

AI-POWERED CROP YIELD PREDICTION AND OPTIMIZATION

¹ Dr. D. Shanthi, ² A.Ruthika, ³ D.Trishitha, ⁴ Y.Sai Priya, ⁵ S.Hindu

¹ Professor, HOD, IT ^(2,3,4) B. Tech 4th year Student, IT, Vignan's Institute of Management and Technology for Women, Hyderabad, India.

drshanthicse@gmail.com, alaneruthika25@gmail.com, trishithadubbaka@gmail.com,
yamasanisaiPriya1@gmail.com, hindusanugula@gmail.com

Abstract:

Agriculture faces increasing challenges due to climate variability, plant diseases, soil degradation, and inefficient resource utilization, necessitating intelligent data-driven solutions for sustainable food production. This work presents an AI-powered agricultural prediction framework that integrates plant disease detection, crop recommendation, yield prediction, rainfall/climate analysis, and soil moisture estimation using machine learning, deep learning, ensemble learning, and explainable AI techniques. For plant disease prediction, deep convolutional neural networks including ResNet50, VGG16, Xception, NASNet, and a hybrid ensemble model are employed with extensive image augmentation. Crop recommendation is addressed using Random Forest, Decision Tree, KNN, XGBoost, AdaBoost, and a Voting Classifier. Yield prediction, rainfall/climate analysis, and soil moisture estimation are modeled using both classification and regression approaches with the same set of ensemble-based algorithms. Explainable AI techniques such as SHAP, LIME, and Grad-CAM are utilized to enhance transparency and interpretability of predictions. Experimental evaluation demonstrates that the Voting Classifier achieves superior performance for crop recommendation with an accuracy of 98.6%. Yield prediction shows the best performance using a voting-based ensemble regressor with an R^2 score of 91.3%. Soil moisture prediction attains high accuracy using a Voting ensemble model with 97.7% performance. Plant disease detection achieves 99.8% accuracy using a hybrid deep learning ensemble, while rainfall analysis is effectively handled using a Voting Classifier. The integrated framework supports precise decision-making for crop management, irrigation scheduling, and disease control.

Keywords: Artificial Intelligence, Crop Recommendation, Plant Disease Detection, Yield Prediction, Soil Moisture Estimation, Rainfall Analysis, Ensemble Learning, Explainable AI.

I. INTRODUCTION

Agriculture remains the backbone of global food security and rural livelihoods, yet it is increasingly constrained by climate variability, declining soil health, water scarcity, and rising pest and disease pressure. Traditional farming practices often rely on experience-

driven decisions, which are insufficient to manage the growing complexity of modern agricultural ecosystems. Recent studies emphasize that sustainable productivity requires intelligent, data-centric approaches capable of handling spatial, temporal, and environmental variability across farms. The shift toward technology-assisted agriculture is therefore essential to ensure long-term food availability and economic stability.

The rapid advancement of artificial intelligence has opened new possibilities for addressing these challenges by enabling accurate prediction, monitoring, and optimization of agricultural activities. AI-driven systems can process large volumes of heterogeneous agricultural data and extract meaningful patterns that are not easily observable through conventional analysis. Such capabilities are particularly valuable in crop production, where decisions related to crop selection, disease control, and irrigation timing directly influence yield and resource efficiency. The integration of explainable and interpretable AI further strengthens trust in intelligent decision support by clarifying how predictions are generated.

Plant disease identification has emerged as a critical application area, as delayed or inaccurate diagnosis can lead to severe yield losses and excessive chemical usage. Vision-based AI approaches allow early detection of diseases, supporting timely intervention and improved crop quality. In parallel, crop recommendation and yield prediction techniques assist farmers in selecting suitable crops and anticipating production outcomes based on environmental and soil conditions, which is vital for planning and market alignment. These predictive insights are complemented by rainfall and soil moisture analysis, which play a central role in irrigation scheduling and climate-resilient farming practices.

Recent research highlights that machine learning regression and classification models significantly enhance the accuracy of yield estimation and climatic assessment when compared to statistical approaches. The convergence of AI with automation, sensing technologies, and intelligent platforms further amplifies agricultural efficiency and scalability. Advanced frameworks combining spatial data, predictive modeling, and real-time analysis demonstrate the potential for precision farming at regional and field levels. Moreover, AI-driven agricultural systems contribute beyond production, influencing supply chains and sustainability-oriented decision-making.

The main objective is to develop an integrated AI-enabled agricultural solution that supports plant disease identification, crop recommendation, yield estimation, rainfall assessment, and soil moisture analysis within a unified framework. The aim is to enhance decision accuracy, optimize resource utilization, and promote sustainable farming practices by leveraging intelligent data analysis and predictive capabilities across multiple agricultural dimensions.

II. RELATED WORK

Recent research highlights the transformative role of artificial intelligence in advancing sustainable and precision agriculture through intelligent resource optimization and data-driven decision support. Padhiary et al. emphasize how AI techniques enable precise monitoring of land, water, and crop conditions, allowing farmers to optimize resource usage while maintaining environmental sustainability. Their work shows that intelligent systems can significantly reduce wastage and improve productivity in modern agricultural ecosystems. Avasthi et al. focus on the adoption of AI-powered agricultural practices in developing regions, where resource constraints and climatic uncertainty pose major challenges. The study explains how intelligent automation supports sustainable farming by improving efficiency, minimizing manual intervention, and enabling adaptive agricultural practices suited to local conditions.

The integration of AI with renewable energy systems in agriculture is explored by Akanbi et al., who demonstrate the effectiveness of AI-powered solar irrigation systems for optimizing water resource management. Their findings indicate that intelligent control mechanisms can balance water demand and energy availability, leading to sustainable irrigation practices and reduced operational costs. Hossain et al. discuss the broader smart farming revolution driven by AI-based solutions that enhance productivity, profitability, and sustainability. The study highlights how intelligent monitoring and predictive systems support farmers in making timely decisions, thereby improving crop health and overall farm performance.

Padhiary and Kumar examine the evolution of smart farming through AI vision and machine learning technologies. Their work illustrates how intelligent visual analysis supports crop monitoring, disease detection, and yield estimation, contributing to more efficient and responsive agricultural management systems. Advancements in crop improvement are addressed by Chen et al., who analyze the application of artificial intelligence in gene editing and crop breeding. The study shows how intelligent modeling and prediction accelerate innovation in crop development, enabling improved resilience and productivity under varying environmental conditions.

Messina et al. propose a general framework for AI-enabled prediction in crop improvement, emphasizing the importance of scalable and adaptable intelligent systems. Their work demonstrates how predictive intelligence supports better planning and decision-making across diverse agricultural scenarios. The role of big data analytics

combined with artificial intelligence is examined by Nimma et al., who focus on optimizing crop yields in sustainable agriculture. Their research indicates that intelligent data analysis enhances the understanding of complex agricultural patterns, leading to improved yield outcomes and resource efficiency.

Kaya explores plant phenomics and high-throughput phenotyping supported by AI in controlled environments. The study highlights how intelligent phenotyping systems enable precise observation of plant traits, supporting optimized crop production and sustainable farming practices. Finally, Fu et al. provide a comprehensive survey of AI applications in agricultural energy systems, highlighting the convergence of intelligence, energy management, and agriculture. Their work underscores the growing importance of AI in building efficient, sustainable, and interconnected agricultural energy ecosystems.

III. MATERIALS AND METHODS

The proposed system introduces an integrated AI-driven framework for precision agriculture that simultaneously addresses plant disease identification, crop type classification, yield estimation, rainfall and climate prediction, and soil moisture assessment. Deep learning-based convolutional neural networks such as ResNet, VGG16, Xception, and NASNet are proposed for automated plant disease detection from leaf images, improving early diagnosis and crop protection. For crop type recognition, yield prediction, rainfall analysis, and soil moisture estimation, machine learning algorithms including Random Forest, Decision Tree, K-Nearest Neighbors, XGBoost, AdaBoost, and ensemble voting models are employed to capture complex relationships among agricultural parameters. The system further incorporates intelligent resource and irrigation insights by aligning predictive outputs with sustainable farming objectives. By unifying multiple predictive models within a single framework, the proposed approach aims to deliver accurate, scalable, and data-driven decision support for efficient crop management, risk mitigation, and sustainable agricultural productivity.

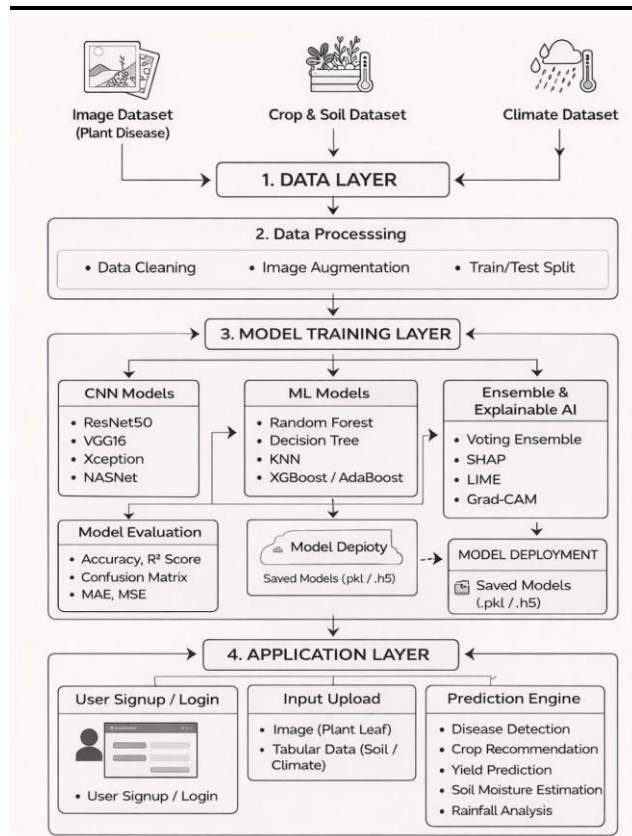


Fig.1 System Architecture

Fig.1 illustrates a machine learning workflow for agricultural analysis. It details a pipeline where raw Dataset inputs undergo Pre-processing and Data Augmentation before being split into Train and Test sets to evaluate diverse deep learning and ensemble models.

A) Dataset Collection:

The dataset collection we used includes five diverse agricultural data sources gathered from publicly available and reliable repositories. Plant disease images were collected from the Plant Village dataset, which contains labeled leaf images representing multiple crops and disease categories under varied conditions. Crop recommendation data was obtained from a Kaggle repository consisting of soil, climate, and nutrient attributes associated with suitable crop types. Crop yield data was sourced from an agriculture yield dataset containing historical records across regions and seasons. Rainfall and climate data were collected from government and research portals, providing temporal rainfall measurements and climatic indicators. Soil moisture data was acquired from Kaggle sources that include soil properties and moisture-related attributes. These datasets together support comprehensive agricultural analysis.

B) Pre-Processing:

Pre-processing prepares raw agricultural data for reliable analysis by improving quality, consistency, and usability. It

removes noise, handles missing values, standardizes formats, and ensures that inputs are suitable for accurate learning and prediction tasks.

Pre-processing for Plant Disease Detection: In this it focuses on enhancing image quality and uniformity before analysis. Leaf images are resized to a fixed dimension to maintain consistency across inputs. Pixel values are normalized through rescaling to improve numerical stability. Image augmentation techniques such as rotation, zooming, shearing, and horizontal flipping are applied to increase data diversity and reduce bias. Noise and irrelevant background variations are minimized to highlight disease patterns. Images are reshaped into suitable tensor formats, enabling efficient learning while improving generalization across different lighting conditions, leaf orientations, and disease severity levels.

Pre-processing for Crop Data: Crop data pre-processing begins with cleaning structured records to remove duplicates and inconsistencies. Missing or invalid entries are handled to ensure data reliability. Categorical attributes such as soil type and crop labels are transformed into numerical representations using encoding techniques. Feature values are standardized or normalized to maintain uniform scales. Data balancing is performed to avoid dominance of specific crop classes. Visualization techniques help identify outliers and trends, supporting informed cleaning decisions. These steps ensure that crop-related inputs are consistent, unbiased, and suitable for accurate classification and recommendation tasks.

Pre-processing for Yield Data: Yield data pre-processing focuses on preparing historical agricultural records for accurate prediction. Duplicate entries and irrelevant records are removed to reduce redundancy. Missing values in climatic or production attributes are treated to maintain completeness. Categorical variables such as region and season are converted into numerical form. Numerical features are normalized to handle variations in scale. Visualization assists in detecting outliers and abnormal yield values. The cleaned and transformed dataset ensures that yield-related patterns are preserved, allowing meaningful relationships between environmental factors and production outcomes to be effectively learned.

Pre-processing for Rainfall Data: Rainfall data pre-processing involves organizing temporal and numerical climate records for consistency. Duplicate rows and incomplete entries are eliminated to improve data quality. Continuous rainfall values may be categorized into meaningful levels such as low, medium, and high for classification tasks. Categorical fields are encoded into numerical formats. Feature scaling is applied to manage variations in measurement ranges. Visualization techniques help analyze seasonal trends and detect anomalies. These steps ensure structured, balanced, and noise-free rainfall data that supports both categorical and continuous climate analysis.

Pre-processing for Soil Moisture Data: Soil moisture pre-processing focuses on cleaning and structuring soil-related measurements. Redundant and inconsistent records are removed to avoid bias. Missing values in soil attributes are treated appropriately to maintain continuity. Categorical soil properties are encoded numerically, while numerical features are normalized to ensure uniform scales. Visualization assists in identifying outliers and irregular moisture patterns. Feature selection may be applied to retain relevant soil characteristics. The resulting dataset becomes consistent and reliable, enabling accurate estimation of moisture levels under varying soil and environmental conditions.

Train and Test Split: The train and test process divides the prepared dataset into two independent subsets to evaluate learning performance objectively. The training set is used to learn patterns and relationships from the data, while the testing set assesses generalization on unseen samples. A common split ratio ensures sufficient data for learning without compromising evaluation reliability. Randomized splitting helps prevent bias and data leakage. This separation enables fair performance assessment, supports comparison across different models, and ensures that predictions reflect real-world behavior rather than memorization of input records.

C) Algorithms:

Plant Disease Detection:

ResNet: ResNet is a deep convolutional network using residual connections to prevent vanishing gradients. It learns hierarchical leaf features from textures to complex disease patterns, enabling accurate plant disease classification while remaining robust to lighting, rotation, and background variations.

VGG16: VGG16 is a deep convolutional network with sixteen layers using small filters. It extracts detailed visual features such as edges, shapes, and lesions from leaf images, enabling consistent and reliable classification of plant diseases across large and diverse datasets.

Xception: Xception employs depthwise separable convolutions to efficiently extract spatial and channel-wise features. It captures subtle disease textures and shapes in leaf images with reduced computation, offering high accuracy, strong generalization, and faster training for complex plant disease datasets.

NasNet: NasNet uses neural architecture search to automatically design optimal convolutional cells. It captures multi-scale disease features from plant leaves, adapts effectively to diverse datasets, and generalizes well across crop varieties, lighting conditions, and image orientations.

Hybrid Model: Hybrid models combine two deep networks to exploit complementary feature strengths. By merging detailed textures and high-level representations, they improve disease classification accuracy, reduce

misclassification of visually similar diseases, and enhance robustness across unseen plant images.

Crop, Yield, Rainfall/Climate, Soil Moisture:

Random Forest: Random Forest is an ensemble of decision trees trained on random samples and feature subsets. It handles non-linear agricultural data effectively, reduces overfitting, and provides reliable predictions for crop selection, yield estimation, rainfall analysis, and soil moisture assessment.

Decision Tree: Decision Tree models split data hierarchically using feature thresholds to form interpretable rules. They handle numerical and categorical agricultural features, capture non-linear relationships, and clearly explain how environmental and soil factors influence crop, yield, and moisture predictions.

K-Nearest Neighbors: K-Nearest Neighbors predicts outcomes based on similarity between feature vectors. It captures local patterns in agricultural data without assumptions, making it effective for estimating crops, yield, rainfall, and soil moisture under closely related environmental conditions.

XGBoost: XGBoost is a gradient boosting technique that builds sequential trees to correct previous errors. It handles missing values, models complex non-linear relationships, reduces overfitting through regularization, and delivers highly accurate predictions for agricultural and climatic datasets.

AdaBoost: AdaBoost combines weak learners sequentially by emphasizing misclassified instances. It improves prediction accuracy for crop, yield, rainfall, and soil moisture tasks, adapts well to noisy agricultural data, and highlights influential features affecting model performance.

Voting Classifier: Voting Classifier aggregates predictions from multiple models using majority voting or averaging. It reduces individual model bias, improves stability, and delivers robust, accurate predictions across crop recommendation, yield estimation, rainfall classification, and soil moisture prediction tasks.

D) Integration of XAI & Flask:

Explainable Artificial Intelligence is integrated to improve transparency and interpretability of predictions generated from both tabular and image inputs. LIME and SHAP are used to explain feature influence in structured predictions such as crop, yield, rainfall, and soil moisture, while Grad-CAM visually highlights critical regions in plant images. These explanations help users understand decision reasoning, validate outputs, and build trust by linking predictions to observable data characteristics and real-world agricultural factors.

Flask is integrated as the web interface to connect trained models with end users in an interactive manner. It

manages user authentication, input handling, preprocessing, and result visualization. The framework ensures smooth communication between backend intelligence and frontend presentation, enabling real-time predictions, clear result display, and user-friendly access to agricultural insights.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall * Precision}{Recall + Precision} * 100 (SEQ "equation" \n \ * MERGEFORMAT 4)$$

Table.1 Performance Evaluation Table – Crop Recommendation

ML Model	Accuracy	Precision	Recall	F1-Score
RF	0.918	0.944	0.918	0.912
DT	0.845	0.868	0.845	0.804
KNN	0.970	0.974	0.970	0.970
XGBoost	0.934	0.948	0.934	0.930
AdaBoost	0.832	0.848	0.832	0.794
Voting Classifier	0.986	0.987	0.986	0.986

Table.1 presents comparative performance metrics of machine learning models for crop recommendation accuracy.

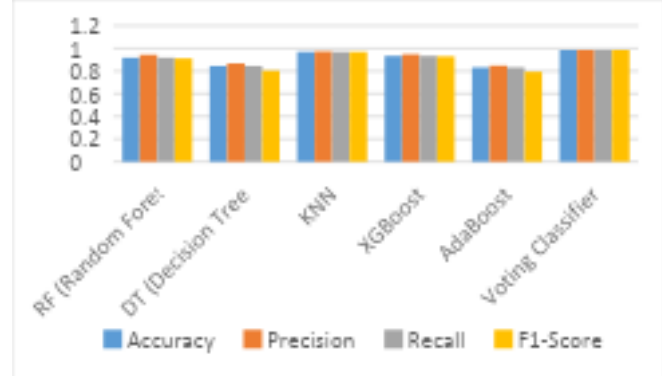


Fig.2 Comparison Graph – Crop Recommendation

Fig.2 compares performance metrics for various crop recommendation models.

Table.2 Performance Evaluation Table – Yield Prediction

ML Model	MSE	RMSE	MAE	R2-Score
Random Forest	1.037	1.018	0.828	0.640
Decision Tree	0.692	0.832	0.681	0.760
KNN	1.162	1.078	0.875	0.597
XGBoost	0.824	0.908	0.734	0.714
AdaBoost	0.573	0.757	0.614	0.801
Voting (LGBM+GBR)	0.251	0.501	0.400	0.913

Table.2 summarizes regression performance of yield prediction models using error metrics and R2-score.

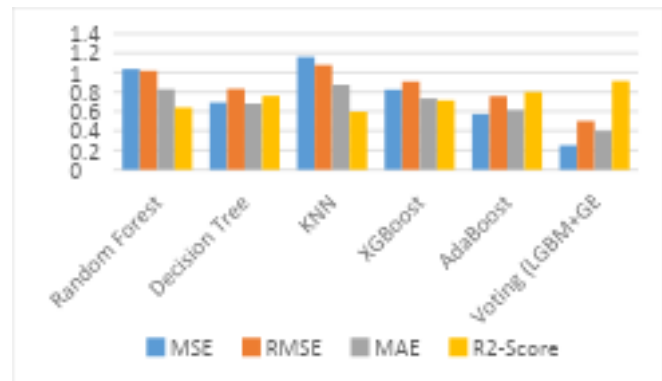


Fig.3 Comparison Graph – Yield Prediction

Fig.3 compares evaluation metrics for diverse crop yield prediction models.

Table.3 Performance Evaluation Table – Soil Moisture Prediction

ML Model	MSE	RMSE	MAE	R2-Score
Random Forest	0.013	0.114	0.061	0.913
Decision Tree	0.014	0.119	0.061	0.905
KNN	0.015	0.124	0.058	0.897
XGBoost	0.005	0.072	0.035	0.965
AdaBoost	0.007	0.082	0.044	0.955

Voting (LGBM+GBR)	0.003	0.058	0.027	0.977
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Table.3 highlights soil moisture prediction performance across models using regression evaluation metrics.

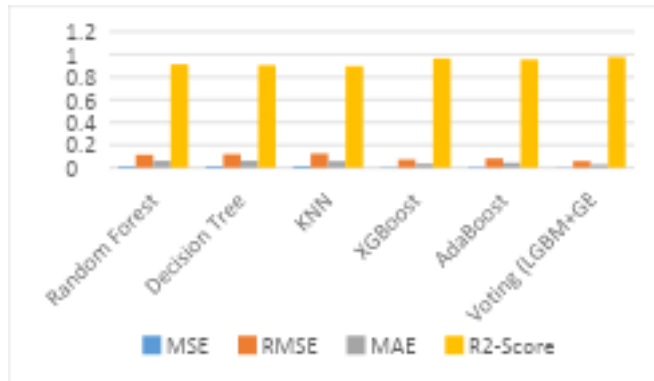


Fig.4 Comparison Graph – Soil Moisture Prediction

Fig.4 displays performance metrics for several soil moisture prediction models.

Table.4 Performance Evaluation Table – Plant Disease Detection

ML Model	Accuracy	Precision	Recall	F1-Score
ResNet50	0.998	0.998	0.997	0.998
VGG16	0.014	0.034	0.014	0.009
Xception	0.911	0.953	0.911	0.922
NASNetLarge	0.482	0.541	0.485	0.473
Hybrid-Ensemble	0.998	0.998	0.998	0.998

Table.4 compares deep learning models performance for accurate plant disease classification.

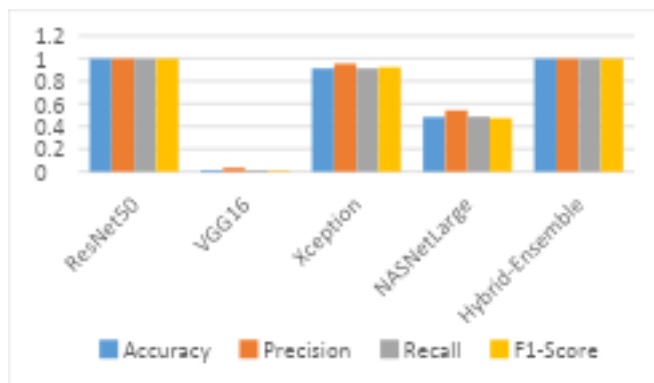


Fig.5 Comparison Graph – Plant Disease Detection

Fig.5 presents performance metrics for various plant disease detection models.

V. CONCLUSION

This work demonstrates the effectiveness of integrating artificial intelligence and ensemble learning techniques to support data-driven, climate-smart agricultural decision-making. By combining machine learning, deep learning, and explainable AI, the system delivers reliable predictions

across multiple critical farming tasks, enabling farmers and stakeholders to improve productivity, reduce risk, and optimize resource utilization. The outcomes highlight that ensemble-based approaches consistently outperform individual models by leveraging the strengths of multiple algorithms, resulting in higher accuracy, robustness, and generalization across diverse agricultural datasets. For crop recommendation, the Voting Classifier achieves superior performance with an accuracy of 98.6%, ensuring accurate crop selection based on soil and climatic conditions. Yield prediction attains strong predictive capability using a Voting-based ensemble regressor, achieving an R^2 score of 91.3%, supporting effective planning and market forecasting. Soil moisture prediction records high reliability with the Voting ensemble model, reaching 97.7% accuracy, which is crucial for precision irrigation and water conservation. Plant disease prediction shows exceptional performance using a hybrid deep learning ensemble model, achieving 99.8% accuracy, enabling early detection and timely intervention to minimize crop losses. Rainfall analysis is effectively handled using a Voting Classifier, providing stable and reliable predictions for weather-aware farming decisions. Overall, the outcomes validate that AI-driven ensemble models can significantly enhance agricultural intelligence, contributing to sustainable farming practices, improved yields, and resilience against climatic uncertainties.

Future advancements in intelligent agriculture can focus on integrating real-time multisource data from IoT sensors, satellite imagery, and UAVs to improve the timeliness and accuracy of agricultural predictions. Incorporating advanced deep learning architectures such as transformers and graph neural networks can enhance the modeling of complex spatial-temporal relationships among soil, weather, and crop parameters. Greater emphasis on Explainable AI can improve transparency and trust by providing farmer-friendly insights and decision justifications. Expanding models to support region-specific adaptability and multilingual advisory systems will improve accessibility for diverse farming communities. Additionally, deploying lightweight and edge-based AI solutions can enable real-time decision support in resource-constrained and remote agricultural environments.

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