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IoT Based Smart Soil Monitoring and Crop Recommendations Using Machine Learning

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***Abstract*—In the face of increasing agricultural challenges such as inefficient resource utilization, poor crop selection, and declining soil health, farmers often lack real-time, data-driven support systems to make informed decisions. This paper presents AgroSmart, an integrated solution leveraging the Internet of Things (IoT) and Machine Learning (ML) to enhance agricultural productivity and sustainability. The proposed system continuously monitors critical soil parameters using cost-effective sensors and employs machine learning algorithms to recommend the most suitable crops based on current soil conditions. Through a user-friendly dashboard, farmers gain accessible and actionable insights, bridging the gap between traditional farming practices and modern precision agriculture. Key challenges such as data quality, model accuracy, cost constraints, and user accessibility were addressed with appropriate technical and design strategies. The system demonstrates strong potential for scalability and can be effectively adapted for use in smart agriculture, greenhouses, agroforestry, and research applications. Our solution promotes sustainable agriculture by enabling optimized resource usage and improved farming efficiency, ultimately contributing to global food security and environmental resilience.**

***Index Terms*—IoT in Agriculture, Machine Learning, Smart Farming, Crop Recommendation System, Soil Monitoring, Precision Agriculture, Sustainable Farming, AgroSmart, Low-Cost Sensors, Data-Driven Farming.**

I. INTRODUCTION

Agriculture plays a crucial role in ensuring food security, economic stability, and sustainable development, particularly in agrarian nations like India. However, farmers continue to face significant challenges such as unpredictable weather patterns, soil degradation, poor crop selection, and inefficient resource utilization. These challenges are often exacerbated by a lack of access to real-time data and scientific decision-making tools, leaving farmers to rely on traditional knowledge or outdated practices. As a result, agricultural productivity remains suboptimal, and the misuse of water, fertilizers, and land resources persists.

Recent advancements in digital technologies have paved the way for smarter, data-driven agricultural practices. The integration of the Internet of Things (IoT) and Machine Learning (ML) has emerged as a transformative approach to support precision agriculture. IoT devices enable real-time monitoring of soil and environmental parameters such as moisture, temperature, pH levels, and nutrient content. When combined with ML models, this data can be used to derive actionable insights, such as crop recommendations tailored to specific soil conditions. This not only aids in increasing yield but also promotes sustainable farming by reducing unnecessary resource consumption.

This paper presents AgroSmart, an intelligent crop advisory system that leverages IoT for soil monitoring and ML algorithms for dynamic crop recommendations. The system collects soil data using low-cost sensors and analyzes it using trained models to suggest optimal crops for cultivation. To enhance usability, a user-friendly dashboard is designed to present insights in a clear and accessible format, catering even to farmers with minimal technological experience.

Despite the emergence of agricultural tech solutions, many existing systems focus either on data collection or analytics in isolation, often lacking seamless integration and context-aware recommendations. Moreover, affordability and user accessibility remain major barriers to adoption among small and marginal farmers. AgroSmart addresses these issues by offering a low-cost, scalable, and intuitive solution that bridges the gap between modern agricultural technologies and traditional farming practices.

The core contributions of this paper include the development of an integrated IoT-ML platform for precision farming, the implementation of a context-aware crop recommendation model, and the creation of an accessible interface for end-users. By providing farmers with timely and relevant information, AgroSmart aims to improve decision-making, enhance productivity, and promote eco-friendly farming practices across diverse agricultural regions.

II. RELATED WORK

In recent years, the integration of Internet of Things (IoT) and Machine Learning (ML) technologies into agriculture has gained significant momentum, aiming to modernize traditional farming practices and enable precision agriculture. The global push toward smart farming solutions arises from the growing need to optimize crop yield, reduce environmental impact, and address challenges such as soil degradation, inefficient resource usage, and the unpredictability of climate change. Multiple research efforts have been carried out to develop intelligent agricultural systems that monitor soil conditions, automate irrigation, and provide crop recommendations using real-time data and advanced analytics.

The work presented by [1] A. Patil et al. introduces a smart agriculture system using an IoT-based soil monitoring network combined with cloud computing. Their system collects data on moisture, temperature, and humidity using sensors and transmits it to a cloud platform where farmers can view it in real time. The main objective was to automate irrigation and alert farmers when critical thresholds are reached. However, the system lacked an intelligent decision-making layer, such as crop recommendation or predictive analysis, limiting its utility to only monitoring functions.

In a study by [2] Sharma et al., the authors proposed a crop recommendation model based on machine learning techniques. The model used a dataset containing soil nutrients, pH level, rainfall, and temperature to suggest the most suitable crops for a region. Algorithms like Decision Tree, Random Forest, and Naive Bayes were compared, with Random Forest delivering the highest accuracy. Although this approach significantly enhanced crop prediction accuracy, it required pre-labeled datasets and did not integrate real-time data collection, which is essential for dynamic field conditions.

Another important contribution was made by [3] Gaurav et al., who developed an integrated system that uses IoT sensors and an ML model to monitor soil health and recommend fertilizers. The system collects soil metrics such as nitrogen, phosphorus, potassium (NPK), and pH levels and feeds this data into a supervised learning algorithm. The primary focus was on suggesting appropriate fertilizers, but crop recommendation was not included. Moreover, user interface design and accessibility for non-technical users were not addressed in detail, making it difficult for average farmers to interpret and act on the data.

In [4], Shinde and Kale proposed a mobile-based crop advisory system that delivers crop selection recommendations based on historical data, soil type, and weather conditions. The system used K-Nearest Neighbor (KNN) algorithm to match a farmer's input with past successful crop profiles. While the mobile-based platform was accessible and user-friendly, the system relied heavily on static databases and did not incorporate real-time monitoring using IoT. The lack of live data integration restricted the effectiveness of the recommendations in dynamic weather and soil conditions.

The study by [5] Kaur et al. explored a smart farming solution focused on optimizing water use through automated irrigation systems. Using moisture sensors, the system could determine the water needs of soil and control irrigation accordingly. While the study effectively addressed water conservation, it did not provide comprehensive crop management support, such as crop type recommendation or soil health evaluation. This limited the system's ability to support farmers holistically across the agricultural cycle.

In contrast, [6] Singh and Tiwari proposed a cloud-integrated IoT platform for precision farming that not only collects data from the field but also provides actionable insights through a centralized dashboard. Their system featured soil and environmental sensors and offered recommendations on both irrigation and crop selection using ML algorithms. While the system marked a major step forward, it still required improvement in model accuracy and needed a more intuitive interface to accommodate users with minimal technical literacy.

The work by [7] Rani et al. focused on developing a low-cost IoT-based smart agriculture system, recognizing the economic limitations of small-scale farmers. However, the model's limitations included scalability issues and lower accuracy due to simplified algorithms used for affordability.

Most existing systems reviewed above tend to focus either on monitoring (e.g., moisture, pH, temperature) or on prediction (e.g., crop or fertilizer recommendation) but rarely offer an integrated solution that covers both in a cohesive framework. Furthermore, many lack usability features such as language support, visual data presentation, or simplified dashboards, which are crucial for widespread adoption among rural farmers. Some systems rely solely on predefined rules or datasets without leveraging the power of real-time learning, which hinders adaptability in fluctuating conditions.

In summary, while a variety of smart agriculture systems have emerged in recent years, gaps still remain in terms of integration, real-time adaptability, user accessibility, and holistic crop advisory capabilities. The proposed AgroSmart system distinguishes itself by combining real-time IoT soil monitoring with a machine learning-powered crop recommendation engine, presented through a user-friendly dashboard. The system is designed to be cost-effective, scalable, and easy to use for farmers with limited technological experience. By addressing limitations in current systems—such as lack of integration, insufficient accuracy, and poor usability—AgroSmart aims to offer a comprehensive, smart solution that supports sustainable and efficient farming practices.

III. SYSTEM ARCHITECTURE

A. System Functioning Steps:

Step 1: User Input via Interface

Farmers input soil data using a simple dashboard (can be mobile/PC based). The interface is built using a web framework like Django.

Step 2: Data Preprocessing

The system cleans the collected data — removing unnecessary parts, converting to lowercase, and standardizing format for analysis.

Step 3: Feature Extraction

The system converts the data into machine-readable format using vectorization or word embeddings.

Step 4: ML Evaluation

Machine Learning models analyze soil data and recommend the best crops. It uses algorithms trained on past soil and crop data.

Step 5: Data Storage

All soil readings and recommendation results are stored in a database securely. Farmers can revisit past recommendations too.

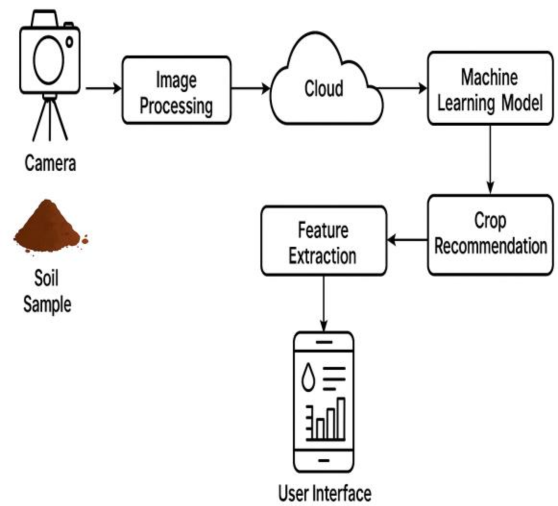


Fig 1. System Architecture

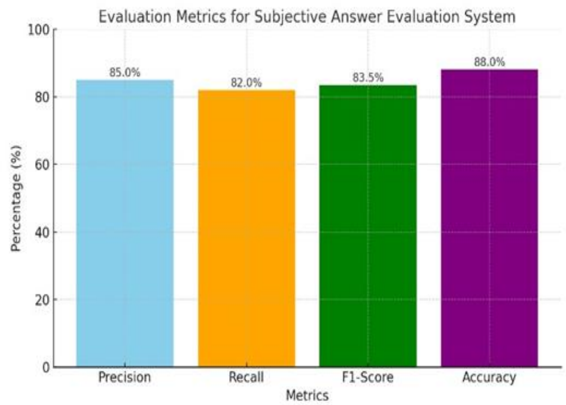
C. Rule-Based Algorithms

- Logistic Regression – For classification of suitable crops based on soil type.
- Support Vector Machines (SVM) – To separate suitable/unsuitable crop options more accurately using decision boundaries.

By combining rule-based approaches and CNN and PART techniques, this system provides a effective and efficient evaluation mechanism for subjective answers.

4)F1 Score: - The F1 score combines precision and recall into a single metric, especially useful in cases of imbalanced datasets. It is determined by calculating the harmonic mean of precision and recall.

Precision + Recall



IV. RESULT AND ANALYSIS

A. Evaluation Metrics

This section presents the outcomes of the proposed Automatic Subjective Answer Evaluation system and analyzes its performance based on various metrics, such as accuracy and efficiency. The results are discussed to highlight the effectiveness of the system in automatically evaluating subjective responses provided by students.

1) *Accuracy:* Accuracy measures the proportion of correct predictions out of the total number of predictions. It is calculated using the formula:

$$A = \frac{TruePositive + TrueNegative}{Total\ Predictions} \quad (\square)$$

2) *Precision:* Precision refers to the ratio of true positive outcomes to the total predicted positive outcomes (both true and false positives). It is calculated as follows:

$$P = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad (\square)$$

3) *Recall:* Recall, also known as sensitivity, measures the proportion of actual positive cases that were correctly identified by the model. The formula used is:

$$R = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (\square)$$

$$F1 = \underline{2 * Precision * Recall} \quad (\square)$$

fig 2: Evaluation metrics for Subjective Answer Evaluation System.

B. *Cosine Similarity Performance for Subjective Answer Evaluation*

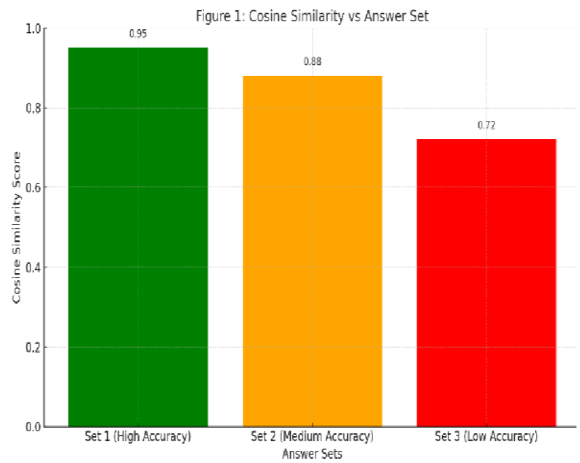


Fig 3: *Cosine Similarity Performance for Subjective Answer Evaluation*

Figure 3: Cosine Similarity vs Answer Set presents the performance of the system in evaluating subjective answers using the Cosine Similarity technique. This metric measures the angle between vectors representing the user's answer and the ideal answer, with values closer to 1 indicating high similarity and semantic alignment between the texts.

Observations

1) High Accuracy Set (Set 1): o Cosine Similarity Score: 0.95 o Description: This set contains answers that are highly similar to the ideal answers, demonstrating excellent performance of the system for accurately written responses.

2) Medium Accuracy Set (Set 2): o Cosine Similarity Score: 0.88 o Description: Answers in this set moderately align with the ideal answers, showing acceptable system performance for partially correct or less detailed responses.

3) Low Accuracy Set (Set 3): o Cosine Similarity Score: 0.72 o Description: This set represents answers with minimal similarity to the ideal answers, highlighting the system's ability to identify less accurate or irrelevant responses.

V. CONCLUSION

The integration of IoT technologies with advanced machine learning algorithms in the AgroSmart system presents a significant step toward modernizing traditional agriculture. By utilizing real-time sensor data—such as soil moisture, temperature, pH, and humidity—the system provides continuous monitoring of critical soil parameters. This data is processed through machine learning models trained on historical agricultural datasets, enabling accurate and context-aware crop recommendations.

The AgroSmart solution directly addresses long-standing agricultural challenges, including inefficient use of water and fertilizers, suboptimal crop selection, and the inability to respond promptly to changing soil conditions. By equipping farmers with timely, science-backed decisions, the system enhances agricultural productivity while minimizing waste and environmental impact.

The platform's user-centric design ensures that even farmers with limited technical knowledge can interact with the system through intuitive dashboards and visual insights. Moreover, its scalability allows for deployment in small farms as well as large-scale agricultural operations, making it suitable for widespread adoption in both developing and developed countries.

In addition to boosting yield and ensuring soil health, AgroSmart promotes precision agriculture—a method that tailors farming practices to specific field conditions. This contributes to sustainable farming, where resources are used judiciously, biodiversity is preserved, and economic outcomes are optimized.

Furthermore, the project showcases how emerging technologies such as IoT and AI/ML can be harmoniously blended to create impactful, low-cost solutions that are aligned with the goals of digital agriculture and rural development. AgroSmart thus exemplifies the transformative potential of smart farming technologies in achieving food security, improving farmer livelihoods, and driving the future of agriculture in the 21st century.

Future Work

To further enhance the effectiveness and impact of the AgroSmart system, the following future enhancements are proposed:

- Integration of Weather Forecasting: Incorporating real-time weather prediction APIs to adjust crop recommendations based on upcoming climatic conditions.
- Expanded Crop Database: Including a wider variety of crops and soil profiles to increase system applicability across diverse geographical regions.
- Advanced Deep Learning Models: Utilizing models like LSTM or BERT for improved prediction accuracy in time-series soil behavior and crop suitability.
- Farmer Feedback Loop: Enabling feedback collection from users to continuously retrain and improve the recommendation models.
- Multilingual and Voice-Enabled Interface: Supporting regional languages and voice commands to make the system more accessible to non-tech-savvy farmers.
- Automated Irrigation Integration: Linking with smart irrigation systems to automate watering based on soil moisture and crop needs.

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