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RECLASSIFICATION OF COUNTRIES ACCORDING TO HUMAN DEVELOPMENT INDEX: AN APPLICATION WITH ANN AND ANFIS METHODS[1]

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ABSTRACT

Classification problems are frequently encountered in the fields of statistics, econometrics and data mining. Techniques used to solve the problem are changing and developing day by day depending on the technology of the age. For this purpose, besides multivariate statistical techniques, methods based on fuzzy and artificial intelligence are also used today. This study aims to make a comparison between the classification performances of artificial neural network (ANN) from machine learning techniques and Adaptive Neural Fuzzy Inference System (ANFIS), which is a combination of ANN and fuzzy logic technique and is based on hybrid learning technique. For this purpose, the countries were classified according to the Human Development Index (HDI) and ANN and ANFIS methods and the results were compared with the HDI. In this context, the HDI of 2015 was measured for 185 countries by using 27 development indicators under eight main topics of health, entrepreneurship, macroeconomics and microeconomics, logistics, trade, social life and natural factors and classification of these countries was estimated. When the analysis results are considered, in economic terms, development is composed of seven factors and eight main subjects according to the estimated index calculated in the study, which is different from the HDI. In terms of statistics, countries have been classified correctly at a rate of 87.5% according to ANN and 91.36% according to ANFIS. In this case, it was observed that the ANFIS method gave better results than ANN.

Keywords: *Human Development Index, Artificial Neural Network, Classification, ANFIS*

JEL Codes*: C45, C44, C38*

ÜLKELERİN İNSANİ GELİŞMİŞLİK ENDEKSİNE GÖRE YENİDEN SINIFLANDIRILMASI: YAPAY SİNİR AĞI VE ANFIS YÖNTEMLERİ İLE BİR UYGULAMA

ÖZ

İstatistik, ekonometri ve veri madenciliği alanlarında sınıflandırma problemlerine sıklıkla karşılaşılmaktadır. Bu amaç doğrultusunda kullanılan yöntemler teknolojiye bağlı olarak günden güne değişmekte ve gelişmektedir. Bu kapsamda çok değişkenli istatistik ve yapay zeka yöntemleri günümüzde kullanılmaktadır. Bu çalışmada, makine öğrenme tekniklerinden yapay sinir ağı (ANN) ve YSA ile bulanık mantık tekniğinin birleşimi olan ve hibrid öğrenme tekniğine dayanan Adaptif Ağ Tabanlı Bulanık Çıkarım Sistemi (Adaptive Neural Fuzzy Inference System-ANFIS) yöntemlerinin sınıflandırma performanslarının karşılaştırılması amaçlanmaktadır. Bu amaç doğrultusunda Birleşmiş Milletler Dünya Gelişmişlik Göstergeleri ve ANN ve ANFIS yöntemleri kullanılarak İnsani Gelişmişlik Endeksi'ne (HDI) göre ülkeler sınıflandırılmış ve elde edilen sonuçlar İGE ile karşılaştırılmıştır. Analiz sonuçları ele alındığında, iktisadi açıdan; çalışmada hesaplanan tahmini endekse göre gelişmişlik, İGE'den farklı olarak, yedi faktör ve sekiz ana konudan oluşmaktadır. İstatistiki açıdan ülkeler; ANN'ye göre %87.5 ve ANFIS'e göre %91.36 oranında doğru sınıflandırılmıştır. Bu durumda ANFIS yönteminin ANN'den daha başarılı sonuçlar verdiği gözlenmiştir.

Anahtar Kelimeler: *İnsani Gelişmişlik Endeksi, Yapay Sinir Ağı, Sınıflandırma, ANFIS*

JEL Kodları: *C45, C44, C38*

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1. INTRODUCTION

Growth and development issues hold an important place in the national and international policies of the countries. Over time, development activities of the countries have been towards owning or governing more land, increasing the amount of production or having advanced technology. Thus, in the past, the countries have made wars in order to grow, subjected the people of the conquered lands to tax and tried to maintain power by financial enforcements.

With the industrial revolution, production opulence factor has started to be used as an indicator of development. During this period, until the beginning of the 20th century, development of countries was evaluated with GDP, which represents the monetary value of the total production amount.

After the Second World War, the idea of income-based growth was intensively criticized due to its inadequacy in explaining development. The basis of these criticisms comprised the idea that it is wrong to evaluate the development only quantitatively and the "human" factor should also be considered. Based on this, it was proposed that not only production but also the quality of life achieved by the income obtained through production should be taken into account while measuring the development of the countries. As a result of these criticisms, utilization of quality of life when measuring development had started with HDI.

HDI is the most important index that measures the development of countries at an international level. Within the scope of the index, development of countries is graded based on whether their citizens are leading a happy, healthy and successful life. Individuals doing research for investment or tourism purposes can obtain information about the countries. In this respect, for countries, the index values and classifications are important at an international level.

This study includes two purposes, which are economic and statistical. In terms of economics, the aim is to bring a different perspective to HDI calculation using different indicators and methods; whereas, in terms of statistics, the aim is to compare the classification performances of ANN and ANFIS methods.

2. LITERATURE REVIEW

In the literature, there are many studies with a critical perspective about HDI and the majority of these studies aim to develop a new index or calculation method based on alternative indicators. Of these studies, Akder (1994) stated that changing indicators without changing the HDI calculation method would not change the ranking. Hicks (1997) developed a new index based on inequality for 20 countries. Hicks found that the obtained results are similar to those obtained by HDI. Chakravarty (2003), instead of classical averages, used different formulas and axioms, and established a new development index called success in life index. Charmes and Wieringa (2003) added gender factor to HDI calculations and established the African gender and development index. Based on this, they found that there is an increase in the development scores of the countries. Despotis (2005) stated that HDI should be calculated using a different method (data envelopment analysis). Crowdhury and Squire (2006) criticized how the indicators were of equal weight during the calculation of the development index published by WB and HDI published by UN.

Çiftçi (2008) argued that, although the concept of life expectancy is used regularly in human development reports, there would actually be separate life expectancies for each age group and thus it should be evaluated differently. Alkire and Foster (2010) criticized the Inequality index calculated within the scope of HDI and developed an alternative, novel calculation model. According to the authors, there are two types of weak points in the calculation of national income. The weak points are how the income ratio disregards the purchase and how the people disregard the claims on aggregate income. According to Harttgen and Klasen (2011), one of the weakest points of HDI is how the countries disregard inequality in distribution. Chang et al. (2013) argued that life expectancy at birth holds great importance in the human development classification of countries. Bravo (2014) criticized how HDI is considered independent of sustainable environmental factors. In this regard, he calculated sustainable HDI (SHDI), which he claims is the corrected version of HDI. Coşkun, Özgenç, and Güneş (2015) investigated the historical development of Social Development Index and the Turkey's place at index ranking. In the study, they argued that the weak points of developed countries and the strong points of underdeveloped countries are disregarded in the economic development classification of HDI.

Deb (2015) criticized the mean-based methodology used in HDI calculation and the lack of using any other indicators than health, education, and income. According to the author, when calculating the index, at least 8 indicators, which are, life standards (income, consumption, and wealth), health, personal activities, political statements and government, social network and relationships, environmental sustainability and economic/physical security indicators, should be used. In their study, Permai, Tanty, and Rahayu (2016) developed a logistic model which estimates HDI using geographical weighting-based multiple logistic regression analysis. Mercimek and Çağlayan (2017) studied the relationship between HDI score, and Global Gender Inequality Index score and life expectancy among genders.

3. METHODS

3.1. Artificial Neural Network

Since the beginning of time, humans have lived at the heart of nature, and inspired by nature, they learned to approach many problems with different solutions. Artificial neural networks (ANN) are defined as "parallel and distributed information processing structures developed based on the human brain, and comprising elements with their own memory which interconnect via sparse junctions" (Elmas, 2003:23). Its structure was developed via mathematical modeling based on the biological neural network. Based on this network, the nerve cell, neuron, of the natural nervous system, is called a node in the artificial neural network and the system comprises many nodes that work in parallel (Rajpal, Shishodia and Sekhon, 2006).

Artificial neural network is a system that consists of input and output nerves. In this regard, nowadays it is utilized in many fields due to its features such as data-based learning, finding solutions to problems on different subjects, the ability to generalize, and fast processing speed. The structure of the artificial neural network is based on the production of an output from multiple inputs. This means that the output can be presented both as a result of the analysis and as an input for another node. A neural network model was given as an example in Figure 1.

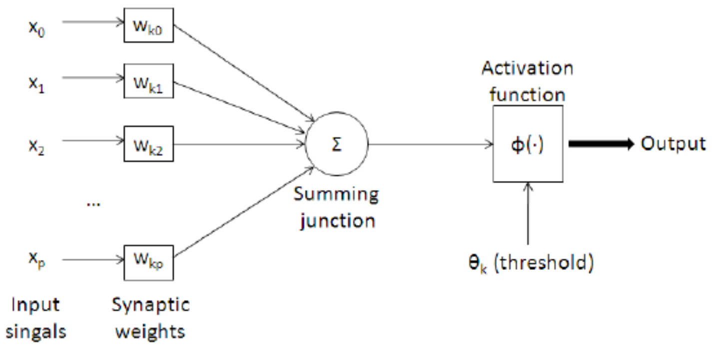

Figure 1. Artificial Neural Network Model

An artificial neural network comprises five main components. These are input, weight, aggregation function, activation function, and output (Şen, 2004). Input is the data set that the artificial neural network is asked to learn. While these data are externally introduced values at the beginning, later they can be the output of the training of another artificial neural network. Weight is the most important subject in the training of the artificial neural network. In this model, inputs are multiplied with the weights and then their sum is calculated. Aggregation Function is defined as the sum of the multiplication of the network inputs with their weights. Activation function is where aggregation value is directed to an output through a function. Functions widely used in the literature are linear, step, threshold, sigmoid and hyperbolic tangent.

Table 1. Activation Functions

Activation Function	Mathematical Formula
Linear	$F(x) = x$
Step Function	$F(x) = \begin{cases} 1, & x > 0 \\ -1, & x \leq 0 \end{cases}$
Threshold Function	$F(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases}$
Sigmoid Function	$F(x) = \frac{1}{1 + \exp(-x)}$
Hyperbolic Tangent Function	$F(x) = \tanh(x)$
Gaussian Function	$F(x) = \exp\left(-\frac{x^2}{2\sigma^2}\right)$

Artificial neural networks also have a layered structure made up of components. ANN sample model is given as an example in Figure 2.

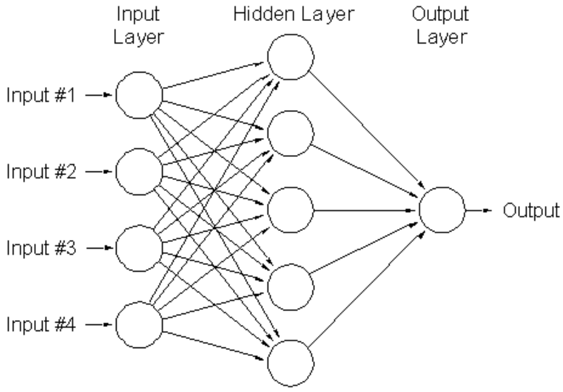

Figure 2. Artificial Neural Network Sample Structure

Artificial nerve cells come together to form the artificial neural network. ANN structure comprises three parallel orders: input, hidden, and output layers. Input layer includes input component, hidden layer comprises the aggregate and transfer function for the transformation of the input to output, output layer includes the process of the network to reach an outcome. There is a single input layer and a single output layer in an artificial neural network. However, the number of hidden layers and the number of neurons within the layer can change. The number of neurons and hidden layers to reach an outcome is left to the experience and initiative of the person performing the analysis. In addition, ANN method is divided into different groups, as supervised and unsupervised learning based on the learning status, and as feedforward and feedback learning based on the working principle of the network. In terms of implementation, ANN method can be utilized for modeling, estimations, classifications or pattern formation. Some of these studies are given in Table 2.

Table 2. Literature Review on ANN

Aim	Author	Year	Aim	Author	Year
Classification	Fish, Barnes and Aiken	1995	**Estimation**	Lee and Park	1992
	Schumacher, Robner and Vach	1996		Dawson and Wlby	1998
	Tu	1996		Ottenbacher et al.	2004
	Zhang, Hu, Patuwa and Indro	1999		Efendigil, Önüt and Kahraman	2009
	Ottenbacher *et al.*	2001		Lee and Yang	2009
	Dreiseitl and Machado	2002		Chang T. S.	2011
	Liew *et al.*	2007		Donel	2012
	Liao and Wen	2007		Gelmereanu, Morar and Bogdan	2014
	Briesch and Rajagopal	2010		Joo et al.	2014
	Hsu	2011		Lee and Choeh	2014
	Khashei, Hamadani and Bijari	2012		Aydın and Cavdar	2015
	Gallo, Conto, Sala and Antonazzo	2013		Bukharov and Bogolyubov	2015
	Omiotek, Burda and Wojcik	2013		Haga, Siekkinen and Sundvik	2015
	Chandra and Babu	2014		Kristjanpoller and Minutolo	2015
	Costea	2014		Bataineh, Marler, Malek and Arora	2016
	Alfonso, Sassi and Barreiros	2015		Özçalıcı	2017
	N. Agrawal and J. Agrawal	2015	**Modeling**	Garrido, Ona and Ona	2014
	A. Bhardwaj, Tiwari, H. Bhardwaj and A. Bhardwaj	2016		Badea	2014
	Toprak	2017		Falat, Staniko, Durisova, Holkova and Pokanova	2015
Pattern Formation	Bourquin, Schmidli, Hoogevest and Leuenberger	1997			
	Pao	2008			
	Yee and Chong	2013			

3.2. ANFIS Method

Basically, ANFIS has a structure which integrates fuzzy logic and ANN methods (Chen, 2013). It can be said that the closest similarity between these two methods is that they both try to understand the structure between the input and output variables. For this purpose, both methods are used to produce models (Özkan and İnal, 2014).

Fuzzy logic is based on the article published by Lotfi Aliasker Zadeh in 1965 on the transition from classical logic to linguistic expression concept. According to Zadeh, belonging of an entity to a set can be expressed with at least three different propositions (Zadeh, 1965). Mathematically speaking, according to classical logic, an entity either belongs to a set, or it does not. However, according to the fuzzy logic, each entity has a degree of belonging to a set. In classical logic, states that can be expressed as 0 (not a member) or 1 (member) are expressed as a degree of membership between 0 and 1 in fuzzy logic (Baykal and Beyan, 2004). These degrees of membership are determined by membership functions in fuzzy logic. Four types of membership functions are used extensively in fuzzy logic. These are; triangular, trapezoidal, gaussian, and bell-shaped membership functions.

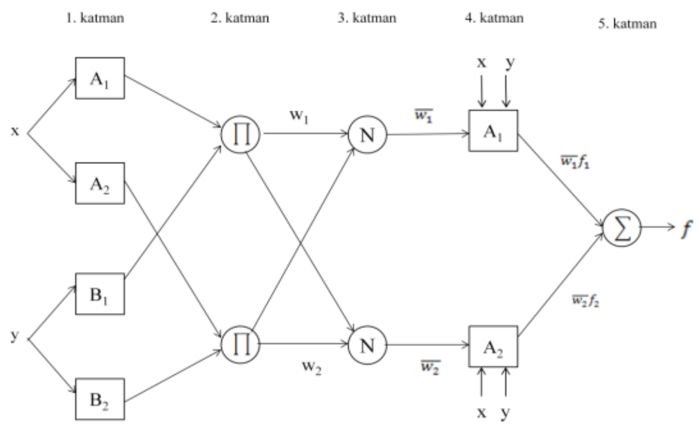

Figure 3. ANFIS Model Structure

Reference: *(Jang, 1993)*

According to the figure, there are two inputs, x and y, and an output, (f) in the ANFIS structure. The first layer shows the input variables in the model and can be described as the place where the data set is defined to the system. The Ai and Bi refer to the linguistic variables in fuzzy logic. After this stage, a previously chosen fuzzy logic membership function is used to multiply the input variables and then these values are normalized in the third step. Normalization is done by dividing the value of each input by the total value. In the fourth layer, Takagi Sugeno-type fuzzy logic is performed and the total output value is obtained (Do and Chen, 2013). Mathematical functions and other operations used in these stages are as follows:

Table 3. ANFIS Implementation Stages

Rule Set		**If x_1 A_1, $f_1=p_1x+q_1y+r_1$** **If x_1 A_2, $f_2=p_2x+q_2y+r_2$** **If x_2 B_1, $f_3=p_3x+q_3y+r_3$** **If x_2 B_2 , $f_4=p_4x+q_4y+r_4$**
1.	**Layer**	In this stage, membership function is selected and the membership degrees of the variables are determined. $(\mu_{Ai}(x), \mu_{Bi}(y))$
2.	**Layer**	This is where the membership functions are multiplied. $w_i = \mu_{Ai}(x).\mu_{Bi}(y)$
3.	**Layer**	This is where the normalization is performed. $\overline{w_i} = \frac{w_i}{\sum w_i}$
4.	**Layer**	This is where Takagi Sugeno system is used. $\overline{w_i}.f_i$
5.	**Layer**	This is where the fuzzy numbers obtained via fuzzy logic are transformed into their real values. $x_0 = \frac{\sum w_i f_i}{\sum w_i}$

In the literature, sample studies done by ANFIS method can be analyzed in three groups based on their theoretical aspect and purpose of implementation: modeling, estimation, and classification. Some of these studies are given in the table below.

Table 4. ANFIS Literature Review

Aim	Author	Year	Aim	Author	Year
Classification	Chen	**2013**	**Estimation**	El-Sebakhy	**2008**
	Güneri, Ertay and Yücel	**2011**		Chien, Wang and Lin	**2009**
	Shekarian and Gholizadeh	**2013**		Boyacıoğlu and Avcı	**2010**
	Özkan and İnal	**2014**		Ho and Tsai	**2011**
Modeling	Wang and Elhag	2008		Iphar	2012
	Moayer and Bahri	**2009**		Roham, Gabrielyan and Archer	**2012**
	Kwong, Wong and Chan	**2009**		Akkoç	**2012**
	Mashrei, Abdulrazzaq, Abdalla and Rahman	**2010**		Bagheri, Mohammadi Peyhani and Akbari	**2014**
	Vasileva-Stojanovska, Vasileva, Malinovski and Trajkovik	**2015**		Oztekin, Kızılaslan, Freund and Iseri	**2016**
	Wu, Huang and Chen	**2015**			
	Atashi, Nazeri, Abbasi, Dorri and Alijani	**2017**			

4. AIM AND SCOPE OF THE STUDY

The structure of the study includes two different purposes in terms of statistics and economics. In terms of statistics, the aim is to compare the correct classification performances of artificial neural network and fuzzy artificial neural network methods used in classification problems; in terms of economics, the aim is to calculate the human development index classification regularly published by the UN using different indicators and alternative methods. At the same time, the aim is to produce the model that can explain the development problem with the least number of indicators the best.

For this purpose, the study was based on the development classification calculated by UN for the year 2015 and the development indicators given on the official UN webpage were used as the source data set. Since the data set comprised different variables, and since each variable was announced on different dates by the countries, not all countries could be included in the analysis. Therefore, 10 of 195 countries were excluded and the remaining 185 countries were included in the study. These countries are divided into four classes: highly developed, developed, moderately developed, and underdeveloped.

To determine the variables to be used in the study, initially 118 variables were taken into account. Then, to determine the indicators that would explain the development problems of the countries the best, the data set was analyzed by anti-image correlation matrix, correlation, and basic component methods. Based on the anti-image correlation matrix, 59 of 118 variables were excluded from the analysis. Then, correlation analysis was done and it was found that the types of GDP, in particular, are fully or highly correlated with each other. Therefore, 19 variables were excluded from the analysis. Then, for the remaining 40 variables, basic component analysis was performed, and the 13 variables which fall under more than one factor due to the factor weights, which are close in terms of value, were excluded from the analysis. Thus, in conclusion, after the necessary elimination processes, 27 variables with different subjects were included in the factor analysis. The list of these variables is given in Table 5.

Table 5. The List of Variables Used in the Study

Subject	Indicator Name
Environmental	Fish species, endangered
Environmental	Plant species (tracheophytes), endangered
Environmental	Bird species, endangered
Environmental	Mammalian species, endangered
Entrepreneurship	Domestic loans provided by the financial sector (as a percentage of GDP)
Entrepreneurship	Ease of doing business index (1=the most business-friendly regulations)
Entrepreneurship	Duration of registration of deed (days)
Entrepreneurship	Total tax rate (as a percentage of commercial profit)
Logistics	Secure Internet servers (per 1 million people)
Logistics	Air freight (million tonnes X km)
Macro Economy	Inflation, consumer prices (annual %)
Macro Economy	GDP (in local currency)
Macro Economy	Imported goods (in current US dollars)
Macro Economy	Consumer price index (2010=100)
Macro Economy	Net income from abroad (in current US dollars)
Macro Economy	Per capita GDP (in current US dollars)
Micro Economy	Trade in goods (as a percentage of GDP)
Micro Economy	External balance of goods and services (as a percentage of GDP)
Micro Economy	PPP conversion factor, private consumption (according to International dollars in local currency)
Micro Economy	Cross-border Trade (as a percentage of GDP)
Micro Economy	Distance to the border (0 = the lowest performance, 100 = border)
Micro Economy	Payment of taxes (number)
Health	Under-five mortality rate (per 1000 live births)
Health	Prevalence of diabetes (percent in population aged 20 to 79)
Social	Urban population (as a percentage of total population)
Social	Rural population (as a percentage of total population)
Social	Proportion of seats held by women in national parliaments (%)
Social	Age-related dependency ratio (as a percentage of the working population)

According to the table, it can be seen that the indicators are of macro and micro economic, social, environmental, logistics, entrepreneurship, and health fields. When the indicators to be used in this study are compared with those used in HDI, it can be said that in this study, the factors that affect the human development indexes of countries will be covered more differently and in detail. However, the most striking result here is that there are no education-related indicators, although education is included in the evaluation since the year it was first calculated by UN. The underlying reason can be that education-related variables are highly correlated with other variables and the education level of the society is explained much better by other variables. However, the superiority of this study in terms of the selected variables lies in the fact that it includes variables from environmental, entrepreneurship, social, logistic and micro economy fields, which are not used when calculating the HDI.

After this stage, sub-indexes to explain the human development of countries were formed. Based on this, 27 indicators were grouped under 7 factors. Eigenvalue weights of the factors are given in Table 5.

Table 6. Total Variance Found After Factor Analysis

Factor	Total	% of Variance	Cumulative %
1	6.543	23.367	23.367
2	3.646	13.021	36.388
3	2.979	10.639	47.027
4	2.784	9.942	56.968
5	1.861	6.646	63.614
6	1.803	6.438	70.053
7	1.739	6.210	76.263

According to the table, factor analysis was performed on 27 variables and the main components were grouped under 7 factors via inference method. These factors explain 76.26% of the development problem of the countries. When the rates of these factors to explain the problem are analyzed, it is seen that the rate of the first factor is 23.37%, the second factor is 13.02%, the third factors is 10.64%, the fourth factor is 9.94%, the fifth factor is 6.65%, the sixth factor is 6.44%, and the seventh factor is 6.21%. In Table 23, it is seen which indicator is explained under which factor.

Table 7. List of Factor Weights of the Variables

Rotated Components Matrix								
Subject	**Indicator Name**	**Factors**						
		F1	F2	F3	F4	F5	F6	F7
Social	Age-related dependency ratio (as a percentage of the working population)	.914						
Micro Economy	Distance to the border (0 = the lowest performance, 100 = border)	.896						
Health	Prevalence of diabetes (percent in population aged 20 to 79)	.893						
Social	Urban population (as a percentage of total population)	.878						
Macro Economy	Per capita GDP (in current US dollars)	.868						
Social	Rural population (as a percentage of total population)	.840						
Entrepreneurship	Total tax rate (as a percentage of commercial profit)	.836						
Social	Proportion of seats held by women in national parliaments (%)	.756						
Health	Under-five mortality rate (per 1000 live births)	.691						
Logistics	Secure Internet servers (per 1 million people)		.940					
Macro Economy	Net income from abroad (in current US dollars)		.914					
Logistics	Air freight (million tones X km)		.880					
Macro Economy	Imported goods (in current US dollars)		.860					
Entrepreneurship	Ease of doing business index (1=the most business-friendly regulations)			.877				
Micro Economy	Payment of taxes (number)			.722				
Entrepreneurship	Duration of registration of deed (days)			.673				
Micro Economy	Domestic loans provided by the financial sector (as a percentage of GDP)			-.628				
Entrepreneurship	External balance of goods and services (as a percentage of GDP)			-.616				
Natural Factors	Plant species (tracheophytes), endangered				.851			
Natural Factors	Mammalian species, endangered				.806			
Natural Factors	Bird species, endangered				.780			
Natural Factors	Fish species, endangered				.670			
Macro Economy	GDP (in local currency)					.879		
Micro Economy	PPP conversion factor, private consumption (according to International dollars in local currency)					.853		
Micro Economy	Trade in goods (as a percentage of GDP)						.887	
Micro Economy	Cross-border Trade (as a percentage of GDP)						.872	
Macro Economy	Inflation, consumer prices (annual %)							.911
Macro Economy	Consumer price index (2010=100)							.841
	Solution was obtained using 6 rotations.							

In the table, it is seen which indicator is explained under which factor. Based on this, the factors are named as follows. At the same time, these factors were used as the independent variables of ANN and ANFIS methods.

Table 8. List of Independent Variables

F1: Socioeconomic Development Index
F2: International Trade-Based Logistic Activities Index
F3: Entrepreneurship Index
F4: Natural Life Index
F5: Income Index
F6: Foreign Trade Index
F7: Inflation Index

5. RESULT OF THE ANALYZES

5.1 Result of the Implementation of ANN

Artificial neural networks are among the methods in which the biological network structure is mathematically simulated and used in problem-solving. Accordingly, the available data set is divided into 3 separate groups; training, validation, and testing. Training data set is used to introduce the problem to the artificial neural network; validation is used to enable the network to generalize the knowledge it learned through training; and test is used to show how strong the estimations of the trained network can be. In this study, 70% of the data set (105 countries) was used for training, 15% (22 countries) was used for validation, and the remaining 15% (22 countries) was used for testing. As the neural network, a feed-forward back-distributed artificial neural network was used. The network's training was completed with 51 iterations, and the screenshot is given below.

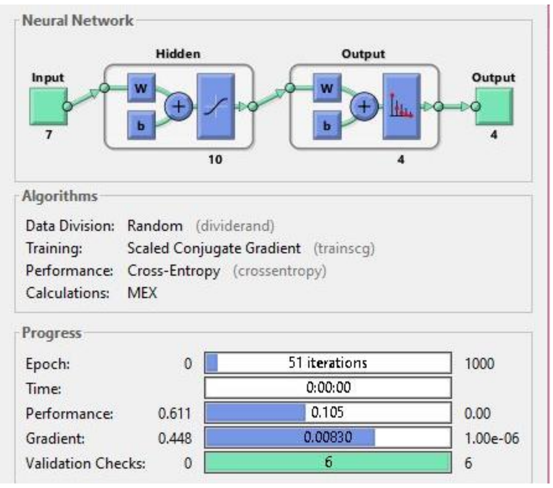

Figure 4. Screenshot of the Success of the Neural Network

The screenshot regarding the success of the neural network to classify the countries is given below.

Figure 5. Screenshot of the Success Rates of the Network in Correct Classification

In the figure, the success rates of the network in training, validation, testing and correct classification in general are given. Based on this, the color green represents the number of correctly classified countries, and the color red represents the number of incorrectly classified countries. The network's overall success rate in education is 85.5%, and 20 countries were incorrectly classified. While the success rate of validation is 84.2% and 3 countries were incorrectly classified; the success rate in test data is 85.7% and 4 countries were incorrectly classified. The overall success rate of the network in correctly classifying the countries based on 7 factors is 85.4%. The countries incorrectly classified by the ANN method are given in the table below.

Table 9. Countries Incorrectly Classified by the ANN Method

	Country	Actual Class (… Development Level)	Estimated Class (…Development Level)
1	Brunei Darussalam	Very High	High
2	Croatia	Very High	High
3	Hungary	Very High	High
4	Mongolia	Very High	High
5	Saudi Arabia	Very High	High
6	Belarus	High	Very High
7	Algeria	High	Moderate
8	Grenada	High	Moderate
9	Samoa	High	Moderate
10	Sri Lanka	High	Moderate
11	Trinidad and Tobago	High	Moderate
12	Bhutan	Moderate	High
13	The Arab Republic of Egypt	Moderate	High
14	El Salvador	Moderate	High
15	Moldova	Moderate	High
16	Montenegro	Moderate	High
17	Paraguay	Moderate	High
18	Vanuatu	Moderate	High
19	Equatorial Guinea	Moderate	Low
20	Kiribati	Moderate	Low
21	Tajikistan	Moderate	Low
22	East Timor	Moderate	Low
23	Zambia	Moderate	Low

According to the table, 23 countries were incorrectly classified by using the artificial neural network. While Brunei Darussalam, Croatia, Hungary, Mongolia and Saudi Arabia of these are very highly developed countries according to the UN HDI, they were estimated as highly developed countries. Similarly, while Algeria, Belarus are developed, they were estimated as highly developed; and Algeria, Grenada, Samoa, Sri Lanka, Trinidad, and Tobago were estimated as having a low level of development. While Bhutan, Arab Republic of Egypt, El Salvador, Moldova, Montenegro, Paraguay, and Vanuatu are moderately developed countries, they were estimated as highly developed countries; and Equatorial Guinea, Kiribati, Tajikistan, East Timor and, Zambia were estimated as having a low level of development. The correct classification rate of the method was found to be 94%. Correct classification rates in terms of classes are given below.

Table 10. ANN Correct Classification Table

Observed Class	Classification				
	Estimated Class				
	Very Highly Developed	Highly Developed	Moderately Developed	Underdeveloped	Percentage Of Accuracy
Very Highly Developed	44	5	0	0	89.8%
Highly Developed	1	48	5	0	88.9%
Moderately Developed	0	7	26	5	68.5%
Underdeveloped	0	0	0	44	100%
Total %	24.3%	32.9%	16.2%	26.5%	87.5%

According to the table, the highest level of success in classification was achieved in underdeveloped countries and all countries were estimated correctly. This is followed by very highly developed countries, with a correct classification rate of 89.9%, and by developed countries with 88.9%, and moderately developed countries with 68.5%. Based on these data, while 162 countries were correctly classified, 23 countries were classified incorrectly. Thus, the correct classification rate for all countries was found to be 87.5%. Based on the classification results of the artificial neural network implementation, it can be said that the countries were estimated to be either in the class immediately superior or immediately inferior to their actual class.

5.2. Result of ANFIS Implementation

In the implementation of ANFIS method, a certain level of decision units in the data set are used in the training of the dataset, and the others are used for testing. The widely accepted opinion in the literature is that the ratio of training and test should be 70%-30%. Therefore, in this study, twelve countries will be used for testing while the rest will be used for training. At the same time, randomly selected twelve countries of those to be used for training are designated as control data. Here, training data is used to teach the network the problem, control data is used to enable the network to generalize, and the test data is used to identify how correct the network's estimations are.

Table 11. ANFIS Data Set Country Numbers

Classes	**Education**	**Test**
Very Highly Developed	37	12
Highly Developed	42	12
Moderately Developed	26	12
Underdeveloped	32	12

To implement fuzzy logic, membership function type and number should be identified. According to this, in this study, since the factor weights are higher than the others, it was decided that three membership functions will be used for F1 and F3, whereas two membership functions will be used for the other factor. The network constructed in this way was trained according to the Mamdani

Sugeno-type fuzzy logic with Gauss combination membership function (Gauss2mf) with 150 iterations. The screenshot regarding the network training is given below.

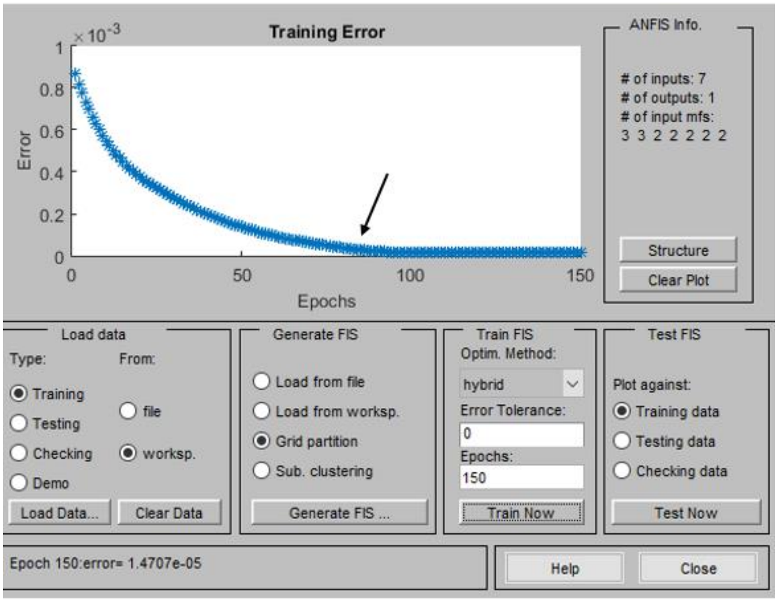

Figure 6. Screenshot of the Network Training

As shown in the figure, training the network was completed in 95 iterations. The error value in the next iterations became constant. Training error of the network is 0.0014%. According to this, high, moderate and underdeveloped countries were estimated correctly whereas 2 very highly developed countries were incorrectly estimated. The mean error rate is 0.0015%. Finally, to make a more accurate comparison, the data of all countries but not the results were provided in the network for testing purposes. Here, the method is expected to estimate which country will be on which side. Based on this, the results obtained are as follows.

Table 12. ANFIS Correct Classification Table

Classification					
	Estimated Class				
Observed Class	Very Highly Developed	Developed	Moderately Developed	Underdeveloped	Percentage Of Accuracy
Very Highly Developed	48	1	0	0	97.9%
Highly Developed	1	49	4	0	90.7%
Moderately Developed	0	6	30	2	78.9%
Underdeveloped	0	0	3	41	93.2 %
Total	26.5%	30.27%	20%	23.5%	91.36%

According to the table, it can be seen that 1 of the very highly classified countries, 5 of the highly classified countries, 8 of the moderately developed countries, and 3 of the underdeveloped countries were incorrectly classified. Moreover, it can be seen that the most successful classification was that of the very highly developed and underdeveloped countries, while the least successful classification was that of the moderately developed countries. In general, the rate of correct classification is 91.36%. Regarding the classifications by ANFIS method, it can be said that the method correctly classified most of the countries, while it incorrectly classified the countries to the class immediately superior or immediately inferior to their actual class.

Table 13. ANFIS Incorrectly Classified Countries

	Country	Actual Class (… Development Level)	Estimated Class (…Development Level)
1	Croatia	Very High	High
2	Oman	High	Very High
3	Bosnia and Herzegovina	High	Moderate
4	Georgia	High	Moderate
5	Suriname	High	Moderate
6	Botswana	Moderate	High
7	Cabo Verde	Moderate	High
8	El Salvador	Moderate	High
9	Montenegro	Moderate	High
10	Paraguay	Moderate	High
11	Turkmenistan	Moderate	High
12	Laos	Moderate	Low
13	East Timor	Moderate	Low
14	Djibouti	Low	Moderate
15	Morocco	Low	Moderate
16	Swaziland	Low	Moderate

According to the table, while Croatia is very highly developed, it was estimated to be highly developed, and while Oman is highly developed, it was estimated to be very highly developed. While Bosnia and Herzegovina, and Georgia belong to the class of highly developed countries, they were estimated to be moderately developed; and while Botswana, Cabo Verde, El Salvador, Montenegro, and Paraguay are moderately developed, they were estimated to be highly developed countries. Laos was estimated to be underdeveloped while it is moderately developed. While Djibouti and Morocco are underdeveloped, they were estimated to be moderately developed countries.

When it is evaluated which factor is more effective in the problem of human development, according to the level of impact, the factors are listed as; entrepreneurship, socio-economic development, inflation, logistics activities based on international trade, foreign trade, natural factors and income indices. The most notable issue here is that the income factor meticulously calculated by the UN has the lowest impact on human development index.

6. CONCLUSION

The aim of this study is to compare the classification performances of artificial neural network (ANN), one of the machine learning techniques used in classification problems, and Adaptive Neural Fuzzy Inference System (ANFIS) method, which is a fuzzy logic-based machine learning technique. For this purpose, HDI was calculated using different methods and alternative indicators, and the countries were classified based on this index. In the study, at the stage of determining the indicators used in measuring the development level of countries, a total of 118 indicators were analyzed and of these, 27 statistically and economically most suitable indicators were used in factor analysis. According to the result of factor analysis, indicators were grouped under 7 factors. These factors include socioeconomic development, logistic activities based on international trade, entrepreneurship, natural life, income, foreign trade and inflation fields. There are many supporting studies in the literature which state that similar subjects should be used in measuring the development level of countries (Çivi, Erol, İnanlı and Erol, 2008) (Karataş and Çankaya, 2010) (Önder and Şenses, 2006) (Koç, 2013) (Çetin and Işıl, 2009) (Burmaoğlu, Oktay and Üstün, 2009) (Aşıcı, 2012) (Yılmazer, 2002) (Karadeniz, 2012).

After obtaining the factors, the countries were classified using ANN and ANFIS methods. In ANN method, the network was trained according to the neural network algorithm with feed-forward back-distribution. Based on this, network training was completed with 85.4% success rate. When the countries were used to test the trained network, it was found that the network incorrectly classified 23 countries and the rate of correct classification was 87.5%. Of the very highly developed countries, 5 were estimated to be highly developed; of the highly developed countries, 1 was estimated to be very highly developed and 5 were estimated to be moderately developed; of the moderately developed countries, 7 were estimated to be highly developed and 5 were estimated to be underdeveloped.

ANFIS implementation was performed with 0.0014% training error according to Gauss2mf membership function. According to this, in total, 16 countries were incorrectly classified and the rate of correct classification was found to be 91.36%. Of the very highly developed countries, 1 was estimated to be highly developed; of the highly developed countries, 1 was estimated to be very highly developed, 4 were estimated to be moderately developed; of the moderately developed countries, 6 were estimated to be highly developed and 2 were estimated to be underdeveloped; and of the underdeveloped countries, 3 were estimated to be moderately developed countries. Countries incorrectly classified by both methods are given in the table below.

Table 14. Countries Incorrectly Classified by Both Methods

ANN			ANFIS		
Country	**G**	**T**	**Country**	**G**	**T**
Belarus	2	1	Bosnia and Herzegovina	2	3
Brunei Darussalam	1	2	Botswana	3	2
Bhutan	3	2	Cabo Verde	3	2
Algeria	2	3	Djibouti	4	3
East Timor	3	4	East Timor	3	4
Equatorial Guinea	3	4	El Salvador	3	2
El Salvador	3	2	Morocco	4	3
Grenada	2	3	Georgia	2	3
Croatia	1	2	Croatia	1	2
Montenegro	3	2	Montenegro	3	2
Kiribati	3	4	Laos	3	2
Hungary	1	2	Paraguay	3	2
The Arab Republic of Egypt	3	2	Suriname	2	3
Mongolia	1	2	Swaziland	4	3
Morocco	3	2	Turkmenistan	3	2
Paraguay	3	2	Oman	2	1
Samoa	2	3			
Sri Lanka	2	3			
Saudi Arabia	1	2			
Tajikistan	3	4			
Trinidad and Tobago	2	3			
Vanuatu	3	2			
Zambia	3	4			

G: Actual class of the country in HDI, T: class estimated based on the method

1: very high, 2: high, 3: moderate, 4: low-level human development

According to the table, Paraguay, Montenegro, El Salvador, Croatia and East Timor were incorrectly classified by both methods. Of these, Croatia was classified as highly developed although it is actually very highly developed; El Salvador and Paraguay were classified as highly developed although they are moderately developed, and East Timor was classified as underdeveloped while it is moderately developed.

When ANN and ANFIS methods are compared, the common feature of both methods is that they utilize artificial intelligence model, which is the simulation of a natural system. However, ANN and ANFIS are different from each other in the way that ANN is based on classical logic while ANFIS is based on hybrid learning, fuzzy logic, and rules. Therefore, the difference between the success rates of the methods can be due to their linear/curvilinear function-based or fuzzy/classical logic-based estimations. Similar studies in the literature also support these results (Burmaoğlu, Oktay and Üstün 2009) (Kuyucu, 2012) (Kaya, Çolak and Özdemir, 2013) (Şengöz and Özdemir, 2016) (Özcan, Şahin, Dikmen and Bayram, 2013) (Doğancı, Erturk, Özsunar and Arcaklıoğlu, 2016).

Further studies on the comparison of the methods can utilize ANFIS, and NEFCLASS, FuNe and FALCON methods, which are other fuzzy logic networks, for estimation, classification and pattern recognition. Studies on human development index can utilize more different and more extensive indicators to classify countries with different methods, and the results can be compared with the results of this study. Similarly, with a large antecedent dataset, the status of countries in the future can be estimated.

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