Crop Classification Using Machine Learning Techniques: a Comparative Study

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Abstract

Crop classification is a crucial task in modern agriculture, enabling farmers to optimize crop selection based on specific soil and climatic conditions, thereby improving yield and resource efficiency. This study presents a comparative analysis of machine learning techniques for crop classification, utilizing key input features such as soil properties (pH, nitrogen, phosphorus, potassium) and local weather data. Several machine learning models were evaluated for their performance in terms of accuracy, precision, sensitivity, and overall robustness. Among the tested models, the Bagging classifier demonstrated superior performance, achieving an accuracy of 99.77%, making it the most effective approach for the given dataset. The findings highlight the significant potential of machine learning in transforming agricultural practices, offering a data-driven pathway for sustainable crop management. The study also identifies future research opportunities, including the integration of diverse data sources and addressing real-world implementation challenges, to further enhance the applicability and scalability of these techniques.

Keywords

Crop Classification, Machine Learning, Agriculture 4.0, Sustainability, Data-Driven Agriculture, Precision Agriculture

1. Introduction

Agriculture, the cornerstone of countless economies, provides sustenance, employment, and economic stability to millions worldwide. Despite its critical importance, the agricultural sector is under immense pressure due to a rapidly growing global population, shifting climate patterns, and widespread land degradation [1, 2]. To address these challenges and ensure food security, the adoption of smart agricultural technologies has become indispensable [3, 4]. Among these technologies, crop classification systems have gained prominence for their ability to provide farmers with data-driven insights that optimize crop yields and profitability. Machine learning (ML) has emerged as a transformative tool, enabling precise and actionable recommendations to improve agricultural outcomes. While a growing body of research explores the application of ML algorithms for crop classification and recommendation, identifying the most effective and adaptable models remains a pivotal research goal [5, 6].

Building on earlier works that leverage deep learning and machine learning in various domains—including computer vision [7, 8, 9], robot control [10, 11, 12], and EEG-based brain activity classification [13, 14, 15]—this study applies these advanced techniques to address critical challenges in agricultural productivity. Previous contributions have demonstrated the effectiveness of machine learning models in complex environments [16, 17], as well as in health-related domains, including anxiety detection through EEG signals [18, 19]. These interdisciplinary efforts highlight the potential of advanced ML models to deliver accurate, scalable, and context-specific solutions across various applications.

In the agricultural domain, several studies have highlighted the potential of ML in advancing crop classification. For instance, one study [20] proposed a system that leverages ML algorithms to identify the top five crops suitable for a specific region, using input parameters such as rainfall, pH, temperature, and humidity. The system also provided recommendations for optimal NPK quantities, with Random Forest achieving the highest accuracy of 95.45% after hyperparameter tuning. Another investigation [21] explored multiple ML models, including Logistic Regression, Random Forest, Support Vector Machines (SVM)[22, 23, 24, 25], and Neural Networks, for predicting suitable crops in a designated region. The models, trained on 80% of the dataset and tested on the remaining 20%, achieved accuracy rates exceeding 97%. Among these, Neural Networks achieved 98.69% accuracy, while Random Forest recorded the best accuracy of 99.31%. Similarly, a study [26] developed a system to assist farmers in predicting suitable crops, improving current crop cultivation, and detecting plant diseases. The Random Forest algorithm demonstrated an accuracy of 99%, demonstrating its effectiveness in agricultural applications. A further investigation [27] employed a Random Forest classifier to create a predictive system for determining the most suitable crops for specific locations. Trained on a dataset featuring 31 crops and

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their distinct attributes, the system achieved an accuracy of 95%. Another research [28] utilized an SVM-based approach to classify soils into four fertility categories, predicting suitable crops and recommending NPK fertilizer proportions for improved yields[29]. Compared with K-Nearest Neighbors (KNN) and Decision Tree (DT) algorithms, SVM demonstrated the highest accuracy of 77.85%. Beyond these, an IoT-based architecture [30] integrated remote sensing data and ML algorithms for crop forecasting, achieving an accuracy of 98.2% with supervised learning techniques. Similarly, an Android-based application [31] employed Decision Tree classifiers to assist farmers in crop selection based on soil nutrient levels, providing high accuracy and efficient predictions. Another study [32] proposed an ensemble learning-based crop recommendation system using a voting classifier to help farmers select optimal crops based on environmental factors. Achieving an accuracy of 99.31%, the system outperforms earlier methods, providing precise recommendations and enabling data-driven decisions to enhance agricultural productivity and sustainability. In the context of region-specific applications, a smart agricultural system designed for Algerian farmers [33] demonstrated the effectiveness of the Multi-Layer Perceptron (MLP) classifier, achieving an accuracy of 91.81% in crop selection. Furthermore, a comparative study [34] assessed popular algorithms such as Random Forest, Decision Tree, and KNN, concluding that Random Forest offered superior performance with an accuracy of 99.32%.

While these studies highlight the potential of ML for crop classification, identifying the most effective algorithm remains an open challenge. This study addresses this gap by performing a comprehensive comparative analysis of several leading ML algorithms, including Multi-Layer Perceptron (MLP), Support Vector Machines (SVM), Decision Trees (DT), Random Forest (RF), K-Nearest Neighbors (KNN), Naive Bayes (NB), Stacking, Bagging, XGBoost, and LightGBM. Leveraging a publicly available dataset that incorporates critical soil and climate attributes, we evaluate these models based on accuracy, adaptability, and computational efficiency.

2. Materials and Methods

2.1. Dataset Description

This study employed a publicly accessible dataset sourced from Kaggle [35]. The dataset consists of 2,200 observations, with each entry corresponding to a specific crop. It includes 100 data points for each of the 22 crops analyzed in this study. The dataset provides comprehensive information on key parameters essential for crop recommendation, including nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall.

2.2. Data Preprocessing

Data preprocessing is a critical step to prepare the dataset for machine learning models by ensuring data quality, compatibility, and consistency. To address missing values and outliers, we employed median imputation, a robust method that replaces missing data points with the median value of the dataset, ensuring the central tendency of the data is preserved. Categorical features, such as crop types, were encoded using the Label Encoding technique, which assigns a unique integer to each category. This method ensures compatibility with machine learning algorithms while maintaining computational efficiency. Furthermore, to address the varying scales of numerical features that could hinder model performance, we standardized the dataset using the MinMax scaler to normalize values to a consistent range between 0 and 1. These preprocessing steps collectively enhance data quality, improve model stability, and optimize training efficiency, ensuring a robust foundation for machine learning applications.

2.3. Machine Learning Models

To ensure accurate crop classification, this study evaluated a variety of machine learning models, each employing distinct approaches to analyze and classify data. The investigated models include:

- **Naive Bayes (NB):** A probabilistic classifier that applies Bayes' theorem to estimate the likelihood of different crop classes based on feature probabilities [36].
- **Support Vector Machines (SVM):** A supervised learning algorithm that identifies an optimal hyperplane to separate crop classes within the feature space [37].
- **Random Forests (RF):** An ensemble learning technique that combines multiple decision trees to enhance classification accuracy and mitigate overfitting [38].
- **K-Nearest Neighbors (KNN):** A distance-based algorithm that classifies data points by comparing their proximity to the nearest neighbors in the dataset [39].
- **Decision Trees (DT):** A tree-structured model that predicts outcomes by sequentially applying conditions based on feature values [40].

In addition, ensemble techniques such as **Stacking** and **Bagging** were employed to combine the predictions of multiple models, improving the overall reliability and robustness of the classification.

The study also explored advanced algorithms, including **XGBoost** and **LightGBM**, which utilize gradient boosting frameworks and decision trees for efficient and accurate classification and regression tasks.

2.4. Evaluation Metrics

To assess the performance of the employed machine learning models in crop classification, this study utilized a range of evaluation metrics: accuracy, recall, precision, and F1-score. Accuracy measures the overall proportion of correctly classified crop types. Recall focuses on the model's ability to identify true positives, meaning the proportion of actual positive cases the model correctly predicted. Precision, on the other hand, evaluates the model's ability to avoid false positives, indicating the proportion of predicted positive cases that were truly positive. Finally, the F1-score provides a harmonic mean between precision and recall, offering a balanced view of model performance. By considering these metrics together, we gain a comprehensive understanding of the model's strengths and weaknesses in classifying crop types [41, 42].

3. Results and Discussion

3.1. Impact of Data Preprocessing on Model Performance

This section examines the role of data preprocessing techniques in enhancing machine learning model performance for crop classification. A systematic evaluation was conducted to determine the impact of various preprocessing steps on commonly used classification models, including Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes (NB). The preprocessing methods analyzed included dataset splitting strategies, feature selection, data cleaning, and normalization.

3.1.1. Dataset Splitting

Splitting the dataset into training and testing subsets is a fundamental step in machine learning to evaluate model generalization. This study assessed two widely adopted data-splitting ratios:

- **50/50 split:** Allocates equal portions of the dataset for training and testing.
- **80/20 split:** Assigns 80% for training and 20% for testing, ensuring a larger training set.

Table 1 illustrates the performance of each model across these splits for two feature sets (4 features and 7 features). The results show that the 80/20 split consistently outperformed the 50/50 split, highlighting the advantage of a larger training set in improving model learning and accuracy. Furthermore, the inclusion of additional features (7 features) resulted in notable performance improvements across all models.

Table 1
Impact of Dataset Splitting and Feature Count on Accuracy

Classifiers	Splitting (50:50) 4 features	Splitting (80:20) 4 features	Splitting (80:20) 7 features
RF	94.54%	96.13%	99.09%
DT	92.27%	94.72%	98.18%
NB	94.27%	94.31%	99.31%
SVM	68.09%	70.00%	96.59%
KNN	82.45%	87.72%	97.50%

3.1.2. Feature Selection

The study evaluated the impact of feature count on model accuracy by comparing models trained on two feature sets:

- **4 features:** Temperature, pH, humidity, and rainfall.
- **7 features:** The above features combined with nitrogen (N), phosphorus (P), and potassium (K) levels.

As indicated in Table 1, the inclusion of all seven features substantially improved classification accuracy. This underscores the importance of incorporating relevant features to enhance the predictive capabilities of machine learning models for crop classification tasks.

3.1.3. Data Cleaning

Handling missing values and outliers is crucial to ensure model reliability. The study compared the performance of models trained on:

1. **Raw data** containing missing values and outliers.
2. **Data with missing values removed.**
3. **Data with missing values imputed using the median.**

Table 2
Impact of Missing Values and Outliers Processing Techniques on Accuracy

Classifiers	Raw Data	Remove Missing	Replace (Median)
RF	94.54%	93.00%	94.72%
DT	92.27%	89.54%	92.27%
NB	94.27%	91.72%	94.27%
SVM	68.09%	61.72%	68.27%
KNN	82.45%	77.45%	82.72%

Table 2 presents the accuracy of each model under these scenarios. The results reveal that median imputation generally outperformed other approaches, demonstrating its effectiveness in preserving the dataset's integrity and boosting model performance. Conversely, removing missing values led to reduced accuracy due to the loss of potentially valuable data.

3.1.4. Data Normalization

Data normalization aligns features to a consistent scale, mitigating issues caused by varying feature magnitudes. The impact of normalization on model performance is detailed in Table 3. Most models, particularly SVM and KNN, exhibited significant accuracy improvements post-normalization, with SVM achieving a notable 20.54% increase. However, tree-based models like DT and RF showed minimal improvements, reflecting their inherent insensitivity to feature scaling.

Table 3
Impact of Data Normalization on Accuracy

Classifiers	No Norm	Norm	Accuracy Improvement
RF	94.54%	95.18%	0.64%
DT	92.27%	92.81%	0.54%
NB	94.27%	94.27%	0.00%
SVM	68.09%	88.63%	20.54%
KNN	82.45%	88.36%	5.91%

3.1.5. Key Insights from Preprocessing Techniques

Figure 5 highlight the impact of various preprocessing steps on the accuracy of the model, demonstrating that an 80/20 data split consistently outperformed the 50/50 split by providing a larger training set, particularly for smaller datasets. Normalization significantly improved performance for models sensitive to feature scaling, such as SVM and KNN, but had minimal impact on tree-based models. The inclusion of seven features instead of four led to better classification accuracy, emphasizing the importance of selecting relevant variables. Additionally, median imputation was shown to be the most effective approach for handling missing values, maintaining the integrity and precision of the data set compared to data removal, which led to a performance drop.

3.2. Model Evaluation and Analysis

This section evaluates the performance of various machine learning algorithms applied to the crop classification task, with an emphasis on analyzing their results before and after hyperparameter tuning. The objective is to identify the optimal model configurations and assess the impact of preprocessing and tuning on model performance.

The dataset was split into 80% training and 20% testing, with model performance measured using standard metrics such as Accuracy, Precision, Recall, and F1-score.

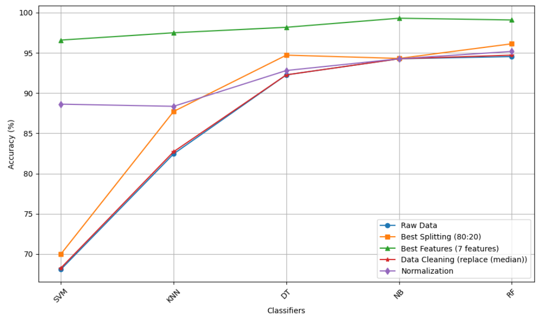

Figure 1: Improvement in Accuracy for Different Preprocessing Steps.

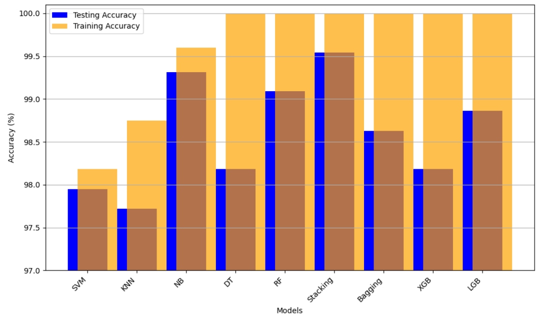

Figure 2: Testing and Training Accuracy of Models (Before Hyperparameter Tuning).

3.2.1. Evaluation Before Hyperparameter Tuning

Initial evaluations focused on assessing the baseline performance of each algorithm without hyperparameter tuning. Table 4 summarizes the results, showcasing the strengths and weaknesses of the models in their default configurations.

Stacking emerged as the best-performing model with a testing accuracy of 99.54% and perfect scores across all other evaluation metrics. Naive Bayes (NB) followed closely with a testing accuracy of 99.31%, demonstrating strong potential for crop classification. Random Forest (RF) achieved 99.09% testing accuracy, further highlighting the reliability of ensemble methods. Other models, including SVM, KNN, and Decision Trees, performed well but did not surpass these top-performing algorithms.

Figure 2 visually compares the testing and training accuracies, reinforcing these observations. The initial evaluation underscores the inherent strengths of each model and sets a benchmark for further improvement through hyperparameter tuning.

Table 4
Performance Evaluation of Machine Learning Models Before Hyperparameter Tuning

Evaluation Criteria	SVM	KNN	NB	DT	RF	Stacking	Bagging	XGB	LGB
Training accuracy (%)	98.18	98.75	99.6	100	100	100	100	100	100
Testing accuracy (%)	97.95	97.72	99.31	98.18	99.09	**99.54**	98.63	98.18	98.86
Precision (%)	98	98	99	98	99	100	98	98	99
Recall (%)	98	98	99	98	99	100	98	98	99
F1 Score (%)	98	98	99	98	99	100	98	98	99

Table 5
Hyperparameter Selection for Each Model

Classifier	**Hyperparameter**
SVM	C = 1000, Gamma = 0.1, kernel = 'rbf'
KNN	Leaf_size = 1, P = 1, N_neighbors = 9, Weights = 'distance', Algorithm = 'brute', Metric = 'Minkowski'
NB	Var_smoothing = 1e-09
DT	Criterion = 'gini', Max_depth = None, Min_samples_leaf = 1, Min_samples_split = 10, Splitter = 'best'
RF	Criterion = 'entropy', Max_depth = None, Max_features = auto, Min_samples_leaf = 1, Min_samples_split = 5, N_estimators = 50
Stacking	final_estimator = LogisticRegression(C=1.0)
Bagging	base_estimator = model_rf, bootstrap = False, max_features = 0.75, max_samples = 1.0, n_estimators = 20
XGB	colsample_bytree = 0.5, learning_rate = 0.01, max_depth = 5, n_estimators = 1000, subsample = 1.0
LightGB	learning_rate = 0.1, max_depth = 3, n_estimators = 500, num_leaves = 31, subsample = 0.5

3.3. Hyperparameter Tuning and Performance Improvement

Hyperparameter tuning was conducted using a grid search to optimize model parameters systematically. Table 5 lists the selected hyperparameters for each model, which were fine-tuned to enhance performance.

Following hyperparameter tuning, we re-evaluated the performance of each model on the test set. Table 6 summarizes the obtained results. The impact of hyperparameter tuning is evident across all models, with significant improvements observed in testing accuracy, precision, recall, and F1-score.

The results are impressive. Across all evaluation metrics, we observed significant gains in performance for each model (Figures 3 & 4). Notably, the Bagging ensemble classifier emerged as the champion, achieving a remarkable testing accuracy of 99.77%. This indicates that the Bagging ensemble, by combining multiple decision trees with optimized hyperparameters, effectively learned complex patterns within the crop data and delivered outstanding classification accuracy.

Following Bagging closely were Random Forest (RF) and Stacking, both reaching an accuracy of 99.54%. This highlights the effectiveness of ensemble methods and combining multiple models for crop classification tasks.

It's also worth noting the consistent performance of Naive Bayes (NB) and XGBoost (XGB). These models

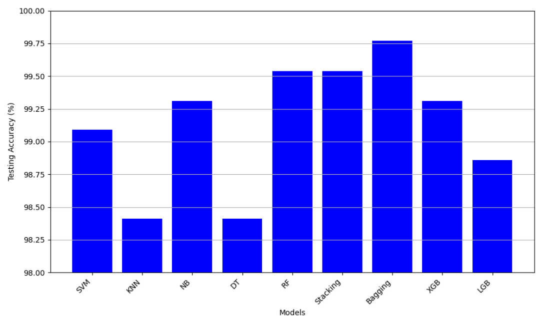

Figure 3: Testing Accuracy of Models (Hyperparameter Tuning).

maintained a high accuracy of 99.31% while achieving perfect scores (100%) for Precision, Recall, and F1-score. This suggests their exceptional ability to correctly identify both positive and negative instances (specific crop types) within the data.

The positive impact of hyperparameter tuning is evident across all models (Figure 5). For instance, SVM saw a significant accuracy improvement of 1.14%, reaching 99.09%. Similarly, the Decision Tree (DT) benefitted from tuning, with its accuracy increasing by 0.23% to 98.41%. These improvements showcase the power of hyperparameter optimization in unlocking the full potential of

Table 6
Performance Evaluation of Machine Learning Models using Hyperparameter Tuning

Evaluation Criteria	SVM	KNN	NB	DT	RF	Stacking	Bagging	XGB	LGB
Training accuracy (%)	99.2	100	99.6	100	100	100	100	100	100
Testing accuracy (%)	99.09	98.41	99.31	98.41	99.54	99.54	**99.77**	99.31	98.86
Precision (%)	99	99	99	98	100	100	100	99	99
Recall (%)	99	98	99	98	100	100	100	99	99
F1 score (%)	99	98	99	98	100	100	100	99	99
Accuracy improvement	1.14	0.69	0	0.23	0.45	0	1.14	1.13	0

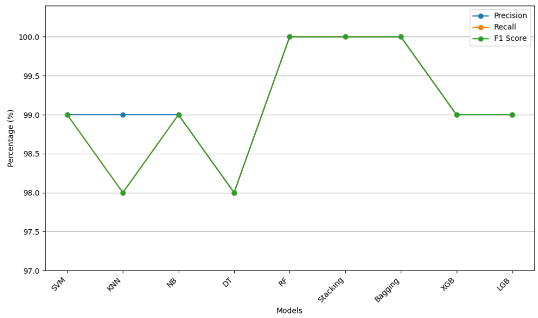

Figure 4: Precision, Recall, and F1 Score of Models (Hyperparameter Tuning).

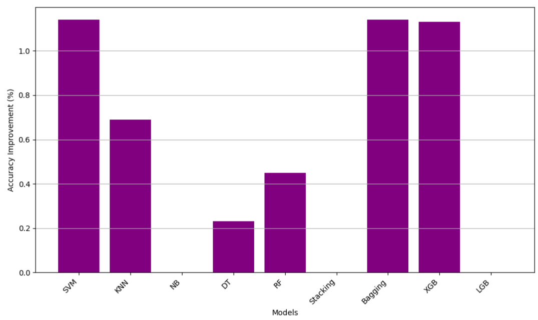

Figure 5: Accuracy Improvement by Model (Hyperparameter Tuning).

each model for crop classification.

Hyperparameter tuning unlocked the full potential of the models, with ensemble methods such as Bagging and Random Forest emerging as the most reliable classifiers for crop identification. These findings provide a robust foundation for deploying machine learning in agricultural applications.

4. Conclusion

The research presented here compared various machine learning algorithms for crop classification. Notably, Bagging classifiers emerged as the frontrunner, achieving an impressive testing accuracy of 99.77%. This superior performance, coupled with high precision and recall, translates to the potential for significant advancements in several key areas: Agricultural Productivity, Resource Optimization, and Sustainable Food Systems.

Building upon this foundation, future research should explore integrating additional data sources, such as satellite imagery or real-time sensor data from fields. Additionally, investigating real-world implementation challenges to ensure accessibility and adoption by farmers will be crucial in realizing the transformative potential of this technology.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT, Grammarly in order to: Grammar and spelling check, Paraphrase and reword. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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