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ARIMA-Based Time Series Modeling for Forecasting Egg Market Prices in Hyderabad

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ABSTRACT: Due to changing eating habits and increasing cost of pulses, the demand for protein -rich food has increased, especially poultry products. Considering the rapid population and egg consumption of poultry products, the country should increase its production. It is important to predict the future egg price with the resources available today. This study aims to predict the price of eggs in Hyderabad by analyzing egg price data from January 2019 to January 2025. The study focuses primarily on the time series model ARIMA and also provides a performance analysis of the model. This work addresses a notable research deficiency concerning the inadequate utilization of advanced error metrics and comprehensive model validation in prior Indian studies on egg price forecasting. Previous research frequently neglects to account for variables such as swift demographic transitions, changing food tastes, and market instability, all of which can significantly impact the precision of predictions. Furthermore, there is a significant deficiency of long-term, city-specific forecasting models designed to address the distinct difficulties and market conditions of the post-pandemic era. This study seeks to address these deficiencies by integrating these factors to enhance the accuracy and applicability of egg price forecasts in India. The ARIMA model is unique because it can use autoregression, differencing, and moving averages in a flexible way. This makes it operate well with both stable (stationary) and changing (non-stationary) time series data, which makes it more accurate at predicting future values in a variety of fields. The accuracy of forecasting models was assessed by analyzing different errors. To test the reliability of the model, (MAPE) mean absolute percentage error, (MSE) mean square error, R -squared, (RMSE) Root mean square error and (BIC) Bayesian Information Criterion were used to test the reliability of the model. The ARIMA (2,1,1) model was most appropriate for this dataset.

Keywords: Egg price, time series, ACF, PACF, ARIMA, prediction.

Contents

1. Introduction

People get protein from different sources. This includes animal derived products as mentioned earlier and also from plant-based sources like pulses. Eggs are an excellent source of protein that has high biological value. It is a term used to describe proteins in food that contain all 9 amino acids that

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our body cannot produce on its own. Eggs are considered a complete source of protein. One of the benefits of eggs versus meat is that one large egg contains about 70-80 calories and around 5 grams of fat (most of it healthy). Meat, especially red meat, can tend to be much higher in calories and saturated fats. For those individuals aiming to manage their calories or follow a low-fat diet, eggs are a lighter Option while still delivering high quality protein.Predicting egg prices in Hyderabad is important for many people, as a large metropolis with its own market dynamics, it needs localized forecasting methods to make more accurate and dependable pricing projections such as chicken farmers, sellers, customers and the government. Correct predictions provide help in making better decisions about how much to produce eggs, handle them and use them when prices go up or down. Proper knowledge of price can help manufacturers produce more eggs at the right time to make money. Sellers do know what prices will be so that they can take care of their stocks and reduce waste when the market changes. Customers can also plan shopping better if they know what prices might change. Even government agencies require these estimates to make good agricultural rules that stabilizes the market and ensure with food safety (Mato et al., 2019). The egg market experiences change every day. Seasonal variations affect the market along with changes in supply and demand. several things outside this industry also influence it too (Uday Shankar & Matta, 2020). Therefore, it is essential to have accurate price prediction methods to manage risks during uncertain times and make the most of favorable market opportunities. Eggs are perishable products that they need efficient forecasting methods because their demand fluctuate depending on several factors including seasonality (Rajendra Prasad 202322), humidity conditions and economic circumstances etc. Time series models generate accurate short-term predictions by examining past trends. This approach enables stakeholders well informed choices regarding production, pricing& distribution thus minimizing wastages. Autoregressive Integrated Moving Average (ARIMA)model is widely adopted because its effectively capture temporal dependencies within the time series dataset. Hyderabad has experienced significant rise in egg consumption over years. Accurate forecasts can greatly improve poultry sector efficiency while contributing to food security stability for larger corona of users.

Farmers, traders, and policymakers must accurately forecast agricultural commodity prices so they can make improved decisions that make market work better and lower the dangers that could happen. The Autoregressive Integrated Moving Average (ARIMA) model is a highly effective method among the many methods to make predictions since it is very good at analyzing and modeling time series data. ARIMA was chosen because it closely matches the characteristics of Hyderabad's egg pricing data and is a quick and easy way to predict future prices. This model is specifically designed for analyzing time series data, including historical price records, making it well-suited for such applications. It does a good job of showing trends and seasonal changes that are common in commodities like eggs. ARIMA fixes non-stationarity in data by using differencing to stabilize the series, which makes forecasts more accurate. Also, ARIMA is a good choice for forecasting in this case since it is simple and easy to understand. It works well with somewhat sized regional datasets like egg prices. Recently, the consumption of egg and a number of people keeping egg as food is increasing rapidly in India. With this, the forecasts about the prices of eggs are looking good. This study aims to analyze the price fluctuations of eggs and to develop (ARIMA) Auto Regressive Integrated Moving Average model and try to predict the average price of eggs in Hyderabad, Telangana state.

2. Literature Review

Allbright et al. Provided comprehensive coverage of data analysis tools and decision -making frameworks that form the basis for many modern expectations, including ARIMA as time series models. Their work plays crucial role in demonstrating how to use statistical models in business and economic contexts to obtain meaningful insight from raw data [1]. Based on such foundation knowledge, Divakara et al. Applied Sarima model to Forecast red prices, showing how to add seasonal elements to ARIMA the performance of agricultural commodities affected by repeated patterns [2]. Michelli et al. Eggs saw deep learning models to predict prices in traditional markets, emphasizing how neural networks can detect non -linear trends and complex dependencies in time series data. Although their approach showed promising accuracy, it required significant calculation resources and lacked ARIMA's interpretability, which made it less unconscious and practical for some stakeholders such as local market analysts and policy devices [3]. In contrast, Ahmad and ongoing conducted a comparative study of several expectations techniques using egg prices as a case study, highlighting the reliability of ARIMA in modeling linear trends and relatively appropriate datasets for several stable datasets [4]. Drekhar and Reddy explored the forecast of cotton prices using several Indian states using the time series model, and demonstrated the relevance of Ariumus for agricultural markets affected by supply demand dynamics and external factors such as weather and policy [5]. Uday Shankar and Sharma implemented Arima in R to forecast the egg prices in Telangana, which provides a regionally relevant example of Arimas efficiency in dealing with local agricultural data, which's closer to Hyderabad focused on Hyderabad [6]. Abdallah ARIMA validated its facility in the price model by depicting the inflammation between production trend and price behavior [7]..Rajendra Prasad study emphasized appropriate preprocessing for chicken egg prices The selection of time series models when forecasting, strengthening the importance of methodological severity in achieving forecast accuracy[8]. While the focus of many studies has been on Arima, introduced Dingari et al. The Arfima (autoregressive fractionally integrated moving average) models to account for long -term memory processes in time series data, especially in air traffic analysis [9]. Their discoveries suggest that some time series, including those in agricultural supply chains, may benefit from fractional differences to better capture patience in data. A follow-up study by the same authors expanded the use of Arfima traffic forecast traffic, and provided insight into the model's suitability for datasets with long -term coordination [10]. HT et al. Forecast the tomato price in Karnataka using BATS model, demonstrating its effectiveness in handling several seasonality's, which can be applicable to egg price data with similar seasonal pattern [11]. Zheng et al. Provided a comparative framework to evaluate forecasting methods regarding hepatitis B incidence, and their systematic use of error metric and validation technique is transferred to agricultural price prediction [12]. Agyemang et al. Forecasting Road Traffic Accidents applied Sarima and Facebook Prophet models, introducing changes pin detection as a strategy for treating spontaneous fluctuations-an approach that can be valuable in a highly volatile egg market [13]. Dayo and Eunice applied Arima to crude oil sales in Nigeria, emphasizing the time series forecast relevance in economic planning for goods sensitive to global and local market conditions [14]. Finally, Sirisha et al. Compared to Arima, the profit prediction LSTM model concluded that although deep learning methods such as LSTM provide higher performance in capturing complex patterns, because of its simplicity, transparency and implementation easiness, it remains a strong candidate for moderate dataset Compared with Arima for profit predictions; The authors found that although LSTM provides higher accuracy, Arima is more practical for small -to -medium datasets. This comparison highlights greater dependence on modern machine learning approaches in commodity forecasting. Together these studies highlight the broad functional form of community forecasts and provide a strong foundation for this research which seeks to apply the ARIMA model forecast eggs prices.

3. Methodology

We obtained daily egg price data from the National Egg Coordination Committee (NECC) website (https://www.e2necc.com/home/eggprice), which publishes prices for all zones across India. For our study, we focused on Hyderabad and converted the daily data into weekly average prices. The dataset spans from January 2019 to January 2025, providing a comprehensive time series for forecasting egg prices in the Hyderabad market using SPSS package. ARIMA is the modeling approach used to forecast eggs. This is a conventional method to use based on the performance of the past dataset. Figure 1 shows the weekly average movement of egg prices during the-Jan period.

To get stability in average, one difference has been done. In addition, to remove non -stationarity in the area, the time series has been changed with natural logarithmic changes.

3.1. ARIMA Model

ARIMA models help in forecasting the future values of a 'response time series' by using a linear combination of its past values. The first proponents of the ARIMA methods were statisticians George Box and David Jenkins. These models are often referred to as Box-Jenkins models. Afterwards, the parameters of the model were accurately estimated using the least squares method. The exam for the stationarity of the temporomandibular data indicated that the prices of eggs were worthless. In order to deal with this, the first -order differences were used to use non -consistent data in a stationary format. Subsequently, ARIMA models were constructed using data from Jan 2019 to Jan 2025 to predict future

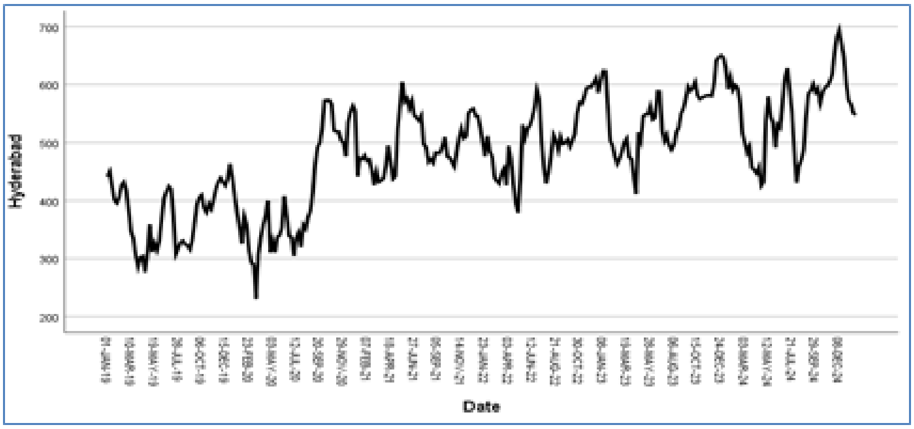

Figure 1: Plot of weekly Average prices

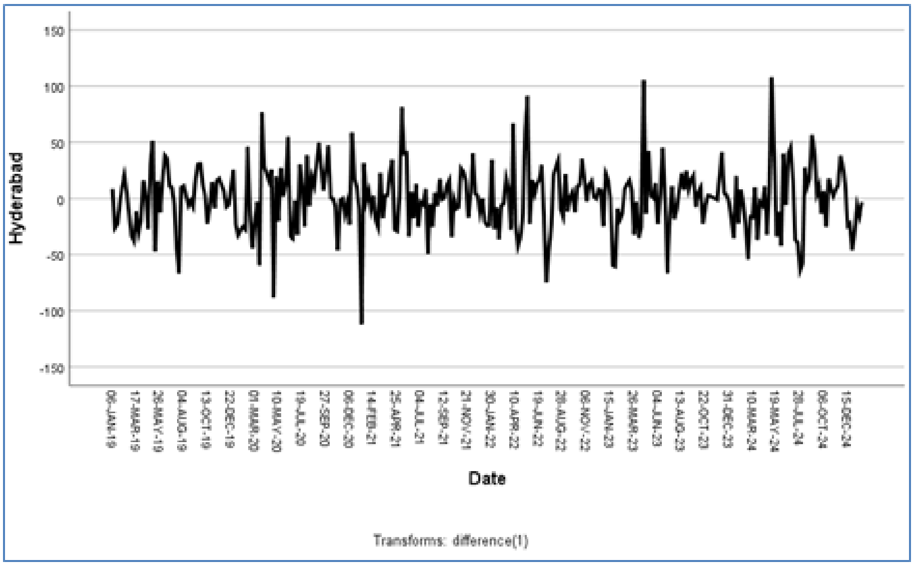

Figure 2: Stationary plot of Egg Weekly Average Prices

prices. The appropriate ARIMA models were determined by establishing starting values for "p" and "q" for unusual parameters. This was done by identifying significant peaks in the Autocorrelation and Partial Autocorrelation functions. During the model identification phase, one or more initial structures were selected, which seemed to adequately represent the statistical data through data analysis.

3.2. AR Model with lag order p

Generally utilized while working with stationary time series, the autoregressive (AR) model is a widely acknowledged method. A linear regression model is used to establish; subsequently, random variables that present themselves in due course of time are described by expressing the current value as a linear amalgamation of previous random variables with a time delay. The AR(p) model indicates the past values taken into account for prediction, with p representing an integer. This can be mathematically depicted as:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + a_t \tag{1}$$

Here, the coefficients ϕ_1, ϕ_2, ..., ϕ_p are referred to as autoregressive coefficients, and these parameters should be evaluated.The sequence of random errors denoted by $\{a_t\}$ represents white noise, characterized by independent and identically distributed values following a normal distribution with mean 0 and variance σ^2. In addition, the random variables Y_{t-1}, Y_{t-2}, ..., Y_{t-p} are mutually independent of $\{a_t\}$.

3.3. MA Model with lag order q

The moving average model represents the current predicted value as a linear mixture of present and past random error terms. The moving average model with lag order q is referred as Moving average MA(q) and is expressed as follows in equation (2):

$$Y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \tag{2}$$

where $\theta_1, \theta_2, \ldots, \theta_q$ are the parameters associated with the moving average coefficients that need to be determined.

3.4. ARMA (p, q) (Autoregressive Moving Average Model)

While $\theta_1, \theta_2, \ldots, \theta_q$ denote the moving average components. Estimating These parameters are essential to build the model. The Autoregressive Moving Average (ARMA) method integrates both autoregressive (AR) model and Moving Average (MA) model to form a unified model that represents the dynamics of the time series. The typical ARMA model mathematically represented as in equation (3)

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q} \tag{3}$$

Terms $\phi_1, \phi_2, \ldots, \phi_p$ corresponding to autoregressive components,

3.5. ARIMA (p, d, q) (Autoregressive Integrated Moving Average Model)

The AR, MA, and ARMA models are stationary time series, as you can see. However, some time series may not be stationary, particularly the weekly egg price data used in this experiment. For those time series, a stationary transformation is required By comparing the process value at time t with that at a historical point, such as (t - d), one might naturally alter the process to lessen variation. Once the time series has stabilized, we can utilize models like Auto Regressive (AR), Moving Average (MA), or combined ARMA approach can be used to generate the time series and make future predictions. The backward shift operator B should be defined more specifically by equation (4)

$$BY_t = Y_{t-1} \tag{4}$$

For each time t, and for a non-negative value of d, the expression can be established in equation (5).

$$(1 - B)^d Y_t = Y_t - Y_{t-d} \tag{5}$$

That is, by differencing the time seriesYt d times using the operator (1 - B) an ARIMA process can be derived. This transformation allows us to substitute Ytby (1 - B)dYt within (1), subsequently, the non-stationary process Ytis governed by the following mathematical relationship in equation (6).

$$(1 - \phi_1 B - \cdots - \phi_p B^p)(1 - B)^d Y_t = (1 + \theta_1 B + \cdots + \theta_q B^q) a_t \tag{6}$$

When a time series Yt satisfies the Previously mentioned equation, it is referred to as the ARIMA process (or model), and it is represented by ARIMA (p, d, q), where the parameter d represents the number of differences applied to eliminate non stationary behavior in the data

3.6. Parameter Metric Evaluation

ARIMA models were developed, and the model's performance was assessed using accuracy related metrics. We used Root Mean Square Error (RMSE) to measure how well the model worked. RMSE is a useful measure since it shows the average size of prediction mistakes, giving more weight to bigger ones. Mean Absolute Error (MAE) is a way to show how accurate a forecast is in percentage terms. It makes it easier to see how close forecasts are to real data by showing the average amount of mistakes compared to actual values. Mean Absolute Percentage Error (MAPE) It measures the average size of mistakes in the same units as the data. This makes it a clear and easy-to-understand way to see how far off the forecasts are from the real values R-Squared Error.

4. Results

4.1. Identification

An essential step in the model identification process involved selecting suitable values for the parameters (p, d, q) and (P, D, Q). To achieve this, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were analyzed. The ACF is particularly useful for identifying appropriate values for Moving Average (MA) terms, while the PACF assists in determining the order of Autoregressive (AR) terms. By examining the patterns in the ACF shown in the fig.3 and PACF plots shown in the fig. 4, one can estimate the values of the parameters p and q effectively.

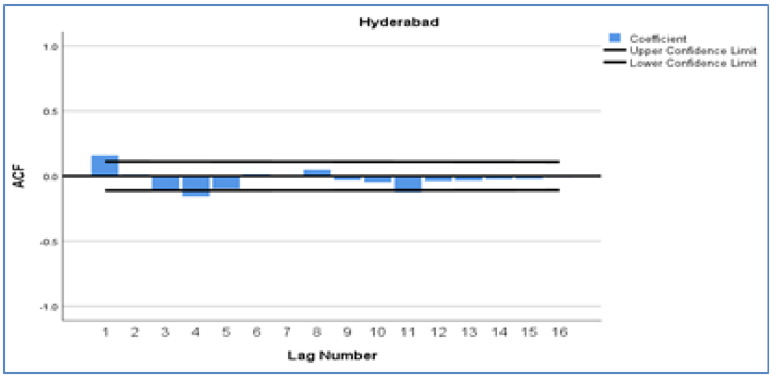

Figure 3: ACF (Auto Correlation plot)

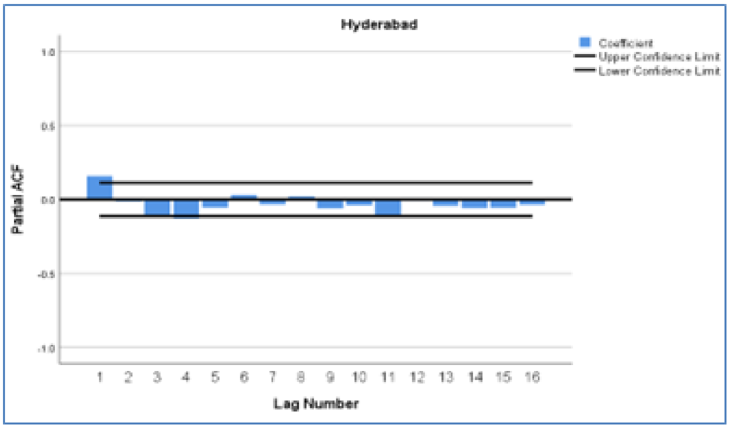

Figure 4: PACF (Partial auto correlation function) plot

4.2. Estimation of the parameters

The order of MA terms is determined by the count of coefficients with non-zero values in ACF plots, and the order of AR terms is determined by the count of coefficients with non-zero values in PACF plots. Using the lowest values of RMSE, MAPE, MAE and BIC, the ARIMA models (0,1,0), (1,1,0), (1,1,1), (1,1,2), (2,1,1) were fitted, based on it, Identified the best ARIMA model was (2,1,1) which was best fitted for Hyderabad egg price data set.

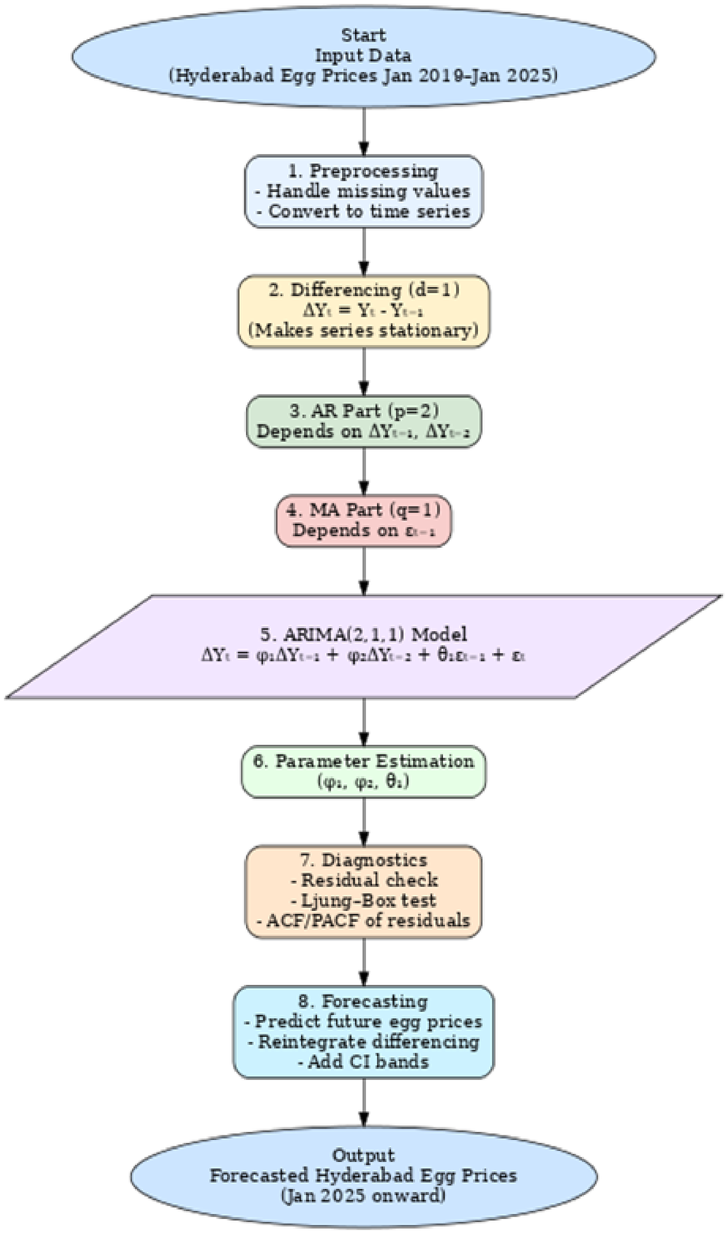

Figure 5: Egg Price Prediction Architecture ARIMA (2,1,1)

Table 1: ARIMA Model Parameters – Hyderabad Model 1

Parameter	Value
Model Name	Hyderabad_model_1
Location	Hyderabad
Data Transformation	No Transformation
Constant (c)	0.729
AR Coefficient ϕ_1	1.111
AR Coefficient ϕ_2	-0.234
Differencing Order (d)	1
MA Coefficient θ_1	1.000

The mathematical expression of the model is

$$Y_t = 1.111\,Y_{t-1} - 0.234\,Y_{t-2} + 1.000\,\varepsilon_{t-1} + \varepsilon_t \tag{4.1}$$

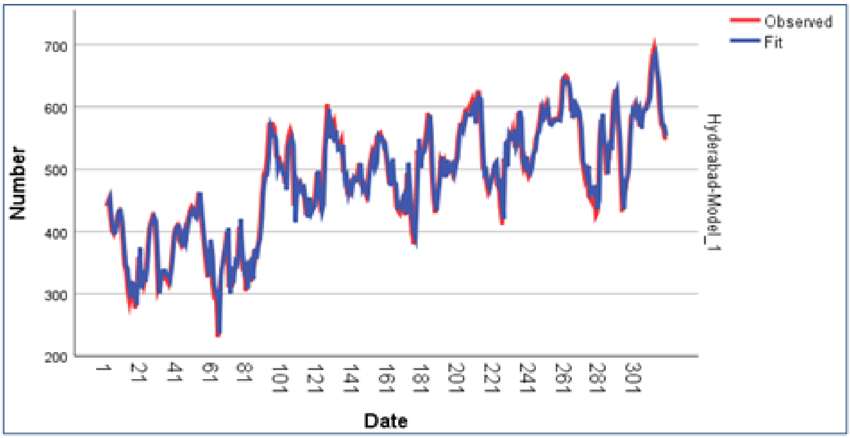

Figure 6: ARIMA Actual vs Predicted values

Table 2: Model Performance Comparison of ARIMA Configurations

Model	ARIMA (0,1,1)	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (2,1,1)
R-squared	0.909	0.909	0.909	0.909	**0.915**
RMSE	28.287	28.235	28.323	28.306	**27.428**
MAPE	4.663	4.640	4.642	4.607	**4.602**
MAE	20.991	20.895	20.895	20.747	**20.727**
BIC	6.721	6.699	6.742	6.759	**6.696**

5. Discussion

As shown in Table-II, for the Egg Prices Dataset, the ARIMA model demonstrated considerable predictive accuracy, with Minimum Root Mean Square Error (RMSE) of 27.428 and Mean Absolute Error (MAE) of 20.727, Minimum Absolute Percentage Error (MAPE) 0f 4.602 and less BIC value of 6.696 and Maximum R-Squared Error of 0. 915.with this ARIMA model achieves an acceptable level of precision on the egg price data set. Fig.5 Shows that actual and predicted values. The findings of this study, based on the ARIMA (2,1,1) model, are authentic and reliable. The model was carefully built following the rules for time series modeling that are already in place. First, the data was checked to see if it was stationary. Then, the necessary alterations, like differencing and logarithmic corrections, were made to stabilize variance and get rid of trends. The choice of model parameters was based on a thorough analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which made sure that the delays used in the AR and MA parts accurately reflected the data's temporal dependencies. We used several statistical tests to see how well the model worked, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R-squared, and Bayesian Information Criterion (BIC). All of these tests showed that the model was quite well at making predictions. Residual diagnostics, including autocorrelation tests, showed that the residuals looked like white noise. This meant that the model did a good job of capturing the underlying patterns. These validation techniques together confirm that the predicted prices appropriately reflect real patterns and that the results are reliable, credible, and strong enough to be used in real-world situations for predicting egg prices.

6. Conclusion

The ARIMA (2,1,1) fitted model in this study was confirmed using the data set. The data set contains nearly 318 weeks of data (January 2019 - January 2025). The comparison of the actual prices and predicted prices was given in figure 5. The Predicted pattern is very close to actual pattern for the data. It was observed that, the models fitted using ARIMA are (0,1,1) (1,1,0), (1,1,1), (1,1,2) (2,1,1). Hence, ARIMA (2,1,1) is a better option to forecasting egg prices as RMSE, MAPE and BIC values are very less and the R- squared value is maximum.

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