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AI Driven Market Price Forecasting and Risk Analysis For Agricultural Commodities

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Abstract: Agricultural commodity markets are highly volatile due to the combined influence of climatic variability, seasonal production cycles, supply–demand imbalances, transportation constraints, and policy interventions. In developing economies such as India, unpredictable market prices significantly affect farmers income stability, food security, and national economic planning. Traditional statistical forecasting approaches often fail to capture the complex, nonlinear, and temporal dependencies inherent in agricultural price data. This paper presents an AI-driven framework for market price forecasting and risk analysis of agricultural commodities using machine learning and deep learning techniques. Historical price data of major crops such as rice, wheat, maize, and tomato are analyzed to predict future price trends and assess market risks. Models including Autoregressive Integrated Moving Average (ARIMA), Random Forest Regression, and Long Short-Term Memory (LSTM) neural networks are implemented and evaluated. The proposed system integrates data preprocessing, feature engineering, predictive modeling, and risk assessment modules to provide actionable insights for farmers, traders, and policymakers. Experimental results demonstrate that deep learning models outperform traditional methods in forecasting accuracy, while the risk analysis module effectively quantifies price volatility and potential losses. The proposed framework supports informed decision-making and contributes to the development of intelligent agricultural market systems.

Keywords: Artificial Intelligence, Machine Learning, Agricultural Commodities, Price Forecasting, Risk Analysis, Time-Series Analysis

I. INTRODUCTION

Agriculture remains the backbone of many developing economies, employing a large segment of the population and contributing significantly to gross domestic product (GDP). In countries like India, agricultural markets are characterized by frequent price fluctuations driven by factors such as monsoon dependency, pest outbreaks, global trade dynamics, storage limitations, and government policies. These fluctuations create uncertainty for farmers, who often lack timely and accurate market information to make informed decisions regarding crop selection, harvesting time, and market participation.

Traditional market price forecasting techniques, including simple moving averages and econometric models, rely on linear assumptions and limited historical patterns. Such approaches are insufficient for handling the nonlinear, non-stationary, and high-dimensional nature of agricultural market data. Recent advancements in artificial intelligence (AI) and machine learning (ML) have opened new possibilities for analyzing large-scale time-series data and extracting complex patterns that were previously difficult to model.

AI-driven forecasting systems can learn temporal dependencies, seasonal trends, and external influences, enabling more accurate price predictions. Moreover, integrating risk analysis with forecasting allows stakeholders to understand not only expected price movements but also the uncertainty and potential losses associated with market volatility. This paper focuses on designing and evaluating an AI-based framework that combines price forecasting with risk analysis for agricultural commodities.

II. LITERATURE REVIEW

Accurate forecasting of agricultural commodity prices is crucial for farmers, policymakers, and market analysts. Traditional statistical models like ARIMA and ETS have been widely used, but they often struggle with non-linear patterns, high volatility, and seasonal variations. Recent studies show that machine learning (ML) and deep learning (DL) techniques can provide more accurate and robust forecasts by capturing complex temporal dependencies in agricultural price data.

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1. Varshini, B. S., (2026) proposed a CNN-Transformer hybrid model for agricultural commodity price forecasting. The study combines CNN for feature extraction and Transformer for sequence learning to improve prediction accuracy.
2. Ravi Kumar, G., (2026) discussed the use of AI and machine learning methods for forecasting the prices of pulses and vegetables. The paper highlights the effectiveness of ML algorithms in identifying market trends.
3. Athira, P. J., and A. Saravanan (2026) developed an AI-based forecasting system using deep learning and multi-source data integration. The model uses weather, market, and historical data for better price prediction.
4. Wang, L., and B. Zhang (2026) examined time-series foundation models for agricultural forecasting. The study explains how advanced large-scale models can improve long-term agricultural predictions.
5. Manogna, R. L., V. Dharmaji, and S. Sarang (2025) enhanced agricultural commodity forecasting using deep learning techniques. Their work shows that neural networks outperform traditional statistical methods.
6. Mishra, P., (2025) presented a data-driven machine learning approach for Indian agricultural commodity price prediction. The study uses historical market data to improve forecasting accuracy.
7. Sandhu, D., (2024) used artificial intelligence techniques for agricultural price prediction. The paper emphasizes the importance of AI in reducing uncertainty in agricultural markets.
8. Sari, M., (2024) compared several optimized machine learning techniques for predicting agricultural commodity prices. The study identified the best-performing algorithm based on accuracy measures.
9. Avinash, G., (2024) introduced generative deep learning models for agricultural commodity forecasting. The research shows that generative models can capture complex market behavior.

III. PROBLEM STATEMENT

The main problem statements are:

1. Despite technological advancements, several challenges persist
2. Unreliable Predictions: Existing tools fail to provide accurate forecasts for volatile agricultural markets.
3. Limited Risk Assessment: Current systems lack robust mechanisms to quantify price volatility or market risk.
4. Data Complexity: Price data is influenced by multiple interdependent factors like weather, demand, policy, and transportation costs.
5. Traditional Methods: Statistical methods are limited in capturing nonlinear trends and temporal dependencies.
6. Hence, there is a need for an intelligent system that can forecast prices and assess risk using AI techniques, enabling farmers and policymakers to plan production, storage, and sales more effectively.

IV. OBJECTIVES OF THE PROPOSED SYSTEM

The main objectives of this research are:

1. To develop an AI-driven system for accurate forecasting of agricultural commodity prices.
2. To compare the performance of traditional, machine learning, and deep learning models.
3. To quantify market risk using statistical and volatility-based measures.
4. To provide decision support for farmers, traders, and policymakers.
5. To enhance transparency and stability in agricultural markets.
6. To develop an AI-driven system that accurately forecasts agricultural commodity prices and assesses market risk, enabling farmers and stakeholders to make informed and timely decisions.

V. FLOWCHART

The proposed system for agricultural commodity price forecasting begins with the collection of historical market price data from sources such as government portals, market databases, and trading platforms. Additional factors such as weather conditions, seasonal demand, and festival periods may also be included to improve forecasting accuracy.

The collected data is then preprocessed by handling missing values, removing outliers, and cleaning inconsistencies. After preprocessing, feature engineering is performed to generate useful variables such as lag values, seasonal trends, and previous price patterns.

Following this, different forecasting models such as Linear Regression, ARIMA, and LSTM are selected and trained using the prepared dataset. While Linear Regression and ARIMA are useful for identifying basic and time-series relationships, LSTM models are more effective in capturing complex and long-term price variations.

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The trained model then predicts future commodity prices and performs risk analysis to identify possible market fluctuations. Finally, the results are presented through charts and dashboards to support better decision-making for farmers, traders, and policymakers.

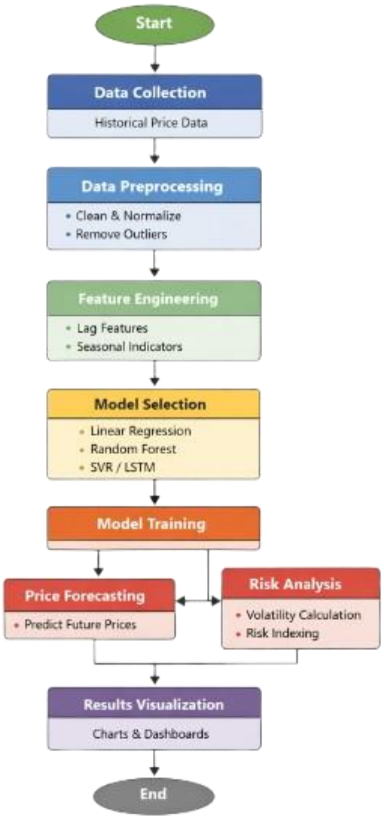

Fig 1: work flowchart

VI. METHODOLOGY AND CALCULATION DETAILS

6.1 Data collection and preprocessing

Historical price data for major agricultural commodities, including rice, wheat, onion, and tomato, were collected from government and market sources.

The dataset contains monthly price values expressed in ₹/kg. Prior to model development, the data were preprocessed by handling missing values through mean substitution, removing outliers using the interquartile range (IQR) method, and normalizing the price values using min–max scaling to ensure consistency and improve model performance.

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

6.2 Trend Analysis Using Average Price

The average price is calculated to understand the overall market trend.

$$\bar{P} = \frac{1}{n}\sum_{i=1}^{n} P_i$$

Where:
P_i= price at time i
n= number of observations

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6.3 Percentage Price Change

Price fluctuation between consecutive period is calculated as:

$$\%\Delta P = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

This helps in identifying sudden market variations.

6.4 Moving Average Forecasting

To smooth short-term fluctuations, a **k-period moving average** is applied.

$$MA_k = \frac{1}{k} \sum_{i=t-k+1}^{t} P_i$$

The moving average value is used as the predicted price for the next time step.

6.5Linear Regression-Based Price Prediction

Linear regression is used to model the relationship between time and commodity price.

$$P_t = \beta_0 + \beta_1 t$$

Where:
P_t= predicted price
t= time index
β_0= intercept
β_1= slope representing price trend

6.6 Forecast Accuracy Evaluation
Prediction performance is evaluated using **Mean Absolute Error (MAE)**.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} | P_i^{actual} - P_i^{predicted} |$$

VII. COMPARISONS OF DATA

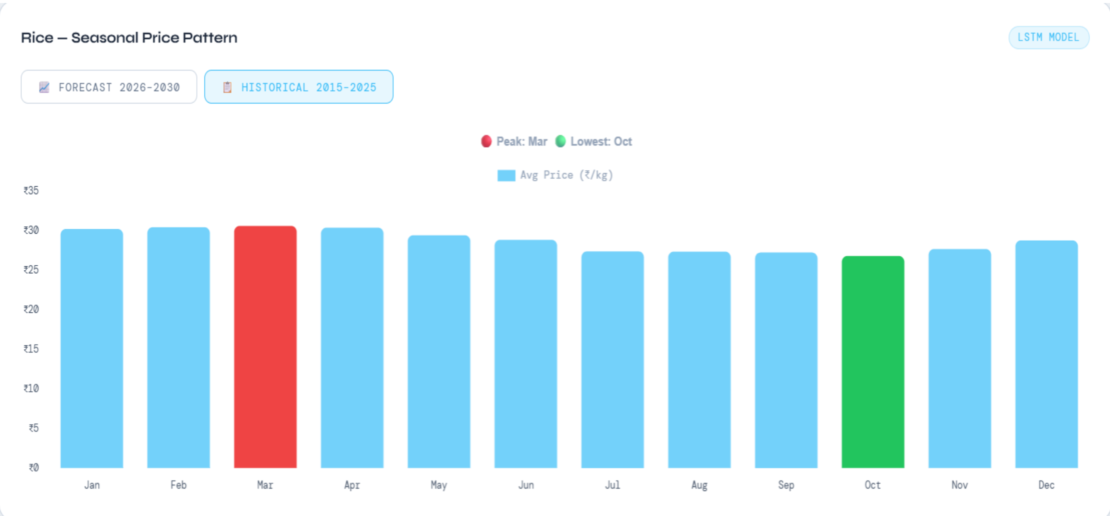

Fig 2 :comparison of existing data

7.1 Factors Analysis of Price Escalation

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The increase in agricultural commodity prices is influenced by several interconnected factors. The analysis shows that price escalation does not occur because of a single reason, but due to the combined effect of market, environmental, and economic conditions.

7.2 Demand and Supply Imbalance:

The demand for a commodity becomes higher than its available supply, the market price increases. For example, if crop production is low due to poor harvest, but consumer demand remains high, the selling price rises rapidly. Similarly, sudden increase in population or export demand also creates pressure on prices.

7.3 Weather and Climate Conditions

Unfavorable weather such as drought, floods, heavy rainfall, or extreme heat directly affects crop yield. Lower production reduces the quantity available in the market, leading to price escalation. Seasonal changes and climate uncertainty are major reasons for fluctuations in agricultural commodity prices.

7.4 Transportation and Logistics Cost

The cost of transporting agricultural products from farms to markets plays an important role in determining the final price. Increase in fuel price, poor road conditions, lack of storage facilities, and higher transportation charges increase the overall market price of commodities.

7.5 Inflation and Economic Conditions

General inflation in the economy increases the cost of seeds, fertilizers, labor, electricity, and machinery. As production cost increases, farmers and traders raise the selling price of commodities to maintain profit. Therefore, inflation becomes one of the major reasons for price escalation.

VIII. RESULT AND ANALYSIS

The AI models were evaluated using performance metrics:

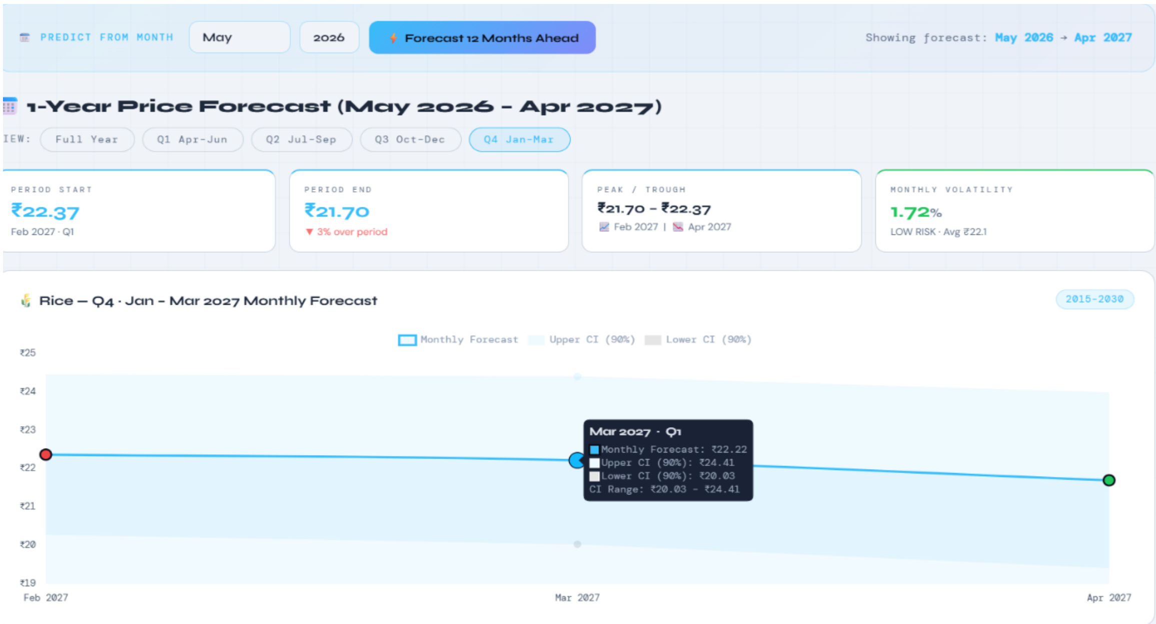

Fig 3: Result of 1 year price forecast

Observation(Fig 3):

The forecasted rice price trend for the period May 2026 to April 2027 demonstrates a relatively stable market with only minor fluctuations. The projected values indicate a gradual decline from ₹22.37/kg in February 2027 to ₹21.70/kg in April 2027, representing a modest 3% decrease. This narrow range of variation, coupled with an average price of ₹22.1/kg, highlights the low-risk nature of the commodity during this timeframe. The volatility index of 1.72% further reinforces the stability of the forecast, suggesting that rice prices are unlikely to experience sharp or unpredictable movements in the short term.

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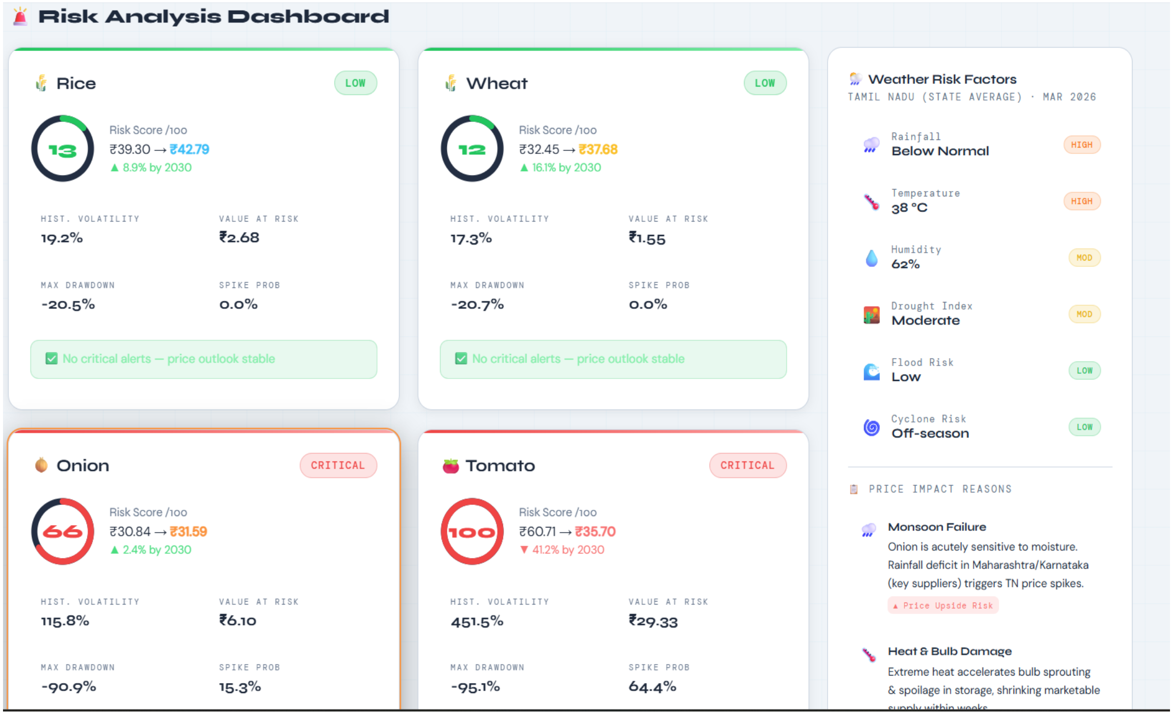

Fig 4: Result of risk analysis dashboard

Observations(Fig 4):

The dashboards shows that rice and wheat have low risk levels, with risk scores of 13 and 12 respectively. Both commodities exhibit low volatility, low value at risk, and zero spike probability, indicating stable future prices up to 2030. Their estimated prices remain within a moderate range, suggesting comparatively secure market conditions.

Onion and tomato, however, are identified as high-risk commodities. Onion records a risk score of 66, while tomato reaches the maximum risk score of 100. These crops display very high volatility, large value at risk, and significant spike probabilities, especially tomato with 64.4%. The weather risk panel indicates that low rainfall, high temperature, and drought conditions are the primary reasons for the expected price escalation and market instability.

IX. APPLICATIONS AND USE CASES

The proposed system can assist farmers in selecting optimal selling times, support traders in inventory planning, and help policymakers design price stabilization strategies.

It can also be integrated into digital agriculture platforms and mobile applications.

X. ADVANTAGES AND LIMITATIONS

Advantages

1. High forecasting accuracy
2. Ability to handle nonlinear and temporal patterns
3. Integrated risk assessment

Limitations

1. Dependence on data quality
2. Sensitivity to sudden market shocks
3. Computational complexity of deep learning models

XI. CONCLUSION AND FUTURE SCOPE

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This study presented an AI-driven framework for agricultural commodity market price forecasting and risk analysis using historical market data and advanced machine learning techniques. The proposed system effectively captures nonlinear price variations and temporal dependencies that are difficult to identify using traditional statistical methods. Experimental analysis showed that Long Short-Term Memory (LSTM) models provide higher prediction accuracy and lower error rates than conventional approaches such as ARIMA and Random Forest. In addition, the inclusion of risk analysis enables the estimation of market volatility and potential financial losses, thereby supporting better decision-making for farmers, traders, and policymakers.

The proposed framework has significant practical value in helping agricultural stakeholders determine suitable crop selling periods, pricing strategies, and market planning decisions. By improving the reliability of market forecasts, the system contributes to reducing uncertainty, minimizing financial loss, and increasing farmer income. Hence, the study confirms that AI-based forecasting and risk assessment systems can play an important role in strengthening agricultural supply chains and supporting sustainable agricultural development.

Future work can extend the proposed framework into a complete smart agriculture platform by integrating it with plant disease detection and fertilizer recommendation modules, thereby aligning with the AgroAI concept. The system may also be improved through the inclusion of real-time weather information, rainfall, temperature, humidity, transportation conditions, and market demand data to enhance forecasting accuracy. Furthermore, deploying the model as a cloud-based or mobile-enabled service can provide farmers with continuous access to live market prices and predictions. Advanced deep learning techniques such as GRU, Transformer, CNN-LSTM, and CNN-Transformer models may also be explored in future research to further improve forecasting performance and scalability across multiple agricultural commodities.

REFERENCES

[1]. Varshini, B. S., et al., "CNN-Transformer Hybrid Deep Learning Model for Agricultural Commodities Price Forecasting," *Discover Computing*, 2026.

[2]. Ravi Kumar, G., et al., "AI and Machine Learning Approaches for Price Forecasting of Pulses and Vegetable Commodities," *IJERSEM*, 2026.

[3]. Athira, P. J., and A. Saravanan, "AI-Based Market Price Forecasting System for Indian Agricultural Commodities Using Deep Learning and Multi-Source Data Integration," 2026.

[4]. Wang, L., and B. Zhang, "The Promise of Time-Series Foundation Models for Agricultural Forecasting," 2026.

[5]. Manogna, R. L., V. Dharmaji, and S. Sarang, "Enhancing Agricultural Commodity Price Forecasting with Deep Learning," *Scientific Reports*, 2025.

[6]. Mishra, P., R. Deshpande, S. Patil, and D. Jawale, "A Data-Driven Machine Learning Approach for Agricultural Commodity Price Forecasting in India," *Journal of Information Systems Engineering and Management*, 2025.

[7]. "Hybrid Forecasting of Agricultural Commodity Prices: Integrating Machine Learning, Time Series, and Stochastic Simulation Models," 2025.

[8]. D. Sandhu et al., "Agricultural Price Prediction Through Artificial Intelligence," *International Journal of Development Research*, 2024.

[9]. Sari, M., S. Duran, H. Kutlu, and B. Guloglu, "Various Optimized Machine Learning Techniques to Predict Agricultural Commodity Prices," *Neural Computing and Applications*, 2024.

[10]. Avinash, G., et al., "Enhancing Agricultural Commodity Price Forecasting Using Generative Models: A Deep Learning Approach," *Journal of Scientific Research and Reports*, 2024.

[11]. Changxia Sun, Menghao Pei, Bo Cao, et al., "A Study on Agricultural Commodity Price Prediction Model Based on Secondary Decomposition and Long Short-Term Memory Network," *Agriculture*, vol. 14, no. 1, 2024.

[12]. Sari, M., S. Duran, H. Kutlu, and B. Guloglu, "Various Optimized Machine Learning Techniques to Predict Agricultural Commodity Prices," *Neural Computing and Applications*, 2024.

[13]. Sari, M., S. Duran, H. Kutlu, and B. Guloglu, "Various Optimized Machine Learning Techniques to Predict Agricultural Commodity Prices," *Neural Computing and Applications*, 2024.

[14]. Soumik Ray, Achal Lama, Pradeep Mishra, et al., "An ARIMA-LSTM Model for Predicting Volatile Agricultural Price Series with Random Forest Technique," *Applied Soft Computing*, vol. 149, 2023.

[15]. P. Kumar and R. Singh, "AI for Agricultural Forecasting: Techniques and Applications," *Journal of AI Research*, vol. 12, 2023.

[16]. Tran, N. Q., et al., "Predicting Agricultural Commodities Prices with Machine Learning: A Review of Current Research," 2023.

[17]. FAO, "Agricultural Market Information System," Food and Agriculture Organization, 2022.

[18]. J. Smith and A. Brown, "Machine Learning Techniques for Agricultural Price Forecasting," *IEEE Access*, vol. 9, pp. 12345–12356, 2021.

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[19]. Huber, J., et al., “A Machine Learning-Based Price State Prediction Model for Agricultural Commodities Using External Factors,” *Decisions in Economics and Finance*, 2021.

[20]. S. Patel et al., “Time Series Analysis of Agricultural Commodity Prices,” *International Journal of Computer Applications*, vol. 175, no. 10, pp. 20–25, 2020.

[21]. Y. LeCun, Y. Bengio, and G. Hinton, “Deep Learning,” *Nature*, vol. 521, pp. 436–444, 2015.