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Comparative Analysis of Deep Learning Models for Forecasting Turkiye's Seafood Exports

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ABSTRACT

As the income level of countries increases with the increasing world population, the demand for aquaculture products increases. As a result of technological developments in the storage and distribution of seafood products, it has become an important sector for national economies. The aim of this study is to determine whether machine learning and deep learning methods can be utilized in forecasting Türkiye's seafood exports and to test which forecasting models will give better results. For this purpose, the performance parameters of LSTM, RNN, BiLSTM and GRU models are compared. The findings show that deep learning method can be utilized in forecasting Türkiye's seafood export volume and better results are obtained with GRU and BiLSTM performance parameters compared to the other two models. Developments in foreign trade in recent years have had a positive impact on aquaculture trade. With its existing potential and the use of modern and advanced technologies, Turkiye's aquaculture sector has made significant progress, and this has had a positive impact on exports. In this sense, estimating Türkiye's aquaculture export volume will help producers to plan supply and sales and exporters to develop marketing strategies.

ملخص

مع ارتفاع مستوى دخل البلدان في ظل تزايد عدد سكان العالم، يزيد الطلب على منتجات تربية الأحياء المائية. ونتيجة للتطورات التكنولوجية في مجال تخزين وتوزيع منتجات المأكولات البحرية، بات هذا القطاع يحظى بأهمية كبيرة بالنسبة للاقتصادات الوطنية. الهدف من هذه الدراسة هو تحديد ما إذا كان يمكن استخدام أساليب التعلم الآلي والتعلم العميق في التنبؤ بصادرات تركيا من المأكولات البحرية

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واختبار نماذج التنبؤ التي من شأنها أن تفضي لنتائج أفضل. لهذا الغرض، أجريت مقارنة نماذج معايير الأداء التالية: LSTM و RNN و BiLSTM و GRU. وتبرز النتائج أن طريقة التعلم العميق يمكن استخدامها في توقع حجم صادرات تركيا من المأكولات البحرية، وأن معايير الأداء GRU و BiLSTM تعطي نتائج أفضل مقارنة بالنموذجين الآخرين. وقد كان للتطورات في التجارة الخارجية في السنوات الأخيرة أثر إيجابي على تجارة تربية الأحياء المائية. وبفضل الإمكانات الراهنة التي يتمتع بها قطاع تربية الأحياء المائية في تركيا واستخدامه للتقنيات الحديثة والمتقدمة، فقد حقق القطاع تقدما كبيرا، وكان لهذا الوضع أثر إيجابي على الصادرات. ومن هذا المنطلق، من شأن القدرة على تقدير حجم صادرات تربية الأحياء المائية في تركيا تمكين المنتجين من تخطيط العرض والمبيعات، كما سيساعد المصدرين على تطوير استراتيجيات التسويق الملائمة.

RÉSUMÉ

Avec l'augmentation du niveau de revenu des pays et la croissance démographique mondiale, la demande en produits aquacoles augmente. Grâce aux progrès technologiques en matière de conservation et de distribution des produits de la mer, ce secteur est devenu un pilier important des économies nationales. L'objectif de cette étude est de déterminer si les méthodes d'apprentissage automatique et d'apprentissage profond peuvent être utilisées pour prévoir les exportations de produits marins turcs et de tester quels modèles de prévision donneront les meilleurs résultats. On procède à la comparaison des paramètres de performance des modèles LSTM, RNN, BiLSTM et GRU. Les résultats montrent que la méthode d'apprentissage profond peut être utilisée pour prévoir le volume des exportations de produits marins turcs et que les paramètres de performance GRU et BiLSTM donnent de meilleurs résultats que les deux autres modèles. L'évolution du commerce extérieur ces dernières années a eu un impact positif sur le commerce aquacole. Grâce à son potentiel existant et à l'utilisation de technologies modernes et avancées, le secteur aquacole turc a réalisé des progrès significatifs, ce qui a eu un impact positif sur les exportations. À cet égard, l'estimation du volume des exportations aquacoles de Türkiye aidera les producteurs à planifier l'approvisionnement et les ventes et les exportateurs à élaborer des stratégies de commercialisation.

Keywords: Seafood export, deep learning, machine learning, time series analysis

JEL Classification: E17, F17, Q17

1. Introduction

Aquaculture is a source of food for a significant proportion of the world's population. This type of food is highly important in terms of high-quality proteins, essential vitamins, minerals and polyunsaturated fatty acids (Prester, 2011). However, seafood is recognized as an inexpensive source of animal protein (Devaraj et al., 2021). Protein content ranges from 15% to 20% of the body weight of the fish. The superior nutritional quality of fish lipids is well known among consumers. Fish is a good source of vitamin B complexes and also a combination of minerals such as calcium, iodine, zinc, iron and selenium (FAO, 2016). Given all this, it is important for people to have access to these sources of nutrients.

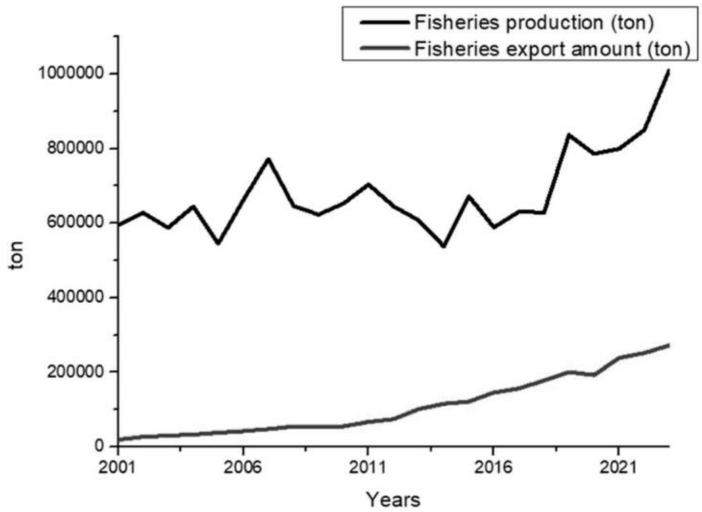
The world population is currently estimated to be 8 billion and will reach 10 billion by 2050 (UNFPA, 2023). Animal protein is vital to meet the nutritional needs of the growing population and is obtained from two important sources: land animals and aquatic animals (Sagun and Saygı, 2021).

Türkiye has great potential in aquaculture production due to its rich inland water resources, being surrounded by seas on three sides and its geographical location. The aquaculture sector in Türkiye has grown rapidly in recent years and continues to growth with production and practices that take into account the export potential and sustainable production approach (TEPGE, 2024). The aquaculture sector has been supported by the state since 2003 (TEPGE, 2023). Moreover, the use of advanced and modern technologies in aquaculture in Türkiye in recent years has contributed to the development of the sector. Thus, Türkiye is an important country in the world aquaculture market due to its growth potential in both foreign and domestic markets and its strategic location (Bilgüven and Can, 2018). In addition, Türkiye is a net exporter in the foreign trade of aquaculture products and the aquaculture sector constitutes one of the important sectors in Türkiye's exports (İZKA, 2024).

The foreign trade volume of aquaculture products in Türkiye is 1.4 billion U.S. dollars, which is 4 per thousand of the world trade volume. 68% of total aquaculture foreign trade is export and 32% is import (FAO, 2019). Countries which Türkiye exports aquaculture products are Russia, the Netherlands, Italy, Greece, the UK and Germany, while countries which

Türkiye imports aquaculture products are Morocco, Norway, Spain, Seychelles, Malaysia and Iceland (TEPGE, 2024). In the last 10 years, the production value of aquaculture products in Türkiye has increased by 7.5% (Yıldırım et al., 2022). Between 2000 and 2010, exports increased seven-fold in terms of value and increased continuously in the following years. Between 2010 and 2023, exports quadrupled and reached approximately 1.6 billion dollars (Ukav, 2023). Türkiye's aquaculture production, which was 582 thousand tons in 2000, increased by approximately 73% to 1 million 10 thousand tons in 2023. The amount of aquaculture products exported, which was 14 thousand 553 kg in 2000, increased significantly and reached 272 thousand 192 kg in 2023 (TUIK, 2025). Figure 1 shows the changes in Türkiye's aquaculture production and exports in the period 2000-2023.

Figure 1: Aquaculture production and exports in Türkiye (2000-2023).



Source: TUIK, (2025)

Figure 1 shows that the production of aquaculture products in Turkiye between 2000 and 2023 showed a fluctuating trend but continued to increase in the whole period. In the same period, the amount of aquaculture products exported increased gradually.

Figure 2 shows the share of Türkiye's aquaculture exports in total exports between 2000 and 2023.

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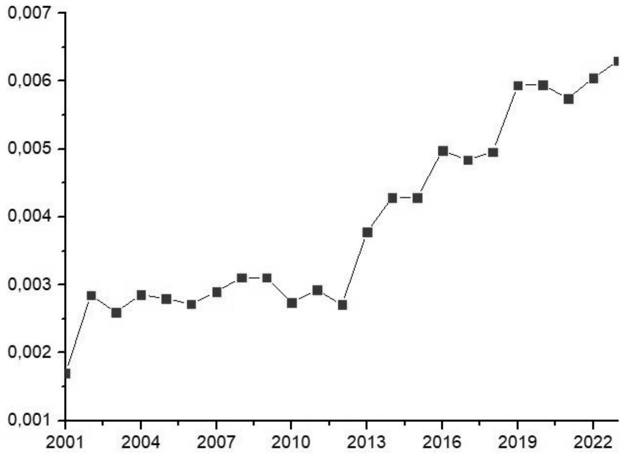


Source: TUIK, (2025)

Figure 2 shows that while the share of aquaculture exports in total exports was approximately 1 per thousand in 2000, it is around 6 per thousand in 2023. There was no significant increase in this ratio from 2000 to 2012, but it increased significantly from 2012 to 2023.

Türkiye's foreign trade in aquaculture products grew by around 15% in the 1990-2016 period, while the world's foreign trade in aquaculture products grew by around 5% in the same period (Dalkıran, 2019). The growth in Türkiye's foreign trade in aquaculture products was realized above the world average. Thus, the importance of the aquaculture sector in Türkiye is increasing day by day.

Machine learning is a sub-branch of artificial intelligence that enables the creation of models through mathematical and statistical algorithms and experiences gained through a set of data and making decisions in the future with these models (Naqa and Murphy, 2015). Machine learning is a subfield of Artificial Intelligence (AI) that has gained popularity over the years due to the increase in computational capacity in the context of data analysis that enables applications to work intelligently. Artificial neural networks (ANNs) in particular have come to the forefront in the last few years due to their increased capacity and the large volumes of data that can now be generated and controlled (Jordan and Mitchell, 2015).

Deep learning is often seen as part of a broader machine learning approach derived from artificial neural networks (ANNs) (Sarker et al., 2021). Deep learning models play a vital role in big data analysis with their structure consisting of many layers. These models represent data at increasingly abstract levels, making it possible to process large amounts of data. While traditional machine learning methods may be limited in analyzing big scale, deep learning overcomes this difficulty and provides meaningful information (Sonmez et al., 2024). The advantages of deep learning in big data analysis, especially in processing complex and voluminous data sets, have made deep learning preferable than supervised learning methods.

Although there have been many forecasting studies on aquaculture production and exports worldwide, most of these studies have been conducted using the ARIMA model. Studies on forecasting seafood exports in Türkiye are very limited and there is no study conducted with artificial neural networks (ANN). In this study, ANNs are used to forecast seafood exports in Türkiye and results obtained are compared. The main objective of the study is to gain a deeper understanding of the data in the time series forecasting and analysis processes and to determine the most appropriate deep learning models accordingly.

The contribution of this study is that, to the best of our knowledge, it is the first study to propose the use of deep learning models as an alternative method for forecasting Türkiye's seafood exports. In addition, this study shows that BiLSTM and GRU parameters offer a strong alternative for forecasting seafood exports.

Türkiye has a high potential for aquaculture production and exports. Therefore, it is important to show that the export volume of aquaculture products can be estimated by deep learning methods and to propose a model for this estimation. It is thought that increasing the accuracy of these predictions will provide advantages such as increasing efficiency in resource utilization, facilitating production and trade planning and developing marketing strategies. In addition, this study will shed light on future studies planned to be carried out to predict aquaculture exports by utilizing deep learning methods.

2. Literature Review

There is a limited literature on the estimation of aquaculture production, consumption, exports and imports. One of the initial ones belongs to Sankar (2011). Sankar in his 2011 study aims to estimate fish product exports in the Indian State of Tamilnadu based on inland and marine fish product export data between 1969 and 2008. In his study, he evaluates Autoregressive (AR), Moving Average (MA) and Autoregressive Integrated Moving Average (ARIMA) processes to determine the most appropriate stochastic model. As a result of the analysis, he determines that ARIMA (0,1,2) is the most appropriate model for fish product export forecasting.

Asiedu et al. (2020) aim to forecast the country's fish consumption, production and imports until 2030 with the ARIMA model using Ghana's fish consumption, production and import data for the period 1961-2018. They estimate that fish consumption in Ghana will increase at an annual rate of 0.61% from 2017 to 2030. In terms of supply, they expect that imports will contribute 46%, aquaculture 9% and capture fisheries 45% to fish production.

Mehmood et al. (2020) aim to forecast Pakistan's fisheries exports to the South Asian Association for Regional Cooperation (SAARC) for the period 2009-2025 using the Box-Jenkins methodology (ARIMA model). For this purpose, the authors use fisheries export data for the period 1975-2009. As a result of the analysis, the authors state that ARIMA (1,1,4) is the model with the best forecasting performance among the ARIMA models examined and predict that the value of the country's fisheries exports to the SAARC region will increase in 2025 compared to 2009.

Roy and Basu (2023), in their study to model and forecast Bangladesh's exports of three main fish products: dried fish, frozen fish and frozen shrimp, compare ARIMA models among themselves using data for the period between 1985-2019. As a result of the analysis, they determine the most appropriate forecasting model for all three products and revealed the future trends of Bangladesh's fisheries exports.

Rajani et al. (2024) conduct a time series analysis by comparing ARIMA models within the Box-Jenkins methodology with fish production data for the period from 1950-51 to 2021-22 to forecast fish production in India.

As a result of the analysis, they find that fish production will tend to increase until 2027.

It is seen that there is a limited number of studies using machine learning methods to estimate the export and import of fishery products. Sun and Yang (2023) use different artificial neural networks to forecast China's fish imports and exports. The authors report that the Bidirectional Long Short-Term Memory Recurrent Neural Network (BiLSTM) method has higher prediction accuracy and stability compared to commonly used models such as Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM) and Back-propagation (BP) neural networks.

Chaudhary and Choi (2023), in their study, focus on forecasting the import quantity of two fish species, Hairtail and Pollock, in South Korea using Deep Learning methods. They choose two Deep Learning methods for forecasting, namely Artificial Neural Network (ANN) and Long-Short Term Memory (LSTM). They state that LSTM performs better with higher accuracy and lower RMSE values among the two applied Deep Learning methods.

There is a single study on the Turkish economy and it belongs to Gür and Eşidir (2024). They utilize ARIMA and Multilayer Perceptron (MLP) methods to forecast Türkiye's monthly trout exports. Using monthly data for the period January 2005 - January 2023, they estimate trout export values for each month in the period February 2023 - December 2023. Their results show that ARIMA and artificial neural network methods are effective in forecasting Türkiye's monthly trout exports.

In the existing literature, it is seen that ARIMA method is utilized in the studies conducted for different countries in forecasting the trade, production and consumption of fish products, which constitute an important part of aquaculture products. In some of these studies, in addition to the forecasts made for the future, it was also investigated which model would give more accurate results in forecasting by comparing both ARIMA method with AR and MA methods and ARIMA models among themselves. However, there are also studies in the literature that investigate the most appropriate artificial neural network methods for forecasting seafood trade with machine learning and deep learning models. In one of these studies, Sun and Yang (2023) conclude that LSTM performed better among the different artificial neural networks compared in forecasting China's fish trade, while Chaudhary and Choi (2023), in another study comparing deep learning models in forecasting imports of two fish species in South Korea, conclude that the BiLSTM method is the most appropriate forecasting method.

There are few studies on forecasting seafood trade. In these studies, ARIMA model is generally used. In this study, LSTM, RNN, BiLSTM and GRU artificial neural networks are compared to predict Turkiye's seafood exports with deep learning models. As a result of the study, GRU and BiLSTM are found to be the most appropriate models. These results indicate that deep learning models can also be utilized in forecasting Türkiye's seafood exports. To the best of our knowledge, this is the first study to examine deep learning models in forecasting Turkey's seafood exports. It is also believed that utilizing deep learning method and determining the most appropriate deep learning model will reduce the margin of error in forecasting. According to Siami-Namini et al. (2018), deep learning based algorithms such as LSTM outperform traditional based algorithms such as ARIMA model in forecasting time series data (Siami-Namini et al., 2018).

3. Data Set

The data used in the model belongs to the period between years 2001 and 2023. The dependent variable of the model is the export value of aquaculture products (US$). The independent variables are monthly aquaculture export value (US$), aquaculture production (tons), monthly average US Dollar exchange rate (TL) and monthly total export value of Turkey (US$). In the analysis, monthly data (January 2001 - January 2023) obtained from the Turkish Statistical Institute (TUIK) and the Central Bank of the Republic of Turkey (CBRT) were used. Aquaculture production data obtained from TUIK database is annual and monthly average values are calculated and included in the analysis. Except for this process, missing data filling and data extraction operations were not performed.

The dataset contains a total of 1380 data and 5 features. The dataset was then divided into two clusters, 70% training and 30% testing.

Python 3.13.2 programming language was used to process, analyze and model the data set. The data analysis and modeling work was carried out in the Jupyter Notebook environment. At the beginning of the study, the basic libraries commonly used in Python were installed. These libraries include pandas for data analysis and manipulation, numpy for mathematical operations, matplotlib.pyplot for graphics and visualization, tensorflow for building and training iterative neural network models, plotly.express for interactive visualizations, and scikit-learn for machine learning algorithms.

4. Theoretical Framework

4.1. Performance Metric

Root Mean Square Error (RMSE) is a measure that evaluates how far the predictions are from the measured true values. it is widely used to assess how well the predictions fit the true values, and a lower RMSE value is considered indicative of a better fit (Liemohn et al., 2023). RMSE is an important measure for examining forecasting accuracy in many fields, as it can be used to compare the performance of various models or to judge how a model evolves over time (Chaudhary and Choi, 2023).

$$\text{RMSE}= \sqrt{\frac{\sum_{i}^{n}=1(\dot{y}i-yi)2}{n}} \quad (1)$$

Mean absolute error (MAE) is a metric that measures the average of the absolute differences between predicted and actual values. The MAE value increases as errors increase and each error is considered positive. MAE is calculated by averaging the absolute differences between predicted and actual values (Frías-Paredes et al., 2018).

$$\text{MAE}= \frac{1}{n}\sum_{i=1}^{n}(\dot{y}i-yi)^2 \quad (2)$$

The Mean Squared Error (MSE) measures the magnitude of the error of a regression model's predictions to the true values. The closer the value of the MSE is to zero, the closer the model's predictions are to the true values, and a lower MSE reflects a better model performance (Sarı et al., 2024).

$$MSE = {}^{1}/_{n}\sum\nolimits_{j=1}^{n}(y-\hat{y})_j^2 \quad (3)$$

Coefficient of Determination (R2) is a metric that measures how much the independent variables explain the variance of the dependent variable in regression analysis. This metric is used to assess how well the regression model is fitted and its predictive ability (Sezikli et al., 2024). It takes a value between 0 and 1; 0 indicates that the independent variables have no effect, while 1 indicates that they fully explain all variance. The higher the R^2, the higher the explanatory and predictive power of the model (Yetiz et al., 2021).

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y})^2}{\Sigma(y_i - \bar{y})^2} \tag{4}$$

4.2. Artificial Neural Networks

Recurrent Neural Network (RNN) is a type of artificial neural network specifically designed to work with sequential data (Alhajeri et al., 2024). Thanks to its built-in state (memory), the RNN learns dependencies between data and can infer meaningful contexts. This is the key feature that distinguishes them from ordinary feed-forward networks (Baruah et al., 2024). RNNs are ideal for working with sequential data thanks to their ability to remember past knowledge. This is a huge advantage in areas such as natural language processing, speech recognition and time series prediction (Mienye et al., 2024). RNNs have been successfully applied in various fields with superior performance in time series applications (Quradaa et al., 2024).

The Gated Recurrent Unit is a slightly simplified variation of the LSTM (Zarzycki and Ławryńczuk 2022). It makes training faster with fewer parameters and can avoid overlearning (Gao et al., 2020). It is effectively used in time series data such as financial data analysis, weather forecasting and energy consumption forecasting (Michael et al., 2020; Hu et al., 2024).

The LSTM model is a type of recurrent neural network (RNN) that works specifically on long sequences. The most widely accepted recurrent neural network in Machine Learning applications is the LSTM architecture (Lin et al., 2022). This architecture maintains a constant error stream by preserving error values from different times and layers, allowing the learning process of recurrent networks to continue uninterrupted (Peng et al., 2023). It is very successful in capturing long-term dependencies. The LSTM network model uses three different gates - input, output and forgetting - to compute the hidden state. The LSTM cell can maintain its latent state over time by processing data sequentially. LSTMs are frequently used in time series, natural language processing and biomedical applications (Yu, 2021).

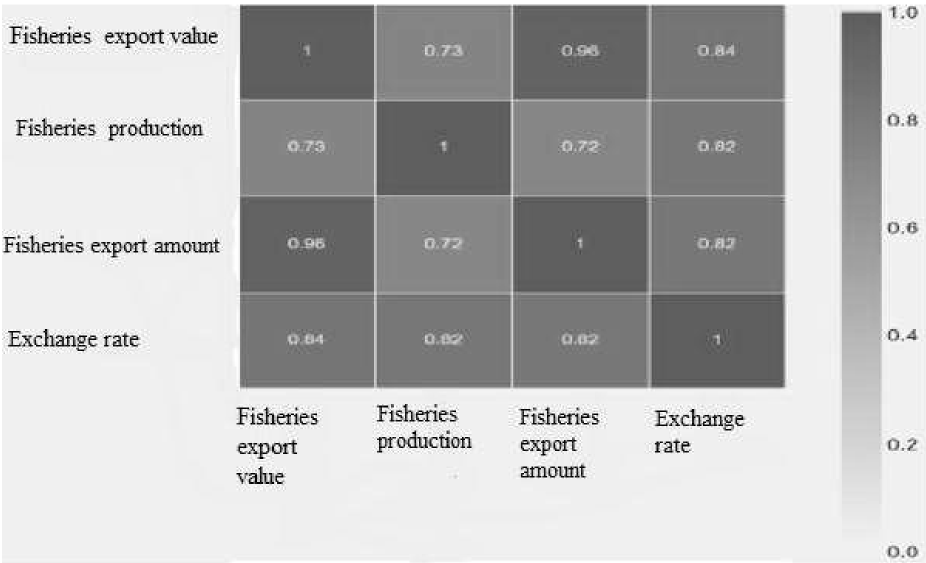
Bi-LSTM is the bi-directional version of the traditional LSTM (Siami-Namini et al., 2019). Bi-LSTMs exhibit higher performance by processing sequences in both forward and backward directions. This structure offers more flexibility when building the output of the model by providing access to past and future information (Xia et al., 2020). Thus, the network can better understand the input sequence. It also addresses the problems of gradient loss and information loss due to the RNN layer, which are commonly encountered during parameter training (Wan et al., 2022; Berus and Yakut 2024). Bi-LSTMs are frequently used in applications such as financial data prediction, sensor data analysis machine translation, sentiment analysis and text classification (Han and Fu 2023; Rath et al., 2024).

5. Application Results

In recent years, deep learning models have been widely used despite the complexity and high probability of bias in estimation processes. These models, which are preferred in many fields, provide the necessary data for the output parameter by learning the data changes in the input parameters independently of statistical approaches. Therefore, in this study, four different deep learning models that are most used are evaluated. To compare the performance of the models and to determine which model provides the most accurate predictions, the performance was measured using MAE, MSE, RMSE and R^2 error metrics. Figure shows the MSE, MAE, RMSE and R^2 results obtained from the models used in the study.

In machine learning applications, selecting and building the right features can improve the performance of the model and prevent overfitting. Therefore, Pearson correlation method was used to examine the relationships between variables. The correlation analysis was performed with Python programming language and illustrated with a heat map (Figure 3). Pearson Correlation Method is widely used to evaluate the relationship between numerical properties (Sezikli et al., 2024). Correlation coefficients less than 0.3 indicate a very weak relationship or no correlation; 0.3-0.5 indicates a weak correlation; 0.5-0.7 indicates a moderate correlation; 0.7-0.9 indicates a strong correlation; and greater than 0.9 indicates a very high correlation (Mukaka, 2012). According to Figure 3, there is a very strong correlation between the export of aquaculture products and the amount of aquaculture products exported among the other variables. These results show that the data are suitable for machine learning.

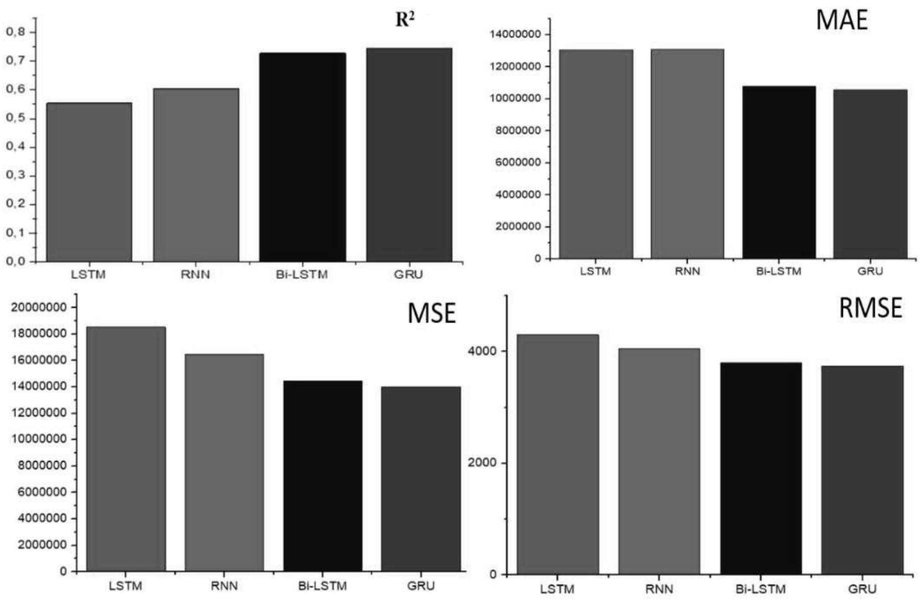
Figure 3. Pearson correlation of aquaculture export parameters.



The fact that the R^2 score is very close to 1 and the error metrics are close to zero indicates that this model works effectively and the predicted values are very close to the actual values (Sezikli, 2024). GRU (0.7449) and Bi-LSTM (0.7281) are the models with the highest R^2 values. This means that the predicted values are closest to the actual values. RNN (0.6032) and LSTM (0.5534) have lower R^2 values and their ability to explain the data is weaker. Therefore, GRU (0.745) was identified as the best performing model on our data set. The BI-LSTM model reached an R^2 value very close to the GRU model.

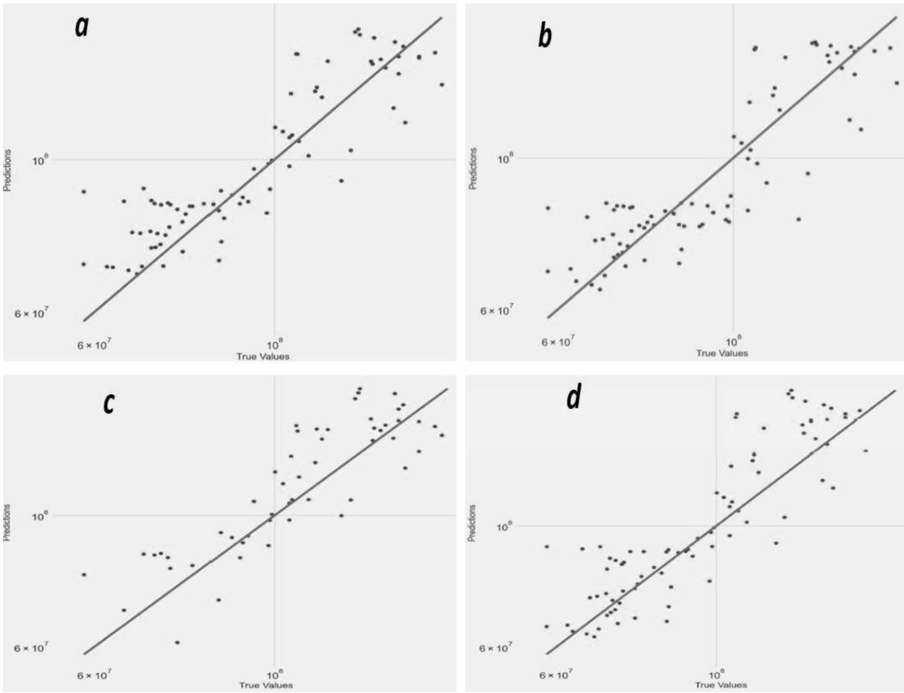
To evaluate the performance of a model, in addition to the R^2 score, error performance metrics such as MAE, MSE and RMSE should also be examined. The lower the error metrics (MAE, MSE, RMSE), the better the performance of a model is considered. As can be seen in Figure 4, the GRU model obtained very low results in terms of MSE, RMSE and MAE values. GRU shows the best prediction performance with the lowest MAE (10582729.22), MSE (13997544.23) and RMSE (3741.32) values. This shows that the performance of the GRU model is the best among the other models used. Bi LSTM performs close to GRU and has the second lowest error rates. LSTM and RNN have higher error values than Bi-LSTM and GRU. Especially LSTM (13074214.07 MAE, 18521242.26 MSE) shows the worst performance as the model with the highest error rate.

Figure 4. Error metrics of models



The fact that GRU has fewer parameters and is more suitable for real-time applications confirms the results obtained (Yang et al., 2020; Pudikov and Brovko 2020; Cahuantzi et al., 2023). The gating mechanisms of Bi-LSTM and GRU effectively manage long-term dependencies in recurrent neural networks, can handle sequences of different lengths, and provide strong generalization and stability (Sun and Yang 2023). These two models exhibited high forecasting accuracy on small-sample time series data on fisheries import and export trade volumes. The performances of RNN and LSTM were lower, LSTM performed weaker than expected. This may be due to the model not learning the data well enough or experiencing overfitting during the training process.

Figure 5. Distributions of actual values and model predictions (a: GRU, b: BI-LSTM, c: RNN, d: LSTM)



In order to visualize the results of the models created in the study, scatter plots of the actual and predicted values produced by these models are presented in Figure 5. In these graphs, the x-axis represents the actual values, and the y-axis represents the predicted values. The scatter plots generated for each model were compared with the y = x line passing through the center of the plot. When the points are close to the y= x line, it means that the model performs well, and when the points are far away, it means that the model performs poorly. When these graphs are analyzed, it is observed that the GRU model has the least difference between the actual values and the predicted values and makes good predictions.

6. Conclusion

Monitoring national and international markets and establishing early warning systems is a critical requirement for sustainable development in the aquaculture sector. Effective market monitoring will support the efficient use of resources by providing guidance to policy makers and sector stakeholders. In addition, bioeconomy-oriented approaches developed by combining biological and economic studies will make significant contributions to the long term growth of the sector.

In this study, four different deep learning models (LSTM, RNN, Bi-LSTM and GRU) are compared to forecast Turkish seafood exports. The GRU model stands out as the most successful model for forecasting seafood exports. Bi-LSTM can also be considered as a good alternative. RNN and LSTM showed relatively lower performance.

In conclusion, the findings of this study show that artificial neural network-based forecasting models can produce successful results in dynamic processes such as seafood exports. The advantages offered by GRU and Bi-LSTM models can be considered as prominent approaches in this type of time series analysis. Future research, supported by more comprehensive data sets and advanced models, can contribute to the realization of aquaculture export forecasts with higher accuracy.

Morever, Türkiye has higly potential of seafood's production and export because of geographical location and its internal and external water resources. Therefore, we believe that estimating seafood export will contribute to making more effective foreign trade policy in the country.

It is estimated that being able to make predictions regarding seafood export, having been increasingly significant to Türkiye's export volume in recent years, could provide a competitive advantage to this sector. Furthermore, the results of this study will encourage other researchers, who are interested in this subject, to conduct forecasting studies for seafood exports. This study is considered an important step towards improving data-driven decision-making processes in the aquaculture sector and may pioneer new studies for future research.

References

Alhajeri, M. S., Ren, Y. M., Ou, F., Abdullah, F. and Christofides, P. D. (2024), "Model predictive control of nonlinear processes using transfer learning-based recurrent neural networks," *Chemical Engineering Research and Design*, 205, 1-12. https://doi.org/10.1016/j.cherd.2024.03.019

Asiedu, B., Iddrisu, S. and Failler, P. (2023), "Yesterday, today, and tomorrow's fish consumption: Analysis of present and prospective fish consumption in Ghana by 2030," *Cogent Food & Agriculture*, 9(1), 2224603. https://doi.org/10.1080/23311932.2023.2224603

Baruah, R. D. and Organero, M. M. (2024), "Explicit context integrated recurrent neural network for applications in smart environments," *Expert Systems with Applications*, 255, 124752. https://doi.org/10.1016/j.eswa.2024.124752

Berus, Y. and Yakut, Y. B. (2024), "Derin Öğrenme (1D-CNN, RNN, LSTM, BiLSTM) ile Enerji Tüketim Tahmini: Diyarbakır AVM Örneği," *Dicle Üniversitesi Mühendislik Fakültesi Mühendislik Dergisi*, 15(2), 311-322. https://doi.org/10.24012/dumf.1415055

Bilgüven, M. and Can, G. (2018), "Balık yemlerinde balık unu yerine tavuk ununun kullanılma olanakları," *Bursa Uludağ Üniversitesi Ziraat Fakültesi Dergisi*, 32(2), 189-197.

Cahuantzi, R., Chen, X. and Güttel, S. (2023), "A comparison of LSTM and GRU networks for learning symbolic sequences," in *Science and Information Conference*, Cham: Springer Nature Switzerland, pp. 771-785.

Chaudhary, A. and Choi, S. (2023), "Forecasting fish import using deep learning: A comprehensive analysis of two different fish varieties in South Korea," *Smart Media Journal*, 12(11), 134-144. https://doi.org/10.30693/SMJ.2023.12.11.134

Dalkıran, G. (2019), *A Study on International Competitiveness of Aquaculture Businesses in Turkey* [Doctoral thesis, Karabuk University Graduate Education Institute Business Administration].

Devaraj, P., Babu, V. and Cengiz, E. I. (2021), "Qualitative detection of formaldehyde and ammonia in fish and other seafoods obtained from Chennai's (India) fish markets," *Environmental Monitoring and Assessment*, 193(2), 1-8. https://doi.org/10.1007/s10661-021-08871-z

FAO (2016), *The State of World Fisheries and Aquaculture*, Rome.

FAO (2019), *Global Statistical Collection*, available at: http://www.fao.org/fishery/en (accessed 08 December 2024)

Frías-Paredes, L., Mallor, F., Gastón-Romeo, M. and León, T. (2018), "Dynamic mean absolute error as new measure for assessing forecasting errors," *Energy Conversion and Management*, 162, 176-188. https://doi.org/10.1016/j.enconman.2018.02.030

Gao, S., Huang, Y., Zhang, S., Han, J., Wang, G., Zhang, M. and Lin, Q. (2020), "Short-term runoff prediction with GRU and LSTM networks without requiring time step optimization during sample generation," *Journal of Hydrology*, 589, 125188. https://doi.org/10.1016/j.jhydrol.2020.125188

Gür, Y. E. and Eşidir, K. A. (2024), "Türkiye alabalık ihracatının ARIMA ve multilayer perceptron modelleri ile tahmini," *Turkish Studies-Economy*, 19(1), 187-206. https://dx.doi.org/10.7827/TurkishStudies.70444

Han, C. and Fu, X. (2023), "Challenge and opportunity: deep learning-based stock price prediction by using Bi-directional LSTM model," *Frontiers in Business, Economics and Management*, 8(2), 51-54.

Hu, J., Jia, Y., Jia, Z. H., He, C. B., Shi, F. and Huang, X. H. (2024), "Prediction of PM 2.5 concentration based on deep learning for high-dimensional time series," *Applied* Sciences, 14(19). https://doi.org/10.3390/app14198745

İZKA, (2024), "*Dünyada ve Türkiye'de Su Ürünleri Sektörü 2024*", İzmir Kalkınma Ajansı. https://izka.org.tr/wp-content/uploads/2024/11/Dunyada-Ve-Turkıyede-Su-Urunlerı-Sektoru.pdf

Jordan, M. I. and Mitchell, T. M. (2015), "Machine learning: Trends, perspectives, and prospects," *Science*, 349(6245), 255-260. https://doi.org/10.1126/science.aaa8415

Liemohn, M. W., Shane, A. D., Azari, A. R., Petersen, A. K., Swiger, B. M. and Mukhopadhyay, A. (2021), "RMSE is not enough: Guidelines to robust data-model comparisons for magnetospheric physics," *Journal of Atmospheric and Solar-Terrestrial Physics*, 218, 105624. https://doi.org/10.1016/j.jastp.2021.105624

Lin, S. S., Shen, S. L. and Zhou, A. (2022), "Real-time analysis and prediction of shield cutterhead torque using optimized gated recurrent unit neural network," *Journal of Rock Mechanics and Geotechnical Engineering*, *14*(4), 1232-1240. https://doi.org/10.1016/j.jrmge.2022.06.006

Mehmood, Q., Sial, M. H., Sharif, S., Hussain, A., Riaz, M. and Shaheen, N. (2020), "Forecasting the fisheries production in Pakistan for the year 2017-2026, using box-jenkin's methodology," *Pakistan Journal of Agricultural Research*, *33*(1),140. http://dx.doi.org/10.17582/journal.pjar/2020/33.1.140.145

Michael, N. E., Bansal, R. C., Ismail, A. A. A., Elnady, A. and Hasan, S. (2024), "A cohesive structure of Bi-directional long-short-term memory (BiLSTM)-GRU for predicting hourly solar radiation," *Renewable Energy*, *222*, 119943. https://doi.org/10.1016/j.renene.2024.119943

Mienye, I. D., Swart, T. G. and Obaido, G. (2024), "Recurrent neural networks: A comprehensive review of architectures, variants, and applications," *Information*, *15*(9), 517. https://doi.org/10.3390/info15090517

Mukaka, M. M. (2012), "Statistics corner: A guide to appropriate use of correlation coefficient in medical research," *Malawi Medical Journal*, 24(3), 69-71.

El Naqa, I. and Murphy, M.J. (2015), What Is Machine Learning? In: El Naqa, I., Li, R., Murphy, M. (eds) "Machine Learning in Radiation Oncology," *Springer, Cham*, pp 3–11 https://doi.org/10.1007/978-3-319-18305-3_1

Quradaa, F.H. and Shahzad, S. (2024), "Almoqbily, R.S. A systematic literature review on the applications of recurrent neural networks in code clone research," *PLoS One*, *19*,1-40 https://doi.org/10.1371/journal.pone.0296858

Peng, F. L., Qiao, Y. K. and Yang, C. (2023), "A LSTM-RNN based intelligent control approach for temperature and humidity environment of urban utility tunnels," *Heliyon*, *9*(2). https://doi.org/10.1016/j.heliyon.2023.e13182

Prester, L. (2011), "Biogenic amines in fish, fish products and shellfish: A review," *Food Additives and Contaminants Part A, Chemistry, Analysis, Control, Exposure and Risk Assessment*, *28*(11), 1547–1560. https://doi.org/10.1080/19440049.2011.600728

Pudikov, A. and Brovko, A. (2020), "Comparison of LSTM and GRU recurrent neural network architectures," In *International Scientific and Practical Conference in Control Engineering and Decision Making* (pp. 114-124). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-65283-8_10

Rajani, M., Balasubramanian, A. and Sudhakar, O. (2024), "Forecasting of Fish Production of India using ARIMA Models," *Ecology, Environment & Conservation (0971765X)*, *7*. http://doi.org/10.53550/EEC.2024.v30i04s.011

Rath, S., Das, N. R. and Pattanayak, B. K. (2024), "Stacked BI-LSTM and E-optimized CNN-A hybrid deep learning model for stock price prediction," *Optical Memory and Neural Networks*, *33*(2), 102-120. https://doi.org/10.3103/S1060992X24700024

Roy, A. and Basu, S. (2023), "Modelling and Forecasting of Frozen Shrimp, Frozen Fish, and Dry Fish Export in Bangladesh," *Barishal University Journal of Social Sciences*, *1719*(398694), 97.

Sagun, O. K. and Saygı, H. (2021), "Consumption of fishery products in Turkey's coastal regions," *British Food Journal*, *123*(9), 3070-3084.

Sankar, T. J. (2011), "Forecasting Fish Product Export in Tamilnadu- A Stochastic Model Approach," *Recent Research in Science and Technology*, *3*(7), 104-108.

Sarı, P., Bedirhan, İ. D., and Sel, Ç. (2024), "Comparıng The Practıcal Dıfferences Between Decısıon Tree And Random Forest Algorıthms In Estımatıng Housıng Prıces," *Current Trends in Computing*, *1*(2), 149-157.

Sarker, I. H., Furhad, M. H. and Nowrozy, R. (2021), "Ai-driven cybersecurity: an overview, security intelligence modeling and research directions," SN Computer Science, 2(3), 1-18. https://doi.org/10.1007/s42979-021-00557-0

Sezikli, M., Alkan, N., Zontul, Ü. and Elabiad, Z. (2024), "Makine Öğrenmesi Yöntemleriyle Yenilenebilir Güneş Enerjisi Üretiminin Meteorolojik Veriler Kullanılarak Tahmin Analizi," *Havacılık ve Uzay Teknolojileri Dergisi*, *17*(2), 180–202.

Siami-Namini, S., Tavakoli, N. and Namin, A. S. (2018), "A comparison of ARIMA and LSTM in forecasting time series," *17th IEEE international conference on machine learning and applications (ICMLA)* (pp. 1394-1401). Ieee. https://doi.org/10.1109/ICMLA.2018.00227

Sun, M. and Yang, H. (2023), "Forecasting Model of Fishery Import and Export Trade Data Using Deep Learning Method," In *2023 International Conference on Blockchain Technology and Applications (ICBTA)* (pp. 48-51). IEEE. https://doi.org/10.1109/ICBTA60381.2023.00017

Sonmez, M. E., Gumus, N. E., Eczacioglu, N., Develi, E. E., Yücel, K. and Yildiz, H. B. (2024), "Enhancing microalgae classification accuracy in marine ecosystems through convolutional neural networks and support vector machines," *Marine Pollution Bulletin*, *205,* 116616. https://doi.org/10.1016/j.micron.2023.103506

TEPGE, (2023), "Ürün Raporu Su Ürünleri 2023," Tarımsal Ekonomi ve Politika Geliştirme Enstitüsü.https://arastirma.tarimorman.gov.tr/tepge/Belgeler/PDF%20%C3%9Cr%C3%BCn%20Raporlar%C4%B1/2023%20%C3%9Cr%C3%BCn%20Raporlar%C4%B1/Su%20%C3%9Cr%C3%BCnleri%20%C3%9Cr%C3%BCn%20Raporu%202023-373%20TEPGE.pdf

TEPGE, (2024), "Ürün Raporu Su Ürünleri 2024," Tarımsal Ekonomi ve Politika Geliştirme Enstitüsü.https://arastirma.tarimorman.gov.tr/tepge/Belgeler/PDF%20%C3%9Cr%C3%BCn%20Raporlar%C4%B1/2024%20%C3%9Cr%C3%BCn%20Rap orlar%C4%B1/Su%20%C3%9Cr%C3%BCnleri%20%C3%9Cr%C3%BCn%20Raporu%202024-403%20TEPGE.pdf

Ukav, İ. (2023), "Türkiye Su Ürünleri Dış Ticareti," *Econharran*, *7*(11), 16-22.

UNFPA (2018), "*The state of world population 2018*," available at: https://turkey.unfpa.org/en/news/state-world-population-2018-0 (accessed 05 October 2024).

Wan, H., Tian, X., Liang, J. and Shen, X. (2022), "Sequence-feature detection of small targets in sea clutter based on Bi-LSTM," *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1-11. https://doi.org/10.1109/TGRS.2022.3198124

Xia, T., Song, Y., Zheng, Y., Pan, E. and Xi, L. (2020), "An ensemble framework based on convolutional bi-directional LSTM with multiple time windows for remaining useful life estimation," *Computers in Industry*, 115, 103182. https://doi.org/10.1016/j.compind.2019.103182

Yang, S., Yu, X., and Zhou, Y. (2020), "Lstm and gru neural network performance comparison study: Taking yelp review dataset as an example," *International workshop on electronic communication and artificial intelligence (IWECAI)* (pp. 98-101). IEEE. https://doi.org/10.1109/IWECAI50956.2020.00027

Yetiz, F., Terzioğlu, M. and Kayakuş, M. (2021), "Makina Öğrenmesi Yöntemleri ile Türk Mevduat Bankalarının Müşteri Tahminine Yönelik Bir Uygulama," *Sosyoekonomi*, 29(50), 413-432. https://doi.org/10.17233/sosyoekonomi.2021.04.19

Yıldırım, Ç., Türkten, H., and Ceyhan, V. (2022), "Evaluation of competitiveness power of fishing and aquaculture industry in Turkey," *Ege Journal of Fisheries and Aquatic Sciences*, 39(3), 243-252. https://doi.org/10.12714/egejfas.39.3.10

Yu, S. Z. (2021), "Explicit duration recurrent networks," *IEEE Transactions on Neural Networks and Learning Systems*, *33*(7), 3120-3130. https://doi.org/10.1109/TNNLS.2021.3051019

Zarzycki, K. and Ławryńczuk, M. (2022), "Advanced predictive control for GRU and LSTM networks," *Information Sciences*, 616, 229-254. https://doi.org/10.1016/j.ins.2022.10.078