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Exponential Smoothing Model and Evaluation of Rice Price Prediction

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Abstract:- Time series analysis is one of the utmost popular forecasting techniques in predicting the upcoming events based on preceding performance. In this paper, monthly regular prices of Rice data were used in seasonal auto regressive integrated moving average (SARIMA), simple exponential smoothing model and naïve method incorporated to predict the upcoming prices of Rice and thereby compared. SARIMA and simple exponential smoothing model was found appropriate for all Indian rice price. The performance evaluation of the fitted model was observed by calculating various measures. The SARIMA model was the most typical model at the cost estimation of paddy in by and large India. Those models were best fitted for predicting of Rice Price in India. Prediction was made for the immediate next two years that is 01-06-2021 to 01-05-2023. The performance evaluation of these models were validated by comparison with percentage deviation from the actual values and mean absolute error (MAPE), which was found to be 4.18% for the price under rice in India.

Keywords:- *SARIMA, Simple Exponential Smoothing, Naïve Model, AIC, BIC and Forecasting.*

I. INTRODUCTION

India is one of the major agricultural product manufacturers around the world. Rice is one of the main and important food grains in India and it is grown in many rain fed areas. During June 2021, the United States Department of Agriculture (USDA) estimated the World Rice Production as 503.17 million metric tons, which is approximately 1.97million tons more than previous month's projection. Rice Production during the period 2019-2020 was 496.40 million tons. It shows rice of 6.77 million tons that is 1.36% in the production of rice through the world. Rice is the staple food in most place in South-East Asia. As mentioned by Rani et al., (2014), about 90 per cent of world's paddy cultivation and production is contributed by Asia. As pointed out by Reddy (2007, 2015), India has the leading area under paddy production as compared to other paddy growing motherlands and it is succeeding China in terms of volume of harvest, whereas productivity is much lower as compared to Egypt, Japan, China, Vietnam, USA and Indonesia.

In India, 65percent of the population prefer rice is their staple food, India plays a vital role in agricultural exports, nearly 25 percent, from the country. One-third of the arena's paddy farming area is in India. Ashwini et al., (2017) noted that paddy cultivation is carried out in almost all the states of India especially inside the river valleys, deltas and low-lying coastal areas of north eastern and southern India. Over 95% of the cultivation is contributed by Assam, West Bengal, Punjab, Bihar, Madhya Pradesh, Orissa, Andhra Pradesh, Tamil Nadu, Kerala, Karnataka, Maharashtra, Gujarat, Uttar Pradesh and Jammu and Kashmir.

Singh et al., (2007) have predicted the rice production forecasting India using statistical models. K.K. Suresh et al., (2011) a try and forecast sugarcane area production and productivity of Tamilnadu thru the use of in time series (ARIMA) models. Shankar and Prabhakaran (2012) applied the ARIMA model for predicting the milk creation in Tamil Nadu. Rahul Tripathi et al., (2014) utilized in ARIMA model rice area, manufacturing and productivity of Odisha, India the model was as compared with forecast. Hemavathi et al., (2018) forecasting from area, production and productivity of rice and also increase reputation from Thanjavur district.

Gregorius Airlangg et al., (2019) have examine on exponential smoothing and neural network technique to forecast rice production in Indonesia and result are compared from Mean Square Percentage Error (MAPE), Mean Square Error (MSE). Zhang et al. (2020) proposed a novel model choice framework which incorporates time series capabilities and forecast horizons. Deepa and Raghuram (2021) analyzed the use of numerous time series algorithms together with ARIMA version, Benchmark technique and Exponential smoothing approach. The analysis uses entire dataset and make predictions for the upcoming years. The decided statistics of each calculation are in comparison

Generally, there are many approaches to forecast rate amongst which we discover the SARIMA, Exponential Smoothing Models and Naïve Method. Be that as it may, while applying these methodologies, we need to have authentic information. In the beginning, there is no information based on similar cases. The paper is organized as follows from five sections: Section. II Materials and Methods to the analysis of experiment technique. Section. III. Result and Discussion, Section IV. Performance Evaluation of accuracy measures, Finally Conclusions in Section V.

II. METHODOLOGY

- *Seasonal Autoregressive Integrated Moving Average*

A seasonal autoregressive integrated moving average (SARIMA) model is one step incredible from an ARIMA model based totally mostly on the idea of seasonal inclinations. In diverse time series information, common seasonal results come into play. The main objective of this procedure is fitting an SARIMA model to identify the stochastic process of the time series and predicting future values. In this work, three different methods, viz., SARIMA, Seasonal Naïve method and Exponential Smoothing have been followed for model construction and their performance are compared.

The SARIMA, Seasonal Naïve method and Exponential Smoothing methods estimates in the same way spaced univariate time series data. The resultant models predict a value in a reaction time series as a linear combination of its own past values. A non-seasonal ARIMA is commonly denoted as ARIMA (*p*,*d*,*q*), where, p - order of AR term (Auto Regressive) q - order of MA term (Moving Average) and d - quantity of differencing required to make the time series stationary.

$$Y_t = C + \phi_t Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + e_t + \phi_t Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p}$$

Similarly, a seasonal ARIMA is generally denoted as SARIMA (p,d,q)(P,D,Q)s, in which, s is the length in each season, p & P are non-seasonal & seasonal orders of AR respectively, d & D are non-seasonal & seasonal orders of differencing the authentic data respectively and q & Q are non-seasonal & seasonal orders of MA respectively.

The SARIMA model is defined as,

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\Theta_Q(B^s)a_t$$

where,

$$\phi_p(B) = \left(1 - \phi_1(B) - \phi_2(B^2) - \dots - \phi_p(B^p)\right)$$

is the stationary AR operator

$$\theta_q(B) = \left(1 - \theta_1(B) - \theta_2(B^2) - \dots - \theta_q(B^q)\right)$$ is

the invertible MA operator.

When *d = 0,* the original process is stationary and θ_0 is related to the mean of the process, *i.e.,* $\theta_0 = (1 - \phi_1 - \phi_2 - \dots - \phi_p)$.

When *d ≥ 1,* then θ_0 is called the deterministic trend.

$$\Phi_P(B^s) = (1 - \Phi_1(B^s) - \Phi_2(B^{2s}) - \dots - \Phi_P(B^{Ps}))$$

is the seasonal AR operator

$$\Theta_Q(B^s) = \left(1 - \Theta_1(B^s) - \Theta_2(B^{2s}) - \dots - \Theta_Q(B^{Qs})\right)$$

is the seasonal MA operator.

The series a_t is a Gaussian $N(0, \sigma^2)$ white noise process.

- *Seasonal Naïve Method*

A comparable method is useful for exceptionally seasonal information. In this situation, we set each forecast to be equal to the last found fee from the equal season (e.g., the equal month of the previous 365 days). Formally, the forecast for time T+h is written as

$$\hat{y}T + h\,|\,T = yT + h - m(k+1)$$

Where, m = the seasonal duration, and k is the numeral a part of (h−1) / m(h−1) / m. (i.e., the number of whole years within the forecast length prior to time T+h), h is the forecast horizon (i.e. Time restriction for which forecast needs to be prepared) and T is the last perceived information. This appears greater tough than it absolutely. Example, with monthly facts, the forecast for all upcoming February values is identical to the closing ultimate found February value. With quarterly data, the forecast of all upcoming Q_2 values is identical to the last located Q_2 value (in which Q_2 way the second quarter). Similar rules follow for other months, quarters and different seasonal durations.

- *Exponential Smoothing Model*

Exponential smoothing estimating techniques are similar in that a forecast is a weighted amount of past perceptions, yet the version unequivocally makes use of a dramatically diminishing load for beyond perceptions. All things considered, the techniques are at times alluded to as ETS models, alluding to the unequivocal demonstrating of Error, Trend and Seasonality.

$$\hat{y}T+1\,|\,T = \alpha yT + \alpha(1-\alpha)T - 1 + \alpha(1-\alpha 1)2\,yT - 2 + \dots$$

In which, α is the smoothing thing, and 0 < α < 1. In other words, T ' is a simple weighted average of the cutting-edge observation yt and the preceding smoothed statistic yt−1. If α fee almost equals to one, then the forecast uses latest commentary of the dataset, and if the value almost equals to 0, the it uses ancient information for forecasting. The traits and seasonality element is eliminated by means of dampening the time series records. The tendencies and seasonality may be linear or exponential based totally at the time series data.

- *Simple Exponential Smoothing Model*

This complex technique is a sort of weighted averaging strategy which assesses the future worth dependent on past conjecture in addition to a level of the anticipated mistake. It is not difficult to execute and process as it doesn't require keeping up with the historical backdrop of past input information. It blurs consistently the impact of uncommon information.

$$F_t = F_{t-1} + (F_{t-1} - A_{t-1})$$

Where, F_t is forecast for term t, Ft-1 is forecast for the preceding length, A_{t-1} is actual demand for the previous length, and α is smoothing steady (0 ≤ α ≤ 1).

III. RESULT AND DISCUSSION

The time series of month-to-month average rate of Rice (consistent with million lots) become collected from AGMARKNET internet site for the duration from January 2002 to May 2021. The facts has been used for forecasting the charge using SARIMA, Seasonal Naïve technique and Exponential Smoothing model.

The stationary checked of time series data was achieved, which discovered that the Rice Prices were Non-stationary. The non-stationary time series facts have been made stationary with the aid of first order differencing and pleasant match for all the forecasting models have been advanced the use of the data from January, 2002 to May, 2021 and used to forecast the prices at some point of harvesting season. They have been received by using trying to find crucial spikes in auto dating and fractional auto connection capacities. At the recognizable proof level, at least one show had been possibly picked which seem to present measurably nice portrayals of the reachable records. Then, at that factor precise value determinations of obstacles of the model have been gotten by means of least squares.

The Rice price forecasting of the real existence facts, and the accuracy and characteristics are studied. This take a look at examines the effectiveness of call for forecasting in a rate forecasting. Based on a few tactics, our have a look at might be finished inside the 3 parts for the all methods: Identification, Estimation and verification. The version shown in figure 1 is based totally at the fee of the Rice in India in the course of January, 2002 to May, 2021; according to million lots also descriptive records for the time collection facts of Rice price for India is given in table 1.

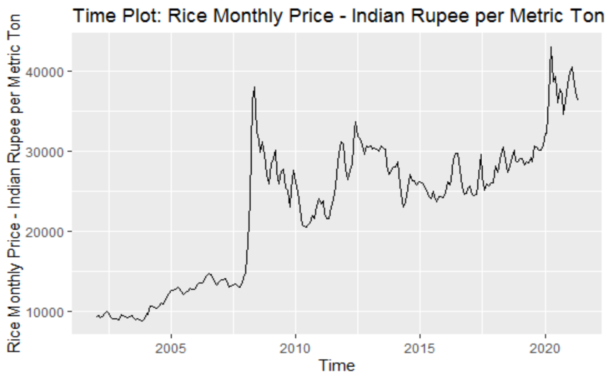

Fig 1: Time plot for the Indian Rice Price (1000 MT)

Table 1: Descriptive Statistics of Rice price in India

Mean	Standard Error	Median	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range
22958.66	564.325	25346.9	8614.04	7.4E+07	-0.98	-0.227	34167.2

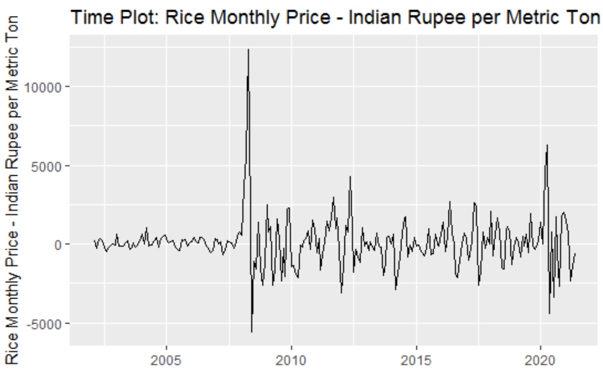

Fig 2: Stationarity Time series plot for Rice Price in India

There are various ways to ascertain this. The extreme normally approach is to check stationary through analyzing the graph or time plot of the data is non-stationary. Non-stationary in imply is hooked up via appropriate differencing of the facts. For this situation difference of request 1 was adequate to perform stationary in imply. The newly constructed variable X_t can now be tested for stationarity. The model shown in figure 2 is primarily based at the stationarity time series plot.

- *SARIMA Model*

Several SARIMA model is used to process the time series data and to forecast the price. The ARIMA model (2, 1, 1) (2, 1, 2) [12] is identified as the excellent suit model based on AIC and BIC values. The coefficient of the ARIMA model is 0.8879 and -0.3778. From the observations, SARIMA model (2, 1, 1) (2, 1, 2) [12] has the values AIC = 3929.77 and BIC 3950.13 that's compare to the other models and the p, d, q, P, D and Q values are calculated as 2, 1 and 1 respectively.

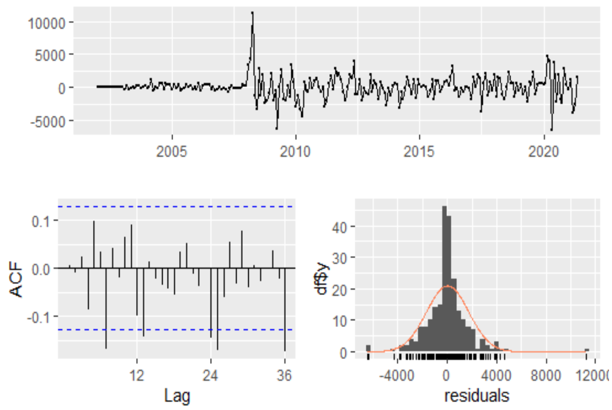

Fig 3: Residual and ACF plot for SARIMA Model

The minor AIC and BIC values are the greater accuracy of model and the Residuals plot also given in the Figure 3. Finally the price is forecasted for the upcoming 24 months, the forecasted price of rice value as given in the Figure 4. The Error factors such as ME, RMSE, MAE, MPE, MAPE and MASE are used to determine the accuracy of the model. The Mean Absolute Error (MAE) is 1084.183, Root Mean Square Error value is (RMSE) 1706.431, Mean Percentage Error is 0.02555342 and the p-value is 0.0378. Which indicates the accuracy is good for prediction.

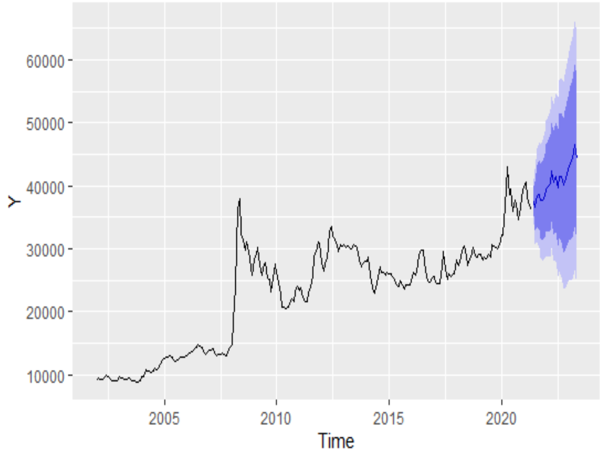

Fig 4: Rice Price Forecasting using SARIMA (2, 1, 1)(2, 1, 0) [12] model

➢ *Seasonal NAÏVE Model*

The Seasonal naïve model of the error factors inclusive of RMSE value 2318.972, MAPE value is 351.8138, MASE price is 1 and p-value is 1.443. Which comes to a decision the exactness is much less for the expected outcomes. The residual standard deviation value is 2318.972.

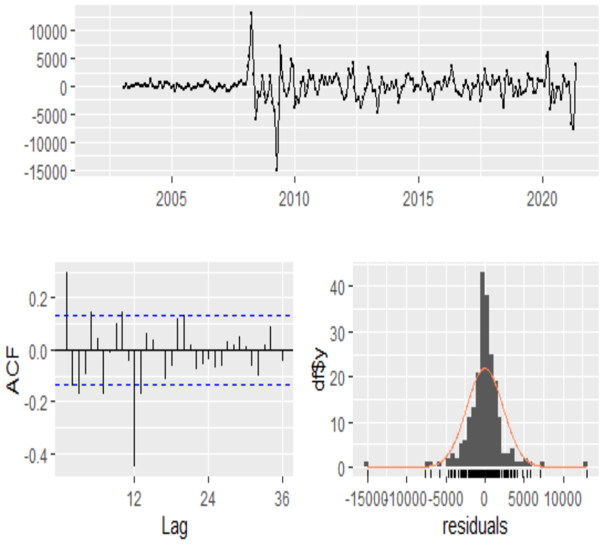

Fig 5: Residuals from Seasonal Naïve Method

The figure 5 shows the residuals plot for seasonal Naïve method and figure 6 shows the forecasted plot of the Seasonal naïve method.

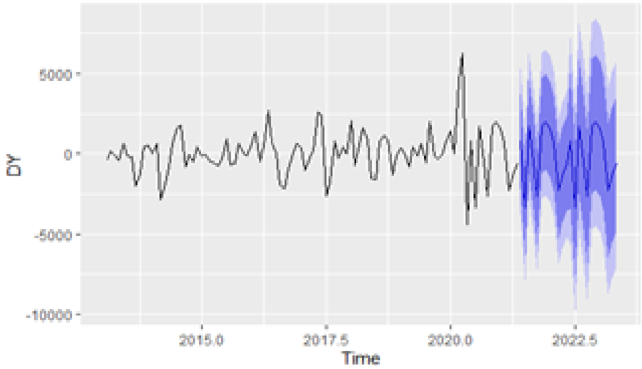

Fig 6: Forecasted diagram from seasonal Naïve method

➢ *Simple Exponential Smoothing Model*

From remark, the alpha value is 0.9999. It uses single exponential smoothing model, which doesn't have any seasonality or trends. Thus, it makes use of only single parameter alpha. The AIC and BIC value of ETS model is 4589.082 and 4609.788, the p-value is determined as 0.001888 which indicates the accuracy is good for prediction.

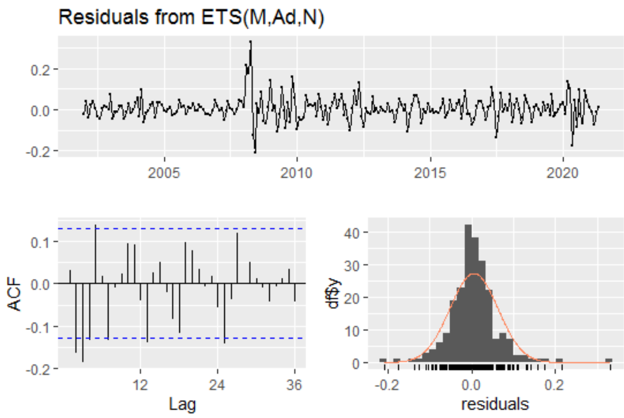

Fig 7: Residual plot for Exponential Smoothing Model

The Exponential smoothing model of the error factors which includes RMSE value 1655.0.5, MAPE value is 3.905789, MASE value is 0.282928. The figure 7 shows that the residual plot for the exponential smoothing model and figure 8 indicates the Rice forecasted diagram for the use of the exponential smoothing model.

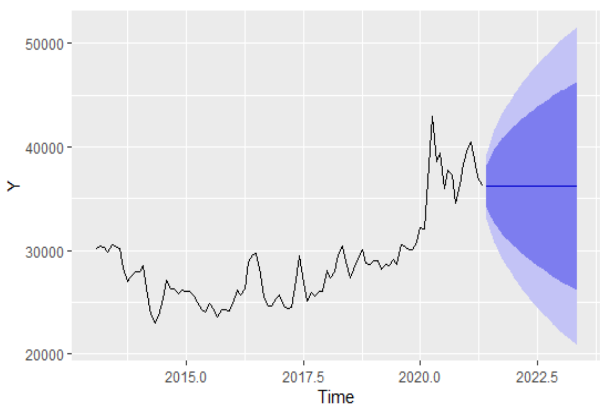

Fig 8: Forecasted plot for the Exponential Smoothing Model

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IV. PERFORMANCE EVALUATION

The Error factors such as RMSE, MASE, MAPE, p-value, MPE and many others, are used to determine the accuracy of every model.

Table 2: Comparison on measures accuracy

Model	ME	RMSE	MAE	MPE	MAPE	MASE	p-value
SARIMA	22.11588	1706.431	1084.183	0.0255	4.180	0.306	0.03
SNAIVE	-12.33	2318.972	1407.533	-28.208	351.8138	1	0.29
ETS	29.3545	1655.005	1000.028	0.1761	3.905	0.282	0.00

Shown in the table 2. Shows that a multiple error factors for all three models. Based on the error factors, the accuracy of the model determined, and the best fit model is ARIMA and Simple exponential smoothing models had been identified. The identified models forecasting values shown in table 3.

After we have characterized the most suitable model of interest for our situation, we need to make the estimating; to do this thus to anticipate drifts and foster gauging. To do this and so to predict trends and develop forecast, we used the R Programming Language.

Table 3: Forecasted value for Rice prices

Month	ARIMA			Exponential Smoothing Model		
	Forecast (MT)	Lower Limit	Upper Limit	Forecast (MT)	Lower Limit	Upper Limit
1-Jun-21	37542	34060.3	41023.8	36226.7	33093.11	39360.3
1-Jul-21	36624	30747.7	42500.3	36226.7	31795.35	40658.05
1-Aug-21	38457.8	31038	45877.6	36226.7	30799.52	41653.89
1-Sep-21	38548.5	30177.1	46920	36226.7	29959.98	42493.42
1-Oct-21	37613.5	28588.1	46638.8	36226.7	29220.33	43233.07
1-Nov-21	37632.1	28065.4	47198.9	36226.7	28551.63	43901.77
1-Dec-21	38433.2	28350.1	48516.3	36226.7	27936.7	44516.71
1-Jan-22	39574.5	28973.8	50175.1	36226.7	27364.33	45089.07
1-Feb-22	39839.9	28724.3	50955.6	36226.7	26826.75	45626.65
1-Mar-22	40383.1	28766.2	52000	36226.7	26318.29	46135.11
1-Apr-22	42231.9	30134.3	54329.5	36226.7	25834.68	46618.72
1-May-22	40468.1	27911.2	53024.9	36226.7	25372.6	47080.8
1-Jun-22	41377.5	28025.7	54729.3	36226.7	24929.4	47524
1-Jul-22	39731.3	25488.3	53974.3	36226.7	24502.95	47950.45
1-Aug-22	41560.3	26501.4	56619.3	36226.7	24091.47	48361.93
1-Sep-22	41395.3	25629.3	57161.3	36226.7	23693.49	48759.91
1-Oct-22	40054.5	23659.1	56449.8	36226.7	23307.77	49145.63
1-Nov-22	40635.3	23651.5	57619	36226.7	22933.24	49520.17
1-Dec-22	41808.3	24254.8	59361.8	36226.7	22568.97	49884.43
1-Jan-23	43174.1	25061.6	61286.6	36226.7	22214.17	50239.24
1-Feb-23	43496.4	24835.8	62157.1	36226.7	21868.13	50585.27
1-Mar-23	44314.6	25119	63510.3	36226.7	21530.24	50923.17
1-Apr-23	46433.8	26717.7	66150	36226.7	21199.94	51253.46
1-May-23	44244.9	24022.5	64467.3	36226.7	20876.75	51576.65

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Shown in table 3 and figure 4, 6 and 8 presents the results of the Rice Price that we obtained by applying our models SARIMA, Naïve Method and Exponential Smoothing method for the next 24 months (2 Years) from June, 2021 to May, 2023. We can without a doubt see that the models selected can be used for modeling and forecasting future Rice Price, but every time new facts to complement it as a way to enhance the new model and forecasting. The forecasts received after modeling facilitated the choice on the price of Rice. In fact the model enabled us to forecast the price and make correct predictions. Once we achieve a price forecast, it will be much easier and really clear to make the right charge planning and hence take away big cost losses. That will help us take right decisions associated with manufacturing and Economical growth of month-to-month price of Rice. Moreover, so that it will affect the complete price procedure eliminating then any form of loss.

V. CONCLUSION

The algorithms intention to expand the maximum accurate predictions for future Rice price with the present day charge dataset. From the evaluation and algorithms, the SARIMA (2, 1, 1) (2, 1, 2) [12] and simple exponential smoothing models offers the best results in comparison with different algorithms furthermore, the change in facts is less, so the anticipated outcomes are extra precise. SARIMA and Simple Exponential smoothing model provides a p-value 0.0378 and 0.000 which is nearly equals to 0.05 and it's statistically large. Rice Price forecasting is an essential feature of dealing with GDP. In any case the model is handy had been efficaciously applied for determining later. Finally comparing these models SARIMA model is extrapolation technique that requires most effective the historic time series facts at the variable below take a look at. The SARIMA model forecasted price discovered an increase inside the price of Rice in the upcoming months and also demand for the crop. This forecast is based totally on beyond information and model that actual marketplace rate might not come to be the same as forecasted.

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