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STACKING ENSEMBLE-BASED PREDICTIVE SYSTEM FOR CROP RECOMMENDATION

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ABSTRACT
Agricultural sustainability relies on crop production, but the task of choosing appropriate crops for certain places is difficult owing to the ever-changing environmental circumstances. Traditional approaches are often limited in scope, failing to adapt to diverse soil types and environmental parameters. This study introduces a novel prediction method that utilizes a machine-learning model with ensemble approaches to provide recommendations for crops. The system was developed using a Design Science Research (DSR) methodology. The proposed model incorporates a wide array of machine-learning techniques, including K-Nearest Neighbors, Decision Trees, Support Vector Machines, Naive Bayes, Logistic Regression, and Extreme Gradient Boosting. The integration utilizes the Random Forest meta-model. The model was trained and validated using a large dataset gathered from Kaggle, which consisted of a wide variety of crops and environmental characteristics. The model's performance was evaluated using metrics such as Accuracy, Recall, F1-Score, and Precision. It exhibited outstanding accuracy of 99.8%, along with superior recall, precision, and F1 scores, outperforming previous research by a significant margin. Furthermore, data flow diagrams illustrate the data processing flow within the system. The implementation was carried out using the Python programming language, with MongoDB employed for database development. The resulting proof-of-concept system demonstrates the practical applicability of the model by providing reliable crop recommendations based on environmental data. This research marks a substantial advancement in optimizing crop management strategies through advanced predictive modeling, offering a robust tool to aid farmers in making informed decisions, ultimately enhancing agricultural productivity and sustainability.

Keywords: Ensemble Learning, Crop Selection, Precision Agriculture, Predictive Modeling, Proof-of-Concept System

INTRODUCTION
Agriculture is a fundamental pillar of human civilization, offering nourishment, employment, and economic security to hundreds of millions of people globally. Within this realm, crop production plays a pivotal role, in driving agricultural productivity and shaping food security outcomes (Amanullah & Khan, 2024; Thakur, Kumari & Kumar, 2024). However, the agricultural landscape is marked by multifaceted challenges, including fluctuating environmental conditions, resource constraints, and evolving market dynamics (COSTEA *et al*., 2023; Hassan, Rai & Maharjan, 2023). In this context, the ability to make informed decisions regarding crop selection is paramount for farmers seeking to optimize yields, mitigate risks, and enhance profitability (Phadke, Goel, Bajpai & Mehta, 2022; Balaska, Adamidou, Vryzas & Gasteratos, 2023).

Traditionally, farmers have relied on empirical knowledge, local practices, and historical data to guide their crop selection decisions (Sunil-Kumar, 2024). Nevertheless, the growing intricacy and fluctuation of environmental elements, such as the composition of the soil, climatic patterns, insect pandemics, and consumer demand, pose substantial obstacles to conventional decision-making methods (Khatri, Kumar, Shakya, Kirlas & Tiwari, 2023). Moreover, traditional methods often lack the scalability and adaptability required to address the diverse and dynamic nature of modern agricultural systems (Akkem, Biswas & Varanasi, 2024).

There has been an increasing recognition in recent years of the potential of modern technology, particularly machine learning (ML), to revolutionize agricultural decision-making processes. ML techniques offer a data-driven approach to analyzing complex agricultural datasets, uncovering patterns, and generating insights that can inform more accurate and timely decisions (Chergui & Kechadi, 2022; Koshariya *et al*., 2024). Among the various ML approaches, ensemble learning has emerged as a powerful paradigm for improving prediction accuracy and robustness (Maheswary *et al*., 2024).

Ensemble learning refers to the procedure of combining the predictions generated by several independent models to obtain a single, more accurate forecast (Yang, Lv, & Chen, 2023). The stacking ensemble is an advanced ensemble approach that combines the predictions of different base models using a meta-learner. The meta-learner is trained to optimize the combination of the base models' outputs (Mohammed & Kora, 2023; Raju, Ashoka & BV, 2024). Stacking ensemble models have shown greater performance in many prediction tasks by using the strengths of several algorithms and addressing their flaws (Kumar, Bajaj, Sharma & Narang, 2022).

In the context of crop recommendation, stacking ensemble-based predictive systems offer several potential advantages over traditional methods. These include the ability to capture complex interactions between environmental factors and crop performance, adapt to changing conditions over time, and provide more accurate and reliable recommendations to farmers (Ganaie, Hu, Malik, Tanveer & Suganthan, 2022). Stacking ensemble models may utilize a wide range of data sources, including satellite images, meteorological data, soil maps, and historical yield records, to provide more accurate forecasts. This integration of varied data sources allows for the leveraging of a multitude of knowledge, resulting in more robust predictions (Satish, Anmala, Rajitha & Varma, 2024).

Despite the considerable promise of stacking ensemble-based predictive systems for crop recommendation, there remains a gap in the literature regarding their development, evaluation, and practical application in real-world agricultural settings (Zhu, Wang, Yang, Xu & Yang, 2024; Ketheneni *et al*., 2024). Therefore, this research paper aims to fill this need by creating and assessing a thorough stacking ensemble-based forecasting system in order to provide farmers with crop recommendations. The objective of this research is to analyze the performance of stacking ensemble approaches and their potential impact on agricultural decision-making processes. This will be done by systematically comparing their efficacy to conventional methods. The results of this study can provide crucial information, enabling farmers, agricultural practitioners, and politicians to make better knowledgeable decisions based on facts. This has the capacity to result in enhanced techniques for choosing and overseeing crops, ultimately improving agricultural production, sustainability, and food security.

MATERIALS AND METHODS

The study utilized a research methodology known as design and creation research, a variant of Design Science Research (DSR) commonly used in the fields of information models and computer research. DSR focuses on problem-solving and the creation of artifacts, encompassing the integration of organizational, human, and technical components to address complex difficulties. The methodology is based on the principles of DSR and is visualized in Figure 1.

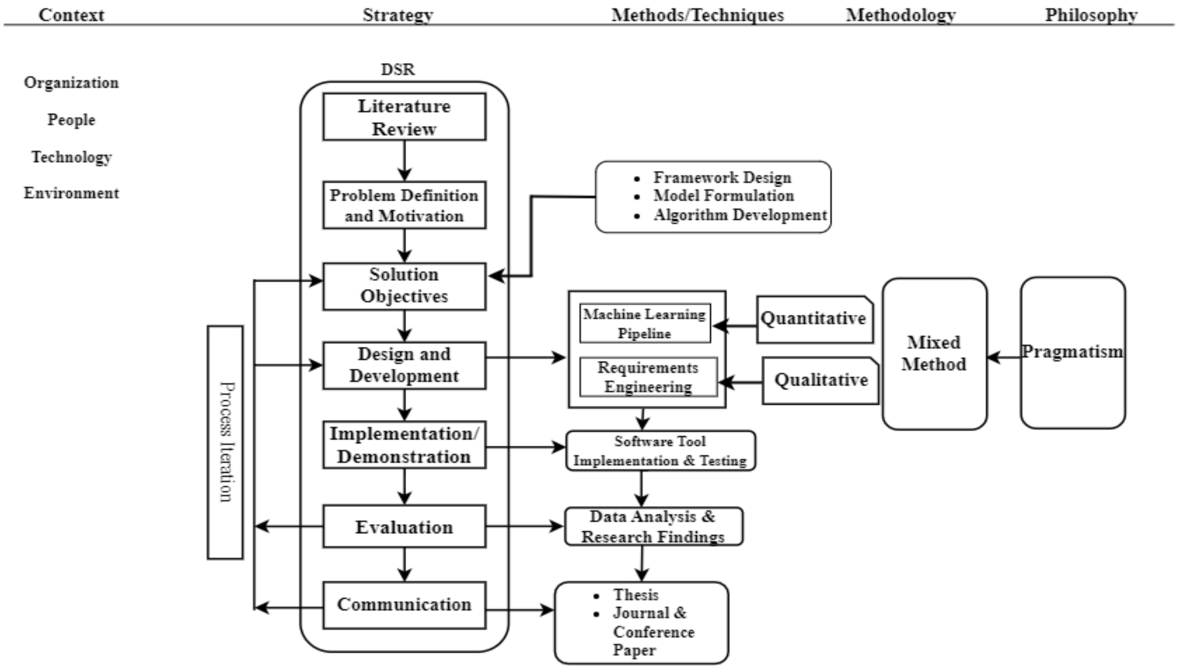

Figure 1: Research Methodology Framework

Solution Objectives

The key goal of the study is to construct a predictive model for crop recommendation using an ensemble-based approach. This phase involves applying methodological, theoretical, and systematic approaches to implement the formulated ensemble-based model to a proof-of-concept system.

Design and Development

This is the phase where the ensemble-based predictive model was developed. With insight from the literature review, the stacking ensembling technique was selected as the appropriate learning algorithm for the model development following the machine learning pipeline procedures.

Evaluation

The ensemble-based prediction model was assessed using several assessment metrics and methods, including accuracy, precision, recall, and f1 score. The model's performance is assessed by comparing it to earlier approaches discovered in the literature review.

Dataset Description

The dataset was obtained from the website https://www.kaggle.com/datasets/aksahaha/crop-recommendation. Table 1 presents a concise dataset summary including 2200 records and 17 columns, all of which include numerical values. The given data include statistics for many factors, including Nitrogen, Phosphorus, Potassium, Temperature, Humidity, pH, Rainfall, Clay, Loamy, Silt, Sandy Loam, Loamy Sand, Silt Loam, Clay Loam, Drainage, Water Retention Moderate, and Water Retention High. The dataset consists of statistical metrics, including the mean, standard deviation, minimum, maximum, and quartiles. These metrics provide crucial information on the average values and range of agricultural indicators, making it easier to analyse and identify any abnormal data points.

Table 1: Statistical summary of study data

	Nitrogen	phosphorus	potassium	temperature	humidity	ph	rainfall	Clay
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.469480	103.463655	0.500000
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.958389	0.500114
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267	0.000000
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.551686	0.000000
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.867624	0.500000
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.267508	1.000000
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.560117	1.000000

Loamy	Silt	Sandy Loam	Loamy Sand	Silt loam	Clay loam	Drainage	WaterRetentionModerate
2200.000000	2200.000000	2200.000000	2200.000000	2200.0	2200.000000	2200.000000	2200.000000
0.045455	0.863636	0.954545	0.909091	0.0	0.045455	1.863636	0.909091
0.208346	0.343252	0.208346	0.287545	0.0	0.208346	0.343252	0.287545
0.000000	0.000000	0.000000	0.000000	0.0	0.000000	1.000000	0.000000
0.000000	1.000000	1.000000	1.000000	0.0	0.000000	2.000000	1.000000
0.000000	1.000000	1.000000	1.000000	0.0	0.000000	2.000000	1.000000
0.000000	1.000000	1.000000	1.000000	0.0	0.000000	2.000000	1.000000
1.000000	1.000000	1.000000	1.000000	0.0	1.000000	2.000000	1.000000

Figure 2 displays the correlation matrix for the input characteristics. It is worth mentioning that there is a significant and positive connection of 0.74 between potassium and phosphorus. With the exception of this particular pair, most of the characteristics exhibit weak associations. This attribute is beneficial for our dataset since it reduces multicollinearity, hence improving the interpretability of the model. Furthermore, it mitigates the likelihood of overfitting, thereby enhancing the precision and generalizability of the model. The diminished correlations also result in less processing time, enabling the model to prioritize pertinent information. Moreover, it streamlines the process of determining the most relevant elements that affect the result variable.

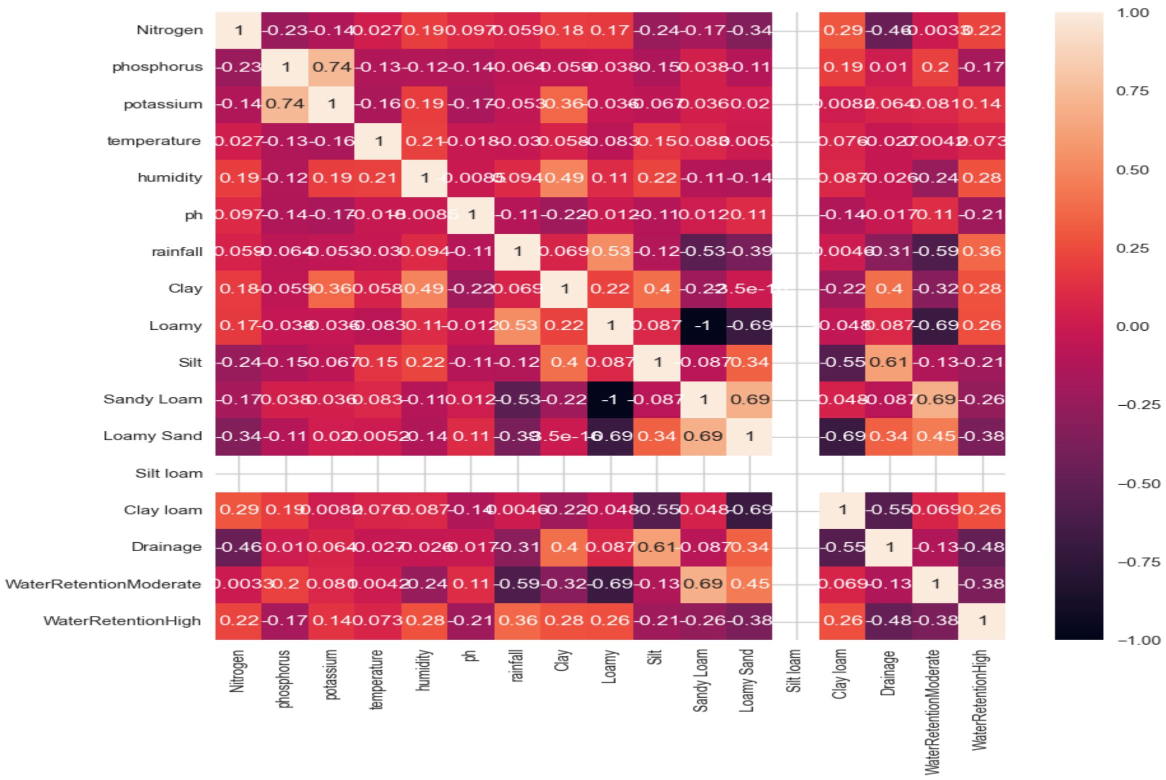

Figure 2: Correlation Matrix for the Input Features

Furthermore, the dataset analysis revealed specific soil and environmental requirements for different labeled crops. For instance, cotton requires a higher amount of nitrogen, while apple has a high phosphorus requirement. Additionally, the study found that Papaya thrives in extreme temperatures, and coconut has a higher moisture content. Chickpeas have a higher pH requirement, and rice requires significant rainfall. Table 2 presents the results of the analysis, including parameters like Rainfall, Temperature, Humidity, Nitrogen, Potassium, Phosphorus, and pH.

Table 2: Crop Characteristics Analysis

S/N	Crop	Rainfall	Temperature	Humidity	Nitrogen	Potassium	Phosphorus	pH
1.	Rice	✓						
2.	Cotton				✓			
3.	Apple					✓	✓	
4.	Grapes					✓		
5.	Papaya		✓					
6.	Coconut			✓				
7.	Chickpea							✓

Feature Selection

Feature selection plays a vital role in this study by minimizing overfitting, enhancing detection accuracy, and reducing the time required for model training. The effectiveness of machine learning models heavily depends on the quality and relevance of the dataset features used for training. Irrelevant, unsuitable, or partially relevant features can negatively impact model performance. To identify and prioritize the most significant features contributing to the target variable, a feature selection process was applied to the dataset. In this study, all features were determined to be relevant and were subsequently utilized for training the models. The dataset was split into 80% for training and 20% for testing, ensuring a balanced evaluation of the model's performance.

Description of Machine Learning Methods Used

This section offers a thorough explanation of the seven selected machine-learning models for this research. The assortment comprises the subsequent models: The machine learning algorithms mentioned include Random Forest, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Logistic Regression (LR), Naïve Bayes, Decision Tree, and Extreme Gradient Boosting.

Random Forest is a machine learning algorithm employed for solving problems associated with regression and classification (Ren, Zhang & Suganthan, 2016). It generates decision trees using random data samples, reducing correlation and overfitting ((Zounemat-Kermani, Batelaan, Fadaee & Hinkelmann, 2021; Dev & Eden, 2019). Widely used in fields like image classification, bioinformatics, and financial forecasting, it provides reliable forecasts (Katuwal, Suganthan & Zhang, 2020).

Support Vector Machine (SVM) is a sophisticated machine learning technology for predictive analysis and pattern recognition, particularly effective for large datasets (Shubham & Kamalraj, 2022; Campbell & Ying, 2022; Cervantes, Garcia-Lamont, Rodríguez-Mazahua & Lopez, 2020).). It is used to build binary classifiers by representing data items as points in an n-dimensional space.

K-Nearest Neighbors Is a regression-based machine learning technique that utilizes similarity learning (Isnaeni, Indriani, Zaman & Nugroho, 2024). It identifies K nearest data points from the training set, determining class or value through majority voting (Bian, Vong, Wong & Wang, 2020; (Cunningham & Delany, 2020). KNN's simplicity and flexibility allow it to adapt to various data patterns and distributions (Rimanic, Renggli, Li, & Zhang, 2020).

The logistic Regression (LR) method is a fundamental machine-learning technique, that transforms linear input attributes into probability-like values (Santoso, Singh, Rajest, Regin & Kadhim, 2021; (Song, Liu, Liu & Wang, 2021). It makes use of the sigmoid function, transforming them into scales representing probabilities(Talpur & O'Sullivan, 2020; Ray, 2019).

Naive Bayes is a commonly employed method in the fields of machine learning and statistics, especially for tasks involving categorization (Veziroğlu, Eziroğlu & Bucak, 2024). The calculation of the likelihood of a hypothesis being true is based on Bayes' theorem, which is a fundamental premise in probability theory (Alnuaimi & Albaldawi, 2024; Reddy *et al.*, 2024). This simplicity simplifies probabilities, making them computationally efficient and easy to implement (Alnuaimi & Albaldawi, 2024; Verma & Sahu, 2024).

Decision Trees are a powerful machine learning model that effectively handles regression tasks by making binary decisions based on the value of features (Costa & Pedreira, 2023; Fong & Motani, 2024). They mimic human decision-making processes, handle numerical and categorical data, and capture complex relationships (Linardatos, Papastefanopoulos & Kotsiantis, 2020; Nanfack, Temple & Frénay, 2022; Glanois et al.,2024).

Extreme Gradient Boosting (XGBoost) XGBoost, an advanced form of gradient-boosting, is renowned for its exceptional speed, precision, and adaptability. (Ali et al.,2024). Developed by Tianqi Chen, it builds an ensemble of weak learners, correcting previous errors (Wade & Glynn, 2020). Unlike traditional methods, XGBoost uses regularized gradient boosting to control overfitting and enhance generalization performance, enhancing performance across various tasks (Wade & Glynn, 2020; Huber, Yushchenko, Stratmann & Steinhage, 2022).

Stacking

Stacking, also known as Stacked Generalization, is a technique that combines predictions from many models using a meta-model (Seireg, Omar & Elmahalawy, 2023). Throughout the stacking process, a sequence of fundamental models is trained separately. Every model possesses certain characteristics or exhibits unique flaws when trained on the data (de-Zarzà, de-Curtò, Hernández-Orallo & Calafate, 2023). The primary models provide forecasts, which are subsequently combined and utilized to train a meta-model. The meta-model, often a less complex algorithm such as linear regression, is trained using the aforementioned forecasts (Chen, Zeb, Nanehkaran, & Zhang, 2023). The

meta-model is designed with the express purpose of improving the combination of results from the fundamental models, resulting in a more precise and accurate prediction during the testing or validation phase (Liang & Liu, 2023).
The core premise of stacking is to leverage the synergistic powers of several models, hence surpassing the predictive capabilities of any one model (Yang et al., 2023). In order to achieve the best results in real-life situations, it is essential to carefully assess many models and select an appropriate meta-model when using the stacking strategy, as it may greatly enhance performance. This research examines many foundational models, including K-Nearest Neighbors (KNN), Decision Tree, Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, and XGBoost. The Random Forest (RF) serves as the metamodel.

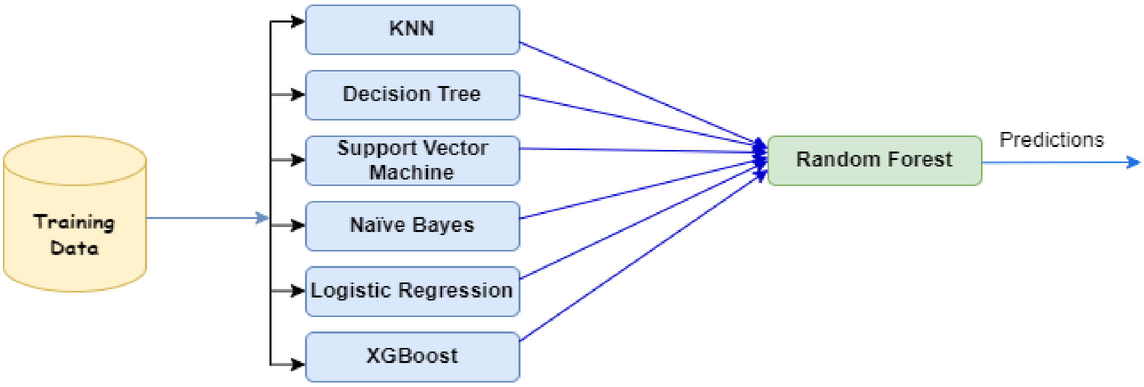

Figure 3: Stacking Ensembling Technique
Source: Author

Framework for Ensemble-Based Model for Crop Recommendation
Figure 3 depicts the fundamental framework of the stacked ensemble model employed for crop recommendation. The framework is organized into two main categories of essential elements for recommendation processes: meteorological variables and ecological factors. Weather factors refer to data regarding temperature, precipitation, and humidity, whereas environmental factors refer to information on soil pH, nitrogen, phosphorus, and potassium levels. The first models, including support vector machine, decision tree, logistic regression, K-nearest neighbor, naïve Bayes, and XGBoost, are trained and evaluated using both meteorological and environmental data. After analyzing the literature study, the random forest is selected as the meta-model because to its outstanding performance. The predictions produced by the core models are combined and used as input for the meta-model, optimizing the integration of their outcomes. During the final prediction phase, the fundamental models are once again utilized to create predictions on fresh data, and the meta-model amalgamates these predictions to generate the ultimate outcome.

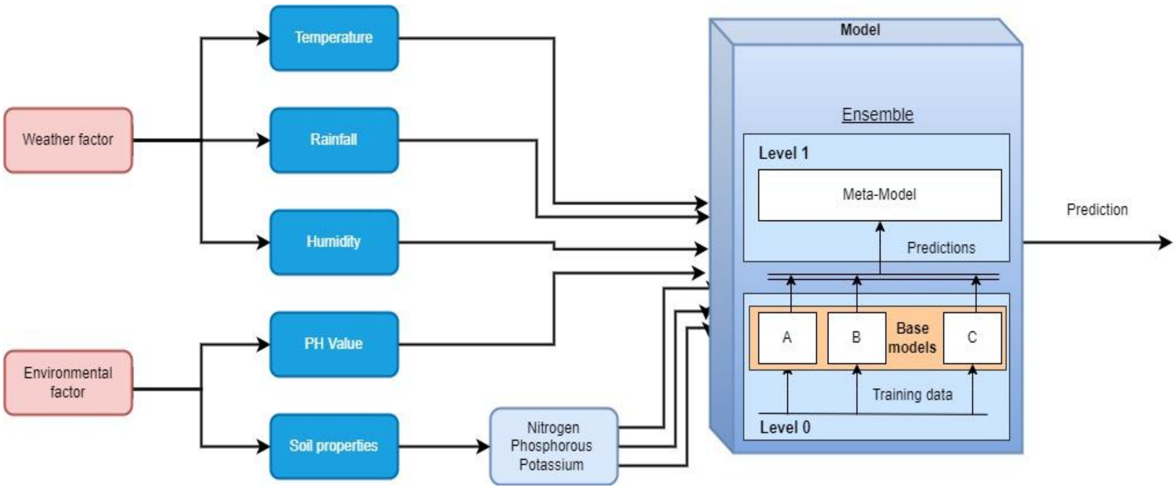

Figure 4: Framework for the Ensemble-Based Predictive Model for Crop Recommendation

Algorithm of the Ensemble-Based Predictive Model for Crop Recommendation
The Stacked Ensemble model for crop selection, as described in Algorithm 1, seeks to improve forecast accuracy by using the capabilities of many base models. At first, the training data is divided into N folds in order to do cross-validation. Afterwards, many core models like as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), Decision Trees (DT), Naive Bayes (NB), and XGBoost are trained on subsets of the data using N-1 folds of a Random Forest. The results of these foundational models are combined by concatenating them and utilized as input for a meta-model, which is trained to maximize the amalgamation of the base model results. During the final prediction step, the underlying models are once again employed to predict fresh data, while the meta-model combines these predictions to produce the final result.

Algorithm 1: Algorithm for Crop Ensemble-Based Model
Start
Split the training Data (TD) into $N\ fold \to D_1, D_2, \ldots D_N$
For each base model, $m \in SVM, KNN, LR, DT, NB\ and\ XGBOOST$
Train $T_{models}, m_1, m_2, \ldots m_N$ on $N-1$ folds of the RF
Keep the predicted outputs $\hat{Z}_{m,t}\ (X)$ for m_t on each test $fold\ D_n$
Concatenate the predicted output from all base models for each test fold:
$X_k = [\hat{Z}SVM, 1(D_n), \hat{Z}SVM, 2(D_n), \ldots yXGBOOST, T(D_n)]$
Train a metal model $f(X)$ on the concatenate the predicted output X_n for each fold.
For each test fold D_n use the base models to predict the output Ẑm(x) and concatenate the outputs:
$X = \{\hat{Z}SVM(D_n), \hat{Z}KNN(D_n), \hat{Z}LR(D_n), \hat{Z}DT(D_n), \hat{Z}NB(D_n), \hat{Z}XGBOOST(D_n)\}$
Use the trained meta-model to predict the final output: $\hat{Z}_{final}(x) = f(x)$
End

System Architecture
The diagram in Figure 4 illustrates the system architecture of the proposed system. This system use a stacking ensemble-based prediction approach to provide crop recommendations to farmers. The system has four primary components: PYQT5, Rendering Engine, Controller, and Model. PYQT5 employs Python bindings for the Qt framework to facilitate the creation of graphical user interfaces (GUIs) and programs that can run on several platforms. The Rendering Engine is accountable for graphically presenting crop recommendation outcomes via data visualization within the graphical user interface (GUI). The Controller manages the transfer of data and commands between the Graphical User Interface (GUI) and the Model. The system gathers user input and sends it to the Model for forecasting. The Model, which serves as the core element of the system, employs a stacking ensemble-based machine learning algorithm to provide crop suggestions. This technique employs an ensemble methodology by combining predictions from many base models, hence enhancing the accuracy of projections. The stacking ensemble technique involves training many base models on input data and aggregating their predictions using a meta-model. The core models encompass a variety of machine learning techniques, including decision trees, support vector machines, and neural networks. The meta-model effectively combines the predictions of the basic model to get the definitive crop recommendation.

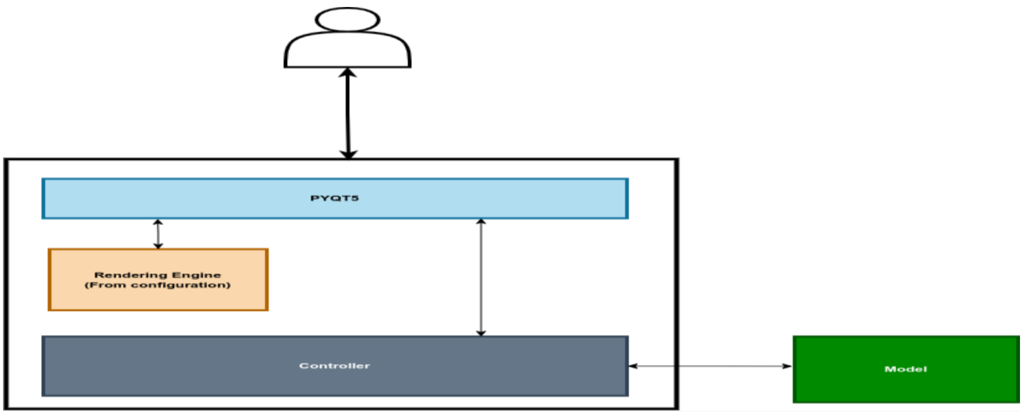

Figure 5: The Proposed System Architecture

Employing a stacking ensemble-based machine learning technique enhances the precision of recommendations by leveraging the advantages of many base models. This notion is particularly beneficial in agriculture, since it necessitates complex and multidimensional factors for predicting crop yields.

Performance Metrics for Classification
The evaluation criteria utilized for gauging the effectiveness of this analysis are as follows:

Accuracy
The efficacy of a model is assessed by the proportion of accurate predictions produced across all sorts of forecasts (Ricciardi, Ramankutty, Mehrabi, Jarvis & Chookolingo, 2018). The evaluation process involves assessing the accuracy of classification by comparing the count of correctly categorized instances to the overall count of occurrences (Petropoulos & Siemsen, 2023). The measure of accuracy is particularly valuable in cases when the distribution of classes in the target variable is uniformly spread throughout the dataset. This is expressed in Equation 1.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

Sensitivity or Recall
Sensitivity is a numerical metric used to calculate the proportion of correctly identified positive situations that were incorrectly labeled as negative by the model. It is sometimes denoted as recall or true positive rate (Hutter, 2012). Mathematically, it is defined as the ratio of the number of true positive (TP) occurrences to the sum of true positive and false negative (FN) cases. It is mathematically expressed as:

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

F1 score rate
The F1 score represents the computed weighted average of both precision and recall (Bach, 2020). As such, this score takes into account the balance between false positives and false negatives.

$$\text{F1 Score} = 2 * \frac{precision*recall}{precision+recall} \quad (3)$$

Precision

Precision is a metric that measures the accuracy of positive predictions made by a model (Davis, 2015). It is defined as the ratio of correctly predicted positive samples to the total number of samples predicted as positive.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

RESULTS AND DISCUSSION

This section evaluates the proposed model's numerical experimental performance using the Kaggle dataset, varying sample and feature counts. The outcomes are displayed in tables and graphs for a comprehensive presentation.

Performance of Selected Machine Learning Models

Table 3 provides analysis of the performance of the selected machine-learning models. This study considered eight models—K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Naive Bayes (NB), Logistic Regression (LR), and XGBoost. Each model was individually trained and evaluated for crop prediction, with their performance metrics computed to inform the development of a stacked ensemble predictive model.

Table 3: Performance Metrics of Selected Machine Learning Models

S/N	Model	Accuracy (%)	Precision	Recall	F-Score	Support
1	KNN	98.4	0.98	0.99	0.99	141
2	DT	99.5	0.99	0.99	0.97	141
3	SVM	98.9	0.96	0.99	0.99	141
4	RF	99.8	0.96	0.99	0.97	141
5	LR	96.1	0.97	0.98	0.98	141
6	NB	99.6	0.99	0.99	0.99	141
7	XGBoost	89.1	0.89	0.88	0.88	141
8	Stacked Model	99.8	0.99	0.99	0.99	141

From the analysis, Random Forest (RF) and the Stacked Ensemble Model demonstrated the highest accuracy of 99.8%, with excellent recall, precision, and F1-scores, underscoring their effectiveness for crop prediction. Naive Bayes (NB) followed closely with an accuracy of 99.6% and consistently strong performance across all metrics. The Decision Tree (DT) achieved an impressive accuracy of 99.5%, while Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) also performed well, with accuracies of 98.9% and 98.4%, respectively.

In comparison, Logistic Regression (LR) exhibited a respectable accuracy of 96.1%. However, XGBoost, with an accuracy of 89.1%, lagged in precision, recall, and F1-score, reflecting areas where its performance could be improved.

These results highlight the superior capabilities of Random Forest and the stacked ensemble model for crop prediction, validating their potential for practical implementation.

Stacking Ensembled-Based Model Performance

As shown in Table 4, the stacking ensemble model delivers outstanding performance in crop prediction, achieving a flawless Precision, Recall, and F1-Score of 1.00 across 20 of the 22 crop categories, with a remarkable overall accuracy of 100%. Even the slight deviations observed for Pomegranate (Precision: 0.95, F1-Score: 0.98) and Coconut (Recall: 0.95, F1-Score: 0.97) do little to detract from the model's exceptional reliability and predictive power. The perfect Macro and Weighted Averages of 1.00 further underscore its ability to deliver consistent and balanced predictions across diverse crop types. These results, detailed in Table 4, highlight the model as a groundbreaking solution for real-world multi-crop recommendation systems, setting a new standard for precision agriculture.

Table 4: Crop Characteristics Analysis

Crop	Precision	Recall	F1-Score	Support
Rice	1.00	1.00	1.00	22
Maize	1.00	1.00	1.00	18
Chickpea	1.00	1.00	1.00	22
Kidneybeans	1.00	1.00	1.00	15
Pigeonpeas	1.00	1.00	1.00	18
Mothbeans	1.00	1.00	1.00	17
Mungbean	1.00	1.00	1.00	22
Blackgram	1.00	1.00	1.00	29
Lentil	1.00	1.00	1.00	25
Pomegranate	0.95	1.00	0.98	20
Banana	1.00	1.00	1.00	18
Mango	1.00	1.00	1.00	20
Grapes	1.00	1.00	1.00	17
Watermelon	1.00	1.00	1.00	24
Muskmelon	1.00	1.00	1.00	24
Apple	1.00	1.00	1.00	26
Orange	1.00	1.00	1.00	15
Papaya	1.00	1.00	1.00	14
Coconut	1.00	0.95	0.97	19

Cotton	1.00	1.00	1.00	23
Jute	1.00	1.00	1.00	13
Coffee	1.00	1.00	1.00	19
Accuracy	1.00			440
Macro Avg	1.00	1.00	1.00	440
Weighted Avg	1.00	1.00	1.00	440

Figure 6 of the dataset shows the classification report of the stacking ensemble-based model. The performance measurements are presented for a comprehensive variety of 22 crops, including apple, banana, blackgram, chickpea, coconut, coffee, cotton, grapes, jute, kidney beans, lentil, maize, mango, moth beans, mungbean, muskmelon, orange, papaya, pigeon peas, pomegranate, rice, and watermelon.

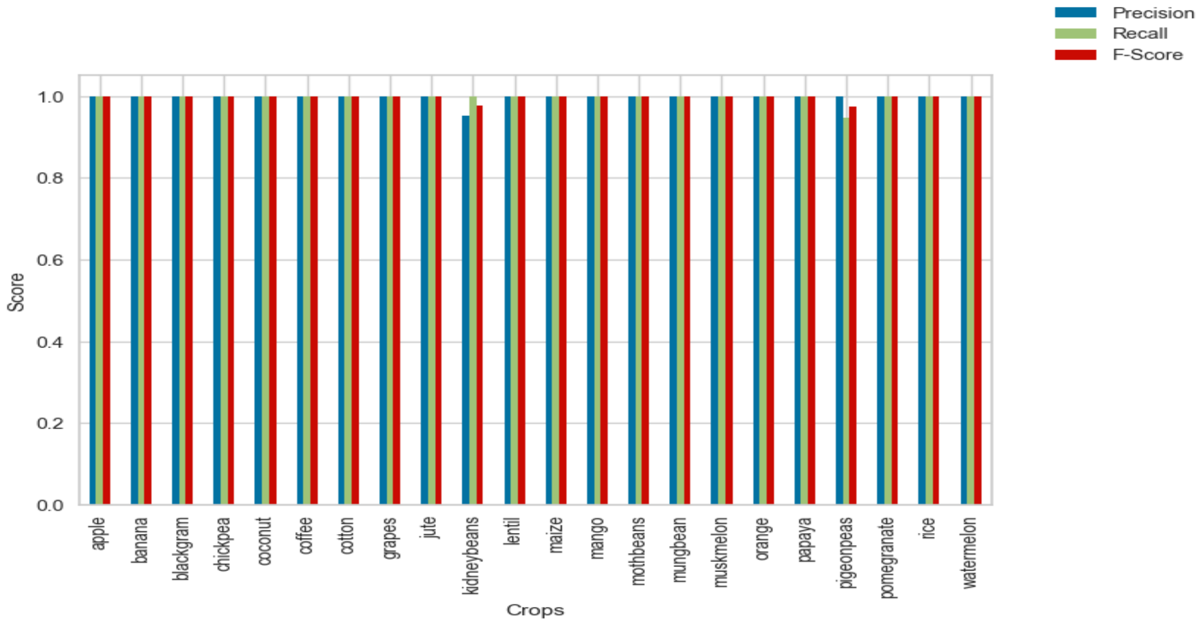

Figure 6: Performance of the Stacked Ensembling Model

The model has outstanding precision and recall scores for several crops, including rice, maize, chickpeas, kidney beans, pigeon peas, moth beans, Mungbean, black gram, lentil, banana, mango, grapes, watermelon, muskmelon, apple, orange, papaya, cotton, jute, and coffee. The accuracy of coconut and pomegranate was substantially lower, with a value of 0.95, suggesting a modest number of additional false positives. The algorithm effectively detects almost all genuine positive instances with just minor discrepancies for pomegranate and coconut. The F1 scores, which quantify the balance between accuracy and recall, consistently exhibit outstanding performance, with the majority of crops earning a perfect F1 score of 1.00. The model's overall accuracy of 1.00 indicates that almost all projections are accurate. Achieving this high degree of performance is crucial for providing precise crop suggestions in real-life situations. The model's outstanding performance emphasizes its robust endurance and reliability, making it highly relevant for practical applications. It provides precise crop recommendations, helping farmers make informed choices based on reliable estimates. The model's ability to consistently achieve high accuracy, precision, recall, and F1-scores across different crop kinds signifies significant advancement in agricultural decision support systems. This enhances the advancement of more sustainable and effective techniques for managing crops, eventually maximizing agricultural output and sustainability.

Ensemble Based Crop Recommendation System

This section will provide details on how the developed model has been integrated into a crop recommendation system. Additionally, the following steps will showcase the Graphical User Interfaces (GUIs) of the system and the procedural aspects required to execute a crop recommendation task within the system.

Training Page Interface

The user interface shown in Figure 6 presents multiple navigation choices, such as Training, Recommendation, Upload, and Train. To start the system's training phase, users are required to provide the crop suggestions dataset. Once the dataset is selected through the "Upload" button, users can proceed to initiate the system's training by clicking on the TRAIN button.

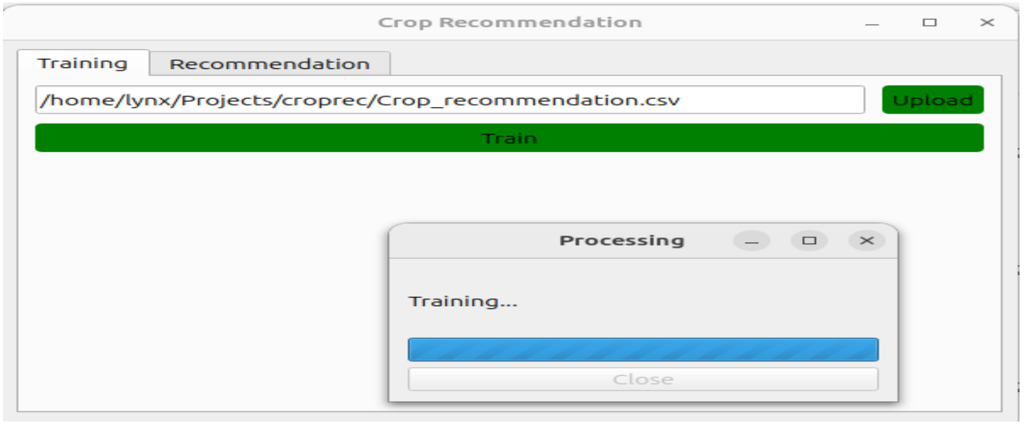

Figure 7: Training Page Interface

After the training phase is completed, the system provides feedback to the user. The feedback message reads "complete...100%," depicted in Figure 7 indicating that the training process is finished.

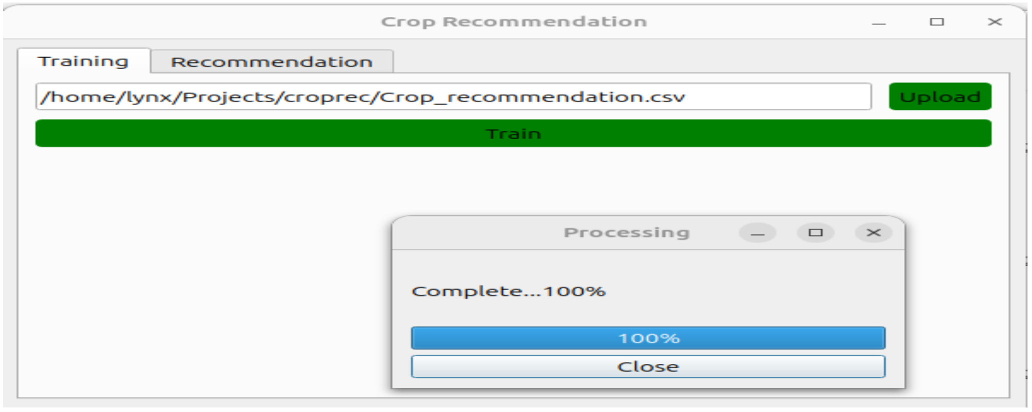

Figure 8: Training Completion

Recommendation Page Interface
The system includes a crop recommendation interface, as seen in Figure 8. The user will be prompted to specify certain qualities of the farmland, such as Nitrogen, Phosphorus, Potassium, Humidity, pH, and Rainfall, in order to receive accurate suggestions. The system will evaluate these criteria to determine the appropriate crops for the specified land.

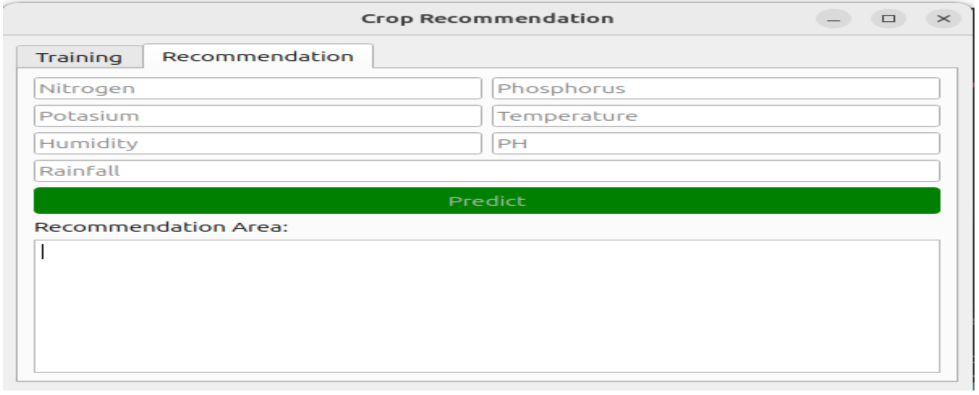

Figure 9: Crop Recommendation Page Interface

Once the required data are supplied to the system, it generates recommendations based on the input, and the feedback is displayed in the Recommendation Area depicted in Figure 10.

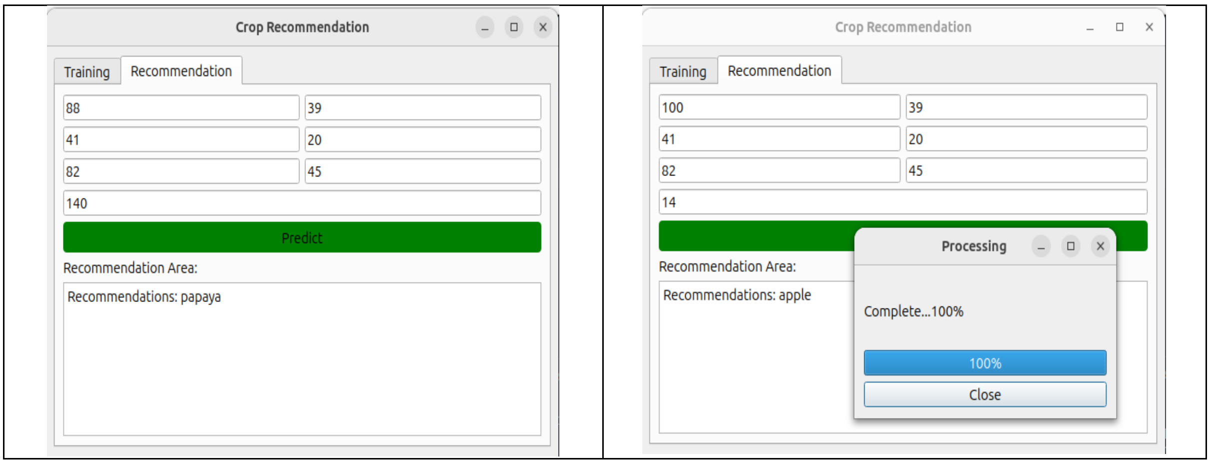

Figure 10: Crop Recommendation Sample

From Figure 10, it can be seen that inputting the following data: Nitrogen = 88, Phosphorus = 39, Potassium = 41, Humidity = 82, pH = 4.5, and Rainfall = 140, the system will recommend growing Papaya. Similarly, when you provide different data such as Nitrogen = 100, Phosphorus = 39, Potassium = 41, Humidity = 82, pH = 4.5, and Rainfall = 14, the system will suggest cultivating Apples. It is worth noting that the system's recommendations are in perfect agreement with that of the ensemble model.

CONCLUSION

This work provides a thorough analysis of the development of a crop recommendation prediction system utilizing an ensemble-based machine learning technique. The study utilizes a Design Science Research (DSR) methodology to create a strong model framework by integrating multiple machine learning techniques, such as K-Nearest Neighbors (KNN), Decision Trees, Support Vector Machines (SVM), Naive Bayes, Logistic Regression, and Extreme Gradient Boosting (XGBoost), with Random Forest acting as the meta-model. The developed technique utilizes a stacking ensemble strategy to successfully combine many models, using the unique capabilities of each model to increase the overall predictive performance. The model underwent training and validation using an extensive dataset collected from Kaggle. The dataset consisted of several crops and their corresponding environmental characteristics, including soil composition, nitrogen levels, temperature, and precipitation. The model's remarkable performance was proved by a comprehensive examination utilizing measures such as accuracy, recall, F1-Score, and precision. The obtained accuracy of 99.8%, together with elevated recall, precision, and F1 scores for various crops, demonstrates a substantial enhancement in comparison to current techniques. The categorization report demonstrates the model's regular provision of precise recommendations for a diverse array of crops, emphasizing its strength and dependability. Data flow diagrams were employed to visually depict the movement of data inside the system, with the objective of improving understanding of its operation. The system was developed using the Python programming language, using its wide range of tools for machine learning and data processing. The use of MongoDB facilitated the efficient construction of the database, guaranteeing the dependable storage and retrieval of extensive datasets. The implemented model was utilized to create a proof-of-concept system that offers practical advice to farmers, relying on the forecasts produced by the ensemble model. This technology has the capacity to increase crop management tactics, ensuring improved response to diverse environmental situations. This research represents a substantial advancement in improving agricultural sustainability and production by employing sophisticated predictive modeling techniques. Additional study might enhance the current foundation by increasing the dataset, integrating supplementary characteristics, and investigating more advanced machine learning approaches to enhance the accuracy of the model. The work we do makes a substantial contribution to the current efforts aimed at achieving sustainable agriculture practices and enhancing food security through the utilization of data-driven decision-making.

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