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Predicting Pre-service Classroom Teachers' Civil Servant Recruitment Examination's Educational Sciences Test Scores Using Artificial Neural Networks

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Abstract
This study predicts the number of correct answers given by pre-service classroom teachers in Civil Servant Recruitment Examination's (CSRE) educational sciences test based on their high school grade point averages, university entrance scores, and grades (mid-term and final exams) from their undergraduate educational courses. This study was therefore designed by using a general survey model. The participants were 219 graduates of the departments of classroom teacher education from the education faculties of two different state universities. Artificial neural networks (ANNs) were used to predict the numbers of correct answers from the CSRE educational sciences test. As a result of different trials, the correlation between the predicted and actual numbers of correct answers was examined, and 10 ANN models were included in the study. Statistically, significant positive correlations were found between the numbers of correct answers predicted by the ANN and the students' actual correct answers in the CSRE. The highest loading was r = .63 ($p < .01$), and the lowest was r = .43 ($p < .05$).

Keywords: Classroom teacher • Artificial neural networks • Prediction • Educational sciences • CSRE

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Because education systems are continuously changing, their components should be made flexible to maintain with these changes and meet the emerging needs. These changes should make the system more successful to be considered as developments. As such, teachers' professional qualifications need to be improved, and they need to be specialized in the profession (Baştürk, 2007); the most important determinant of the success of any educational system is the qualifications of the teachers trained by the system (Erden, 1998). Quality in teacher education, that is, training qualified teachers, is the fundamental objective of educational sciences and has constantly been a topic of discussion by those who contribute to the field. As a result of these discussions, it is contended that pre-service teachers demonstrate differences in terms of their pedagogical and professional competencies, and it is argued that these differences should be revealed through a centralized exam (Yüksel, 2013). The employment of pre-service teachers in state schools is regulated according to the general legislation about the exams to be taken by the people who will be appointed as a civil servants for the first time, and the decree was prepared in line with this legislation by the Student Selection and Placement Center's (SSPC) procedures and principles related to exams to be taken by people who will be appointed to a state post for the first time (Öğrenci Seçme ve Yerleştirme Merkezi [SSPC], 2011). According to these procedures and principles, pre-service teachers need to take the required CSRE general ability, general culture, and educational sciences tests to be appointed to a teaching position in state schools. The pre-service classroom teachers in this study took the three main sections of the CSRE educational sciences test: educational psychology, program development and instruction, and counseling. The subsections of each section and their percentage distributions across all of the educational sciences questions are presented in Table 1.

Table 1
Percentage Distribution of Educational Sciences Test Questions across Sub-fields (SSPC, 2011)

	Fields		
Sub-fields	Educational Psychology	Program Development and Instruction	Counseling
Development Psychology	10%		
Learning Psychology	25%		
Measurement and Evaluation	15%		
Program Development		10%	
Teaching Methods		25%	
Counseling			15%
TOTAL	50%	35%	15%

This exam is of great importance for pre-service teachers as it can measure their academic achievements during undergraduate education (Yeşil, Korkmaz, & Kaya, 2009) because their academic achievement is considered to be an indicator of their success in the fields of general culture, subject area knowledge, and professional teaching knowledge during their teacher training periods (Bahar, 2011, p. 170). Simultaneously, the ability to predict academic performance is vital for selecting and placing teachers in programs and for eliminating the shortcomings of these programs (Everson, Chance, & Lykins, 1994) because these predictions lay the basis for evaluating the entire higher education process. The Ministry of National Education appoints teachers based on their CSRE exam results. Specific contents of this exam, such as the general ability, general culture, and educational sciences tests have been under discussion. Therefore, there is a great need for studies that focus on the content validity of these tests. It is hoped that this study will elucidate the content validity of the CSRE educational sciences test because the extent to which the achievements of pre-service teachers in their undergraduate educational sciences courses can predict their achievement in the CSRE educational sciences test will be important for establishing the content validity of it.

Researchers who study the CSRE focus on two dimensions. Gündoğdu, Çimen, and Turan (2008) and Kablan and Turan (2006) studied the affective impacts of the CSRE, such as exam anxiety based on student opinions, and such studies comprise the first dimension. The second dimension includes studies that investigate the correlations between pre-service teachers' CSRE achievement scores and their undergraduate academic achievement; whether they attended daytime or evening classes; their gender; university entrance exam scores; and achievements in subject area courses (Açıl, 2010; Bahar, 2006; Bahar, 2011; Baştürk, 2008; Büyüköztürk, Altun, & Eyidoğan, 2009; Doğan & Şahin, 2009; Ergün, 2005; Ergün & Kamer, 2010; Kablan, 2010; Kösterelioğlu, Kösterelioğlu, & Kilmen, 2008; Özkan & Pektaş, 2011; Şahin, 2007; Yeşil et al., 2009). Moreover, Özçınar (2006), based on similar variables, attempted to predict the CSRE achievement of pre-service classroom teachers using various statistical techniques such as ANNs and data mining. However, the research investigating centralized exams that are similar to the CSRE overseas, similar to the case in Turkey, has focused on the affective impacts of the exam and on correlations between exam achievement and academic performance (Cochran-Smith, 2001; Daniel, 1993).

The linear discrimination function analysis and multiple linear regression analysis tools that were employed in this study are generally used to predict the validity of test scores and to make decisions regarding placement and classification (Crocker & Algina, 1986; Cronbach, 1971 as cited in Everson et al., 1994). For many reasons, such as the nonlinear nature of academic achievement models and the complexity of the interactions of predictor variables, these linear statistics may not arrive at accurate predictions or classifications (Everson et al., 1994). This limitation gives rise to the necessity of using statistical analyses by which researchers can identify the complex interactions between variables and thus make predictions. ANNs that structurally imitate the functioning of the human brain are a statistical method that can be used to satisfy this necessity. ANNs are used in many fields ranging from modeling stock market behaviors to predicting bank failures (Schawartz, 1992; Tam & Kiang, 1992 as cited in Kumar, Rao, & Soni, 1995) In the literature, the potential of ANNs to find solutions to predict and classify problems has been greatly emphasized. This potential indicates the reality of modeling the abilities of the human brain (Paliwal & Kumar, 2009). The human brain resembles a highly complex, nonlinear computer, however, it is much faster than today's computers and has the capacity to complete tasks such as organizing the structural components known as neurons, recognizing patterns, perceiving, and motor control (Haykin, 2009). Inspired from the structure of the brain, ANNs comprise processing elements that are designed to imitate their biological counterparts, neurons, or relationally connected series called units (Oladokun, Adebanjo, & Charles-Owaba, 2008). ANNs can be defined as machines that are used to model how the human brain accomplishes tasks using computers or other electronic components (Haykin, 2009). They have many useful properties such as a nonlinear structure, input-output mapping, changing adaptation according to environmental variables whose synaptic weights , providing empirical feedback to selections that have already been made, structurally presenting information along with the context, error tolerance, scale integration to a great extent, and consistent analysis and design (Haykin, 2009). This study predicts the number of correct answers given by pre-service classroom teachers in the CSRE educational sciences test based on their high school grade point averages, university entrance scores, and grades (mid-term and final exams) in their undergraduate educational science courses, with specific reference to introduction to educational sciences, educational psychology, educational sociology, principles and methods of teaching, measurement and evaluation, classroom management, counseling, and instructional materials design.

Method

This study was designed on the basis of one of the general survey models, the descriptive approach, and relational analysis. The architecture of the constructed ANN was designed using the MATLAB® platform, within which there are many ANN structures. Among these, the most widely used is the feed-forward neural network because of its flexible structure, good representation capacity, and inclusion of numerous training algorithms (Haykin, 1998; Kardan, Sadeghi, Ghidary, & Sani, 2013). This study used the multi-stratified feed-forward neural network, which can predict any function that can be specifically, satisfactorily, and delicately measured (Hornik, Stinchcombe, & White, 1989).

During the training of the network, variables such as the number of layers, training algorithms, training function, performance function, and intermediate-level numbers of neurons were tested in different combinations. As a result of these trials, the set-up that yielded the best root-mean-squared error (RMSE) and the best regression (*R*) was selected and stabilized. The mathematical expression of the RMSE that was used is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x}_i)^2}$$

In addition, the correlation between the data produced by the stabilized model and the actual predicted numbers of correct answers given by pre-service teachers on the CSRE educational sciences test was also used as a criterion in selecting the models. Because the conjugate gradient algorithm uses simple calculations (Shin Shi & Guo, 2009), it was used to train the network to solve large-scale minimization problems. These algorithms require far less memory than simple algorithms (Powell, 1977), and thus they are well suited for use in ANN structures that involve numerous weights. Conjugate gradient algorithms have different versions, such as the Fletcher–Reeves, Polak–Ribiere, Powell–Beale, and scaled algorithms. The Powell–Beale conjugate gradient algorithm was used in this study, and the following equation was used in its calculation:

$$\left| g_{k-1}^{T} g_{k} \right| \geq 0.2 \left\| g_{k} \right\|^{2}$$

When this condition is satisfied, each variable is corrected according to the following equation:

*X = X + a*dX*

where *dX* is search direction. A parameter was selected to minimize the performance along the search direction. For iterations to be successful, the search direction was calculated from the new curve and the previous search direction according to the following formula:

*dX = -gX + dX_old*Z*

The mean square error with regularization performance criterion was used to test the training function, and the hyperbolic tangent sigmoid transfer function was used in the architecture of the web that was modeled for this study (Figure 1).

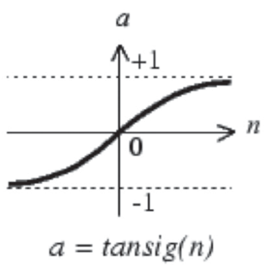

Figure 1: Tangent Sigmoid transfer function.

In the developed ANN, there were 1 input layer, 2 hidden layers, and 1 output layer. The illustration of the constructed ANN is given in Figure 2.

Input Layer: The input layer of the constructed ANN comprised the pre-service teachers'

1. High school achievement scores
2. University entrance scores
3. Mean grades in introduction to educational sciences, educational psychology, educational sociology, principles and methods of teaching, measurement and evaluation, classroom management, counseling, and instructional materials and design (50% + 50%)
4. Actual numbers of correct answers in the CSRE educational sciences test

Output Layer: The output layer comprised the numbers of correct answers given by the teachers in the CSRE educational sciences test.

Study Sample

This study comprised 233 classroom teacher education graduates from two state universities. Of these 233 graduates, 6 were discarded because their high school achievement scores could not be obtained, 5 were discarded because they had transferred from their previous universities to the current one, and 3 were discarded because at least one of their course achievement scores could not be obtained. Therefore, 14 pre-service teachers were excluded from the study. Thus, 219 pre-service teachers participated in this study, and the data for the independent and dependent variables was obtained from them.

Dataset

Among the entire dataset for the 219 participants (n_1), including the numbers of correct answers given in the CSRE educational sciences test, 33 participants (n_2) were randomly selected, and their data was not included in the set to establish the correlations between the scores that the network predicted after learning the model (n_4) and their actual scores. The ANN that was developed for this study was constructed and used for training on the data that was

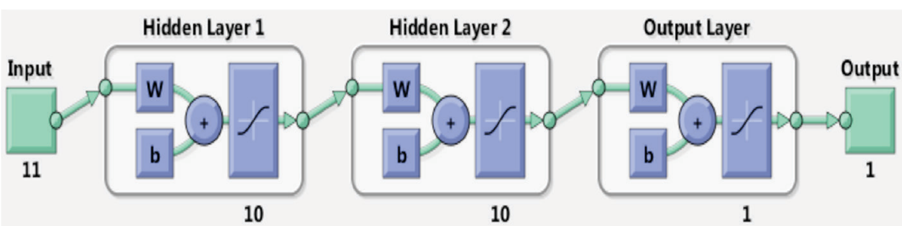

Figure 2: The constructed ANN.

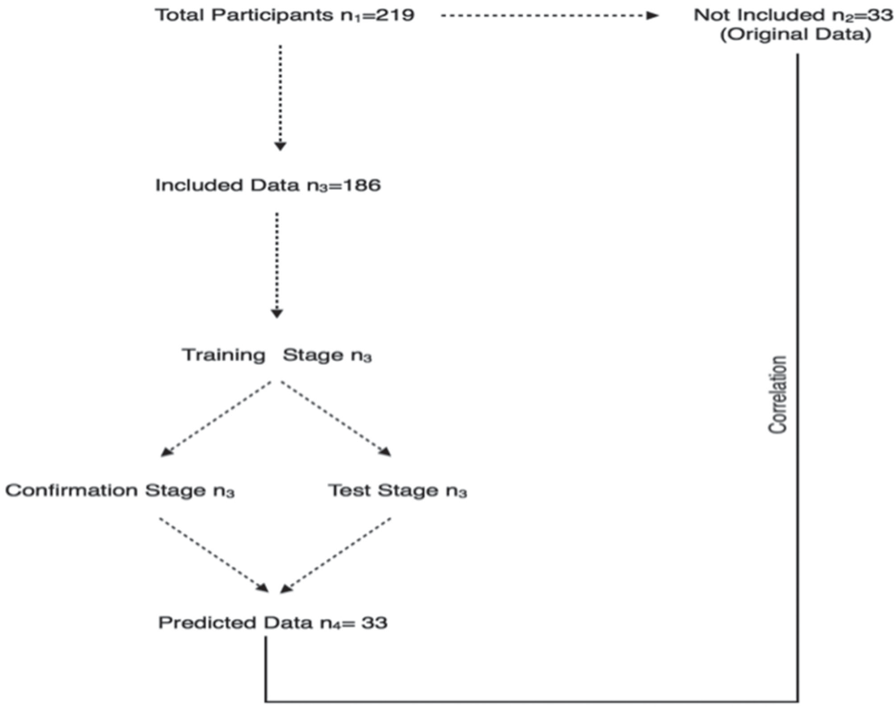

Figure 3: Data set distribution.

collected from the remaining 186 participants (n_3). The dataset that was employed while constructing the ANN underwent three stages: training (n_3), confirmation (n_3), and testing (n_3). Prior to each stage, to improve the network's performance and to prevent the negativities that can be brought about by overrated cumulative sums of input values (Sağıroğlu, Beşdok, & Erler, 2003, pp. 20–85; Yavuz & Deveci, 2012), the data was normalized in the range of 0–1. The dataset is illustrated in Figure 3.

There were 11 variables observed among the 186 pre-service classroom teachers constituting the *n3 group. Some of them were high school achievement scores, university entrance scores, educational sciences course scores, and number of correct answers in the CSRE educational sciences test.

*n4 = the number of correct CSRE answers predicted by the ANN using the input layer variables of the 33 participants who were not included in the data set during the training stage.

Table 2
ANN Performances Obtained Through Different Set-ups

ANN	Number of Epochs	Network Performance			
		Regression			Root Mean Square Error
		Training	Confirmation	Test	
Model I	18	.419	.594	.617	.1851
Model II	17	.386	.542	.516	.1921
Model III	16	.593	.231	.105	.1749
Model IV	45	.460	.693	.579	.1833
Model V	20	.558	.386	.221	.1732
Model VI	20	.604	.297	.162	.1685
Model VII	24	.416	.601	.638	.1681
Model VIII	25	.563	.200	.417	.1596
Model IX	23	.535	.421	.457	.1750
Model X	21	.454	.038	.441	.1963

Findings

To train the network for the current study, ten different models were tested that consisted of the same functions; the network performances of the constructed models are given in Table 2. Among these models, the output that contained the best correlation was constructed with the data set that was not included in Model VI.

The table above shows the R values of the ten models that were constructed from the ANN and the RMSE values that show the compliance of the constructed models.

S: Student Number; OD: Original Value; P_{1-10}: Predicted Value

The above table displays the normalized data of the numbers of correct answers in the CSRE educational sciences test of the 33 participants who were not included in the network architecture (OD) and also of their correct answers on the educational sciences test that were predicted by the 10 ANN models. In order to determine the relation between the predicted and the original data, the Pearson product-moment correlation was used; these data are summarized in Table 4.

As can be seen in the table above, there are positive and statistically significant correlations ranging from $r = .63$ ($p < .01$) to $r = .43$ ($p < .05$) between the data predicted by the ANN and the actual data. In social sciences, correlations between .40 and .60 are considered to be moderate (Dancey & Reidy, 2004). However, this study determines the relation between the predicted and actual data, and thus the loadings between .40 and .60 can be higher here than they are in other social sciences.

Table 3
Normalized Data

S	OD	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
1	0.47	0.78	0.8	0.77	0.76	0.7	0.61	0.75	0.71	0.75	0.77
2	0.66	0.77	0.71	0.77	0.76	0.7	0.66	0.7	0.71	0.73	0.76
3	0.54	0.78	0.78	0.76	0.75	0.71	0.66	0.7	0.7	0.74	0.76
4	0.75	0.63	0.61	0.6	0.63	0.52	0.35	0.54	0.54	0.53	0.55
5	0.85	0.79	0.75	0.78	0.76	0.71	0.67	0.72	0.74	0.74	0.75
6	0.78	0.82	0.86	0.81	0.78	0.72	0.72	0.78	0.75	0.79	0.78
7	1	0.85	0.88	0.81	0.82	0.72	0.79	0.81	0.79	0.8	0.78
8	0.8	0.77	0.73	0.76	0.77	0.7	0.71	0.73	0.73	0.75	0.75
9	0.47	0.66	0.62	0.66	0.66	0.62	0.48	0.59	0.55	0.62	0.64
10	0.73	0.83	0.85	0.8	0.79	0.72	0.74	0.78	0.76	0.77	0.77
11	0.8	0.85	0.86	0.81	0.8	0.72	0.76	0.79	0.78	0.79	0.77
12	0	0.59	0.61	0.57	0.61	0.54	0.35	0.53	0.51	0.56	0.69
13	0.64	0.76	0.74	0.74	0.73	0.69	0.63	0.7	0.69	0.73	0.76
14	0.76	0.75	0.68	0.73	0.76	0.69	0.67	0.67	0.68	0.72	0.77
15	0.76	0.77	0.76	0.71	0.75	0.7	0.63	0.7	0.68	0.68	0.76
16	0.39	0.64	0.63	0.55	0.61	0.56	0.37	0.56	0.49	0.54	0.63
17	0.71	0.69	0.63	0.65	0.72	0.59	0.5	0.62	0.6	0.6	0.64
18	0.92	0.71	0.69	0.69	0.68	0.68	0.67	0.68	0.68	0.64	0.66
19	0.68	0.82	0.85	0.8	0.8	0.72	0.75	0.79	0.77	0.78	0.77
20	0.49	0.73	0.67	0.78	0.73	0.69	0.57	0.69	0.63	0.76	0.78
21	0.71	0.66	0.64	0.67	0.65	0.62	0.42	0.62	0.53	0.64	0.69
22	0.37	0.59	0.61	0.56	0.63	0.53	0.37	0.59	0.53	0.53	0.63
23	0.69	0.79	0.73	0.77	0.77	0.71	0.68	0.72	0.72	0.75	0.76
24	0.44	0.69	0.61	0.62	0.73	0.63	0.6	0.57	0.61	0.61	0.65
25	0.71	0.76	0.68	0.77	0.74	0.69	0.61	0.7	0.69	0.73	0.73
26	0.85	0.76	0.72	0.74	0.75	0.7	0.68	0.72	0.71	0.72	0.74
27	0.25	0.5	0.6	0.34	0.42	0.5	0.22	0.42	0.31	0.4	0.38
28	0.66	0.66	0.62	0.68	0.71	0.58	0.51	0.61	0.62	0.67	0.74
29	0.53	0.82	0.82	0.8	0.79	0.72	0.74	0.78	0.77	0.78	0.76
30	0.81	0.73	0.68	0.69	0.73	0.67	0.6	0.64	0.66	0.68	0.75
31	0.86	0.71	0.68	0.68	0.7	0.66	0.53	0.64	0.61	0.66	0.71
32	0.53	0.64	0.62	0.61	0.64	0.63	0.4	0.55	0.5	0.63	0.74
33	0.73	0.8	0.83	0.81	0.75	0.72	0.76	0.77	0.77	0.78	0.77

Table 4
Correlations Between the Original and the Predicted Data

Original Data with Predicted Data	Correlation	*p*	*N*
Original Data with Model I	0.626**	.000	33
Original Data with Model II	0.456**	.008	33
Original Data with Model III	0.595**	.000	33
Original Data with Model IV	0.597**	.000	33
Original Data with Model V	0.598**	.000	33
Original Data with Model VI	0.633**	.000	33
Original Data with Model VII	0.595**	.000	33
Original Data with Model VIII	0.629**	.000	33
Original Data with Model IX	0.555**	.001	33
Original Data with Model X	0.433*	.012	33

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

Moreover, considering that the achievements of the pre-service teachers in the CSRE educational sciences test are affected not only by the independent variables of this study (high school achievement, university entrance scores, undergraduate educational sciences course scores) but also by other variables such as exam anxiety, motivation, and participation in private courses, the calculated correlation coefficients can be considered high in this study. Moreover, these statistically significant and relatively high correlation coefficients may indicate that the constructed ANN was successful. Thus, it can be claimed that the variables that were entered as input data can predict the number of correct answers given by pre-service teachers in the CSRE educational sciences exam.

Table 4 shows that the trial in which the highest correlation was obtained was Model VI. The line chart that was constructed to determine the extent to which the data obtained from Model VI corresponded to the actual data is shown in Figure 4.

It is seen that the number of correct answers in the CSRE educational science test that were predicted by Model VI correspond to the pre-service teachers' actual numbers of correct answers in this test and that there were no large deviations.

Discussion and Results

Unlike in other studies that focused on predicting pre-service teachers' CSRE educational sciences test scores (Açıl, 2010; Bahar, 2006, 2011; Baştürk, 2008; Büyüköztürk et al., 2009; Doğan & Şahin, 2009; Ergün, 2005; Ergün & Kamer, 2010; Kablan, 2010; Kösterelioğlu et al., 2008; Özkan & Pektaş, 2011; Şahin, 2007; Yeşil et al., 2009), this study utilized the number of correct answers given by the pre-service teachers in the test rather than their overall test scores; this contributed to standardizing the predicted variable. Another difference is that in addition to the independent variables that were used in other studies (university entrance exam scores, professional competency course scores) this study incorporated the high school achievement scores of the pre-service teachers to improve performance prediction.

Unlike the above-mentioned studies, Özçınar (2006) attempted to predict pre-service classroom

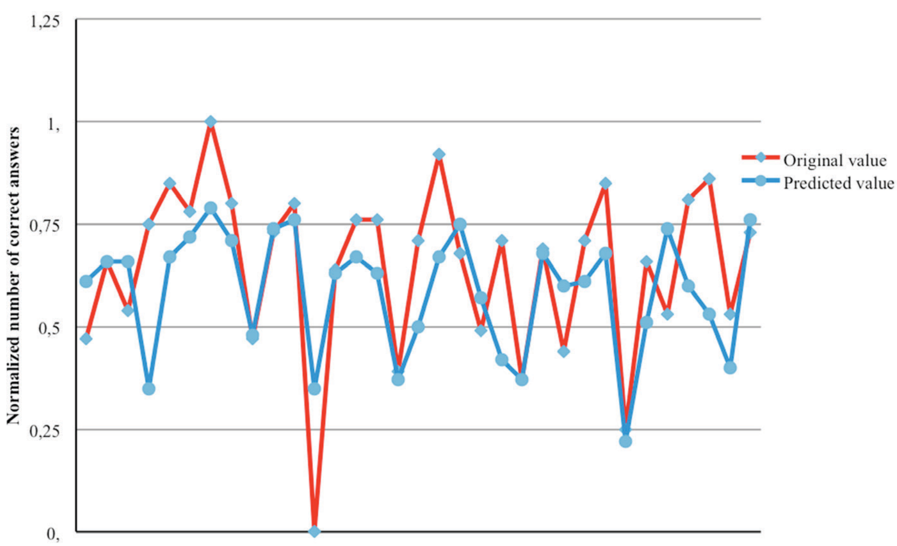

Figure 4: Matching level graph.

teachers' CSRE achievement using ANNs, data mining, and regression analysis models and found that whether the teachers had attended day or evening classes, their undergraduate course achievements, and their grade point averages constituted 22% of the variance in their CSRE scores. In this study, however, a correlation (r = .63) was found between the pre-service teachers' actual numbers of correct CSRE answers and their numbers of correct answers predicted by the ANN model. The difference between these two studies was derived from the independent variables that were used, the predicted variables (achievement scores versus numbers of correct answers), and the ANNs that were used (preferred functions, numbers of neurons, layer iterations).

Given that prior research was mostly conducted using the correlation and regression analysis, this study's use of ANNs allowed for comparing regression analysis with ANN performance. Zaidah and Daliela (2007) compared the performance of a linear regression decision tree with that of ANNs in predicting university students' academic performances, and they concluded that the model derived through the ANNs yielded better results than the others. Similarly, Özçınar (2006) reported that the statistical errors in the ANN predictions were smaller than the regression analysis predictions. Rather than predicting the dependent variable using the explained variance, this study generated data other than the dependent variable using an ANN model. All the independent variables that were employed in the current study comprised cognitive features. Affective factors such exam anxiety, stress, and attitude that could have affected the predicted variable (Gündoğdu et al., 2008; Kablan & Turan, 2006; Temur, Özkan, Atlı, & Zırhlıoğlu, 2011) were not among the independent variables of this study. Thus, it is seen that the correlation (r = .63) found between the actual number of correct answers given by pre-service teachers in the CSRE educational sciences test and the number of correct answers predicted by the ANN model is quite high.

Considering this study's findings, it can be argued that datasets to be produced and conducted on larger samples by future research will improve the prediction performance of this study's constructed ANN model. In Turkey, the classroom teacher subject area knowledge test in the CSRE has been a subject of fierce debates in the last two years. In this regard, it is believed that a research that uses ANN modeling can make great contributions to improving the content validity of the subject area test in the CSRE.

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