Research Article

Journal of Innovative Research in Teacher Education, *3*(3), 321-338
ISSN: 2757-6116
http://www.jirte.org
DOI: 10.29329/jirte.2022.479.5
Received: 06/09/2022
Revised: 07/11/2022
Accepted: 21/11/2022

Prediction of primary education HSEE (LGS) science achievement through artificial neural networks*

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Abstract

This study aimed to investigate the prediction level of science success in high school entrance exams (HSEE /LGS) using artificial neural networks (ANNs) by associating students' success in science classes from the 4th-grade elementary level. The Pearson Moment Product Correlation analysis results were analyzed using the SPSS program to examine the connection between students' performance on the LGS science subtest and their academic achievement in science. In the MATLAB program, artificial neural network modeling performance was examined to understand the level of prediction. The data sets were obtained from the electronic school system of the Ministry of National Education for the 4th to 8th-grades of 1027 students graduating from 24 schools in 17 districts of Bursa in the 2017-2018 academic year and entered the 2018 LGS and LGS result documents without personal information. When the correlations between the LGS science sub-test and science test success were examined ($p < .001$), the highest and lowest correlations were found in the 8th-grade science exams ($r = .70$) and the 4th-grade ones ($r=.57$), respectively. The highest performance values were learning $R=.80$, verification $R=.74$, and test $R=.75$, $RMSE=2.35$ at the network architecture, generated in the second sub-problem and the trained network with 845 student data. A high-level relationship with $r=.75$ ($p<.001$) using the data of 182 students was obtained, while the correct numbers of simulated real LGS science sub-tests compared with the correct numbers predicted by the computer after the training process of the network. In addition, it was obtained that 124 students out of 182 were correctly estimated in the [+ 2, -2] error value range.

Keywords: Science, High school entrance exam, Classroom training, Artificial neural network.

Cite: Atasayar, A. & Demir, M. (2022). Prediction of primary education HSEE (LGS) science achievement through artificial neural networks. *Journal of Innovative Research in Teacher Education*, *3*(3), 321-338. https://doi.org/10.29329/jirte.2022.479.5

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*This research was carried out after being approved by the decision of Kütahya Dumlupınar University Ethics Committee dated 30.11.2021, and numbered "2021/09"

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INTRODUCTION

The student's academic life is shaped according to the centrally held exams, which can change their life preferences such as career planning, career choice, and even residence. It is seen that exams play a significant role in our lives and significantly affect our lives (Hanımoğlu & İnanç, 2011). To have a promising career in the future, it is essential to achieve good grades in the exams for the transition to the next education level (Ocak, Akgül & Yıldız, 2010). For students who want to study at a qualified educational institution over the years to move from primary education to secondary education, many types of exams such as Secondary Education Institutions Selection and Placement Exam (OKS), Placement Exam (SBS), Transition from Basic Education to Secondary Education (TEOG) exam and High School Entrance Exam (LGS) have been applied. It can be said that the primary purpose of the test-style central exams is to measure students' future success on a large scale (Başol & Zabun, 2014). Through the results obtained with these types of exams tried, checking the high school score that the student wants to study, evaluating the results as a whole together with the education and training activities carried out before the exam are seen as one of the most significant elements of central exams (Özkan & Özdemir, 2014). According to the curricula in which the constructivist approach is adopted, the positive effects of the knowledge and skills acquired by the students in the previous grades on their success in the next grade levels (Baş, 2013; Cortez & Silva, 2008; Güzeller, 2005; Güzeller, 2012; Kan, 2005; Kotsiantis, Pierrakeas & Pintelas, 2004; Önen, 2003) and it is expected that there is a positive correlation between the success of the related course and the success of the students in the central exams.

It is aimed to determine the type of department or school that students will go to in higher education and to rank according to the level of having sufficient qualifications among students in the applied selection and placement exams. In this sense, since the purpose of the selection and placement exams is to select the student with a higher potential to be successful in the following education, predictive validity should be the essential feature in such exams. The student's performance in the school or institution is generally considered for predictive validity. The level of relationship between students' success in their future education and their previous learning situations is proof of the validity of selection and placement exams (Aiken, 1971; Baykul, 2000; Özçelik, 1998). In the study by Çırak (2012), the fact that the student's academic background is the most guiding factor in predicting the student's academic success supports this situation. In this context, students' academic success in previous years can be used to predict their academic success in central exams.

It is significant to understand the reasons that affect the success situation to ensure and maintain success in the education and training process. When the variables of academic success are determined and used as prediction parameters for future situations, accurate classification and planning can be made in educational understanding. In the framework of future planning, prediction models based on students' past and current data will enable more accurate and precise guiding and coaching research. In this sense, the student's performances in the lessons appear as an essential variable (Çırak, 2012). Course achievements can be essential in planning the student's future within the data-based decision-making framework. According to the future scenarios that emerge because of sensitive measurements to be made based on course achievements, plans such as vocational orientation, choosing a high school type or department, and determining the quota of departments can be made.

In some aspects, a data-driven decision-making process meshes with modern organizational and management theories. In this sense, proactive management strategy, scientific method, statistical thinking, and continuous process development are some of the main underlying ideas of the new-wave organization and management theories (Altun, Kayıkçı & Irmak, 2019). Continually monitoring, controlling, and improving the process with the preferred understanding of minimizing possible errors can enable a more effective and efficient operation toward the goal in the contemporary management approach (Aydın, 2007; Öztürk, 2009). Thus, the continuous monitoring and control of the process and the improvement of the process within education can be counted among the main objectives of modern education supervision (Aydın, 2007). Therefore, it can be thought that the prediction model applications' more accurate and realistic output, which can enable the process to be monitored and directed, will increase the probability of achieving realistic targets. In this context, in recent years, different statistical methods have been used in research to increase the quality of education and training processes and minimize errors in the prediction models. Nowadays, it is seen that artificial neural networks and fuzzy logic-based modeling methods are started to be used mainly in estimation studies. The use of artificial neural networks in the field of education in Turkey started in the 2000s (Ayık, Özdemir & Yavuz 2007; Çırak 2012; Güneri & Apaydın 2004; Özdemir 2014; Şengür & Tekin 2013; Tepehan 2011; Tosun 2007). These studies also include comparing the prediction performance of artificial neural networks with classification and regression performances (Abu-Naser, Zaqout, Abu-Ghosh, Atallah & Alajrami, 2015; Bahadır 2013; Çırak 2012; Demir, 2015; Karamouzis & Vrettos, 2008; Kardan, Sadeghi, Ghidary & Sani, 2013; Oancea, Dragoescu & Ciucu, 2013; Tepehan 2011; Turhan, Oladokun, Adebanjo & Charles-Owaba, 2008; Turhan, Kurt & Engin 2013). Thus, estimating students' academic performance in science courses with artificial neural networks is at the heart of this research. Accordingly, this study aimed to predict the science course success in the high school entrance exam with artificial neural networks by associating the students' success from the 4th grade of primary school with their success in the next grade level. To that end, within the scope of this study, an answer to the question "What is the level of predicting the correct numbers of the 4th-grade, 5th-grade, 6th-grade, 7th-grade, and 8th-grade science course written exam scores of the students starting from primary school in the science subtest in the high school transition exam?" is sought. In this regard, the sub-problems of the research are as follows:

1. What is the relationship between the students' 4th, 5th, 6th, 7th, and 8th-grade science course written exam mean scores and the number of correct answers in the LGS science subtest?
2. To what extent do students' science course written exam scores from primary school (4th, 5th, 6th, 7th, and 8th grades) predict the number of correct answers in the LGS science subtest with ANN?

METHOD

Research Design

In this study, since the relationship between the number of correct answers in the LGS science subtest and the science course written exam score means was examined, the research was designed following the relational research model. The research was conducted by the correlation (Karasar, 1999) type that tries to determine the existence and degree of co-variation between two or more variables of the relational research, which has two different types of comparison and correlation.

Participants and Procedure

The research population consists of students who sat for the 8th grade LGS in the 2017-2018 academic year from 24 secondary schools in 17 districts of Bursa. The cluster sampling method was used in the research. While determining the schools in the context of the cluster sampling method, the population density of the districts in Bursa and the most crowded student population in the district where the schools are located were considered. In addition, considering different school types, secondary schools, Imam Hatip secondary schools, and regional boarding secondary schools were determined. Considering the population densities of 17 districts, three secondary schools were determined from each of the three most crowded districts (Osmangazi, Nilüfer & Yıldırım), two secondary schools from one district (İnegöl), which is not a central district but very crowded in terms of population density, and one secondary school from other districts. With the change in the education system from the 2012-2013 academic year, (4+4+4) primary and secondary school buildings were separated. Therefore, the primary schools to reach the primary school 4th-grade data of the students who graduated in 2018 in the 2013-2014 academic year were determined among the primary schools closest to the secondary school according to the address-based registration system.

LGS result documents of the students who graduated from secondary school in 2018 and grade slips of the past (4th, 5th, 6th, 7th, and 8th grades) Grade charts of the past periods in the e-school system reports section in Excel file format with .xls extension taken. In total, data from 5135 secondary school 8th-grade students were collected. However, since the data of the students who did not attend the 4th, 5th, 6th, 7th and 8th grades in the same school were not visible on the grade slips, no necessary data could be reached, and the data of the students with missing data were excluded from the study. In addition, since the 2018 LGS exam was not compulsory for all students, some student data had to be deleted. Therefore, the student's exam grades were arranged by performing data cleaning in the Microsoft Excel program. Then, the extracted data of 1027 students were made ready for use in the study.

During the creation of the network architecture, after defining the independent and dependent variables, in other words, the input and output data of the network, the stage of determining the number of hidden cells that will take place in the hidden layer has started. Although there is no definitive method in artificial neural network modeling, the “geometric pyramid rule” method was used to obtain the optimum number of hidden cells. Assuming that the number of input cells is and the number of output cells is j, the number of hidden cells cannot be less than the square root of the product of the input and output cell numbers according to the geometric pyramid rule for this network. In addition, within this rule, the upper limit of the number of hidden cells should not exceed twice the number of input cells. In this case, the number of hidden cells to be used in the network architecture of the research should be between 5 and 58 (Masters, 1995).

In this study, a "Feed Forward Back Propagation" neural network from the "Multilayer Perception Model" class, which is frequently used for prediction and classification problems, was chosen as the learning algorithm. The learning dataset was divided into three clusters using the random distribution command. In the study, 70 percent of the existing learning set was reserved for education. Of the remaining 30 percent, half was reserved for validation testing and the other half for testing operations and measuring the network's success. Later, the logarithmic sigmoid function was defined as the transfer function. The logsig function is widely used in the backpropagation network type used for forecasting. Then, the logarithmic sigmoid function was defined as the transfer function. The logsig function is widely used in the backpropagation network type used for forecasting. Because this function gives meaningful and effective results in nonlinear data, it is a continuously increasing function between 0-1. At each iteration step, in terms of approaching the error surface with a parabolic approach, and the parabola creating the solution for that step, it also produces results very quickly (Yetkin, 2014) compared to other algorithms, the Levenberg-Marquardt algorithm (trainlm) was chosen as the learning function. The Levenberg-Marquardt learning algorithm is a method of searching for the minimum. As a performance function, the mean of squares of error “MSE” was determined. This method selects the network's performance based on the squared error mean.

In this study, to find the best learning network architecture, 54 networks were obtained in the range of 5 to 58 neurons with a single hidden layer each time the written code block was run. The generated code block was run ten times. Within these ten runs, the learning that occurs in the learning phase of the network with the performance learning, performance validity, and performance test values with the highest performance was recorded with the correlation coefficient values of validity (validation) and test processes.

In this case, while determining the most suitable network architecture for the problem situation, 540 different network architectures were examined. Figure 1 below shows the formation of a single hidden layer network architecture from a feed forward back propagation network type.

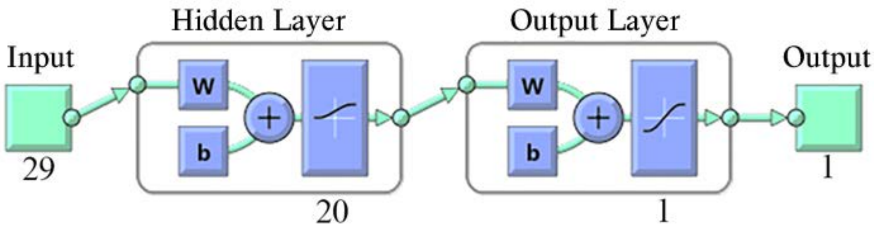

Figure 1. The Sample Feed Forward Backpropagation Network Architecture with 29 Input Variables, One Hidden Layer, and 20 Hidden Cell Numbers

In a multilayer neural network, the best and most important performance measure is the accuracy of the prediction. The accuracy criterion is defined as the difference between the actual value and the predicted values. This difference is called the estimation error (Zhang, 1998). When the performance of an artificial neural network is mentioned, it is understood that the learning ability is measured. It is measured whether the neural network model learns the data well. In this study, when evaluating the model performance, it was accepted that the models with the correlation coefficient (R) value of the simulated (estimated) network closest to 1 perform more successfully. Another essential criterion frequently used in research is the root mean square error (RMSE) value. This value is a quadratic metric frequently used to find the distance between the estimated values of the estimator and the actual values and measures the size of the error. The RMSE is the standard deviation of the estimation errors (residues) (Zhang, 1998). Also, the fact that the training, validation, and test R values in the learning performance of the network are close to each other means that the network has more balanced and consistent results, even if it is not the highest value. Distance R values mean the network found inconsistent results in each training, validation, and testing phase (Yılmaz, 2015).

Data Analysis

The data set was divided into two to create the network and test the problem situations constituting the purpose of the research. The data of 1027 students were randomly selected and divided into the data set of 845 students as the "learned data set" and the data of 182 students as the "data set to be estimated." The primary purpose of this separation process is to find the best network performance and then evaluate the performance of the prediction data that the artificial neural network will generate against the new data set it encounters for the first time. In general, it is seen that at least 15% of the whole data set is used as estimation data. Within the scope of this research, approximately 18% (N=182) of the whole data set was reserved for comparing the prediction data with the actual data after the network was taught (Figure 2).

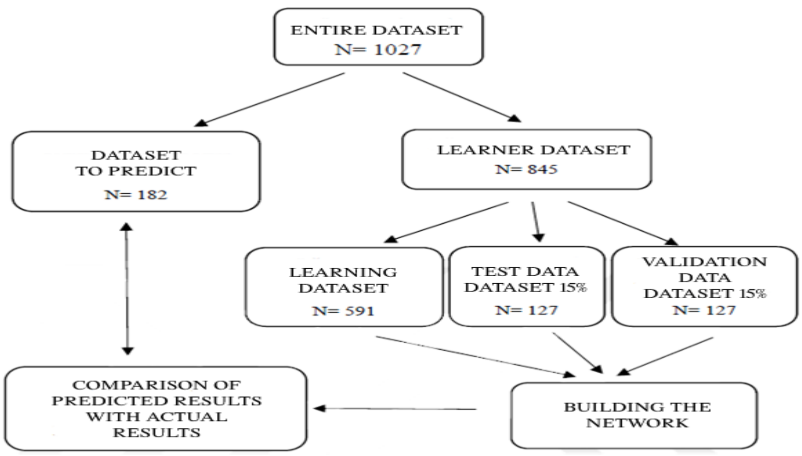

Figure 2. Data Set Processes to Create the Network

After the separation of data was completed, in the first sub-problem of the research, the relationship between the 4th-grade, 5th-grade, 6th-grade, 7th-grade, and 8th-grade science have written exam and LGS science subtest correct numbers of 845 students was examined with the Pearson Product-Moment Correlation using SPSS 23 software. In the second sub-problem of the research, artificial neural network analysis in MATLAB 2018 software was used in the statistical analysis process. The 29 variables formed by the 4th-grade, 5th-grade, 6th, 7th-grade, and 8th-grade science course written exam scores of the students in the range of 0-100 constitute the network's inputs. Furthermore, the number of correct answers in the 2018 LGS science subtest constitutes the output part of the network. Categorical data were not used in the study. While providing network learning in this dataset, it tries to learn the relationships between dependent and independent variables by using learning functions determined by the researcher by randomly selecting a selection from the data within itself. It then tests the performance of the network it creates and generates prediction data. The steps of creating the network are described in detail as follows.

Validity, Reliability, and Ethical Considerations

The study's dependent variable, the LGS science subtest, was prepared based on the learning outcomes determined in the 8th-grade curriculum (MoNE, 2018). This can be considered a basis for the content validity of the LGS science subtest. It was assumed that the teachers provided the content validity of the written exam questions by making a table of specifications in the preparation of the written exams of the science course (4th, 5th, 6th, 7th, and 8th grades), which is the independent variable of the study. No scale was used to obtain the data used in the study. The students' science course written exam scores and LGS science sub-test correct numbers were taken from the past semesters' grade charts in the e-school system reports section in Excel format with .xls extension. Two field experts other than the researcher to prevent errors affecting the data set's reliability controlled the process of structuring the data set. Kütahya Dumlupınar University Institute of Educational Sciences and Bursa Provincial Directorate of National Education Research Evaluation Commission approved the research permission.

FINDINGS

In the first sub-problem of the research, an answer was sought to the question, "What is the level of relationship between students' 4th, 5th, 6th, 7th, and 8th-grade science course written exam achievements and LGS exam science subtest achievements?". The arithmetic means, standard deviation, and correlation results regarding the number of correct answers in the science written exams and LGS science subtest are given in Table 1.

Table 1. Arithmetic Mean and Standard Deviation and Correlation Results of the Number of Correct Answers in the Science Written Examination and LGS Science Subtest

Variables	$\bar{x}$	s	n	4	5	6	7	8	LGS
4th Grade Exam Grades	82.25	12.53	845	1					
5th Grade Exam Grades	73.75	14.65	845	.72*	1				
6th Grade Exam Grades	70.46	16.37	845	.73*	.82*	1			
7th Grade Exam Grades	70.42	17.05	845	.65*	.74*	.83*	1		
8th Grade Exam Grades	72.25	18.12	845	.60*	.68*	.76*	.80*	1	
LGS Number of Correct Answers	9.44	3.95	845	.57*	.62*	.69*	.66*	.70*	1

*p<.01

When Table 1 is examined, it is seen that the highest average of the 4th-grade, 5th-grade, 6th-grade, 7th-grade, and 8th-grade science written exams belongs to the 4th-grade level, with 82.25, respectively. It was determined that the average number of correct answers in the LGS science subtest was 9.44. It is seen that the correlation coefficients vary between .57 and .83, and all correlation coefficients are significant at the .01 significance level. When the correlations between the LGS science subtest given in the table and the science written exam scores are examined, it is seen that the highest significant correlation is between 8th-grade science written exam scores (r=.70). The lowest significant correlation is between LGS science subtest and 4th-grade science written exam scores (r=.57). When the correlations between the science written exam scores are examined, it is seen that the highest significant correlation is between 7th-grade and 6th-grade science written exam scores (r=.83). The lowest significant correlation is between 8th grade and 4th-grade science written exam scores (r=.60).

In the second sub-problem, an answer was sought for the question, "To what extent do students' science course achievements from primary school (4th, 5th, 6th, 7th and 8th grades) predict the number of correct answers in the LGS exam science subtest?". Accordingly, the features of the artificial neural network architecture created are given in Table 2.

Table 2. Features of Created Network Architecture

Trials	Network Type	Performance Function	Transfer Function	Learning Function	Layers	Hidden Layers	Hidden Cells
10	Feed Forward Backpropagation	Mean Squared Error (MSE)	Logarithmic Sigmoid (LOGSIG)	Levenberg – Marquardt (TRAINLM)	3	1	5-58

The algorithm prepared within the scope of this study was run ten times, and after each trial, correlation coefficient graphs of the network architectures, histogram graphs, and graphs comparing the estimation results with the actual result data were recorded. Table 3 presents the results containing the best network performances for each trial.

Table 3. Chart of Best Performances at Ten Trials

Number of Trials	Number of Hidden Cells That Performed Best in Each Trial	Estimated Correlation Coefficient	Learning Correlation Coefficient	Training Correlation Coefficient	Confirmation Correlation Coefficient	Test Correlation Coefficient	General Correlation Coefficient	Best Validation Performance	Root Mean Squares of Error (RMSE) Value
1.	6	.7470	.7866	.7932	.7797	.7682	.7866	6.7910	2.4461
2.	24	.7506	.8059	.8329	.7408	.7568	.8059	7.0282	2.3504
3.	6	.7398	.7766	.7988	.7984	.6534	.7766	5.4728	2.5763
4.	41	.7396	.7882	.8049	.7364	.7553	.7882	6.0488	2.4349
5.	38	.7394	.7779	.7965	.7415	.7340	.7779	6.8253	2.4879
6.	13	.7333	.7885	.7989	.7894	.7531	.7885	5.6871	2.4363
7.	41	.7487	.7888	.8036	.7447	.7655	.7888	6.7137	2.4450
8.	36	.7216	.7897	.8206	.6999	.7502	.7897	7.5789	2.4491
9.	30	.7365	.7713	.7920	.7073	.7290	.7713	7.2343	2.5369
10.	45	.7493	.8020	.8021	.8271	.7785	.8020	4.9762	2.3705

When Table 3 is examined, it is seen that the hidden cell numbers of the best performances in each trial show different values between 6 and 45. According to the results of ten trials, the best performance was achieved with 6 hidden cells twice and 41 hidden cells twice. Among the attempts made to predict the number of correct answers made by the students in the LGS science subtest and to ensure the learning of the network, when the network architectures that provide the best performance are examined, in the second trial, it is seen that the network has the best network performance in general with 24 hidden cells and Prediction R = 0.7506. Moreover, when the other values of this network architecture are examined, it is seen that learning R= .8059, training R= .8329, test R= .7568, validation performance value .7408, and RMSE= 2.3504. Considering the performances observed as a criterion among these values, it can be said that compared with other network architectures, it has the closest learning correlation coefficient value to 1, and the root-mean error squares value is the lowest. The graph showing the regression coefficients and curve for the training, validation, and test results of the best-performing network architecture is shown in Figure 3.

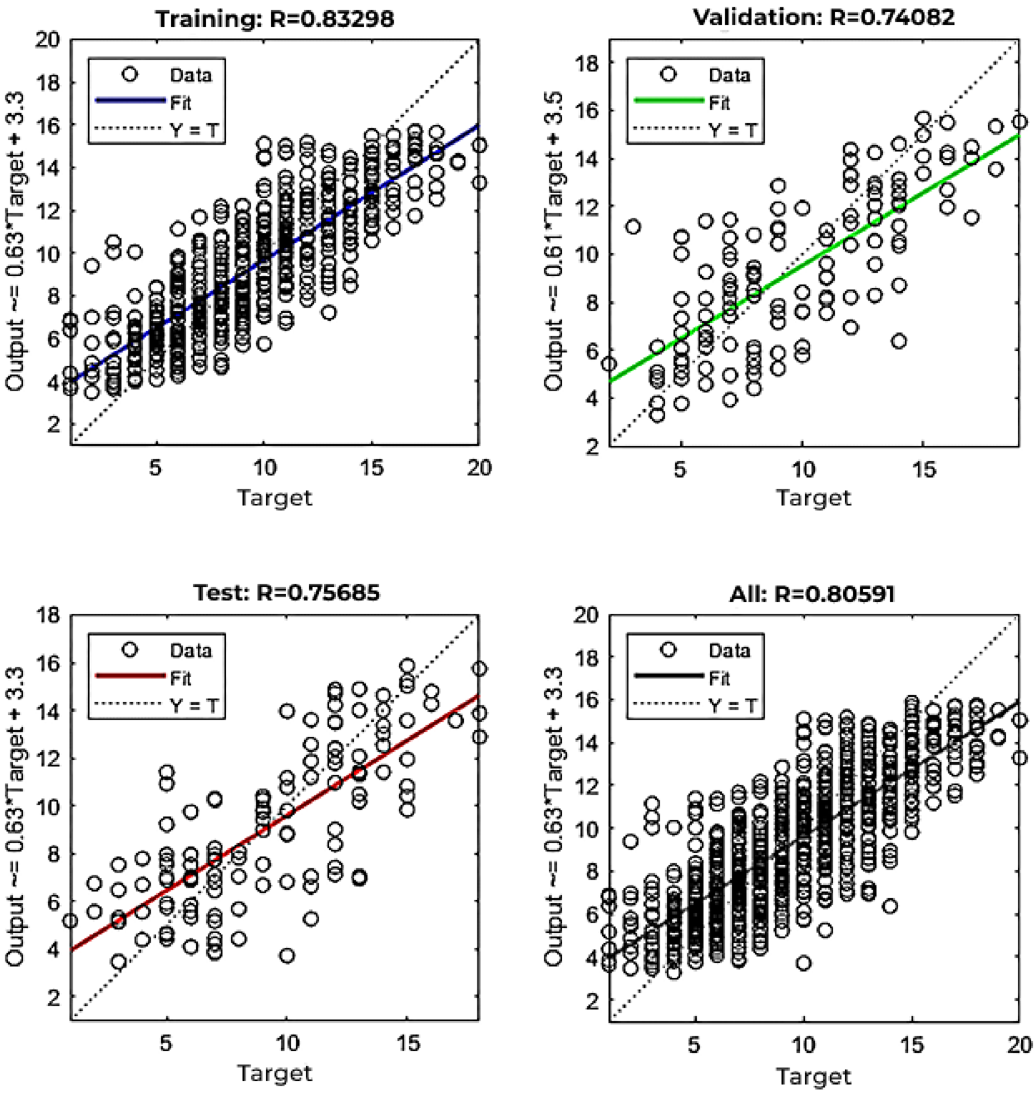

Figure 3. Regression graphs of learning, validation, and testing processes.

When the fitness curves in Figure 3 are examined, it is seen that the data learned by the network are clustered on this curve. The regression coefficient, which expresses the total R-value, expresses the correlational comparison of the output values learned by 845 students by introducing the input data to the network and the actual data. In other words, it is seen that there is a statistical relationship between the actual number of correct answers of the students in the LGS Science Subtest and the correct numbers (r=.80) produced by the artificial neural network. Accordingly, it can be said that the network performs successful modeling by interpreting that there is a high correlation between the actual data and the data produced by the network.

After the learning process of the artificial neural network was completed, the network estimated the actual number of correct answers of the students in the LGS Science Subtest, using the input values of 182 people, which the network had not seen before, which was allocated as prediction data at the beginning of the research, and the existing network structure and connections. Compared with the dataset, which includes the correct numbers that the network predicts after being simulated, and the number of correct answers students get in the exam, $r = .75$ ($p < .001$) correlational relationship was found. Thus, a high positive correlation was found between the predicted values resulting from learning the network and the actual values. Based on this finding, it can be said that the artificial neural network predicts the number of correct answers made by the students in the LGS Science Subtest. In Figure 4, the graph containing the comparison of the correct answer numbers estimated by the artificial neural network based on the written scores of 182 students from primary school (4th, 5th, 6th, 7th and 8th grade) and the actual correct numbers they obtained in the exam is given.

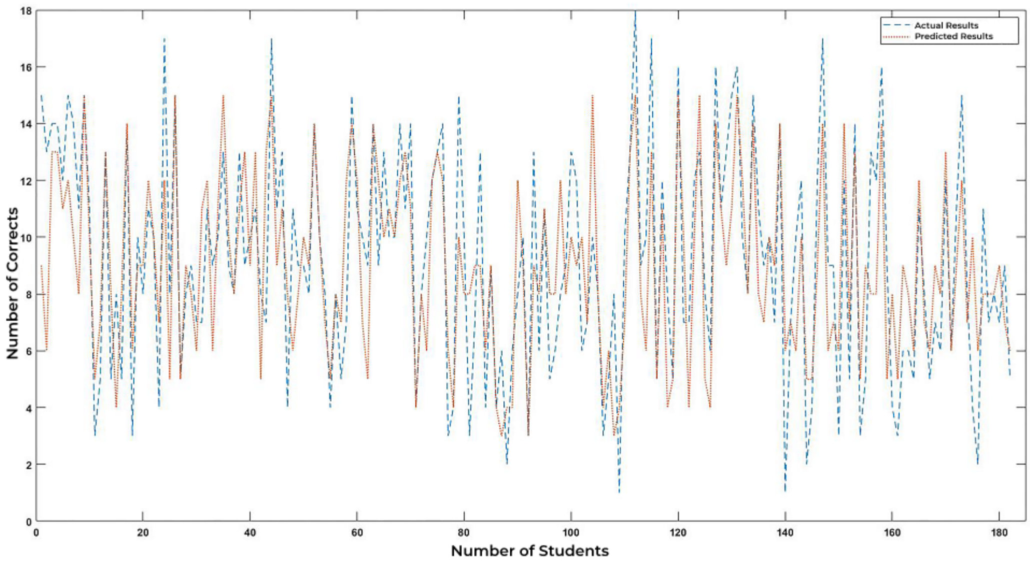

Figure 4. Graphical comparison of the correct numbers predicted by the Artificial Neural Network and the actual number of correct answers in the LGS science subtest of the students.

When Figure 4 is examined, it is seen that the lines showing the number of correct answers predicted by the network and the actual number of correct answers made by the students in the exam provide parallelism and overlap in many places. For a better understanding of forecasting success, a Histogram graph showing the error values of the network is given in Figure 5.

Error-values consisting of the number of correct answers given by the students out of 20 questions in the LGS Science Subtest and the number of correct answers predicted by the network are shown in the histogram above. It is seen that the majority of the error values of the estimated correct numbers are in the range of [+2, -2] (N= 124). The estimated number of correct answers is N=21 with an error value of three (negative or positive) compared to the actual number of correct answers. In addition, it is seen that the network estimated the number of correct answers by N=47 students with an error of four or more (negative or positive).

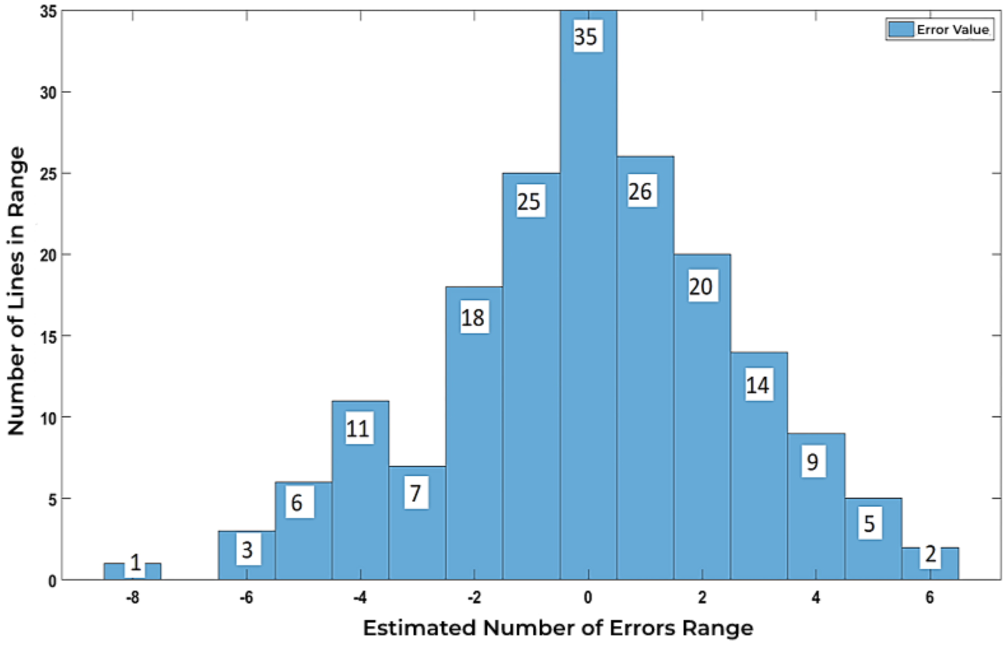

Figure 5. Distribution of error values of the predicted network

DISCUSSION AND CONCLUSION

It is seen that the highest average of the 4th-grade, 5th-grade, 6th-grade, 7th-grade, and 8th-grade science course written exam scores belongs to the 4th-grade level (82.25) because of the study. As per this result, it is understood that students' science achievement at the primary school level is higher than in secondary school. In this sense, a study conducted by Bursal (2013) supports this one. In the study, the science course achievements of the students from the fourth to the eighth grades were examined longitudinally, and it was determined that although the 4th-grade students had high average scores, there was a decrease in their average scores as the grade level increased. The results of the study by Nas (2015) are consistent with this finding. This situation may indicate a significant difference in academic achievement between primary and secondary school. In addition, another study's results determined that the average of the LGS science subtest number of correct answers was 9.44. When the LGS science subtest number of correct answers is compared with the science written exam scores, it is seen that the students are more successful in the written exams compared to the standardized central exam.

When the correlations between the science written exams are examined, the highest significant correlation is seen between 7th-grade and sixth-grade science written exam scores (r=.83). However, the lowest significant correlation was observed between 8th-grade and 4th-grade science written exam scores (r=.60). When the results are examined, it can be said that the correlations between consecutive classes are high. However, the correlation values decrease towards the middle level as the interval between the grades increases. According to different subjects and grade levels, because of the curricula prepared in a spiral structure, one after the other, it can be seen as a typical situation that the correlation decreases with the widening of the difference between grade levels. The spiral structure of the curriculum is also emphasized in the science curriculum published by the Ministry of National Education. In this regard, the low level of correlation between the scores may be evidence of the success of the spiral structure of the program.

When the correlation between the 4th-grade, fifth-grade, sixth-grade, 7th-grade, and 8th-grade science course written exam scores of the students and the number of correct answers in the LGS science subtest

were examined, it was determined that the highest significant correlation was between 8th-grade science written exam scores (r=.70). The lowest significant correlation was between 4th-grade science written exam scores (r=.57). In this context, it is seen that there are high and moderate relations between the variables. This result can be considered an indicator of the content validity of the LGS science subtest.
This study differs from other studies on using ANN in predicting student achievement in two fundamental ways. ANN was used in the studies of Aydoğan and Zırhlıoğlu (2018), Musso et al. (2013), Rahmani & Aprilianto (2014), and Turhan, Kurt & Engin, 2013. However, the predicted variable is not the standard test. In addition, studies in the relevant literature (Deniz & Kelecioğlu, 2005; Karakoç & Köse, 2018; Öntaş, Çoban & Yıldırım, 2020; Özdemir & Gelbal, 2016; Parlak & Tatlıdil, 2013; Sarı, 2018; Sarı, 2019) tried to predict academic achievement through regression and correlation analyses. In studies in which ANN is used as a method (Aghalarova & Bozkurt Keser, 2021; Çırak & Çokluk, 2013; Hamoud & Humadi, 2019; Karamouzis & Vrettos, 2008; Naser, Zaqout, Ghosh, Atallah & Alajrami, 2015), it is seen that classification analyses are widely used. In this research, however, using the artificial neural network model, alternative data were produced for the dependent variable instead of classification. In this context, unlike other studies, it can be said that the result is estimated more precisely by generating numerical values in this study.

As a result of the analysis with the artificial neural network (ANN), it has been determined that there is a statistically high correlation between the number of correct answers given by the students in the LGS Science Subtest and the correct numbers produced by the artificial neural network (r=.8059). Similar results were obtained in other studies with ANN. Demir (2015) reached a correlation value of .63 for central exam success, while Başer (2022) reached a correlation value of .79. Apart from ANN, in studies examining the relationship between students' exam grades and the number of correct answers in central exams, in addition to studies with a correlation value of .70 and above (Öntaş, Çoban & Yıldırım, 2020; Parlak & Tatlıdil, 2013; Sarı, 2018), there are also studies with a correlation lower than .70 (Deniz & Kelecioğlu, 2005). Considering the results obtained from both this study and other studies, it proves that the essential variable in predicting students' central exam success, in general, is their school course success (Dharmasaroja & Kingkaew, 2016; Güzeller, 2012; Ibrahim & Rusli, 2007).

The data employed in the study were obtained from only one province. Therefore, the impact of regional and cultural factors (Deyhle, 1995; Lau, 2003; O'Connor, 1997), which are known to have an impact on academic achievement, on the data is unknown. In addition, the data handled for analysis in this study are limited to written exam scores reflecting the cognitive dimension only. However, academic achievement is also affected by affective and demographic variables. In terms of demographics, it has been determined that the variables such as high school graduation, student's age, school type, gender, parental education, and family income (Buldu & Olgan, 2018; Cameron & Heckman, 2001; Çırak 2012; El-Refae & Al-Shayea, 2010; Kahraman & Çelik, 2017; Karamouzis & Vrettos, 2008; Naser, Zaqout, Ghosh, Atallah & Alajrami, 2015; Oancea, Dragoescu & Ciucu, 2013; Oladokun, Adebanjo & Charles-Owaba, 2008; Oral & Mcgivney, 2013; Üstün, Özdemir, Cansız & Cansız, 2019), and in the context of affective characteristics, variables such as well-being towards school, motivation and attitudes towards the course, self-efficacy, and self-perception (Arslandaş, 2019; Bozdağ, 2019; Chan & Norlizah, 2017; Leong, Tan, Lau, & Young, 2018; Liou & Ho, 2018; Mo, 2008; Sarıer, 2021; Shen & Talavera, 2003; Zajacova, Lynch & Espenshade, 2005) affect academic achievement. As a result of the research, the source of errors in estimating the correct answer numbers in the LGS science subtest may be the lack of data on the abovementioned variables. Considering the estimation level obtained only on the cognitive dimension from this point of view, it can be said that a high estimation rate was achieved in this study. Therefore, the result obtained from this research showed that artificial neural networks could be used to predict students' science achievements with high accuracy.

Statement of Researchers

Researchers' contribution rate statement: The First author contributed the Methodology, Validation, Formal Analysis, and Writing sections. The second author contributed Methodology, Supervision, Validation, Formal Analysis, and Writing sections.

Conflict statement: The authors declare no conflict of interest.

Support and thanks: None

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