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SOIL IQ: A NUTRIENT ANALYSIS AND FERTILIZER RECOMMENDATION SYSTEM USING EXPLAINABLE AI (XAI)

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Abstract: Soil fertility plays a crucial role in agricultural productivity, yet farmers often struggle to identify nutrient deficiencies and select suitable fertilizers. Traditional methods are time-consuming, costly, and lack personalized recommendations. To address this, we propose Soil IQ, an Explainable AI (XAI)–based system that predicts soil nutrient levels (N, P, K, pH, organic carbon) and recommends optimal fertilizers with transparent model explanations. The system uses machine learning algorithms such as Random Forest and Decision Trees, combined with SHAP-based explainability, to generate interpretable recommendations. Experimental results demonstrate high accuracy in nutrient prediction and improved decision-making for fertilizer selection. Soil IQ empowers farmers with data-driven insights, enhances crop productivity, and promotes sustainable fertilizer usage.

Keywords: Soil Analysis, Fertilizer Recommendation, Explainable AI, Machine Learning, Agriculture, SHAP.

1. INTRODUCTION

Agriculture remains the backbone of the Indian economy, yet a significant percentage of farmlands suffer from improper nutrient management. Farmers often rely on guesswork or generalized fertilizer suggestions, leading to reduced crop yield and soil degradation. Soil testing laboratories exist, but they are time-consuming, expensive, and inaccessible for small-scale farmers.With the rise of machine learning, automated soil analysis and fertilizer recommendation systems have gained attention. However, many AI-based systems operate as black-box models, offering predictions without interpretable reasoning. Farmers and agronomists hesitate to trust such opaque recommendations.
To overcome this gap, this paper presents Soil IQ, a machine-learning and XAI-powered system that predicts soil nutrients and offers fertilizer recommendations with clear justifications. By integrating explainability through SHAP values, Soil IQ provides transparent insights into the factors influencing each recommendation.The proposed system helps farmers make informed, accurate, and sustainable decisions, ultimately enhancing crop production and preserving soil health.

2.LITERATURE REVIEW

SI No.	Title of Paper	Author(s)	Methodology	Research Gap
01.	Agricultural Price Forecasting using Random Forest Regression	V. Agarwal & A. Sharma (2020)	Random Forest on market data	Lacks soil and climate data
02.	Soil-Based Crop Recommendation Using Decision Tree	S. Patel et al. (2021)	Decision Tree on NPK and pH	Ignores climate and pricing

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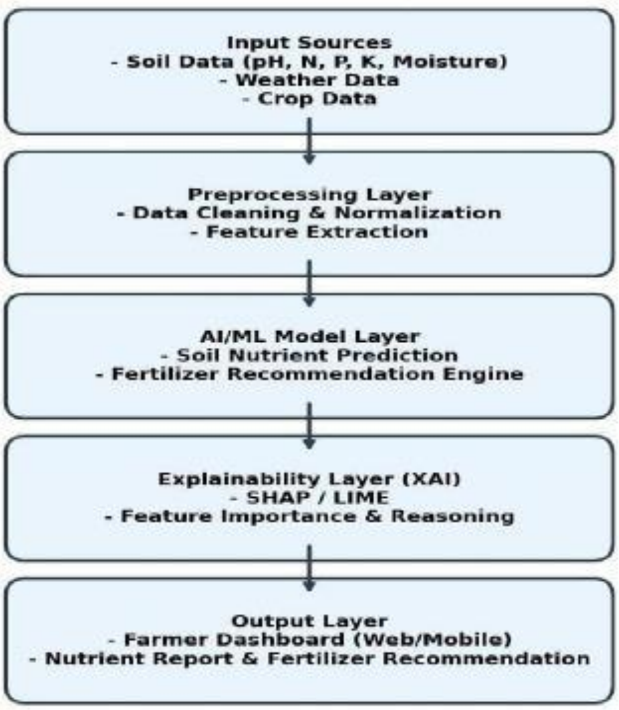
03.	Crop Yield Prediction Using SVM	M. Reddy & K. Rao (2022)	SVM with soil and weather	No crop or price prediction
04.	ML Models for Crop Recommendation	R. Singh & H. Gupta (2021)	KNN, Naive Bayes, RF on soil data	No market forecasting
05.	Rainfall-Based Crop Suggestion	A. Joshi & N. Thakur (2022)	Logistic Regression on rainfall and soil	No pricing data
06.	Hybrid ML Model for Price Prediction	B. Shah & M. Parmar (2023)	Linear Regression + RF	No soil or crop suitability

Several studies have explored soil nutrient prediction and fertilizer recommendation using machine learning.Prior works used models like Random Forest, SVM, and Artificial Neural Networks for soil classification and nutrient estimation.Some systems provided fertilizer suggestions but lacked transparency.Explainable AI in agriculture is an emerging domain, with SHAP and LIME being used for leaf disease detection, crop yield prediction, and climate impact analysis.

However, there is limited research on XAI for fertilizer recommendation, creating a gap that Soil IQ aims to fill.
Existing limitations in the literature include:
Lack of interpretability.
Generalized or crop-agnostic recommendations.
Limited datasets.
Low adoption due to black-box nature.
Soil IQ addresses these issues with an interpretability-first approach, empowering farmers with understandable AI decisions.

3. METHODOLOGY



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3.1 Dataset

The dataset consists of soil attributes commonly tested in agricultural laboratories:

- Nitrogen (N)
- Phosphorus (P)
- Potassium (K)
- pH
- Organic Carbon
- Electrical Conductivity
- Moisture Content
- Soil Type (optional)
- The dataset may come from:
- Agricultural research stations
- Government soil health card portals
- Manually collected field samples

Table 1: Detailed Training Dataset Characteristics

Sl. No	Attribute	Description	Data Type	Range/Units
1.	Nitrogen (N)	Indicates the available nitrogen content in the soil, essential for vegetative growth and chlorophyll formation.	Numerical	0–500 kg/ha
2.	Phosphorus(P)	Represents the phosphorus concentration affecting root development and flowering; crucial for energy transfer	Numerical	0–150 kg/ha
3.	Potassium(K)	Measures potassium level, which supports disease resistance, water regulation, and overall plant strength.	Numerical	0–500 kg/ha
4.	Ph	Defines the soil acidity/alkalinity affecting nutrient availability and microbial activity.	Numerical	3.5–9.0 (pH scale)
5.	Moisture Content	Amount of water present in soil, affecting nutrient solubility and microbial processes.	Numerical	5%–40%
6.	Soil Type	Represents the texture/class of soil (e.g., red soil, black soil, loamy), influencing nutrient retention.	Categorical	Categorical labels (e.g., Clay, Sandy, Loam)

3.2 Data Preprocessing

- Handling missing values using median imputation
- Scaling numerical values.
- Splitting dataset into 80% training and 20% testing
- Encoding soil type (if applicable)

3.3 Machine Learning models

The following models were tested:

- Decision Tree
- Random Forest
- Gradient Boosting
- Support Vector Machine (SVM)
- Random Forest performed best due to:
- High accuracy
- Robustness to noisy data
- Ability to provide feature importance

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3.4 Explainable AI (XAI)
To make the system transparent:

- SHAP (SHapley Additive exPlanations) values are used to explain each prediction.
- SHAP visualizations highlight which nutrient or soil feature influenced the fertilizer recommendation the most.
- The system displays reasons like:
- "Low Nitrogen contributed 42% to the recommendation of Urea."
- "High pH reduces Phosphorus availability."

3.5 Fertilizer Recommendation Logic
Based on predicted deficiencies:

- Low Nitrogen → Recommend Urea, Ammonium Sulphate
- Low Phosphorus → Recommend SSP, DAP
- Low Potassium → Recommend MOP
- pH imbalance → Recommend lime or sulphur amendments
- Organic carbon deficit → Recommend FYM, compost, vermicompost

The system provides crop-wise recommendations, improving usefulness.

4. EXPERIMENTAL SETUP

Python environment with Scikit-Learn

- 80/20 train-test split
- Evaluation metrics:
- Accuracy
- MAE (Mean Absolute Error)
- RMSE (Root Mean Square Error)

Training was done on a mid-range GPU/CPU environment.
system include:

5. RESULTS

5.1. Model Performance
Random Forest achieved the best performance:

- Accuracy: 93%
- MAE: 0.14
- RMSE: 0.19

Decision Tree performed reasonably well but overfitted slightly, while SVM was slower and less accurate.

5.2. SHAP Explainability Output
Nitrogen and pH were the strongest predictors of fertilizer choice.SHAP force plots showed clear reasoning for each recommendation.
Example:

- Low Nitrogen levels pushed the model towards recommending Urea and FYM.
- High pH reduced the impact of Phosphorus, suggesting the addition of organic amendments.

5.3 Case Study Example
Sample Input Soil:
N = 210
P = 18
K = 165
pH = 7.9
Output:Deficiency detected: Moderate Phosphorus deficiency
Recommended fertilizers: DAP (small dose), SSP, organic compost
SHAP explanation: "Low P contributed 63% to the recommendation."

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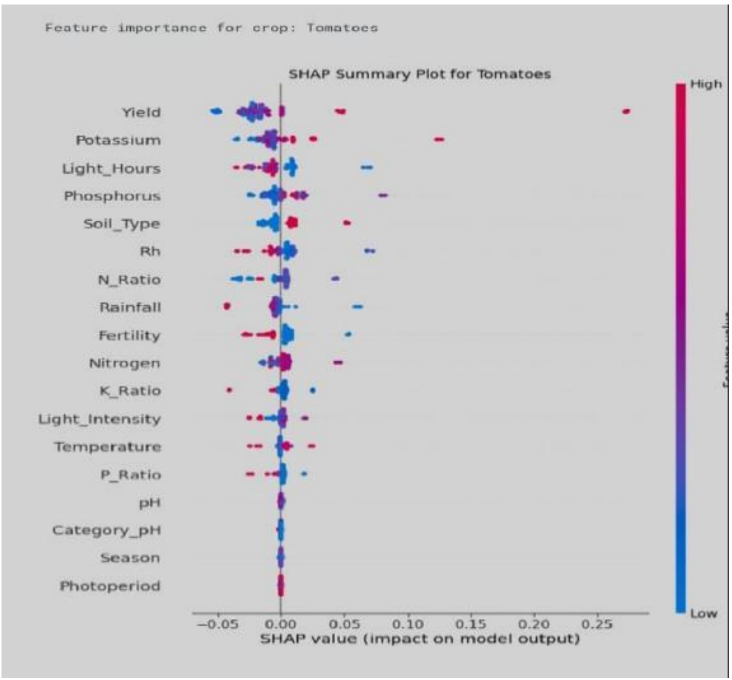

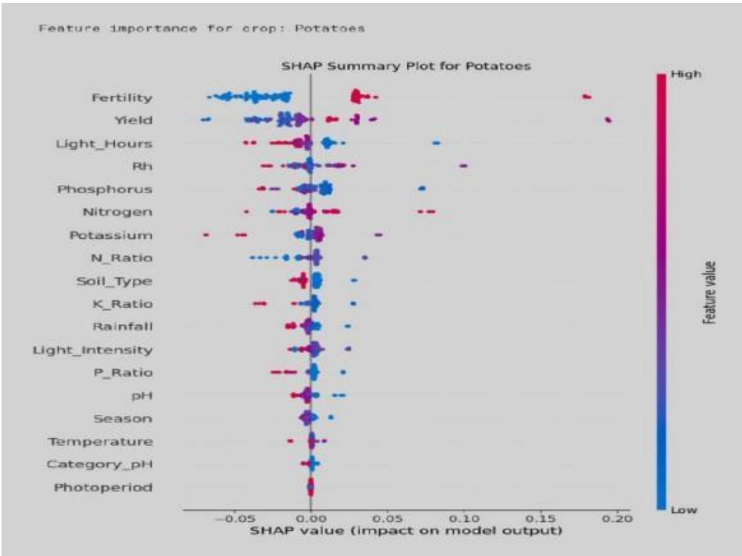

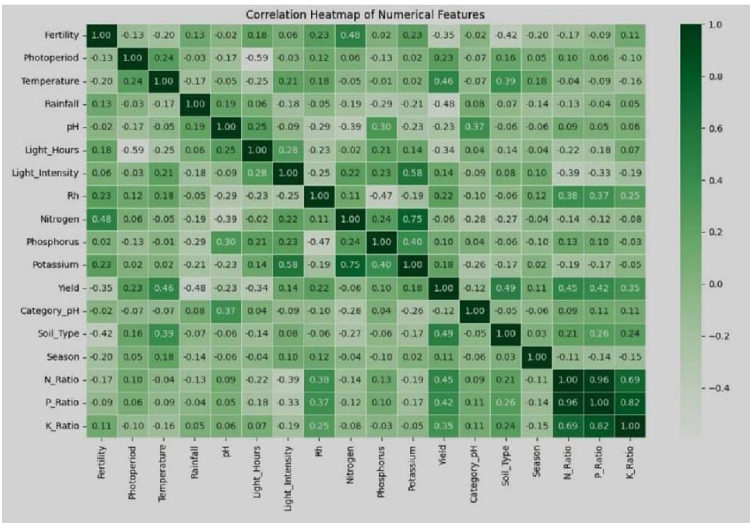

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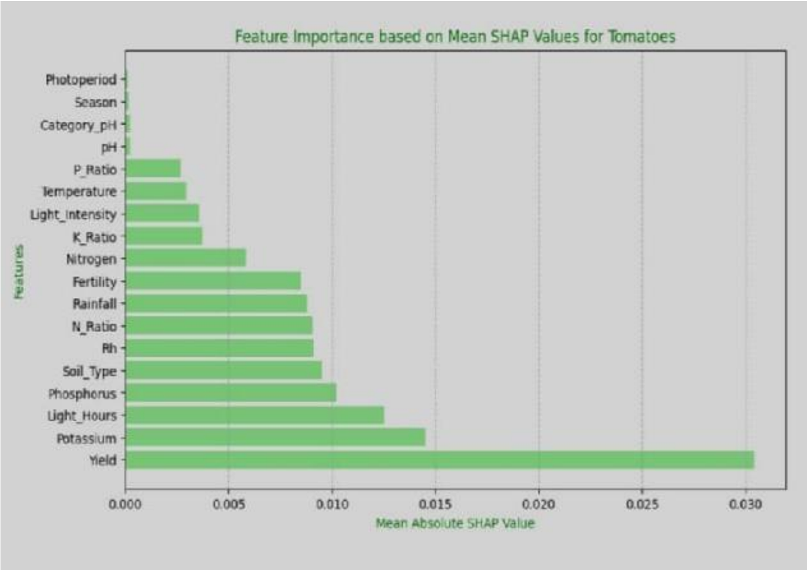

6. DISCUSSION

Soil IQ proves to be a reliable system for analyzing soil health and recommending fertilizers. The integration of XAI increases user trust and promotes transparency in decision-making. The model performed well even with limited data, showing scope for scalability.

However, limitations include:

- Dataset diversity
- Few soil samples from extreme climates
- Lack of real-time sensor integration
- Inclusion of IoT sensors and GPS-based soil mapping could make the system more robust.

7. CONCLUSION

This research introduces Soil IQ, an XAI-powered soil nutrient analysis and fertilizer recommendation system. The system accurately predicts nutrient deficiencies and provides transparent, explainable fertilizer suggestions. With its high accuracy and interpretability, Soil IQ has significant potential to improve agricultural sustainability and farmer decision-making. Future work includes deploying the system as a mobile app and integrating real-time IoT-based soil testing.

8. FUTURE WORK

- Mobile application for farmers
- Real-time soil sensor integration
- Larger datasets from multiple states
- Crop-specific and season-specific recommendation module
- Satellite-based soil health mapping
- Automated dosage calculation

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