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AI driven smart soil and crop recommendation system using an embedded IOT platform.

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ABSTRACT

Precision agriculture has emerged as a promising solution to address the challenges of declining soil health, inefficient resource utilization, and improper crop selection in traditional farming practices. Conventional soil analysis methods are often time-consuming, costly, and incapable of providing real-time insights required for timely decision-making. To overcome these limitations, this paper presents an AI-driven smart soil and crop recommendation system built on an embedded Internet of Things (IoT) platform.The proposed system integrates a multi-parameter soil sensor with an ESP32 microcontroller to continuously monitor critical soil and environmental attributes such as nitrogen, phosphorus, potassium, pH, moisture, and temperature. The sensed data is transmitted to a cloud platform using wireless communication protocols, where advanced machine learning models perform intelligent analysis. Transformer-based and deep learning models are employed to recommend suitable crops, optimal fertilizer usage, and irrigation schedules based on real-time and historical data. The generated recommendations are delivered to farmers through a user-friendly mobile application and IoT dashboard, enabling informed and timely agricultural decisions. Experimental evaluation demonstrates improved prediction accuracy, efficient resource utilization, and enhanced accessibility compared to conventional farming approaches. The proposed system offers a scalable, cost-effective, and sustainable solution for smart agriculture applications.

Keywords: Smart agriculture, Internet of things (IoT), Soil analysis, Crop recommendation, Machine learning, Embedded systems, Precision farming

1. INTRODUCTION:

Agriculture plays a vital role in ensuring food security and economic stability, especially in developing countries where farming remains the primary source of livelihood. However, traditional agricultural practices often rely on manual soil testing, seasonal experience, and generalized recommendations, which may not accurately reflect the real-time condition of the soil. Such approaches can lead to improper crop selection, excessive fertilizer usage, inefficient irrigation, and long-term degradation of soil fertility.

With the rapid advancement of digital technologies, precision agriculture has gained significant attention as an effective solution to these challenges. The integration of the Internet of Things (IoT) enables continuous monitoring of soil and environmental parameters, while Artificial Intelligence (AI) facilitates intelligent analysis and decision-making based on complex data patterns. By combining sensing, communication, and intelligent computation, smart agriculture systems can provide accurate and timely recommendations to farmers, improving productivity and sustainability.

Fig 1: Soil And Crop Recommendation

Several existing studies have explored IoT-based soil monitoring and machine learning-based crop prediction systems. While these solutions demonstrate the potential of smart farming, many of them operate on static datasets, lack real-time adaptability, or focus on a single aspect such as crop recommendation or irrigation control. Moreover, limited interaction with end users and the absence of explainable intelligence reduce their practical adoption at the field level.

To address these limitations, this paper proposes an AI-driven smart soil and crop recommendation system using an embedded IoT platform. The system continuously collects soil parameters through a multi-sensor module and processes the data using an ESP32 microcontroller. The sensed data is transmitted to a cloud-based intelligence layer, where advanced machine learning models analyze soil health and environmental conditions to generate personalized recommendations. These recommendations are delivered to farmers through an intuitive mobile application and IoT dashboard.

The main contributions of this work include the integration of real-time soil sensing with cloud-based AI intelligence, the application of advanced machine learning models for accurate crop and fertilizer recommendation, and the development of a user-friendly interface that bridges the gap between complex analytics and practical farming needs. The proposed system aims to support data-driven decision-making, optimize resource utilization, and promote sustainable agricultural practices.

2. RELATED WORK

Recent advancements in smart agriculture have encouraged the adoption of Internet of Things (IoT) and machine learning techniques to improve crop productivity and resource management. Early research primarily focused on IoT-based soil monitoring systems that employed sensors to measure parameters such as soil moisture, temperature, and humidity. These systems enabled real-time data collection; however, they were largely limited to data visualization and lacked intelligent decision-making capabilities.

Subsequent studies introduced machine learning algorithms for crop prediction and yield estimation using historical soil and weather datasets. Traditional classifiers such as Decision Trees, Support Vector Machines, and Naïve Bayes were commonly applied to recommend crops based on nutrient content and climatic conditions. While these approaches improved prediction accuracy compared to rule-based systems, their performance was constrained by static datasets and limited adaptability to real-time soil variations.

More recent research explored deep learning and cloud-based analytics for agricultural applications. Neural networks and ensemble learning methods were employed to capture complex relationships among soil nutrients, environmental factors, and crop growth patterns. Although these methods demonstrated enhanced accuracy, many systems required high computational resources and lacked transparency, making them less suitable for deployment in low-cost, resource-constrained environments.

Several works have also investigated integrated smart farming platforms that combine soil analysis, irrigation control, and fertilizer management. Despite their potential, these systems often addressed only one or two agricultural aspects and did not provide a unified, end-to-end solution. Additionally, limited user interaction and the absence of mobile-based decision support reduced their usability for farmers.

In contrast to existing approaches, the proposed system integrates real-time soil sensing, cloud-based intelligence, and advanced machine learning models within a single framework. By employing explainable and efficient AI models and delivering personalized recommendations through a mobile application, the system overcomes the limitations of previous works and supports practical, data-driven agricultural decision-making.

Table IV. Comparison of Existing Systems and Proposed System

Feature	Existing Systems	Proposed System
Processing Speed	Delayed (7-14 days for lab results)	Real-time monitoring
Learning	Static rule-based or basic ML	AI/Deep Learning (TTL, SwiFT)
Explainability	Black-box decisions	Explainable AI (XAI) integrated
Accessibility	Limited in remote areas	Mobile App for small-scale farmers
Data Usage	Manual/Localized data	IoT & Cloud-based data fusion

Fig 2: Comparison of Existing and Proposed System

3. PROBLEM STATEMENT

Agricultural productivity is highly dependent on soil quality, appropriate crop selection, and efficient use of resources such as water and fertilizers. In traditional farming practices, soil analysis is typically performed through manual sampling and laboratory testing, which is time-consuming, costly, and unsuitable for continuous monitoring. As a result, farmers often rely on experience-based decisions that may not accurately reflect the current soil condition.

Existing smart agriculture solutions attempt to address these challenges using sensor-based monitoring or machine learning techniques. However, many of these systems operate on static datasets, lack real-time adaptability, or focus on isolated functions such as soil monitoring or crop recommendation. The absence of integrated intelligence leads to inaccurate recommendations, inefficient resource utilization, and limited practical adoption.

4. PROPOSED SYSTEM

The proposed system is an AI-driven smart agriculture platform designed to provide real-time soil analysis and intelligent crop recommendations using an embedded IoT framework. The system integrates sensing devices, edge processing, cloud-based intelligence, and a user interaction layer to support data-driven agricultural decision-making. The overall design ensures scalability, accuracy, and ease of use for farmers.

A. Soil Sensing and Data Acquisition Module

This module is responsible for collecting real-time soil and environmental data from the agricultural field. A multi-parameter soil sensor is deployed to measure essential soil attributes such as nitrogen (N), phosphorus (P), potassium (K), pH, moisture, and temperature. These parameters provide a comprehensive representation of soil fertility and condition.

The sensors continuously monitor the soil and transmit the collected data to the embedded controller. Real-time data acquisition enables dynamic analysis and eliminates the need for manual soil testing, making the system suitable for continuous field deployment.

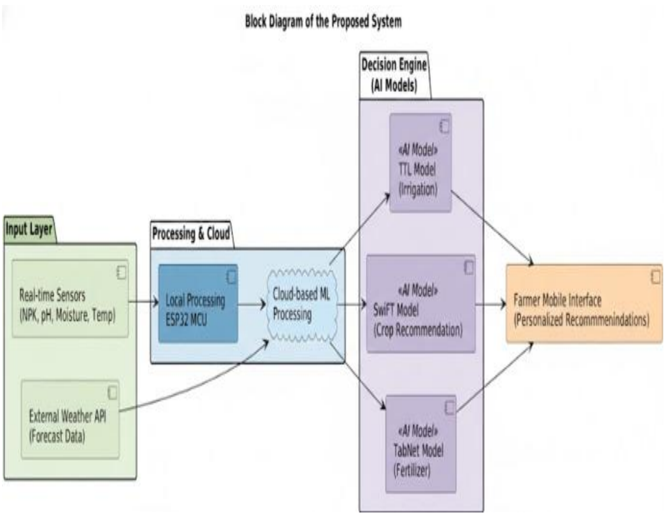

Fig 3: Proposed System

B. Embedded Processing and Communication Module

The embedded processing unit, based on an ESP32 microcontroller, acts as the core controller of the system. It receives raw sensor data and performs initial preprocessing, including noise filtering and data validation. This preprocessing reduces communication overhead and improves the reliability of transmitted data.

Table I. Soil and Environmental Sensors Used in the System

Sensor	Parameter	Purpose
NPK Sensor	Nitrogen, Phosphorus, Potassium	Measure macronutrient levels for growth
pH Sensor	Soil Acidity/Alkalinity	Determine optimal chemical balance
Moisture Sensor	Water Content	Irrigation planning and scheduling
Temperature	Ambient Temperature	Monitoring environmental stress
Humidity	Air Moisture	General field health assessment

Fig 4: Soil and Environmental Sensors

The processed data is transmitted to the cloud platform using wireless communication protocols such as Wi-Fi or MQTT. The use of low-power embedded hardware ensures energy efficiency and cost-effectiveness, enabling deployment in resource-constrained agricultural environments.

C. Cloud-Based Intelligence and Machine Learning Module

The cloud layer serves as the intelligence backbone of the proposed system. It stores real-time and historical soil data and executes machine learning algorithms for data analysis and prediction. Advanced learning models analyze soil nutrient levels and environmental conditions to recommend suitable crops, fertilizer quantities, and irrigation schedules.

By leveraging cloud computing, the system supports scalable processing and continuous model improvement. The intelligent analysis enables personalized and location-specific recommendations, improving decision accuracy and agricultural productivity.

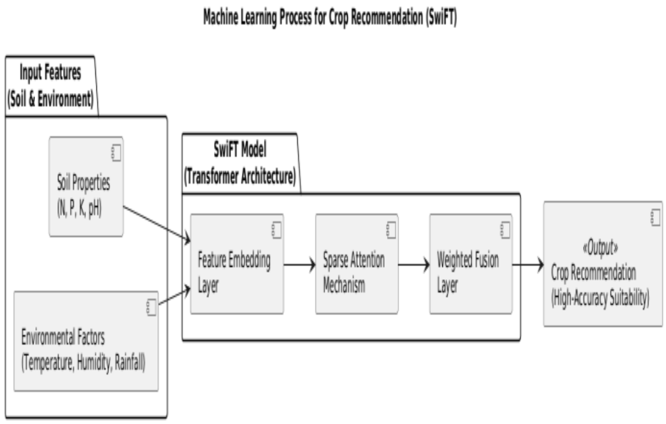

Fig 5: Machine Learning Process for Crop Recommendation

D. User Interface and Decision Support Module

The final module provides interaction between the system and the end user. A mobile application and IoT dashboard display real-time soil parameters, historical trends, and AI-generated recommendations in a simple and intuitive format. Visual indicators and alerts assist farmers in understanding soil health and required actions.

This decision support interface ensures accessibility for users with minimal technical knowledge and enhances practical adoption. By presenting actionable insights rather than raw data, the system bridges the gap between advanced analytics and real-world farming practices.

5. SYSTEM ARCHITECTURE

The system architecture of the proposed AI-driven smart agriculture system is designed as a layered and modular framework to ensure reliability, scalability, and real-time performance. The architecture integrates sensing, embedded processing, cloud intelligence, and user interaction components. The overall structure of the system is illustrated in the system architecture diagram.

A. Perception Layer (Sensor Layer)

The perception layer is responsible for capturing real-time soil and environmental parameters from the agricultural field. This layer consists of a multi-parameter soil sensor capable of measuring essential attributes such as soil moisture, temperature, pH value, and nutrient levels including nitrogen, phosphorus, and potassium. These parameters play a critical role in assessing soil fertility and crop suitability.

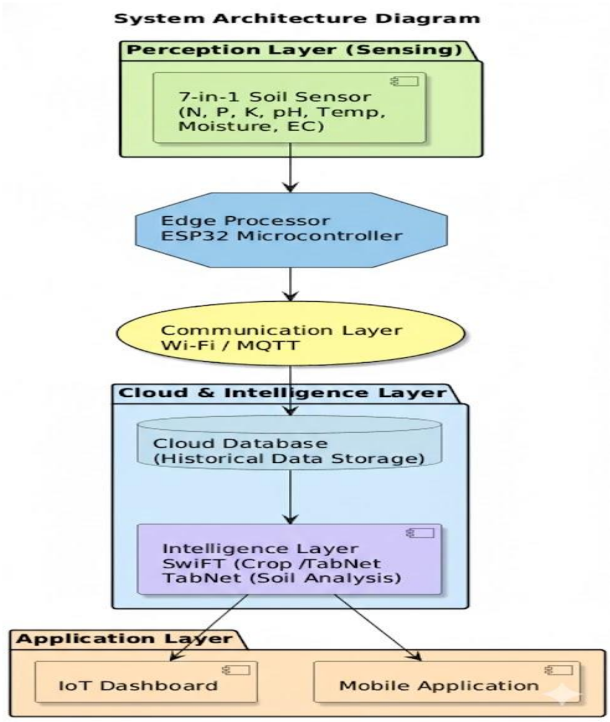

Fig 6: System Architecture

The continuous monitoring performed at this layer provides accurate and up-to-date field data, forming the foundation for intelligent analysis and decision-making.

Table II. Dataset Parameters Used for Machine Learning

Parameter	Description
Nutrients	N, P, K values (Numerical, scaled 0-1)
Environment	Temperature, Humidity, Rainfall
Soil Health	pH levels and moisture content
Target Labels	Crop categories (Rice, Wheat, Maize, etc.)

Fig 7: Dataset Parameters

B. Edge Processing Layer (Embedded Controller)

The edge processing layer consists of an embedded ESP32 microcontroller that interfaces directly with the soil sensors. This layer performs initial data handling tasks such as sensor calibration, noise filtering, and data formatting. Processing data at the edge reduces unnecessary cloud communication and improves system responsiveness.

In addition, the ESP32 manages power-efficient operation and ensures reliable data transmission to higher layers of the system.

Table III.Performance Evaluation of the Proposed System

Metric	Model	Value
Accuracy	SwiFT (Crop Recommendation)	98.75%
Accuracy	TTL (Irrigation Advice)	99.13%
Accuracy	TabNet (Fertilizer Rec.)	99.30%
R^2 Score	TabNet (Soil Analysis)	98.70%

Fig 8: Performance Evaluation

C. Communication and Cloud Intelligence Layer

This layer enables seamless data transfer between the embedded system and the cloud platform using wireless communication protocols such as Wi-Fi or MQTT. The cloud infrastructure stores real-time and historical soil data and hosts the machine learning models responsible for intelligent analysis.

Advanced machine learning algorithms analyze the incoming data to generate accurate crop recommendations, fertilizer suggestions, and irrigation advice. The cloud-based design allows scalable processing, continuous learning, and easy integration of additional intelligence modules.

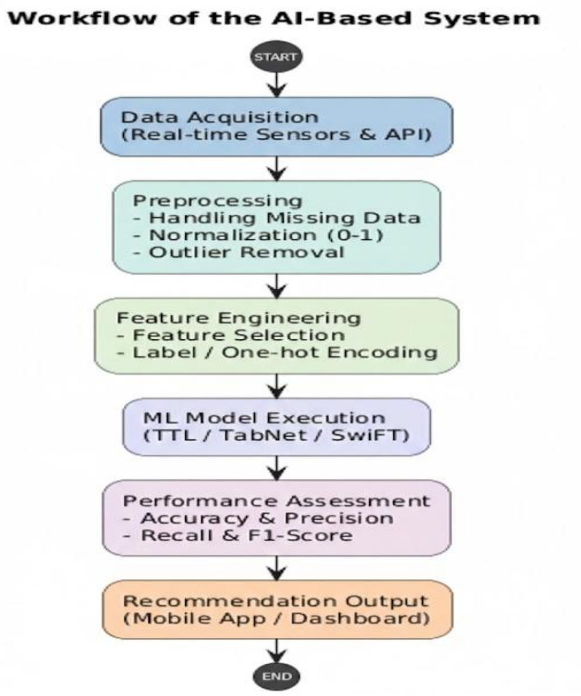

Fig 9: Work Flow

D. Application and User Interaction Layer

The application layer provides an interface between the intelligent system and the end user. A mobile application and IoT dashboard present real-time soil conditions, historical trends, and AI-generated recommendations in a clear and user-friendly manner. Visual indicators, alerts, and notifications assist farmers in understanding system outputs and taking timely action.

This layer enhances accessibility and usability, ensuring that farmers can effectively benefit from the intelligent recommendations without requiring technical expertise.

6. RESULTS AND DISCUSSION

The proposed AI-driven smart agriculture system was evaluated to analyze its effectiveness in real-time soil monitoring and intelligent crop recommendation. The system performance was assessed based on prediction accuracy, system responsiveness, usability, and overall efficiency. Experimental validation was carried out using real-time sensor data and historical agricultural datasets.

A. Dataset and Experimental Setup

The evaluation was conducted using a combination of real-time soil sensor data collected from the field and publicly available agricultural datasets. The dataset included key soil parameters such as nitrogen, phosphorus, potassium, pH, moisture, and temperature. These parameters were used as input features for training and testing the machine learning models.

The system was implemented using an ESP32-based embedded platform, and cloud-based processing was employed to execute machine learning algorithms. The experimental setup ensured consistent data acquisition and reliable communication between the sensing, processing, and application layers.

B. Performance of Machine Learning Models

The machine learning models demonstrated effective performance in analyzing soil conditions and recommending suitable crops. The intelligent models successfully captured the relationship between soil nutrients and crop requirements, resulting in accurate and consistent recommendations.

The system showed improved prediction accuracy compared to conventional rule-based approaches. The use of advanced learning techniques enabled the system to adapt to varying soil conditions and provide personalized recommendations, enhancing decision-making reliability.

C. System Responsiveness and Resource Efficiency

The proposed system achieved low latency in data transmission and response generation due to efficient edge processing and cloud integration. The embedded controller reduced unnecessary data communication by preprocessing sensor values, thereby optimizing bandwidth usage.

Additionally, the system demonstrated efficient resource utilization by minimizing excessive fertilizer application and optimizing irrigation schedules. This contributes to cost reduction and sustainable farming practices.

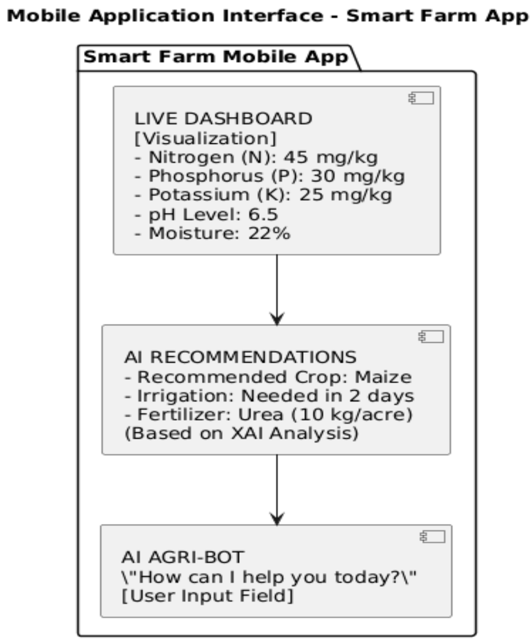

Fig 10: Mobile Application

D. User Interface and Practical Usability

The mobile application and IoT dashboard provided clear visualization of soil parameters and recommendations, enabling farmers to easily interpret system outputs. The user interface displayed real-time values, historical trends, and actionable alerts, improving usability and user engagement.

The practical deployment results indicate that the proposed system is user-friendly and suitable for real-world agricultural environments. The integration of intelligent analytics with an accessible interface significantly enhances farmer adoption and trust.

7. CONCLUSION

This paper presented an **AI-driven smart soil and crop recommendation system** using an embedded IoT platform to support precision agriculture. The proposed system integrates real-time soil sensing, edge-level processing, cloud-based intelligence, and a user-friendly application interface to provide accurate and timely agricultural recommendations.

By continuously monitoring key soil parameters such as nutrient levels, moisture, pH, and temperature, the system enables data-driven decision-making for crop selection, fertilizer application, and irrigation planning. The use of machine learning models enhances prediction accuracy and adaptability to varying soil conditions, while the embedded IoT architecture ensures cost-effective and scalable deployment.

Experimental results demonstrate that the proposed system improves resource utilization, reduces manual effort, and enhances accessibility to intelligent agricultural insights. The intuitive mobile interface further bridges the gap between advanced analytics and practical farming needs, promoting real-world adoption.

In the future, the system can be extended by incorporating weather forecasting data, satellite imagery, and adaptive learning techniques to further enhance prediction accuracy. The integration of multilingual voice assistance and regional customization can also improve usability for farmers across diverse agricultural environments. Overall, the proposed solution contributes toward sustainable and intelligent farming practices..

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