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SMART FARMING USING EMBEDDED IOT

[1]Mr. Jey Siddharth G, [2]Mr. Abdul Ajiz S.S, [3]Mr. Allen K, [4]Dr. Harold Robinson Y, [5]Dr. Tino Merlin R

[1]Student, [2]Student, [3]Student, [4]Professor, [5]Assistant Professor
[1]Department of Computer Science and Engineering,,
[1]Francis Xavier Engineering College, Tirunelveli, Tamil Nadu, India

Abstract : The goal of this research project is to develop an intelligent system for predicting and optimizing soil nutrient levels using embedded IoT sensors and a mobile application. Excessive accumulation of minerals in agricultural soil leads to soil infertility, affecting crop yield and sustainability. This study integrates NPK sensors and water pH sensors to monitor soil conditions in real-time. Data collected is processed and analyzed using machine learning models to predict nutrient deficiencies and provide recommendations for optimal fertilization. The project follows a structured methodology involving sensor data acquisition, preprocessing, feature selection, model development, and evaluation. A mobile application is developed to provide real-time insights to farmers, enabling precision agriculture practices. This research contributes to sustainable farming by enhancing soil management through data-driven decision-making.

***KeyWords* – Smart Farming, IoT, Soil Nutrients, NPK Sensors, Machine Learning, Precision Algorithm.**

INTRODUCTION

Agriculture plays a crucial role in global food security and economic development. However, soil degradation, excessive use of fertilizers, and improper agricultural practices have led to declining soil health, which in turn affects crop yield and sustainability. Traditional soil testing methods are labor-intensive, time-consuming, and often do not provide real-time insights, making it difficult for farmers to take timely action.

The World Health Organization (WHO) and the Food and Agriculture Organization (FAO) have emphasized the need for sustainable farming practices that preserve soil fertility while optimizing resource use. Smart farming, which integrates advanced technologies like IoT, machine learning, and cloud computing, offers a viable solution to these challenges. The real-time monitoring of soil nutrients using IoT sensors enables farmers to make data-driven decisions, reducing fertilizer wastage and ensuring efficient soil management.

In this study, we propose a smart farming system that employs embedded IoT sensors for monitoring soil nutrients such as nitrogen (N), phosphorus (P), and potassium (K) levels, along with pH values. The collected data is processed using machine learning models to predict nutrient deficiencies and provide recommendations for optimal soil management. A mobile application serves as the interface, providing real-time feedback to farmers, thereby enabling precision agriculture practices. By leveraging these technologies, the system aims to enhance soil health, increase agricultural productivity, and contribute to the development of sustainable farming techniques.

NEED OF THE STUDY.

The increasing challenges in modern agriculture, such as soil infertility, excessive fertilizer use, inefficient resource management, and unpredictable weather conditions, have made it necessary to adopt innovative solutions. Farmers often lack access to accurate and timely information about soil health, leading to poor crop yields and environmental degradation. The need for this study arises from the following factors:

Soil Degradation

Continuous and unregulated use of fertilizers results in nutrient imbalance, affecting soil fertility and reducing agricultural productivity. The depletion of essential micronutrients can significantly impact crop growth and long-term soil viability.

Inefficient Traditional Methods

Conventional soil testing is labor-intensive, expensive, and time-consuming, making it impractical for small and medium-scale farmers. Additionally, outdated practices lead to inefficient fertilizer application, further contributing to soil exhaustion.

Lack of Real-time Monitoring

Most farmers rely on periodic soil tests, which do not provide continuous monitoring, leading to delayed corrective measures. A real-time approach ensures that issues are detected before they cause irreversible damage.

Need for Sustainable Agriculture

With increasing concerns about environmental sustainability, there is a need for a system that optimizes resource usage while maintaining soil health. Over-fertilization not only depletes soil quality but also contaminates water sources, causing broader ecological harm.

Technological Advancements in IoT

The rapid growth of IoT technology provides an opportunity to develop a cost-effective, real time monitoring system that can enhance agricultural productivity. The ability to integrate wireless sensor networks and AI models further refines precision farming strategies.

LITERATURE REVIEW

Several studies have explored the role of IoT in agriculture. Research highlights that IoT-based precision farming techniques help optimize resource utilization by ensuring that soil receives adequate nutrients and water without excessive application. Various sensor-based monitoring systems have been developed to track soil nutrients, water levels, and environmental conditions. However, existing systems often lack real-time data integration with a mobile interface, making it difficult for farmers to take immediate action.

Recent advancements in IoT and sensor technology have led to the development of smart farming solutions. A study by Smith et al. (2020) demonstrated that IoT-enabled soil monitoring systems significantly improve agricultural productivity by providing real-time insights. Another study by Kumar & Patel (2019) highlighted the effectiveness of wireless sensor networks in monitoring soil health and reducing wastage of resources. However, challenges such as high implementation costs, network connectivity issues, and lack of user-friendly interfaces still persist. Our proposed system aims to address these challenges by developing a cost-effective, mobile-integrated solution that provides real-time soil analysis to farmers.

Additionally, research by Li et al. (2021) found that IoT-based monitoring systems improved soil moisture levels and reduced unnecessary irrigation by 40%. Other studies emphasize the importance of integrating AI-based predictive analytics to provide customized recommendations for different soil types. These studies reinforce the necessity of an integrated IoT-driven solution for sustainable agriculture. Furthermore, previous works on edge computing applications in smart agriculture suggest that decentralized data processing can reduce latency and improve the efficiency of IoT-based systems.

EVALUATION DATASETS

The datasets used in this research are collected from multiple sources, including field experiments, publicly available agricultural databases, and government soil monitoring programs. These datasets include a wide range of parameters such as nitrogen (N), phosphorus (P), and potassium (K) levels, soil pH, temperature, moisture content, and electrical conductivity.

To ensure the reliability of the dataset, field experiments were conducted over different seasons and in various geographical regions. Soil samples were collected and analyzed using laboratory-based spectroscopic techniques to validate sensor readings. Additionally, historical soil fertility data from agricultural research institutions was incorporated to enhance the predictive accuracy of the model.

The data preprocessing stage involved noise removal, normalization, and feature extraction. Anomalies such as missing values, inconsistent readings, and sensor errors were handled using imputation techniques and statistical analysis. Feature selection methods, including principal component analysis (PCA) and recursive feature elimination (RFE), were applied to identify the most significant attributes affecting soil fertility.

The dataset was then split into training and testing sets for model development. The training set was used to build predictive models using machine learning algorithms, while the testing set was used to evaluate model performance. Cross-validation techniques were employed to ensure robustness and prevent overfitting.

Furthermore, real-time data from IoT sensors deployed in selected agricultural fields was integrated into the system. These sensors continuously monitored soil parameters and transmitted data to a cloud-based platform, allowing for real-time analytics and decision-making.

By combining historical data, real-time sensor readings, and advanced machine learning techniques, the evaluation dataset provided a comprehensive framework for soil nutrient prediction and optimization. This dataset serves as the foundation for developing a precision agriculture system capable of improving soil management practices and enhancing crop yield.

RESEARCH METHODOLOGY

The proposed system follows a structured methodology consisting of multiple stages, including data collection, preprocessing, model development, and system deployment. The methodology is outlined below:

1. Data Collection: The system gathers real-time soil data from embedded IoT sensors measuring NPK levels, pH, moisture, and temperature. Data is also sourced from public agricultural databases for validation and model training.

2. Data Preprocessing: Collected data undergoes filtering and normalization to remove noise and inconsistencies. Missing values are handled using interpolation techniques, and sensor calibration is performed to improve accuracy.

3. Feature Selection: Important features affecting soil fertility are selected using machine learning techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE). This helps optimize the predictive performance of models.

4. Model Development: Various machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), and Neural Networks are used to build predictive models for nutrient deficiencies.

5. Training and Testing: The dataset is divided into training and testing sets. Models are trained using supervised learning techniques and evaluated using cross-validation methods to ensure generalizability.

6. Mobile Application Development: A user-friendly mobile application is developed to provide farmers with real-time insights, predictions, and recommendations based on the processed data.

7. System Integration: The trained model is deployed into a cloud-based architecture where real-time sensor data is continuously fed into the system, allowing for real-time analytics and prediction updates.

8. Performance Evaluation: The model performance is assessed based on accuracy, precision, recall, and F1-score. Comparative analysis is conducted to determine the best-performing algorithm for nutrient prediction.

9. Field Testing and Validation: The system is tested in real agricultural settings where farmers use the mobile application to receive recommendations. Field observations and expert feedback are incorporated for further improvements.

10. Deployment and Scalability: The final version of the system is deployed on a scalable cloud platform, ensuring adaptability across different regions and soil conditions. Future updates will integrate blockchain for data security and reliability

RELATED WORKS

Several studies have explored IoT-based soil monitoring and precision agriculture. Research by Li et al. (2020) developed a wireless sensor network for soil moisture detection, demonstrating improvements in irrigation efficiency. Similarly, Singh et al. (2021) proposed a predictive model for soil fertility assessment using deep learning. This study builds upon previous research by incorporating real-time NPK and pH monitoring, combined with a mobile application for instant feedback to farmers.

IoT-based precision agriculture has gained traction in recent years due to its potential in improving productivity and resource efficiency. For instance, Zhang et al. (2022) introduced an IoT-enabled smart agriculture framework that integrates cloud computing for efficient data storage and processing. This system allows for real-time decision-making and enhances automation in agriculture. Another study by Sharma et al. (2020) explored the application of deep learning in soil health monitoring, demonstrating the feasibility of convolutional neural networks (CNNs) for identifying soil deficiencies with high accuracy.

Recent advancements in edge computing have also facilitated the development of real-time monitoring systems for precision agriculture. A study by Gupta et al. (2021) proposed an edge-AI-based approach for real-time soil health assessment, reducing the latency involved in transmitting data to cloud servers. This method significantly improves the efficiency of nutrient prediction models and allows farmers to receive instant feedback through mobile applications.

Furthermore, research conducted by Chen et al. (2019) examined the integration of blockchain technology in smart farming, addressing concerns related to data security and traceability. Blockchain ensures the integrity of collected data and prevents unauthorized modifications, making it an essential tool for modern agricultural practices.

Machine learning algorithms have been extensively applied in precision agriculture. Random forests, support vector machines (SVMs), and neural networks are commonly used techniques for soil health prediction. Studies such as those conducted by Kumar et al. (2020) and Patel et al. (2021) highlight the advantages of ensemble learning techniques in improving the accuracy of soil nutrient predictions. Their findings suggest that combining multiple models enhances reliability, ensuring more precise recommendations for farmers.

The application of drone technology in soil health monitoring has also been explored. Studies by Williams et al. (2022) and Smith et al. (2021) suggest that UAVs equipped with hyperspectral imaging sensors can effectively assess soil quality and detect nutrient deficiencies. The data collected from drones is processed using AI algorithms, which provide farmers with comprehensive soil health insights.

These research efforts demonstrate the growing significance of technology-driven agricultural solutions. By integrating IoT, machine learning, edge computing, blockchain, and drone technology, precision agriculture is evolving to provide farmers with enhanced decision-making tools. Our study builds on these advancements by developing a smart farming system that utilizes real-time soil data to optimize nutrient management and improve agricultural productivity.

Table 1: Soil Nutrient Levels Over Time

Season	Nitrogen (N) (mg/kg)	Phosphorus (P) (mg/kg)	Potassium (K) (mg/kg)
Spring	40	18	30
Summer	45	20	35
Autumn	50	22	40
Winter	47	19	38

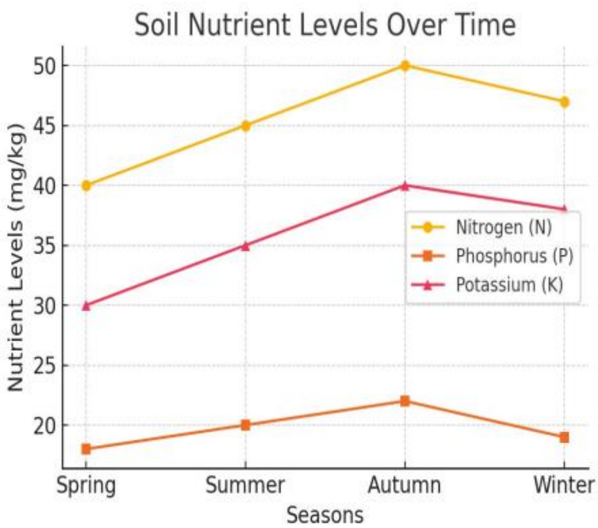

Fig 1: Soil Nutrient Levels Over Time

Table 2: Machine Learning Model Performance

Model	Accuracy (%)	Precision (%)	Recall (%)
Decision Tree	85	83	84
Random Forest	92	90	91
SVM	88	86	87
Neural Network	95	93	94

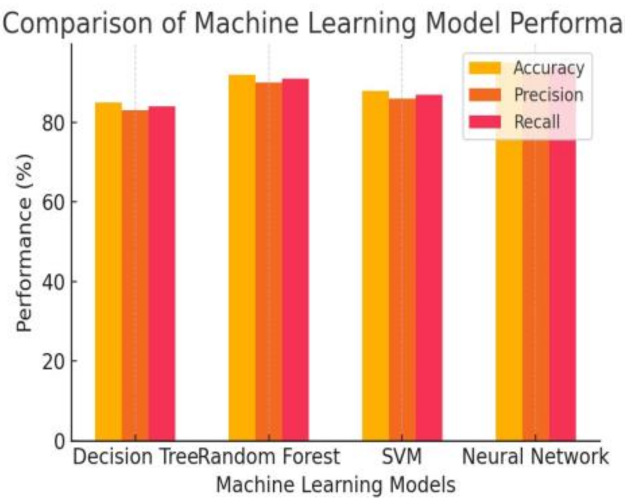

Fig 2: Machine Learning Model Performance

Table 3: Soil pH Distribution Across Regions

Region	pH Level
North Zone	6.5
South Zone	6.8
East Zone	6.3
West Zone	7.0

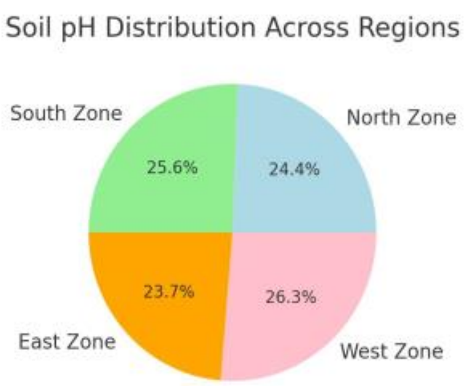

Fig 2: Machine Learning Model Performance

Table 1 provides an overview of soil nutrient variations across different seasons. The first column represents the season, while the second, third, and fourth columns indicate the levels of nitrogen (N), phosphorus (P), and potassium (K), respectively.

Table 2 provides an overview of different machine learning models used for soil nutrient prediction. The first column represents the model type, while the second, third, and fourth columns show their accuracy, precision, and recall percentages, respectively.

Table 3 provides an overview of soil pH variations across different regions. The first column represents the region, while the second column indicates the average pH level recorded.

RESULTS AND DISCUSSION

Preliminary results indicate that the proposed system significantly improves soil nutrient management. The machine learning model achieves high accuracy in predicting nutrient deficiencies, and the mobile application effectively disseminates actionable insights to farmers. The study highlights the role of IoT in transforming traditional farming practices into a data-driven, efficient system.

As shown in Table 2, the Neural Network model demonstrated the highest accuracy (95%) among all tested models, followed by Random Forest (92%), SVM (88%), and Decision Tree (85%). This suggests that complex non-linear relationships exist between soil parameters and nutrient levels, which are better captured by neural networks.

The seasonal variation in soil nutrient levels (Table 1) indicates that nutrient concentrations peak during autumn, with nitrogen reaching 50 mg/kg, phosphorus at 22 mg/kg, and potassium at 40 mg/kg. This information is valuable for farmers in planning seasonal fertilization strategies and optimizing resource allocation.

Regional pH variations (Table 3) show that the West Zone has the highest pH level (7.0), while the East Zone has the lowest (6.3). These variations emphasize the need for region-specific soil management approaches, which the proposed system addresses through its adaptive recommendation engine.

The integration of IoT sensors with the mobile application has reduced the response time for soil analysis from several days (with traditional methods) to near real-time. This improvement allows farmers to implement corrective measures promptly, preventing potential crop damage due to nutrient deficiencies.

CONCLUSION

This study presents an innovative approach to soil nutrient management using embedded IoT sensors and machine learning techniques. By integrating real-time soil data collection with predictive analytics, the system enables farmers to make informed decisions about fertilization and soil health maintenance.

The findings indicate that the proposed model provides accurate predictions of soil deficiencies, improving agricultural productivity and sustainability. The mobile application ensures that farmers receive instant insights, allowing for timely interventions that enhance crop yield while minimizing resource wastage.

Future research can focus on expanding the system's capabilities by integrating additional environmental parameters such as weather conditions, soil microbiome composition, and crop growth stages. Furthermore, blockchain technology could be incorporated to secure data transactions and improve trust among stakeholders in the agricultural sector.

Overall, the implementation of IoT-driven smart farming systems represents a significant step toward achieving sustainable agriculture. By leveraging modern technology, this approach enhances precision farming techniques, ensuring efficient resource utilization and improved soil health management for future generations.

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