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A Season-Aware Ensemble Bagged Machine Learning Approach for Crop Recommendation Based on user-Defined Month Input

Amit Patwal[1], Gaurav Agarwal[2] and Akash Sanghi[3]
[1]Research Scholar, Department of Computer Applications, Invertis University, Bareilly, Uttar Pradesh, India
Email: amitp5676@gmail.com
[2]Associate Professor, Department of Computer Science and Engineering, Invertis University, Bareilly, Uttar Pradesh, India
[3]Associate Professor, Department of Computer Applications, Invertis University, Bareilly, Uttar Pradesh
Email: gaurav.a1@invertis.org, sanghiakash@gmail.com

***Abstract*— Agricultural productivity is significantly impacted by a number of factors, including seasonal patterns, the quality of the soil, and the climate. Within the scope of this study, we proposed a crop recommender system that takes into account the seasons by employing a collection of machine learning techniques that are tailored to accept monthly inputs according to the requirements of the user. The user-provided month (1–12) is dynamically mapped to its associated season (in this case, winter, spring, summer, or autumn), and the system then combines this seasonal data with environmental elements in order to make recommendations on the top three crops that are best suited for that particular time period. In order to create a bagged ensemble model, the fundamental methodology involves training and testing a number of different supervised learning models. These models include Decision Tree, Random Forest, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Deep Neural Networks, and a custom ensemble voting classifier that makes use of XGBoost and AdaBoost. In order to determine the effectiveness of these models, they were evaluated on a curated dataset of agricultural data using performance indicators such as accuracy, F1 score, and area under the curve (AUC). The results of the experiments demonstrate that ensemble models, such as the bagged combination of XGBoost and AdaBoost, perform more effectively than single classifiers, resulting in higher precision in crop recommendation. The incorporation of seasonal context enhances the flexibility of models and synchronizes agricultural planning with the cycles of nature. Using this technology, the real-world application of ensemble bagging methods in precision agriculture is demonstrated, hence providing support for agricultural strategies that are both data-intensive and environmentally sustainable.**

***Index Terms*— Crop Recommendation, Machine Learning, Season-aware, Ensemble Methods, Soil Nutrients, Crop Prediction.**

I. INTRODUCTION

Agriculture is the backbone of most economies, generating food security and jobs [1]. However, low crop yields due to inefficient selection caused by customary wisdom as opposed to data-informed decision-making end up wasting resources and costing economies immensely [2].

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It is difficult for farmers to pick the best crop to grow under conditions of soil, weather, and seasons. With the increasing demand for precision agriculture, machine learning (ML) and deep learning (DL) methods have promising solutions to suggest the most appropriate crops depending on soil nutrients and climatic conditions [3].

The conventional method of crop choice is dependent on the experience of farmers, past records, and government recommendations [4]. Yet, these sources do not take into account regional differences in soil composition and seasonal climatic conditions, resulting in ineffective choice of crops and low yield [5]. With climate change disrupting seasonal patterns, conventional practices are becoming less dependable, and computer-based suggestions are a priority for contemporary farming [6].

Machine learning algorithms, including Decision Trees, Random Forest, Support Vector Machines (SVM), and Neural Networks, have the ability to process large volumes of agricultural data and determine the best crops based on soil nutrients (Nitrogen, Phosphorus, Potassium), pH, rainfall, and temperature [7]. Furthermore, deep learning models are capable of learning intricate relationships among these parameters, which will enhance the accuracy of crop prediction [8].

The major goal of this research is to create a crop recommendation system that recommends appropriate crops based on soil and seasonal information. The system will help in analysing soil nutrient levels, pH, and climate conditions for the determination of appropriate crops. It will also help in analysing various machine learning and deep learning algorithms. This will also aid a solution for farmers to predict an accurate, data-based crop recommendation system.

In spite of the development of smart agriculture, intuition-based decision-making is still prevalent among many conventional farmers, which will not necessarily give the best results [9]. With rising climatic uncertainty, varying soil fertility, and market pressures, the demand for a scientific approach to crop choice has never been higher. Machine learning and deep learning provide a rigorous, data-centric approach to support farmers in decision-making, limiting the risks from crop loss and low productivity. Using historical data on agriculture, environmental conditions, and computational intelligence, ML-driven crop recommendation systems can offer highly personalized suggestions in accordance with targeted soil and weather conditions. Soil nutrients, environmental conditions, and seasonality are among the key challenges faced by crop recommendation due to the intricate interaction involved.

While certain crops grow well with high nitrogen levels, others need a balanced proportion of phosphorus and potassium for proper growth. Likewise, certain crops are resistant to harsh weather conditions, while others need stable temperature and humidity levels. Current research in precision agriculture is based on either soil composition or climatic conditions, but few studies combine both parameters effectively [10]. This research intends to bridge this gap by taking into account soil pH, nitrogen, phosphorus, potassium, temperature, rainfall, and seasonality to suggest the most appropriate crop.

Furthermore, conventional ML models like Decision Trees, Random Forest, and SVMs have been proven to possess high classification accuracy in crop choice, yet they tend not to have the capability to uncover more profound relationships within large-scale agriculture datasets. Conversely, deep learning models and neural networks can potentially learn high-level feature representations, thus being best suited for applications in real-world smart farming. Deep learning models are, however, computationally intensive, demanding extensive processing power and data. This study, therefore, compares deep learning methods to conventional ML methods in order to assess their potential for use in agricultural decision-making.

By using a comparative method, the study not only determines the best-performing crop recommendation model but also presents the strengths and weaknesses of each model. The outcome will be worth much to agricultural researchers, policy-makers, and farmers seeking technology-based solutions to better crop planning. Finally, the application of AI-based decision-making in farming has the possibility to transform traditional farming and the world's global food security through enhanced sustainable and optimized farming practice.

II. Related Work

Agriculture is a science-driven discipline that has traditionally used environmental factors, soil type, and seasonal trends to decide on best crop choices. Conventional agricultural practices have frequently been based on experience-led information and local agricultural norms.

Yet with the accelerated development of ML and DL technologies, scientists are interested in creating computerized crop recommendation systems that yield data-driven advice. This section discusses current research in machine learning-based crop suggestion, deep learning methods, climate and soil integration, and knowledge gaps that this research covers.

A. Crop Recommendation with Machine Learning

Machine learning methods have been widely used in agriculture for crop categorization, disease detection, and yield estimation. Some researchers have suggested ML models to forecast appropriate crops according to soil characteristics and climate conditions.

Decision Trees (DT) and Random Forest (RF) are popular classification models in agriculture [11]. Senapaty et. al. proposed a Decision Tree-based crop recommender that took into account soil nutrients (N, P, K) and pH content [12]. The experiment proved that Decision Trees yielded an interpretable model, which enabled farmers to recognize how various soil conditions affect crop selection. Nevertheless, the model experienced overfitting, resulting in poor accuracy on unseen data.

In order to reduce overfitting, Random Forest (RF) has been used as an ensemble method. Garg et. al. [13] used an RF-based system that took into account past crop yield records and soil contents. According to their findings, RF performed better than Decision Trees with an improved accuracy in crop prediction. This was because RF could combine several decision trees, thus decrease variance and enhance generalization. Despite these advantages, RF models are computationally expensive, making real-time recommendations challenging for small-scale farmers with limited processing power.

Moreover, a study carried out by Parashar et. al. [14], provides a comprehensive overview of advanced methods of crop production forecasting, with a particular emphasis on the developments and challenges associated with the utilization of computational approaches. By categorizing the many models of yield prediction into crop development modelling, machine learning methods, deep learning approaches, and meta-modelling approaches that integrate these, it offers an integrated evaluation of the various models of yield prediction. The purpose of this study is to evaluate the effectiveness of several input parameters, such as weather patterns, soil data, and information obtained from satellites, in terms of enhancing the accuracy of predictions over a wide range of crops and areas.

The purpose of the research carried out by Gupta et. al. [15], is to employ weather-based models in order to investigate the prediction of wheat production at different phases of growth in India's semi-arid region. These stages include tillering, flowering, and grain filling. Stepwise multi linear regression (SMLR), support vector regression (SVR), and a hybrid method that integrates SMLR and SVR (SMLR-SVR) were the three methods that were utilized by the researchers in order to construct the prediction models.

As a novel strategy for enhancing agricultural yield prediction, the Decision Tree-KNN Hybrid Algorithm (DT-KNN) is proposed in the work carried out by Dsouza et. al. [16], as a potential solution. The intricate relationships that exist between the many different agricultural variables are typically difficult to deal with the methodologies that have been used in the past, which is why more inventive approaches are required. In order to ensure the sustainability of resource management and the safety of food supplies around the world, the essay argues that accurate agricultural yield forecasts are essential. It is pointed out by the authors that decision trees (DT) are effective at modelling complicated relationships and may be interpreted, making them suitable for capturing non-linear trends in agricultural data. K-Nearest Neighbors (KNN), on the other hand, is an algorithm that is effective in recognizing local patterns by analysing the similarities between data points. The suggested DT-KNN technique takes advantage of these capabilities in order to improve the prediction precision and resilience of the forecast.

B. Crop Recommendation with Deep Learning

Deep learning models have been widely used in precision agriculture, especially for crop classification and recommendation. Deep neural networks (DNNs) are different from conventional ML models because they are able to learn hierarchical representations of complicated agricultural data, enhancing predictive performance.

In the study carried out by Ngugi et. al. [17], a comprehensive review of the application of computational deep learning (DL) for the purpose of altering the detection of agricultural diseases is presented. In the research, it is discussed how deep learning techniques, such as convolutional neural networks (CNN), have proven to be superior to traditional methods when it comes to identifying and diagnosing crop illnesses based on photographs. The study presents a number of different machine learning (ML) and deep learning (DL) techniques that are utilized for disease diagnosis, classification, and severity determination.

Research by Zubair et. al. [18] presents a smart agriculture recommendation system for Bangladesh that protects farmers against bad weather and a lack of agricultural knowledge. Multivariate weather forecast model produced by a modified Stacked Bi-LSTM network is the system's heart. This model uses historical meteorological data from 35 weather stations across Bangladesh to accurately anticipate rainfall, temperature, humidity, and sunshine. Additionally, the technology provides context-dependent agricultural advice based on forecasts, flood and drought-prone areas, and Bangladeshi cropping patterns. The method also uses the Haversine formula to determine the closest weather station to a point of interest, allowing localized forecasts even in areas without weather stations. The study found that the multivariate Stacked Bi-LSTM model accurately predicted weather, with an average R^2 value of 0.9824 for validation and 0.9838 for testing. This outperformed baseline LSTM and other Bi-LSTM models. Three Bi-LSTM layers and a time-distributed dense layer with linear interpolation for missing data were the best model configuration. Based on these forecasts, the system can recommend drought- or water-lodging-tolerant crops for specified areas and warn of extreme weather events. This method may help Bangladeshi farmers make better decisions and boost agricultural productivity, the authors suggest.

An improved Long Short-Term Memory (LSTM) network with an attention block is used to create an autonomous crop expert system that recommends the best crop. The study that is carried out by Sikandar et. al. [19], aims to automate crop suggestion, which is time-consuming and often leads to poor crop choices and losses. The suggested system suggests one of twenty-two crops using seven input features: nitrogen, potassium, phosphorus, PH, humidity, temperature, and rainfall. A 27-layer LSTM model with a residual attention block was created for the investigation. The ACTGAN model added 5300 observations to a Kaggle crop recommendation dataset for training, validation, and testing. The model's accuracy (97.26%), precision (96.9%), recall (96.56%), and F1-score (95.69%) showed great crop recommendation accuracy. The article compared the proposed model to other machine learning-based crop recommendation systems and found equal or better results. The authors suggest that their method could assist farmers make informed crop-growing decisions, increasing agricultural production.

RFXG (Random Forest and Extreme Gradient Boosting) is a novel ensemble learning algorithm proposed by Afzal et al. [20] to recommend the best crop among twenty-two significant crops based on soil and meteorological variables. The study addresses farmers' crop selection difficulties, which affect agricultural production and profitability. The study collected and pre-processed data on nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. The suggested RFXG ensemble model was compared to Extra Trees Classifier (ETC), Multilayer Perceptron (MLP), Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), and XGBoost (XGB). For best results, hyperparameter tuning and k-fold cross-validation were used. The paper's key contribution is that the innovative RFXG ensemble method has the highest crop recommendation accuracy of 98% across all single machine learning models. The combination of Random Forest and Extreme Gradient Boosting can give farmers more accurate and robust crop recommendations.

C. Integration of Climate, Soil, and Seasonal Data

Although soil-based models have been well researched, climate and seasonality are not considered in most crop recommendation systems. It has been established through recent research that the inclusion of seasonal data enhances model accuracy and flexibility.

Reddy et al. [21] constructed a hybrid ML model that used data on soil, temperature, and rainfall. Their research revealed that the use of seasonal factors enhanced accuracy by 15% over models using only soil information. The research highlighted the value of seasonal adaptation in precision agriculture.

Sapkota et. al. [22] investigated a multi-modal system that merged weather forecasting models with soil analysis. Their model combined meteorological forecasts with real-time soil nutrient analysis, giving dynamic crop advice. The model was, however, very reliant on the accuracy of weather forecasts, which can be inaccurate in some areas.

Kaack et. al. [23] also came up with a machine learning paradigm that accounted for long-term effects of climate change on agriculture. They utilized Random Forest and LSTM models in forecasting historical temperatures and rainfall patterns. They discovered that climate-resilient models were superior to conventional models in climate-variable-impacted regions. Climate data, however, still pose challenges for collection, since most rural locations do not have dependable weather observation infrastructure.

D. Research Gap and Contribution

Although earlier research has investigated crop recommendation systems, there are some gaps:

Most of the current models are based mainly on soil parameters (N, P, K, pH) and do not consider seasonal effects. Moreover, there are few research studies that compare conventional ML models with deep learning models for crop recommendation leading to limited research on combining climate adaptation with soil-based models.

This study proposes a season-aware crop recommendation system that takes into account soil nutrients, environmental conditions, and seasonal effects. The comparative analysis of Random Forest, MLP, SVM, Decision Tree, and a Deep Learning Neural Network is shown giving an overall assessment of model performance. In contrast to other existing research that takes into consideration solely historical soil information, this study also includes seasonality in the recommender system in order to respond to climate adjustments.

III. Methodology

In order to improve the accuracy of crop forecasts and their applicability to specific contexts, the crop suggestion model that has been proposed intends to include seasonal consciousness into machine learning algorithms. The procedure is built on a pipeline that consists of multiple stages, including data preprocessing, seasonal mapping, model training, ensemble learning, and performance evaluation.

A. Description of the Dataset and General Preprocessing

An agricultural dataset named crop recommendation was obtained which was then modified according to the season based on different months and then this processed data was named as Train_Dataset_Modified.csv that serves as the foundation for this investigation. This dataset contains a variety of characteristics, including temperature, humidity, pH value, rainfall, and other elements, as well as some additional soil or environmental parameters. The goal column in the database is the crop type, which is categorical data that needs to be predicted through the use of the input features that have been provided. Starting from the beginning, the dataset did not contain any temporal or seasonal characteristics. Nevertheless, because seasonality is a primary consideration in determining whether or not a crop is suitable for cultivation, a synthetic feature called "season" was implemented based on the input of the user.

Before beginning the training of the models, a few preprocessing activities were carried out. In the first step of the process, the target labels, which were crop names, were encoded into numeric form using label encoding. This was done to make the target labels compatible with machine learning algorithms. After that, the newly created categorical 'season' column was subjected to one-hot encoding, which converts it into several binary columns that each represent a different season (Winter, Spring, Summer, and Autumn). This is done so that the model can learn from the distinctions between seasons without having to impose an ordinal relationship between them. To further standardize the feature space, all continuous numerical features were scaled using Standard Scaler, which normalizes them to a mean of 0 and a standard deviation of 1. This served to further standardize the feature space. Support Vector Machines (SVM) and neural networks are two examples of algorithms that benefit greatly from this. These algorithms are particularly sensitive to the magnitudes of certain features.

B. Mapping: Month - to - Season

One of the most important advances that this system offers is the ability to dynamically adjust to different seasons based on the input of the users. The system will prompt the user to enter a number value for a month, ranging from one to twelve, while it is running. By using a deterministic rule-based function, the month that was entered is then programmatically transformed into one of the four seasons. The months 12, 1, and 2 are translated into winter, the months 3, 4, and 5 are translated into spring, the months 6, 7, and 8 are translated into summer, and the months 9, 10, and 11 are translated into autumn. Following this, the season that was produced is encoded and subsequently incorporated into the dataset as a new feature. Without the requirement for separate seasonal datasets or further human filtering, the same dataset may be used to simulate different seasonal settings dependent on the user's input. This eliminates the need for additional manual filtering.

C. Learning Methods and Model Architecture Learning Techniques

Additionally, certain machine learning classifiers were applied in order to carry out an exhaustive analysis of the influence of season-conscious modeling. One of the first classifiers is called the Decision Tree classifier. It is a rule-based model that is readily interpretable and straightforward, and it is widely used as a baseline classifier. After that, a Random Forest classifier was utilized. This classifier is an ensemble that constructs a large number of decision trees on different subsets of the dataset using bootstrap aggregation (bagging), and then uses the average prediction of these trees to generalize more effectively.

In addition, the Support Vector Machine with an RBF kernel was utilized in order to comprehend non-linear decision limits. This is due to the fact that it is efficient in managing high-dimensional feature space. The implementation of patterns in the data that were relatively sophisticated was also accomplished with the help of a Multi-Layer Perceptron (MLP) shallow neural network that contained a single hidden layer. An even more profound neural network was created with many layers (256, 128, and 64 neurons respectively), which enabled the extraction of higher-order feature interactions. This was done in order to achieve a more advanced learning capability.

A dedicated ensemble voting classifier was constructed by merging two robust gradient boosting techniques, namely XGBoost and AdaBoost. This occurred in addition to the construction of individual models. Extreme Gradient Boosting, also known as XGBoost, is a technique that makes use of complex regularization and parallel computation to achieve optimal performance. AdaBoost, on the other hand, is designed to adjust weights in an iterative manner in order to provide priority to instances that are more challenging to organize. These two classifiers were combined in a soft-voting ensemble, which is a type of ensemble in which the final prediction is based on the averaged class probabilities of both classifiers. By utilizing the benefits of both paradigms, this ensemble strategy is able to effectively balance variance reduction (via bagging) and bias correction (by boosting), so capitalizing on the advantages of both approaches. A model that was built for the study is depicted below in Figure - 1.

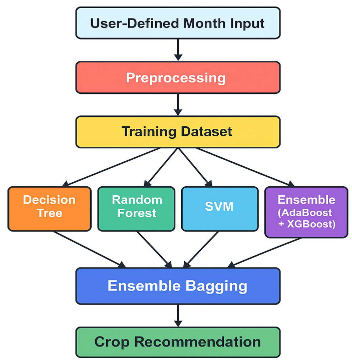

Figure 1: A Season-Aware Ensemble Bagged Machine Learning Model

D. Assessment of Recent Performance

A number of different performance indicators were taken into consideration in order to facilitate the evaluation of the effectiveness of each classifier. Calculations were made to determine the accuracy in order to determine the overall ratio of accurate forecasts. For the purpose of correlating precision and recall, the F1 Score was applied. This was particularly crucial in multiclass classification, which is a situation in which the distribution of classes can become inaccurate. In addition, the Area Under the Receiver Operating Characteristic Curve (AUC) was generated in order to evaluate the capability of the classifiers to differentiate between various crop classes as a function of the thresholds that were applied.

During the training process, every model generated probability distribution that encompassed all of the possible crop classes. The method determines the averages of these probabilities, and the top three crops that received the greatest scores are selected as the most recommended crops for the input season. This type of probabilistic ranking provides a suggestion that is based on confidence rather than a single-point forecast, which helps to improve the system's robustness and reliability in real-world situations.

IV. Result Analysis and Discussion

This study presents a crop recommendation system that is based on machine learning. The system takes into account user input (month, nitrogen, phosphorus, and potassium levels) in addition to climatological characteristics (rainfall, temperature) in order to make recommendations for the best three crops to cultivate during a specific month and agro climatic condition. For the purpose of confirming that the dataset is consistent with seasonality, the dataset was enriched by extracting seasonal labels from rainfall and temperature through the application of regression thresholds. These labels were then mapped against user-input months.

A. Evaluation of the Method

Six distinct machine learning models were utilized in the process of developing the model. These models include Decision Tree, Random Forest, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), Deep Learning (based on MLP), and XGBoost. Additionally implemented was a model that was a blend of XGBoost and Deep Learning. The accuracy, F1-score, and Area Under the ROC Curve (AUC) were the three key performance metrics that were used to evaluate and compare all of the potential models. The findings are presented in the Table 1 that follows:

TABLE I: ACCURACIES OF DIFFERENT ML AND DL ALGORITHMS APPLIED

Model	Accuracy	F1–score	AUC
Decision Tree	0.933	0.935	0.994
Random Forest	0.936	0.936	0.997
SVM	0.933	0.907	0.997
MLP	0.941	0.935	0.998
Deep Learning	0.936394	0.931357	0.998418
XGBoost	0.937777	0.937815	0.998623
Ensemble (XGB+DL)	0.938053	0.937787	0.998552

All of the models performed quite well, as evidenced by accuracy and area under the curve (AUC) values that were greater than 93% and 0.99, respectively. On the basis of F1-score and AUC, XGBoost performed marginally better than other classifiers, and as a result, it stood out as the most effective individual classifier in this context. The MLP algorithm performed the best in terms of accuracy, which indicates that it has a strong generalization performance on new data.

A well-balanced performance on all of the metrics was achieved by the combination ensemble model of XGBoost and Deep Learning, which achieved an accuracy of 93.81%, an F1-score of 93.78%, and an area under the curve (AUC) of 0.9986. With the help of this ensemble model, we were able to combine the high precision of XGBoost with the deep representation learning of MLP. This resulted in more believable probability estimations, which is critical for ranking crop recommendations.

Using the numbers that the user has defined for the soil nutrients (nitrogen, phosphorus, and potassium) and the month, the system is able to accurately forecast the appropriate season and recommend the three crops that have the highest priority percentages. This was demonstrated through the utilization of both bar charts and pie charts in order to provide the users with an easy way to comprehend the results.

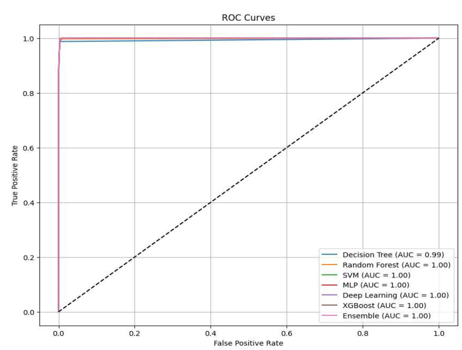

Figure 2. ROC curve for different algorithms

A bar chart showing the result analysis of different accuracies obtained for the considered algorithms is depicted in Figure 3. It is vital to have a good precision-recall balance in applications where both false positives and false negatives have real-world repercussions for farmers. The high AUC scores attest to the model's good discriminatory power, and the high F1 scores suggest that the model has a solid balance between precision and recall.

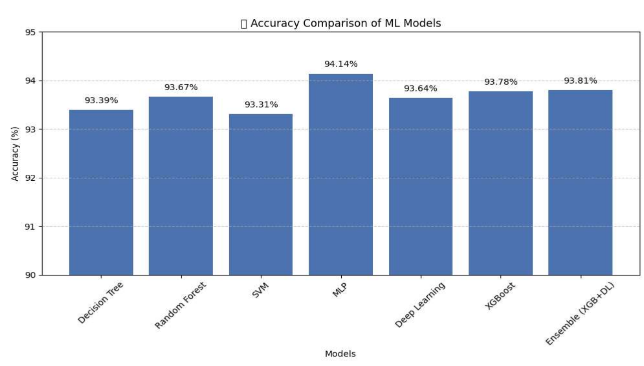

Figure 3. Accuracy representation in Bar Chart

V. CONCLUSION

This research successfully demonstrates the potential of machine learning and deep learning models in the construction of a crop recommendation system that is both dependable and intelligent. The proposed system provides accurate and prioritized crop suggestions based on specific agricultural conditions by leveraging agro-climatic parameters such as rainfall, temperature, and nutrient content (N, P, K). Additionally, the system integrates season mapping depending on environmental inputs as well as the month that the user specifies.

With an accuracy of 93.81%, an F1-score of 93.78%, and an area under the curve (AUC) of 0.9986, the ensemble model that involved the combination of XGBoost and Deep Learning had the highest overall performance among the models that were evaluated. With the use of these indications, the system is able to demonstrate that it is capable of producing extremely accurate forecasts while simultaneously preserving class balance and delivering dependable probability estimates for crop prioritizing.

User-driven design of the system, which takes into account monthly seasonality and the input of soil nutrients, ensures that the system will be used in a realistic manner and will be useful for practical agricultural planning. A further improvement in user comprehension and utilization can be achieved by the incorporation of visual representations such as bar and pie charts.

Expanding the model to include additional characteristics, such as the pH of the soil, crop market prices, and insect risk variables, is something that can be done in subsequent work. Integration of Internet of Things devices in real time and satellite data could potentially contribute to an increase in the system's adaptability and accuracy. In general, the findings of this study offer a very helpful framework for data-driven agriculture and decision support systems. These systems have the potential to enable farmers and agricultural consultants to utilize crop planning that is supported by scientific evidence.

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