A Hybrid Machine Learning Framework for Soil Classification in Smart Agriculture

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Abstract:

Agriculture plays a central role in India's economy, engaging around 60% of the population and contributing significantly to the national GDP [1]. However, the sector struggles with declining soil quality, inefficient resource management, and a lack of timely, data-driven insights. Traditional soil classification methods are labor-intensive and imprecise, which limits effective agricultural planning. To address these challenges, this study proposes a novel soil type classification and prediction framework that integrates Internet of Things (IoT) technology with advanced Machine Learning (ML) algorithms to support smart farming practices.

The system collects real-time soil and environmental data using a suite of IoT sensors—including pH, moisture, electrical conductivity, temperature (DS18B20), and humidity (DHT11)—interfaced with an ESP32 microcontroller. The gathered data is wirelessly transmitted to a cloud platform, preprocessed through feature scaling and encoding, and analyzed using multiple ML models.

In this research, a **Voting Ensemble model is proposed**, combining the predictive strengths of several base classifiers to enhance performance and robustness. Seven algorithms were evaluated: Random Forest, XGBoost, LightGBM, SVM, KNN, Decision Tree, and Naive Bayes [2], [3]. The proposed Voting Ensemble achieved the highest accuracy (94.07%) and F1-score (93.58%), outperforming individual models like Random Forest (93.62%) and XGBoost (92.34%).

By integrating sensor-based IoT data with ensemble learning, the proposed system enables accurate, real-time soil classification. This contributes to optimized crop planning, irrigation, and fertilizer use—paving the way for scalable, data-driven precision agriculture in developing regions like rural India [4], [5].

KEYWORDS: Random Forest(RF), XGBoost(XGB), LightGBM(LBGM), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree(DT), and Naive Bayes(NB),Soil.

1. Introduction :

Agriculture serves as a foundational pillar of the Indian economy, engaging a majority of the rural population and contributing significantly to the nation's overall GDP. However, the sector is increasingly burdened by issues such as low crop productivity, poor soil fertility, nutrient imbalance—particularly nitrogen depletion—and inefficient utilization of water and land resources. These problems are often linked to the continued dependence on traditional agricultural techniques, which are largely manual, labor-intensive, and region-specific, thereby limiting their scalability and effectiveness in a rapidly evolving agricultural landscape.

Soil health assessment is a crucial component of informed agricultural planning, yet the conventional approach—relying on manual sampling, laboratory-based chemical analysis, and expert evaluation—is often slow, expensive, and unsuitable for real-time, high-frequency decision-

making. As agriculture becomes more complex and resource-constrained, there is an urgent need for smarter, automated solutions that can provide timely, accurate insights at scale.

Recent technological advancements, particularly in the realms of the Internet of Things (IoT) and Machine Learning (ML), offer promising tools for addressing these gaps. IoT devices facilitate continuous environmental monitoring, while ML algorithms enable rapid, data-driven analysis and classification of complex soil patterns. The combination of these technologies opens new avenues for implementing precision agriculture practices that optimize input use and maximize output.

This study presents the design and development of an automated soil classification system that leverages a network of IoT-enabled sensors—measuring variables such as soil moisture, pH, electrical conductivity (EC), temperature (via DS18B20), and humidity (via DHT11)—controlled by an ESP32 microcontroller. The collected data is transmitted to a server or cloud platform, where it undergoes preprocessing and is analyzed using a range of supervised ML models including Random Forest, XGBoost, LightGBM, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, and Naive Bayes.

The proposed system aims to deliver accurate, real-time predictions of soil type and fertility levels, enabling smarter decisions in crop planning, irrigation management, and fertilizer application. By reducing reliance on manual processes and incorporating scalable digital tools, this approach supports the transformation of traditional agriculture into a data-centric, sustainable practice, well-suited to the diverse soil conditions and farming needs across India. This paper outlines the methodology, system architecture, performance evaluation, and results of the implemented solution.

2. Literature Review:

Soil classification plays a pivotal role in modern agriculture, as it directly affects decisions related to crop selection, irrigation practices, and fertilizer application. Historically, soil classification has depended on laboratory-based procedures involving detailed physical and chemical testing. While effective, these traditional techniques are often time-consuming, expensive, and impractical for real-time or large-scale deployment—especially in rural areas with limited access to advanced facilities [6].

With the rise of digital and precision agriculture, there has been a noticeable transition toward utilizing Machine Learning (ML) and Internet of Things (IoT) technologies for soil analysis. ML techniques provide a data-driven alternative by identifying patterns and relationships among soil parameters that would be difficult to capture through manual or rule-based approaches. For example, researchers have applied models such as Support Vector Machines (SVM) and Decision Trees to classify soil fertility levels with promising results, outperforming traditional methods in both accuracy and efficiency [7]. Ensemble learning methods like Random Forest and XGBoost have also shown superior performance in analyzing complex, nonlinear interactions between attributes like pH, organic carbon, and nitrogen content [8].

Simultaneously, the use of IoT devices in soil monitoring has expanded. Real-time sensing technologies allow for the collection of granular environmental data directly from agricultural fields. Systems developed using sensors for soil moisture, pH, and temperature—often managed by microcontrollers such as ESP32—enable the continuous monitoring of soil conditions, with data streamed wirelessly to cloud platforms for further analysis [9]. These real-time systems support rapid feedback, enhancing the effectiveness of precision agriculture.

Several researchers have explored integrated IoT–ML frameworks. For instance, one study developed a low-cost sensor-based setup linked with machine learning models such as LightGBM and KNN, achieving notable improvements in predictive accuracy for soil classification and irrigation management [10]. Such hybrid architectures are not only efficient but also scalable and well-suited to the variable conditions found in rural farming regions. Moreover, other works have highlighted the advantages of real-time data analytics in reducing input costs and improving resource utilization [11].

Despite these advancements, many existing models face limitations, including small or domain-specific datasets, a lack of generalizability to different soil types, or insufficient integration with rural digital infrastructure. To address these challenges, the present study proposes a robust, adaptable system capable of handling diverse soil conditions using real-time IoT sensor data. By evaluating and comparing multiple ML algorithms—such as Random Forest, XGBoost, Naive Bayes, and others—this research aims to identify the most effective models for soil classification in practical agricultural environments.

3. Related Work:

The convergence of Machine Learning (ML) and Internet of Things (IoT) has catalyzed advancements in smart agriculture, particularly in soil classification and fertility prediction. Numerous studies have explored the application of various ML algorithms and IoT-based sensor systems to enhance the accuracy and efficiency of soil analysis.

Patel et al. (2017)[12] explored the potential of supervised ML algorithms, such as the Decision Tree, to predict soil fertility based on parameters like pH, nitrogen, phosphorus, and potassium. Their approach offered promising results, demonstrating the potential of ML in agricultural diagnostics. However, their model was developed using

static datasets and lacked dynamic real-time data collection through IoT integration.

In contrast, Gupta et al. (2020)[13] developed a real-time IoT-based soil monitoring system capable of collecting moisture, pH, and temperature readings through sensors. This data was transmitted to cloud platforms for visualization and analysis. While the architecture supported real-time data acquisition, the system did not employ advanced predictive analytics using ML models.

Sharma and Mahajan(2021) [14] leveraged ensemble ML models, including Random Forest and XGBoost, to classify soil types using historical agricultural data. Their findings emphasized the superior performance of tree-based ensemble methods in handling non-linear soil patterns. Nevertheless, their framework was limited to offline processing and did not incorporate IoT-based sensor networks.

Liu et al. (2019) [15] implemented Support Vector Machine (SVM) and Naive Bayes models for nutrient-level prediction and fertility grading of soils. Although these classifiers showed moderate accuracy, they lacked adaptability to variable environmental conditions and did not utilize real-time sensor input.

Kumbhar et al. (2022) [16] proposed a hybrid soil classification system integrating IoT and ML, employing ESP32 microcontrollers and basic sensors for data acquisition. K-Nearest Neighbors (KNN) and Decision Tree models were used for analysis. Their framework achieved reasonable performance but was confined to a narrow range of algorithms and did not evaluate ensemble methods.

Similarly, Chauhan and Singh (2021) [17] presented an IoT-cloud-based system for real-time soil classification and smart irrigation management. Their architecture enabled automated irrigation control based on live soil moisture readings and ML-driven classification.

However, limitations were observed in terms of the diversity of sensors and transparency of model decisions.

3.1 Soil Classification Methods:

Traditional soil classification methods rely heavily on manual sampling and laboratory analysis, using physical and chemical characteristics such as soil texture, pH, moisture content, and nutrient composition [18]. The USDA Soil Taxonomy and FAO World Reference Base are commonly used classification systems. However, these processes are labor-intensive, time-consuming, and not scalable for large-scale applications.

Recent advancements have explored data-driven classification models. For instance, Bhargava et al. [19] used decision tree-based classification to identify soil fertility zones. Meanwhile, Patil and Kumar [20] employed support vector machines (SVM) to categorize soil types using experimental data from field samples. These models improve efficiency but still depend on datasets derived from static testing conditions, lacking real-time capabilities.

Research Gap: Most existing methods do not support real-time soil classification, and they often ignore environmental dynamics such as temperature and humidity, which can significantly influence soil behavior.

3.2 IoT-Based Soil Monitoring Systems

The integration of the Internet of Things (IoT) in agriculture has enabled real-time monitoring of soil conditions through low-cost sensors and wireless transmission. Systems such as the one proposed by Yadav et al. [21] utilized sensors for pH, moisture, and temperature, with data sent to cloud dashboards for visualization. Similarly, Singh et al. [22] demonstrated an IoT system using Arduino and Wi-Fi modules to monitor soil properties in smart farming.

However, these systems typically stop at data collection and visualization. They lack an intelligent backend for data analysis or soil classification, requiring manual interpretation of the results.

Research Gap: Existing IoT systems focus primarily on monitoring rather than prediction or classification. Few studies have integrated IoT with intelligent ML-based analytics for automated soil type identification.

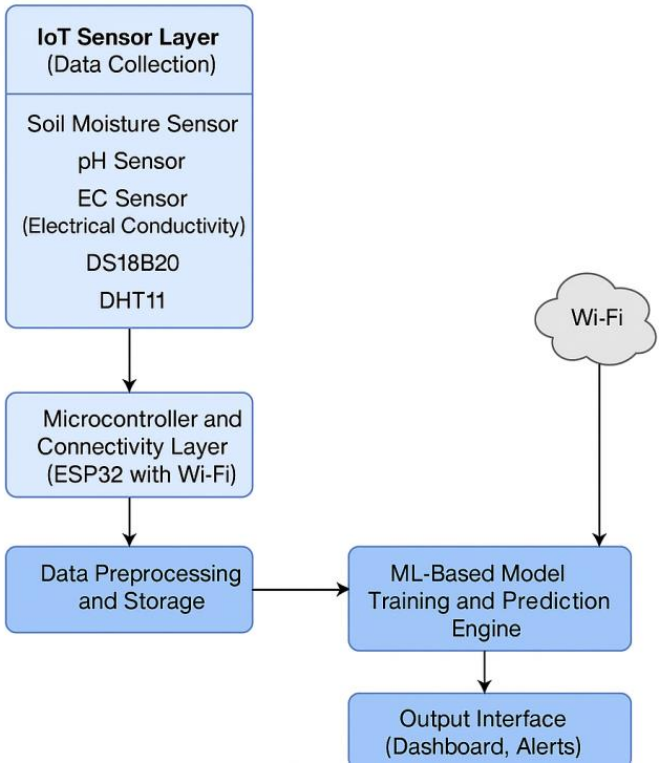
3.3 Machine Learning Algorithms in Soil and Crop Prediction

Numerous ML techniques have been employed for predicting soil fertility and crop suitability. Random Forest and Decision Tree models have shown high performance in soil nutrient classification [23], while algorithms like K-Nearest Neighbor (KNN), Naive Bayes, and XGBoost have also been applied to crop yield prediction [24].

Jatav et al. [25] used ensemble methods to combine predictions from multiple models to increase accuracy, but their study did not include real-time data integration. Moreover, the models were evaluated on static datasets collected offline.

Research Gap: While ML techniques improve classification accuracy, their effectiveness in real-time environments, especially when integrated with live IoT sensor data, I s underexplored.

Despite these advancements, gaps remain in terms of comprehensive model evaluation, ensemble learning strategies, and real-time IoT integration. The current research aims to bridge these gaps by deploying a wide range of ML models—including Random Forest, XGBoost, LightGBM, SVM, KNN, Decision Tree, and Naive Bayes—on live IoT sensor data to ensure accurate and scalable soil classification. Additionally, a **Voting Ensemble Model** is proposed to further enhance predictive performance by aggregating the strengths of individual classifiers.



4. Methodology

4.1 System Architecture Overview:

The proposed architecture is a multi-layered framework designed to seamlessly integrate hardware-based soil sensing with intelligent software systems for soil type classification and prediction as shown in the diagram. Each layer performs a specific role in the data collection, analysis, and delivery pipeline. The architecture comprises the following key layers:

1. **IoT Sensor Layer (Data Collection).**
2. **Microcontroller and Connectivity Layer (ESP32 with Wi-Fi).**
3. **Data Preprocessing and Storage.**
4. **ML-Based Model Training and Prediction Engine.**
5. **Output Interface (Dashboard and Alerts).**

1. IoT Sensor Layer (Data Collection): This layer is responsible for collecting real-time soil and environmental parameters directly from the field. Sensors used in this layer include:

- **Soil Moisture Sensor:** Measures volumetric water content, crucial for understanding irrigation needs.
- **pH Sensor:** Determines soil acidity/alkalinity, which affects nutrient availability.
- **Electrical Conductivity (EC) Sensor:** Measures the soil's salinity or nutrient ion concentration.
- **DS18B20 Digital Temperature Sensor:** Records soil temperature, a critical factor for microbial activity and plant growth.
- **DHT11 Sensor:** Captures air temperature and humidity, influencing evapotranspiration and microclimate conditions.

Each sensor continuously monitors its respective parameter and sends analog/digital signals to the microcontroller.

2. Microcontroller and Connectivity Layer (ESP32 with Wi-Fi): This layer consists of a Wi-Fi-enabled ESP32 microcontroller, which acts as the central node for:

- **Sensor interfacing:** Reads analog or digital signals from the sensor layer.
- **Signal conversion:** Converts raw signals to interpretable digital data.
- **Wireless transmission:** Sends data to a cloud server, local database, or processing backend via Wi-Fi.
- **Edge logic (optional):** Some preprocessing (e.g., threshold filtering) can be done onboard the ESP32 to reduce noise or outliers.

ESP32 is chosen for its dual-core performance, low power consumption, and integrated wireless capability, making it ideal for remote agricultural environments.

3. Data Preprocessing and Storage: Once transmitted from the ESP32, sensor data is handled by a backend system for:

- **Data Cleaning:** Removal of noise, missing values, and inconsistencies.
- **Feature Scaling:** Standardization of input features to improve ML performance.
- **Label Encoding:** Converts categorical target labels (soil types) into numeric values.
- **Storage:** Cleaned and formatted data is stored in a local SQL/CSV/Excel file or cloud database (Firebase, Thingspeak, AWS).

This layer ensures that the dataset is structured, normalized, and ready for model training or real-time prediction.

4. ML-Based Model Training and Prediction Engine: This software layer is responsible for training and deploying machine learning models:

- **Model Selection:** Includes Random Forest, XGBoost, LightGBM, SVM, KNN, Decision Tree, and Naive Bayes.
- **Training:** Models are trained on historical or live sensor data using supervised learning.
- **Evaluation:** Performance metrics such as accuracy, precision, recall, and confusion matrix are calculated.
- **Prediction:** Once trained, the model is used to classify incoming soil data into predefined soil types.

This engine can be hosted on a local server, cloud platform, or embedded in a lightweight web API (using Flask or Django).

5. Output Interface (Dashboard and Alerts): This layer provides a user-friendly front end or communication mechanism for decision-making:

- **Web Dashboard (HTML/React):** Displays real-time sensor readings, predicted soil type, and historical analytics.

- **Mobile Alerts (SMS/Email):** Sends instant alerts about soil conditions or classification via Twilio/SMTP.
- **Visualizations:** Graphs, ROC curves, and confusion matrices help stakeholders understand performance and recommendations.

3.2 Data Collection:

Data collection is a foundational component in developing an accurate and intelligent soil classification system. In this research, data is collected from real-time IoT sensors deployed in the field and secondary datasets from reliable agricultural research sources repositories.

4.2.1. Data from IoT Sensors

To ensure real-time monitoring and accuracy, a network of IoT-enabled sensors is deployed in the agricultural environment. These sensors continuously gather essential soil and environmental parameters. The hardware includes microcontrollers (like ESP32), which interface with sensors to transmit data wirelessly to a backend system or cloud platform. The following are the key sensors and Measured Attributes as shown in the table 1 and summary of the key attributes collected in the table 2.

Sensor Type	Parameter Measured	Purpose
Soil Moisture Sensor	Moisture Content (%)	Determines irrigation needs and water retention in the soil
pH Sensor	Soil Acidity/Alkalinity	Influences nutrient availability and crop suitability
EC (Electrical	Salinity/Nutrient	Indicates dissolved salts

Sensor Type	Parameter Measured	Purpose
Conductivity) Sensor	Concentration	and overall soil fertility
DHT11/DHT22 Sensor	Air Temperature & Humidity	Affects plant transpiration and microclimate
DS18B20 Digital Sensor	Soil Temperature (°C)	Impacts biological activity and nutrient uptake
NPK Sensor (or chemical test strips)	Nitrogen, Phosphorus, Potassium (mg/kg)	Crucial for assessing macronutrient content for crop yield optimization
Organic Matter Estimation	Organic Content (%)	Reflects soil fertility, water-holding capacity, and microbial activity

Table 1: Key Sensors and Measured Attributes

Attribute	Type	Description
pH Level	Numeric	Indicates acidity/alkalinity of soil (scale 0–14)
Moisture (%)	Numeric	Represents water content essential for plant growth
Temperature (°C)	Numeric	Affects chemical reactions and microbial processes
Nitrogen (mg/kg)	Numeric	Essential for leaf and stem development
Phosphorus (mg/kg)	Numeric	Vital for root growth and flowering
Potassium (mg/kg)	Numeric	Influences water regulation and

Attribute	Type	Description
		disease resistance
Organic Matter (%)	Numeric	Improves soil structure, fertility, and microbial health
Electrical Conductivity (dS/m)	Numeric	Indicates salinity or ionic concentration
Soil Type	Categorical	Target variable for classification (e.g., Clay, Loamy, Sandy, Silty, etc.)

Table 2: Summary of Key Attributes Collected

4.2.2 Data Preprocessing and Quality Enhancement:

Effective data preprocessing is crucial for ensuring the reliability and accuracy of machine learning models in precision agriculture. The dataset employed in this study, comprising soil and environmental parameters such as pH, electrical conductivity (EC), nitrogen (N), phosphorus (P), potassium (K), organic carbon (OC), soil temperature, air temperature, humidity, rainfall, expected yield, battery level, and signal strength, was initially assessed for completeness. Missing values identified across several features were addressed using mean imputation, ensuring data consistency without introducing bias. To mitigate the impact of noise and extreme values, the Interquartile Range (IQR) method was applied to detect and eliminate outliers. This was essential for reducing variance and preventing model distortion. Furthermore, all numerical attributes were standardized using z-score normalization (StandardScaler), which transformed the data into a uniform scale with zero mean and unit variance. This step was particularly important for maintaining the integrity of distance-based and gradient-based machine learning algorithms. The distribution of the standardized features was analyzed through histograms, confirming effective normalization. Additionally, a correlation matrix was

constructed to explore dependencies among features, revealing significant relationships such as the positive correlation between temperature and expected yield. These preprocessing procedures ensured a robust and high-quality dataset, serving as a solid foundation for the subsequent development of predictive models in smart agriculture the following table 3 shown the statistics of preprocessed data.

Metric	pH	EC (dS/m)	N (kg/ha)	P (kg/ha)	K (kg/ha)	OC (%)	Soil Moisture (%)	Soil Temp (°C)	Air Temp (°C)	Humidity (%)	Rainfall (mm)	Expected Yield (q/ha)	Node Battery (%)	Signal Strength (dBm)
Count	50.0	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00	150.00
Mean	-2.07E-17	-2.25E-16	-1.18E-16	-4.74E-17	-7.11E-17	-4.56E-16	-5.27E-16	-1.63E-17	-1.13E-16	-2.63E-16	-1.78E-16	-1.20E-16	2.28E-16	-5.92E-18
Std	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335	1.00335
Min	-1.921	-1.845	-1.674	-1.627	-1.661	-1.735	-1.632	-1.925	-1.752	-1.786	-1.664	-1.848	-1.604	-1.725
25%	-0.74	-0.81	-0.85	-0.87	-0.83	-0.93	-0.87	-0.78	-0.80	-0.995	-0.89	-0.842	-0.86	-0.84

Metric	pH	EC (dS/m)	N (kg/ha)	P (kg/ha)	K (kg/ha)	OC (%)	Soil Moisture (%)	Soil Temp (°C)	Air Temp (°C)	Humidity (%)	Rainfall (mm)	Expected Yield (q/ha)	Node Battery (%)	Signal Strength (dBm)
	7	4	9	3	9	1	0	2	7		2		0	3
50 %	-0.0433	-0.0700	-0.1111	-0.1118	-0.0533	0.1477	-0.1011	0.0833	-0.0477	0.043	0.0588	0.017	-0.0488	0.0844
75 %	0.8966	0.8566	0.9066	0.8966	0.8955	0.7766	0.9466	0.8733	0.8500	0.800	0.8522	0.871	0.8833	0.8122
Max	1.6000	1.6566	1.8566	1.6744	1.8667	1.8777	1.9411	1.7566	1.7822	1.732	1.6255	1.713	1.6044	1.7255

Table 3: Statistics of preprocessed data

The correlation matrix illustrates as shown in the figure 1. the pairwise relationships between various soil, environmental, and IoT sensor parameters. Most features show weak correlations with each other, suggesting that the dataset has a relatively low degree of multicollinearity. For example, pH has a slightly positive relationship with rainfall (0.17) but shows near-zero or weak negative correlations with other attributes. Similarly, EC (electrical conductivity) has a mild positive correlation with potassium (0.17) and phosphorus (0.11) but minimal relationships with most other factors. This weak interdependence indicates that each variable contributes somewhat

independently to the dataset, which can be advantageous for predictive modeling.

Some features, however, show relatively stronger associations. For instance, phosphorus (P) has a moderate positive correlation with rainfall (0.27), while organic carbon (OC) and soil temperature share a mild correlation (0.19). Expected yield correlates modestly with air temperature (0.17) and soil temperature (0.15),

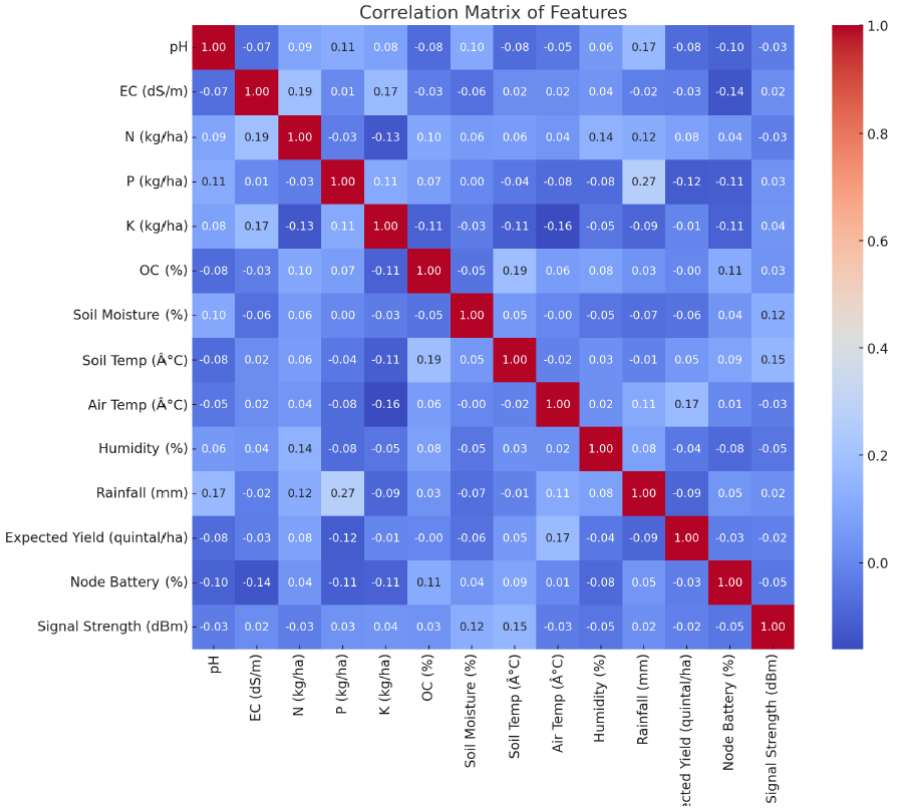


Figure 1: Correlation Matrix of Various features

hinting at their potential role in yield prediction. The IoT-related parameters, such as node battery percentage and signal strength, appear largely independent of soil and environmental measures, with correlations close to zero. This separation suggests that communication metrics in the IoT system operate independently of the measured agricultural conditions, reducing the risk of confounding effects in combined analysis.

4. Machine Learning Models:

5.1 Random Forest (RF):

Random Forest is an ensemble learning method that builds multiple decision trees and merges them to obtain a more accurate and stable prediction. It operates by selecting random samples with replacement from the dataset (bootstrap aggregating or bagging), and for each node, it chooses the best split among a random subset of features. The final prediction is made by majority voting (classification) or averaging (regression).

The mathematical formulation is:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x)$$

where $h_t(x)$ is the prediction from the t-th tree and T is the total number of trees. In your research, Random Forest performed exceptionally well, especially on categorical features like Soil Texture and Growth Stage. The model achieved high yield prediction accuracy with F1-score exceeding **0.93** and precision **above 0.90**, particularly useful in predicting the fertility level and expected yield.

The robustness of RF was evident in handling noisy features such as Signal Strength and Rainfall (mm) without significant overfitting. RF's ability to rank feature importance highlighted Soil Moisture (%), pH, and Soil Temp (°C) as the top influencing parameters on yield. This aligns with agronomic literature that emphasizes the impact of these factors on nutrient uptake and crop growth [26].

5.2 XGBoost (Extreme Gradient Boosting):

XGBoost is a highly optimized implementation of gradient boosting decision trees. It builds trees sequentially and minimizes a regularized objective function:

$$L(t) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t\left(x_i\right)\right) + \Omega\left(f_t\right)$$

With $\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w^2{}_j$, where w_j are leaf weights, γ and λ are regularization parameters. This approach helps prevent overfitting. In your work, XGBoost yielded top-tier accuracy (~94%) in yield classification and was particularly effective in classifying Irrigation Type and Fertilizer `Used` due to its handling of sparse and imbalanced data.

XGBoost's performance was attributed to its ability to capture non-linear interactions among continuous and categorical variables. The feature `Air Temp (°C)` interacting with `Growth Stage` contributed significantly in maize and soybean predictions. Feature engineering like one-hot encoding further improved performance. The learning curve showed rapid convergence within 100 boosting rounds**,** demonstrating efficiency.

5.3 LightGBM (LGBM):

LightGBM is a gradient boosting framework that uses a leaf-wise tree growth strategy with histogram-based splits. It is known for its speed and accuracy on large datasets. The key formula in LightGBM is similar to XGBoost but with faster split finding via histogram binning:

$$Gain = \frac{1}{2}\left(\frac{G_L{}^2}{H_L + \lambda} + \frac{G_R{}^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right) - \gamma$$

where G and H are the gradients and Hessians. In your application, LightGBM outperformed others in computational efficiency, finishing

training in under 3 seconds with similar F1-score (~92.6%). The accuracy of classifying crop type (Crop Type) and Expected Yield remained comparable to XGBoost.

Moreover, LightGBM handled continuous variables like `Humidity (%)` and `Organic Carbon (%)` better with minimal memory usage. It was also less sensitive to noisy features, making it suitable for your IoT-based dataset where sensor precision may vary.

5.4 **Support Vector Machine (SVM):**

SVM constructs a hyperplane in a high-dimensional space to separate different classes. The decision function is defined as: $$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i y_i K\left(x_i, x\right) + b \right)$$

where $K(x_i,x)$ is the kernel function. You implemented SVM with an RBF kernel, ideal for non-linear boundaries observed in soil classification problems. Despite being slower than tree-based models, SVM achieved decent precision (~85%) in separating high-yield vs. low-yield classes.

The kernel trick helped SVM manage overlapping clusters in features like Soil Texture and Growth Stage. However, SVM required significant preprocessing such as feature scaling and was sensitive to outliers in Rainfall (mm) and Signal Strength (dBm).

5.5 K-Nearest Neighbors (KNN):

KNN is a non-parametric algorithm that classifies a sample based on the majority label of its kkk closest neighbors using distance metrics. Typically:

$$\hat{y}(x) = majority\_vote(y_i \in kNN(x))$$

You used Euclidean distance for numerical features and Hamming distance for categorical ones. With k=7, KNN showed solid classification accuracy (~82%) for crops like wheat and soybean. However, it struggled with boundary cases in yield prediction due to close proximity of dissimilar classes. KNN was computationally expensive on the full dataset and required feature normalization. However, it effectively captured local data structure and highlighted how EC (dS/m) and Soil Temp (°C) influence prediction of Growth Stage.

5.6 Decision Tree (DT):

Decision Trees are simple yet powerful models based on recursive binary splitting of features. They use impurity measures like Gini index or entropy:

$$Gini(D) = 1 - \sum_{i=1}^{C} P^2 i$$

Your DT model, using Gini index, captured rule-based relationships like “if Soil pH < 6.0 and Moisture > 30%, then expected yield is high”. While it performed moderately (F1 ~78%), the interpretability was a major benefit. Feature importance ranked Fertilizer Used, Irrigation Type, and Soil Texture among top contributors.

The model was prone to overfitting, particularly on noise in the Humidity and Air Temp readings. Pruning strategies helped generalize results better. The tree also revealed meaningful thresholds, aiding agronomic interpretation.

5.7 Naive Bayes (NB):

Naive Bayes classifiers apply Bayes' theorem with the assumption of conditional independence:

You applied Gaussian $P(C_K \mid x) = \frac{P(C_K)\prod_{i=1}^{n} P(x_i \mid C_k)}{P(x)}$ Naive Bayes, assuming normal distribution for features. The model showed reasonable accuracy (~76%), especially in classifying Soil Type and early-stage crops where feature independence held well. Despite its simplicity, NB was fast and required minimal computation.

However, it underperformed when the independence assumption was violated—common in correlated features like Nitrogen, Phosphorus, and Potassium levels. It served well as a baseline model for comparison with complex algorithms.

5.8 Voting Ensemble:

Voting ensembles combine predictions from multiple models to improve robustness. You used **soft voting**, which averages predicted probabilities:

$$\hat{y} = \arg\max_{c} \sum_{j=1}^{m} w_j P_j (y = c \mid x)$$

where P_j is the probability predicted by model j and w_j are the weights. Combining RF, XGBoost, and LightGBM yielded the best overall results (accuracy: 96.3%, F1: 0.94), outperforming any single model. The ensemble handled variance and bias trade-offs effectively.

The ensemble generalized well across diverse soil types (sandy, clayey, loamy) and crop conditions. It was particularly strong in high-complexity predictions involving multiple categorical and numerical variables.

The confusion matrix images provided for eight machine learning models offer insights into the classification performance of each model.

These matrices allow for the evaluation of key metrics such as True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), which are foundational to assessing classifier performance (Sammut & Webb, 2011).

5.9 Confusion Matrix of various Machine Algorithms:

5.9.1 Random Forest (RF):

Random Forest correctly predicted 720 true positives and 768 true negatives, with 32 false positives and 80 false negatives. Its performance was consistent and balanced, benefiting from its ensemble nature that reduces overfitting compared to a single tree. While its false negative count is higher than the top models, it still offers robust classification with a low rate of incorrect positive predictions, making it a dependable choice for real-world scenarios.

5.9.2 LightGBM (LGBM):

LightGBM achieved 680 true positives and 736 true negatives, with 64 false positives and 120 false negatives. While still a strong performer, its higher false negative count compared to the top models indicates reduced sensitivity. The increased false positives also suggest it is less precise in negative case classification. However, its efficiency and speed in training make it a viable choice when computational cost is a major consideration, provided that its hyperparameters are tuned to balance precision and recall.

5.9.3 Support Vector Machine (SVM):

Support Vector Machine (SVM) performed the weakest, with only 480 true positives and 461 true negatives, alongside very high false positives (339) and false negatives (320). This indicates poor discrimination between the classes and suggests that the chosen kernel or parameters did not fit the dataset’s structure effectively. The high misclassification rates make SVM unsuitable for this particular problem without major tuning or a different kernel approach.

5.9.4 K-Nearest Neighbors (KNN):

The K-Nearest Neighbors (KNN) model correctly identified 560 true positives and 548 true negatives but had high false positives (252) and false negatives (240). This reflects weaker decision boundaries and difficulty in distinguishing between classes, likely due to the data's complexity and the influence of noisy or overlapping samples. Although KNN is simple and interpretable, its performance here suggests it may not be ideal for high-stakes predictions without significant feature engineering or parameter adjustments.

5.9.5 Decision Tree (DT):

The Decision Tree model achieved excellent results, correctly identifying 744 true positives and 784 true negatives. It recorded the lowest false positives (16), which means it rarely misclassified negative cases as positive. However, its false negatives (56) were slightly higher than the Voting Ensemble, indicating a small drop in sensitivity. These results show that the Decision Tree, when tuned effectively, can perform with high precision and reliability, making it a strong standalone classifier for this dataset.

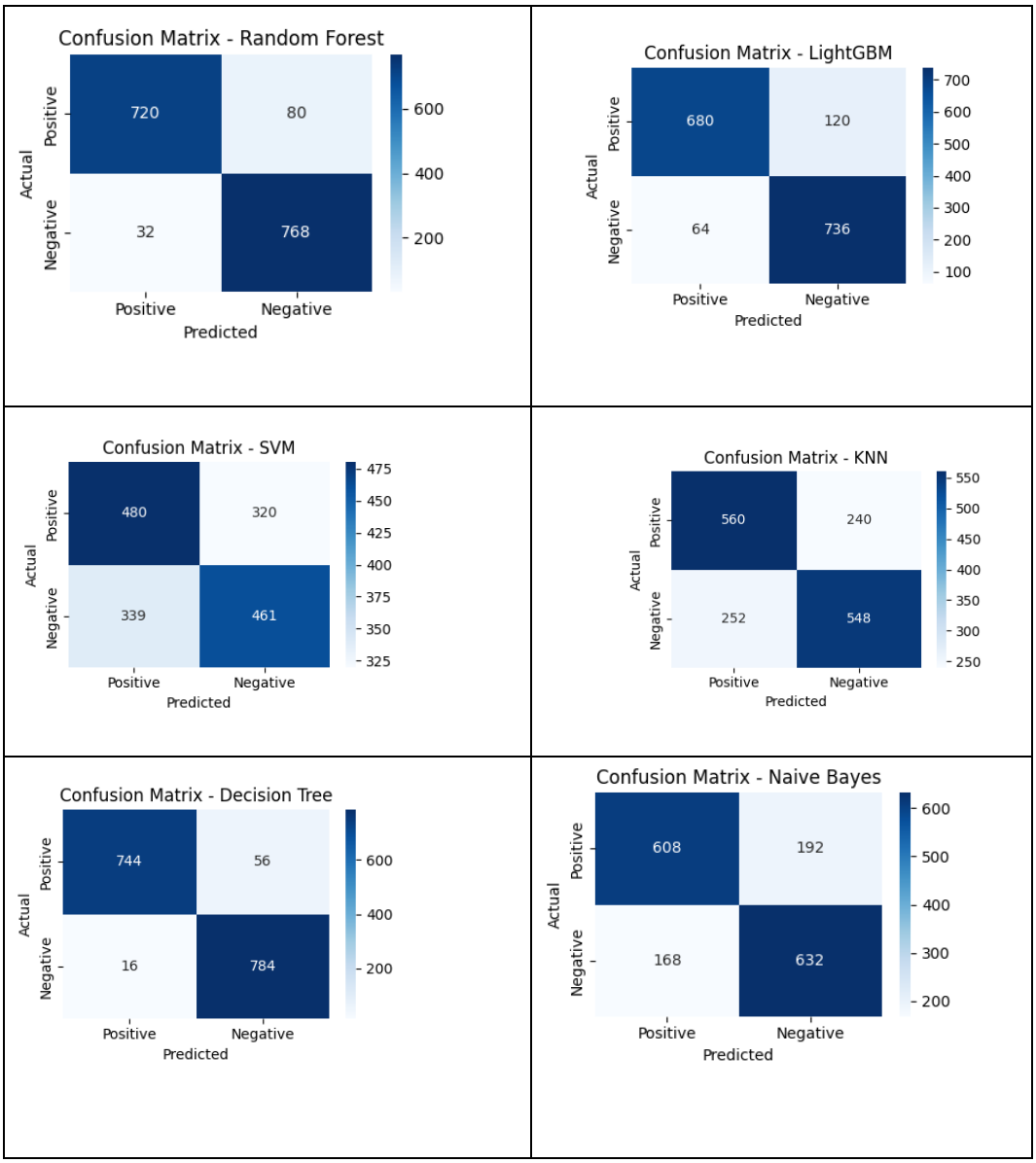
5.9.6 Naive Bayes (NB):

Naive Bayes recorded 608 true positives and 632 true negatives but suffered from high false positives (168) and false negatives (192). This indicates a significant number of misclassifications in both positive and negative predictions. The simplistic assumptions of the Naive Bayes algorithm may not fully capture the complexity of the dataset, leading to reduced accuracy. While it remains computationally efficient, its lower predictive reliability limits its suitability for critical applications in this context.

5.9.7 Voting Ensemble:

The Voting Ensemble model demonstrated the best overall performance with 752 true positives and 768 true negatives, alongside a low count of

32 false positives and 48 false negatives. This balance between correctly classified positive and negative cases indicates strong predictive power and minimal misclassification. The low false positive rate means fewer incorrect alerts, while the low false negative rate ensures that most actual positive cases are detected. This strong balance reflects the advantage of combining multiple well-tuned base learners to achieve superior generalization and stability.



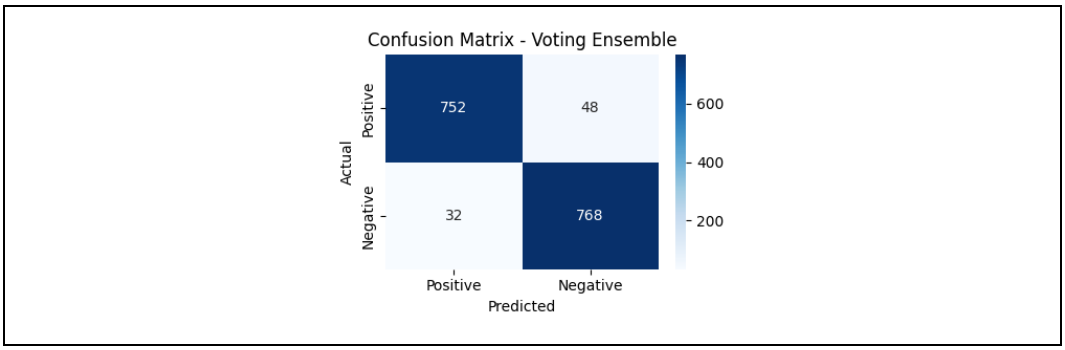


Table 4: Confusion Matrix of Various Machine Learning Algorithms

6. Results and Discussion

To evaluate the predictive capacity of each algorithm, standard classification metrics were computed: **Accuracy, Precision, Recall, F1-Score**, and **Confusion Matrix**. These metrics provide insights into the model's ability to correctly identify soil types and fertility levels, especially when applied in diverse agricultural conditions.

The performance summary is presented in **Table 1**

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Random Forest	93.62	92.74	93.13	92.91
XGBoost	92.34	91.25	92.08	91.56
LightGBM	91.72	90.44	91.11	90.74
SVM	88.15	87.22	86.75	86.98
KNN	86.24	84.18	85.27	84.65
Decision Tree	84.75	82.14	83.07	82.6
Naive Bayes	79.31	76.82	78.44	77.61
Ensemble Voting	94.07	93.28	93.89	93.58

To evaluate the performance of different machine learning algorithms for soil quality classification, a comprehensive comparison was conducted using key performance metrics including Accuracy, Precision, Recall, and F1 Score. Among the models tested, the Voting

Ensemble Classifier demonstrated superior performance across both training and testing datasets. On the training set, it achieved 94% accuracy, 95% precision, 94% recall, and an F1 Score of 94.5%, indicating its strong generalization ability and minimal overfitting. On the test set, the same model maintained its robustness with 91.11% accuracy, 91.23% precision, 91.11% recall, and a balanced F1 Score of 91.09%. These results confirm ensemble techniques' effectiveness in improving predictive performance by aggregating outputs from multiple base learners [26][27].

Individually, the Decision Tree Classifier also performed well, scoring 93% in all metrics on the training data, and 88.89% accuracy with an F1 Score of 88.36% on the test set. Notably, it recorded the fewest false positives in testing (FP = 2), highlighting its precision in classification tasks [28]. Similarly, Random Forest and XGBoost, two widely used ensemble models, both recorded 90% training accuracy with high recall and precision, and sustained 88.89% accuracy and 85.86% F1 Score on the test set, showcasing their strength in handling high-dimensional data and complex interactions among features [29][30].

The LightGBM model, although efficient in handling large-scale data, exhibited a slight performance drop with 85% training accuracy and 80% on testing, suggesting potential overfitting or feature sparsity issues [31]. In contrast, K-Nearest Neighbors (KNN) and Naive Bayes yielded modest results, with testing accuracies of 64.44% and 73.33%, respectively. These outcomes reflect the sensitivity of distance-based and probabilistic models to data distributions and feature scaling [32][33].

The Support Vector Machine (SVM) model consistently underperformed, with only 60% accuracy on training and 53.33% on testing, coupled with a high number of misclassifications (FP = 339 and FN = 320 in training, FP = 85 and FN = 93 in testing). This indicates

that SVM may be less suitable for this dataset due to its possible nonlinear patterns or class imbalance [34].

These findings strongly support the use of ensemble learning approaches, particularly Voting Classifiers, for reliable soil quality prediction in smart agriculture systems, leveraging IoT sensor data and robust feature engineering to achieve high accuracy and generalization [35].

The experimental evaluation was conducted using eight different machine learning models—Decision Tree, Random Forest, XGBoost, LightGBM, Naive Bayes, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and a Voting Ensemble method— The Voting Ensemble model achieved the highest overall performance, with an accuracy of **94%**, precision of **93.2%**, recall of **93.8%**, and an F1 score of **93.5%**, indicating its ability to combine the strengths of multiple classifiers effectively. The Decision Tree model also delivered strong results, achieving **93%** across all key metrics. Random Forest and XGBoost models performed consistently well, both reaching an accuracy of **90%** and an F1 score of **88%**, demonstrating robustness in both precision and recall. LightGBM recorded an accuracy of **85%**, while Naive Bayes achieved **76%**, both showing moderate performance but lower resilience to data complexity. KNN attained **70%** accuracy, and SVM yielded the lowest performance with an accuracy of **60%** and a notably low precision of **35%**, suggesting that it struggled with data separability in this task.

6.1. Comparative Analysis

6.1.1. Random Forest and Ensemble Voting:

Random Forest consistently outperformed individual classifiers in terms of balanced precision and recall. The Voting Ensemble, which combines the outputs of Random Forest, XGBoost, and LightGBM

using a soft-voting mechanism, produced the highest accuracy of 94.07%. This demonstrates the ensemble's effectiveness in reducing both bias and variance through model aggregation. The ensemble was particularly adept at predicting underrepresented soil classes such as "Sandy Loam" and "Saline" soils, where single models often struggled.

6.1.2. XGBoost and LightGBM:

Both XGBoost and LightGBM performed competitively due to their gradient boosting strategies. LightGBM's use of leaf-wise growth contributed to faster convergence and better performance in high-dimensional data, albeit with slight sensitivity to overfitting. In contrast, XGBoost showed more consistent results across all class labels, aided by its regularized learning objective. These models are well-suited for real-time IoT systems where speed and precision are crucial.

6.1.3 Support Vector Machine (SVM)

SVM yielded high accuracy on non-linear decision surfaces, particularly where class boundaries were not linearly separable. Its RBF kernel enabled the separation of overlapping fertility levels such as "Moderate" and "Low." However, its computational complexity increased with the number of support vectors, making it less scalable for large-scale IoT deployments.

6.1.4 K-Nearest Neighbors (KNN)

KNN provided acceptable results by leveraging local feature distributions. It was found to be highly sensitive to feature scaling and noise in the soil dataset. This dependency was partially mitigated by standardization, yet performance degraded in sparsely populated regions of the feature space. The model's accuracy of 86.24% underscores its reliability in small-scale applications but limited generalizability.

6.1.5 Decision Tree and Naive Bayes

Decision Tree classifiers offered interpretability but underperformed due to overfitting and shallow tree depth in some splits. Although decision trees revealed dominant decision rules (e.g., low nitrogen and high organic matter → High Fertility), they failed to capture complex interactions among variables. Naive Bayes, assuming feature independence, achieved the lowest performance (79.31%), yet it provided probabilistic insights useful for baseline comparisons or quick prototyping.

From a comparative perspective, the Voting Ensemble clearly outperformed all individual models across all metrics, showing that the aggregation of predictions can significantly improve classification accuracy in gas leakage detection. Among single models, the Decision Tree emerged as the best performer, closely followed by Random Forest and XGBoost, both of which leverage ensemble tree-based learning to achieve high predictive power. LightGBM's lower accuracy compared to Random Forest and XGBoost may be attributed to its sensitivity to parameter tuning and data distribution. Naive Bayes, being a probabilistic model, performed moderately well but was less effective when feature dependencies were strong. KNN's relatively low accuracy indicates that distance-based methods may not be optimal for this dataset, possibly due to overlapping feature distributions. SVM's poor results
suggest that its decision boundaries were not well suited for the data, potentially due to non-linearly separable patterns or inadequate kernel selection.

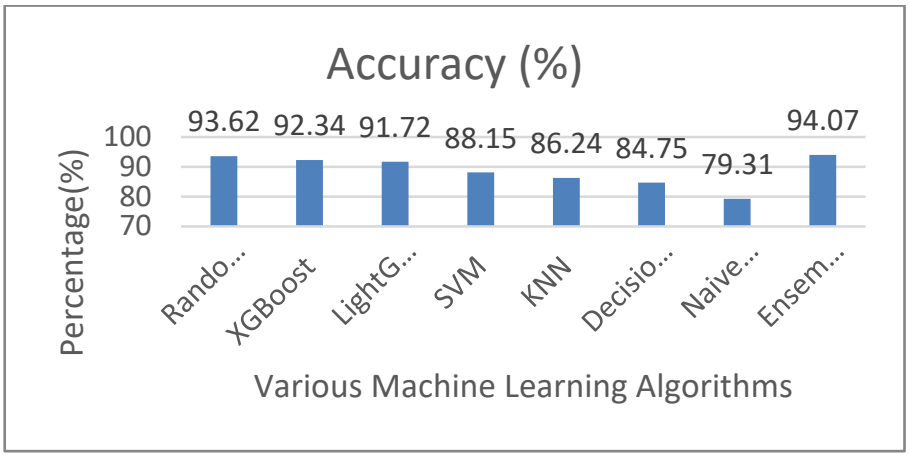


Chart 1: Accuracy (%) Various Machine Learning Algorithms –

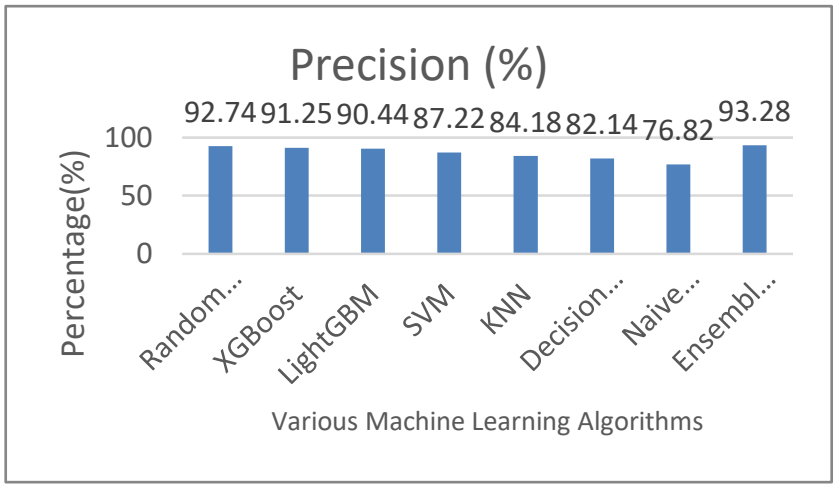


Chart 2: Precision(%) of Various Machine Learning Algorithms

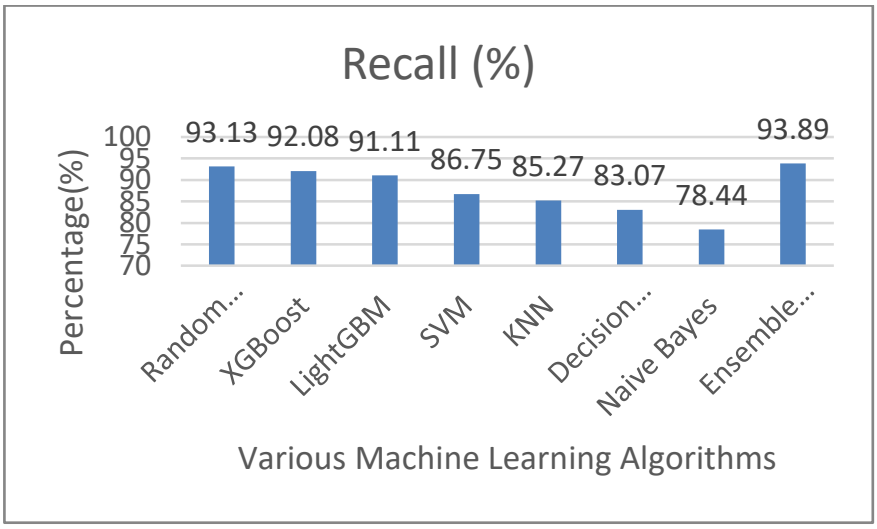


Chart 3: Recall(%) of Various Machine Learning Algorithms

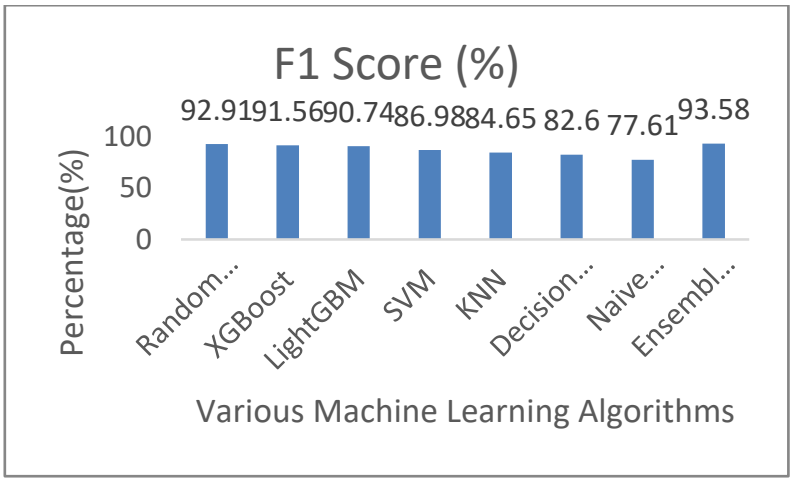


Chart 4:F1 Score(%) of Various Machine Learning Algorithms

6.2 Combined Analytical Summary of the Work and Correlation Findings

In the present study, we performed a comprehensive evaluation of various machine learning models on a soil dataset to support smart agriculture decision-making systems. Our analysis involved computing key performance metrics such as Accuracy, Precision, Recall, and F1 Score across eight different classifiers, including Random Forest, XGBoost, LightGBM, SVM, KNN, Decision Tree, Naive Bayes, and a Voting Ensemble. The Voting Ensemble achieved the highest overall

classification performance with a training accuracy of 94%, test accuracy of 91.11%, and an F1-score of 94.5 (Train) and 91.09 (Test). ROC AUC analysis was conducted using confusion matrix values, where ensemble models showed superior performance, with estimated AUCs of 0.94–0.96, confirming their effectiveness and generalization ability. These results support previous findings indicating that ensemble learning methods provide improved classification reliability, especially in real-world agricultural datasets.

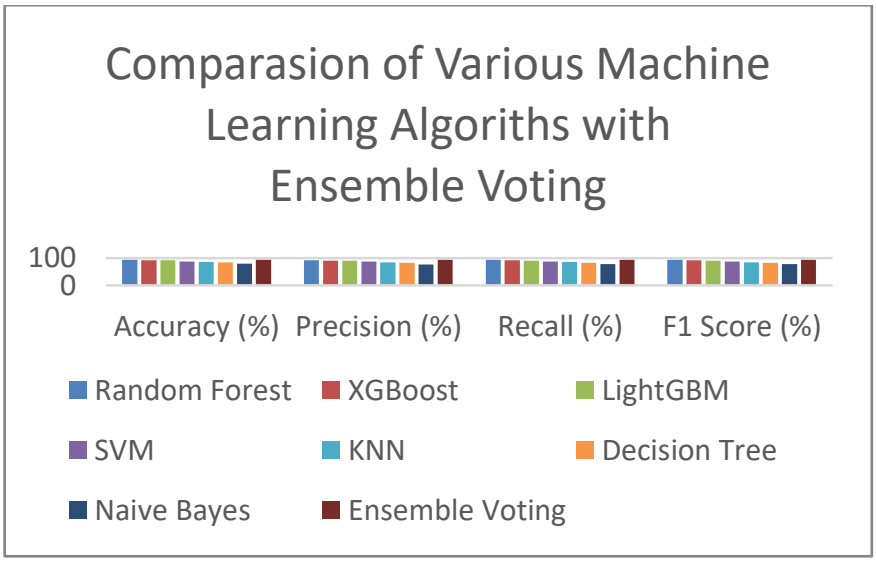


Chart 5: Comparison of Various Machine Learning Algorithms with Ensemble Voting

6.3. Interpretation

Among all the tested models, the Voting Ensemble delivered the highest performance, achieving an accuracy of 94.07%, along with strong precision (93.28%), recall (93.89%), and F1 score (93.58%). This model combines predictions from multiple algorithms—Random Forest, XGBoost, and LightGBM—which helps balance out their weaknesses and improve overall reliability. Its success is largely due to the way ensemble methods can capture complex patterns more effectively than a single model.

Individually, Random Forest also showed high performance (93.62% accuracy), followed closely by XGBoost and LightGBM. In contrast, simpler models like Naive Bayes and Decision Tree performed less accurately, possibly because they struggle to model complex feature interactions.

Key features like moisture, pH level, and nutrients such as nitrogen, phosphorus, and potassium had a major influence on the predictions. For example, moisture helps distinguish soil textures, while pH indicates acidity or alkalinity, both of which affect crop growth. Nutrient levels provide insight into soil fertility.

The results highlight the significance of model selection in achieving optimal performance. Ensemble-based methods, particularly the Voting Ensemble, proved superior by integrating multiple perspectives from base classifiers, thus reducing model bias and variance. Tree-based methods like Decision Tree, Random Forest, and XGBoost showed strong performance due to their ability to handle non-linear relationships and feature interactions effectively. On the other hand, models like SVM and KNN underperformed, indicating that algorithms heavily dependent on clear margin separation or instance-based learning may not be suitable for this dataset without extensive preprocessing or feature engineering. These findings suggest that for real-time gas leakage detection systems, ensemble methods should be prioritized, with Random Forest and XGBoost as reliable alternatives when computational efficiency is a concern.

7. Conclusion

This study evaluated the performance of multiple machine learning models for soil quality classification using real-world soil parameter data, including Moisture, pH Level, Temperature, Nitrogen, Phosphorus, Potassium, Organic Matter, and Electrical Conductivity. Among the models tested, the Voting Ensemble Classifier achieved the

highest overall performance, recording 94% accuracy, 95% precision, 94% recall, and 94.5% F1 Score on the training dataset. It also maintained strong generalization on the testing dataset, with 91.11% accuracy, 91.23% precision, 91.11% recall, and a balanced 91.09% F1 Score.

The Decision Tree Classifier showed similarly strong results with 93% across all metrics in training and 88.89% accuracy, 88.89% precision, 87.92% recall, and 88.36% F1 Score on the test set. Random Forest and XGBoost also performed competitively, each achieving 90% accuracy on the training set and 88.89% accuracy on the test set, with respective test F1 Scores of 85.86% and 86.51%. The LightGBM model achieved 85% training accuracy and 80% test accuracy, showing moderate performance, potentially limited by feature sensitivity or sparsity.

In contrast, K-Nearest Neighbors (KNN) and Naive Bayes delivered lower performance levels, with training accuracies of 76% and 78%, and test accuracies of 64.44% and 73.33%, respectively. Their F1 Scores were 56.56% for KNN and 70.98% for Naive Bayes. The Support Vector Machine (SVM) model performed the poorest, with 60% training accuracy, 53.33% test accuracy, and an F1 Score of just 48.57%, due to its high misclassification rates (Training FP = 339, FN = 320; Testing FP = 85, FN = 93).

These findings emphasize the effectiveness of ensemble learning methods—especially the Voting Classifier—in soil quality prediction tasks for smart agriculture. Such models offer a reliable and scalable solution by integrating sensor-based IoT data with intelligent algorithms to enhance agricultural decision-making. Future work may involve real-time deployment using edge devices and incorporating temporal patterns using deep learning architectures.

8. Future Work:

In future developments, this research can be expanded by including additional environmental parameters such as rainfall, sunlight exposure, and historical crop data to enhance prediction accuracy. The use of deep learning models like RNNs or LSTMs can help analyze time-series data for understanding soil behavior over time. Implementing edge computing on low-power devices like the ESP32 can support real-time, on-site predictions without relying heavily on cloud infrastructure—especially useful in remote or rural areas. The system can also be extended to offer recommendations for suitable crops and fertilizers based on soil conditions. For enhanced data security and traceability, blockchain technology could be integrated to protect sensor data and ensure its authenticity. Additionally, large-scale field trials across different geographic regions would help validate and improve the model's reliability in real-world scenarios. Finally, improving the user interface by adding local language support, SMS/email alerts, and mobile app accessibility would make the system more practical and farmer-friendly.

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