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Original Research Article

Explainable AI-Driven Machine Learning for Predictive Analytics in Agricultural Markets: Forecasting Commodity Price Trends

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Abstract: Agricultural price fluctuations create significant challenges for farmers and policymakers, making accurate price forecasting vital for agro-economic stability. This study introduces an Explainable Artificial Intelligence (XAI)-driven Random Forest model for forecasting weekly modal prices of agricultural commodities in Bangladesh and India. The model utilizes the Agricultural Commodity Price Forecasting Dataset, containing 23,093 weekly price records across Indian and Bangladeshi markets. Following rigorous preprocessing and feature engineering, multiple models were evaluated, among which the Random Forest achieved superior performance (RMSE = 397.07, MAE = 100.96, and R^2 = 0.9931), outperforming XGBoost, CatBoost, MLP, and LSTM. Integration of SHapley Additive exPlanations (SHAP) provides interpretability by identifying key influential factors such as Max Price, Min Price, Market, and Commodity Type. The proposed XAI-based Random Forest framework ensures both high predictive accuracy and transparency, offering valuable insights for data-driven decision-making in agricultural market forecasting.

Keywords: Agro-Economics, Price Forecasting, Commodity Prices, Explainable AI.

I. INTRODUCTION

Agricultural markets in South Asia, particularly in countries like Bangladesh and India, play a critical role in ensuring food security, stabilizing the economy, and supporting the livelihoods of millions of smallholder farmers [1, 2]. Price volatility of agricultural commodities, driven by seasonal variations, regional demand-supply imbalances, and market inefficiencies, poses significant challenges for both policymakers and farmers. Accurate forecasting of commodity prices is therefore essential for strategic planning, risk mitigation, and informed decision-making in the agro-economic sector [3].

In recent years, machine learning (ML) models have shown remarkable capability in predicting complex patterns in agricultural datasets, capturing non-linear relationships among price, market, and temporal variables [4]. Models such as XGBoost, CatBoost, Long Short-Term Memory (LSTM), and Multi-Layer Perceptrons (MLP) have been widely applied for price prediction tasks. However, a major limitation of these approaches is their black-box nature, which obscures the underlying reasoning behind predictions [5]. The lack of interpretability restricts trust and limits practical adoption, especially in agricultural policymaking, where stakeholders require transparent, explainable insights to make informed decisions.

Explainable Artificial Intelligence (XAI) has emerged as a promising solution to address this challenge by providing interpretable and transparent explanations for complex model predictions [6]. Techniques such as SHapley Additive exPlanations (SHAP) [7], enable the identification of feature importance and the contribution of individual predictors to the model output. Incorporating XAI into agricultural price forecasting allows stakeholders to understand the influence of factors such as market location, commodity type, seasonal effects, and price trends on predicted prices.

This study proposes a Random Forest–based predictive framework integrated with XAI to forecast weekly modal prices of agricultural commodities in India and Bangladesh. The proposed approach not only achieves high predictive accuracy but also ensures interpretability, bridging the gap between performance and transparency. By integrating XAI into the Random Forest model, this research provides actionable insights for farmers, traders, and policymakers, enabling data-driven decision-making and enhancing trust in machine learning applications in agricultural markets.

The primary contributions of this study are as follows:

- Development of a robust Random Forest model for forecasting agricultural commodity prices.
- Integration of XAI through SHAP to provide both global and local interpretability of predictions.
- Analysis of feature importance to identify key factors influencing commodity price trends in India and Bangladesh.
- Demonstration of the effectiveness of explainable machine learning in improving transparency and usability of predictive models for agro-economic applications.

II. Related Works

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have enhanced the accuracy of agricultural commodity price forecasting, providing adaptive alternatives to traditional econometric models like ARIMA and VAR. However, interpretability, generalization, and adaptability across regions remain major challenges.

A study in [8], applied Shapley Additive exPlanations (SHAP) to interpret global food price fluctuations, integrating explainability with prediction for greater transparency. Its limitation lies in focusing on global data, lacking regional relevance for South Asia.

The work in [9], used ensemble ML algorithms for price forecasting, outperforming linear and time-series models while aligning with the UN's Zero Hunger goal. However, it lacked interpretability, reducing usability for policymakers & farmers. The review in [10], summarized ML approaches, emphasizing preprocessing, feature selection, and ensemble modeling. Despite strong predictive insights, it lacked explainable frameworks to interpret model behavior. In [11], a hybrid VMD–EEMD–LSTM model effectively captured multi-scale temporal patterns, achieving high accuracy and robustness against noise. Yet, its deep structure increased computational cost and reduced interpretability.

The study in [12], proposed an explainable deep learning model that balanced accuracy and transparency but required heavy computational resources and lacked validation on developing-country data.

A regional study in [13], employed deep learning for predicting Indian crop prices, demonstrating adaptability to local datasets but facing issues with overfitting and the lack of explainable mechanisms.

Lastly [14], explored AI–XAI integration in precision agriculture, showing that interpretability enhances trust and performance. However, it focused on crop yield rather than price forecasting.

In summary, prior studies highlight ML and DL models' strong forecasting potential but reveal gaps in transparency, computational efficiency, and regional adaptability [15]. Building upon these findings, the present work proposes an XAI-driven Random Forest framework with SHAP analysis to achieve high accuracy, interpretability, and regional applicability for Bangladesh and India.

III. METHODOLOGY

This study proposes a framework for forecasting agricultural commodity prices using a Random Forest model with Explainable AI (XAI). The methodology covers dataset description, preprocessing, feature engineering, model training, and explainability analysis, ensuring both accuracy and interpretability. The overall workflow is shown in Fig. 1, illustrating the sequential steps from data collection to model evaluation and SHAP-based insights.

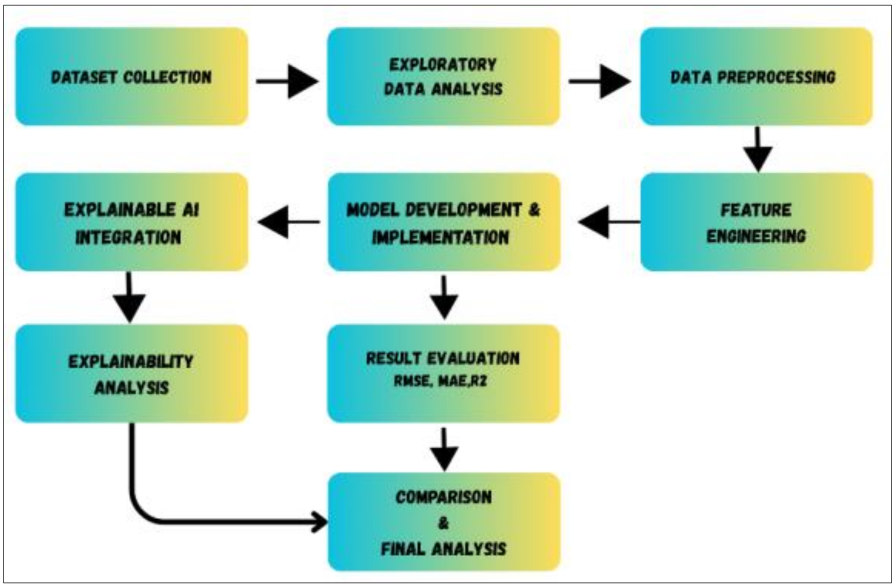

Fig. 1: Workflow Diagram

A. Dataset Description

The study uses the Agricultural Commodity Price Forecasting Dataset [16], which contains weekly price records of commodities. The raw dataset has 23,093 rows and 10 columns, including *State, District, Market, Commodity, Variety, Grade, Arrival_Date, Min Price, Max Price,* and *Modal Price*.

Modal Price is the target variable. After preprocessing and feature engineering, the dataset contains 22,124 rows and 19 features (17 predictors: 11 numerical, 6 categorical). Missing values were imputed, duplicates removed, numeric features scaled, and categorical variables encoded.

B. Exploratory Data Analysis (EDA)

EDA was conducted to understand the characteristics, trends, and variability of commodity prices, guiding feature engineering.

Table 1 summarizes key statistics of numeric features (*Modal Price, Max Price, Min Price, Price Spread*), showing variability and skewness.

Table I: Descriptive Statistics Table

Statistic	Modal Price	Max Price	Min Price	Price_Spread
Count	23,093	23,093	23,093	23,093
Mean	4,602.92	4,976.03	4,187.08	788.96
Std	5,843.82	6,277.31	5,472.78	1,944.63
Min	0.83	0.00	0.00	-7,000.00
25th %	1,955.00	2,000.00	1,750.00	100.00
Median	3,000.00	3,400.00	2,725.00	270.00
75th %	5,500.00	6,000.00	5,000.00	850.00
Max	225,500.00	227,500.00	223,500.00	103,000.00
Skewness	8.96	8.44	9.53	15.50
Kurtosis	170.60	145.36	198.36	524.79

Fig. 2 shows the distribution of modal prices with a histogram and KDE plot, revealing a highly right-skewed pattern where most prices are below INR 25,000 and peak under INR 10,000, with a long tail up to INR 225,000. This distribution reflects typical commodity markets with few high-value outliers and requires careful handling, such as logarithmic transformation. Fig. 3 depicts the weekly average price trend from 2023-07-27 to 2023-08-02, where prices rise from INR 4,270 to INR 4,700, drop to INR 3,600, and recover to nearly INR 5,400, highlighting non-stationarity and short-term volatility. Fig. 4 presents the Pearson correlation heatmap of Modal, Max, and Min Prices, showing strong correlations of 0.99, 0.98, and 0.95, respectively, indicating multicollinearity and suggesting that Modal Price alone can serve as the target or that dimensionality reduction may be applied.

Fig. 2: Distribution of Modal Prices

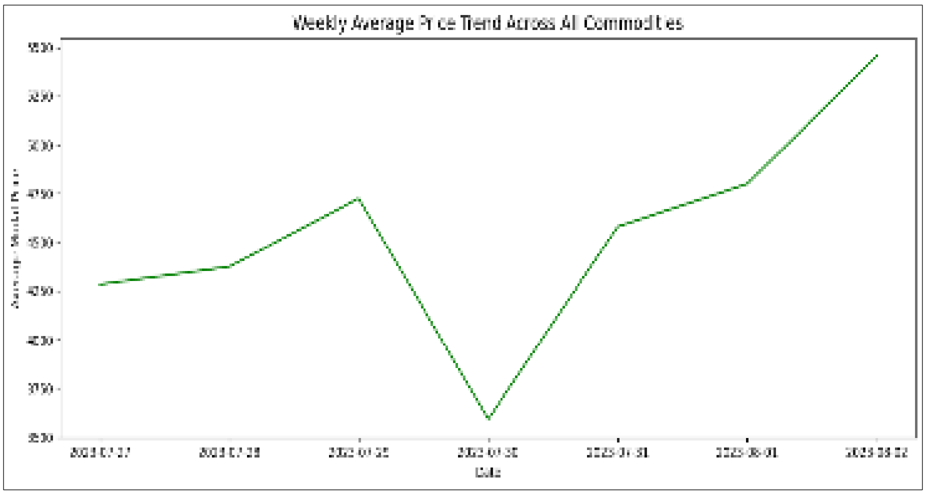

Fig. 3: Weekly Average Price Trend

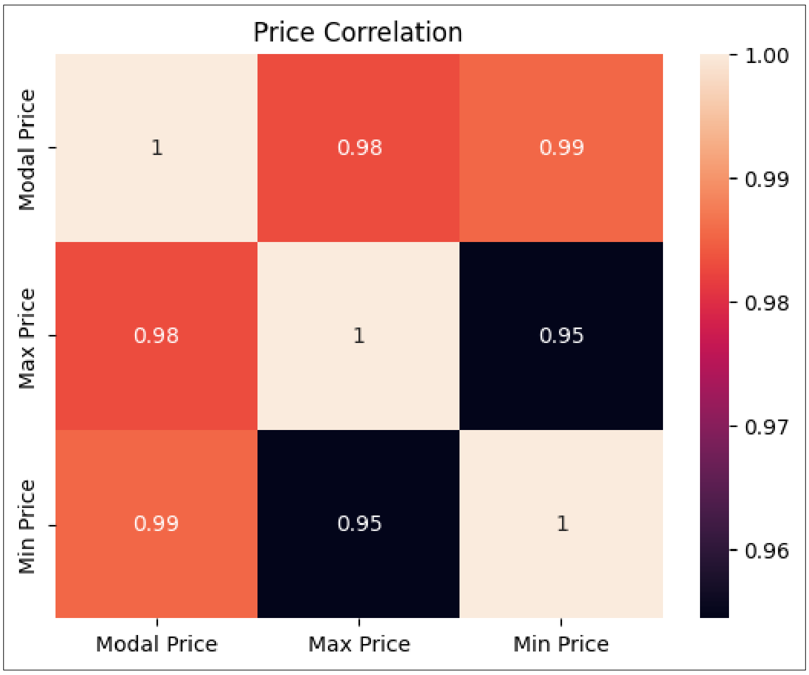

Fig. 4: Price Correlation Heatmap

C. Data Preprocessing

a) Handling Missing Values: Median for numeric columns, mode for categorical columns.
b) Duplicate Removal: Eliminated duplicate records.
c) ***Date Conversion and Sorting:*** Arrival_Date converted to datetime and sorted by Commodity and Arrival_Date.
d) ***Normalization:*** StandardScaler applied to numeric features.
e) ***Categorical Encoding:*** Label Encoding applied to categorical columns (State, District, Market, Commodity, Variety, Grade).

D. Feature Engineering

Nine additional features were generated to capture volatility, temporal trends, and seasonality:

Table II: Additional Features

Feature	Type	Description
Price_Range	Numeric	Max Price – Min Price
Avg_Price	Numeric	(Max Price + Min Price)/2
Year	Numeric	Extracted from Arrival_Date
Month	Numeric	Extracted from Arrival_Date
Day	Numeric	Extracted from Arrival_Date
DayOfWeek	Numeric	Day of the week (0–6, Mon–Sun)
IsWeekend	Binary	1 if Saturday/Sunday, else 0
Rolling_Mean_Price	Numeric	7-day rolling mean of Modal Price
Log_Modal_Price	Numeric	Natural logarithm of Modal Price

E. Model Development

The proposed framework implements five supervised learning models: Random Forest (RF), Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), XGBoost, and CatBoost for predicting weekly modal prices of agricultural commodities. The dataset was divided into 80% training and 20% testing, with numerical features scaled for neural network models and categorical features label-encoded to ensure compatibility across tree-based and neural models.

The Random Forest Regressor was selected as the proposed model due to its robustness, interpretability, and ability to handle multicollinearity. XGBoost and CatBoost were tuned as gradient-boosted decision tree models, while MLP and LSTM were designed to capture nonlinear and temporal dependencies, respectively. Early stopping was applied to neural network models to prevent overfitting.

Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 score to assess predictive accuracy and reliability. The hyperparameters, architectural details, and evaluation metrics of all models are summarized in Table III, providing a clear overview of the model construction strategy used in this study.

Table III: Model Construction Summary

Model	Parameters	Key Features
Random Forest (RF)	500 trees, max depth 12, MSE criterion, random state 42	Robust, interpretable, handles multicollinearity
Multi-Layer Perceptron (MLP)	2 hidden layers (128, 64 neurons), ReLU activation, linear output	Captures nonlinear relationships, early stopping applied
Long Short-Term Memory (LSTM)	1 LSTM layer (64 units), linear output	Captures temporal dependencies, early stopping applied
XGBoost	500 estimators, learning rate 0.05, max depth 6, subsample 0.8, colsample_bytree 0.8	Gradient-boosted decision trees, robust to overfitting
CatBoost	500 iterations, learning rate 0.05, max depth 6	Gradient boosting with categorical feature handling, low preprocessing

F. Explainable AI (XAI) Integration

To enhance interpretability, Explainable AI (XAI) techniques were applied to tree-based models, providing both global and local insights into predictions. While most machine learning models act as black boxes [5], XAI enables understanding of feature contributions and decision-making processes, which is crucial for actionable insights in agro-economic forecasting.

SHAP is grounded in cooperative game theory and attributes the prediction of a model *f(x)* to a baseline expectation value and additive feature contributions, expressed as a formula [7] as,

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i \qquad (1a)$$

Each feature's contribution, represented by the Shapley value ϕi, is defined as,

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(M - |S| - 1)!}{M!} \left[f(S \cup \{i\}) - f(S) \right], \qquad (1b)$$

Global explainability was achieved using SHAP summary plots and feature importance bar plots, highlighting the most influential variables such as commodity type, price spread, and recent price trends. Local explainability was provided through SHAP waterfall plots, illustrating how individual features contribute to specific predictions and supporting detailed analysis for stakeholders.

By integrating XAI into tree-based models, the methodology ensures both high predictive accuracy and transparent interpretability, bridging the gap between model performance and actionable insights in commodity price forecasting.

IV. RESULTS

The predictive performance of all developed models was assessed using three standard evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). These metrics jointly measure model accuracy, consistency, and explanatory strength. The comparative results are summarized in Table IV.

Table I: Comparative Results of All Models

Model	RMSE ↓	MAE ↓	R^2 ↑
XGBoost	495.12	127.34	0.9892
Random Forest	397.07	100.96	0.9931
CatBoost	683.60	158.47	0.9795
MLP	773.51	501.62	0.9737
LSTM	591.14	198.70	0.9847

Among all models, the Random Forest achieved the highest predictive performance, recording the lowest RMSE and MAE values, as well as the highest R^2 score, indicating its superior generalization capability and stability. XGBoost and CatBoost also delivered competitive results due to their efficient boosting algorithms. At the same time, MLP and LSTM captured nonlinear and temporal dynamics but showed slightly higher error levels due to sensitivity to data irregularities.

Fig. 5-Fig. 6 presents the *Actual vs. Predicted* plots, illustrating strong alignment between observed and predicted prices, particularly for Random Forest, with minimal deviation.

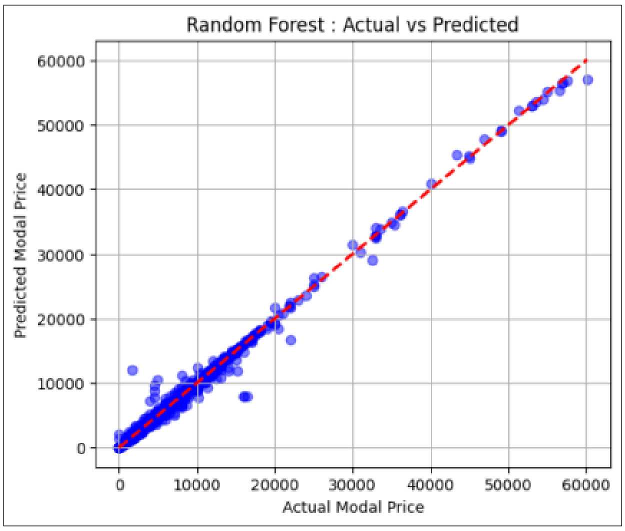

Fig. 5: Actual vs Predicted (Random Forest)

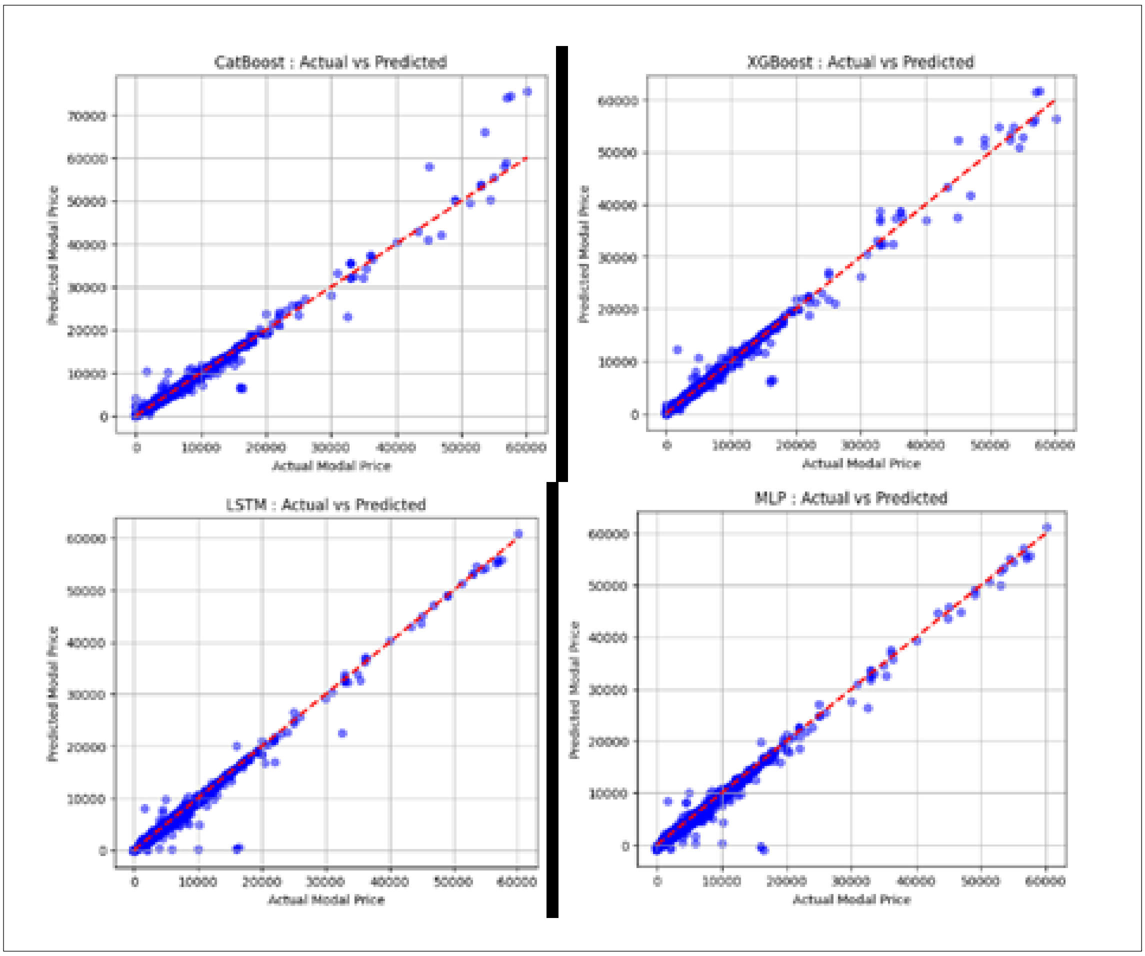

Fig. 6: Actual vs Predicted (CatBoost, XGBoost, LSTM, MLP)

The *Residual Plots* (Fig.7 – Fig. 8) show that Random Forest residuals (Fig. 7) are symmetrically distributed around zero, reflecting reduced bias and robust model calibration.

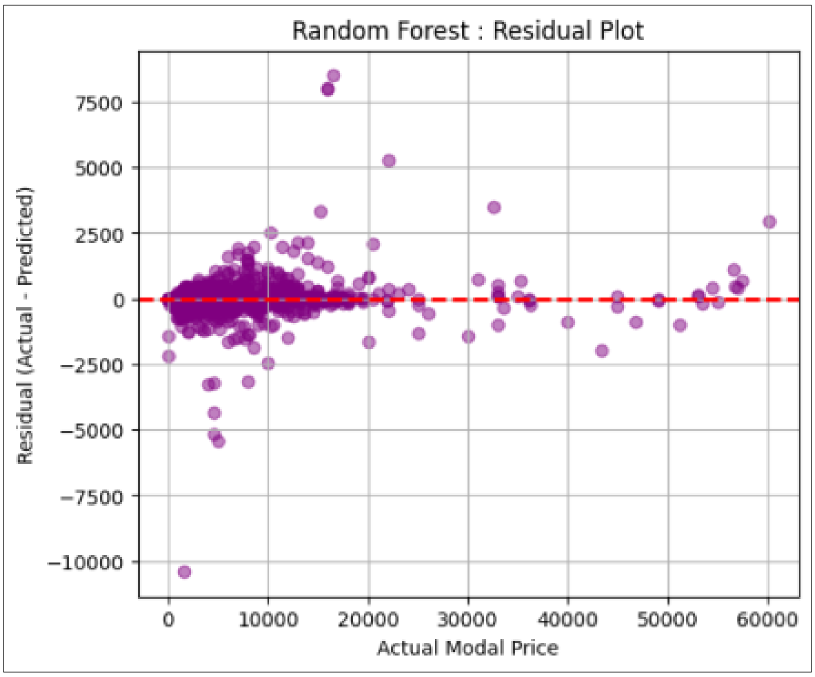

Fig. 7: Residual Plot (Random Forest)

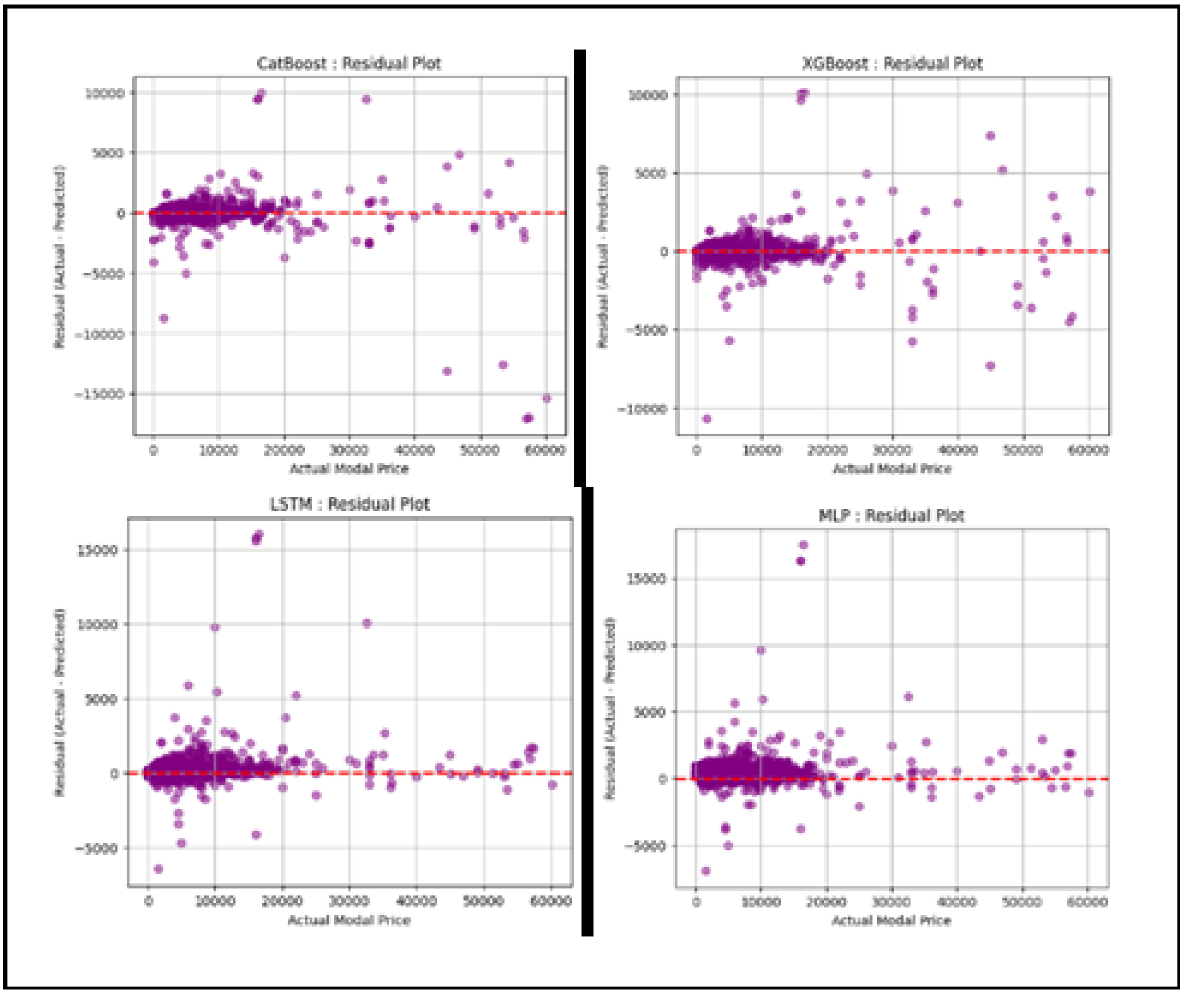

Fig. 8: Residual Plot (CatBoost, XGBoost, LSTM, MLP)

Further, Fig. 9–Fig. 11 display the comparative visualization of R^2, MAE, and RMSE across all models, reaffirming Random Forest's consistent superiority in predictive accuracy.

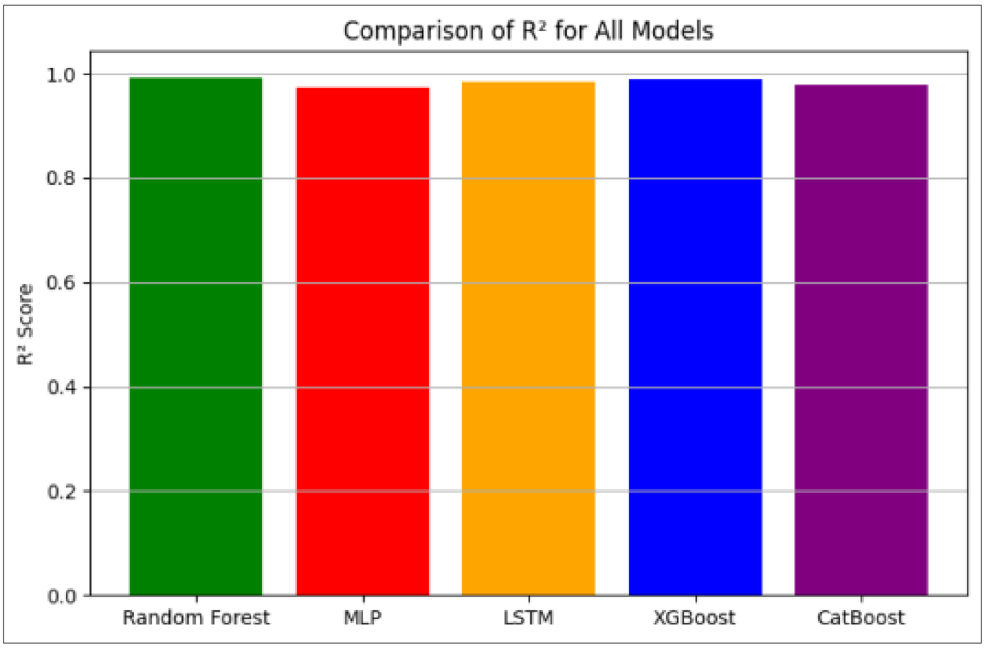

Fig. 9: Comparison of R^2 for All Models

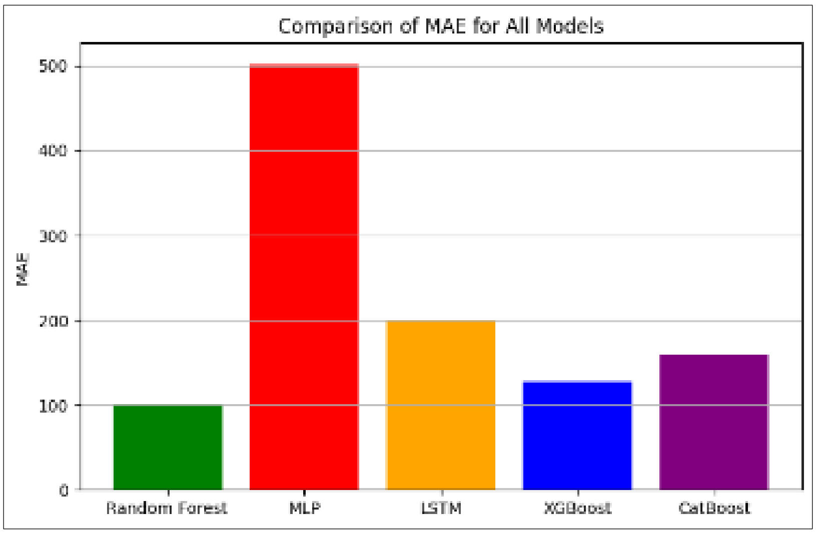

Fig. 10: Comparison of MAE

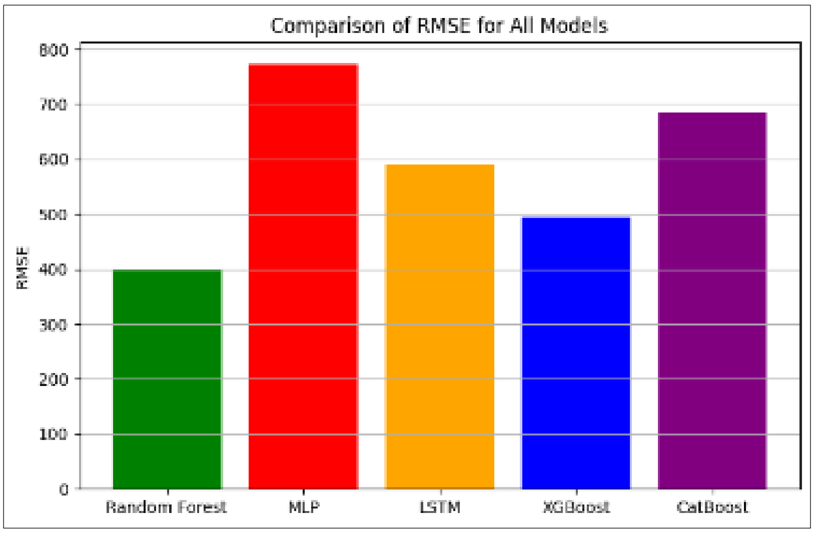

Fig. 11: Comparison of RMSE

These findings establish Random Forest as the most effective model for weekly agricultural price forecasting, striking a balance between accuracy, reliability, and interpretability for integration with Explainable AI (XAI).

V. Explainability with Shap

To enhance interpretability and transparency of the forecasting framework, SHapley Additive exPlanations (SHAP) were applied to all tree-based models—Random Forest, XGBoost, and CatBoost. SHAP provides both global and local explanations by quantifying the contribution of each feature to the model's output, thereby transforming the predictive models from black-box systems into interpretable analytical tools.

A. Global Explainability

Global interpretability was achieved using SHAP summary and SHAP bar plots, revealing the overall influence and relative importance of input features across all model predictions. The SHAP Summary Plots (Fig. 12 for Random Forest, Fig. 14 for XGBoost, and Fig. 16 for CatBoost) illustrate each feature's contribution to the output, showing both magnitude and direction of impact. The vertical axis lists features ranked by global importance, while the horizontal axis represents SHAP values, with red indicating high and blue low feature values. Positive SHAP values increase predictions, and negative values decrease them.

Across all models, Max Price and Min Price are the dominant predictors with the largest SHAP ranges, while secondary features like *Rolling_3*, *Rolling_5*, and *Price_Spread* show smaller impacts. CatBoost exhibits tighter clustering for lower-ranked features, indicating a more focused influence distribution.

The SHAP Bar Plots (Fig. 13 for Random Forest, Fig. 15 for XGBoost, and Fig. 17 for CatBoost) quantify feature importance by averaging absolute SHAP values. The top five feature rankings are:

- **Random Forest:** Max Price, Min Price, Rolling_3, Rolling_5, Modal_Price_Lag_1
- **XGBoost:** Max Price, Min Price, Rolling_5, Price_Spread, Market
- **CatBoost:** Max Price, Min Price, Modal_Price_Lag_2, Modal_Price_Lag_3, Modal_Price_Lag_1

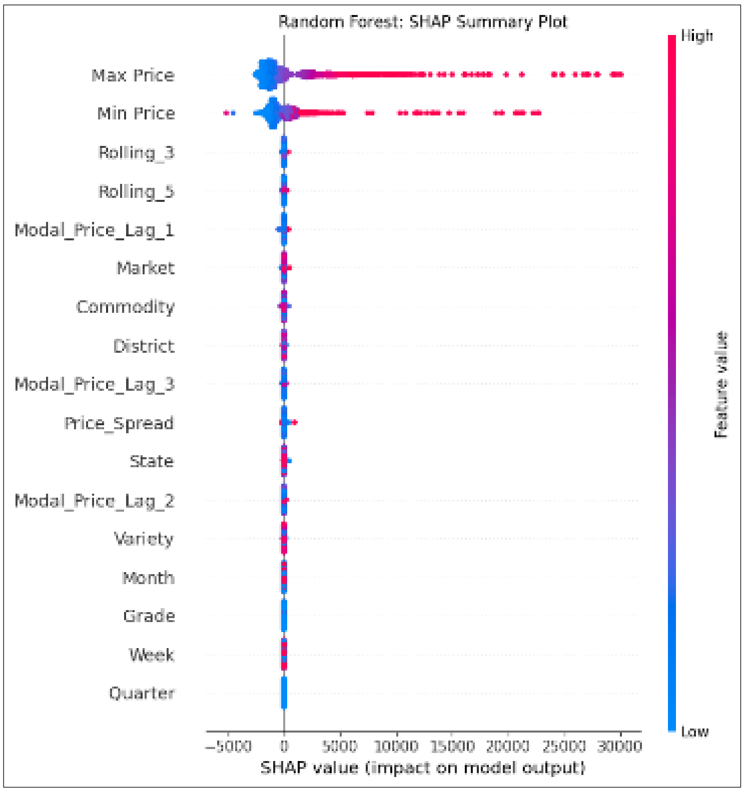

Fig. 12: SHAP Summary Plot (RF)

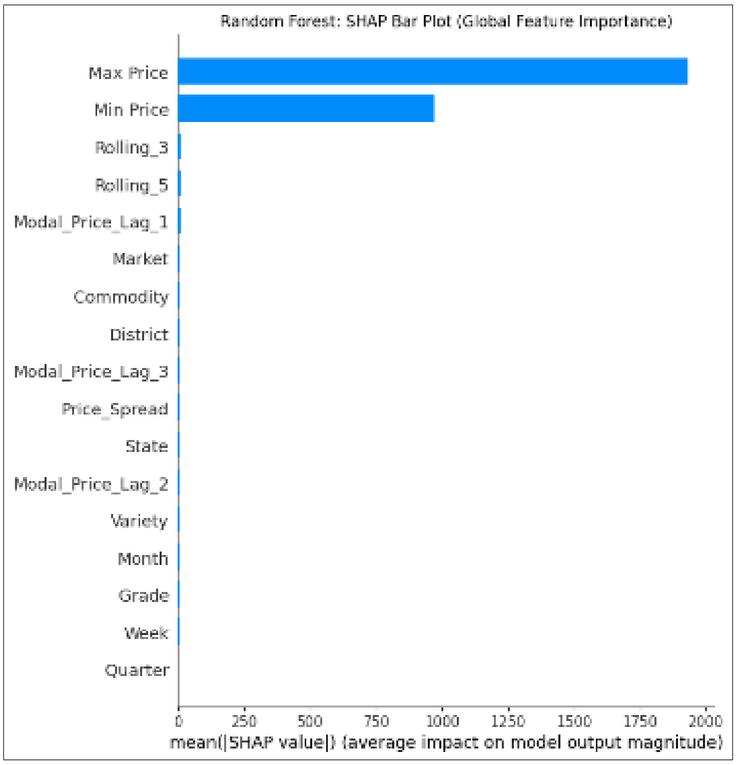

Fig. 13: SHAP bar Plot (RF)

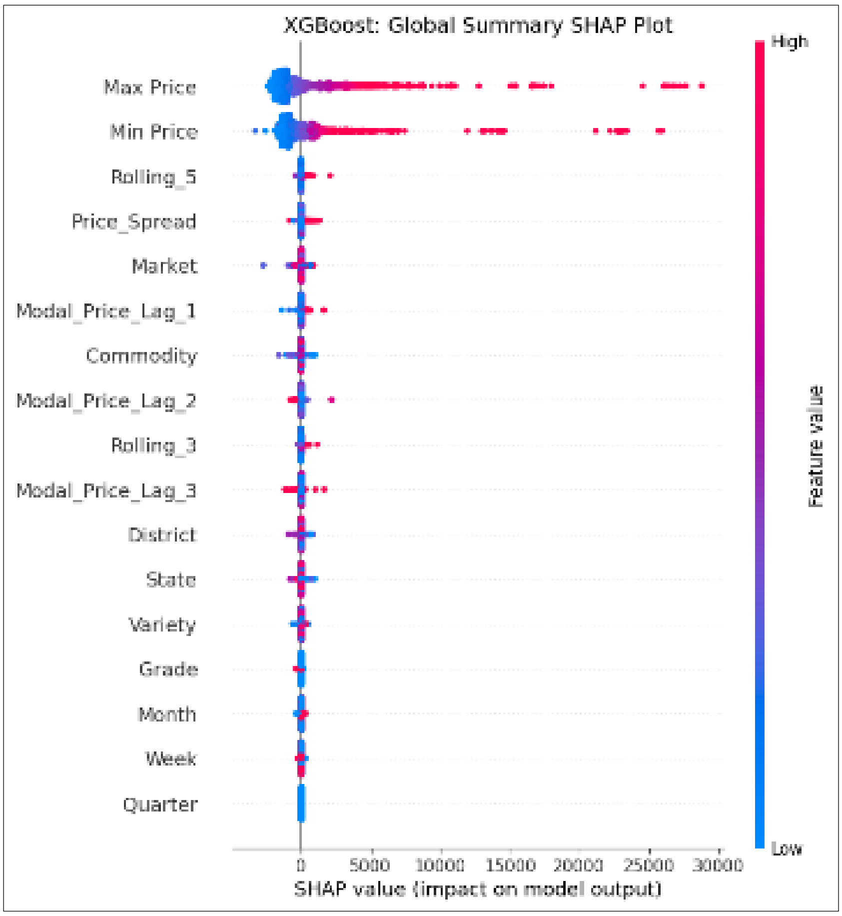

Fig. 14: SHAP Summary Plot (XGBoost)

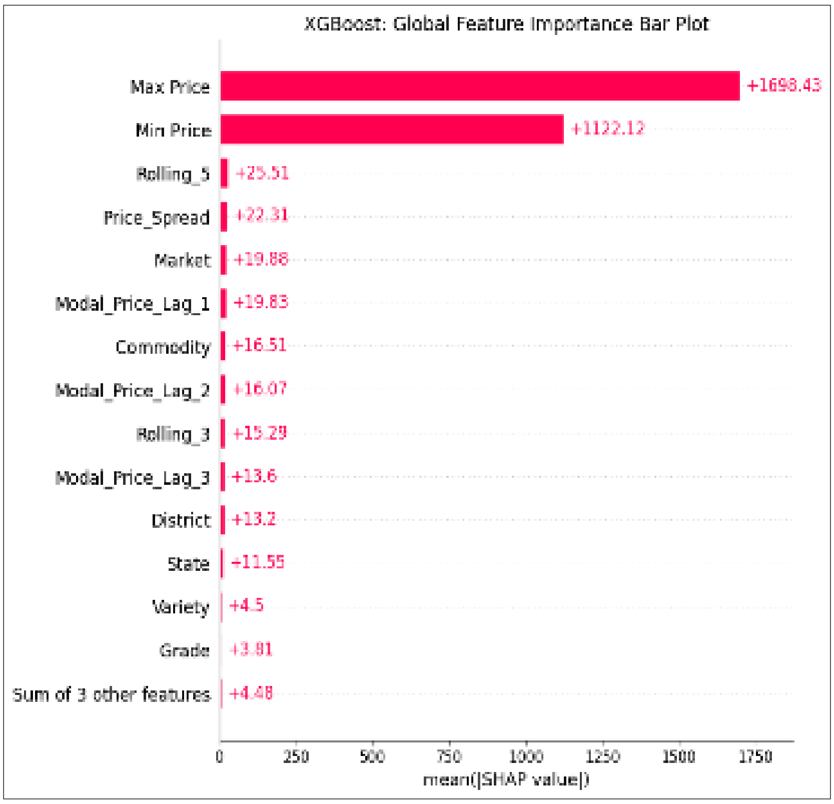

Fig. 15: Bar Plot (CatBoost)

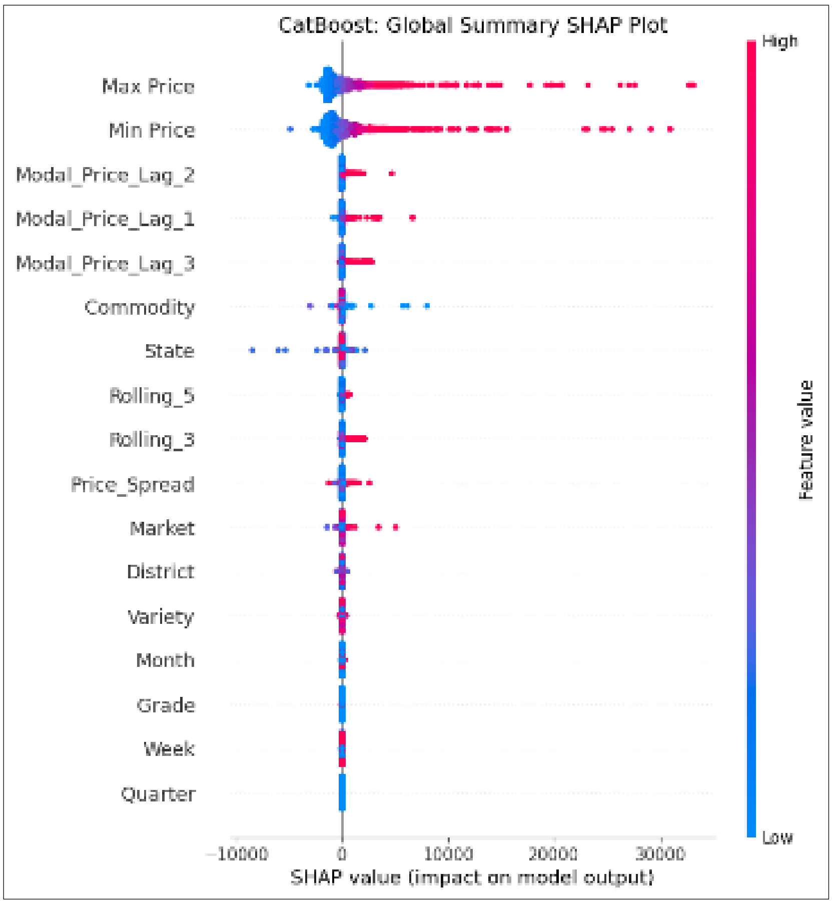

Fig. 16: SHAP Summary Plot (CatBoost)

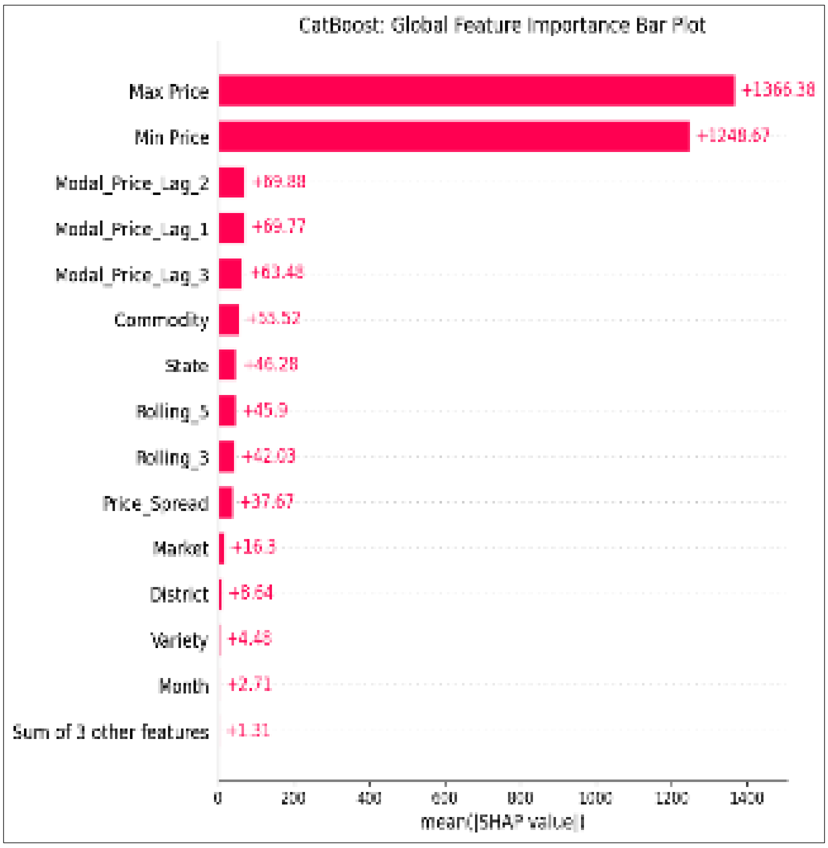

Fig. 17: SHAP bar Plot

B. Local Explainability

Fig. 17– Fig. 19 present the SHAP Waterfall Plots for the CatBoost, Random Forest, and XGBoost models, illustrating local interpretability for a representative data instance (Sample 0). Each plot explains how individual feature values contribute to the final prediction, showing the transition from the model's base value **E[f(x)]** to the predicted output **f(x)** through cumulative SHAP contributions.

Red bars denote features that increase the prediction, while blue bars represent those that decrease it, with bar lengths and numeric values indicating the magnitude of each contribution. Across all three models, Max Price and Min Price consistently exhibit the strongest negative SHAP values, significantly reducing the predicted price. For instance, in XGBoost these are approximately −977.24 and −515.59, in CatBoost −658.86 and −532.37, and in Random Forest −879.81 and −582.89, respectively—corresponding to relatively high feature values (≈−0.284 and ≈−0.253).

While Max Price and Min Price dominate across models, secondary features vary slightly: XGBoost shows small negative effects from Rolling_5**,** Modal_Price_Lag_1**,** and Price_Spread**;** CatBoost displays a balanced effect among lag variables and categorical features like State (which contributes +51.56); and Random Forest emphasizes the two main price features with minor influence from others.

In summary, the SHAP Waterfall analysis reveals consistent key drivers (Max Price and Min Price) across models, but differing secondary feature behaviors, reflecting each model's unique reasoning. These insights improve model transparency, interpretability, and trust in agro-economic forecasting.

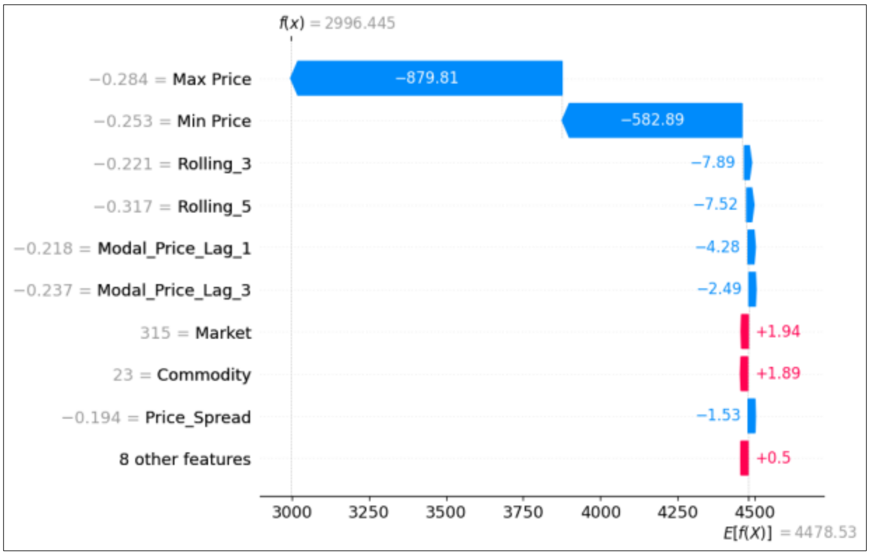

Fig. 18: SHAP Waterfall plot (Random Forest)

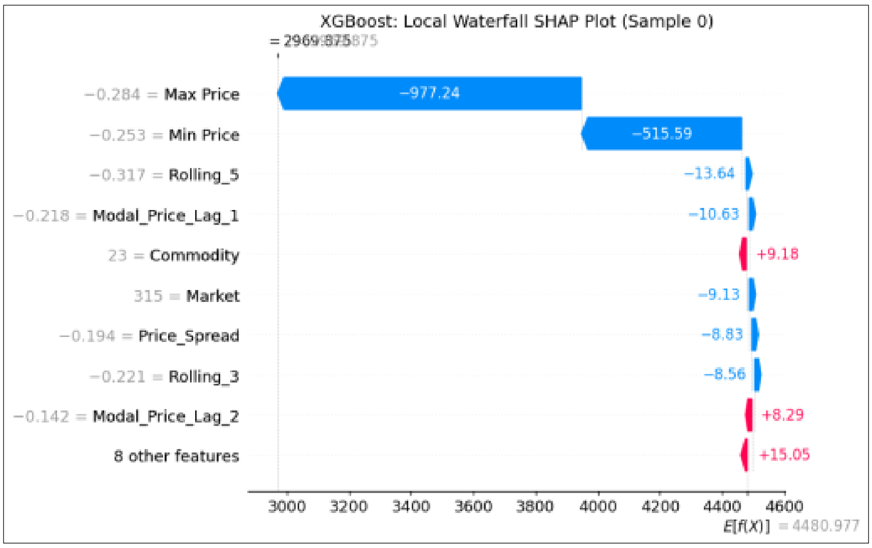

Fig. 19: Waterfall Plot (XGBoost)

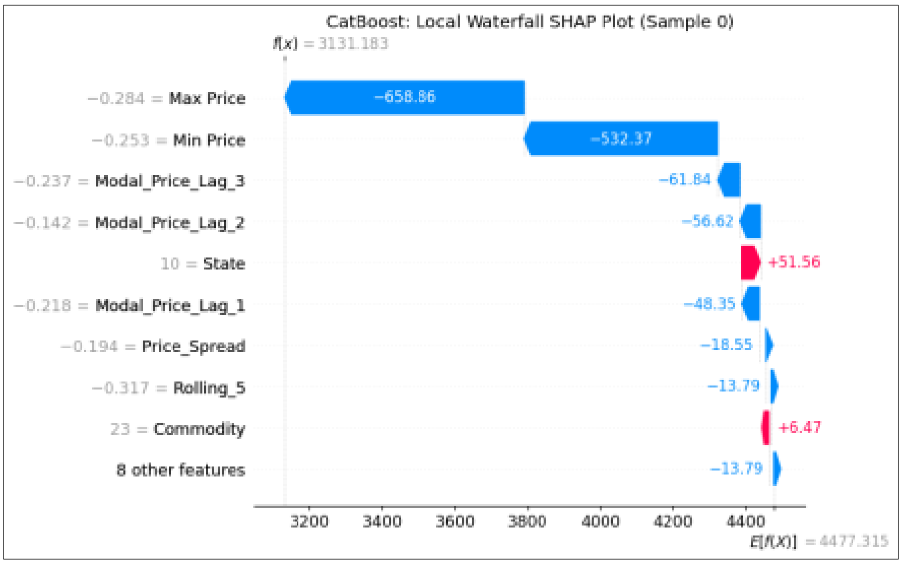

Fig. 20: Waterfall Plot (CatBoost)

VI. CONCLUSION & FUTURE WORKS

This study proposed an Explainable Artificial Intelligence (XAI) driven framework for forecasting agricultural commodity price trends in Bangladesh and India. The Random Forest–based model achieved superior predictive performance (RMSE = 397.07, MAE = 100.96, $R^2 = 0.9931$) compared with XGBoost, CatBoost, MLP, and LSTM models. Through SHapley Additive exPlanations (SHAP), the framework ensured both global and local interpretability, identifying key drivers such as maximum price, minimum price, market, and commodity type. By integrating explainability with high accuracy, the proposed system enhances transparency and supports data-driven decision-making in agricultural policy and market management.

The study highlights the potential of explainable machine learning to bridge the gap between predictive analytics and actionable agro-economic insights. However, its reliance on a single dataset and static modeling limits generalizability. Future research will extend the framework to multi-seasonal and multi-regional datasets, incorporating exogenous variables such as weather and policy indicators. Moreover, hybrid ensembles and advanced XAI techniques (e.g., LIME, counterfactuals, attention-based models) will be explored, along with temporal deep learning architectures like Explainable LSTMs and Temporal Fusion Transformers. The ultimate goal is to develop a fully explainable, real-time forecasting system for sustainable agricultural market intelligence.

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