Ekonomi Yönetim Politika 2023 1(1) 36-45

Ekonomi Yönetim Politika
Economics Management Politics

Araştırma Makalesi ● Research Article

Categorization of Countries with Artificial Neural Networks and Support Vector Machines

Yapay Sinir Ağları ve Destek Vektör Makineleri ile Ülkelerin Sınıflandırılması

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Abstract: In this study, the possibilities of ranking or classifying countries, which are generally made using panel data analysis, are investigated using artificial intelligence models. In other words, the answer to the question of whether artificial intelligence (AI) provides better performance than statistical tests in this field has been investigated. For this, countries are classified using economic indicators such as unemployment, inflation, GDP Growth Rate, 5-year GDP Growth Rate, Foreign Direct Investment (FDI) Inflow and Business Freedom. Artificial Neural Networks (ANN), Support Vector Machines (SVM) and statistically Logistic Regression (LR) methods were used for classification. In the analyzes repeated ten times, LR (average 62.4%) gave the best result and SVM (2%) gave the lowest standard deviation.

The results obtained are promising for modern methods, but modern artificial intelligence methods, which have become an alternative to traditional methods in almost every field, are still behind traditional methods in this field. In order for modern methods to be an alternative to traditional methods in this regard, they need to further develop their theories (on matters such as the curse of dimension) or adapt the data structures used on the subject to these methods.

Keywords: Country Classification, Artificial Neural Network, Support Vector Machines.

Özet: Bu çalışmada genelde panel veri analizi kullanılarak yapılan ülkelerin kategorizasyonu çalışmalarının yapay zekâ modelleri kullanılarak yapılmasının imkanları araştırılmıştır. Yani yapay zekâ (AI) bu sahada istatiksel testlere göre daha iyi performans sağlıyor mu sorusunun cevabı araştırılmıştır. Bunun için ülkeler işsizlik, enflasyon, GSYİH Büyüme Hızı, 5 yıllık GSYİH Büyüme Hızı, Doğrudan Yabancı Yatırım (FDI) Girişi ve İş Özgürlüğü gibi ekonomik göstergeler kullanılarak sınıflandırılmıştır. Sınıflandırma için Yapay Sinir Ağları (ANN), Destek Vektör Makineleri (SVM) ve istatistiksel olarak da Lojistik Regresyon (LR) yöntemleri kullanılmıştır. Onar kez yinelenen analizlerde, en iyi sonucu veren LR (ortalama 62,4%), en küçük standart sapmayı veren SVM (2%) olmuştur.
Elde edilen sonuçların modern yöntemler için ümit vadettiği fakat geleneksel yöntemlerin bu konudaki alternatifsizliğinin bir süre daha devam edebileceği sonucuna varılmıştır. Modern yöntemlerin bu konuda geleneksel olanlarına alternatif olabilmesi için teorilerinin (boyut laneti gibi konularda) daha da geliştirilmesi ya da konuyla alakalı kullanılan veri yapılarının bu yöntemlere adaptasyonu gerekmektedir.

Anahtar Kelimeler: Ülke Sınıflandırması, Yapay Sinir Ağları, Destek Vektör Makineleri.

Introduction

After computers started to record all business processes with cost-effective sensors, transforming the information accumulated in large data banks into useful information needed for decision makers by establishing a model with the help of database management systems has become the focus of current

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Received/Geliş: 20 Ekim *2023*
Accepted/Kabul: *27 Kasım 2023*
Published/Yayın: *27 Aralık 2023*

scientific data analytics studies. Especially in social sciences, these modeling studies, which we can collect under the headings of prediction, classification, clustering, and optimization, have been a matter of curiosity in terms of the results of artificial intelligence methods after statistical techniques.

As new artificial intelligence methods, techniques, architectures, and algorithms are developed, research problems that were previously sought to be solved by statistical methods come to the fore again and the results of new solutions to these problems are wondered. In the field of finance, predicting the financial failures of companies, predicting bankruptcy, credit risk valuation, predicting the direction of stocks, in the field of medicine; diagnosis of patients with cancer or diabetes, differentiation of asthma and COPD, etc. many old problems are just a few examples of this research (Vellido et al., 1999).

The above-mentioned research problems in finance and medicine are an important application methodology of artificial intelligence models, and they have become a workshop where advantages and disadvantages are determined compared to the old ones. Naturally, the methods that produce successful results in the above-mentioned applications using real-world data have naturally become more popular in the literature and application fields. The results obtained by artificial intelligence methods are evaluated by comparing them with some other artificial intelligence methods or by comparing them with the most appropriate statistical technique for the current problem, and gain popularity in proportion to the accuracy of the results. Or, it cannot catch any follow-up wind due to low performance or difficulty in implementation and remains only a study in the literature.

Apart from the problems mentioned above, artificial intelligence techniques within the scope of data mining; It is actively used in solving many problems such as creating customer profiles and market profiles, determining the value of goods, making sales forecasts, determining production needs, measuring market performance and determining environmental economic risks(Şimşek Gürsoy, 2009). Many artificial intelligence methods, especially ANN, are used in evaluating loan applications within the scope of banking, detecting credit card frauds, borrowing and risk assessments, within the scope of existing internal measurement approaches(Öztemel, 2003). The subject of this research is whether AI models, which are indispensable for individual or corporate lending processes, can also be used in calculating the credibility of countries.

Related artificial intelligence methods are ANN, SVM, k-means, k nearest neighbor, decision trees intuitively particle swarm optimization, artificial ant colonies, artificial bee colonies, genetic algorithm, simulated annealing etc. are some prominent artificial intelligence methods (Cura, 2008).

Within the mentioned application areas, artificial intelligence methods have undergone a natural selection process, determining which models thrive in specific problem domains and data structures. Although many artificial intelligence methods are used in classification, ANN, which has become widespread in almost every field, and SVM, which is a partially new method, are two important classification methods that stand out in terms of outcome success. Since the data size is limited and the solution does not require excessive time, there is no need to resort to heuristic methods in such studies.

Another point is that artificial intelligence methods, unlike statistical methods, prefer to create a model from the data whose results are certain, instead of determining the relationship values in the background of the data one by one (analysis). In other words, like statistical science, it prefers to make practical evaluations from existing results, rather than dealing with analytical proofs (Cherkassky and Mulier, 2007). Therefore, AI methods can relatively take into account the effect of explanatory variables that are not included in the data group on the dependent variable, compared to traditional statistical methods. This puts AI methods one step ahead of traditional methods in terms of the use of real-life data and the ability to draw meaningful conclusions from these data. In addition, the fact that they do not depend on any distribution and do not require any assumptions makes these methods more preferable for researchers.

ANN is a very common method with high generalization and learning ability. In addition, as experienced in this research, due to the unpredictability of the optimum architecture, the results of architectures containing different numbers of hidden layers and nodes have to be tested one by one, which requires serious time and effort. Also catching local minimum etc. has handicaps. However, SVM does not require trial and error in the process of creating such an architecture, it directly reaches the global minimum, can show a more stable performance in high-dimensional and low-observation datasets, and sometimes gives a higher accuracy rate compared to ANN (Shen, 2005). This makes SVM a popular modeling tool recently in the field of classification and regression. Although SVM has its roots in the 1960s, it was first applied to a research problem by its developer, Russian mathematician Vladimir Vapnik, in 1995, and its performance was noticed and started to be used in a very practical way. While it is a relatively new method, new modules are continuously being developed.

Literature Review

There are countless classification applications in the literature. However, studies on country classification using artificial intelligence are unfortunately very scarce. An important reason for this is that datasets with a high number of dimensions (explanatory variables) and low number of observations (countries) push the limits of artificial intelligence models. It is known that artificial intelligence models cannot solve almost any problem (especially the forward curvilinear ones) as accurately as the existing methods, if we consider starting from simple sensors (perceptron) but they have achieved an incredible level of effectiveness at the point reached today. It is expected that these methods, which have gained widespread popularity as a natural result of this activity, will soon be used for the solution of all problems. The limited number of studies that have been classified by country using artificial intelligence techniques are given below.

Fernandez et al. have applied inferential data mining techniques such as C5.0 and smart learning techniques such as ANN to the dataset to develop smart models used to classify the investment risk of a country according to various factors. The dataset contains 27 variables from 52 countries. The investment risk category has shown promising results from the application of their technique to the dataset when compared with the results evaluated in the Wall Street Journal survey of international experts, and most countries have been successfully classified according to the experts' classifications (Becerra-Fernandez et al., 2002).

Yim and Mitchell used traditional ANN, hybrid ANN, Self-Organization Maps (SOM), Logit Models (LM), Discriminant Analysis (DA), and Hierarchical Cluster Analysis (HCA) to rank countries by risk and compared their results. This article mainly aims to estimate the country risk rating of hybrid ANN. At the end of the study, they concluded that hybrid neural networks outperform all other models and that this type of network can be an effective tool for researchers as well as policymakers and other experts interested in early warning systems in assessing the country's risk dimensions (Yim and Mitchell, 2005).

In the study by Patuelli et al., a series of ANN models were developed to calculate short-term forecasts of regional employment patterns in Germany. Two different ANN models were used in the study. First, an ANN architecture is constructed for the estimation of regional employment in former West and East Germany. The applied model calculates single estimates of employment growth rates with a 2-year forecast interval for each German region. Then, additional estimates were calculated by combining ANN methodology with Shift-Share Analysis (SSA). Since SSA aimed to describe the observed variations between study regions, its results were used as more explanatory variables in ANN models. The dataset used in the experiments consists of a panel of 439 German regions. Due to differences in the size and time horizons of the data, estimates for West and East Germany were calculated separately. As a result, it was stated that a real integration of linear methods with ANN should be the main target, therefore, this situation can be used in ANN estimation (Patuelli et al., 2007).

1. Method

Although classification is a method that assigns existing observations categorically and labels to predetermined result classes, it can be applied to problems where all (supervised) or some (semi-supervised) observations are certain. DA was first used in classification with the recommendation of

Fischer in 1932 (Lee and Chen, 2005), and since the 1950s, LR has come to the forefront, which provides ease of application because it does not require assumptions and has been proven to give better results in general. Although many methods are used for classification problems apart from the aforementioned methods, ANN and SVM in the modern sense and LR in the traditional (statistical) sense are the most accepted methods in the problems where supervised learning is in question over time.

In this study, using the descriptive data of a total of 186 countries around the world, taken from the worldbank, the problem of classifying them according to unemployment, inflation and growth rate, 5-year growth rate, foreign direct investment and job specifics, using the methods listed above will be discussed.

1.1. Artificial Neural Network

Multilayer and back propagation neural networks are one of the most widely used ANN models, with overall superior performance over other neural network architectures for most traditional classification problems. During the ANN implementation, different architectures should also be tried in order to prevent the model from being exposed to under-fitting and upper-fitting problems from the training data. The fact that the architecture in question has too many hidden layers can cause the neural network to memorize the training examples (over-learning) and often give poor generalization performance because of this. In addition, since the shape and complexity of the classification surfaces are not known, it would be appropriate to apply both one and two hidden layer ANN architectures for backpropagation, consider the results and try different neuron numbers. The addition of the second hidden layer allows modeling of a more complex decision surface, such as a convex surface with concaves versus a simple nonlinear surface (Becerra-Fernandez et al., 2002).

In this study, experiments were made with various node numbers with one and two hidden layers, and the application results of the ANN architecture with two hidden layers and ten nodes in each layer, which gave the best results, were reported. While the data of 186 countries in total were forming the input nodes, observation data were assigned to three different categories named “low”, “medium” and “high” by passing through two hidden layer architecture with ten nodes.

ANN is an iterative method that optimizes its coefficients (delta learning rule) by changing its coefficients in the direction of a certain learning rate through backpropagation. Sometimes in applications, a thousand, ten thousand or even a hundred thousand iterations are made until the model establishes stability. As a result of the trials in this study, ten thousand (10000) iteration levels were decided.

1.2. Support Vector Machines

With the development of artificial intelligence methods over time, new nonlinear models have been developed and these methods have been more successful than linear models and methods that require normal and similar distributions. It has been observed that this method, which has developed with statistical learning theory since the 1960s and became possible to apply with kernel functions (Theodoridis and Koutroumbas, 2009), was applied to a problem for the first time in 1995 and then found a wide place in the literature, and gave better results than ANN in terms of accuracy rates (Huang et al., 2004). The success of SVM, which has a very comprehensive, proven, and complex theoretical background, especially in multidimensional (with too many explanatory variables) low-observation problems, makes it an effective alternative to other artificial intelligence methods (Vapnik, 1999).

SVM can avoid over-learning by developing a new risk minimization (Structural Risk Minimization, HRM) principle by adding a new VC (Vapnik - Chervonenkis) dimension to the Empirical Risk Minimization (ARM) principle on which least squares or maximum likelihood methods are based. By using the VC size, SVM maximizes the distance between two data classes, thus offering very efficient classification performance. Because the important thing here is that which of the millions of directs that can be drawn between these two data classes is the optimal distinction. In ANN, it assigns the observations to one of the two classes with the same method. In fact, the stage of optimizing the coefficients, which is also called the training process in ANN, means changing the slope of the dividing line seen in the figure. SVM can realize the optimal separation by controlling the complexity level of the model by using the VC coefficient, that is, by controlling the training error with least squares, and the generalization error with the VC dimension.

The training data set and the test data set are two separate data sets, and it does not seem possible in practice for a model developed on one to extract the other data set. In order to overcome this problem, some assumptions about these two datasets are needed. In machine learning, it is assumed that the probability distributions of the training data and the test data are the same so that a model optimized on the training dataset can make an effective evaluation on a different test data. However, the assumptions that each observation, that is, the input vectors in the datasets, are independent observation vectors from each other and that both datasets are distributed in the same way are considered valid. These assumptions are known as “independent identically distributed, i.i.d.” assumptions. The factors that determine how well a machine learning algorithm will perform in this case are its ability to fulfill the two conditions outlined below. These:

1. Minimize the training error.

2. Minimize the gap between training and test error.

SVM comes to the fore when the number of observations is low and the number of explanatory variables, that is, the number of dimensions, is high compared to other methods. In addition, it is stated in various studies that it is a method to overcome the curse of dimensionality problem.

In the application, the min-max normalization method (Equation 1) was used, which is one of the normalization methods (Shen, 2005).

$$x' = \frac{x - x_{min}}{x_{maks} - x_{min}} \qquad \text{(Equation 1)}$$

1.3. Logistic Regression

Logistic regression is a nonlinear method that measures the probability of events occurring by using the ratio of the probability of an event occurring to the probability of it not occurring. Logistic regression replaced discriminant analysis, which was widely used until then, in discrimination problems after the seventies. Because it provides better performance and is more practical because it does not have any assumptions to be met. Logistic regression is the traditional model widely used in many binary and multiple (categorical) statistical discrimination problems (Lavalley, 2008).

2. Application

The variables included in the 2019 index data obtained from the World Bank are listed in the table below.

Table 1: 2019 Index data variables used in the application

1.	World Ranking	2.	Region Ranking
3.	2019 Score	4.	Property rights
5.	Judicial Efficiency	6.	State Integrity
7.	Tax burden	8.	Government Expenditures
9.	Financial Health	10.	Freedom of Work
11.	Labor Freedom	12.	Monetary Freedom
13.	Freedom of Trade	14.	Freedom of Investment
15.	Financial freedom	16.	Tariff Rate (%)

17.	Income tax rate (%)	18.	Corporate tax rate (%)
19.	Tax Burden as a % of GDP	20.	Spending % of GDP
21.	Population (Millions)	22.	GDP (Billion, PPP)
23.	GDP Growth Rate (%)	24.	5-Year GDP Growth Rate (%)
25.	GDP Per Capita (PPP)	26.	Unemployment (%)
27.	Inflation (%)	28.	FDI Inflows (Millions)
29.	Public Debt (per. of GDP)		

Source: https://databank.worldbank.org/source/world-development-indicators.

The application was carried out under six headings. These headings are unemployment, inflation, GDP growth rate, 5-year GDP growth rate, foreign direct investment (FDI) inflow and job freedom classification practices.

2.1. Unemployment

All variables except unemployment were added to the model as explanatory variables in the unemployment application. Based on unemployment data presented as a percentage, countries are categorized into three groups: those with low, medium, and high unemployment rates. The models were trained on 149 observations, 80% of the available 186 data, and tested on 37 observations, the remaining 20%. Since these training and test data are randomly selected by the program the applications are also stabilized against good or bad luck by taking the average and standard deviation of the selection ten times (cvv: 10) against the risk of a very good or very bad selection. The method was added to the model in this way (cvv: 10) throughout the application process.

The categorization of the countries and the number of countries falling into each category are shown in Table 2.

Table 2: Categorization of countries in terms of unemployment

Classification Criteria	Class	Class Name	Country Number
Less than 4%	1	Low Unemployment	48
4% to 8%	2	Moderate Unemployment	72
8% and above	3	High Unemployment	66
		TOTAL	186

2.2. Inflation

In this application phase, other than “inflation”, twenty-eight variables were entered into the model as explanatory variables. Likewise, this time, on the basis of inflation data, the countries with low (below 3%) inflation rate, medium level (under 5% and 3% and above) and high level (5% and above) divided into three categories. The test data set rate was kept at 20% as in unemployment (cvv:10).

The categorization of the countries and the number of countries falling into each category are shown in Table 3.

Table 3: Categorization of countries in terms of inflation

Classification Criteria	Class	Class Name	Country Number
Less than 3%	1	Low Inflation	72
3% to 5%	2	Moderate Inflation	58
5% and above	3	High Inflation	56
		TOTAL	186

2.3. GDP Growth Rate

At this stage, other than "GDP growth rate", twenty-eight variables were added to the model as explanatory variables. Likewise, this time, countries are divided into three different categories based on their growth rates: countries with low (less than 3%) growth rate, medium level (from 3% to 6%) and high level (6% and above) separated. The test data set rate was kept at 20% (cvv: 10).

The categorization of the countries and the number of countries falling into each category are shown in Table 4.

Table 4: Categorization of countries in terms of GDP growth rate

Classification Criteria	Class	Class Name	Country Number
Less than 3%	1	Low GDP Growth Rate	48
3%-6%	2	Medium GDP Growth Rate	79
6% and above	3	High GDP Growth Rate	59
		TOTAL	186

2.4. 5-Year GDP Growth Rate

At this stage, twenty-eight variables other than "5-year GDP growth rate" were entered into the model as explanatory variables. This time, the countries are divided into three different categories, based on 5-year growth rates, as countries with low (less than 3%) 5-year growth rate, medium level (from 3% to 6%), and high level (6% and above) divided into categories. The test data set rate was kept at 20% as in other indicators (cvv: 10).

The categorization of the countries and the number of countries falling into each category are shown in Table 5.

Table 5: Categorization of countries in terms of 5-year GDP growth rate

Classification Criteria	Class	Class Name (5 Years)	Number of Countries
Less than 3%	1	Low GDP Growth Rate	88
3% to 6%	2	Medium GDP Growth Rate	73
6% and above	3	High GDP Growth Rate	25
		TOTAL	186

2.5. FDI Inflow

Twenty-eight variables, excluding FDI, were entered into the model as explanatory variables. This time, countries are divided into three categories, based on FDI inflows, as low (less than $500M), moderate ($500M to $5B) and high ($5B and above) investment. The test data set rate was kept at 20% as in other indicators (cvv: 10).

The categorization of the countries and the number of countries falling into each category are shown in Table 6.

Table 6: Categorization of Countries in terms of FDI Inflow

Classification Criteria (Million$)	Class	Class Name	Number of Countries
Less than 500 Inflow	1	Low FDI	69
500-5000 Inflow	2	Medium FDI	69
5000 and above	3	High FDI	48
		TOTAL	186

2.6. Freedom of Work

At this stage, twenty-eight variables, excluding "job freedom", were added to the model as explanatory variables. This time, countries are divided into three categories, based on their job freedom rates, as low (less than 50%), medium (50%-70%) and high (70% and above) job freedom. The test data set rate was kept at 20% as in other indicators (cvv: 10).

The categorization of the countries and the number of countries falling into each category are shown in Table 7.

Table 7: Categorization of countries in terms of freedom of work

Classification Criteria	Class	Class Name	Number of Countries
Less than 50(%)	1	Low Level of Job Freedom	29
(%)50 to - (%)70	2	Moderate Job Freedom	109
70(%) and above	3	High Levels of Job Freedom	48
		TOTAL	186

3. Results

The parameters used to classify the countries and the accuracy and standard deviations of the methods used in line with these parameters are shown in Table 8.

Table 8: Application results

Titles	Methods Used: Accuracy Rates & Standard Deviations		
	ANN (%)	SVM (%)	LR (%)
Unemployment	32 (**σ**=14)	39 (**σ**=2)	51 (**σ**=18)
Inflation	42 (**σ**=17)	39 (**σ**=3)	57 (**σ**=15)
GDP Growth rate	43 (**σ**=18)	43 (**σ**=3)	63 (**σ**=13)
5 Year GDP Growth rate	48 (**σ**=13)	48 (**σ**=3)	63 (**σ**=14)

FDI Input	56 (**σ**=19)	40 (**σ**=3)	70 (**σ**=14)
Business Freedom	53 (**σ**=14)	60 (**σ**=2)	71 (**σ**=9)

Conclusion

The search for the "most efficient architecture" in ANN takes a lot of time, and in SVM it requires less effort than ANN, as it is possible to use four different core functions. Again, LR, which does not require any assumptions like ANN and SVM, stands out as the most practical method to use in the study.

The accuracy rates of the LR method, which is a traditional method, were significantly higher in all tests compared to artificial intelligence methods. This may also be due to the fact that the dataset used has a simple pattern. In addition, it may be a forced interpretation, but the reason why LR is more dominant in terms of the accuracy of the results is that the model that comes closest to these outputs is a traditional model, since the outputs included in the training data used while training the artificial intelligence models are the outputs created with traditional methods. The result may not be surprising. To give an example to support this interpretation, the i.i.d. recalls his assumptions. As a result, the result classes of these countries are created with traditional methods like LR. In this case, it is necessary to use result classes independent of all techniques, which can be another important research (indexing) topic.

It is frequently stated in the literature that SVM gives effective results in conditions where the curse of the dimension conditions is quite valid. The curse of size is also effective in this study (28 explanatory variables and only 186 observations). However, in this study, in terms of accuracy rates, although there are titles where SVM is relatively better than ANN, it lags far behind LR. However, it makes itself felt deeply as a reliable method in terms of consistency, as it gives the lowest standard deviations in every application without exception.

Until now, statistical techniques with a much broader background in classification, clustering, estimation, and optimization problems have performed unrivaled well in the infancy of AI models. But now, standing up and running artificial intelligence models are becoming a good alternative to statistical techniques day by day. An important reason why there are very few studies in the literature on the classification of countries with artificial intelligence methods, which are classified by credit institutions and the world bank with the time series method using panel data, is due to the fact that artificial intelligence methods do not give good results (for now) while the number of observations is low. Over time, as in some literature studies summarized above, it seems possible to successfully create global economic maps with AI by starting to use ANN, SVM and other more advanced methods, which can make good classification with few observations, or by creating the index data in accordance with these methods. However, it can be added that the dominance of traditional methods in this field may be in question for a while.

References:

Becerra-Fernandez, I., Zanakis, S. H., and Walczak, S. (2002). Knowledge discovery techniques for predicting country investment risk. *Computers and Industrial Engineering*, 43(4), 787–800.

Cherkassky, V. S., and Mulier, Filip. (2007). *Learning from data : concepts, theory, and methods*. Published: John Wiley&Sons.

Cura, T. (2008). *Modern sezgisel teknikler ve uygulamaları*. İstanbul: Papatya Publisher.

Huang, Z., Chen, H., Hsu, C. J., Chen, W. H., and Wu, S. (2004). Credit rating analysis with support vector machines and neural networks: a market comparative study. *Decision Support Systems*, 37(4), 543–558.

LaValley, P., M. (2008). Logistic Regression. *Circulation.* 117(18), 2395-2399.

Lee, T. S., and Chen, I. F. (2005). A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. *Expert Systems with Applications*, 28(4), 743–752.

Öztemel, E. (2003). *Yapay sinir ağları*. İstanbul: Papatya Publisher.

Patuelli, R., Reggiani, A., Nijkamp, P., and Blien, U. (2007). New neural network methods for forecasting regional employment. *Research.* 1(1), 7–30.

Shen, J. (2005). Fusing support vector machines and soft computing for pattern recognition and regression. https://search.proquest.com/openview/d2b5e228d906f45d2b282e084f88c3ca/1?pq-origsite=gscholarandcbl=18750anddiss=y

Şimşek Gürsoy, U. T. (2009). *Veri madenciliği ve bilgi keşfi*. İstanbul: Pegem Akademi Publisher.

Theodoridis, S., and Koutroumbas, K. (2009). *Pattern recognition*. Burlington: Elseiver Inc.

Vapnik V (2022). I. transactions on neural, and 1999, undefined. (n.d.). An overview of statistical learning theory. Ieeexplore.Ieee.Org. Retrieved December 9, 2022, from https://ieeexplore.ieee.org/abstract/document/788640/.

Vellido, A., Lisboa, P. J. G., and Vaughan, J. (1999). Neural networks in business: a survey of applications (1992–1998). *Expert Systems with Applications*, 17(1), 51–70..

Yim, J., and Mitchell, H. (2005). Comparison of country risk models: hybrid neural networks, logit models, discriminant analysis and cluster techniques. *Expert Systems with Applications*, 28(1), 137–148.

Beyan ve Açıklamalar (Disclosure Statements)

1. Araştırmacıların katkı oranı beyanı / Contribution rate statement of researchers: Birinci yazar /First author % 100

2. Yazarlar tarafından herhangi bir çıkar çatışması beyan edilmemiştir (No potential conflict of interest was reported by the authors).