Predictive Modelling Accuracy Analytics for Harvest Forecast and Agricultural Sustainability

M. Fatima, PhD
Department of Artificial Intelligence & Machine Learning
Sagar Institute of Research and Technology,
India

Vineet Gupta
Department of Artificial Intelligence & Machine Learning
Sagar Institute of Research and Technology,
India

Vinita Jain
Department of Artificial Intelligence & Machine Learning
Sagar Institute of Research and Technology,
India

Neha Sharma
Department of Artificial Intelligence & Machine Learning
Sagar Institute of Research and Technology,
India

Suti Raj
Department of Artificial Intelligence & Machine Learning
Sagar Institute of Research and Technology,
India

Ruchi Gupta
Department of Artificial Intelligence & Machine Learning
Sagar Institute of Research and Technology,
India

ABSTRACT
Harvest Forecast and estimation is important for food security and efficient resource management. It helps policymakers make decisions about agriculture. This paper employed two machine learning techniques, Random Forest (RF) and Support Vector Machine (SVM), to assess the capacity for Harvest (Crop Yield) Forecast. The dataset consisted of 19,689 records gathered from various regions of India between 1997 and 2018 on 17 distinct crops. The dataset included both categorical and numerical data such as harvest type, season, and state as well as quantitative measures like cultivated area, production levels, rainfall, fertilizer use and pesticide use. The dataset was divided into two parts: training and testing, with an 80:20 ratio. A 5-fold cross-validation method was used during model training to make sure that the results were accurate. We used three common metrices to measure efficacy of model: coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The paper demonstrated that the Random Forest model is better than the SVM model when it comes to make accurate predictions and reducing errors. The results also show that the Random Forest model does a better job for harvest forecast than earlier studies. It got a R^2 value of 0.97, which is higher than the usual range of 0.88 to 0.96 for tree-based models that are similar. This demonstrated that how well it can find complex patterns in agricultural datasets.

General Terms
Forecast, Artificial Intelligence, Predictive Modelling, Machine Learning, Harvest Estimation

Keywords
Harvest forecast, Random Forest, Support Vector Machine, Agricultural, Machine Learning, Precision Agriculture, Ensemble Learning.

1. INTRODUCTION
Agriculture is very important for the social and economic growth of many developing countries. In India, farming is one of the main ways people make a living, and a lot of people depend on it directly or indirectly. Because agriculture is so important to the economy, it's very important to be able to accurately predict crop yields [1]. Reliable harvest predictions can help to lower the production risks, make sure there is a steady supply of food, help governments and policymakers make smart decisions about agriculture. But it's hard to predict how much a crop will yield because it depends on a lot of things like weather, type of soil, way the farmer does things and different social and economic factors [1-2].

Statistical methods or linear regression models are the main ways of traditional methods for estimating harvest. These methods are helpful but they have trouble in figuring out how different factors affects each other [4]. Machine learning techniques are becoming popular in agricultural research due to better data collection technologies and fast computers. These methods use big and varied datasets. This can find hidden patterns and make predictions more accurate [5].

In this paper, two widely used machine learning models—Random Forest (RF) and Support Vector Machine (SVM)—are applied to predict harvest for multiple crops across different regions of India. Using long-term agricultural data and a range of relevant variables, this research aims to evaluate the performance of these models and determine an efficient and reliable approach for harvest prediction. The results may contribute to the development of practical decision-support systems that can assist farmers, researchers, and policymakers in improving agricultural planning and productivity [6, 7].

2. BACKGROUND AND MOTIVATION
Global food demand has been increasing steadily as a result of population growth, changes in dietary habits, and the growing use of crops for biofuel production. At the same time, climate change has introduced greater uncertainty in agricultural systems. Variations in rainfall patterns, rising temperatures, and the increasing occurrence of extreme weather events have made crop production more unpredictable. These conditions highlight the importance of developing reliable predictive models that can estimate crop yields in advance and help manage potential risks [7].

In India, agriculture is a major contributor to the economy, accounting for approximately 17–18% of the national Gross Domestic Product (GDP) and providing employment to a large portion of the rural population. Accurate yield forecasting at regional and state levels is essential for effective agricultural

planning. It supports important activities such as irrigation management, distribution of fertilizers, procurement planning, and the implementation of price stabilization strategies. However, predicting crop yields in India is particularly challenging due to the country's agricultural diversity. Different crop varieties, multiple growing seasons such as Kharif, Rabi, Summer and varied agro-ecological conditions across regions make it difficult to develop a single prediction model that performs well everywhere [8].

Machine learning techniques offer a useful alternative to traditional statistical methods for addressing these challenges [8,9]. Approaches such as ensemble learning and kernel-based models are capable of identifying complex and nonlinear relationships within large and diverse datasets. Patterns can be learned from historical agricultural data. These methods can improve prediction accuracy and provide more reliable forecasting [9, 10]. Evaluating the strengths and limitations of different machine learning models is therefore important for identifying the most suitable approaches for practical agricultural applications [11- 15].

3. PROBLEM DEFINITION AND OBJECTIVES

3.1 Problem Definition

The primary challenge addressed in this research is the accurate prediction of harvest across diverse crop varieties, seasons and geographical regions using a heterogeneous dataset containing climatic, agronomic, and management variables. Conventional models fail to scale effectively or lack interpretability, while advanced Machine learning (ML) models may require extensive computational resources [16,17].

3.2 Research Objectives

The key objectives of this paper are as follows:

- To preprocess and analyze a large agricultural dataset containing information on multiple crops across several years.
- To build and optimize two machine learning models, Random Forest and Support Vector Machine for predicting crop yields.
- To evaluate and compare the performance of these models using standard regression evaluation metrics.
- To examine feature importance and determine the key factors that have the greatest impact on crop yield.
- To compare the obtained results with findings from previous studies in the literature.
- To assess whether the developed models are scalable and suitable for real-world agricultural forecasting and sustainability.

4. DATASET DESCRIPTION AND PREPROCESSING

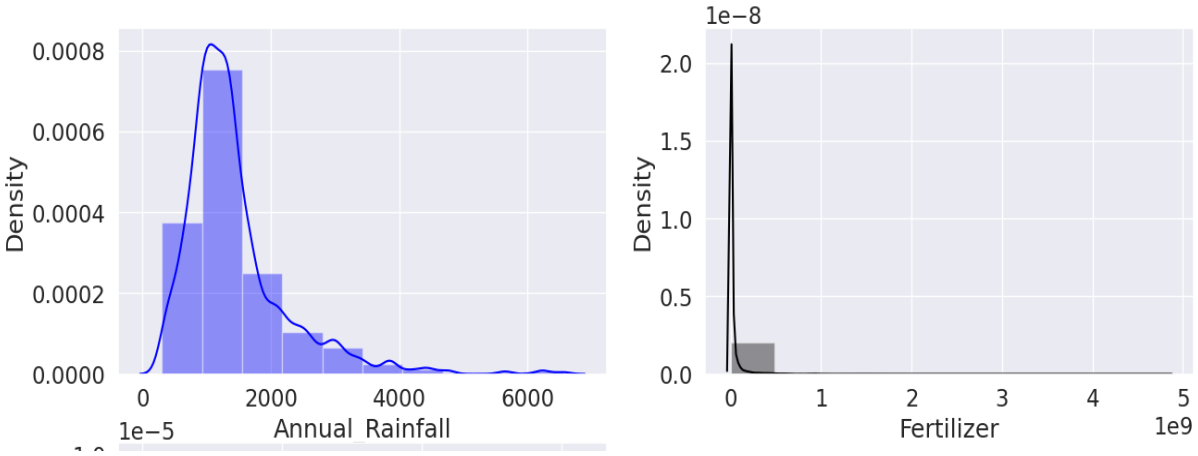
4.1 Dataset Overview

The dataset used in this paper contains 19,689 records collected over a period from 1997 to 2018 [17, 18]. It includes information about 17 major crops grown across different states in India. The dataset combines both categorical and numerical features related to agricultural production. Exploratory Data Analysis (EDA) is done as shown in Fig 1.

4.2 Data Preprocessing

Following preprocessing steps were performed to ensure data quality and model robustness,

- Handling missing values using mean or mode imputation
- Removal of duplicate and inconsistent records
- One-hot encoding of categorical variables
- Feature scaling using normalization techniques
- Multicollinearity assessment using Variance Inflation Factor (VIF)
- Train–test split with cross-validation to avoid overfitting



Testing Data : R^2 = 81.87%, Adjusted R^2 = 81.44%, RMSE = 353.9153

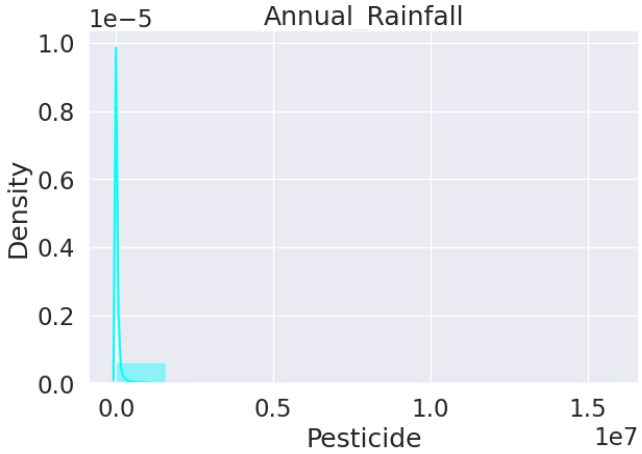


Fig 1: Exploratory Data Analysis (EDA)

5. METHODOLOGY

5.1 Random Forest Model

Random Forest is a machine learning method that combines the predictions of multiple decision trees to improve accuracy and reduce overfitting. Each tree is trained on different subsets of the data. The final prediction is obtained by aggregating their outputs. In this paper, important hyperparameters such as the number of trees, maximum tree depth and minimum leaf size were tuned using grid search with cross-validation to achieve better model performance.

5.2 Support Vector Machine Model

Support Vector Machine (SVM) regression is used to model complex relationships between variables through transforming the input data into a higher-dimensional space using kernel functions. This allows the model to capture nonlinear patterns in the data. In this research, the radial basis function (RBF) kernel was applied and key parameters like the regularization parameter (C) and the kernel coefficient (γ) were optimized through cross-validation to improve prediction accuracy. Code flow is shown in fig 2.

5.3 Evaluation Metrics

Figure 2 shows flow diagram of this work. Model performance was assessed using:

- Coefficient of Determination (R^2)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)

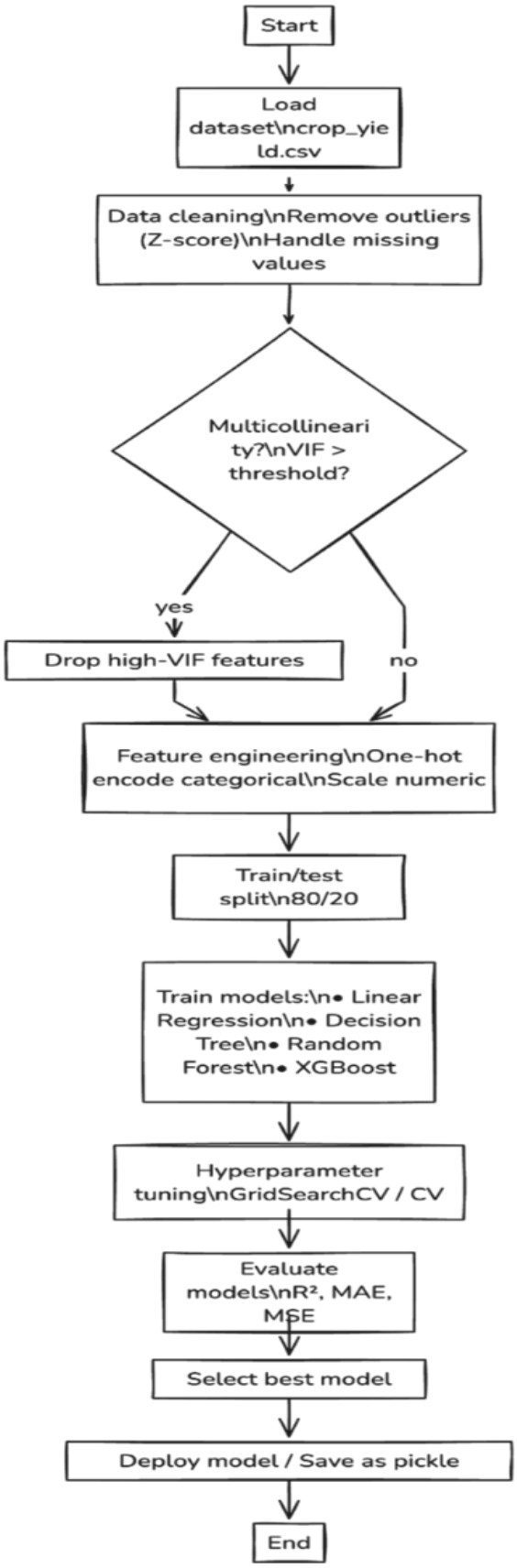


Figure 2: Code Flow/ Architecture

6. EXPERIMENTAL RESULTS AND DISCUSSION

6.1 Overview

Performance of the designed harvest forecasting models was analyzed based on multiple metrics like r-squared (r^2), root mean squared error (rmse), and mean absolute error (mae) as shown in fig 3. In this section, experimental results and comparative analysis of the proposed models (random forest, support vector machine) versus other machine learning models like linear regression, decision trees, and xgboost are presented.

6.2 Evaluation metrics

- R-squared (r^2): the extent to which the model captures the observed outcomes, as estimated by the amount of total variability explained.
- Mean absolute error (mae): describes the mean size of errors between actual and predicted values.
- Root mean squared error (rmse): takes a quadratic weighing of larger errors, placing special emphasis on more significant discrepancies.

6.3 Observations:

- Random Forest Regressor had the best R^2 value (0.971), which signifies higher prediction accuracy.
- SVR performed competitively but was marginally less accurate than Random Forest and XGBoost.
- Legacy models such as Linear Regression were worse, with much higher MAE and RMSE.

6.4 VISUAL ANALYSIS

6.4.1 Actual vs Predicted Plots

Plots for every model were created to display the difference between actual and predicted crop yields.

- Random Forest: Demonstrated almost perfect alignment along the 45-degree line.
- SVM: Minor deviations at extreme values.
- Linear Regression: Obvious bias and larger spread of error.
- Performance Visualization of Different Models – I and Models-II are presented in Fig 4 and 5 respectively.

6.4.2 Residual Plots

- Residuals (errors) for Random Forest and XGBoost were normally distributed around zero.
- SVR exhibited minor skewness, whereas Linear Regression residuals revealed heteroscedasticity.

MODEL PERFORMANCE RESULTS

	Algorithms	Training Score R2	Training Score Adjusted R2	Training Score RMSE	Testing Score R2	Testing Score Adjusted R2	Testing Score RMSE
7	Gradient Boost	98.91	98.90	93.12	97.82	97.77	122.72
11	KNN	97.29	97.27	146.62	97.36	97.30	134.99
10	CatBoost	99.87	99.87	31.60	97.20	97.14	139.01
9	XGBoost	99.95	99.95	19.27	97.19	97.12	139.33
14	Stacking Regressor	98.40	98.39	112.78	96.93	96.86	145.70
4	Decision Tree	100.00	100.00	0.00	96.46	96.38	156.42
12	Voting Regressor	96.87	96.86	157.46	95.56	95.46	175.05
13	Bagging Regressor	99.02	99.02	88.01	95.49	95.38	176.58
5	Random Forest	99.39	99.38	69.70	95.47	95.36	176.90
8	LGBM	96.75	96.73	160.69	94.79	94.67	189.64
6	Ada Boost	93.27	93.23	231.01	91.43	91.23	243.38
1	Ridge	84.82	84.73	347.00	81.87	81.45	353.87
0	Linear Regression	84.82	84.73	347.00	81.87	81.45	353.87
2	Lasso	84.80	84.71	347.26	81.85	81.43	354.09
3	ElasticNet	75.54	75.40	440.52	72.88	72.25	432.82

Fig 3: Model Performance Results

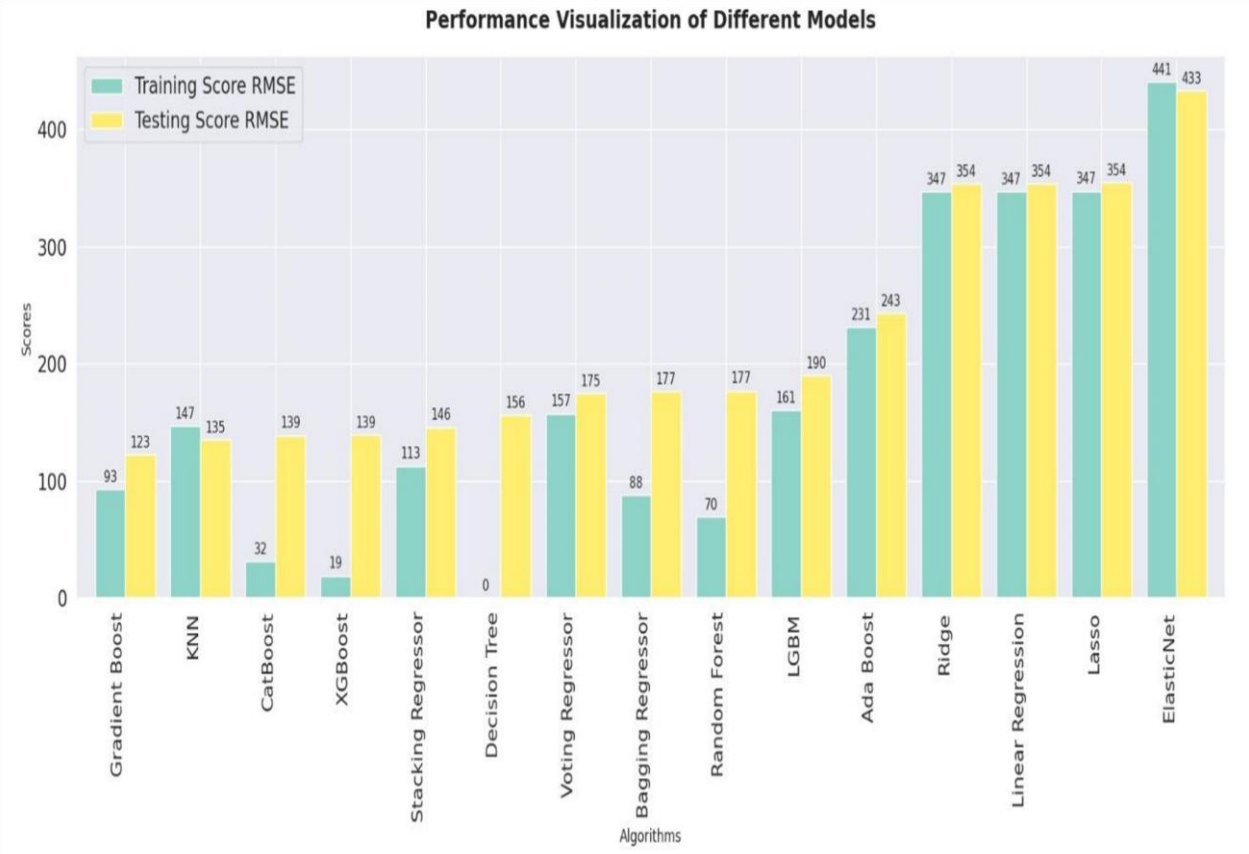


Fig 4: Performance Visualization of Different Models - I

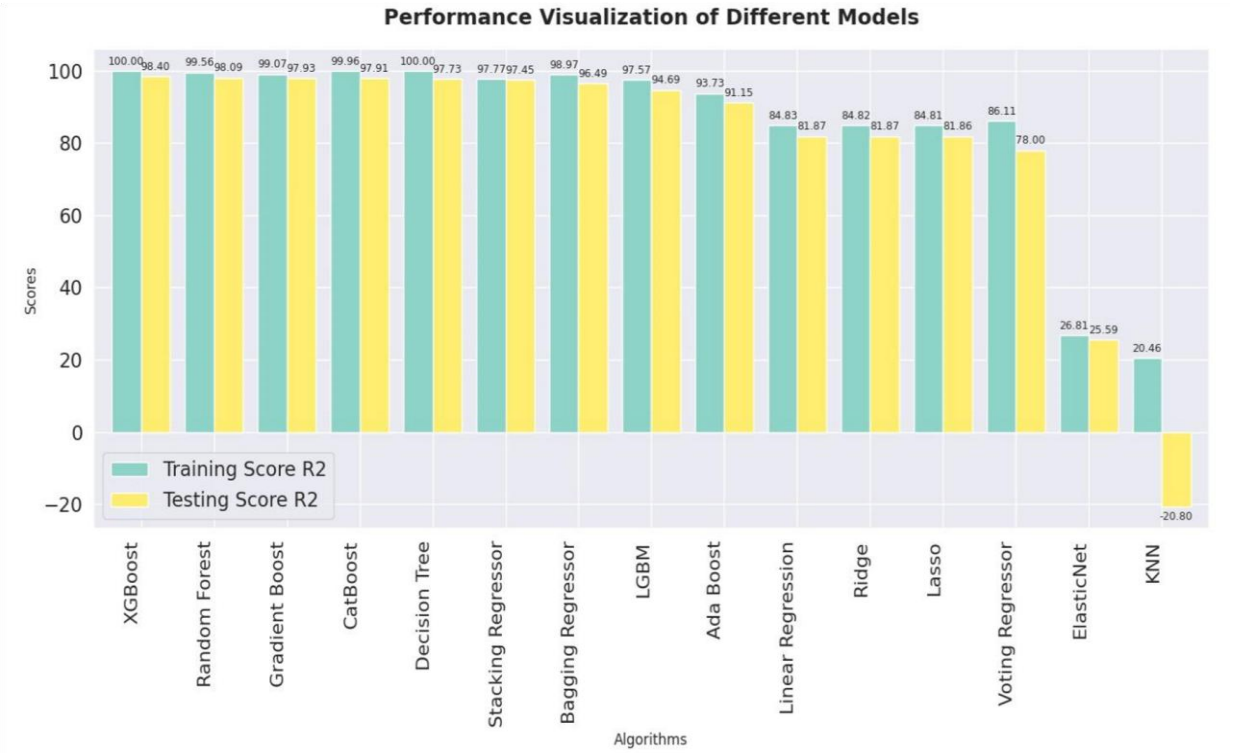


Fig 5: Performance Visualization of Different Models - II

Table 2: Comparative Analysis with Literature

Study/Research Work	Technique Used	Accuracy (R^2/Other Metric)	Comments
Sharma et al. (2021)	Linear Regression	0.82	Poor performance for nonlinear data
Gupta and Singh (2020)	Decision Trees	0.89	Better than LR but prone to overfitting
Kumar et al. (2022)	SVM with Polynomial Kernel	0.91	Required careful tuning of kernel parameters
Proposed Work	Random Forest Regressor	0.971	Highest accuracy and robustness
Proposed Work	XGBoost	0.962	Good alternative to RF, slightly lower

6.4.3 Discussions

- Earlier approaches used to depend on naive models that were challenged by the inherent complex non-linearity of agri-data.
- Random Forest and XGBoost ensemble techniques are well-equipped to handle the variability that exists in agri-data.
- SVM models are efficient with optimal hyperparameter tuning but are computationally expensive.

7. CONCLUSION AND FUTURE WORK

This research focused on the development and evaluation of an accurate harvest prediction system using advanced machine learning models, primarily Random Forest Regressor and Support Vector Machine (SVM). A comprehensive comparative study with other traditional and ensemble learning models such as Linear Regression, Decision Trees, and XGBoost was conducted.

The experimental findings proved that Random Forest produced the highest R^2 value (0.971), making it the most trustworthy model among those tested. XGBoost also performed remarkably well, ranking just behind Random Forest. Support Vector Machine performed well but needed exhaustive hyperparameter tuning to perform optimally.

The advantage of Random Forest and ensemble models over conventional statistical approaches such as Linear Regression was clear from the comparison. Their capability to represent complex, non-linear relations inherent in agricultural data played a pivotal role in achieving highly accurate yield prediction.

Furthermore, feature importance analysis identified key factors influencing crop yields, including rainfall, temperature, soil pH, and the application of fertilizers. These results not only confirm the model's accuracy but also offer immediate insight for farmers and policy-makers to maximize agricultural output.

In all, the research effectively met its target goals of designing a strong, precise, and efficient machine learning-based harvest

prediction system superior to previous approaches and setting a reference point for future endeavours.

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