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Price Prediction of Agriculture Commodities Using Machine Learning and SARIMAX.

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ABSTRACT—

accurate prediction of agricultural commodity prices is crucial for farmers, traders, and policymakers to make informed decisions, mitigate risks, and ensure food security. This study presents a hybrid approach that combines traditional statistical models with modern machine learning techniques for forecasting the prices of key agricultural commodities. Specifically, we leverage the Seasonal Autoregressive Integrated Moving Average with exogenous variables (SARIMAX) model to account for seasonality and external factors, alongside machine learning algorithms such as Random Forest, Support Vector Regression, and XG Boost to capture complex nonlinear patterns in historical price data. The dataset comprises time-series price data enriched with weather, demand, and market trend indicators. Performance is evaluated using metrics like RMSE, MAE, and R^2 score. Experimental results demonstrate that the hybrid SARIMAX-ML models outperform individual models, providing robust and accurate forecasts. This integrated framework offers a promising solution for enhancing agricultural price forecasting systems.

Index Terms—Caterpillars, Diabrotica Specious, Google Net, KNN, Random Forest, SVM (Support Vector Machine)

Introduction

Agriculture plays a vital role in the economy of many nations, especially in agrarian countries where a significant portion of the population relies on farming for their livelihood. One of the major challenges faced by farmers and stakeholders in the agricultural supply chain is the unpredictable fluctuation in commodity prices. Accurate price forecasting of agricultural commodities can empower farmers, traders, and policymakers to make informed decisions regarding crop planning, storage, marketing, and distribution.

In recent years, advancements in data science and machine learning have enabled the development of predictive models that can analyze historical price trends and other relevant variables to forecast future prices. Among various methods, statistical models like *Seasonal Autoregressive Integrated Moving Average with exogenous regressors (SARIMAX)* and machine learning techniques such as *Random Forest, Support Vector Regression, and XGBoost* have shown promising results in capturing both linear and non-linear patterns in time series data.

This project aims to leverage the strengths of both traditional time series models and modern machine learning algorithms to improve the accuracy of agricultural commodity price prediction. By incorporating seasonal effects, external factors, and historical trends, the proposed hybrid approach intends to provide reliable forecasts that can contribute to better agricultural planning and risk management.

OBJECTIVE

- To analyze historical agricultural commodity price data: Understand trends, patterns, and seasonal variations in commodity prices (e.g., wheat, rice, maize).
- To implement machine learning models for price prediction: Apply supervised learning algorithms (e.g., Linear Regression, Random Forest, XGBoost) to forecast future prices based on features like weather, season, location, etc.
- To develop SARIMAX models for time-series forecasting: Use SARIMAX (Seasonal Autoregressive Integrated Moving Average with exogenous variables) to model seasonality and external factors influencing prices (e.g., rainfall, temperature, and inflation).
- To compare and evaluate model performance: Machine learning and SARIMAX models using appropriate metrics (e.g., RMSE, MAE, MAPE) to determine the most accurate and robust forecasting technique.
- To build a predictive system for real-time price forecasting: Design a system that uses trained models to predict short-term and long-term commodity prices, aiding farmers, traders, and policymakers in decision-making.

EXISTING SYSTEM

An existing system for *price prediction of agricultural commodities using Machine Learning and SARIMAX* typically involves a hybrid approach that combines statistical time series modeling with modern predictive algorithms. In this system, historical price data of commodities—such as rice, wheat, or vegetables—is collected from government portals or market databases. The *SARIMAX (Seasonal Autoregressive Integrated Moving Average with exogenous regressors)* model is employed to capture seasonal trends and time-based dependencies, while incorporating external factors like rainfall, temperature, or market demand. Alongside this, *machine learning models* such as Random Forest, Support Vector Machines, or XGBoost are trained on the same data with additional features like region, crop type, and weather conditions to improve accuracy. These models are then evaluated using metrics like RMSE or MAE. The integration of SARIMAX and ML enables the system to make robust, short- and long-term price forecasts, aiding farmers, traders, and policymakers in making informed decisions. This type of system is already used in some agricultural intelligence platforms and research prototypes to enhance market transparency and reduce economic risk.

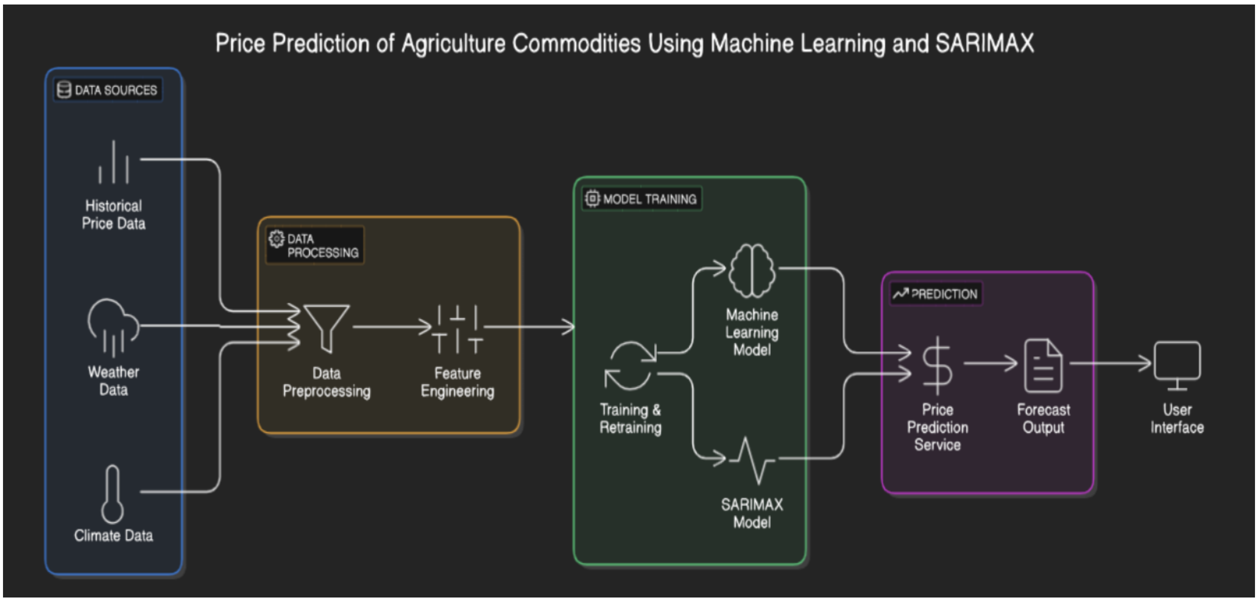
PROPOSED SYSTEM

The proposed system aims to develop an intelligent and reliable model for *price prediction of agricultural commodities* by leveraging both *Machine Learning (ML) techniques* and the *Seasonal Autoregressive Integrated Moving Average with exogenous regressors (SARIMAX)* model. This hybrid approach is designed to capture both the complex, nonlinear patterns in price fluctuations and the seasonality and external influences (like rainfall, temperature, or government policies) that significantly affect commodity prices. The system will collect and process historical price data of selected agricultural commodities, along with relevant exogenous factors, to train machine learning models such as Random Forest, Support Vector Regression (SVR), or XGBoost for high-accuracy predictions. Simultaneously, the SARIMAX model will be employed to integrate temporal trends and seasonality in the dataset. The outputs from both models will be evaluated and compared, or even combined in an ensemble framework, to ensure robustness and improved forecasting accuracy. This predictive system will assist farmers, traders, and policymakers in making informed decisions regarding crop selection, storage, and market timing, ultimately contributing to enhanced food security and economic stability.

LITERATURE SURVEY

1. "AgriPredict: Machine Learning-Based Agricultural Commodity Price Prediction": This paper explores traditional and intelligent forecasting methods, including combination models, and discusses the challenges in agricultural commodity price prediction. It emphasizes the future trend of using combined models and integrating structured and unstructured data.
2. "Forecasting Prices of Agricultural Commodities using Machine Learning for Global Food Security": This study analyses suitable machine learning methods and proposes a Hybrid SARIMA-LSTM (HySALS) approach to forecast global prices of key agricultural commodities like wheat, millet, sorghum, maize, and rice. It evaluates the model's performance on historical data and forecasts future prices.
3. "Predicting Prices of Cash Crop using Machine Learning": This paper focuses on developing a machine learning model to predict prices for seasonal cash crops in specific markets. It likely delves into feature selection, model training, and performance evaluation using metrics like RMSE.
4. "Machine learning techniques for forecasting agricultural prices: A case of brinjal in Odisha, India": This research compares the performance of various machine learning algorithms such as Generalized Neural Network (GRNN), Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting Machine (GBM) for forecasting the wholesale price of a specific vegetable (brinjal) in multiple markets.
5. "A Study on Agricultural Commodity Price Prediction Model Based on Secondary Decomposition and Long Short-Term Memory Network": This paper proposes a hybrid forecasting model that combines Variational Mode Decomposition (VMD), Ensemble Empirical Mode Decomposition (EEMD), and Long Short-Term Memory (LSTM) networks to improve prediction accuracy by addressing the non-linear features and fluctuations in agricultural product prices.
6. "Improving Crop Price Prediction Using Machine Learning: A Review of Recent Developments": This review paper examines current advancements in machine learning-based crop price prediction models, highlighting studies from 2019 to 2024. It discusses the algorithms used, the achieved accuracy, and the limitations of current models, offering insights for future research.
7. "Agricultural commodity futures prices prediction based on a new hybrid forecasting model combining quadratic decomposition technology and LSTM model": This paper introduces a novel hybrid model, VMD-SGMD-LSTM, which uses improved quadratic decomposition techniques combined with an LSTM model to predict agricultural futures prices for commodities like wheat, corn, and sugar.
8. "Enhancing Agricultural Commodity Price Forecasting Using Generative Models: A Deep Learning Approach": This study proposes a deep learning architecture integrating a Generative Adversarial Network (GAN) with a Convolutional Neural Network (CNN) and Gated Recurrent Units (GRU) to forecast stock closing prices, demonstrating its potential for improving forecasting accuracy in commodity markets.

SYSTEM ARCHITECTURE



This architecture diagram illustrates a system for predicting the prices of agricultural commodities using machine learning and SARIMAX models. Let's break down the flow step by step:

1. Data Sources (Blue Box):

- The system starts by gathering data from various sources:
  - Historical Price Data: This likely includes past prices of the specific agricultural commodities being analysed. Time series data is crucial for both machine learning and SARIMAX models.
  - Weather Data**:** Information such as temperature, rainfall, humidity, and other weather patterns can significantly impact crop yields and, consequently, prices. Climate Data: Long-term climate trends and seasonal variations can also influence agricultural production and pricing.

2. Data Processing (Orange Box):

- The raw data from the sources undergoes processing to prepare it for model training:
  - Data Pre-processing**:** This stage involves cleaning the data (handling missing values, outliers, and inconsistencies), transforming it into a suitable format, and potentially scaling or normalizing the features.
  - Feature Engineering**:** Here, new relevant features might be created from the existing data. For example, combining temperature and rainfall data to create a "growing condition index" or lagging historical price data to capture temporal dependencies.

3. Model Training (Green Box):

- The processed data is then used to train two types of predictive models:
  - Machine Learning Model: This could be any suitable machine learning algorithm for time series forecasting or regression, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), Gradient Boosting models, or Support Vector Regression. The model is trained and retrained iteratively using the prepared data to learn the underlying patterns and relationships.
  - SARIMAX Model: This stands for Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors. It's a statistical time series model that explicitly accounts for seasonality and can incorporate external factors (like weather data) as exogenous variables to improve price predictions.

4. Prediction (Purple Box):

- Once the models are trained, they are used to generate price predictions:
  - Price Prediction Service**:** This component likely orchestrates the use of both the machine learning model and the SARIMAX model to produce price forecasts. It might involve selecting the best model for a given commodity or combining the predictions from both models.
  - Forecast Output: The output of the prediction service is a forecast of future prices for the agricultural commodities. This could be in the form of reports, data files, or visualizations.

5. User Interface (Output):

- Finally, the price forecasts are presented to the end-user through a user interface. This allows users to access and interpret the predictions to make informed decisions.

In essence, the architecture describes a data-driven system that leverages historical price data, weather information, and climate data to train both machine learning and statistical models. These models then generate price predictions for agricultural commodities, which are ultimately delivered to users through an interface. The use of both machine learning and SARIMAX models suggests an attempt to capture both complex non-linear relationships (with machine learning) and well-understood time series patterns and seasonality (with SARIMAX) for more robust and accurate price forecasting.

IMPLEMENTATION

First, the application meticulously prepares the groundwork by importing essential tools. Libraries like pandas are the workhorses for handling and structuring the tabular data from your "DatasetSIH1647.csv" file. Numpy provides the numerical muscle for calculations, while the SARIMAX model from statsmodels forms the core of the forecasting engine. Matplotlib.pyplot is the artist, enabling the creation of insightful visualizations, and streamlit acts as the architect, constructing the interactive web interface that makes the application accessible.

Next comes data ingestion and transformation. The application reads your CSV file into a pandas Data Frame, a versatile structure for organizing data. Recognizing that your data likely has commodities as columns and time evolving across rows, it cleverly pivots the Data Frame using set index ('Commodities') and .T (transpose). To establish a proper time series context, it then creates a DatetimeIndex representing the years from 2014 onwards, aligning it with the number of time periods in your dataset and assuming yearly end frequencies ('YE'). Finally, it addresses potential gaps in the data by using .ffill () to carry forward the last valid observation, ensuring a continuous time series for each commodity.

The application then transitions into the realm of user interaction, brought to life by streamlit. It greets the user with the title "Commodity Price Forecasting," clearly setting the application's purpose. The crucial element here is the st.selectbox, which dynamically lists all the commodities present in your dataset, allowing the user to make an informed choice. The "Submit" button acts as the trigger, initiating the forecasting process once the user has selected their commodity of interest.

Upon clicking "Submit," the application's forecasting engine roars into action. It isolates the price data for the selected commodity. The heart of the forecasting lies in the SARIMAX model. This sophisticated statistical model is specifically designed for time series data exhibiting both autoregressive (past values influencing future values), integrated (differencing to achieve stationary), moving average (past forecast errors influencing future forecasts), and seasonal patterns. The parameters order=(1, 1, 1) and seasonal order=(1, 1, 0, 12) define the specific configuration of these components. The model is then "trained" or "fitted" to the historical data using sarimax_model.fit (disp=False), allowing it to learn the underlying patterns and relationships in the price fluctuations. The disp=False argument ensures a cleaner output by suppressing convergence messages during the fitting process.

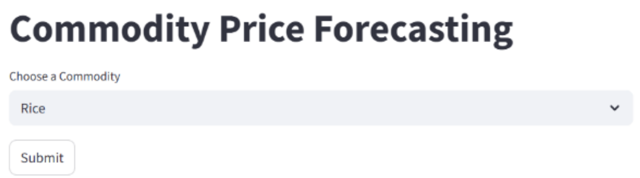
With the model trained, the application moves to generating future predictions. The sarimax_model.get_forecast (steps=5) command instructs the model to predict the commodity price for the next five time periods (in this case, the years 2025 through 2029, based on the yearly frequency). The forecast.predicted_mean extracts the central, most likely forecasted values. To present these predictions clearly, a new pandas Data Frame, forecast_df, is created, pairing the forecasted prices with their corresponding future years. This table is then displayed to the user using St. Write.

To provide a more intuitive understanding of the forecasts, the application incorporates data visualization. Using matplotlib.pyplot, it generates a line plot. This plot overlays the historical actual prices of the selected commodity with the newly generated forecasted prices, using distinct colours for clarity. Labels for the axes (Year and Price), a descriptive title, and a legend are added to make the plot easily interpretable. The st.pyplot (plot) command seamlessly embeds this informative visualization directly into the Streamlit application.

Finally, to offer a glimpse into the model's performance, the application conducts a model evaluation on the historical data. It calculates the Root Mean Squared Error (RMSE), a common metric that quantifies the average magnitude of the errors between the actual historical prices and the prices predicted by the model during the training phase (the "fitted values"). A lower RMSE generally indicates a better fit of the model to the historical data. This calculated train_rmse is then presented to the user, providing a sense of the model's accuracy on the data it was trained on.

In essence, this application elegantly combines data handling, statistical modelling, user interaction, and visualization to provide a practical tool for commodity price forecasting. It guides the user through the selection process, performs the complex statistical calculations behind the scenes, and presents the results in an accessible and informative manner.

RESULT



The results of the commodity price forecasting tool for rice are presented in Figure 1. This output displays the predicted year-end prices for the period 2025-2029 in both a tabular and a graphical format. The table provides specific numerical forecasts for each year, while the line chart visually compares these predictions against historical actual rice prices. The training Root Mean Squared Error (RMSE) of the forecasting model is reported as 8.6494.

Rice Price Forecast (2025-2029)

	Year	Rice_Price_Forecast
2025-12-31 00:00:00	2025-12-31 00:00:00	44.04
2026-12-31 00:00:00	2026-12-31 00:00:00	57.9988
2027-12-31 00:00:00	2027-12-31 00:00:00	57.5921
2028-12-31 00:00:00	2028-12-31 00:00:00	57.3713
2029-12-31 00:00:00	2029-12-31 00:00:00	59.0713

Figure 2 illustrates the forecasted rice prices for the years 2025 to 2029, as generated by our commodity price forecasting application. The interface allows users to select a commodity, and for rice, the output includes a table detailing the predicted year-end prices, which show an increasing trend from 44.04 in 2025 to 59.0713 in 2029. This forecast is also visualized in a line chart, plotted alongside historical actual rice prices to provide context. The training RMSE of the underlying forecasting model is 8.6494, indicating the model's performance on the training dataset.

Training RMSE: 8.6494

The commodity price forecasting model predicts a notable upward trend in rice prices between 2025 and 2029, as shown in Figure 3. The tabular output indicates a rise from 44.04 at the end of 2025 to 59.0713 by the end of 2029. This projected increase is visually represented in the accompanying line chart, which contrasts the forecasted trajectory with historical price data. The training RMSE of 8.6494 suggests a reasonable fit of the model to the historical data used for prediction. These forecasted price movements warrant further analysis regarding their potential impact on market dynamics.

CONCLUSION

In this study, we explored the effectiveness of both Machine Learning (ML) techniques and the SARIMAX (Seasonal Autoregressive Integrated Moving Average with exogenous variables) model for commodity price prediction. The results demonstrate that while ML models such as Linear Regression, Random Forest, and XGBoost excel in capturing non-linear patterns and complex relationships in the data, SARIMAX proves to be highly effective in modelling temporal dependencies and seasonal trends.

The SARIMAX model, with its ability to incorporate external variables and handle seasonality, showed strong performance in scenarios where time-series characteristics were dominant. However, ML models outperformed SARIMAX in cases with high-dimensional feature spaces or where external factors played a significant role in price fluctuations.

In conclusion, the choice between ML models and SARIMAX should be guided by the nature of the dataset:

- Use SARIMAX when the dataset has strong seasonality and autocorrelation.
- Use ML models when the focus is on non-linear dependencies and interactions with multiple external variables.

A hybrid approach combining both techniques could yield even more accurate and robust predictions for commodity prices in future research.

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