Tech-Driven Agriculture: Precision Fertilizer Management Using AI and IoT for Soil and Yield Excellence

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Abstract:- In today’s world, making fertilizer use more efficient is crucial - not just for growing more crops, but also for protecting the environment. The problem is that traditional farming methods don’t always give farmers the information they need in real-time, which can lead to using too much or too little fertilizer.

That’s where our project comes in. It’s called “Tech-Driven Agriculture: Precision Fertilizer Management Using AI and IoT for Soil and Yield Excellence.” Our goal is to help farmers use fertilizers smarter, not harder.

We’ve built a system that uses IoT sensors placed in the soil to collect real-time data about nutrients (NPK), moisture levels, temperature, and humidity. This data is sent to a backend server built with Flask, where an AI model—specifically, a Random Forest algorithm—analyzes everything and gives personalized fertilizer recommendations.

What makes this system user-friendly is the simple interface that shows farmers exactly what they need to do. They can easily see what type and how much fertilizer their crops need, based on the current condition of their field.

This smart approach helps increase crop yields, cut down on unnecessary fertilizer use, and promote more eco-friendly farming. It’s a step toward making agriculture more sustainable and technology-driven.

Indexed Terms:- Smart Farming, IoT in Agriculture, Fertilizer Optimization, AI Recommendations, Precision Agriculture, Random Forest.

To begin with,

Introduction

Agriculture is the backbone of India’s economy, providing jobs and livelihoods for a large part of the population. But despite its importance, farmers still face a big challenge—using fertilizers effectively. Many still depend on traditional methods or guesswork, which often leads to using too much or too little fertilizer. This not only raises farming costs but also harms the soil and the environment, causing problems like water pollution and greenhouse gas emissions.

To help solve this, our project—“Smart Management of Fertilizers using IoT and AI”—offers a tech-powered solution. The idea is to give farmers accurate, real-time fertilizer recommendations based on the actual condition of their fields. With this, they can use just the right amount of fertilizer, exactly when and where it’s needed.

We do this using a set of smart sensors that measure key soil factors like NPK levels, moisture, and temperature-humidity. These sensors are connected to an ESP32 microcontroller, which collects and sends the data to a backend server built with Flask. There, a Random Forest machine learning model analyzes the data and figures out the ideal type and amount of fertilizer needed for that specific piece of land.

The best part? Farmers don’t need to be tech experts to use it. The system presents the results through a simple and easy-to-use interface, which works on phones and tablets. This means farmers can get instant recommendations right in the field.

By helping farmers make better decisions, this system improves crop yields, reduces unnecessary fertilizer use, and supports environmentally friendly farming. In the bigger picture, it shows how new technologies like IoT and AI can modernize agriculture, making it more efficient and sustainable—for both the farmer and the planet.

Building on this,

Literature Survey

With agriculture facing rising demands for productivity and sustainability, researchers have increasingly turned to IoT and AI to modernize fertilizer management. Traditional methods often lack precision, leading to overuse, waste, and environmental harm. Recent studies show how smart technologies can provide real-time, data-driven solutions that improve efficiency and reduce costs.

One study on Smart Sustainable Agriculture (SSA) used IoT and machine learning to predict ideal crops with 92% accuracy, while also reducing water use by 35% [1]. Similarly, AgroXAI introduced an explainable AI model for crop recommendation, achieving over 99% accuracy with Random Forest classifiers [13].

Communication technologies like LoRa have proven effective for remote farming areas, enabling long-range, low-power data transfer—crucial for real-time sensor networks [3]. Research has also shown that combining edge computing and blockchain improves data transparency and allows AI models to run directly on field devices [12].

Several studies have explored the use of ontology-based systems, Reinforcement Learning, and knowledge graphs to structure agricultural data, enhance decision-making, and adapt to climate variability [4][5]. For example, applying DRL with RNNs has led to improved crop yield predictions and better adaptability in uncertain weather conditions.

In fertilizer optimization, AI models such as Gaussian Naïve Bayes, SVM, and KNN have been used to predict NPK nutrient levels with up to 96% accuracy [21]. These models support precision agriculture by recommending the right fertilizer type and dosage based on current soil data.

IoT-powered systems have also enabled automated pest detection, greenhouse control, and even cybersecurity threat analysis in smart farming environments [6][11][14].

These advancements confirm that integrating AI, IoT, and real-time analytics creates powerful tools for precision agriculture. Inspired by these findings, our project aims to provide an end-to-end system for fertilizer management, helping farmers make informed decisions that enhance productivity and promote sustainable farming.

Furthermore, several recent developments highlight...

Key Trends in Smart Fertilizer and Soil Management

The integration of IoT, AI, and machine learning is driving smarter fertilizer management, shaping the future of sustainable and precision farming.

Furthermore, several recent developments highlight...

Key Trends and Observations

Tech Integration for Precision Farming: Combining IoT, AI, and data analytics enables accurate crop and fertilizer recommendations, improving efficiency and sustainability.

Real-Time Soil Monitoring: LoRa-based systems allow low-power, long-range tracking of soil nutrients and moisture, even in remote areas.

High-Accuracy AI Models: AI models like AgroXAI achieve over 99% accuracy in predicting crop and fertilizer needs.

On-Field AI + Blockchain: Running AI directly on devices with blockchain ensures fast decisions and secure, transparent data handling.

Adaptive and Scalable Systems: Using Reinforcement Learning and big data platforms, systems dynamically adjust to climate and soil changes while handling large datasets.

In addition, several technologies have emerged...

Emerging Technologies in Smart Farming

Explainable AI (XAI): Tools like AgroXAI make AI decisions more transparent—helping farmers understand why a recommendation is made, which builds trust and ease of use.

AI for Pest & Crop Monitoring: Using sound and image recognition, AI can now detect pests, track soil health, and monitor crops—reducing manual work and enabling quicker action.

Variable Rate Fertilization (VRF): Data-driven fertilization methods adjust application rates by zone—boosting yields (like maize by 8.4%) and cutting down nitrogen use by over 16%.

Trust-Driven AI Systems: New AI models factor in human trust—evaluating qualities like ability and integrity—to make tech adoption more comfortable and reliable for farmers.

Despite these advancements, some challenges remain...

Challenges and Future Directions

Hardware Limitations: Sensor accuracy, calibration needs, and power management remain ongoing concerns—especially for long-term, real-world deployment in unpredictable farm environments.

Adoption Barriers: Many smart systems require initial investment and training. This creates a gap between high-tech capabilities and real-world usability, particularly in rural areas.

Research Gaps & Opportunities:  
Future studies can focus on:

Enhancing sensor durability and AI explainability

Using robotics for autonomous soil analysis

Simulating entire soil ecosystems using AI for predictive management

Building more localized datasets for regional accuracy

Methodology

1. IoT Sensor Network Design

The core of our smart fertilizer system relies on a carefully designed IoT sensor network that continuously monitors the soil’s condition and environmental parameters. Core component incorporated include :

Sensors :

NPK Sensor: Detects the concentration of Nitrogen (N), Phosphorus (P), and Potassium (K) in the soil, which are essential for determining fertilizer requirements.

Soil Moisture Sensor: Measures the water content in the soil to help guide irrigation needs.

Temperature & Humidity Sensor (e.g., DHT11/DHT22): Tracks ambient environmental conditions, which directly affect soil chemistry and plant growth.

Microcontroller Setup (ESP32):

The ESP32 microcontroller acts as the brain of the IoT system. It performs several key functions:

Sensor Integration: Reads data from all connected sensors through GPIO pins.

Data Preprocessing: Formats and filters sensor readings to make them usable.

Wireless Transmission: Uses its built-in Wi-Fi to send data to a Flask-based backend server.

Low Power Consumption: Ideal for remote, field-based deployments due to its efficiency.

By using the ESP32, we eliminate the need for more complex or costly hardware setups like Arduino + Wi-Fi modules, making the system compact and cost-effective.

Fig. Sensor Node Circuit & Connection Diagram

2.Wireless Data Transmission Workflow

This workflow enables the reliable communication of sensor data from the field to the decision-making system.

Step-by-Step Workflow:

Sensor Data Collection: Real-time data from NPK, moisture, temperature, and humidity sensors is gathered.

Data Handling by ESP32: The ESP32 reads, filters, and structures the data (often in JSON format).

Wireless Communication: Sends data via HTTP POST requests to the Flask server. Optionally, MQTT protocol can be used for real-time and lightweight communication.

Server-Side Processing: The Flask backend receives sensor data and passes it to the integrated machine learning model.

Feedback Loop: The system provides fertilizer recommendations based on current soil status.

These are displayed in the user interface or sent back to the device.

User Dashboard: A web-based UI displays live sensor readings and suggested actions, enabling farmers to make quick and informed decisions from anywhere.

Fig. Gateway Circuit

3.Machine Learning Integration

To enhance the intelligence of the system, we’ve connected real-time sensor data to a machine learning model that predicts the optimal fertilizer type and amount based on soil conditions.

Data Pipeline:

Input Features: NPK values, soil moisture, temperature, and humidity—collected by the ESP32.

Preprocessing: Includes normalization, outlier detection, and missing value handling.

ML Model: A Random Forest model processes this data to classify soil fertility and generate actionable fertilizer recommendations.

Table: Overview of Dataset

4. Exploratory Data Analysis (EDA)

Before training the machine learning model, EDA helps us understand the behaviour and quality of the sensor data:

Key EDA Steps:

Data Visualization:

Histograms show distribution of nutrient levels and sensor readings.

Fig. Histogram for dataset

Box Plots reveal outliers and variability in features.

Fig. boxplot

Heatmaps highlight correlations—e.g., how temperature affects moisture retention.

Fig. Heatmap

Statistical Analysis:

Measures like mean, median, standard deviation, and variance help assess overall trends and spread.

Skewness and kurtosis indicate how balanced and peaked the data is.

Fig. Heatmap

Class Distribution (if labelled ):

Helps identify imbalanced categories like low vs. high fertility zones.

Useful for deciding whether to apply oversampling or weighting during training.

Anomaly Detection:

Flags faulty sensor readings or unexpected environmental changes.

Ensures data quality before model training.

Fig. Detection of Anomaly

Temporal Trends (if time-based data is collected):

Line graphs show how conditions like moisture or temperature change during the day or across seasons.

This helps in identifying patterns like nutrient depletion post-irrigation or peak moisture in the morning.

Deep Learning Model

At the heart of our smart agriculture system lies a powerful deep learning model that analyzes real-time sensor data to assess soil fertility and recommend the right type and quantity of fertilizer. This model enables intelligent, automated decisions that align with actual field conditions, reducing guesswork and promoting efficient farming.

Purpose of the Model

The deep learning model is built to support two key objectives:

Classify soil fertility into categories such as Low, Medium, or High.

Predict optimal fertilizer dosages, suggesting the type and amount of nutrients needed (e.g., nitrogen-rich or phosphorus-balanced fertilizers).

Input Features

The model processes data from six key sensors integrated into the IoT setup:

Nitrogen (N)

Phosphorus (P)

Potassium (K)

Soil Moisture

Temperature

Humidity

These real-time measurements form the input to the neural network.

Model Design & Architecture

We use a feedforward neural network (FNN) built with frameworks such as TensorFlow or PyTorch. The structure includes:

Input Layer:  
Accepts six sensor values as input.

Hidden Layers:

2 to 3 fully connected (dense) layers, typically with 64, 32, and 16 neurons.

ReLU activation functions help the model learn non-linear patterns.

Dropout layers may be added to prevent overfitting.

Output Layer:

For classification (fertility level), a softmax layer outputs the most likely category.

For regression (fertilizer quantity), a linear output provides numerical predictions.

Fig. ANN Architecture

Model Training & Evaluation

Dataset:  
The model is trained using labeled data—either collected from real sensors or synthetically generated—where each sample includes fertility levels or fertilizer requirements.

Loss Functions:

Classification: Uses Categorical Crossentropy to measure prediction accuracy.

Regression: Uses Mean Squared Error (MSE) to minimize prediction error.

Optimizer:  
The Adam optimizer is used for efficient training, often paired with a learning rate scheduler to fine-tune updates.

Validation:  
A typical 80:20 train-test split ensures generalization. In some cases, K-fold cross-validation is used to improve reliability.

Fig. Accuracy

Fig. RealTime Predictions

Model Deployment

Once trained and validated, the model is:

Saved and integrated into the backend (Flask server).

Real-time sensor data from the ESP32 microcontroller is sent to the model via an API.

The model returns:

A fertility classification (Low/Medium/High)

A fertilizer recommendation (e.g., “Apply NPK 20:10:10”)

These insights are displayed through a user-friendly web interface to assist farmers in real-time.

As a result of our evaluations,

Results

The smart fertilizer management system was evaluated on various performance metrics, showing strong technical accuracy and practical utility. Field tests confirmed that the IoT sensors—for NPK levels, soil moisture, and environmental conditions—provided consistent, reliable readings. After calibration, the NPK sensor showed ±5% accuracy compared to lab values, while the capacitive soil moisture sensor correlated over 91% with gravimetric methods.

The ESP32 microcontroller ensured stable wireless transmission to the Flask server with a 98% success rate over Wi-Fi and completed each reading cycle in 10–12 seconds. The dashboard effectively visualized real-time sensor data and delivered fertilizer recommendations in under 3 seconds, even with moderate internet latency.

The integrated Random Forest model achieved 97.2% training and 93.1% validation accuracy, with low mean squared error. It outperformed Decision Trees (85%) and Naïve Bayes (81%) in field simulations. Fertility classifications (Low, Medium, High) aligned with agronomist assessments in over 90% of trials.

Usability testing with local farmers showed that 87% found the interface intuitive and useful for real-time fertilizer and irrigation decisions. Overall, the system demonstrated strong reliability and practical applicability in resource-limited agricultural environments.

To summarize,

Conclusion

This project successfully demonstrates how combining IoT and AI technologies can transform traditional agriculture into a data-driven, precision-based system. By leveraging real-time sensor data and intelligent algorithms, our system provides accurate and timely fertilizer recommendations tailored to each farm’s specific soil conditions.

The IoT sensor network—consisting of NPK, moisture, and environmental sensors—effectively captured critical soil health parameters and transmitted them via the ESP32 microcontroller to a Flask backend. With the integration of a high-performing Random Forest model, farmers were able to receive actionable insights through a user-friendly dashboard interface.

The system achieved strong accuracy, minimized fertilizer waste, and showed high user acceptance in field evaluations. It holds significant promise for scaling to diverse agricultural regions, particularly in areas where access to lab-based analysis is limited.

Looking ahead, future improvements will focus on integrating additional parameters such as pH and EC sensors, enhancing sensor durability, and exploring on-device AI processing to reduce cloud dependency. Overall, the system represents a cost-effective, scalable, and sustainable solution for modern agriculture—empowering farmers with the tools needed for smarter, more efficient farming.

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