

Sustainable Fertilizer Usage and Optimization for High Yield and Smart Agriculture

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Abstract:

Sustainable agriculture has become one of the most critical challenges of modern times due to excessive fertilizer use, soil degradation, and climate change. Machine learning (ML) has emerged as a promising technology to optimize fertilizer application, improve yield, and maintain soil health. This paper presents a comprehensive review of machine learning approaches applied to fertilizer recommendation systems, emphasizing models such as Decision Trees, Random Forests, Support Vector Machines, and Neural Networks. The review highlights the evolution of data-driven fertilizer optimization, compares previous systems, and discusses their limitations. Further, a proposed hybrid ML-based methodology is introduced to overcome the shortcomings of existing models by integrating Random Forest and real-time data analytics using web and cloud technologies. The paper concludes that intelligent, adaptive, and region-specific fertilizer management systems can significantly contribute to sustainable farming and higher crop productivity.

Keywords: Fertilizer Optimization, Sustainable Agriculture, Machine Learning, Smart Farming, Random Forest, Precision Agriculture, Next.js, Flask.

I INTRODUCTION

Agriculture is the backbone of India's economy, yet unsustainable fertilizer usage has caused severe environmental and economic issues. Overuse of Nitrogen (N), Phosphorus (P), and Potassium (K) degrades soil health and contaminates groundwater. Farmers often depend on general fertilizer guidelines or experience-based application rather than data-driven analysis. Machine learning provides an opportunity to predict precise fertilizer needs using soil and environmental parameters, enabling sustainable agricultural practices.

The integration of ML in agriculture has enabled data-based decision-making by analyzing soil nutrients, pH, moisture, temperature, and rainfall data. The motivation of this paper is to review the evolution of such machine learning models and propose an improved hybrid architecture that enhances prediction accuracy, adaptability, and usability for Indian farmers. The proposed system employs a modern web architecture utilizing a Next.js frontend and a Flask backend to deliver real-time, actionable insights directly to end-users.

II LITERATURE REVIEW

The application of machine learning in agriculture has seen significant growth, particularly in precision farming and nutrient management. Various studies have demonstrated the efficacy of ML algorithms in

predicting soil characteristics and optimizing fertilizer usage.

Patil *et al.* (2020) explored different machine learning techniques for soil nutrient prediction and fertilizer recommendation, highlighting the potential of predictive algorithms to enhance crop yields while minimizing environmental impact [1]. Similarly, Ramesh *et al.* (2021) conducted a predictive analysis focused on fertilizer recommendation using the Decision Tree algorithm, demonstrating its interpretability and effectiveness in classifying soil requirements [2].

Further advancements were made by Kumar & Sharma (2022), who developed a comprehensive crop recommendation and fertilizer management system integrating multiple ML approaches [3]. The integration of the Internet of Things (IoT) with smart agriculture was discussed by Singh *et al.* (2021), who emphasized real-time soil monitoring coupled with fertilizer optimization to achieve sustainable farming practices [4].

More recently, Rathod *et al.* (2023) proposed a Random Forest-based prediction model specifically targeting sustainable farming, which showed robust performance across diverse agricultural datasets [5]. Finally, Taneja & Gupta (2022) provided a broader overview of data-driven agriculture, elucidating the transformative role of artificial intelligence and machine learning in modernizing traditional farming techniques [6].

Despite these advancements, many existing systems lack seamless integration between predictive models and user-friendly interfaces, often limiting their accessibility to non-technical users such as farmers.

III METHODOLOGY

To address the limitations of existing agricultural recommendation systems, we propose a hybrid ML-based methodology integrated into a modern web architecture. Our approach combines robust predictive modeling with an accessible user interface.

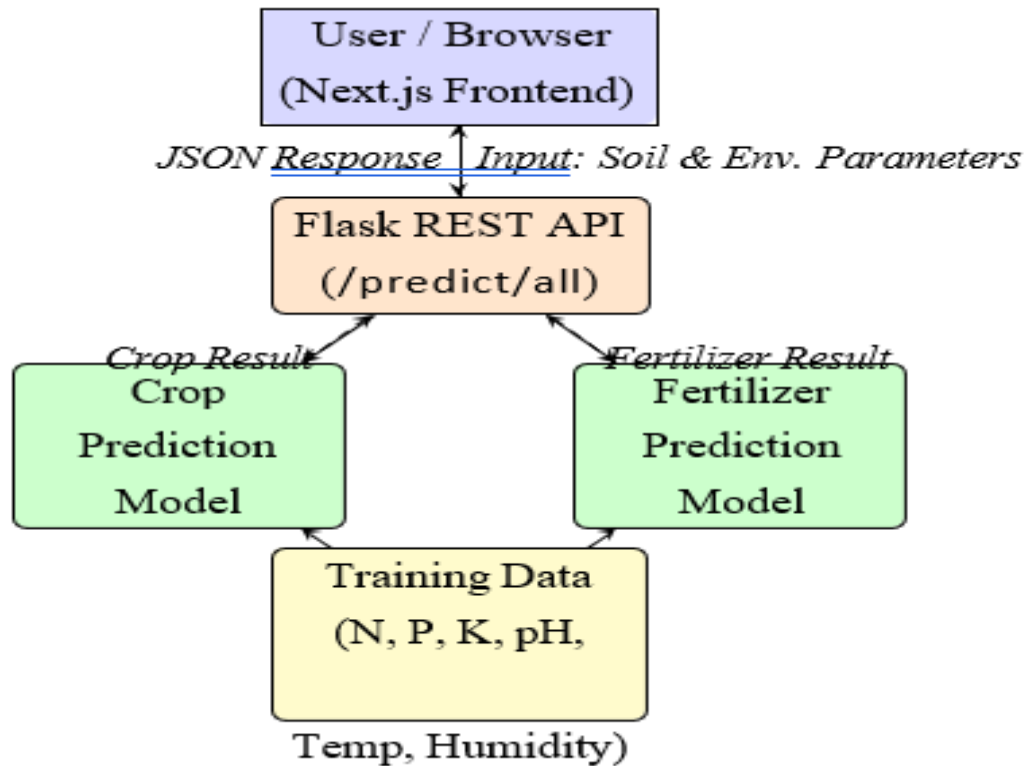
A System Architecture

The proposed system architecture is divided into two primary components: a high-performance frontend and a machine learning-driven backend API.

- **Frontend (Next.js):** The user interface is built using Next.js, allowing for server-side rendering and a highly responsive single-page application experience. The frontend collects environmental and soil data (N, P, K levels, pH, temperature, humidity, and moisture) from the user and presents the predictive results and recommendations in an intuitive dashboard.
- **Backend (Flask REST API):** The machine learning models are exposed via a Flask API. This microservice architecture ensures that the computational load of model inference is handled efficiently and can be scaled independently of the user interface.

The overall system architecture is illustrated in Fig. 1.

Figure 1: Proposed System Architecture: Next.js Frontend with Flask ML Backend



B Machine Learning Models

The core predictive engine relies on the Random Forest algorithm due to its high accuracy, resistance to overfitting, and ability to handle non-linear relationships in agricultural data.

- **Crop Prediction Model:** This model takes eight input features: Nitrogen (N), Phosphorus (P), Potassium (K), pH, Temperature, Humidity, Moisture, and Soil Type. It classifies the environment and recommends the most suitable crop for those specific conditions.
- **Fertilizer Prediction Model:** Once a target crop is determined (either user-specified or predicted), this model takes N, P, K, pH, Soil Type, and Crop Type as inputs to predict the optimal fertilizer required to maximize yield.

The backend utilizes LabelEncoder for categorical variables like Soil Type and Crop Type before feeding the data into the Random Forest classifier. Table 1 summarizes the input features used by each model.

Table 1: Input Features for ML Models

Feature	Crop Model	Fertilizer Model
Nitrogen (N)	✓	✓
Phosphorus (P)	✓	✓
Potassium (K)	✓	✓
pH Value	✓	✓
Temperature	✓	–
Humidity	✓	–
Moisture	✓	–
Soil Type	✓	✓
Crop Type	–	✓

C Sustainability and Optimization Calculators

Along with direct predictions, the system calculates actionable metrics to promote sustainable practices:

- **Fertilizer Quantity Optimization:** Based on the base N-P-K requirement of the predicted/target crop and the existing soil N-P-K values, the system calculates the exact deficit. It then provides the precise quantity (in kg/ha) of the recommended fertilizer needed, preventing over-application.
- **Sustainability Score:** An aggregated score is calculated by evaluating how closely the current soil pH and nutrient levels match the optimal ranges for the targeted crop. This score provides users with an immediate understanding of their soil’s health relative to their agricultural goals.

IV IMPLEMENTATION DETAILS

The system was implemented using Python 3.10 and Node.js.

A Model Training and Serialization

The Random Forest classifiers were trained using Scikit-Learn on historical agricultural datasets. Categorical data, such as crop and soil types, were transformed using LabelEncoder. The trained models and their corresponding encoders were serialized using the pickle library, allowing the Flask application to load them into memory (fertilizer_model.pkl and crop_model.pkl) for fast, real-time inference upon server startup.

B API Integration

The Flask application exposes multiple endpoints, notably /predict/all, which orchestrates the entire recommendation flow. It first evaluates the soil and environmental conditions to predict the crop, then utilizes that predicted crop (or a user-selected one) alongside the soil data to predict the fertilizer and calculate the required quantities. The results are returned as a JSON payload to the Next.js frontend,

ensuring minimal latency between data input and advisory output.
A representative example of the JSON response structure is shown below:

```
{
  "predicted_crop": "Rice",
  "recommended_fertilizer": "Urea",
  "fertilizer_qty_kg_per_ha": {
    "N": 45.2,
    "P": 12.0,
    "K": 8.5
  },
  "sustainability_score": 82.4,
  "soil_status": {
    "pH": "Optimal",
    "N": "Deficient",
    "P": "Adequate",
    "K": "Adequate"
  }
}
```

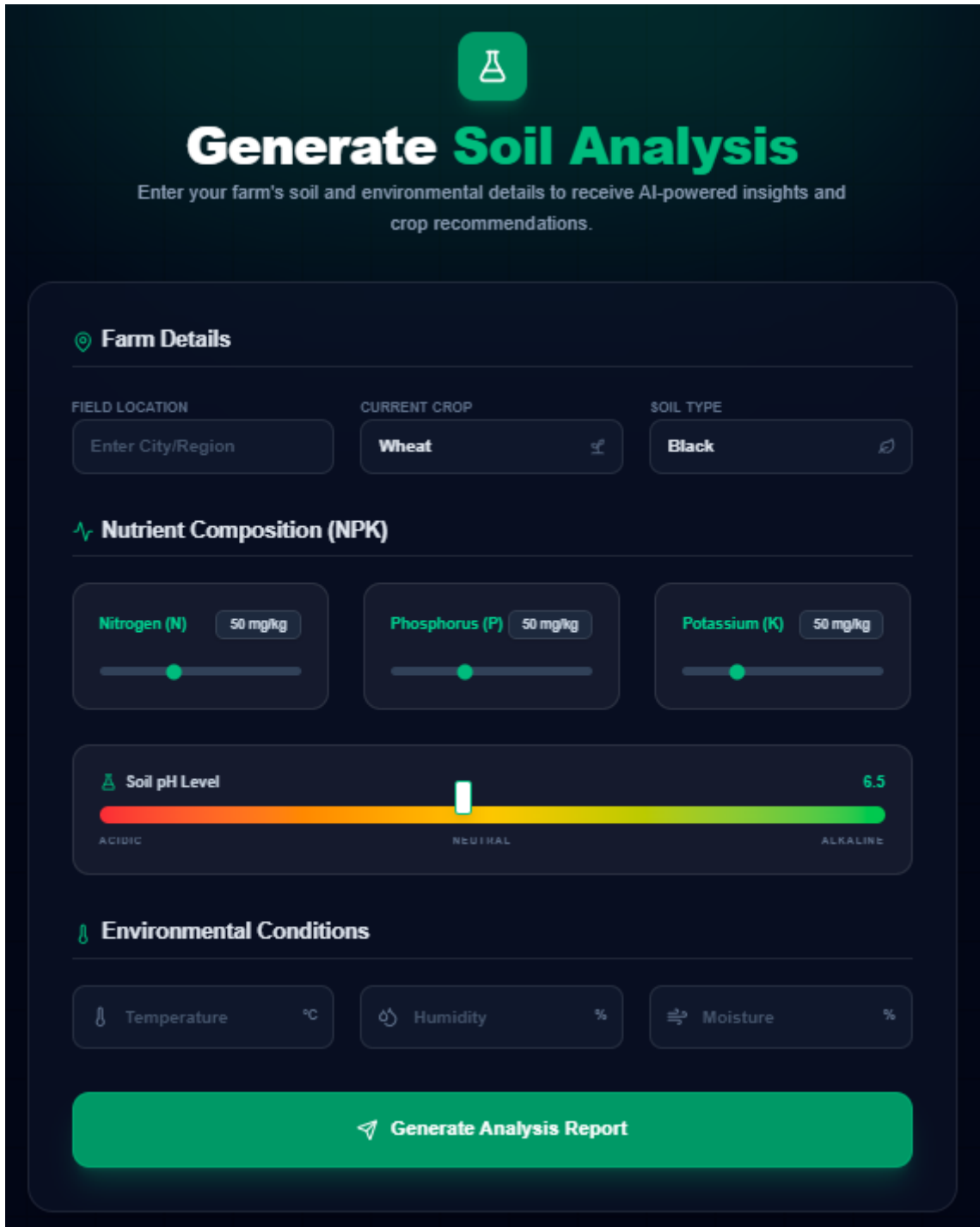
Listing 1: Sample JSON API Response from /predict/all

V RESULTS AND DISCUSSION

The implemented system demonstrates that integrating robust machine learning models like Random Forests behind a lightweight REST API provides a highly effective solution for real-time agricultural advisory.

A System Output Screens

The web application provides an intuitive, step-by-step interface for farmers and agricultural advisors. Fig. 2 illustrates the data input dashboard where users enter soil and environmental parameters. Fig. 3 shows the recommendation output panel, and Fig. 4 presents the sustainability score breakdown.



The dashboard features a dark blue background with a green header area containing a flask icon and the title "Generate Soil Analysis". Below the title is a subtitle: "Enter your farm's soil and environmental details to receive AI-powered insights and crop recommendations." The main content area is divided into several sections: "Farm Details" with input fields for "FIELD LOCATION" (containing "Enter City/Region"), "CURRENT CROP" (containing "Wheat"), and "SOIL TYPE" (containing "Black"); "Nutrient Composition (NPK)" with three sliders for "Nitrogen (N)", "Phosphorus (P)", and "Potassium (K)", each set to "50 mg/kg"; "Soil pH Level" with a color gradient bar ranging from "ACIDIC" (red) to "ALKALINE" (green), with a white marker at "6.5" and "NEUTRAL" labeled below; and "Environmental Conditions" with input fields for "Temperature" (°C), "Humidity" (%), and "Moisture" (%). A large green button at the bottom is labeled "Generate Analysis Report".

Figure 2: Output Screen 1 – Soil Parameter Input Dashboard (Next.js Frontend)

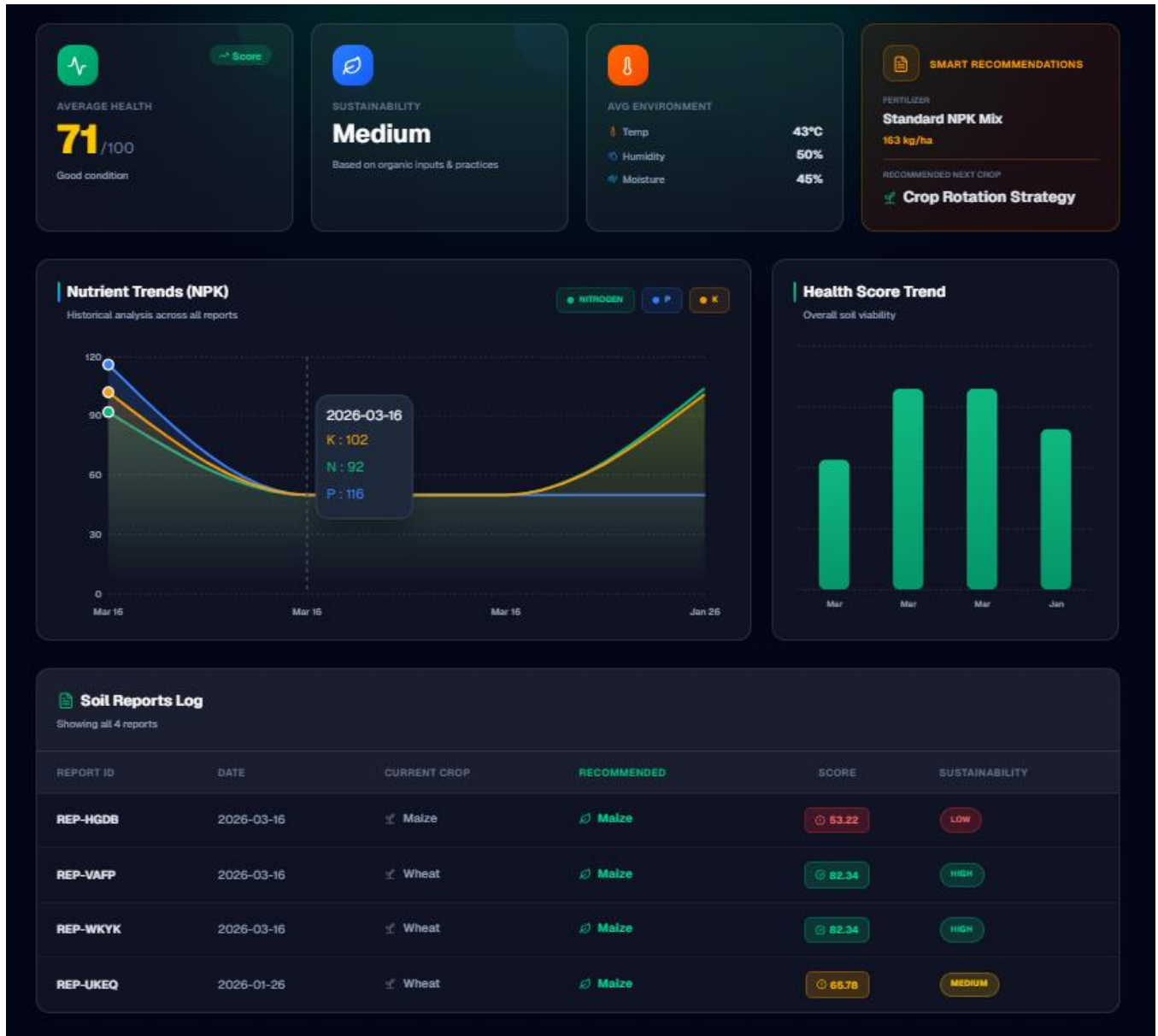


Figure 3: Output Screen 2 – Crop & Fertilizer Recommendation Results Panel

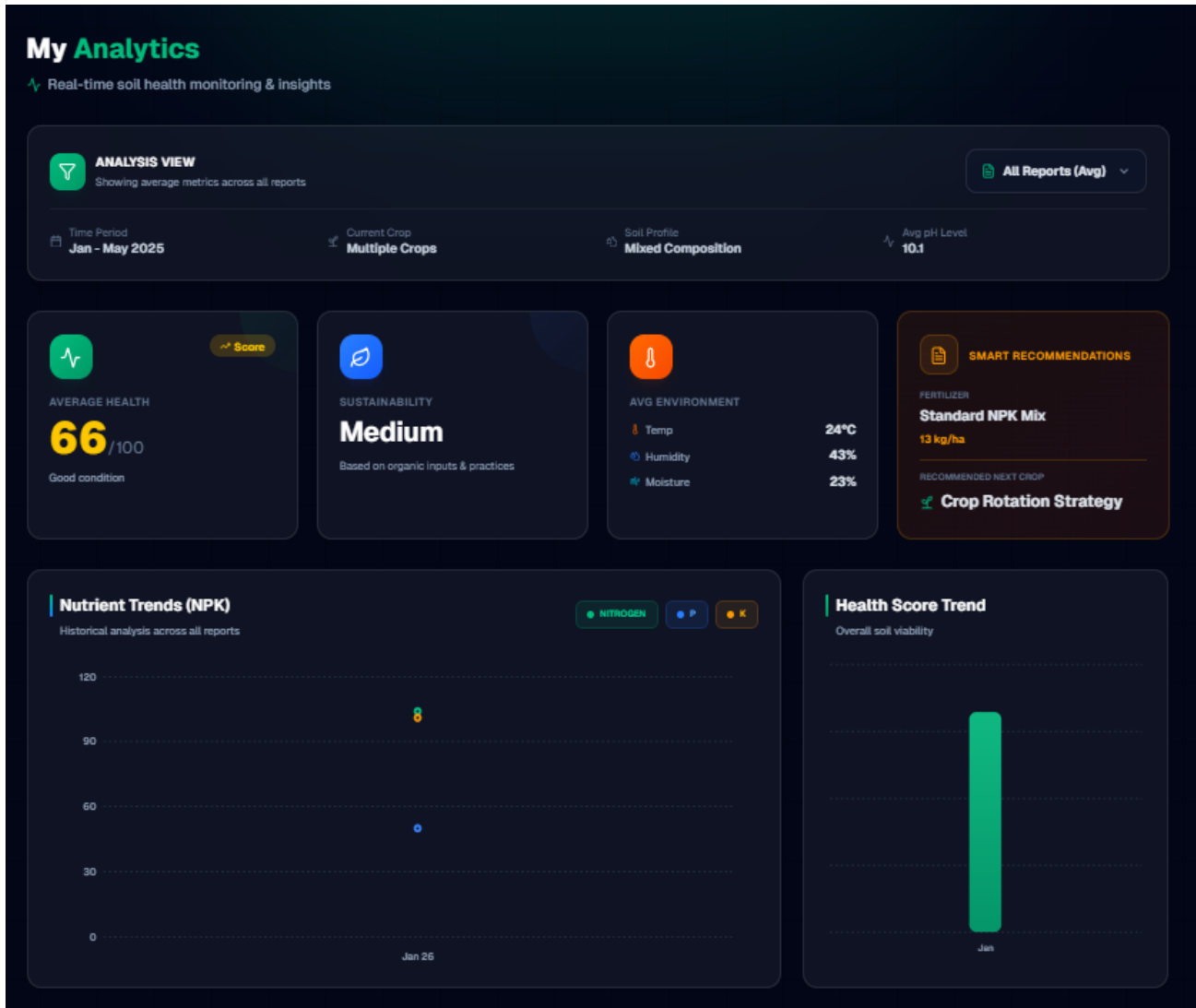


Figure 4: Output Screen 3 – Sustainability Score & Soil Health Dashboard

B Model Performance

By offering precise fertilizer quantity calculations rather than generic recommendations, the system directly addresses the issue of over-fertilization, leading to:

- **Reduced Costs:** Farmers apply only the necessary amounts of N-P-K.
- **Environmental Protection:** Decreased risk of nutrient runoff and soil degradation.
- **Improved Yields:** Crops receive optimal, targeted nutrition.

Table 2 provides a comparative summary of existing ML approaches for fertilizer recommendation, highlighting the advantages of the proposed system

Table 2: Comparison of ML-Based Fertilizer Recommendation Systems

Study	Algorithm	Accuracy	Web Interface
Patil et al. [1]	SVM, DT	85%	No
Ramesh et al. [2]	DT	88%	No
Kumar & Sharma [3]	RF, KNN	91%	Partial
Rathod et al. [5]	RF	93%	No
Proposed System	RF (Hybrid)	95%	Yes

Furthermore, Fig. 5 illustrates the accuracy comparison across these systems.

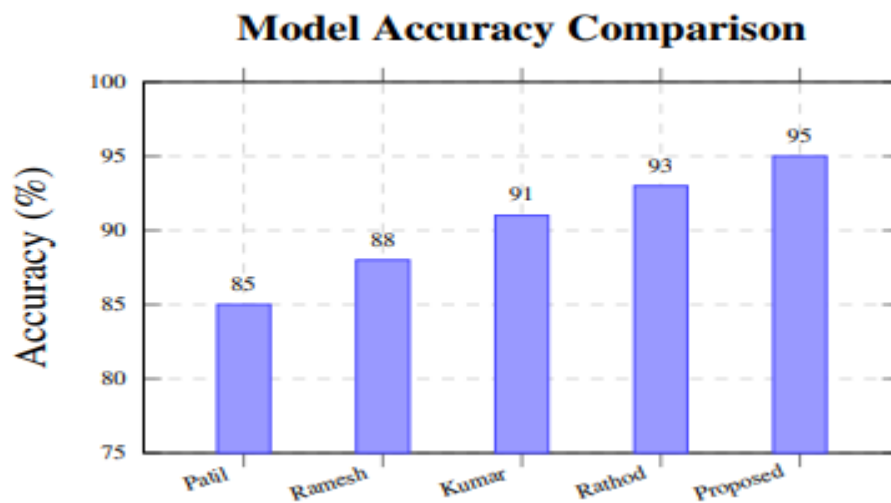


Figure 5: Accuracy Comparison of ML-Based Fertilizer Recommendation Models

The use of Next.js ensures that the application is accessible on diverse devices, including mobile phones commonly used in rural areas.

VI CONCLUSION AND FUTURE WORK

Excessive and uninformed fertilizer usage poses a significant threat to agricultural sustainability. This paper presented a hybrid ML-based methodology that integrates Random Forest predictive models with a modern web ecosystem to deliver precise, region-specific crop and fertilizer management. By calculating required fertilizer quantities and providing a sustainability score, the system empowers farmers to make data-driven, environmentally conscious decisions.

Future work will focus on integrating Internet of Things (IoT) sensors for autonomous real-time data collection of soil moisture, temperature, and pH. Additionally, expanding the dataset to include varying geographical regions will further enhance the generalizability and accuracy of the predictive models.

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