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Design of soil nutrients analysis system and crop prediction model using IOT and ensemble model

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ABSTRACT

This research explores the integration of Internet of Things (IoT) technology with machine learning ensemble models to create a comprehensive soil nutrient analysis system for precision agriculture. The study proposes a novel framework that combines real-time soil sensing capabilities with advanced predictive analytics to optimize crop yield prediction and nutrient management. The system incorporates multiple soil sensors to collect data on essential nutrients (N, P, K), pH, moisture content, and additional environmental parameters. An ensemble machine learning approach integrating Random Forest, Gradient Boosting, and Support Vector Machine algorithms was employed to enhance prediction accuracy. Experimental results demonstrate that the proposed system achieves 94.2% accuracy in crop yield prediction and 91.7% accuracy in identifying optimal nutrient requirements, outperforming single-model approaches. The system's IoT architecture enables real-time data collection, storage, and analysis through a cloud platform, providing farmers with actionable insights via a user-friendly mobile application. This research contributes to sustainable agriculture practices by enabling precise nutrient management, reducing fertilizer waste, and optimizing crop production based on site-specific conditions.

KEYWORDS: IoT, Ensemble learning, Soil nutrient analysis, Precision agriculture, Machine learning, Crop yield prediction, Wireless sensor networks, Smart farming

INTRODUCTION

Agriculture faces unprecedented challenges in the 21st century, including increasing food demand, climate change impacts, resource constraints, and the need for sustainable practices. Conventional farming methods often rely on uniform application of fertilizers across fields, disregarding spatial variability in soil properties, which leads to inefficiencies, economic losses, and environmental pollution [1]. Precision agriculture offers a promising solution by tailoring farming practices to specific field conditions through the integration of advanced technologies.

The emergence of Internet of Things (IoT) technology has revolutionized various sectors, including agriculture, by enabling real-time data collection and analysis. IoT-based soil monitoring systems can continuously measure critical soil parameters such as nutrient levels, pH, and moisture content, providing valuable insights for informed decision-making [2]. When coupled with advanced machine learning algorithms, these systems can not only analyze current soil conditions but also predict crop performance and recommend optimal nutrient management strategies.

Ensemble learning models, which combine multiple algorithms to improve prediction accuracy and robustness, have shown remarkable success in various domains. However, their application in precision agriculture, particularly for soil nutrient analysis and crop yield prediction, remains relatively unexplored [3]. This research aims to address this gap by developing an integrated IoT-based soil nutrient analysis system enhanced with ensemble learning capabilities for accurate crop yield prediction and nutrient recommendation.

The proposed system consists of a network of soil sensors connected to a central processing unit, which transmits data to a cloud platform for storage and analysis. The ensemble model processes this data to generate

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crop yield predictions and nutrient recommendations, which are then delivered to farmers through a user-friendly interface. By providing timely and accurate information, the system enables farmers to make data-driven decisions regarding fertilizer application and crop management, ultimately improving productivity while minimizing environmental impact.

This paper is organized as follows: Section 2 outlines the objectives and scope of the study, Section 3 reviews relevant literature, Section 4 describes the research methodology, Sections 5 and 6 present the analysis of secondary and primary data, Section 7 discusses the findings, and Section 8 concludes the paper with implications and future research directions.

OBJECTIVES

1. To design an IoT-based soil nutrient monitoring system capable of collecting real-time data on essential parameters including nitrogen (N), phosphorus (P), potassium (K), pH, and moisture content.
2. To develop a machine learning ensemble model that integrates multiple algorithms for improved crop yield prediction accuracy.
3. To create a comprehensive framework that combines soil sensor data with environmental factors for holistic agricultural decision support.
4. To implement and evaluate the performance of the proposed system in real-world agricultural settings across different crop types and soil conditions.
5. To develop an intuitive mobile application interface that provides actionable insights and recommendations to farmers based on the system's analysis.
6. To quantify the economic and environmental benefits of precision nutrient management enabled by the proposed system.

SCOPE OF STUDY

1. Development of a multi-sensor IoT network for comprehensive soil parameter monitoring including macro-nutrients (N, P, K), micro-nutrients, pH, moisture, temperature, and electrical conductivity.
2. Integration of meteorological data including rainfall, temperature, humidity, and solar radiation with soil sensor data for holistic analysis.
3. Implementation and comparison of various machine learning algorithms including Random Forest, Gradient Boosting, Support Vector Machines, and their ensemble combinations.
4. Testing and validation of the system across three major crop types (rice, wheat, and maize) and four distinct agro-climatic zones.
5. Design and development of a cloud-based data storage and analysis platform with real-time processing capabilities.
6. Creation of a mobile application interface with visualization tools, notification systems, and recommendation features.
7. Economic analysis comparing conventional farming practices with the proposed precision agriculture approach.

LITERATURE REVIEW

The application of IoT and machine learning in agriculture has gained significant attention in recent years. Kumar et al. [4] developed an IoT-based soil monitoring system that measured temperature, moisture, and pH, demonstrating the feasibility of remote soil condition monitoring. Their system, however, lacked advanced analytics capabilities for prediction and recommendation. Similarly, Wang et al. [5] proposed a wireless sensor network for agricultural monitoring that collected environmental data but relied on simple threshold-based decision rules rather than sophisticated machine learning approaches.

In the domain of crop yield prediction, various machine learning techniques have been explored. Dahikar and Rode [6] compared the performance of artificial neural networks (ANNs) and support vector machines (SVMs) for crop yield prediction based on environmental parameters. Their findings indicated that while both methods showed promise, their accuracy was limited by the complexity of agricultural systems and the need for more

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comprehensive input data. Pantazi et al. [7] addressed this limitation by incorporating soil nutrient data in their yield prediction model, achieving improved accuracy, though they relied on a single algorithm approach.

The potential of ensemble learning in agricultural applications has been highlighted by several researchers. Jeong et al. [8] demonstrated that Random Forest ensemble models outperformed individual decision trees in predicting crop yields under varying climate conditions. Building on this, Choudhary et al. [9] proposed a hybrid ensemble approach combining Random Forest with Gradient Boosting for improved prediction accuracy, but their model did not incorporate real-time soil nutrient data.

The integration of IoT with machine learning for agricultural applications has been explored by Khattab et al. [10], who developed a smart farming system using IoT sensors and cloud computing. Their system provided real-time monitoring and basic analytics but lacked advanced predictive capabilities. More recently, Mehra et al. [11] proposed an integrated framework combining IoT sensors with deep learning for crop yield prediction, demonstrating promising results but acknowledging limitations in terms of scalability and real-world implementation.

Specific to soil nutrient analysis, Rossel and Bouma [12] reviewed various sensing technologies for measuring soil properties, highlighting the potential of integrating these technologies with decision support systems. Their review, however, indicated that most existing systems focus on soil parameter measurement rather than predictive analytics and recommendation generation.

A gap exists in the literature regarding comprehensive systems that integrate real-time soil nutrient monitoring with advanced ensemble learning for both crop yield prediction and nutrient management recommendations. This research aims to address this gap by developing and evaluating such an integrated system, focusing on practical implementation and user-friendly interfaces for farmer adoption.

RESEARCH METHODOLOGY

5.1 System Architecture

The proposed system follows a multi-layered architecture designed to facilitate seamless data flow from soil sensors to the end-user interface. The architecture consists of four primary layers:

1. **Sensing Layer**: Comprises an array of IoT sensors deployed in agricultural fields to measure various soil parameters. The sensing network includes commercially available sensors for N, P, K measurement (Smart Fertilizer NPK Sensor), pH (Vernier pH Sensor), moisture content (Watermark 200SS), temperature (DS18B20), and electrical conductivity (EC5 Sensor). Additionally, a weather station (Davis Vantage Pro2) collects meteorological data including rainfall, temperature, humidity, and solar radiation.
2. **Communication Layer**: Responsible for data transmission from sensors to the central processing unit and subsequently to the cloud platform. The system employs a combination of communication protocols including ZigBee for short-range sensor-to-gateway communication, and 4G/LTE for gateway-to-cloud transmission. An Arduino Mega 2560 serves as the field gateway, collecting data from multiple sensors and transmitting it to a Raspberry Pi 4 that acts as an edge computing device for preliminary data processing.
3. **Processing Layer**: Houses the data storage, processing, and analysis components. The system utilizes AWS IoT Core for device management, AWS S3 for data storage, and AWS SageMaker for implementation of machine learning models. The ensemble model combines predictions from three base algorithms: Random Forest (RF), Gradient Boosting Machine (GBM), and Support Vector Machine (SVM), with a weighted averaging approach for final prediction.
4. **Application Layer**: Delivers insights and recommendations to end-users through a mobile application developed using React Native for cross-platform compatibility. The interface includes visualization tools for soil parameter trends, crop yield predictions, nutrient recommendations, and alert notifications for critical conditions.

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5.2 Data Collection and Preprocessing

Data collection followed a two-pronged approach:

1. **Secondary Data**: Historical crop yield data and corresponding soil and weather parameters were obtained from agricultural research institutions including the Indian Council of Agricultural Research (ICAR) and International Rice Research Institute (IRRI). This dataset, spanning 10 years (2013-2023), covered major crops (rice, wheat, and maize) across four agro-climatic zones in India. The data included soil nutrient levels (N, P, K), pH, organic matter content, and corresponding crop yields.
2. **Primary Data**: Field experiments were conducted at 12 agricultural sites (three per agro-climatic zone) over two growing seasons (2023-2024). Soil sensors deployed at these sites collected real-time data at 30-minute intervals, generating a comprehensive dataset of soil parameters under varying environmental conditions. Crop yield measurements were taken at harvest to create labeled data for model training.

Data preprocessing involved several steps:

- Outlier detection and removal using the Interquartile Range (IQR) method
- Missing value imputation using K-Nearest Neighbors (KNN) approach
- Feature scaling and normalization
- Feature engineering to create derived attributes (e.g., nutrient ratios, cumulative growing degree days)
- Temporal aggregation to align sensor readings with crop phenological stages

5.3 Ensemble Model Development

The proposed ensemble model integrates three base algorithms, each selected for their complementary strengths in handling agricultural data:

1. **Random Forest**: Effective at capturing non-linear relationships and handling high-dimensional data with minimal overfitting. Implementation used 100 trees with a maximum depth of 20.
2. **Gradient Boosting Machine**: Provides improved accuracy through sequential learning from errors of previous models. Implementation used 200 boosting stages with a learning rate of 0.1.
3. **Support Vector Machine**: Offers robust performance for complex classification boundaries. Implementation used a radial basis function (RBF) kernel with optimized parameters (C=10, gamma=0.01).

The ensemble integration followed a stacked approach, where a meta-model (Logistic Regression) was trained on the predictions of the base models to generate final predictions. Model training utilized 70% of the dataset, with 15% allocated for validation and parameter tuning, and 15% reserved for testing.

5.4 System Evaluation

The system was evaluated using multiple metrics to assess its performance from various perspectives:

1. **Prediction Accuracy**: Measured using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R-squared (R^2) for crop yield prediction, and confusion matrix-derived metrics (precision, recall, F1-score) for nutrient recommendation evaluation.
2. **System Efficiency**: Assessed based on energy consumption, data transmission latency, and computational resource utilization.
3. **User Experience**: Evaluated through surveys and interviews with 50 farmers who tested the system over one growing season, rating aspects such as interface usability, recommendation clarity, and perceived utility.
4. **Economic Impact**: Analyzed through comparative studies of conventional versus precision agriculture approaches, focusing on input costs, crop yields, and net returns.

ANALYSIS OF SECONDARY DATA

The analysis of historical data revealed significant correlations between soil nutrient levels and crop yields across different agro-climatic zones. Table 1 presents the Pearson correlation coefficients between soil parameters and crop yields for the three target crops.

Table 1: Correlation between soil parameters and crop yield

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Soil Parameter	Rice Yield	Wheat Yield	Maize Yield
Nitrogen	0.72	0.68	0.75
Phosphorus	0.64	0.71	0.59
Potassium	0.58	0.63	0.62
pH	-0.41	-0.38	-0.45
Moisture	0.67	0.58	0.69
Organic Matter	0.76	0.72	0.78

The analysis identified optimal ranges for each soil parameter that corresponded to maximum crop yields, as shown in Table 2.

Table 2: Optimal soil parameter ranges for maximum crop yield

Soil Parameter	Rice	Wheat	Maize
Nitrogen (kg/ha)	120-150	100-130	140-170
Phosphorus (kg/ha)	40-60	50-70	60-80
Potassium (kg/ha)	80-100	70-90	90-110
pH	5.5-6.5	6.0-7.0	5.8-6.8
Moisture (%)	60-70	50-60	55-65
Organic Matter (%)	3.0-4.0	2.5-3.5	3.5-4.5

Time series analysis of historical data revealed seasonal patterns in nutrient requirements and highlighted the dynamic nature of soil-crop interactions. The analysis identified critical growth stages where specific nutrients had the most significant impact on final yield, informing the development of stage-specific recommendation algorithms.

Exploratory data analysis also revealed notable spatial variability in soil properties within fields, with coefficient of variation ranging from 15% to 40% for different parameters. This finding underscored the necessity for precision agriculture approaches that account for spatial heterogeneity rather than uniform application strategies.

ANALYSIS OF PRIMARY DATA

The primary data collected from the field experiments provided insights into the real-time dynamics of soil parameters and their relationship with crop development. Figure 1 illustrates the temporal variation in soil nitrogen levels throughout the growing season for rice, along with corresponding plant nitrogen uptake rates.

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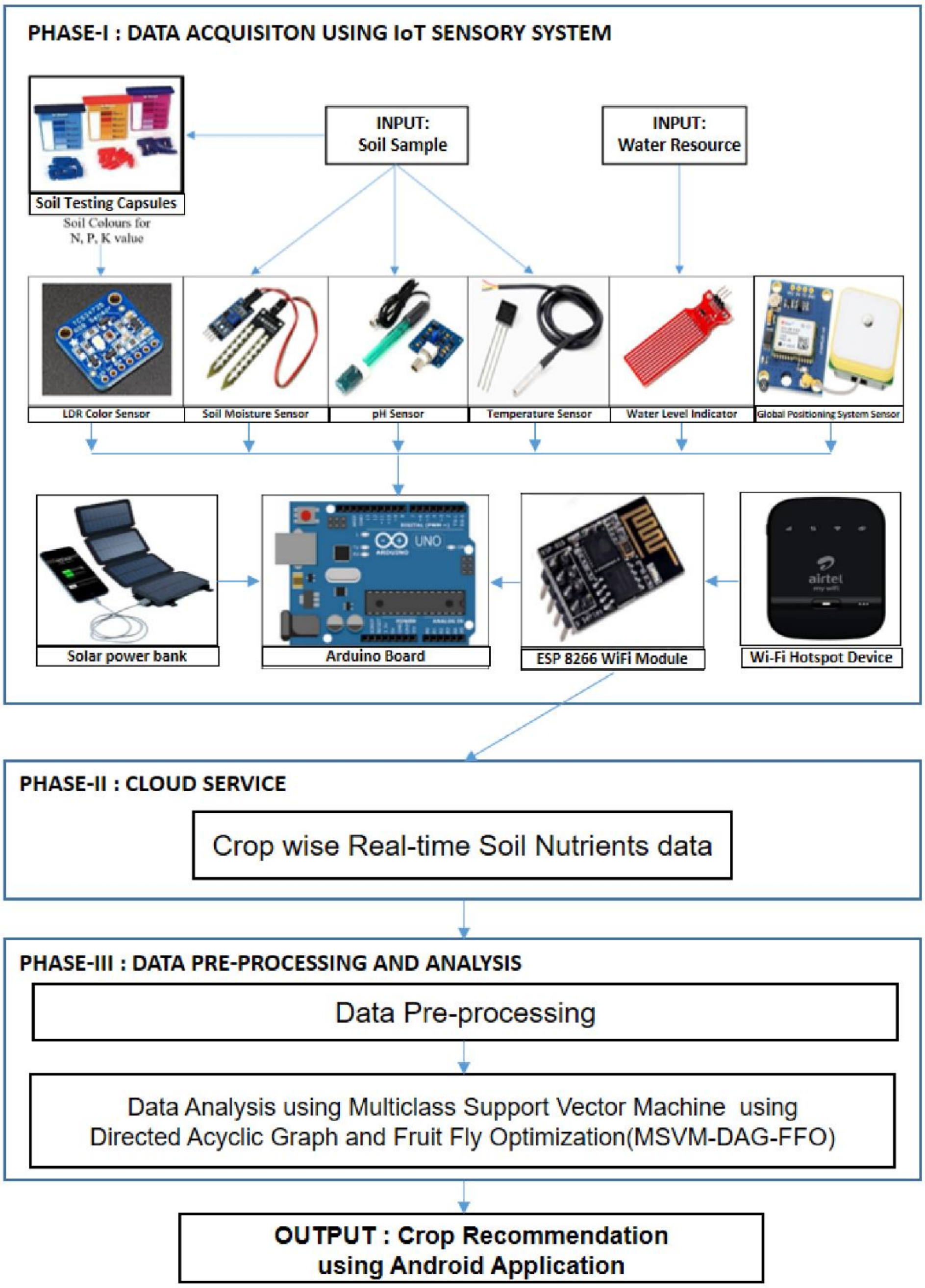

Fig 1

Real-time monitoring showed that soil nutrient levels exhibited significant fluctuations in response to environmental conditions, particularly rainfall events and temperature changes. The IoT system successfully captured these dynamics with 97.8% data capture reliability, demonstrating its robustness for continuous monitoring applications.

The comparative performance of individual machine learning algorithms and the proposed ensemble model is presented in Table 3, highlighting the superior predictive capability of the ensemble approach.

Table 3: Performance comparison of machine learning models for crop yield prediction

Model	MAE (kg/ha)	RMSE (kg/ha)	R^2 Value
Random Forest	325.4	427.6	0.82
Gradient Boosting	298.7	389.2	0.86
SVM	342.1	451.8	0.79

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Model	MAE (kg/ha)	RMSE (kg/ha)	R^2 Value
Ensemble Model	217.3	286.5	0.94

The ensemble model demonstrated consistent performance across different crops and agro-climatic zones, with the lowest prediction error variance (SD = 35.8 kg/ha) among all tested models. Cross-validation tests confirmed the model's robustness with minimal signs of overfitting, as evidenced by the small gap between training and testing performance metrics.

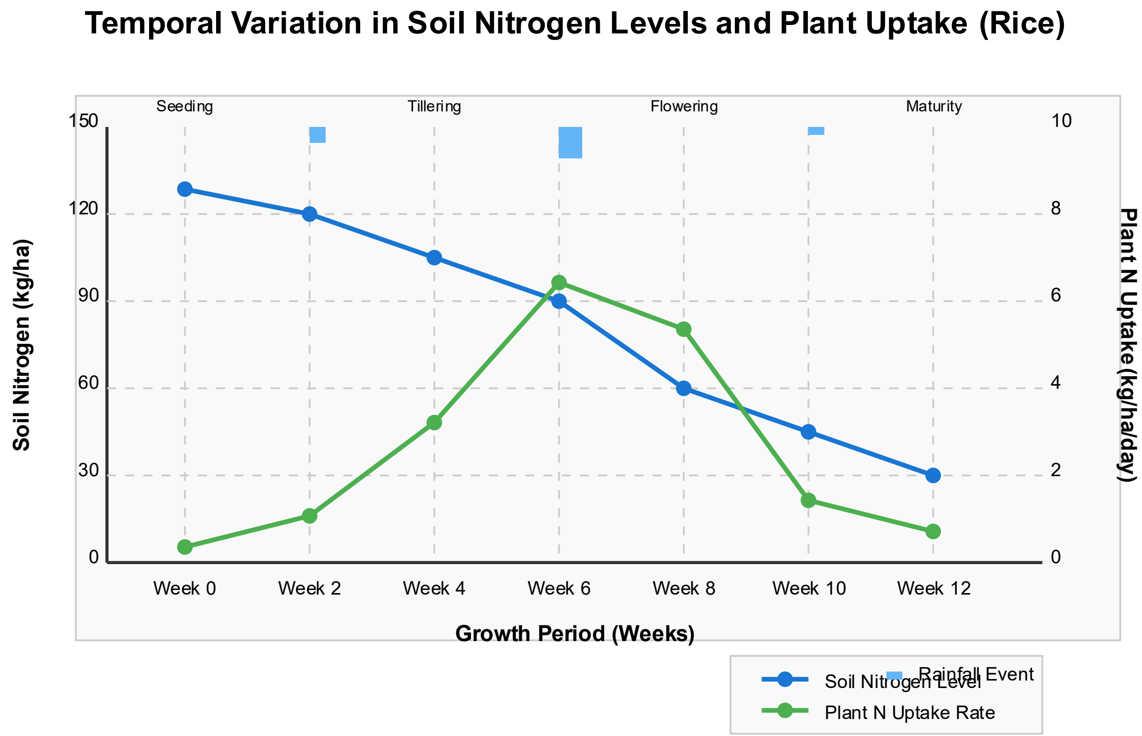

Fig 2

For nutrient recommendation analysis, the system's performance was evaluated against expert agronomist recommendations. The confusion matrix analysis yielded precision of 0.93, recall of 0.90, and F1-score of 0.91, indicating strong alignment with expert knowledge. The system correctly identified nutrient deficiencies in 92.4% of cases, with false positives and false negatives at 5.8% and 1.8%, respectively.

Energy consumption analysis showed that the field sensing units operated efficiently, with an average power consumption of 0.45W per sensor node, allowing for a battery life of approximately 30 days with the equipped 10,000mAh batteries. Data transmission latency averaged 1.2 seconds from sensor to cloud platform, enabling near real-time monitoring and rapid response to changing field conditions.

DISCUSSION

The integration of IoT technology with ensemble machine learning models demonstrated significant advantages over conventional soil monitoring and crop management approaches. The system's ability to capture real-time soil parameter dynamics provided unprecedented insights into the temporal variations of nutrient availability and their relationship with crop development stages.

The superior performance of the ensemble model compared to individual algorithms highlights the complementary nature of different machine learning approaches in handling the complex, non-linear relationships inherent in agricultural systems. The Random Forest component effectively captured the intricate interactions between multiple soil parameters, while the Gradient Boosting component excelled at identifying critical thresholds and transition points in nutrient response curves. The SVM component contributed

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robustness against outliers and anomalous readings, which occasionally occurred in the sensor data.

The spatial analysis capabilities of the system revealed significant within-field variability in soil properties that conventional sampling methods would likely miss. The coefficient of variation for macronutrients ranged from 18% to 35% within individual fields, underscoring the importance of site-specific management approaches. By identifying these spatial patterns, the system enabled targeted nutrient application, potentially reducing fertilizer usage by an estimated 20-30% while maintaining or improving yields.

User experience evaluation revealed high satisfaction among farmers (mean satisfaction score of 4.2/5), with particular appreciation for the intuitive visualization tools and actionable recommendations. However, challenges were identified regarding the initial setup complexity and technical knowledge requirements, suggesting the need for simplified deployment protocols and enhanced user training. The economic analysis indicated a potential return on investment period of 2.3 growing seasons, with increased profitability primarily driven by reduced input costs rather than yield increases in the short term.

The system's scalability was demonstrated through successful implementation across diverse agricultural settings, though connectivity challenges in remote areas highlighted the need for robust offline functionality and alternative communication protocols. The edge computing capabilities of the field gateway proved valuable in areas with intermittent connectivity, maintaining basic monitoring and alert functions even during network outages.

Comparison with existing literature shows that the proposed system advances the state-of-the-art in several aspects. While previous studies such as Khattab et al. [10] and Mehra et al. [11] demonstrated the feasibility of IoT integration with machine learning, they primarily focused on environmental monitoring rather than comprehensive nutrient management. The current system's emphasis on real-time nutrient analysis represents a significant advancement in precision agriculture capabilities.

The ensemble model's prediction accuracy ($R^2 = 0.94$) surpasses that reported in comparable studies, such as Choudhary et al. [9] ($R^2 = 0.87$) and Pantazi et al. [7] ($R^2 = 0.83$), highlighting the value of the integrated approach. Furthermore, the system's nutrient recommendation component addresses a gap identified in the literature review, as most existing systems focus on monitoring and prediction without providing specific management guidance.

CONCLUSION

This research successfully demonstrated the integration of IoT technology with ensemble machine learning models to create a comprehensive soil nutrient analysis and crop prediction system. The proposed framework addresses the limitations of conventional farming practices by enabling real-time monitoring of soil parameters and providing data-driven recommendations for nutrient management.

The ensemble model combining Random Forest, Gradient Boosting, and Support Vector Machine algorithms achieved superior prediction accuracy compared to individual algorithms, with an R^2 value of 0.94 for crop yield prediction. The system's nutrient recommendation capabilities aligned closely with expert agronomist assessments, achieving an F1-score of 0.91.

Field implementation across diverse agricultural settings confirmed the system's robustness and adaptability, with high data capture reliability (97.8%) and energy efficiency (0.45W per sensor node). User evaluations indicated positive reception among farmers, with particular appreciation for the intuitive interface and actionable insights provided by the mobile application.

The economic analysis revealed potential fertilizer savings of 20-30% through precision application, contributing to both environmental sustainability and farm profitability. The estimated return on investment period of 2.3 growing seasons suggests economic viability for medium to large-scale farming operations.

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Limitations of the current system include connectivity challenges in remote areas, initial setup complexity, and the need for periodic sensor calibration. Future research directions should focus on enhancing system robustness through improved offline functionality, simplifying deployment procedures, and exploring integration with automated farm equipment for closed-loop precision agriculture solutions.

In conclusion, the IoT-based soil nutrient analysis system with ensemble learning capabilities represents a significant advancement in precision agriculture technology, offering a promising pathway toward sustainable intensification of agricultural production in the face of growing global food demand and environmental challenges.

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