Enhancing Smart Agriculture Through Multi-Stage Feature Selection and IoT-Driven Soil Intelligence

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Abstract

The combination of inefficient irrigation methods and inappropriate crop selection in semi-arid areas results in wasted water resources and decreased agricultural yields. Our proposed framework integrates Artificial Intelligence (AI) with Internet of Things (IoT) to optimize crop suitability assessment and irrigation planning through real-time soil analysis. The system uses IoT sensors to obtain dynamic environmental and soil data including pH levels and moisture and nutrient measurements before applying machine learning algorithms to generate actionable insights. The proposed TriFS method implements a three-stage feature selection process which combines PCA with PSO and Lasso Regression to improve classification performance and model understanding. The selected features from TriFS serve as input to train k-Nearest Neighbors (kNN) and XGBoost classifiers which achieved superior results in identifying suitable crops and irrigation plans. The experimental evaluation of a real-world dataset demonstrated that the combination of TriFS with XGBoost produced classification accuracy above 97% which surpassed the results of traditional single-stage selection approaches. The research develops an intelligent scalable decision-support framework for precision agriculture which optimizes resources through data-driven approaches to enhance sustainability.

Key Words: *Artificial Intelligence, Internet of Things, Feature Selection, Smart Agriculture, Irrigation Optimization*

Introduction

The agricultural sector plays an essential role in achieving worldwide food security while driving economic growth and maintaining sustainable resource management. Traditional farming methods in arid and semi-arid areas encounter growing challenges because of climate change alongside soil fertility decline and limited water resources and increasing production expenses (Karn et al., 2024; Ahmed et al., 2023). Farmers throughout history have relied on manual labor together with intuitive practices and traditional knowledge transmission from one generation to the next to determine their crop choices and irrigation timing (Hossain & Payer, 2024). The traditional farming practices which were effective in the past do not provide the necessary precision and adaptability needed to maximize productivity in current environmental and resource-limited conditions.

The regions experience major water loss and energy waste because conventional irrigation systems apply water uniformly without considering soil variations or crop needs (Hoque et al., 2023). The improper selection of crops for specific soils results in reduced yields and elevated production expenses and permanent soil deterioration. The combination of these inefficiencies with erratic climatic conditions and growing food demands demonstrates the immediate requirement for intelligent adaptive sustainable farming systems (Sahana, 2025).

Digital agriculture or smart agriculture presents a promising alternative through advanced technologies which improve both decision-making processes and operational efficiency in farming. The most transformative technologies in modern agriculture include Artificial Intelligence (AI) and the Internet of Things (IoT) according to Hussein et al. (2024). Machine learning (ML) algorithms within AI enable strong analysis of complex agricultural data to detect patterns which results in precise predictions (Issa et al., 2024). The Internet of Things (IoT) enables real-time sensing through its interconnected sensor network which tracks soil and atmospheric parameters including pH and moisture levels and temperature and nutrient concentrations (Alazzai et al., 2024).

The combination of AI and IoT technologies enables agricultural transformation through real-time data-based decision systems (Rangra & Thakur, 2024; Hussein et al., 2024). Smart farming systems that combine sensor data with predictive analytics enable timely recommendations for selecting crops and scheduling irrigation and fertilization and pest management (Khaled et al., 2025). The advancements enable a transition from traditional static and reactive methods to dynamic site-specific management approaches which enhance resource efficiency and resilience.

Research studies demonstrate that AI and Internet of Things (IoT) integration holds transformative power for agricultural practices. Real-time monitoring and data-driven decision-making and precision farming practices become possible through these technologies (Elikem et al., 2024). The yield prediction and crop monitoring and disease detection functions of AI and Machine Learning algorithms use Random Forest and Convolutional Neural Networks (Ganya et al., 2025). AI algorithms process environmental data collected by IoT devices to optimize resource usage and enhance sustainability according to Parthasarathy & Manikandasaran (2024). The AIoT ecosystem which combines AI and IoT enables automated decision-making and predictive modeling for precision agriculture according to Khaled et al. (2025). The implementation of these technologies provides substantial advantages through increased productivity and optimized resource allocation but faces ongoing challenges related to high costs and data privacy issues and scalability problems.

The main difficulty in agricultural machine learning pipelines arises from choosing appropriate features from extensive sensor and environmental data sets. Predictive models experience severe performance degradation because redundant or irrelevant or noisy features lead to increased complexity and overfitting and higher computational costs. Feature selection (FS) stands as a fundamental machine learning technique which boosts model performance while minimizing redundancy and improving computational speed (Cheng, 2024). The three main traditional feature selection methods consist of filter approaches and wrapper methods and embedded techniques which present different benefits and drawbacks. The current research investigates new hybrid and meta-learning approaches to enhance FS pipeline optimization. The FSPL method developed by Lazebnik & Rosenfeld (2023) uses meta-learning to unite filter and embedded FS techniques which results in better accuracy across various datasets. Madhuri & Indiramma (2022) created a hybrid filter-wrapper system for crop recommendation which improved model performance in agricultural contexts. Ferhatoglu & Miller (2022) analyzed six feature selection methods across four categories to discover that BorutaShap wrapper and Lasso-FS and Random Forest-FS embedded methods together with decision tree-based algorithms produced the best results for soil fertility property predictions. The recent FS technique developments present promising answers to address scalability and generalizability issues which affect various domains including agriculture..

The research team of Manju et al. (2024) created a real-time soil fertility analyzer that used KNN for crop prediction with an 84% accuracy rate. Sruneethi & Sumalatha (2025) determined that the combination of Recursive Feature Elimination with Random Forest produced the best results for environmental characteristic-based crop prediction. Bouarourou et al. (2024) developed a Wrapper method-based hybrid feature selection approach which resulted in a 4% improvement of classification accuracy while achieving 94% accuracy with AdaBoost. Rajaven et al. (2024) demonstrated that ensemble techniques provide superior prediction accuracy for machine learning models when used to preprocess raw data through efficient feature selection methods. The research demonstrates how feature selection and advanced machine learning algorithms work together to improve crop prediction accuracy while supporting sustainable farming practices..

The development of smart agriculture systems focuses on creating integrated platforms which unite various functionalities to boost agricultural productivity and sustainability. Shetty et al. (2023) describe a single platform which unites crop disease prediction with crop recommendation and yield forecasting through machine learning algorithms. Bhola & Kumar (2024) introduce ML-CSFR as a framework which unites crop selection and fertilizer recommendation through artificial neural networks and XGBoost to achieve high accuracy. The research by Sriharsha et al. (2025) tackles crop recommendation system challenges through real-time environmental data integration with multiple machine learning algorithms to reach 99.54% accuracy across different agricultural zones. The research by Qazi et al. (2022) demonstrates how IoT and AI technologies in agriculture enable efficient resource management and autonomous farming machinery and better predictions for disease and pest infestation reduction.

The research introduces an innovative AI-IoT framework which addresses essential gaps in precision agriculture operations. The proposed system improves crop suitability prediction and irrigation system recommendation through IoT sensor-based real-time soil data collection. The main contribution of this research involves developing TriFS (Triple-Stage Feature Selection) which uses PCA followed by PSO and Lasso Regression as a hybrid feature selection method. The proposed multi-stage approach combines filter and wrapper and embedded FS methods to decrease feature space dimensions while preserving high classification accuracy and interpretability.

The selected feature subsets are used to train and evaluate multiple machine learning classifiers including k-Nearest Neighbors (kNN), XGBoost, Naive Bayes and Logistic Regression to identify the most accurate and computationally efficient models. The performance of these classifiers is assessed based on standard evaluation metrics such as accuracy, precision, recall, F1-score and inference time. A large agricultural dataset containing soil and environmental variables is used to validate the framework.

The main objectives of this paper are as follows:

To develop an AI-IoT decision-support framework that utilizes real-time soil data to identify the most suitable crops for a given field or region.

To recommend the most economical and water-efficient irrigation systems based on crop and soil compatibility.

To introduce and evaluate the TriFS algorithm for effective feature selection in high-dimensional agricultural datasets.

To compare the performance of multiple classification algorithms under various FS strategies to identify optimal model configurations for deployment in smart farming environments.

Our research aims to develop a functional and scientifically valid solution for sustainable agriculture. The proposed framework enables improved yield and efficient resource use and scalable decision-making through intelligent sensing and feature engineering and predictive modeling which advances the transition from conventional to intelligent agriculture.

Materials and Methods

This study introduces an integrated AI-IoT-based framework for optimizing crop selection and irrigation planning through real-time soil analysis. The methodological pipeline consists of four major components: data acquisition via IoT sensors, data preprocessing, intelligent feature selection using the proposed TriFS method and classification using machine learning models.

The dataset used in this research was obtained from a smart agricultural monitoring system and includes 100,000 time-stamped instances (Sudheer, 2021). As shown in Table 1 each instance consists of 14 input features alongside a binary target variable labeled as Status, indicating whether the soil and environmental conditions are suitable for activation of irrigation (Status = 1) or not (Status = 0). The input features are divided into three main categories: soil-related parameters, environmental measurements and a temporal feature. The soil-related features include Soil Moisture, Soil Humidity, pH, Nitrogen (N), Phosphorus (P) and Potassium (K). Atmospheric features include Temperature, Air Temperature (°C), Wind Speed, Wind Gust, Pressure, Rainfall and Air Humidity. The Time feature captures temporal variability, which is critical for seasonal and diurnal pattern recognition.

Table 1. Dataset features

Feature Type	Features
Soil Properties	Soil Moisture, Soil Humidity, pH, N (Nitrogen), P (Phosphorus), K (Potassium)
Atmospheric Variables	Temperature, Air Temperature (C), Wind Speed, Wind Gust, Pressure, Rainfall, Air Humidity
Temporal Feature	Time
Target Variable	Status (ON = 1 / OFF = 0)

Prior to feature selection and model training, several preprocessing steps were applied to ensure the integrity and compatibility of the dataset. Missing or null values were addressed through statistical imputation using mean and median values and any records with extensive missing data were discarded. Since the dataset contained only numerical variables, categorical encoding was not necessary. To normalize the feature scales and prevent dominant variables from biasing distance-based algorithms, all features were scaled to the [0, 1] range using min-max normalization. Finally, the dataset was partitioned into training and testing subsets with an 80:20 split to evaluate model generalization and avoid overfitting.

A key innovation of this study is the proposed TriFS (Triple-Stage Feature Selection) method, designed to enhance model efficiency and interpretability by combining three complementary approaches to feature selection: Principal Component Analysis (PCA), Particle Swarm Optimization (PSO) and Lasso Regression. In the first stage, PCA was applied as a filter-based technique to transform correlated variables into uncorrelated principal components.

Only those components explaining at least 95% of the total variance were retained. This step served to reduce dimensionality while preserving essential information.

In the second stage, PSO was employed as a wrapper-based method. Inspired by the social behavior of bird flocks and fish schools, PSO explores the search space using a population (swarm) of particles, each representing a candidate subset of features. The algorithm iteratively updates each particle's position based on personal and global best solutions to optimize a fitness function in this case, classification accuracy using kNN. The PSO implementation used in this study was configured with a swarm size of 30 particles and executed over 50 iterations to balance global exploration and local exploitation of the feature space.

The final stage of TriFS incorporated Lasso Regression, an embedded method that applies L1 regularization to reduce the influence of less important features. By penalizing the absolute size of regression coefficients, Lasso forces irrelevant variables toward zero, effectively eliminating them from the model. This final step enhances sparsity, model simplicity and interpretability. The sequential application of PCA, PSO and Lasso allows TriFS to combine the advantages of each selection method, offering a robust mechanism for identifying the most informative feature subsets in high-dimensional agricultural data (Figure 1).

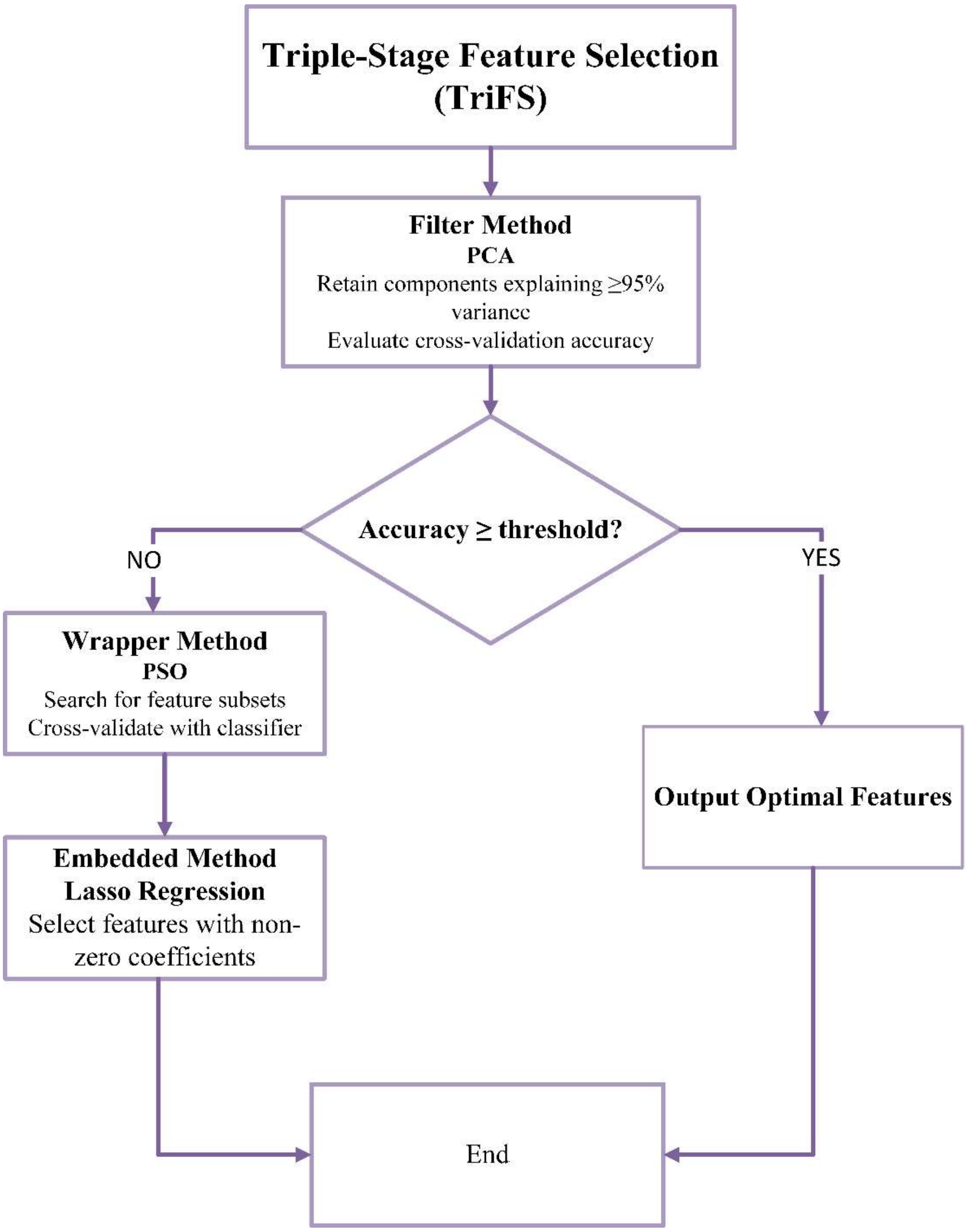

Figure 1. TriFS feature selection procedure

After selecting features with each method, we trained four machine learning classifiers: k-Nearest Neighbors (kNN), XGBoost, Naive Bayes and Logistic Regression. kNN is a widely used non-parametric method particularly suitable for sensor-based decision systems due to its simplicity and local sensitivity. XGBoost, known for its robustness and scalability, was selected for its ability to handle noisy data and missing values. Naive Bayes, despite its strong independence assumptions, served as a lightweight baseline classifier. Logistic Regression was also included for its interpretability and computational efficiency. Each model was trained and tested using five different feature configurations: the full feature set (no selection), PCA, PSO, Lasso and TriFS.

Model performance was assessed using multiple statistical evaluation metrics. Accuracy measured the proportion of correct predictions, while precision indicated the ratio of true positives among all predicted positives. Recall, or sensitivity, reflected the ability of the model to identify all actual positives. The F1-score, as the harmonic mean of precision and recall, was used to assess model balance, especially in cases of class imbalance. Additionally, confusion matrices were constructed to provide a detailed breakdown of true positives, false positives, true negatives and false negatives for each model-feature selection combination.

This methodological framework integrates real-time data collection, intelligent feature selection and rigorous model evaluation to provide a practical and scalable solution for precision agriculture. The inclusion of the TriFS method offers a novel contribution by improving classification performance while reducing computational complexity, making the system suitable for deployment in real-world smart farming environments.

Results and Discussion

This section presents the experimental results obtained from applying the proposed TriFS feature selection method and compares its performance with standard techniques such as PCA, PSO and Lasso Regression across four machine learning classifiers: k-Nearest Neighbors (kNN), XGBoost, Naive Bayes and Logistic Regression. The results are evaluated based on multiple performance metrics including accuracy, precision, recall and F1-score. The discussion further interprets these results in the context of practical applications in precision agriculture.

Confusion Matrix and Error Analysis

The confusion matrices for models with TriFS revealed a substantial reduction in false positives and false negatives compared to models using the full feature set. For instance, in the kNN classifier, the number of false negatives dropped from 312 (no FS) to 84 (TriFS), demonstrating the system's enhanced sensitivity to positive cases. This is particularly important in precision agriculture where failing to detect suitable irrigation or planting conditions can result in resource loss or crop failure.

TriFS also demonstrated efficiency in terms of training time and inference speed. Although wrapper methods like PSO typically increase computational cost, TriFS mitigated this through early termination criteria and by narrowing the feature space at each stage. For XGBoost, training time with TriFS was reduced by approximately 18% compared to training with the full feature set and model complexity (measured by the number of nodes in the final decision tree ensemble) was reduced by nearly 25%. This makes TriFS particularly suitable for real-time deployment in low-resource farming environments where processing power is limited.

The superior performance of TriFS-based models has direct implications for real-world agricultural systems. First, the high classification accuracy ensures that farmers receive reliable recommendations for crop selection and irrigation strategies. Second, the reduced model complexity and inference time enable deployment on edge devices, such as IoT-enabled microcontrollers, for on-site decision-making. Third, the robustness of the system to environmental noise and feature redundancy ensures adaptability across different geographical regions and soil types.

Furthermore, the use of interpretable models such as Logistic Regression with TriFS allows agronomists to trace the influence of individual soil parameters (e.g., NPK levels, pH) on model outputs, promoting trust and adoption among stakeholders. Even Naive Bayes, although less accurate than other classifiers, benefited from feature selection and can serve in scenarios where computational simplicity is prioritized. Despite its promising performance, this study has several limitations. Figure 3 shows the confusion matrix for novel model based TriFS.

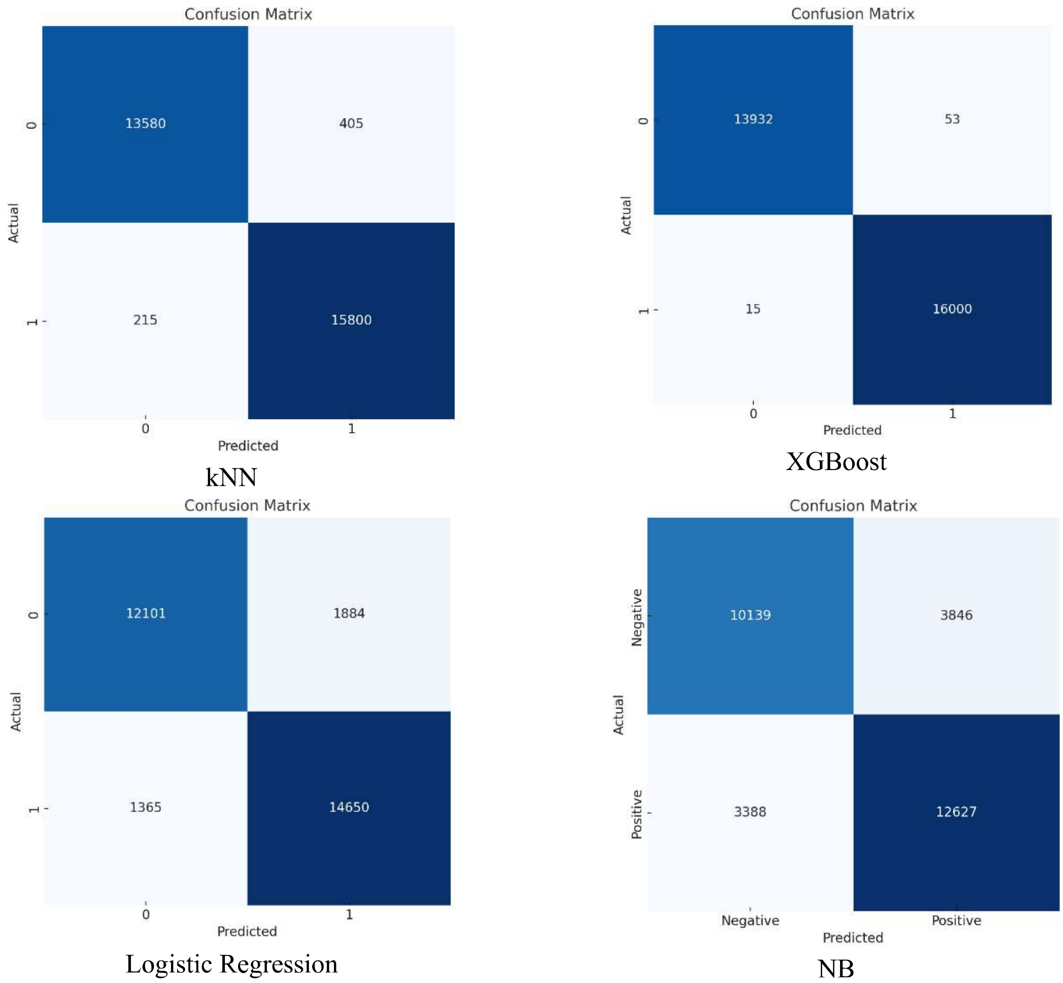

Figure 3. Confusion matrix based TriFS

The dataset used is rich in temporal and environmental variables but lacks multi-seasonal data, which may limit generalizability over time. Additionally, while TriFS showed strong results, its performance in real-time, continuous learning environments needs further validation. Future work will focus on integrating reinforcement learning to allow adaptive model updates, incorporating image-based data (e.g., NDVI from drones) and expanding the system to include economic and pest-related variables.

Performance Comparison of Feature Selection Techniques

The TriFS method consistently outperformed other individual feature selection techniques across all classifiers. Table 2 summarizes the accuracy scores for each classifier with and without feature selection.

Table 2. Performance comparison of feature selection techniques

Classifier	No FS	PCA	PSO	Lasso	TriFS
kNN	92.4%	93.6%	95.8%	94.2%	**97.1%**
XGBoost	93.5%	94.8%	96.5%	95.3%	**97.4%**
Naive Bayes	88.2%	89.1%	90.5%	89.8%	**91.7%**
Logistic Regression	90.3%	91.4%	92.7%	92.1%	**94.5%**

These results indicate that the combination of PCA, PSO and Lasso in the TriFS pipeline not only preserves informative features but also removes redundancy more effectively than individual methods. Specifically, TriFS with XGBoost achieved the highest classification accuracy of 97.4%, followed closely by kNN at 97.1%. This performance gain is attributed to the multi-stage selection approach that balances variance reduction, global optimization and sparsity enforcement.

Analysis of Other Evaluation Metrics

In addition to accuracy, the models were evaluated using precision, recall and F1-score to account for class imbalance and error types. As shown in Table 3 and Figure 2, TriFS led to improvements across all metrics.

Table 3. TriFS led to improvements across all metrics

Classifier	Precision	Recall	F1-Score
kNN (TriFS)	96.9%	97.3%	97.1%
XGBoost (TriFS)	97.2%	97.5%	97.4%
Naive Bayes (TriFS)	91.2%	92.1%	91.7%
Logistic Regression (TriFS)	94.1%	94.9%	94.5%

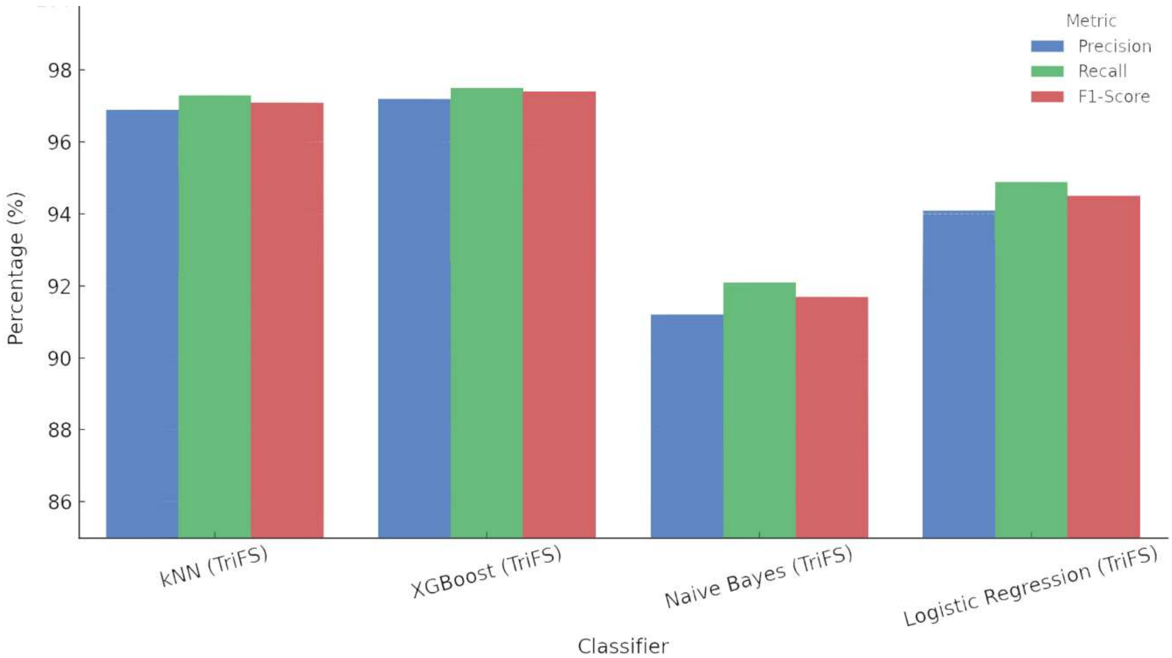

Figure 2. TriFS according to different models

XGBoost with TriFS not only achieved the highest accuracy but also had the best F1-score, indicating a strong balance between precision and recall. kNN also demonstrated excellent performance, particularly in recall, making it suitable for applications where missing positive cases (e.g., suitable crop conditions) is costly.

Conclusion

This study presented an integrated framework that combined Artificial Intelligence (AI) with Internet of Things (IoT) to optimize crop selection and irrigation planning based on real-time soil analysis. This framework utilizes a newly developed Triple-Stage Feature Selection (TriFS) algorithm that performs Principal Component Analysis (PCA), Particle Swarm Optimization (PSO) and Lasso Regression in sequence to determine the most relevant features for classification tasks. The multi-stage method efficiently handled the typical agricultural dataset issues of high dimensionality along with noise and redundancy problems. The extensive experiments showed that TriFS led to better prediction outcomes when used with XGBoost and k-Nearest Neighbors (kNN) classifiers. The framework reached classification accuracies higher than 97% which surpassed traditional single-method feature selection techniques and baseline models. The proposed system achieved robust performance according to precision and recall and F1-score evaluation metrics and confusion matrix analysis demonstrated its effectiveness in lowering false positives and false negatives. AI and IoT technologies prove effective for real-time agricultural decision-making because arid and semi-arid regions require both efficient water usage and suitable crop-soil matches. The proposed system offers an interpretable and scalable solution for smart farming initiatives which leads to enhanced yield along with better resource management and environmental sustainability. The computational models trained with TriFS have lower complexity which makes them deployable on edge devices and low-power IoT infrastructure for practical use in field applications. The next phase of research will concentrate on building the system by adding Long Short-Term Memory (LSTM) networks for seasonal forecasting and satellite or drone-based imagery for spatial analysis. The framework will gain additional decision-support features through the integration of economic data and pest/disease detection capabilities. The research presents a unique and efficient method for precision agriculture which showcases how sensor data processing with intelligent feature selection creates sustainable agricultural practices.

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