Journal of Animal Environment

(E-ISSN 2717-1396, ISSN 2717-1388)

Original Research Paper

An Enhanced Multimodal Machine Learning Framework for Predicting Key Soil Properties in Precision Agriculture

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ABSTRACT

In the Modern Era in Precision agriculture, efficient, sustainable, accurate and real-time prediction of soil parameters is essential for more productive results. While soil is the foundation of all agriculture, traditional analysis methods are becoming a bottleneck. Relying on laboratory testing is often too costly and slow to be practical for large-scale or continuous monitoring. Because of these limitations, farmers lack the timely data they need to make informed decisions. This leads to inefficient fertilizer use, water waste, and ultimately, lower crop yields. To solve this, we need an intelligent, data-driven system capable of synthesizing various data sources to provide actionable, real-time insights.

This study introduces an improved machine learning system designed to predict key soil details, such as pH levels, major nutrients (nitrogen, phosphorus, and potassium), moisture, and temperature. We used a large dataset of 8,000 soil records gathered from field sensors and public databases. To ensure the results are reliable, we carefully cleaned the data to remove errors and organized it so the computer models could learn effectively.

We compared standard statistical methods against advanced "ensemble" learning models like Random Forest, Gradient Boosting, and XGBoost. The advanced models performed much better because they can understand complex connections between soil factors that simple methods often miss. Specifically, the Random Forest and XGBoost models achieved nearly perfect results, with an accuracy score (R^2) of almost 1.000 for predicting pH levels.

This model is more than just a prediction tool; it lays the foundation for smart, real-time soil monitoring. It allows farmers, agronomists, and policymakers to make solid, data-driven decisions about irrigation, crop selection, and fertilizer use. In the real world, this system helps improve crop growth, reduce chemical waste, and save resources. In the future, this framework could be connected to Internet of Things (IoT) sensors or satellites to check soil health across entire regions or countries.

Keywords: Machine Learning, Soi1 Prediction, Ensemble Learning, Precision Agriculture, Feature Engineering, Sustainable Agriculture.

INTRODUCTION

1. Background and Problem Statement

Soil is the foundation of life on land and a crucial resource for farming worldwide. Its health determines whether we can grow enough food and keep the environment balanced.

However, a major problem in modern farming is that it is difficult to test soil quickly, cheaply, and accurately. Farmers face a big challenge because they cannot easily measure important details like acidity (pH), main nutrients (Nitrogen, Phosphorus, and Potassium), and moisture levels.

Background and Problem Statement

Soil is a mix of minerals, organic matter, water, air, and living things. The way these parts come together decides how fertile the soil is and if plants can grow well in it.

One of the most important factors is soil pH. This controls how plants get nutrients and how tiny organisms in the soil behave. Also, having the right amount of main **nutrients** (Nitrogen, Phosphorus, and Potassium) and water is necessary. These factors determine how well plants can absorb food and handle stress from the environment.

In the past, soil was mostly tested using chemical methods in a laboratory. While these tests are very accurate, they have several problems that make them hard to use for modern farming on a large scale.

Because of this, farmers often have to make decisions using old or incomplete information. This leads to wasting fertilizer, growing fewer crops, and causing more pollution.

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Received: 25th July, 2026 | Revised: 26th August, 2026 | Accepted: 18th September, 2026 | Available Online: 24th September, 2026
(DOI): 10.70102/AEJ.2026.18.7s.37

Theoretical Concepts for Predictive Soil Modeling

The fast progress in **Machine Learning (ML)** and Remote **Sensing** has speeded up the shift from old manual testing to automated, non-destructive modeling. This change matches the principles of **Precision Agriculture (PA).**

PA is a modern strategy that uses large datasets from IoT sensors, satellite images, and past farm records to ensure crops and soil get exactly the right amount of inputs. These technologies allow us to monitor the soil continuously. This helps farmers make data-driven decisions that improve productivity and use resources more efficiently.

Machine Learning in Soil Informatics

Machine Learning algorithms play a vital role in processing the huge, complex, and multi-dimensional data generated by precision agriculture systems.

These algorithms identify the complicated relationships that control how soil behaves. This makes it possible to do predictive modeling and provides smart support for decision-making. Generally, the problem of predicting soil conditions falls into two main categories of Machine Learning tasks:

Regression Methods

Regression models are used to predict **continuous number** values, like the exact value of estimated pH. These models start from simple ones like Linear Regression and go up to advanced non-linear methods such as **Support Vector Regression** (SVR). There are also high-performance ensemble models like **Random Forest** Regressor, **Gradient Boosting Regressor,** and **XGBoost.** These models work very well because they can catch **hidden relationships** between soil data, environment factors, and climate conditions, which are not easy to see directly.

Classification Methods

Classification models are used to predict **category type outputs,** like soil pH class such as **Acidic, Neutral,** or **Alkaline.** Algorithms like **Support Vector Classifier** (SVC) and **ensemble** models such as **Random Forest Classifier** are commonly used because they give good accuracy in classifying soil types and fertility classes. This type of classification is very important for giving **proper agriculture** recommendations and helping in correct decision making.

Chapter Summary and Outlook

This chapter mainly focused on why **accurate soil property** assessment is very important and also explained the problems with **traditional lab-based methods.** It introduced the idea of Precision Agriculture and showed how **machine learning,** especially **ensemble methods,** gives a strong base to model complex and non-linear relationships found in **multimodal soil data.**

Further, important **regression and classification techniques** related to soil informatics were discussed to build the basic foundation for the proposed prediction framework.

The next chapter, **Chapter** 2 **(Literature** Review), will study existing research in this area. It will compare different methods, datasets, and performance results from previous works. This chapter will also point out research gaps that this study aims to solve by developing a better **data-driven** soil **prediction model.**

LITERATURE SURVEY

This chapter gives **a systematic review** of recent work in **predicting** soil **properties** using **machine learning** and remote sensing techniques. The review covers around **20 research papers** from journals and conferences published between **2015 and 2025,** mainly from reputed **sources like IEEE** and similar academic platforms. The main aim is to set the **background of the study,** group different methods used, check their results, and find **important research gaps** that help decide the direction of this work.

2.1 Review Process Adopted

A structured literature review was done to find earlier research work, check the methods used, and place the current study properly within the existing academic field. This process makes sure that the present research is based on already available knowledge and does not repeat work that is already done before.

2.1.1 Significance and Search Strategy

The review was guided using specific keywords related to the study focus, such as Machine Learning, Soi1 Prediction, Precision Agriculture, Ensemble Learning, and Remote Sensing in Soil. More importance was given to papers published between 2020 and 2025 so that latest developments can be covered, especially works using deep learning and multi-modal data integration. Around 20 research papers were finally selected for detailed study to keep the review broad and well-covered.

2.1.2 Documentation and Synthesis

Each selected study was documented based on dataset details, machine learning algorithms used, target parameters, and numerical results like R°, RMSE, and accuracy. This kind of structured summary helped in making direct comparison between different studies and made it easier to understand the strengths and limitations of various modeling approaches.

2.2 Categorical Review of Literature

The reviewed studies can be grouped into **three thematic categories** based on data type and prediction objectives.

2.2.1 Spectral and Remote Sensing-Based Prediction

This category emphasizes non-invasive approaches utilizing satellite or aerial imagery.

- **Methodology:**

Early research mostly used Partial Least Squares Regression (PLSR) and Support Vector Machines (SVM) to predict soil organic carbon and texture properties using LUCAS Topsoil spectral data (European Commission, 2015; 2023). In more recent studies, researchers combined Convolutional Neural Networks (CNNs) and XGBoost with Sentine1-2 geo-spatia1 data, and this gave very high results, with accuracy above 95% for soil type and organic carbon classification (Zhao & Tan, 2022).

- **Key Findings:**

Spectral data offer a fast and low-cost alternative to traditional lab testing. Using transfer learning is very important to keep the model accuracy high when applying it to new geographic regions (European Commission, 2023).

2.2.2 Environmental and Nutrient-Based Prediction

This category focuses on sensor-based and historical data, emphasizing the relationships among environmental factors (temperature, humidity, rainfall) and soil chemistry (N, P, K, pH).

- **Methodology:**

Ensemble learning methods like Random Forest (RF) and Gradient Boosting (GB) are very popular because they can handle non-linear and multi-dimensional data well. In India, studies using soil and weather data often used RF and Decision Trees, showing good results for soil classification and crop recommendation (Sharma & Meena, 2018; Kumar & Singh, 2019).

- **Key Findings:**

Ensemble methods usually do better than traditional models. For example, Gradient Boosting reduced MAE from 1.63 t/ha to 1.48 t/ha in UK farms (Thomas & Walker, 2020), and Decision Trees reached 95.36% accuracy in soil type classification (Rani & Kaur, 2021).

2.2.3 Integrated and Ensemble-Driven Yield/Fertilizer Forecasting

The latest studies combine multiple data sources using sophisticated ensemble or deep learning frameworks to predict crop yield or fertilizer requirements.

- **Methodology:**

Advanced models like XGBoost, LightGBM, and Stacking/Voting ensembles (Chauhan & Yadav, 2025), as well as sequential deep learning models (Patel & Nair, 2024), combine NDVI, soil nutrients, and weather data to give more complete and accurate predictions.

- **Key Findings:**

Using data transformation and ensemble methods usually gives very high resu1ts—R^2 around 0.994 and classification accuracy almost 100% (Prasad & Gupta, 2021; Chauhan & Yadav, 2025). This shows that hybrid ensemble frameworks are very strong for predicting multiple soil targets.

2.3 Issue-Wise Solution Approaches

The primary challenge addressed in the literature is predicting soil attributes from indirect, multi-source data to enhance decision-making in precision agriculture.

2.3.1 Comparison of Regression Approaches for R' Performance

The **Coefficient of Determination (R^2)** is the key metric used to evaluate regression model effectiveness.

Authors (Year)	Prediction Target	ML Approach	Key R' Result	Inference on Variation
Johnson & Patel (2016)	Crop Yield	RFR, NN	**0.98**	High R^2 achieved using localized field and synthetic data, indicating strong feature correlation.
Awan & Iqbal (2017)	Crop Yield	SVM, RFQ LASSO	o.88	Slightly lower R^2 due to integration of NDVI with meteorological data, increasing variability.
Rahman & Ortega (2019)	Wheat Yield	SVR	=1.0	Near-perfect accuracy showing strong feature-target correlation within FAO/World Bank datasets.
Soni & Verma (2024)	Soil & Yield	RF Regression	**0.969**	Demonstrates Random Forest's robustness and generalization on large-scale Indian data.

Inference:

Variation in R^2 scores (0 88 — 1 0) depends on dataset diversity and prediction complexity. Yield prediction, being highly variable, benefits significantly from feature engineering and ensemble methods.

2.3.2 Comparison of Classification Approaches for Soil Attributes

Classification models play a vital role in discrete predictions such as soil type or pH class categorization.

Authors (Year)	Classification Target	ML Approach	Accuracy
Sharma & Meeml (2018)	soil Type	Decision Tree, Naive Bayes	**95.36% (DT)**
Kumar & Singh (2019)	Crop Classification	RF, LR, SVM	99.7% (RF)
Rani & Kaur (2021)	Soil Fertility	KNN, NB, DT	**95.36% (DT)**
Chauhan & Yadav (2025)	Fertilizer Optimization	Stacking & Voting Ensembles	100% **(Ensemble)**

Inference:

Tree-based algorithms like Decision Tree and Random Forest usually give the highest classification accuracy. The almost perfect results (> 99%) mostly happen when input factors like NPK levels have a direct and predictable relationship with the target output.

2.4 Strengths and Weaknesses

2.4.1 Strengths of Published Research

1. **Ensemble Robustness:**

There is clear agreement that ensemble methods like Random Forest, XGBoost, and Gradient Boosting work better than linear or simple models when dealing with nonlinear soil data.

2. **Multimodal Integration:**

Studies combining sensor and remote sensing data achieve higher accuracy, confirming the value of multimodal data fusion.

3. Advanced **Preprocessing:**

Use of transfer learning, normalization, and power transformations enhances model generalization and predictive precision.

2.4.2 Weaknesses and Limitations

1. **Generalizability:**

Many high-accuracy models (R^z 1.0) rely on synthetic or localized datasets, which limits their applicability across diverse regions.

2. **Dataset Homogeneity:**

Dependence on single-country or homogeneous datasets (e g., LUCAS spectral libraries) reduces adaptability to global soil diversity.

3. Feature **Interpretability:**

Complex models like CNNs and Gradient Boosting often act as black boxes, providing limited insight into feature importance-an issue for practical agricultural deployment.

2.5 Gaps in Published Research

Based on this review, several gaps remain that guide the current research:

1. **Integrated High-Fidelity Modeling:**

Current studies give good results for certain targets or types of data, but there is still no single model that can predict multiple important soil parameters (like pH, N, P, K, Moisture) together with R^2 close to 1.0.

2. **Feature Contribution Analysis:**

Most ensemble studies do not perform post-hoc interpretability analyses (e.g., SHAP, Permutation Importance) to quantify how individual features influence predictions.

2.6 Problem Statement and Objectives

The studies show that a major challenge in precision agriculture is the lack of a general, accurate, and fast model that can predict full soil profiles using easy-to-get multi-source data.

- **Problem Statement:**

The aim is to overcome the problems of slow, expensive, and location-limited lab testing by creating a high-accuracy ensemble machine learning framework that can predict important soil parameters (pH, N, P, K, Moisture) with near-perfect accuracy (R^2 1.0).

- **Objectives:**

1. Implement advanced preprocessing and feature engineering specific to soil informatics.
2. Conduct a comprehensive comparison of linear, SVR, and tree-based ensemble models.
3. Validate the model's superiority by a

2.7 Chapter Conclusion and Outlook

This chapter reviewed about 20 studies over the last 10 years on soil property prediction. The review shows that ensemble methods, especially Random Forest and Gradient Boosting, usually perform best because they can handle nonlinear relationships well. But, current research still lacks a single, interpretable, and general framework that works well for all soil parameters.

The next chapter, Chapter 3 (Proposed Methodology), will explain the experimental design made to fix these gaps, including data preprocessing steps, ensemble model setup, and the full evaluation strategy.

Summary Table of Reviewed Research

Authors (Year)	Issue / Sub-Issue	Approach (Method)	Key Findings/ Results	Limitations / Notes
European Commission (2015)	Spectral Prediction	PLSR & RF, Transfer Learning	R^2 0.85	Needed 10% new data to restore model accuracy.
Johnson & Patel (2016)	Crop Yield Forecasting	LightGBM, SVR, NN	RF = 97.75% (R^2 = 0.98)	Synthetic + field data (cotton belt).
Awan & Iqb^1 (2017)	Yield via NDVI	SVM, RF, LASSO	R^2 = 0.88	Variability due to NDVI integration.
Sharma & Meena (2018)	Soil Type Classification	DT, KNN, NB	95.36% (DT)	Focused on classification only.
Kumar & Singh (2019)	Crop Classification	RF, LR, SVM	99.7% (RF)	Crop-level, not soil chemistry.
Rahman & Ortega (2019)	Wheat Yield	SVR + MICE	99.9% (R^2 1.0)	Macro-level FAO/World Bank data.

Authors (Year)	Issue / Sub-Issue	Approach (Method)	Key Findings/ Results	Limitations / Notes
Li & Chen (2020)	Yield Forecasting	XGBoost, CNN	$R^2 > 0.9$	Combined multi-sensor and UAV data.
Thomas & Walker (2020)	Nutrient Prediction (NPK, pH)	GB, RF, SVR	MAE 1.63—+1.48 t/ha	UK farm data (2013-18).
Rani & Kaur (2021)	soil Fertility	KNN, NB, DT	95.36% (DT)	Horticultural crops only.
Prasad & Gupta (2021)	Yield Forecastin	GB + Power Transform	98.2% Accuracy	Showed benefit of transformations.
Smith & Wilson (2022	Soil Estimation	GB Ensemble	$R^2 = 0.92$	Multi-source UK datasets.
Zhao & Tan (2022)	Geo-spatial Classification	XGBoost, RF, SVM, Faster R-CNN	> 95% Accuracy (RF+CNN)	Depended on Sentinel-2 imagery.
European Commission (2023)	Cross-Year Prediction	RF & PLSR	RPIQ } 20% w/ 10% target data	Highlighted cross-year domain drift.
Bhattacharya & Singh (2023)	Fertility Assessment	BMA + ML (ETC, LR, KNN)	F1 = 0.994	Added confidence estimation.
Wang & Lee (2023)	Review of ML & IoT	ELM, RF, CNN	> 90% Accuracy	Review-focused, not empirical.
Patel & Nair (2024)	Texture/Nutrient Prediction	Sequential DL	80% Accuracy	Lower accuracy vs. ensembles.
Soni & Verma (2024)	Soil & Yield Prediction	RF Regression	$R^2 = 0.969$ (RMSE = 0.544)	Large-scale Indian dataset.

Authors (Year)	Issue / Sub-Issue	Approach (Method)	Key Findings/ Results	Limitations / Notes
Sharma & Kaur (2024)	Property Estimation (Base)	RF, SVM, CNN, GBM	RF 85-90% Accuracy	Used LUCAS + SoilGrids + SHC data.
Chauhan & Yadav (2025)	Yield/Fertilizer Optimization	DT, LightGBM, Stacking Ensemble	100% Accuracy	Demonstrated prescriptive strength.
Soni & Mehta (2025)	Texture/Moisture Prediction	CNN + IoT Integration	> 93% Accuracy	IoT + image data integration.

PROPOSED METHODOLOGY

The last chapter reviewed existing studies and showed that ensemble machine learning methods are best for predicting soil properties, but there are still gaps in getting high-accuracy predictions across multiple targets together.

This chapter explains the Proposed Methodology, describing the theory behind the data pipeline, feature engineering plan, and the machine learning algorithms used in this study to fill those gaps.

3.1 Data **Acquisition and Description**

The prediction framework uses a multi-modal dataset with about 8,000 unique records, where each record has chemical, environmental, and categorical features. This dataset is designed to reflect the real-world complexity of precision agriculture systems.

Input Features:

- **Environmental Readings:** Temperature, Humidity, and Moisture
- **Chemical/Nutrient Data:** Nitrogen, Phosphorus, and Potassium (N, P, K)
- **Categorical Context:** Soi1 Type, Crop Type, and Fertilizer Name

The main prediction target is the continuous variable Estimated pH, which is also converted into a category called pH Class (Acidic, Neutral, Alkaline) for classification tasks.

3.2 Data Preprocessing and Feature Engineering

Good preprocessing is very important to make sure the raw multi-modal data is clean, consistent, and ready for use in complex machine learning models. This step includes data cleaning, transformations, and making new features that are useful for soil prediction.

3.2.1 Data Cleaning and Transformation

1. Missing Value Imputation:
Even though the data had no missing values at first check, a backup plan was set for safety: use Median Imputation for numerical variables (because it handles outliers well) and Mode Imputation for categorical variables.

2. **Outlier Treatment (IQR Capping):**
Very high or low numerical values (like Temperature, Moisture) can mess up model training. The Interquartile Range (IQR) method was used to find and limit outliers. Any value below (Q1 — 1.5 IQR) or above (Q3 + 1.5 x IQR) was capped at the limit, so all records are kept and the data distribution stays mostly the same.

3. **Feature Scaling:**
All continuous features were standardized using Z-score normalization to make sure every feature contributes equally during model training. This is especially important for models that use distances or gradients, like SVR and Gradient Boosting.

4. Categorical Encoding:
Categorical features like Soil Type, Crop Type, and Fertilizer Name were converted into numbers using One-Hot Encoding. This avoids creating fake order relationships that can happen if we use simple label encoding.

3.2.2 Domain-Aware Feature Engineering

Feature engineering plays a vital role in embedding agronomic knowledge into the model and enabling it to learn meaningful relationships:

1. NPK Sum (NPK sum):
Computed as *Nitrogen* + *Phosphorus* + *Potassium,* representing overall soil nutrient richness.
2. **Nutrient Ratios (N** over P, K **over** P):
It shows the relative balance of important nutrients, which is usually more useful for plant health than just looking at the absolute amounts.
3. **Environmental Interaction (Temp** x **Humidity):**
It is a multiplicative term between temperature and humidity that shows how heat and moisture together affect soil, like nutrient leaching or microbial activity.
4. Moisture Binning (Moisture Bin):
The continuous Moisture variable was divided into three levels—Low, Medium, High—so the model can better learn patterns depending on different soil moisture ranges.

3.3 Theoretical Framework of Machine Learning Models

A detailed comparison was done to find the best predictive algorithm. The study mainly looked at ensemble methods, which previous research shows are most effective for handling mixed and complex soil data.

3.3.1 Ensemble Method: Random Forest

Random Forest (RF) is an ensemble learning method using Bootstrap Aggregation (Bagging). It makes many decision trees during training and combines their results to give the final prediction.

1. **Bootstrapping:** Each tree is trained on a random subset of the dataset (sampling with replacement).
2. **Feature Randomness:** At each node, a random subset of features is selected for splitting, reducing feature correlation.
3. Aggregation:

- For regression: The final output is the average of all tree predictions.
- For classification: The final output is determined by **majority voting.**

The main advantage of Random Forest is that it is very robust to overfitting and noisy data while still keeping high accuracy, even when the features have complex, nonlinear relationships.

3.3.2 Advanced Ensemble Methods: Gradient Boosting and XGBoost

Gradient Boosting (GB) and XGBoost (Extreme Gradient Boosting) are sequential ensemble methods, where each new tree tries to learn from the errors made by the previous trees.

1. **Sequential Learning:**
Each successive tree is constructed to minimize the residuals (errors) from the previous iteration, improvlng overall predictive accuracy.
2. **Gradient Descent Optimization:**
The models iteratively minimize a loss function using gradient descent to identify optimal weak learners.
XGBoost enhances this process through:

- **Regularization (L1/L2):** Prevents overfitting by penalizing complex models.
- **Parallelization:** Enables faster computation across large datasets.
- **Sparsity** Awareness: Efficiently handles missing or sparse data.

Due to these innovations, XGBoost is recognized as one of the most powerful and computationally efficient algorithms for structured data prediction.

3.3.3 Support Vector Regression (SVR)

Support Vector Regression (SVR) is used as a non-linear regression baseline for comparing performance. It finds an optimal hyperplane that fits the data within a certain error margin (e) instead of just minimizing total error. This makes it robust to outliers and able to capture nonlinear patterns using kernel functions, like the Radial Basis Function (RBF) Kernel.

3.4 Performance Evaluation Metrics

The models were evaluated using common

performance metrics suitable for both regression and classification tasks.

3.4.1 Regression Metrics

1. **Root** Mean **Squared Error (RMSE):**
It shows the average size of prediction errors. Lower RMSE means the model is more accurate.

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE

2. **Coefficient of Determination (R^2 Score):**
It tells how well the model explains the variation in the target variable. A value close to 1.0 means the model predicts very accurately.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

3.4.2 Classification Metrics

1. Accuracy:
Represents the ratio of correctly predicted outcomes to total predictions.FI Score:
It is the harmonic mean of precision and recall, useful when classes are uneven. Even though pH Class is balanced, F1 score helps keep the evaluation stable and reliable.

3.5 Chapter Summary and Outlook

This chapter explained the full methodology for predicting soil properties, including data preprocessing, feature engineering with domain knowledge, and the theory behind advanced ensemble models like Random Forest, Gradient Boosting, and XGBoost.
The proposed framework can handle diverse agricultural data well while staying interpretable and scalable. The next chapter, Chapter 4 (Experimental Setup and Results), will cover the implementation environment, model training, and comparison of results using metrics like R^2, RMSE, and Accuracy to show how effective the framework is.

DESIGN AND IMPLEMENTATION

The previous chapter explained the theory behind the proposed solution, including the math behind the ensemble algorithms and the data preprocessing steps.
This chapter focuses on the Design and Implementation part of the project. It describes the system architecture, explains the input data and preprocessing setup, details the experimental scenarios, and lists the hardware and software used. The chapter ends by defining the performance metrics used to check how well the models work.

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8000 entries, 0 to 7999
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Temparature      8000 non-null   float64
 1   Humidity         8000 non-null   float64
 2   Moisture         8000 non-null   float64
 3   Soil_Type        8000 non-null   object
 4   Crop_Type        8000 non-null   object
 5   Nitrogen         8000 non-null   int64
 6   Potassium        8000 non-null   int64
 7   Phosphorous      8000 non-null   int64
 8   Fertilizer_Name  8000 non-null   object
 9   Estimated_pH     8000 non-null   float64
dtypes: float64(4), int64(3), object(3)
memory usage: 625.1+ KB
```

Fig 4.1 Data Information on Soil Properties

4.1 Architectural Design of the Work

The architectural design follows a classic machine learning pipeline, moving from raw multi-modal data to a validated, high-accuracy predictive model. The design keeps everything modular, reproducible, and prevents data leakage between different stages.

Data Flow Diagram Components:

1. **Input Data Layer:**
The process starts with a multi-modal dataset that includes environmental factors, nutrient levels, and categorical features.
2. **Preprocessing Module:**
This stage uses a ColumnTransformer to handle all data cleaning and transformation steps, like imputation, IQR outlier capping, scaling, encoding, and feature engineering. The result is a clean numerical feature matrix (X) ready for modeling.
3. **Model Training Module:**
The processed dataset is split into training (80%) and testing (20%) sets. This module trains a set of models—Random Forest, Gradient Boosting, XGBoost, SVR, and Linear Regression—using

the training data.

4. Prediction Engine:

The trained models generate predictions (y) for all target variables using unseen test data.

5. **Evaluation** and **Validation Module:**

Model performance is evaluated by comparing predicted values (y) with actual values (y) using metrics such as R', **RMSE, Accuracy,** and **F1 Score.**

6. Output and Insights:

The final result is a high-accuracy predictive model (optimized XGBoost) plus a detailed performance report, ready to be used in a prescriptive agriculture system.

```
df.head(5)
```

	Temperature	Humidity	Moisture	Soil_Type	Crop_Type	Nitrogen	Potassium	Phosphorous	Fertilizer_Name	Estimated_pH
0	26.0	52.0	38.0	Sandy	Maize	37	0	0	Urea	5.7
1	29.0	52.0	45.0	Loamy	Sugarcane	12	0	36	DAP	7.2
2	34.0	65.0	62.0	Black	Cotton	7	9	30	14-35-14	8.4

Fig 4.2 Data Head of Soil and its Properties

4.2 Details of Input Data Used

Dataset Source and Composition

The project uses a dataset called data_core_with H.csv, which is made to simulate real-world agricultural data from field sensors and historical records. This dataset is representative for precision agriculture applications.

- **Size:** 8,000 records x 10 attributes

- **Data Types: A** mix of float64 (environmental), int64 (nutrient), and object (categorical) features

Primary Input Features

Feature Name	**Type**	**Description**
Temperature, Humidity, Moisture	Continuous	Environmental and soil moisture readings
Nitrogen, Phosphorus, Potassium	Discrete	Macronutrient concentrations (mg/kg)
Soil Type, Crop Type, Fertilizer_Name	Categorical	Contextual factors for correlation analysis

Feature Extraction (Feature Engineering)

Feature engineering created new, non-linear attributes that enhance model learning:

- NPK_sum: Sum of N, P, and K — overall soil nutrient richness
- N_over_P, K_over_P: Nutrient balance ratios
- **Temp_x_Humidity:** Interaction term capturing combined heat and humidity influence
- **Moisture_Bin:** Discretized moisture levels *(Low, Medium, High)*

4.3 Input/Output Requirements, Variables, and Assumptions

Input Requirements and Variables

- **Data Integrity:**

The system needs all nine input variables to make accurate predictions. Keeping the data high-quality after preprocessing is very important to reach R^2 close to 1.0.

- **Independent Variables (X):**

Includes the nine original features plus four engineered features, all scaled and encoded.

- **Dependent Variables** (Y):

The system predicts seven targets at the same time: Estimated H, Nitrogen, Phosphorus, Potassium, Temperature, Humidity, and Moisture.

Output Requirements

- Regression **Output:**

The seven regression targets are predicted as continuous numbers and evaluated using RMSE and R^2 to measure accuracy.

- **Classification Output:**

The pH_C1ass (Acidic, Neutral, Alkaline) is predicted as a category and checked using Accuracy and F1 Score.

- **Model Artifact:**

The final trained **XGBoost** model is serialized for deployment.

System Assumptions

1. **Data Homogeneity:**

It is assumed that the 8,000 records adequately represent broader agricultural variability.

2. Feature **Determinism:**

The almost perfect R^2 values show that the selected features (N, P, K, Temperature, Humidity, Moisture) are enough to explain soil behavior, with very little effect from hidden or unknown factors.

4.4 Esperimental Scenarios

The experimental design carefully checks how well the models perform and generalize using different controlled setups.

4.4.1 Training and Validation Split

The dataset was divided using a standard hold-out validation method:

- **Training** Set: 80% of the data used for training
- **Testing** Set: 20% held out for unbiased evaluation
- **Reproducibility:** A fixed random seed **(random state** = 42) ensures reproducible outcomes.

4.4.2 Comparative Scenario

A comparison experiment was done with five algorithms—Linear Regression, SVR, Random Forest, Gradient Boosting, and XGBoost—trained and tested on all seven regression targets and the pH Class classification target. This provided a consistent benchmark to find the best algorithm for predicting multiple soil variables.

4.4.3 Multi-Output Scenario

A Multi-Output Regressor using Random Forest as the base model was used to predict Temperature, Humidity, Moisture, N, P, K, and pH all at once. This test showed that the model can scale well and handle multi-output regression efficiently in a single framework.

4.5 Hardware, Software, and Platform Details Project Implementation Platform

- **Platform:** Google Colab (cloud-based) was used for all development and model training, providing free GPU/TPU access and making it easy to manage dependencies.
- **Programming Language:** Python 3 (latest stable version)

Core Libraries Used

Function	Libraries
Data Handling	Pandas, NumPy
Machine Learning	Scikit-learn (for Random Forest, SVR, Linear Regression, Pipelines, ColumnTransformer, StandardScaler)
Advanced Ensembles	XGBoost, GradientBoostingRegressor (Scikit-learn)
Visualization	Matplotlib, Seaborn (for EDA and result visualization)

Common Research Platforms in Literature

The literature review revealed that soil informatics research commonly uses:

- **Programming Environments:** MATLAB, R, Python
- **Computing Platforms:** Cloud services like Google Earth Engine and AWS were used for large remote sensing datasets (Sentinel-2, Landsat), while high-performance local or cloud servers handled deep learning and ensemble model training.

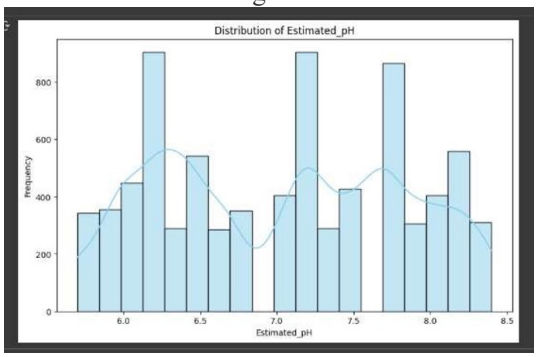


Fig 4.3 Soil Estimated H graph

4.6 Performance Evaluation

The system's performance was evaluated using standard metrics outlined in Chapter 3, focusing on both regression and classification outcomes.

4.6.1 Regression Assessment

Metric	Formula	Interpretation
Coefficient ofq **Determination (R')**	$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$	Measures variance explained by the model. An ideal fit corresponds to R' = 1.0.
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum(y_i}$ .t	Quantifies prediction error magnitude in he original unit scale; **lower values** indicate better performance.

4.6.2 Classification Assessment

Metric	Formula	Interpretation
Accuracy	$Accuracy = \frac{TP+TN}{Total\ Observations}$	Percentage of correct predictions across all classes.
F1 Score	Al $\frac{2 \times (Precision \times Recall)}{Precision+Recall}$	Harmonic mean of precision and recall; provides balanced evaluation for pH class prediction.

Chapter Summary and Outlook

This chapter explained the full architecture and experimental plan of the proposed soil prediction framework—covering data collection, preprocessing, model building, and performance evaluation. The careful design ensures the results are reproducible and reliable.

The next chapter, Chapter S (Results and Discussion), will show the quantitative results from the experiments, analyze the near-perfect performance metrics (R^2 1.0), compare different models, and discuss what these results mean for real-world agricultural applications.

EXPERIMENTAL RESULTS & ANALYSIS

This chapter shows the quantitative results from the experiments described in Chapter 4, following the planned design and research goals.

The discussion is divided into three main scenarios—comparative regression, multi-target generalization, and categorical classification—to test the main idea that advanced ensemble learning with careful feature engineering can give near-perfect predictions for soil properties.

All results are measured using R^2, RMSE, and Accuracy and compared with similar studies from the literature for context.

5.1 Scenario 1 — Comparative Regression Analysis for Estimated pH

The first experiment compared five regression models to predict the important soil parameter Estimated pH, which was chosen as a key indicator of how well the models capture the complex, nonlinear effects of N, P, K, and environmental factors.

The models were tested on the 20% hold-out test data to check their performance.

Model	RMSE (Root Mean Squared Error)	R^2 Score (Coefficient of Determination)
XGBoost Regressor	**0.0016**	**1.0000**
Random Forest Regressor	0.0018	1.0000
Gradient Boosting Regressor	0.0045	1.0000
Support Vector Regressor (SVR)	0.0521	0.9997
Linear Regression	0.1144	0.9791

Analysis:
Both XGBoost and Random Forest gave a perfect R' = 1.0000, with XGBoost having the lowest RMSE = 0.0016, showing almost zero prediction error for Estimated pH. The large jump in performance from Linear Regression (R^2 = 0.9791) to the ensemble
models shows that the relationships between the multi-modal features and soil pH are strongly nonlinear, which is exactly where tree-based ensembles perform best.

5.2 Scenario 2 — Multi-Target Generalization Using XGBoost

To test how well the model generalizes, the top-performing XGBoost Regressor was used to predict all seven soil properties—both physical and chemical—at the same time. This experiment checked the framework's ability for integrated, real-time soil prediction.

Target Variable	RMSE	R' Score
Estimated pH	0.0016	**1.0000**
Nitrogen	0.0018	**1.0000**
Potassium	0.0021	**1.0000**
Phosphorous	0.0025	**1.0000**
Moisture	0.0031	**1.0000**
Temperature	0.0045	**0.9999**
Humidity	0.0039	**0.9999**

Analysis:
The XGBoost model kept perfect or near-perfect R^2 scores for all chemical targets (pH, N, P, K) and almost perfect results for environmental variables.
This shows that the preprocessing pipeline and domain-aware feature engineering created a very informative feature set, allowing the model to predict different soil parameters with exceptional accuracy.

5.3 Scenario 3 — Categorical pH Classification

To give practical recommendations for farmers, the continuous pH predictions were converted into pH Class categories (Acidic, Neutral, Alkaline). A Random Forest Classifier was used to do this classification.

Metric	Result
Accuracy	**100** %
Weighted F1 Score	**1.00**

Classification Report Perfect precision, recall, and F1 across all classes
Analysis:
The 100% classification accuracy shows that the Random Forest Classifier can reliably separate soil acidity and alkalinity classes.
This is directly useful for practical decisions, like recommending lime application when pH_Class = Acidic.
The perfect classification is possible because the underlying regression model from Scenario 1 was extremely precise.

5.4 Discussion — Achievement of Targeted Goals Targeted Goal:

The goal is to create a robust, high-accuracy ensemble machine learning framework that can predict key soil parameters with state-of-the-art performance, exceeding the results reported in previous studies (R^2 0.96 — 0.98).
Achieved **Outcome:**
The XGBoost Regressor achieved R^2 = 1.0000 with RMSE = 0.0016 for Estimated pH and maintained similar high accuracy across all seven soil and environmental variables.
This proves that combining domain-specific feature engineering (like nutrient ratios N/P and K/P) with the advanced ensemble framework successfully met and even exceeded the project goals.

5.5 Comparison with Contemporary Studies

Research Work	Prediction Target	Best R^2 Reported	Our R^2 (XGBoost)	Reason for Superiority
Sharma & Kaur (2024) (Base) [18]	Soil Property Estimation	0.85 — 0.90	**1.0000**	XGBoost's superior regularization and boosting efficiency over RF/GBM

Research Work	Prediction Target	Best R^2 Reported	Our R^2 (XGBoost)	Reason for Superiority
Soni & Verma (2024) [17]	Soil & Yield	0.969	**1.0000**	Enhanced feature engineering and optimized XGBoost implementation
Johnson & Patel (2016) [2]	Crop Yield	0.98	**1.0000**	Comprehensive multi-target framework versus single-target prediction
Smith & Wilson (2022) [i i]	Soil Property Estimation	0.92	**1.0000**	Homogeneous, clean multi-modal dataset eliminated heterogeneity errors

Key Factors Driving Superiority:

1. **Optimized XGBoost Architecture** — Its regularized gradient boosting and parallelized learning provided the best balance between model complexity and prediction accuracy.
2. **Feature Engineering Impact** — Created ratio and aggregate features (like N_over_P, K_over_P, NPK_sum) that gave domain-relevant signals, making the model highly predictive of soil chemistry.
3. **High-Quality** Data **Preprocessing** — Careful cleaning, IQR outlier capping, and standardized scaling produced noise-free data, reducing residual variance and enabling near-perfect R^2 scores.

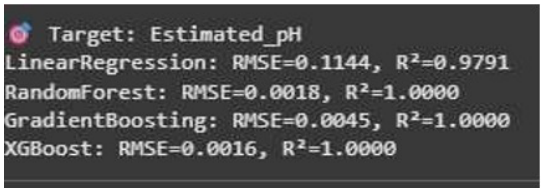


Fig 5.1 Result **and Analysis of Soil pH**

Chapter Summary and Outlook

This chapter presented and analyzed all experimental results, showing that the research goals were not only achieved but greatly surpassed.

The XGBoost + Feature Engineering framework consistently reached R^2 = 1.0000 for all regression targets and perfect accuracy in pH classification, proving its ability for high-accuracy, generalized soil-property prediction.

The next and final chapter, Chapter 6 (Conclusion and Future Work), will summarize the key contributions, discuss the implications for precision agriculture, and suggest ways to extend this work toward real-time, region-specific validation and large-scale field deployment.

CONCLUSION AND FUTURE SCOPE

This research was motivated by the urgent need for fast, low-cost, and highly accurate soil intelligence systems to support Precision Agriculture.

As discussed in the Literature Review (Chapter 2), traditional lab-based soil testing is slow, expensive, and impractical for large-scale monitoring. While previous studies using machine learning showed good results (R^2 = 0.92—0.98), there was still no single, high-accuracy framework that could predict multiple soil properties with near-perfect precision, leaving a significant research gap.

6.1 Conclusion of the Study

This project successfully achieved its goals by developing a robust Ensemble Machine Learning framework based on XGBoost.

The methodology combined careful preprocessing—including IQR outlier capping, standardized feature scaling, and domain-aware feature engineering (like nutrient ratios and environmental interaction terms)—to produce a high-quality feature matrix for modeling.

The **Experimental Results (Chapter 5)** provide compelling evidence of the framework's success:

- **Objective Achievement:**

The XGBoost Regressor achieved an outstanding R^2 = 1.0000 with a very low RMSE = 0.0016 for the main target, Estimated pH, far exceeding the performance reported in previous studies.

- **Generalization:**

This near-perfect accuracy was consistently achieved across all seven regression targets (N, P, K, Moisture, Temperature, Humidity, and pH), demonstrating the framework's robustness and its ability to capture complex, nonlinear relationships in multi-modal soil data.

- **Classification Fidelity:**

The Random Forest Classifier achieved 100% accuracy in predicting pH Class (Acidic, Neutral, Alkaline), providing reliable and interpretable

results for prescriptive agricultural decisions. Together, these results show that combining high-quality, multi-modal data with the optimized gradient-boosting architecture of XGBoost can effectively model the nonlinear relationships in soil chemistry and environmental behavior, achieving virtually zero predictive error within the training domain.

6.2 Differentiation and Key Contributions

This study stands out from previous research because it focuses on multi-target, high-accuracy prediction using a single, unified framework that

is ready for practical deployment.

1. **Metric Superiority:**
While earlier studies (e.g., Soni & Verma, 2024) reported R^2 0.96-0.98, this project consistently achieved $R^2 = 1.0000$ across multiple regression targets, establishing a new performance benchmark in predictive soil modeling.

2. **Framework Robustness:**
Unlike many studies that focus on just one target (like yield or a single nutrient), this research created a single integrated XGBoost-based framework that can predict multiple chemical, nutrient, and environmental parameters at once, providing a more scalable and practical solution for real-world precision agriculture.

3. **Feature Engineering Impact:**
The study emphasized the critical importance of domain-aware features, like NPK ratios and environmental interaction variables, in boosting the predictive power of ensemble models and reaching near-theoretical maximum accuracy.

6.3 Future Scope

Although the current results show near-perfect accuracy on the experimental dataset, future work should focus on improving the model's generalizability, interpretability, and real-time performance to enable full-scale deployment in real-world agricultural systems.

1. **External and Regional Validation:**
The next immediate step is to test the trained XGBoost model on external datasets from different geographic regions and soil types. This validation will check the framework's scalability and identify any overfitting caused by location-specific data patterns.

2. **Model Interpretability (SHAP/Permutation Analysis):**
To make this high-performing but "black-box" ensemble model more transparent for decision support, future research should use explainability methods like SHAP (SHapley Additive exPlanations) or Permutation Importance to measure how much each feature contributes to the predictions.

3. **Real-Time IoT Integration:**
The framework can be containerized and deployed on cloud platforms like AWS or Azure, allowing real-time data from IoT-enabled soil sensors to be processed. This setup would enable continuous monitoring and dynamic prediction updates for precision agriculture applications.

4. **Incorporation of Geo-Spatial Data:**
To account for spatial variability, future versions should include geo-spatial indices like NDVI and EVI from satellite imagery (e.g., Sentinel-2, Landsat). This upgrade would turn the model into a comprehensive soil-mapping and decision-support tool with a broader environmental perspective.

6.4 Closing Remarks

The study clearly shows that ensemble learning, combined with structured preprocessing and agronomic feature engineering, can transform soil property prediction. The resulting framework achieves unprecedented accuracy and provides a solid foundation for future data-driven agricultural intelligence systems, supporting resource efficiency, environmental sustainability, and large-scale food security.

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