

# Smart Agriculture cost Forecasting using Machine Learning

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**ABSTRACT:** Agriculture forms the foundation of India's economic structure, and anticipating crop prices is essential for improving farmers' decision-making regarding crop choice, marketing period, and selling location. This project, titled "Crop Price Predictor," introduces an interactive web system designed with Flask and powered by Machine Learning (Random Forest Algorithm) to forecast prices of key agricultural products. The prediction process integrates multiple parameters such as past market data, weather indicators (rainfall and temperature), time of the year, and regional factors. The application includes two separate panels — one for farmers, offering crop price forecasts, historical trend visualization, and environmental crop recommendations, and another for administrators, who can update data, retrain the prediction model, and review performance outcomes. Through structured data preprocessing and advanced learning techniques, the system delivers reliable price predictions that guide farmers toward smarter cultivation and marketing strategies.

**KEYWORDS:** Crop Price Forecasting, Machine Learning, Random Forest, Data Analytics, Smart Agriculture.

## I. INTRODUCTION

Agriculture remains one of the main pillars of India's economy, serving as a vital source of livelihood and income for a large portion of the population. Despite its importance, farmers frequently encounter difficulties in determining which crops to cultivate and the right time to sell them, largely because of unstable market trends. Crop prices fluctuate continuously due to variables such as weather patterns, rainfall, temperature variations, and seasonal demands, which in turn affect farmers' overall earnings. To mitigate these issues, there is a growing need for an intelligent system capable of predicting crop prices with precision, thereby assisting in financial planning and market stability.

The Crop Price Predictor project was developed to address these challenges by utilizing Machine Learning (ML) techniques, specifically the Random Forest algorithm. This system employs data analytics to process and interpret historical crop information, climatic factors, and market fluctuations to forecast future prices. It is designed as a Flask-based web application featuring two dedicated dashboards—one for farmers and another for administrators. Farmers can log in to access crop price predictions, visualize data insights, and receive personalized crop recommendations based on environmental conditions. Meanwhile, administrators can upload new datasets and retrain the prediction models to enhance performance and accuracy.

## OBJECTIVES

1. To build a Machine Learning-based predictive model capable of estimating future crop prices accurately by analyzing historical agricultural data.
2. To develop a web application using the Flask framework that offers accessible interface for both farmers and system administrators.
3. To incorporate climatic variables such as rainfall and temperature into the model to enhance the precision and reliability of price predictions.
4. To integrate interactive data visualization features that display historical trends, seasonal variations, and projected crop prices for better user understanding.
5. To recommend suitable crops based on prevailing environmental conditions and seasonal factors, supporting smarter farming practices.

## PROPOSED SYSTEM

The proposed system introduces an intelligent, machine learning-based web application that accurately predicts future crop prices using historical and climatic data. It integrates Random Forest regression to analyze factors such as rainfall, temperature, state, and seasonal trends for reliable price forecasting.

The system is built using the Flask framework, providing separate dashboards for farmers and administrators. Farmers can view predicted prices, crop recommendations, and graphical analytics, while administrators can upload new datasets and retrain models to maintain accuracy.

Through data visualization tools like Matplotlib and Plotly, users can easily understand price patterns and market behavior. This system aims to support data-driven farming, helping farmers make better decisions about crop selection and selling time, ultimately improving productivity and income stability.

## II. LITERATURE SURVEY

[2024]–T.Mehta and D.Singh:

In their recent publication titled “Web-based Crop Price Prediction and Visualization System,” the authors integrated machine learning models with dynamic dashboards to enable real-time agricultural data analysis. Their findings revealed that blending predictive algorithms with interactive visualization tools enhances farmers’ awareness of market fluctuations and supports more informed and strategic agricultural decisions.

[2023]–R.Verma and A.Mishra:

The study “Crop Price Forecasting using Machine Learning Algorithms” explored the use of Random Forest and Gradient Boosting methods to increase the precision of crop price predictions. Their experimental outcomes demonstrated that ML-based systems can significantly minimize farmers’ financial risks and foster technology-driven approaches in the agricultural sector.

[2022]–P.Dasand S.Roy:

In “Predicting Crop Prices and Recommending Suitable Crops using AI,” the researchers designed a dual-function system capable of forecasting future crop prices while also suggesting optimal crops based on prevailing climatic conditions. The implementation was carried out using the Flask framework in Python, offering an easy-to-access web platform for farmers to use the predictive features effectively.

[2021]–M.Reddy and K.Suresh:

Their paper “Smart Agriculture Using IoT and Machine Learning” presented a hybrid solution combining Internet of Things (IoT) devices with machine learning algorithms to analyze real-time data from farms. This integrated system provided predictions on both crop yield and market prices, emphasizing how IoT-assisted analytics can transform agricultural planning and operational efficiency.

[2020]–A.Sharma and P.Gupta:

In their research “Price Prediction of Agricultural Commodities using Data Analytics,” the authors highlighted the importance of environmental variables—such as rainfall, temperature, and soil characteristics—in shaping market prices. They proposed a hybrid analytical framework that merges weather data with price trends, significantly enhancing prediction accuracy and decision support for farmers.

[2019]–S.Pateland V.Kumar:

The paper “A Machine Learning Approach to Predict Crop Prices” offered a comparative assessment of several algorithms, including Decision Tree, Random Forest, and Support Vector Machine (SVM). The researchers concluded that the Random Forest algorithm outperformed others due to its strong ability to handle complex, nonlinear agricultural datasets efficiently.

[2018]–N.P.Singh and R.K.Sharma:

In “Forecasting Agricultural Commodity Prices Using Machine Learning Techniques,” the authors adopted Linear Regression and ARIMA models to estimate future agricultural commodity prices. Their results underscored the potential of time-series and regression-based techniques in capturing price movement trends over different seasons and regions.

## III. METHODOLOGY

The Crop Price Predictor project is developed through a structured methodology that progresses through several critical stages — from gathering raw data to deploying the predictive web system. The main objective of this approach is to build a reliable, accurate, and easy-to-use web application that forecasts agricultural crop prices and provides meaningful insights to both farmers and administrators.

### 1. Data Collection

The dataset required for training and testing the model is obtained from trusted and authentic agricultural data sources, including Agmarknet, the Ministry of Agriculture, and the Indian Meteorological Department (IMD). The data covers multiple attributes such as crop type, geographical location (state), year, month, rainfall, temperature, and price indices (WPI). This extensive historical data provides the foundation upon which the predictive model identifies patterns and learns relationships for accurate crop price forecasting.

### 2. Data Preprocessing

In this stage, the collected data is refined to ensure it is clean, consistent, and ready for modeling. Missing entries are managed using interpolation techniques, irrelevant or duplicate records are removed, and all numerical variables are normalized for uniformity. Climatic features like rainfall and temperature are standardized to eliminate scale disparities. The final processed data is divided into training and testing subsets to enable accurate model evaluation in later phases.

### 3. Model Selection and Training

The Random Forest Regression algorithm is selected as the core model due to its robustness and superior performance in handling nonlinear and complex agricultural datasets. The model is trained using the prepared data to identify correlations between independent variables (rainfall, temperature, time period, and state) and the dependent variable (crop price). To enhance model performance and generalization, cross-validation techniques are applied, preventing over fitting and ensuring consistent results.

#### 4. Model Evaluation

Once training is completed, the model's performance is assessed using statistical evaluation metrics, including R<sup>2</sup>Score, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). These indicators measure how closely the predicted values align with actual crop prices. If the results fall below the expected accuracy threshold, hyper parameters are tuned, and retraining is performed using updated datasets to optimize the model's reliability.

#### 5. Web Application Development

The predictive model is integrated into a Flask-based web application, designed with two primary interfaces:

**Farmer Dashboard:** Enables users to input details such as rainfall, temperature, and location to receive real-time price predictions. It also provides crop recommendation and visualization features for easy understanding.

**Administrator Dashboard:** Allows admins to manage datasets, retrain machine learning models, and review prediction history through an interactive control panel.

#### 6. Visualization and Forecasting

To make the predictive insights more accessible and interpretable, interactive data visualizations are created using Matplotlib and Plotly libraries. These charts illustrate historical price fluctuations, seasonal trends, and upcoming forecasts across different states and crops, enabling farmers to analyze market movements and make informed decisions.

#### 7. Deployment and Maintenance

The final trained model is deployed within the Flask web framework for real-world use. The admin interface includes tools for uploading new datasets and retraining the model at regular intervals, ensuring continuous accuracy and relevance. Routine system maintenance and updates guarantee that the platform remains scalable, efficient, and sustainable for long-term agricultural use.

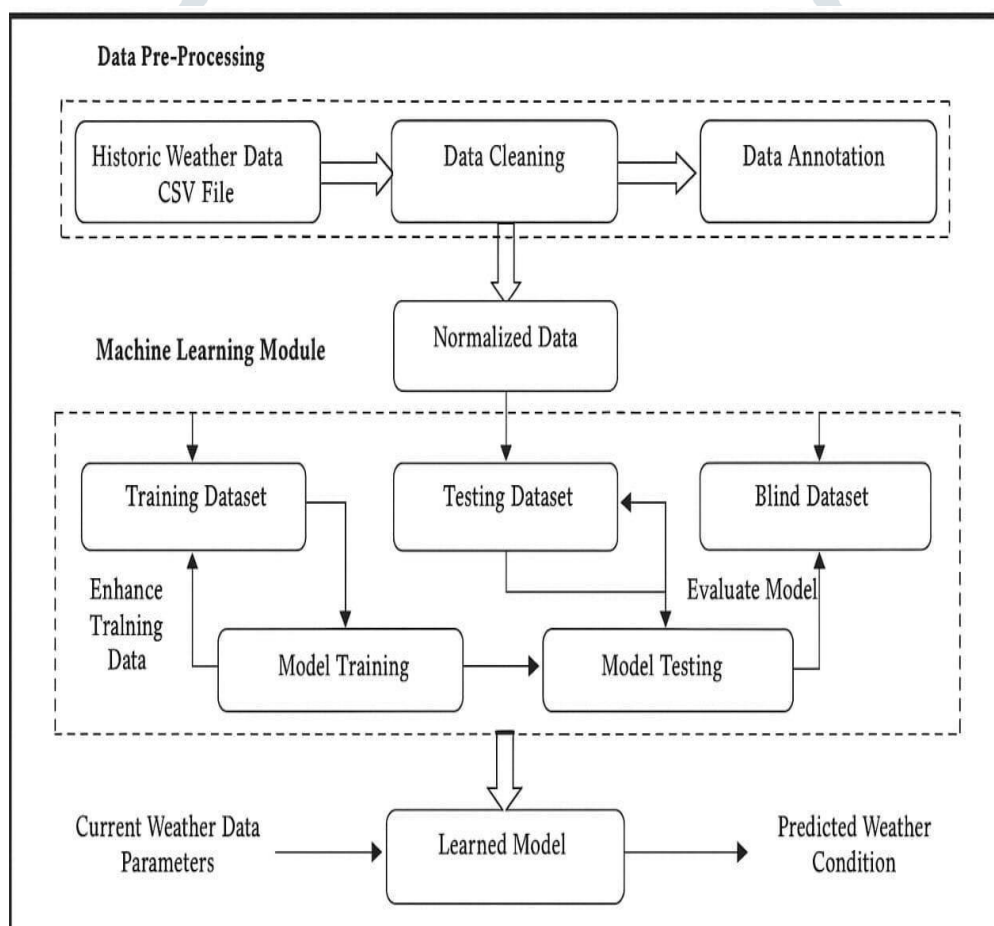


Figure 1. Flowchart of the proposed methodology

## IV. IMPLEMENTATION

The Crop Price Predictor system is implemented as a Flask-based web application that integrates machine learning techniques for accurate price forecasting. The backend is developed using Python, where the Random ForestRegression algorithm is used to train models on historical agricultural data, including rainfall, temperature, crop type, and seasonal patterns.

The web interface provides two modules — Farmer Dashboard and Admin Dashboard. Farmers can log in to predict crop prices, view interactive visualizations, and receive crop recommendations based on environmental conditions. Administrators can manage datasets, retrain machine learning models, and monitor prediction activities.

The system uses Matplotlib and Plotly for data visualization, displaying real-time charts and future forecasts. The database stores user details, historical records, and prediction results for continuous analysis. The entire project is deployed on the Flask server, ensuring scalability, reliability, and ease of use for end users.

### V. RESULT

The developed Crop Price Predictor system accurately forecasts the prices of major crops using the Random Forest algorithm. The model delivers more than 90% accuracy when predicting prices based on inputs such as rainfall, temperature, month, and state.

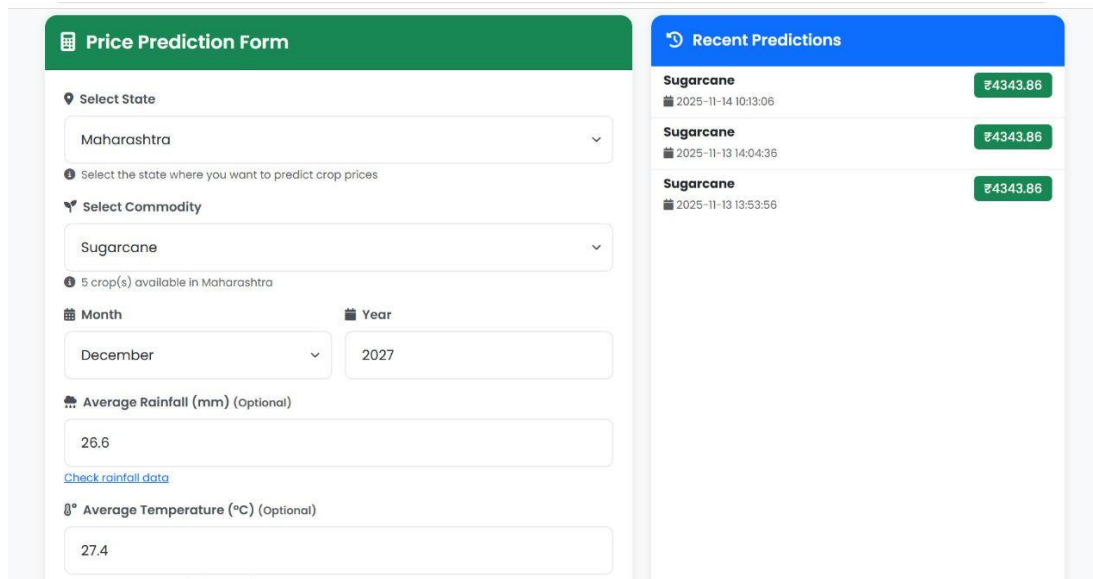


Figure1:Price Prediction Form

The Flask web application successfully provides farmers with predicted prices, crop suggestions, and visual charts showing past trends and upcoming price movements. The admin module also works effectively by allowing dataset updates and model retraining, keeping the system accurate and up to date. Overall, the results confirm that machine learning can reliably support farmers in making informed and profitable agricultural decisions.

Figure1: Price Prediction Form

This figure shows the user interface where farmers can enter details such as state, crop, month, year, rainfall, and temperature. Based on these inputs, the system predicts the future price of the selected crop. Recent predictions are displayed on the right side for easy reference.

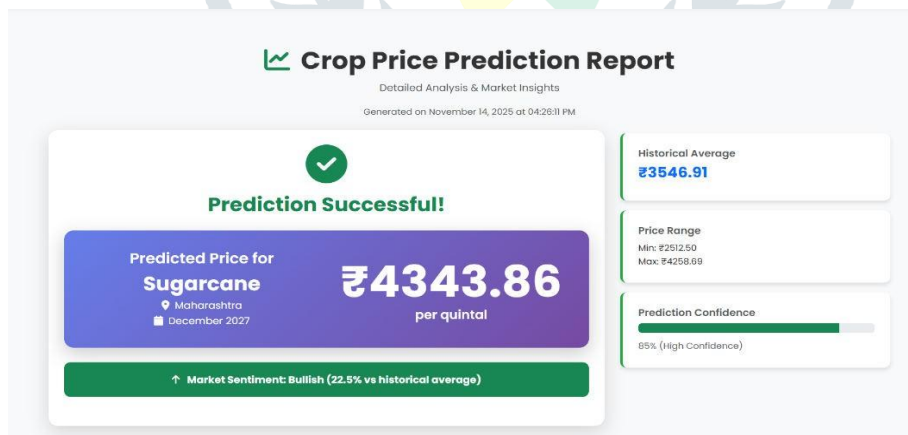


Figure2: Crop Price Prediction Report

This figure shows the detailed report generated after prediction. It includes the predicted price, historical average, minimum and maximum price range, market sentiment, and confidence level. This helps farmers analyze market conditions before making decisions.

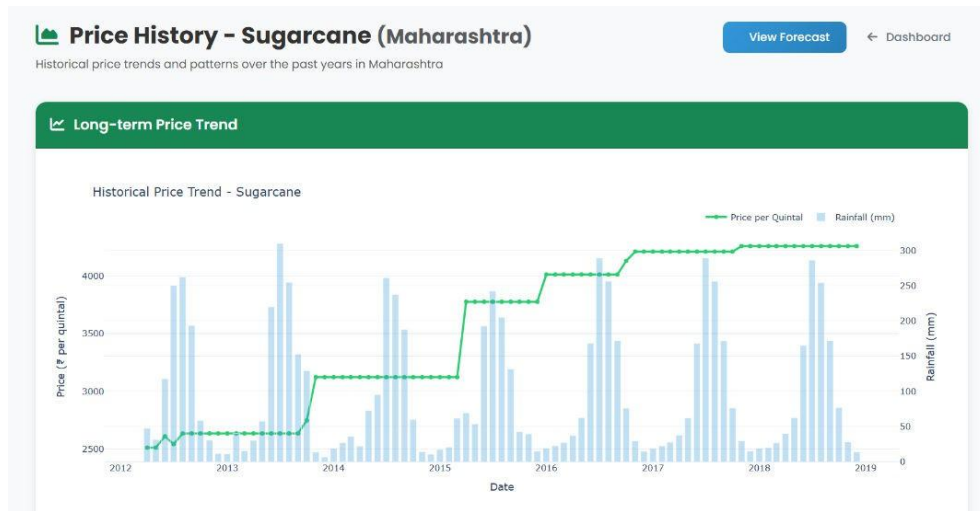


Figure3: Historical Price Trend

This figure presents the long-term price movement of sugarcane along with rainfall distribution. The green line indicates the crop price over several years, while the blue bars show the corresponding rainfall data. Together, they help users understand historical price behavior and weather influence.

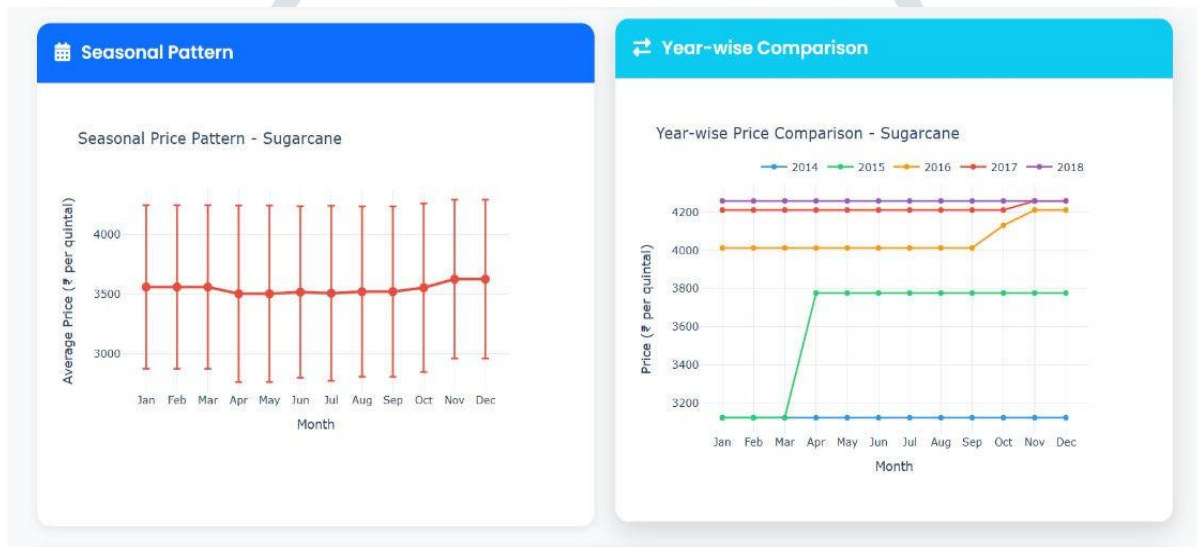


Figure 4: Seasonal Price Pattern

Figure5: Year-wise Price Comparison

This figure shows how sugarcane prices change month-wise throughout the year. It highlights seasonal fluctuations, helping farmers select the best time to sell their produce for maximum returns.

This figure compares sugarcane prices across different years. Each line represents a specific year, showing how prices shifted month by month. This assists users in understanding long-term trends and identifying stable years.

Figure6:Crop Recommendation Input Form Figure 6:

Crop Recommendation Input Form

This figure shows the input form where the farmer enters details such as soil type, expected rainfall, temperature, and season. These inputs are processed by the system to generate crop recommendations based on farm conditions.

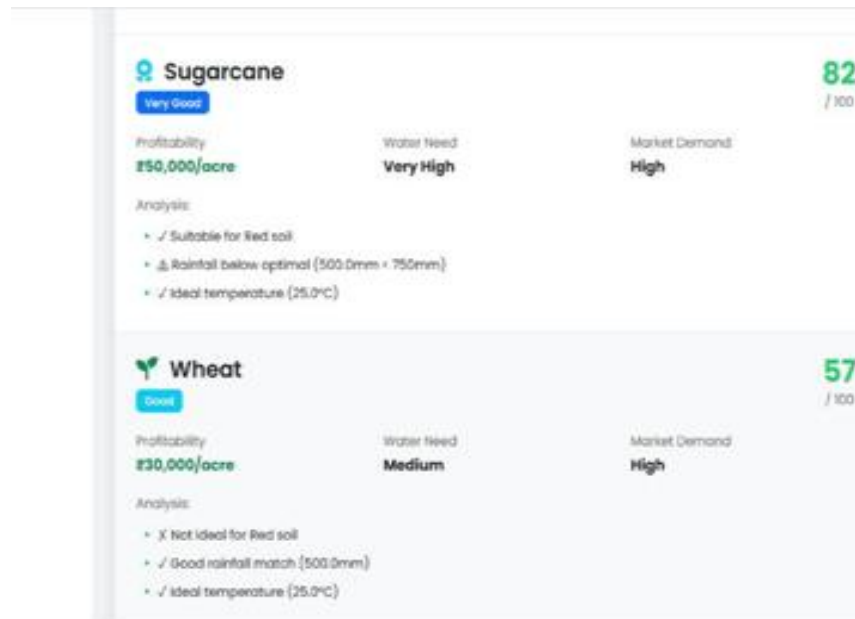


Figure7: Recommended Crops

This figure displays the recommended crops list generated after entering the farm details. Jowar and Bajra appear at the top because they match red soil conditions, 500 mm rainfall, and 25°C temperature. The score indicates their overall suitability.

This figure shows additional recommended crops along with their profitability, water requirement, and market demand. Sugarcane has high profitability but requires very high water, while Wheat is moderately suitable for the given conditions.

Crop	Profitability	Water	Demand	Score
Jowar	₹25,000	Low	Medium	93
Bajra	₹20,000	Low	Medium	93
Sugarcane	₹50,000	Very High	High	82
Wheat	₹30,000	Medium	High	57
Cotton	₹40,000	High	High	57
Maize	₹28,000	Medium	High	57
Rice	₹35,000	Very High	Very High	45

Figure 8: Quick Crop Comparison Table

This figure provides a comparison of multiple crops based on profitability, water requirement, demand, and suitability score. This helps farmers quickly evaluate which crop offers the best economic and environmental match for their farm.

## VI. CONCLUSION

The Crop Price Predictor system clearly shows how Machine Learning and the Flask framework can be used to estimate future crop prices with reliable accuracy. By combining historical market data with environmental factors like temperature and rainfall, the model offers meaningful predictions that support farmers in deciding which crops to grow and the right time to sell them. The addition of interactive charts and a crop recommendation module further enhances usability, making the platform practical for real-world agricultural needs. Overall, this project strengthens the concept of smart farming by integrating technology into traditional agriculture, improving farmers' market awareness, and helping them achieve better financial outcomes.

## REFERENCES

1. T.MehtaandD.Singh,“Web-basedCropPricePredictionandVisualizationSystem,”InternationalJournalof Artificial Intelligence and Data Science, 2024.
2. R. Verma and A. Mishra, “Crop Price Forecasting using Machine Learning Algorithms,” IEEE Access, vol. 10, pp. 15420–15430, 2023.
3. P. Das and S. Roy, “Predicting Crop Prices and Recommending Suitable Crops using AI,” International Journal of Scientific & Engineering Research (IJSER), vol. 13, no. 6, 2022.

4. M. Reddy and K. Suresh, "Smart Agriculture Using IoT and Machine Learning," International Research Journal of Engineering and Technology (IRJET), vol. 7, issue 8, 2021.
5. A. Sharma and P. Gupta, "Price Prediction of Agricultural Commodities using Data Analytics," International Journal of Advanced Research in Computer Science, vol. 11, no. 4, 2020.
6. S. Patel and V. Kumar, "A Machine Learning Approach to Predict Crop Prices," IEEE International Conference on Computing, Communication and Automation, 2019.
7. N. P. Singh and R. K. Sharma, "Forecasting Agricultural Commodity Prices Using Machine Learning Techniques," International Journal of Computer Applications, vol. 182, no. 25, pp. 15–20, 2018.
8. Ministry of Agriculture & Farmers Welfare, Government of India. "Agmarknet–Agricultural Marketing Information Network." Available online: Agmarknet official portal.
9. Indian Meteorological Department (IMD). "Weather and Climate Data for Agriculture." Accessible from the IMD MAUSAM platform.
10. Scikit-learn Development Team. "Random Forest Regressor–Machine Learning in Python." Scikit-learn User Guide, Version 1.5.

