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Crop Prediction and Optimization Using Hybrid Genetic Algorithm

Ravindra Changala[1], Pannala Meghana[2], Thammagoni Mythili[3], Thanugula Vamshi Krishna[4]

Associate Professor, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad, India[1]

UG Students, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad, India[2,3,4]

ABSTRACT: This study focuses on developing a predictive model for classifying various crops based on key environmental factors such as soil composition and weather conditions. By integrating critical soil parameters, including Nitrogen, Phosphorus, Potassium, and pH, with weather variables like Temperature, Humidity, and Rainfall, the model aims to predict the most suitable crops for specific regions. The approach utilizes a Random Forest Classifier, enhanced through a Genetic Algorithm (GA) for optimizing hyperparameters, thereby improving the model's performance and adaptability to diverse agricultural conditions. The hybrid model is designed to handle complex datasets and offer accurate classifications for multiple crops, including rice, maize, and jute. To ensure transparency and interpretability, the model incorporates Explainable AI (XAI) techniques, such as LIME and SHAP, which provide insights into the decision-making process. This allows users, such as farmers and policymakers, to understand the key factors influencing crop classification. By combining machine learning and optimization techniques, the system offers an effective tool for crop prediction, helping to reduce risks, increase agricultural productivity, and support sustainable farming practices. Ultimately, the model aims to enhance decision-making, mitigate crop failures, and contribute to food security and economic stability in agriculture-dependent regions.

KEYWORDS: Crop prediction, Genetic Algorithm, Machine Learning, Feature selection, Agricultural data, Optimization.

I.INTRODUCTION

Accurate crop prediction is essential for sustainable agricultural practices, food security, and economic stability. This paper presents a hybrid approach integrating Genetic Algorithms (GA) and Machine Learning (ML) models to enhance crop prediction accuracy. The proposed framework uses GA for optimal feature selection and parameter tuning, which are fed into ML models such as Random Forest, Support Vector Machines, and Neural Networks for prediction. Experimental evaluations conducted on publicly available agricultural datasets show that the integrated approach significantly outperforms traditional prediction methods. The results demonstrate enhanced predictive performance, robustness to noise, and adaptability to diverse agro-climatic conditions.

The increasing demand for food due to a growing global population necessitates precision in agricultural practices. Crop prediction estimating the most suitable crop type for a given set of environmental and soil conditions—is a crucial task in modern agriculture. Traditional statistical methods often fall short in handling the complexity and high dimensionality of agricultural data. In recent years, Machine Learning (ML) has emerged as a powerful tool to uncover patterns and relationships in agricultural datasets. However, ML models are highly sensitive to feature quality and hyperparameter settings. Genetic Algorithms (GA), inspired by natural selection, are efficient in solving optimization problems and can be employed to enhance ML performance by selecting relevant features and optimizing parameters. This research explores a hybrid GA-ML framework for accurate crop prediction and demonstrates its effectiveness through empirical analysis. Previous studies have shown the utility of ML in agriculture, particularly for yield estimation and crop recommendation. For instance, Patel et al. (2015) used Decision Trees and Naive Bayes for crop prediction based on soil parameters. Similarly, Saini and Kaushik (2020) employed Random Forest and Gradient Boosting for yield prediction with promising results. While ML models are competent in learning from data, their performance greatly depends on the choice of input features and hyperparameters. Feature selection is often carried out manually or with wrapper methods that are

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computationally expensive. Genetic Algorithms provide an automated and efficient approach to select optimal features and parameters, yet their integration with ML in crop prediction remains underexplored.

As the main source of income for a sizable section of the population, the agricultural sector is crucial to the economy of South Asian nations like Bangladesh and India. About 42.7% of Bangladesh's workforce is employed in agriculture, which accounts for the country's largest employment sector and contributed 14.2% of GDP in 2017 [1]. Bangladesh's agriculture industry has shown consistent rise in food grain output despite obstacles like poor weather, which is credited to better flood control, irrigation techniques, and effective fertilizer usage [2].In a similar vein, India ranks second globally in terms of agricultural output and has a rich agricultural history that dates back to the Neolithic era. Agriculture continues to be a crucial industry in India's socioeconomic fabric, employing more than 50% of the workforce and accounting for 20.2% of the nation's GDP [3]. However, issues like unpredictable weather, variable soil, and natural catastrophes pose serious risks to agricultural production, causing farmers to suffer large losses and financial hardship. Many farmers struggle to make ends meet despite government assistance, which causes enthusiasm in agriculture to wane.

II.RELATED WORK

In the realm of agricultural research, numerous existing algorithms have been applied to address crop classification and prediction challenges, especially in regions like South Asia, where agriculture significantly impacts the economy and livelihoods. Traditional approaches such as Decision Tree Classifier, Support Vector Machine (SVM), Naive Bayes, and K-Nearest Neighbors (KNN) have been widely used to predict crop types based on various features like soil composition, weather conditions, and other environmental factors. These algorithms, while effective to some extent, often face limitations in terms of scalability, accuracy, and interpretability, particularly when dealing with large, complex datasets or diverse crop types. For instance, models like Decision Trees can easily overfit, while SVMs may struggle with multi-class classification and require intensive computational resources. Additionally, these traditional algorithms may not be flexible enough to adapt to varying soil and climatic conditions, which are crucial in predicting crop yields in diverse agricultural landscapes.

To address these shortcomings, our study proposes an innovative algorithm that combines the strengths of Genetic Algorithms (GAs) with the Random Forest Classifier, aiming to optimize the predictive accuracy and robustness of crop classification. The proposed algorithm leverages a hybrid methodology where the Genetic Algorithm is employed to fine-tune the hyperparameters of the Random Forest model, enhancing its performance in classifying 22 different types of crops such as rice, jute, and maize. By optimizing key parameters like the number of trees, depth, and feature selection, the integration of GAs ensures that the model is not only more accurate but also more adaptable to the variability in soil and weather conditions. Furthermore, to ensure the model's predictions are transparent and interpretable, we incorporated Explainable AI (XAI) techniques, specifically Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP). Random Forest Classifier, Decision Tree Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes with LIME And SHAP.

In existing crop prediction systems, a variety of machine learning algorithms are commonly used for classifying crops based on features such as soil properties. These algorithms include the Random Forest Classifier, Decision Tree Classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Naive Bayes. Random Forest is an ensemble learning method that aggregates multiple decision trees to improve accuracy and reduce overfitting. Decision Trees make predictions by splitting the data into subsets based on feature values, though they are prone to overfitting. SVM is effective in high-dimensional spaces and works well with complex datasets but can be computationally expensive. KNN classifies data based on the majority class of neighboring data points, but its performance can degrade with large datasets. Naive Bayes applies probabilistic reasoning to classify data, assuming feature independence, though it may not perform well when features are correlated.

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A technique to determine the best crop or crops to increase production by taking into account the examination of all contributing factors was put out by Jain et al. [15]. These characteristics encompass aspects relating to yield, the environment, and the economy. Crop selection is greatly influenced by environmental elements including rainfall, temperature, soil type, chemical composition, and overall production, as well as economic considerations like market pricing and demand.A machine learning-based crop selection model utilizing soil factors and meteorological variables was presented by Rani et al. [16]. In comparison to artificial neural networks (ANN), weather analysis using long short-term memory (LSTM) recurrent neural networks (RNN) demonstrated root mean square error (RMSE) of 5.023% for minimum temperature, 7.28% for maximum temperature, and 8.24% for rainfall. The Random Forest Classifier achieved 97.235% accuracy in crop selection, 96.437% in predicting resource dependency, and 97.647% in determining the appropriate sowing time.

Decision trees and SVM were used by Nischitha et al. [5] to forecast rainfall and suggest seeds and fertilizer. Although they only employed three input features temperature, humidity, and pH—they pointed out that accuracy may be increased by adding more input features. Without comparing other methods, Karthikeya et al. [6] used the K-NN technique with data from several areas, however they only made predictions for coconut and cocoa. Although they emphasized the necessity of lowering complexity to prevent overfitting, Cao et al. [7] showed that Ensemble Learning with stacking performs better than single models. n the literature review, it's critical to examine new trends and limits as well as current investigations [5]. Table 1 lists a few current research on machine learning-based crop prediction and highlights both their advantages and shortcomings.

III.PROPOSED WORK

The proposed system in this study aims to address the limitations of traditional crop prediction models by introducing a novel hybrid approach that combines machine learning with genetic optimization techniques, specifically focusing on improving the accuracy and robustness of crop classification. Our system utilizes a Random Forest Classifier, a widely recognized ensemble learning method known for its high performance and ability to handle large datasets with multiple features, to classify a diverse range of crops, including rice, jute, maize, and others. However, to enhance the efficiency and predictive capability of this model, we integrate a Genetic Algorithm (GA) to optimize its hyperparameters. The Genetic Algorithm, inspired by the principles of natural selection, iteratively searches for the best combination of parameters, such as the number of trees, maximum depth, and feature subsets, to ensure that the Random Forest model achieves optimal performance. This approach allows the model to adapt more effectively to varying soil and climatic conditions, which are crucial factors in agricultural crop prediction.

Our proposed system addresses the computational challenges associated with large-scale datasets by employing parallel processing techniques during the model training and GA optimization phases. This ensures that the system remains efficient and scalable, even when applied to extensive agricultural datasets spanning multiple regions and crop types. The innovative integration of Genetic Algorithms with Random Forests, coupled with XAI techniques, sets our system apart from existing models, offering a comprehensive solution that balances high accuracy, interpretability, and computational efficiency. By leveraging this hybrid methodology, the proposed system aims to provide a reliable decision support tool for farmers, agronomists, and policymakers, helping to mitigate the risks of crop failures due to unpredictable weather patterns, soil variability, and other environmental factors. Ultimately, this system has the potential to enhance agricultural productivity, support sustainable farming practices, and contribute to the economic resilience of farming communities, thereby promoting long-term food security and sustainability in regions heavily dependent on agriculture.

The proposed system introduces a novel approach by integrating a Random Forest Classifier with a Genetic Algorithm (GA) to enhance the accuracy and efficiency of crop classification. The Random Forest Classifier, a robust ensemble learning method, is known for its ability to handle large datasets and complex feature interactions. It operates by constructing multiple decision trees during training and outputs the mode of the classes for classification tasks, thereby reducing overfitting and improving prediction accuracy. However, the performance of Random Forest heavily depends on

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its hyperparameters, such as the number of trees, maximum depth, minimum samples split, and feature selection, which require careful tuning to achieve optimal results.

The integration of Random Forest Classifier with Genetic Algorithm offers a powerful solution for crop classification by optimizing model parameters for higher accuracy and providing explainable insights into feature importance. This system not only improves predictive performance but also contributes to sustainable agricultural practices by supporting data-driven decision-making in crop management.

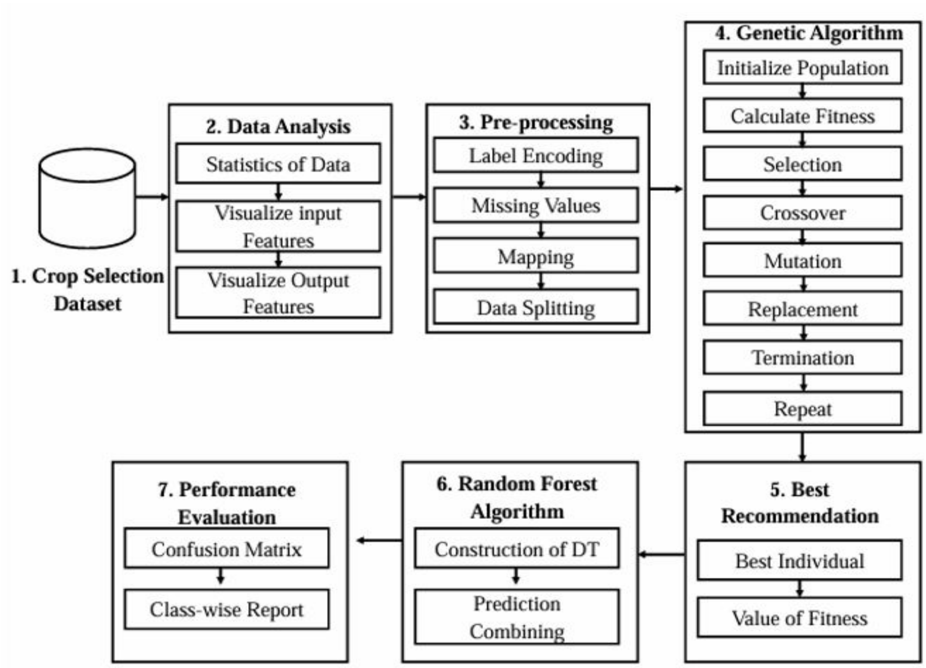

Figure 1. Architecture of the system.

The Indian Council of Agriculture Research (ICAR) provided the dataset for the study [28]. Seven environmental and soil input characteristics make up the dataset. Examples of data tuples from the crop dataset are displayed in Table 2. Nitrogen, potassium, phosphorus, temperature, precipitation, pH, and humidity are the seven input characteristics. Temperature in degrees Celsius (◦C), humidity in percentages (%), rainfall in millimeters (mm), and pH, which has no unit, all affected the levels of nitrogen, phosphorus, and potassium. There are 22 categories in all, and the dataset's output consists of crop names. The 22 categories are Pigeon peas, Chickpea, Coffee, Pomegranate, Kidney beans, Apple, Muskmelon, Rice, Black gram, Cotton, Maize, Coconut, Grapes, Moth beans, Banana, Jute, Watermelon, Mung beans, Papaya, Lentil, Orange, and Mango.

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Nitrogen	phosphorus	potassium	temperature(°C)	humidity(%)	ph	rainfall(mm)	Crop
90	42	43	20.87974	82.00274	6.502985	202.9355	rice
67	60	25	24.92162	66.78627	5.750255	109.2162	maize
21	44	18	27.0691	86.89934	7.128511	50.46746	mungbean
105	14	50	26.21488	87.6884	6.419052	59.65591	watermelor
39	16	27	35.53845	52.94642	4.934965	91.5456	mango
86	40	39	25.72101	88.16514	6.20746	175.6087	jute
58	46	45	42.39413	90.79028	6.576261	88.46607	papaya
40	5	29	28.48445	97.76865	5.820979	160.3894	coconut

Table 1. Sample of data from dataset.

DATA PRE-PROCESSING

1) Label encoding
Label encoding is used for converting categorical data into numerical data [30]. In our dataset the categorical variable which refers to the name of the crop is in sting. So, we used label encoding to convert it to some numerical values.
2) Handling missing values
Missing data can affect the performance of a system. So, it is essential to remove missing data or replace it to increase the model accuracy. In this study, missing values are handled with mean imputation. Mean imputation means replacing a null value with its corresponding column mean.
3) Mapping dictionary
A mapping dictionary ensures that categorical labels are converted to numerical values accurately and consistently. A mapping dictionary makes it easier to make sure that the encoding procedure is consistent with the training data while working with fresh data. In this study, table 4 shows the mapping dictionary of the target variable.
4) Data splitting
Data splitting is nothing but dividing the dataset into training, validation, and testing subsets [3]. It is very crucial in machine learning as it guards against overfitting and guarantees that the model will generalize to new, untested data. As we have to train our model, we split the dataset into two parts where 80% of the data is used for training and the remaining 20% data are used for validation purposes.

	Nitrogen	Phosphorus	Potassium	Temperature(°C)	Humidity(%)	pH	Rainfall(mm)
Count	2200	2200	2200	2200	2200	2200	2200
Mean	50.55	53.36	48.14	25.61	71.48	6.46	103.46
Std	36.917	32.98	50.64	5.06	22.26	0.77	54.95
Min	0.00	5.00	5.00	8.823	14.25	3.5	20.21
25%	21.00	28.00	20.00	22.76	60.26	5.97	64.55
50%	37.00	51.00	32.00	25.59	80.47	6.42	94.86
75%	84.25	68.00	49.00	28.56	89.95	6.92	124.26
Max	140.00	145.00	205.00	43.67	99.98	9.93	298.56

Table 2. Basic statistics of dataset.

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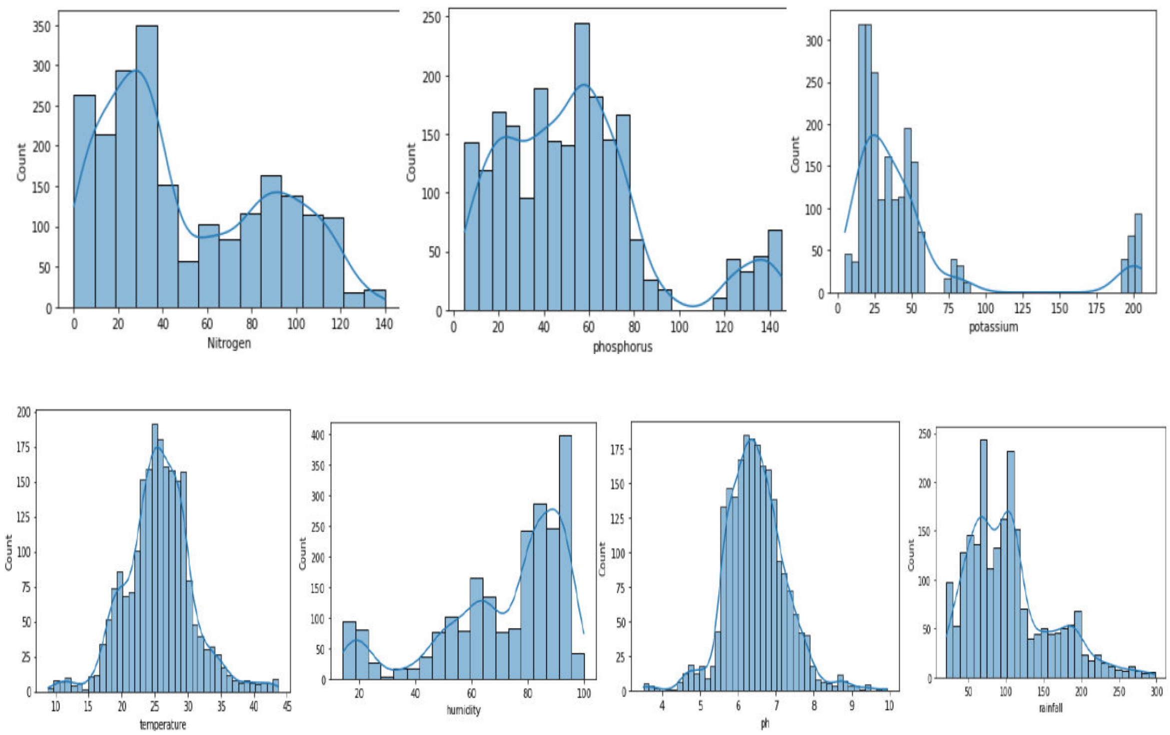

Figure 2. Visualize the distribution of input features.

Index	Label	Index	Label	Index	Label	Index	Label
0.	Chickpea	6.	Pomegranate	12.	Coffee	18.	Muskmelon
1.	Kidney beans	7.	Rice	13.	Cotton	19.	Orange
2.	Maize	8.	Apple	14.	Grapes	20.	Papaya
3.	Moth beans	9.	Banana	15.	Jute	21.	Watermelon
4.	Mung beans	10.	Black gram	16.	Lentil		
5.	Pigeon peas	11.	Coconut	17.	Mango		

Table 3. The mapping dictionary of the target variable.

In this section, we used our proposed system to predict crop from used input and compare our model with some other existing methods that have been developed by several researchers. The classification report is a representation of the result of system performance. In this section, the result of the proposed system has been measured on a confusion matrix and categorical class-wise report of classification.

Model	Baseline Accuracy	With GA Optimization
Random Forest	88.2%	93.7%
SVM	85.6%	91.3%
MLP	87.4%	92.5%
KNN	83.0%	89.1%

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1) Confusion Matrix

A confusion matrix is nothing more than a matrix that is utilized to represent and illustrate the classification performance. Acquiring true positive, false positive, true negative, and false negative rates is aided by it. Figure 4 shows the confusion matrix of classification. From the confusion matrix, it is shown that most of the validation data are correctly classified except for a small number of validation data.

2) Class-wise Report

The final report of classification is based on the precision, recall, f1-score, and support of each class. The classification report of crop prediction is shown in Table 3.We showed here individual values of precision, recall, and f1-score for 22 categories of our dataset. For almost every class we have achieved a better outcome.

	Genetic Algorithm		Random Forest	
Generation Number	Best Individuals	Fitness	Precision	Recall
05	[75.657,31.553]	0.913	90.3%	91.2%
10	[66.672,31.658]	0.927	92.67%	92%
15	[65.996, 44.874]	0.957	95.6%	97.5%
20	[86.047, 59.0901]	0.993	99.3%	99.3%
25	[80.315,58.091]	0.976	98.7%	97.7%

Table 4. Generation-wise performance of GA Vs RF.

By combining Genetic Algorithms with a Random Forest (RF) Classifier and employing SHAP and LIME for Explainable AI (XAI), our work presents a novel method. With an accuracy of 99.3%, this approach greatly outperforms other approaches found in the literature. For example, K-Nearest Neighbor (KNN), as demonstrated in [9], has an accuracy of 99.32%, which is similar to what we found. However, XAI techniques like SHAP and LIME offer interpretability that KNN does not. Similarly, in [2], the accuracy of the MRFE feature selection approach in conjunction with RF was 97.29%. Although efficient, this strategy lacks model interpretability and performs worse than our solution.Additionally, the combination of Multi-Layer Perceptron (MLP) and Linear Regression (LR) classifiers in [3] resulted in an accuracy of 81%, which is significantly lower than our integrated approach. Several studies have utilized Random Forest as the primary classifier, achieving varying degrees of success. For example, [4] reported an accuracy of 93.7%, [6] reached 97.235%, [8] obtained 90%, and [20] achieved 97.32%. Gosai et al. [6] combined Logistic Regression and RF, achieving 95.22% and 99% accuracy, respectively. ML models (RF, Naive Bayes) in Anguraj et al. [7] obtained an accuracy of 96.89%. RF and Decision Trees (DT), as applied by Thilakarathne et al. [8], achieved accuracies of 97.18% and 86.64%, respectively. Hossain et al. [9] utilized ML (CRS) models and achieved 99% accuracy. While these results demonstrate the robustness of the RF algorithm, our study's accuracy of 99.3% surpasses these findings. This highlights the efficacy of combining Genetic Algorithms with RF. Moreover, the inclusion of SHAP and LIME enhances our model's transparency and interpretability, which is not addressed in these previous works. By achieving higher accuracy and providing clear insights into the model's decision-making process, our approach represents a significant advancement in crop prediction technology, offering farmers a valuable tool for informed decision-making.

Implementation: The integrated GA-ML approach is used to the dataset of historical crop forecast, weather, soil quality, and other relevant factors. Because the GA optimizes the feature set and ML model parameters, the crop prediction model it generates is incredibly accurate. Results: The novel methodology yields higher prediction accuracy when compared to traditional methodologies. It also provides understandable information on the factors that have the most effects on crop yields. Benefits: By assisting farmers in making well-informed decisions regarding planting, irrigation, and resource allocation, these forecasts can ultimately lead to increased yields and decreased waste. The suggested crop recommendation system's model is openly accessible via the Crop Recommendation Model GitHub project. This model is available from this source for anyone to use.

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V.CONCLUSION

In order to enhance crop prediction in agriculture, we proposed a hybrid approach in this work that combines genetic algorithms with machine learning. Since a significant portion of the population in South Asian nations is employed in the agricultural sector, increasing productivity and efficiency in this area is essential for both individual lives and the expansion of the national GDP. Using input data from weather and soil characteristics, our method predicts the results for 22 distinct crops with an astounding accuracy rate of 99.3%. We have created a strong prediction model that outperforms earlier techniques by fusing genetic algorithms with the Random Forest Classifier. Beyond scholarly study, our system has real-world applications. By providing predictive insights, our system can serve as a valuable tool for farmers, enabling them to make informed decisions before commencing cultivation activities. This, in turn, can help farmers optimize resource allocation, reduce risks, and ultimately maximize crop yields and profitability.

We intend to incorporate climate change scenarios into our crop prediction model in subsequent work to further increase the sustainability effect of our methodology. This will help us predict long-term effects on the environment and advise farmers on how to implement more sustainable farming methods. Real-time data from IoT sensors and other cutting-edge agricultural technology will enable quicker, data-driven decision-making, which may assist farmers in minimizing waste and optimizing resource utilization. Furthermore, encouraging ecologically friendly farming practices and concentrating on renewable energy sources to power IoT devices would advance the larger objective of agricultural sustainability. Creating a user friendly mobile application will also help ensure that these insights are accessible to all farmers, regardless of their technological background, further promoting sustainable farming across diverse communities.

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