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CONSISTENCY MEASUREMENT USING THE ARTIFICIAL NEURAL NETWORK OF THE RESULTS OBTAINED WITH FUZZY TOPSIS METHOD FOR THE DIAGNOSIS OF PROSTATE CANCER

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Abstract. In recent years great attention has been paid to studies on artificial intelligence since it can be applied easily to several areas like medical diagnosis, engineering and economics, among others. In this paper we present an example in medicine which aims to diagnose the patients with high prostate cancer risk using a multi-criteria decision making method.Our datas set is prostate specific antigen (PSA), free prostate specific antigen (fPSA), prostate volume (PV) and age factors of 78 patients from Necmettin Erbakan University Meram Medicine Faculty. An artificial neural network related to the consistency of convergence coefficients calculated by the Fuzzy TOPSIS method [32] is established.Thus, we understand the accuracy of the results from the Fuzzy TOPSIS method.

Keywords: Artificial neural network, Multi-criteria decision making, Prostate cancer, Fuzzy TOPSIS Method.

AMS Subject Classification: 03E72, 90B50, 06D72

1. Introduction

In recent years vague concepts have been used in different areas as medical applications, pharmacolorgy, economics, engineering since the classical methods are inadeque to solve many complex problems in these areas. So some theories were developed such as fuzzy set theory [38],rough set theory [24],soft set theory [20] and fuzzy soft set theory [18]. In a short time these theories gave rise to many researchers and applications. For example, these were introduced to solve multi-criteria decision making problems [5, 9, 25, 26, 12, 4, 34, 37].

Prostate cancer is the second most common cause of cancer death among men in most industrialized countries. It depends on various factors as family's cancer history, age, ethnic background, and the level of prostate specific antigen (PSA) in the blood. Since PSA is a substance produced by the prostate, it is very important factor to an initial diagnosis for patients [3, 31, 33]. As known, if the prostate cancer can be diagnosed earlier, the patient can be completely treated. The definitive diagnosis of the prostate cancer is

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possible the process of biopsy. The results of PSA test, rectal examination, and transrectal findings help the doctor to decide whether biopsy is necessary or not [19, 21, 29]. However the datas of the level of PSA, fPSA, the age of patient and the prostate volume can give an idea to the doctor about the cancer risk. If the risk is low then the biopsy operation which has high cost and possible complications, is unnecessary. There are several researches in the area of the prostate cancer prognosis or diagnosis [27, 1, 17, 28, 36].

Artificial Intelligence learning, justification, problem solving etc. is a computer science that deals with systems that can show human behavior. We aim to develop similar artificial instructions by analyzing human thinking methods by using the artifical intelligence. The main methods of artificial intelligence used today are expert systems, fuzzy logic and artificial neural networks.

Artificial neural networks are the computer systems that are developed with the aim of automatically generating new information and discovering them without any help [22]. Artificial neural networks are known as a method developed by the simulation of the cognitive learning process of the brain. The method helps to find the solutions to many problems such as forecasting, classification and clustering. The most important feature of the neural networks is to provide a solution to the problem by learning on the basis of past knowledge of complex systems [10].

In this study, we use artificial neural network to test the consistency of the results from the Fuzzy TOPSIS Method [32]. For this process, prostate specific antigen (PSA), free prostate specific antigen (fPSA), prostate volume (PV) and age of 78 patients are used as laboratory data. According to Fuzzy Topsis Method [32], biopsy is necessary only 46 patients who are under high cancer risk. This group also contain 44 patients who were diagnosed with cancer. In this case, the first question that comes to mind is "How reliable is this method?". Therefore, we develope an artificial neural network and control the accuracy of the results obtained in Fuzzy Topsis Method [32]. As a result, we conclude that this would be a useful method for doctors to make decisions faster.

2. Preliminaries

In this section, some basic definitions are recalled and fuzzy TOPSIS method is mentioned briefly.

Definition 2.1. [38] *A fuzzy set $\widetilde{A}$ in a universe of discourse U is characterized by a membership function $\mu_{\widetilde{A}}(x)$ which associates with each element x in U a real number in the interval $[0,1]$. The function value $\mu_{\widetilde{A}}(x)$ is termed the grade of membership of x in $\widetilde{A}$. The family of all fuzzy subsets of U is denoted by $P(U)$.*

Definition 2.2. [15]

1) A fuzzy set $\widetilde{A}$ on the universe of discourse U is convex if and only if for any $a, b \in U$, $\mu_{\widetilde{A}}(\alpha a + \beta b) \geq \mu_{\widetilde{A}}(a) \wedge \mu_{\widetilde{A}}(b)$, where $\alpha + \beta = 1$.

2) A fuzzy set $\widetilde{A}$ on the universe of discourse U is called a normal fuzzy set if there exists a point $a_i \in U$ such that $\mu_{\widetilde{A}}(a_i) = 1$.

3) A fuzzy number is a fuzzy subset in the universe of discourse U which is both convex and normal.

A triangular fuzzy number $\widetilde{n}$ can be defined by a triplet (a, b, c). The membership function $\mu_{\widetilde{n}}(x)$ is defined as [15]:

$$\mu_{\widetilde{n}}(x) = \begin{cases} 0, & x < a, \\ \frac{x-a}{b-a}, & a \leq x \leq b, \\ \frac{x-c}{b-c}, & b \leq x \leq c, \\ 0, & x > c. \end{cases}$$

Let $\widetilde{m} = (m_1, m_2, m_3)$ and $\widetilde{n} = (n_1, n_2, n_3)$ be two triangular fuzzy numbers. Then addition and multiplication of $\widetilde{m}$ and $\widetilde{n}$ as given in [15] are

$$\widetilde{m} \oplus \widetilde{n} = (m_1, m_2, m_3) \oplus (n_1, n_2, n_3) = (m_1 + n_1, m_2 + n_2, m_3 + n_3)$$

and

$$\widetilde{m} \otimes \widetilde{n} = (m_1, m_2, m_3) \otimes (n_1, n_2, n_3) = (m_1 \times n_1, m_2 \times n_2, m_3 \times n_3).$$

Definition 2.3. [2] *$\widetilde{D}$ is called a fuzzy matrix, if at least an entry in $\widetilde{D}$ is a fuzzy number.*

Definition 2.4. [39] *A linguistic variable is a variable whose values are linguistic terms.*

The concept of linguistic variable is very useful in dealing with situations which are too complex or too ill-defined to be reasonably described in conventional quantitative expressions [39].

Definition 2.5. [5] *Let $\widetilde{m} = (m_1, m_2, m_3)$ and $\widetilde{n} = (n_1, n_2, n_3)$ be two triangular fuzzy numbers, then the vertex method is defined to calculate the distance between them as*

$$d(\widetilde{m}, \widetilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]}.$$

Chen [5] gave a systematic approach to extend the TOPSIS to the fuzzy environment. We have applied this method to a medicine problem to obtain the optimal choice for the patients who are potential carrier of prostate cancer. Chen's method can be summarized as follows:

Assume that there is a set of m patients $U = \{u_1, u_2, ..., u_m\}$ with a set of n symptoms $S = \{s_1, s_2, ..., s_n\}$ for prostate cancer.

Step 1: Form a committee of doctors, then identify the evaluation symptoms.

Step 2: Choose the appropriate linguistic variables for the importance weight of the symptom and the linguistic ratings for patients with respect to symptom.

Step 3: Aggregate the weight of symptom to get the aggregated fuzzy weight $\widetilde{w}_j$ of symptom s_j and pool the doctors' opinions to get the aggregated fuzzy rating $\widetilde{p}_{i\ j}$ of patient u_i under symptom s_j.

Step 4: Construct the fuzzy decision matrix P and then obtain the normalized patient-symptom matrix R.

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to $[0, 1]$.

Step 5: Construct the weighted normalized fuzzy decision matrix Q, called symptom-weight matrix, where the entries are triangular fuzzy numbers $\widetilde{w}$. W is the set of importance weights of symptoms.

Step 6: Perform the transformation operation $R \otimes Q$ to get the weighted normalized patient-symptom matrix $\widetilde{V}$.

Step 7: Determine $FPIS$ (fuzzy positive-ideal solution) and $FNIS$ (fuzzy negative-ideal solution).

Step 8: Calculate the distance of each patient from $FPIS$ and $FNIS$, respectively.

Step 9: Calculate the closeness coefficient CC_i of each patient.

Step 10: According to the closeness coefficient, the doctors find opportunity to evaluate patients who are under high degree prostate cancer risk. Hence the doctors may decide that the biopsy is necessary or not for these patients. (see Figure 5 for closeness coefficient of several patients)

3. ARTIFICIAL NEURAL NETWORK

In artificial neural networks, different network structures are used to solve each problem.Which type of problem is more suitable for which type of decision is determined by the decision maker.In this study, Multilayer Detection Model (MDM) is used since, this network structure is especially preferred in problems such as classification, estimation.

Back propagation algorithm is used in MDM model.This algorithm makes it possible to use the artificial neural networks with intermediate layer in order to learn the relationship between complex, non-linear and process parameters [30].Artificial nerve cells formed by mimicking the biological nerve cell come together and form a three-layer artificial neural network [23].These layers are input, output and intermediate layers. Network weights should be adjusted to obtain correct outputs during the learning process [35].

The learning rule of the MDM network is a generalized version of the Delta Learning Rule based on the least-squares method. According to the delta rule used in the back propagation algorithm, it is a rule based on the idea of constantly adjusting and improving the input connections, ie weight, to reduce the difference between the actual output value of a neuron and the desired output value [14].Each vektor associated with target output values in learning is presented to the network for the network to learn. Weights are corrected based on the stated learning rule [13].

Artificial neural networks, in contrast to statistical methods, does not require any preliminary assumptions on the data set [16].Artificial neural networks are widely used in the case of non-linear, multi-dimensional, complex, uncertain, incomplete, defective data and especially in the absence of a mathematical model and algorithm for solving the problem.

Figure 1 shows the input values x_i and the weights w_{nj} that determine the importance of the inputs in the artificial neural network. Each entry and its weight are multiplied and all these values are summed to obtain a number. An activation function is used to make this number between 0 and 1. Although there are many activation functions, the use of sigmoid function is common.

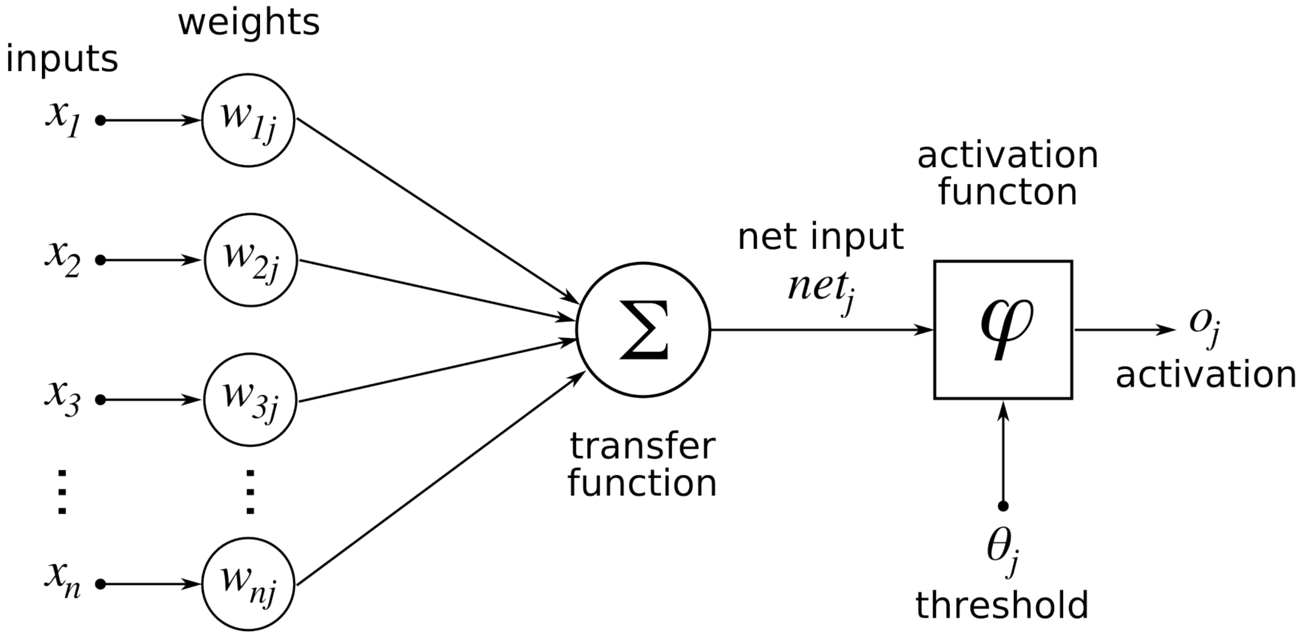


FIGURE 1. Basic Working Mechanism of Neural Networks

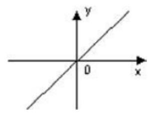
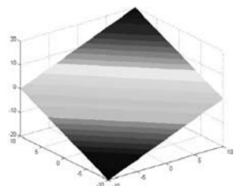
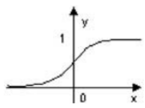
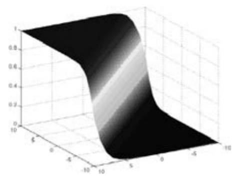
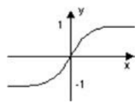
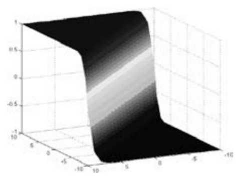
Activation Function	Mathematical Equation	2D Graphical Representation	3D Graphical Representation
Linear	$y = x$		
Sigmoid (logistic)	$y = \frac{1}{1+e^{-x}}$		
Hyperbolic tangent	$y = \frac{1-e^{-2x}}{1+e^{2x}}$		

FIGURE 2. Activation Function Types

4. ANALYSIS OF FUZZY TOPSIS USING THE ARTIFICIAL NEURAL NETWORKS METHOD

We use the Artificial Neural Networks to measure the coherence of the closeness coefficients which obtained for 78 patients in the Fuzzy TOPSIS method on Matlab.In this way, we come to a conclusion about how accurate or how wrong of results obtained in the

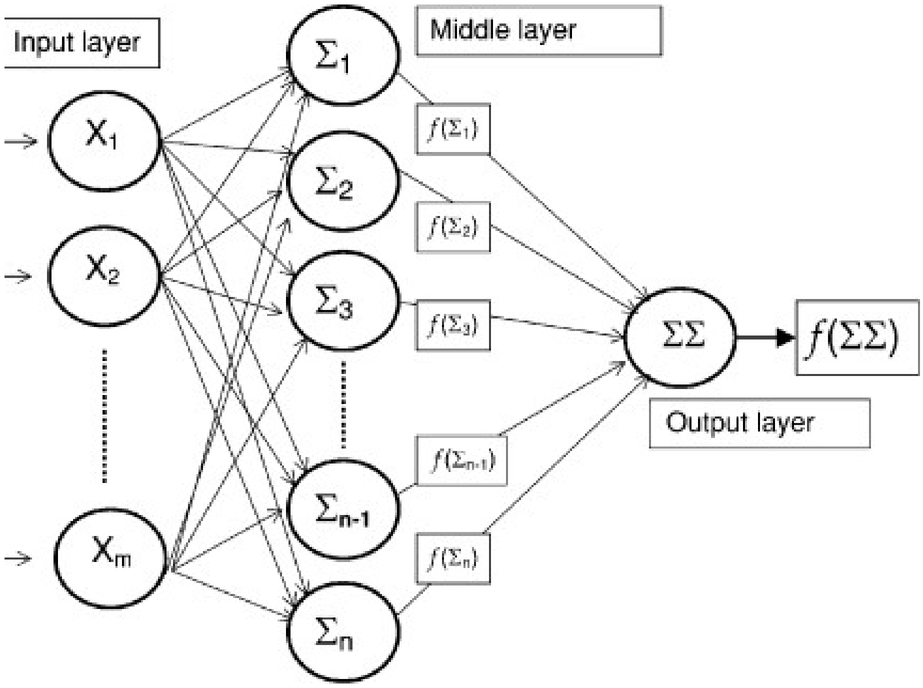


FIGURE 3. Operation of a Basic Artificial Neural Network

Fuzzy TOPSIS method.Let's start to establish an artificial neural network that tries to predict our closeness coefficients obtained by Fuzzy TOPSIS method.

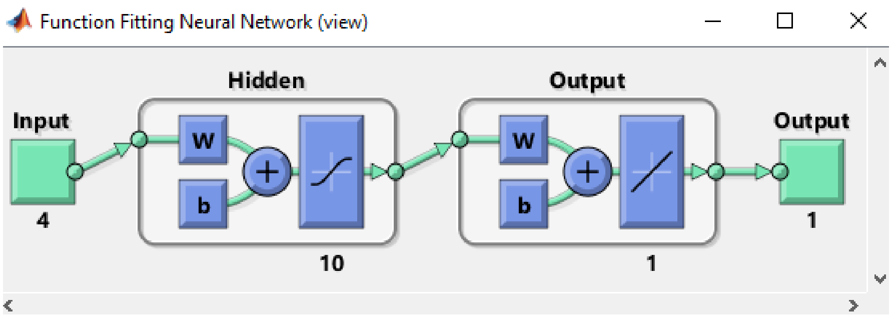
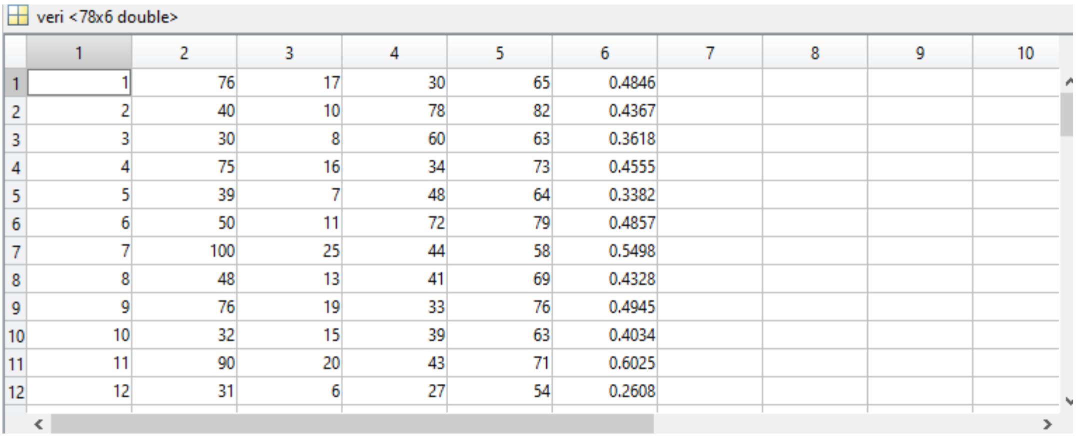


FIGURE 4. An Overview of the Artificial Neural Network Introduced to MATLAB

We enter 4 symptoms into the neural network and also use 10 hidden layers for better analysis of data.

In Figure 5, the first column contains the patient number, the other columns include the values of PSA, fPSA, PV, AGE and Closeness Coefficient, respectively. Here, the values of PSA, fPSA, PV, AGE are introduced as input to the artificial neural network. Also, the values of closeness coefficient of the patients are introduced as output.

We divide our data into two parts, training and testing. First we train our network with our training datas and then try to test the accuracy of test datas on the network. Thus, we determine whether the results of Fuzzy TOPSIS method is consistent or not.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	1	2	3	4	5	6	7	8	9	10
1	1	76	17	30	65	0.4846				
2	2	40	10	78	82	0.4367				
3	3	30	8	60	63	0.3618				
4	4	75	16	34	73	0.4555				
5	5	39	7	48	64	0.3382				
6	6	50	11	72	79	0.4857				
7	7	100	25	44	58	0.5498				
8	8	48	13	41	69	0.4328				
9	9	76	19	33	76	0.4945				
10	10	32	15	39	63	0.4034				
11	11	90	20	43	71	0.6025				
12	12	31	6	27	54	0.2608				

FIGURE 5. Input of Datas into Artificial Neural Network

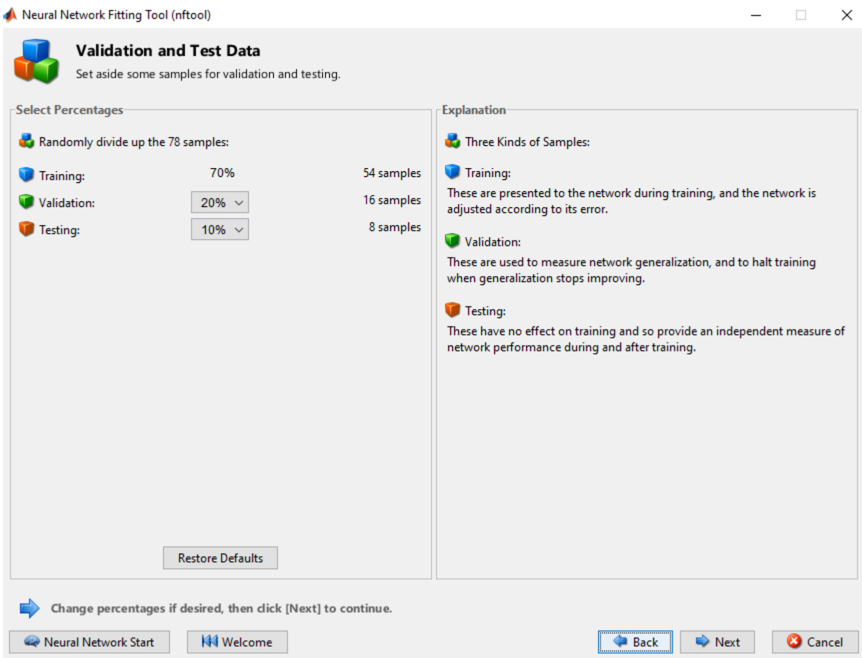


FIGURE 6. Classification of Entered Values as Education and Testing

While closeness coefficients in the Fuzzy TOPSIS method was estimated for each patient, we wanted that the datas be grouped as 70% of the learning data and 30% of the test data.

Now, we examine the results of the artificial neural network:

As seen here, the correlation coefficients are very close to 1. This is normal for the memorized datas during the training state. However, the values in the test state are quite close to 1, too. Thus, it can be said that the closeness coefficient values in Fuzzy TOPSIS method are quite successful.

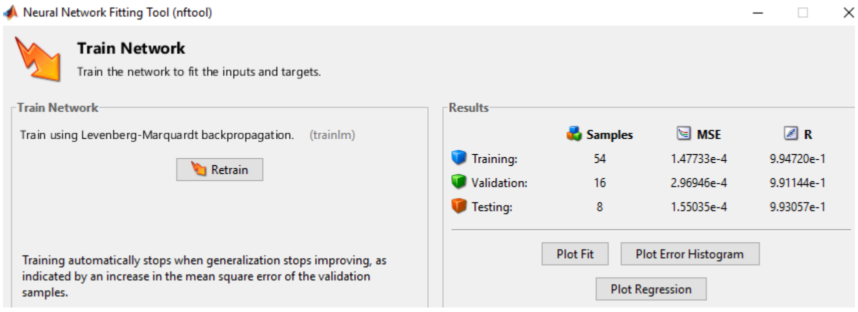


FIGURE 7. Training Result of Artificial Neural Network

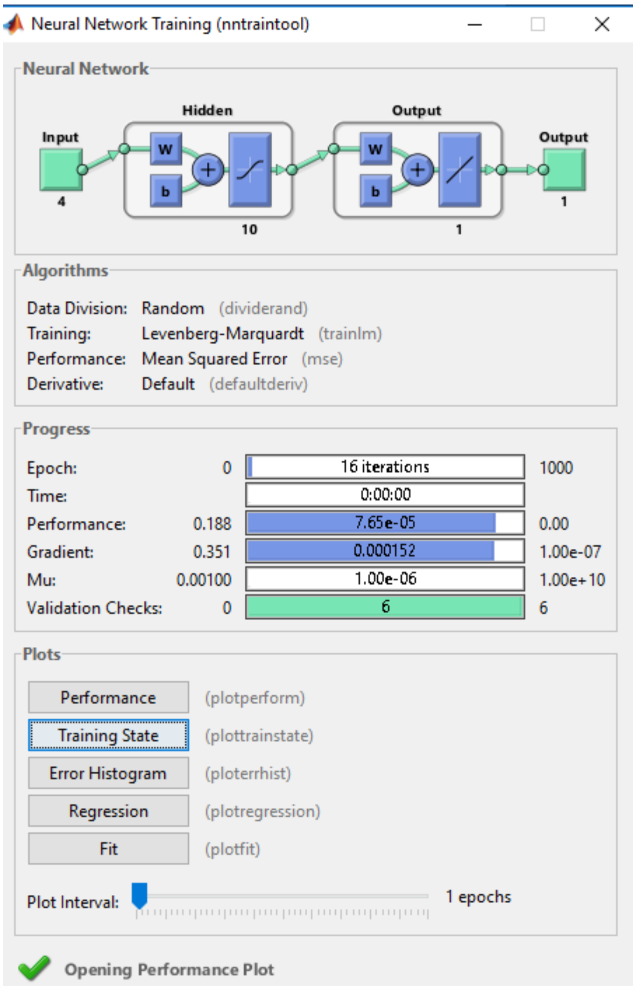


FIGURE 8. Evaluation Results during Training

Estimated performance measurements were taken into account when deciding on network structures. The most commonly used formulas in the literature for estimated performance measurements; RMSE (Mean Square Root of Error Squares), MAPE (Average of Absolute Error Rates), MSE (Average of error squares) [40, 6, 8].

In the evaluation of networks, prediction performance measurements have been preferred. According to the measurements, Witt (2000) categorized models with MAPE that values less than 10% as "high accuracy" and between 10% and 20% as "correct estimates". However, Lewis (2002) categorized models with MAPE that values less than 10% are "very good", models with 10% to 20% are "good", models with 20% to 50% are "acceptable", and models with less than 50% are "incorrect and inaccurate" [7].

$$RMSE = \sqrt{\frac{\sum (y_t - \hat{y}_t)^2}{T}}$$

$$MAPE = \frac{1}{T} \sum \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100$$

$$MSE = \frac{\sum (y_t - \hat{y}_t)^2}{T}$$

Here, y_t is the actual observation value, $\hat{y}_t$ is estimated value and T is the number of estimates. According to the best network structure, the values of these measurements were found as $MSE = 0.000179091$, $RMSE = 0.01338247$, $MAPE = 0.024873$. Since the MAPE value is calculated as 2.4873% in this study, the estimation is in the high accuracy class.

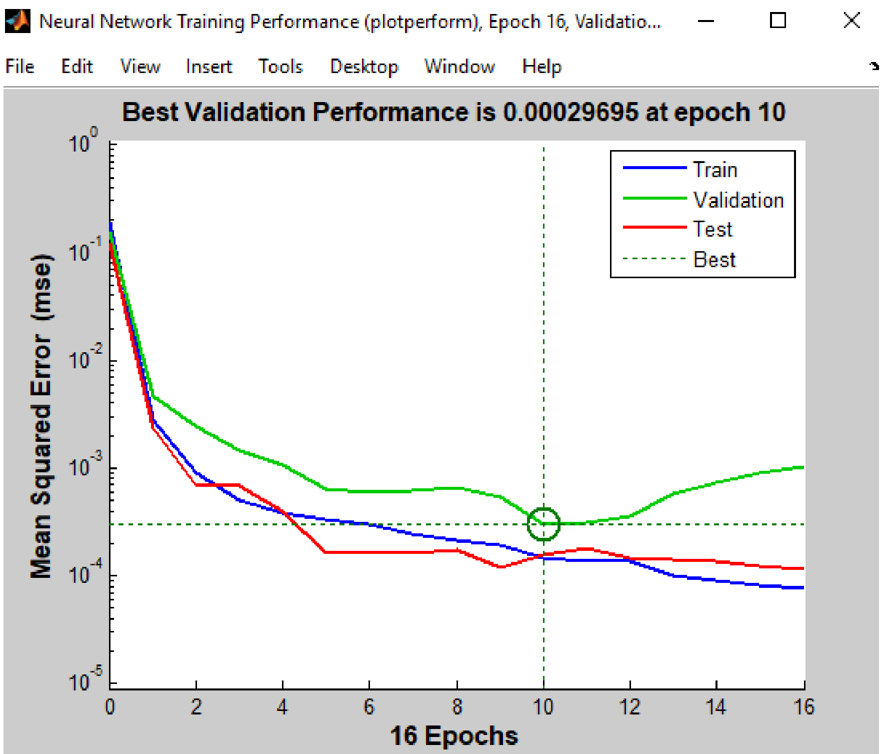


FIGURE 9. MSE-Epoch Graphic

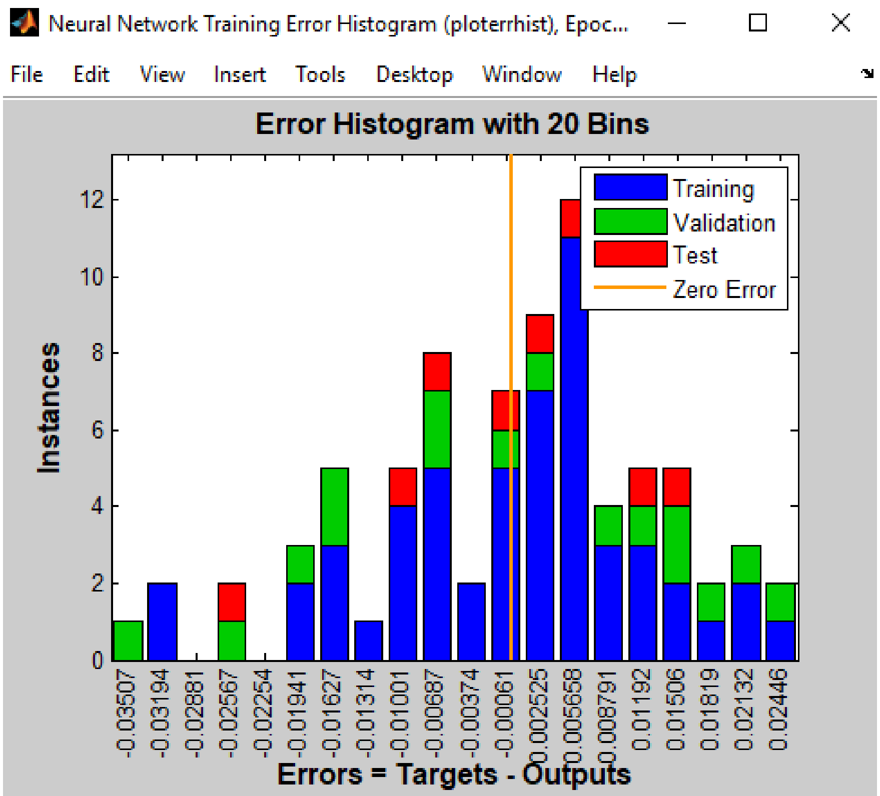


FIGURE 10. Errors in Training and Testing States

When we look at all the results in Figure 11, we see that the margin of error is 0.003 and the regression is quite close to 1. Since the drawings were very close to line Y=T, very good results were achieved.

In Figure 12, There are closeness coefficients calculated by the Fuzzy TOPSIS method in the first column and in the second column, there are closeness coefficients estimated by the Artificial Neural Network. In the third column, the error amounts between the two data are given. As can be seen, the Artificial Neural Network found the numbers which are quite close to the closeness coefficients obtained in the fuzzy TOPSIS method.

Thus, we have determined that the convergence coefficients obtained by the Fuzzy TOPSIS method are consistent and this method can be used as an adjunct to a doctor in making a biopsy decision.

5. Discussion

In this paper, we used the datas of 78 patients with prostate complaint from Necmettin Erbakan Universty Medicine Faculty. After the biopsy operation to 78 patients, it is seen that only 44 patients are diagnosed with cancer. According to Fuzzy Topsıs method [32], biopsy is necessary only 46 patients who are under high cancer risk. This group also contain 44 patients who were diagnosed with cancer. In this situation, the question which is through of fistly is "How reliable are the results from the Fuzzy Topsıs method?". Therefore, we have developed an artificial neural network to control the results obtained

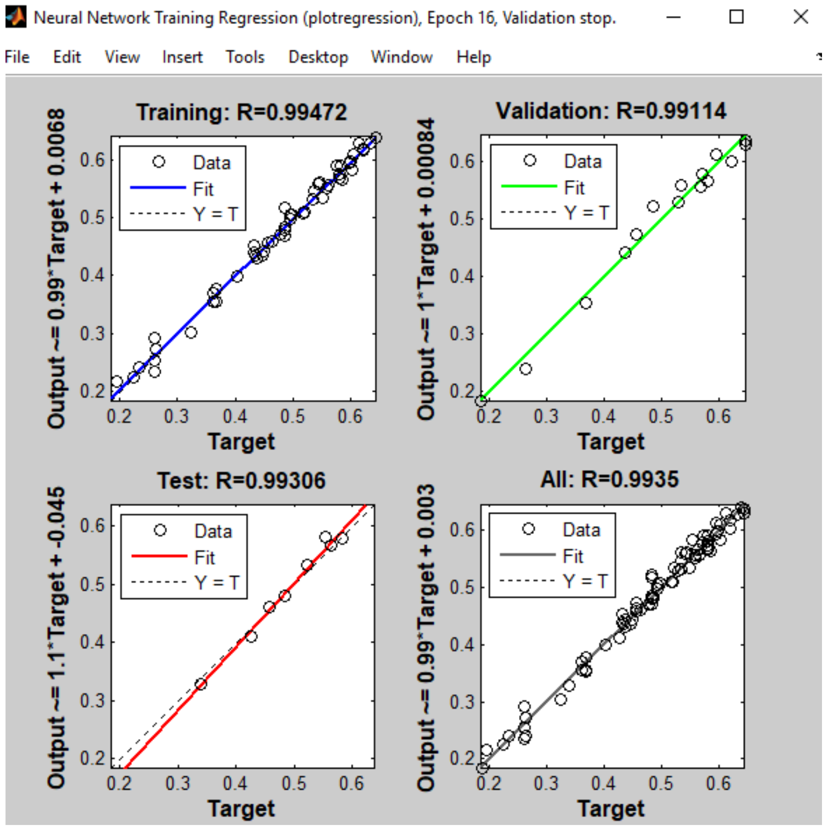
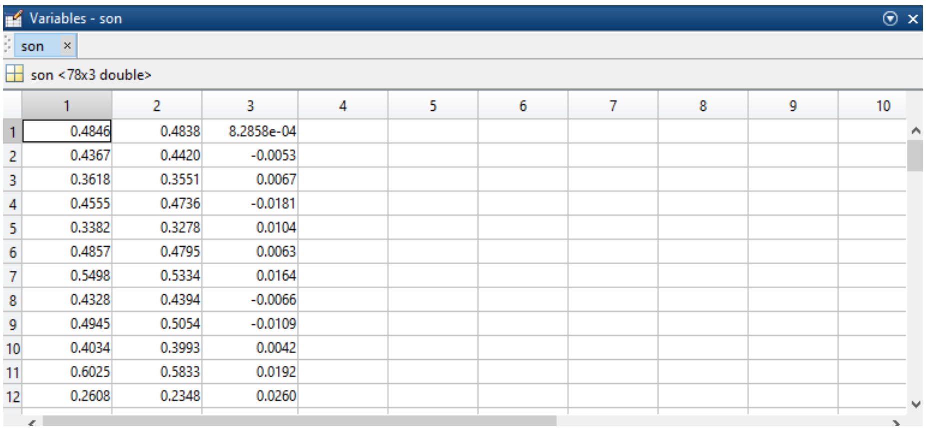


FIGURE 11. Regression Results



	1	2	3	4	5	6	7	8	9	10
1	0.4846	0.4838	8.2858e-04							
2	0.4367	0.4420	-0.0053							
3	0.3618	0.3551	0.0067							
4	0.4555	0.4736	-0.0181							
5	0.3382	0.3278	0.0104							
6	0.4857	0.4795	0.0063							
7	0.5498	0.5334	0.0164							
8	0.4328	0.4394	-0.0066							
9	0.4945	0.5054	-0.0109							
10	0.4034	0.3993	0.0042							
11	0.6025	0.5833	0.0192							
12	0.2608	0.2348	0.0260							

FIGURE 12. Comparison of Results

in Fuzzy Topsıs. We used the criteria expressed by Lewis (2002) for the measurement of the success of the developed artificial neural network. Since the MAPE value is calculated as 2.4873% in our study, the estimation is "very good" according to the values of Lewis (2002).Thus, we conclude that the evaluation can be made according to the results of Fuzzy TOPSIS method. We tested the accuracy of the results obtained in [32] by using artificial neural network and concluded that it would be a helpful method for the doctors.

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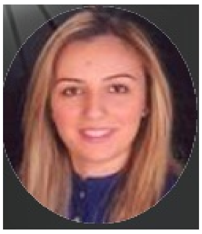

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