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AI-Powered Precision Agriculture Advisor

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Abstract: Agricultural productivity is increasingly affected by unpredictable weather conditions, plant diseases, inefficient irrigation practices, and limited access to timely market and advisory information. These challenges are more prominent among small and medium-scale farmers who rely on traditional decision-making methods. To address these issues, this research presents an **AI-Based Precision Agriculture Support System** that provides comprehensive and intelligent assistance for modern farming. The proposed system integrates multiple analytical modules, including crop recommendation, crop yield prediction, plant disease detection, irrigation planning, market price analysis, and weather forecasting. Machine learning algorithms are employed to analyze soil characteristics, climatic parameters, historical crop data, and market trends, while deep learning techniques are used to identify plant diseases from leaf images at an early stage. The irrigation planning module utilizes predictive insights combined with weather forecasts to optimize water usage and reduce resource wastage. All modules are unified through a web-based platform that delivers real-time, user-friendly recommendations without dependence on complex sensing infrastructure. Experimental results demonstrate that the system produces reliable predictions and actionable insights, contributing to improved crop management, efficient resource utilization, and enhanced decision-making. The proposed solution offers a scalable, cost-effective, and sustainable approach toward intelligent agriculture and supports the adoption of data-driven farming practices.

Keywords: Precision Agriculture, Artificial Intelligence, Crop Recommendation, Yield Prediction, Plant Disease Detection, Smart Irrigation, Market Price Analysis, Weather Forecasting.

I. INTRODUCTION

Agricultural production is increasingly affected by climatic variability, soil heterogeneity, plant diseases, inefficient irrigation practices, and fluctuating market prices. These factors significantly influence crop yield, farm profitability, and long-term sustainability. Traditional farming practices, which rely mainly on experience-based decision-making and generalized advisories, often fail to address the dynamic and data-intensive requirements of modern agriculture, leading to inefficient resource utilization and increased production risks. Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have enabled the creation of intelligent decision-support systems for agriculture. These technologies facilitate the analysis of complex and non-linear relationships among soil properties, weather conditions, historical crop performance, and market trends. Supervised learning techniques have proven effective in crop recommendation and yield prediction, while deep learning models support early detection of plant diseases through image-based analysis. However, many existing smart agriculture solutions depend heavily on Internet of Things (IoT)-based sensing infrastructure for real-time data collection. Although effective, such systems are often expensive, complex to maintain, and difficult to deploy in resource-constrained and cost-sensitive farming environments, thereby limiting their scalability and widespread adoption. To overcome these challenges, this research proposes an **AI-Powered Precision Agriculture Advisor**, a modular web-based system that integrates crop recommendation, yield prediction, plant disease detection, irrigation planning, market price analysis, and weather forecasting. By leveraging ensemble machine learning models, convolutional neural networks, and real-time weather data from external APIs, the proposed system delivers accurate, scalable, and cost-effective agricultural advisories to support informed and sustainable farming decisions. The system aims to reduce production uncertainty, improve input efficiency, and enhance decision-making accuracy at the farm level. Furthermore, its modular architecture allows easy extension and adaptation to diverse crops and regional conditions. Overall, the proposed framework contributes toward promoting data-driven, sustainable, and technology-enabled agricultural practices.

II. LITERATURE REVIEW

Kamduri et al. [1] proposed a cost-effective smart agriculture advisory system using machine learning techniques to support precision farming. Their approach focuses on crop selection, fertilizer recommendations, and disease identification using historical agricultural data and farmer inputs. The system emphasizes affordability and accessibility for small and

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medium-scale farmers by avoiding expensive IoT infrastructure. However, the absence of real-time adaptability limits its effectiveness under rapidly changing field conditions.

Aryan et al. [2] developed an integrated AI-based farmer support platform that combines crop disease detection, irrigation advisory, and expert consultation services. The system employs deep learning models, predictive analytics, rule-based mechanisms, and natural language processing to deliver intelligent recommendations. While the integrated architecture improves decision-making efficiency, its reliance on continuous internet connectivity and external APIs may restrict deployment in remote agricultural regions.
Iniyan et al. [3] investigated the application of various machine learning algorithms for crop yield prediction, including Linear Regression, Support Vector Machines, Random Forest, K-Nearest Neighbors, and Decision Trees. The study demonstrated that ensemble and advanced models generally outperform simpler techniques in predicting yield. However, the performance of these models is highly dependent on dataset quality and feature diversity, highlighting the need for robust data preprocessing.

Li et al. [4] reviewed recent advancements in plant disease detection using deep learning techniques. The study analysed convolutional neural network architectures such as VGG, ResNet, and Inception models and compared them with traditional classifiers. Although high accuracy was achieved on benchmark datasets, the authors noted challenges in real-world deployment due to variations in lighting, background noise, and image quality.

Krishna et al. [5] explored the use of artificial intelligence in precision agriculture with a particular focus on irrigation and water management. The study highlighted AI-based approaches for soil moisture estimation, irrigation planning, and sustainable water usage. While intelligent irrigation systems demonstrated improved efficiency, large-scale implementation remains challenging due to infrastructural and data availability constraints.

Pauzi et al. [6] examined the role of artificial intelligence in precision agriculture by reviewing its application in crop monitoring, yield estimation, irrigation scheduling, and disease identification. The authors emphasized that AI-based decision support systems can significantly enhance agricultural efficiency and sustainability. However, the study identified the lack of integrated, real-time deployment frameworks as a key limitation for large-scale practical adoption.

Dolli et al. [7] investigated machine learning-based crop recommendation systems utilizing algorithms such as Support Vector Machines, Random Forests, Decision Trees, and Neural Networks. The findings indicated that analytical crop selection improves agricultural decision-making and productivity. Nevertheless, the effectiveness of these systems is often reduced by inconsistent data quality and limited adaptation to region-specific agricultural conditions.

Jhajharia et al. [8] explored crop yield prediction using a combination of machine learning and deep learning models, including Random Forest, Gradient Boosting, and Long Short-Term Memory networks. The study demonstrated that modelling temporal dependencies enhances prediction accuracy. Despite these improvements, the authors reported challenges related to data scarcity and reduced model generalization across diverse geographical regions.

III. METHODOLOGY

The proposed **AI-Powered Precision Agriculture Advisor** is designed as a modular, web-based decision support system that integrates multiple machine learning and deep learning models to assist farmers in crop planning and management. The system consists of six major components:

- Crop Recommendation using a hybrid ensemble model
- Crop Yield Prediction using ensemble regression
- Plant Disease Detection using deep learning
- Irrigation Planning and Water Optimization
- Market Price Analysis using regression models
- Weather Forecasting using real-time API integration

Each module operates independently while sharing common inputs such as soil parameters, climatic conditions, and location-specific data.

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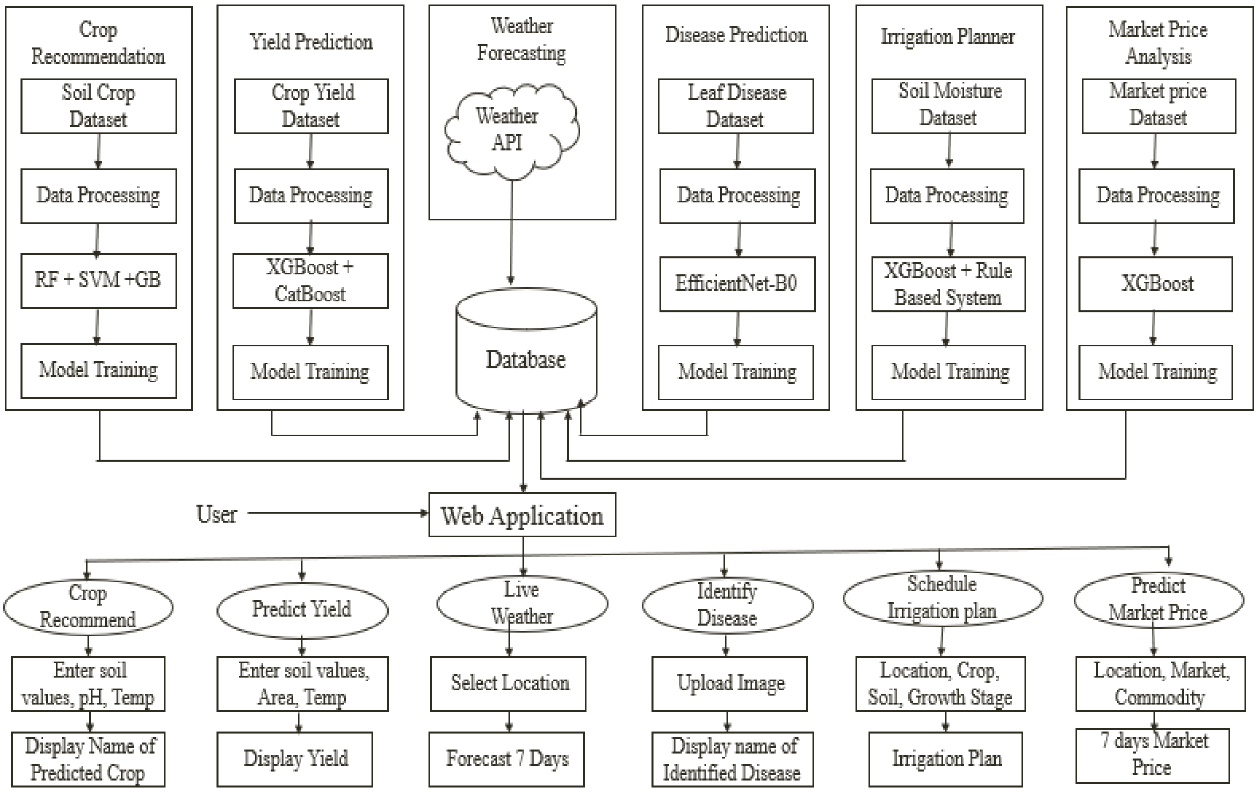

Fig. 1 Workflow of Proposed Model

A. Crop Recommendation Using a Hybrid Ensemble Model

Hybrid Ensemble Model

A hybrid ensemble model is a machine learning approach that improves prediction reliability by combining the outputs of multiple classifiers. By aggregating diverse models, the system benefits from their individual strengths while reducing errors caused by model-specific limitations. Such ensemble techniques are especially effective in agricultural applications where data is complex and non-linear.

In this work, crop recommendation is performed using a hybrid ensemble consisting of Random Forest, Support Vector Machine, and Gradient Boosting algorithms. These models are chosen for their strong performance on structured agricultural data and their ability to model interactions between soil and climate conditions. The dataset includes soil nutrients (N, P, K), pH level, temperature, rainfall, and humidity, along with suitable crop labels, and is divided into 80% for training and 20% for testing to evaluate model performance.

Base Models

Random Forest Classifier

The Random Forest classifier is trained using the training dataset to predict suitable crops based on soil and weather conditions. It consists of multiple decision trees, where each tree independently predicts a crop class. The final prediction is obtained by aggregating the predictions of all trees.

$$Prediction_{RF} = \frac{1}{N}\sum_{i=1}^{N} Tree_i(x)$$

Where

N is the number of decision trees,

Tree $_i$ ***(x)*** represents the prediction of the i^{th} tree for input vector **x**.

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Support Vector Machine

The Support Vector Machine classifier constructs an optimal hyperplane in a high-dimensional feature space to separate different crop classes. Kernel functions are applied to handle non-linear separations between classes.

$$f(x) = w \cdot \phi(x) + b$$

Where
w is the weight vector,
ϕ(x) is the kernel transformation,
b is the bias term.

Gradient Boosting Classifier

The Gradient Boosting classifier builds an additive model by sequentially training weak learners, where each learner focuses on correcting the errors made by previous models.

$$Prediction_{GB} = \sum_{m=1}^{M} \alpha_m h_m(x)$$

where
M is the number of boosting iterations,
a_m is the weight of the m^{th} learner,
$h_m(x)$ is the weak learner prediction for input ***x***.

Ensemble Prediction Using Soft Voting

The final crop recommendation is obtained by averaging the probability outputs of all base classifiers using soft voting.

$$P_{final}(c \mid x) = \frac{1}{3}(P_{RF}(c \mid x) + P_{SVM}(c \mid x) + P_{GB}(c \mid x))$$
$$\hat{c} = \arg\max_{c} P_{final}(c \mid x)$$

where
$\hat{c}$ is the predicted crop class.

The hybrid ensemble model is evaluated using test accuracy and k-fold cross-validation to ensure reliability. Once validated, the trained model is saved for future use, enabling real-time crop recommendations without retraining.

B. Crop Yield Prediction using ensemble regression

Crop yield prediction is essential for estimating agricultural output prior to harvesting and supporting informed planning decisions. In the proposed system, crop yield is predicted using a hybrid ensemble regression approach that combines XGBoost and CatBoost models. These algorithms are selected due to their strong performance on structured agricultural datasets and their ability to model non-linear relationships among features.
The input dataset consists of soil parameters, crop type, and climatic attributes such as temperature, rainfall, and humidity, along with historical yield values. The dataset is pre-processed and divided into 80% training data and 20% testing data. Both regression models are trained independently on the training dataset.

Regression Models

XGBoost Regressor

XGBoost predicts yield by learning additive decision tree models:

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$$Y_{XGB} = \sum_{m=1}^{M} f_m(x)$$

where
$f_m(x)$ is the m^{th} decision tree,
M is the total number of trees.

CatBoost Regressor
CatBoost improves regression accuracy by efficiently handling categorical variables and ordered boosting:

$$Y_{CAT} = f(x;\theta)$$

where
θ represents learned model parameters.

Final Yield Prediction

$$Y_{final} = \frac{Y_{XGB} + Y_{CAT}}{2}$$

C. Plant Disease Detection using deep learning

Convolutional Neural Network Model
Plant disease detection is performed using a deep learning-based image classification approach to enable early identification of crop diseases. The proposed system employs EfficientNet-B0, a lightweight and high-performance convolutional neural network architecture, using transfer learning. The disease detection dataset consists of labelled leaf images belonging to healthy and diseased classes. Images are resized, normalized, and augmented before training. The dataset is divided into training and validation sets to evaluate model performance.

CNN Mathematical Representation

Given an input image *I:*

$$f(I;\theta) \rightarrow z$$

Softmax probability:

$$P(y = k \mid I) = \frac{e^{z_k}}{\sum_{i=1}^{K} e^{z_i}}$$

where
K is the number of disease classes.

D. Irrigation Planner and Water Optimization Module

Hybrid Predictive and Rule-Based Model
Efficient irrigation planning is essential for conserving water and improving crop growth. The proposed irrigation planner integrates XGBoost regression for soil moisture prediction with a rule-based expert system to determine optimal irrigation schedules. The dataset includes soil type, crop type, growth stage, temperature, rainfall, and location-specific parameters. Weather forecasts are fetched dynamically to refine irrigation decisions.

Irrigation requirement

$$IR = ETo - R_f$$

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where
ET_o= evapotranspiration,
R_f= effective rainfall.

E. Market Price Analysis Module

Regression-Based Price Forecasting
Market price volatility directly affects farmer income. This module predicts short-term crop prices using **XGBoost regression models**, trained separately for each commodity and market. Historical market price datasets include commodity name, market location, date, and price values. Data preprocessing includes handling missing values and trend normalization.

Price Prediction Formula

$$\hat{P}_{t+1} = f(P_t, M, C)$$

where
P_t = historical prices,
M = market,
C = commodity.

F. Weather Forecasting Module

API-Based Weather Prediction
Weather forecasting is performed using real-time data integration through the Open-Meteo API. Weather parameters support irrigation, crop recommendation, and yield prediction modules.

Weather Representation

$$W_t = API(L, t)$$

where
W_t represents weather parameters at time t.

IV. SYSTEM EVALUATION AND RESULTS

A. System Evaluation

1) The proposed stacked ensemble **crop recommendation model** achieved an overall accuracy of **99.32%**, indicating highly reliable performance. As shown in **Fig. 2**, the confusion matrix exhibits strong diagonal dominance with minimal misclassification, while most crop classes achieved precision and recall values close to **1.00**, confirming the robustness of the ensemble approach.

Table -1: Model Evaluation Metrics for Crop Recommendation

Model	Accuracy	Precision	Recall	F-1 score
Proposed model	0.9932	0.9926	0.9933	0.9926

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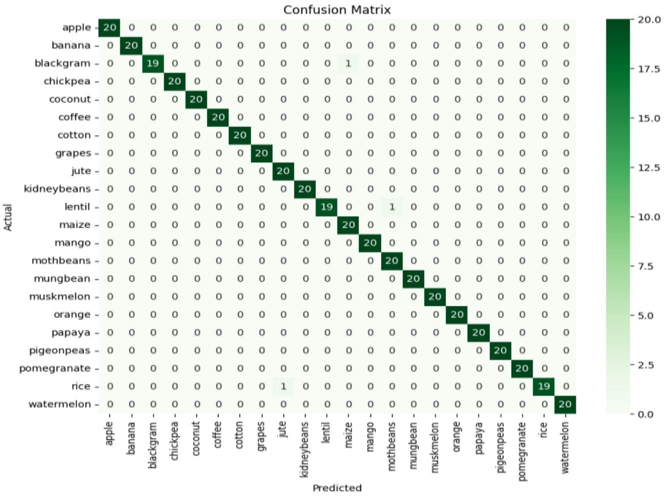

Fig -2 Confusion matrix

2) The **crop yield prediction** module was evaluated using ensemble regression models based on XGBoost and CatBoost. The dataset was split into training (3240 samples), validation (1080 samples), and testing (1080 samples). Model performance was assessed using RMSE, MAE, and R² score. The ensemble models demonstrated superior performance compared to individual regressors, indicating improved prediction accuracy and stability

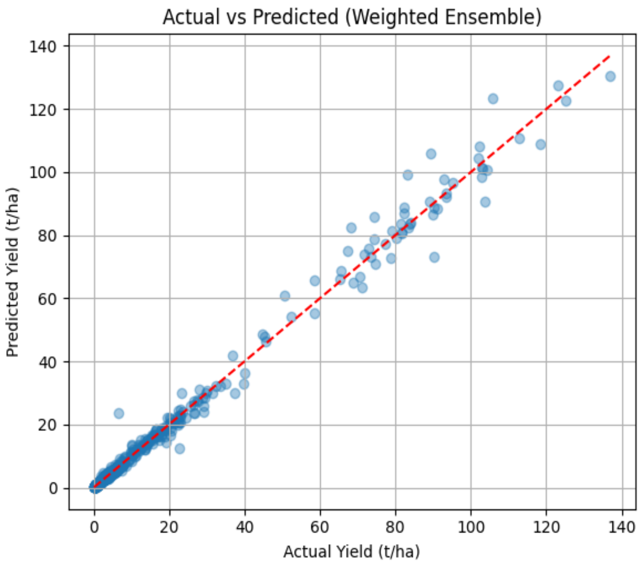

Fig -3 Actual vs Predicted output

Table – 2: Model Evaluation Metrics for Crop Yield Prediction

Model	RMSE	MAE	R^2 Score
XGBoost	2.0602	0.6638	0.9885
CatBoost	1.8357	0.6409	0.9909
Ensemble (Average)	1.7684	0.5845	0.9915
Ensemble (Weighted)	1.7681	0.5845	0.9915

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3) The performance of the **plant disease detection** module was evaluated using standard classification metrics. The deep learning model achieved high accuracy with low loss values on both training and testing datasets, indicating effective learning and good generalization capability.

Table – 3: Model Evaluation Metrics for Disease Detection

Model	Accuracy	Loss
Training	0.9867	0.0383
Testing	0.9865	0.0400

4) The **irrigation planner** module utilizes a time-series forecasting approach to support water management decisions. A global XGBoost regression model was trained using cleaned and daily reindexed historical data collected across Karnataka. The model achieved a low prediction error, indicating reliable forecasting performance. District-wise forecasts were generated from the current date onwards to support location-specific irrigation planning.

Table – 4: Model Evaluation Metrics for Irrigation Planner

Model	Metric	Value
XGBoost	RMSE	1.569

B. Results

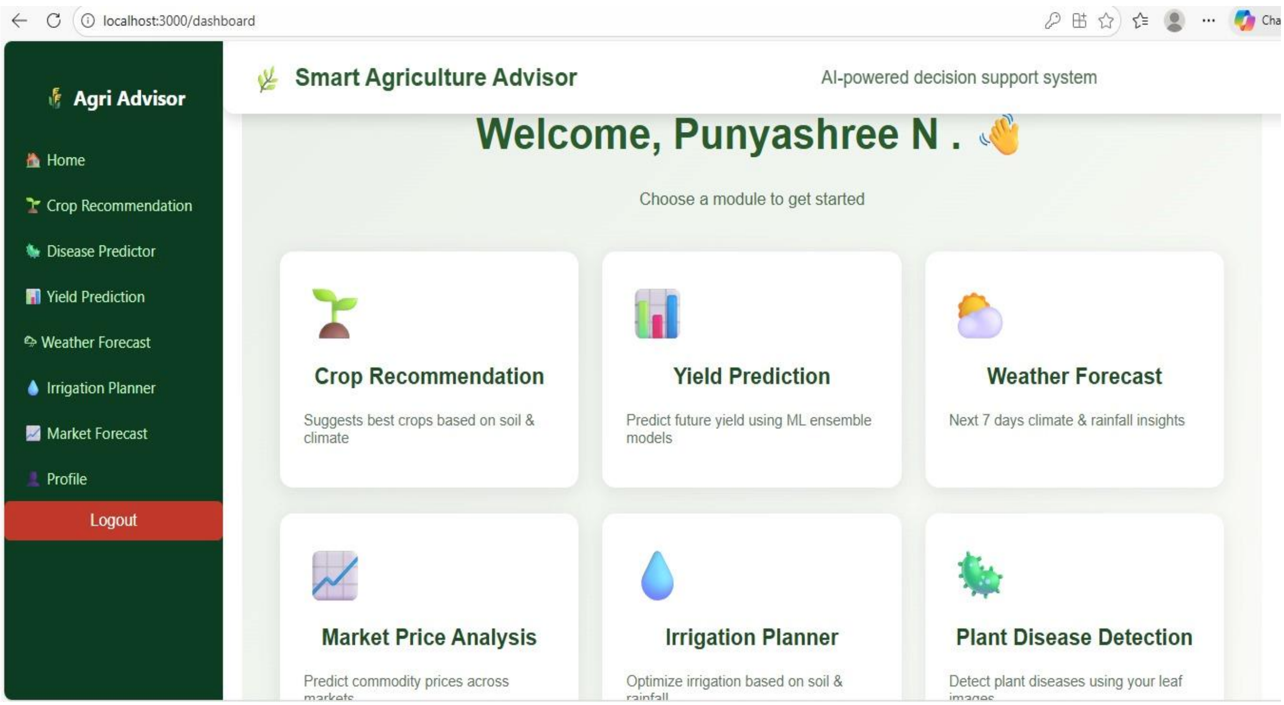

Fig -4 Dashboard of Proposed Model

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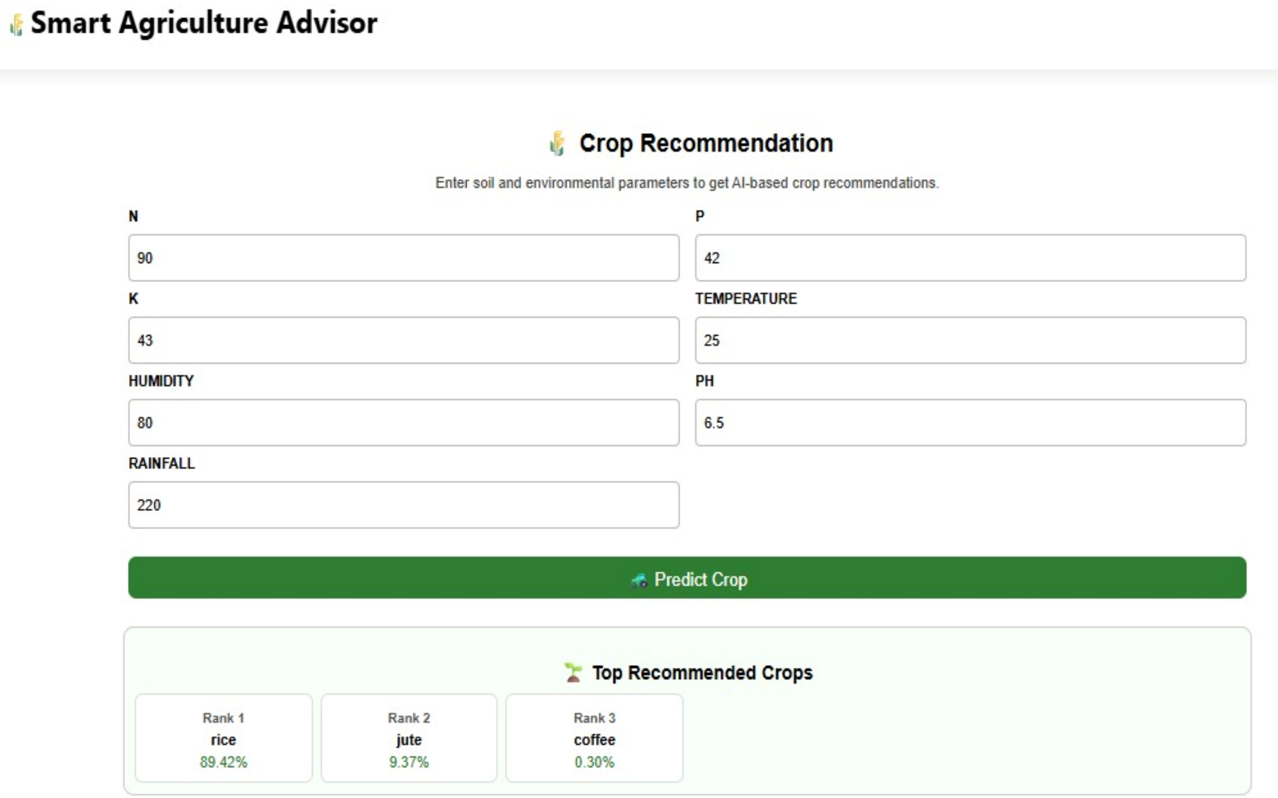

Fig -5 Crop Recommendation Module

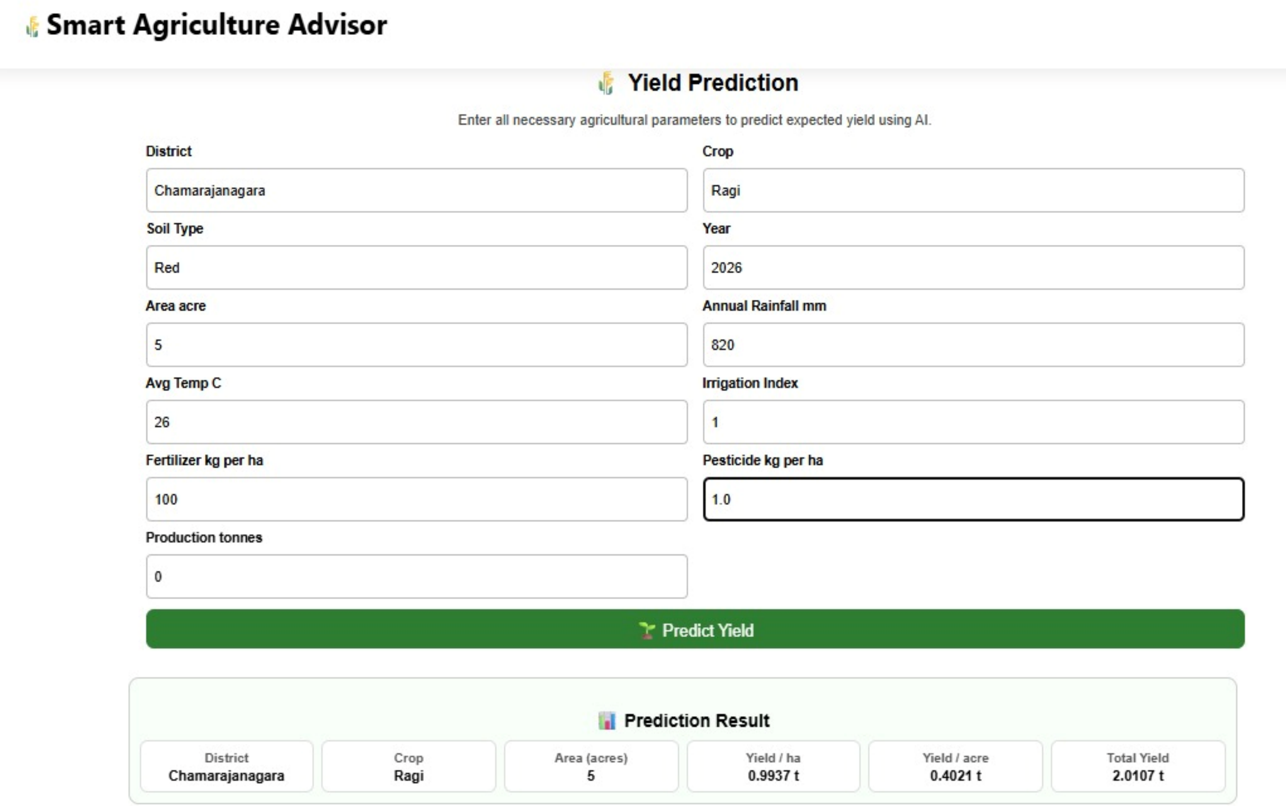

Fig -6 Yield Prediction Module

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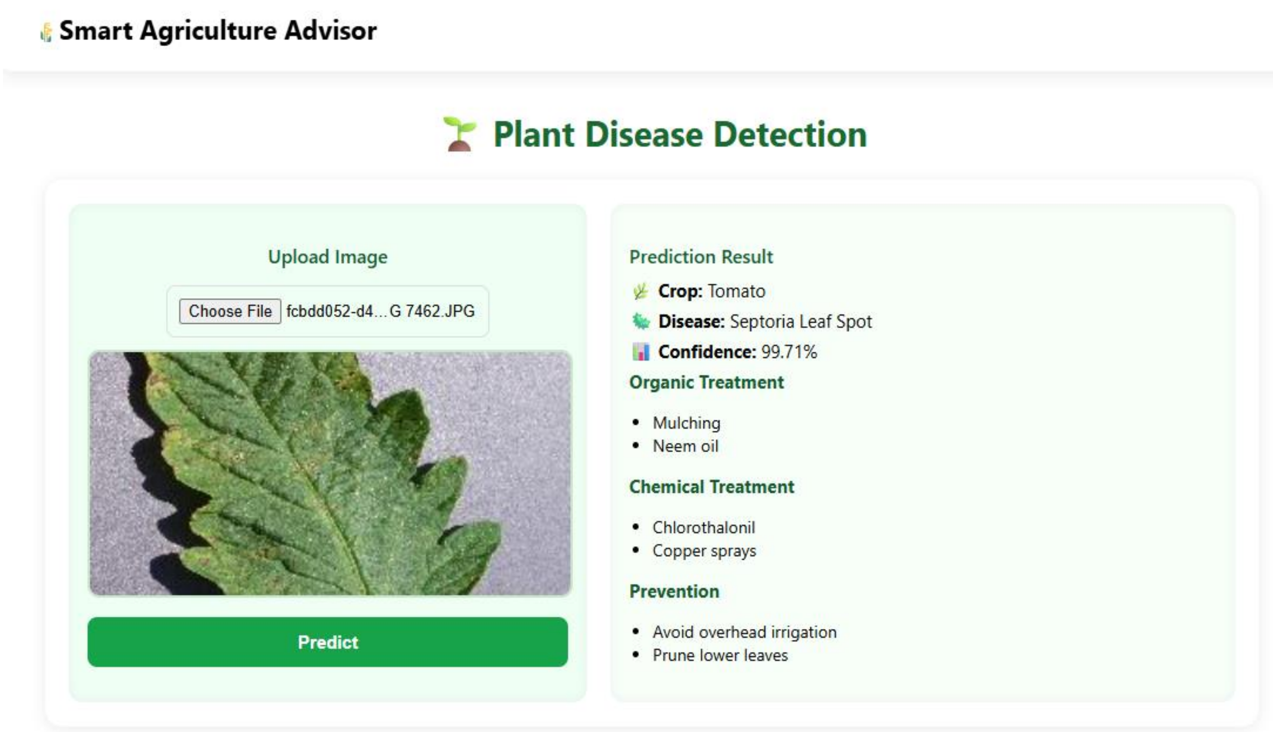

Fig -7 Disease Detection Module

Fig -8 Market Price Analysis

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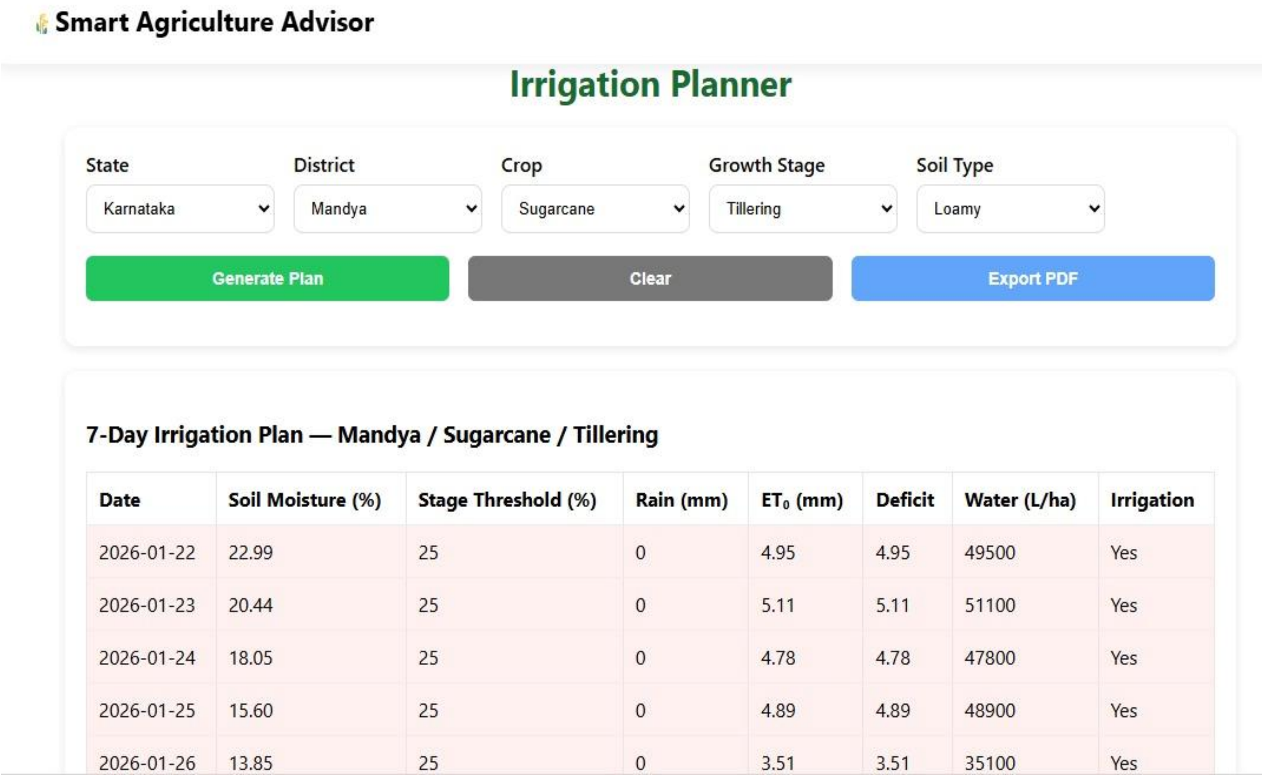

Fig -9 Irrigation and Water Optimization Module

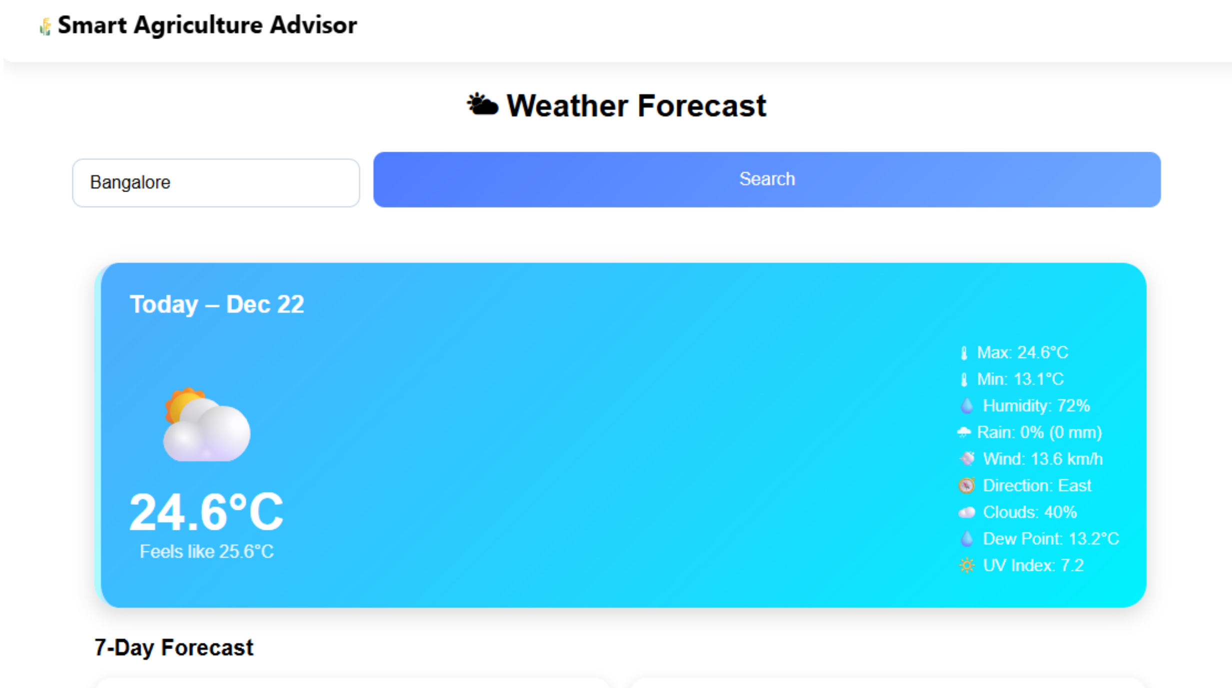

Fig -10 Weather Forecast Module

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V. CONCLUSION

This research presented an AI-Powered Precision Agriculture Advisor that integrates crop recommendation, yield prediction, plant disease detection, irrigation planning, market price analysis, and weather forecasting within a unified web-based platform. By leveraging ensemble machine learning models for structured agricultural data and deep learning techniques for image-based disease detection, the system provides accurate and actionable decision support for farmers. Experimental evaluation confirmed that the integrated approach improves prediction reliability and supports efficient resource utilization, while the inclusion of real-time weather data enhances advisory accuracy for crop planning and irrigation management. The proposed system offers a scalable and cost-effective solution for precision agriculture, particularly suited for small and medium-scale farming environments. In future work, the platform can be extended by incorporating IoT-based soil and environmental sensors, mobile and regional language support, satellite imagery, and advanced time-series forecasting models, along with large-scale field deployment to further improve accuracy, automation, and real-world applicability.

REFERENCES

[1] R. Kamduri and A. Gupta, “Smart Agriculture Advisor: A Machine Learning Approach to Precision Farming,” *International Journal of Advanced Computer Science and Applications*, vol. 16, no. 3, pp. 245–252, 2025.

[2] A. Aryan, S. Mehta, and R. Sharma, “AI-Powered Integrated Platform for Farmer Support: Real-Time Disease Diagnosis and Precision Irrigation Advisory,” *Journal of Intelligent Agriculture Systems*, vol. 7, no. 2, pp. 110–120, 2025.

[3] P. Iniyan, R. Kumar, and S. Prakash, “Crop Yield Prediction Using Machine Learning Techniques,” *International Journal of Engineering Research & Technology (IJERT)*, vol. 12, no. 4, pp. 85–90, 2023.

[4] X. Li, Y. Zhang, and Z. Wang, “Plant Disease Detection and Classification Using Deep Learning: A Review,” *Computers and Electronics in Agriculture*, vol. 198, pp. 107016, 2023.

[5] M. Krishna, R. Patel, and A. Verma, “Artificial Intelligence for Precision Agriculture and Water Management,” in *Advances in Smart Farming Technologies*, Springer, 2025, pp. 45–60.

[6] N. Pauzi, H. Abdullah, and A. Rahman, “Artificial Intelligence in Precision Agriculture: A Review,” *Sustainable Computing: Informatics and Systems*, vol. 39, pp. 100742, 2025.

[7] R. Dolli, S. Patil, and V. Kulkarni, “An Analysis of Crop Recommendation Systems Using Machine Learning Techniques,” *International Journal of Computer Applications*, vol. 184, no. 25, pp. 15–20, 2023.

[8] S. Jhajharia, P. Singh, and R. K. Verma, “Crop Yield Prediction Using Machine Learning and Deep Learning Techniques,” *International Journal of Agricultural Data Science*, vol. 5, no. 1, pp. 30–38, 2023.

[9] S. Roy, A. Das, and P. Mukherjee, “Machine Learning Techniques for Precision Agriculture and Crop Yield Optimization,” *IEEE Access*, vol. 11, pp. 45812–45825, 2023.

[10] A. Priyanka, N. Reddy, and S. Rao, “AgriBot: An AI-Driven Crop Recommendation and Disease Prediction System,” *International Journal of Advanced Research in Computer Engineering & Technology*, vol. 14, no. 2, pp. 95–101, 2025.

[11] M. Shaari, N. Hassan, and R. Ahmad, “Recent Trends and Challenges in Precision Agriculture,” *Journal of Agriculture and Food Research*, vol. 12, pp. 100624, 2024.

[12] H. Patel and K. Singh, “Weather-Based Crop Advisory Systems Using Machine Learning,” *International Journal of Agricultural Informatics*, vol. 9, no. 3, pp. 41–48, 2023.