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**| RESEARCH ARTICLE**

# Predictive Analytics and Decision Intelligence for Climate-Resilient Agritech Systems

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## | ABSTRACT

In this study, an architecture of climate-resilient crop recommendation is proposed that uses various machine learning models along with Decision Intelligence to ensure reliable crop recommendation. Five models, namely Logistic Regression, Decision Tree, Random Forest, SVM, and KNN, were used to predict the best crop based on soil and environmental factors. With an accuracy of 99.32%, F1-score of 0.993, and AUC of 0.9999, Random Forest had the best performance. Meanwhile, the Decision Intelligence layer used majority voting to aggregate predictions in order to reconcile contradictory outputs and generate recommendations based on consensus. Excellent crop class discrimination and few misclassifications were validated by confusion matrix and ROC studies. In order to enable well-informed decision-making for climate-resilient agriculture, the suggested framework shows how combining predictive analytics with decision intelligence can produce extremely accurate, comprehensible, and useful crop recommendations.

## | KEYWORDS

Agritech Systems, Artificial Intelligence (AI), Climate Change, Decision-making, Machine Learning (ML), Predictive Analytics

## | ARTICLE INFORMATION

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## 1. Introduction

Climate change, population increase, and the growing need for food security are posing hitherto unheard-of challenges to agriculture. Crop productivity and agricultural sustainability are being severely impacted by rising global temperatures, erratic rainfall patterns, droughts, floods, and extreme weather events. The stability of the world's food systems is threatened by these climate-related changes, which need creative technical solutions to improve agricultural practices' resilience. Conventional farming techniques, which mostly rely on past practices and expertise, are frequently unable to adapt to quickly changing environmental conditions. Therefore, it is of utmost importance to integrate cutting-edge digital technologies in agriculture to increase production as well as ensure sustainable agriculture [1, 2, 3].

Agricultural technology, or AgriTech, has emerged as a viable solution to the problems of agriculture in recent years. Conventional agriculture has been revolutionized into a data-driven ecosystem by technologies like artificial intelligence (AI), machine learning (ML), Internet of Things (IoT), remote sensing, and big data analytics. Large quantities of data in agriculture, like weather, soil, crop, and satellite data, can be collected using these technologies. Precision agriculture, i.e., the optimization of various agricultural activities such as fertilizers, water supply, etc., through the help of various data-driven techniques like real-time data and prediction systems, is the result of these data-driven approaches. Precision agriculture can help in the improvement of sustainable agriculture, elimination of wastage, etc. [4, 5].

Predictive analytics, being the most recent technology in smart agriculture, has received considerable attention because of the potential benefits that can be derived from the prediction of the consequences of agriculture using both historical and real-time data. To accurately predict crop yields, diseases, and irrigation, predictive analytics uses machine learning algorithms that analyze environmental factors such as temperature, rainfall, humidity, and soil composition. Farmers can take preventative measures before environmental hazards cause huge crop losses using their predictive capabilities. Thus, predictive analytics is an essential tool for improving crop productivity and agricultural management [6]. Another significant term in the contemporary agricultural system is decision intelligence, which is an extension of the concept of predictive analytics. Decision intelligence is the application of the results of predictive analytics towards decision-making. Decision intelligence, in the context of agricultural systems, incorporates data analytics and domain expertise towards the development of decision intelligence systems. Such systems can help in providing recommendations for the best crop varieties, practices for plantation, practices for irrigation, and practices for the application of fertilizers based on predicted environmental factors. Farmers and agricultural managers can make informed and effective decisions that enhance productivity and minimize the risks of climate change using predictive analytics and intelligent decision-support systems [7].

Furthermore, in developing Agritech solutions that are resilient to climate change, there is a need to integrate decision intelligence and predictive analytics. The main aim of developing resilient agriculture is to change farming techniques to be resilient to environmental changes, yet sustainable. Real-time sensor data, satellite imaging, and weather data can be analyzed by advanced analytics tools to generate predictions. This will, in turn, help in mitigating losses due to environmental unpredictability. Consequently, it will improve long-term sustainability in agriculture [8]. Predictive analytics and decision intelligence in agriculture have tremendous potential, yet there are a number of challenges to be resolved. Despite the rising trend of embracing data-driven technologies in the agricultural sector, some practical barriers still pose a challenge to the effective adoption of this technology in the field of agriculture. One of the barriers is related to the reliability of the models used, as they are based on data availability. Adequate data availability may be an issue in some agricultural systems, especially in poor nations. New technology's successful implementation in agriculture depends on its ability to work with existing agricultural technologies. Technology faces multiple challenges because small-scale farmers need to overcome three main obstacles which include budget restrictions and insufficient technical skills and limited technology access [9]. The following succinctly describes the primary contributions of this study:

- The study recommends an integrated framework which combines predictive analytics with decision intelligence to enhance climate-resilient agricultural decision-making.
- The research combines multiple agricultural data sources which include weather patterns and soil characteristics and crop-related metrics to create more accurate and trustworthy predictive analysis results.
- The system employs a predictive model that uses ML to assess climatic and agricultural data which helps determine crop production levels while identifying environmental factors that impact crop growth.
- The system includes a decision support system which interprets data from the predictive model to provide farmers with irrigation and crop management recommendations.

## 2. Literature Review

Recent developments in data analysis and machine learning and artificial intelligence have driven progress in developing smart agricultural systems. Researchers developed decision support systems and predictive models and remote sensing systems to help farmers increase their agricultural output and cope with climate change challenges. Researchers have studied crop production prediction through ML algorithms as one of the main research areas in smart agriculture. Researchers used ML algorithms to analyze agricultural datasets that contained multiple types of data including rainfall and temperature and soil types and fertilizer usage to enhance crop production. The systematic review of ML-based crop production prediction found that researchers used ANN and SVM and RF and Gradient Boosting algorithms to forecast agricultural datasets [10].

Multiple research studies have applied DL techniques to enhance the prediction accuracy of agricultural forecasting models [11]. The researchers developed a deep neural network-based system for predicting crop selection and yield that utilized more than forty different environmental factors which included soil conditions and climate data and fertilizer information. The study demonstrated that neural networks function as a tool to improve agricultural planning and decision-making by replicating the complex relationships between environmental factors.The research followed a comparable path to study how CNNs process environmental and phenological data from multiple sources for predicting winter wheat yields [12]. The research showed that deep learning models outperformed traditional linear models at predicting climate parameter wind speed and radiation and moisture temporal patterns. The research demonstrated that climate parameters need to be included in agricultural prediction models used for weather forecasting.

The agricultural analytics field currently experiences a major development which combines geographic information systems with machine learning algorithms. Researchers designed a GNN-RNN model to extract geographical and temporal links from agricultural data [13]. The proposed approach demonstrated superior predictive performance compared to traditional machine learning methods when assessing crop yields across multiple locations. Agricultural monitoring systems now rely on satellite imaging and remote sensing technology as essential tools. Satellite image-based data provides crucial information that helps researchers understand crop growth patterns and soil moisture levels. Machine learning algorithms use satellite pictures to predict agricultural growth conditions and yields in specific geographic areas. The models function as key elements which advance agricultural practices that withstand climate change [14].

The structure of intelligent agricultural systems uses predictive modeling together with decision support systems to establish their entire operational framework [15]. Farmers use predictive analytics and decision support systems because they enable access to domain knowledge which helps them make informed decisions regarding crop selection and required fertilizer and pest control and irrigation scheduling. Research in precision agriculture develops better farming methods through its application of sensor networks and weather stations and Internet of Things technology. The ML models use multiple data sets to analyze and predict trends in crop management. The implementation of precision agriculture methods increases crop production while decreasing water usage and improving environmental sustainability in agriculture. Although there is significant progress in the application of ML and predictive analytics in agriculture, there are still some hurdles that have to be overcome. The accuracy level of predictive models could be affected by the diversity level of the used data. The unpredictable aspect of climate variability is also an issue that could affect predictive models [17]. However, to enhance the accuracy level of predictive models, researchers have emphasized the need to develop effective data integration models that involve satellite images, soil conditions, and climatic conditions [18]. Generally, studies have shown that machine learning and predictive analytics have a lot of potential to transform modern agriculture. The integration of predictive models with decision intelligence models is an emerging area of study. Instead of directly applying predictive models to decision-making in agriculture, most studies have focused on prediction aspects. To ensure the resilience of agriculture, Agritech models that include climate data, predictive models, and decision intelligence need to be integrated [19].

## 3. Methodology

This section discusses the methodology used in the development of the proposed climate-resilient Agritech solution. The methodology is proposed to facilitate predictive analytics and intelligent decision-making in the field of agriculture. Data collection, data preprocessing, predictive modeling, and decision support production are some of the steps included in the proposed methodology. Figure 1 below illustrates the system architecture of the proposed Agritech solution.

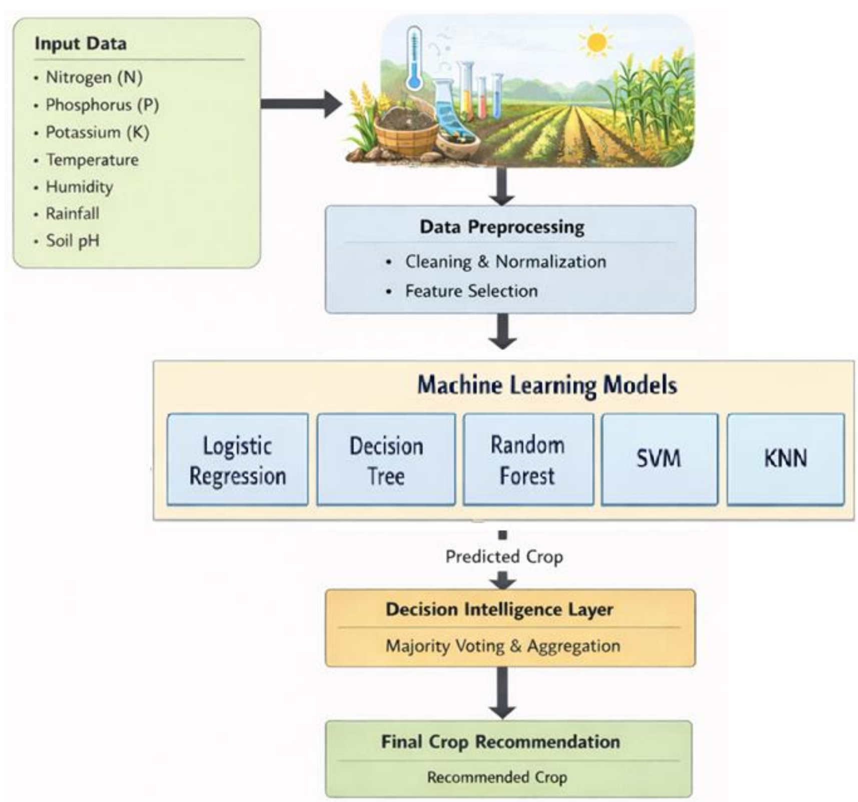


**Figure 1.** Architecture of the Proposed Climate-Resilient Crop Recommendation Framework.

### 3.1 Data Collection

The step of collecting data is focused on acquiring effective agricultural data with information about the qualities of the soil and meteorological conditions, as well as crop yields. Such types of data are very vital in creating predictive analytics models that are effective in discovering connections between various environmental conditions and agricultural outcomes. The dataset used in this research investigation is the Crop Recommendation dataset. The dataset includes information about the soil nutrient content and the surrounding conditions affecting crop growth. The information includes nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, soil pH, rainfall, and the appropriate crop label. All this information is vital in the agricultural field since these are some of the significant agricultural elements affecting crop flexibility under different environmental conditions. The dataset is used in various machine learning-based crop recommendations under specific soil and meteorological conditions. The dataset has over 2,200 samples and includes information about 22 different crop types [20]. Table 1 below describes the features used in this dataset.

**Table 1.** Description of Crop Recommendation Dataset

| ***Attribute*** | ***Description*** |
|---|---|
| *N* | Nitrogen content in the soil |
| *P* | Phosphorus content in the soil |
| *K* | Potassium content in the soil |
| *Temperature* | Average temperature suitable for crop growth |
| *Humidity* | Relative humidity level in the environment |
| *pH* | Soil acidity or alkalinity level |
| *Rainfall* | Amount of rainfall received |
| *Label* | Type of crop recommended |

This dataset is stored in a structured CSV format and is publicly available. The dataset can be efficiently handled using the data analysis tool based on the Python programming language. The framework that is proposed is able to perform predictive analytics and intelligent decision-making for climate-resilient agriculture systems using various types of information [21].

### 3.2 Data Preprocessing

The effectiveness of the ML model could also be adversely affected by the irregularities, duplicates, and scale of the features that are present in the original agricultural data. In order to ensure the quality of the data and the efficacy of the data model, the data preliminary processing step is carried out. The dataset was first checked to determine if there are any inconsistent types of data, duplicates, and missing values. The duplicates have been removed from the dataset to avoid any bias during the training of the ML model. The numerical values of the soil and climatic parameters such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH of the soil, and rainfall are examples of the features that are present in the crop recommendation dataset. It has been checked that the data is present in the correct format with correct numerical values.

The most significant characteristics that affect crop suitability are then identified with the help of feature selection. The input features selected are soil pH, temperature, humidity, rainfall, and nutrient levels such as N, P, and K. The target variable represents the crop label that corresponds to the best crop under the given environmental conditions. Figure 2 illustrates the number of samples present in the dataset for different crop classes.

Feature scaling was employed for the normalization of the input features in order to improve the efficiency of the ML algorithms. Normalization ensures that no single characteristic is dominant in the training of the machine learning models since the features are measured in many ranges and units. All the features were scaled in the range of 0 and 1 using the Min-Max normalization method, enabling each characteristic to have a fair contribution in the training of the models. Ultimately, the 80:20 ratio was employed for the division of the prepared dataset into training and testing sets. The machine learning models were trained using the training set, and their ability to generalize was checked using the testing set.

The dataset was standardized using the preparation procedures discussed in the above section and is therefore ready for predictive modeling in the proposed climate-resilient Agritech framework.

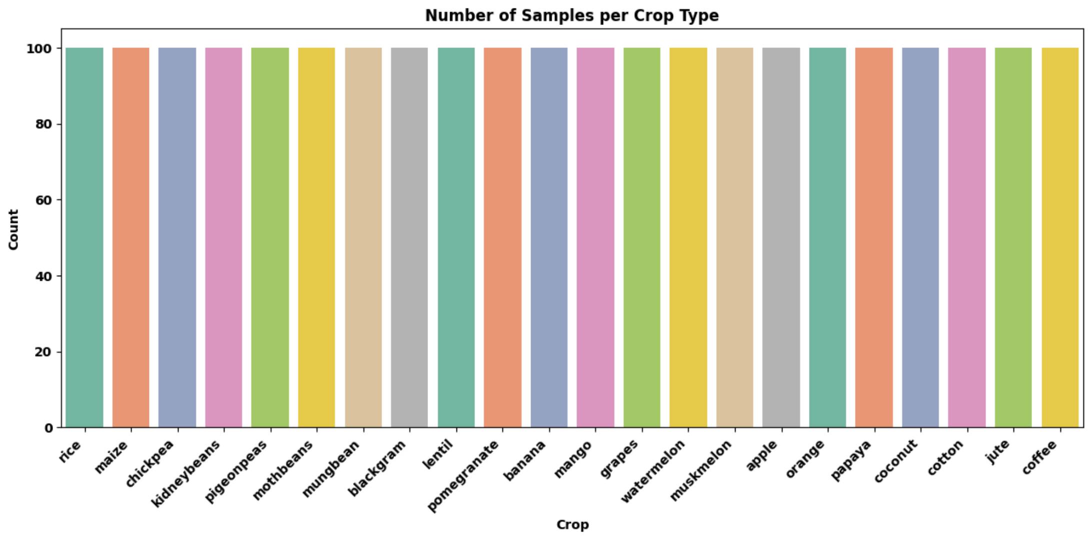


**Figure 2.** Distribution of Crop Labels.

### 3.3 Predictive Modeling

Intelligent decision support systems in agriculture place significant reliance on predictive modeling. This study utilized ML methods in predictive modeling to forecast what would be the best crop to cultivate based on the climate and soil nutrients. This aims to improve climate-resilient agriculture practices by assisting farmers in choosing the right crops that are more in line with climate consideration. An 80:20 ratio was used in splitting the data set. ML models were trained using the training set, while the performance of the models was tested using the testing set. Various supervised learning algorithms were put into practice. Five widely used classification algorithms were selected for predictive modeling:

i. **Regression Logistic (LR)**

A popular statistical classification technique for multiclass prediction issues is logistic regression. It provides a robust baseline model for classification problems and uses the logistic function to predict the probability of class membership.

ii. **Decision Tree (DT)**

A rule-based machine learning model called Decision Tree divides the dataset into subsets according to feature values. It creates a structure like a tree, with internal nodes standing in for feature criteria and leaf nodes for class labels. Agricultural decision-making systems can benefit from the excellent interpretability of decision trees.

iii. **Random Forest (RF)**

Several decision trees are combined in the Random Forest ensemble learning techniques to increase prediction accuracy and decrease overfitting. A randomly selected subset of data and features is used to train each tree, and majority voting is used to determine the final forecast.

iv. **Support Vector Machine (SVM)**

A powerful classification method named Support Vector Machine can find the best hyperplane for classification in a high-dimensional feature space. SVM is particularly effective in handling complex classification boundaries.

v. **K-Nearest Neighbors (KNN)**

K-Nearest Neighbors is a Rank-based statistical technique where the class label of a new object is determined based on the majority class of the nearest objects in the feature space. These models were trained using the processed crop recommendation dataset and were validated using various performance metrics for a comprehensive comparison.

### 3.4 Model Evaluation Metrics

The effectiveness of the prediction models was assessed using a number of classification performance metrics. The most dependable crop recommendation model can be found using performance metrics. The metrics shed light on a number of performance-related issues.

**a. Accuracy**

Accuracy measures the overall proportion of correctly identified samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

**b. Precision**

Precision determines how many of the samples predicted as true were actually true cases.

$$Precision = \frac{TP}{TP + FP}$$

**c. Recall**

Recall (sensitivity) assesses the model's ability to correctly detect true cases:

$$Recall = \frac{TP}{TP + FN}$$

**d. F1-Score**

A balanced indicator of categorization performance, the F1-score is calculated as the harmonic mean of precision and recall.

$$F1 - Score = 2 \times \frac{Precison \times Recall}{Precision + Recall}$$

**e. Area Under the Curve (AUC)**

The AUC makes use of the Receiver Operating Characteristic (ROC) curve in the evaluation of the level of differentiation between the classification model and the classes. To visually evaluate the classification model's performance, confusion matrices and ROC curves have been implemented. Such evaluation methods provide a deeper level of understanding of the classification model.

### 3.5 Decision Intelligence Framework

A new level of decision-making is required for the effective agricultural system, even though the predictive models can recognize the most appropriate crops based on the environment. For facilitating the selection of climate-resilient crops, this research has proposed the incorporation of the Decision Intelligence (DI) framework. The operational workflow of the proposed Decision Intelligence framework is presented in Figure 3. For effective agricultural decision-making, the DI framework combines the decision rules with the predictions of ML models. The proposed approach has used ML models for the exploration of soil nutrients and climatic features. The decision logic layer for the evaluation of the prediction confidence and the crop recommendation has been utilized for the crop label prediction. The proposed DI framework assures that the farmers are provided with effective, understandable, and data-driven recommendations. The proposed system enhances the reliability of the decision and diminishes the possibilities of inaccurate recommendations using the predictions of the ML models.

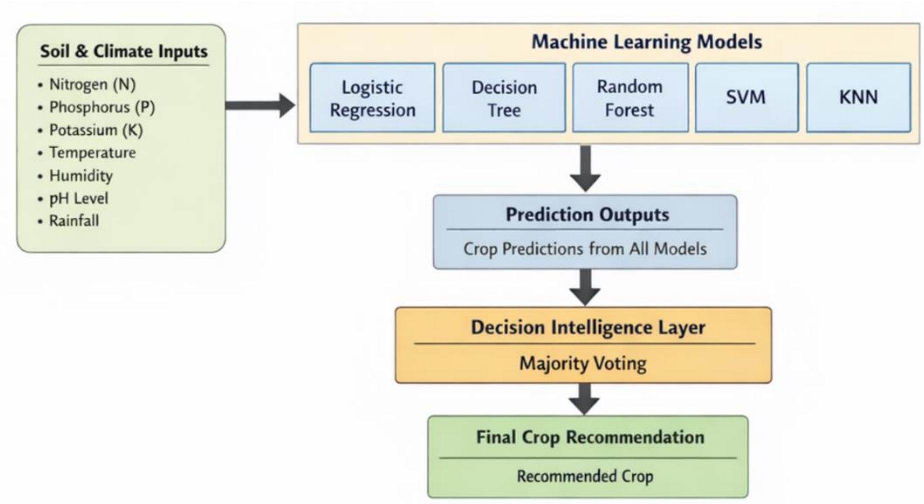


**Figure 3.** Decision Intelligence Workflow Diagram.

The framework works based on the following steps:

a. Input of parameters for the environment and soil.
b. Preprocessing of the parameters based on the same scaling used during the training process.
c. Multiple ML models used for generating predictions.
d. Using a voting mechanism to aggregate the predictions.
e. Selecting the crop based on the highest number of agreements among models.
f. Output of the final recommended crop.

The use of both rule-based decision techniques and machine learning prediction capabilities makes this method better for decision-making.

There are various advantages to integrating decision intelligence:

- By using multi-model consensus, suggestion dependability is increased.
- Lowers individual model prediction errors
- Increases farmers' trust and interpretability
- Encourages agricultural planning that is climate resilient

The suggested framework converts unprocessed forecasts into useful insights that can promote sustainable agricultural methods by fusing machine learning with intelligent decision logic.

## 4. Results and Discussion

The research findings of using various ML models in crop recommendation are demonstrated in this section. The performance analysis of various models in the prediction of the best crop for planting based on the nutrient level of the soil and the meteorological factors is demonstrated in this section. The research findings presented in this study indicate that all the ML models performed well in crop recommendation. The results of the study indicate that the meteorological factors and the nutrient level of the soil are good hints in the prediction of the best crop for planting. Table 2 presents the performance of various models.

**Table 2.** Performance Comparison of Crop Recommendation Models

| ***Model*** | ***Accuracy*** | ***Precision*** | ***Recall*** | ***F1 Score*** | ***AUC*** |
|---|---|---|---|---|---|
| *Logistic Regression* | 0.945 | 0.948 | 0.945 | 0.946 | 0.999 |
| *Decision Tree* | 0.989 | 0.989 | 0.989 | 0.989 | 0.994 |
| *Random Forest* | **0.993** | **0.994** | **0.993** | **0.993** | **0.9999** |
| *SVM* | 0.961 | 0.967 | 0.961 | 0.961 | 0.999 |
| *KNN* | 0.970 | 0.974 | 0.970 | 0.970 | 0.999 |

With 99.3% accuracy, 99.4% precision, 99.3% recall, and 99.3% F1-score, the RF classifier performed better than all the models. Additionally, the RF model showed excellent classification performance for all the crop classes with the highest AUC value of 0.9999. The excellent performance of the Random Forest model can be attributed to the fact that the model is based on the concept of ensemble learning, where the decision trees are combined in order to identify the intricate relationships that exist between the environmental conditions and the crops.

The DT model showed excellent performance with 98.8% accuracy and 0.994 AUC score. This shows that rule-based classification can be performed effectively for decision boundaries in agricultural datasets. DTs are particularly useful in agricultural scenarios due to the transparent ability of the model in representing the decision rules. The KNN model showed excellent classification performance with 97.0% accuracy for the classification of the crop species based on the environmental characteristics. However, the high computational cost of the model during the prediction makes the model less effective. With an accuracy of 96.1%, the SVM proved to be a powerful classification tool in high-dimensional feature spaces. SVM did not perform as well as ensemble-based models like Random Forest, despite its good performance.

With an accuracy of 94.5%, the LR model performed the worst out of all the algorithms that were tested. In spite of this, Logistic Regression continued to generate accurate forecasts and functioned as a helpful reference model. Figure 4 shows the performance comparison of machine learning models.

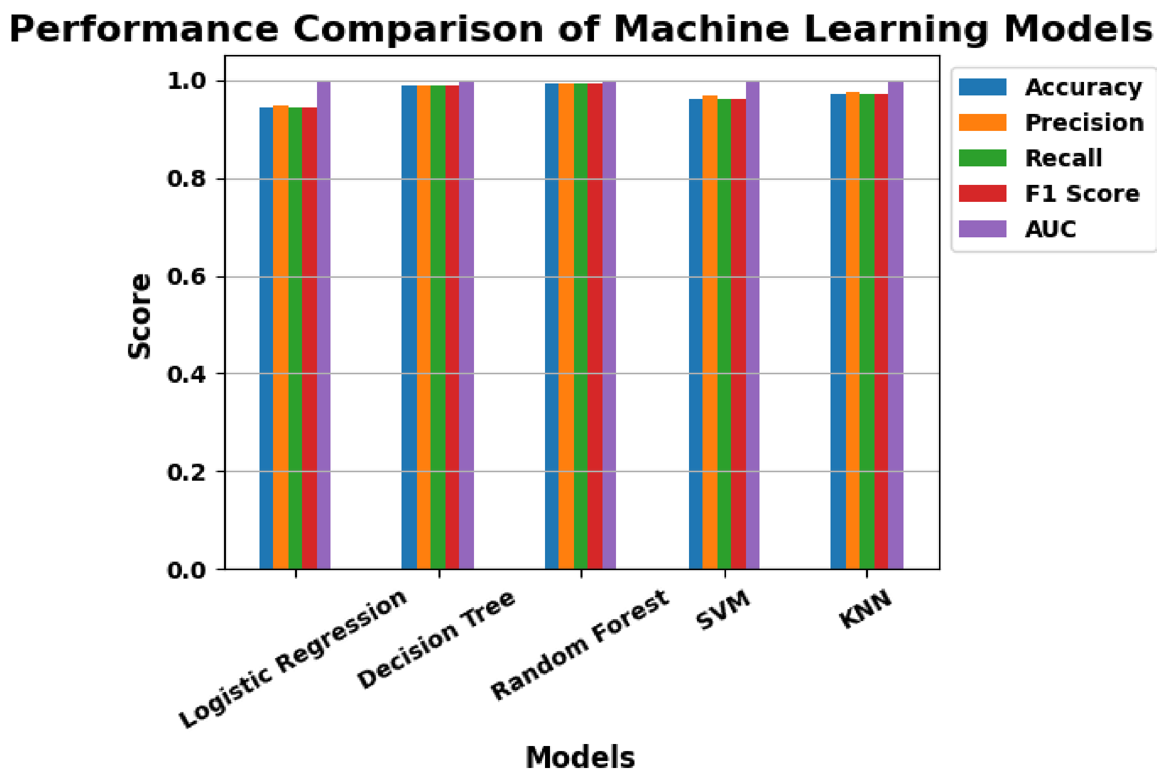


**Figure 4.** Performance Comparison of Models.

Confusion matrices were created for every ML model in order to further examine classification performance, as shown in Figure 5. The confusion matrices offer a thorough overview of crop categories that have been correctly and erroneously classified. The results show that the models were able to predict the majority of the crop classes with minimal misclassifications. In the prediction of the crop recommendation, the RF model recorded the least misclassification rate, which proves the reliability and robustness of the model. The proposed method can be used to differentiate between various types of crops based on soil nutrients and meteorological parameters, as indicated by the analysis of the confusion matrix.

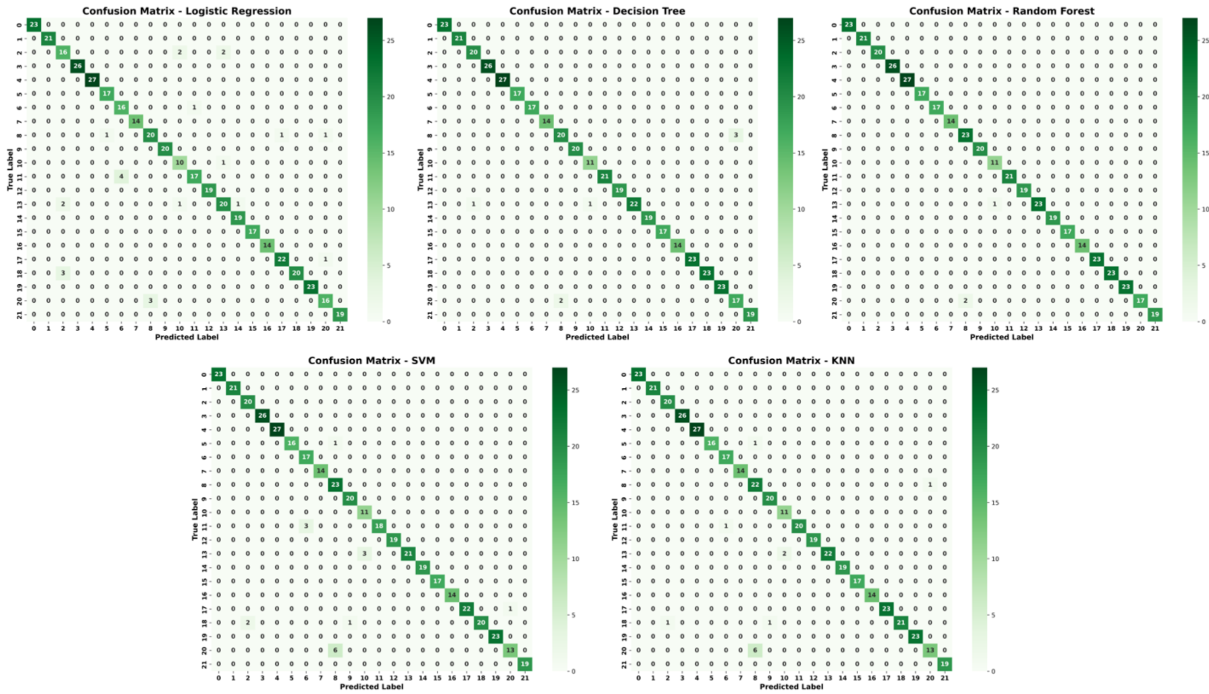

**Figure 5.** Confusion Matrix for Crop Recommendation Models

In order to find out how well each model classified using different thresholds, Receiver Operating Characteristic or ROC curve analysis was also performed, as shown in Figure 6 below. The ROC curve analysis results indicate how well each model classified by using the true and false positive results. From the results, it is clear that all models classified very well, as indicated by the high AUC values, close to 1. The high efficiency of the Random Forest model in efficiently dividing the types of crops with minimal classification errors was also confirmed by the model's ROC curve results, as shown below: The presence of nitrogen, phosphorus, potassium, temperature, humidity, rainfall, and soil pH in the dataset provides great discriminatory power in predicting appropriate crops, as shown by the high AUC values.

The results of the experiments have shown that intelligent crop recommendation for climate-resilient agriculture can be effectively supported by ML models. The high accuracy and AUC values of the models used in the experiments have clearly indicated the relationship between soil nutrients, climate conditions, and crop suitability. The best results for all the evaluation parameters have been achieved by the RF classifier, indicating its highest reliability among the models used. The use of a majority voting approach to aggregate the predictions of multiple machine learning models has increased the reliability of the DI framework. The proposed framework has shown its potential to be used as a useful decision support system for recommending crops that can be best cultivated based on the local climate conditions. The proposed framework can be used to support climate-resilient and sustainable farming practices, thus promoting productivity in agriculture.

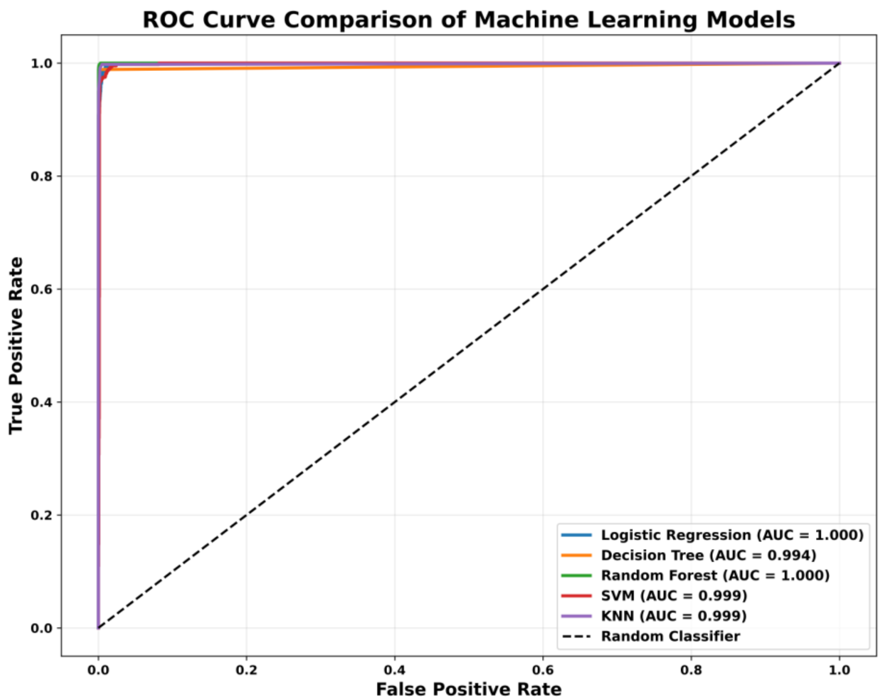


**Figure 6.** ROC Curve Comparison for Crop Recommendation Models

The suggested system not only assesses each ML model's performance but also uses the DI layer to produce a final crop recommendation. Based on the consensus of model outputs, the DI module generates the final crop recommendation by combining predictions from all trained classifiers. Figure 7 shows an example of a recommendation produced by the system. Separate models generated the following predictions for the specified environmental input parameters: maize was predicted by the KNN model, while rice was predicted by LR, DT, RF, and SVM. Rice was ultimately recommended by the system based on the majority vote technique. Figure 7 demonstrates an example crop recommendation generated by the system.

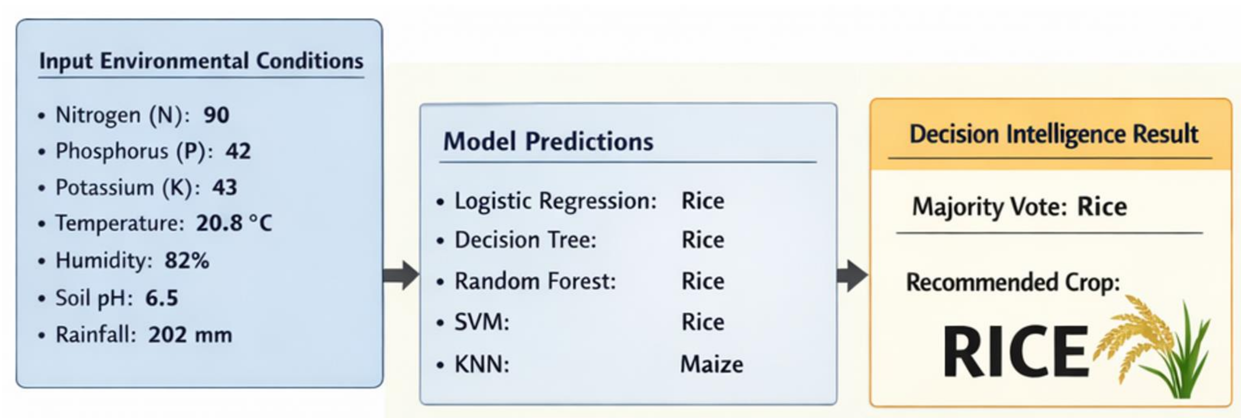


**Figure 7.** Example Output of Crop Recommendation using Decision Intelligence

Strong agreement among the classifiers was demonstrated by the findings, which show that most models generated consistent predictions for the specified environmental conditions. The usefulness of the chosen soil and climate characteristics for crop recommendation is further validated by the high degree of agreement between models. The system's final suggestion is in line with the predictions of the best-performing models, especially the Random Forest and Decision Tree classifiers, which performed the best in the previously mentioned evaluation measures. This shows that the integrated system can generate trustworthy crop recommendations based on environmental factors.

## 5. Conclusion and Future Work

This study suggested a framework for climate-resilient crop recommendations that combine a DI layer with several machine learning models. For the crop recommendation data set, all models performed well. However, the highest accuracy rate was recorded for the RF model (99.32%), accompanied by the highest F1 score (0.993) and AUC score (0.9999). In terms of accuracy rates, the DT model and the KNN model recorded high dependability with 98.86% and 97.05%, respectively.

Through the implementation of the majority voting method for combining predictions, the DI layer added robustness to the overall system. The DI module was able to provide trustworthy final recommendations for the contradicting predictions from the models in the testing environment. For example, the DI layer was able to demonstrate its robustness in imposing a consensus-driven decision-making approach by choosing the final crop to be rice when all the models had chosen it except for one model that had chosen maize.

These findings show that the inclusion of predictive analytics with a decision intelligence system can enhance the accuracy of predictions, lower the likelihood of incorrect classification, and offer useful suggestions to farmers under various environmental conditions. The low number of incorrect classifications based on confusion matrix evaluations indicates the efficiency of the selected soil and climate parameters, while the high AUC values of the system (>0.99 for all) show good crop class discrimination.

We can enhance the framework by:

- Leveraging sensor data in live monitoring of crops to offer area-based, adaptive recommendations.
- Extending to datasets with several regions and crops to achieve more comprehensive generalization.
- Applying seasonal and temporal modeling to uncover patterns of crop suitability over extended periods.
- Incorporating Explainable AI approaches to improve transparency and comprehension of feature contributions.
- Combining resource optimization technologies for fertilization, irrigation, and climate risk reduction with crop recommendations.

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**Conflicts of Interest**

The authors declare no conflict of interest.

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