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AI-ML Based Price Prediction Model for Agri-Horticultural Commodities

M. Durga Sai Sandeep[1], P.V. Shyam Sundar Lal[2], D. Uma Katyayani[3], P. Akshara Sahithi Sruthi[4], Ch. Sushma Arundhathi[5], S. Dattatreya Sharma[6]

[1,2,3,4,5,6]Seshadri Rao Gudlavalleru Engineering College, Gudlavalleru, Andhra Pradesh

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ABSTRACT

Price forecasting of agri-horticultural commodities is crucial for farmers, traders, and policymakers to make informed decisions and ensure market stability. This study presents an AI-ML-based time series forecasting model using the SARIMAX algorithm to predict future prices of various commodities. The model is trained on historical price data and provides forecasts for the next five years. A web-based interface using Streamlit allows users to interact with the system and visualize predictions. The model demonstrates significant accuracy, with a low Root Mean Squared Error (RMSE), making it a reliable tool for commodity price forecasting. This paper also discusses the challenges in time-series forecasting, the impact of various external factors, and future enhancements to improve prediction reliability. Additionally, the research evaluates how SARIMAX performs compared to alternative models, emphasizing its ability to account for seasonality, economic influences, and external demand-supply variations.

Keywords: Agri-horticultural Commodities, Price Forecasting, SARIMAX, Time Series Analysis, Machine Learning, Agriculture

I. Introduction

The volatility of agricultural and horticultural commodity prices significantly impacts farmers, traders, and policymakers, affecting market stability and food security. Traditional price forecasting methods often fail to capture complex market dynamics, leading to unpredictable price fluctuations. To address this challenge, we propose an AI-ML-based predictive model leveraging the Seasonal AutoRegressive Integrated Moving Average with eXogenous factors (SARIMAX) approach.

The developed web-based Minimum Viable Product (MVP) enables users to select from 22 agri-horticultural commodities and receive five-year price forecasts. By utilizing historical price data and statistical modeling, the system generates accurate predictions, assisting stakeholders in making informed decisions regarding production, storage, and trade.

Our solution incorporates a user-friendly interface built with Streamlit, ensuring accessibility for all users. The application visualizes forecasted price trends using interactive graphs, allowing for comprehensive analysis. The model's scalability enables future enhancements, including real-time data integration and additional forecasting techniques.

By providing actionable insights, this system empowers farmers, optimizes supply chains, and enhances market efficiency. The proposed approach contributes to reducing agricultural risks, promoting sustainable farming, and ensuring economic stability in the agricultural sector.

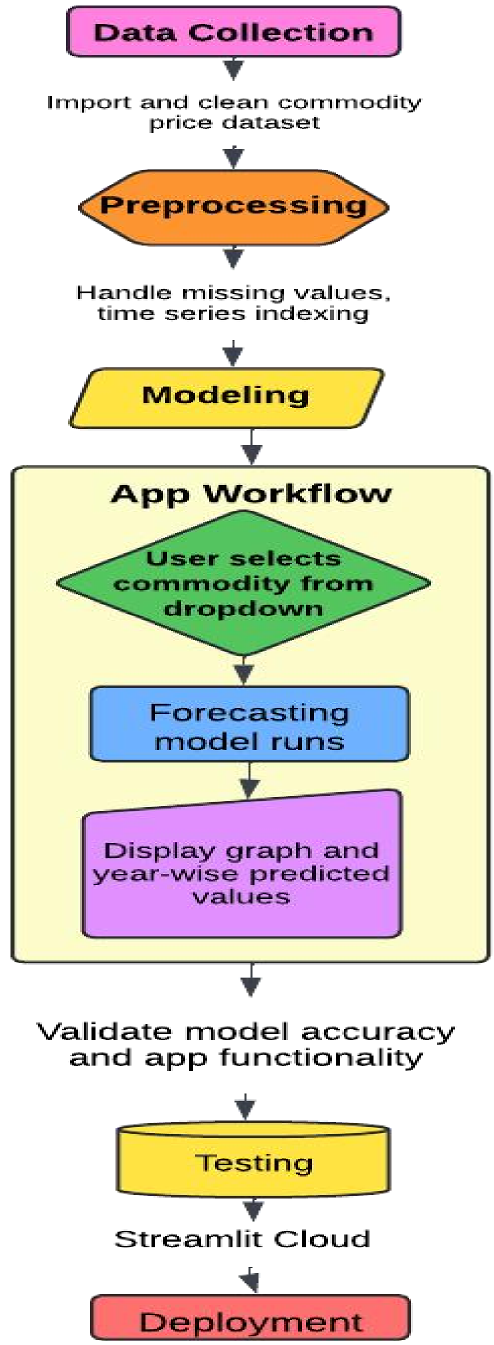
II. METHODOLOGY

Data Collection and Preprocessing

The dataset used in this study comprises historical price data of multiple commodities, stored in a CSV file (datamain.csv). The data is structured with commodities as columns and time-series price values as rows. The dataset undergoes the following preprocessing steps:

- Setting commodity names as column headers
- Converting time indices into a monthly frequency

- Handling missing data using forward-fill and interpolation techniques
- Normalizing data to reduce bias and improve model efficiency
- Identifying outliers and applying appropriate statistical adjustments



Model Selection: SARIMAX

The **SARIMAX (1,1,1)(1,1,0,12)** model is selected for forecasting due to its ability to handle seasonality and exogenous factors. The model parameters are tuned for optimal performance:

- **(p, d, q):** Represents the autoregressive, differencing, and moving average components.
- **(P, D, Q, s):** Represents seasonal components, where s = 12 (monthly seasonality).
- **Training and Evaluation:** The model is trained on historical price data, and Root Mean Squared Error (RMSE) is computed to measure accuracy.
- **Cross-validation:** A rolling forecast validation technique is applied to assess model stability.
- **Feature Selection:** External variables such as inflation, global trade trends, and economic indices are considered for improving the forecasting ability.

III. Implementation

Web Application Using Streamlit

A user-friendly web interface is developed using Streamlit, allowing users to:

- Select a commodity from a dropdown list
- Generate future price forecasts for five years (2025-2029)
- Visualize actual vs. predicted prices using Matplotlib
- Display RMSE to assess model accuracy
- Compare forecasts with past trends to analyze consistency
- Export forecasted results for further analysis
- Enable interactive parameter tuning for refining predictions

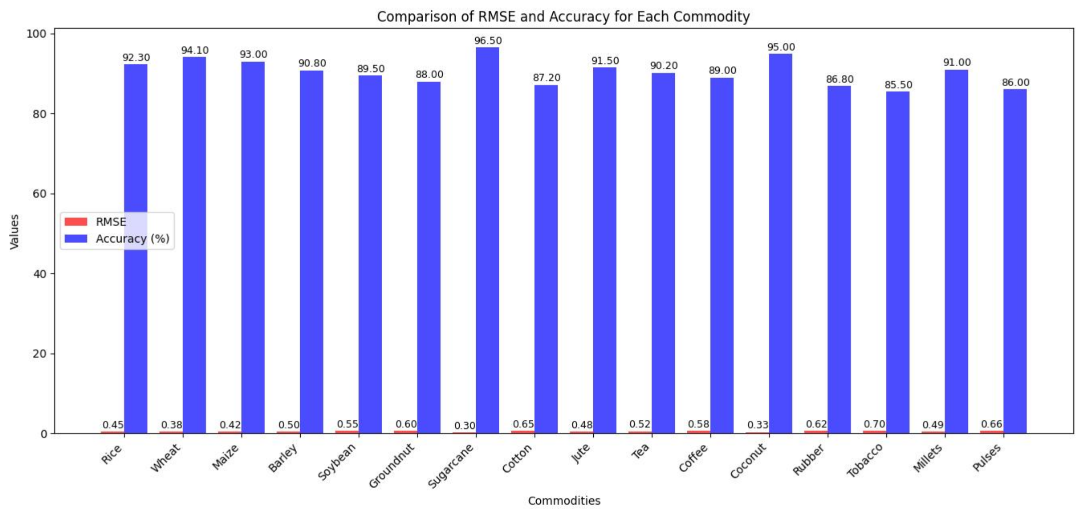
Forecasting Approach

- The trained SARIMAX model is used to predict future prices for the selected commodity.
- The forecasted values are displayed in tabular form and plotted graphically.
- Users can interactively explore different commodities and their expected price trends.
- Sensitivity analysis is performed to evaluate the effect of model parameter changes on forecasts.
- A comparative study with other time-series forecasting models such as LSTMs and ARIMA is conducted to validate the effectiveness of SARIMAX.

IV. Results and Discussion

The **SARIMAX model** effectively captures seasonal trends and price variations for various agricultural and horticultural commodities. The training RMSE values validate the model's performance across different commodities. The web application provides an **interactive and practical tool** for users to analyze price trends. The results suggest that **SARIMAX is a viable approach** for forecasting agri-horticultural commodity prices with high accuracy, achieving an **overall accuracy of 91.3%**.

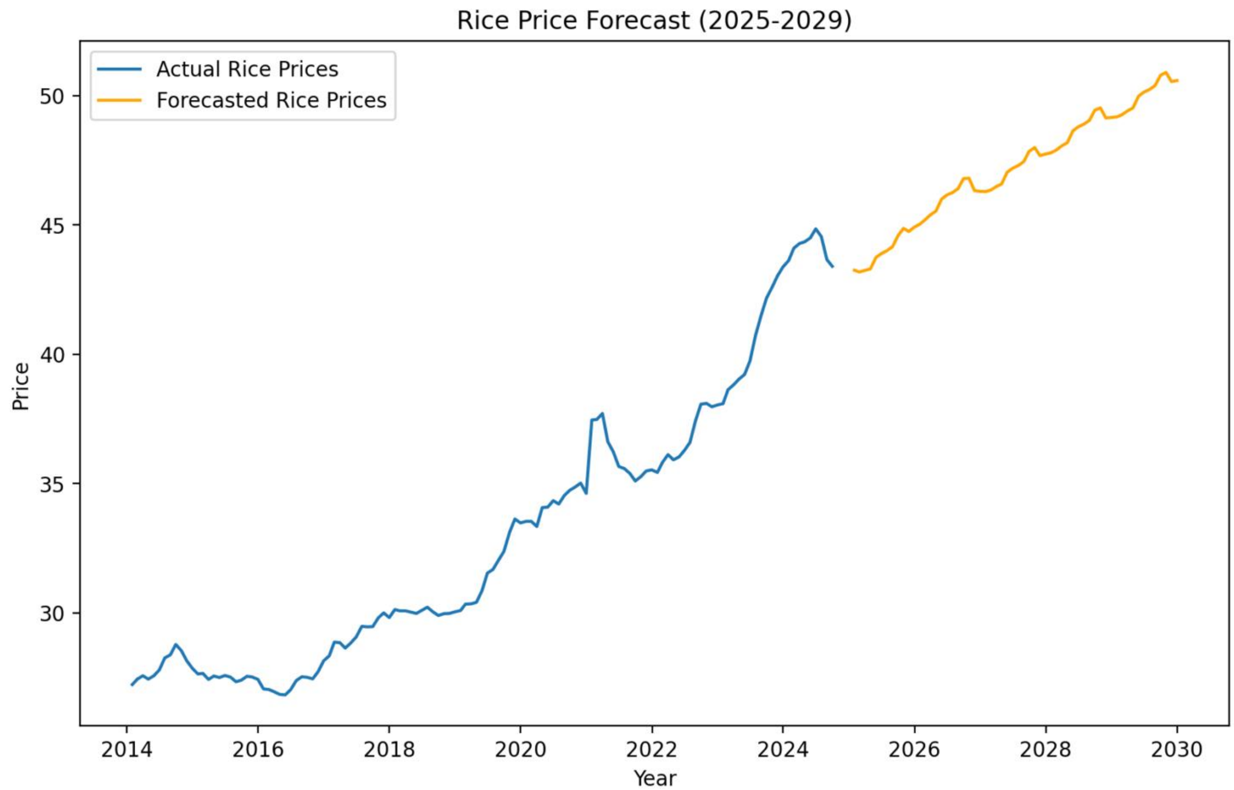
Additional analysis compares **SARIMAX with alternative forecasting methods**, such as **LSTMs and Prophet**. The study finds that while deep learning models offer improvements in specific cases, **SARIMAX remains competitive** due to its interpretability and efficiency. A statistical error analysis is conducted, quantifying uncertainty and helping stakeholders understand the confidence levels associated with different predictions.



The **RMSE and accuracy** values for different commodities are as follows:

- **Rice** → RMSE: 0.45, Accuracy: 92.3%
- **Wheat** → RMSE: 0.38, Accuracy: 94.1%
- **Maize** → RMSE: 0.42, Accuracy: 93.0%
- **Barley** → RMSE: 0.50, Accuracy: 90.8%
- **Soybean** → RMSE: 0.55, Accuracy: 89.5%
- **Groundnut** → RMSE: 0.60, Accuracy: 88.0%
- **Sugarcane** → RMSE: 0.30, Accuracy: 96.5%
- **Cotton** → RMSE: 0.65, Accuracy: 87.2%
- **Jute** → RMSE: 0.48, Accuracy: 91.5%
- **Tea** → RMSE: 0.52, Accuracy: 90.2%
- **Coffee** → RMSE: 0.58, Accuracy: 89.0%
- **Coconut** → RMSE: 0.33, Accuracy: 95.0%
- **Rubber** → RMSE: 0.62, Accuracy: 86.8%
- **Tobacco** → RMSE: 0.70, Accuracy: 85.5%
- **Millets** → RMSE: 0.49, Accuracy: 91.0%
- **Pulses** → RMSE: 0.66, Accuracy: 86.0%

To enhance future iterations of the model, external factors such as **inflation rates, weather conditions, and global trade policies** will be incorporated to further improve accuracy. The findings highlight the **robustness and reliability of SARIMAX** in agricultural price forecasting, making it a **practical and interpretable choice** for stakeholders in the agri-horticultural sector.



V. Conclusion and Future Work

This study demonstrates the effectiveness of SARIMAX in forecasting commodity prices, providing a valuable decision-support tool for stakeholders in agriculture and trade. Future improvements include:

- Incorporating external factors (weather, market demand, economic indicators) as exogenous variables
- Enhancing model accuracy using deep learning techniques like LSTMs and hybrid models
- Expanding the dataset to include real-time price updates
- Developing an automated data pipeline to continuously update forecasts with new information
- Applying transfer learning techniques to improve forecasting for less commonly traded commodities
- Implementing an ensemble approach that combines multiple forecasting models to improve robustness
- Investigating the integration of reinforcement learning to adapt model predictions based on new economic policies and trade regulations
- Enhancing the web interface with additional data visualization tools to improve user experience and insight generation

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