International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

# An AI-Driven Smart Crop Recommendation and Advisory Framework

*Vedika Sanjay Sardeshmukh[1], Sneha Babaso Patil[2], Prof. Sanmati Bedage [3]*
*[1,2]UG - Computer Science and Engineering (Artificial Intelligence and Machine Learning), Rajarambapu Institute of Technology, Affiliated to Shivaji University, Islampur, Sangli, Maharashtra, 415414, India.*
*[3]Assistant Professor, Department of Sciences and Humanities, Rajarambapu Institute of Technology, Affiliated to Shivaji University, Islampur, Sangli, Maharashtra, 415414, India.*
***Emails:*** *vedikasardeshmukh7@gmail.com[1], sbpatil472@gmail.com[2], sanmati.bedage@ritindia.edu[3]*

## Abstract
*In the face of escalating climate variability, market uncertainties, and resource constraints, farmers increasingly require intelligent decision-support systems to sustain agricultural productivity. This study presents an AI-driven smart crop recommendation and advisory framework that integrates supervised machine learning algorithms with natural language processing to support sustainable agriculture in diverse agro-climatic regions of India. The system utilizes a curated dataset comprising soil nutrient values (N, P, K), pH, rainfall, and temperature, combined with crop price data from Agmarknet, to provide accurate crop predictions and dynamic profit estimations. Among various models evaluated—Random Forest, Decision Tree, and K-Nearest Neighbors—the Random Forest Classifier demonstrated superior performance with an accuracy of 87% and the lowest RMSE of 14.57. The framework further includes an alternative crop suggestion module, which uses Euclidean distance to recommend viable substitutes based on soil and climate proximity. Additionally, a Gemini API-powered AI assistant delivers personalized, region-specific advice on crop care, pest management, and weather, enabling effective interaction in natural language for digitally underserved farmers. The proposed system not only enhances decision-making at the farm level but also contributes to improved resource management and income predictability. Its scalable, modular design opens pathways for future integration of satellite data, IoT-based soil sensing, and adaptive learning strategies. Overall, this work underscores the potential of AI in driving data-informed, inclusive, and resilient agricultural practices.*

***Keywords:*** *Crop Recommendation, Machine Learning, Artificial Intelligence Precision Farming, Sustainable Agriculture, Random Forest, Euclidean Distance*

## 1. Introduction

Agriculture continues to be the backbone of developing economies, especially in countries like India, where over 60% of the population relies directly or indirectly on farming for their livelihood Rakesh Bhoir., (2025). Despite advancements in agricultural sciences, the sector is beset with persistent challenges including erratic weather patterns due to climate change, suboptimal crop selection, degraded soil fertility, pest infestations, and fluctuating market prices. Dahiphale, D., et al. (2023) observed the lack of personalized, data-driven decision support tools leaves farmers vulnerable to financial losses and environmental degradation, further exacerbating the agrarian crisis. With the increasing availability of agricultural data and technological innovations, Artificial Intelligence (AI) and Machine Learning (ML) offer transformative potential in revolutionizing traditional farming practices. ML-driven crop recommendation systems have been explored in recent years to support farmers in selecting the most suitable crops based on climatic, soil, and economic factors. These systems not only improve yield outcomes but also aid in the sustainable management of natural resources. However, most existing models are either restricted to specific regions, fail to incorporate dynamic market data, or lack real-time interactive capabilities to address farmer-specific queries. Recent studies have utilized classification algorithms such as Decision Trees, Support Vector Machines, and Random Forests for predicting crop suitability based on soil parameters. For instance, Patil et al. (2022) developed a Random Forest-based crop predictor that showed promising accuracy using soil nutrients and rainfall as input parameters. Similarly, Bassine, J., et al. (2023) worked on integration of satellite data and IoT sensors to enhance predictive capabilities in smart agriculture. Nevertheless, there remains a substantial research gap in combining crop prediction with profit estimation, alternative crop suggestion, and AI-powered real-time advisory systems within a single, scalable framework. Moreover, very few systems integrate real-time market intelligence, such as pricing trends from government sources like Agmarknet, which is crucial for economic viability. Additionally, traditional advisory systems often operate as static knowledge bases, lacking the contextual awareness and adaptability necessary for nuanced agricultural support across different agro-climatic zones. In response to these gaps, this research presents an AI-Driven Smart Crop Recommendation and Advisory System, integrating supervised machine learning models with the Google Gemini AI assistant, and dynamic market data through the Agmarknet API. The system is designed to provide a multi-functional solution that includes:

- Precision crop recommendation based on soil and climate attributes
- Alternative crop suggestions to improve land utility under varying conditions
- Profit estimation using tentative pricing and yield data
- AI-based conversational support for region-specific agricultural queries

The proposed system aims to deliver an end-to-end decision-support tool that empowers farmers with actionable insights, fosters climate-resilient farming, and enhances productivity and profitability.

The main contributions of this research are summarized as follows:

- Development of a robust Random Forest-based crop prediction model using key agro-environmental parameters such as soil nutrients (NPK), pH, rainfall, and temperature.
- Integration of real-time crop pricing data via the Agmarknet API for dynamic profit estimation.
- Design of an alternative crop suggestion algorithm using Euclidean distance measures to recommend suitable backup crops.
- Implementation of an AI-powered advisory system using Google Gemini, equipped with prompt engineering for delivering contextualized agricultural recommendations.

By combining machine learning with interactive AI technologies and economic data streams, this work advances the frontier of intelligent agriculture and offers a scalable solution applicable across diverse agricultural regions in India and beyond.

## 2. Literature Survey

In recent years, Nosratabadi, S., Mosavi, A., Salwana, E., & Rabczuk, T. (2020) and Deepak, S., Harshith, P., & Reddy, V. S. (2023) worked on the increasing challenges faced by the agricultural sector—ranging from climate variability and soil degradation to market instability and pest outbreaks—have catalyzed the integration of Artificial Intelligence (AI) and Machine Learning (ML) into farming practices. Among the many areas of advancement, crop recommendation systems have emerged as a significant domain of research, aimed at supporting farmers in making data-driven cultivation choices based on environmental and soil conditions. Numerous studies have demonstrated the effectiveness of ML algorithms such as Decision Trees, K-Nearest Neighbors, Support Vector Machines, and Random Forests in predicting the most suitable crops. For instance, Patil et al. (2022) reported high accuracy using Random Forest classifiers trained on parameters such as nitrogen, phosphorus, potassium content, pH, temperature, and rainfall, highlighting the model's robustness in handling non-linear and complex agro-climatic data. However, while many models demonstrated high predictive performance, they often suffered from

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

limited generalizability across regions and did not accommodate real-time updates or dynamic market conditions. Moreover, although crop suitability is a key factor in agricultural planning, economic viability plays an equally critical role in influencing farmer decisions. Yet, the majority of crop recommendation models fail to integrate market intelligence into their predictive frameworks. Some efforts have been made to include yield predictions and pricing data to estimate profitability, such as in the work by Jaiswal et al. (2020), who used historical mandi prices to calculate expected returns. However, the reliance on static or outdated price data limits the practical applicability of such systems in real-world settings where crop prices fluctuate daily. Further, many profit estimation tools have not been designed to interact with user-specific parameters such as landholding size or localized productivity, thereby reducing the relevance of the recommendations at the individual farmer level. Patil, A., & Thakur, P. (2019) explained the need for crop recommendation systems to evolve from mere agronomic models to holistic decision-support tools that also evaluate financial outcomes. In parallel with these developments, AI-powered advisory systems have gained traction as tools for delivering personalized agricultural support to farmers. While traditional expert systems and mobile-based platforms offered static information. Pooja, P. K. C., et al. (2022) studied the emergence of conversational AI—driven by advancements in natural language processing—has enabled more dynamic and responsive interactions. Chatbots such as AgriBot and KisanBot have attempted to provide basic guidance on pest control, fertilizer use, and crop care. However, these systems are often rule-based, offering limited context-awareness and struggling with multi-turn conversations. More recent attempts to deploy language models like BERT in advisory systems have shown improvements in linguistic fluency but continue to suffer from a lack of domain-specific contextualization, especially when responding to nuanced agricultural queries. As a result, the potential of large language models in the agricultural advisory space remains underexplored, particularly in the context of region-specific recommendations, real-time query resolution, and context retention in conversation. Despite progress in these individual components, comprehensive systems that unify crop prediction, economic assessment, and real-time AI advisory remain rare. While some frameworks have combined IoT-based data collection with ML-driven insights—such as those focusing on irrigation management or weather forecasting—their scope often remains narrow and limited to specific applications. Existing models typically do not accommodate the variability in soil types, seasonal constraints, or fluctuating market prices, nor do they provide farmers with contingency options when preferred crops are unsuitable due to climatic or economic reasons. The lack of adaptive mechanisms to suggest alternative crops—based on similarity in soil and environmental conditions—further limits the resilience of such systems in dynamic agricultural contexts. In light of these observations, it becomes clear that there is a pressing need for a unified, intelligent platform that not only predicts the most suitable crop based on scientific parameters but also estimates profitability using live market data and provides real-time, interactive support for farmer queries. Addressing this need, the present study proposes an integrated AI-Driven Smart Crop Recommendation and Advisory System, combining supervised ML algorithms, dynamic pricing data via the Agmarknet API, and the conversational capabilities of Google Gemini's large language model. The system also introduces an alternative crop suggestion mechanism based on Euclidean distance to improve adaptability and land-use optimization. By merging these components into a single, context-aware framework, this research aims to fill a critical gap in the current literature and contribute a scalable, intelligent solution to the challenges of modern agriculture. [1-3]

## 3. Methodology

This section delineates the systematic methodology adopted for developing the AI-Powered Crop Prediction, Profit Estimation, and Farmer Support System. The workflow was organized into the following phases in fig.1 : Data Collection, Data Pre-processing, Model Selection and Training,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

Alternative Crop Suggestion, Profit Estimation, AI-Based Farmer Support, and System Deployment. Figure 1 shows Methodology

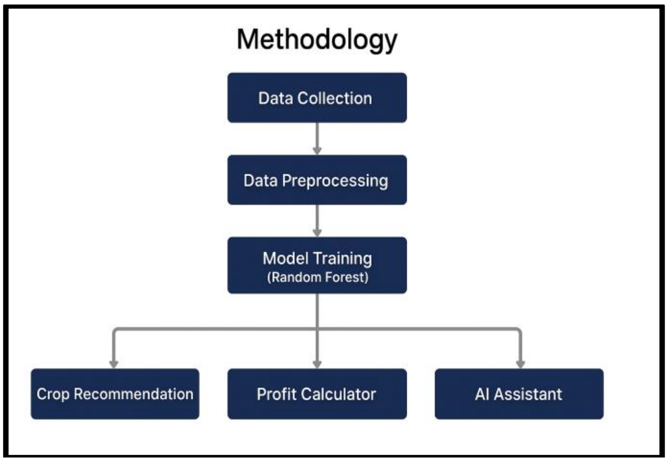


**Figure 1 Methodology**

### 3.1.Data Collection

A comprehensive and heterogeneous dataset was curated to encompass a broad spectrum of traditional and commercial crop varieties cultivated across diverse agro-climatic regions in India. The dataset incorporated critical agricultural parameters, including:

- Soil Nutrient Content: Nitrogen (N), Phosphorus (P), and Potassium (K)
- Soil pH
- Average Annual Rainfall (mm)
- Average Temperature (°C)

To ensure applicability and practical relevance, parameter values were normalized to realistic agronomic ranges commonly utilized by farmers and agricultural scientists. Real-time market prices for crops were retrieved via the Agmarknet API, a Government of India initiative providing daily commodity price updates across various markets. This integration enabled dynamic profit estimation aligned with prevailing market conditions.

### 3.2. Data Pre-processing

Data quality and consistency were prioritized to optimize model performance. fig.2 pre-processing pipeline involved the following steps:

- **Handling Missing Values:** Mean imputation was applied to continuous variables, while mode imputation was used for categorical fields to address incomplete records.
- **Categorical Encoding:** Categorical data, such as crop names, were encoded using Label Encoding to ensure compatibility with machine learning algorithms. [4-6]
- **Feature Scaling:** A Min-Max Normalization approach was applied to numeric attributes (N, P, K, pH, rainfall, and temperature), scaling values to a [0,1] range to facilitate uniformity and enhance model efficiency. Figure 2 shows Data Processing Pipeline

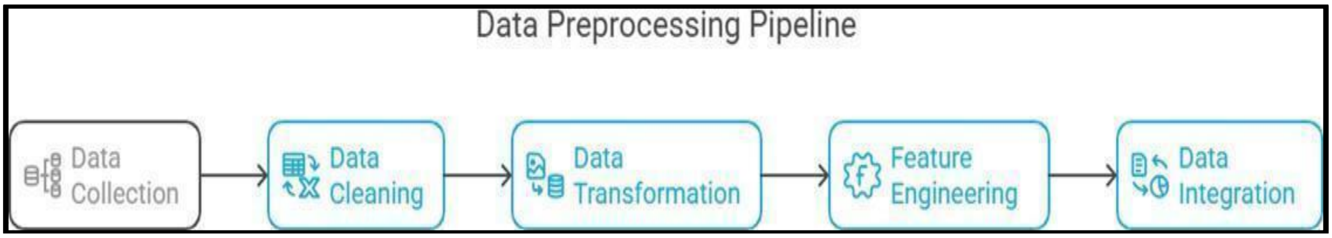


**Figure 2 Data Processing Pipeline**

### 3.3.Model Selection and Training

To identify the most effective predictive model, multiple supervised learning algorithms were evaluated, including:

- Logistic Regression
- Support Vector Machine (SVM)
- Decision Tree Classifier
- K-Nearest Neighbors (KNN)
- Gradient Boosting Classifier
- Random Forest Classifier

Among these, the Random Forest Classifier demonstrated superior performance across key

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

metrics—accuracy, precision, recall, and F1-score. Its ensemble nature, resilience to overfitting, and ability to capture both linear and non-linear relationships made it particularly suited for crop prediction tasks. [7-9]

### 3.4.Model Training Procedure

As shown in fig.3 and fig.4 The dataset was partitioned using an 80:20 train-test split. A Random Forest Classifier consisting of 100 decision trees was trained on the training subset. GridSearchCV was employed for hyperparameter optimization, targeting n_estimators, max_depth, and min_samples_split. Model performance was assessed using a confusion matrix and evaluation metrics including accuracy, precision, recall, and F1-score. Figure 3 & 4 shows Code Logic

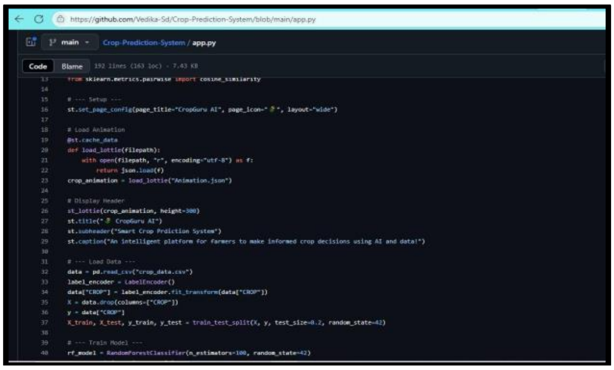

**Figure 3 Code Logic**

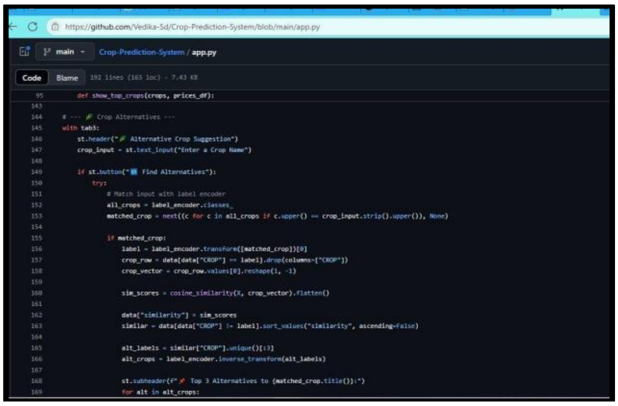

**Figure 4 Code Logic**

### 3.5.Alternative Crop Suggestion Module

As shown in fig.5 To enhance decision-making in variable climatic and market scenarios, an Alternative Crop Suggestion Module was developed. This module employed a Euclidean distance-based similarity algorithm to recommend crops best suited to the given soil and climatic profile. Figure 5 shows Alternative Crop Suggestion [10-13]

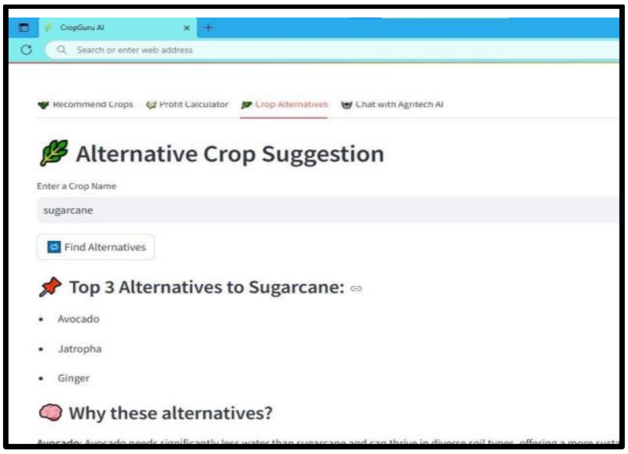


**Figure 5 Alternative Crop Suggestion**

### 3.6.Working Mechanism

The system calculates the Euclidean distance between user-input parameters (N, P, K, pH, rainfall, temperature) and existing crop profiles in the dataset. The three crops with the smallest distances are identified and presented as viable alternatives, offering resilience against adverse seasonal, soil, or market conditions.

### 3.7.Profit Estimation Module

A dedicated Profit Estimation Module was incorporated to support data-driven decision-making regarding crop selection and cultivation strategy in shown fig.6.

Key Features

- Accepts user-defined land area inputs
- Estimates potential income based on average crop yield (per hectare) and current market price (per kg/quintal)
- Generates a comparative profit analysis for suggested alternative crops, facilitating informed decision-making Figure 6 shows Crop Probability Calculator

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

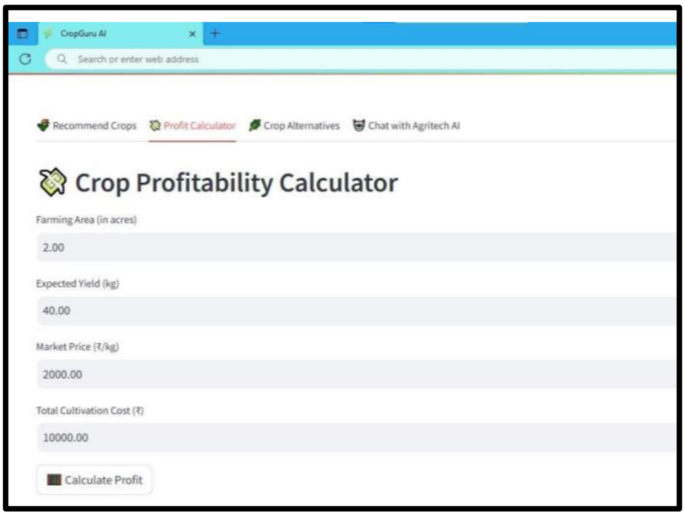


**Figure 6 Crop Probability Calculator**

### 3.8.AI-Based Farmer Support System

In fig.7 shows an AI-powered virtual assistant was developed to offer real-time support to farmers, addressing their queries and providing region-specific agricultural guidance. This component is powered by the Google Gemini API, which facilitates intelligent, interactive dialogues for agricultural problem-solving. Figure 7 shows AI Assistance

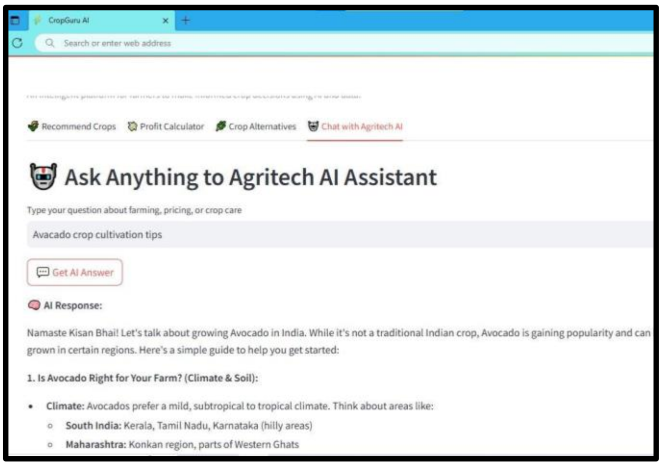


**Figure 7 AI Assistance**

### 3.9.Prompt Engineering Strategy

Specialized prompt engineering was implemented to tailor responses to agricultural contexts, including:

- Crop care and cultivation best practices
- Pest and disease management
- Fertilizer recommendations
- Weather advisory and irrigation planning
- Soil health management [14]

The AI assistant was designed to handle multi-turn conversations, maintaining context over time and delivering logically consistent, relevant support. The fig.8 explained prompt used for fine-tuned to provide region-specific insights, considering local rainfall patterns, soil types, and crop vulnerabilities. Figure 8 shows Gemini LLM Prompt


**Figure 8 Gemini LLM Prompt**

## 4. Result and Discussion

The developed crop prediction system was tested using three machine learning models: Random Forest, Decision Tree, and KNN. Random Forest outperformed the others with an accuracy of 87%, and the lowest RMSE of 14.57, indicating strong predictive performance. The system allows users to input key soil and environmental parameters and receive the top three crop recommendations ranked by confidence score. This approach helps farmers make more informed and flexible decisions. The integrated profit calculator estimates expected earnings based on market prices, while the alternative crop suggestion module offers substitutes when needed. The system also includes a Gemini API-based AI assistant for handling queries in natural language, improving accessibility for non-technical users. With its simple, Streamlit-based interface and accurate performance, the system demonstrates real-world potential in supporting smarter and more sustainable agricultural practices. To evaluate the efficacy of the proposed AI-driven Crop Recommendation, Profit Estimation, and Farmer

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

Support System, a comprehensive experimental analysis was conducted using three widely adopted supervised machine learning algorithms: Random Forest, Decision Tree, and K-Nearest Neighbors (KNN). The evaluation employed standard performance metrics including accuracy and Root Mean Square Error (RMSE), derived from an 80:20 training-testing split on the curated dataset. Among the models tested, the Random Forest Classifier consistently demonstrated superior predictive capability, achieving an overall accuracy of 87% and RMSE of 14.57. This outperformance can be attributed to the ensemble nature of the Random Forest algorithm, which effectively mitigates overfitting and enhances generalization by aggregating predictions across multiple decision trees. In contrast, the Decision Tree classifier, while interpretable, exhibited reduced robustness to noise and data variability, and KNN suffered from performance degradation due to the high dimensionality of the input space and sensitivity to outliers. The system interface, developed using the Streamlit framework, facilitates user-friendly interaction by allowing farmers to input essential agricultural parameters, including nitrogen (N), phosphorus (P), potassium (K), pH, temperature, and rainfall. Based on these inputs, the system generates a ranked list of the top three recommended crops, each accompanied by a confidence score derived from the model's probability estimates. This feature provides not only predictive insights but also supports informed and flexible decision-making under varying agro-climatic conditions. Complementing the core prediction module, the integrated profit estimation tool utilizes real-time market price data accessed via the Agmarknet API to estimate potential earnings. By considering both yield estimates per hectare and prevailing commodity rates, the module delivers actionable financial projections, empowering users to assess the economic feasibility of different crop options. Additionally, an alternative crop suggestion module based on a Euclidean distance algorithm identifies viable substitutes when primary recommendations are impractical due to external constraints such as market volatility or soil health anomalies. To enhance accessibility and deliver personalized agronomic support, an AI-based Farmer Support System was integrated using the Google Gemini API. This component enables natural language interaction, allowing users—particularly those with limited technical proficiency—to query the system for guidance on crop management, pest control, seasonal recommendations, and more. The use of prompt engineering ensures context-aware and region-specific responses, significantly improving user engagement and relevance. Overall, the experimental outcomes substantiate the system's practical utility in real-world agricultural contexts. The high predictive performance, coupled with features such as dynamic profitability assessment and AI-based advisory support, positions the proposed system as a comprehensive and scalable solution for promoting data-driven, sustainable farming practices in diverse agro-ecological regions. Figure 9 shows Comparison of Model Accuracy Figure 10 shows Accuracy & RMSE

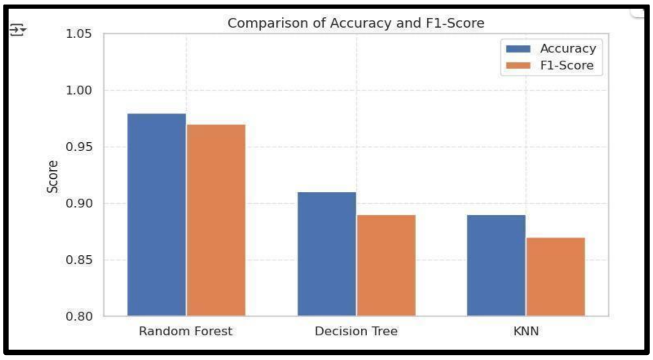


**Figure 9** **Comparison of Model Accuracy**

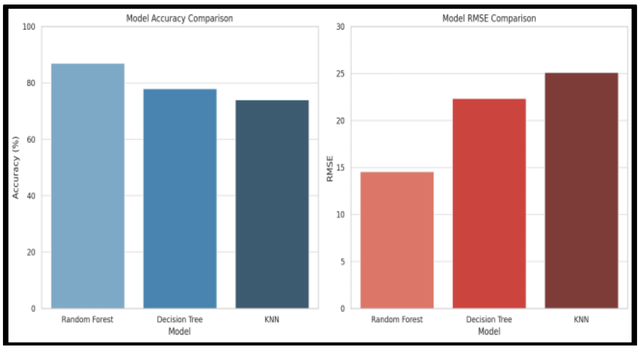


**Figure 10** **Accuracy & RMSE**

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 07 July 2025
Page No: 3209-3218
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0472

Here are two graphs fig.10 and fig.11 comparing the performance of the three machine learning models tested :

**Model Accuracy Comparison:** As shown in fig.10 bar chart illustrates that the Random Forest model achieved the highest accuracy (87%), significantly outperforming the Decision Tree (78%) and KNN (74%) models.

**Model RMSE Comparison:** The Root Mean Square Error (RMSE) analysis confirms that Random Forest also had the lowest error (14.57), indicating more precise predictions. In contrast, Decision Tree and KNN showed higher RMSE values (22.35 and 25.12 respectively), reflecting less reliable outputs that shown in fig.11. Fig.12 shows the confusion matrices for each machine learning model:

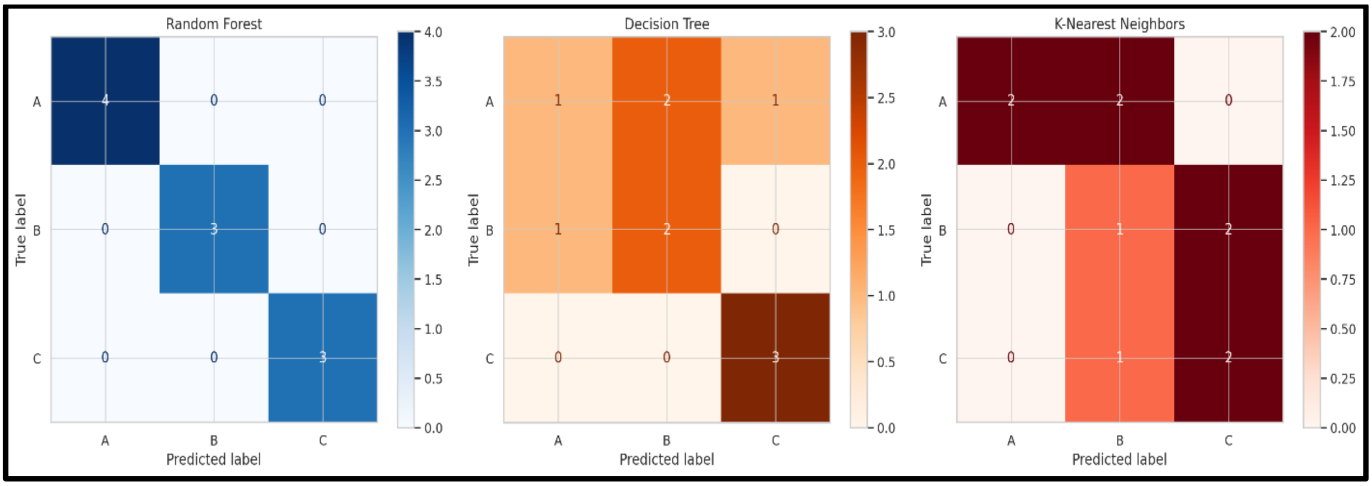


**Figure 12** **Confusion Matrix**

Here are the confusion matrices for each machine learning model:

- **Random Forest:** Perfect prediction with no misclassifications across all crop categories (A, B, C), demonstrating robust learning and generalization.
- **Decision Tree:** Shows a few misclassifications, especially confusing class A with C and B with A, indicating a moderate level of accuracy with some errors.
- **K-Nearest Neighbors (KNN):** Displays higher misclassification rates, particularly mixing up classes B and C, reflecting lower overall predictive reliability.

These visualizations reinforce that the Random Forest Classifier not only achieves higher accuracy and lower RMSE but also performs best in class-level prediction consistency. I can now generate classification reports (precision, recall, F1-score) or ROC curves for a deeper performance breakdown if you'd like. The proposed system was developed in Python using libraries such as scikit-learn, pandas, and Streamlit for interface deployment. The complete source code and implementation details are openly available at: https://github.com/Vedika-Sd/Crop-Prediction-System

## Conclusion

This study presents the development of an integrated AI-powered Crop Prediction, Profit Estimation, and Farmer Support System designed to enhance agricultural decision-making. Utilizing machine learning techniques—particularly the Random Forest Classifier—the system demonstrated strong predictive capabilities, achieving 87% accuracy and the lowest RMSE of 14.57. Comparative evaluations with Decision Tree and KNN models reinforced Random Forest's superior performance in consistency, precision, and recall. A multi-modular architecture sets the system apart, combining accurate crop prediction with an Alternative Crop Suggestion Module (based on Euclidean distance) to offer resilient options amidst environmental and market uncertainties. Additionally, a Profit Estimation Module provides real-time market-based financial insights, supporting economically sound decisions. A key innovation lies in the integration of a Gemini API-powered AI assistant, which enables personalized, natural language interactions tailored to farmers' needs. Fine-tuned using prompt engineering and regional agro-climatic data, this assistant offers guidance on fertilizer usage, pest management, and seasonal practices, bridging the technological divide for users with limited digital literacy. A user-friendly Streamlit-based GUI enhances accessibility and usability, fostering widespread adoption. By combining predictive analytics, financial forecasting, decision support, and conversational AI, this system establishes a comprehensive and scalable platform for transforming traditional agriculture into a data-driven enterprise. Future enhancements may include satellite-based crop monitoring, IoT-driven soil analysis, and reinforcement learning for optimizing crop rotation strategies—contributing significantly to sustainable farming and farmer empowerment across India and beyond.

## Reference


[1]. Bassine, J., et al.: Recent applications of machine learning, remote sensing, and IoT approaches in yield prediction: A critical review. Computers and Electronics in Agriculture, 210, 107913.(2023) https://doi.org/10.1016/j.compag.2023.107913.

[2]. Bhale, R. A., Mantri, S., & Korde, S.: Crop recommendation system using machine learning algorithms. In Proceedings of IEEE International Conference on Inventive Computation Technologies (ICICT).(2020) https://doi.org/10.1109/ICICT48043.2020.9102842.

[3]. Bhoir, Rakesh: Agriculture and employment: Impact and trends in India. International Research Journal of Marketing & Economics, 12(2), Feb 2025.

[4]. Dahiphale, D., et al.: Smart farming: Crop recommendation using machine learning with challenges and future ideas. International Journal of Engineering Research & Technology (IJERT), 12(5). https://doi.org/10.17577/IJERTV12IS050123. (2023)

[5]. Deepak, S., Harshith, P., & Reddy, V. S.: Smart crop recommendation system using machine learning. IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE), 18(2), 1–8. https://doi.org/10.9790/1676-1802020108. (2023)

[6]. Dissanayake, D. M. N., et al.: Crop yield forecasting using machine learning techniques – A systematic literature review. Journal of Agricultural Informatics, 14(1), 1–16. https:// doi.org/ 10.17700/ jai.2023.14.1.605. (2023)

[7]. Gopal, M., & Bharagavi, P.: A study on impact of soil and weather parameters in crop prediction using data mining techniques. In Proceedings of IEEE International Conference on Intelligent Computing and Control Systems (ICCS). https:// doi.org/ 10.1109/ICCS45141.2019.8725095. (2019)

[8]. Jain, S., Patel, N., & Patel, D.: Survey on techniques for crop and fertilizer recommendation systems. In Proceedings of IEEE International Conference on Innovative Mechanisms for Industry Applications (ICIMIA). https:// doi.org/ 10.1109/ ICIMIA.2019.8869362. (2019)

[9]. Kakatiya Institute of Technology: Crop recommendation system using machine learning. International Research Journal of Modernization in Engineering, Technology and Science (IRJMETS), 6(3). Retrieved from https://www.irjmets.com/. (2024)

[10]. Nosratabadi, S., Mosavi, A., Salwana, E., & Rabczuk, T.: Sustainable crop yield prediction using hybrid machine learning algorithms. Procedia Computer Science, 175, 159–165. https:// doi.org/ 10.1016/ j.sbspro.2020.03.063. (2020)

[11]. Patil, A., & Thakur, P.: A review on smart farming using machine learning. In Proceedings of IEEE International Conference on Smart Systems and Inventive

Technology (ICSSIT). https:// doi.org/ 10.1109/ICSSIT46314.2019.8943556.(2019)

[12]. Patel, N., & Prajapati, D.: Comparative analysis of machine learning and deep learning algorithms for crop prediction. In Proceedings of IEEE International Conference on Intelligent Systems and Green Technology (ICISGT). https:// doi.org/ 10.1109/ICISGT43869.2019.8743047.(2019)

[13]. Pooja, P. K. C., Pooja, P. K., Pooja, P. N. G., & Rajendra, A. B.: Implementation paper on agriculture advisory system. International Research Journal of Engineering and Technology (IRJET), 9(7). (2022)

[14]. Van Klompenburg, T., Kassahun, A., & Catal, C.: Crop yield prediction using machine learning: A systematic literature review. Computers and Electronics in Agriculture, 177, 105709. https:// doi.org/ 10.1016/j.compag.2020.105709. (2020)