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Forecasting of Export Volume Using Artificial Intelligence Based Algorithms

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Abstract
Technological breakthroughs have transformed communication and taken transportation, health, and commerce to an unprecedented level. In this way, sudden developments have rapidly affected all countries. In this context, analysis methods are changing compared to the past, and annual analyses fail to catch the trend even for macroeconomic indicators. In this paper, new artificial intelligence-based estimation methods were used to see the future trend of export volume, and their estimation performances were compared by adding them to the classical econometric method. Historical quarterly data from 2013 to 2021 were used in the training and testing phases of the models. For this purpose, the variables of gross domestic product, foreign direct investment, and dollar exchange rate, which affect the export volume, were determined as inputs in estimating the export volume. According to the analysis results, support vector machine model was determined as the best method for predicting export volume in Turkey. This study can provide an essential basis for policymakers to export estimation and formulate their export-enhancing policies effectively.

1. Introduction

The Covid-19 pandemic, which affected the whole world in 2019, radically changed the economy, trade, and how countries and companies do business. This change has shaken the economies profoundly, and as a result, most countries have experienced economic constriction, reaching 20% of their GDP [1]. According to this report, this economic shrinkage is the most severe recession after World War II. In terms of Turkey, there was no constriction in GDP after the pandemic. On the contrary, there was a growth of 1.8% in 2020 and 11% in 2021 [2], [3]. The most crucial driving force behind the growth in this period was Turkey's exports.

In the post-1980 neoliberal period, Turkey was in a position to import more in its trade with other countries (see Figure 1) and thus was in a situation where there was a trade deficit. The foreign trade deficit causes the current account deficit. Therefore, even if the economy continues to grow, it is compensated by increasing the current account deficit. Although this situation partially supports the growth of the country's economy, it is not sustainable. The growth provided by the increase in exports is the healthiest among others. In this respect, exports and their future trend are essential for Turkey.

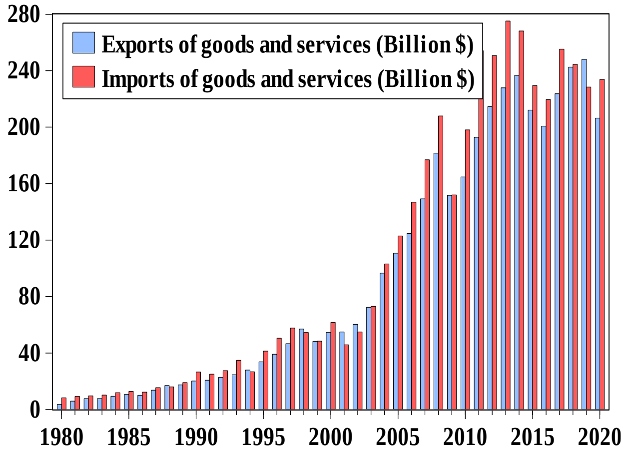

Figure 1. Turkey's exports and imports

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With globalization, trade between economies has increased and accelerated simultaneously. The changes are experienced rapidly, and a situation that comes into being in one country affects other countries much faster than before. Therefore, this situation should be considered when establishing prediction models. For this reason, datasets created with as short intervals as possible will be beneficial both in capturing changes quickly and predicting the future. With this motivation, this study uses quarterly data between 2013 and 2022. Then, artificial intelligence-based (AI-based) and classical multilinear regression (MLR) estimate the export volume and determine the best estimating method.

The literature about estimation and forecasting methods for export is reviewed in the second part of the study. In the third part, the dependent and independent variables and the created data set and statistics are examined, then the details of the models used in the study are discussed. Finally, the results are evaluated and compared according to the selected performance criteria in the fourth section.

2. Literature Review

The relationship between exports and the other indicators has been determined using statistical and econometric models in the previous studies. However, the prediction performance of artificial intelligence-based models draws attention in today's literature. While statistical models can adequately model linear relationships between data, they have difficulty seeing nonlinear relationships. For this reason, it is tried to eliminate this deficiency with artificial intelligence-based models [4], [5]. In particular, the kernel functions of machine learning models have effective results in responding to nonlinear relationships. Therefore, MLR and AI-based models were developed in this study, and their results were compared. The variables were determined by examining previous studies. Some studies in this area are summarized below.

Shetewy et al. (2022) evaluated the financial sector development and the effect of internet use on export volume for thirty Chinese provinces using two distinct approaches and a data set spanning 18 years. The study developed prediction models using Panel-Corrected Standard Error (PCSE), an econometric method, and Gaussian Process Regression (GPR) moles as an ML model. According to the study results, panel data analysis showed that internet usage increased exports for all provinces of China. In addition, internet usage in high-middle-developed provinces significantly affects exports. The results of the GPR model revealed that GDP, internet use, and financial development are essential indicators for predicting export growth.

Qiu (2022) developed three different models to model and predict the export value from China to the USA, considering six variables and the seasonal variations of these variables. ARIMA and AR-GARCH statistical models were compared with the artificial neural network model. Performance metrics were chosen to evaluate the estimation results of the developed models. Although there are differences in the estimation results, the estimation results in the three models were satisfactory. It has been suggested that the developed forecasting models can be used for planning to improve China's exports.

Liu (2021) developed a forecasting model using artificial neural networks and fuzzy theory for index estimation of foreign trade exports. The ANFIS model, which is used by combining the two methods, was used. In addition, the ARIMA model was also estimated to compare the results of this model. As a result, the estimation adequacy of both models is at an acceptable level. Furthermore, the study's findings show that the fuzzy neural network estimating model gives better results for export trend forecasting.

Costantiello et al. (2021) estimated the import of goods for 28 countries in their study. In the study, a data set for 2010-to 2019 was designed. The study consisted of two stages. First, analyses were made using classical statistical methods. Then, prediction models were developed using different machine learning techniques to compare the results of these analyses.

Jia et al. (2021) proposed a machine learning-based model to predict the destination of oil exports using oil shipment information. Crude oil shipment dataset covering the years 2013-2016 was created using cargo, ship, geographical, and macroeconomic variables. According to the estimation model results, it was determined that quality and cargo size were adequate for destination estimation. Furthermore, the study has shown that it effectively predicts oil trading models in microdata.

Suler et al. (2021) estimated exports from the Czech Republic to China using artificial neural networks (ANN). An ANN model with the best estimation ability was developed using historical data in the study. Models were constructed with three different scenarios. These scenarios are established with time series of data with a time delay of 1 month, five months, and ten months. As a result, it has been observed that the applied Multi-Layer Perception is the most efficient in estimating exports.

Minh Khiem et al. (2021) developed a model that predicts the price of shrimp products exported from Vietnam to the USA using ML algorithms. A data set covering the years 1995-2019 was used in the study. Thirty-three different variables were determined as input variables. First, however, the Akaike Information Criterion (AIC) was calculated, and 15 variables that gave the most accurate result were used. Next, prediction models are developed using random forest and gradient boosting decision tree algorithms. The study's findings showed that the random forest algorithm for six-month predictions and the gradient boosting algorithm for shorter predictions perform more effectively.

Research on exports draws attention to the literature in economics and econometrics. Moreover, many studies have long examined the link between exports and the economy. In the continuation of the literature review, current studies using econometric methods were examined to set an example for this research.

Nugroho and Lakner (2022) conducted a panel data analysis using a data set covering the years 1990-2018 to examine the effect of globalization on coffee exports. The GDP and exchange rate variables positively affect coffee exports. Furthermore, the relationship between mike coffee exports with GDP, exchange rate, and commercial and political globalization index has been examined. As a result of the study, it has been seen that the commercial globalization index has a negative effect on coffee exports, while the political globalization index has a favorable impact on exports.

Lazarov (2019) applied the vector autoregression (VAR) model and Granger causality test to analyze Macedonia's export structure based on products and observe the contribution of exports to the country's development. According to the findings, exports and economic growth have a favorable and statistically significant association.

Mukhlis and Qodri (2019) used a data set spanning the years 1980 to 2017 to investigate the relationship between Indonesia's export, import, foreign direct investment, and economic development variables. The link between the variables was modeled using the vector error correction model (VECM). The study's conclusions revealed that foreign direct investment had an impact on Indonesia's economic growth.

3. Material and Method

3.1. Data Collection Process

In the study, gross domestic product (GDP), foreign direct investment (FDI), and exchange rate are used to estimate Turkey's export volume. As of the study period, the most up-to-date data were collected quarterly from different data sources. Table 1 describes variables, abbreviations, and units.

The relations between economic growth and exports and imports of countries have been discussed in detail in the economics literature. Most studies have looked at the causality between economic growth and exports. There is a causality running from exports to growth in [16]–[18] studies. In [19]–[21] studies, on the other hand, the opposite is the case. In other words, growth affects exports positively. In [22]–[25] studies, on the other hand, a two-way causality can be mentioned. Exports were chosen as the dependent variable in this study, and the predictive power of growth on exports was examined to measure the effect of change in the Turkish economy on exports.

Table 1. Definition and descriptive statistics of the variables

Variables	**Export Volume**	**Gross Domestic Products**	**Foreign Direct Investment**	**USD/TRY Exchange Rate**
Abbrivaition	EXP	GDP	FDI	ER
Unit	US Dollars, Billions - Quarterly	US Dollars, Billions - Quarterly	US Dollars, Billions - Quarterly	1 US Dollar Equivalence
Source	UN Comtrade, 2021	Turkstat	CBRT	CBRT
Mean	42.93	897.83	43.92	4.43
Std	6.31	441.47	7.35	2.34
Max	64.44	2,313.81	58.54	11.16
Min	32.40	388.66	32.07	1.78
Skewness	1.37	1.34	0.11	0.93
Kurtosis	5.54	4.61	1.89	3.17

In the economic literature, it has been shown that foreign direct investment generally positively affects economies' exports. Countries where foreign investment comes from, have developed their export supply capacity strongly over time. In this way, the export content changed, which led to the production of higher technological products. In addition, this development contributed to the structural development of exports. This contribution is not always linear. UNCTAD reported a U-shaped relationship between exports and FDI [26]. Accordingly, while FDI is beneficial for a newly developing country in exports, this relationship weakens over time. Then, the export structure continues to strengthen, and when it comes to the stage of development, the FDI-export relationship gets stronger again. [27], [28] studies also reveal a positive relationship between FDI and exports.

One of the best-known hypotheses in economics is the one that reveals the relationship between the value of money and foreign trade. For example, if the country's currency depreciates against foreign currencies, exports will increase because they will become cheaper, and imports will decrease because they will become expensive. Many studies test this hypothesis, such as [29], [30]. However, the period in which this hypothesis was put forward was when the countries' economies accepted the fixed exchange rate regime. Each country fixed the external value of its currency to the reserve currencies, and the currency of the devaluing country became cheaper, and imports decreased while exports increased. A similar situation cannot be fully mentioned in the floating exchange rate regime.

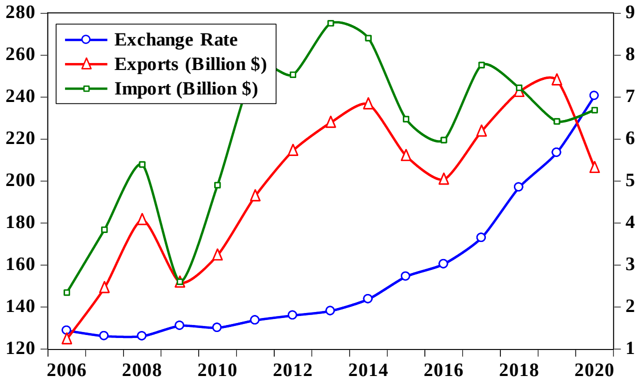

Figure 2. Export, Import and Exchange rate in Turkey

Figure 2 shows that despite the rapid depreciation of the Turkish lira against the dollar in recent years, the increase in exports remained more limited. In fact, when we look at the last period, it is seen that there has been an increase in imports, contrary to expectations. The main reason behind this situation is that after the pandemic, even though the prices for the economies of the countries to which goods are exported, the demand has decreased. On the other hand, domestic demand increased in the growing Turkish economy, which led to an increase in imports towards the end of 2020.

In this study, the pattern between these variables, which significantly impact exports, and export volume, will be investigated. Based on this pattern, it will try to find the most reliable forecasting method. Two different AI-based techniques were used in the study, and these techniques were compared with the classical econometric method. The data set was divided into 70% training and 30% test set to compare these methods.

It is seen in Figure 3 that the data used in the application are on different scales. These scale differences in terms of both econometric and artificial intelligence-based methods may cause the results to be erroneous and biased. Preprocessing is required to prevent these disruptions. In this respect, there are two most commonly used methods to scale the variables in the data set to a particular scale. One of them is to normalize the data set to a specific range. The other is standardization. In this study, the standardization method was applied. This method is represented as $X' = \frac{X-\mu}{\sigma}$. Here μ is the mean of the feature values, and σ is the standard deviation of the feature values. In this way, more meaningful comparisons can be made, and more meaningful results can be achieved.

3.2. Multilinear Regression (MLR)

One of the most frequently used tools in examining the relationship between dependent and independent variables is MLR. In its general structure, the MLR is represented as follows:

$$Y_i = \beta_1 + \beta_2 X_{2i} + \beta_3 X_{3i} + \cdots + \beta_k X_{ki} + u_i \quad (1)$$

In this equation, the variable Y is the dependent variable, the variables Xs are the explanatory variables, and u is the random term. In this study, the data set is the time series data of Turkey. For an MLR method to be made on the time series, specific preliminary tests must be made for the data set beforehand. The most important thing is to test whether the variables are stationary to avoid spurious regression. If the variables are not stationary, it is ensured that all variables are stationary at the same level so that the analysis can be performed. Another critical assumption for the MLR model is that there is no multicollinearity between the variables in the regression [31]. This problem arises when there is a high correlation between variables, which leads to unreliable and unstable regression coefficient estimates. After these tests are done, MLR analysis can be done.

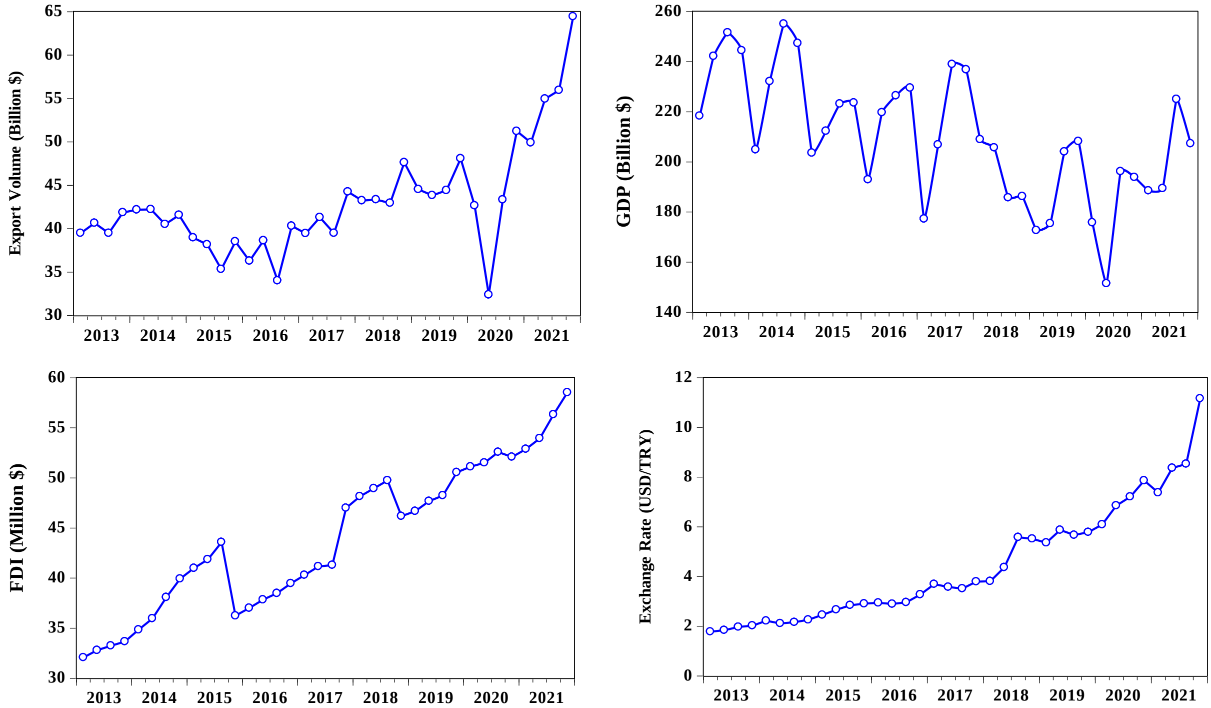

Figure 3. The change of the variables by years

3.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

By combining different methods, models can produce more effective and efficient results. New models created by different models are called hybrid models. Using the two models together will create an efficient framework, considering each model has different advantages. The Adaptive Neuro-Fuzzy Inference System (ANFIS), which was first used in 1991, is one of the best examples of hybrid models. Many applications have been made with the developed framework, and effective results have been obtained. This method allows the use of artificial neural networks and fuzzy systems together. Fuzzy systems are rule-based systems and provide results by making inferences according to the determined rules [32]–[34].

On the other hand, artificial neural networks have the ability to learn. They can learn the model's relationship between input and output thanks to their learning ability. When combined with fuzzy-based models' ability to understand verbal expressions better, this ability can produce effective results. Therefore, this study used the ANFIS method to develop a forecasting model [35].

The ANFIS architecture is made up of layers that contain nodes. The second, third, and fifth layers have fixed nodes, while the first and fourth layers have adaptive nodes. Fuzzy, product, normalized, defuzzification, and total output layers are the names of these layers [36]. ANFIS is related to the Takagi-Sugeno fuzzy inference system because of its structure. In Figure 4, the basic ANFIS structure is modeled. This structure has two inputs and one output variable.

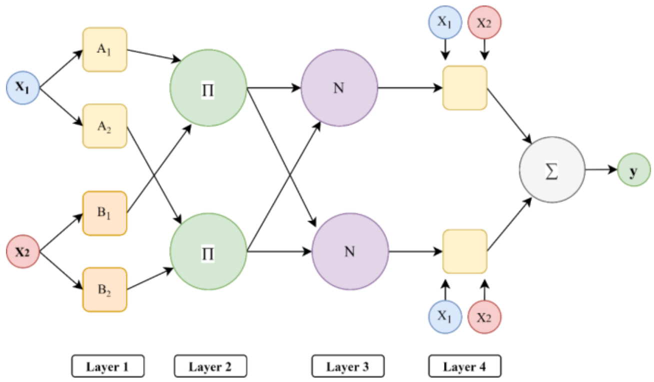

Figure 4. ANFIS framework with two inputs and one output

Layer 1 is the layer where the data becomes fuzzy. The input values are transferred to the next layer thanks to the nodes in this layer. The input value determines the output value of the layer, and the membership degrees are determined according to the selected membership function. The rule layer is the second layer. The effect of the Sugeno-type fuzzy logic structure may be seen at each node's output.

The layer containing the normalization process is the third layer containing fixed nodes. It takes the second layer's outputs as input and ensures that the data is scaled. The layer where the fuzzy expressions are clarified is the fourth layer. Normalized rules are recalculated by multiplying them with linear functions in this layer. Finally, the fifth layer is the layer containing a single node from which the total output is calculated, known as the total output layer [34].

Fuzzy inference systems, which are similar in general structure, have different types when studies are examined. The structure of the membership function used reveals this difference. For example, Mamdani, Tsukamoto, and Sugeno inference systems are inference systems that differ according to the membership function [34], [37].

3.4. Support Vector Machine (SVM)

Support vector machines are one of the methods used to solve classification problems. There are many applications in this field, such as Chandrasekaran et al. (2019), Chong & Pu, (2006), Diao et al. (2015), Ozden & Guleryuz (2021), and Zhang et al. (2016), who proposed a forecasting model using SVM. The fact that support vector machines produce effective results for regression problems has caused the method to be used frequently in solving regression problems and is called Support Vector Regression (SVR). SVM is a supervised learning approach that is based on structural risk minimization and statistical learning theories [38], [43]. SVR carries almost all the principles of the SVM method. Since the output for the regression is a real number, there are unlimited possibilities for the outcome. The tolerance (epsilon) limitation is used to limit these possibilities. While the model can be used for linear data, it can also be used for nonlinear data through kernel functions. Therefore, effective modeling of nonlinear relationships between datasets is possible with SVR. The mathematical formulation for SVR is given in Eq (2).

$$\text{maximize}\begin{cases}\dfrac{1}{2}\sum_{i=1}^{j}(\omega_i-\omega_i^{*})(\omega_i-\omega_i^{*})\,K\langle x_i,x_j\rangle \\ -\,\epsilon\sum_{i=1}^{j}(\omega_i+\omega_i^{*})+\sum_{i=1}^{j}y_i(\omega_i-\omega_i^{*})\end{cases}$$

$$\text{s.t}\begin{cases}\sum_{i=1}^{k}(\omega_i-\omega_i^{*})=0\ and\ \omega_i,\omega_i^{*}\in[0,C] \\ 0\le\ \omega_i\,,\omega_i^{*}\le\dfrac{C}{j} \\ i=1,2,\dots,j\end{cases} \tag{1}$$

Eq. (2), ω_i and ω_{i*} are nonnegative multipliers, and x_i is observed data. The data size is indicated by l, and the penalty coefficient and the penalty dimension are shown by C, ϵ respectively. The kernel function is represented as K (x_i, x_j.). Eq. (3) shows the regression equation [43].

$$f(x)=\sum_{i=1}^{j}(\omega_i-\omega_i^{*})\,K(\omega_i-\omega_j)+b^{*} \tag{3}$$

4. Results and Discussion

4.1. Comparing the performance of models

There are different performance criteria to compare the models' performances used in the study. The most commonly used ones are mean black root error (RMSE), correlation (R^2), mean absolute percentage error (MAPE), and Mean Absolute Deviation (MAD). The formulas for these criteria are given below in Table 2.

In order to compare the performances, the data set was divided into training (70%) and testing (30%). In this way, the estimation sensitivities of the models in the study will be measured, and the best estimating method will be determined.

At this stage, there are some points to be considered while analyzing with the classical method. First of all, this method must undergo certain preliminary tests. One of them is the stationarity test, which is very important for the time series. Figure 3 shows that even without analysis, the variables are in an increasing trend. Therefore, it is essential to determine the degree of stationarity of the series. Therefore, the most commonly used Augmented Dickey-Fuller (ADF) unit root test was conducted for this purpose, and the results are shared in Table 3.

Table 2. The formulas for the metrics

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(EXP_t^{observed} - EXP_t^{predicted})^2} \quad (2)$$

$$R^2 = \left(\frac{\sum_{t=1}^{n}(EXP_t^{observed} - \overline{EXP_t^{observed}})\,(EXP_t^{predicted} - \overline{EXP_t^{predicted}})}{\sqrt{\sum_{t=1}^{n}(EXP_t^{observed} - \overline{EXP_t^{observed}})^2\,(EXP_t^{predicted} - \overline{EXP_t^{predicted}})^2}}\right)^2 \quad (3)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{EXP_t^{observed} - EXP_t^{predicted}}{EXP_t^{predicted}}\right| \text{ x } 100\% \quad (4)$$

$$MAD = \frac{1}{n}\sum_{t}^{n}\left|EXP_t^{observed} - EXP_t^{predicted}\right| \quad (5)$$

Table 3. The ADF and PP Unit Root Tests

ADF Unit Root Test		**EXP**	**GDP**	**FDI**	**ER**
Level	t-Stat.	-1.65	-3.66**	-2.43	0.40
	Prob.	0.75	0.04	0.36	0.99
1st Difference	t-Stat.	-6.88***	-3.83**	-5.72***	-5.29***
	Prob.	0.00	0.03	0.00	0.00

Notes: a: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1% and (no) Not Significant, b: Lag Length based on AIC, c: Prob. Based on MacKinnon's (1996) one-sided p-values.

According to Table 3, only GDP is stationary at the level, while other variables are not stationary at the level. In order to be able to perform time series analysis, all variables must be stationary at the same level. In this respect, the differences of all variables are taken, and all variables are stationary in their first order. The graphs of the stationary variables can be seen in Figure 5.

Figure 5 shows that the variables oscillate around the mean zero and do not show a particular trend. As a result, the stationary data set will be used while performing the classical econometric analysis.

Another critical challenge is the problem of multicollinearity. Again, the variance inflation factor (VIF) will be used to determine whether such a problem exists.

As shown in Table 4, the average VIF value of the model was 1.305. Some studies have pointed out that values of five and above can cause problems. Since the VIF value is below the critical value, which is five, it states that there is no multicollinearity problem [44].

Table 4. Multicollinearity Test

Variable	**Coefficient Variance**	**Uncentered VIF**	**Centered VIF**
GDP	3.05E-05	1.725	1.444
FDI	97328.90	1.212	1.043
Exchange Rate	1.71E+12	1.803	1.428
Mean VIF			1.305

As a result of all these tests, it can be passed to the stage of estimating with the classical method. However, there is a critical point to be mentioned at this stage. One of the most important advantages of artificial intelligence-based applications is that they do not require much pre-testing as classical econometric methods. Therefore, after the normalization or standardization of the data set, analyzes were performed for SVM and ANFIS. For this purpose, Table 5 compares the models according to their performance criteria.

Table 5. The performance of all models

	Measure	**MLR**	**SVM**	**ANFIS**
Training	RMSE	0.0869	0.0816	0.0302
	MAPE	0.2251	0.1830	0.0967
	MAD	0.0678	0.0557	0.0213
	R2	0.8035	0.8716	0.9746
Testing	RMSE	0.0768	0.0901	0.0934
	MAPE	0.2096	0.1614	0.2636
	MAD	0.0648	0.0648	0.0730
	R2	0.7957	0.8329	0.7163

Looking at Table 5, low MAPE, MAD, and RMSE values and high R^2 values mean that that method is a better estimator. This table should be examined in two stages. First, the best predictive model is the ANFIS model for all performance criteria during the training phase. At this stage, SVM gave the second-best result. In the testing phase, situations have changed. At this stage, the best predictive method is SVM. MLR, on the other hand, seems to be better than the ANFIS method during the testing phase. The performance of these methods during the training and testing phases can be seen in Figure 6.

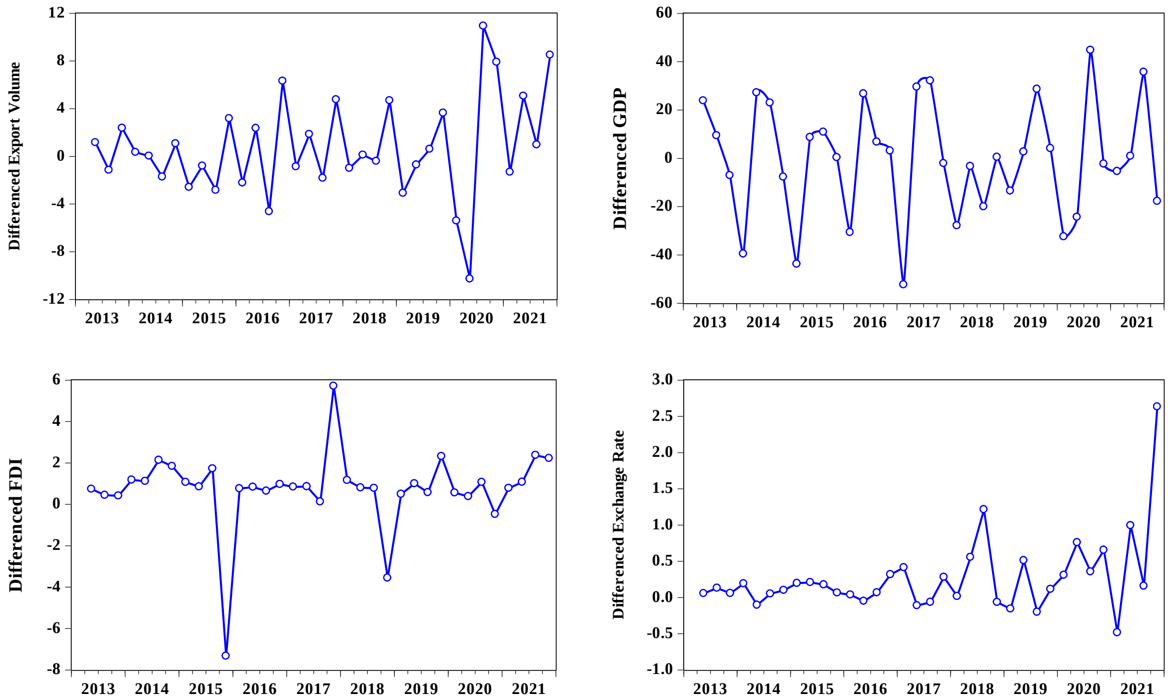

Figure 5. Change of stationary variables by years

Testing accuracy is always more important than training accuracy when comparing forecasting performances. Although ANFIS is high accuracy in the training phase, it did not give successful results in the testing phase compared to other models. In fact, it fell behind even the classical regression estimator during the testing phase. Although the ANFIS method is superior to MLR in capturing nonlinear patterns, this example observed the opposite. The main reason for this may be overfitting in the ANFIS method. Therefore, these over-learned data do not perform well in forecasting. Therefore, on the other hand, the SVM method performs much better in the testing phase than the others.

5. Conclusion and Suggestions

One of the crucial problems of the Turkish economy is the current account deficit, which has been going on for many years. The fact that the products subject to export are produced using raw materials, intermediate goods, and energy and that these final goods also carry exchange rate risk creates a serious added value problem. Despite the increase in the country's growth rate, export goods are exposed to price competition with their competitors. Therefore, Turkey's external demand elasticity is low (solid), and this may cause cost inflation due to the exchange rate and negatively affect growth. One of the most important tools to overcome this is to increase the country's exports and make them sophisticated. Therefore, policymakers need to evaluate their export estimation well.

Estimating the future trend of export volume has frequently found its place in the economic literature. These estimates were measured and evaluated by econometric methods. However, the use of econometric methods has certain limitations. First, the relationship between the variables is expected to have a structure suitable for economic theory. In addition, the variables must be stationary in terms of time series. Another significant limitation is that there is no multicollinearity between the variables. On the other hand, there are no such constraints in artificial intelligence-based forecasting methods. In addition, it gives much more reliable results in capturing the nonlinear patterns between the variables.

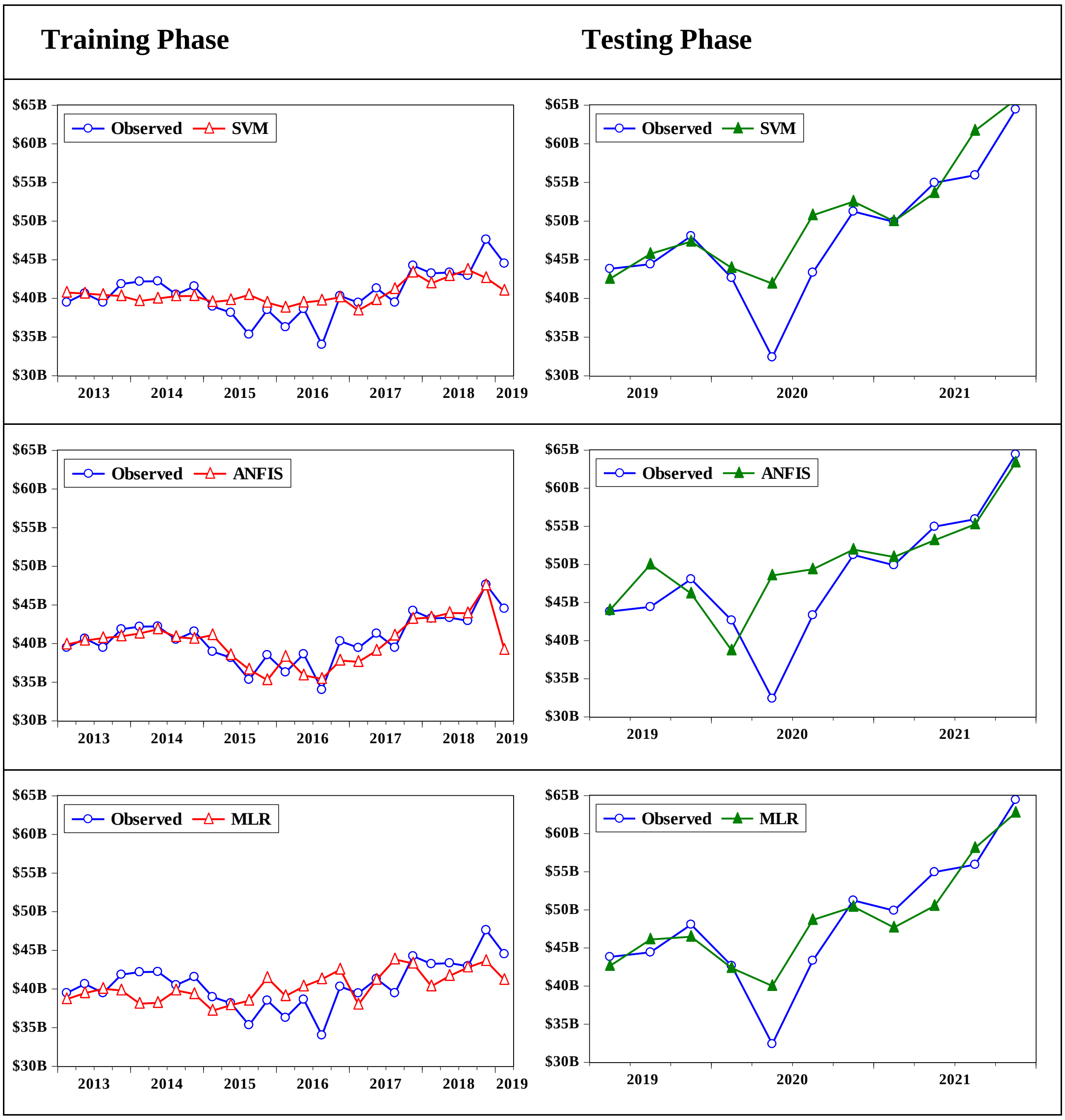

Figure 6. Observed and predicted export volume in the training phase and in the testing phase

In the light of all these, an export volume estimation was made in this study. Unlike other studies, in this study, quarterly data were used, not annual data. In this way, it has been tried to find a reliable estimation method for policymakers and sectoral managers in today's fast data flow.

The models' performances were evaluated using various well-known statistical measures such as R2, RMSE, MAPE, and MAD. As a result of the analysis, SVM was determined as the best method for export volume forecasting with R^2 = 0.8329, RMSE = 0.0901, MAPE = 0.1614, MAD = 0.0648.

In future studies, while estimating exports, other economic determinants not included in this study can be added to the model, and the forecast accuracy can be increased. Furthermore, estimates can be made with different econometric forecasting methods. Finally, predictions can be made with different AI-based methods, and it can be observed whether the prediction accuracy can be increased with hyperparameter optimization. The conclusion section should be stand alone. The aim of the study and its significant results should be given briefly in a concrete way. In addition, suggestions and opinions that are requested to be conveyed to the readers regarding the results of the study can be stated.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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