Results in Engineering 26 (2025) 105505

Contents lists available at ScienceDirect

Results in Engineering

journal homepage: www.sciencedirect.com/journal/results-in-engineering

An approach for crop recommendation with uncertainty quantification based on machine learning for sustainable agricultural decision-making

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ARTICLE INFO

Keywords:
Crop recommendation
Machine learning
Uncertainty
Precision agriculture

ABSTRACT

While machine learning (ML) models for crop recommendation have demonstrated high predictive accuracy, a critical gap persists in their practical reliability: the omission of uncertainty quantification. Existing studies predominantly deliver deterministic recommendations, neglecting inherent uncertainties arising from data noise. This raises concerns about the reliability of the decision support systems for crop recommendation. To address this, we propose an ensemble ML framework incorporating entropy-based uncertainty quantification. Trained on a publicly available Indian agricultural dataset with 2200 samples across seven agro-climatic features (nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall) and 22 crop classes, the model achieves a predictive accuracy of 99.54 %. By estimating prediction confidence using entropy, the framework offers probabilistic recommendations that support environmentally informed decision-making under uncertainty. These findings suggest that integrating uncertainty measures into ML-driven crop recommendation systems can enhance reliability and promote sustainable agricultural practices.

1. Introduction

Machine learning (ML) and deep learning (DL) have become integral to modern agriculture, particularly in applications like crop recommendation, where data-driven models support informed decision-making [1–4]. Crop recommendation techniques typically rely on key soil parameters (Nitrogen, Phosphorus, and Potassium), temperature, moisture content, pH level, rainfall, and humidity analysis. These techniques often utilize traditional machine learning algorithms, including Logistic Regression (LR), Random Forest (RF), Naïve Bayes (NB), Decision Tree (DT), K-nearest neighbor (KNN), and Extreme Gradient Boosting (XGB) [5].

Recent studies have explored enhancing accuracy through ensemble learning, IoT integration, and advanced model architectures.

Hasan et al. [6] introduced a K-nearest Neighbor Random Forest Ridge Regression (KRR) ensemble for crop production prediction in Bangladesh. The model outperformed traditional and ensemble baselines via the Diebold–Mariano test. Deep ensemble model, integrating Long Short-term Memory (LSTM), Bi-directional LSTM (BiLSTM), and Gated Recurrent Unit (GRU) with Red Fox Optimization, has demonstrated improved yield prediction and crop recommendation [7]. Other works have employed majority voting ensembles [8] or tree-based ensemble models [9] to enhance reliability, achieving classification accuracies exceeding 99 %. These models underscore the value of ensemble techniques in handling diverse agricultural variables and boosting model performance. However, they primarily offer deterministic outputs, with limited attention to uncertainty quantification (UQ).

To maximize crop productivity, Elbasi et al. [10] demonstrated how

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https://doi.org/10.1016/j.rineng.2025.105505
Received 6 March 2025; Received in revised form 25 May 2025; Accepted 25 May 2025
Available online 26 May 2025

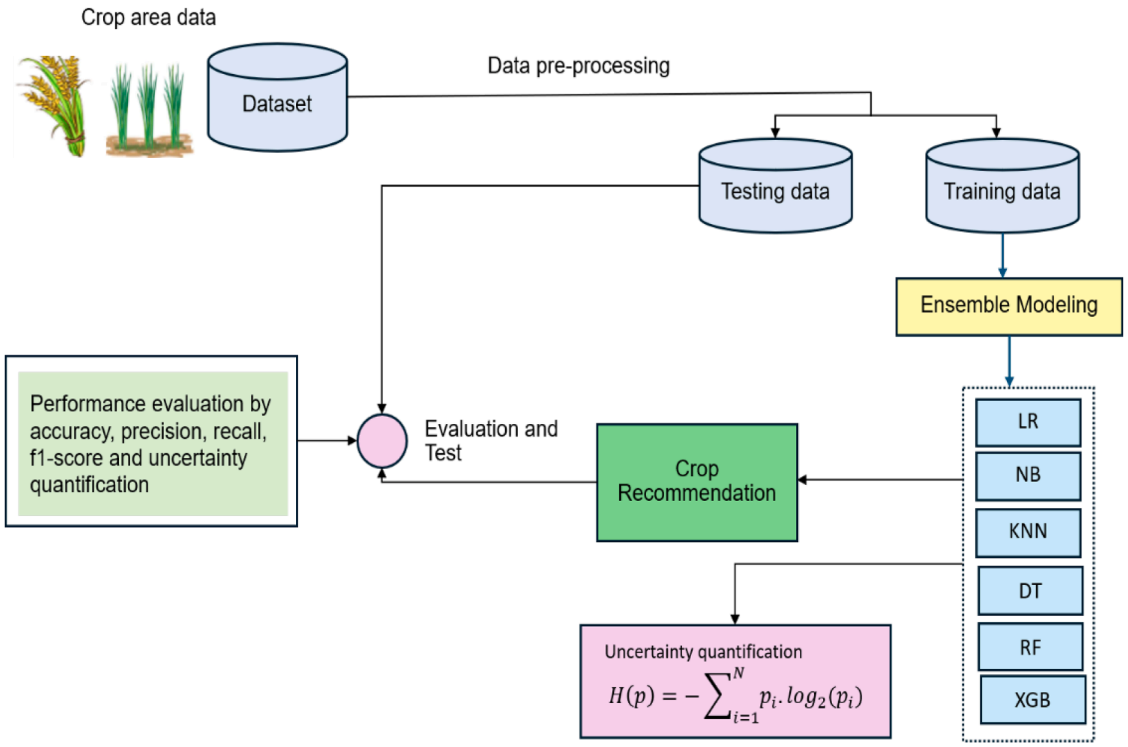

Fig. 1. Methodology for building a crop recommendation model.

Fig. 2. Number of samples per class.

important it is to integrate ML algorithms and IoT sensors into contemporary agriculture. A multimodal ML-based crop recommendation and yield prediction approach was described by Gopi & Karthikeyan [11]. In order to estimate a land's agricultural production and suggest an appropriate crop, Bera et al. [12] developed an IoT architecture based on edge computing, dew computing, and federated learning. A machine learning-driven crop recommendation platform was built by Thilakarathne et al. [13] that runs on the cloud and talks about how to provide farmers access to these tools for free. For crop recommendation, a random forest machine learning classifier was developed by Shingade

Table 1
Crop recommendation dataset features and respective descriptions.

No	Feature	Description
1	N	Nitrogen level in soil composition
2	P	Phosphorus level in soil composition
3	K	Potassium level in soil composition
4	Temperature	Temperature measured in °C
5	Humidity	Relative humidity (%)
6	pH	Soil pH value
7	Rainfall	Rainfall amount in millimeters (mm)

Table 2
List of crops in the dataset.

Rice	Mango
Maize	Banana
Jute	Pomegranate
Cotton	Lentil
Coconut	Blackgram
Papaya	Mungbean
Orange	Mothbeans
Apple	Pigeonpeas
Muskmelon	Kidneybeans
Watermelon	Chickpea
Grapes	Coffee

et al. [14] and put into practice. Senapaty et al. [15] integrated satellite data with ML for yield forecasting, while Afzal et al. [16] employed RF and XGB to optimize recommendations. However, existing studies predominantly deliver deterministic outputs, neglecting the inherent uncertainties arising from environmental variability, sensor noise, and data sparsity. Similarly, frameworks like [17] and [18] prioritize regular prediction performance or cost-effective sensing but lack robust decision-support mechanisms with quantified reliability. Despite the advancements in crop recommendation models, the absence of uncertainty quantification poses a substantial limitation in their practical applicability.

Considering uncertainty in agricultural systems is crucial due to the dynamic and multifaceted nature of factors influencing crop growth, pest dynamics, and environmental conditions. Therefore, machine learning models must be aware of that variability and adapt to different noises/uncertainties. Models should remain robust when subjected to data noise or variations. Uncertainty in machine learning models defines how confident the model is in its prediction [19]. While no existing study has specifically addressed uncertainty analysis in crop recommendation, recent research has increasingly highlighted the importance of incorporating uncertainty modeling in agricultural decision-making and predictive modeling. For instance, a Bayesian model averaging framework combining multiple machine learning models has been proposed to improve the prediction reliability of groundwater storage by addressing structural and parametric uncertainties [20]. Similarly, in the context of nitrogen fertilization in maize, a combination of Bayesian statistics and machine learning revealed weather as the dominant source of uncertainty. It highlighted the necessity of probabilistic approaches for improved nitrogen management [21].

Advanced modeling techniques have also been applied to remote sensing; the enhanced transformation-enabled fuzzy graph network integrates fuzzy logic, 3D Convolution Neural Network (CNN), graph attention network, and principal component analysis to handle uncertainty in hyperspectral imagery classification [22]. In forest fire modeling, deep neural networks and ensemble machine learning approaches have been used not only to map susceptibility zones but also to perform sensitivity and uncertainty analysis of ignition parameters, identifying evapotranspiration and rainfall as key factors [23]. Other applications include the use of Boltzmann machines for smart farming to mitigate uncertainty in sensor-based control [24], and a data-driven robust model predictive control framework that captures weather forecast uncertainty for greenhouse climate regulation [25]. Furthermore, a Bayesian ensemble model has demonstrated superior interpretability and robustness for crop yield prediction by jointly estimating climate and technological effects, in contrast to the limitations of black-box machine learning models [26]. These contributions collectively underscore the significance of UQ for building reliable, interpretable, and context-sensitive models in agricultural systems.

By introducing uncertainty quantification into the crop recommendation model, this study aims to enhance the robustness and reliability of these systems. While recent research has incorporated uncertainty modeling in various agricultural applications, to the best of our knowledge, no prior study has specifically explored uncertainty analysis in crop recommendation. In addition to addressing this gap, we aim to advance the current state-of-the-art performance on the dataset used in our experiments. By taking this uncertainty into account and measuring it, the proposed model can give farmers more reliable and realistic recommendations. This ultimately helps farmers make choices that are good for the environment in the long run (sustainable practices). The objectives of this research work are as follows:

i. Develop and implement machine learning models for crop recommendation by incorporating uncertainty in the developed models.
ii. Evaluate the performance of the proposed model against the state-of-the-art techniques in terms of different model performance evaluations (accuracy, precision, recall, and F1 score).
iii. Analyze the significance of uncertainty quantification in the developed models.

2. Importance of uncertainty quantification in machine learning models for agricultural decision-making

Recognizing and quantifying uncertainties in agricultural decision-making processes is essential for sustainable and efficient farming practices. Two key dimensions in understanding this significance are the “potential for sustainable and efficient farming” and “lessons learned from other domains”.

2.1. Potential for sustainable and efficient farming

Farming involves a lot of unknowns. This is because so many things can affect crops, from weather and pests to the very nature of the soil itself. Incorporating uncertainty quantification (UQ) into decision-making models has a significant potential to enhance the sustainability and efficiency of farming practices. Robust decision-support systems that account for uncertainties can guide farmers to make informed choices under varying conditions, mitigate risks, and improve resource allocation. By calculating uncertainty, the robust ML model can be selected. This approach contributes to the development of precision agriculture, where interventions are tailored to specific uncertainties, leading to the optimal use of resources, reduced environmental impact, and ultimately fostering sustainable agricultural practices.

2.2. Lessons learned from other domains

Drawing lessons from other domains, successfully implementing UQ underscores its importance in agricultural decision-making. Industries such as finance, healthcare, and climate science have long recognized the value of quantifying uncertainties in their models to make informed and reliable decisions [20–24]. For example, the work by Seabra et al. [27] on AI-enhanced data assimilation for geological carbon storage shows improved performance and efficiency through surrogate-assisted UQ; similarly, the study on clinical trial approval prediction illustrates how incorporating UQ and selective classification significantly enhances both predictive accuracy and interpretability [28]. In the hydrological

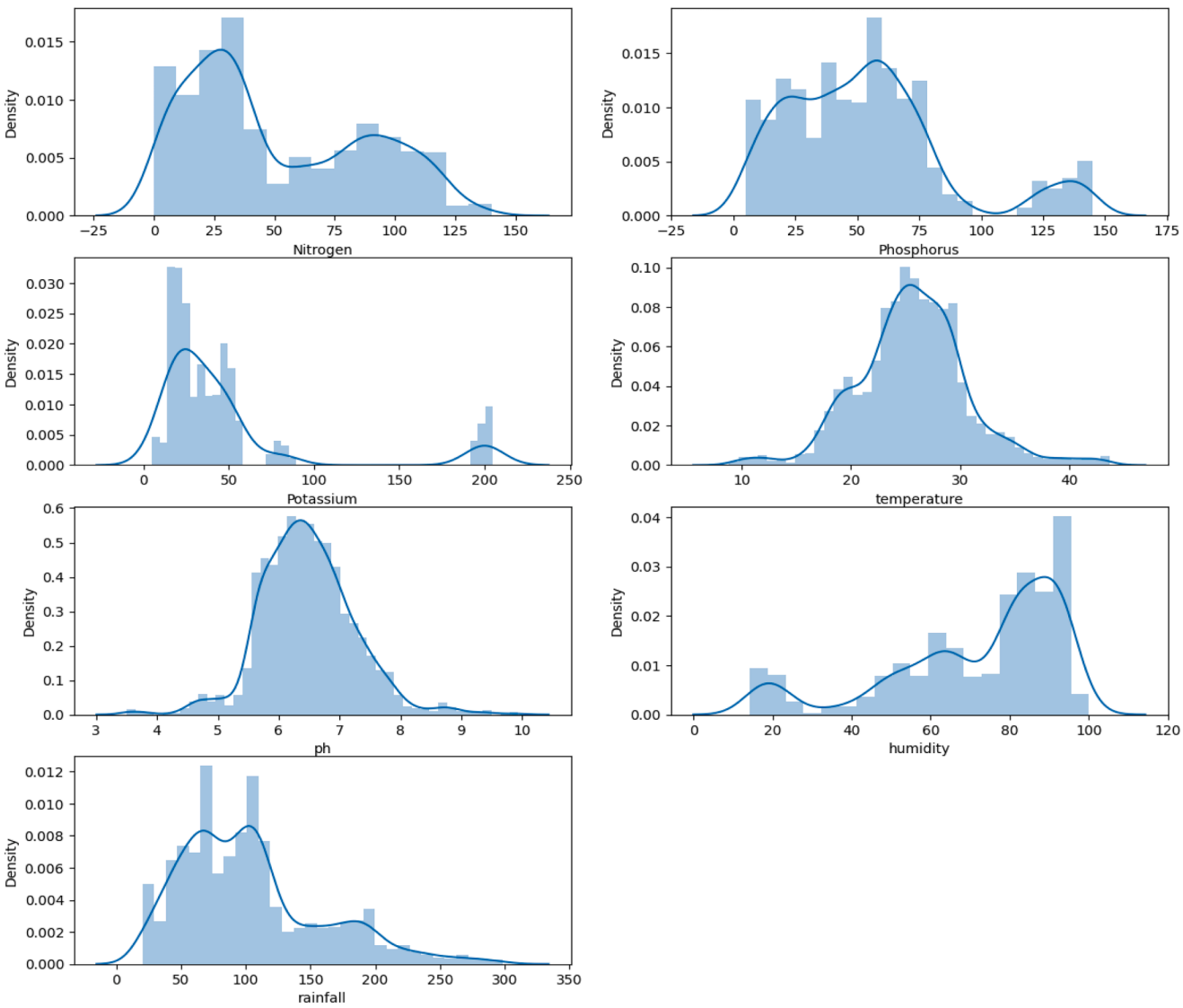

Fig. 3. Distributions of seven key features used in the crop recommendation model. Nitrogen and humidity exhibit skewed distributions, phosphorus shows a bimodal trend, and temperature follows an approximately normal distribution.

domain, UQ has proven essential for forecasting under uncertain climatic and system conditions [29]. As shown in [30], deep learning models are applied to reservoir inflow-outflow prediction and water pipe failure rate estimation. These examples underscore the critical role UQ plays in managing real-world uncertainty across disciplines. Adapting these successful methodologies to the agricultural domain can address current gaps in existing crop recommendation systems, which predominantly offer deterministic outputs. Learning from the experiences of other domains enables the adaptation of proven strategies to address the specific challenges inherent in agricultural decision-making.

3. Methodology

3.1. Crop recommendation model development

The methodology for building the crop recommendation model is represented in Fig. 1. The crop recommendation process was initiated with data preprocessing, dividing datasets into train and test sets for constructing the machine learning (ML) model. Subsequently, an ensemble model was built by aggregating various algorithms, including Logistic Regression (LR), Random Forest (RF), Naïve Bayes (NB), Decision Tree (DT), K-nearest neighbor (KNN), and Extreme Gradient Boosting (XGB), which are briefly discussed in the Appendix A. Machine learning models used in the experiment were selected based on insights gained from related works in the field. In the next step, the prediction of our proposed model is evaluated. At the same time, the uncertainty of the model is calculated by analyzing the entropy of the prediction probabilities.

3.2. Dataset

This study utilized a publicly available dataset collected from the Indian region for crop recommendation [31], accessible on Kaggle. There are a total of 2200 instances in the dataset. The dataset was developed by combining augmented data on rainfall, climate, and fertilizers specific to India. This dataset encompasses seven features (soil parameters and climate data) and 22 distinct crops. Each of the 22 crop classes (e.g., rice, wheat, maize) includes 100 instances (Fig. 2), ensuring a balanced representation. However, the dataset exhibits geographical bias, overrepresenting Indian states and temperate climates, limiting generalizability to diverse regions. For a detailed overview of the features and their descriptions, refer to Table 1. Additionally, Table 2 provides an overview of the crop names included in the dataset.

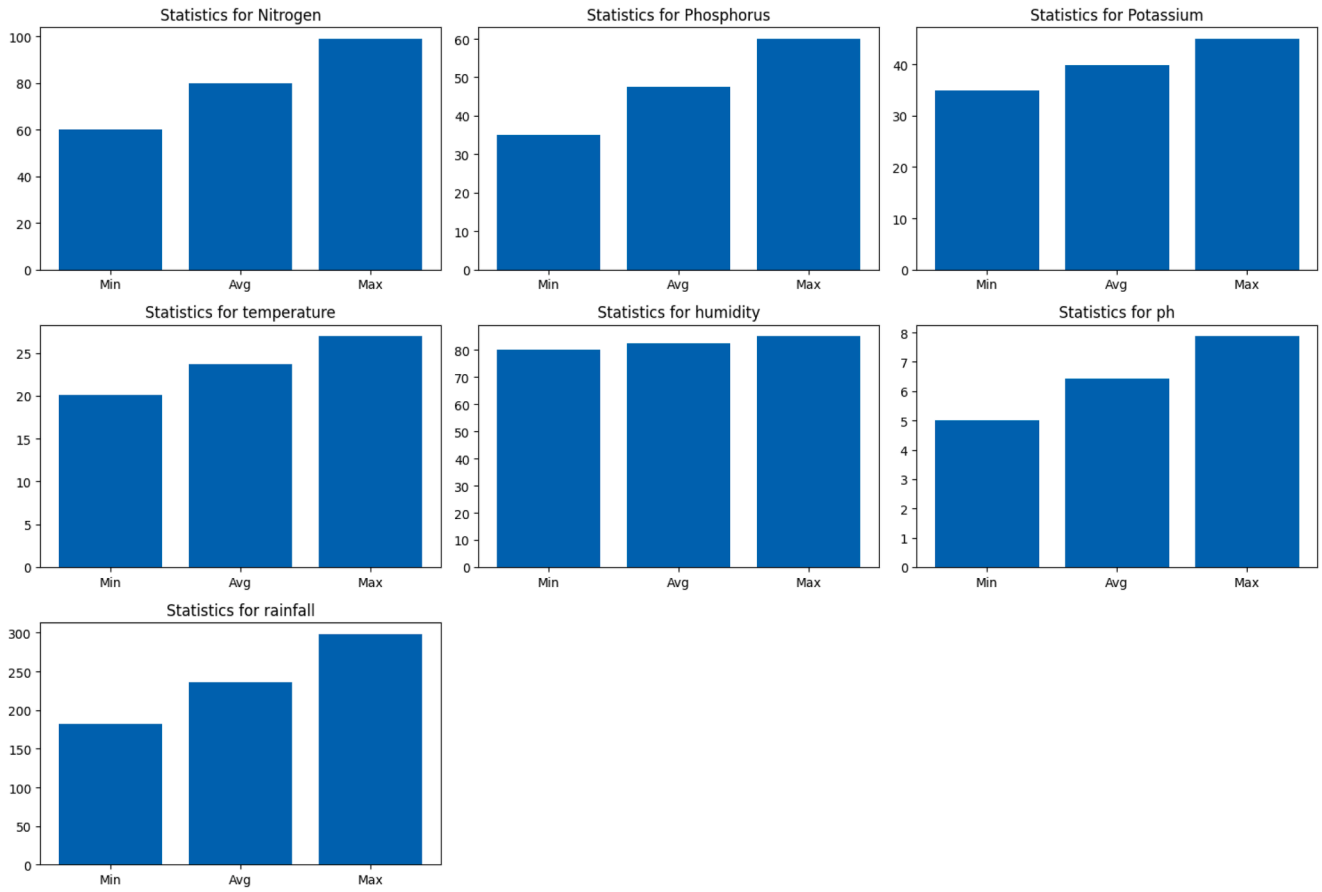

Fig. 4. Summary statistics of agro-climatic requirements for rice cultivation. This figure presents the feature distributions specifically associated with rice crops, illustrating their dependence on high nitrogen levels, moderate temperatures, abundant rainfall, and slightly acidic to neutral soil pH.

3.3. Exploratory data analysis and data pre-processing

Fig. 3 presents the distributions of seven critical agro-climatic features through subplots: soil nutrients (Nitrogen, Phosphorus, Potassium), climatic variables (Temperature, Humidity, Rainfall), and soil pH. Nitrogen exhibits a left-skewed distribution, indicating predominant moderate-to-high requirements across crops. Phosphorus displays a bimodal pattern, reflecting distinct crop groups with low and high phosphorus needs. Temperature follows an approximately normal distribution, suggesting balanced utilization among crops. Humidity is right-skewed, with most crops cultivated in moderate ranges (80–100), while rainfall peaks at 100–200 mm, aligning with monsoon-dependent crops like rice. Soil pH is centered around 6–7 (slightly acidic to neutral), optimal for general crop growth. These distributions collectively underscore the variability in agricultural requirements, necessitating tailored approaches for crop management.

Figs. 4 and 5 illustrate the key agro-environmental features required for cultivating rice and watermelon, respectively. In Fig. 4, rice cultivation depends heavily on high nitrogen levels, substantial rainfall, moderate temperatures, and slightly acidic to neutral soil pH, reflecting its preference for water-abundant and nutrient-rich conditions. In contrast, Fig. 5 highlights that watermelon requires relatively lower rainfall levels compared to rice, with a preference for higher temperatures and neutral pH, indicating its suitability for drier and warmer climates. These figures emphasize how crop-specific requirements vary significantly, underlining the importance of tailored recommendations in precision agriculture.

The initial assessment checked for missing values in the variables, revealing an absence of any such values. Subsequently, the total number of instances for each class was examined to ensure dataset balance, and satisfactory results showed a consistent count of 100 samples for each class, indicating a well-balanced dataset. Upon scrutinizing outliers, it was noted that the potassium variable harbored several outliers. Maximum and minimum values were computed using the interquartile range, and the outliers were replaced with the calculated maximum values. Figs. 6 and 7 visually depict the variable values both before and after the outlier removal process.

3.4. Uncertainty quantification

For the crop recommendation model, where an ensemble model is built, the uncertainty was calculated by the entropy of the softmax probabilities of the classifier.

$$H(y) = -\sum_{i=1}^{N} p_i \log(p_i)$$

Where N defines the total class number, and p_i is the predicted probability for class i.

In our ensemble setup, we used 'VotingClassifier' from the 'scikit-learn' library with the voting='soft' option. Under this configuration, the ensemble prediction probabilities are computed as the average of the predicted class probabilities output by each base learner. Specifically, each base model (e.g., Logistic Regression, Naïve Bayes, KNN, Decision Tree, Random Forest, XGBoost) produces a probability distribution over the output classes. These individual distributions are then averaged element-wise across all models to produce the final softmax-like probability distribution for each test sample. The entropy used to quantify prediction uncertainty was calculated using this aggregated probability distribution.

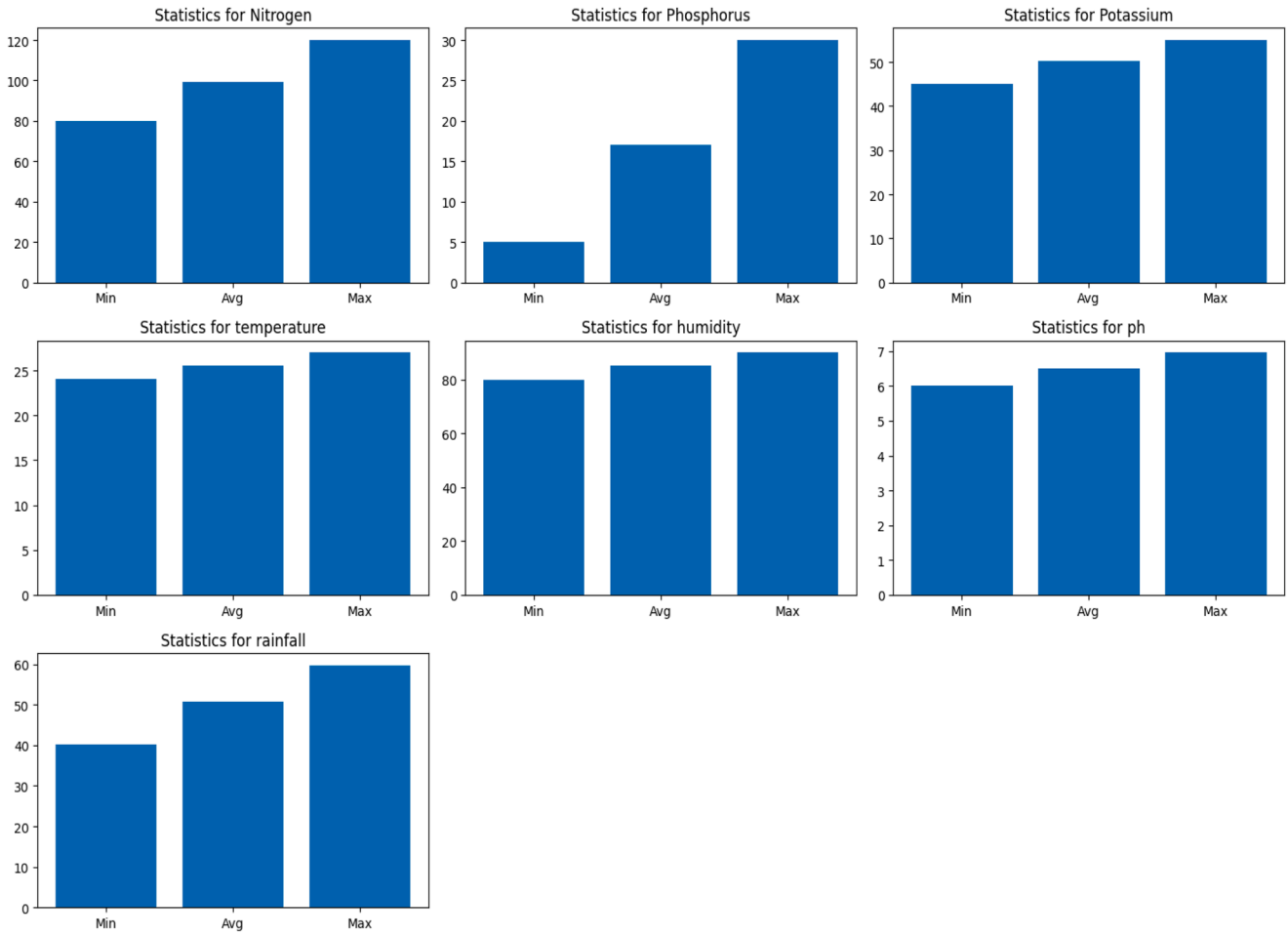

Fig. 5. Summary statistics of agro-climatic requirements for watermelon cultivation. This figure displays feature distributions for watermelon cultivation, contrasting with rice, which requires lower rainfall and higher temperatures.

4. Results and discussion

Using an 80:20 split ratio, the entire dataset was categorized into training and testing sets for predictive analysis. Subsequently, five distinct machine learning (ML) algorithms (LR, NB, KNN, DT, RF, XGB) were applied to conduct predictive analysis. Table 3 details the parameter settings used across the ML models. Ensemble models were then constructed by combining these ML algorithms. Prior to model training, the data preprocessing stage was finalized. As previously mentioned, the dataset was split into training and test subsets, employing random splitting with an 80:20 ratio. Following dataset partitioning, ML models were trained, and their performance was evaluated using metrics such as accuracy, F1 scores, recall, and precision. After that, the performance of various ML algorithms, including ensemble models, was analyzed. Moreover, the uncertainty of the ensemble models was quantified to identify the most robust model. In the case of the crop recommendation model employing an ensemble approach, uncertainty was assessed using the entropy of the softmax probabilities generated by the classifier.

Table 4 illustrates the accuracy, precision, recall, and F1-score of various ML algorithms, including the developed ensemble model. The results indicate that all ML algorithms performed admirably, achieving accuracy rates exceeding 90 %. Notably, the ensemble model outperformed others, achieving an accuracy of 99.54 %. Multiple ensemble models and their performance were explored alongside uncertainty quantification analysis. Following the ensemble models, RF and NB demonstrated notable performance, achieving an accuracy of 99.31 %. As shown in the results, models such as Naïve Bayes, Random Forest, and the ensemble classifier achieved test accuracies exceeding 99 %, yet their corresponding training accuracies (e.g., 99.54 % for NB and 99.48 % for the ensemble) are similarly high, with very small gaps between training and test performance. This narrow margin across all evaluated models (e.g., LR: 96.87 % train vs. 96.36 % test, XGB: 99.60 % vs. 98.86 %) suggests that the models generalize well and are not significantly overfitting.

Table 5 presents critical insights into model robustness and data dependency. While all models exhibit notable accuracy (>93 %) across splits, the ensemble model consistently outperformed others, achieving near-perfect scores (100 % at 90:10 split) and maintaining stability (99.18 % at 50:50), underscoring its resilience to reduced training data. Notably, Naive Bayes (NB) demonstrated exceptional performance (99.27–100 %), likely due to its suitability for the dataset's feature independence assumptions, though its lack of decline with smaller training sets raises questions about overfitting risks. In contrast, Logistic Regression (LR) and XGBoost (XGB) showed pronounced sensitivity to data volume, with XGB's accuracy dropping from 99.09 % (90:10) to 94.81 % (50:50), suggesting overreliance on larger training samples. Decision Trees (DT) and Random Forests (RF) exhibit moderate stability, but their slight declines (e.g., RF: 99.54 % to 97.27 %) highlight limitations in generalizing from smaller datasets. These trends emphasize the ensemble's superiority in balancing bias-variance trade-offs and its practical reliability for agricultural applications where data availability may vary. Table 6 compares our proposed model's performance with existing studies on similar datasets, highlighting significant improvements achieved by our model.

The confusion matrix (Fig. 8) and the classification table (Table 7)

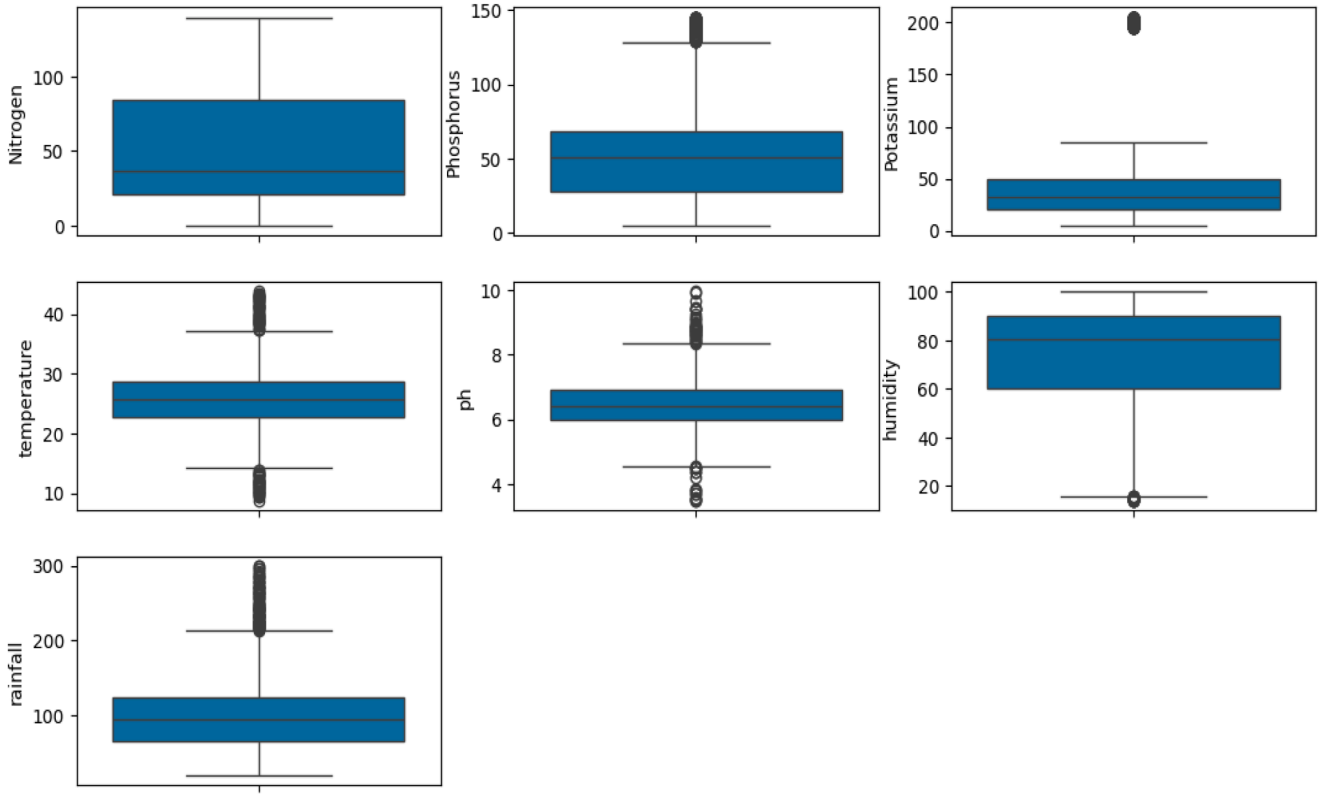

Fig. 6. Analyzing the outlier in the crop dataset.

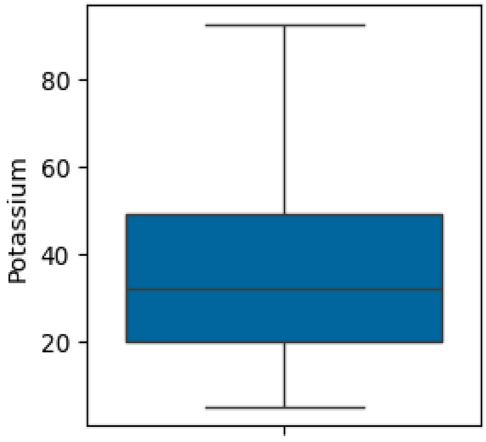

Fig. 7. Potassium data after removing the outlier.

Table 3
ML model parameters.

ML models	Parameters
LR	multi_class='multinomial', solver='lbfgs'
NB	Default parameters
KNN	n_neighbors=5
DT	criterion='entropy', max_depth=7, min_samples_split=5
RF	max_depth=7
XGB	objective='multi:softmax', max_depth=7, learning_rate=0.01, n_estimators=20

Table 4
Performance of ML models for crop recommendation.

ML models	Train accuracy (%)	Test accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
LR	96.87	96.36	96.60	96.36	96.36
NB	99.54	99.31	99.40	99.31	99.31
KNN	98.86	97.72	97.86	97.72	97.72
DT	98.92	98.40	98.52	98.40	98.40
RF	99.65	99.31	99.35	99.31	99.31
XGB	99.60	98.86	98.88	98.86	98.85
Ensemble model	99.48	99.54	99.58	99.54	99.54

Table 5
Accuracy (%) of models across different data splits.

Data splits	LR	NB	KNN	DT	RF	XGB	Ensemble model
90:10	97.72	100	98.18	98.63	99.54	99.09	100
80:20	96.36	99.31	97.72	98.40	99.31	98.86	99.54
70:30	95.60	99.39	97.87	97.57	99.54	97.87	99.54
60:40	95.22	99.31	98.06	98.18	98.63	96.25	99.43
50:50	93.63	99.27	97.36	97.81	97.27	94.81	99.18

present the model's performance in classifying instances into 22 classes. Each row in the confusion matrix refers to the true class, whereas each column refers to the predicted class. Looking at the diagonal elements of the confusion matrix, we observe that most cases have been correctly classified. The classification results indicate exceptionally high model performance. Nearly all classes demonstrated perfect scores across precision, recall, and F1-score (all 1.00), suggesting the model effectively discriminated between them without any false positives or false negatives, as verified by the confusion matrix. However, a minor

Table 6
Comparing our crop recommendation model performance with existing studies.

Reference	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
[32]	97.00	97.00	98.00	97.00
[12]	98.00	98.00	98.00	98.00
[33]	98.18	98.31	98.18	98.20
[13]	97.40	97.00	97.00	97.00
[14]	95.06	95.06	94.90	94.80
[34]	95.45	93.00	93.00	92.00
Present study	**99.54**	**99.58**	**99.54**	**99.54**

deviation was observed in class ‘jute’, where the model attained a precision of 0.91, a recall of 1.00, and an F1-score of 0.95. Although all 21 true instances of class ‘jute’ were correctly identified (no false negatives), two samples from class ‘rice’ were incorrectly predicted as class ‘jute’, indicating false positives that slightly reduced precision. Conversely, class ‘rice’ achieved a precision of 1.00 but a recall of 0.92, with two of its 25 instances misclassified as class ‘jute’, resulting in false negatives. This mutual confusion between ‘jute’ and ‘rice’ highlights a slight overlap in their feature representations and suggests a potential area for refinement in future work.

In this experiment, feature importance was calculated using permutation importance. This method evaluates the significance of each feature by observing the decline in model performance when the values of that feature are randomly shuffled. First, the permutation importance method was applied from scikit-learn’s *permutation_importance* function to the trained ensemble model using the test data. This function computes the importance of scores for each feature by evaluating the model’s performance before and after permuting the feature values. The results indicated that the most important feature for predicting the target variable (classes) was ’rainfall’, with an importance score of 0.366. This suggests that variations in rainfall have a notable impact on the model’s predictions. Following closely was ’humidity’ with an important score of 0.358, referring to its strong influence on the performance of the model. Next in importance was ’Phosphorus’ with a score of 0.272, followed by ’Potassium’ with a score of 0.216, and ’Nitrogen’ with a score of 0.183. These features also contribute significantly to the model’s predictions. However, temperature and pH had relatively low importance scores of 0.005 and 0.003, respectively, suggesting that they influence the model’s predictions less than other features. We chose to retain all features during model training. Fig. 9 illustrates the findings of the feature importance.

Six ensemble models were constructed to assess the impact of uncertainty on the effectiveness of the developed crop recommendation models, all achieving similar or nearly identical accuracy levels but varying in uncertainty. We investigated how these models performed under different uncertainty conditions by introducing noise into the dataset. The results in Table 8 and Fig. 10 highlight distinct trends. As shown in the table and the figure, the models with more uncertainty cannot be predicted robustly. They showed more zigzag patterns in accuracy with noises, i.e., unstable level of accuracy. Typically, models’ performance declines with increasing noise. But here, models with more uncertainty showed a drop and random rise (zigzag pattern) in their performance. On the other hand, models with less uncertainty showed a smoother, consistent graph. This means the models with less uncertainty are more confident and robust in terms of prediction. That makes a

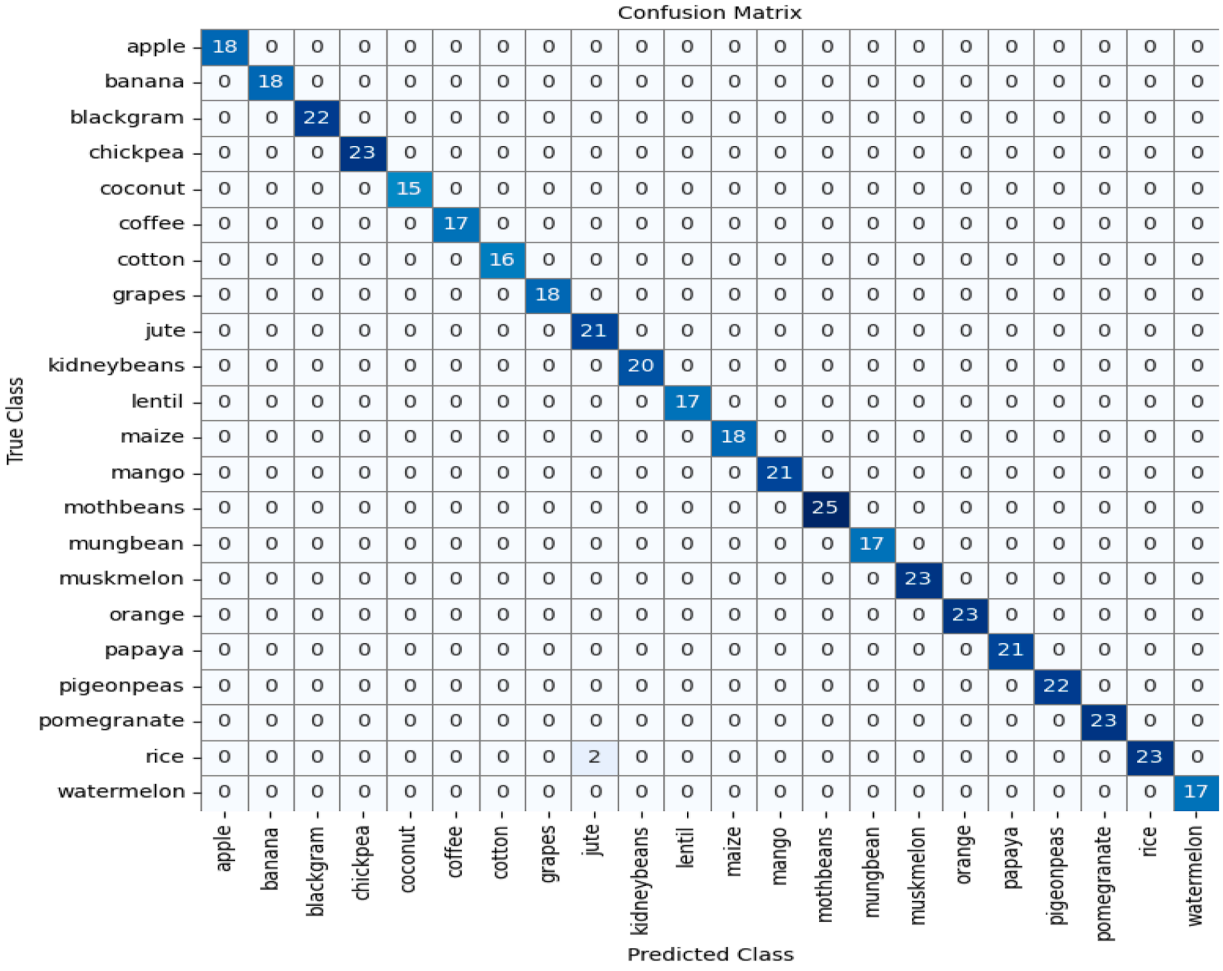

Fig. 8. Confusion matrix of the crop recommendation model (ensemble).

Table 7
Classification report of the ensemble model.

Class	Precision	Recall	F1-score
apple	1.00	1.00	1.00
banana	1.00	1.00	1.00
blackgram	1.00	1.00	1.00
chickpea	1.00	1.00	1.00
cocunut	1.00	1.00	1.00
coffee	1.00	1.00	1.00
cotton	1.00	1.00	1.00
grapes	1.00	1.00	1.00
jute	0.91	1.00	0.95
kidneybeans	1.00	1.00	1.00
lentil	1.00	1.00	1.00
maize	1.00	1.00	1.00
mango	1.00	1.00	1.00
mothbeans	1.00	1.00	1.00
mungbean	1.00	1.00	1.00
muskmelon	1.00	1.00	1.00
orange	1.00	1.00	1.00
papaya	1.00	1.00	1.00
pigeonpeas	1.00	1.00	1.00
pomegranate	1.00	1.00	1.00
rice	1.00	0.92	0.96
watermelon	1.00	1.00	1.00

model reliable in real-life implementations.

A grid of noise factors was defined initially, ranging from 1.0 to 10.0, incremented by 1.0 for each step. The common practice is to use noise factors from some specific range, incremented by 0.1 or 0.05 [19]. While the standard practice is to use smaller increments like 0.1 or 0.05 for noise factors, we opted for larger increments to produce more pronounced variations in the data. This approach was beneficial given the small size of our test set, allowing us to create a diverse range of data instances for robust testing and analysis. Due to the relatively small size of the test set, we opted for a coarser granularity (increments of 1.0) to ensure that each noise level introduced statistically significant and observable changes in the data distribution. This decision aligns with our objective to explore broad behavioral shifts in model confidence and uncertainty rather than fine-scale perturbation analysis. These noise factors represent the standard deviation of the Gaussian distribution used to generate the noise. For each noise factor, Gaussian noise was generated with an average value of 0 and a standard deviation corresponding to the noise factor. This noise was added to the original test set to create a noisy test set. The ensemble models were then used to make predictions on the noisy test set. Accuracy, precision, recall, and F1-score were calculated for each model based on these predictions. The architecture of different ensemble models is shown in Table 9.

To further investigate the impact of uncertainty on model interpretability, Shapley Additive Explanations (SHAP) were utilized. As illustrated in Fig. 11, models with high uncertainty were compared to those with low/medium uncertainty to assess the stability of feature importance. A summary of key patterns is shown in Table 10.

To further illustrate, we analyzed the feature 'Nitrogen' across these uncertainty levels. In low-uncertainty models, the SHAP values of Nitrogen were tightly clustered, showing a clear and consistent directional influence; higher Nitrogen levels reliably increase or decrease predictions. In medium-uncertainty models, SHAP values of Nitrogen began

Table 8
Varying accuracy of models with noises having similar/nearly the same accuracy (base) and different uncertainty. Gaussian noise was generated with a mean value of 0 and a standard deviation corresponding to the noise factor.

Noise factor	Acc: 0.9931, un: 2.09	Acc: 0.9954, un: 1.04	Acc: 0.9954, un: 0.94	Acc: 0.9954, un: 0.41	Acc: 0.9954, un: 0.37	Acc: 0.9954, un: 0.28
1	0.9840	0.9909	0.9909	0.9909	0.9886	0.9909
2	0.9818	0.9886	0.9681	0.975	0.975	0.9863
3	0.9590	0.9772	0.975	0.9772	0.9659	0.9704
4	0.9681	0.9431	0.9590	0.9477	0.9363	0.9431
5	0.9777	0.955	0.9227	0.9431	0.9159	0.9318
6	0.9272	0.925	0.9136	0.8954	0.9113	0.9045
7	0.93	0.86	0.8659	0.8704	0.8977	0.8977
8	0.8560	0.8590	0.8659	0.825	0.8272	0.8613
9	0.8154	0.8363	0.8318	0.8363	0.8045	0.8204
10	0.79	0.7636	0.8068	0.7977	0.8068	0.81

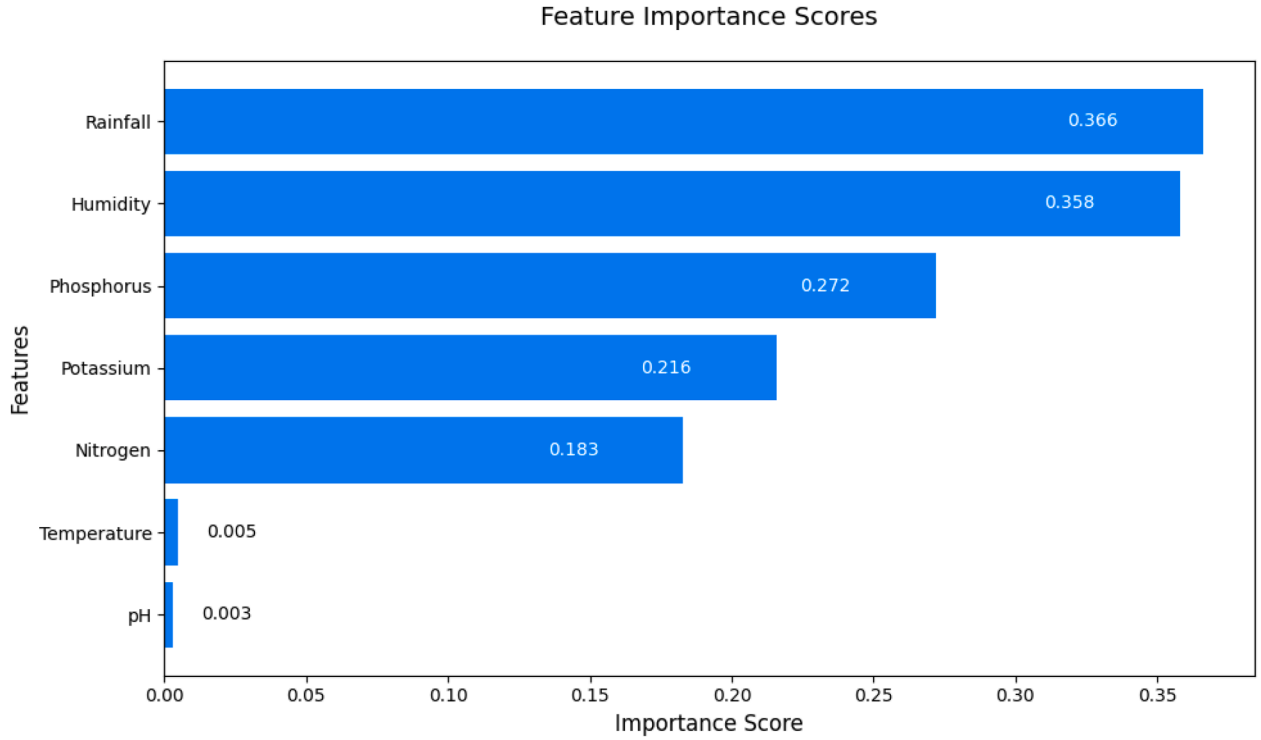

Fig. 9. Feature importance scores.

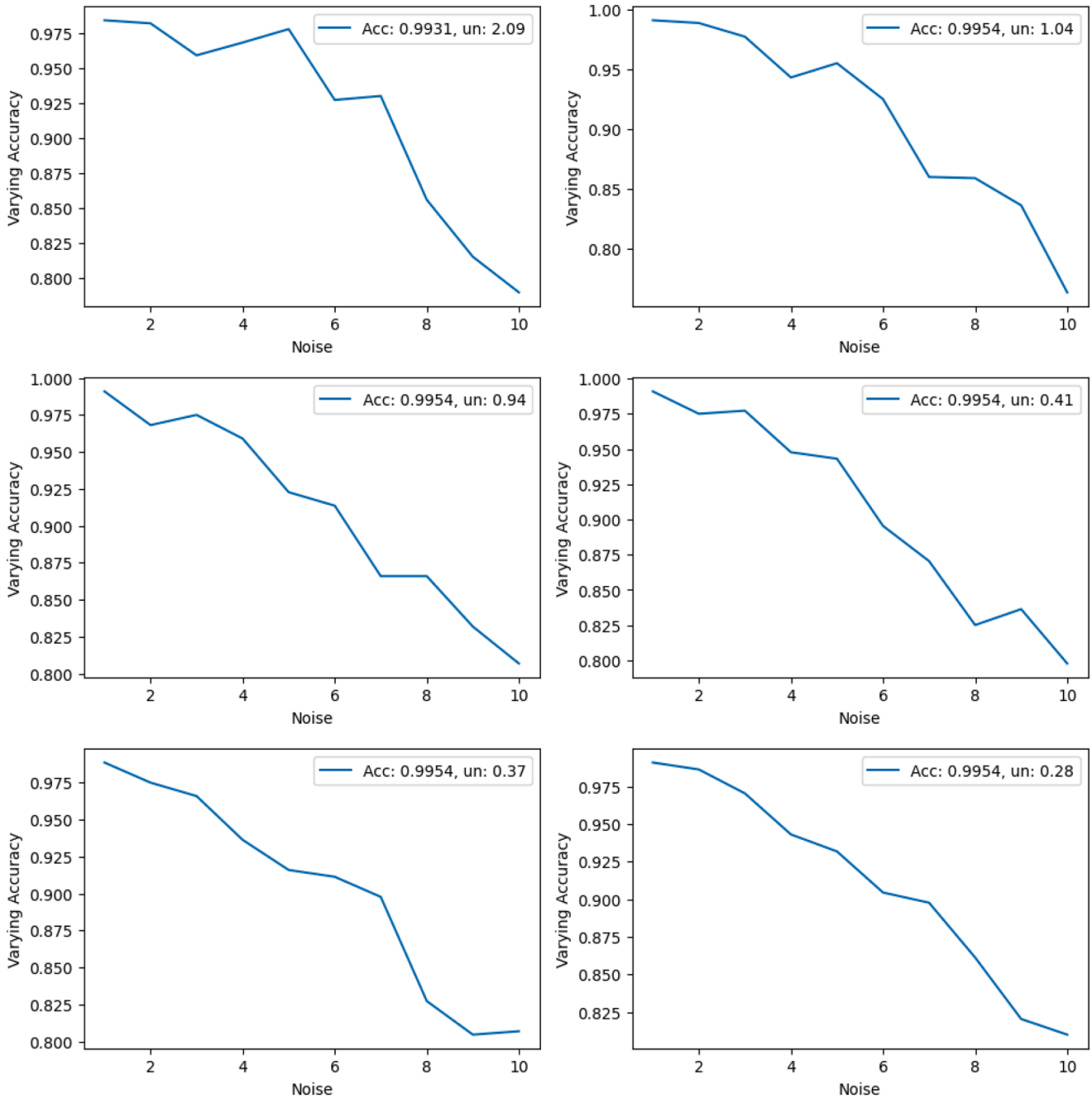

Fig. 10. Accuracy trends of ensemble models under varying noise conditions and uncertainty levels. This figure visualizes how ensemble models with similar base accuracy but different uncertainty levels perform as Gaussian noise is introduced into the input data.

to overlap and occasionally contradictory contributions, reflecting growing model indecisiveness. Under high uncertainty, Nitrogen's SHAP values were widely scattered with no discernible pattern, indicating that the model struggles to interpret its role consistently. This trend reinforces that models with lower uncertainty offer more accurate, interpretable, and trustworthy predictions - an essential quality in high-stakes agricultural decision-making.

Based on the range of entropy observed in our experiments (0.28 to 2.09), we propose an empirical thresholding framework: entropy values below 1.0 generally correspond to high-confidence predictions, where the model's class probabilities are sharply peaked and more reliable for decision-making. Entropy values in the 1.0–1.5 range reflect moderate confidence, suggesting that additional verification (e.g., expert consultation or additional sensor data) may be warranted before acting. Values above 1.5 indicate low confidence or high uncertainty, where predictions should be cautiously treated. While this thresholding is dataset and model-specific, it provides a practical guide for interpreting model outputs in an agricultural context, helping stakeholders assess the trustworthiness of recommendations in varying scenarios.

Ablation analysis of ensemble components

The ablation study results (Table 11) demonstrate that removing individual models from the ensemble has minimal impact on accuracy, which remains consistently significant ($\geq$ 0.9954) across all configurations. However, uncertainty varies notably depending on which model is excluded. Interestingly, the highest accuracy (0.9977) is achieved when either LR or KNN is removed, but this comes at the cost of increased

Table 9
The architecture of different ensemble models.

Ensemble model	Architecture
Ensemble model with accuracy 0.9931 and uncertainty 2.09	- LogisticRegression (multi_class='multinomial') - GaussianNB () - KNeighborsClassifier (n_neighbors=1) - DecisionTreeClassifier (max_depth=1, min_samples_split=2) - RandomForestClassifier (max_depth=1) - XGBClassifier (max_depth=1, learning_rate=0.01, n_estimators=1)
Ensemble model with accuracy 0.9954 and uncertainty 1.04	- LogisticRegression (multi_class='multinomial', solver='lbfgs') - GaussianNB () - KNeighborsClassifier (n_neighbors=5) - DecisionTreeClassifier (criterion='entropy', max_depth=7, min_samples_split=5) - RandomForestClassifier (max_depth=7) - XGBClassifier (objective='multi:softmax', max_depth=7, learning_rate=0.01, n_estimators=20)
Ensemble model with accuracy 0.9954 and uncertainty 0.94	- LogisticRegression (multi_class='multinomial', solver='lbfgs') - GaussianNB() - KNeighborsClassifier (n_neighbors=10) - DecisionTreeClassifier (criterion='gini') - RandomForestClassifier (max_depth=15) - XGBClassifier (objective='multi:softmax', learning_rate=0.01, n_estimators=15)
Ensemble model with accuracy 0.9954 and uncertainty 0.41	- LogisticRegression (multi_class='multinomial', solver='lbfgs') - GaussianNB () - KNeighborsClassifier (n_neighbors=30) - DecisionTreeClassifier (criterion='entropy', max_depth=20, min_samples_split=10) - RandomForestClassifier (max_depth=7) - XGBClassifier (objective='multi:softmax', max_depth=15, learning_rate=0.1, n_estimators=30)
Ensemble model with accuracy 0.9954 and uncertainty 0.37	- LogisticRegression (multi_class='multinomial', solver='lbfgs') - GaussianNB () - KNeighborsClassifier (n_neighbors=10) - DecisionTreeClassifier (criterion='gini', max_depth=20, min_samples_split=10) - RandomForestClassifier (max_depth=10) - XGBClassifier (objective='multi:softmax', max_depth=15, learning_rate=0.1, n_estimators=20)
Ensemble model with accuracy 0.9954 and uncertainty 0.28	- LogisticRegression (multi_class='multinomial', solver='lbfgs') - GaussianNB () - KNeighborsClassifier (n_neighbors=10) - DecisionTreeClassifier (criterion='entropy', max_depth=50, min_samples_split=20) - RandomForestClassifier (max_depth=7) - XGBClassifier (objective='multi:softmax', max_depth=50, learning_rate=0.1, n_estimators=50)

uncertainty (0.31 and 0.32, respectively), suggesting that while these models may not strongly influence classification accuracy, they contribute to ensemble stability. The most significant drop in uncertainty occurs when the RF is removed, reducing it to 0.11 without any gain in accuracy. This suggests that RF may introduce prediction variability despite being accurate. Overall, the full ensemble (with all models included) offers the best balance, achieving superior accuracy with relatively low uncertainty (0.28), indicating that model diversity enhances confidence in predictions without compromising performance.

A comparative evaluation of the proposed crop recommendation model against previous studies is provided in Table 12, which highlights its novel contribution through the integration of uncertainty quantification (UQ). Unlike earlier works primarily focused on deterministic predictions using various machine learning or IoT-integrated frameworks, this study distinguishes itself by incorporating an entropy-based UQ mechanism within a robust ensemble framework. While other studies achieved commendable performance in terms of accuracy and real-time applicability, they lacked mechanisms to assess the confidence of their predictions, an essential feature for real-world agricultural decision-making. The present study achieves the highest accuracy (99.54 %) among all compared works and ensures greater reliability under uncertainty, a critical advancement for sustainable precision agriculture. This positions the proposed model as a technically superior and practically more trustworthy alternative.

5. Conclusion and future recommendations

This research focused on the critical issue of uncertainty quantification (UQ) in crop recommendation models in precision agriculture. While previous studies had made significant advancements in aiding farmers, the lack of uncertainty awareness in these models posed limitations in practical applicability, particularly in addressing the inherent uncertainties of real-world agricultural systems. The study utilized a publicly accessible dataset for crop recommendation. Data preprocessing methods, including normalization and cleaning techniques, were applied to prepare suitable datasets for the models. Data balancing in the training and test sets was also verified. The dataset comprised 2200 instances, 7 features, and 22 distinct crops. However, the dataset is geographically biased toward Indian states and temperate climates, limiting its generalizability.

The proposed crop recommendation model employed an ensemble method that combined logistic regression, naïve Bayes, k-nearest neighbors, decision trees, random forests, and XGBoost. The model was then subjected to UQ, and its performance was evaluated using multiple metrics. Through extensive evaluation, the findings demonstrated the superior performance of the ensemble model, which achieved an accuracy of 99.54 %, surpassing existing studies. Six ensemble models were developed to assess how uncertainty influenced performance. While these models achieved comparable accuracy levels, they exhibited varying uncertainty. By introducing Gaussian noise into the dataset, the models' performance was analyzed under diverse conditions. UQ was performed using the entropy of the classifier's softmax probabilities. Incorporating uncertainty into the models aimed to enhance their reliability, thereby improving agricultural decision-making processes.

Moving forward, there are several aspects for further development in this area:

(a) Enhanced Uncertainty Quantification Techniques: Explore different UQ techniques to improve the performance and reliability of the proposed models.
(b) Integration of Sensor Data: Incorporate real-time sensor data, including weather conditions and soil moisture levels, into the proposed models to enhance their predictive capabilities and adaptability to changing environmental conditions.
(c) Generalization to Different Regions: Extend the study to different regions with diverse environmental and agronomic conditions to assess the generalizability of the proposed models and ensure their applicability across various agricultural contexts.
(d) Collaboration with Domain Experts: Collaborate with agriculturists and stakeholders to validate the effectiveness of the models in real-world agricultural settings and to incorporate domain-specific knowledge into the model development process.

CRediT authorship contribution statement

Md. Sakib Bin Alam: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Vatcharaporn Esichaikul:** Resources, Methodology, Formal analysis, Conceptualization. **Aiman Lameesa:** Writing – original draft, Visualization, Methodology, Formal analysis. **Shams Forruque Ahmed:** Writing – review & editing,

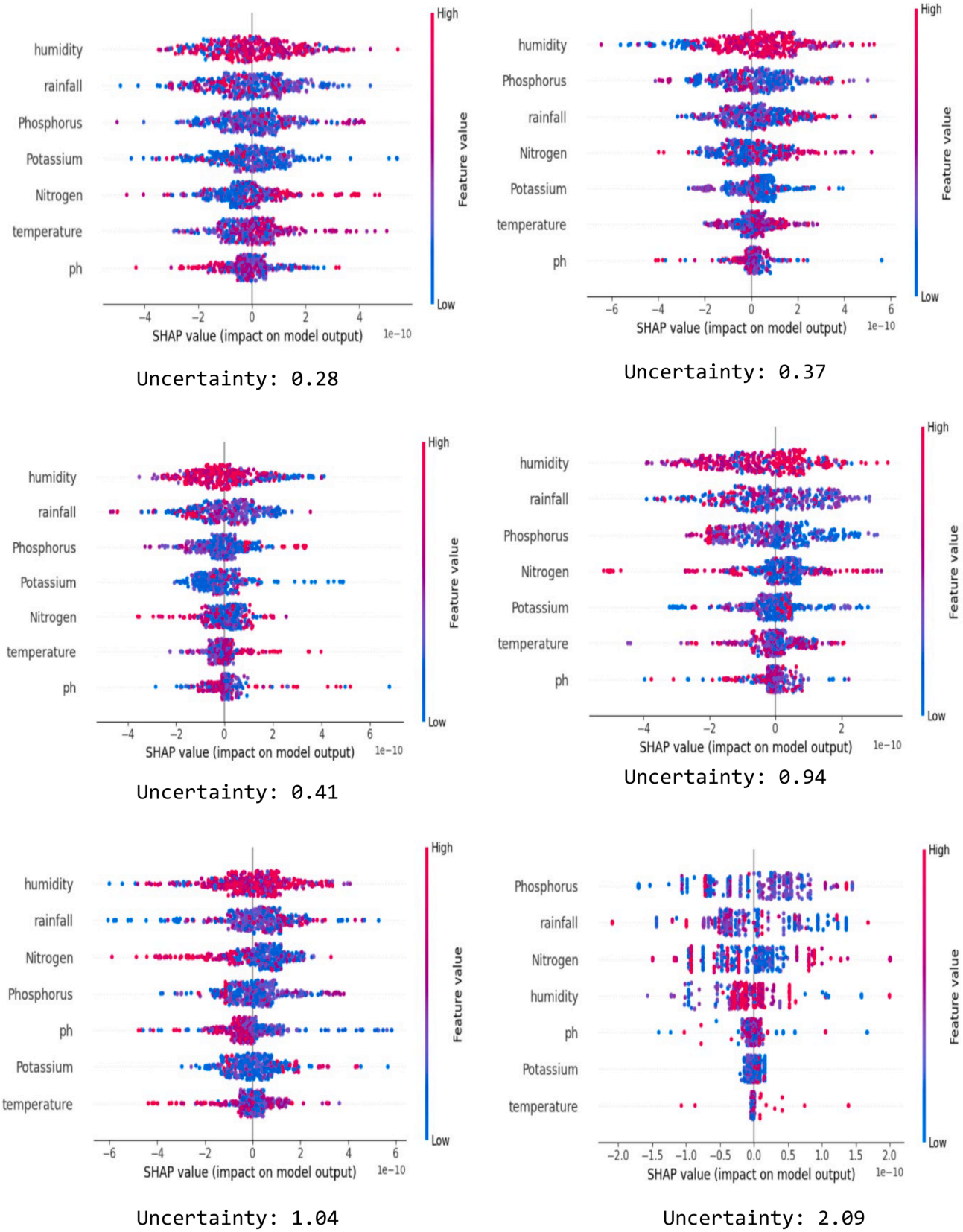

Fig. 11. SHAP value distributions across ensemble models with different uncertainty levels. Models with low entropy (0.28–0.41) show stable and consistent feature importance, while those with high entropy (up to 2.09) reveal dispersed and unstable SHAP values.

Table 10
Summary of SHAP value behavior and model characteristics across different uncertainty levels.

Uncertainty level	SHAP value behavior	Feature importance stability	Model behavior
Low (0.28 - 0.41)	SHAP values are stable and show smooth distributions across samples.	Consistent top feature rankings; steady influence of features.	Confident and reliable predictions.
Medium (0.94 - 1.04)	SHAP values show moderate spread with minor shifts in feature contributions across samples.	Dominant features remain, but their weights fluctuate.	Reduced consistency in predictions.
High (2.09)	SHAP values are highly dispersed and unstable across instances.	Feature importance rankings vary unpredictably.	The model is sensitive to input changes; it is less reliable.

Table 11
Impact of removing individual models from the best ensemble (Baseline uncertainty = 0.28).

Model removed	Accuracy	Uncertainty
None	0.9954	0.28
LR	0.9977	0.31
NB	0.9954	0.33
KNN	0.9977	0.32
DT	0.9954	0.34
RF	0.9954	0.11
XGB	0.9954	0.30

Table 12
Comparison with previous studies.

Study	Methods	Key Features	Strengths	Weaknesses	Uncertainty Quantified?
Present study	Ensemble (LR, NB, KNN, DT, RF, XGB)	Entropy-based uncertainty quantification	99.54 % accuracy, noise resilience	Limited to Indian climate data	Yes
Elbasi et al. [10]	15 different ML algorithms (e.g., RF, Bayes Net, NB, J48) and IoT sensors.	Focus on IoT-ML synergy	- High accuracy (97 %) - Broad algorithm comparison	Deterministic outputs.	No
Gopi & Karthikeyan [11]	Multimodal ML	Multimodal ML integrates soil, weather, and yield data for dual crop recommendation and prediction.	Addresses both crop selection and productivity.	Computationally intensive.	No
Bera et al. [12]	SVM, KNN, Linear Discriminant Analysis (LDA), DT, dew computing, edge computing, federated learning	Capable of showing efficiency in real-time data processing.	The proposed framework achieves an approximate reduction of 12–35 % in delay compared to the edge-cloud framework.	High computational complexity (edge-dew infrastructure)	No
Thilakarathne et al. [13]	Cloud-based IoT platform for crop management.	Real-time monitoring for a tomato plant.	Low-cost sensorized IoT platform for real-time monitoring	Narrow scope (only for one crop)	No
Shingade et al. [14]	RF classifier	Seed-specific recommendations	Specialized for seed optimization	Narrow scope, lacks generalizability	No

Supervision, Formal analysis. **Amir H. Gandomi:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Description of base learners and ensemble construction strategy

To construct the ensemble, we employed a diverse set of well-established machine learning algorithms, each representing a distinct model family. Logistic Regression is a linear classifier that models the log-odds of class membership and supports multiclass classification via multinomial extensions [35]. Naïve Bayes is a probabilistic method based on Bayes' theorem with the simplifying assumption of conditional independence among features [36]. K-Nearest Neighbors is a non-parametric approach that classifies samples based on majority voting among the k-nearest data points in feature space [37]. Decision Trees iteratively split the feature space based on measures such as Gini impurity or information gain to build interpretable decision structures [38]. Random Forests extend decision trees through bagging, where multiple trees are trained on different features and data subsets to reduce overfitting [39].

Extreme Gradient Boosting (XGBoost) is a highly efficient and regularized implementation of boosting that sequentially builds trees to correct errors made by previous ones, improving generalization and performance [40]. To enhance robustness and prediction confidence, an ensemble technique [41] was employed, which combines the outputs of multiple base learners. The core idea was that aggregating diverse models, each capturing different data aspects, can produce superior performance compared to any single model. A soft voting ensemble was utilized, where class probabilities from individual classifiers were averaged to make the final prediction.

Data availability

Data will be made available on request.

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