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Predicting High Technology Exports of Countries for Sustainable Economic Growth by Using Machine Learning Techniques: The Case of Turkey

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Abstract: In this study, the estimation of high-tech exports for Turkey's foreign trade target in line with sustainable development was carried out. The research was carried out for Turkey since it has been focusing on sustainable and environmentally friendly production and an export-oriented growth model, with a transformation in its economic growth strategy as of 2021, and high-tech products are a determining factor in the export target. In this research, three different machine learning techniques, namely artificial neural networks, logistic regression, and support vector regression, were used to determine a successful prediction method close to the ideal scenario. In the models, high technology exports for the period of 2007–2023 with data obtained from the World Bank were taken as the dependent variable, while the gross national product, number of patents, and research and development expenditures were taken as independent variables. By calculating the R^2, MAPE, and MSE metrics, the success of the model with the least error was evaluated, and it was seen that artificial neural networks (ANNs) were the most successful model, with values of 94.2%, 0.011, and 0.073, respectively. The ANN model was followed by support regression and logistic regression.

Keywords: technology; export; economy; machine learning

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1. Introduction

Foreign trade is one of the main economic variables that accelerates growth and development for developing countries, affects macroeconomic targets, and plays a decisive role in the level of development of countries. Foreign trade is characterized as the building block of economies by strengthening the strong and solid positions of countries in the field of international competition, creating new markets, and strengthening the employment structure.

The production structures of countries started with the Industrial Revolution of the 18th century and has been changing and transforming with the transition from labor-

intensive production to industry-intensive production. The classical understanding of production is a growth- and profit-oriented system that is output-oriented in the processing natural resources from production factors with labor and capital, does not use raw materials effectively, and uses unsustainable resources such as fossil fuels. The negative environmental impacts of this approach have become a growing problem today. The problems of these negative effects appear as climate changes, such as increases in global temperatures, changes in seasonal norms, and depletion of water resources, which require countermeasures. Sustainable growth and development constitute the most important pillars of this package of measures. The evolution of economic systems, which have been in constant change from the past to the present from a raw material-based structure to an information-based structure, and the same directional change in consumption habits create different areas of competition. For this reason, countries that want to continue their growth and development must keep up with this competition today. The change necessitated by sustainable development, which is described as the new world order in the production and trade structure, is environment-oriented clean production and consumption understanding within the scope of sustainable development initiated by developed countries and which developing countries are trying to adapt.

Technology investments and transfers constitute an important pillar of this change. Today, technology has become the determinant of economic performance by assuming an inevitable role in combining and presenting the factors of production. For this reason, to sustain growth and development targets, the production of new technology and its outsourcing and opening to the world are important driving forces of growth to stay competitive and gain a place in the power hegemony, making countries obliged to adapt to the production of new technology and opening up to the world.

Despite the increasing population in the world, the limitation of resources and the effects of climate change require continuous restructuring and renewal of the economies of countries for them to sustain themselves and exist in international competition. Today, the most important element of this restructuring is sustainable development based on environmentally compatible production structures and policies aimed in this direction. Considering the impact of human capital on carbon emissions, the creation of new and alternative fields becomes necessary within the scope of sustainability. Since technology investments and transfers play a major role in the development policies of countries, the creation of new, environmentally friendly technological areas and developments strengthens sustainable policies.

Transport, one of these sectors, constitutes one of the main actors in global warming, with its weight in fossil fuel use. Among the types of transport, the intensive use of road transport with increasing populations and needs and its feature of connecting rural and urban areas create the need for alternative, environmentally sensitive resource use in this field. For this reason, the use of alternative resources in transportation and vehicles produced with this technology have recently become a focus of attention. In parallel with this, scientific studies in the field have gained increasing importance.

In the research conducted in the field to examine the positive and negative effects of technology exports on environmental pollution, developed and developing economies specifically have been kept within the scope. Some studies on human capital, which is defined as the labor force effective in R&D activities and technology production and exportation, have drawn attention. Some studies on this subject revealed that human capital, which plays a role in high technology production and exports, negatively affects environmental sustainability, and they suggest that the human factor negatively affects sustainable policies [1]. In addition, studies that found a positive relationship between carbon emissions, which is a determinant of sustainability, and high-tech exports, have drawn attention [2]. The impact of R&D expenditures, which are considered the main input of innovation, on sustainability can be effective in shaping macroeconomic policies [3]. Within the scope of these policies, some studies support that technology developed to

produce renewable energy sources which support energy transformation is effective in preventing carbon emissions and environmental pollution [4].

Today, technology has assumed an inevitable role in combining and presenting the factors of production and has become the determinant of economic performance. For this reason, to sustain sustainable growth and development goals, the production of new technology and its outsourcing and opening to the world, as important driving forces of growth to stay competitive and gain a place in the power hegemony, obliges countries to adapt to the production of new technology and opening to the world.

Turkey is a developing country that focuses on exports in its foreign trade, with the aim of producing new technology and opening up to the outside world to remain dynamic in its growth and development strategy, creating employment areas for the young population structure and strengthening its position in international competition. The 2019 pandemic period's effect on the world's economies, the problems experienced in the supply chain, and the volatility in price movements have caused Turkey to make some changes in its economic policies and targets. Based on this change, the aim of this study in Turkey is transformation in the economic structure in line with the sustainable economic transformation model, targeting low-cost-based production, export-oriented growth, and environmentally friendly new approaches. In addition, forecasting the future of high-tech exports for Turkey through machine learning, which is one of the artificial neural network methods, offers a methodological innovation that is open to improvement. This approach addresses the relationship between artificial intelligence and the environment, accompanied by variables considered in supporting sustainable policies.

In addition, Turkey's proximity to Europe, the fact that it constitutes the largest share of Turkey's exports, Europe's sanctions on compliance with sustainable economic transformation, and its geographical location as a bridge to Asia make the country stand out as an important foreign trade partner. For this reason, it is thought that accurate forecasting methods which can be determined to see the future horizon of high-tech exports for Turkey will be important in analyzing and interpreting the success of the sustainable growth model applied.

Machine learning, a sub-branch of artificial intelligence, is a branch of science that imitates human behavior and expresses it statistically and mathematically. It is widely used in many fields, especially in health, economics, agriculture, and communication. Predictions are made with the model, created by performing training and testing operations on the data set, with proven accuracy. Thus, predictions can be made quickly and with high accuracy in large and complex data sets [5–7].

In the introduction of this research, an attempt is made to emphasize the importance of new technology exports in line with Turkey's sustainable growth targets. In the second part of this study, similar studies and the achievements of these studies in the literature are discussed. In the third part of this study, the Materials and Methods section, the data set and methods used in the study are given. In the Results and Discussion section, which is the fourth part of the study, the parameters used in the methods, error and success metrics, findings, and comparisons with similar studies are given. In the Conclusions section, which is the last part of the study, the findings of this study are interpreted, and the superior and successful features and points that need to be improved are stated. Also, future studies are mentioned.

2. Literature Review

When studies on this subject were examined, the research could be categorized into two main areas: the relationship between artificial neural networks and new technology exports and the relationship between sustainable policies and new technology exports. In this study, the related literature was analyzed in two categories: foreign and domestic.

In the studies that stand out for their methods, forecasts have generally been made within the scope of many economic variables using artificial neural networks. When the foreign and domestic literature on the subject are examined, many studies can be

observed. Alam (2019) used artificial neural networks (ANNs) and autoregressive integrated moving average (ARIMA) models to forecast the total annual exports and imports of the Kingdom of Saudi Arabia for the future. According to the findings, both methods were successful in forecasting future exports and imports, but the ANN method was found to be more robust than the ARIMA model [8]. In addition, Batarseh et al. (2019) examined the applicability of machine learning techniques in foreign trade forecasts. In their study, ARIMA, Gradient Boosting (GBoosting), High Gradient Boosting (XGBoosting), and Light Gradient Boosting (LightGBM) were applied from machine learning algorithms to the future forecasting of international trade, and the results emphasized that successful forecasts made with machine learning are effective [9]. Similarly, in a study conducted by Wanto et al. (2019), foreign trade forecasts for Indonesia were created using artificial neural networks. In the study, an artificial neural network backpropagation algorithm was applied with four architectural models named 12-5-1, 12-8-1, 12-10-1, and 12-14-1. According to the results obtained, it was observed that the model called 12-5-1 reached the lowest MSE value, emphasizing that forecasts made with artificial neural networks provide realistic predictions with a low error rate [10]. Suler et al. (2021) estimated the exports from the Czech Republic to China using an artificial neural network model in their study. The research was shaped around two factors: whether the export value between the Czech Republic and China was going in the expected direction and the success of the multilayer perceptron (MLP) method in export forecasting. The findings of the study, which used data from the 2000–2019 period, show that MLP is extremely effective in forecasting exports between the Czech Republic and China [11]. Dai (2022) examined the effectiveness of the backpropagation multilayer neural network (BPNN) model in forecasting the volume of foreign trade exports to China. It was observed that the BPNN model achieved a higher forecasting accuracy in export volume predictions and had a better data fit compared with other approaches [12]. Yang et al. (2023) aimed to provide an accurate forecasting method due to the difficulties caused by the complex structural relationships between exports, imports, and other economic variables in forecasting. In this study, variables such as the export price, import price, world price, total imports, domestic income, and consumer price index for 10 countries (Brazil, Canada, China, France, Germany, India, Italy, Japan, the UK, and the USA) were analyzed for the period of 1970–2019. It was determined that the neural network forecasting model is a more effective method in foreign trade forecasting, with low RMSE and MAPE values compared with time series methods [13]. When the domestic research in the field is analyzed, it can be observed that there were many prominent studies in Turkey. For example, Özdağ et al. (2017) forecasted furniture foreign trade between Turkey and Germany using the artificial neural network method. In the study, conducted for the period of 2017–2023, the population, gross domestic product (GDP), and real exchange rate index values of the two countries were used as independent variables, while the import and export values for the sector and time were used as dependent variables. It was emphasized that artificial neural networks are an effective method in foreign trade forecasting [14]. Another similar study was conducted by Yaman and Akgül (2020), who used the artificial neural network method to forecast Turkey's export values for the future. In the study, covering the period of 2002–2017, the export dependent variable was estimated using the independent variables of gross capital formation, industry, savings, exchange rates, logistics, GDP, GDP per capita, exports of commercial services, and exports of goods. The results obtained show that artificial neural networks are a powerful method in export forecasting with low error rates [15]. In a study by Turaç (2020), where similar results were obtained, future export forecasts of the total exports and food, textile, and beverage products for Turkey were made using artificial neural networks. When the R-squared values of the results obtained were examined, the export forecasting performance of the artificial neural network method was found to be quite high, with a success rate close to one for the total exports and the other three sectors [16]. Kurt (2022) performed export and import forecasting for the Turkish economy using the artificial neural network method. This research was conducted to

evaluate the effectiveness of machine learning and artificial neural networks in foreign trade forecasting and to guide future studies. According to the findings obtained, the prediction results for both exports and imports closely matched the actual values with a high degree of success. From this point of view, it is emphasized that artificial neural networks are a successful method for predicting foreign trade and other macroeconomic variables, and they can provide successful results close to reality in future studies [17]. Gür and Eşidir (2023) used artificial neural networks to predict the future imports of the plastics sector in Turkey. The results obtained were evaluated with the MAPE statistic, and the resulting low error rate demonstrated the high potential of artificial neural network models in the plastics sector import forecasting [18]. Tekin (2023) forecasted the monthly export values of investment, raw materials, and consumer goods, which are characterized as Turkey's broad economic groups, using the artificial neural network method. According to the results obtained with a low error rate, and where prediction success was evaluated with the MAE, MSE, and MAPE, it was seen that the artificial neural network method was successful in forecasting Turkey's future exports [19]. Burciu et al. (2020), in one of the prominent studies on the relationship between sustainability and new technology exports, considered the R&D expenditures of Romania and the economies of Czechia, Hungary, Poland, and Slovakia from the Visegrad community, known as the V4 economies, as inputs in their study. They aimed to investigate the importance of technology exports in sustainable economic growth. The results obtained in the study, which covered the period of 1995–2017, show that the export structures in the selected countries revealed country-specific differences. At the same time, it was emphasized that R&D expenditures, which are the main input of the innovation process, will be effective in shaping macroeconomic policies focused on sustainable growth and economic development [3]. Another study in the same direction was conducted by Wang et al. (2020). The aim of the study was to analyze the importance of high- and new technology industries in sustainable economic development and the improvement of environmental quality. The results obtained show that progress in the field of high and new technology in China led to a decrease in carbon emissions in developed countries and an increase in carbon emissions in developing countries. There is a nonlinear relationship between the economic benefits and environmental costs of high- and new technology exports. It was also emphasized that technological progress in the electrical equipment sector can be encouraged to reduce environmental pollution [2]. A different study on the subject was conducted by Han et al. (2022), which examined the role of high-tech product exports in mitigating climate change impacts in Belt and Road countries. In addition, this study analyzed the impact of renewable energy and investment in human capital on carbon emissions, including 50 countries along the Belt and Road Initiative for the period of 2005–2019. The findings showed that increasing the share of high-tech exports in total exports plays an effective role in sustainable development goals. It was emphasized that increasing the use of renewable energy and investments in human capital play a critical role in the relationship between high-tech exports and carbon emissions [4]. Wang et al. (2023) examined the impact of high-tech exports on environmental sustainability. The study was carried out within the scope of 25 countries considered to have advanced technology, with data for the period of 2009–2018. According to the findings, it was concluded that human capital and high-tech exports have a positive and significant effect on the level of carbon intensity; both variables increased carbon emissions and negatively affected environmental sustainability [1].

The literature on the subject shows that research has been primarily focused on China as a prominent country in foreign trade. Additionally, it can be observed that there is a linear relationship between new technology exports and carbon emissions in terms of sustainability, and machine learning techniques are used effectively in forecasting the foreign trade dynamics of countries. The fact that countries' foreign trade structures and economic variables are closely related, along with the rapidly changing complex structure of these variables, makes forward-looking forecasting difficult. In this context, the fact that machine learning methods offer quick and easy solutions and produce successful forecasts

with low error rates compared with traditional methods proves that they can be a guide for future policy proposals.

3. Materials and Methods

The literature review started by identifying the research problem and defining the topic. Keywords were searched for in appropriate databases, and the sources found were evaluated in terms of reliability, methodology, and findings. These sources were then synthesized to compile the available information in the literature. The literature review was included in the introductory part of the research, forming the context of the study, and it was updated as new information emerged. This process forms the basis of the research and emphasizes the importance of this study.

3.1. Data Set

In the machine learning models in the study, Turkey's high-tech exports were estimated using three independent variables. With the data obtained from the World Bank, high-tech exports for the period of 2007–2023 were determined as the dependent variable, while the gross national product (GNP), number of patents, and research and development expenditures were determined as independent variables [20]. There are many studies which analyzed the effect of the number of patents on technology exports [21,22]. Patents and patent statistics are indicators for determining the rate of technological change and economic growth rates and making comparisons with other countries [23]. The gross national product is another important variable affecting high-tech exports [24,25]. A higher GNP indicates that the country produces more goods and services and, therefore, can export more. Another important variable affecting high-tech exports is research and development expenditures [26–28]. R&D expenditures have an important role in producing innovation and thus in being competitive in exports.

Table 1 shows the statistical metrics of the means, minimums, maximums, and standard deviations of the variables used in the data set of this study.

Table 1. Statistical properties of variables.

	Average	**Minimum**	**Maximum**	**SD**
GDP (USD)	10.125	7.842	12.072	1.461
Number of patents	4.996	1.810	8.175	2.109
Research and development expenditure (% of GDP)	0.871	0.686	1.088	0.122
High-tech exports (% of manufactured exports)	2.67	1.83	3.43	0.556

According to the statistical metrics of the dependent and independent variables in Table 1, the data were evenly distributed, and there were no missing, outlier, or noise data. Therefore, all of the data in the data set were included in the model.

3.2. Artificial Neural Networks

Artificial neural networks are a biologically inspired information processing system. Like the structure of the human brain, neural network models are composed of neurons in a complex and nonlinear manner. Neurons are connected by weights. A connection between two neurons has a weight, which is used to determine how much one neuron will influence the other [29].

Artificial neural networks consist of input, hidden, and output layers. The input layer of a neural network brings data into the system to be processed by subsequent layers. The hidden layer is the intermediate layer between the input and output layers where all calculations are performed. The hidden layer in a neural network is where neurons use an activation function to produce an output after receiving a collection of weighted inputs. The outputs are passed on to the next layer. A model may have one or more hidden layers, depending on the state of the network. The output layer is the last layer in neural networks

where the desired predictions are obtained. The output layer receives the inputs from the previous layers, performs calculations through neurons, and then calculates the output. A neural network has an output layer which produces the final desired prediction [30]. Activation functions are mathematical functions used to determine the output of neurons in artificial neural networks (ANNs). A variety of activation functions are available, each with its own characteristics and advantages. Commonly used functions include sigmoid, tanh, ReLU, and softmax. Each function is known to perform differently in different situations. The sigmoid activation function is

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

The summation function calculates the net input to the cell in artificial neural networks. The most used aggregation function is multiplication and summation of the input values and their weights. This is carried out for each input, and the result is the net input of the cell:

$$f(x) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \quad (2)$$

In the above equation, x_i represents the input values of the neuron, and w_i represents their respective weights. The nonlinear activation function, denoted as f, is utilized across the network. The bias value b sets the activation threshold for the neuron.

Artificial neural networks are divided into two types according to their learning types: feedforward and feedback. In feedforward neural networks, information is processed in only one direction, moving from the input layer to the output layer. The connections between neurons do not form a loop. Feedback neural networks do not follow a single path when transmitting signals to reach the optimum result and minimize errors. Such networks can have signals moving in both directions (i.e., from input to output as well as from output to input) [31].

3.3. Logistic Regression

According to the statistical metrics of the dependent and independent variables in Table 1, the data were evenly distributed, and there were no missing, outlier, or noise data. Therefore, all of the data in the data set were included in the model.

Logistic regression is a supervised machine learning algorithm which performs binary classification tasks by estimating the probability of an outcome, event, or observation. Logistic regression is a statistical method used to predict the outcome of a dependent variable based on previous observations. It is a regression analysis algorithm commonly used to solve binary classification problems [32]. In logistic regression, the odds ratio (OR) represents the ratio of the probability of an event or outcome occurring to the probability of it not occurring. The odds formula is shown below:

$$Odds = \frac{p(x)}{1 - p(x)} \quad (3)$$

The odds take values between 0 and +∞. The odds ratio is asymmetrical, but it can be transformed into a symmetrical ratio by taking its natural logarithm. By applying the natural logarithm to both sides of the logistic function, which can be used in linear regression analysis, a linear structure is obtained:

$$\ln(Odds) = \ln\frac{P}{1 - P} \quad (4)$$

While the odds of a probability take values between 0 and +∞, the logit value of the same probability takes values between −∞ and +∞.

Logistic regression calculates the likelihood of an unidentified event transpiring by utilizing a specified collection of independent factors. Because the result is a probability,

the dependent variable has a range from 0 to 1. The probabilities in logistic regression are transformed using a logit function, which is the probability of success divided by the probability of failure [33]:

$$\text{Logit(pi)} = \frac{1}{1 + e^{-\text{pi}}} \quad (5)$$

In this logistic regression equation, logit (pi) is the dependent variable, and e is the natural logarithm base. The natural log of probabilities is the definition of the logit function. A logit value of 0 is associated with a probability of 0.5. Positive logit values are associated with probabilities larger than 0.5, and negative logit values are associated with probabilities less than 0.5 [34].

3.4. Support Vector Regression

Support vector machine (SVM) analysis, first described by Vladimir Vapnik in 1992, is a machine learning tool for classification and regression. Support vector regression (SVR) is a supervised learning algorithm for predicting discrete values. SVR is identical in structure and principle to support vector classification, with a few differences. The basic working logic of support vector regression is to find the most appropriate curve using the data points in the data set. In SVR, the optimal curve is the hyperplane with the maximum number of points. In regression, the main goal is to minimize the error rate, while in SVR, the error can be kept at a certain threshold value. The threshold is the distance between the hyperplane and the boundary line [35]. There are two types of support vector regression: linear and nonlinear. Linear support vector regression is expressed as follows:

$$f(x) = w \times x_i + b \quad (6)$$

where f(x) is the output vector, w is the weight vector, x is the input vector in an n-dimensional space, and b is the deviation.

The kernel allows for finding a hyperplane in a higher-dimensional space without increasing the computational cost. The types of kernels used in SVR are sigmoidal, RBF, polynomial, Gaussian, etc. The hyperplane is basically the line separating two data classes in support vector machines. But in support vector regression, this is the line that will be used to predict the continuous output. The decision boundary can be thought of as a boundary line, with positive examples on one side and negative examples on the other [36,37].

4. Results and Discussion

The data obtained from the World Bank between 2007 and 2020 were used in this study. In the model created in this study, Turkey's high-tech exports were used as the dependent variable, and the gross national product, number of patents, and research and development expenditures were used as independent variables to predict this dependent variable. Three different machine learning techniques, namely artificial neural networks, logistic regression, and support vector regression were used in this study. The R2, MSE, and MAPE statistical methods were used to measure the success and error rates of the model. Figure 1 shows the working structure of this study.

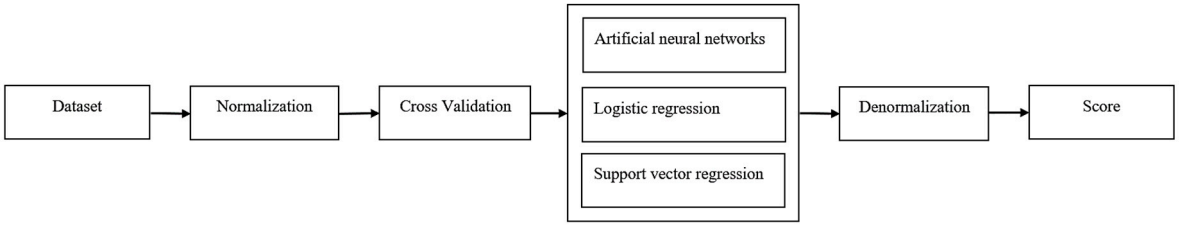


Figure 1. The working structure of this study.

In the data preprocessing phase of the study, the feature selection method was used first. Feature selection is the process of finding and selecting the most useful features in the data set [38,39]. This process greatly affects the performance of the machine learning model. Attribute selection focuses primarily on removing non-explanatory or redundant predictors from the model. Using too many variables can degrade the performance of the model. To obtain the best performance results, it is necessary to determine the most optimal variables and build the model with them. In machine learning, there is a need to obtain faster-running models. By reducing the number of features, the model can obtain faster results without sacrificing performance. Machine learning requires models that are easy to understand and interpret. When understanding the model's results, actions should be determined accordingly, and benefits should be obtained from that model. It is easier to apply easy-to-understand model results to real life. This will also reduce the risk of overlearning. With too many variables, the model complexity will increase. Using fewer variables will also reduce the risk of overlearning [40]. For all of these reasons, a filtering method, one of the feature selection methods, was used in this study. Filtering methods evaluate the relevance of the variables in a model to the target variable and then include or exclude these variables from the model. Filter variable selection methods use statistical techniques to evaluate the relationship between each input variable and the target variable [41]. In this study, the Pearson correlation method, the most widely used correlation measure, was used to measure the relationship degree between linearly related variables. All three independent variables in the study were found to be within the desired value range to be included in the model.

The second operation on the data was the normalization phase. Normalization is a technique usually applied as part of data preparation for machine learning. The data in a data set can vary in terms of size and range of values. Normalization aims to apply a standard scale to the values of a data set's numeric columns while preserving information and preventing distortion of the value range differences. This enhances the model's functionality and training stability [42].

In this study, the data for the logistic regression method were normalized using the Z-score method. Z-score normalization is a data normalization strategy that avoids the outlier problem. If a value is exactly equal to the mean of all values in the data, then it is normalized to zero. If it is below the mean, then it is normalized to a negative number, and if it is above the mean, then it is normalized to a positive number. The sizes of these negative and positive numbers are determined by the standard deviation of the original feature. The raw data have a large standard deviation, while the normalized data are close to zero [43,44]. The Z-score normalization equation is

$$z = \frac{x - \mu}{\sigma} \tag{7}$$

where x represents the variable, μ is the mean, and σ is the standard deviation.

For the other machine learning methods in this study, the data were normalized using the Min-Max method. On the original data, a linear transformation was carried out. The linkages between the original data values were maintained during this normalizing process. The data were rescaled using this method so that they fell between 0 and 1. For each value, the minimum value in that data set was converted to zero, the maximum value was converted to one, and all other values were converted to a decimal number between 0 and 1. Smaller standard deviations were obtained, and the impact of outliers was mitigated as a result of this process's restricted range between 0 and 1 [40]. The Min-Max normalization equation is

$$x' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{8}$$

where x' is the normalized result, x_i is the value to be normalized, x_{min} is the smallest value in the data set, and x_{max} is the largest value in the data set.

In machine learning, cross-validation is a technique used to assess a model's performance on data. Cross-validation is primarily used to prevent overestimation, which can happen when a model performs poorly on new data despite performing quite well on training data. Cross-validation offers a more accurate assessment of a model's generalization performance and its capacity to function well on fresh, untested data by testing the model across several validation sets. In order to accomplish this, the available data must be divided into many multiples or subsets. One of these multiples must be used as a validation set, and the remaining multiples must be used to train the model. This is performed numerous times, with a different fold serving as the validation set each time. Ultimately, an average of the outcomes obtained from every validation phase yields a more dependable approximation of the model's efficiency [45,46]. In this study, the data set was divided according to K-fold cross-validation, which is one of the cross-validation techniques. The K-fold method can be used if the data set is not particularly large or if the importance of each data point is the same. The data set is divided into "k" equal parts, validation data are created for each part individually, and the validation process is performed. Thus, each data point is used as validation data at least once, and the overall performance of the model can be evaluated more accurately. For this study, the k value was set to 10.

The coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE) were used to evaluate, analyze, and interpret the study results [47].

When predicting the outcome of a certain event, the coefficient of determination (R^2) is a statistical measure which looks at how variations in one variable may be explained by differences in another one. Stated differently, the coefficient of determination is a statistical metric that assesses the accuracy with which a statistical model forecasts a result. The strength of the linear relationship between two variables is evaluated by this coefficient. The dependent variable in the model represents the result. R^2 has a lowest value of zero and a maximum value of one [48,49]. It is the percentage of the dependent variable's variance that the model can account for. The solution for R^2 is shown in Equation (9):

$$R^2 = 1 - \frac{\text{Unexplained Variation}}{\text{Total Variation}} \quad (9)$$

Regression models commonly employ the MSE as a model evaluation statistic. The mean squared difference between the expected and actual data was calculated. Large errors were reduced since MSE the squared the error. The MSE is a metric with a range from zero to infinity, where values closer to zero are regarded as superior. The more accurate the model, according to the MSE metric computed for the same set of data, the lower the MSE value [50]. Equation (10) shows the calculation of the MSE:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \quad (10)$$

where n is the number of data points and e is the error value.

Regardless of direction, the average magnitude of errors in a set of predictions was measured by the statistical metric known as the MAE. This was computed by averaging the absolute difference between the values that were predicted and the values that were seen throughout the data set. The MAE does not care about the direction of errors; it merely measures their quantity. The accuracy of a model increases with a decreasing MAE [51]. Equation (11) shows the calculation of the MAE:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |e_i| \quad (11)$$

This study included three distinct machine learning methodologies: support vector regression, artificial neural networks, and logistic regression.

The main purpose of logistic regression is to estimate the probability of belonging to a given categorical output using input data. In the training of the model, the maximum likelihood approach is generally used for fitting nonlinear models. In logistic regression,

a likelihood function is used to express the probability of the observed data. This function depends on the parameters of the model and is used to measure how well the model fits. The aim here is to estimate the probability of an element selected from the data set by estimating the values of β_0, β_1, β_2, β_3, and so on. After 100 iterations in this investigation, the likelihood was −15.882.

By using an artificial neural network, a feedback model with three input neurons and one output neuron was created. The model's trial-and-error techniques revealed that the structure with three hidden levels and three neurons in each layer yielded better outcomes. The designed model's construction is depicted in Figure 2.

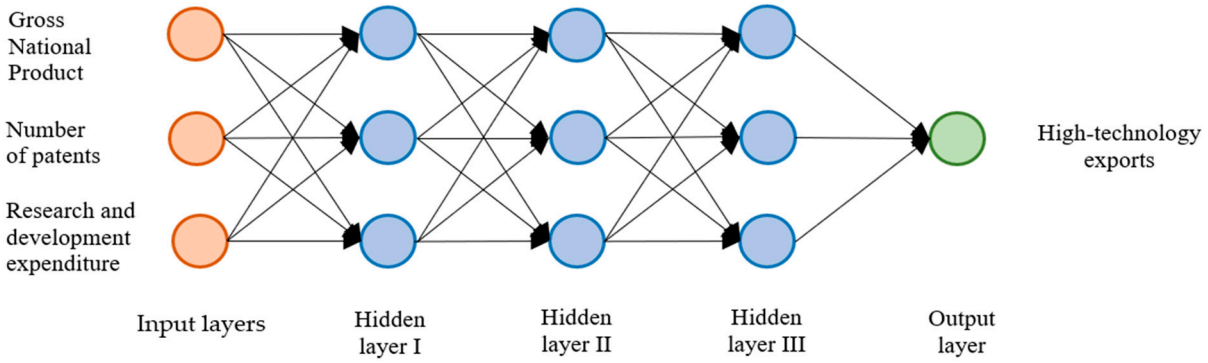


Figure 2. The designed ANN model's construction

After testing various functions for the activation function, the sigmoid function was preferred because it gave the most successful result. A feedback learning algorithm was used in the learning method, which is one of the most important parameters affecting the success of a model in artificial neural networks. It took 1000 iterations to determine the best result in the model. The ideal values for the momentum, which averages the weight updates, and the learning rate, which determines the amount of updating the weights, may vary depending on the data set, model architecture, and optimization algorithm. The learning rate of the ANN model was chosen to be 0.01, and the selected momentum was 0.9.

Another machine learning technique employed in this study was support vector regression, which was performed using nonlinear SVR. The SVR algorithm uses kernel functions to transform data into a high-dimensional space. The radial basis function (RBF), hyper-tangent, and polynomial were investigated as potential kernel functions. The RBF was shown to be the most effective model, and thus the RBF was chosen for this study. The RBF calculates the similarity of two points in a data set according to their locations. It is one of the most widely used kernels due to its similarity to Gaussian distribution. The other parameters of the model were an overlapping penalty value of 100 and an RBF sigma value of 0.1.

Table 2 shows the evaluation of the models according to artificial neural networks, logistic regression, and support vector regression methods.

Table 2. Evaluation of the models.

	Artificial Neural Networks	Logistic Regression	Support Vector Regression
R^2	0.942	0.897	0.908
MSE	0.011	0.088	0.062
MAE	0.073	0.207	0.121

As can be seen in Figure 3, the R^2 value was 94.2% for artificial neural networks, 89.7% for logistic regression, and 90.8% for support vector regression, and it was found to be within the acceptable value range.

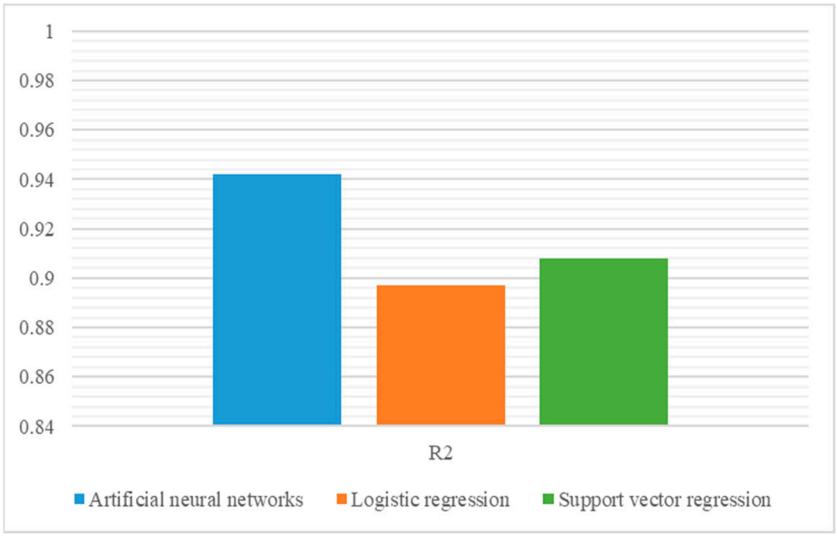


Figure 3. R^2 analysis.

An R^2 value of one, which indicates how well the data fits a linear curve, indicates that the test data provided a linear curve. As a result of this study, the R^2 value was 94.2% for artificial neural networks, 89.7% for logistic regression, and 90.8% for support vector regression, and it was found to be within the acceptable value range.

As can be seen in Figure 4, it was observed that the MSE values were 0.011 for artificial neural networks, 0.088 for logistic regression, and 0.062 for support vector regression, which were close to the ideal value.

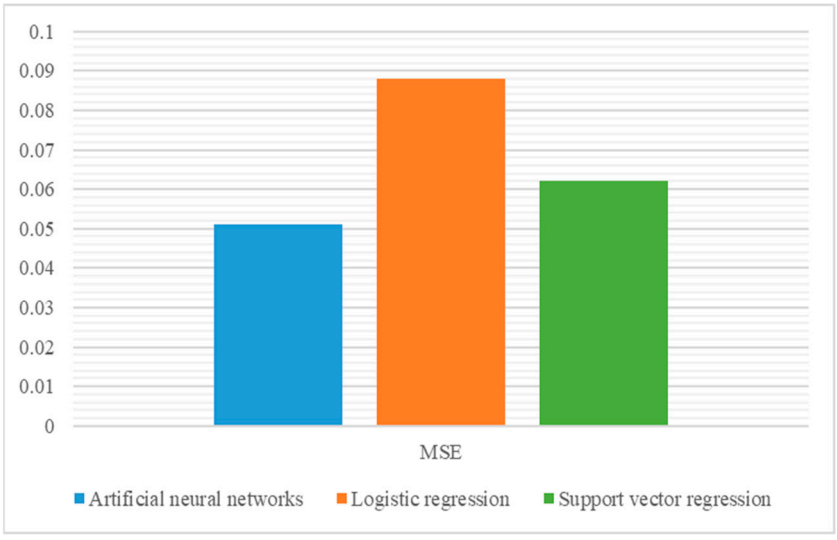


Figure 4. MSE analysis.

Machine learning algorithms' error levels are assessed using the MSE statistical metric, which indicates that values near zero have lower error rates. Therefore, it is desirable that the MSE value be close to zero. In this study, it was observed that the MSE values were 0.011 for artificial neural networks, 0.088 for logistic regression, and 0.062 for support vector regression, which were close to the ideal value.

As can be seen in Figure 5, it was discovered in the study to be 0.121 for support vector regression, 0.207 for logistic regression, and 0.073 for artificial neural networks.

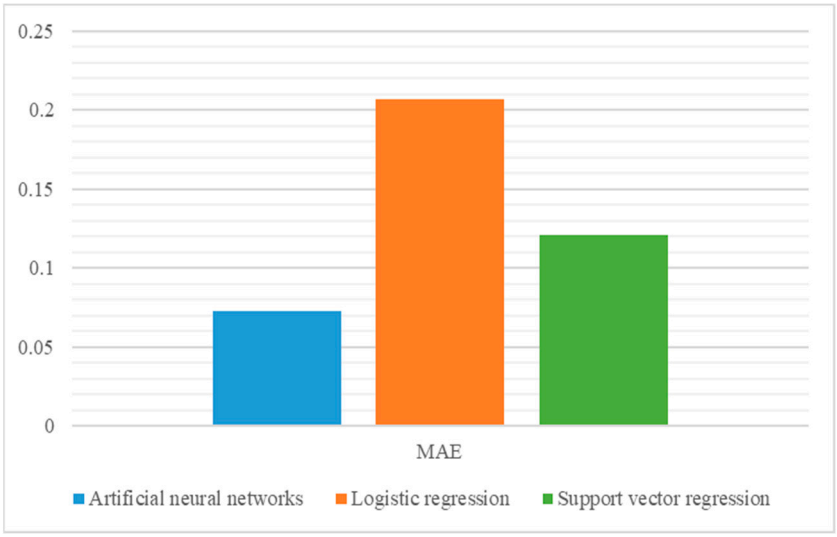


Figure 5. MAE analysis.

The error's magnitude was measured using the MAE metric. It was discovered in the study to be 0.121 for support vector regression, 0.207 for logistic regression, and 0.073 for artificial neural networks. All three models had excellent MAE values. Based on the error and success numbers, support vector regression, logistic regression, and artificial neural networks were the models with the least error and the most success, respectively.

Data visualization is the process of organizing complex and scattered data to make them easily understandable and interpretable. In other words, it enables abstract data to be visualized and concretized as well as obtain preliminary information from them. In this study, the relationship between the prediction and actual data was analyzed using scatter and line plots.

A scatter plot, one of the data visualization techniques, was used to identify and interpret the relationship between two different continuous variables. A scatter plot is a simple, intuitive, and natural way to visualize two-dimensional point data. Scatter plots show data trends and correlations between any two variables. They also facilitate the detection of outliers. Scatter plots provide a tool for comparing different data sets when plotted on the same axes [52]. With this diagram, it can be seen whether there is a relationship and, if so, how strong the relationship is. The relationship between two variables can be classified as strong positive, weak positive, strong negative, weak negative, or no relationship [53]. Figure 6 shows the scatter plot curve of the ANNs, Figure 7 shows the scatter plot curve of logistic regression, and Figure 8 shows the scatter plot curve of the support vector regression results.

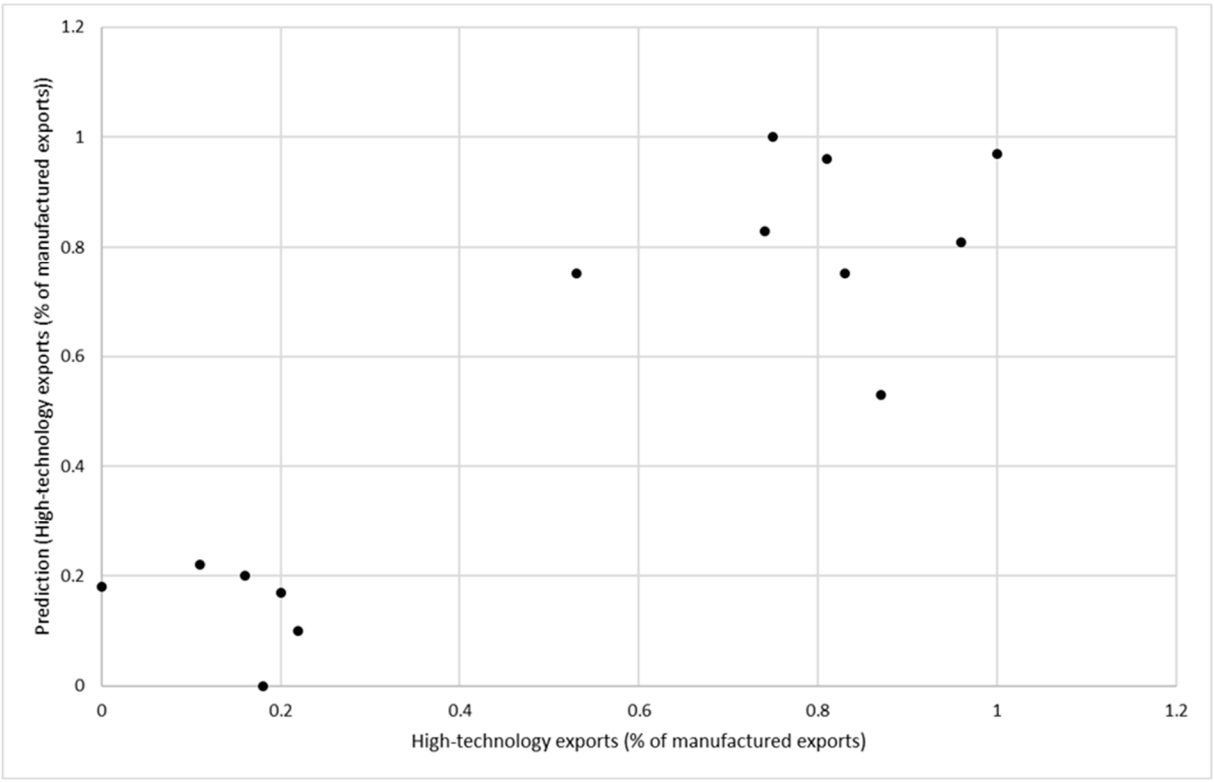


Figure 6. Scatter plot of the ANNs.

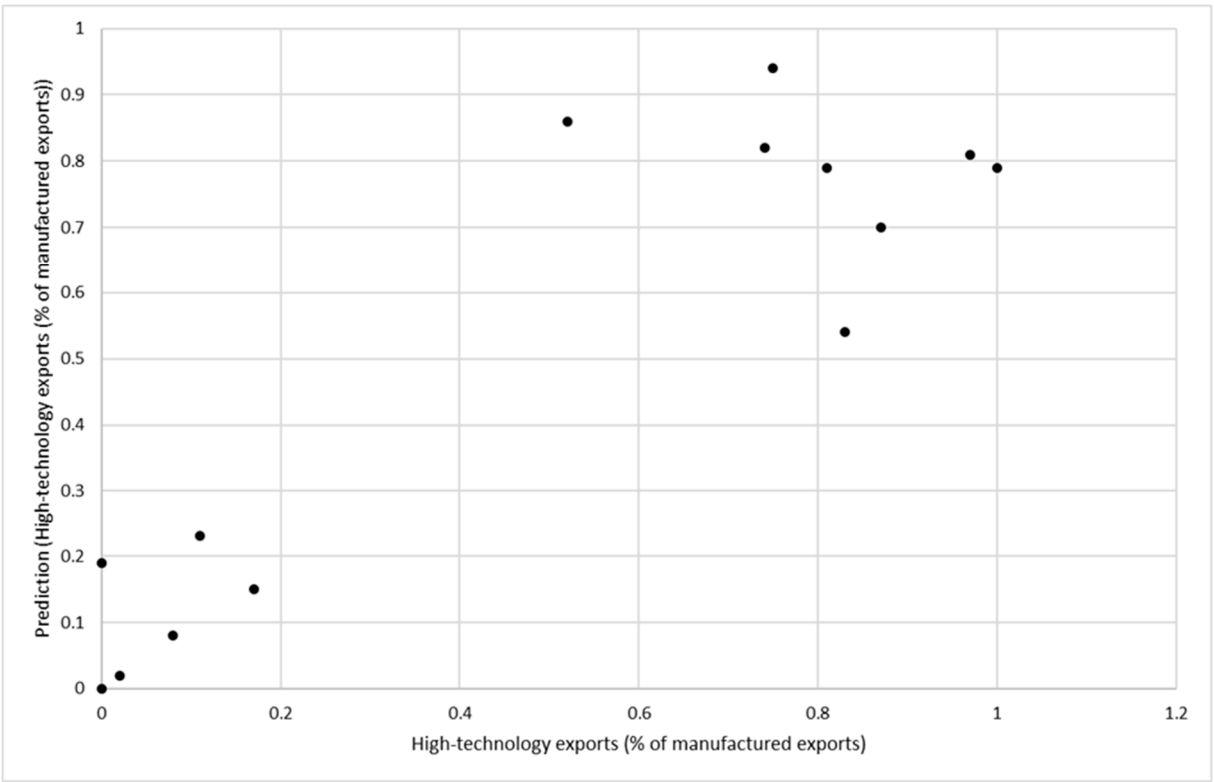


Figure 7. Scatter plot of logistic regression.

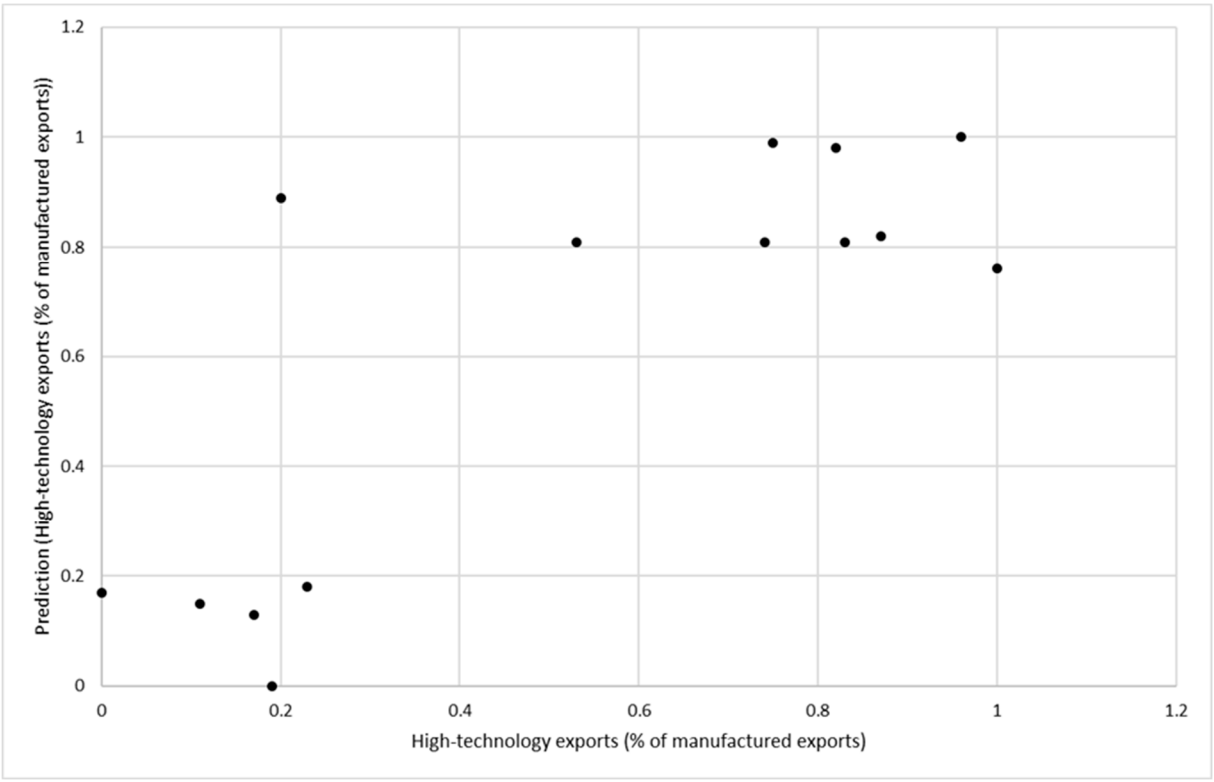


Figure 8. Scatter plot of support vector regression.

Figures 6–8 show the scatter plot curves between the actual and predicted values of high-tech exports of machine learning models. The X axis shows the actual value, and the Y axis shows the predicted value. One can discern a distinct pattern in the data based on how closely the points are clustered. The stronger the association, or the higher the correlation between two variables, the closer the data points are to making a straight line. A positive correlation exists between the variables if a straight line connecting a point close to the origin to high Y values is formed by the data points. The variables are negatively connected if the data points begin with high Y values and progress toward low values on the Y axis [21]. According to the figures, there was a weak positive relationship between the predicted value and the actual value. Accordingly, the values of both variables increased at the same time, but the points were scattered.

A line chart is a graph which shows the frequency or number of occurrences of a value in a data set. A line chart is used to show trends over time. The dimension is always on the X axis, and the measures are always on the Y axis. A line graph connects discrete data points, usually displaying quantitative values over a given time interval. A line must consist of at least two data points to be plotted. A data set with a single value is represented as a point. Line graphs often lose clarity when there are too many data points. Figure 9 shows the line plot for ANNs, Figure 10 shows the line plot for logistic regression, and Figure 11 shows the line plot for support vector regression.

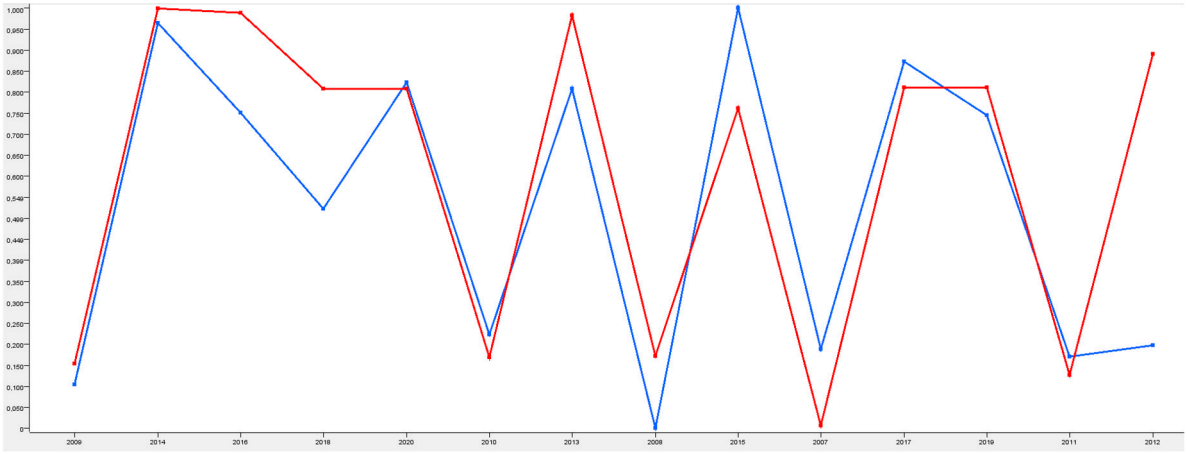


Figure 9. Line plot of the ANNs (the red lines show the actual value, and the blue lines show the forecast values).

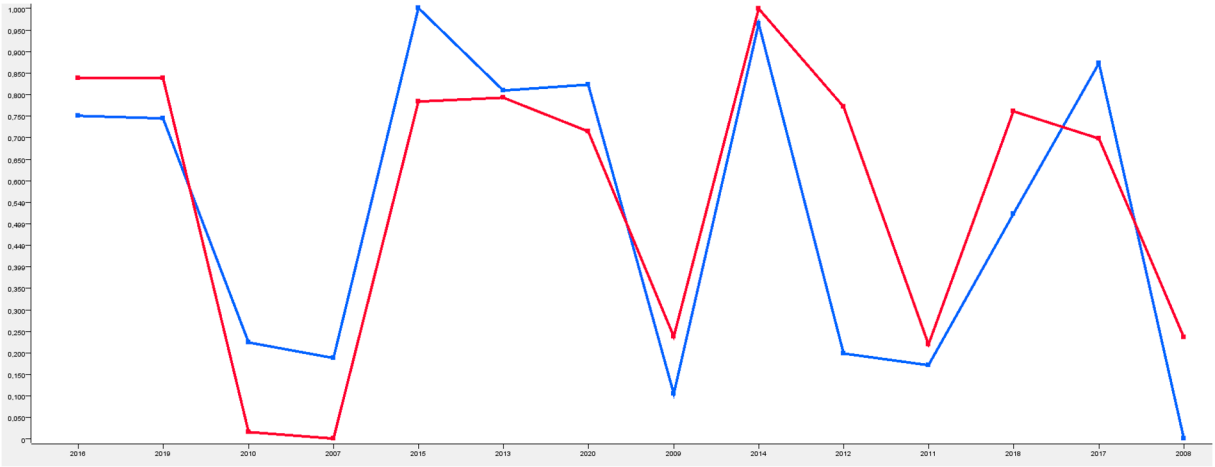


Figure 10. Line plot of logistic regression (the red lines show the actual value, and the blue lines show the forecast values).

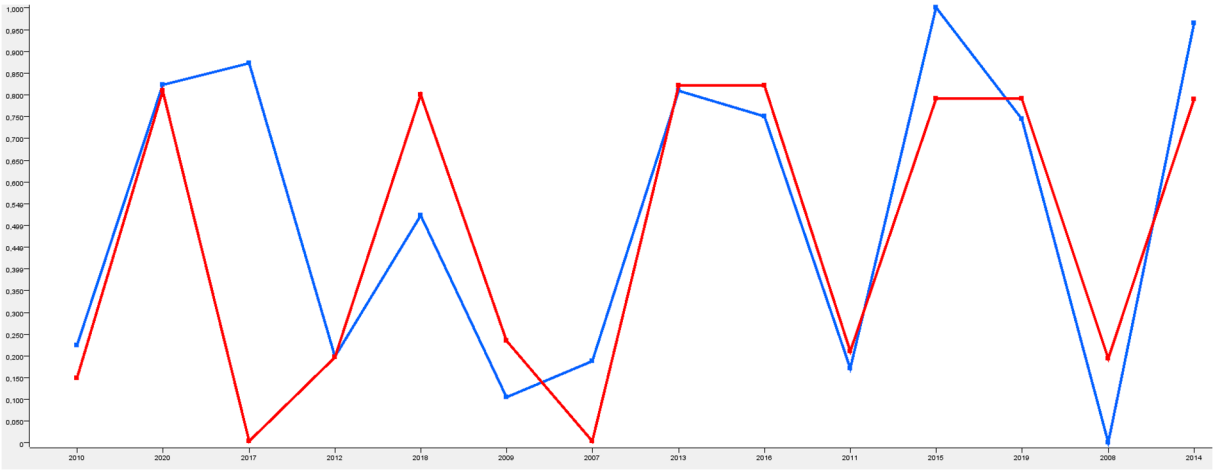


Figure 11. Line plot of support vector regression (the red lines show the actual value, and the blue lines show the forecast values).

Figures 9–11 show the line plots between the actual value of high-tech exports and the prediction values of the machine learning models. Here, the X axis shows the time interval, and the Y axis shows the normalized high-tech exports. In the figure, the red lines show the actual value, and the blue lines show the forecast values. According to the figures,

it can be seen that the forecasting success of all three methods was high. According to the line graphs in the figures, it can be seen that the best fit was ANNs, followed by SVR and logistic regression. This shows that the ANN method had the best fit and prediction power.

A comparison of this study with similar studies in the literature was made. Tekin's MAPE metric was 5.11 in his study on forecasting the monthly export values of broad economic groups belonging to Turkey's foreign trade using the artificial neural networks method [19]. Yang et al., in their study, created an economic model based on exports and imports to forecast global trade using time series management. The highest average MAPE and RMSE values for the time series models were 2.979 and 2.933, respectively, for exports and 4.194 and 4.475, respectively, for imports [13].Wanto et al. estimated the development of oil and gas export and import volumes in Indonesia using an ANN backpropagation algorithm. The MSE metric of their study was 0.028 [10]. Süler et al. forecasted the exports of the Czech Republic to China using ANNs. The R^2 metric of their study was 99% [11]. Gür and Eşidir forecasted Turkey's plastic imports using artificial neural networks. The MSE value of their forecasts was 1.21 [18]. Dai developed a method for forecasting the volume of merchandise exports based on a backpropagation neural network, and the R^2 value of this method was 80% [12].

As can be seen in the studies in the literature, it is evident that the most widely used and successful method is ANNs. When this study is compared with the literature, it can be seen that this model was more successful than other models. The most successful method in the study was ANNs, as in the studies in the literature.

5. Conclusions

This study was conducted to forecast high-tech exports within the framework of sustainable development. Technological development and its integration into the world are realized through foreign trade between countries. For this reason, it is thought that the transfer of technology between countries in line with the goal of sustainability will reduce the margin of error in human-induced production and will be effective in preventing carbon emissions and environmental pollution, which emerge as negative externalities of real production. However, past research on the subject shows that high technology increases carbon emissions during the production and export of high technology. For this reason, forecasts for the future of exports are thought to help policymakers determine the extent to which measures should be taken to combat climate change on a global scale.

In most of the research on foreign trade forecasts to date, it has been observed that machine learning techniques produce successful forecasts with low errors. Therefore, the use of machine learning techniques in this study and the values obtained with low error rates support the results of previous studies. High technology and its products appear to be an important external economic variable that strongly triggers the sustainable growth dynamics of developing countries like Turkey and accelerates international competition in the ongoing transformation with digitalization in the new world order. In this context, an attempt has been made to put forward an accurate and realistic forecasting method. It is thought that the determination and implementation of low-error and realistic forecasting methods for the future are effective in guiding decision makers in economic policy.

In this study, Turkey's high-tech exports were estimated using three different machine learning methods. As a data set, 17 data points obtained from the World Bank between 2007 and 2023 were used. The cross-validation technique was used to increase the success, reliability, and accuracy of the model. According to the results of the study, all three models were successful in predicting Turkey's high-tech exports. The R^2, MAPE, and MSE metrics were calculated to evaluate the error and success of the model, and it was found that the most successful model was the artificial neural network (ANN) model, with results of 94.2%, 0.011, and 0.073%, respectively. The ANN model was followed by support regression and logistic regression. The findings of this study show that artificial neural networks are the most successful method, as is shown in the literature. When the results of this study are compared with the literature, it can be seen that the model was more

successful and had lower error rates. In most of the studies on foreign trade forecasts to date, machine learning techniques have been observed to produce successful forecasts with low error rates. Therefore, the use of machine learning techniques in this study and the values obtained with low error rates support the results of previous studies. High technology and its products appear to be an important external economic variable that strongly triggers the growth dynamics of developing countries like Turkey and accelerates international competition in the ongoing transformation with digitalization in the new world order. In this context, this study aimed to present a forecasting method that provides accurate and realistic results. It is thought that the determination and application of low-error and realistic forecasting methods for the future are effective in guiding decision makers in economic policies.

High-tech exports are an effective way to promote sustainable economic growth. This type of export not only generates economic gains but also supports development in important areas such as innovation, skilled employment, and environmental sustainability. By investing in high-tech sectors and promoting exports in these areas, countries can sustain long-term economic growth.

In future studies, it is planned to apply and compare additional complex models, such as deep learning models, which are trained with large amounts of data. In particular, the success of the model can be increased by working on the number of data sets and the number of independent variables. In addition, it is thought that the success of the model can be increased by using new or hybrid machine learning models. Machine learning models which have been developed can potentially be tailored to suit other nations sharing similar economic and technological attributes to Turkey [54].

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