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Price forecasting models for rice in West Bengal, India

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Abstract
Rice “a staple crop in India” plays a pivotal role in ensuring food security and sustenance for a significant portion of the global population. This study focuses on the development and evaluation of price forecasting models for rice in West Bengal, India, a region renowned for substantial rice production. Accurate price forecasts are crucial for various stakeholders, including farmers, policymakers, and agribusiness industries. The research assesses a range of forecasting methods, including traditional statistical models: AutoRegressive Moving Average (ARMA) and AutoRegressive Integrated Moving Average (ARIMA) and modern machine learning models: Recurrent Neural Networks (RNN), Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Stacked Long Short-Term Memory (SLSTM). The evaluation metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used to measure accuracy of the models. The scores of evaluation metrics were used to select the best model. The results show that machine learning models outperform traditional statistical models, with Stacked LSTM being the most suitable for accurately forecasting rice prices as it had lowest RMSE (8.718) and MAPE (0.010) values. These insights are valuable for decision-making within the rice market, aiding farmers in optimizing production and assisting traders and policymakers in making profitable decisions and formulating effective policies to ensure food security and economic stability.

Keywords: Rice, price forecasting, statistical models, machine learning models, root mean square error (RMSE)

Introduction
Rice plays a pivotal role in ensuring food security and sustenance for a significant portion of the global population, especially in India, where it is a staple food crop. West Bengal, one of the prominent states in India, is renowned for its substantial rice production and consumption. The state's agricultural landscape is characterized by a rich diversity of rice varieties and a dynamic market that constantly adapts to various economic and environmental factors. Accurate forecasts of food prices could be helpful to farmers, policymakers and agribusiness industries (Jha & Sinha, 2023) [16]. Accurate forecasting in rice market is crucial to make informed decisions and mitigate potential food security concerns.

Choosing rice crop and the Burdwan market in West Bengal for rice price forecasting is a strategically sound decision driven by a compelling set of factors. To begin with, India's ranking as the second-largest rice producer globally (Annon, 2022(b)) emphasizes the economic and cultural significance of this staple crop. Within India, West Bengal holds the distinction of being the largest rice producer with 16.91 MT production (Annon, 2022(b)) which is 12.87 per cent to all-India (Annon, 2022(a)). Within this rice-producing state, Burdwan district known as ‘Rice bowl of West Bengal’ is the foremost contributor to this vital crop, as rice is cultivated in all the three seasons (*viz. Aus* or Autumn rice, *Aman* or Winter rice and *Boro* or Summer rice) in the district (Ali & Ahmad, 2018) [2]. This regional proficiency extends to the Burdwan Market, recognized as the largest rice market in the area. As such, the Burdwan market becomes the prime source for gathering reliable and comprehensive price data, making it an ideal location for accurate rice price forecasting.

This paper focuses on the development and evaluation of price forecasting models for rice in the major market of West Bengal, India. The primary aim is to provide a comprehensive analysis of various time series forecasting methods, including AutoRegressive Moving Average (ARMA), AutoRegressive Integrated Moving Average (ARIMA), Recurrent Neural Networks (RNN), Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Stacked Long Short-Term Memory (SLSTM). These models are applied to historical price data to forecast future rice prices accurately and efficiently.

The choice of forecasting models considered in this study reflects the diverse range of methodologies available, catering to both traditional statistical approaches and modern deep learning techniques. ARMA and ARIMA models are well-established statistical models, while RNN, ANN, GRU, LSTM, and SLSTM are part of the contemporary machine learning and deep learning arsenal. The comparison and evaluation of these models allow us to assess their respective strengths and weaknesses in the context of rice price forecasting, which is subject to seasonality, trends, and external factors like government policies, weather conditions, and global market dynamics.

The significance of this research extends beyond academic interest, as it addresses real-world issues of economic importance and food security. Accurate price forecasts can assist farmers in making informed planting and selling decisions, traders in managing their stocks and pricing strategies, and policymakers in formulating agricultural and trade policies. Furthermore, consumers benefit from more stable and predictable rice prices, contributing to their overall economic well-being.

In the following sections, we will delve into the methodologies of each forecasting model, present the data sources and pre-processing techniques, and discuss the results of our experiments. By the end of this study, we aim to provide valuable insights into which forecasting models perform best for rice price forecasting in the major markets of West Bengal, India, and offer recommendations for their practical implementation.

Materials and Methodology

Database

For this study, we gathered daily rice price data from the Burdwan market in Burdwan district, West Bengal, covering the period from 2003 to 2022, from secondary sources available on the official website Agmarknet (https://agmarknet.gov.in/). Choosing rice crop and the Burdwan market in West Bengal for rice price forecasting is a strategically sound decision driven by a compelling set of factors. To begin with, India's ranking as the second-largest rice producer globally emphasizes the economic and cultural significance of this staple crop.

Methodology

The analytical models utilized in the present study are as follows:

Statistical Models

Statistical models are essential tools in data analysis and decision-making. These models utilize mathematical relationships, probability theory, and historical data to describe and understand the underlying patterns and trends in data. They are widely employed in fields such as economics, epidemiology, and social sciences to draw meaningful insights and make informed predictions based on empirical evidence. In the present study we will consider following statistical models:

ARMA (AutoRegressive Moving Average) Model

ARMA is a statistical model used for time series forecasting. It combines two components: AutoRegressive (AR) and Moving Average (MA) introduced by Yule (1926) [8] and Slutsky (1937) [25] respectively. The AR component models the relationship between a variable and its lagged values, while the MA component models the relationship between a variable and the lagged forecast errors. ARMA models are effective for capturing linear dependencies in time series data. Mathematically it can be expressed as,

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

Where, y_t is the value of the time series at time t, ϕ_1 to ϕ_p are the coefficients of the past values, p is the order of the autoregression and ε_t is the error term at time t. θ_1 to θ_q are the coefficients of the past errors, q is the order of moving average.

ARIMA (Auto-Regressive Integrated Moving Average)

ARIMA model is a famous time series prediction method proposed by Box and Jenkins in the early 1970s (Box *et al.*, 1994) [10]. The ARIMA model transforms the nonstationary time series into stationary time series and then regresses the dependent variable due to the lag value of its independent variable and the present value and lag value of its random error term (Luo *et al.*, 2013) [6]. The parameters p, d, and q represent the autoregressive term, the times of differences when the time series becomes stationary, and the number of moving average terms, respectively. Mathematically it can be expressed as,

$\phi L(1-L)^d y_t = \theta(L)\varepsilon_t$ i. e.,

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right) = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_t$$

Here p, d and q are integers greater than or equal to zero.

Machine Learning Models

Machine learning techniques are a subset of artificial intelligence that empower computers to learn from data and improve their performance on specific tasks without being explicitly programmed. By leveraging algorithms and statistical models, machine learning enables computers to identify patterns, make predictions, and provide insights across various domains, from image recognition and natural language processing to financial forecasting and healthcare diagnostics. These techniques have revolutionized the way businesses and researchers extract valuable information from large datasets, driving advancements in automation, decision-making, and problem-solving. In the present study we will consider following machine learning models:

ANN (Artificial Neural Network) Model

ANN is a versatile machine learning model inspired by the human brain. In time series forecasting, it can be used as a feed forward network with input features relevant to the prediction task. ANN can handle non-linear relationships and adapt to various data patterns. The ANN architecture (Fig. 1) comprises of: (a) input layer: Receives the input values. (b) hidden layer(s):

A set of neurons between input and output layers. There can be single or multiple layers. (c) output layer: Usually it has one neuron, and its output ranges between 0 and 1, that is, greater than 0 and less than 1 (Kukreja, 2016) [17]. But multiple outputs can also be present (Shukla & Abdelrahman, 2004) [24]. The processing ability is stored in inter-unit connection strengths, called weights (Kuldeep & Anitha, 2015) [18].

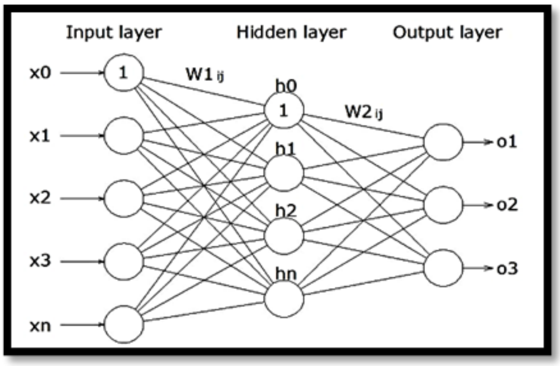

Fig 1: Architecture of Artificial Neural Network

RNN (Recurrent Neural Network) Model

Recurrent Neural Networks (RNNs) are neural networks that employ recurrence, which basically uses information from a previous feedforward pass over the neural network (Fig. 2) (Kumar *et al.*, 2018) [29] RNN is a kind of neural network used to process sequential data (Williams & Zipser, 1989) [27]. RNNs have been incredibly successful when applied to problems where the input data are in the form of a sequence for which predictions are to be made (Gamboa & Borges, 2017,) [11]. The basic idea of RNN is that the network will memorize the previous information and apply it to the calculation of the current output, i.e., the nodes between the hidden layers are connected, and the input of the hidden layer includes not only the output of the input layer but also the output of the hidden layer at the last moment. Based on the idea of graph expansion and parameter sharing, we can design various kinds of RNN (Weng *et al.*, 2019) [26].

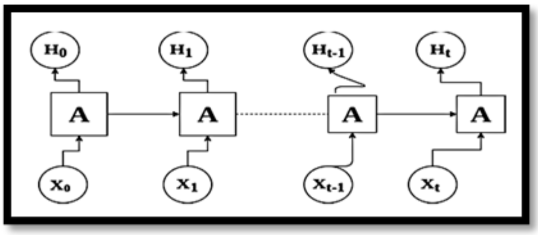

Fig 2: Architecture of Recurrent Neural Network

GRU (Gated Recurrent Unit) Model

The GRU is a variant of the LSTM and was introduced by K, Cho (Chung *et al.*, 2014) [8]. The GRU was inspired by the LSTM unit but is considered simpler to compute and implement. It retains the LSTM's resistance to the vanishing gradient problem, but its internal structure is simpler and therefore easier to train since fewer computations are needed to make update to its hidden state. Fig 3. Shows that the GRU has an update gate & a reset gate similar to the forget & input gates in the LSTM unit. The update gate defines how much previous memory to keep around and the reset gate defines how to combine the new input with the previous memory. The major difference is that the GRU fully exposes its memory content using only integration (but with an adaptive time constant controlled by the update gate) (Kumar *et al.*, 2018) [29].

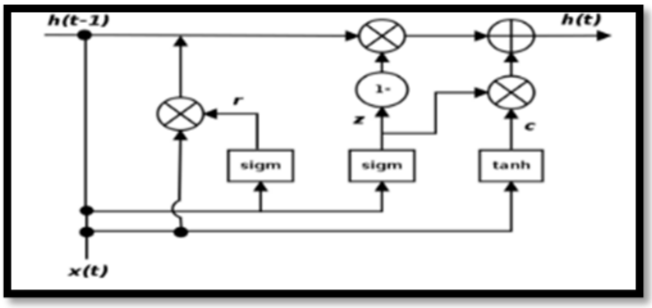

Fig 3: Architecture of Gated Recurrent Unit Architecture

LSTM (Long Short-Term Memory)

In the mid-90s, Sepp Hochreiter & Juergen Schmidhuber, 1997) [15] proposed a variation of existing RNN having Long Short-Term Memory units, or LSTMs (Bengio *et al.*, 1994) [5]. However, the full gradient can instead be calculated with backpropagation through time (Graves & Schmidhuber, 2005) [12]. LSTMs help preserve the error that can be back propagated through time and layers. LSTMs contain information in a gated cell. The cell makes decisions about what to store, and when to allow reads, writes and erases, via gates that open and close. The cells learn when to allow/leave/delete the data, through the iterative guesses, back propagating errors, and adjusting weights. The structure of the LSTM network is shown in Fig. 4.

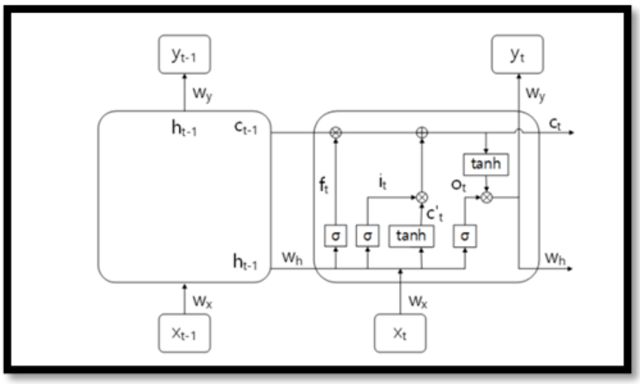

Fig 4: Architecture of LSTM

SLSTM (Seasonal Long Short-Term Memory)

Stacked LSTMs or Deep LSTMs were introduced by Graves, *et al.* (2013), in their application of LSTMs to speech recognition. A Stacked LSTM architecture can be defined as an LSTM model comprised of multiple LSTM layers (Fig. 5). An LSTM layer above provides a sequence output rather than a single value output to the LSTM layer below. Specifically, one output per input time step, rather than one output time step for all input time steps. These models represent a mix of traditional statistical approaches (ARMA, ARIMA) and modern machine learning techniques (RNN, ANN, GRU, LSTM, SLSTM). Each model has its strengths and weaknesses, and their performance may vary depending on the specific characteristics of the rice price data in West Bengal's major markets.

The paper aims to compare these models to determine which one is best suited for accurate rice price forecasting in this context.

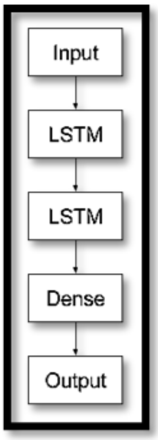

Fig 5: Architecture of Stacked LSTM

Evaluation of analytical models

These analytical models have been evaluated using the conventional metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Root Mean Square Error (RMSE): it is defined as the square root of mean square error which is the sum of squared errors divided by total numbers of observations (Salman *et al.*, 2018) [23]. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2} \quad (1)$$

Mean Absolute Percentage Error (MAPE): It is a measure of accuracy of a method for constructing fitted time series values in statistics, specifically in trend estimation (Mitra & Paul, 2017) [20]. It usually expresses accuracy as a percentage and is defined by the formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{(F_t - A_t)}{A_t}\right| \times 100 \quad (2)$$

Results and Discussion

Dataset Description

The secondary data on daily prices of cumin for Burdwan market, Burdwan, West Bengal for present study was collected for 2003 to 2022 from official website (https://agmarknet.gov.in/) and the dataset were divided inti training set which comprised 85% per cent of the data and a testing set which consisted of the remaining 15 per cent of the data to evaluate the models accuracy. Table 1 presents the mean value of the dataset for cumin prices ₹ 7305/quintal. The first and third quartile are ₹ 1280/quintal and ₹ 2450/quintal respectively, which suggests that the data distribution is not normal. The rice price has a high degree of variation ranging from a minimum of ₹ 930/quintal to a maximum of ₹ 3300/quintal. The skewness of the dataset is -0.01, indicating a slightly negative skewness which means that the data is slightly skewed to left. The kurtosis of the dataset is -1.32, which indicates that the distribution of the data is slightly flatter than the normal distribution.

Table 1: Descriptive statistics of time series data for rice prices in Burdwan market

Sr. No.	Statistic	Price (₹/q)
1.	Number of observations	7305.00
2.	Mean	1891.49
3.	Standard Deviation	606.07
4.	Minimum Value	930.00
5.	1st Quartile	1280.00
6.	3rd Quartile	2450.00
7.	Maximum Value	3300.00
8.	Skewness	-0.01
9.	Kurtosis	-1.32

Performance of the Forecasting Models

To precisely assess the performance of the models, the dataset of each model was partitioned into two distinct sets, namely training and testing data. Subsequently, each model was executed on the testing data during the testing phase and the resulting values were compared with their corresponding actual values.

The models were subjected to performance evaluation using the testing dataset. The main approach involved comparing the predicted values with the actual values to ascertain the model's efficacy. The study aimed to determine the RMSE and MAPE values as the primary evaluation metrics (Table 2). A visual comparison of the RMSE values of all the models under study is depicted in Fig. 7 with the help of bubble diagram. The Stacked LSTM models marked the lowest RMSE value and thus, showed the highest accuracy among all the models under study.

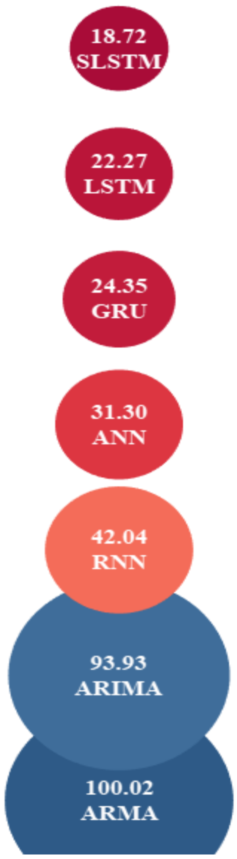

Fig 7: Model Performance based on RMSE values

A visual representation of the dataset of Stacked LSTM showing comparison of predicted and actual prices is provided in Fig. 8.

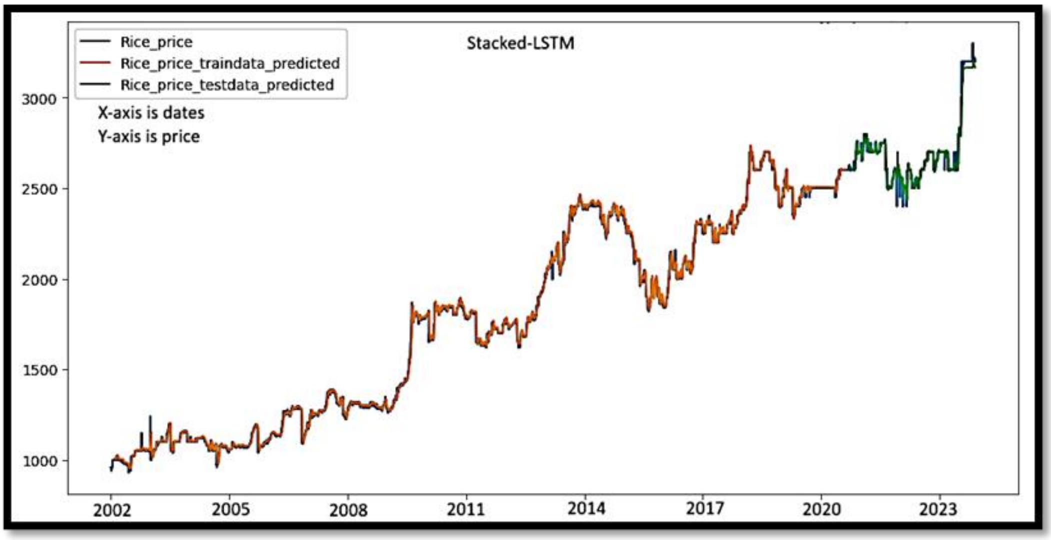

Fig 8: Actual v/s forecasted rice prices of test data for the years 2002 to 2023

The graph clearly depicted that the predicted prices very closely coincided with the actual prices. The Stacked LSTM model was chosen for its ability to handle long-term dependencies in time series data, making it suitable for predicting future prices of rice. Makama *et al*. (2016) [19] have highlighted that in India, market prices of rice fall during the harvest period and it rises through the lean season due to law of demand applied. It is observed that price rate of rice fluctuates from months to months and year to year due to production of rice crops, carryout from earlier year, climatic circumstance, local entrepreneurial management, and sells to other countries or another state (Dey & Mistri, 2019) [9].

Model Accuracy

The evaluation metrics including Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values on the test data was generated to test model performance (Table 2).

Table 2. Comparison of models based on RMSE and MAPE values on evaluating test data

Model	RMSE	MAPE
Stacked LSTM	18.718	0.010
LSTM	22.271	0.192
GRU	24.347	0.355
ANN	31.305	0.515
RNN	42.037	0.955
ARIMA	93.925	3.737
ARMA	100.022	3.847

The outcomes of various models applied for forecasting rice prices in 2023 along with their corresponding RMSE and MAPE values in evaluating test dataset are displayed in Table 1. The results indicate that the Stacked LSTM model outperformed all other models considered, exhibiting the lowest RMSE and MAPE values (Muzaffar & Afshari, 2019, Sabu & Kumar, 2020, and Harshith, 2023) [21, 22]. The LSTM, GRU, ANN and RNN models followed the Stacked LSTM model respectively. In contrast, the ARIMA and ARMA displayed the highest RMSE and relatively high MAPE values respectively, indicating its inferior predictive performance compared to other models.

ARIMA model performs well for average monthly data but not fare as well for daily data; whereas, the neural network approaches were effective at forecasting the daily trends in price fluctuation (Weng *et al.*, 2019) [26].

Conclusion

The results of the study indicated that when it comes to forecasting rice prices, machine learning models such as Stacked LSTM, LSTM, GRU, ANN and RNN outperformed the traditional statistical models ARMA and ARIMA. These ML models exhibited greater accuracy and efficiency in capturing the intricate patterns and dynamics present in rice price data. Their capacity to learn from historical patterns and adjust to evolving market conditions played a key role in their superior forecasting capabilities. These findings suggested that leveraging advanced machine learning algorithms can significantly improve the accuracy of price forecasts and offer valuable insights for decision making within the rice market.

The Stacked LSTM model demonstrated the lowest values for evaluation metrics such as RMSE (18.718) and MAPE (0.010) establishing it as the most suitable and reliable approach for accurate forecasting of rice prices for the year 2023.

The market prices of rice fall during the harvest period and it rises through the lean season. It is observed that price rate of rice fluctuates from months to months and year to year due to various factors. These insights are valuable for farmers as they can optimize their production to coincide with periods of high prices. Additionally, traders and policymakers can leverage this information for making profitable decisions and formulating effective policies.

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