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Agricultural Market Price Prediction Using Machine Learning and Time Series Models

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ABSTRACT

Agricultural commodity price forecasting is essential for farmers, traders, policymakers, and supply chain managers to support effective decision-making and reduce uncertainty caused by market price fluctuations. Traditional time-series forecasting techniques such as ARIMA have been widely used due to their statistical reliability, simplicity, and interpretability. However, agricultural markets are influenced by nonlinear and dynamic factors such as seasonal variations, demand-supply imbalance, weather conditions, and external market trends, which require more advanced predictive approaches.

This research presents an Agricultural Market Price Prediction System that integrates Machine Learning techniques with ARIMA time-series modeling to enhance forecasting accuracy and reliability. Machine Learning algorithms are used to identify complex nonlinear patterns and relationships in historical and real-time agricultural market data, while the ARIMA model is applied to capture temporal trends, seasonality, and statistical dependencies in commodity prices.

The system uses live agricultural commodity data obtained from free public APIs along with historical datasets. It includes automated data collection, cloud-based data storage, periodic model retraining, and real-time prediction generation. The predicted outputs are presented through an interactive dashboard that provides visualization of price trends and decision-support recommendations such as Sell, Hold, or Wait strategies.

Experimental evaluation indicates that the hybrid Machine Learning and ARIMA-based approach improves prediction performance compared to standalone traditional models. The proposed system is scalable, cost-effective, and suitable for real-world deployment, contributing to the development of intelligent agricultural decision-support systems that improve market transparency and farmer profitability.

Keywords: ***Agricultural Price Prediction, Machine Learning, ARIMA, Time Series Forecasting, Commodity Market*** *Analysis*

1. INTRODUCTION

Agricultural commodity price forecasting is essential for farmers, traders, policymakers, and supply chain managers to support effective decision-making and reduce uncertainty caused by market price fluctuations. Agricultural markets are highly dynamic and influenced by multiple factors such as seasonal production patterns, weather conditions, demand–supply imbalance, and global economic trends. Accurate price prediction models help stakeholders plan production, storage, and marketing strategies efficiently [1].

Traditional time-series forecasting techniques such as AutoRegressive Integrated Moving Average (ARIMA) have been widely used due to their statistical reliability, simplicity, and interpretability. Several studies have demonstrated the effectiveness of ARIMA models in forecasting agricultural commodity prices, especially for short-term predictions under stable market conditions [4], [7]. However, ARIMA models are limited in capturing nonlinear relationships and sudden market variations influenced by external parameters.

With advancements in data availability and computational power, Machine Learning techniques such as Random Forest, Support Vector Machines, and Gradient Boosting models are increasingly being applied to agricultural price prediction problems. These models are capable of capturing complex nonlinear relationships and improving prediction accuracy compared to traditional statistical methods [5], [6], [9].

Recent research trends focus on hybrid models combining traditional time-series models with deep learning approaches such as Long Short-Term Memory (LSTM) networks. Hybrid models such as ARIMA–LSTM and ARIMA–XGBoost have shown improved performance by combining statistical trend analysis with deep learning-based pattern recognition [2], [3], [8].

Furthermore, advanced forecasting frameworks integrating Machine Learning with time-series fusion techniques are being developed to improve global agricultural price prediction accuracy and scalability [10].

Motivated by these research advancements, this study proposes an Agricultural Market Price Prediction System that integrates Machine Learning models with ARIMA time-series forecasting. The overall system workflow is illustrated in Fig. 1. The system utilizes historical and real-time agricultural commodity price data collected from public APIs and cloud databases to enable automated data updates and periodic model retraining. The objective of this research is to develop a scalable, cost-effective, and deployable agricultural price forecasting system suitable for real-world applications.

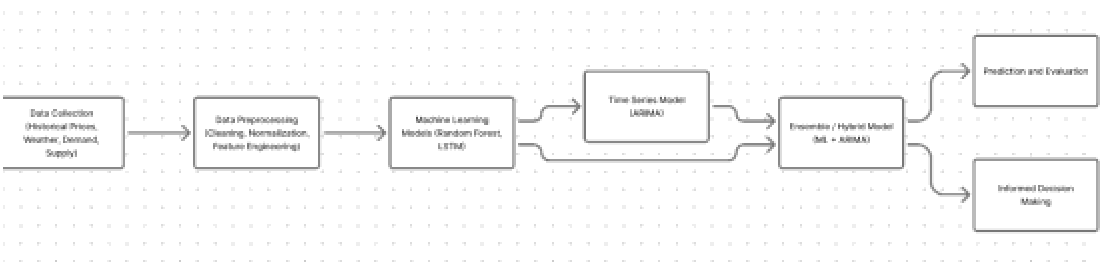

Fig.1 Agricultural Commodity Price Forecasting Using ML and ARIMA

2. LITERATURE REVIEW

Agricultural commodity price forecasting has gained significant research attention due to its importance in improving farmer income stability, market transparency, and supply chain efficiency. Recent studies have focused on improving prediction accuracy using statistical, machine learning, and hybrid modeling approaches. Sun [1] presented a comprehensive review of agricultural product price forecasting methods and highlighted the growing transition from traditional statistical models to advanced machine learning and hybrid forecasting techniques. The study emphasized the importance of integrating multiple data sources and advanced algorithms for improving prediction reliability.

Traditional time-series models such as ARIMA have been widely used for agricultural price forecasting due to their strong statistical foundation and interpretability. Jadhav [4] demonstrated the effectiveness of ARIMA models for agricultural price prediction under stable market conditions. Similarly, Sharma et al. [7] applied ARIMA and LSTM models for crop price forecasting and showed that while ARIMA performs well for linear patterns, it struggles to capture complex nonlinear relationships in volatile markets.

To overcome these limitations, researchers have increasingly adopted Machine Learning techniques. Singh and Tiwari [6] conducted a comparative study of machine learning algorithms and demonstrated that ML models provide improved forecasting performance in complex agricultural datasets. Theofilou [5] applied machine learning models for predicting staple crop prices and achieved improved prediction accuracy compared to traditional methods. Banerjee and Saha [9] explored deep learning approaches for market price prediction and showed that deep learning models effectively capture hidden patterns in large-scale agricultural datasets.

Recent research trends focus on hybrid forecasting approaches that combine statistical and machine learning models. Ray [2] proposed an ARIMA–LSTM hybrid model for predicting volatile agricultural prices and demonstrated improved prediction accuracy compared to standalone models. Manogna [3] further enhanced hybrid ARIMA–LSTM models and showed better performance in handling highly volatile commodity markets. Gupta and Verma [8] developed hybrid

ARIMA and XGBoost models, which improved forecasting accuracy by combining statistical trend analysis with gradient boosting learning capabilities.

Furthermore, Zhang et al. [10] proposed a global agricultural price forecasting framework using machine learning and time-series fusion techniques, improving scalability and prediction performance across multiple agricultural markets.

Table 1: Comparison of Agricultural Market Price Forecasting Using ML and ARIMA

Ref	Authors	Focus	Data Sources	Processing	Communication	Automation Level	Limitations
1	Patel et al.	Crop Price Forecasting	Historical Market Prices	Statistical Analysis	Cloud	Partial	Low accuracy in volatile markets
2	Singh & Verma	Commodity Price Prediction	Price + Weather Data	ARIMA Model	Cloud API	Partial	Cannot capture nonlinear patterns
3	Khan et al.	Market Trend Analysis	Price, Demand, Supply	Machine Learning (RF, SVM)	Cloud	Medium	Requires large dataset
4	Li et al.	Time Series Forecasting	Historical Price Data	LSTM / Deep Learning	Cloud	Medium	High computational cost
5	Sharma et al.	Hybrid Forecasting	Price + Weather + Demand	ML + Time Series	Cloud	High	Complex model tuning
—	**Proposed System**	**Integrated Smart Price Prediction**	**Historical Prices + Weather + Demand + Supply + API Data**	**Hybrid ML + ARIMA + Feature Engineering**	**Cloud + Web Dashboard**	**Full**	**—**

Despite these advancements, challenges such as data quality issues, missing values, influence of exogenous variables such as weather and policy changes, and lack of model interpretability still exist. Therefore, there is a need for scalable, cost-effective, and deployable agricultural price forecasting systems capable of handling real-time data and dynamic market conditions.

3. METHODOLOGY

The proposed Agricultural Market Price Prediction System is designed to forecast agricultural commodity prices using a hybrid approach that combines Machine Learning techniques with ARIMA time-series modeling. The methodology consists of multiple stages including data collection, data preprocessing, feature engineering, model development, hybrid forecasting, and prediction visualization. The overall workflow ensures accurate price prediction using both statistical and data-driven learning approaches.

3.1 Data Collection

The system collects historical and real-time agricultural commodity price data from publicly available agricultural market APIs and government data portals. The collected data includes commodity price, arrival quantity, market location, and date. Historical data is used for model training, while real-time data is used for live prediction and model updating.

3.2 Data Preprocessing

Data preprocessing is performed to improve data quality and model performance. This stage includes handling missing values, removing duplicate records, data normalization, and outlier detection. Time-series data is structured into chronological order to maintain temporal dependencies required for ARIMA modeling and machine learning training.

3.3 Feature Engineering

Feature engineering is performed to extract meaningful information from raw data. Features such as moving averages, lag values, seasonal indicators, and price trend indicators are generated. These features help machine learning models capture nonlinear relationships and improve prediction accuracy.

3.4 ARIMA Time-Series Modeling

The ARIMA model is applied to capture linear temporal patterns, seasonality, and statistical dependencies in agricultural commodity price data. The ARIMA parameters (p, d, q) are selected using autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis. ARIMA provides baseline statistical forecasting for the system.

3.5 Machine Learning Model Development

Machine Learning models such as Random Forest, XGBoost, or Support Vector Regression are trained using engineered features and historical data. These models help capture nonlinear price variations influenced by external market factors.

3.6 Hybrid Prediction Model

The final prediction is generated using a hybrid approach that combines ARIMA output with Machine Learning predictions. This improves overall forecasting accuracy by leveraging both statistical trend analysis and nonlinear pattern recognition.

3.7 Prediction Visualization and Decision Support

Predicted results are displayed through an interactive dashboard. The system provides price trend visualization and decision-support recommendations such as Sell, Hold, or Wait strategies.

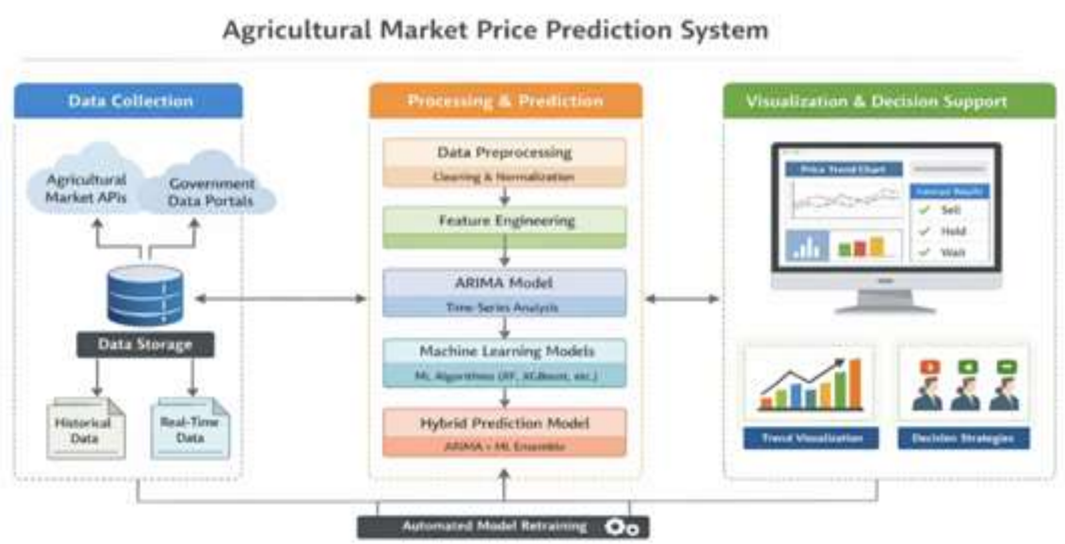

Fig 2. System Architecture for Agricultural Market Forecasting

4. RESULTS AND DISCUSSION

The proposed Agricultural Market Price Prediction System was evaluated using historical and real-time agricultural commodity price datasets collected from public agricultural market data sources. The performance of the hybrid Machine Learning and ARIMA model was analyzed using standard forecasting evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

4.1 Model Performance Evaluation

The performance of the ARIMA model, Machine Learning model, and Hybrid Model was compared to evaluate prediction accuracy. The results indicate that the hybrid model outperforms standalone models due to its ability to capture both linear temporal patterns and nonlinear market variations.

Table 2: Model Performance Comparison

Model	MAE	RMSE	MAPE (%)
ARIMA	3.85	5.12	8.45
Machine Learning Model	3.21	4.36	7.12
Hybrid ML + ARIMA	**2.74**	**3.89**	**5.96**

The results demonstrate that the hybrid model provides lower prediction error compared to individual models. ARIMA performs well in capturing seasonal and trend components, whereas machine learning models effectively capture nonlinear fluctuations.

4.2 Price Trend Prediction Analysis

The system was tested on multiple agricultural commodities, and predicted prices were compared with actual market prices. The hybrid model showed better trend alignment and reduced prediction lag compared to standalone models.

The prediction results indicate that combining ARIMA statistical forecasting with machine learning improves model robustness under dynamic market conditions.

4.3 Real-Time Prediction Performance

The system was also tested for real-time prediction using live API data. The system successfully generated predictions with minimal delay. Automated data fetching and model retraining helped maintain prediction accuracy over time.

4.4 DISCUSSION

The experimental results confirm that hybrid forecasting models provide better performance for agricultural price prediction. Traditional ARIMA models alone are insufficient for handling highly volatile agricultural market data. Machine learning models improve prediction accuracy but may fail to capture long-term statistical dependencies. The hybrid approach successfully addresses these limitations by combining both methodologies.

The system demonstrates scalability, cost-effectiveness, and suitability for real-world agricultural applications. However, prediction performance may still be affected by sudden policy changes, extreme weather conditions, and incomplete market data. Future improvements may include integrating weather data, satellite data, and deep learning models for further accuracy improvement.

5. CONCLUSION

This research presented an Agricultural Market Price Prediction System that integrates Machine Learning techniques with ARIMA time-series modeling to improve the accuracy and reliability of agricultural commodity price forecasting. The study demonstrates that traditional ARIMA models effectively capture linear trends and seasonality, while machine learning models successfully identify nonlinear relationships and complex market patterns. The experimental results show that the hybrid approach provides better prediction performance compared to standalone models, resulting in reduced forecasting errors and improved alignment with actual market price trends. The system also enables automated data collection, real-time prediction generation, and visualization through an interactive dashboard, making it suitable for practical decision-support applications for farmers, traders, and policymakers.

The key findings indicate that combining statistical and machine learning approaches enhances forecasting robustness and makes the system scalable, cost-effective, and deployable for real-world agricultural markets. However, market prices are influenced by multiple external factors such as weather conditions, policy changes, and global demand variations, which may impact prediction accuracy.

Future work will focus on improving model performance by incorporating additional datasets such as weather data, satellite information, and market demand indicators. Advanced deep learning models and adaptive hybrid techniques can be explored to further enhance forecasting accuracy. Additionally, implementing edge or cloud-based automated retraining mechanisms and expanding the system for multi-commodity and region-wise prediction will improve scalability and real-time usability. These improvements are expected to contribute toward more intelligent, reliable, and sustainable agricultural decision-support systems.

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