RESEARCH ARTICLE

An Analysis of Time Series Models for Predicting Global Rice Price

Suraj Arya[1] and **Singara Singh Kasana**[1,*]

[1] Central University of Haryana, Mahendergarh 123031, India

Abstract

Rice plays a crucial role globally, as it is widely consumed across nations. Therefore, studying rice prices is vital, since fluctuations in the price can affect both its consumption and availability. This study analyzes time-series models using an international dataset. After preprocessing, the dataset comprises 71,856 samples and eight input features from six countries. The original dataset contained 300,816 rows and 23 columns. This study aims to predict rice inflation rates using time series models such as ARIMA, LSTM, and BiLSTM. The ARIMA model achieved the best combination of values (4,1,4)(0,0,0). Various statistical techniques that calculate inflation rates require expert knowledge and are time-consuming. However, with the advancement of intelligent computing and machine learning models, the rice inflation rate can now be predicted efficiently. These models play a vital role in managing unjustified surges in global rice prices.

Keywords: machine learning, time series analysis, global rice price prediction, ARIMA, LSTM, BiLSTM.

Submitted: 19 October 2025
Accepted: 20 January 2026
Published: 23 March 2026

Vol. 2, **No.** 3, 2026.
10.62762/TMI.2025.272892

***Corresponding author:**
Singara Singh Kasana
singarasingh@cuh.ac.in

1 Introduction

Rice, often referred to as the "staff of life," is a crucial crop and primary nutrient source worldwide, playing a significant role in global diets [1–4]. Similar to other crops, the price of rice affects its use. This study analyzes the rice inflation rates in six countries (Nigeria, Philippines, Iraq, Yemen, Congo, and Chad) and explores potential future trends in rice inflation. The ARIMA and LSTM models [5–7] were used to predict the inflation rate of rice. The opening, highest, lowest, and closing prices of rice are determinants of the inflation rate. Given the importance of rice crops, it is essential to predict the inflation rate so that prices can be maintained accordingly [8–10]. Recently, fluctuations in rice crop prices have been observed worldwide. For example, in July 2023, India imposed export restrictions on non-basmati white rice, disrupting the global market. Thai white rice price increased by over 20 % by early August 2023.

In the Philippines, rice inflation reached 24.4% , with a rate increasing since 2009. The steep rise in the prices of food items in Nigeria can be gauged from the fact that the prices of rice have risen sharply from 737.11 Naira in August 2023 to 1,831.05 Naira in August 2024, reflecting a 3.6 % month-on-month increase. These trends highlight the importance of accurately predicting rice inflation in order to ensure price stability.

Traditionally, calculating inflation rates relied on statistical techniques that demanded expert knowledge. However, owing to advancements in the

Citation
Arya, S., & Kasana, S. S. (2026). An Analysis of Time Series Models for Predicting Global Rice Price. *ICCK Transactions on Machine Intelligence*, 2(3), 116–126.

computing domain, machine learning techniques enable the prediction of rice prices at the global level and forecast inflation rates. The advantage of these predictive models is that they can help prevent unjustified surges in global rice price.

1.1 Motivation of the Proposed Work

Most research has been conducted on rice production, its types, disease detection, and the import or export of rice for a specific country, market, and region. However, due to the limited scope of these studies, their findings are not applicable at the international level. Various international organizations and researchers have empirically investigated vegetable prices such as tomates, potatoes, soybeans, and onions using ARIMA, GARCH, FIGARCH, and artificial neural networks. No analysis in the literature on rice crops has been based on the international inflation rates of various countries. Rice is a crop consumed internationally, therefore, the inflation rate must be analyzed to ensure its worldwide availability.The proposed model contributes by analyzing the time series data of six countries with the help of ARIMA and LSTM models to predict the international rice inflation rate.

1.2 Contribution of the Proposed Work

- Most studies are based on domestic datasets that represent the specific domains of a particular country and market such as: Uttarakhand, Dehradun, Haldwani Mandi, Delhi market, Aligarh, Madhya Pradesh, Maharashtra, Rajasthan, Karnataka, Gujarat, Keshopur, Azadpur markets, Shahdra, Agra, Mumbai, Bengaluru, Ahmedabad, Haryana, and Nigeria. The results of these price analyses cannot be applied at the international level. In contrast, our dataset analyzes the rice inflation rate at an international level.

- Prior research has focused on potato, soybean, cabbage, bok choy, watermelon, and cauliflower prices. Some researchers have found the effect of sessions on the prices of a particular crop or vegetable, but none of these predict the inflation rate.

- Existing studies have defined the relationship between the arrivals and prices of vegetables such as potatoes.Background studies are based on GARCH, ARIMA, ANN, TDNN, Wavelet-ANN, IGARCH, FIGARCH, EMD-ANN, MGARCH, BEHKK, DCC, Cuddy Della Valle index (CDVI), ARCH-LM, Partial Least Squares (PLS), ETS-ANN, ETS-LSTM and ETS-SVM models to determined out the relationship between vegetable availability, arrivals, and prices. They also determine which model is suitable for long and short-term predictions. Some researchers also measure vegetable price instability and do not focus on the inflation rate.

- Food price prediction can be effective only when it is based on an international dataset, which was missing in previous work.

Thus, all of the above research gaps motivate the current study to produce novel results and contribute to crop price prediction.

The paper is structured as follows: Section 1 provides the Introduction and also covers the motivation and contribution of the proposed work. Section 2 outlines the Literature Review; Section 3 outlines the dataset details, and proposed technique; Section 4 presents the Experimental Results. Section 5 discusses the results. The Conclusion and Future Scope are discussed in Section 6.

2 Literature Review

Literature [11] analyzed time-series datasets: sunspot data, Lynx trapping data, and exchange rate data. Each dataset contains both linear and nonlinear characteristics. Neither ARIMA nor ANNs alone were sufficient for predicting time-series analysis. The study suggests that combining dissimilar models can reduce the uncertainty and prediction errors of the ensemble model. The ensemble model exhibits a lower generalization variance. The overfitting problem commonly associated with neural network models can be mitigated by initially fitting an ARIMA model.

Literature [12] predicted Gram prices using two models- GARCH and ARIMA. The authors observed that the GARCH model was more effective in detecting time-varying volatility than the ARIMA model. Although ARIMA predictions were acceptable and reasonable, they struggled to generate effective results in the presence of volatility in the data series. Therefore, GARCH has emerged as a superior model because of its ability to capture volatility. The Akaike information criterion (AIC) and Sure Independence Screening (SIC) values for the ARIMA model were 10.06004 and 10.07023, respectively, whereas those for the GARCH model were 9.779861 and 9.796822, respectively

Literature [13] compared the performance of four models: Regularized Sparse Multivariate Partial Least Squares (RSMPLS), Partial Least Squares(PLS), ANN, and ARIMA in predicting the prices of crops such as cabbage, bok choy, watermelon, and cauliflower. The models were evaluated based on the mean absolute percentage error (MAPE). The study concludes that PLS is effective for short-term price forecasting, whereas ANN is suitable for long-term price forecasting. The data used in this analysis were sourced from the first wholesale fruit and vegetable market in Taipei. RSMPLS provided the most accurate forecasts for cabbage and bok choy compared with ARIMA, PLS, and ANN. The experiments utilized training datasets varying in size, 1070 for PLS and ANN, 1004 for RSMPLS, and 1069 for ARIMA. Three hundred recent data entries were used for testing. The researchers also explored the impact of different values, such as the number of referred lags and size of forecasting gaps on the performance of the models. Based on the results, PLS and ANN were the most effective models for crop price forecasting, with their specific strengths depending on the time frame and crop type.

Literature [14] analyzed time series data of onion prices from Delhi markets from 2005 to 2015, which were sourced from the AGMARKNET website. They implemented the ARIMA, ARCH, and GARCH models for forecasting. The ARIMA(1,1,0)-EGARCH(1,1) models yielded the best results for the Keshopur and Azadpur markets, whereas the ARIMA(1,1,0)-GARCH(1,1) models were the most suitable for Shahdara. The study found that onion prices ranged from Rs 1800 to 1950 per quintal in Azadpur and Shahdara, and from Rs 2178 to 2413 per quintal in Keshopur between March and July 2015.

Literature [15] utilized yellow soybean data from 2006 to 2016 from AGMARKNET to forecast average prices using the ARIMA model. For the harvesting period of 2017-18, the predicted prices were estimated to range between INR 2,600 and 3,600 per quintal in India. ARIMA (1,1,2)(0,0,2), (0,1,1)(0,0,2), (0,1,1) (1,1,2), (0,1,0), and (0,1,0) had the lowest normalized BIC value for Madhya Pradesh, Maharashtra, Rajasthan, Karnataka, Gujarat, and overall India, respectively. However, they concluded that the ARIMA model does not guarantee perfect forecast accuracy. For reference, soybeans were priced at INR 2,693 compared with their MSP from the previous year.

Literature [16] highlighted the significance of the decomposition levels in forecasting. The authors implemented three models- ARIMA, TDNN, and Wavelet-ANN- and concluded that TDNN is better than ARIMA for short-term forecasting. The TDNN was also more effective for long-term predictions. However, the Wavelet-ANN model consistently outperformed ARIMA and TDNN across all scenarios. Data were collected from the Office of the Economic Adviser of the Government of India. The ARIMA model outperformed the TDNN for 1-month and 3-month ahead forecasting, whereas the TDNN model performed better than ARIMA for 6-month and 12-month ahead forecasting. ARIMA achieved an RMSPE of 1.77, whereas TDNN achieved an RMSPE of 6.29 compared to the ARIMA model.

Literature [17] analyzed the relationship between vegetable arrivals and prices of **potatoes, tomatoes, and onions** in Uttarakhand using the Dehradun and Haldwani Mandi Datasets. The authors observed an inverse relationship between arrivals and price of potatoes. This means that potato prices reduced with higher of potato production arrivals in the market. The analysis indicated 92% of the variation in onion prices. Predicted growth rates for tomatoes and Potatoes were 7.38% and 7.94%, respectively. A linear regression model was used to forecast the prices of the potatoes, tomatoes, and onions.

Literature [18] focused on future crop demand and addressed the importance of forecasting long-term crop production. This study focused on rice yield data from the Aligarh District of Uttar Pradesh. This study reveal the limitations of the traditional ARIMA model in enhancing yield forecasting accuracy. A hybrid approach was proposed by combining the Artificial Neural Networks (ANN) and ARIMA techniques. The hybrid model demonstrated a significant reduction in MAPE and achieved 4.65% as compared with 17.677% for the ARIMA model.

Literature [19] combined Empirical Mode Decomposition and Artificial Neural Networks (ANNs) to predict daily potato prices in the Delhi market. The forecasted prices of potatoes for the Delhi wholesale market EMD-ANN model performed better because of the lower RMSE(EMD-ANN 23.95, ANN 92.72) and higher (EMD-ANN 75.00, ANN 66.67) values.

Literature [20] focused on Nigeria's exchange rate volatility, highlighting the necessity for operative modeling techniques to understand the implications for economic stability. Two models, IGARCH and FIGARC, were developed to determine the limitations of GARCH models'. The results endorsed the competence of the ARIMA-FIGARCH model in capturing the dynamics of NSE returns and highlighted its effectiveness in forecasting instability.

Literature [21] focused on monthly retail and wholesale price predictions of three major vegetable crops in India: tomatoes, onions, and potatoes. Data were collected from the Horticultural Statistics Division, Department of Agriculture, Cooperation and Farmer Welfares, Govt. of India. The authors proposed two additive hybrid methods (ETS-SVM and ETS-LSTM) and several multiplicative hybrid methods, including ETS-ANN, ARIMA-SVM, and ARIMA-LSTM. Their technique combines statistical models with nonlinear machine learning models to capture the effects of both linear and nonlinear patterns in time-series data. To evaluate the performance of the proposed hybrid methods, an extensive statistical analysis was conducted using metrics such as the mean absolute error (MAE), symmetric mean absolute percentage error (SMAPE), and root mean square error (RMSE). The study used The Wilcoxon signed-rank test with a 95% confidence level.

Literature [22] analyzed the potato price volatility of five major Indian markets: Delhi, Agra, Mumbai, Bengaluru, and Ahmedabad. This study applied multivariate generalized autoregressive conditional heteroscedastic (MGARCH) models, specifically DCC and BEKK, to analyze price volatility. These studies highlight the importance of understanding price dynamics in India's agricultural markets. The study utilized the Volatility Impulse Response Function to evaluate how specific shocks affect price volatility spillovers among markets and reveal significant spillover effects across all locations. The study applied various unit tests such as Augmented Dickey-Fuller (ADF) and Phillips–Perron to check the stationarity in the data. Accordingly, accommodate the conditional heteroscedasticity and inter-dependence of the studied markets, MGARCH models, namely BEKK and DCC, have been applied. Price volatility depends on the market's past and cross-market volatility.

Literature [23] the data source used for this study is taken from the AGMARKNET website from January 2005 to December 2021 predicted The prices stability of Tomato, Onion & Potato. These crops account for 30% of agricultural GDP in India. This analysis revealed a high seasonal index variation for tomatoes in West Bengal, onions in Madhya Pradesh, and potatoes in Haryana. All the TOP crop prices were unstable. The Cuddy Della Valle index (CDVI) is employed to measure price instability, and it is divided into three categories - low, medium, and high levels. This study found a correlation between the periods and crops. For example, tomato prices typically rise from July to November owing to the limited supply during this period. Onion prices experience seasonal pressure, decreasing during the Rabi harvest and peaking between October and December. Haryana had the highest seasonal price index variation for potatoes, whereas Punjab exhibited the highest price instability. The ARCH-LM test results showed that onions exhibit the highest and most persistent volatility, followed by tomatoes and potatoes. Literature [10] proposed a hybrid approach using ARIMAX and LSTM models. This study provided the more accurate results by capturing the linear dependence and temporal dynamics in the data.

3 Material and methods

Initially, the combined dataset contains 300816 rows and 23 columns. The data source is the World Bank Microdata Library (downloaded from www.microdata.worldbank.org), which provides different market-level food price data. The rice inflation dataset covers the period 2008–2024, with prices observed at a monthly frequency. It also contains information regarding the inflation of 26 types of food consumed in these countries. Since the use of all these 26 types of food was not uniform across the world and all six countries, it was decided to find the inflation rates of only those food items commonly used in these six countries.

Rice, a widely used food item in all these countries, compared to other food items. In the original dataset, prices and inflation rates were recorded in local currencies{XAF, CDF, IQD, NGN, PHP, YER} of a particular country. To determine the inflation rate of rice, it is necessary to convert the local currency of all six countries into a common currency such as the dollar. After that during the preprocessing, only 71856 rows and eight columns were selected for the analysis, and all other irrelevant columns and rows were removed . Finally, we had data on rice inflation for six different countries {Chad, Congo, Iraq, Nigeria, Philippines, and Yemen} across the world shown in Table 1.

3.1 Proposed Technique

The steps of data preprocessing are as follows:

1. *Load Dataset:*

Table 1. Dataset details.

S.no	Feature name	Description
1	country	Chad, Congo, Iraq, Nigeria, Philippines, Yemen
2	mkt_name	Market names
3	year	2007–2024
4	o_rice	Monthly opening price
5	h_rice	Highest price achieved
6	l_rice	Lowest price point
7	c_rice	Closing price estimate
8	IR_Dollar	Inflation rate

- Import the "Rice inflation" dataset as a CSV file.
- Identify the description of the dataset (e.g., rows, columns, properties, and data types).

2. *Handle Missing Data:*
   - Detection of the most popular food at the international level (commonly used in many countries).
   - Identify the currency type of each country.
   - Convert the currency into dollars to ensure uniformity.
3. *Remove Unwanted Data:*
   - Initially, the dataset contains 300,816 rows and 23 columns.
   - All unwanted rows and columns are removed and the dataset is prepared.
4. *Implementation of Tools:*
   - Check the "stationary" property of the time series data through the Augmented Dickey-Fuller (ADF) test.
   - If the dataset is "stationary", use any of the ARIMA, LSTM, or BiLSTM models to predict international rice inflation, because these are the most widely used time series models in machine learning.

3.2 ARIMA Model

ARIMA is widely used time-series model. It has three main parts given below:

- Autoregressive Process(AR) (p): AR(P) is the first component of the ARIMA model, that shows the autoregressive Process of order P. This model uses the dependent relationships between several lagged observations. It can be written as:

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + \epsilon_t \quad (1)$$

- Degree of difference(I) (d): I (d) is the second component of the ARIMA model, where (d) is the difference order. With the help of the first difference, the data can be non-stationary to stationary.
- Moving Average(MA) (q): The moving average process MA (q) is the third component of the ARIMA model. This model uses the dependence between residual errors and observations, which are applied to lagged observations, and it can be written as:

$$Y_t = \epsilon_t + \beta_1 \epsilon_{t-1} + \beta_2 \epsilon_{t-2} + \cdots + \beta_q \epsilon_{t-q} \quad (2)$$

The time series must be stationary in order to implement the ARIMA model. Therefore, to check the stationarity property, the (augmented Dickey–Fuller). ADF test is applied to the rice inflation data. The ADF output is based on the p-value. If the p-value is less than 0, reject H_0, which means that the series is stationary, as shown in Figure 1, and the alternative hypothesis (H_1) is accepted. The ADF test details are as follows:

ADF Statistic
ADF Statistic: -27.425916
p-value: 0.000000
nlags: 0.0
Critical Values:
1: -3.430
5: -2.862
10: -2.567

where Y_t = current value, $\alpha_1, \ldots, \alpha_p$ = AR coefficients, ϵ_t = white noise, $\beta_1, \ldots, \beta_q$ = MA coefficients. The series is shown to be stationary in Figure 2.

Figure 3 shows that the series data has an ACF plot showing the strong peaks at regular intervals, which indicates seasonal patterns in the data.

Figure 4 shows the Partial autocorrelation Function, which is used to estimate the correlation between a

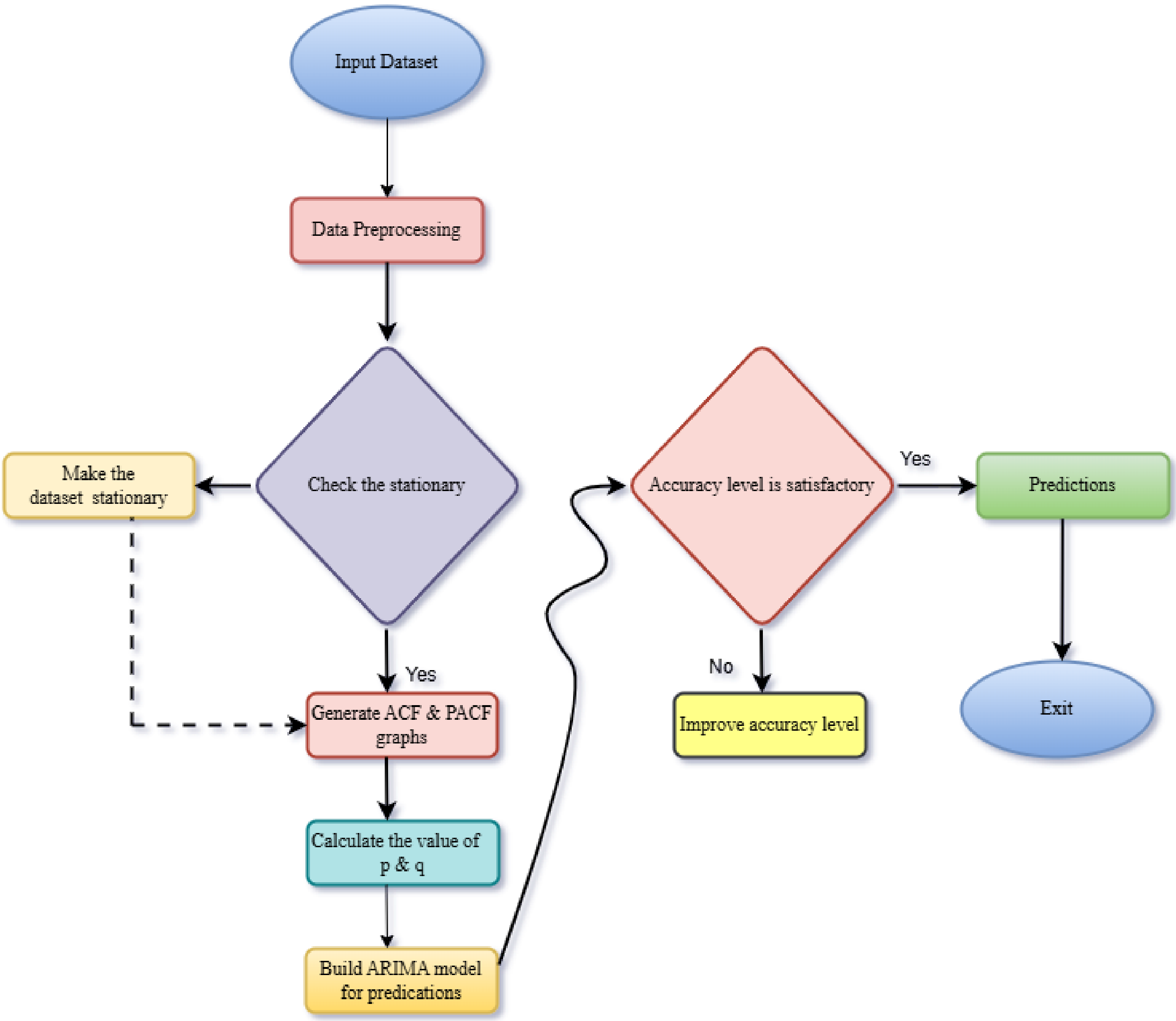


Figure 1. Workflow of ARIMA model.

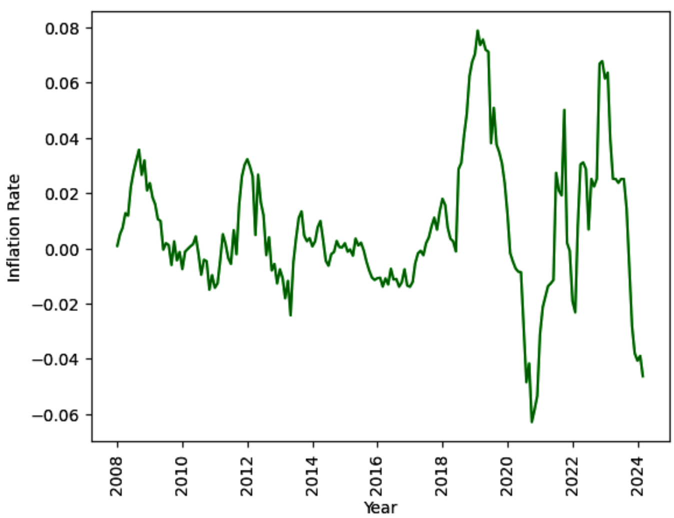


Figure 2. Year-wise Inflation rate.

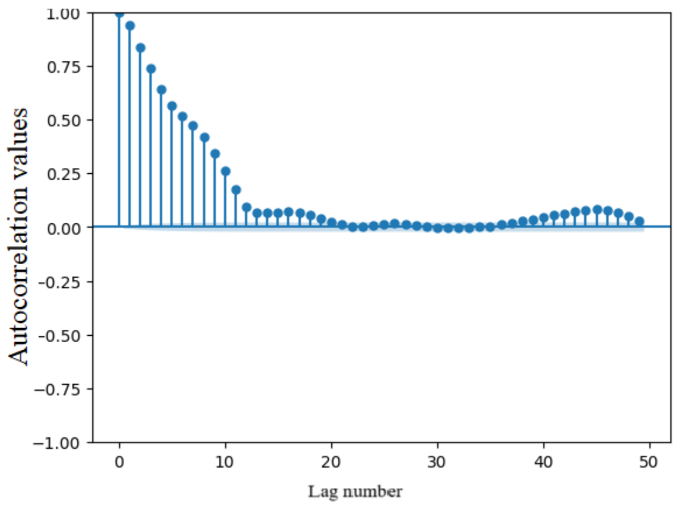


Figure 3. Autocorrelation.

time series and its lagged values. It is also used to detect seasonality. To find out the minimum Akaike Information Criterion (AIC), the ARIMA model was trained and tested, and the best-fitted model values are as follows:ARIMA (4,1,4) (0,0,0) [17].

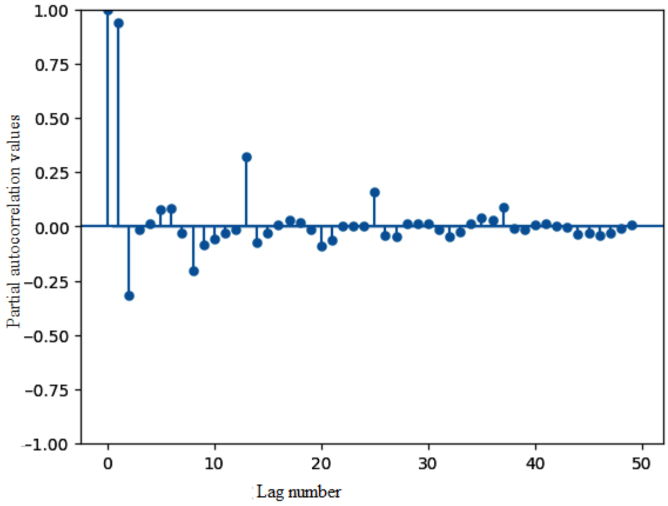


Figure 4. Partial autocorrelation.

Both ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) are used for time series model building (ARIMA) based on past values by identifying how past values affect the future values at different lags. ACF understands the auto correlation at various lags and decides the order of the MA model, where PACF separates the direct correlation between a variable and its lagged values and determines the order of the AR model.

3.3 Long Short-Term Memory Networks

LSTM is a recurrent neural network that forms better neural connections when the input data are sequential. As HSD is sequential, LSTM is an ideal deep learning framework that takes advantage of the sequence input. The gate operations in LSTM are measured as follows.

The LSTM model can remember the relevant information for a long time with the help of gates. The LSTM model is based on four components: (a) Cell State is used to store and act as a memory. (b) The forget gate will discard the unimportant information. (c) input decides which new information will be added to the cell state. The sigmoid function σ is used to regulate the flow of information in gates. (d) The output gate will determine which part of the cell state will be used to generate the output, as shown in Figure 5.

3.4 BiLSTM Model

The BiLSTM model is an extended LSTM, which processes the input sequence in both forward and backward directions. This bidirectional feature allows the model to capture both past and future information. Because of this property, this model is suitable for time series forecasting. The BiLSTM model consists of two layers. Forward LSTM processes the data from past to future(left to right), whereas Backward LSTM processes the data from future to past(right to left) Figure 6. The merging layer is used to the output of both layers forward and backward and share this information with the output layer for classification or regression.

4 Results

This study uses data from 2008 to 2024 from six countries. It is a time series problem as data are available year and monthly, so to forecast rice price inflation, ARIMA, LSTM, and BiLSTM models are implemented. The stochastic model of that series determines the best forecast for the future value of a time series. Stochastic processes are either stable or unstable. In most cases, time nonstationary is nonstationary, however, the ARIMA model can be applied to the stationary time series. A time series is said to be stationary if its mean and covariance remain constant over time. If the data are non-stationary, we need to convert them into stationary data before implementing time series models have three components.

Figures 7 and 8 show the training and validation loss curves of the LSTM and BiLSTM models, respectively. Both figures indicate that as the number of epochs increased, the loss decreased steadily, suggesting effective learning and convergence in minimizing the difference between actual and predicted values.

4.1 Model's performance evaluation

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{5}$$

Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

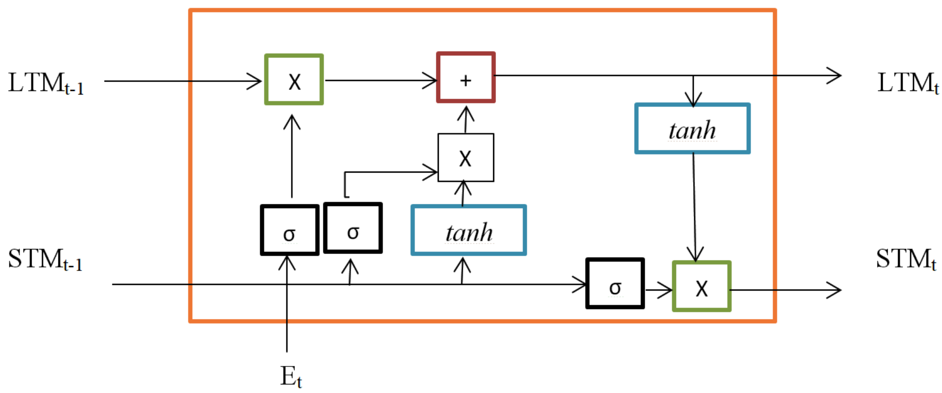


Figure 5. Architecture of LSTM model.

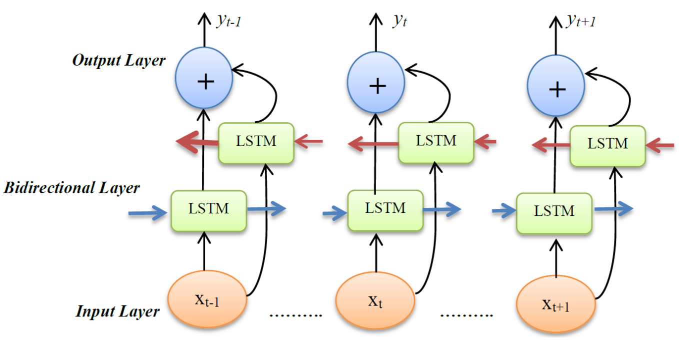


Figure 6. Architecture of BiLSTM model.

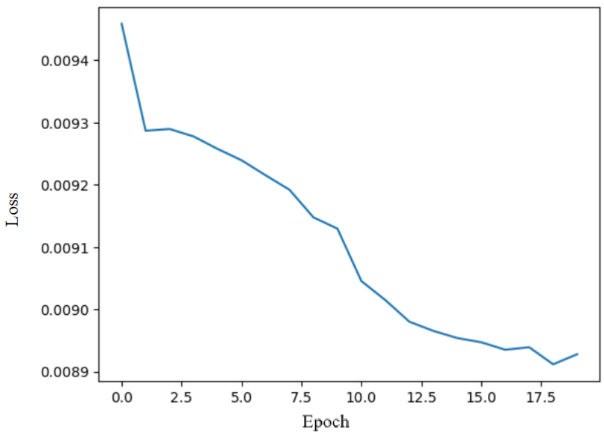


Figure 7. LSTM model loss.

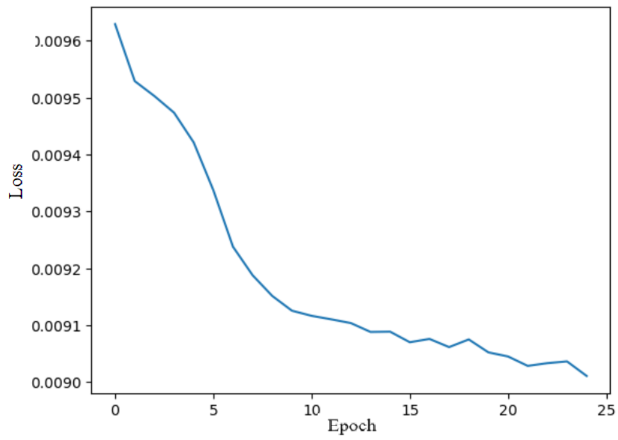


Figure 8. BiLstm model loss.

Median Absolute Error (MedianAE):

$$\text{MedianAE} = \text{median}\left(|y_i - \hat{y}_i|\right) \tag{7}$$

Maximum Error (MaxError):

$$\text{MaxError} = \max\left(|y_i - \hat{y}_i|\right) \tag{8}$$

Explained Variance Score (EVS):

$$\text{EVS} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{9}$$

R-squared (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{10}$$

Adjusted R-squared (R^2_{adj}):

$$R^2_{\text{adj}} = 1 - \left(\frac{1 - R^2}{n - 1}\right) \times (n - p - 1) \tag{11}$$

where n = Number of observations, p = Number of predictors, R^2 = R-squared value, y_i = Actual value, $\hat{y}_i$ = Predicted value, $\bar{y}$ = mean of actual values

5 Discussion

Table 2 presents the performance metrics of the ARIMA, LSTM, and BiLSTM models. The deep learning models (LSTM and BiLSTM) exhibit significantly lower values in most absolute error metrics compared to ARIMA. Specifically, LSTM and BiLSTM achieved MAE values of 0.085 and 0.078, respectively, compared to 0.475 for ARIMA, indicating that their predictions are generally closer to the actual values in absolute terms. Similarly, RMSE (0.129 and 0.124 vs. 0.564), MSE (0.016 and 0.0154 vs. 0.318), and MedianAE (0.045 and 0.039 vs. 0.468) are notably lower for the deep models, suggesting better robustness in handling prediction deviations.

Table 2. Performance comparison of ARIMA, LSTM, and BiLSTM models.

Performance Metrics	ARIMA	LSTM	BiLSTM
MAE	0.475	0.085	0.078
RMSE	0.564	0.129	0.124
MAPE	253.189	253.189	3752.06
MSE	0.318	0.016	0.0154
MedianAE	0.468	0.045	0.039
MaxError	1.847	0.641	0.992
EVS	-3.891	0.120	0.194
R-sq.	0.914	0.12	0.19
Adj.R-sq.	0.913	0.12	0.19

However, the MAPE values are unusually high across all models (253.189% for ARIMA and LSTM, 3752.06% for BiLSTM). This inflation of MAPE is likely due to the presence of near-zero or small inflation rate values in the dataset, which causes division by very small denominators and leads to exaggerated percentage errors—a known limitation of MAPE when actual values approach zero. Therefore, MAPE should be interpreted with caution in this context, and greater emphasis is placed on absolute error metrics (MAE, RMSE, MSE) and MedianAE. Regarding variance explained, ARIMA shows substantially higher R-squared (0.914) and adjusted R-squared (0.913) values, indicating strong explanatory power, possibly reflecting better in-sample fit or linear pattern capture. In contrast, LSTM and BiLSTM yield lower R-squared values (0.12 and 0.19, respectively), which is not uncommon in out-of-sample forecasting of highly volatile time series data using nonlinear models. The Explained Variance Score (EVS) for ARIMA is negative (-3.891), suggesting poorer performance than a simple mean-based predictor in terms of variance, while LSTM and BiLSTM show positive though modest EVS (0.120 and 0.194). Overall, while ARIMA provides high explanatory power in certain metrics, the LSTM and BiLSTM models demonstrate superior performance in absolute and median error terms, making them more suitable for practical rice inflation rate prediction under volatile global conditions.

6 Conclusions

The proposed analysis effectively predicts the international rice inflation rate using ARIMA, LSTM, and BiLSTM models. While ARIMA offers strong explanatory power in variance-related metrics, the deep learning models (LSTM and BiLSTM) achieve lower absolute and median errors, demonstrating greater robustness in capturing complex patterns in the data. Prior knowledge of rice price trends provided by these models can support policy-making, supply chain adjustments, consumer decisions, and international food security efforts. This analysis is also helpful for tracking food security risks at the international level. International humanitarian support can be provided through international organizations such as the UN, WHO, and the World Bank, and food scarcity can be prevented. This study also offers solutions for economic and long-term sustainability. This analysis reveals data-driven decisions that encourage sustainable practices. This analysis can be further utilized to predict the inflation rate of other essential crops and goods at the international level.

Data Availability Statement

Data will be made available on request.

Funding

This work was supported without any funding.

Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

References

[1] Setivani, L., Handayani, H. H., & Geraldine, W. A. (2023, November). Rice Price Forecasting Using GridSearchCVand LSTM. In *2023 International*

Conference on Modeling & E-Information Research, Artificial Learning and Digital Applications (ICMERALDA) (pp. 127-131). IEEE. [CrossRef]

[2] Reddy, P. C. S., Suryanarayana, G. L. P. K., & Yadala, S. (2022, November). Data analytics in farming: rice price prediction in Andhra Pradesh. In *2022 5th International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT)* (pp. 1-5). IEEE. [CrossRef]

[3] Yusri, N. H. M., Shafie, N. A., & Ghani, N. A. M. (2022, November). Rice price prediction in Malaysia. In *2022 IEEE International Conference on Computing (ICOCO)* (pp. 249-252). IEEE. [CrossRef]

[4] Bilal, M., Alrasheedi, M. A., Aamir, M., Abdullah, S., Norrulashikin, S. M., & Rezaiy, R. (2024). Enhanced forecasting of rice price and production in Malaysia using novel multivariate fuzzy time series models. *Scientific Reports, 14*(1), 29903. [CrossRef]

[5] Duyapat, C. (2025). Forecasting Philippine Rice Prices: Comparison of Traditional Time Series and Machine Learning Models. *Journal of Mathematics and Statistics Studies, 6*(6), 18-28. [CrossRef]

[6] Zaw, T., Oo, A. N., & Kyaw, S. S. (2020, November). Combination of ARMA and BPNN model to predict rice type and rice price. In *2020 International Conference on Advanced Information Technologies (ICAIT)* (pp. 159-164). IEEE. [CrossRef]

[7] Yusup, M., Prasetyo, S. Y. J., & Wellem, T. (2024, August). Evaluation of prediction accuracy in ARIMA and LSTM algorithms for agricultural commodity prices. In *2024 3rd International Conference on Creative Communication and Innovative Technology (ICCIT)* (pp. 1-7). IEEE. [CrossRef]

[8] Haerani, E., Aulia, S. D., Darmawan, I., Rahmatulloh, A., Rizal, R., & Gunawan, R. (2025, February). Predicting the future: Using AdaBoost to forecast food commodity prices across Indonesian markets. In *2025 International Conference on Advancement in Data Science, E-learning and Information System (ICADEIS)* (pp. 1-5). IEEE. [CrossRef]

[9] Phan, H., Nguyen, V., Vo, V., Tran, N. Q., Tran, L., Dao, S., & Pham, H. (2024, December). Leveraging automatically optimized forecasters and large language model for predicting Vietnamese rice export price. In *2024 RIVF International Conference on Computing and Communication Technologies (RIVF)* (pp. 237-241). IEEE. [CrossRef]

[10] Mahawan, A., Jaiteang, S., Srijiranon, K., & Eiamkanitchat, N. (2022, February). Hybrid ARIMAX and LSTM model to predict rice export price in Thailand. In *2022 International Conference on Cybernetics and Innovations (ICCI)* (pp. 1-6). IEEE. [CrossRef]

[11] Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing, 50*, 159-175. [CrossRef]

[12] Bhardwaj, S. P., Paul, R. K., Singh, D. R., & Singh, K. N. (2014). An Empirical Investigation of Arima and Garch Models in Agricultural Price Forecasting. Economic Affairs, 59(3), 415-428. [CrossRef]

[13] Peng, Y. H., Hsu, C. S., & Huang, P. C. (2015, November). Developing crop price forecasting service using open data from Taiwan markets. In *2015 Conference on Technologies and Applications of Artificial Intelligence (TAAI)* (pp. 172-175). IEEE. [CrossRef]

[14] Paul, R. K., Rana, S., & Saxena, R. (2016). Effectiveness of price forecasting techniques for capturing asymmetric volatility for onion in selected markets of Delhi. *The Indian Journal of Agricultural Sciences, 86*(3), 303-309.

[15] Darekar, A., & Reddy, A. A. (2017). Predicting market price of soybean in major India studies through ARIMA model. *Journal of Food Legumes, 30*(2), 73-76. [CrossRef]

[16] Anjoy, P., Paul, R. K., Sinha, K., Paul, A. K., & Ray, M. (2017). A hybrid wavelet based neural networks model for predicting monthly WPI of pulses in India. *Indian J Agric Sci, 87*(6), 834-839.

[17] Agarwal, P., Singh, R., & Singh, O. P. (2018). Dynamics of prices and arrivals of major vegetables: a case of Haldwani and Dehradun markets, Uttarakhand. *Journal of Agricultural Development and Policy, 28*(1), 1-11.

[18] Pandit, P., Sagar, A., Ghose, B., Dey, P., Paul, M., Alqadhi, S., ... & Abdo, H. G. (2023). Hybrid time series models with exogenous variable for improved yield forecasting of major Rabi crops in India. *Scientific Reports, 13*(1), 22240. [CrossRef]

[19] Choudhary, K., Jha, G. K., Das, P., & Chaturvedi, K. K. (2019). Forecasting potato price using ensemble artificial neural networks. *Indian Journal of Extension Education, 55*(1), 73-77.

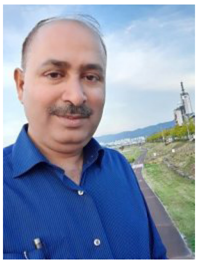
[20] Bawa, M. U., Dikko, H. G., Shabri, A., Garba, J., & Sadiku, S. (2021). Forecasting performance of hybrid ARIMA-FIGARCH model and hybrid of ARIMA-GARCH model: a comparative study. *Journal of Mathematical Problems, Equations and Statistics, 2*(2), 48-58.

[21] Purohit, S. K., Panigrahi, S., Sethy, P. K., & Behera, S. K. (2021). Time series forecasting of price of agricultural products using hybrid methods. *Applied Artificial Intelligence, 35*(15), 1388-1406. [CrossRef]

[22] Paul, R. K., Yeasin, M., & Paul, A. K. (2022). The volatility spillover of potato prices in different markets of India. *Current Science (00113891), 123*(3). [CrossRef]

[23] Ajmal, S., Rohith, S., Unniravisankar, P., & Nabay, O. (2024). Price dynamics of tomato, onion and potato (TOP) in India. *Asian Journal of Agricultural Extension, Economics & Sociology, 42*(3), 134-143. [CrossRef]

Dr. Suraj Arya currently working as Assistant Professor in the Department of Computer Science and Information Technology and Deputy Director (Training and Placement) at Central University of Haryana, India. His academic qualifications are Ph.D.(Computer Science), M.Phil.(Computer Science) and M. Tech (Computer Science and Engineering). His research interests focus on machine learning (ML), Deep Learning , internet of things (IoT), Data warehousing and mining, system automation and patents writings. He has granted and files many patents. He has also published many research articles in international journals, book chapters, and conferences. (Email: surajarya@cuh.ac.in)



Prof. Singara Singh Kasana working as Professor of Computer Science and Information Technology, Central University of Haryana, Mahendergarh. Prior to joining the Central University of Haryana, he worked with Thapar Institute of Engineering and Technology, Patiala, India, for around 19 years. He has around twenty-three years of teaching and research experience. He received his PhD degree in Image Compression from Thapar University Patiala. He has guided 8 Ph.D. and 27 post-graduate thesis. His research interests include digital twins, image processing, machine learning, information security and computer vision. He has published more than seventy research papers in reputed international journals and conferences. (Email: singarasingh@cuh.ac.in)