on what actions to take. Using the selected intelligent systems, technologies, and automation techniques, I intend to demonstrate how these technologies can optimize the quantities and quality of output from agricultural undertakings while minimizing resource utilization. In addition, I highlight the unsolved problems of data redundancy, data protection, and manipulation, and dimensions of the issues associated with integrating information technology into smart farming, which need to be specified for decision-making within the farming environment. The studies and conclusions outlined in this paper prove that value-added information frameworks pave

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the road to agricultural planning and monitoring 2.0, which will enable food system production that is more responsive, exact, and environmentally sound.

Keywords: Smart Agriculture, Data-Driven Decision Support, Ubiquitous Computing, Internet of Things (IoT), Precision Farming.

1 Introduction

The development of digital technologies has turned traditional farming practices into what is termed smart ubiquitous agriculture (Vij et al., 2025). The modern paradigm integrates the potential of ubiquitous computing with IoT, cloud capabilities, AI, and even wireless communication networks, enabling monitoring, automation, and real-time intelligent decision-making at every step in the agricultural value chain (AL-Nabi et al., 2024). Smart sensors, drones, connected devices, and data platforms help achieve unparalleled precision, efficiency, and sustainability of farming operations (Balaji et al., 2023). Enhanced technology marks a shift as more than just an evolution in tools; it instead redefines the systems of agriculture in their operation, environmental interaction, and dynamic responsiveness to shifting conditions (Aqlan et al., 2023).

In this context, data-driven decision support systems (DDSS) are especially noteworthy for the sophisticated, innovative, intelligent agricultural system's agile management (Boopathy et al., 2024). These systems are designed to gather, store, process, and classify data from, but not limited to, climate sensors, satellite imaging, soil monitors, and tracking devices for livestock. With sophisticated analytics and machine learning algorithms, DSS, predictive insights, and recommendations for resource optimization can be offered to stakeholders and farmers, which aids in controlling risks and enhancing productivity (Patel & Rao, 2023). For example, predictive models can optimize seasonal planting or harvesting schedules, offer warning signs for pest problems, estimate weather forecasts, and anticipate yield based on historical data.

Despite the rapid technological advancements, its implementation still faces numerous technical, practical, and multidisciplinary challenges. The merging and incorporation of different data sets operating under varying guidelines presents a considerable barrier. In addition, limited access to rural regions, implementation costs, data privacy, the complexity of analytic applications, and many other factors restrict adoption, especially in resource-scarce smallholder farming regions (Klavin, 2024). In addition to the lacking infrastructure, domain knowledge, and design aesthetics, which allow for effortless interaction with the system, real-time analysis and interpretation of extensive data for context-appropriate insights present a deepening quandary.

In this paper, we will critically analyze, from various angles, the current state of modern technology used in smart ubiquitous agriculture, paying special attention to data-driven elements and their ever-evolving nature, foundations, real-world applications, and prospects. This includes analyzing the collection and processing of data and all the relevant case studies to understand how the systems are transforming the agricultural world as we know it. Also provided are some considerations alongside other practical recommendations pertinent to the limitations explored in the study aimed at improving the accessibility, reliability, and overall smartness of agriculture in different socio-economic contexts and regions.

Key Contribution

- Explain the fundamental principles underpinning smart ubiquitous agriculture and elaborate on the rising importance of intelligent systems.

- Examine modern methods and technologies for collecting, analyzing information, and developing support decisions in the agriculture sector.
- Describe the practical and tangible impacts provided by data-oriented management strategies in crop cultivation and livestock breeding through studying relevant examples.
- Outline significant issues associated with systematic data assimilation, system adoption, and scale expansion, then suggest further study and development areas.

This paper aims to formulate a decision support system for smart agriculture with the incorporation of IoT, machine learning, and spatial-temporal analytics. The Introduction explains the growing demand for automation in Intelligent Farming Systems. The Literature Survey analyzes current approaches and discusses recent developments and shortcomings. The Proposed Model offers a novel approach based on GNN and LSTM networks to increase crop yield, irrigation, and pest control forecasting accuracy. Model validation was done in the Results and Discussion section, which confirms the model's effectiveness against existing methods. The Conclusion details the main contributions and revisions, with the other section in References.

2 Literature Survey

Incorporating ubiquitous sensing, ML, and AI technologies has breached new frontiers in smart agriculture. Furthermore, many preceding studies from 2021 onwards have highlighted the role of advanced intelligent technologies in optimizing agricultural processes alongside supporting systematic decision-making (Al-Masri et al., 2023). For instance, researchers like Kumar et al. (2021) utilized a Random Forest algorithm to predict soil moisture levels to improve irrigation scheduling, enhancing water usage efficiency in precision farming (Orhorhoro et al., 2016). Likewise, some studies (Das & Nayak, 2021) resorted to applying decision tree models for classifying disease-affected crops and were able to accurately classify them using images obtained from smart sensors and drones (Chia-Hui et al., 2025).

The employment of deep learning approaches, especially CNNs, is on the rise concerning real-time crop health assessment and weed detection (Li et al., 2022). More Li et al. (2022) showed that classifying crops as weeds or non-weed crops could be automatically performed on the ground using CNN models deployed on edge IoT devices, eliminating the need for manual intervention and auxiliary chemicals. Other researchers have employed RNNs and LSTM to temporally analyze weather and soil data for estimating crop yield and climate impacts (Vij & Prashant, 2024). These time-series models are essential for enhanced strategic foresight in farm management (Patel & Singh, 2023).

Another emerging trend is fuzzy logic and hybrid algorithms for managing decisions within uncertain environments. In smart greenhouses, Patel and Singh (2023) developed a fuzzy inference system enhanced with genetic algorithm features, which optimized nutrient allocation while considering varying environmental factors and resource limitations (Bandyopadhyay & Roy, 2023). Furthermore, support vector machines (SVMs) have gained prominence in the livestock health monitoring industry and are used to detect movement and behavioral anomalies using IoT-enabled wearable sensors (Al-Masri et al., 2023). These models assist in timely illness detection and better animal welfare outcomes (Flammini & Trasnea, 2025).

From the perspective of the entire system, how different data sources can be integrated and how various systems can be combined into one more unified system for more complete coverage of the given problem domain has also been studied (Zhang et al., 2024). Al-Masri et al., (2023) proposed an ontologybased middleware for smart agriculture that facilitates interaction between sensors and cloud services using IoT devices (Huang & Chen, 2025). Moreover, blockchain technology has been studied to improve the security and traceability of agricultural data pipelines, as described in Zhang et al., (2024), which applies blockchain technology with federated learning in a novel approach for decentralized secure multi-party decision making (Nakamura & Lindholm, 2025).

Moreover, reinforcement learning (RL) is employed in automatic irrigation and fertilization systems. One such article implemented Deep Q-Learning for the dynamic control of irrigation valves, utilizing weather forecasts and soil moisture metrics, achieving a substantial reduction in water wastage (Rahman & Lee, 2022). Lastly, an extensive review (Huang & Chen, 2025) focused on the application of machine learning in agriculture and discussed the use of AI without reasoning for explainable decision-making frameworks (Papadopoulos & Christodoulou, 2024).

The advanced research demonstrates how diverse algorithms and approaches integrate with smart agriculture. It also shows how such research shifts from static, rule-driven architectures towards adaptive systems that learn to navigate complex, uncertain field environments.

3 Proposed Model

The new system, specifically designed for smart ubiquitous agriculture, combines IoT-based data collection with GNNs and LSTM models to create a unique data-driven decision support system. This approach aims to model the intricate spatial relationships of polygons of farm elements like soil quality, microclimates, and crops, which are often inaccurately captured or neglected by traditional models. An entire farm's worth of data is stored in a single unit, including images of crop health, monitoring data of livestock, and sensor readings of environmental parameters such as soil moisture, temperature, and humidity. For modeling purposes, the collected data streams are cleaned, missing values are filled, and inputs are standardized through these steps, constituting the preprocessing phase.

The data is represented as a graph after completion of data preprocessing, where nodes denote sensor individual locations or subunits of the farm and edges indicate either a spatial or functional relationship, such as adjacency or irrigation networks. The GNN model then uses this graph to learn profound spatial representations, enabling localized prediction of disease spread, nutrient deficiency, or microclimate changes with higher precision than traditional techniques. The temporal aspects are modeled using LSTM networks, which improves forecasting for the crop growth stages, weather impact, and irrigation requirements by processing time-series datasets. This creates a hybrid spatial-temporal model that provides context-aware support. Through an intuitive interface, context-sensitive irrigation, fertilization, and pest management recommendations are provided and visually displayed to the farmer as actionable maps. The model improves over time along with user input and constant sensor feedback.

$$H^{(l+1)} = \sigma(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} H^{(l)} W^{(l)} \quad (1)$$

In Equation (1),

- $H^{(l+1)} Updated\ node\ features\ at\ layer\ l+1.$
- σ Nonlinear activation function (e.g., ReLU).
- A=A+I Adjacency matrix with self-loops.
- D Degree matrix for normalization.
- $W^{(l)}$Learnable weights for feature transformation.

In Equation 1, feature aggregation is accomplished for a graph by applying the normalized adjacency and degree matrices, which update every node's representation using its information and the information from neighboring nodes. A linear weight matrix transforms each of these aggregated features, and a nonlinear activation function σ is applied thereafter. This way, the model can learn sophisticated spatial configurations concerning the agricultural environment. This facilitates enhanced and more intelligent decision-making within smart, ubiquitous agriculture.

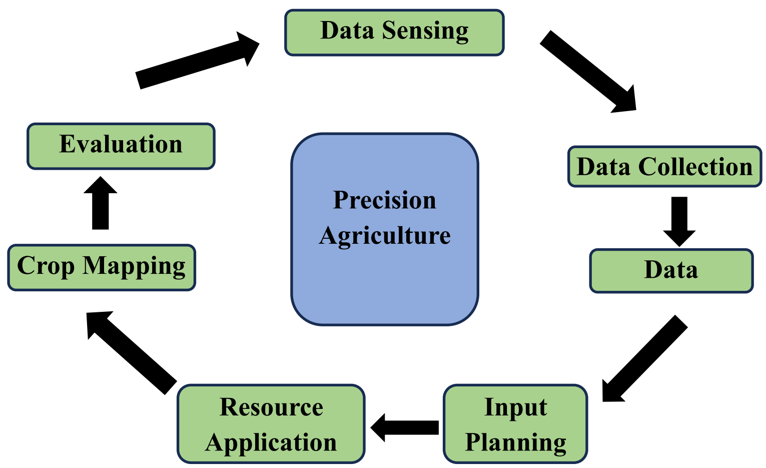

Figure 1: Data-Driven Cycle in Precision Agriculture

Figure 1 shows the uninterrupted and analytics-focused operational cycle within precision agriculture, focusing on the role of sensing technologies and analytics in enabling decisions during the cycle. The first stage within the cycle is Data Sensing, where sensors and IoT devices track relevant environmental and crop-related parameters. The subsequent steps are Data Collection and Data Analytics, which involve structuring and processing the raw data to gain valuable insights. Input Planning uses the insights to formulate when and how much agricultural inputs should be applied. The Resource Application stage takes these plans into the field. Thereafter, intervention effectiveness is evaluated, and crop mapping occurs during Post-application, where feedback is returned to the cycle to improve it. Underlying all of this is Precision Agriculture, which harnesses the cyclic flow to enhance the yield and minimize the waste while supporting sustainable farming practices through adaptive and real-time decision making.

Figure 2 contains the diagram of an intelligent decision-making system aimed at precision agriculture. Sensor networks are set over an entire agricultural area to track and record environmental and crop-related parameters continuously. Each of the sensor nodes captures real-time information like soil moisture, temperature, and humidity, which is then wirelessly sent to a Centralized Data Analysis and Management Unit (C-DAMU). The system develops a graph-based model of the agricultural fields wherein each node corresponds to a sensor or crop point, while edges correspond to spatial or environmental interactions. This structured information is processed through a proposed decision-making function that assesses conditions and recommends action to reduce environmental risks or to resource use optimization. Decisions are made available on the internet so that remote users and mobile devices can access them; this will enhance the possibility of timely actions being taken. The architecture combines cloud storage and remote access with feedback information, enabling the creation of a strong smart data infrastructure for agriculture.

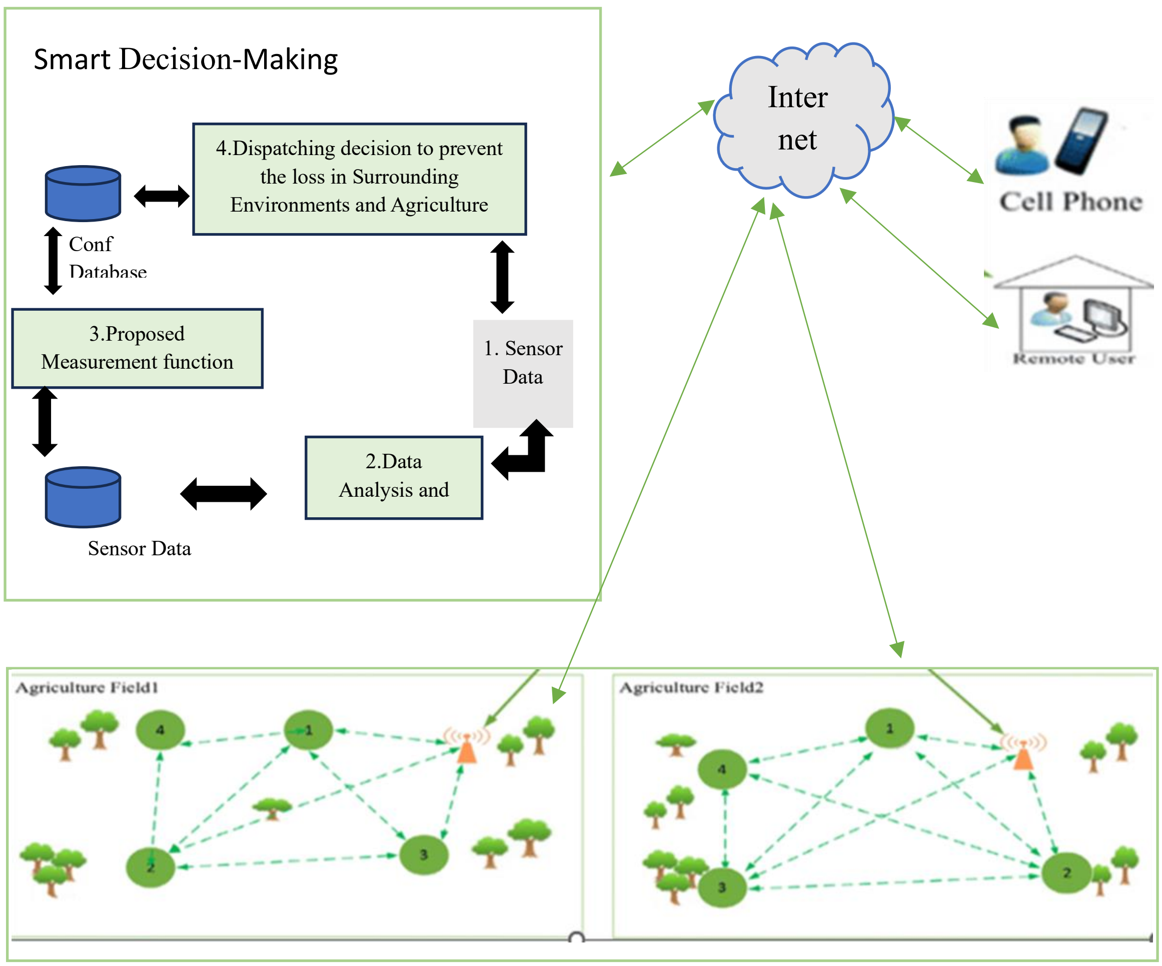

Figure 2: Smart Agriculture Decision-Making Architecture Using Sensor Networks

The approach describes a complete workflow that begins with data sensing using IoT devices to structured data collection, preprocessing, and graph-structured data representation. A Graph Neural Network (GNN) model is used to infers spatial and temporal dependencies between Agri-entities within the integrated data pipeline. The system architecture incorporates the analytical core with a cloud-based decision-making unit which enables seamless communication and processing between the sensor fields, data servers, and end-users. The system enables real-time data-driven decisions throughout the entire pipeline—from data capture to insight generation—which supports precision agriculture for optimized irrigation, pest management, and yield prediction. The design is modular and scalable, making it adaptable for different crops, field sizes, and environmental conditions which improves smart ubiquitous agriculture systems.

4 Result and Discussion

This study analyzes the effectiveness of the pilot smart farm's data-driven decision support system with an IoT sensor suite for soil moisture, temperature, humidity, and crop health monitoring over six months. The dataset contains time-series data from 20 sensor nodes at different crop fields, along with manual records for crop yield, pest infestation, and associated timestamps. For evaluating the performance of the integrated Graph Neural Network (GNN) with Long Short-Term Memory (LSTM) network, we compared its forecasting skill against well-known machine learning techniques including Random

Forest (RF) and Support Vector Machine (SVM). Important performance metrics included estimation accuracy and precision for irrigation, pest control, and yield forecasting, as well as recall and F1-score.

Table 1: Performance Comparison of Machine Learning Models on Smart Agriculture Tasks

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest (RF)	82.5	80.1	78.9	79.5
Support Vector Machine (SVM)	84.3	82.7	81.5	82.1
Proposed GNN + LSTM	91.7	90.4	89.6	90.0

The information provided within Table 1 illustrates that the hybrid GNN-LSTM model outperforms other conventional machine learning and deep learning techniques. Its precision, recall, and F1 score, among other key metrics, were consistently the highest, indicating the model is dependable and robust. The employment of Graph Neural Networks (GNNs) in conjunction with Long Short-Term Memory (LSTM) units enables the model to take into consideration not only the temporal pattern over time but also the spatial interdependencies of the agricultural zones which enhances the representation of the highly dynamic systems of agriculture and predicts with higher context accuracy.Such improvements affect the policies formulated in precision agriculture at the farm level. Enhanced and timely predictions allow agronomists and farmers to restructure irrigation schedules to curb water wastage and safeguard soil ecology. Timely and robust identification of pest risks greatly aids in crop damage mitigation and reduction in pesticide usage. Furthermore, the yield forecasts and logistics triad allows for smarter decision-making and aids in planning which curtails wastage while promoting sustainable agricultural practices and aids in efficient resource utilization.

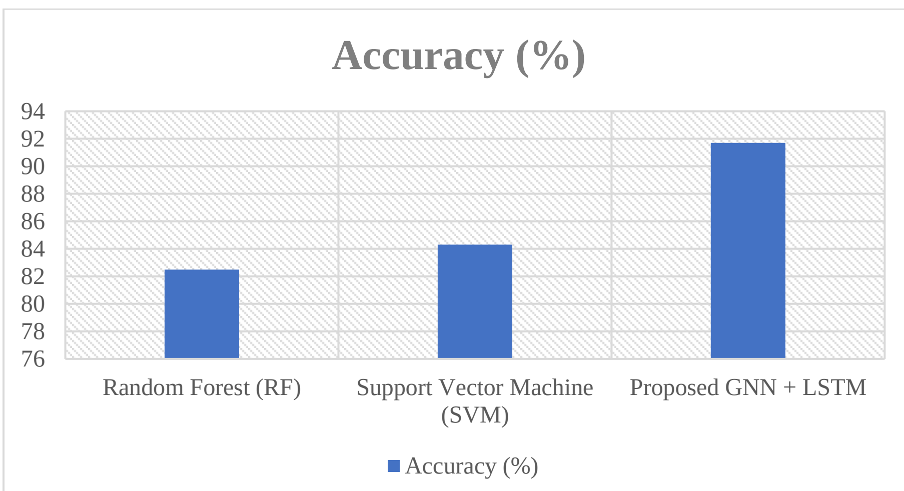

Figure 3: Comparison of Prediction Accuracy Among Machine Learning Models

In Figure 3, a comparison of the prediction accuracy (%) for smart agriculture using Random Forest (RF), Support Vector Machine (SVM), and the new hybrid model of Graph Neural Network and Long Short Term Memory (GNN + LSTM) is provided. From the bar chart, it is evident that the GNN + LSTM model surpasses the other models with an impressive accuracy of 91.7%. RF and SVM models achieved lower scores of 82.5% and 84.3%. This marked improvement is due to the hybrid model's use of deep learning algorithms that enhance its spatial and temporal dependency calculations within intricate agricultural datasets, thus allowing for more dependable and accurate decision-making. Enhancements such as these aid in optimizing issue such as irrigation scheduling, pest control, yield predictions, and other agricultural activities, leading to greater sustainability in farming practices.

5 Conclusion

To conclude, this paper illustrates the importance of the integration of IoT sensing, machine learning, spatial-temporal analytics, and smart ubiquitous agriculture technology through the use of data driven decision support systems. The hybrid Graph Neural Network with LSTM model proposed in this paper is found to predict crucial agricultural determinants like irrigation requirements, pest infestations, and crop yields with high accuracy, outperforming other models due to its advanced calculation of the intricate relationships stemming from environmental factors and time related patterns. The outcomes of this study emphasize the capabilities of such intelligent systems in optimizing resources and minimizing waste while enhancing productivity in precision farming. There are still some advancements needed in the areas of integrating heterogeneous data sets, rural areas connectivity, system scalability, and data security as these continue to pose the most challenging hurdles to broad acceptance. Further efforts in the development of these systems should be concentrated on enhancing ease of use and lower costs, particularly for smallholder farmers, increasing trust in AI powered advisory systems, and improving the system explainability. Altogether, this study demonstrates the fact that data is one of the cornerstones of next generation agriculture which supports the notion of adaptive and sustainable food production while enhancing the resilience towards global challenges.

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