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AgroAdviser: A Multi-Model Framework Integrating DeepFM with Random Forest and Gradient Boosting for Smart Crop Yield and Fertilizer Prediction

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***Abstract*— AgroAdvisor integrates crop yield prediction, crop recommendation, and fertilizer recommendation using a hybrid Random Forest with Extreme Gradient Boosting (RFXGB) and Deep Factorization Machine (DeepFM) approach. By analyzing historical data, soil conditions, and weather patterns, it enhances decision-making with high accuracy. RFXGB ensures efficient feature selection, while DeepFM captures complex feature interactions, outperforming traditional models like SVM, XGBoost, and ANN. The system provides actionable insights for optimal crop selection, yield forecasting, and fertilizer application, improving productivity and sustainability. Its modular design allows seamless integration of features like weather forecasting and pest control, ensuring scalability and adaptability for modern agriculture.**

***Index Terms*— AgroAdvisor, Crop Yield Prediction, Crop Recommendation, Fertilizer Recommendation, Random Forest Extreme Gradient Boosting (RFXGB), Deep Factorization Machine (DeepFM), Machine Learning in Agriculture, Precision Agriculture.**

I. INTRODUCTION

Agriculture is a crucial pillar of India's economy and employment, playing a vital role in economic growth. With globalization, the sector has undergone significant changes, yet many farmers still face challenges in selecting crops suitable for their soil. Poor crop selection negatively impacts productivity, leading to declining yields, food shortages, and even contributing to farmer distress. Additionally, improper use of technology and excessive reliance on hybrid crops have deteriorated soil quality. Continuous cultivation on the same land depletes soil nutrients, while excessive fertilizer use further erodes soil health. Studies suggest that using fertilizers in recommended amounts can enhance crop yields by 10%–20% compared to traditional farming practices [21]. Ensuring sustainable agricultural practices and proper crop selection is essential for maximizing productivity and maintaining soil health.

Agriculture relies on predicting the most suitable crops, selecting appropriate fertilizers, and estimating crop yield based on environmental factors. In recent years, machine learning and deep learning have become essential tools in this process.

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With the rise of data science and technology, the agriculture sector can greatly benefit from advanced analytical methods [20]. Two key techniques, feature selection and classification, play a crucial role. Feature selection extracts the most relevant attributes from a dataset to enhance classification performance, which is vital in machine learning applications. The primary objective of this work is to develop a recommendation system that ensures accurate crop selection, enhances productivity, and minimizes incorrect crop choices. By recommending harvesting strategies before sowing, the system helps farmers make informed decisions, leading to better agricultural outcomes.

This study introduces AgroAdvisor, a hybrid machine learning and deep learning-based crop recommendation system for farmers. While previous research has utilized Random Forest (RF) for crop yield prediction and fertilizer recommendation, comparisons with other models have been common. Researchers have also explored the performance differences between classical machine learning and deep learning models for crop yield prediction. However, no existing study has analyzed the impact of applying Random Forest with Boosting (RFGB) to the DeepFM input layer's weight and bias or examined their intrinsic relationship. This work develops a hybrid RFGB-DeepFM model, demonstrating how integrating RFGB into DeepFM enhances the accuracy of crop yield prediction, crop selection, and fertilizer recommendations.

The AgroAdvisor system, implemented using the RFXGB-DeepFM technique, focuses on three key agricultural areas:

Crop Recommendation: Suggests the most suitable crop based on environmental conditions to enhance productivity.

Fertilization Recommendation: Identifies the optimal fertilizer and its application timing for improved growth.

Crop Yield Prediction: Estimates the total yield of a crop based on environmental factors.

Performance Evaluation: Compares AgroAdvisor's accuracy and error rate with existing models to assess its effectiveness.

II. Literature Survey

Y. Jeevan et al. [3] developed a crop yield prediction system using Decision Tree (DT) and Random Forest (RF), incorporating environmental factors like soil pH, temperature, and humidity. Their results showed that RF outperformed DT, offering better accuracy and reducing overfitting. Reddy et al. [4] designed a mobile application for crop yield prediction, comparing Logistic Regression (LR), Naïve Bayes (NB), and RF, achieving 87.8%, 91.5%, and 92.81% accuracy, respectively. Based on these results, RF was selected for implementation. The system, built using an API platform, takes inputs like temperature, rainfall, and humidity to analyze patterns and predict yield.Nigam et al. [5] applied various machine learning techniques to predict crop yield using factors like temperature, rainfall, and production. Their study found that LSTM performed best for temperature prediction, while Random Forest (RF) outperformed XGBoost, KNN, and LR, achieving 67.80% higher accuracy when combining all factors. Nischitha et al. [6] developed a rainfall prediction model using SVM and a crop prediction model using DT, where rainfall forecasts—based on soil pH, humidity, and temperature—were used to recommend suitable crops for improved success rates.

Suruliandi et al. [7] applied feature selection algorithms (Boruta, SFFS, RFE) and classification models (KNN, DT, RF, SVM, Bagging, NB) to categorize crop datasets. Their study found that Boruta, SFFS, and RFE performed best with the Bagging classifier. Pudumalar et al. [8] used the Majority Voting Technique, combining RF, CHAID, NB, and KNN, where models voted on data labels. Higher competency among learners improved accuracy, achieving 88%.Doshi et al. [9] developed two models: one for crop recommendation and another for rainfall prediction. For crop recommendation, Neural Networks (NN) achieved the highest accuracy, while for rainfall prediction, Logistic Regression (LR) performed best with 71% accuracy. Pande et al. [10] proposed a mobile app to support farmers, offering crop recommendation and yield prediction. Users can either check the yield of a known crop or input soil and weather conditions to receive the best crop suggestion. Additionally, the system provides fertilizer recommendations for optimal productivity. Among various models like SVM, ANN, RF, MLR, and KNN, RF achieved the highest accuracy of 95%.Kumar et al. [11] developed a crop prediction and fertilizer recommendation system using soil (N, P, K) and weather factors (temperature, humidity, rainfall). They compared RF, SVM, and KNN, selecting SVM for model development. Archana et al. [12] implemented a similar system using KNN, achieving 80% accuracy. Verma et al. [13] proposed a crop prediction model with KNN, SVM, RF, DT, and Gradient Boosting, achieving 99.4% accuracy in identifying the best crop based on weather and soil conditions.

Molares et al. [14] developed a crop prediction system using RF, ANN, and regularized linear models, where RF achieved the lowest RMSE (35-38%). Iniyan et al. [15] analyzed 18 years of agricultural data in Maharashtra and found that LSTM achieved the highest accuracy (86.3%) among eight machine learning models. Panigrahi et al. [16] predicted maize, peanut, and Bengal bean yields using linear regression and DT, based on temperature and rainfall data in Telangana. Tiwari et al. [17] combined CNN with geographical factors for crop yield prediction, using BPNN for training, but faced challenges with agricultural drift affecting accuracy. Gopal et al. [18] introduced a MLR-ANN model, utilizing ANN, statistical methods, and MLR, where Feedforward ANN with backpropagation was applied to enhance yield forecasting accuracy.Khaki et al. [19] explored Deep Neural Networks (DNN) for crop yield prediction, aiming to establish relationships between yield and influencing factors. Their study found that regression trees outperformed traditional supervised models, though the need for more advanced models remained. Mariammal et al. [20] proposed Modified Recursive Feature Elimination (MRFE), a feature selection method combined with six classifiers (KNN, NB, DT, RF, SVM, and Bagging). Their results showed that Bagging improved crop prediction accuracy, while MRFE effectively selected key features, achieving 95% accuracy and outperforming other feature selection techniques.

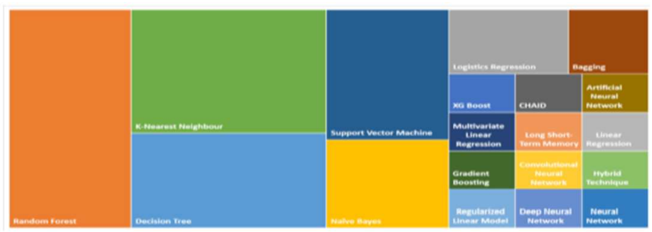

Figure 1: Comparison of Recommendation Technique used by Previous Researchers.

After reviewing the literature, we found that most researchers use similar features for predictions, primarily relying on machine learning techniques, while fewer have explored deep learning methods like ANN, LSTM, CNN, and DNN [21-24]. Random Forest (RF) is commonly used for feature selection and recommendations due to its effectiveness in handling numerical data. To enhance performance, this study employs an improved Random Forest Extreme Gradient Boosting (RFXGB) model for feature selection and integrates it with a DeepFM-based deep learning model. Since DL-based recommendations in agriculture are still emerging, this hybrid ML-DL approach aims to improve crop yield, fertilizer, and crop recommendations using a benchmark dataset [25-27].

III. METHODOLOGY

The AgroAdvisor system introduces a hybrid approach by integrating Random Forest with Extra Tree (RFEXT) and Deep Factorization Machine (DeepFM). This framework addresses three key agricultural areas: crop recommendation, crop yield prediction, and fertilizer recommendation. By utilizing advanced feature selection and machine learning, it improves prediction accuracy and efficiency. RFEXT optimizes feature selection for dense numerical data, while DeepFM captures both high-order and low-order feature interactions. This combination creates a robust, scalable, and precise system that outperforms traditional models in accuracy and reliability for modern agriculture.

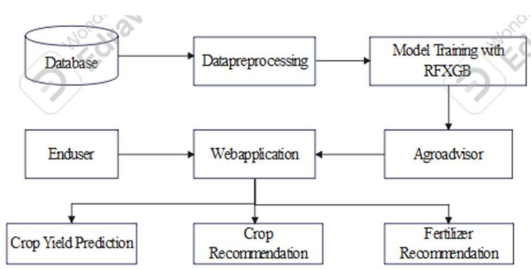

Fig 2: Proposed block diagram

The AgroAdvisor system leverages advanced machine learning to provide crop yield prediction, crop recommendation, and fertilizer recommendation, aiming to enhance agricultural productivity. It employs a structured methodology comprising data collection, preprocessing, model training, recommendation generation, and performance evaluation. The core models, Random Forest with Extreme Gradient Boosting (RFXGB) and

Deep Factorization Machine (DeepFM), ensure accurate predictions and recommendations, making the system highly effective for modern farming.
The AgroAdvisor system begins by collecting agricultural datasets from sources like government agencies, weather forecasting services, soil testing labs, and past farming records. This data includes soil properties (pH, nitrogen, phosphorus, potassium), weather conditions (temperature, humidity, rainfall), crop types, fertilizer usage, and past yield records.
Once collected, the data undergoes preprocessing to ensure quality and usability for machine learning models. This involves handling missing values with imputation techniques, feature selection to retain key attributes, normalization for scaling numerical data, and categorical encoding for non-numeric features. Min-Max Scaling, a key normalization technique, ensures all numerical values fall within a standard range, optimizing model training efficiency.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where X′ is the normalized value, X is the original value, and Xmin and Xmax represent the dataset's minimum and maximum values, respectively.
The system employs a hybrid machine learning approach, integrating Random Forest (RF) and Extreme Gradient Boosting (XGBoost) to enhance prediction accuracy. Random Forest, an ensemble learning method, builds multiple decision trees and averages their predictions, reducing overfitting and improving model stability.
The Random Forest prediction formula is expressed as:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} f_i(x)$$

Here, N represents the total number of decision trees, and fi(x) denotes the prediction from each tree.
XGBoost enhances model performance by optimizing the loss function using gradient descent. It constructs decision trees sequentially, with each new tree correcting the errors of the previous ones. The update formula for XGBoost is as follows:

$$F_{t+1}(x) = F_t(x) + \gamma h_t(x)$$

Here, Ft(x) represents the current model prediction, ht(x) is the weak learner, and γ denotes the learning rate.
For crop yield prediction, the system utilizes a Deep Factorization Machine (DeepFM), which combines deep learning with factorization machines (FM). The FM component captures pairwise feature interactions, while deep neural networks (DNNs) learn higher-order interactions, enhancing predictive accuracy. The mathematical representation of the FM component is as follows:

$$y = w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n}\sum_{j=i+1}^{n} v_i v_j x_i x_j$$

Where xi and xj represent input features, w0 is the bias term, and vi, vj are latent feature vectors. The DeepFM model enhances predictions by integrating neural networks for further refinement.
After predicting crop yield, the system recommends the most suitable crops based on soil and environmental conditions. The crop recommendation module utilizes Random Forest and DeepFM-based classification models, assigning a suitability score to each crop using a weighted formula.

$$S = w_1 \times pH + w_2 \times Temp + w_3 \times Rainfall + w_4 \times SoilType$$

Here, w_1, w_2, w_3, and w_4 represent the weights assigned to various environmental factors, and the crop with the highest suitability score is recommended. The fertilizer recommendation module assists farmers in selecting the optimal fertilizers based on soil nutrient levels. This module utilizes a decision tree classifier combined with logistic regression for fertilizer classification. The probability estimation follows the logistic regression formula.

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \sum \beta_i X_i)}}$$

Here, P(Y=1 | X) represents the probability of selecting a specific fertilizer, while X_i denotes input features such as soil nitrogen, phosphorus, and potassium content. The coefficients β_0 and β_i define the model's relationship with these features.
The AgroAdvisor system provides predictions and recommendations through a web-based application, allowing farmers to input soil parameters, weather conditions, and location details to receive real-time crop recommendations, yield predictions, and fertilizer suggestions.
The system's performance is evaluated using multiple metrics to ensure high reliability. One key metric is Mean Absolute Error (MAE), which measures the average magnitude of prediction errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Root Mean Squared Error (RMSE) – Penalizes large errors more heavily:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Classification Accuracy – Used for the crop and fertilizer recommendation models:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Here, TP (True Positives) and TN (True Negatives) represent correctly classified results, while FP (False Positives) and FN (False Negatives) indicate misclassifications.
The AgroAdvisor system follows a structured methodology, integrating data preprocessing, hybrid machine learning models (RFXGB, DeepFM, Decision Trees), and a web-based application to assist farmers in making informed decisions. By combining Random Forest, XGBoost, and Deep Learning, the system ensures high accuracy in yield prediction, crop selection, and fertilizer recommendation. Designed to enhance agricultural productivity and optimize resource usage, it empowers farmers with AI-driven insights. Through continuous performance evaluations and real-time data updates, AgroAdvisor aims to revolutionize smart farming and precision agriculture.

A. Random Forest with Extreme Gradient Boosting

Random Forest is an ensemble learning technique that selects the most important features by averaging multiple decision trees.
Feature Importance Calculation:

$$FI(X_i) = \frac{1}{N}\sum_{t=1}^{N}(I_t(X_i))$$

where:

- FI(Xi)= Feature importance of Xi,
- It(Xi) = Importance of feature Xi in tree t,
- N = Total number of trees.

Gini Index (Used for Feature Selection):

$$Gini = 1 - \sum_{i=1}^{c} p_i^2$$

where:

- pi = Probability of class i,
- c = Total number of classes.
- The top-ranked features are selected and passed to the XGBoost model.

B. Prediction Using Extreme Gradient Boosting (XGBoost)

XGBoost is a boosting algorithm that optimizes predictions by sequentially improving weak learners.
Objective Function in XGBoost:

$$\mathcal{L}(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(f_t)$$

where:

- ➢ l(yi,y^i)= Loss function (e.g., Mean Squared Error),
- ➢ Ω(ft)= Regularization term to avoid overfitting.

C. Gradient Boosting Tree Update Rule

$$g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i}, \quad h_i = \frac{\partial^2 l(y_i, \hat{y}_i)}{\partial \hat{y}_i^2}$$

where:

- ➢ Gi and hi are first and second derivatives of the loss function,
- ➢ Used to optimize the next tree.

Prediction Score Calculation:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(X_i)$$

where:

- ➢ y^i(t) = Updated prediction at step t,
- ➢ η = Learning rate,
- ➢ ft(Xi) = Prediction function at iteration t.

After iterative boosting, the final predicted output is given by:

$$Y_{\text{final}} = \sum_{t=1}^{T} f_t(X)$$

where:

- ➢ T = Number of boosting rounds,
- ➢ ft(X) = Output of each tree.

IV. RESULTS

A. Fertilizer Accuracy Comparison and Correlation Matrix

AgroAdvisor leverages Random Forest, Gradient Boosting, and DeepFM for accurate crop yield prediction and fertilizer recommendations. The "Fertilizer Accuracy Comparison" image highlights an R^2 score analysis of regression models, where Extreme Trees (0.984) outperforms others, followed by Gradient Boosting (0.966), Hybrid (GB+ET) (0.956), and LightGBM (0.929). CatBoost (0.808) also shows solid performance. These results indicate that combining these advanced models can significantly improve agricultural predictions, ensuring optimized farming practices and sustainability.

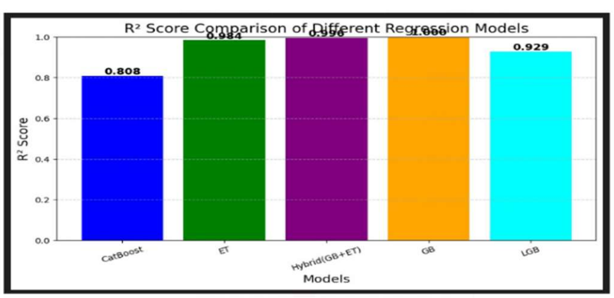

Fig 3

AgroAdvisor utilizes Random Forest, Gradient Boosting, and DeepFM for precise crop yield prediction and fertilizer recommendations. The "Correlation Matrix Fertilizer" image highlights relationships between key agricultural factors, showing a strong correlation (0.97) between Temperature and Humidity, Nitrogen (0.77) with Fertilizer Name, and a negative correlation (-0.82) with Potassium. These insights enable data-driven fertilizer selection, optimizing yield and sustainability in agriculture.

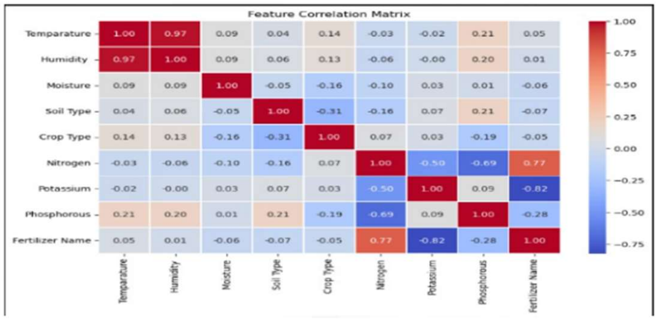

Fig 4

B. Crop Accuracy Comparison and Correlation Matrix

The image titled "Crop Accuracy Comparison" presents the R^2 score performance of different regression models used for crop yield prediction. CatBoost and Gradient Boosting (GB) achieve the highest R^2 scores (0.975), demonstrating their superior predictive capability, while Extreme Trees (ET) and the Hybrid Model (CatBoost + ET) also perform well, scoring 0.967 and 0.962, respectively. LightGBM (LGB) follows closely with an R^2 score of 0.955, indicating its efficiency in handling large datasets. These results validate AgroAdvisor's robust machine learning framework, which integrates Random Forest, Gradient Boosting, and DeepFM to deliver precise crop yield forecasts, enabling data-driven and optimized agricultural decision-making.

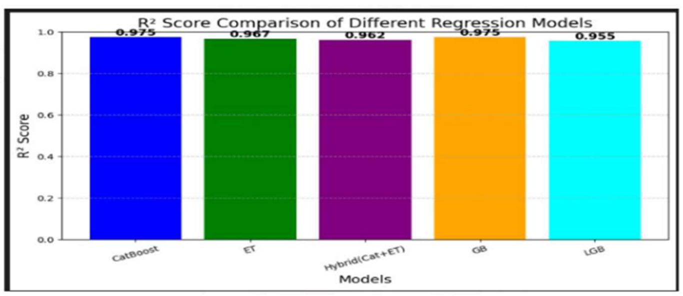

Fig 5

The image titled "Correlation Matrix Crop" illustrates the relationship between key agricultural features influencing crop yield prediction. Phosphorus (P) and Potassium (K) exhibit a strong positive correlation (0.74), indicating their joint importance in soil fertility. Humidity and temperature have low correlations with other factors, suggesting their independent influence on crop growth. The label (yield or crop type) has a negative correlation with Phosphorus (-0.49) and Potassium (-0.35), highlighting their impact on crop selection. These insights enable AgroAdvisor to optimize crop recommendations by leveraging advanced machine learning models like Random Forest, Gradient Boosting, and DeepFM, ensuring precise and data-driven agricultural planning.

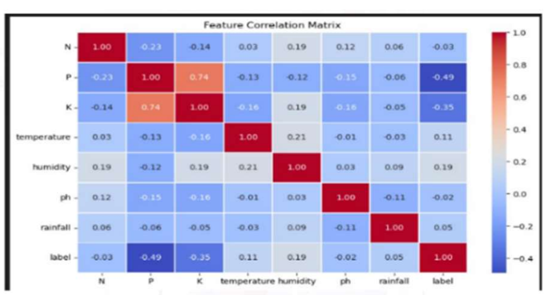

Fig 6

C. Yield Accuracy Comparison and Correlation Matrix

The image titled "Yield Accuracy Comparison" presents the R^2 score comparison of different regression models used in crop yield prediction. The models evaluated include CatBoost (0.988), Extra Trees (ET) (0.984), Hybrid (LGB+ET) (0.987), Gradient Boosting (GB) (0.980), and LightGBM (LGB) (0.981). The high R^2 scores (close to 1) indicate that these models provide highly accurate predictions.The CatBoost model achieves the highest R^2 score (0.988), indicating superior predictive performance. These results highlight AgroAdvisor's effectiveness in yield prediction, leveraging advanced machine learning techniques like Random Forest, Gradient Boosting, and DeepFM to enhance agricultural productivity with data-driven recommendations.

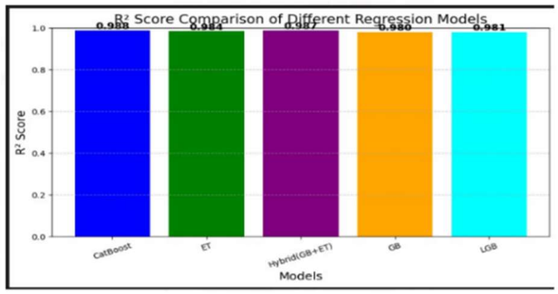

Fig 7

The "Correlation Matrix Yield" heatmap displays the correlation coefficients between various agricultural factors that influence crop yield, such as area, item type, year, yield per hectare (hg/ha_yield), average rainfall, pesticide usage, and average temperature. The correlation values range from -1 to 1, where:

- 1 represents a perfect positive correlation,
- -1 represents a perfect negative correlation, and
- 0 indicates no correlation.

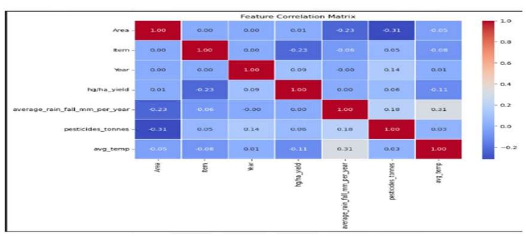

Fig 8

The coefficient of determination (R^2) is computed using the formula:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where:

- Yi is the actual crop yield,
- y^I is the predicted crop yield,
- y¯ is the mean of the actual yield values.

V. CONCLUSION

The AgroAdvisor system seamlessly integrates machine learning, deep learning, and web-based technologies to enhance agricultural decision-making. Utilizing Random Forest with Extreme Gradient Boosting (RFXGB), Deep Factorization Machine (DeepFM), and Decision Tree classifiers, the system delivers precise crop yield predictions, optimal crop recommendations, and fertilizer suggestions based on soil and environmental parameters. A robust data preprocessing pipeline ensures high-quality inputs, while hybrid learning models enhance prediction accuracy through feature interactions and gradient optimization. The web application offers an interactive platform for farmers, enabling real-time data input and AI-driven recommendations. System performance, evaluated using MAE, RMSE, and classification accuracy, validates its effectiveness in predictive analytics for agriculture.By continuously refining models and leveraging data-driven insights, the system advances precision farming, resource optimization, and improved crop productivity. Future enhancements may incorporate real-time satellite data, IoT-based soil sensors, and blockchain technology for transparent farm analytics, paving the way for sustainable, AI-driven agriculture.

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