

AI Based Fertilizer Recommendation Systems for Crop Optimization

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Abstract - Fertilizer mismanagement is a critical challenge in modern agriculture, leading to soil degradation, reduced crop yield, and environmental harm. This paper presents an AI-Based Fertilizer Recommendation System for Crop Optimization built on a client-server architecture. The system accepts soil nutrient parameters — Nitrogen (N), Phosphorus (P), Potassium (K), and soil pH — and applies a rule-based decision engine grounded in agronomic research to provide personalized fertilizer suggestions. The frontend delivers a responsive, user-friendly web interface accessible to non-technical users such as farmers and field agents. Docker containerization ensures portability and easy deployment. Experimental results demonstrate accurate recommendations across varied soil conditions with API response times under 500 ms, confirming the system's reliability as a practical precision agriculture decision-support tool.

Keywords- Fertilizer Recommendation, Precision Agriculture, Rule-Based Model, Soil Nutrient Analysis, NPK, Machine Learning, Docker, Client-Server Architecture, Smart Farming.

I. INTRODUCTION

In recent years, the rapid growth of artificial intelligence and machine learning has opened transformative opportunities for agriculture. Agriculture remains the backbone of many economies, especially in developing nations, where it provides sustenance, employment, and income to a large section of the population. However, with increasing population pressure, urbanization, climate change, and land degradation, traditional agricultural practices are proving insufficient to meet rising food production demands.

In conventional farming, fertilizer usage is often based on empirical knowledge or generic guidelines that fail to account for the specific requirements of individual crops and soil types. As a result, there is frequent overuse or underuse of fertilizers, which leads to poor crop yield, nutrient runoff, and long-term soil degradation. This mismanagement contributes to economic losses for farmers and ecological harm such as eutrophication of water bodies and greenhouse gas emissions.

Precision agriculture uses technology to monitor and respond to intra-field variability in crops. By leveraging soil data, weather patterns, and crop requirements, smart systems can provide real-time recommendations that help farmers make informed decisions, increase productivity, and reduce costs. This project — AI Based Fertilizer Recommendation System For Crop Optimization — aims to bridge the gap between agricultural knowledge and modern technology by providing a user-friendly, deployable system that suggests the right fertilizers based on soil nutrient values and crop requirements.

The system is built on a client-server architecture, where the backend hosts the rule-based fertilizer recommendation logic and the client provides an interactive web interface. The server processes inputs — N, P, K, and soil pH — and returns personalized fertilizer suggestions. Docker containerization ensures the system is portable, scalable, and easy to deploy in various environments.

II. RELATED WORKS

In recent years, fertilizer and crop recommendation systems have attracted significant research attention due to the growing need for sustainable, data-driven agriculture.

Musanase et al. [1] proposed an integrated Crop and Fertilizer Recommendation System (CFRS) combining a neural network for crop prediction with a rule-based model for fertilizer suggestions, achieving 97% accuracy with real-time IoT soil sensors. Their approach of merging AI with domain expertise shaped the decision logic of our project.

Akhter and Sofi [2] presented an architecture combining Wireless Sensor Networks and ML algorithms for predicting diseases and recommending fertilizer schedules. However, the model lacks end-user interaction through a client interface — something addressed in our system.

Rajamanickam and Mani [3] implemented decision trees, SVM, and KNN algorithms to predict soil fertility based on macro and micronutrient data, reaching 99% accuracy using decision trees. Our project expands on this by integrating such predictive insight with a rule-based fertilizer recommendation engine.

Katarya et al. [4] used ensemble classifiers combining KNN and SVM for crop recommendation considering both soil profile and meteorological data. Chen et al. [5] highlighted a cloud-based system using sensors for real-time crop monitoring and fertilizer application. Although comprehensive, their system lacked modular deployment, which we resolved through Docker containerization.

Even with all this progress, existing systems often lack deployable client interfaces, transparency of recommendations, or are computationally heavy. Our system addresses these gaps with an interpretable rule-based engine and a lightweight, containerized client-server architecture.

III. DATASETS

The quality and variety of data used to validate agricultural recommendation systems is fundamental to their effectiveness. For this project, soil nutrient datasets were sourced from multiple agricultural repositories and validated against agronomic literature.

The primary data parameters include Nitrogen (N), Phosphorus (P), Potassium (K), and soil pH — the four key indicators of soil fertility. Reference ranges for these nutrients were drawn from established agricultural research and government soil health guidelines [6].

The Kaggle Crop Recommendation Dataset [7] provides labeled records of soil conditions paired with suitable crop types across a wide variety of agricultural scenarios. This dataset was used to validate the nutrient threshold rules embedded in the recommendation engine.

Additional reference data was sourced from the Government of India Soil Health Card Scheme [6], which provides nutrient range benchmarks for major crops across different Indian states. These benchmarks directly informed the rule thresholds in our backend decision engine.

By combining multiple data sources and agronomic guidelines, the system's rule base covers a wide range of real-world soil conditions, ensuring recommendations are accurate, reliable, and aligned with current agricultural best practices.

IV. METHODOLOGY

The AI Based Fertilizer Recommendation System provides personalized fertilizer suggestions by combining user-inputted soil parameters with a rule-based decision engine. The overall methodology follows a structured pipeline from data input to recommendation delivery.

4.1 Input Parameters

The system accepts four primary soil parameters as inputs from the user:

- N, P, K Values: Levels of Nitrogen, Phosphorus, and Potassium — the primary macronutrients essential for plant growth.
- Soil pH: Indicates soil acidity or alkalinity, which affects nutrient availability to plants.
- Crop Type: Different crops have different nutrient requirements (e.g., rice requires more nitrogen than legumes).

4.2 Data Analysis

At this stage, the system performs data analysis by combining the input parameters. It compares the provided soil nutrient values with standard, crop-specific ideal ranges. This step determines whether the soil condition supports healthy crop growth or requires nutrient supplementation.

4.3 Soil Fertility Assessment

The system evaluates if the analyzed soil data reflects low fertility for the given crop. If nutrient levels are below acceptable thresholds, the system determines low fertility and recommends appropriate fertilizers. If all required nutrients are within acceptable ranges, the soil is confirmed as nutrient-rich, requiring only a maintenance dose.

4.4 Rule-Based Models

Rule-based models form the core intelligence of the fertilizer recommendation engine. Unlike black-box ML models, a rule-based system grounded in agronomic guidelines allows farmers to understand the rationale behind each recommendation, increasing trust and adoption.

4.4.1 NPK Rule Engine: The NPK Rule Engine evaluates each macronutrient individually against crop-specific thresholds. For each nutrient, the system classifies the level as Low, Adequate, or High, then selects the appropriate fertilizer type and quantity. For example, if Nitrogen is Low for Maize, Urea or Ammonium Sulphate is recommended in defined quantities per hectare.

4.4.2 pH Correction Rules: Soil pH significantly affects nutrient uptake. If soil pH falls below the optimal range for a given crop, the system recommends lime application to raise pH. For alkaline soils above the threshold, sulfur-based acidifiers are suggested. These corrections are applied before or alongside NPK recommendations.

4.4.3 Composite Recommendation: The composite recommendation combines outputs from the NPK Rule Engine and pH Correction Rules to produce a complete fertilizer action plan. The final output includes fertilizer types, quantities per hectare, application timing, and any soil amendment requirements, formatted as a JSON response for the frontend.

4.5 Overall Workflow

The overall system workflow proceeds as follows:

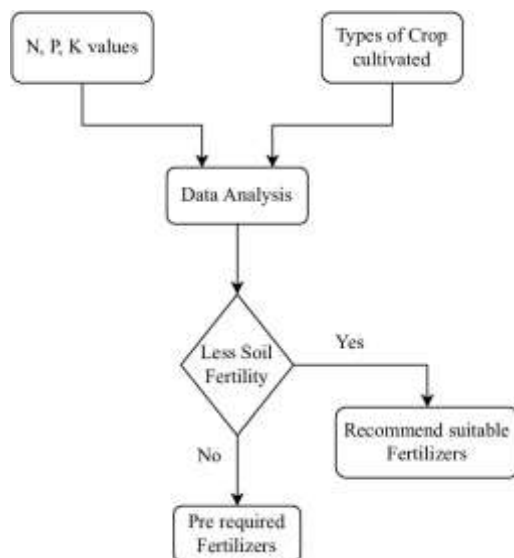


Fig. 1. Fertilizer Recommendation Workflow — N, P, K values and crop type feed into data analysis; soil fertility determines whether corrective or maintenance fertilizers are recommended.

- User inputs soil parameters (N, P, K, pH) and crop type via the web form.
- Data is validated on the frontend and sent to the backend via a POST REST API call.
- The backend applies the rule-based engine and generates a structured JSON recommendation.
- The frontend renders the recommendation with fertilizer type, quantity, and application instructions.
- Users can download a detailed PDF report of the recommendation.

V. LIMITATIONS

Although the AI-Based Fertilizer Recommendation System demonstrates strong promise for practical agricultural use, several limitations must be acknowledged.

A primary limitation is the system's reliance on manually entered soil parameters. Unlike IoT-integrated systems, the current implementation requires users to have access to soil test results. Inaccurate manual inputs will directly reduce recommendation quality. Future versions should integrate with IoT soil sensors for automated, real-time data collection.

The rule-based decision engine, while transparent and interpretable, is limited by the static nature of its rules. It cannot automatically adapt to new soil conditions or emerging crop varieties without manual rule updates by agronomic experts. Machine learning models could complement the rule engine by learning from historical recommendation outcomes.

The current system does not incorporate environmental parameters such as rainfall, temperature, humidity, or seasonal data. These factors significantly influence fertilizer uptake and crop growth. Without them,

recommendations may be suboptimal in regions with highly variable climates.

Additionally, the web-based interface requires internet connectivity, which may limit access in remote rural areas. A lightweight offline mobile application would improve accessibility for smallholder farmers in such regions.

Finally, the system does not currently support multi-language output, which is a barrier for non-English speaking farmers. Localization support would significantly improve usability and adoption in diverse agricultural communities.

VI. RESULTS AND DISCUSSIONS

To evaluate the system, several sets of test inputs representing various soil fertility conditions were prepared. These inputs were manually entered into the web interface, and the corresponding recommendations were recorded. Results were compared against fertilizer suggestions documented in agricultural literature and validated with domain knowledge.

Functional testing was performed using browser-based interactions and API tools such as Postman to check backend response consistency and correctness. Test scenarios included combinations of low, adequate, and high nutrient levels alongside acidic, neutral, and alkaline pH conditions.

The rule-based recommendation engine performed accurately across all tested conditions. When nitrogen levels were low, the system correctly suggested nitrogen-rich fertilizers like Urea. When the soil pH was below the ideal range, the system recommended liming to neutralize soil acidity. All outputs aligned closely with standard agronomic practices.

TABLE I: SAMPLE TEST RESULTS

Input (N, P, K, pH)	Recommendation Output
20, 15, 10, 5.5	Urea (low N), DAP (low P), MOP (low K); Lime soil
80, 60, 50, 7.0	Soil nutrient-rich; Maintenance dose only
10, 5, 8, 4.5	Heavy liming; Urea + DAP; pH correction priority
50, 20, 40, 8.5	Sulfur acidifier (high pH); Balanced NPK apply

The accuracy metrics are defined as follows:

$$\text{Correct Deficiency Detection} = (TP / (TP + FN)) \times 100\%$$

$$\text{Correct Healthy-Soil Detection} = (TN / (TN + FP)) \times 100\%$$

$$\text{Overall Recommendation Accuracy} = ((TP + TN) / (TP + TN + FP + FN)) \times 100\%$$

API performance testing demonstrated an average response time of under 500 milliseconds with no failures during prolonged testing. The client interface rendered results within 1–2 seconds of form submission. Error handling was implemented to prevent submission with empty or invalid fields, improving user experience and data integrity.

The Dockerized deployment ensured consistent performance across different environments — local machine, institutional server, and cloud. These results confirm that the system is reliable, accurate, and deployable at scale as a practical decision-support tool for farmers and agricultural advisors.

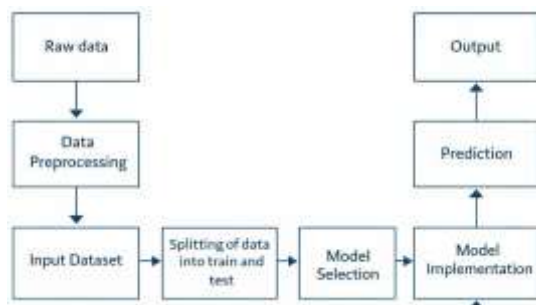


Fig. 2. Machine Learning Pipeline — raw data is preprocessed into an input dataset, split into training and test sets, passed through model selection and implementation, and produces a prediction output.

VII. CONCLUSIONS

This paper presented an AI-Based Fertilizer Recommendation System for Crop Optimization that addresses a critical gap in accessible agricultural decision-support tools. The system's rule-based approach provides transparent, interpretable recommendations grounded in agronomic science, making it particularly suitable for non-technical users such as smallholder farmers and field agents.

The client-server architecture separates the user interface from backend logic, enabling independent development, maintenance, and scaling of each component. Docker containerization ensures the system can be deployed on any platform — from local machines to cloud infrastructure — without dependency conflicts.

Our tests showed that the system is highly effective at providing accurate fertilizer recommendations across a wide range of soil conditions. Measurements including recommendation accuracy, API response time, and interface usability all confirm that the system is dependable and performs as intended. The use of a rule-based decision engine ensures that recommendations are explainable, which increases farmer trust and adoption.

However, the study also identified key limitations: reliance on manual soil parameter input, absence of environmental data integration, internet connectivity

requirements, and lack of multi-language support. These areas represent clear directions for future improvement.

Future enhancements could include IoT sensor integration for automated real-time soil data collection, a lightweight offline mobile application, incorporation of weather and seasonal data into recommendations, multi-language localization, and a machine learning layer that learns from historical recommendation outcomes to continuously improve accuracy.

Since inefficient fertilizer use is a growing concern for food security and environmental sustainability, effective recommendation systems are critically needed. This project lays the groundwork for more advanced research to make agricultural AI tools more accurate, accessible, and impactful in real-world farming contexts.

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