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Prediction of life quality index value rankings of countries after the COVID-19 pandemic by artificial neural networks

COVID-19 pandemisi sonrası ülkelerin yaşam kalitesi indeksi değer sıralamalarının yapay sinir ağları ile tahmini

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Prediction of Life Quality Index Value Rankings of Countries After the COVID-19 Pandemic by Artificial Neural Networks

Highlights

- *Prediction of quality of life by Artificial Neural Networks*
- *The relationship between the perception of quality of life and the level of prosperity*
- *Using Artificial Neural Networks in alternative history prediction*

Graphical Abstract

In this study, the quality of life index for the year 2020, which is assumed not to be COVID-19, was predicted by artificial neural networks. We compared predicted outcomes with actual outcomes to determine how much citizens will be affected by COVID-19.

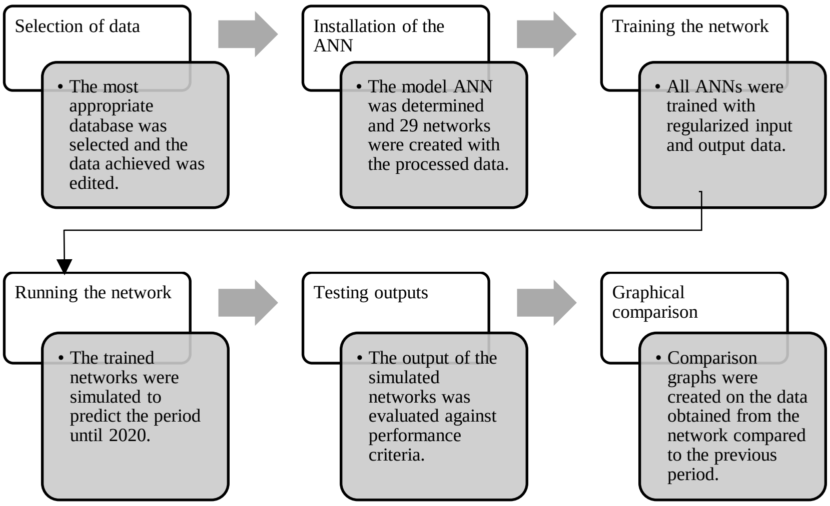

Figure. Graphical summary of the procedure used in the study

Aim

Measuring the impact of the COVID-19 pandemic on the quality of life of countries on the European continent.

Design & Methodology

The Artificial Neural Network trained with 13 periods of quality of life data predicted the quality of life index for the year 2020 when COVID-19 was not experienced. The quality of life index predicted by the network and the actual quality of life index were compared, and countries were ranked by percentage difference.

Originality

Artificial neural networks were used to generate an alternative prediction of history and the results were compared with the actual results.

Findings

In our study, which included 29 countries, quality of life turned out to be lower than expected in 25 countries, while it was higher than expected in 4 countries. Quality of life decreased by 28.87% in Germany and by 13.23% in Norway, while it increased by 1.40% in Ukraine and by 2.35% in Bulgaria.

Conclusion

At the end of the study, it was found that countries with a high quality of life index were more affected by COVID-19. It is believed that the reason for this is related to the perception of citizens living in countries with a higher level of prosperity than in other countries.

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Prediction of Life Quality Index Value Rankings of Countries After the COVID-19 Pandemic by Artificial Neural Networks

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Araştırma Makalesi / Research Article

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ABSTRACT

There are some indexes that affect the quality of life of countries. Economic crises, pandemics, natural events, etc. affect these indexes. The COVID-19 pandemic also had a direct impact on all these indexes. In this study, the impact of the COVID-19 pandemic on the quality of life of countries was investigated. In this context, 29 different artificial neural networks were trained between 2012 and 2019 with the data of 29 countries in the European continent, consisting of a total of six indexes. The countries' quality of life indexes for 2020 were predicted and compared with the quality of life indexes realized in 2020. The study was evaluated according to the performance criteria R, R2, RMSE and MAPE in the range "very good, good, valid and invalid" and showed "very good" results. In this study, it was found that the country with the highest decrease in quality of life after the pandemic was Germany and the country with the highest increase was Bulgaria. In Turkey and Spain, the change in quality of life indexes was close to zero. In accordance with the results, evaluations were made and suggestions were made.

Keywords: COVID-19 pandemic, quality of life, artificial neural networks, prediction.

COVID-19 Pandemisi Sonrası Ülkelerin Yaşam Kalitesi İndeksi Değer Sıralamalarının Yapay Sinir Ağları ile Tahmini

ÖZ

Ülkelerin yaşam kalitelerini etkileyen bazı indeksler bulunmaktadır. Ekonomik krizler, pandemiler, doğa olayları vb. koşullar bu indeksleri etkilemektedir. COVID-19 pandemisi de tüm bu indeksleri doğrudan etkilemiştir. Bu çalışmada COVID-19 pandemisinin ülkelerin yaşam kalitesine ne kadar etki ettiği araştırılmıştır. Bu kapsamda 2012 ile 2019 yılları arasında toplam altı indeksten oluşan Avrupa kıtasında bulunan 29 ülkenin verileri ile 29 ayrı Yapay Sinir Ağı (YSA) eğitilmiştir. 2020 yılı için ülkelerin yaşam kalitesi indeksleri tahmin edilmiş ve 2020 yılında gerçekleşen yaşam kalitesi indeksleri ile karşılaştırılmıştır. Çalışma R, R2, RMSE ve MAPE performans kriterlerine göre "çok iyi, iyi, geçerli ve geçersiz" aralığında değerlendirilmiş ve "çok iyi" sonuçlar vermiştir. Çalışma sonucunda pandemi sonrası yaşam kalitesi en fazla azalan ülkenin Almanya olduğu, en fazla yükselen ülkenin ise Bulgaristan olduğu görülmüştür. Türkiye ve İspanya'ya ait yaşam kalitesi indekslerinin değişimleri ise neredeyse sıfır olduğu görülmüştür. Sonuçlar doğrultusunda değerlendirmeler yapılmış ve öneriler sunulmuştur.

Anahtar Kelimeler: COVID-19 salgını, yaşam kalitesi, yapay sinir ağları, tahminleme.

1. INTRODUCTION

Extraordinary situations such as wars, economic crises, natural disasters and pandemics have a negative impact on societies and countries. These negative issues can have a direct impact on the economy, public health, social life, environmental policy, and thus on the quality of life. Some indexes are used to measure these negative impacts. These indexes are created by processing data that are regularly collected from the citizens of the countries. Indexes provide information about the economy, health status, environmental systems, and social life in the countries. Indexes can be used to observe how exceptional situations affect society as well. Taking into account the index changes, countries take measures and update their economic, safety, health and social policies.

COVID-19 outbreak that occurred in the last quarter of 2019 have affected countries both socially and economically. With the fear brought by the pandemic and the subsequent closure decisions, 2020 was the year when the pandemic was felt the most. The year 2020 is the first year of the fight against the pandemic, and it is a period in which the unknown treatments, vaccines and

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living conditions with the virus are insufficient worldwide. The pandemic has negative impacts on many sectors. For example, in 2020, international sports competitions were cancelled [1], the tourism sector suffered heavy losses [2], [3], tens of thousands of cultural and artistic events could not take place [4], and the global economy shrank [5]. For these reasons, 2020 is considered a lost year. The first COVID-19 vaccine was authorized on 11 December 2020 [6]. In other words, in 2020, no vaccine could be used in the fight against the pandemic. Therefore, in this study, the impact of the COVID-19 pandemic on the quality of life indexes of countries in the 2020 period was examined.

There are studies that try to measure how countries are affected by the epidemic in literature. According to the results of the survey conducted by Lieberoth (2021) with 173.429 participants from 48 countries in 2021, it was found that the stress level of citizens of Poland, Portugal, Turkey, Bulgaria and Bosnia and Herzegovina after the COVID-19 pandemic was lower than in other countries. It was found that citizens in Western Europe had higher stress levels and less confidence in their own government to fight the epidemic than in other countries studied [7].

Bittmann (2022) examined the life satisfaction of citizens living in Germany using the data of The German National Education Panel Study (NEPS). As a result of the review, it was seen that the life satisfaction of citizens decreased sharply with the onset of the COVID-19 pandemic [8]. It appears that the impact of COVID-19 on life can be predicted by Artificial Neural Networks (ANNs) using data from freely available databases [9].

While ANNs produce software solutions to problems, they make decisions based on information and can make predictions about future outcomes by learning the events with the time-serious data. These systems are highly robust and reliable problem-solving techniques that lend themselves to solve abstract problems. These systems mimic the working principles of the human brain, such as learning information, generating new information, recognizing and predicting. Although ANNs remain primitive compared to the speed of the human brain, they can process very quickly. These speeds can be measured in nanoseconds [10].

Lin, Yen, and Yu (2018) studied crimes committed in the Taiwanese city of Taoyuan and tried to identify patterns in crimes being committed. The study used Random Decision Forest, Support Vector Machine, K-Nearest Neighbors algorithms and Deep Neural Networks. Deep neural networks provided the best results. As a result of the study, it is argued that police forces can reach the crime scene and prevent the crime before it is committed [11]. The Deep Neural Networks term is used to describe the multilayer ANNs [12].

ANNs able to work with incomplete information, adapt to problems, make decisions under uncertainty, and be tolerant of mistakes. Many factors affecting social life can be predicted by ANN. ANNs were used in financial predicting [13], demand predicting [14], climate predicting [15], price predicting [16], and disease diagnostic predictioning [17] and provide successful results. For this reason, ANN was preferred to build the prediction model of this study.

In this study, quality of life index was predicted using ANN and compared with the current situation. In the study, ANN was trained with index data before 2020. Index values for 2020, when it is assumed that there is no COVID-19 pandemic, were predicted. The prediction results obtained are compared with the indexes published for the 2020 period and presented in a table. Among the countries affected by the COVID-19 pandemic, the countries with the most positive and negative perceptions and the least affected (almost neutral) countries were interpreted in detail.

As a result of the study, the data of all countries whose quality of life was investigated were presented numerically and the state of the countries affected by the epidemic was interpreted. The opinions of the countries on the reasons for their success in the fight against the pandemic were presented. Suggestions have been developed to increase the index scores determined by the citizens. It is expected that the policies and strategies to be produced by determining this difference between the alternative predict for the past, where the COVID-19 pandemic did not occur, and the past, dexic occurred, will contribute to the literature.

2. CONCEPTUAL FRAMEWORK

In the conceptual framework section, country quality of life indexes, ANNs and performance criteria are explained.

2.1. Country Indexes

There are some indexes in the literature that measure quality of life. Some of these indexes consist of objective data and some of them are subjective data. Objective data reflect statistical facts, while subjective data reflect perceptions [18].

There are institutions that determine the quality of life index of countries with subjective or objective data. These institutions try to measure the quality of life by collecting data from countries and processing this data. Some indexes determined by these institutions are presented below.

2.1.1. Heritage economic freedom index: The economic freedom index determined by Heritage consists of four categories: Rule of Law, Government Size, Regulatory Efficiency and Open Markets. Each category consists of three indexes. While calculating the economic freedom index, each category (12 indexes) is scored between 0 and 100. Then, all indexes are averaged with the same weight [19].

2.1.2. Legatum prosperity index: This index consists of three categories: Inclusive Societies, Open Economies and Empowered People. There are four indexes in each category. The Legatum prosperity index was developed using data from 167 countries and ranks countries according to their level of welfare [20].

2.1.3. Numbeo life quality index: The Numbeo quality of life index consists of six indexes. These indexes are: Property Price Index, Pollution Index, Health Care Index, Crime Index, Traffic Index and Cost of Living Index. The Quality of Life Index is formed by weighting these six indexes. The biggest advantage of Numbeo is that it has a common database for all countries in the world. The lack of peer-reviewed data can be seen as both an advantage and a disadvantage of Numbeo. Anyone with an internet connection can contribute to the Numbeo data. For this reason, this study used Numbeo data, which contains subjective data. The explanations for the country indexes are as follows [21].

Property price index is measured by processing some information such as the ratio of the purchase, price of the dwelling to income, the ratio of the mortgage to income, the ratio of the loan to income, the ratio of the rent to the price of the dwelling, and the gross rental income. The pollution index is measured by an eight-question survey focusing on air and water pollution. The traffic index is measured by the time spent in traffic, the inefficiency rate caused by non-use of public transport and the carbon dioxide emission rate that occurs depending on the traffic duration. The crime index is determined based on the results of a twelve-question survey that measures citizens' perceptions of security. The cost-of-living index is measured by the prices of rents, markets, restaurants and cafes, and local purchasing power. The health care index is measured by the overall quality of the health care system, health care workers, doctors and health care cost data.

The above indexes are created with the data entered by the citizens. These data are processed in the Java programming language. The quality of life index is obtained by evaluating the above indixes with certain weights.

2.2. Artificial Neural Networks (ANN)

ANN Cell is similar to biological nervous system. The function of ANN is to produce an output in response to the electrical signals it uses as input, just as the biological nervous system does. For this to be possible, the network must be trained with certain data sets. In this way, the network reaches the level of generalization and determines the outputs with these capabilities. The neurons of the input layer receive the input data and transmit it via connections to the layer where the data is processed. This transmission process continues until the data reaches the output layer [22]. The cell structure of ANNs is shown in Figure 1.

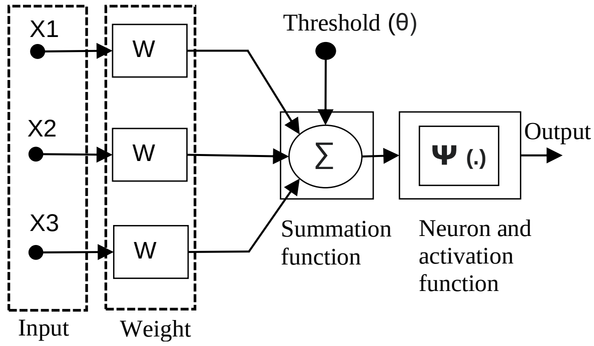

Figure 1. Artificial nerve cell model [23]

2.2.1. Input layer: The input layer is the first layer of the ANNs. In this layer, the connection of the network with the outside world is established. There are as many neurons in the input layer as there are data coming from the outside. Neurons operating in the input layer pass the information they collect directly to the hidden layer without modifying it [24]. The input units X1, X2, and X3 shown in Figure 1 represent information used to train, test, and validate the network. Weights (W1, W2, W3) highlight the importance of the input information [23].

2.2.2. Hidden layer: The answer to the question of how many layers a ANNs consists of is the number of hidden layers. ANNs without hidden layers can be used to solve linear problems. However, to solve complex and nonlinear problems, a hidden layer is always used, and the number of hidden layers increases with the complexity of the problem to be solved [25]. The neurons in the hidden layer are in constant communication with the neurons in the other layer, so the number of neurons in the hidden layer is very important and must be chosen very carefully. There is no rule for determining the hidden layer and the number of hidden neurons. The number is determined by trial-and-error method [26], [27].

2.2.3. Output layer: The output layer is the layer where the generated values are presented after the development of the trained ANN is completed. The values generated in this layer can be used as input to another cell or accepted directly as program output [28]. It is not known how the output value generated by ANN is calculated or how it is generated [29].

2.2.4. Summation function: The summation function is the first function encountered by the data. In this function, information such as the frequency of data arrival, the time of data arrival, and the number of incoming data are added together to calculate the net input to the system. There are several summation functions in the literature, and there is not one most accurate summation function. Therefore, ANNs need not use the same summation function. Different summation functions can be used for different data sets. The summation function to be used is determined by the trial-and-error method [25].

2.2.5. Activation function: The activation function processes the net input and determines what the output will be by either generating a response to the incoming information or absorbing the incoming information. A wide range of functions can be used for the activation function. Regardless of which aggregation function is used in the activation function, the resulting net input value is processed and determines the output to be produced by ANNs. The most commonly used function in the activation functions is the sigmoid function. In this function, the weighted average value from the addition function is normalized to a value between 0 and 1. The function processes the achieved net input value regardless of which aggregation function is used and determines the output to be generated by ANNs. The sigmoid function can be used for both linear and nonlinear functions and can be modeled by generating balanced outputs for both functions [25].

The representation of the sigmoid function is as follows:

$$F(Net) = \frac{1}{1+e^{-Net}}$$

The "net" value in the equation is the net input value you get with the summation function.

2.3. Performance Criteria

The prediction error in ANN consists of the difference between the true value and the predicted value for a given period [30]. The accuracy of the information produced by ANNs is checked using error criteria. The network should be tested with the error criteria from the literature and should be within acceptable limits. It is very important for the accuracy of the network that the error values are within acceptable limits.

The R value is represented by the ANNs and the R^2 value can be calculated using the R value. The R value reflects the correlation coefficients and this value takes values between 1 and -1. 1 represents an absolute positive correlation, 0 represents no correlation and -1 represents an absolute negative correlation [31].

The Root Mean Square Error (RMSE) criterion is determined by taking the square root of the mean of the squares of the errors. The RMSE value ranges from 0 to $+\infty$. 0 represents for the best result [32].

The mean absolute percentage error (MAPE) metric provides more accurate results than other metrics and is sufficient to explain the change. The corresponding MAPE values are listed in Table 1 [33].

Table 1. MAPE value and descriptions

MAPE value	Descriptions
MAPE<10%	High accuracy
MAPE>10% and <20%	Medium accuracy
MAPE>20% and <50%	Low accuracy but acceptable
MAPE>50%	No predictive value

3. METHOD

In this study, Quality of Life Index for the year 2020 was predicted for 29 countries on the European continent, including Turkey, using ANNs. The reason for limiting the study to 29 countries is the lack of data integrity in other countries of the European continent.

All ANNs presented in the study were created using the MATLAB 2019B program developed by MathWorks. At the same time, a multilayer feedback network was chosen in the construction of the ANN as shown in Figure 2. The trainlm function was used as the summation function and the sigmoid function as the activation function. Analyzes were made by creating 29 separate networks for 29 countries.

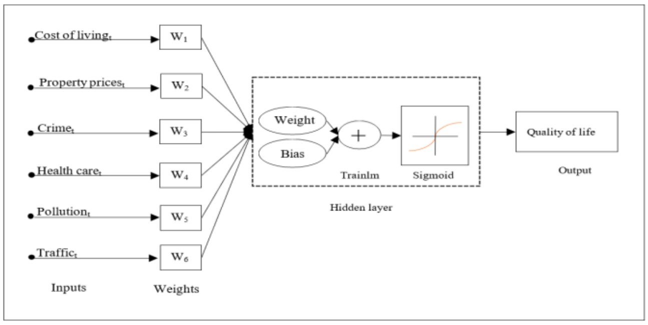

Figure 2. ANN model

The data used to train the network is divided into three parts. The parts are: Data to train the network, Data to validate, and Data to test. In this study, 70% of the data was used for training, 15% for validation, and the remaining 15% for testing. The data used for training from these phases is used to learn the network, the data used for validation is used to determine when to stop training, while the data used for testing verifies that the network has achieved the desired performance [34].

It is not possible to follow specific rules in determining the summation function, the activation function, the number of hidden layers, and the number of hidden neurons. In the absence of a systematic approach, it was proposed to use the trial and error method [25]. In this study, the summation function, the activation function, the number of hidden layers, and the number of hidden neurons were determined by numerous trials.

3.1. Index data used: The data used to train the network are from 2012, the first year for which all data are available, and from 2019, when the pandemic has not yet started. The Data presented annually from 2012 to 2014, then presented bi-annually. Therefore, each country has fourteen data period in each index. These data are Property Price Index, Pollution Index, Health Care Index, Crime Index, Traffic Index, Cost of Living Index, and Quality of Life index, and these data are used in this study. ANN Is trained by shifting by one period. Therefore, 6 index data of 13 period (13x6) were used as input layer and quality of life index data of 13 period (13x1) were used as output layer.

3.2. Creation and training of the ANN: 6 indexes for each country for the periods 2012, 2013, 2014, 2014-2, 2015, 2015-2, 2016, 2016-2, 2017, 2017-2, 2018, 2018-2, 2019 were taken from Numbeo life quality index and these data were used in the input layer. Since the data are given in the six-month periods after 2014, it can be seen that two sets of data have been received each year since 2014. For each country, data from the 2013, 2014, 2014-2, 2015, 2015-2, 2016, 2016-2, 2017, 2017-2, 2018, 2018-2, 2019, 2019-2 period data were used as output.

4. RESULTS

This section compares the quality of life index for 2020 and the projected quality of life indexes for 2020. ANN Results and performance analyzes related to these results for all countries are presented in Table 2 and Table 3. ANN results were ranked by expected and predicted difference. As a result of the ranking, the regression analyzes, and comparative index detailed plots of the networks of Germany, Turkey, Bulgaria and Spain were shared. The reason for sharing the detailed information about these four countries is that Germany is in the first place, Bulgaria is in the last place and the expected-predicted difference of Turkey and Spain is almost non-existent.

4.1. Analysis of the ANN

In the literature, there are some performance criteria for the analysis of ANN. The most accepted criteria are R^2, mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE). In this study, trained networks were tested. The performance analyzes for countries are shown in Table 2.

Table 2. ANN performance analysis by country

Countries	R	R^2	RMSE	MAPE
Austria	0.999	0.998	0.07	0.28
Belgium	0.993	0.986	0.55	1.79
Bosnia and Herzegovina	0.998	0.996	0.94	1.55
Bulgaria	0.999	0.998	0.73	0.96
Croatia	0.998	0.996	0.76	1.91
Czech Republic	0.999	0.998	0.28	0.72
Denmark	0.995	0.990	0.35	2.06
France	0.990	0.980	1.03	2.10
Germany	0.990	0.980	2.16	0.76
Greece	0.989	0.978	2.21	4.75
Hungary	0.999	0.998	0.19	0.45
Ireland	0.996	0.992	0.45	1.21
Italy	0.997	0.994	1.21	2.53
Lithuania	0.999	0.998	0.23	0.73
Netherlands	0.997	0.994	0.22	1.40
Norway	0.995	0.990	0.41	1.49
Poland	0.995	0.990	1.26	2.23
Portugal	0.999	0.998	0.23	0.84
Romania	0.999	0.998	0.30	0.58
Russia	0.999	0.998	2.33	1.25
Serbia	0.998	0.996	0.81	1.59
Slovakia	0.997	0.994	0.59	1.65
Slovenia	0.998	0.996	0.43	1.46
Spain	0.999	0.998	0.32	0.85
Sweden	0.991	0.982	0.71	2.26
Switzerland	0.996	0.992	0.56	2.62
Turkey	0.999	0.998	0.36	0.78
Ukraine	0.999	0.998	1.81	1.64
United Kingdom	0.999	0.998	0.25	0.60

As a result of the analysis in Table 2, the network outputs were found to have high accuracy (MAPE<10%).

Comparisons of the quality of life indexes of the 29 countries and the country ranks in 2020 predicted by ANN can be found in Table 3.

Table 3. Country impact rates from COVID-19

Countries	Realized	Predicted	Difference	Difference (percent)
Germany	179.78	229.90	50.12	27.87
Norway	175.19	198.37	23.18	13.23
Serbia	116.30	127.30	11.00	9.45
Sweden	175.95	191.30	15.35	8.72
Italy	140.76	152.02	11.26	8.00
Portugal	162.91	175.46	12.55	7.70
Belgium	153.47	164.43	10.96	7.14
Croatia	159.01	170.20	11.19	7.03
Czech Republic	156.24	167.16	10.92	6.98
Hungary	128.16	135.37	7.21	5.62
Poland	141.83	149.59	7.76	5.47
Switzerland	192.01	201.88	9.87	5.14
Bosnia and Herzegovina	121.89	126.46	4.57	3.74
Austria	182.50	187.05	4.55	2.49
United Kingdom	162.71	166.70	3.99	2.45
France	153.95	157.69	3.74	2.42
Ireland	153.53	157.16	3.63	2.36
Denmark	192.67	196.89	4.22	2.19
Slovenia	172.15	175.75	3.60	2.09
Holland	183.67	186.49	2.82	1.53
Russia	102.31	103.82	1.51	1.47

Greece	133.07	134.30	1.23	0.92
Slovakia	152.53	153.77	1.24	0.81
Romania	132.44	133.12	0.68	0.51
Turkey	127.10	127.60	0.50	0.39
Spain	169.82	169.72	-0.10	-0.05
Lithuania	159.42	158.98	-0.44	-0.27
Ukraine	104.77	103.30	-1.47	-1.40
Bulgaria	129.80	126.74	-3.06	-2.35

As can be seen in Table 3, when comparing the predicted and actual quality of life indexes for 2020, Germany and Norway were the countries with the largest decline in quality of life. It can be seen that the quality of life index showed low difference percent in Turkey, Spain and Lithuania, while it increased in Ukraine and Bulgaria.

According to the designed ANN, the quality of life index for 2013 was predicted with input data from 2012, and the quality of life index for 2014 was predicted with input data from 2013. The ANN, trained and simulated with 2019-2 period input data and predicted the 2020 quality of life index without COVID-19.

4.2. The ANN of Germany

The regression values of the training, testing and validation phases of the ANN created for Germany are shown in Figure 3.

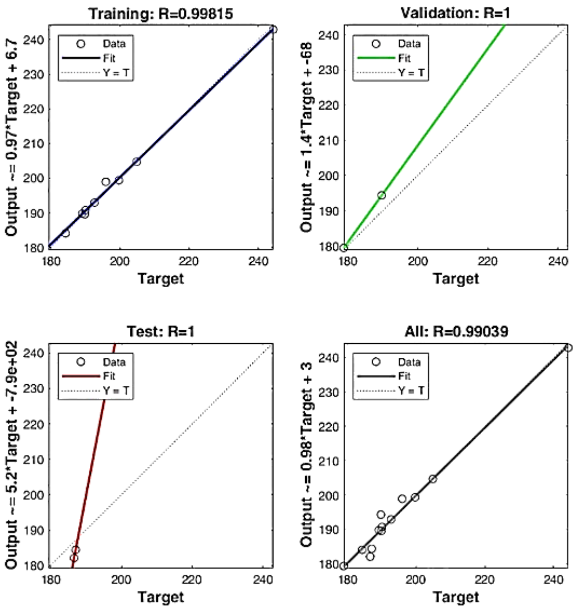

Figure 3. ANN regression results for Germany

The ANN prepared for Germany predicted the quality of life of citizens in 2020 to be 229.90, but the actual quality of life index was 179.78. This shows that the standard of living of German citizens has declined. The country where the quality of life index for 2020 has decreased the most is Germany. The output of the comparison chart for Germany is shown in Figure 4.

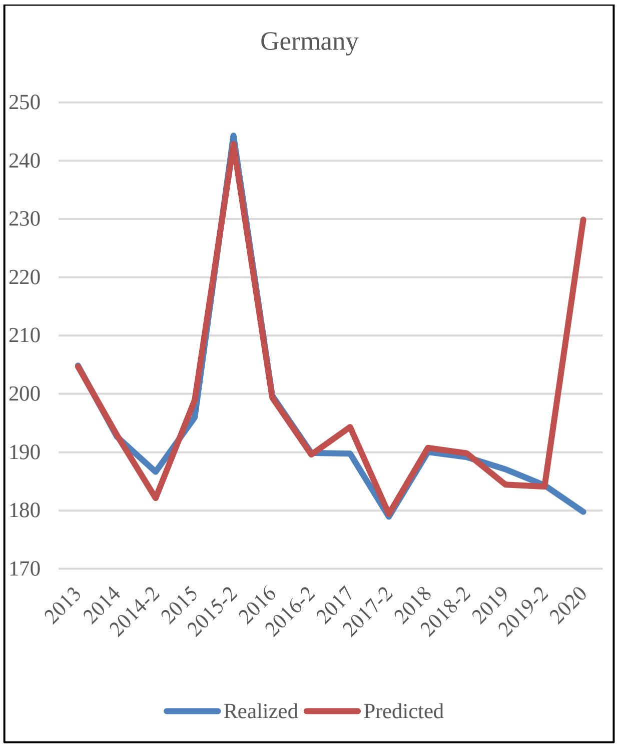

Figure 4. Predicted-realized comparison of Germany

4.3. The ANN of Turkey

The regression values of the training, testing and validation phases of the ANN created for Turkey are shown in Figure 5.

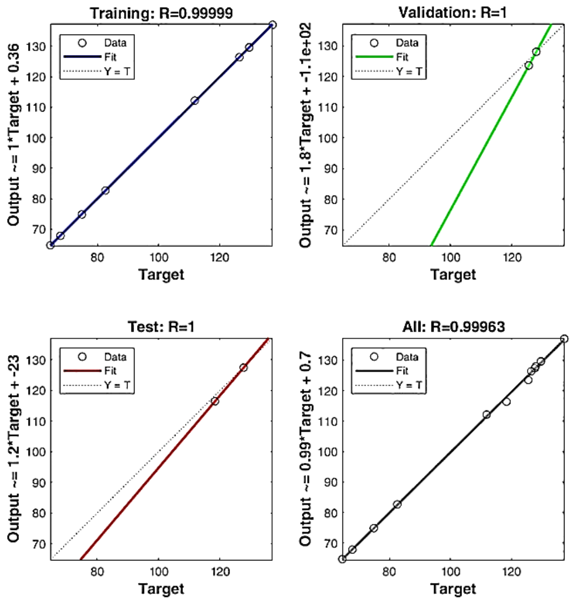

Figure 5. ANN regression results for Turkey

The ANN prepared for Turkey predicted the quality of life of citizens in 2020 to be 127.60, but the actual quality of life index was 127.10. Since the index predicted by ANN and the actual index are very close, it can be said that the citizens of the Turkey were not affected by the pandemic in 2020. The output of the comparison chart for Turkey is shown in Figure 6.

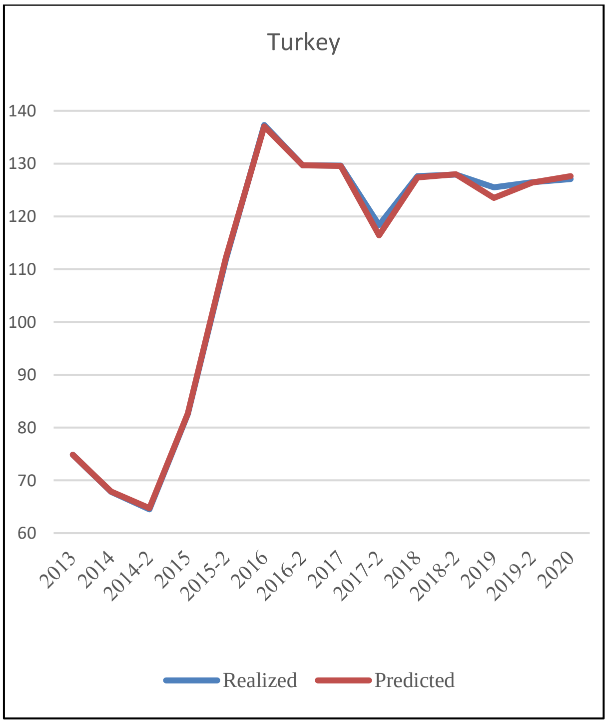

Figure 6. Predicted-realized comparison of Turkey

4.4. The ANN of Spain

The regression values of the training, testing and validation phases of the ANN created for Spain are shown in Figure 7.

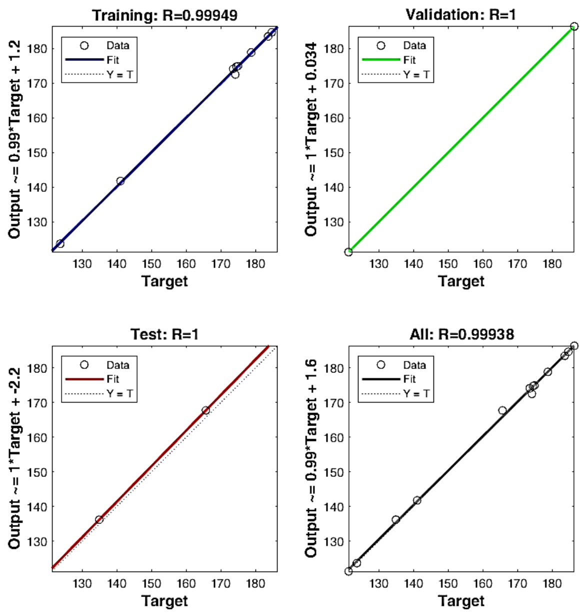

Figure 7. ANN regression results for Spain

The ANN prepared for Spain predicted the quality of life of citizens in 2020 to be 169.72, but the actual quality of life index was 169.82. In this case, the quality of life index of Spanish citizens was almost as high as expected. In other words, the quality of life of Spanish citizens did not change. The output of the comparison chart for Spain is shown in Figure 8.

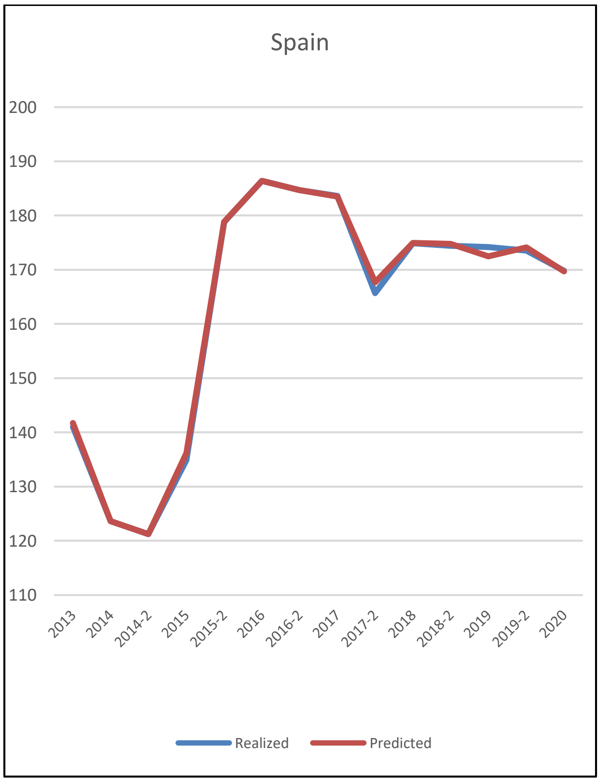

Figure 8. Predicted-realized comparison of Spain

4.5. The ANN of Bulgaria

The regression values of the training, testing and validation phases of the ANN created for Bulgaria are shown in Figure 9.

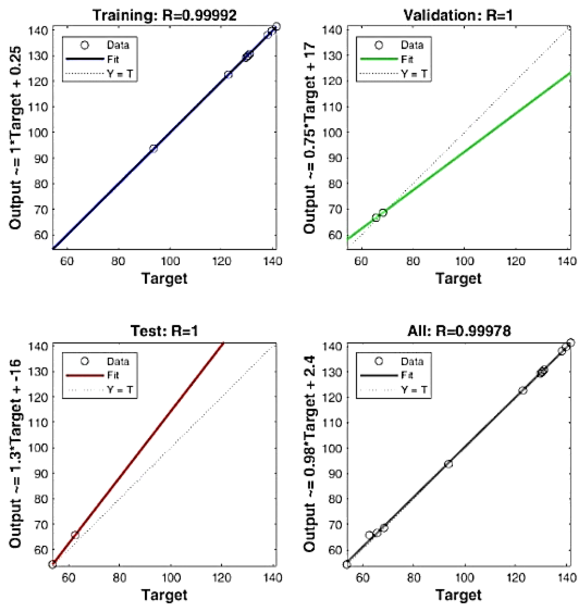

Figure 9. ANN regression results for Bulgaria

The ANN prepared for Bulgaria predicted the quality of life of citizens in 2020 to be 126.74, but the realized quality of life index was 129.80. It was found that the quality of life of Bulgarian citizens was not affected by the COVID-19 pandemic in 2020, on the contrary, interestingly actually improved. The output of the comparison chart for Bulgaria is shown in Figure 10.

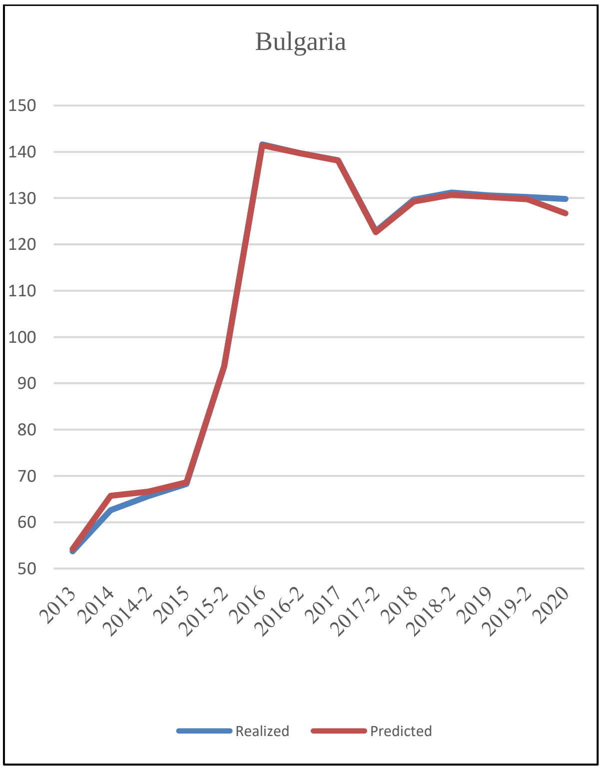

Figure 10. Predicted-realized comparison of Bulgaria

5. CONCLUSION

The results of the study were obtained thanks to the data from the Numbeo database. Under the assumption of validity of Numbeo database, the results of this study supports previous studies in the literature.

The study examined the index of 29 countries on the European continent that did not have missing data. Among the countries affected by the epidemic COVID 19, detailed comments were made on the countries with the most positive and the most negative perceptions, as well as on the countries that were least affected by the pandemic (almost neutral).

The predicted and actual quality of life indexes for 2020 were compared. It was found that Germany and Norway are the countries with the highest decline in quality of life, in Turkey, Spain and Lithuania, the quality of life remained almost unchanged. It was found that the quality of life increased in Ukraine and Bulgaria.

The results show that the quality of life index was 27.87% lower than expected in Germany, 0.39% lower than expected in Turkey, 0.05% higher than expected in Spain, and 2.35% higher than expected in Bulgaria. In other words, In 2020, citizens in Germany were most affected by the COVID-19 epidemic. For citizens in Turkey and Spain, the epidemic had less impact in 2020. For the citizens of Bulgaria, the quality of life index for 2020 was higher than the predicted quality of life index, i.e., the quality of life of Bulgarian citizens increased.

Citizens living in Germany seem to be much more affected by the COVID-19 pandemic than other countries. Although Germany placed great emphasis on closures and citizen support in the first wave of the epidemic, it was unwilling to let its economy pause any longer, as it was one of the largest economies in the world, and experienced normalization in the second wave [35]. In addition, the capacity and economic inadequacy of hospitals in Germany met with the reactions of citizens. The fact that German citizens were shocked by the COVID-19 pandemic that entered their lives while they were living with a high quality of life explains that the real quality of life index is much lower than expected [36].

When the results of Bulgaria were examined, it was found that the actual quality of life index was 2.37% higher than the predicted one. According to this result, it can be said that the citizens living in Bulgaria are positively affected by the COVID-19 pandemic. The first case in Bulgaria was detected later than in other countries. As a result, the number of cases and deaths increased slowly. In addition, the number of doctors per capita in Bulgaria is 8% higher than the European average and the number of patient beds is 40% higher than the European average. In addition, simplified health procedures and established online hotlines demonstrate Bulgaria's fight against the COVID-19 pandemic [37]. It can be said that all these factors affect the perception of Bulgarian citizens positively. From this point of view, it becomes understandable that the actual quality of life index of citizens living in Bulgaria is higher than expected.

When analyzing the results for Turkey, it was found that the real quality of life index was 0.39% lower than expected. For Spain, it was found that the real quality index was 0.05% higher than expected. In this context, it can be said that there is no significant difference between the predicted and real quality of life index for Turkey and Spain. The citizens of the Republic of Turkey believe that their country is more successful in fighting the pandemic COVID-19 than the European Union. On the other hand, it was found that the trust rate of Spanish citizens in their own government is 0.5%, the highest rate in Europe [38].

The results of this study, in which the examples from Germany, Turkey, Spain, and Bulgaria were explained in detail, were interpreted and these comments were supported by other studies in the literature. At the end of the study, it was found that countries with a high quality of life index were more affected by COVID-19. In other words, since the welfare level of citizens in countries with a high quality of life is higher than the welfare level of citizens in countries with a relatively low quality of life, it is assumed that a negative change in the factors affecting the welfare level of countries is felt more strongly in countries with a high quality of life.

In this study, some suggestions will be given to the states. These suggestions include areas where investment should be increased following the pandemic, actions that can be taken to be prepared for future extraordinary situations, and strategies that can be developed. In the study, the predictions to be made with ANN did not predict the future, but instead the alternative past.

The mortality rate of the COVID-19 pandemic is much higher in the elderly and people with chronic diseases. Due to the high proportion of the elderly population, it has been observed that the mortality rate from this epidemic has increased in Europe. In this context, countries on the European continent should prepare for exceptional situations such as epidemics that may occur in the future by focusing on geriatrics (medicine for the elderly) and doing more work in this area. In the countries examined in the study, which were not negatively affected by the COVID-19 pandemic in periods of quality of life index, health care was not disrupted as much as it was felt throughout Europe. For this reason, these countries are recommended to give more importance to the health sector by relying on their health systems and increasing the share of this sector in the country's economy.

Due to the disruptions in the supply chain during the COVID-19 pandemic, production generally effected negatively and factories that could not produce were severely damaged economically. In the supply chain, there were problems not only in the supply of raw materials, but also in the supply of final products of basic needs. In this case, it is recommended that countries reduce their imports, especially in basic food and basic medical products, and invest enough to meet their own needs through their own production.

Goverment transparency means that administrators share information about their work and are open to citizens' criticism and discussion [39]. As government transparency increases, citizens' perceptions and reality will converge, public memory's trust in the state will increase, and consensus will be reached. For this reason, states are recommended to publish real data in a way that citizens do not doubt, rather than publishing incomplete or false information to manipulate citizens' perceptions.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Ali UÇUCU: Performed the experiments and analyzed the results.

Başak GÖK: Wrote the manuscript.

Hadi GÖKÇEN: Designed and supervized the study.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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