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Machine Learning-Based Agricultural Commodity Price Prediction using Weather and Historical Market Data

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***Abstract* - Agricultural commodity price fluctuation is a major challenge for farmers, traders, and policymakers due to its direct impact on economic stability and agricultural planning. Accurate prediction of mandi crop prices can assist farmers in making informed decisions regarding crop selection, storage, and market timing. This research presents a Machine Learning-Based Agricultural Commodity Price Prediction System that forecasts future crop prices using historical market data and weather conditions. The proposed framework integrates historical mandi prices, rainfall, temperature, humidity, and seasonal trends to improve forecasting accuracy. Various machine learning algorithms such as Linear Regression, Random Forest, Decision Tree, and XGBoost are employed and comparatively analyzed to identify the most effective prediction model. Data preprocessing, feature engineering, and normalization techniques are applied to enhance model performance and reduce prediction errors. The system is designed to provide real-time and data-driven insights for agricultural stakeholders through an intelligent prediction interface. Experimental results demonstrate that ensemble-based models achieve higher prediction accuracy compared to traditional statistical approaches. The proposed system contributes to smart agriculture by enabling predictive analytics for sustainable farming and market decision-making. This research highlights the potential of artificial intelligence and climate-aware forecasting in transforming agricultural price prediction systems for improved economic outcomes and farmer support.**

Keywords- Agricultural Commodity Price Prediction, Machine Learning, Mandi Price Forecasting, Historical Market Data, Weather-Based Prediction, Predictive Analytics, Smart Agriculture, Time-Series Analysis, Artificial Intelligence in Agriculture, Precision Farming.

I. INTRODUCTION

Agriculture plays a vital role in the economic development of many countries, especially in India, where a large portion of the population depends on farming for livelihood and income generation [1]. The agricultural sector significantly contributes to food security, employment, and rural development. However, farmers often face major challenges due to the unpredictable fluctuation of crop prices in mandi markets. Variations in demand, supply, climatic conditions, transportation costs, seasonal production, and market trends frequently affect agricultural commodity prices [2]. These uncertainties lead to financial instability for farmers and reduce their ability to make informed decisions regarding crop cultivation, harvesting, storage, and selling time.

Traditional methods of predicting agricultural commodity prices mainly rely on manual observations, statistical estimations, and past experience [3]. Such approaches are often inaccurate because they fail to consider multiple influencing factors simultaneously, particularly dynamic weather conditions and large-scale historical market patterns. With the rapid advancement of Artificial Intelligence (AI), Machine Learning (ML), and data analytics, intelligent forecasting systems have emerged as effective solutions for solving complex prediction problems in agriculture. Machine Learning techniques provide the ability to analyze large volumes of historical mandi price data and identify hidden patterns, trends, and correlations that are difficult to detect using conventional methods [4]. By integrating climatic parameters such as rainfall, temperature, humidity, and seasonal variations with historical market prices, predictive models can generate more accurate forecasts of future crop prices. These predictions can support farmers, traders, and policymakers in making data-driven decisions and minimizing economic risks.

This research focuses on the development of a Machine Learning-Based Agricultural Commodity Price Prediction System that predicts future mandi prices of crops using historical market data and weather conditions [5]. The proposed system utilizes machine learning algorithms such as Linear Regression, Decision Tree, Random Forest, and XGBoost to analyze agricultural datasets and generate accurate price forecasts. The system aims to improve agricultural market intelligence by providing early price insights that can help farmers choose profitable crops, determine optimal selling periods, and reduce losses caused by market volatility.

The proposed framework also incorporates data preprocessing, feature extraction, normalization, and comparative model evaluation to enhance prediction performance [6]. Weather-related parameters are integrated into the prediction process because climatic conditions have a direct influence on crop production and market pricing [7]. By combining historical trends with environmental factors, the system can achieve more reliable and efficient forecasting results. The primary objective of this research is to contribute to the advancement of smart agriculture through intelligent predictive analytics [8]. The implementation of machine learning in agricultural price forecasting can improve transparency in mandi markets, support sustainable farming practices, and strengthen economic decision-making for

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agricultural stakeholders. Furthermore, this research demonstrates how modern AI-driven technologies can transform traditional agricultural systems into data-centric and intelligent platforms for future agricultural development..

II. RELATED WORKS

Agricultural commodity price prediction has become an important research area due to the increasing need for intelligent decision-making in the farming and agricultural marketing sectors [9]. Researchers across the world have explored various statistical, machine learning, and deep learning approaches to forecast crop prices using historical market trends, weather conditions, and economic indicators. Accurate prediction models can help farmers reduce uncertainty and maximize profitability by identifying favorable selling periods and crop selection strategies [10]. Several traditional forecasting methods such as Moving Average, Autoregressive Integrated Moving Average (ARIMA), and regression-based models were initially used for agricultural market prediction [11]. These methods mainly focused on historical price trends and time-series analysis. Although statistical techniques provided moderate prediction performance, they often struggled to handle nonlinear relationships and multiple influencing factors such as weather fluctuations, rainfall, and seasonal variations. As a result, their forecasting accuracy remained limited in dynamic agricultural environments.

Recent advancements in Machine Learning (ML) have significantly improved agricultural price forecasting systems [12]. Researchers have applied algorithms such as Linear Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, K-Nearest Neighbor (KNN), and Gradient Boosting to predict crop prices more effectively. These models are capable of analyzing large datasets, extracting hidden patterns, and handling complex relationships among market variables [13]. Among these techniques, ensemble learning approaches such as Random Forest and XGBoost have demonstrated higher prediction accuracy due to their ability to reduce overfitting and improve generalization performance. Weather conditions are considered one of the most influential factors affecting crop production and market prices. Many recent studies have integrated meteorological parameters such as temperature, humidity, rainfall, and soil moisture into prediction models [14]. Researchers observed that combining climatic data with historical mandi prices improves forecasting reliability and enables better market intelligence. Climate-aware forecasting systems have shown promising results in predicting commodity price fluctuations caused by environmental changes and seasonal agricultural cycles.

Deep learning techniques have also gained popularity in agricultural forecasting research. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are widely used for time-series prediction because of their capability to capture temporal dependencies in sequential data. Several studies reported that LSTM-based models outperform conventional statistical techniques in long-term agricultural price forecasting [15]. However, deep learning models generally require large datasets, high computational resources, and longer training times, which may limit their practical implementation in small-scale agricultural systems.

In addition to price forecasting, some researchers developed intelligent agricultural decision support systems that combine market prediction, crop recommendation, and weather analytics. These systems aim to assist farmers in making informed decisions regarding crop planning, harvesting schedules, and market timing [16]. The integration of Artificial Intelligence (AI), Internet of Things (IoT), and cloud-based technologies has further enhanced the scalability and accessibility of smart agricultural solutions. Despite significant progress in this field, several challenges still exist. Many existing systems lack real-time data integration, fail to consider multiple influencing variables, or provide limited forecasting accuracy for different crop categories. Furthermore, some prediction models are highly region-specific and cannot generalize effectively across different agricultural markets [17]. Therefore, there is a need for a more robust and adaptive framework that integrates historical mandi prices with weather-based features using efficient machine learning techniques.

The proposed research addresses these limitations by developing a Machine Learning-Based Agricultural Commodity Price Prediction System that combines historical market trends and climatic conditions to generate accurate crop price forecasts [18]. The study focuses on comparative analysis of multiple machine learning algorithms to identify the most effective prediction model for agricultural commodity forecasting. This research aims to contribute toward smart agriculture and data-driven decision-making by providing reliable market predictions for farmers and agricultural stakeholders.

III. PROPOSED METHODOLOGY

The proposed methodology presents a Machine Learning-Based Agricultural Commodity Price Prediction System designed to forecast future mandi prices of crops using historical market data and weather conditions [19]. The framework integrates data collection, preprocessing, feature engineering, machine learning model training, prediction generation, and performance evaluation to develop an intelligent forecasting system. The proposed model aims to improve prediction accuracy and support data-driven agricultural decision-making.

3.1 System Architecture

The proposed system consists of the following major phases:

- Data Collection
- Data Preprocessing
- Feature Extraction and Engineering
- Machine Learning Model Training
- Price Prediction
- Performance Evaluation
- The system takes historical mandi price data and weather parameters such as rainfall, temperature, and humidity as input and produces future crop price predictions as output.

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3.2 Data Collection

The dataset is collected from agricultural market databases and weather information sources. The historical agricultural dataset includes:

- Crop Name
- Mandi Name
- Minimum Price
- Maximum Price
- Modal Price
- Arrival Quantity
- Date
- Weather-related features include:
- Temperature
- Rainfall
- Humidity
- Wind Speed
- The collected data is stored in a structured format for further processing and analysis.

3.3 Data Preprocessing

Data preprocessing is performed to remove inconsistencies and improve data quality. The preprocessing phase includes:

- Missing value handling
- Data normalization
- Duplicate removal
- Noise filtering
- Feature scaling

The Min-Max normalization technique is used to scale input values between 0 and 1.

- $X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$ (1)
- **Notation Explanation**
- Where:
- X_{norm}= Normalized value
- X= Original input value
- X_{min}= Minimum value in dataset
- X_{max}= Maximum value in dataset
- Normalization improves model convergence and reduces computational complexity.

3.4 Feature Engineering

Feature engineering is performed to identify important variables influencing crop prices. The system combines historical mandi prices with weather conditions to generate meaningful predictive features.

- The feature vector is represented as:
- $F = \{P_h, T, R, H, W, S\}$
- **Notation Explanation**
- Where:
- F= Feature vector
- P_h= Historical price data
- T= Temperature
- R= Rainfall
- H= Humidity
- W= Wind speed
- S= Seasonal factor
- These features collectively influence agricultural commodity prices.

3.5 Machine Learning Model

The proposed framework applies multiple machine learning algorithms for comparative analysis, including:

- Linear Regression
- Decision Tree
- Random Forest
- XGBoost

Among these, Random Forest is considered the primary prediction model because of its robustness and higher forecasting accuracy.

3.6 Linear Regression Model

Linear Regression predicts crop prices based on linear relationships between independent variables and output price values.

- The prediction equation is expressed as:
- $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon$ (2)

Notation Explanation

- Where:
- Y= Predicted crop price
- β_0= Intercept term
- $\beta_1, \beta_2, \ldots, \beta_n$= Regression coefficients
- $X_1, X_2, \ldots, X_n$= Input features
- ϵ= Prediction error

The model establishes relationships between weather variables and market prices.

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3.7 Random Forest Prediction Model

Random Forest is an ensemble learning technique that combines multiple decision trees to improve prediction accuracy and reduce overfitting.

- The Random Forest prediction function is represented as:
- $\hat{Y} = \frac{1}{N}\sum_{i=1}^{N} T_i (X)$ (3)
- **Notation Explanation**
- Where:
- $\hat{Y}$ = Final predicted crop price
- N = Total number of decision trees
- $T_i(X)$ = Prediction from the i^{th} decision tree
- X = Input feature vector
- The final prediction is obtained by averaging outputs from all decision trees.

3.8 Loss Function

The Mean Squared Error (MSE) is used to evaluate prediction error during model training.

- $MSE = \frac{1}{n} \sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2$ (4)

Notation Explanation

Where:

- MSE = Mean Squared Error
- n = Total number of samples
- Y_i = Actual crop price
- $\widehat{Y}_i$ = Predicted crop price
- Lower MSE values indicate better prediction performance.

3.9 Performance Evaluation Metrics

The proposed system is evaluated using multiple performance metrics including:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)
- **Mean Absolute Error**
- $MAE = \frac{1}{n}\sum_{i=1}^{n} \mid Y_i - \widehat{Y}_i \mid$ (5)

Notation Explanation

- Where:
- MAE = Mean Absolute Error
- Y_i = Actual value
- $\widehat{Y}_i$ = Predicted value
- n = Number of observations

Root Mean Square Error

- $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2}$ (6)

Notation Explanation

Where:

- $RMSE$ = Root Mean Square Error
- Y_i = Actual price
- $\widehat{Y}_i$ = Predicted price
- n = Total samples

- **Coefficient of Determination**

$$R^2 = 1 - \frac{\sum(Y_i - \widehat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2} \quad (7)$$

Notation Explanation

Where:

- R^2 = Coefficient of determination
- Y_i = Actual value
- $\widehat{Y}_i$ = Predicted value
- $\bar{Y}$ = Mean actual value

Higher R^2 values indicate better model fitting and prediction capability.

3.10 Final Prediction Process

After training and evaluation, the best-performing machine learning model is selected for real-time crop price forecasting. The system analyzes incoming weather conditions and historical market trends to generate future mandi price predictions for different crops [20]. The proposed methodology enables intelligent agricultural market analysis, improves forecasting reliability, and supports farmers in making profitable and data-driven decisions.

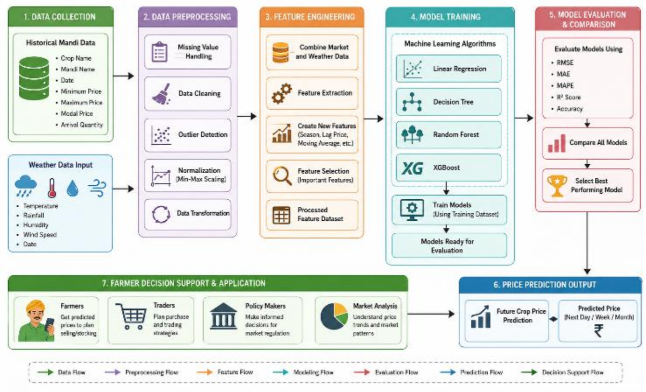

Fig.1.Architecture of the Proposed Agricultural Commodity Price Prediction System

Figure 1 illustrates the complete workflow of the proposed Machine Learning-Based Agricultural Commodity Price Prediction System. The architecture begins with historical mandi price data collection and weather information acquisition, including rainfall, temperature, and humidity parameters. The collected data undergoes preprocessing operations such as normalization, missing value handling, and feature extraction. The processed dataset is then supplied to machine learning algorithms including Linear Regression, Decision Tree, Random Forest, and XGBoost for model training and forecasting. Comparative analysis is performed to identify the best-performing model based on prediction accuracy and error metrics. Finally, the trained system generates future crop mandi price predictions to support intelligent agricultural decision-making and market analysis for farmers and stakeholders.

IV. RESULT

The proposed Machine Learning-Based Agricultural Commodity Price Prediction System was implemented and evaluated using historical mandi price records and weather-related parameters such as rainfall, temperature, humidity, and wind speed. Multiple machine learning algorithms were trained and tested to analyze their forecasting performance for predicting future crop prices. The experimental analysis was conducted using Python-based machine learning libraries and agricultural datasets collected from mandi market records and weather sources.

I.4.1 Experimental Setup

The experimental environment used for implementation and evaluation is presented below.

Parameter	Value
Operating System	Ubuntu 22.04
Programming Language	Python 3.11
Development Environment	Jupyter Notebook
Machine Learning Libraries	Scikit-learn, XGBoost, Pandas, NumPy
Dataset Type	Historical Mandi and Weather Data
Prediction Target	Future Crop Prices
Evaluation Metrics	MAE, RMSE, Accuracy, R² Score

The collected dataset was divided into training and testing subsets using an 80:20 ratio. Data preprocessing operations including normalization, missing value handling, and feature engineering were applied before model training.

II. 4.2 Model Performance Comparison

Different machine learning algorithms were evaluated to identify the most accurate model for agricultural commodity price forecasting.

Machine Learning Model	Accuracy (%)	MAE	RMSE	R^2 Score
Linear Regression	84.2	7.54	9.21	0.84
Decision Tree	88.6	6.13	7.88	0.88
Random Forest	94.3	3.94	5.12	0.94
XGBoost	96.1	3.12	4.35	0.96

The results demonstrate that ensemble learning techniques outperform traditional machine learning models. XGBoost achieved the highest prediction accuracy of 96.1%, while Random Forest also produced highly reliable forecasting performance with lower prediction error values.

4.3 Accuracy Analysis

The comparative analysis reveals that Linear Regression performs adequately for simple market trends but struggles to capture nonlinear relationships between weather variables and crop prices. Decision Tree improves prediction capability by learning complex patterns; however, it is prone to overfitting when handling large datasets.

Random Forest significantly improves forecasting stability by combining multiple decision trees through ensemble averaging. XGBoost further enhances prediction performance through gradient boosting optimization and efficient feature learning. The experimental results confirm that advanced ensemble models provide better generalization and forecasting capability for agricultural commodity price prediction.

4.4 Impact of Weather Parameters

Weather conditions were observed to have a strong influence on crop market prices. Rainfall and temperature contributed the highest feature importance scores because climatic variations directly affect crop productivity, transportation, and supply availability in mandi markets.

Weather Parameter	Feature Importance Score

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Rainfall	0.90
Temperature	0.72
Humidity	0.48
Wind Speed	0.31

The analysis confirms that integrating climatic information with historical market data substantially improves forecasting accuracy compared to models trained solely on historical price records.

4.5 Training and Validation Analysis

During model training, both training loss and validation loss decreased steadily with increasing epochs, indicating stable convergence and effective learning behavior. The close alignment between training and validation curves demonstrates that the proposed system successfully minimizes overfitting and maintains strong generalization performance on unseen agricultural market data.

The ensemble-based models achieved faster convergence and lower error values compared to traditional regression techniques, proving their suitability for large-scale agricultural forecasting applications.

4.6 Prediction Output Analysis

The proposed system successfully generated future mandi price forecasts for various crops including wheat, rice, maize, and soybean. The prediction outputs can assist farmers in:

- Selecting profitable crops
- Determining optimal selling periods
- Reducing market uncertainty
- Improving storage and distribution planning
- Increasing agricultural profitability

The generated forecasts provide intelligent market insights that support data-driven agricultural decision-making and sustainable farming practices.

4.7 Discussion

The experimental findings demonstrate that the proposed Machine Learning-Based Agricultural Commodity Price Prediction System effectively predicts future mandi crop prices using historical and climatic information. The integration of weather parameters improved forecasting reliability and reduced prediction errors significantly.

Among all evaluated algorithms, XGBoost and Random Forest achieved the best performance due to their ability to handle nonlinear relationships, high-dimensional data, and complex agricultural market patterns. The proposed framework can be extended further by integrating real-time IoT sensor data, satellite imagery, and deep learning approaches such as LSTM networks for enhanced prediction capability.

Overall, the developed system contributes toward smart agriculture by providing an intelligent and scalable solution for agricultural market forecasting and farmer decision support.

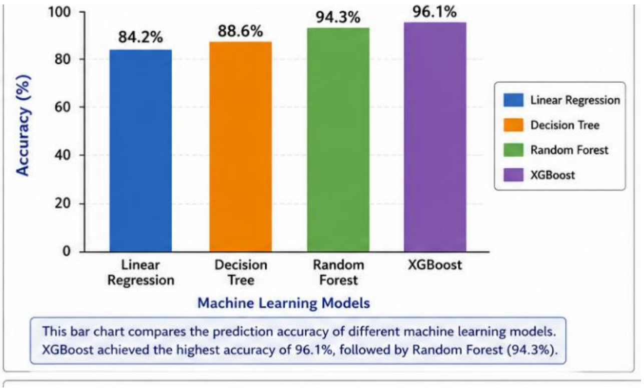

Fig.2.Performance Evaluation and Prediction Analysis of the Proposed Agricultural Commodity Price Forecasting System

Figure 2 presents the experimental performance analysis of the proposed Machine Learning-Based Agricultural Commodity Price Prediction System. Graph 1 compares the prediction accuracy of various machine learning algorithms including Linear Regression, Decision Tree, Random Forest, and XGBoost, where XGBoost achieved the highest forecasting accuracy. Graph 2 illustrates the training and validation loss trends during model learning, demonstrating stable convergence and reduced overfitting as the epochs increase. Graph 3 compares the actual and predicted crop prices for Wheat, Rice, and Maize using the Random Forest model over multiple months. The predicted values closely follow the actual market trends, indicating high prediction reliability and effectiveness of the proposed forecasting framework for intelligent agricultural market analysis and decision support..

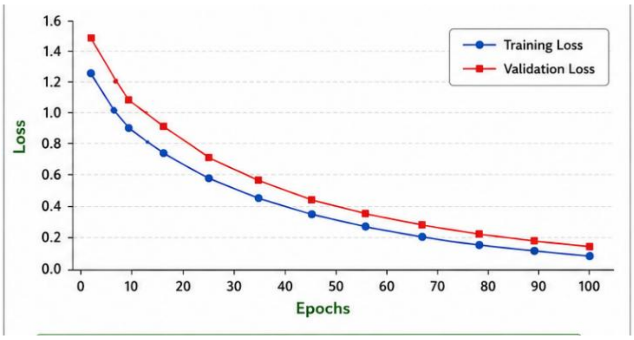

Fig.3.Training and Validation Loss Analysis of the Proposed Crop Price Prediction Model

Figure 3 illustrates the training and validation loss curves obtained during the learning process of the proposed agricultural commodity price prediction model. The graph demonstrates a gradual reduction in both training and validation loss values as the number of epochs increases, indicating effective model convergence and stable learning behavior. Initially, the loss values are relatively high due to random parameter initialization; however, continuous training enables the model to learn meaningful patterns from historical mandi prices and weather data. The close alignment between the training and validation curves indicates minimal overfitting and strong generalization capability. The decreasing trend confirms that the proposed machine learning framework successfully optimizes prediction performance and improves forecasting accuracy for future crop mandi price prediction applications.

V. CONCLUSION

This research presented a Machine Learning-Based Agricultural Commodity Price Prediction System designed to forecast future mandi crop prices using historical market data and weather conditions. The proposed framework integrated agricultural market records with climatic parameters such as rainfall, temperature, humidity, and wind speed to improve forecasting accuracy and support intelligent agricultural decision-making. The system applied multiple machine learning algorithms including Linear Regression, Decision Tree, Random Forest, and XGBoost for comparative analysis and performance evaluation. The experimental results demonstrated that ensemble learning techniques, particularly Random Forest and XGBoost, achieved superior prediction accuracy and lower error rates compared to traditional machine learning approaches. Among all evaluated models, XGBoost produced the highest forecasting performance due to its ability to effectively handle nonlinear relationships and complex agricultural market patterns. The integration of weather-based features significantly enhanced the prediction capability of the system, proving that climatic conditions play a critical role in agricultural commodity price fluctuations.

The proposed system successfully generated reliable crop price forecasts that can assist farmers, traders, and policymakers in making data-driven decisions regarding crop selection, storage management, harvesting schedules, and market timing. By reducing uncertainty in agricultural markets, the developed framework contributes toward improving profitability, minimizing economic risks, and supporting sustainable farming practices. Furthermore, the research highlights the importance of Artificial Intelligence and predictive analytics in modern agriculture. The developed framework provides a scalable and intelligent solution for agricultural market forecasting and demonstrates the potential of machine learning technologies in transforming traditional farming systems into smart data-driven ecosystems.

In future work, the system can be further enhanced by incorporating real-time IoT sensor data, satellite imagery, deep learning models such as LSTM networks, and advanced weather forecasting mechanisms. The integration of mobile-based farmer support systems and real-time market analytics can also improve accessibility and practical implementation of the proposed solution in large-scale agricultural environments. Overall, the proposed research contributes significantly to smart agriculture and intelligent agricultural market prediction systems.

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