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DETERMINING THE FACTORS THAT MOST AFFECT THE ECOLOGICAL FOOTPRINT USING THE ARTIFICIAL NEURAL NETWORK CLASSIFICATION FEATURE: THE CASE OF TURKEY

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Abstract

Since the end of the 20th century, ecological problems have become a priority problem due to industrialization, urbanization, technological developments and rapid population growth. The change in human living standards causes many ecological problems such as unconscious consumption of natural resources, extinction of forests and living species. Ecological Footprint is developed to measure the demand pressure that people exert on the environment. In study, Neural Network Fitting Model was used in MATLAB, for the development Artificial Neural Network (ANN) by using the data of 1996-2018 to estimate Turkey's ecological footprint. Urban Population, Renewable Energy Consumption, R&D Expenditures and Human Development Index were chosen as independent variables. The data were obtained from the database of "World Bank Group" and "Human Development Reports". For the ANN, Levenberg-Marquardt algorithm was used to determine the appropriate hidden layer and hidden neurons in each layer. The data used to train an artificial neural network using feedforward and backpropagation were randomly divided into three groups for training, testing and validation purposes. R values for each stage, respectively; 0.999, 0.948, was obtained as 1. According to the results obtained, the independent variable with the greatest effect on the ecological footprint was found to be the Urban Population.

Keywords **:** *Ecological Footprint, Artificial Neural Networks, Forecasting***.**

JEL Classification **:** *Q57, C45, C53.*

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EKOLOJİK AYAK İZİNE EN ÇOK ETKİ EDEN FAKTÖRLERİN YAPAY SİNİR AĞI SINIFLAMA ÖZELLİĞİ KULLANILARAK BELİRLENMESİ: TÜRKİYE ÖRNEĞİ

Öz

20. yüzyılın sonlarından itibaren sanayileşme, kentleşme, teknolojik gelişmeler ve hızlı nüfus artışı, ekolojik sorunları tüm dünyanın karşı karşıya olduğu öncelikli sorunlardan biri haline getirmiştir. İnsanların yaşam standartlarının değişmesi, doğal kaynakların bilinçsizce tüketilmesine, doğadaki endüstriyel ve evsel atıkların çoğalmasına, tarım arazilerinin, ormanların, canlı türlerinin yok olması gibi ekolojik sorunlara neden olmaktadır. Ekolojik Ayak İzi, insanların çevreye uyguladığı talep baskısını ölçmek için geliştirilmiş bir ölçüttür. Bu çalışmada, Türkiye'nin ekolojik ayak izini tahminlemek amacıyla 1996-2018 dönemine ait verilerden yararlanılıp, yapay sinir ağının geliştirilmesi için MATLAB uygulamasında Neural Network Fitting Modeli kullanılmıştır. Araştırmada, kentsel nüfus, yenilenebilir enerji tüketimi, araştırma ve geliştirme faaliyetleri ve insani gelişme endeksi bağımsız değişkenler olarak seçilmiştir. Tahminlemede kullanılan veriler, "World Bank Group" ve "Human Development Reports"un veri tabanından elde edilmiştir. Yapay sinir ağı modeli için ileri beslemeli yapay sinir ağları kullanılmış olup, uygun gizli katman ve her katmandaki gizli nöronların belirlenmesi aşamasında Levenberg-Marquardt algoritmasından yararlanılmıştır. İleri besleme ve geri yayılım kullanarak bir yapay sinir ağını eğitmek için kullanılan veriler eğitim, test ve doğrulama amacı ile rastgele üç gruba ayrılmıştır. Her aşama için sırası ile R değerleri; 0.999, 0.948, 1 olarak elde edilmiştir. Elde edilen sonuçlara göre, ekolojik ayak izi üzerinde en fazla etkisi olan bağımsız değişken kentsel nüfus olarak bulunmuştur.

Anahtar Kelimeler ***:*** *Ekolojik Ayak İzi, Yapay Sinir Ağları, Tahminleme***.**

JEL Sınıflandırması ***:*** *Q57, C45, C53.*

INTRODUCTION

Rapid population growth, urbanization, industrialization, technological advancements, and changes in consumption patterns have upset the natural order since the 1980s and created environmental issues that affect all living things. Studies on how to meet present demands of future generations without using their resources have started to gain importance as environmental problems affecting all nations in the world worsen (Özsoy & Dinç, 2016). The main goal is to protect and develop existing resources in the current global world order, where competitiveness is rising quickly. This situation serves as the foundation for the sustainability concept (Tosunoğlu, 2014). It was the goal of Mathis Wackernagel, William Rees, and colleagues to ascertain how long people could continue to use the environment's resources while discarding their waste. They have developed a method for calculating ecological footprints in order to quantify the amount of biological space needed by an individual to meet all of their needs, to show how much of the natural resources are still available, and to develop strategies for halting environmental degradation (Kaypak, 2012). By comparing the consumption and production of resources, ecological footprint and biocapacity are used to evaluate a country's (or a region's) potential for ecological security and sustainable development. The term "biocapacity" describes the biologically productive lands required for fishing, grazing, building, and the manufacture of forest products (Gao and Tian, 2016).

Since the late 1980s, the Artificial Neural Networks (ANN) method has been used to predict time series. Today, ANN estimation techniques are widely used for estimation in a variety of fields (Ataseven, 2013). ANNs are computer programs with teachable and modelable algorithms that take their cue from how nerve cells (neurons) are arranged in the human brain (Atik et al., 2007). Artificial neural networks, which are based on how the human brain functions, are able to generalize and learn from experience. Future prediction is one of the main uses of neural networks (Hamzaçebi & Kutay, 2004). In artificial neural networks, input, hidden, and output neurons all fall under these three categories. Output neurons send information outside the network, input neurons receive information from outside the network, and hidden neurons receive input from the previous layer's neurons and transmit the output to the subsequent layer's neurons (Biçen, 2006). An additional set of fundamental components in artificial neural networks are weights, summing (addition) functions, and activation functions.

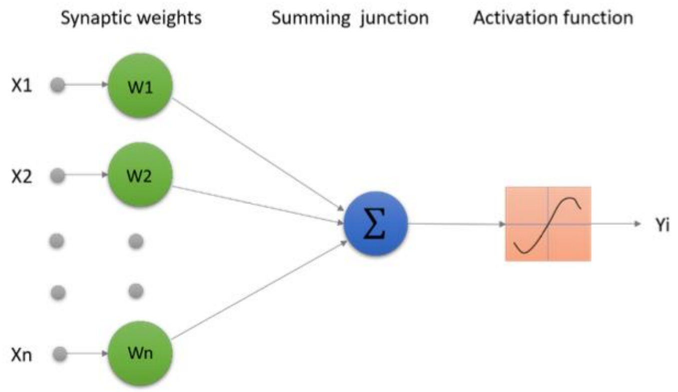

Figure 1. Basic Artificial Neural Network Components

Source: (Ali, 2022).

According to Figure 1, artificial neural networks are made up of an input layer made up of neurons that take in information from the outside world, an output layer made up of neurons that create the network's outputs, and one or more hidden layers in between (Hamzaçebi, 2011). Depending on the training methodology, ANNs are divided into three categories: supervised, unsupervised, and reinforcement learning. Feedback is given in supervised learning models based on the network's error. The difference between the intended output and the output obtained from the network is used to calculate the error. When ANNs are being trained, these errors are utilized. As the error increases, the weights are updated more frequently. To guarantee that the output converges to the target value at each iteration, this process is repeated numerous times. The training is finished when the desired outcome is obtained, and the trained ANN is then obtained. Models that are not supervised do not provide feedback. The network classifies data based on the specified cost function. Both rewards and penalties are used in the reinforcement learning approach. Another name for this approach is the trial and error approach. The network adjusts the weights until a successful output is obtained (Yılmaz, 2022).

I. CONCEPTUAL FRAMEWORK

I.I. Literature Research

According to Akıllı et al. (2008), a survey was given to the faculty, staff, and students of the Akdeniz University Faculty of Economics and Administrative Sciences in order to determine each person's ecological footprint. Out of the 1886 people who made up the research universe, 241 people completed the individual ecological footprint questionnaire. The research used the T Test and Kruskal Wallis H Test to analyze the food, waste, housing, and transportation footprints calculated based on gender, age, income, occupation, and consumption items. The analyses conducted revealed that the ecological footprint ratios could not vary by gender and that as income rose, consumption rose along with it, increasing the overall footprint. Additionally, it has been found that people who own homes and cars have larger ecological footprints.

Using data from developed and developing nations for the years 1961–2009, Ulucak and Erdem (2017) investigated the relationship between the environment and growth using the panel data method. In the study, the ecological footprint serves as a proxy for the environment. The results show that environmental protection measures will cost more in developing countries because the environment has a huge effect on revenue.

The activities of humans pose a threat to the ecosystem and the availability of fundamental necessities for human survival, such as food, water, shelter, clean energy, and air that is free of pollution. In their research, Ahmed and Wang (2019) analyze the influence that human capital has on India's ecological footprint during the years 1971-2014. Their focus is on India. According to the findings, human capital makes a substantial contribution, both positively and negatively, to the ecological footprint. In addition, although the use of energy contributes to a larger ecological footprint, there is an inverted U-shaped pattern in the relationship between economic growth and ecological footprint. The findings suggest that there is a possibility of lowering one's ecological footprint by increasing one's human capital.

The study conducted by Kongbuamai et al (2020) aimed to examine the impact of economic growth, energy consumption, tourism, and natural resources on the ecological footprint of ASEAN countries over a period spanning from 1995 to 2016. The findings of the study indicate a negative correlation between the ecological footprint and the impact of tourism and natural resource utilization in ASEAN nations. The results of the estimation suggest that tourism has a positive impact on the environmental conditions of ASEAN countries, supporting the validity of the inverted U-shaped Environmental Kuznets Curve (EKC) relationship between GDP and ecological footprint.

In BRICS economies from 1992 to 2016, Ulucak et al. (2020) looked at the connections between real income, renewable energy, urbanization, natural resource rent, and ecological footprint. Panel data estimators Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) were applied in the study. They came to the conclusion that natural resource leasing, renewable energy, and urbanization all lessen ecological footprints and improve environmental quality.

Kılınç (2021) evaluated the impact of energy R&D and demonstration spending on the ecological footprint in OECD countries from 2002 to 2016 using panel data methodologies. The study found that the ecological footprint gets smaller as money is spent on energy research, development, and demonstration. It has also been demonstrated that as energy use and GDP per capita rise, so does the ecological footprint.

To investigate the achievement of sustainable development, Ullah and colleagues (2021) conducted a study that focused on analyzing the non-linear association among renewable energy consumption, natural resource rent, and ecological footprint. The research was conducted in the context of the 15 largest economies in terms of renewable energy consumption. Panel time data spanning from 1996 to 2018 was utilized for the analysis. The study utilized the Panel Smooth Transition Model. The outcomes of the study indicate a significant inverse relationship between the utilization of renewable energy and ecological footprint in both low and high regimes. Additionally, a positive association is observed between the ecological footprint and natural resource rent throughout these 15 economies.

The phenomenon of globalization has posed a significant challenge to the concept of environmental sustainability. The objective of the study conducted by Özkan and Çoban (2022) was to examine the association between financial development and ecological footprint in Turkey from 1980 to 2018. This investigation utilized the dynamic autoregressive distributed lag (ARDL) simulation model, a contemporary econometric technique. Based on the findings of the ARDL limits test, it was established that there exists a significant and enduring association between financial development and ecological footprint. Upon careful examination of the findings, it has been ascertained that a lasting positive correlation exists between financial development and ecological footprint factors in the context of Turkey.

The study undertaken by Chen et al. (2022) presents a novel approach to utilizing industrial robots in order to accomplish concurrent economic development and ecological conservation. An investigation was conducted to examine the relationship between industrial robots, which contribute to economic growth, and ecological impact, using data from 72 nations spanning the period from 1993 to 2019. The observation has been made that industrial robots have both positive and negative effects on the ecological footprint. On the positive side, they contribute to reducing the ecological footprint through their time-saving impact, green employment effect, and energy upgrading effect. However, on the negative side, they also have the potential to raise the ecological footprint through the industry mobilization effect. The findings suggest that as economic development and human capital levels increase, industrial robots demonstrate a greater capacity to successfully mitigate the ecological impact. The impact of industrial robots on reducing the ecological footprint has been clearly noticed in OECD countries, where a significant percentage of ecological footprint is present. The analysis proposes that governments across different nations should proactively capitalize on the potential to foster the advancement of industrial robotics, persistently enhance investments in human capital, and expedite the progress of energy sectors.

The structural equation model was employed by Çam and Çelik (2022) to quantitatively identify the variables influencing the ecological footprint. The study's sample consists of 425 adults in Gümüşhane who are at least 18 years old. According to the research's findings, waste and the factors of shelter and transportation have no bearing on the ecological footprint factor, while the variables of food, energy, and water consumption have a negative impact on it.

The study conducted by Usman et al. (2022) examined the influence of nuclear energy and human capital on the ecological footprint of twelve industrialized economies from 1980 to 2015. The projection for nuclear energy has a statistically significant negative relationship, providing evidence that the utilization of nuclear energy has the potential to safeguard the environment through the preservation of water, soil, and forest resources, as well as the mitigation of carbon emissions. Likewise, empirical evidence has substantiated the notion that human capital have the capacity to mitigate the ecological footprint within developed economies. The consumption of electricity is a variable that has the potential to stimulate economic activity, thereby influencing ecological footprints. The escalation of economic activity within industrialized economies is concurrently associated with the depletion of vital resources, including water, soil, and forests, thus resulting in an augmentation of ecological footprints. Based on the findings of the study, it is evident that nuclear energy have the potential to address the challenges associated with energy security and environmental degradation. Consequently, the expansion of nuclear energy production ought to be integrated into the energy and environmental agendas of all nations globally.

In 2023, Appiah et al. conducted a study to assess the efficacy of environmental policies in reducing the ecological footprint. Based on the findings of the study, it has been determined that the utilization of renewable energy sources yields a favorable effect on the ecological footprint. Moreover, the study reveals that innovation plays a crucial role in improving the environmental quality. Additionally, the research indicates that higher population density is associated with a reduction in the ecological footprint, while industrialization is found to contribute to an increase in the ecological footprint. The findings of the study indicate that the implementation of environmental regulation has a significant impact in reducing the ecological footprint within OECD nations.

The study conducted by Saqib N. et al. (2023) investigated the relationship between technical innovation, economic growth, renewable energy, and the ecological footprint during the period spanning from 1990 to 2019. According to the findings, there is evidence to suggest that the introduction of technology advancements and the utilization of renewable energy sources have a notable effect on the reduction of ecological footprint levels. Based on empirical study, it has been observed that there exists a notable correlation between economic growth, financial inclusion, and the levels of ecological footprint in developing nations. Based on the research outcomes, it has been determined that the incorporation of cutting-edge technology and sustainable energy sources in developing nations necessitates financial involvement. This integration is crucial for mitigating long-term environmental harm and promoting sustainable economic development. It has been proposed that developing economies ought to expeditiously adopt technical advancements and enhance financial development in order to mitigate ecological concerns while maintaining a steady pace of sustainable economic growth. To attain this objective, it is imperative for the government to allocate resources towards research and development (R&D) initiatives, while simultaneously providing assistance to the commercial sector.

II. METHOD AND MATERIALS

I.I. Obtaining Data

The study considered the ecological footprint as a dependent (output) variable, the urban population, R&D expenditure, renewable energy consumption, and the parameters of the human development index as independent (input) variables. The figures for the Urban Population, R&D expenditure, and Renewable Energy Consumption parameters as the independent variables for the years 1996–2018 were obtained from "World Bank Group–The World Bank." The Ecological Footprint was used as the dependent variable. The "Human Development Reports" site was used to obtain the data of the Human Development Index (HDI) until 1996-2018. A summary of the data for the study's parameters can be found in Table 1.

Table 1. Range of Parameter Change

Parameter Name	Range of Change
Year	1996-2018
Urban Population	31923298-61872814
R&D Expenditure (percent of GDP)	0,36-1,02
Human Development Index (HDI)	0,6-0,839
Renewable Energy Consumption (REN)	11,40-24,51
Ecological Footprint (EF)	1,30-1,94

I.II. Establishing The Artificial Neural Networks Model

The Levenberg-Marquardt algorithm was applied to identify the hidden layer and hidden neurons in each layer. As stated in the previous section, the input layer of the artificial neural network consists of the following four variables:

(i) Urban Population,

(ii) R&D expenditures,

(iii) Human Development Index,

(iv) Renewable Energy Consumption.

The output layer consists of a variable and contains the Ecological Footprint information. Figure 2 models the artificial neural network built for the study. In the study, the ecological footprint was calculated using four independent variables, and modeling with 25 neurons in each hidden layer was developed.

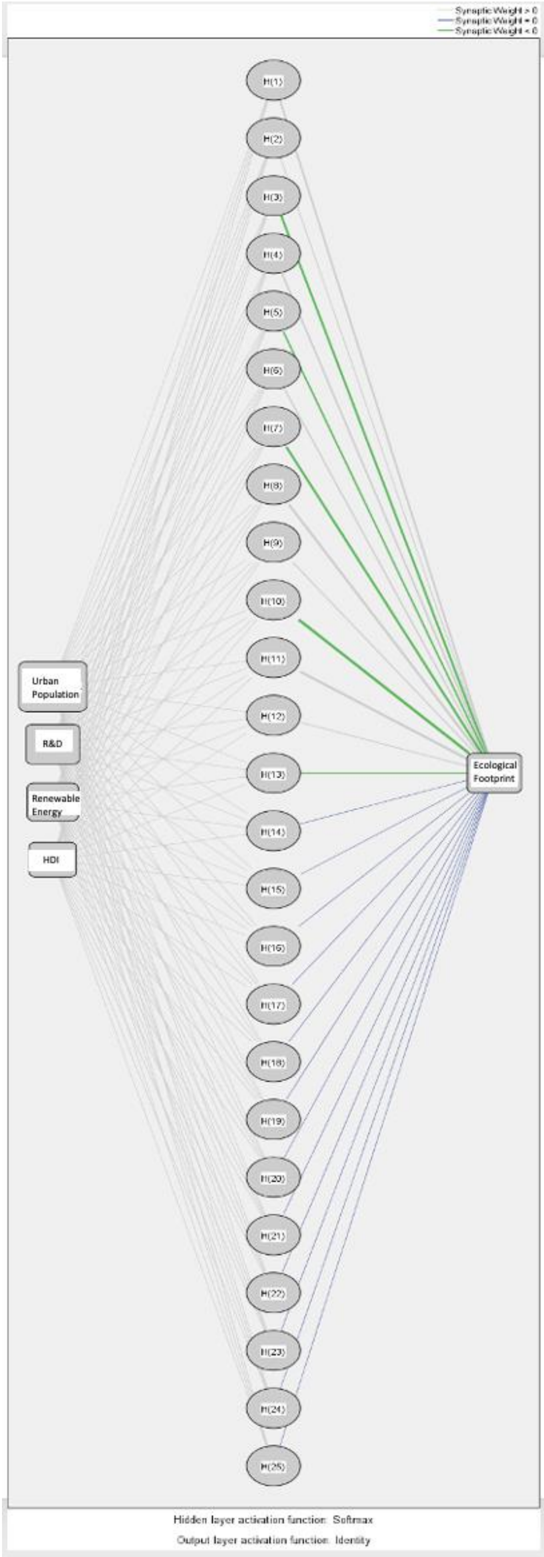

Figure 2. Artificial Neural Networks Architecture

I.III. Determining The Parameters Of Artificial Neural Networks

The right parameter choice is crucial to the neural network's success. The selection of parameters is crucial because the estimation outcomes of an ANN may be negatively impacted by selecting the incorrect parameter values (Kuvvetli et al., 2015). The "Human Development Index" was developed in earlier studies as an alternative to GDP per capita as a measure of human well-being. Given that it takes into account information on people's health and education in addition to their income, it is widely recognized as a welfare theory (Lind,2010; Taner et al., 2011). Adedoyin and others According to the study of (2020), the ecological footprint grows as GDP and non-renewable energy consumption grow; however, the ecological footprint shrinks as spending on research and development and renewable energy use grow.

The impact of each independent variable on the dependent variable was examined, and the urban population was found to have the greatest impact on research and development costs, renewable energy use, and the human development index, as shown in Table 2. The normalized significance of the independent variables is also shown in Figure 3.

Table 2. Importance of Independent Variable

	Importance	Normalized Importance
Urban Population	,469	100,0%
R&D Expenditure (percent of GDP)	,231	49,3%
Renewable Energy Consumption	,184	39,2%
Human Development Index (HDI)	,116	24,8%

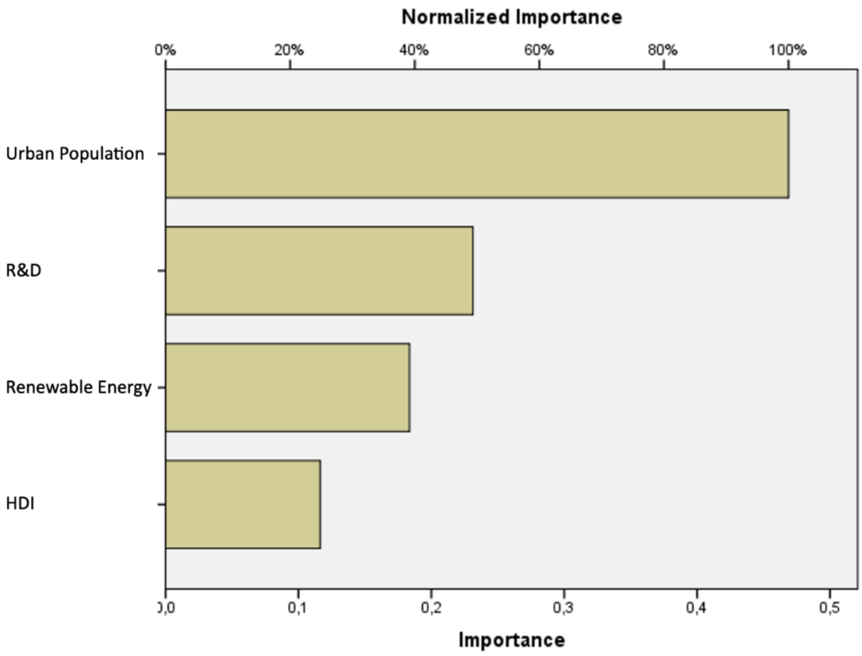

Figure 3. Normalized Importance

Different network architectures were evaluated to identify the ideal number of neurons in the hidden layer and network structure for estimating the ecological footprint. The neural network underwent training employing a diverse set of training algorithms specific to the selected network design, ultimately identifying the most optimal training method.

The Mean Absolute Percentage Error (MAPE) is determined by dividing the absolute error in each period by the corresponding observed values for that period. Subsequently, computing the mean of the aforementioned constant proportions. This strategy is beneficial when the magnitude or scale of a predictive variable plays a substantial role in assessing the precision of a prediction. The Mean Absolute Percentage Error (MAPE) quantifies the degree of discrepancy between predicted values and actual values (Khair et al., 2017).

$$MAPE = \frac{\sum \frac{|y1 - yt^{t}|}{y1}}{n} \times 100\%$$

Uncertainty is inherent in the process of forecasting. A disparity between the projected value and the observed value is consistently present, with the magnitude of this disparity being referred to as the error value. While it is inevitable to encounter errors in predicting, the primary objective is to mitigate the magnitude of these errors. There exist multiple methodologies for assessing the magnitude of error in a time series data model (Liantoni and Agusti,2020). One of the most commonly favored methodologies is the Mean Absolute Percentage Error (MAPE). It is simple to interpret and grasp, making it an excellent alternative to mean squared error, which is one of the primary reasons for its widespread use and widespread appeal. Additionally, MAPE is employed for the purpose of assessing the level of accuracy across various data sets, such as in the selection of a forecasting technique. Consequently, the Mean Absolute Percent Error (MAPE) was employed as a reference point.

In this article, we examine the traditional regression scenario, where we consider a random pair Z = (X,Y) with values in the Cartesian product of a metric space X and the real numbers, denoted as X × R. The objective is to acquire knowledge of a mapping function g that transforms the elements in set X to real numbers, such that the output of g(X) closely approximates the elements in set Y. In order to assess the efficacy of the regression model g, it is necessary to employ a metric for evaluating its quality. In certain scenarios, the mean absolute percentage error (MAPE) can provide a more practical and informative assessment of the predictive performance.

The study involved the calculation of Mean Absolute Percentage Error (MAPE) values for each model, which had a single layer and a varying number of hidden layer neurons within the range of 2 to 26, using Artificial Neural Networks (ANN).

The interpretation of the analysis results involved considering the mean square error (MSE), mean absolute percent error (MAPE), and R values. Based on the obtained results, it was found that the optimal number of neurons in the hidden layer for achieving optimal performance in artificial neural networks is 25. The resulting results exhibit a high degree of accuracy and closely align with the actual observations. Table 3 displays the outcomes pertaining to MSE, MAPE and R value for varying numbers of neurons.

Table 3. Findings Obtained for Different Network Designs

Number of Neurons in the Hidden Layer	MSE	R	MAPE
10	1,319e^{-3}	0,974	0,076
15	6,939e^{-3}	0,980	0,075
20	2,250e^{-3}	0,983	0,063
25	**2,584e^{-4}**	**0,988**	**0,032**
26	3,234e^{-3}	0,968	0,079

The weights of the artificial neural network, which has a single hidden layer and 25 neuron cells in the layer, are shown in Figure 4.

Parameter Estimates

Predictor		Predicted: Hidden Layer[a] H(1)	H(2)	H(3)	H(4)	H(5)	H(6)	H(7)	H(8)	H(9)	H(10)	H(11)	H(12)	H(13)
Input Layer	Urban_Population	-1,465	-1,332	-1,061	-,925	-,628	-,779	-,477	-,327	-,179	,408	,110	,573	,750
	R&D	-1,094	-,866	-1,072	-1,015	-,767	-,691	-1,016	-,835	-,456	,908	,240	,852	,853
	Renewable_Energy	1,717	1,594	1,508	,502	,564	,757	,195	,345	-,098	-,781	-,977	-,445	-,916
	HDI	-1,416	-1,283	-1,050	-,800	-,568	-,734	-,468	-,385	-,301	,164	-,019	,514	,730
Hidden Unit Width		1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183	1,183

Predictor		Hidden Layer[a] H(14)	H(15)	H(16)	H(17)	H(18)	H(19)	H(20)	H(21)	H(22)	H(23)	H(24)	H(25)	Output Layer: Ecological Footprint
Input Layer	Urban_Population	,937	1,133	1,332	1,930	,912	,122	,940	,045	,628	,284	,623	,608	
	R&D	1,036	,956	1,209	1,757	,059	,218	,666	,916	,806	,485	,234	,342	
	Renewable_Energy	-,808	-,571	-1,276	-1,310	,581	,929	,572	,332	,607	,563	,499	,893	
	HDI	,846	1,345	1,512	1,911	,420	,994	,416	,544	,297	,378	,315	,525	
Hidden Unit Width		1,183	1,183	1,183	1,183	,000	,000	,000	,000	,000	,000	,000	,000	
Hidden Layer	H(1)													-179,928
	H(2)													288,580
	H(3)													-1,309
	H(4)													152,758
	H(5)													1185,903
	H(6)													-980,973
	H(7)													-303,590
	H(8)													-247,983
	H(9)													107,101
	H(10)													15,532
	H(11)													-60,221
	H(12)													-49,344
	H(13)													157,723
	H(14)													-113,138
	H(15)													30,870
	H(16)													-40,280
	H(17)													17,161
	H(18)													,000
	H(19)													,000
	H(20)													,000
	H(21)													,000
	H(22)													,000
	H(23)													,000
	H(24)													,000
	H(25)													,000

a. Displays the center vector for each hidden unit.

Figure 4. Weights

III. FINDINGS

The analysis of the proposed artificial neural network model was carried out in the MATLAB software environment, and the results of the Neural Network application were evaluated. The Levenberg-Marquardt method (trainlm), the application's default training method, was used to choose the appropriate hidden layer and the number of hidden neurons in each layer in the first step of the research. This training algorithm is a frequently used fast function and is also the default strategy in the MATLAB Neural Network application. The ANN model displayed the best performance during the fifth iteration of the validation stages, and the training was judged to be finished. The performance of the artificial neural network in each iteration is shown in Figure 5.

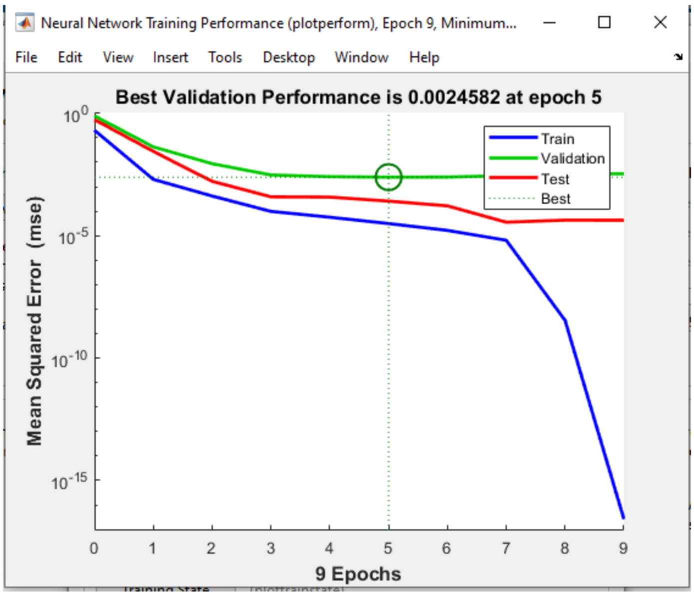

Figure 5. Performance of Artificial Neural Networks Model

Regression values were 0.9994 for the training data set, 0.94753 for the validation data set, 1 for the test data set, and 0.98849 for the entire data set as a result of the analysis performed using the artificial neural network model.

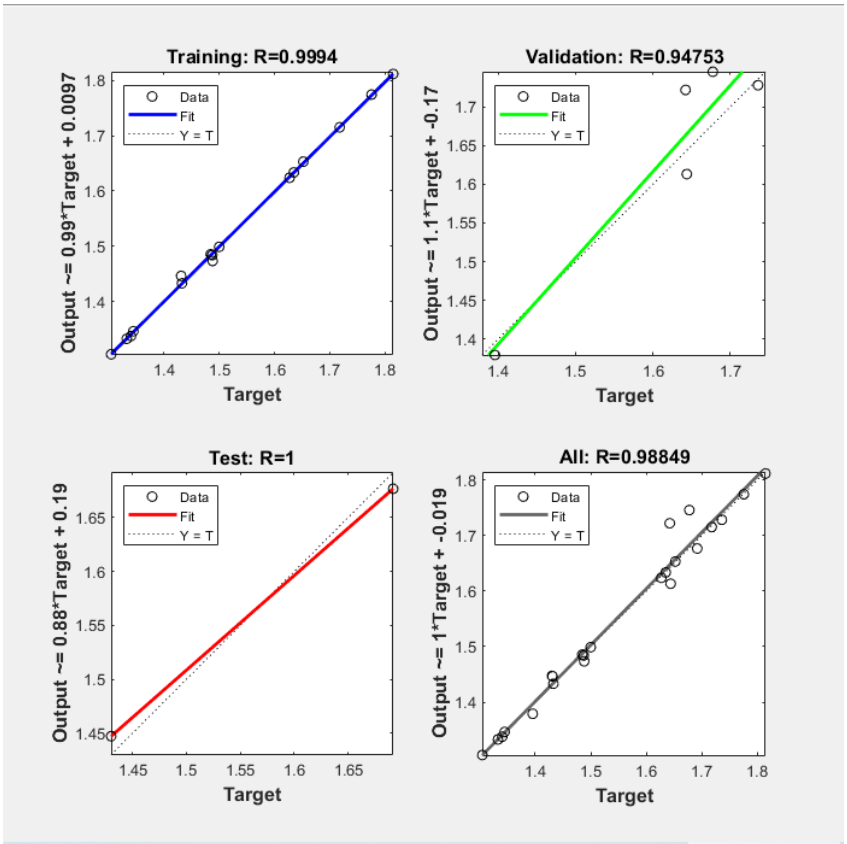

Figure 6. Estimated Performance

CONCLUSION AND RECOMMENDATIONS

Anyone who needs to make wise decisions about the future should be able to accurately predict the future. With the success of the prediction, the accuracy of the decisions made increases. The use of artificial intelligence technology for prediction has been increasing recently and it is known that predictions using artificial intelligence give successful results (Hamzacebi, 2011). This study was conducted with the aim of estimating the ecological footprint of Turkey, and the Neural Network Fitting Model was used in the MATLAB application for the development of the neural network.

The application was carried out with a feedforward and backpropagation artificial neural network. In the study, human development index, urban population, renewable energy consumption, research and development activities, and human development index were chosen as independent variables (input). These variables are among those most frequently used in literature studies on the estimation of ecological footprint.

First, data from the "World Bank Group" and "Human Development Reports" databases from 1996 to 2018 were gathered. These data were then preprocessed and used as the input of the artificial neural network. The neural network was trained using different network architectures to determine the best network structure in terms of mean square error and R value. The network structure with 25 hidden neurons in each hidden layer was discovered to be the most suitable based on the average of the performance parameters. The best training method is then chosen after this network has been trained using a variety of training algorithms. The Levenberg-Marquardt algorithm and the aforementioned network topology training method produced the best results in terms of performance parameters.

The data used to train an artificial neural network using feedforward and backpropagation were randomly divided into three groups for training, testing and validation purposes. R values for each stage, respectively; 0.999, 0.948, was obtained as 1. 1000 repetitions were used as the stopping criterion. According to the results obtained, the independent variable with the greatest effect on the ecological footprint was found to be the urban population.

Calculating an individual's ecological footprint is crucial for assessing their environmental consciousness because it makes them more aware of the effects that will result from ecological issues. By utilizing various input parameters, ecological footprint estimates in upcoming studies can be enhanced and diversified. There should be fewer estimation errors if the input parameters are chosen correctly and across a range of variables.

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