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Türkiye's Egg Export to Iraq: Performance Comparison of Seasonal ARIMA and Artificial Neural Network Models

Türkiye'nin Irak'a Yumurta İhracatı: Mevsimsel ARIMA ve Yapay Sinir Ağı Modellerinin Performans Karşılaştırması

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Türkiye's Egg Export to Iraq: Performance Comparison of Seasonal Autoregressive Integrated Moving Average and Artificial Neural Network Models

Abstract

This study aims to identify the most effective model for predicting the monthly export volumes of eggs from Türkiye to Iraq by comparing two primary forecasting methods: the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and the Artificial Neural Network (ANN) model. Both models were applied to monthly export data of egg products from 2010 to 2020, sourced from reliable databases such as the UN Comtrade and Turkish Statistical Institute (TURKSTAT). The performance of both models was assessed using key statistical metrics, including the Akaike Information Criterion (AIC), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). According to the results, the Feed-Forward Neural Networks (FFNN) model demonstrated superior predictive accuracy compared to the SARIMA model. This conclusion is supported by the FFNN model's lower MAE, RMSE, and AIC values, indicating fewer forecasting errors and a better overall fit to the data. Therefore, the study concludes that the FFNN model is more effective and accurate than the SARIMA in predicting the export values of eggs from Türkiye to Iraq.

Keywords: Forecasting, Artificial neural networks, Time series, Autoregressive integrated moving average, Egg export

Türkiye'nin Irak'a Yumurta İhracatı: Mevsimsel ARIMA ve Yapay Sinir Ağı Modellerinin Performans Karşılaştırması

Öz

Bu çalışma, Türkiye'den Irak'a ihraç edilen aylık yumurta miktarını tahmin etmek için en iyi modeli belirlemek amacıyla iki temel tahmin yöntemini karşılaştırmaktadır. Birinci yöntem Mevsimsel Otoregresif Bütünleşik Hareketli Ortalama (SARIMA) modeli, ikinci yöntem ise Yapay Sinir Ağı (ANN) modelidir. Her iki model de BM Comtrade ve Türkiye İstatistik Kurumu (TÜİK) resmi internet sitelerinden alınan 2010-2020 yılları arasındaki yumurta ürünleri aylık ihracat verilerine uygulanmıştır. Analiz üç yazılım programı kullanılarak gerçekleştirildi: Alyuda NeuroIntelligence, RStudio ve SPSS. Modeller AIC, MAE, RMSE ve R^2 metrikleri kullanılarak karşılaştırıldı. Sonuçlar, İleri Beslemeli Sinir Ağları (FFNN) modelinin SARIMA modelinden daha iyi performans gösterdiğini göstermektedir. Spesifik olarak, FFNN modeli daha az hata sergiler ve daha düşük MAE, RMSE ve AIC değerleriyle kanıtlandığı gibi, önemli ölçüde daha iyi uyum iyiliğini göstermektedir. Sonuç olarak, FFNN modelinin Türkiye'den Irak'a yumurta ihracat değerlerini tahmin etmede SARIMA modelinden daha doğru sonuçlar verdiği saptanmıştır.

Anahtar kelimeler: Tahmin, Yapay sinir ağları, Zaman serileri, Otoregresif hareketli ortalama, Yumurta ihracatı

1. INTRODUCTION

International trade plays a crucial role in improving living standards, creating employment, and providing consumers with access to a broader variety of goods and services. While international trade has been a fundamental aspect of human civilization for millennia, its importance has grown in recent decades, with imports and exports constituting an increasingly substantial portion of the Gross Domestic Product. Various techniques and models are available for analyzing time-series data; but selecting an ideal forecasting model for trade rates between two countries, such as Iraq and Türkiye, is challenging. This challenge is heightened by Türkiye's position as Iraq's main import origin.

Among the various forecasting techniques, the Box-Jenkins method, particularly the ARIMA, is one of the most renowned and widely employed approaches. It is frequently favored over traditional statistical methods due to its robust time-series analysis capabilities. However, ANNs, a newer method developed in recent years, have proven their ability to predict and solve problems with ease, accuracy, and effectiveness. The primary distinction between classical models like ARIMA and ANNs is the absence of a prior hypothesis required for applying these classic models (Box & Jenkins, 1976; Hyndman and Athanasopoulos, 2018).

The selection of these two countries and their egg exports was not random. Türkiye and Iraq have a historical relationship in terms of economics, politics, and culture, with changes in one country directly impacting the other. Iraq is Türkiye 's main partner in importing various goods, particularly agricultural products. Egg is the one of the top three agricultural products imported to Iraq from Türkiye, and Türkiye is the top exporter of this product to Iraq. The interaction between Iraq and Türkiye has increased rapidly, making Iraq Türkiye's most crucial trading partners. The trade volume between Türkiye and Iraq has been increasing annually, and over the last decade, Iraq has consistently ranked among the top ten importers of Turkish goods (UN Comtrade, 2023).

The development of ANNs marked a significant advancement in data analysis, benefiting researchers across various fields, including economics, commerce, and statistics. Based on the literature, this study hypothesizes that ANNs will provide a more accurate forecast of Türkiye's monthly egg exports to Iraq compared to the ARIMA model. This hypothesis is supported by several studies demonstrating the superiority of ANNs over traditional time series models across various domains. For instance, Bozkurt et al. (2017) found that ANNs outperformed SARIMA in forecasting electricity demand in Türkiye. Similarly, Abraham et al. (2020) and Abdoli et al. (2020) reported better accuracy with ANNs and LSTM (Long Short-Term Memory) models over ARIMA for agricultural and stock market predictions, respectively. Furthermore, Abhinandithe et al. (2021) highlighted the higher accuracy of LSTM models compared to ARIMA in their review. Zhang et al. (1998) reported ANNs' ability to capture nonlinear relationships that ARIMA models could not, while Pai and Lin (2005) showed that a hybrid approach combining ARIMA and neural networks could yield more accurate predictions. Wang et al. (2019) also illustrated the superiority of ANNs in forecasting agricultural commodity prices. These studies collectively suggest that ANNs are likely to yield more reliable and precise forecasts for complex and nonlinear time series data, such as egg exports.

Furthermore, the application of advanced forecasting techniques in trade analysis is crucial for policymakers and businesses to make informed decisions. The use of models such as ARIMA and ANNs provides valuable insights into future trade trends, helping to optimize trade policies and strategies (Hamilton, 1994; Makridakis and Hibon, 2000).

The primary goal of this study is to investigate new approaches developed by computer scientists, particularly ANNs, for the creation of forecasting models. More specifically, this study compares two models to select the best one for forecasting the monthly average of eggs exports from Türkiye to Iraq and determining Türkiye's position and importance in egg exports to Iraq from 2010 to 2020.

2. MATERIALS AND METHODS

This study's data for comparing the two forecasting models consists of monthly egg export figures from Türkiye to Iraq, spanning from January 2010 to December 2019. The data were obtained from the official UN Comtrade and TÜİK websites (UN Comtrade, 2023; TÜİK, 2023). The collection process utilized the Harmonized System, a universal standard for product classification, which allows countries to categorize traded goods for customs and statistical analysis systematically. The egg data contain fresh, preserved, or boiled bird eggs in the shell.

The data analysis was conducted using three statistical software programs: Alyuda NeuroIntelligence, R, and SPSS. The ARIMA model was developed using both R and SPSS, whereas the ANN model was constructed with the assistance of Alyuda NeuroIntelligence and R.

The ARIMA model is specifically tailored for analyzing non-seasonal and non-stationary data. To accommodate seasonality, the Box-Jenkins methodology extends this model, resulting in the SARIMA model. In SARIMA, appropriate seasonal differencing is applied to eliminate non-stationarity from the time series. Specifically, a first-order seasonal difference is calculated by taking the difference between an observation and its corresponding observation from the same period in the previous year (Adhikari and Agrawal, 2013):

$$Z_t = y_t - y_{t-s}$$

Where s=12 for monthly time series and s=4 for quarterly time series. This model is commonly referred to as the SARIMA (p,d,q)(P,D,Q)s.

$$Z_t = C + \varphi_s Z_{t-s} + .. + \varphi_{ps} Z_{t-ps} + e_t - \varphi_s Z_{t-s} + .. + \varphi_{qs} Z_{t-qs}$$

For several types of data, Box-Jenkins is an essential forecasting approach producing more accurate forecasts than other time series methods (Urrutia et al., 2014). The Box-Jenkins methodology does not rely on assumptions about the underlying data. Instead of this, it uses a three-step iterative strategy of model identification, parameter estimation, and diagnostic checking to select the best accurate model from a large class of SARIMA models. This three-step approach is done multiple times until a suitable model is found. The model can then be used to forecast future values of the time series (Zhang, 2003; Flaherty and Lombardo, 2000; Adhikari and Agrawal, 2013).

While the Box-Jenkins methodology is a traditional approach to time series forecasting, ANNs offer a more flexible and adaptive alternative. The ANNs are a class of computational tools that operate analogously to the biological processes of human brain (Box and Jenkins, 1976; Hyndman and Athanasopoulos, 2018). An ANN is a collection of several simple processes connected together (PEs or Neurons). Each unit is equipped with a modest local memory. Communication channels (Connections) that transmit numerical data connect these neurons.

An ANN model, commonly referred to as a network, is structured with three distinct layers: the input layer, one or more hidden layers, and the output layer (Figure 1). Each layer consists of multiple nodes, or "neurons," with each node in a given layer generally connected to every node in the subsequent layer via weighted connections. These weights facilitate the transfer of information between neurons as numerical values. The input layer is where data is fed into the NN. The hidden layer's nodes process the input data they receive as the sum of the input layer's weighted outputs. The output layer's nodes process the input data they receive as the total of the weighted outputs of the hidden layers' units and produce the system output, which refers to the final result or prediction produced by the neural network after processing the input data (Mishra et al., 2018; Mehlig, 2019; Fiesler and Beale, 2020).

Input signals or data delivered to the neural network are represented by arrows reaching the input layer neurons. The synapse is shown by arrows linking neurons in one layer to neurons in another. The output signals provided by the trained network are represented by arrows coming out of the output layer neurons (Gurney, 2018). The flow of information from an artificial neuron can be schemed as (Figure 2).

To incorporate nonlinearity into the network, activation functions for the hidden units were required. Hidden units would not make nets more strong than simple perceptron without nonlinearity. Multilayer networks, on the other hand, are particularly powerful because of their nonlinearity (the ability to express nonlinear functions). The job can be done with almost any nonlinear function (Zhang et al., 1998; Wang et al., 2020).

Figure 1. Architecture of Neural Network

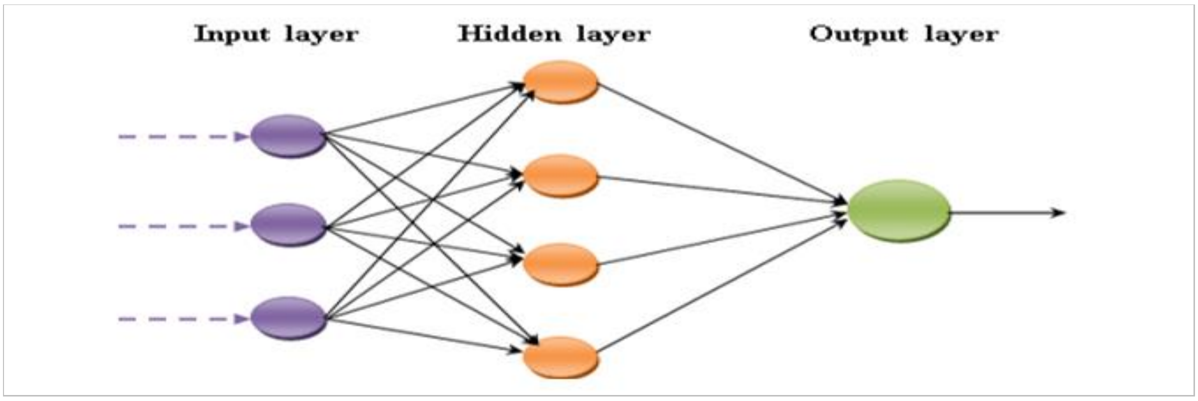
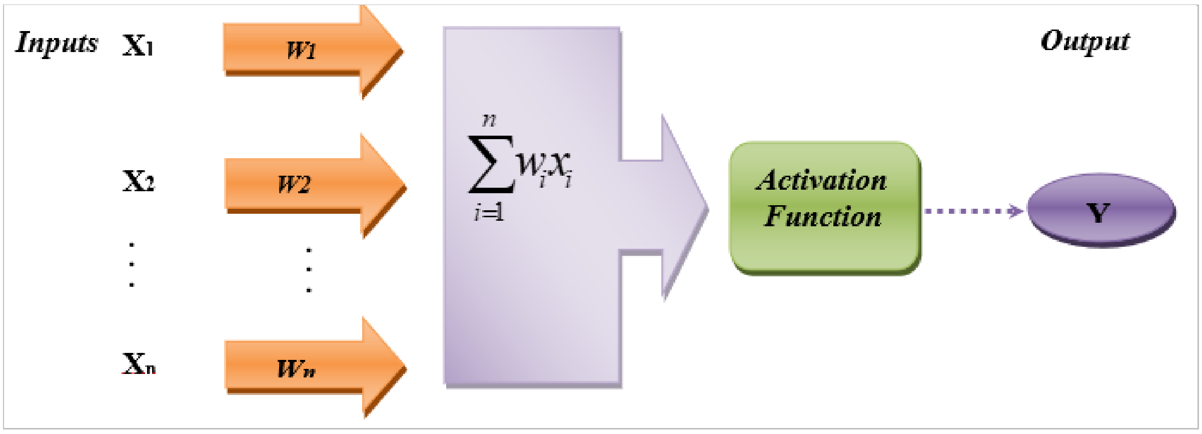


Figure 2. Depicts All the Basic Components of a Neuron



3. RESULTS AND DISCUSSIONS

3.1. Trade of Eggs between Türkiye and Iraq

The relationship between Iraq and Türkiye has intensified significantly, positioning Iraq as Türkiye's most significant commercial partner. Data from UN Comtrade reveals a consistent increase in trade volume between the two countries, positioning Iraq among the top ten importers of Turkish goods over the past decade. In 2003, Turkish exports to Iraq were valued at $829 million, which was 0.02% of Türkiye’s total global exports. The value of these exports rose substantially, peaking at $11,949 million in 2013. However, the export value declined to $10,888 million in 2014 and continued to decrease until 2016. Post-2016, Türkiye's export values began to recover, reaching $10,223 million in 2019, which constituted 6% of Türkiye's total global exports. This data indicates a significant positive correlation between Türkiye’s overall global exports and its exports to Iraq.

Over the past decade, Iraq has consistently been one of the leading importers of goods from Türkiye. In 2010, Iraq was the fifth largest importer of Turkish goods, rising to the second position from 2011 to 2014, behind only Germany. In 2015 and 2016, Iraq ranked third after Germany and the United Kingdom, and from 2017 to 2019, it held the fourth position.

These trends extend to the egg trade between Türkiye and Iraq. As global demand for eggs increases due to their nutritional value and health benefits, Türkiye's poultry industry, particularly egg production, has seen significant growth over the past decade.

From 2001 to 2019, there was a notable surge in Türkiye 's egg exports (Table 1). In 2001, egg exports were valued at $18.4 million, accounting for 1.8% of global egg exports. By 2007, this figure nearly quadrupled to $67.4 million, capturing a 2.93% market share. The upward trend continued, with export reaching $156.17 million in 2010. Despite a sharp decline in 2015, Turkish egg exports rebounded to $430.27 million in 2018, constituting 10% of total global exports. Türkiye emerged as a leading egg exporter globally, consistently ranking among the top ten from 2010 to 2019 (Table 2).

In recent years, Türkiye has solidified its position as one of the largest egg exporters in the world, surpassing nearly all its competitors. Over the last five years, Türkiye has maintained its position as the third-largest egg exporter globally, trailing only the Netherlands and the United States.

Table 1. Türkiye's Egg Export Values (2001-2019) in Million Dollars (UN Comtrade, 2023)

Year	Türkiye's Export	World Export	Share (%)
2001	18.40	1018.28	1.81
2002	3.76	1084.28	0.35
2003	10.68	1369.00	0.78
2004	14.10	1425.08	0.99
2005	18.51	1580.39	1.17
2006	18.32	1718.02	1.07
2007	67.40	2297.01	2.93
2008	118.96	2892.15	4.11
2009	126.61	3431.14	3.69
2010	156.17	3409.46	4.58
2011	284.05	3494.54	8.13
2012	350.48	3952.54	8.87
2013	406.16	4338.66	9.36
2014	401.83	4621.92	8.69
2015	273.46	4238.50	6.45
2016	289.41	3658.82	7.91
2017	376.15	3987.43	9.43
2018	430.27	4313.93	9.97
2019	296.84	3974.37	7.47

In 2010, Türkiye's egg export value to the global market was $156.17 million, with 70% of these exports directed to Iraq. However, Türkiye's total exports to Iraq declined in 2014 due to ISIS's invasion, leading to a significant drop in egg exports by 10% compared to 2013. The year 2019 marked the worst period for Türkiye's egg exports, primarily because the Iraqi government imposed a ban on egg imports, resulting in a 30% decrease in export volume to Iraq, plummeting to $132.05 million. This data clearly indicates a strong positive correlation between Türkiye's global egg exports and its exports to Iraq; an increase in exports to Iraq corresponds with an increase in global exports and vice versa.

To understand the role Türkiye has played in Iraq's egg imports from 2010 to 2019, we can examine the annual egg import data of Iraq (Table 2). In 2010, Iraq's total egg imports were valued at $108.65 million, with Türkiye supplying 37% of this amount. Despite a decline in Iraq's total egg imports in 2011, imports from Türkiye surged to $211.78 million, constituting 80% of Iraq's total egg imports. The peak was reached in 2013, with

Iraq imports from Türkiye hitting US$360.2 million, representing 77% of the total imports. The subsequent years, 2014 and 2015, saw a sharp decline to $194.41 million due to regional instability. Nonetheless, imports from Türkiye increased from 2016 onwards until the 2019 import ban, which drastically reduced Iraq's egg imports, especially from Türkiye, to $132.05 million.

Thus, over the past decade, Türkiye has undeniably been the leading exporter of eggs to Iraq, despite various geopolitical and market challenges. This strong trade relationship underscores Türkiye's critical role in supplying eggs to the Iraqi market and highlights the impact of regional stability and policy changes on this trade.

Table 2. The Value of Egg Exports from Türkiye and Imports to Iraq (in million dollars)

Year	Eggs exported from Türkiye			Eggs imported by Iraq		
	Total Export	Export to Iraq	Share (%)	Total Import	Import from Türkiye	Share (%)
2010	156.17	108.65	69.57	294.35	108.65	36.91
2011	284.05	211.78	74.56	264.58	211.78	80.04
2012	350.48	322.55	92.03	388.69	322.55	82.98
2013	406.16	360.21	88.69	470.02	360.21	76.64
2014	401.83	325.33	80.96	491.20	325.33	66.23
2015	273.46	194.41	71.09	384.71	194.41	50.53
2016	289.41	232.79	80.44	323.83	232.79	71.89
2017	376.15	314.15	83.52	402.72	314.15	78.01
2018	430.27	306.07	71.13	396.72	306.07	77.15
2019	296.84	132.05	44.49	214.47	132.05	61.57

Source: UN Comtrade, 2023

According to the law of demand, there is a negative relationship between the price and the quantity demanded for a specific product. Thus, when the price of a product increases, the quantity demanded decreases, and vice versa (Krautmann and Hadley, 2017). To analyze the relationship between the monthly egg price and the quantity of eggs exported from Türkiye to Iraq, logarithmic regression was applied. This method was used to determine the relationship between price and export volume, as well as the effect of price on the export quantity.

As shown in Table 3, the Pearson correlation between price and export volume is 0.647, indicating a positive correlation between the price and the monthly export volume from Türkiye to Iraq. Furthermore, the R^2 value is 0.419, suggesting that the price of eggs explains 42% of the variation in the quantity of egg exports. The relatively low R^2 value implies that other factors may also be influencing the quantity of eggs exported.

Regarding the influence of price on the export quantity, Table 3 shows that price has a significant effect on export volume ($p<0.001$). Specifically, if the price of eggs rises by 1%, the monthly export volume decreases by 2.23%, and vice versa. This finding aligns with the law of demand, demonstrating the sensitivity of export volumes to price changes.

3.2. Application of ARIMA and ANN models to forecast the monthly egg export from Türkiye to Iraq

Research has demonstrated a robust agricultural trade relationship between Türkiye and Iraq, with each country being a significant trading partner for the other. ARIMA and ANN models were applied to the datasets. The best model, determined from these analyses, was subsequently used to predict the export value of eggs from Türkiye to Iraq for the year 2021.

Table 3. The results of regression analysis for egg exports and egg prices

	Coefficients	Standard Error	t- value	P-value
Constant	17.030	0.103	165.034	0.000
LnPrice of Egg	-2.235	0.231	-9.677	0.000
F =93.638;	P-value = 0.000;	R = 0.647;	R^2 = 0.419	

3.2.1. Application of ARIMA on eggs exports time series

The first step in constructing the ARIMA model involved examining the characteristics of the dataset. Figure 3 presents the trend of monthly egg exports from Türkiye to Iraq, covering the period from January 2010 to December 2020. This dataset includes 132 observations, which provide a comprehensive view of the export trends over the past decade. The Kolmogorov-Smirnov test was employed to determine the dataset's normality. The test indicates that the data are normally distributed (p=0.061).

Despite this, as shown in Figure 3, the data were non-stationary, necessitating conversion to stationary data-a prerequisite for creating time series models. The Augmented Dickey-Fuller test will be employed in this study to determine the dataset's stationarity. The results show that the P value is 0.1537, which is significantly greater than the significant level (0.05). As a result, the time series data can be classified as having a unit root and not stationary. There, the first differential computed and determine whether it is stationary. Otherwise, the second difference is applied. Following the initial differentiation, the P-value falls to 0.01, suggesting that the time series is stationary with no unit root (Table 4). Subsequently, the time series data, along with the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, were reanalyzed and redrawn to understand the underlying patterns and dependencies better. Figure 4 confirms that the series became stationary after these transformations.

Table 4. The results Dickey-Fuller test

	Dickey-Fuller value	P-value
Before Differencing	-3.0182	0.1537
After Differencing	-6.0106	0.010

Figure 3. Time series plot of monthly amount of egg export from Türkiye to Iraq

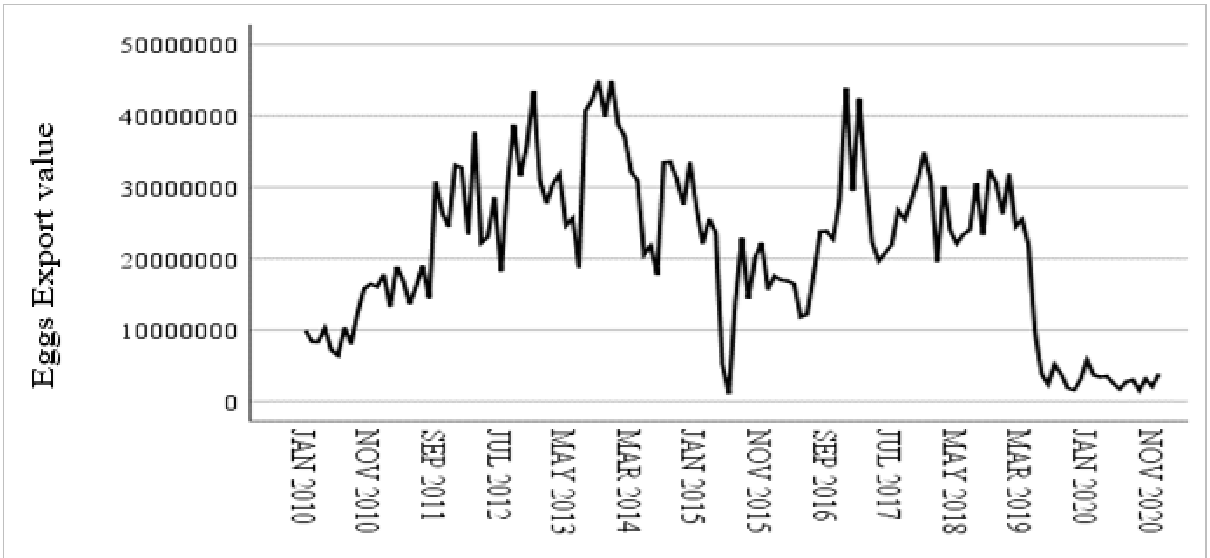
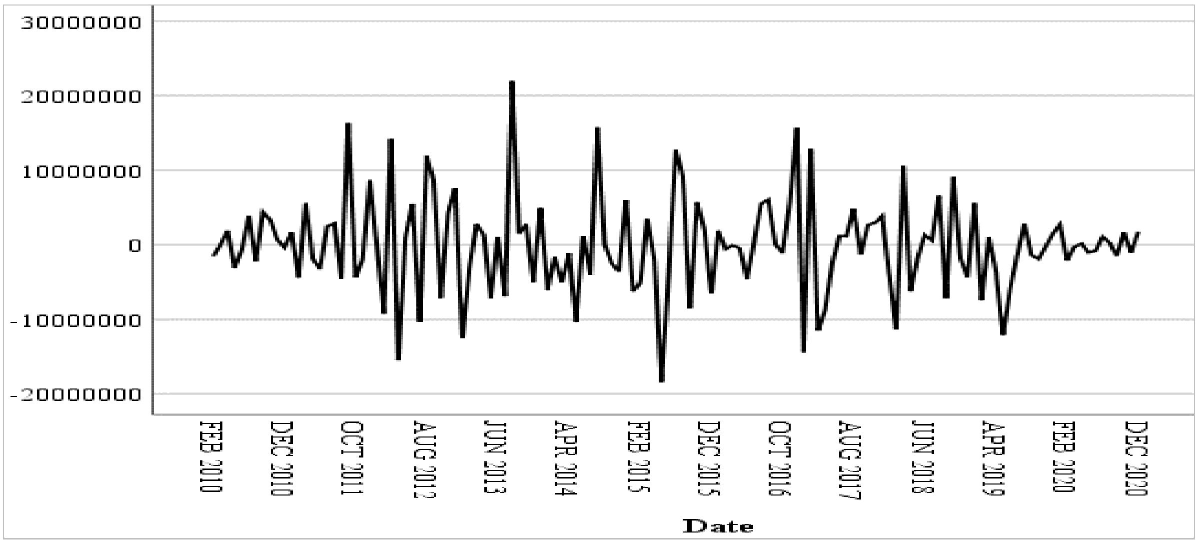


Figure 4. Time series plot of monthly amount of egg export from Türkiye to Iraq after first differencing



Box and Jenkins (1976) introduced an interactive technique for fitting ARIMA to time series data, focusing on stationarity around the mean and variance. Their method, known as the Box-Jenkins approach, involves a cyclical process of identifying the model, estimating its parameters, and performing diagnostic checks to verify the model's suitability and performance

In total, 192 different models were fitted to the data, and the AIC was employed to compare these models, with a lower AIC value indicating a more suitable model (Akaike, 1974). However, the selection of an optimal model based on AIC alone is insufficient; additional diagnostic checks are necessary to ensure the validity of the model. These evaluations involve checking the relevance of the model parameters and assessing the residuals for randomness (Box and Jenkins, 1976). In this case, a SARIMA (2,1,0)(1,0,1)[12], was selected as it exhibited the lowest AIC value among the candidate models. Furthermore, the parameters of this model were found to be highly significant, adding to its appeal. The significance of the parameters and the adequacy of the model were confirmed through rigorous statistical testing, as shown in Table 5 and Figure 5. The SARIMA model was chosen not only for its optimal fit to the data, as indicated by the AIC, but also for its robust statistical properties and the significance of its parameters (Hyndman and Athanasopoulos, 2018). By adhering to these principles, the chosen SARIMA model provides a reliable and accurate representation of the underlying data.

Once the SARIMA (2,1,0) (1,0,1) (12) model has been identified and estimated, it's crucial to evaluate its fit to the data. This involves analyzing both the model parameters and the residuals. Diagnostic testing of the residuals for the SARIMA (2,1,0) (1,0,1) (12), as illustrated in Figure 6, utilized ACF and PACF plots. The results show that all residual values are statistically significant, suggesting that the residuals are random white noise and confirming the model's suitability for available data.

Table 5. SARIMA (2,1,0)(1,0,1)(12) model parameters and statistics

	Estimate	SE	T-test	P-value
AR1	-0.370	0.088	-4.206	0.000
AR2	-0.277	0.086	-3.224	0.002
SAR1	0.807	0.127	6.349	0.000
SMA1	0.538	0.185	2.916	0.004
R-squared: 0.77; RMSE: 5583356.23; MAPE: 33.39; MAE: 3901600.89; AIC: 4814.12				

Figure 5. Predicted value and actual values of eggs exports time series by using SARIMA

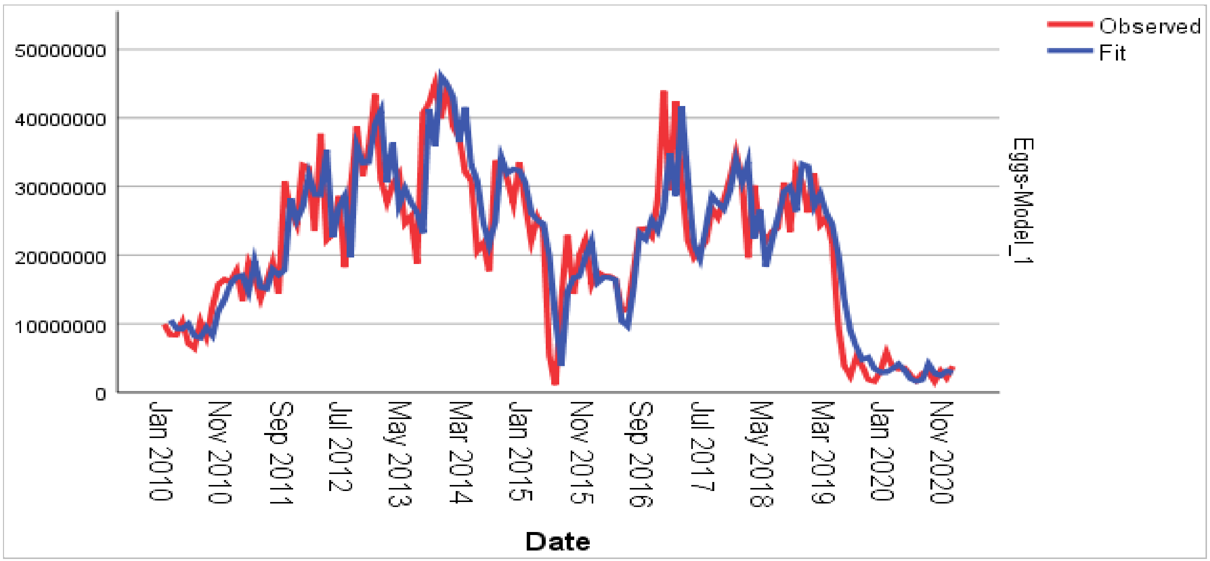
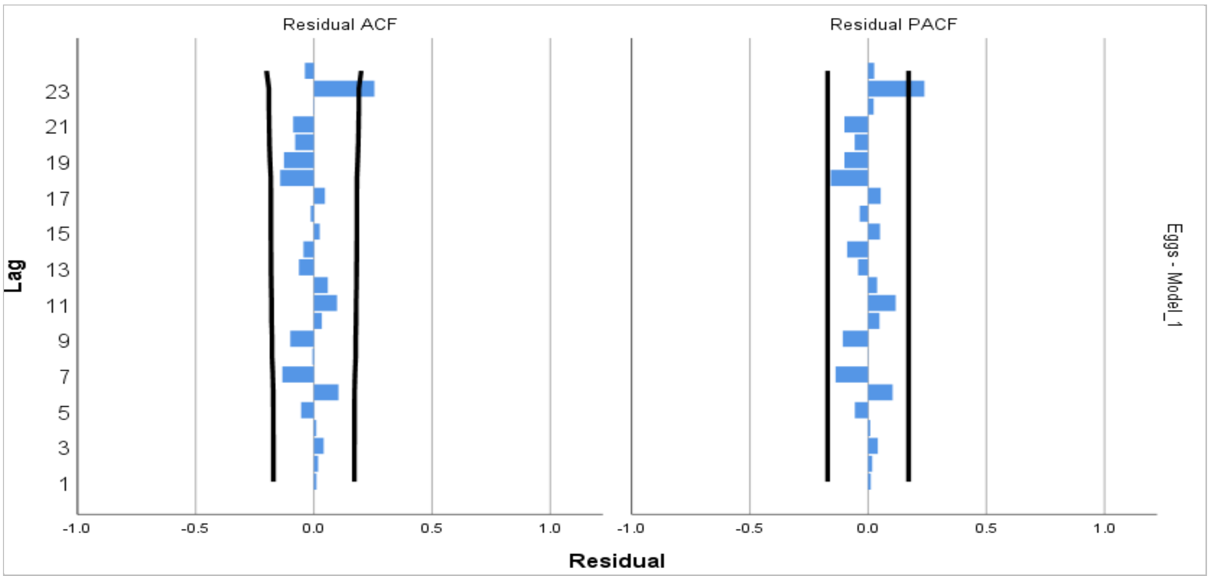


Figure 6. Residual's ACF and PACF for SARIMA(2,1,0)(1,0,1)(12)



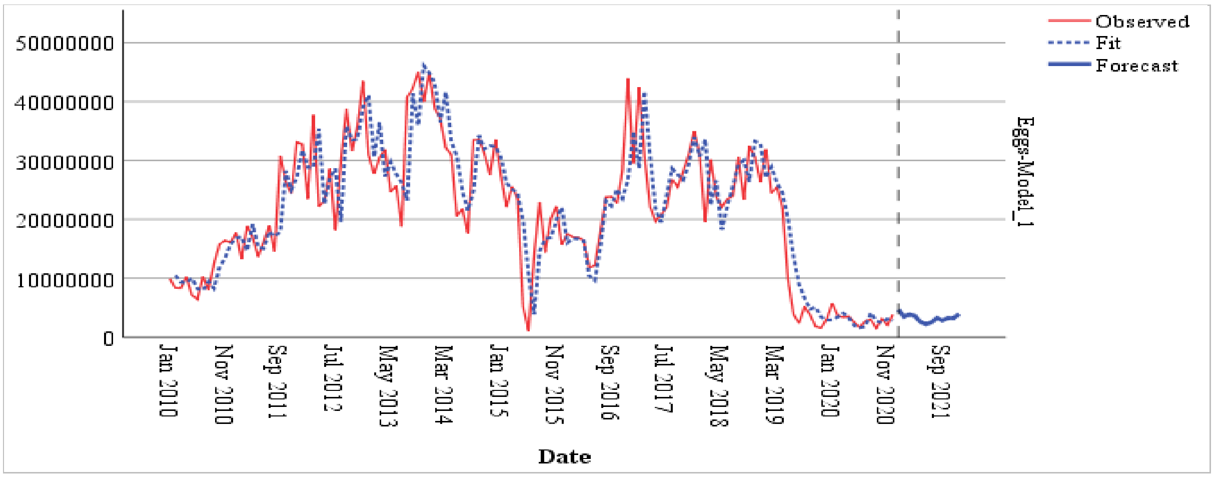
In the final stage of evaluating model performance, the Box-Pierce test was employed to confirm the validity of the chosen model. In contrast the residual autocorrelation test was conducted to check for any autocorrelation. The results of the Box-Pierce test indicate a P-value of 0.551, which is well above the 0.05 threshold. This suggests that the residuals do not exhibit significant autocorrelation and can be considered white noise. Therefore, the SARIMA(2,1,0)(1,0,1)(12) model is deemed the best fit for the egg export data, having passed all diagnostic tests for model construction. As shown in Figure 6, the predicted values closely align with the actual values, indicating a good model fit.

The final step in the time series analysis involved forward forecasting. Using the original data and the estimated model, forecasts for the monthly egg exports from Türkiye to Iraq for 2020 were made, as detailed in Table 6. Furthermore, as illustrated in Figure 7, the plot demonstrates that predicted values of egg exports in 2021 behave similarly to actual values, with the predicted values converging with the actual series.

Table 6. Actual and forecasted value of monthly eggs exports from Türkiye to Iraq in 2020

No.	Date	Actual	Forecast
1	Jan-20	5,806,542	2,978,670
2	Feb-20	3,714,149	3,443,200
3	Mar-20	3,410,105	4,123,408
4	Apr-20	3,564,296	3,324,011
5	May-20	2,542,958	2,004,793
6	Jun-20	1,726,521	1,627,769
7	Jul-20	2,788,869	1,876,948
8	Aug-20	3,027,192	4,157,383
9	Sep-20	1,543,568	2,806,779
10	Oct-20	3,162,211	2,470,368
11	Nov-20	2,097,042	3,128,462
12	Dec-20	3,852,094	2,858,670

Figure 7. Predicted values of egg exports in 2021



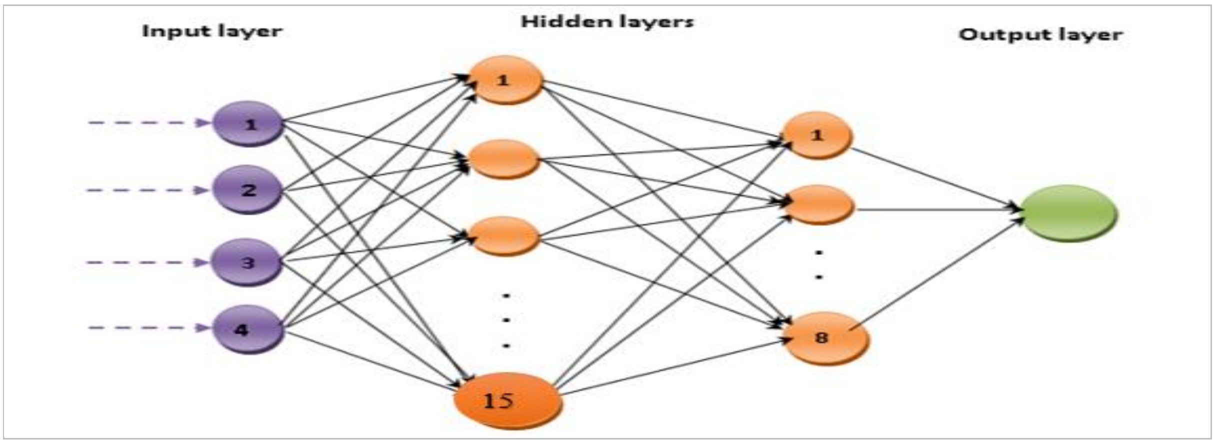
3.2.2. Application of ANNs

The application of neural networks on time series does not require a sequential processing approach. The structure of a multilayer FFNN model must include the number of input layer nodes, the number of hidden layers and hidden nodes, the number of output nodes, and the activation functions for hidden, and output nodes (Zhang, 2003; Haykin, 1999). Because the data is seasonal, the total number of input neurons required in this model is four. Only one output unit is required, and it indicates monthly egg export forecasts from Türkiye to Iraq. As mentioned previously, there is no easy way to determine the optimum number of hidden units without training and testing. The best approach to find the optimal number of hidden units is trial and error (Bishop, 1995). The common practice is to iteratively train and test different network configurations to identify the optimal number of hidden nodes (Hornik, Stinchcombe, and White, 1989). In the study, the data was divided such that 80% was used for training, 10% for validation, and 10% for testing. This split helps to prevent overfitting and ensures that the model generalizes well to unseen data (Ripley, 1996).

The logistic activation function was applied to both the hidden and output layers. To optimize the network architecture, the conjugate gradient descent algorithm was employed for training. The network was trained over 1,000 iterations with a single retrain, using a learning rate of 0.9 and a momentum of 0.5.

The model requires a total of 12 input neurons, given that the data is monthly and exhibits no seasonal patterns (Tang et al., 1991; Sharda and Patil, 1992; Khalil D.M., 2022). After training the network multiple times and evaluating 380 different network configurations, it was determined that the optimal neural network consists of two hidden layers. The first hidden layer comprises 15 nodes, while the second layer contains 8 nodes. The structure of the selected network is illustrated in Figure 8.

Figure 8. FFNN (4:15:8:1) for predicting the amount of egg exports



As is clear from appendix I, the FFNN (4-15-8-1) has less error than the other networks. Through the process of training and testing, the neural network developed the capability to predict values and compute statistical parameters for comparison with those derived from statistical methods. The results of the FFNN (4-15-8-1) network are shown in Table 7 and Figure 9 and 10. The actual and forecast values of eggs exported from Türkiye to Iraq in 2020 based on FFNN (4-15-8-1) are represented in Table 8.

Table 7. Statistical measurements for FFNN (4-15-8-1)

R-squared	MAE	AIC	RSME
0.88	2121836.56	1414.65	3929733

Figure 9. Predicted and actual values of egg exports time series by using FFNN (4-15-8-1).

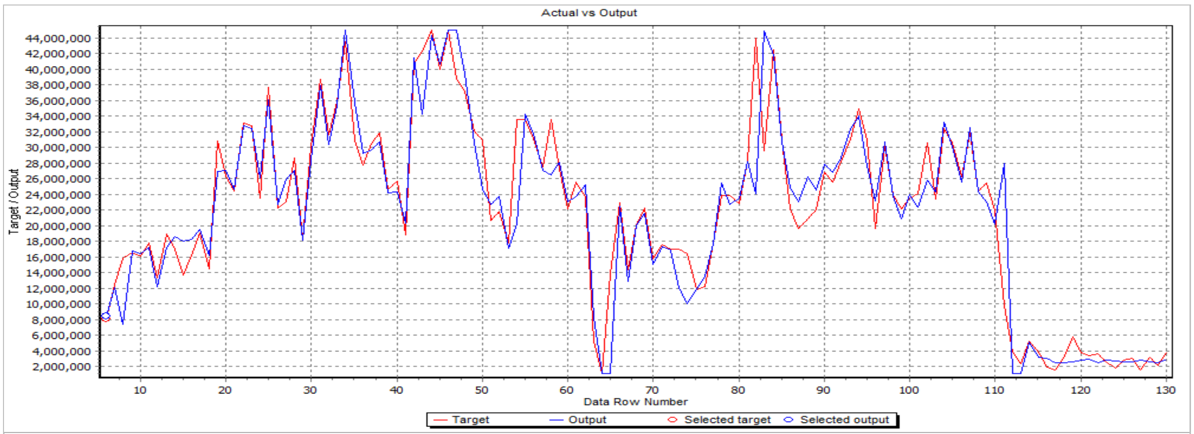


Figure 10. The value of monthly egg exports from Türkiye to Iraq from January 2010 to December 2021

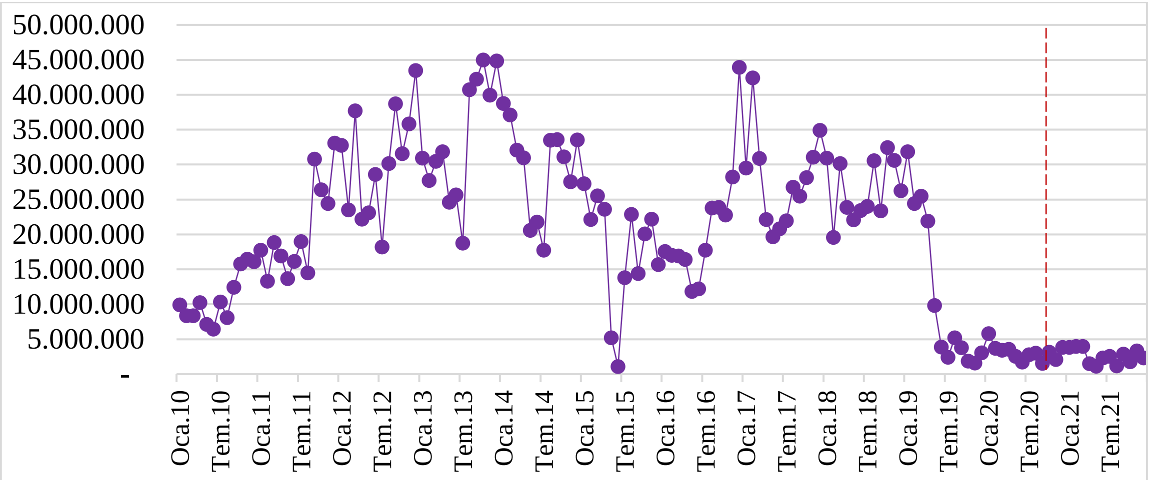


Table 8. Actual and predicted values of FFNN (4:15:8:1) for egg export value from Türkiye to Iraq in 2020

Date	Actual	Forecast
Jan-20	5,806,542	2,339,031
Feb-20	3,714,149	3,287,846
Mar-20	3,410,105	4,420,649
Apr-20	3,564,296	4,209,204
May-20	2,542,958	3,102,986
Jun-20	1,726,521	2,892,623
Jul-20	2,788,869	2,581,021
Aug-20	3,027,192	2,420,972
Sep-20	1,543,568	2,554,453
Oct-20	3,162,211	2,729,989
Nov-20	2,097,042	2,625,781
Dec-20	3,852,094	2,363,348

3.3. Comparison of ARIMA and FFNN Results

After using the FFNN and ARIMA models to forecast the amount of monthly exports of eggs from Türkiye to Iraq, we can draw several conclusions based on the metrics presented in Table 9. Firstly, the Mean Absolute Error (MAE) values for the FFNN models are lower than those for the ARIMA models across the eggs time series, indicating that the FFNN model achieves a better fit. This lower MAE suggests that the FFNN model has less prediction error compared to the ARIMA model. Secondly, the R^2 values, which measure the proportion of variance explained by the model, are higher for the FFNN models than for the ARIMA models. This higher R^2 value further supports the conclusion that the FFNN model provides a better fit to the data, capturing more of the underlying variance in the export time series. Lastly, the AIC values for the FFNN models are significantly lower than those for the ARIMA models. Since lower AIC values indicate a better model in terms of the trade-off between goodness of fit and model complexity, this further confirms the superiority of the FFNN models over the ARIMA models.

In summary, the comparative analysis using MAE, R^2, and AIC metrics demonstrates that the FFNN models outperform the ARIMA models in forecasting the monthly exports of eggs, vegetables, and poultry meat from Türkiye to Iraq.

The FFNN models exhibit lower prediction errors, better fit, and more efficient complexity handling, making them the preferred choice for this forecasting task.

Table 9. Comparison of the MAE, RMSE, R^2, and AIC value of both models

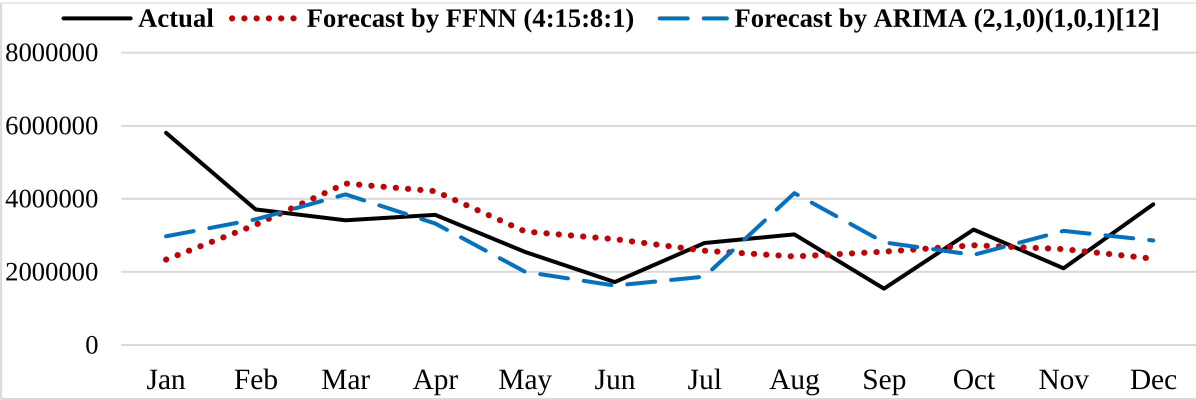
Model	FFNN	SARIMA
MAE	2121836.56	3901600.89
RMSE	3929733.00	5583356.23
R^2 value	0.88	0.77
AIC	1414.65	4814.12

When both models are used for prediction, the results show that the FFNN models are more accurate and have less error than the ARIMA models, as shown in the Table 10. Figure 11 proves that forecast values produced by both methods follow the actual values However, the FFNN model value seem to have a superior forecasting performance in comparison to the ARIMA model, confirming the FFNN model prediction and accuracy for these data.

Table 10. Actual and predicted values of egg exports from Türkiye to Iraq in 2020

Date	Actual	Forecast by FFNN (4:15:8:1)	Forecast by ARIMA (2,1,0)(1,0,1)[12]
Jan-20	5806542	2,339,031	2,978,670
Feb-20	3714149	3,287,846	3,443,200
Mar-20	3410105	4,420,649	4,123,408
Apr-20	3564296	4,209,204	3,324,011
May-20	2542958	3,102,986	2,004,793
Jun-20	1726521	2,892,623	1,627,769
Jul-20	2788869	2,581,021	1,876,948
Aug-20	3027192	2,420,972	4,157,383
Sep-20	1543568	2,554,453	2,806,779
Oct-20	3162211	2,729,989	2,470,368
Nov-20	2097042	2,625,781	3,128,462
Dec-20	3852094	2,363,348	2,858,670

Figure 11. Actual and predicted values of egg exports in 2020 using FFNN and SARIMA models.



4.CONCLUSIONS and RECOMENDATIONS

This research set out to test the hypothesis that modern forecasting methods, particularly ANN, would provide significantly better forecasting accuracy compared to traditional statistical and time series approaches like ARIMA and SARIMA. The findings of the study confirm this hypothesis, demonstrating that FFNN models outperform the SARIMA models in predicting agricultural export values from Türkiye to Iraq. Additionally, the SARIMA models showed higher sensitivity to outliers than the FFNN models. Forecast values produced by the FFNN models exhibited superior performance, closely aligning with actual values, unlike those generated by the SARIMA models.

From an economic perspective, Iraq is a major trading partner for Turkish exports, with annual exports to Iraq constituting 6% of Türkiye's total global exports. Specifically, in the egg export sector, Türkiye holds a dominant position, supplying approximately 76% of the annual egg imports by Iraq. This underscores Türkiye's significant role, as it accounts for 68% of Iraq's total egg imports. The average monthly value of Turkish egg exports to Iraq $19,281,609 with the peak export value recorded in December 2016 at $40,704,409, and the lowest in June 2015 at $1,002,621.

In conclusion, the comparative analysis clearly indicates that the FFNN model is more effective and reliable than the SARIMA model for forecasting the export values of agricultural products from Türkiye to Iraq. This finding is crucial for policymakers and stakeholders in the agricultural export sector, highlighting the need for adopting more advanced forecasting techniques to enhance accuracy and support better economic planning.

Given the superior accuracy and lower error rates demonstrated by neural network models compared to traditional time series models, it is strongly recommended that neural networks be used to predict the export amounts of eggs. When designing the architecture of a neural network, it is advisable to limit the number of hidden layers to a maximum of two, as exceeding this number tends to reduce the network’s accuracy.

Despite Iraq's status as Türkiye's principal partner in agricultural exports, Türkiye should actively seek to diversify its markets. This recommendation is based on the significant decline in Türkiye's egg exports to Iraq in recent years. To bolster trade volume between the two countries, it is crucial to open additional border crossings and enhance facilities for traders to streamline the export and import processes.

For future research, exploring other forecasting methods, such as Bayesian approaches, will be essential to determine the most effective techniques for predicting Turkish export values to Iraq and other global markets. Since the price of products appears to have a minimal impact on export quantities, future studies should investigate other factors influencing the volume of exports.

This study faced challenges due to a need for accurate and reliable data on the exports from Iran and Syria, partly due to illegal border activities between these countries and Iraq. This data gap has implications for the study, as the volume of exports from these neighboring countries directly affects Türkiye's exports to Iraq. The current study did not account for the high rate of illegal cross-border imports into Iraq, for which accurate and reliable data is unavailable. Addressing these data deficiencies in future research will provide a clearer picture of the competitive landscape and enhance the accuracy of export forecasts.

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