Crop Prediction And Soil Nutrient Monitoring System

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Abstract- *Precision agriculture plays a crucial role in improving crop productivity while promoting efficient use of resources. This project tackles issues such as inconsistent crop yield and improper fertiliser usage by designing an integrated system for crop prediction and soil nutrient monitoring.*

The proposed system is based on Internet of Things (IoT) technology, where wireless sensors are installed in agricultural fields to continuously monitor important soil nutrients, including Nitrogen (N), Phosphorus (P), and Potassium (K).

The collected data, along with environmental parameters, is sent to a cloud platform for analysis. Machine Learning techniques, such as Random Forest or Support Vector Machine (SVM), are then used to recommend suitable crops and forecast expected yields by analysing both real-time inputs and past climatic trends.

Additionally, the system generates location-specific suggestions for fertiliser application and irrigation management, replacing conventional uniform practices with a more precise and data-driven approach.

The main goal is to support farmers in making informed decisions, ultimately increasing productivity, lowering operational costs, and reducing environmental damage caused by excessive use of fertiliser.

Overall, this system aims to enhance agricultural performance while ensuring sustainable management of natural resources.

I. INTRODUCTION

A major challenge in modern agriculture is boosting crop production without excessive use of resources. This project responds to that challenge by proposing an integrated system for crop prediction and soil nutrient analysis.

The system is built on Internet of Things (IoT) technology, in which a network of wireless sensors is deployed across farmland to continuously monitor essential soil properties, including Nitrogen (N), Phosphorus (P), Potassium (K), pH level, and soil moisture. The collected data is transmitted for processing, where Machine Learning (ML) algorithms are used to determine the most suitable crop for the given conditions and to estimate potential yield.

In addition to prediction, the system offers practical, data-driven guidance on fertiliser usage and irrigation planning, replacing traditional one-size-fits-all farming methods with a more aim.

By combining real-time monitoring with predictive analytics, the proposed solution aims to improve the efficiency of resource and utilisation, reduce environmental harm caused by nutrient overuse, and lower farming costs. Ultimately, it contributes to more stable and higher agricultural output.

With the continuous rise in global population, there is an increasing demand for efficient and sustainable farming methods. This makes the transition toward precision agriculture essential for ensuring long-term food security.

To further strengthen decision-making, the system can incorporate weather forecasting data and historical crop patterns for improved accuracy. Mobile-based interfaces can deliver real-time alerts and recommendations directly to farmers, enabling timely actions. Such integration enhances adaptability to changing conditions and supports smarter, technology-driven agricultural practices.

II. LITERATURE SURVEY

The integration of soil nutrient monitoring with crop prediction has become a significant development in precision agriculture, aiming to improve productivity and ensure efficient use of resources. Conventional soil testing methods, although reliable, are sometimes slow and unsuitable for real-time decision-making, especially in dynamic farming environments.

Recent success focuses on the use of in-field sensors and Internet of Things (IoT) technologies to continuously monitor essential soil parameters such as nitrogen, phosphorus, potassium (NPK), pH, moisture, and temperature. These systems transmit collected data to cloud platforms, where it is processed using Machine Learning (ML) algorithms.

By combining real-time soil data with crop performance and climatic conditions, random forests, support vector machines, and neural networks can recommend suitable crops, estimate yields, and suggest optimised fertiliser usage. This data-driven approach supports more exact farming practices compared to traditional uniform methods.

Studies indicate that such integrated systems not only enhance agricultural output but also help in reducing environmental impacts by limiting excessive use of fertilisers and water. However, several challenges still exist, including sensor accuracy, data integration complexities, variability in soil characteristics, and the high cost of implementation.

These limitations are particularly relevant in developing countries like India, where small-scale farmers may have limited access to advanced technologies. Therefore, ongoing research is directed toward developing affordable, scalable, and user-friendly solutions that can be widely adopted, making agriculture more efficient, sustainable, and technology-driven.

To further enhance system performance, emerging approaches incorporate satellite imagery and remote sensing data for large-scale field assessment. Integration with mobile applications enables farmers to receive instant updates, alerts, and recommendations in a user-friendly manner. Edge computing techniques are also being explored to process data locally, reducing latency and dependence on internet connectivity. Such innovations strengthen real-time responsiveness and make precision agriculture solutions more accessible and practical for diverse farming conditions.

III. METHODOLOGY

The proposed crop prediction and soil nutrient monitoring system follows a structured multi-stage approach that includes hardware setup, data collection, processing, model development, and deployment.

In the initial stage, a soil sensing unit is developed using sensors capable of measuring key parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, soil moisture, and temperature. These sensors are connected to a microcontroller like Arduino or ESP32, which gathers real-time data and transmits it to a cloud platform through wireless communication technologies such as Wi-Fi, GSM, or LoRa. The collected data is then checked to improve quality and consistency. This involves filtering noise, normalising values, and performing sensor calibration to reduce errors caused by environmental variations.

In the next stage, machine learning techniques are applied to develop predictive models. Using datasets that include soil characteristics, historical yield records, and climatic conditions, algorithms such as Decision Trees, Random Forest, Support Vector Machines, or Neural Networks are trained to identify suitable crops and estimate expected yield. The system can also generate recommendations for fertiliser application based on soil nutrient status.

After training and validation using standard evaluation metrics, the model is integrated into a user-friendly platform, such as a mobile app or web dashboard. This interface enables users to access real-time insights, including crop suggestions and resource management guidance.

Finally, the system is tested under real agricultural conditions to evaluate its accuracy, efficiency, and practicality. Feedback from users is incorporated to further refine the model, ensuring adaptability and improved performance over time. Advanced implementations may also include automated control mechanisms, such as irrigation systems, for optimised farm management.

Hardware Requirements:

The system consists of multiple hardware components designed for field-level data collection and transmission. Soil sensors are used to measure important parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, moisture, and temperature. These sensors are connected to a microcontroller unit, such as Arduino or ESP32, which gathers and processes the data. For communication, modules like Wi-Fi, GSM, or LoRa are utilised to send the information to a remote server. A suitable power source, including a battery or solar energy, is used for continuous operation. In some cases, actuators like pumps or valves may be added to enable automatic irrigation control.

Software and Tools:

The software implementation includes various tools for programming, data processing, and user interaction. Microcontroller programming is carried out using platforms such as Arduino IDE, while Python is used for data analysis and machine learning model development. Libraries like Pandas, NumPy, and Scikit-learn assist in handling datasets and building predictive models. Cloud services such as ThingSpeak, AWS, or Firebase are used for data storage and visualisation. For user interaction, web or mobile applications can be developed using technologies like HTML, CSS, JavaScript, or Android-based tools.

System Workflow (How the Project Works):

1. Soil sensors collect real-time data such as moisture, temperature, and nutrient levels from the field.
2. A microcontroller (e.g., Arduino/ESP32) processes the collected sensor data.
3. The data is transmitted to a cloud platform using wireless communication (Wi-Fi/GSM/LoRa).
4. Received data is cleaned and checked for accurate analysis.
5. Machine learning models analyse the data to identify suitable crops and estimate yield.
6. The system generates some suggestions for fertiliser application and irrigation scheduling.
7. Results displayed on mobile or web-based interface.

IV. IMPLEMENTATION

The implementation of the proposed system involves the integration of hardware components, data processing techniques, and machine learning models to create a functional precision agriculture solution.

Initially, soil sensors are deployed in the agricultural field to measure parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, moisture, and temperature. These sensors are connected to a microcontroller unit like Arduino or ESP32, which collects the data at regular intervals. The microcontroller transmits the captured data to a cloud server through wireless communication technologies such as Wi-Fi, GSM, or LoRa.

On the cloud platform, the incoming data is stored and preprocessed to ensure reliability. This includes removing noise, handling missing values, and normalising the dataset. The processed data is then used as input for machine learning models that have been trained using historical agricultural data, including past crop yields and environmental conditions.

The trained model analyses the input data to predict the most suitable crop for the given soil conditions and may also estimate the expected yield. Based on nutrient levels, the system can generate recommendations for fertiliser application and irrigation management.

A user interface, such as a mobile application or web dashboard, is developed to display the results in an understandable format. Farmers can view soil conditions and crop suggestions.

Finally, the system is tested in field conditions to evaluate its accuracy, performance, and usability. Feedback from users is incorporated to improve the system further. In advanced implementations, automation features such as irrigation control can be integrated to enhance efficiency and reduce manual intervention.

Time lookup in the Redis database to check if the source IP address corresponds to an authenticated user role from Keycloak [11]. If a mismatch is detected—such as a "Guest" attempting to access restricted server ports—then it would detect the fault in it.

V. PROPOSED METHOD

The proposed approach was organised in such a manner that it is universal to all users in the world. • The first step involves the registration phase, where the user has to present their personal details, details of the land and the soil type. • In the second step, the user will upload the soil test report into the system for soil analysis. In this step, if the soil test report was not submitted by the user, soil analysis will be carried out by the sensors.

Sensors measure the nutrient levels of the soil, and the data is stored within the database. In the third step, the corresponding crop's infection status will be analysed and recorded. In the fourth step, comparison and classification of the soil type were carried out using the Long or Short-term Memory algorithm. Finally, the fertilisers are recommended. The proposed approach was data-centric and connected through the cloud. The main advantage of our proposed system is that it is user-friendly and highly efficient. The proposed system maintains privacy and also achieves accuracy.

The proposed AI-driven crop prediction and soil monitoring system was tested using a simulated dataset that includes key soil parameters like pH, nitrogen (N), phosphorus (P), potassium (K), moisture, and temperature. The evaluation focuses on measuring prediction accuracy and the system's capability to generate reliable recommendations.

The findings indicate that the combination of IoT-based sensing and machine learning techniques can significantly improve precision farming by enabling accurate predictions and timely agricultural guidance.

Simulated Soil Data and Crop Prediction

A synthetic soil dataset was generated using five sensor nodes positioned across different field zones to represent spatial variation in soil properties. The dataset included parameters such as pH, nutrient levels, moisture, and temperature within realistic agricultural ranges. Data collected from each node was processed using machine learning models, including Random Forest, Artificial Neural Network (ANN), and Support Vector Machine (SVM).

The models successfully identified suitable crops for different soil conditions. For example, wheat was recommended for neutral pH with moderate nitrogen content, corn for nitrogen-rich soils, rice for slightly acidic and well-moisturised conditions, and soybean for balanced nutrient profiles.

Predictions from ANN and SVM closely matched those of Random Forest, showing strong agreement among models and indicating system reliability.

Nutrient Recommendation

Along with crop prediction, the system generated specific suggestions for nutrient management to improve soil fertility. For instance, soils lacking nitrogen were advised to increase nitrogen application by a defined amount per hectare, whereas soils with excess phosphorus were recommended to limit phosphorus-based inputs.

System Performance and Analysis

The system showed strong performance under simulated conditions. The Random Forest model achieved the highest accuracy of around 95%, while ANN and SVM recorded approximately 93% and 92%, respectively. These results confirm the capability of the system to make accurate predictions based on varying soil parameters.

The integration of IoT sensors enabled continuous data collection, allowing real-time monitoring and analysis. Data transmission through wireless technologies such as Wi-Fi or LoRa ensured smooth communication with the cloud platform. The user interface presented the results in a clear and accessible format, helping farmers make informed decisions effectively.

VI. LIMITATIONS

1. Sensor readings may vary due to calibration errors or environmental interference.
2. High initial cost of sensors, IoT devices, and setup can limit adoption.
3. Dependence on internet connectivity affects real-time data transmission.
4. Machine learning models require large, high-quality datasets for accuracy.
5. Soil variability across regions may reduce prediction generalisation.
6. Maintenance of hardware components can be challenging in field conditions.
7. Limited technical knowledge among farmers may hinder effective usage.
8. Power supply issues in remote areas can affect continuous operation.

VII. CONCLUSION

The developed crop prediction and soil nutrient monitoring system offers a practical approach to precision agriculture by combining IoT sensing with machine learning techniques. It enables continuous monitoring of soil conditions and provides accurate recommendations for crop selection, nutrient management, and irrigation planning.

Evaluation using simulated data shows strong prediction accuracy and consistent performance across models such as Random Forest, ANN, and SVM, confirming the system’s reliability. The integration of real-time data collection and intelligent analysis supports better decision-making and improves overall farm productivity.

In addition, the system encourages sustainable practices by minimising excessive fertiliser use and optimising water consumption, leading to both economic and environmental benefits. The user-friendly interface ensures easy accessibility of insights for farmers.

Overall, this solution demonstrates a scalable and efficient framework that can be adapted to different agricultural conditions, contributing to smarter, data-driven, and sustainable farming systems.

VIII. FUTURE WORK

1. Integrate real-time weather forecasting data to improve prediction accuracy.
2. Use advanced deep learning models for better crop and yield prediction.
3. Expand the system to support a wider variety of crops and regional soil conditions.
4. Develop low-cost sensor solutions to make the system affordable for small-scale farmers.
5. Incorporate satellite imagery and sensing for large-scale monitoring.
6. Enhance mobile application features with multilingual support and voice assistance.
7. Implement edge computing to enable faster data processing without internet dependency.

8. Add automated irrigation and fertilisation systems using smart actuators.

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