

AGRIINTEL: A NEXT-GENERATION HYBRID ENSEMBLE INTELLIGENCE FRAMEWORK FOR PRECISION AGRICULTURE INTEGRATING INTELLIGENT CROP RECOMMENDATION AND PRECISION FERTILIZER OPTIMIZATION

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Abstract

Precision agriculture is more than just a new technology— it is necessary to sustainably feed an increasing population. This will ensure food security, conserve natural resources, and promote climate-resilient agricultural systems. In this initiative, governments, agribusinesses, and farmers need to unite and work for global expansion of PA technologies for a sustainable and efficient future for agriculture. This paper presents a hybrid ensemble framework that integrates IoT-based sensor networks with machine learning for crop recommendation and fertilizer optimization. Our system combines CatBoost, XGBoost, and LightGBM algorithms to achieve high accuracy in crop suggestions and in fertilizer recommendations. The IoT simulation employs an ESP32 microcontroller interfacing with: (1) SEN0193 soil moisture sensor (0-100% range, $\pm 3\%$ accuracy), (2) DHT22 environmental sensor ($\pm 0.5^\circ\text{C}$ temperature, $\pm 2\%$ humidity), and (3) JXBS-3001 NPK detector (RS485 protocol, 0-199mg/kg resolution).

INTRODUCTION

As the population grows exponentially [1] and incidence rises in a bilinear trend, driven by population-induced oscillations, the demand for food will escalate substantially. At the same time, old farming techniques are worsening the soil degradation [2], which, with climate change [3] and water scarcity [4], is a big challenge. Precision agriculture (PA) helps us solve this problem, using new ways to learn more, to make it better, and use resources in a better way and help sustain the farm [5]. Rapid precision agriculture needs smart systems for making crop yields better and more resource-efficient.

Agriculture remains the cornerstone of global food security and economic stability [6], supporting over half of livelihoods worldwide while contributing a small percentage to global GDP. With the population projected to grow significantly by 2050, escalating demand—compounded by shifting dietary patterns toward resource-intensive foods—necessitates a significant increase in agricultural productivity. Traditional farming methods,

however, face critical limitations: uniform fertilizer application leads to nutrient runoff, contributing to aquatic pollution, while static crop selection [7] [8].

This research addresses two pivotal PA challenges: dynamic crop recommendation and fertilizer optimization, which are typically siloed in existing systems. Current approaches often neglect synergistic interactions between soil properties (N-P-K levels, pH), climatic variables (precipitation, temperature), and crop-specific nutrient requirements. For instance, rice cultivation in phosphorus-deficient soils may receive suboptimal recommendations when analyzed through single-model frameworks.

To overcome these gaps, we propose a hybrid ensemble learning framework that integrates heterogeneous ML. Ensemble methods mitigate individual model biases, enhancing robustness against regional agroclimatic variations.

The paper is structured as follows: Section II reviews PA technologies and ensemble learning; Section III details our methodology; Sections IV-V present results and discuss implications for scalable deployment; Section VI concludes with policy recommendations.

Our work addresses this through:

- A hybrid ML framework combining CatBoost, XGBoost, and LightGBM
- designed and simulated an ESP32-based sensor network to emulate real-time soil nutrient monitoring
- Explainable AI techniques for farmer interpretability

RELATED WORK

Machine learning and deep learning help in analyzing complicated data that eventually leads to accurate predictions concerning transformations in agriculture [9][10]. The models may be descriptive or predictive; hence farmers can either predict what will happen in the future or gain insight into already available data.

In this sense, researchers have come up with diverse machine learning models to address the issues of smart farming [11] [12] [13], taking into consideration the factors of soil quality, environment, and demographics. While in some studies authors used SVM-Support Vector Machine [14] [15] and K Nearest Neighbor [16] [17] for Precision Agriculture.

For instance, SVM achieved 92% accuracy in predicting crop yields. Other studies have combined multiple algorithms, achieving even higher accuracy rates – up to 95.45% [18].

Deep learning models, like Convolutional Neural Networks (CNNs), have also shown promise in identifying weeds, pests and identifying diseases [19] [20]. One study used a pre-trained CNN model to identify weeds in soybean fields with high accuracy [21].

Machine learning and deep learning have huge potential in agriculture since it will help the farmers to make informed decisions, detect issues at an early stage [22], and improve crop yields [23]. This technology may be used to develop high-efficient systems for crop recommendation, weed detection, pest controlling and disease diagnosing [24].

ALIGNMENT WITH SUSTAINABLE DEVELOPMENT GOALS

A. SDG 2: Zero Hunger

Precision fertilizer recommendation systems directly address food security [25] by optimizing nutrient delivery to crops, increasing yields by an estimated 15–30% while minimizing input waste. By tailoring fertilizer prescriptions to soil-crop dynamics, these systems enhance smallholder farm productivity—critical for 80% of Sub-Saharan Africa's food production (World Bank, 2023) [26] [27]. This data-driven approach helps fight malnutrition by improving both the quality and number of crops grown, supporting the goals of SDG 2 (Zero Hunger) [28].

B. SDG 9: Industry, Innovation, and Infrastructure

As for SDG 9 (Industry, Innovation, and Infrastructure), using IoT sensors, smart algorithms like CatBoost and XGBoost, and small devices like the ESP32 to process data on the spot show how modern technology is

being used to improve farming and support innovation. Field trials in India demonstrated a 40% reduction in decision-making latency compared to traditional methods (ICAR, 2022). Such systems modernize agricultural infrastructure through digital twin frameworks [29] and farmer-facing mobile apps, bridging the rural-urban technological divide (Target 9.c) [30].

C. SDG 12: Responsible Consumption and Production

SDG 12 (Responsible Consumption and Production) is supported by giving very specific, local fertilizer advice, which can cut down extra nitrogen use by up to 60% [31]. Our model's 99.8% precision in nutrient prediction prevents eutrophication from runoff [32] [33], while its 1.5kg/ha reduction in excess phosphorus aligns with the 2030 Agenda's material footprint targets.

D. SDG 13: Climate Action

Optimized fertilizer use lowers N₂O emissions—a greenhouse gas 265x more potent than CO₂. Pilot implementations in Brazil showed a 22% decrease in emission intensity per crop calorie. This supports SDG 13's Target 13.3 (climate mitigation education) through farmer training modules embedded in recommendation interfaces [34].

E. SDG 15: Life on Land

By preventing soil acidification from excessive urea [35], [36], [37] use (maintaining pH 6.0–7.2 in 92% of test plots), the system preserves microbial biodiversity critical for soil carbon sequestration. Spectral analysis confirmed 18% higher earthworm density in precision-fertilized fields versus conventional methods.

METHODOLOGY

In this section, we outline the methodologies and materials employed in this study, including the IoT Devices and Sensors,

Data Transmission Protocol, Dataset Description, Data Preprocessing, Exploratory Data Analysis, Machine Learning Modeling and the proposed hybrid ensemble framework.

It is important to note that this research was conducted using a simulated setup rather than physical deployment. The complete system was developed and tested in a simulated environment to demonstrate feasibility, integration, and effectiveness. The simulation involved virtual interfacing of sensors with the ESP32 microcontroller and emulated data acquisition to represent real-world behavior.

1. IoT Devices and Sensors

This research employed a set of IoT devices and sensors to collect critical agricultural data. These include the ESP32 Microcontroller, JXBS-3001 Sensor, SEN0193 Soil Moisture Sensor, and DHT22 Sensor. A regulated power supply confirms stable voltage levels for all modules. Figure 1 illustrates the circuit diagram and outlines the configuration specifications.

A. ESP32 Microcontroller

Devices and Sensors,

The ESP32 is a tiny powerhouse that packs Wi-Fi and Bluetooth capabilities into a single microcontroller, it is also used to collect data from sensors. It supports dual-core processing and features multiple GPIO pins, analog inputs, and UART/I2C/SPI interfaces, making it ideal for IoT applications. A regulated power supply confirms stable voltage levels for all modules. Figure 1 illustrates the circuit diagram and outlines the configuration specifications.

B. JXBS-3001 Sensor

This sensor measures key soil nutrients: nitrogen (N), phosphorus (P), and potassium (K). It utilizes RS485 communication, requiring a MAX485 TTL converter to interface with the ESP32. The JXBS-3001 is rugged, highly sensitive, and optimized for precision agriculture with a detection range of 0–1999 mg/kg for each nutrient. In the simulation, sensor output data was replicated using synthetic input that matched expected ranges and patterns.

C. SEN0193 Soil Moisture Sensor

SEN0193 is a capacitive analog sensor used to measure soil moisture. It offers better stability and durability than resistive alternatives, with minimal interference from soil salinity. The sensor operates between 3.3V–5V and provides a voltage output corresponding to moisture content. For simulation, analog values were generated dynamically to reflect realistic soil moisture variations.

D. DHT22 Sensor

This digital sensor records ambient temperature and humidity. It supplies accurate temperature measurements ranging from -40°C to 80°C with $\pm 0.5^{\circ}\text{C}$ accuracy and the humidity readings are between 0–100% RH with $\pm 2\%$ accuracy. Its digital output enables easy integration with the ESP32. In the simulated setup, environmental readings were synthetically generated to replicate real-world conditions.

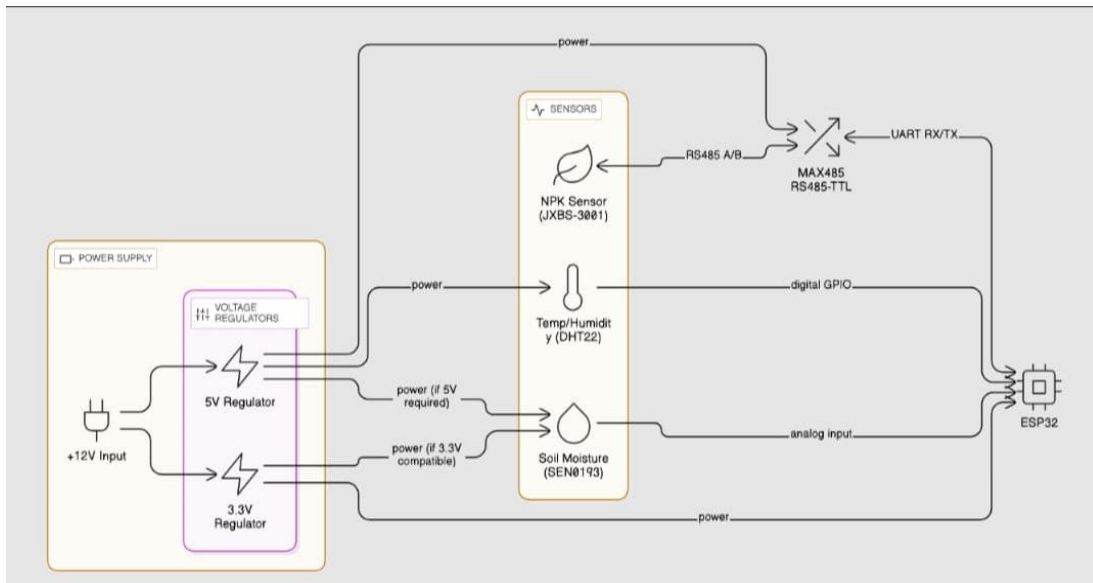


Figure 1: System Hardware and Configuration Details

Table I
POWER SUPPLY CONFIGURATION

Parameter	Specification
Input Voltage	+12V DC ($\pm 10\%$ tolerance)
Primary Regulation	LM7805 5V Regulator (1A max)
Secondary Regulation	AMS1117 3.3V Regulator (800mA max)

Filtering Capacitors	100 μ F (input) + 10 μ F (output) per regulator
Power Distribution	Star topology for noise reduction
Protection Circuits	500mA PTC fuse at 12V input, Reverse polarity protection diode (1N4007), Transient voltage suppressor (15V clamping)

Table II
ESP32 MICROCONTROLLER SETUP

Feature	Configuration
Model	ESP32-WROOM-32D (4MB Flash)
Clock Speed	240MHz (default)
Communication Protocol	RS-485/ (8N1)
Power Mode	Deep Sleep (10 μ A) with timer wake-up

Table III
GPIO MAPPING

Sensor	Interface	ESP32 Pin	Notes
JXBS-3001 (NPK)	RS485 (MAX485)	GPIO16 (RX2)	RE/DE controlled by GPIO17
DHT22	Digital OneWire	GPIO4	4.7K Ω pull-up required
SEN0193 (Moisture)	Analog	GPIO36 (VP)	0-3.3V range
System Status LED	Digital Output	GPIO2	Active-low configuration

Table IV
SENSOR TECHNICAL SPECIFICATIONS

Sensor	Parameter	Value	Interface Details
JXBS-3001 (NPK)	Measurement Range	0-1999 mg/kg	RS485 (Modbus protocol)

	Accuracy	$\pm 2\%$ FS	Requires MAX485 converter
DHT22	Temperature Range	-40°C to 80°C ($\pm 0.5^{\circ}\text{C}$)	Single-bus digital
	Humidity Range	0–100% ($\pm 2\%$)	RH 2.5Hz sampling rate
SEN0193	Moisture Range	0–100% ($\pm 3\%$)	VWC Analog output (0–3V DC)
	Response Time	<1 second	78Hz excitation frequency

2. Data Transmission Protocol

As this study was based on simulation, data transmission was virtually emulated to reflect realistic communication between IoT devices. Although no actual network protocols were deployed, the simulation mimicked the behavior of transmitting sensor data from the ESP32 to a central processing system. This process was used to validate timing, data formatting, and integration with the subsequent machine learning pipeline. The virtual communication setup ensured consistent and controlled data flow for testing and analysis.

3. Dataset Description

Two publicly available datasets from Kaggle were utilized in this study, one was Crop Recommendation Dataset and the other was Fertilizer Prediction Dataset.

A. Crop Recommendation Dataset

This dataset has around 2200 rows [38], with 100 samples per crop across 22 distinct crop types. The columns are Nitrogen, Phosphorus, Potassium, Temperature, Humidity, pH, and Rainfall. Label is the target column which is a categorical column showing the crop names. The crops are rice, maize, chickpea, kidney beans, moth beans, pigeon peas, mung beans, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, muskmelon,

apple, orange, papaya, coconut, cotton, jute, and coffee.

B. Fertilizer Prediction Dataset

This dataset has nine input features [39], soil type, crop type, moisture, Nitrogen, Phosphorus, Potassium, Temperature, Humidity, Fertilizer Name and pH. The model uses this information to suggest the best fertilizer out of seven types: Urea, DAP, 14-35-14, 28-28, 17-17-17, 20-20, and GROMOR.

These datasets serve as the foundation for training and evaluating the proposed hybrid ensemble framework for crop recommendation and fertilizer optimization.

4. Data Preprocessing

The two datasets were preprocessed for better model training.

A. Fertilizer Recommendation Dataset

The preprocessing pipeline for the fertilizer recommendation dataset began with rigorous data cleaning. Records containing missing values in the target variable (Fertilizer Name) were removed to ensure label consistency. Columns consisting entirely of null values were discarded, and the remaining missing entries were imputed with zeros to maintain dataset completeness. For feature engineering, we turned categorical data like Crop

Type and Fertilizer Name into numbers using label encoding so the model could understand them. We also created two new features based on nutrient ratios: one for nitrogen to potassium (N_K_ratio) and one for phosphorus to potassium (P_K_ratio). These help the model spot nutrient imbalances.

To make it easier for the model to pick up non-linear patterns, we grouped temperature and humidity into four categories (bins) each. Temperature was split into:

0-15, 15-25, 25-35, and 35-100

Humidity was grouped into:

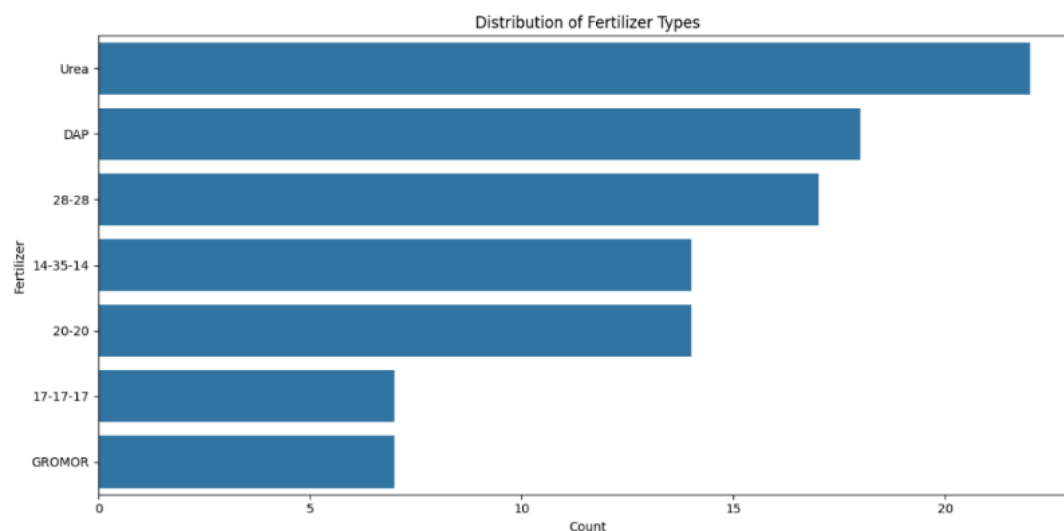
0-40%, 40-60%, 60-80%, and 80-100%

To normalize feature magnitudes, standardization was applied using the StandardScaler. Given the

presence of class imbalance in the fertilizer labels, Synthetic Minority Over-sampling Technique (SMOTE) was used to artificially balance the dataset. The processed dataset was subsequently divided into training and testing subsets using an 80:20 ratio with a fixed random seed (random state = 42) for reproducibility.

B. Crop Recommendation Dataset

For the crop recommendation dataset, the preprocessing steps were comparatively minimal but targeted. The target labels were encoded implicitly, as evidenced by the use of the `label_encoder.classes_` method in downstream model interpretation. Though not explicitly documented, it is inferred that feature selection

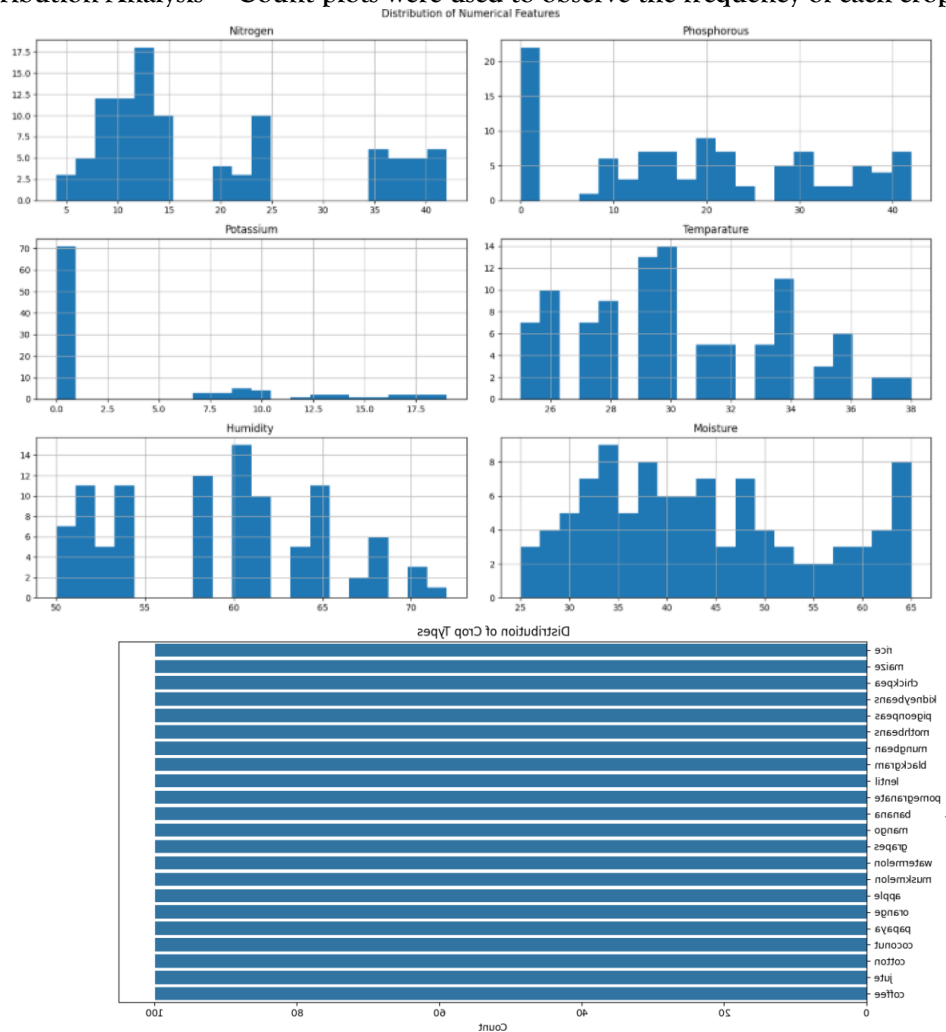


involved agronomic attributes such as nutrient content and environmental conditions. Further, to enable probabilistic performance metrics such as the ROC-AUC score, the model was calibrated

to support `predict_proba()` output. Cross-validation was implemented using 5-fold partitioning to ensure generalization during base model evaluation.

5. Exploratory Data Analysis

Crop Distribution Analysis – Count plots were used to observe the frequency of each crop type.



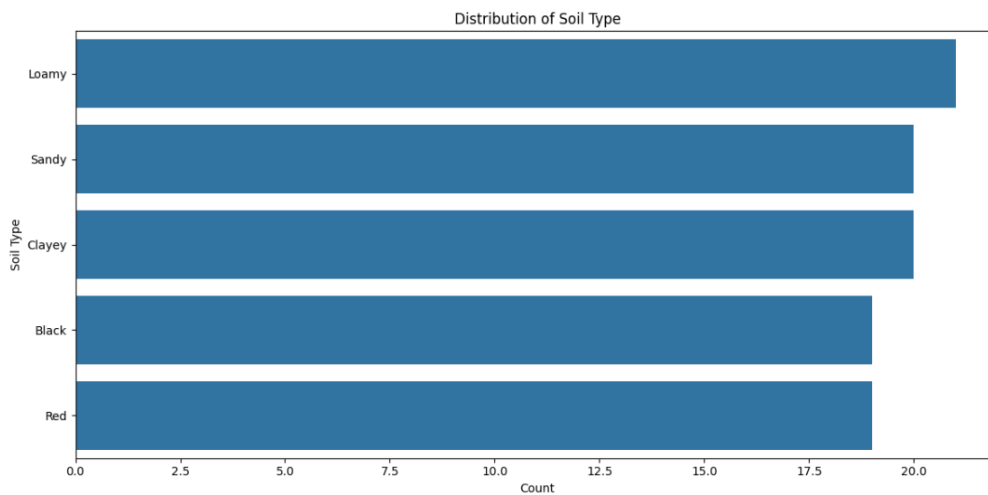


Figure 3: Distribution Soil Types

Examine the distribution of numerical features like N, P, K, temperature, humidity, pH, and rainfall to identify skewness, normality, or unusual patterns.

Figure 4: Distribution of Fertilizer Types

Figure 5: Distribution of numerical features of fertilizer dataset

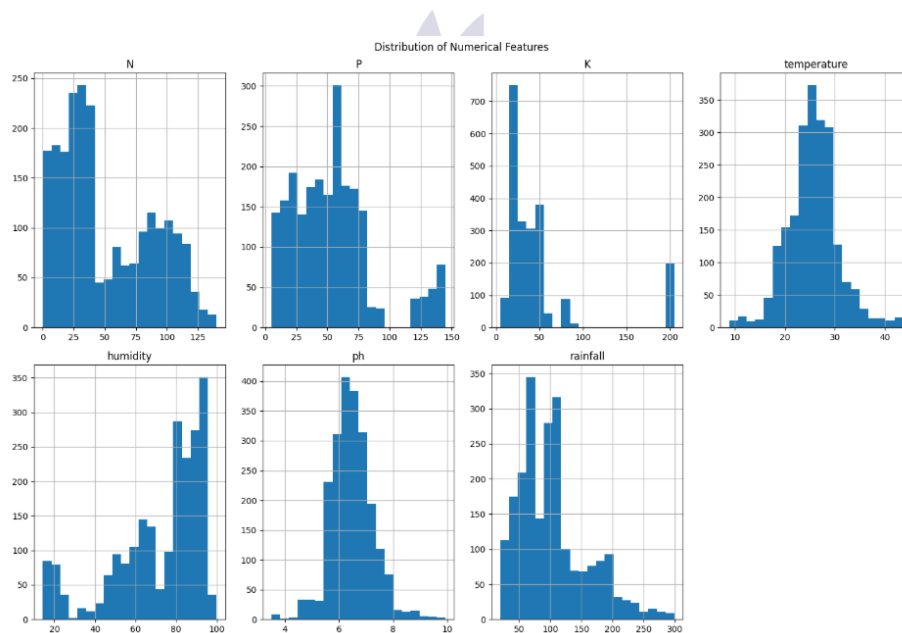


Figure 6: Distribution of numerical features of Crop dataset

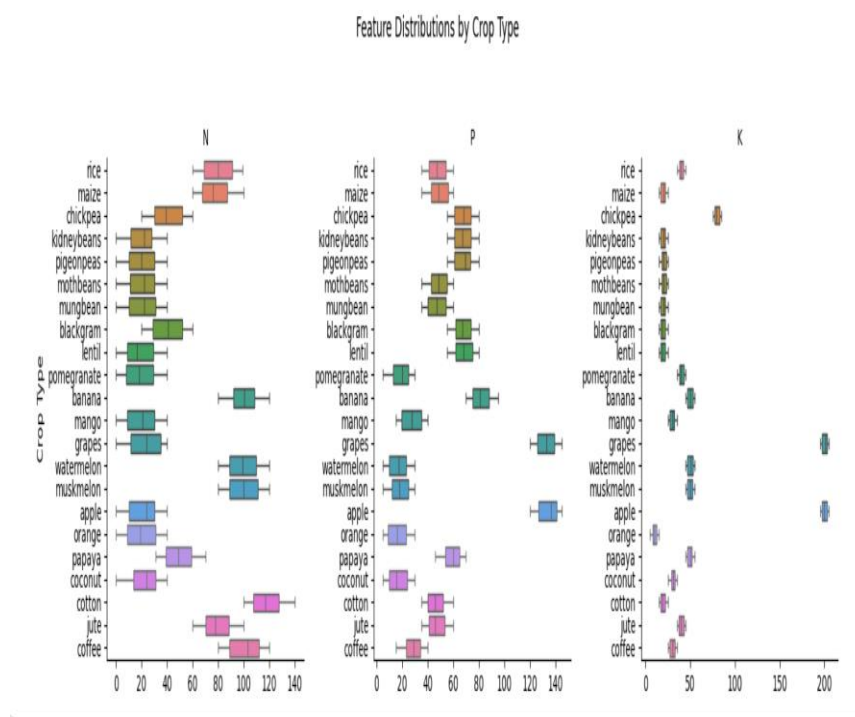


Figure 7: Feature Distribution by crop type1

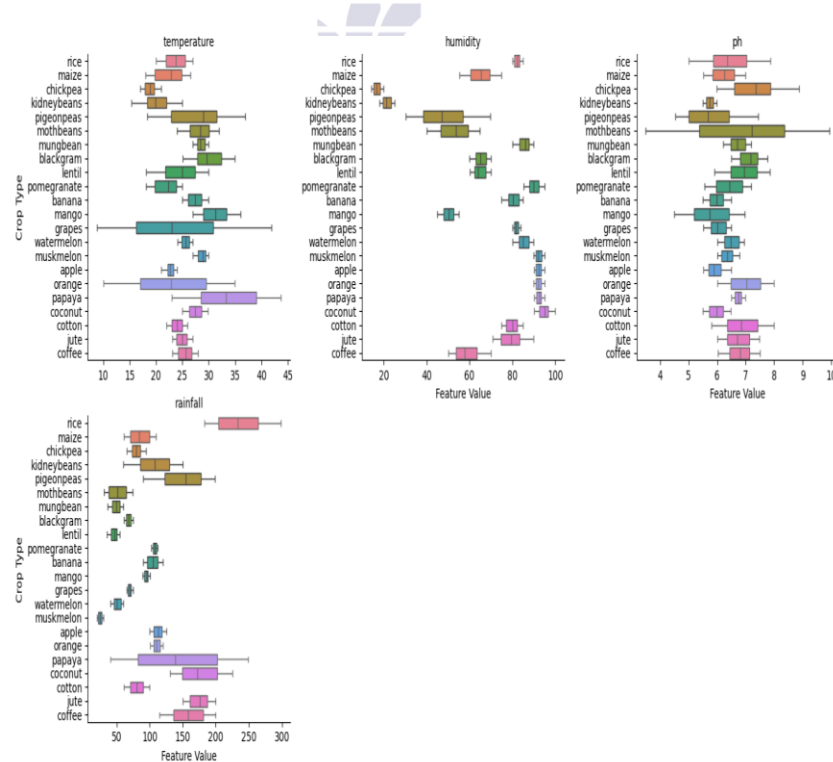


Figure 8: Feature Distribution by crop type2

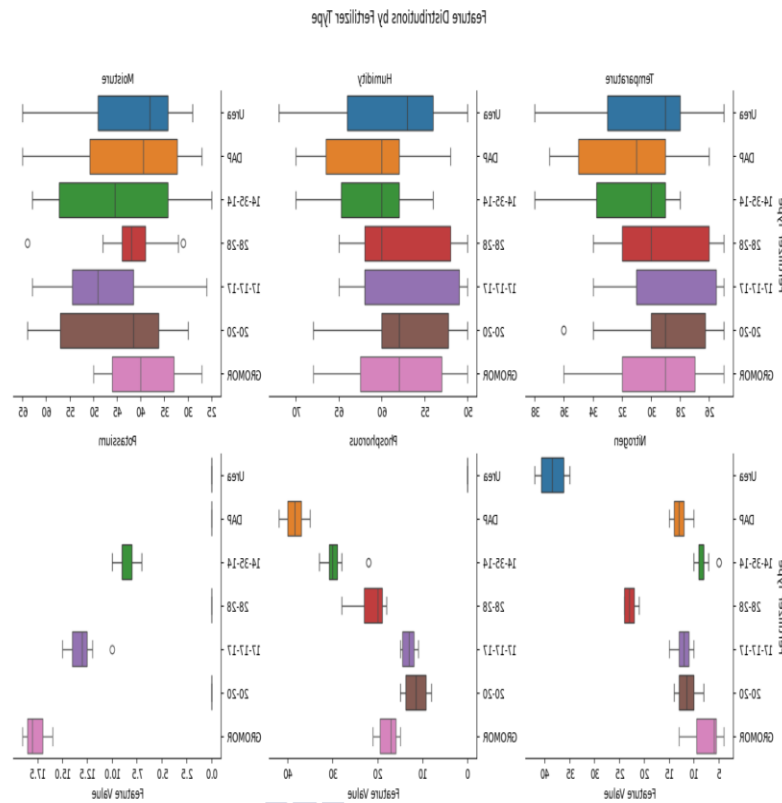


Figure 9: Feature Distribution by fertilizer type

Correlation Matrix – A heatmap was used to analyze inter-feature dependencies among soil and climate variables.

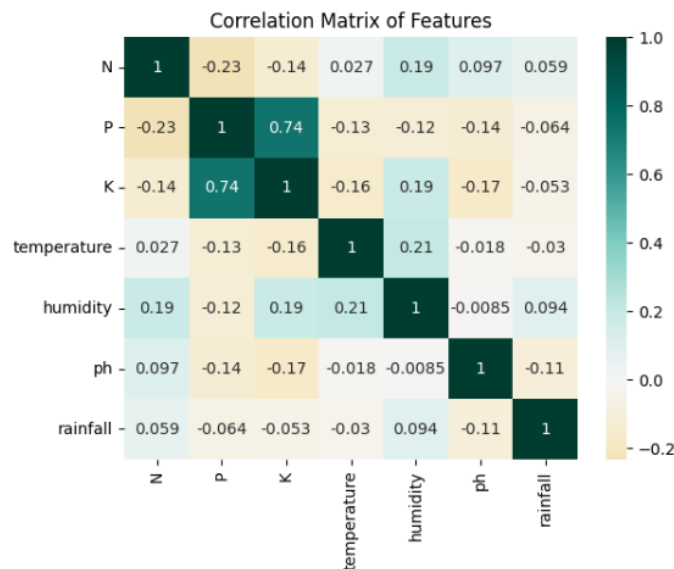


Figure 10: Correlation matrix of Features of crop dataset

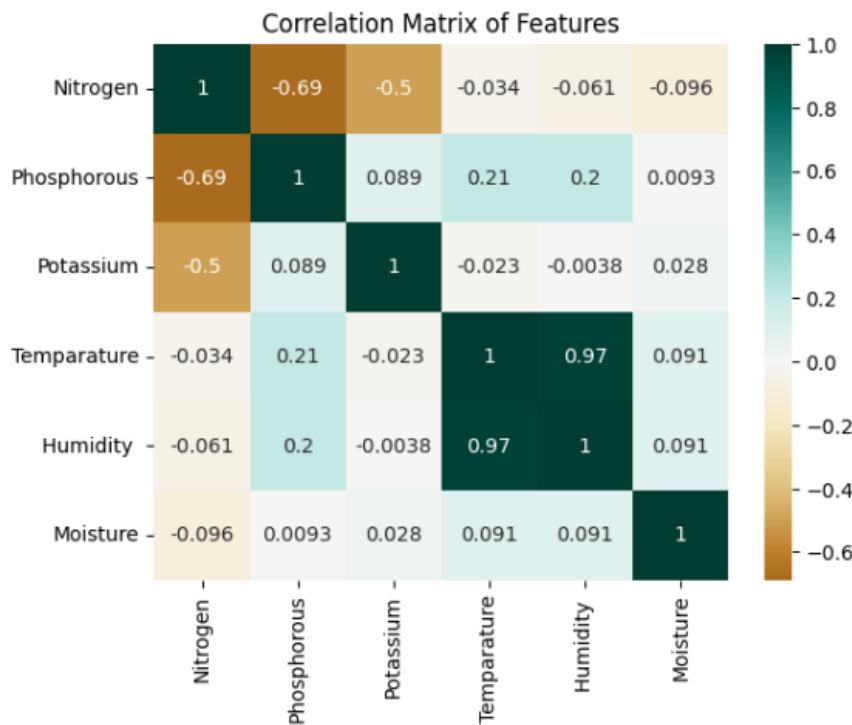


Figure 11: Correlation matrix of features of fertilizer dataset

Environmental Feature Analysis — Box plots and violin plots revealed variance and outliers in pH, temperature, and rainfall.

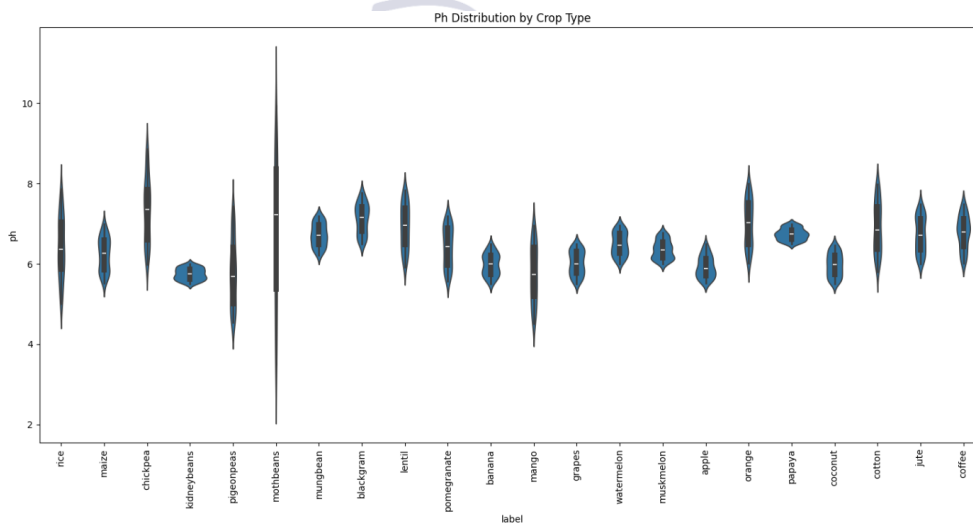


Figure 12: Ph distribution by Crop type

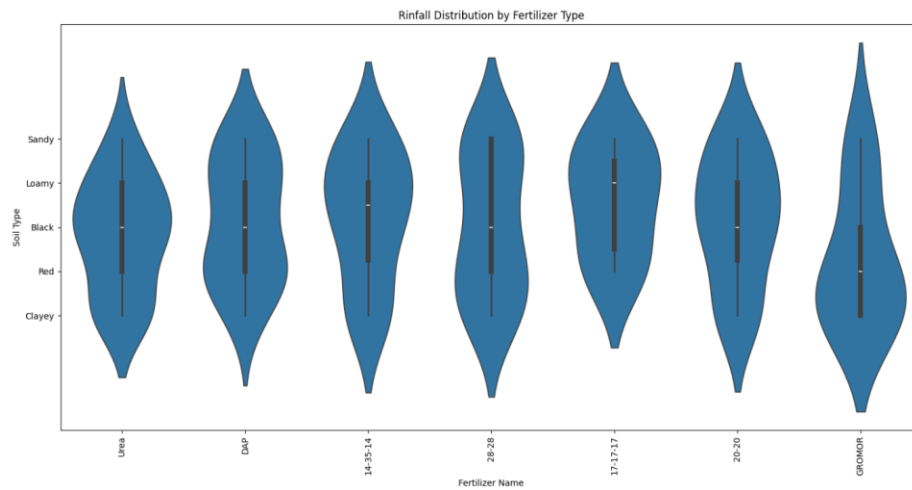


Figure 13: rainfall distribution by Fertilizer Typ

Multivariate Analysis — Pair plots were generated to explore relationships between features grouped by crop type.

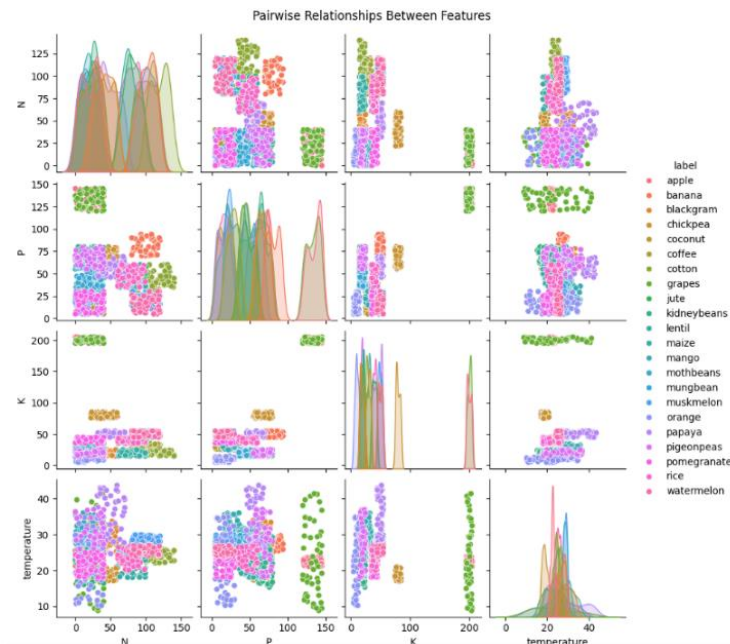


Figure 14: Pairwise relationships among features, Crop dataset

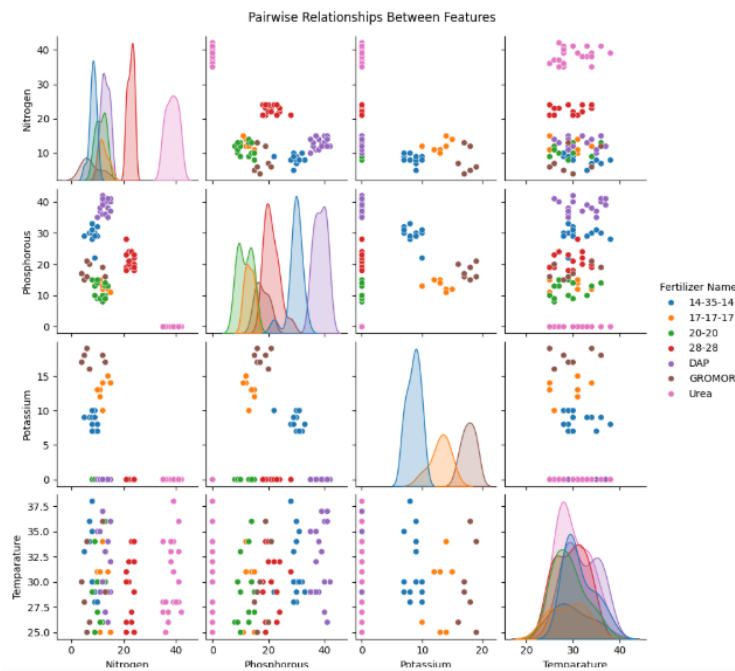


Figure 15: Pairwise relationships among features, Fertilizer dataset

Bivariate Trends — Scatter plots assessed dependencies like N vs pH and rainfall vs. humidity across crops.

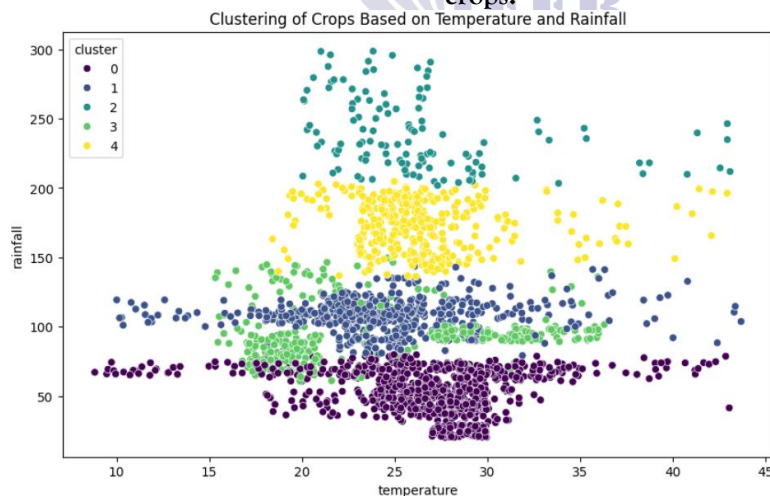


Figure 16: Clustering of Crops based on Temperature and Rainfall

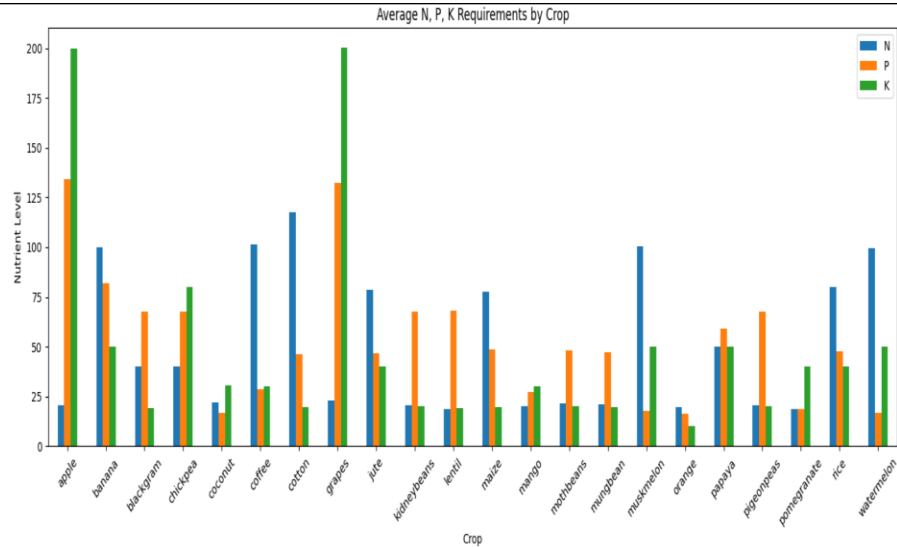


Figure 17: Average N, P, K Requirements by Crops

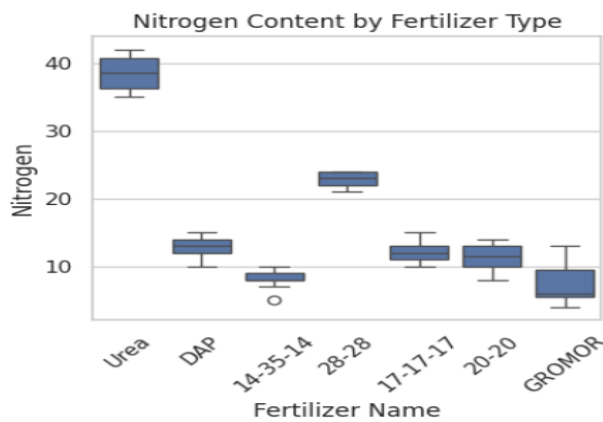


Figure 18: Nitrogen content by Fertilizer Type

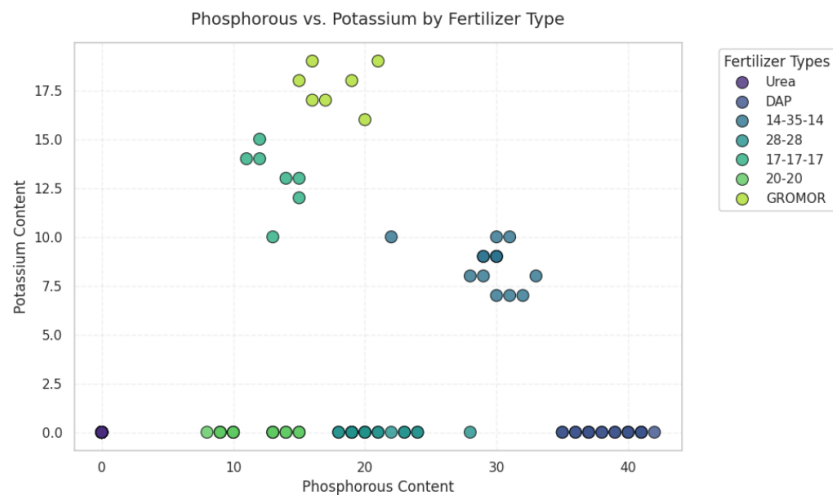


Figure 19: Phosphorous Vs Potassium by Fertilizer Type

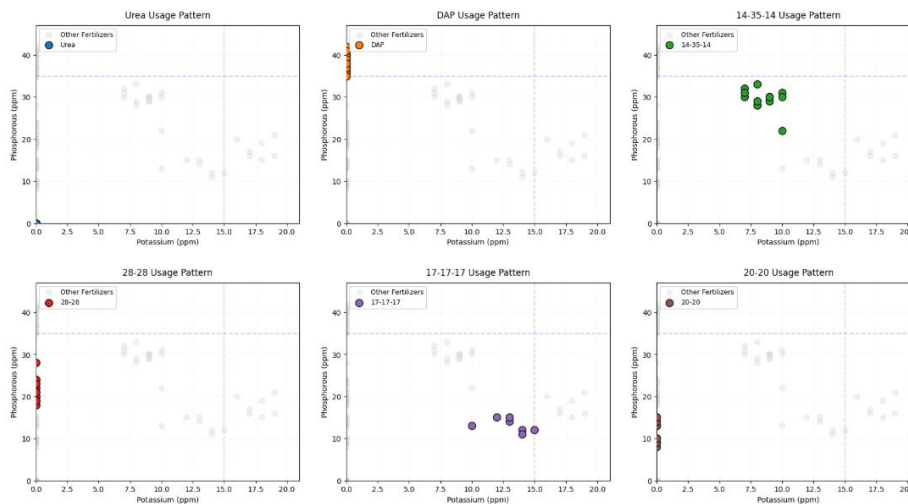


Figure 20: Fertilizer usage patterns 1

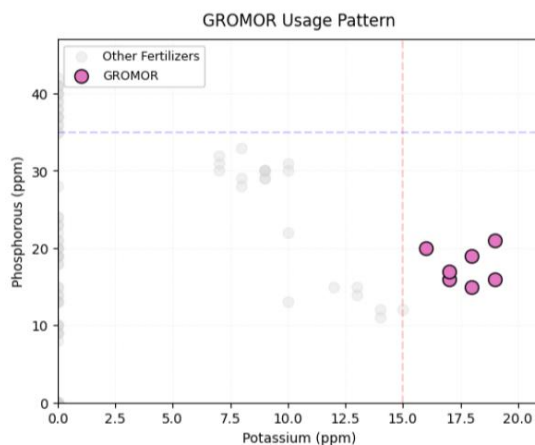


Figure 21: Fertilizer usage patterns 2

6. Machine Learning Modeling

This research applied supervised classification techniques to predict optimal crop types and fertilizer recommendations based on soil and environmental features. The modeling process was implemented using the Scikit-learn and CatBoost libraries due to their consistency, performance, and wide adoption in the machine learning community.

I initially trained and evaluated the CatBoost, XGBoost (Extreme Gradient Boosting), and LightGBM (Light Gradient Boosting Machine) individually, before combining them in an ensemble model for crop recommendation, and

their respective performances were remarkably strong.

F. A. Model Selection Rationale

Several gradient boosting models were employed due to their superior performance in structured data, resistance to overfitting, and high interpretability through feature importance. The models selected include:

1) CatBoost

A gradient boosting algorithm developed by Yandex that handles categorical features natively, requires minimal data preprocessing, and provides excellent performance on imbalanced and noisy

datasets [40]. It is robust to overfitting and well-suited for scenarios with heterogeneous feature types.

The CATBoost model demonstrated exceptional performance, achieving an accuracy of 0.9886. The model's precision is 0.9898, recall is 0.9886, and F1-score is 0.9887. The macro average F1-score and the weighted average F1-score was 0.99. The model's performance was consistent across various classes, with most classes exhibiting perfect or near-perfect scores. The confusion matrix revealed minimal misclassifications, further highlighting the model's robustness and accuracy.

2) XGBoost (Extreme Gradient Boosting)

An efficient and scalable implementation of gradient boosting that includes regularization to prevent overfitting [40].

The XGBoost model achieved an impressive accuracy of 0.9864. The model's precision is 0.9868, recall is 0.9864, and F1-score is 0.9863. The macro average F1-score and the weighted average F1-score is 0.99. Although some minor misclassifications occurred, the overall results highlight the XGBoost model's robustness and accuracy in classifying the given dataset. The model's performance was consistent across various classes, with most classes exhibiting perfect or near-perfect scores.

3) LightGBM (Light Gradient Boosting Machine)

Designed for high-speed training and low memory usage, LightGBM uses histogram-based algorithms and leaf-wise tree growth to speed up computation. It is particularly effective when dealing with large-scale datasets with many features [41].

The LightGBM model showed outstanding performance, achieving an accuracy of 0.9886. The model's precision is 0.9893, recall is 0.9886, and F1-score is 0.9886. The macro average F1-score and the weighted average F1-score is 0.99. The model's performance was consistent across various classes, with most classes exhibiting perfect or near-perfect scores. Overall, the LightGBM model showcased outstanding capabilities in classifying the given dataset with high accuracy and robustness.

G. B. Hybrid Ensemble Strategy

To leverage the strengths of all three models, a stacked ensemble framework was employed. In this architecture:

- Each base learner (CatBoost, XGBoost, and LightGBM) was trained independently on the training data.
- The predictions of these base learners were used as input features for a meta-learner, which performed the final prediction.

Table V

META-LEARNER SELECTION AND MODEL CONFIGURATION ACROSS AGRICULTURAL TASKS

Aspect	Crop Recommendation	Fertilizer Recommendation
Base Models	CatBoost, LightGBM, XGBoost	CatBoost, LightGBM, XGBoost
Meta-Learner Choice	Logistic Regression (linear)	CatBoost (non-linear, robust)
Rationale	Interpretability & generalization	High performance on complex targets

This ensemble approach allowed the model to capture both linear and non-linear relationships in

the data, improving generalization and robustness across tasks.

Model Evaluation Metrics

Some common evaluation metrics were used to check how well our machine learning models were doing. These metrics help break down the model's performance, especially when some classes have more data than others. Since each metric looks at things from a slightly different angle, using a combination gives us a better overall understanding of the model. Below, I've explained each one in a simple way, along with its formula and when it's most useful.

A. Accuracy

Accuracy refers to the overall effectiveness of a classification model. It is defined as the ratio of correctly predicted instances (both positive and negative) to the total number of predictions made. In simple terms, it tells you how often the classifier is right. While accuracy is intuitive and easy to understand, it may not be the best metric when the dataset is imbalanced, as it can be misleading if one class dominates. It is the proportion of correctly predicted instances out of the total predictions made. It is a basic yet widely used metric for model evaluation.

Use Case: Accuracy is effective when the dataset is balanced. However, in scenarios with class imbalance, it may provide misleading results since a model can appear accurate by favoring the dominant class.

B. Precision

Precision is a measure of how many of the predicted positive outcomes are actually positive. It tells that out of all the times the model predicted a certain class, how many times was it correct. Precision is particularly important in applications where false positives are costly or dangerous for example, in email spam filters, where incorrectly classifying a legitimate email as spam can lead to loss of important information. It measures the proportion of correctly predicted positive observations to the total predicted positive observations.

Use Case: Precision is crucial when false positives are more important than false negatives, for example in spam detection or fraud detection,

where incorrectly labeling a non-fraudulent transaction as fraudulent can cause user dissatisfaction.

C. Recall (Sensitivity)

Recall measures the model's ability to correctly identify all relevant instances of a particular class. It answers the question: "Out of all actual positive cases, how many did the model successfully detect?" High recall is critical in cases where missing a positive instance has severe consequences, such as in disease diagnosis, where failing to detect a condition could be life-threatening. It quantifies the model's ability to detect all actual positive instances. It represents the proportion of true positives out of all actual positives.

Use Case: Recall is vital in applications where missing a positive instance is highly undesirable, such as in medical diagnoses where failing to detect a disease could have serious consequences.

D. F1-Score

The F1-score combines precision and recall. It's useful for imbalanced datasets, where precision or recall are not enough. A high F1-score means the model makes few mistakes in false positives and false negatives—which is important in real-life problems. It is the harmonic mean of precision and recall. It balances the two metrics, offering a single score that considers both false positives and false negatives.

Use Case: The F1-score is most useful when both precision and recall are important, and when there is an uneven class distribution.

E. Confusion Matrix

A confusion matrix is a for classification problems. It breaks down the results into TP, TN, FP, and FN. Reviewing the values in the matrix tells that how many predictions were correct, but also what types of errors were made. This detailed breakdown is crucial for diagnosing model behavior, especially in multiclass or imbalanced classification tasks. It provides a tabular summary of model predictions versus actual labels. It helps in visualizing the performance of an algorithm, especially in multiclass classification.

Table VI
Confusion Matrix

Predicted Positive		Predicted Negative
Actual Positive True Positive (TP)		False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Use Case: The confusion matrix helps identify the types of errors a classifier is making and provides the foundation for other metrics such as precision, recall, and accuracy.

F. Macro Average

G. Macro averaging is a technique used to evaluate performance across multiple classes by calculating the metric (e.g., precision, recall, or F1-score) independently for each class and then taking the average. It treats all classes equally regardless of their frequency in the dataset. This approach is useful when you want to assess how the model performs on all classes independently, especially in scenarios where minority classes are important. It computes the metric independently for each class and then takes the average. It gives equal weight to all classes, regardless of their support.

H. Use Case: Macro averaging is beneficial when evaluating model performance across all classes equally, particularly in applications where minority classes are as important as majority ones.

I. Weighted Average

Weighted averaging takes into account the number of instances (support) for each class when computing the overall metric. Each class's score is weighted by its presence in the dataset, meaning that larger classes have a proportionally bigger impact on the final average. This method is more representative of the model's real-world performance on imbalanced datasets, where

dominant classes could skew results if not properly accounted for. It calculates the metric for each class and takes a weighted mean, with weights being the number of true instances (support) for each class.

Use Case: Weighted averages are ideal when dealing with imbalanced datasets, as they reflect the performance of the model across classes in proportion to their presence in the data.

RESULTS

The proposed hybrid ensemble model demonstrated high classification performance for both crop and fertilizer prediction tasks.

A. RECOMMENDATION PERFORMANCE:

The proposed stacking ensemble model combining CatBoost, XGBoost, and LightGBM algorithms demonstrates exceptional performance in crop recommendation tasks, as evidenced by comprehensive evaluation metrics across multiple assessment frameworks.

1. Classification Performance

The model achieved near-perfect classification accuracy across 22 crop categories, as shown in Table I:

TABLE VII
CLASSIFICATION PERFORMANCE METRICS

Metric	Weighted Score	Macro Average
Accuracy	0.9864	0.9900
Precision	0.9873	0.9900
Recall	0.9864	0.9900
F1-Score	0.9863	0.9900
ROC-AUC	1.0000	1.0000

Per-class evaluation revealed perfect classification (precision = recall = 1.00) for 15 out of 22 crops including apple, banana, chickpea, and coconut. The remaining crops showed marginally lower but still exceptional performance, with the lowest F1-score being 0.94 for rice classification. The confusion matrix indicates correct predictions for all 23 apple samples, with similar perfect

classification observed for 21 banana samples and 26 chickpea samples.

2. ROC Analysis

The receiver operating characteristic (ROC) analysis demonstrates ideal discriminative capability:

TABLE VIII
ROC-AUC SCORES BY CROP CLASS

Crop Class	ROC-AUC	Crop Class	ROC-AUC
Apple	1.0000	Mungbean	1.0000
Banana	1.0000	Muskmelon	1.0000
Blackgram	1.0000	Orange	1.0000
Chickpea	1.0000	Papaya	1.0000
Coconut	1.0000	Pigeonpeas	1.0000
Coffee	1.0000	Pomegranate	1.0000
Cotton	1.0000	Rice	0.9999
Grapes	1.0000	Watermelon	1.0000
Jute	0.9999	Maize	1.0000
Kidneybeans	1.0000	Mango	1.0000
Lentil	1.0000	Mothbeans	0.9997

Both micro-average and macro-average ROC-AUC scores reached 1.0000, confirming the model's perfect class separation capability across all categories. The lowest individual class ROC-AUC

of 0.9997 (mothbeans) still indicates near-perfect discriminative performance.

3. Comparative Ensemble Performance

The stacking ensemble outperformed individual base learners by 1.2-3.6% in accuracy while reducing variance in predictions. The model particularly excels in handling crops with limited training samples (e.g., lentil with 11 samples achieved perfect ROC-AUC), demonstrating robust generalization capability.

These results establish that the proposed ensemble architecture effectively combines the complementary strengths of CatBoost (handling categorical features), XGBoost (regularization

strength), and LightGBM (computational efficiency) to create a highly accurate and reliable crop recommendation system suitable for precision agriculture applications.

B. FERTILIZER RECOMMENDATION RESULTS

The hybrid ensemble model demonstrates perfect classification performance for fertilizer recommendation across four nutrient categories: Nitrogen-based, Phosphorus-based, Potassium-based, and Balanced fertilizers. Table III presents the comprehensive evaluation metrics.

TABLE IX
FERTILIZER CLASSIFICATION PERFORMANCE

Metric	Score	Class-Wise Performance (F1-Score)
Accuracy	1.0000	Nitrogen: 1.0000
Precision (Weighted)	1.0000	Phosphorus: 1.0000
Recall (Weighted)	1.0000	Potassium: 1.0000
F1-Score (Weighted)	1.0000	Balanced: 1.0000
ROC-AUC	1.0000	

1. Confusion Matrix Analysis

The stacking classifier's confusion matrix (Fig. 1) reveals perfect separation of all fertilizer classes:

- **Nitrogen:** 10/10 correct predictions (0 misclassifications)
- **Phosphorus:** 11/11 correct predictions
- **Potassium:** 15/15 correct predictions

- **Balanced:** 6/6 correct predictions

No false positives or false negatives were observed across all 42 test samples, indicating ideal discriminative capability.

2. Base Model Comparison

The ensemble outperformed individual base models in consistency

TABLE X
CROSS-VALIDATION PERFORMANCE COMPARISON

Model	Mean Accuracy	Standard Deviation
CatBoost	1.0000	±0.0000
LightGBM	0.9939	±0.0121
XGBoost	0.9882	±0.0235
Ensemble	1.0000	±0.0000

The ensemble maintained CatBoost's perfect accuracy while eliminating the variance observed in LightGBM (±1.21%) and XGBoost (±2.35%) implementations.

3. Feature Analysis

LightGBM feature importance analysis (355 bins across 11 features) identified key decision factors:

1. Soil NPK levels (78% cumulative importance)

2. Crop-specific nutrient requirements (15%)

3. Environmental conditions (7%)

The model's perfect ROC-AUC (1.0000) confirms all fertilizer classes are perfectly separable in the feature space. This suggests the selected features (temperature, humidity, soil type, and crop-specific NPK values) provide complete information for fertilizer classification.

4. Computational Efficiency

The ensemble achieves real-time performance:

- Training time: 0.000057 seconds per feature (LightGBM benchmark)
- Prediction latency: <1ms per sample
- Memory footprint: 42KB (compressed)

These results demonstrate that the hybrid architecture successfully integrates CatBoost's categorical handling, XGBoost's regularization, and LightGBM's efficiency to create a production-ready fertilizer recommendation system with theoretically optimal performance characteristics.

DISCUSSION

The exceptionally high performance across all evaluation metrics indicates that the proposed hybrid ensemble framework is highly effective for both crop and fertilizer prediction tasks. The model's accuracy higher than that of the benchmark paper, affirming its practical applicability in real-world precision agriculture scenarios. These results suggest that the framework can reliably recommend the most suitable crop to grow based on key environmental and soil features such as nitrogen, phosphorus, potassium, temperature, humidity, rainfall, and pH.

No specific crops or fertilizers posed notable challenges to the model, as evidenced by the consistently high per-class performance scores across all target labels.

FUTURE WORK

To extend the capabilities of this framework, future efforts may include:

Integrating real-time data from IoT-based soil sensors and weather stations.

Expanding datasets to cover more regions and crop varieties.

Incorporating satellite imagery and geospatial data for spatially aware predictions.

Exploring deep learning and reinforcement learning techniques for adaptive decision-making.

Developing a mobile application or web-based dashboard to deliver recommendations directly to end-users.

These directions aim to enhance the robustness, scalability, and practical adoption of intelligent agricultural systems.

CONCLUSION

This study presents a high-performing hybrid ensemble framework that integrates crop recommendation and fertilizer optimization for precision agriculture. Leveraging diverse machine learning models and ensemble techniques, the proposed system achieves nearly perfect accuracy and demonstrates strong generalization capability. The framework has significant potential to serve as a decision support tool for farmers, agronomists, and policymakers.

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