Education and Science tedmem

Vol 45 (2020) No 202 393-415

Analysis of Factors Effecting PISA 2015 Mathematics Literacy via Educational Data Mining *

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Abstract

The aim of this study is to determine the factors affecting PISA 2015 Mathematics literacy by using data mining methods such as Multi-layer Perceptron Artificial Neural Networks and Random Forest. Cause and effect relation within the context of the study was tried to be discovered by means of data mining methods at the level of deep learning. In terms of Prediction Ability, the findings of the method whose performance was high were accepted as the factors determining the qualifications in Mathematics literacy in Turkey. In this study, the information, which was collected from a total of 4422 students, 215 (49%) of whom were boys and 2257 (51%) of whom were girls participating in PISA 2015 test, was used. The scores, which the students, having gone in for PISA 2015 test, got from mathematics test, and dependent variables and 25 variables, which were thought to have connection with dependent variables institutionally, were included in the analysis as predictors. As a result of analysis, it was witnessed that Random Forest (RF) method made prediction with smaller errors in terms of a number of performance indicators. The factors that random forest method found important after anxiety variable are Turkish success level of students, mother education level, motivation level, the belief in epistemology, interest level of teachers and class disciplinary environment, respectively. The statistical meaning, significance and impact levels of other variables were tackled together with their details in this study. It is expected that this study will set an example for data mining use in the process of educational studies and that the factors whose affects were found out about the students' mathematics literacy will shed light on National Education system.

Keywords

PISA
Mathematics literacy
Educational Data Mining
Multi-layer Perceptron
Random Forest

Article Info

Received: 02.05.2019
Accepted: 01.13.2020
Online Published: 04.05.2020

DOI: 10.15390/EB.2020.8477

* This article is derived from Özlem Bezek Güre's phd thesis entitled " comparison of mathematics achievement of students with Random Forest, Multi-Layer Perceptron and Radial Function Neural Network methods in terms of forecasting ability: Turkey example ", conducted under the supervision of Murat Kayri and Fevzi Erdoğan.

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Introduction

Programme for International Student Assessment – PISA, financed by Organization for Economic Co-operation and Development (OECD), is a large scale research targeting to collect information about Mathematics, Science literacy and reading skills of students of 15 year age group enrolled to formal education as well as student motivation, thoughts about himself/herself, learning styles and school and family environment (Akyüz & Pala, 2010; Kamaliyah, Zulkardi, & Darmawijoyo, 2013). And also PISA aims to measure how much basic knowledge and skills that they achieve during school life can be used in their real life by them (Bautier & Rayou, 2007).

PISA, during the end of compulsory education, evaluates knowledge and skill achievement levels, which are necessary to provide 15 year old students with full participation in modern societies. PISA helps to monitor the students to achieve knowledge and skills throughout the world and in the sub-groups of the countries possessing different demographical features. In addition, it presents the opportunity to understand the real aspect of education policies and applications (OECD, 2016a).

PISA was hold for the first time in 2000. In this examination, the countries of OECD and other participating countries take part. Our country as well took part in this exam for the first time in 2003 so as to determine our education level within international context. This exam is hold once in three years periodically; and in each period, a field is focused on. In the exam held in 2015, science literacy was specified as the focus field. In the exam, problem solving skills based on corporation as well as science, Mathematics and reading-writing literacy were evaluated (Ministry of National Education [MoNE], 2016; OECD, 2016b).

In modern societies, comprehending Mathematics is vital with respect to the fact that the youth be ready for their everyday lives. Today, it is necessary that Mathematics, Mathematical reasoning and Mathematical tools be understood very well before comprehending the problems substantially together with growing problems encountered in the occupational environment. Mathematics is an important tool owing to the fact that the youth, throughout their lives, may come across problems and challenges in terms of individual, professional, social and scientific circumstances (OECD, 2016b; Türkan, Üner, & Alcı, 2015). In parallel with technological developments, it gains importance that Mathematics literacy understanding directed to setting up a model and from theory to application, different from traditional perspective of mathematics, should be formed (Uysal & Yenilmez, 2011).

According to PISA, Mathematics literacy is defined as "the individuals' ability to formulize, use and interpret Mathematics they need so that they can understand the role that Mathematics play in the world, and carry out judgement relying on truths, and make their living as a constructive, creative and idealistic citizen". In other words, Mathematics literacy can be defined as the skill to make reasoning using mathematics and mathematical concepts in order to explain, describe and estimate the events in solving the problems that they will encounter (Akyüz & Pala, 2010; Bautier & Rayou, 2007; Kamaliyah et al., 2013; OECD, 2016b; Türkan et al., 2015; Uysal &Yenilmez, 2011).

The researches carried out indicate that Mathematics literacy in Turkey is at low level (Çelen, Çelik, & Seferoğlu, 2011; OECD, 2007; OECD, 2016b). In the field of Mathematics literacy, Turkey has an average score of 420, while the average of OECD is 490 and the average of all countries is the score of 461. As is known, the Mathematics literacy consists of six levels in PISA: The first level demonstrates the lowest level; however, the sixth level shows the highest level (OECD, 2016b). Moreover, another level has been created for the countries that fall below first level. When looked at the distribution of the students' qualifications levels in the field of Mathematics literacy of PISA 2015, the students' proportion below sub sufficiency level, that is, first and below first level students in Turkey is 51.3%, while it is 23.4% for OECD member countries and 35.8% for all participating countries. In our country, the students' proportion at sub sufficiency level was 42% in PISA 2012, while it increased up to 51.3% in PISA 2015. Furthermore, in PISA 2015, at 5th and upper levels, namely the students' proportions taking place at the highest level was 2.01% for Turkey, while it was 10.7% for OECD member countries and

8.2% for all countries. In our country, while the students' proportion occupying the highest level was 5.9% in PISA 2012, it is seen that it dropped to 2.01% in PISA 2015 (MoNE, 2016).

When the literature is examined, although there are many studies using PISA data, it is seen that there are limited studies using the methods used in the present study (Aksu, 2018; Aksu & Doğan, 2018; Benzer & Benzer, 2017; İnal & Turabik, 2017; Saarela, Yener, Zaki, & Karkkainen, 2016; Tepehan, 2011; Toprak, 2017). Either artificial neural network or decision trees were used in these studies. The present study is considered to be important since it is the first study in which Multi-Layer Perceptron Neural Networks from the Artificial Neural Networks family and Random Forest methods from the Decision Trees family are used together.

The aim of this study is to investigate the factors influencing Mathematical literacy of students at the age of 15 in Turkey using advanced level statistical methods. The aim here is not only to establish the present case but also to find out the significant factors having impact on Mathematics literacy and also to present clues for the development of educational policies and curriculums about the issue. PISA 2015 data will be studied by means of ANN and decision tree of data mining and the factors affecting Mathematics literacy will be revealed according to their importance degree. By this way, alternative models were compared to each other in discovering cause and effect.

Data mining is the process to take out the valuable knowledge from a great amount of data. Data mining is the analysis of very large data sets which summarize the comprehendible and available data with certain methods and try to find the complex relations between them (Hand, Mannila, & Smyth, 2001).

Data mining uses a comprehensive quantitative method family similar to statistical analysis, decision trees, artificial neural networks, deduction and graphic visualization (Shaw, Subramaniam, Tan, & Welge, 2001).

The decision trees used for classification in the field of data mining are highly preferred since they are easy to set up, and can be interpreted easily, can provide an easy integration with data bases and their reliability rate is at high level (Emel &Taşkın, 2005).

Using the data of PISA, it was seen that, several studies about Mathematics literacy were performed (Aksu & Güzeller, 2016; Akyüz & Pala, 2010; Azapağası İlbağı, 2012; Azapağası İlbağı & Akgün, 2012; Güzeller & Akın, 2014; İnal & Turabik, 2017; Okatan, 2017; Saarela et al., 2016; Satıcı, 2008; Ziya, 2008). In this study carried out, different from the previous studies, including some variables, whose affects were not examined before, were taken into the analysis of this study, and Mathematic literacy was put under the magnifier. In this study, some variables (anxiety level, parental education level, motivation level, belief in epistemology, teacher's interest, disciplinary classroom environment) used in different years similar to PISA researches are examined, and also the effects of some variables which are not taken into consideration or taken into account at a very low level (such as achievement level in Turkish, having educational software at home, having technical books at home, setting goals in school life) were also investigated. Moreover, statistic methods used within the perspective of this study are at innovative levels to establish an example for researches of education sciences.

The main aim of the study is to reveal the factors affecting mathematics literacy based on the findings of the method with strong predictive ability. In line with this basic aim, the cause-effect relations between factors affecting Mathematics literacy of students in Turkey were analysed by means of Random Forest and Multilayer Perceptron Artificial Neural Network; and in the direction of aims to determine the prediction with the least error and highest accuracy rate, and to compare the performances of methods, answers to the following questions are looked for:

1. What are the effects of predictive variables on Mathematics literacy?
2. What are the importance levels of variables in the model according to both methods?
3. What is the predictive ability of both methods?

Method

This investigation is a study carried out via related screening model of screening models. Related screening model is an investigation method examining the interaction between more than one variable with cause-effect basis (Karasar, 2006).

Population and Sampling

In 2015 in PISA, a computer based assessment was carried out for the first time. A total of 72 countries, 35 of which were OECD member countries, participated in PISA 2015. The sampling group was composed of about 540 thousand students, representing 2 million students at the age of 15, attending to schools in the participating countries (MoNE, 2016). PISA 2015 was applied as computer based examination to the students of 15 years of age attending to formal education in our country. According to level 1 of Statistical Area Classification (SAC), taking 12 areas as basis, 187 schools from 61 provinces were selected randomly. 5895 students randomly selected among the ones attending these schools participated in this application (MoNE, 2016). In this study, the information gathered from a total of 4422 students, participating PISA 2015 examination, 2165 (49%) of whom were boys and 2257 (51%) of whom were girls.

Measurement Tools

In this survey, students' questionnaire belonging to PISA 2015 Turkey example and scales and points received from Mathematics literacy test were used as data collecting tool. This data file of PISA 2015 application was obtained from www.pisa.oecd.org , the official web page of PISA. As these data are open to the utilization of everyone, no special permission was demanded to use the data. Downloading the PISA 2015 data from abovementioned web page, they were formed in accordance. with the context of the study.

In the study, initially, the variables thought to affect Mathematics literacy were chosen depending on the conceptual framework. Within the context of the investigation, Student Anxiety Scale (Anxiety), Student Motivation Scale (Motivation) and Epistemological Beliefs Scale (Epistemological Beliefs) were used.

Student Anxiety Scale had one factor which was made up of five items; and student attitudes were scaled in four scales as "1- I certainly agree", "2- I agree", "3- I don't agree", "4-I surely don't agree". The lowest point that can be received from this scale is calculated as 5 and the highest as 20. The low point obtained from this scale points out low anxiety, on the other hand high point indicates high level anxiety. Cronbach Alpha reliability coefficient of the scale was found to be 0.83.

Epistemological Beliefs Scale used within the context of the study consists of six items and presents a structure with single factor. As in the other scales used, students' attitudes are degreed with scale of four. The lowest point that is possible to be taken from this scale is calculated as 6, while the highest is computed to be 24. The low point to be obtained from the scale exhibits low belief, whereas the high point shows high belief. Cronbach reliability coefficient of this scale is found to be 0.92.

In addition to the scales used in the study, some demographic and personal information of the students were also used (Table 1).

Table 1. Descriptive Statistics Belonging to Predictor Variables

Predictors	Predictor Type	Categories	%
Class	Classified (Nominal)	Grade 7	0.3
		Grade 8	1.5
		Grade 9	19.8
		Grade 10	75.2
		Grade 11	3.0
		Grade 12	0.1
Gender	Classified (Nominal)	Female	51
		Male	49
Mother education level	Sequential (Ordinal)	High school	14.8
		Vocational/Technical High School	13.8
		Secondary school	19.8
		Primary school	38.4
		Non-primary school graduate	13
Father education level	Sequential (Ordinal)	High school	16.3
		Vocational/Technical High School	19.7
		Secondary school	27.2
		Primary school	31.2
		Non-primary school graduate	5.2
Do you have study desk at home?	Classified (Nominal)	Yes	85.8
		No	14.2
Do you have your own room at home?	Classified (Nominal)	Yes	72.6
		No	27.4
Do you have a quiet place to study at home?	Classified (Nominal)	Yes	84.5
		No	15.5
Do you have a computer at home to use for school work?	Classified (Nominal)	Yes	69.2
		No	30.8
Do you have educational software at home?	Classified (Nominal)	Yes	41.6
		No	58.4
Do you have an internet link at home?	Classified (Nominal)	Yes	63.9
		No	36.1
Do you have auxiliary books to help you with the school	Classified (Nominal)	Yes	84.6
		No	15.4
Do you have technical reference books at home?	Classified (Nominal)	Yes	42.2
		No	57.8
Which point do you target to reach at your school life?	Sequential (Ordinal)	Secondary school	1.6
		Vocational/Technical HighSchool	14.1
		High school	6.9
		College	5.3
		University /Graduate/ PhD	72.1
Teachers call on me less often than they call on other students.	Continuous (Interval-scale)	Never or almost never	35.3
		A few times a year	19.9
		A few times a month	20.2
		Once a week or more	24.6
Teachers force me harder than they force	Continuous (Interval-scale)	Never or almost never	56.2
		A few times a year	21.3
		A few times a month	14.9
		Once a week or more	7.6

Table 1. Continued

Predictors	Predictor Type	Categories	%
Teachers give me the impression that I am less smart than I really am.	Continuous (Interval-scale)	**Never or almost never**	**59.7**
		A few times a year	15.9
		A few times a month	14.1
		Once a week or more	10.4
Teachers discipline me more harshly than other students.	Continuous (Interval-scale)	Never or almost never	69.2
		A few times a year	15.6
		A few times a month	8.0
		Once a week or more	7.2
Teachers ridicule me in front of others.	Continuous (Interval-scale)	Never or almost never	75.1
		A few times a year	13.3
		A few times a month	6.4
		Once a week or more	5.3
Teachers insult me in front of others.	Continuous (Interval-scale)	Never or almost never	72.4
		A few times a year	14.8
		A few times a month	6.6
		Once a week or more	6.1
Number of lessons per week	Continuous (Interval-scale)	Low	20.1
		Medium	79.5
		High	0.3
Turkish success status	Classified (Nominal)	Low	71.8
		Medium	27.9
		High	0.3
Learning time allocated to Mathematics on weekly basis	Classified (Nominal)	Low	22.4
		Medium	75.6
		High	2.1
Student Anxiety Scale	Continuous (Interval-scale)		
Student Motivation Scale	Continuous (Interval-scale)		
Belief Scale about Epistemology	Continuous (Interval-scale)		

In the study, as dependent variable; the average of ten different possible values (PV1MATH-PV10MATH) in terms of mathematical literacy cognitive field competence at the student level were taken. The average scores were grouped according to the threshold values of PISA 2015 mathematics proficiency levels, and then the proficiency levels were transformed into three-level categorical as low-medium-high (Table 2). In this case, the predicted variable in the model presents a categorical data structure. As it is known, in the statistical processes, the data type of the variables included in the model is considered to be important, and analyses appropriate to this data structure should be preferred (Kayri, 2015).

Table 2. Thresholds and categories of PISA 2015 mathematics literacy sufficiency levels

Sufficiency levels	Score (X)	Category
Below level 1	$0 < \mathbf{X} < 357.77$	Low
Level 1	$357.77 < \mathbf{X} < 420.07$	Low
Level 2	$420.07 < \mathbf{X} < 482.38$	Low
Level 3	$482.38 < \mathbf{X} < 544.68$	Medium
Level 4	$544.68 < \mathbf{X} < 606.99$	Medium
Level 5	$606.99 < \mathbf{X} < 669.30$	High
Level 6	669.30 - 1000	High

(IES>NCES, 2018)

Analysis

Within the context of the study, the methods from the family of artificial neural networks, Multi-Layer Artificial Neural Networks (MLANN) and from the decision family, Random Forest (RF) have been used. In the literature, it is reported that these methods find out robust (robust) and unbiased (unbiased) findings, and that they reduce the error variant belonging to estimate by iterative (iterative) algorithms, and that they can make classification with high accuracy rate (Becerra et al., 2013; Biau & Scornet, 2016; Eriksson & Varathharajah, 2016). Within the scope of the study, not only Multi-layer Perceptron method of Artificial Neural network family, which has strong prediction ability, was used but also random Forest method of Decision Trees family, known to be strong, was applied to the data. By this way, alternative methods have been compared in finding out the cause-effect relation.

For the analyses carried out within the context of the survey, Weka, SPSS, SPSS Modeler, Matlab and MS Excel programs have been used. With Weka software, predictions were made with Multilayer Perceptron Neural Networks and Random Forest Method, and predictions were performed and the performance indicator (Root of Mean Square Error, Mean Absolute Error, Root of Relative Square Error) values were obtained for the predictions. In the study, Weka software failed to discover the ideal cell (neuron) number with minimum error in the Multilayer Artificial Neural Networks (Hidden Layer); therefore, Matlab software was used. While downloading the PISA data file, the data was first converted to Excel format and transferred from Excel to SPSS. Data clearance was performed in SPSS and descriptive statistics of the variables in the model were obtained. In SPSS Modeler software, the visual objects (Figure 3, Figure 4) of the predictions obtained by Multilayer Perceptron Artificial Neural Networks and Random Forest Method were produced.

Multi-Layer Perceptron Artificial Neural Networks (MLPANN)

Artificial Neural Networks (ANN) is a knowledge processing system invented by being inspired from biological neural networks in the human brain (Fausett, 1994). ANN is a Mathematical model successful in classification; clustering and prediction developed being inspired from the functioning of neurons making the basis of biological neural system (Hamzaçebi, 2011; Priddy & Keller, 2005). A number of scientists of various branches use ANN in order to solve the problems encountered in the fields of pattern recognition, prediction, optimization, associative memory and control (Jain & Mao, 1996).

ANN is preferred due to the fact that it has fewer assumptions compared to classic statistical methods. In this method, the basic assumptions sought for parametric tests (linearity, normality, homogeneity and additivity) are not taken into consideration (İnal & Turabik, 2017). Therefore, ANN is accepted as a non-parametric method (Comrie, 1997). ANN, due to its readily applicability to everyday problems, has been widely used in recent days. It has the capacity to determine high level non-linear relations that classic statistic methods have not been able to find answers (Akbilgiç, 2011; Cganh, Liang, & Chen, 2011).

ANN constitutes from various types of bindings of artificial neural cells and it is arranged in forms of layers. ANN is studied in two broad groups according to their structures: Feed-forward Neural Networks and Back Propagation Networks.

MLPANN generally has a high performance in issues such as classification, prediction, recognition and interpretation (Öztemel, 2012). This model, where inputs and outputs are shown together in training stage, is the mostly used model in ANN (Seyman & Taşpınar, 2009).

In Multilayer Artificial Neural Networks, it is aimed to minimize the error between the expected result and the result obtained from the network. MLPANN uses back propagation learning algorithm to minimize the estimating errors. In this algorithm, errors are tried to be reduced backward from output to input (Seyman & Taşpınar, 2009). In these networks, it is possible to use the network for prediction by determining network architecture (Çuhadar, 2013; Kaynar, Taştan, & Demirkoparan, 2010; Kayri, 2015).

In MLPANN, there is an input layer, an output layer and one or two hidden layer between input and output layers. The process unit in the layers are in association with each other. In these networks, the information to be solved via input layer is taken into the system; and the information processed via output layer is given out (Gönül, Ulu, Bucak, & Bilir, 2015; Hamzaçebi, 2011; Kaynar & Taştan, 2009). The architectural structure belonging to MLPANN can be shown as in Figure 1.

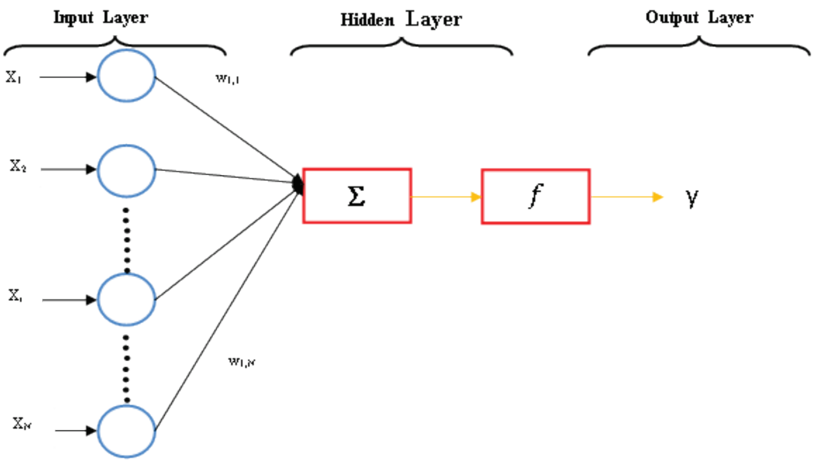

Figure 1. A basic MLPANN presentation (Kayri, 2015)

The basic structure of multi-layer perceptron is in the form of a single neuron or a ganglion. In this method, a ganglion takes a number of values such as xi, …, xn, and the resulting values are added after input values of wi, …, wm are multiplied by a number of weights. A constant θ value, known to be ganglion threshold, is added to this nominal input total. The ganglion output is obtained by assessing a function of the non-linear total. Ganglion activation function of "f" is demonstrated in Equation 1 (Gibson, Siu, & Cowan, 1989).

$$f(x) = (1 - e^{-x})/(1 + e^{-x}) \quad (1)$$

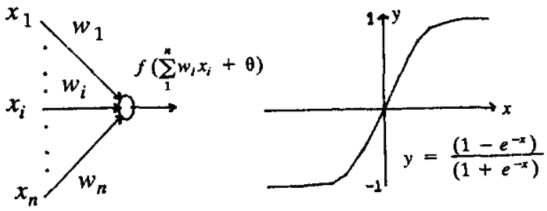

Figure 2. Ganglion structure and activation function belonging to MLPANN (Gibson et al., 1989)

MLPANN, as shown in Figure 2, is made up of a number of ganglions arranged in layers. In this method, a multiple dimension input passes to each ganglion in the first layer. That's to say, the outputs of ganglions in the first layer become the input for the ganglions in the second layer afterwards, and the process continues this way. Therefore, the outputs of the network are the outputs of ganglions taking part in the last layer. Here, while there are connections from each ganglion in the following layer to the other ganglion, there are no connections between the ganglions on the same layer (Gibson et al., 1989).

The error term in MLPANN is calculated through forward feed and back propagation algorithm. In general, error variant is computed by means of Squared Error Function.

$$\varepsilon = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\left[y_j(x_i) - t_{ij}\right]^2 \quad (2)$$

$y_j(x_i)$, taking place in Equation 2 is the prediction value belonging to dependent variable of MLPANN, and t_{ij} shows real value of dependent variable. As is known, error is calculated as distance between real values and predicted value with basic form (Karadeniz, Yüncü, & Aydemir, 2001; Kayri, 2015). While some of algorithms used in MLPANN target to minimize the error, some others realize the learning process to identify the pattern.

To train the network in MLPANN, the importance of connections change according to the knowledge learnt. The network learns the output of each input model by comparing it with a target output for this model; afterwards, it calculates the error and it spreads an error process backward along the network. To operate the network after being trained, the values of input parameters are presented to the network. After this, the network calculates node outputs using available importance values and thresholds developed during training process. The operating of the network is extremely fast because the system calculates network node values merely once. So as to test the accuracy of a trained network, the coefficient of determination R^2 is used. The coefficient is a criterion which shows how well independent variables can explain the measured dependent variable or variables. The higher the R^2 value the better the relation between the variables (Yeh, 1998).

Random Forest Method (RF)

RF is a method which is designed to form a prediction for decision trees growing up in the sub-spaces belonging to data randomly chosen in 2000s by Leo Brieman (Biau, 2012). While this method combines clustering and bootstrap ideas via decision trees, it is a strong non-parametric statistical method used in two class and multi class classification problems as well as single or multi direction regression problems (Geneur, Poggi, Tuleao Malot, & Villa-Vialanix, 2017).

RF is a method whose prediction performance is very high in cases where the number of independent variables is high in big data sets and missing data is a lot. However, RF method measures the importance levels of independent variables (Bilgen, 2014).

The algorithm of RF is generally quite successful in classification and regression processes. In this approach, more than one random decision trees are combined and they are brought together by taking the mean of predictions. In cases when the number of variable is more than observant, it displays excellent results (Biau & Scornet, 2016). In RF method, it is possible to work with as many trees as possible. Moreover, it is strong in correct predictions among algorithms, and is also durable to over fitting and very fast (Breiman & Cutler, 2017).

In RF method, pruning and interruption rules are not valid (Archer & Kimes, 2008; Breiman, 2001). According to Quinlan (1993), the fact that there is no pruning is one of the biggest advantages of RF method compared to other decision tree methods (Quinlan, 1993).

RF method, compared to constituting classification and regression trees, constitutes each tree using a different bootstrap example showing change. In standard trees, in each node, division occurs by utilizing the best division among variables. In RF, on the other hand, each node is created by using the best division provider among the predictors chosen randomly among all nodes (Liaw & Wiener, 2002).

RF uses the best variable among the ones chosen randomly in each node to split the node into branches. Data sets are generated iteratively from original data set; and the trees are developed by using the property of random (Akar & Güngör, 2012; Archer & Kimes, 2008; Breiman, 2001). Therefore, RF method uses Classification and Regression Tree (CART) algorithm making up dual decision tree of decision tree algorithms to generate trees (Archer & Kimes, 2008; Breiman, 2001). In CART algorithm, the branches in each node is made up according to GINI index which separates the widest class in data set from the others in dual form. GINI index is a measurement giving information about class homogeneity, thus it shows that if the index is small, the class is homogeneous; if it is big, the class is heterogeneous (Akar & Güngör, 2012).

Gini coefficient is calculated through the formula below as below to show that data set containing examples from n class is D and p; and that j is the relative frequency of class j; and that p(j/t) is the relative probability belonging to class j at t node (Akar, Güngör, & Akar, 2010).

$$Gini\ (t) = 1 - \sum_j [p(j \backslash t)]^2 \tag{3}$$

In RF method, at the stage of establishing the model, it should be decided whether the original data set or another data set will be utilized to test the model. If the original data set is to be used, it is necessary that 2/3 of this data set be separated as training data (preloading examples-inBag) and the rest be separated as test data (Out of Bag (OOB)). In case a different data set is used or the test data is separated from the original data set, 2/3 of these separated data are used as training data set, the rest are used as test data (Akman, 2010; Atasever, 2011). The trees are changed without a need to prune from these uploaded examples (Akar & Güngör, 2012). The error proportion is determined by testing the developed trees by means of test data set (OOB). Taking the mean of all trees, the mean error rate for prediction is found out. The tree with the least error rate is weighted with the highest weight, while the highest with the lowest (Atasever, 2011).

RF classifier is shown as { h(x, θK) k=1, …….,} to indicate θK as random vector and x as input data.

In order to find out the winner class, each of the developed decision tree is given vote, by this way the winner class is determined. After this, all trees are appointed to a vote or the most popular class. All these actions and processes carried out are called as Random Forest (Breiman, 2001).

Algorithm of Random Forests is as follows for classification and regression problems:

1. n pieces of bootstrap examples are chosen from the original data. 1/3 of these are used for training and 2/3 is used for learning.
2. Unpruned classification and regression trees are grown for each preloading examples. For this, instead of choosing the best division provider among all variables present in learning data set (inBag), initially m pieces examples are chosen randomly and then the one that will provide the best division is determined.
3. A new data set is predicted collecting n pieces decision trees' predictions. For example, new data is predicted taking mean for regression and majority of votes for classification into consideration (Liaw & Wiener, 2002).

Performance Criteria

Root Mean Square of Error (RMSE), Mean Absolute Error (MAE), Relative Absolute Error (RAE) and Root Relative Square Error (RRSE) and the correlation coefficient showing the relation between observed value and real value are the performance criteria used in evaluating the network structure. And this is expressed in the equations given below (Kayri, 2015, 2017).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \tag{4}$$

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}|\mathrm{P_i} - \mathrm{O_i}| \tag{5}$$

$$RAE = \frac{\sum_{j=1}^{n} P_{ij} - O_i}{\sum_{j=1}^{n}|O_j - \bar{O}|} \tag{6}$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{j=1}^{n}(|O_j - \bar{O}|)^2}} \tag{7}$$

$$CE = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(P_i - O_M)^2} \tag{8}$$

Here, Pi shows the predicted values, and Oi shows observed values. It is necessary that the values of RMSE and MAE be close to zero and CE coefficient to 1 (Kayri, 2015).

Before PISA 2015 data set was analysed with MLPANN and RF, it was tested whether there was a problem of multicollinearity between the variables included in the analysis. In the test of multicollinearity, Variance Inflation Factor (VIF) and Tolerance of multicollinearity are taken into consideration. In case the VIF value is bigger than 10 and Tolerance value is smaller than 0.1, it is understood that there is the problem of multicollinearity between variables (Keller, El-Sheikh, Granger, & Buckhalt, 2012). In this study that was carried out, it was observed that VIF values changed between 1.088 and 4.201 and Tolerance value between 0.238 and 0.901. As a result, it was comprehended that there was no multicollinearity problem between the variables used in the study.

Findings

Initially, MLPANN method was applied to data set. Within the context of the present study, the number of hidden layers in MLPANN architecture was operated a number of times and it was determined that the methods presented different performance in each trial. It was seen that MLPANN architecture was formed from two hidden layers. In the first hidden layer, there were 11 neurons, and in the second neuron the same number of neurons was present. As a result of the analyses conducted, it was observed that hidden layer activation function was hyperbolic tangent, while output layer activation function was softmax. In MLPANN analysis, the accurate classification rates of predictions are displayed in Table 3.

Table 3. Accurate classification rate according to MLPANN Method

Prediction Method	MLPANN
Dependent variables	Math achievement status
Number of independent variables	25
Accurate classification rate	%86.7
Misclassification rate	%13.3

In MLPANN architecture, the significant levels of predictors effective on predictor variable are exhibited in Figure 3.

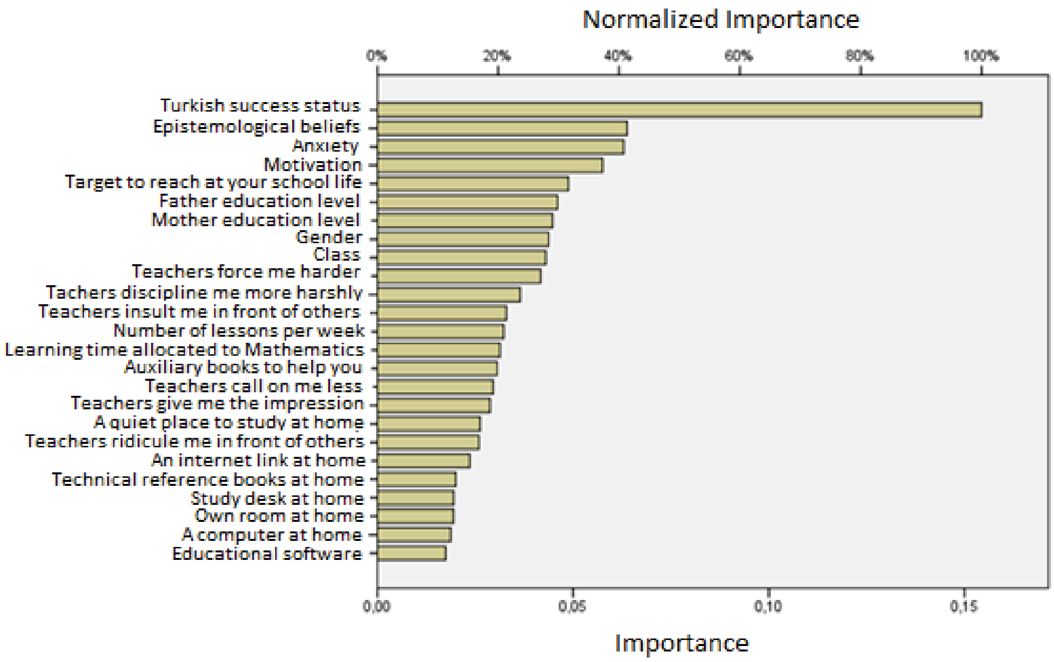

Figure 3. Standardized importance levels of variables according to MLPANN Method

When Figure 3 is examined it is seen that the most important predictor influencing predictor variable was Turkish language success level of the students, and that some other variables were the students' Epistemological Beliefs, Anxiety, motivation, target point in school life, father education and mother education, respectively. It was found to be surprising that the success level of Turkish language was in positive correlation with Mathematics literacy level (r=0,647, p<0.01). In the literature review, it was seen that the relationship between mathematics literacy and Turkish success of PISA students was tested by very few researches. In general, while mathematical literacy, which is a numerical field, is expected to be related to a numerical field such as Science (Güleç & Alkış, 2003; Gürsakal, 2009; İnal & Turabik, 2017), it is seen that mathematics literacy has in the first-line relationship with the Turkish course within the scope of verbal field. In parallel with our results, there are studies investigating the relationship between mathematics and Turkish. In these studies, it is stated that there is a statistically significant relationship between the success of the mathematics course and the success of the Turkish course (Coşguner, 2013; Göktaş & Gürbüztürk, 2012; Güleç & Alkış, 2003; Gürsakal, 2009; Tatar & Soylu, 2006). This result shows that understanding the problem correctly and reading comprehension skills are closely related to success in mathematics. It can be said that other variables taking part in the model had a high level effect on predictor. The relative importance of all predictors taking place in the model is shown in Table 4.

Table 4. The importance levels of predictor in MLANN architecture

Predictors	**Importance**	**Standardized Importance (%)**
Turkish Success Status	.154	100.0
Belief about Epistemology	.064	41.3
Anxiety	.063	40.8
Motivation	.058	37.3
Which point do you target to come in school?	.049	31.6
Father Education Level	.046	29.8
Mother Education Level	.045	29.0
Gender	.044	28.3
Class	.043	27.9

When Table 4 is looked through, it is seen that the most important variable is Turkish language success with 100% standardized importance, following this, the Epistemological Beliefs of the students with 41,3% and then Anxiety with 40,8% and then motivation with 37,3% and then 31,6%, and then point targeted in school life with 29.8%, and then father education level with 29%, and mother education level with 28.3%, and then gender with 27.9% which belong to class variables.

And then, Random Forest was applied to the data set. Accurate classification rate belonging to RF method is shown in Table 5.

Table 5. Accurate classification rate according to RF method

Model Building Method	Random Forest
Dependent variable	Math achievement status
Number of independent variables	25
Correct classification rate	%81.2
Misclassification rate	%18.8

When prediction is made with the help of RF, one of the methods of Educational data mining, it is seen that the findings did not exhibit a close parallelism with MLPANN. In the prediction made with RF, the predictors effective on predictor variable is shown in Figure 4.

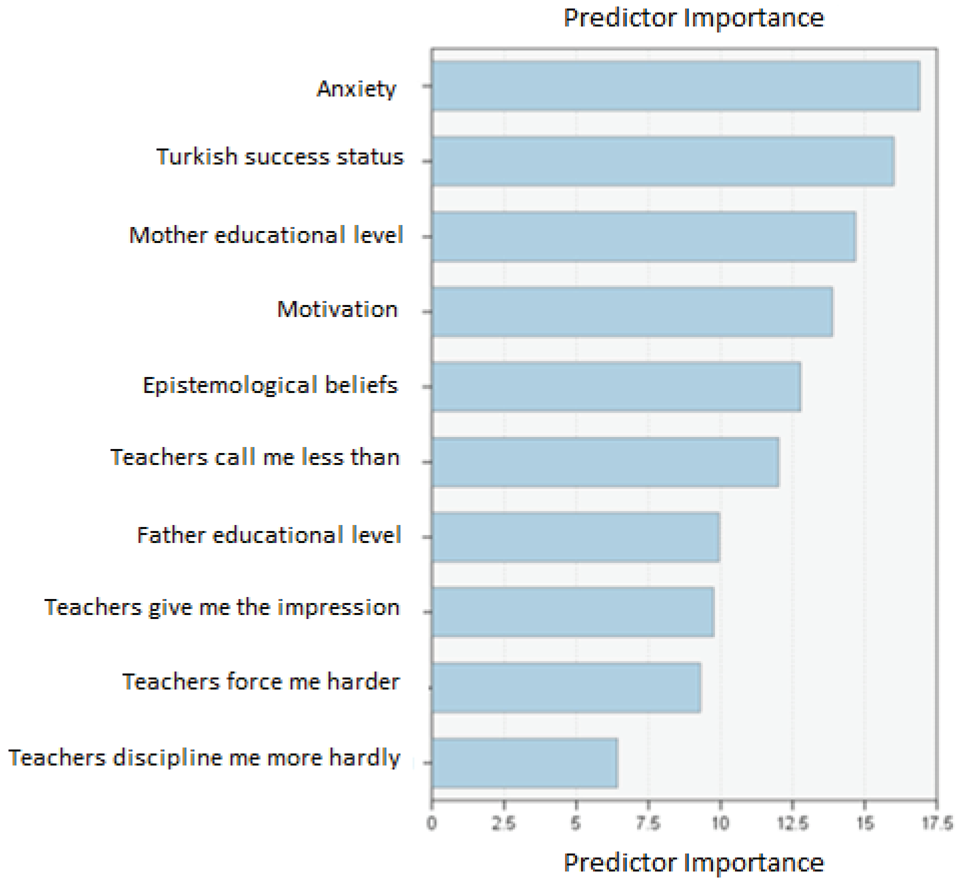

Figure 4. The importance level of variables according to Random Forest method

When Figure 4 is examined, it is seen that the most important variable influencing predictor variable is anxiety variable and the other variables are respectively Turkish language success, mother education level, motivation, the Epistemological Belief of the student, father education level, finding teachers' intelligence to be low, teacher force and disciplined class environment.

In the study, to compare predicting abilities of MLPANN and RF methods, accurate classification percentage, correlation, Root Mean Square (RMSE), Mean Absolute Error (MAE) and Root Relative Square Error (RRSE) are used. Within the context of investigation, in terms of accurate prediction, the performance indicators of MLPANN and RF are presented in Table 6.

Table 6. Performance of MLPANN and RF methods

	Correct Classification Rate %	Correlation	RMSE	MAE	RAE	RRSE
MLPANN	86.7	0.638909	0.3927	0.2449	0.6831	0.9005
RF	81.2	0.676193	0.3217	0.2064	0.5756	0.7377

When Table 6 is examined, it is seen that MLPANN has done a higher level of accurate classification than RF (MLPANN accurate classification rate= 86,7%, RF accurate classification rate=81,2%). When the rest of the indicators are examined, it is possible that RF has exhibited a higher performance than MLPANN. In terms of correlation coefficient, it is seen that RF has exhibited a higher level performance than that of MLPANN, and that RMSE, MAE RAE and RRSE indicators have exhibited a case for RF. Because of all these facts, it can be accepted that the model which RF prediction ability has turned out be more rational and consistent than MLPANN.

Discussion, Conclusion and Suggestions

The aim of this study was to determine the factors affecting PISA 2015 mathematical literacy and compare the predictive capabilities of both methods using data mining methods, Multilayer Perceptron Neural Networks and Random Forest. As a result of the analysis; it was found that the Random Forest method yielded better results in terms of performance criteria and the ability of prediction was slightly higher than MLPANN. However, it seems to be possible that the cause-effect relationship of the Random Forest method can be robust and consistent.

Although there are many studies using PISA data, it is seen that there are limited studies using the methods used in the present study (Aksu, 2018; Aksu & Doğan, 2018; Benzer & Benzer, 2017; İnal & Turabik, 2017; Saarela et al., 2016; Tepehan, 2011; Toprak, 2017). Aksu (2018) and Aksu and Doğan (2018) used Decision Stump, Hoeffding Tree, J.48, Logistic Model, RepTree, Random Forest, Random Tree, and Ridge Logistic Regression methods to classify students' science literacy using PISA 2015 data and obtained the best results with the Random Forest method. Saarela et al. (2016), in their study where they compared Discriminant Analysis, Support Vector Machines and Random Forest methods to estimate the mathematical achievement of Finnish students, found that Support Vector Machines predicted better in terms of predicting performance.

Using PISA 2012 data to determine the factors that affect mathematics achievement, Toprak (2017) used Multilayer Perceptron Artificial Neural Networks, CHAID algorithm from Decision Trees and Linear Separation analysis. In the study, MLPANN was found to be more successful in terms of classification performance in sub-groups. Tepehan (2011) compared the performances of Multilayer Perceptron Artificial Neural Networks and Logistic Regression methods to predict mathematics achievements on PISA 2006 data and found that Multilayer Perceptron Neural Networks performed better. Benzer and Benzer (2017) evaluated the current PISA test results of OECD countries with MLPANN and Regression Analysis; and they found that MLPANN gave better results. İnal and Turabik (2016) used the MLPANN method to determine the factors affecting the success of the students attending PISA 2012; and they identified that the most important variables were in science success, reading success, attitudes towards mathematics, and interest variables to mathematics.

In the literature, while PISA data using studies that used the methods used in the present study together were not come across, it was seen that classical statistical methods were frequently used in the studies.

In our country, there are studies using different methods to determine the variables that are thought to have an impact on PISA mathematic literacy (Aksu & Güzeller, 2016; Gürsakal, 2009; Karabay, 2013; Karabay, Yıldırım, & Güler, 2015; Koğar, 2015). In these studies; factors affecting students' achievement levels were determined as follows: Gürsakal (2009); gender, age at the beginning of school, the education level of the parents, and Karabay (2013); the opportunities in the home, the education level of parents and the quality of education resources in the school, and Karabay et al. (2015); class, gender, father's education level, facilities at home, where the school is located and the school's selectivity, and Koğar (2015); gender, economic, social and cultural status index and time spent learning mathematics, and Aksu and Güzeller (2016), on the other hand, self-efficacy, attitudes towards mathematics and working discipline.

While there are no studies in the literature where the methods used in the current study are used together in the field of education, it is seen that there are many studies comparing these methods together out of education field (Bansal, Chhikara, Khanna, & Gupta, 2018; Becerra et al., 2013; Eriksson & Varatharajah, 2016; Fern´andez-Delgado, Cernadas, & Barro, 2014; Guo, Zhao, & Yin, 2017; Kayri, Kayri, & Gençoğlu, 2017; Marin, Martinez-Capel, & Vezza, 2013; Maroco et al., 2011; Nawar & Mouazen, 2017; Raczko & Zagajewski, 2017; Shah et al., 2017; Shichkin, Buevich, & Sergeev, 2018). In parallel with the findings of this study, it is seen that RF method performs better than forecasting method in terms of prediction (Bansal et al., 2018; Çuhadar, 2013; Fern´andez-Delgado et al., 2014; Maroco et al., 2011; Nawar & Mouazen, 2017; Raczko & Zagajewski, 2017; Shah et al., 2017; Shichkin et al., 2018). Contrary to the results of our study, there are also studies in which MLPANN is more successful than RF (Eriksson & Varatharajah, 2016; Kayri et al., 2017; Raczko & Zagajewski, 2017; Shah et al., 2017).

In the present study, as the RO method performs better than other methods, the variables that this method deems important will be discussed in this section.

In this study; in prediction of MLPANN, while the most important independent variable affecting the dependent variable was the Turkish success status of the students, it was seen that the students had anxiety level in the estimation of RF. In the literature, it has been observed that anxiety level is often influential on students' mathematics success (Aksu & Güzeller, 2016; Delice, Ertekin, Aydın, & Dilmaç, 2009; İnal & Turabik, 2017; Şentürk, 2010; Yücel & Koç, 2011). When this finding is taken into consideration, it will be beneficial to organize training programs and seminars to reduce or control the anxiety level of students. One of the factors that decrease the anxiety level of the students is to receive family support. In this sense, it should be considered important to organize programs for family education in schools.

The second independent variable which RF method found to be important after anxiety variable is the Turkish success status variable. In parallel with our study; İnal and Turabik (2017) stated that reading success has a significant effect on mathematics achievement. Considering that Turkish success is an issue related to reading habits, it is important to consider scenarios that tempt and encourage reading for students. Considering that mathematics literacy is directly related to analytical thinking ability (Yıldız & Baltacı, 2016) and analytical thinking skill is related to imagination (Çetinkaya, Yeşilyurt, Yörük, & Şanlı, 2012), it is important to accept that the habit of reading books will significantly increase the success of mathematics course. Because reading is known to increase imagination and analytical thinking (Tanju, 2010).

Within the scope of the research, the independent variables that RF found important after the variables of "anxiety level of students" and "Turkish lesson success" were as follows; mother education level and motivation levels of students. Parallel to the findings of this study, in many other studies, it has been reported that mother education levels of students have positive effects on student success (Dursun & Dede, 2004; Gürsakal, 2009; Karabay, 2013; Karabay et al., 2015; Savaş, Taş, & Duru, 2010). In our study, while mother education level was found to be more important than father education level, Anıl (2009) stated that, contrary to the findings in our study, father education level was more effective than mother education level. On the other hand, another important variable in the present study is motivation. Many studies show that there is a statistically significant positive relationship between motivation level and academic success of students and this is also valid for mathematics literacy of the individuals (Aksu & Güzeller, 2016; İnal & Turabik, 2017; Üredi & Üredi, 2005). Considering that there is a correct relationship between motivation and performance (Bayraktar, 2015), in this sense, it is important to see approaches that improve / increase students' motivation in the school environment. Factors affecting the internal and external motivation of the students should be taken into consideration and attention should be paid to improving the motivation of the classroom or school climate.

Another independent variable that RF finds important is the student's belief related to epistemology (knowledge philosophy). In many studies, the effect of this variable on success has been frequently investigated (Aydın & Geçici, 2017; Deryakulu, 2004; Deryakulu & Büyüköztürk, 2005; Eroğlu & Güven, 2006; Koç-Erdamar & Bangir-Alpan, 2011; Sadıç & Çam, 2015; Özkan, 2008; Ünal Çoban & Ergin, 2008). In parallel with the results of our study; Aydın and Geçici (2017) stated that there was a statistically significant relationship between students' beliefs in epistemology and mathematics success ($p < 0.01$). However, Dursun and Dede (2004) and Dursun Sürmeli and Ünver (2017) determined that there is no statistically significant relationship between this variable and mathematics success. When belief in epistemology is considered in the most general way as individuals' subjective beliefs about what knowledge is, how knowledge and learning take place (Deryakulu, 2004) in organizing students' cognitive and affective diagrams towards learning mathematics should be met. In the context of belief in knowledge theory, learning mathematics; ability, effort or belief that there is a single line

(Delice et al., 2009), taking into account the students' beliefs at this point is necessary to determine the belief. Thus, some scenarios (such as confidence-building psychological support programs) need to be arranged to eliminate the factors that prevent learning.

According to RF, “teacher interest” on students' mathematical literacy was determined as a significant independent variable. Akyüz (2006) and Akyüz and Pala (2010) found a statistically significant negative correlation between the interest of Turkish and Greek teachers to their students and mathematics literacy; however, they found no statistically significant relationship for Finnish teachers. In a related study, İlgün Dibek and Demirtaşlı (2017) found statistically significant negative relationship between students' success in mathematics in Turkey and " teacher's interest" Yılmaz (2006) found a positive statistically significant relationship between teacher interest and mathematics success. Considering the significant relationship between mathematics literacy and teacher interest; the individual differences in cognitive, sensational and psychomotor levels should be taken into consideration by the teacher. It should be emphasized that approaches should be taken according to the fact that students will be affected by any attitude towards them, such as being condescending by their teachers.

Another important variable that RF finds important is the father's education level, and in parallel with the findings of our study, it has been reported that the father's education levels of the students have a positive effect on students’ success (Anıl, 2009; Karabay et al., 2015). In this context, the continuation of education in formal or informal environments (such as allocating time for undergraduate and graduate programs) within the framework of lifelong learning philosophy can be seen as important for the role model of the student.

It is stated that the disciplined classroom environment variable, which is another important variable determined by RF, positively affects mathematics success in many studies (Akyüz, 2006; Akyüz & Pala, 2010; Aydın, 2001; Dursun & Dede, 2004; İlgün Dibek & Demirtaşlı, 2017; Küçükahmet, 1999). Class discipline should be considered as a general concept that includes many features from teacher's stance to control of assignments, students' class placement and teacher's body language (Pala, 2008). In this context, it should be seen significant that teachers use body language and spoken language well in classroom environment. In addition, the teacher should organize the individual and group work well.

In the present study, another important variable that RF considers as important is that teachers see the students' mathematical intelligence to be at low level. According to mathematics teachers, mathematical intelligence of students has a significant effect on mathematics success (Dursun & Dede, 2004). As mentioned above, variables such as teacher's interest, motivation and anxiety of students are very important factors on mathematics literacy, and likewise, teachers’ considering the low level of mathematics intelligence of the students affects mathematics success negatively. It should be seen significant that the teacher is trying to develop different teaching styles for students with learning difficulties.

Within the scope of this study, in order to generalize the findings, it is recommended that new studies be conducted on different samples. However; it is thought that this study will serve as an example for the use of data mining methods in the process of educational research. On the other hand; it will be possible to contribute to the improvement of our performance in PISA exams with the implementation of projects that will be prepared taking into account the factors that have an impact on students' mathematics proficiency.

References

Akar, Ö., & Güngör, O. (2012). Rastgele orman algoritması kullanılarak çok bantlı görüntülerin sınıflandırılması. *TMMOB Harita ve Kadastro Mühendisleri Odası Jeodezi ve Jeoinformasyon Dergisi, 1*(2), 139-146. doi:10.9733/jgg.241212.1

Akar Ö., Güngör O., & Akar A. (2010), Rastgele orman sınıflandırıcısı ile arazi kullanım alanlarının belirlenmesi. In *III. Uzaktan Algılama ve Coğrafi Bilgi Sistemleri Sempozyumu* (pp. 142-152). Gebze.

Akbilgiç, O. (2011). *Hibrit radyal tabanlı fonksiyon ağları ile değişken seçimi ve tahminleme: menkul kıymet yatırım kararlarına ilişkin bir uygulama* (Unpublished doctoral dissertation). İstanbul University, İstanbul.

Akman, M. (2010). *Veri madenciliğine genel bakış ve random forests yönteminin incelenmesi: Sağlık alanında bir uygulama* (Unpublished master's thesis). Ankara University, Ankara.

Aksu, G. (2018). *PISA başarısını tahmin etmede kullanılan veri madenciliği yöntemlerinin incelenmesi* (Unpublished doctoral dissertation). Hacettepe University, Ankara.

Aksu, G., & Doğan, N. (2018). Veri madenciliğinde kullanılan öğrenme yöntemlerinin farklı koşullar altında karşılaştırılması. *Ankara Üniversitesi Eğitim Bilimleri Fakültesi Dergisi, 51*(3), 71-100.

Aksu G., & Güzeller C. O. (2016). PISA 2012 matematik okuryazarlığı puanlarının karar ağacı yöntemiyle sınıflandırılması: Türkiye örneklemi. *Eğitim ve Bilim, 41*(185), 101-122. doi:10.15390/EB.2016.4766

Akyüz, G. (2006). Türkiye ve Avrupa Birliği ülkelerinde öğretmen ve sınıf niteliklerinin matematik başarısına etkisinin incelenmesi. *İlköğretim Online, 5*(2), 61-74. Retrieved from http://ilkogretim-online.org.tr/

Akyüz G., & Pala M. N. (2010). PISA 2003 sonuçlarına göre öğrenci ve sınıf özelliklerinin matematik okuryazarlığına ve problem çözme becerilerine etkisi. *İlköğretim Online, 9*(2), 668-678. Retrieved from http://ilkogretim-online.org.tr/

Anıl, D. (2009). Uluslararası öğrenci başarılarını değerlendirme programı (PISA)'nda Türkiye'deki öğrencilerin fen bilimleri başarılarını etkileyen faktörler. *Eğitim ve Bilim, 34*(152), 87-100. Retrieved from http://egitimvebilim.ted.org.tr/index.php/EB/article/view/594/74

Archer, K. J., & Kimes, R. V. (2008) Empirical characterization of random forest variable importance measures. *Computational Statistics and Data Analysis, 52*(4), 2249-2260. Retrieved from https://www.sciencedirect.com/science/article/pii/S0167947307003076

Atasever, Ü. H. (2011). *Uydu görüntülerinin sınıflandırılmasında hızlandırma (boosting), destek vektör makineleri, rastgele orman (random forest) ve regresyon ağaçları yöntemlerinin kullanılması* (Unpublished master's thesis). Erciyes University, Kayseri.

Aydın, B. (2001). *İlköğretim okullarında sınıf disiplininin sağlanması* (Unpublished doctoral dissertation). Abant İzzet Baysal University, Bolu.

Aydın, M., & Geçici, M. E. (2017). 6. sınıf öğrencilerinin epistemolojik inançlarının bazı değişkenler açısından incelenmesi. *Ahi Evran Üniversitesi Kırşehir Eğitim Fakültesi Dergisi, 18*(1), 213-229. Retrieved from https://www.researchgate.net/publication/328615177

Azapağası İlbağı, E. (2012). *PISA 2003 matematik okuryazarlığı soruları bağlamında 15 yaş grubu öğrencilerinin matematik okuryazarlığı ve tutumlarının incelenmesi* (Unpublished doctoral dissertation). Atatürk University, Erzurum.

Azapağası İlbağı, E., & Akgün, L. (2012). PISA 2003 öğrenci anketine göre 15 yaş grubu öğrencilerinin tutumlarının incelenmesi. *Western Anatolia Journal of Educational Science, 3*(6), 67-90. Retrieved from http://dergipark.gov.tr/download/article-file/39530

Bansal, D., Chhikara, R., Khanna, K., & Gupta, P. (2018). Comparative analysis of various machine learning algorithms for detecting dementia. *Procedia Computer Science, 132*, 1497-1502. Retrieved from https://www.sciencedirect.com/science/article/pii/S1877050918308342

Bautier, E., & Rayou, P. (2007). What PISA really evaluates: Literacy or students' universes of reference?. *Journal of Educational Change, 8*(4), 359-364. doi:10.1007/s10833-007-9043-9. Retrieved from https://www.researchgate.net/journal/1389-2843_Journal_of_Educational_Change

Bayraktar, V. H. (2015). Student motivation in classroom management and factors that affect motivation. *Turkish Studies, 10*(3), 1079-1100. Retrieved from http://www.turkishstudies.net/files/turkishstudies/20934147_60VatanseverBayraktarHatice-egt-1079-1100.pdf

Becerra, R., Joya, G., Bermúdez, R. V. G., Velázquez, L., Rodríguez, R., & Pino, C. (2013). Saccadic points classification using Multilayer Perceptron and Random Forest classifiers in EOG recordings of patients with Ataxia SCA2. In *Repositorio Institucional Universidad De Málaga* (pp .10-23). Retrieved from https://core.ac.uk/download/pdf/62898259.pdf

Benzer, S., & Benzer, R. (2017). Examination of international PISA test results with artificial neural networks and regression methods. *Savunma Bilimleri Dergisi, 16*(2), 1-13.

Biau, G. (2012). Analysis of a random forest. *Journal of Machine Learning Research, 13*(2012), 1063-1095. Retrieved from http://www.jmlr.org/papers/volume13/biau12a/biau12a.pdf

Biau, G., & Scornet, E. (2016). A random forest guided tour. *An Official Journal of the Spanish Society of Statistics and Operations Research, 25*(2), 197-227. Retrieved from doi:10.1007/s11749-016-0481-7. http://www.lsta.upmc.fr/BIAU/test-bs.pdf

Bilgen, İ. (2014). *İnsan ve HIV-1 proteinleri arasındaki etkileşimlerin rastgele orman yöntemi ve birlikte öğrenme yaklaşımı ile tahmin edilmesi* (Unpublished master's thesis). İstanbul Technical University, İstanbul.

Breiman, L. (2001). Random forests. *Machine Learning, 45*, 5-32. Retrieved from https://link.springer.com/content/pdf/10.1023/A:1010933404324.pdf

Breiman, L., & Cutler, A. (2017). *Random forests*. Retrieved from https://www.stat.berkeley.edu/~breiman/RandomForests/

Cganh, F. J., Liang, J. M., & Chen, Y. C. (2001). Flood forecasting using radial basis function neural networks. *IEEE Transaction on Systems, Man, and Cybernetics Part C: Applications and Rewievs, 31*(4), 530-535.

Comrie, A. (1997). Comparing neural networks and regression models for ozone forecasting. *Journal of the Air and Waste Management Association*, 47(6), 653-663. Retrieved from https://arizona.pure.elsevier.com/en/publications/

Coşguner, T. (2013). *Uluslararası öğrenci başarı değerlendirme programı (PISA) 2009 uygulaması okuma becerileri okuryazarlığını etkileyen faktörler* (Unpublished master's thesis). Akdeniz University, Antalya.

Çelen, F. K., Çelik, A., & Seferoğlu, S. S. (2011). Türk eğitim sistemi ve PISA sonuçları. In *Akademik Bilişim'11-XIII, Akademik Bilişim Konferansı Bildirileri* (pp. 765-773). Malatya.

Çetinkaya, İ., Yeşilyurt, E., Yörük, S., & Şanlı, Ö. (2012). Öğretmen adaylarında yaratıcı düşünmenin yordayıcısı olarak değişime açıklık ve hayal gücü. *Uşak Üniversitesi Sosyal Bilimler Dergisi, 5*(2), 46-62. Retrieved from https://www.pegem.net/dosyalar/dokuman/138919-201401271547-4.pdf

Çuhadar, M. (2013). Türkiye'ye yönelik dış turizm talebinin MLP, RBF ve TDNN yapay sinir ağı mimarileri ile modellenmesi ve tahmini: Karşılaştırmalı bir analiz. *Journal of Yasar University, 8*(31), 5274-5295.

Delice, A., Ertekin, E., Aydın, E., & Dilmaç, B. (2009). Öğretmen adaylarının matematik kaygısı ile bilgibilimsel inançları arasındaki ilişkinin incelenmesi. *Uluslararası İnsan Bilimleri Dergisi, 6*(1), 361-375. Retrieved from http://www.insanbilimleri.com/ojs/index.php/uib/article/view/637/352

Deryakulu, D. (2004). Üniversite öğrencilerinin öğrenme ve ders çalışma stratejileri ile epistemolojik inançları arasındaki ilişki. *Kuram ve Uygulamada Eğitim Yönetimi, 38*, 230-249. Retrieved from http://dergipark.gov.tr/download/article-file/108404

Deryakulu, D., & Büyüköztürk, Ş. (2005). Epistemolojik inanç ölçeğinin faktör yapısının yeniden incelenmesi: Cinsiyet ve öğrenim görülen program türüne göre epistemolojik inançların karşılaştırılması. *Eurasian Journal of Educational Research, 18*, 57-70. Retrieved from https://www.researchgate.net/profile/Deniz_Deryakulu2/publication/285660584

Dursun, Ş., & Dede, Y. (2004). Öğrencilerin matematikte başarısını etkileyen faktörler: Matematik öğretmenlerinin görüşleri bakımından. *Gazi Eğitim Fakültesi Dergisi, 24*(2), 217-230. Retrieved from http://gefad.gazi.edu.tr/article/view/5000078798

Dursun Sürmeli, Z., & Ünver, G. (2017). Öz-düzenleyici öğrenme stratejileri, epistemolojik inançlar ve akademik benlik kavramı ile matematik başarısı arasındaki ilişki. *Turkish Journal of Computer and Mathematics Education, 8*(1), 83-102. Retrieved from http://dergipark.gov.tr/download/article-file/284109

Emel, G. G., & Taşkın, Ç. (2005). Veri madenciliğinde karar ağaçları ve bir satış analizi uygulaması. *Eskişehir Osmangazi Üniversitesi Sosyal Bilimler Dergisi, 6*(2), 221-239. Retrieved from http://dergipark.ulakbim.gov.tr/ogusbd/article/view/5000080834/5000074968

Eriksson, V., & Varatharajah, T. (2016). *A comparative study on artificial neural networks and random forests for stock market prediction*. KTH Royal Institute of Technology School of Computer Science and Communicatıon. Retrieved from https://www.diva-portal.org/smash/get/diva2:927335/FULLTEXT01.pdf

Eroğlu, S. E., & Güven, K. (2006). Üniversite öğrencilerinin epistemolojik inançlarının bazı değişkenler açısından incelenmesi. *Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 16*, 295-312. Retrieved from http://dergisosyalbil.selcuk.edu.tr/susbed/article/view/529

Fausett, L. (1994). *Fundamentals of neural networks: Architectures, algorithms and applications*. New Jersey, NJ: Prentice-Hall. Retrieved from http://www.csbdu.in/csbdu-old/pdf/Fundamentals%20Of%20Neural%20Networks.pdf

Fern´andez-Delgado, M., Cernadas, E., & Barro, S. (2014). Do we need hundreds of classifiers to solve real world classification problems?. *Journal of Machine Learning Research, 15*(2014), 3133-3181. Retrieved from http://jmlr.org/papers/volume15/delgado14a/delgado14a.pdf

Geneur, R., Poggi, J. M., Tuleao Malot, C., & Villa-Vialaneix, N. (2017). Random forest for big data. *Big Data Research*. Retrieved from http://www.nathalievialaneix.eu/doc/pdf/genuer_etal_BDR2017.pdf

Gibson, G. J., Siu, S., & Cowan, C. F. N. (1989). Multilayer perceptron structures applied to adaptive equalisers for data communications. In *International Conference on Acoustics, Speech and Signal Processing* (pp. 1520-6149). Glasgow: UK.

Göktaş, Ö., & Gürbüztürk, O. (2012). Okuduğunu anlama becerisinin ilköğretim ikinci kademe matematik dersindeki akademik başarıya etkisi. *Uluslararası Eğitim Programları ve Öğretim Çalışmaları Dergisi, 2*(4), 53-66.

Gönül, Y., Ulu, Ş., Bucak, A., & Bilir, A. (2015). Yapay sinir ağları ve klinik araştırmalarda kullanımı. *Genel Tıp Dergisi, 25*(3), 104-111. doi:10.15321/GenelTipDer.2015313147

Guo, H., Zhao, J. Y., & Yin, J. H. (2017). Random forest and multilayer perceptron for predicting for dielectric loss of polyimide nanocomposite films. *Royal Society of Chemistry, 7*, 30999-31008. doi:10.1039/C7RA04147K. Retrieved from https://pubs.rsc.org/ru/content/articlepdf/2017/ra/c7ra04147k

Güleç, S., & Alkış, S. (2003). İlköğretim birinci kademe öğrencilerinin derslerdeki başarı düzeylerinin birbiriyle ilişkisi. *İlköğretim-Online, 2*(2), 19-27.

Gürsakal, S. (2009). PISA 2009 öğrenci başarı düzeylerini etkileyen faktörlerin değerlendirilmesi. *Süleyman Demirel Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 17*(1), 441-452. Retrieved from http://dergipark.gov.tr/download/article-file/194442

Güzeller, C. O., & Akın, A. (2014). Relationship between ICT variables and mathematics achievement based on PISA 2006 database: International evidence. *The Turkish Online Journal of Educational Technology, 13*(1), 184-192.

Hamzaçebi, C. (2011). *Yapay sinir ağları*. Bursa: Ekin.

Hand, D. J., Mannila, H., & Smyth, P. (2001). *Principles of data mining*. Cambridge: A Bradford Book The MIT Press. Retrieved from https://doc.lagout.org/Others/Data%20Mining/Principles%20of%20Data%20Mining%20%5BHand%2C%20Mannila%20%26%20Smyth%202001-08-01%5D.pdf

IES>NCES. (2018). *National center for education statistics*. Retrieved from https://nces.ed.gov/surveys/pisa/pisa2015/pisa2015highlights_8f.asp

İlgün Dibek, M., & Demirtaşlı, R. N. (2017). Öğrenme ve öğretme süreci değişkenleri ile PISA 2012 matematik okuryazarlığı arasındaki ilişkiler. *İlköğretim Online, 16*(3), 1137-1152. Retrieved from http://ilkogretim-online.org.tr/

İnal, H., & Turabik, T. (2017). Matematik başarısını etkileyen bazı faktörlerin yordama gücünün yapay sinir ağları ile belirlenmesi. *Uşak Üniversitesi Eğitim Araştırmaları Dergisi, 3*(1), 23-50. doi:10.29065/usakead.287754

Jain, K. A., & Mao, J. (1996). *Artificial neural network; A tutorial*. Retrieved from http://metalab.uniten.edu.my/~abdrahim/mitm613/Jain1996_ANN%20-%20A%20Tutorial.pdf

Kamaliyah, K., Zulkardi, Z., & Darmawijoyo, D. (2013). Developing the sixth level of PISA-like mathematics problems for secondary school students. *Journal on Mathematics Education, 4*(1), 9-28. doi:10.22342/jme.4.1.559.9-28. Retrieved from http://ejournal2.unsri.ac.id/index.php/jme/issue/view/87

Karabay, E. (2013). *Aile ve okul özelliklerinin PISA okuma becerileri, matematik ve fen okuryazarlığını yordama gücünün yıllara göre incelenmesi* (Unpublished master's thesis). Gazi University, Ankara.

Karabay, E., Yıldırım, A., & Güler, G. (2015). Yıllara göre PISA matematik okuryazarlığının öğrenci ve okul özellikleri ile ilişkisinin aşamalı doğrusal modeller ile analizi. *Mehmet Akif Ersoy Üniversitesi Eğitim Fakültesi Dergisi, 36*, 137-151. Retrieved from http://dergipark.gov.tr/download/article-file/181503

Karadeniz, M., Yüncü, S., & Aydemir M. T. (2001). Asenkron motorlarda stator direncinin yapay sinir ağları ile tahmini. *TMMOB Elektrik Mühendisliği Elektrik-Elektronik-Bilgisayar ve Biyomedikal Mühendisliği Kongresi Bildirileri*. Retrieved from http://www.emo.org.tr/ekler/b9de3fb364d8d87_ek.doc

Karasar, N. (2006). *Bilimsel araştırma yöntemi*. Ankara: Nobel Yayın Dağıtım.

Kaynar, O., & Taştan S. (2009). Zaman serisi analizinde MLP yapay sinir ağları ve arima modelinin karşılaştırılması. *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 33*, 161-172. Retrieved from http://iibf.erciyes.edu.tr/dergi/sayi33/9.k%FDs%FDm.pdf

Kaynar, O., Taştan, S., & Demirkoparan, F. (2010). Ham petrol fiyatlarının yapay sinir ağları ile tahmini. *Ege Akademik Bakış, 10*(2), 559-573. Retrieved from https://www.researchgate.net/publication/227427978

Kayri, İ. (2017). *Güneş panelleri ile üretilen enerjinin ortam bilgileri kullanılarak yapay sinir ağlarıyla tahmini* (Unpublished doctoral dissertation). Fırat University, Elazığ.

Kayri, M. (2015). An intelligent approach to educational data: Performance comparison of the multilayer perceptron and the radial basis function artificial neural networks. *Educational Sciences: Theory & Practice, 15*(5), 1247-1255. doi:10.12738/estp.2015.5.0238

Kayri, M., Kayri, İ., & Gençoğlu, M. T. (2017). The performance comparison of multiple linear regression, random forest and artificial neural network by using photovoltaic and atmospheric data. In *2017 14th International Conference on Engineering of Modern Electric Systems (EMES)* (pp. 1-4), Oradea, Romania.

Keller, P. S., El-Sheikh, M., Granger, D. A., & Buckhalt, J. A. (2012). Interactions between salivary cortisol and alphaamylase as predictors of children's cognitive functioning and academic performance. *Physiology & Behavior, 105*, 987-995. Retrieved from https://asu.pure.elsevier.com/en/publications/interactions-between-salivary-cortisol-and-alpha-amylase-as-predi

Koç-Erdamar, G., & Bangir-Alpan, G. (2011). Öğretmen adaylarının epistemolojik inançları. *E- Journal of New Word Sciences Academy, 6*(4), 2689-2698. Retrieved from http://dergipark.gov.tr/download/article-file/185533

Koğar, H. (2015). PISA 2012 matematik okuryazarlığını etkileyen faktörlerin aracılık modeli ile incelenmesi. *Eğitim ve Bilim, 40*(179), 45-55. doi:10.15390/EB.2015.4445

Küçükahmet, L. (1999). *Öğretimde planlama ve değerlendirme*. İstanbul: Alkım Yayınevi.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomforest. *R News, 2*(3), 18-22. Retrieved from https://www.researchgate.net/publication/228451484_Classification_and_Regression_by_RandomForest

Marin, E. J. O., Martinez-Capel, F., & Vezza, P. (2013). A comparison of artificial neural networks and random forests to predict native fish species richness in Mediterranean rivers. *Knowledge and Management of Aquatic Ecosystems, 409*, 19. doi:10.1051/kmae/2013052. Retrieved from http://www.kmae-journal.org/

Maroco, J., Silva, D., Rodrigues, A., Guerreiro, M., Santana, I., & Mendonça, A. (2011). Data mining methods in the prediction of Dementia: A real-data comparison of the accuracy, sensitivity and specificity of linear discriminant analysis, logistic regression, neural networks, support vector machines, classification trees and random forest. *BMC Research Notes, 4*(1), 299. doi:10.1186/1756-0500-4-299

Ministry of National Education. (2016). *PISA 2009 projesi ulusal ön raporu*. Ankara: MEB Eğitimi Araştırma ve Geliştirme Dairesi Başkanlığı. Retrieved from http://odsgm.meb.gov.tr/test/analizler/docs/PISA/PISA2015_Ulusal_Rapor.pdf

Nawar, S., & Mouazen, A. M. (2017). Comparison between random forests, artificial neural networks and gradient boosted bachines methods of on-line Vis-NIR spectroscopy measurements of soil total nitrogen and total carbon. *Sensors, 17*(10), 2428. doi:10.3390/s17102428. Retrieved from https://www.mdpi.com/1424-8220/17/10/2428

OECD. (2007). *PISA 2006*. Paris: OECD Publishing. Retrieved from https://www.oecd.org/pisa/data/42025182.pdf

OECD. (2016a). *PISA 2015 results in focus*. Paris: OECD Publishing. Retrived from https://www.oecd-ilibrary.org/education/pisa-2015-results-in-focus_aa9237e6-en.

OECD. (2016b). *PISA 2015 mathematics framework. PISA 2015 assessment and analytical framework: science, reading, mathematic and financial literacy*. Paris: OECD Publishing. Retrieved from http://www.oecd.org/publications/pisa-2015-assessment-and-analytical-framework-9789264281820-en.htm

Okatan, Ö. (2017). *Uluslararası öğrenci başarılarını değerlendirme programı'na (PISA) göre öğrencilerin matematik başarıları ile ilişkili değişkenlerin incelenmesi* (Unpublished master's thesis). Mehmet Akif Ersoy University, Burdur.

Özkan, Ş. (2008). *İlköğretim öğrencilerinin fen başarıları ile ilgili bir modelleme çalışması: Epistomolojik inançlar, öğrenme yaklaşımları ve öz-düzenleme becerileri arasındaki ilişkiler* (Unpublished doctoral dissertation). Middle East Technical University, Ankara.

Öztemel, E. (2012). *Yapay sinir ağları*. İstanbul: Papatya Yayıncılık.

Pala, M. N. (2008). *PISA 2003 sonuçlarına göre öğrenci ve sınıf özelliklerinin matematik okuryazarlığına ve problem çözmeye etkisi* (Unpublished master's thesis). Balıkesir University, Balıkesir.

Priddy, K. L., & Keller, P. E. (2005). *Artificial neural networks: An introduction*. Washington: SPIE Press.

Quinlan, J. R. (1993). *C4.5: Programs for machine learning*. California: Morgan Kaufmann Publishers. Retrieved from https://books.google.com.tr/books?hl=tr&lr=&id=b3ujBQAAQBAJ&oi=fnd&pg=PP1&dq=Quinlan,+J.R.,+(1993),+C4.5:+Programs+for+Machine+Learning&ots=sQ5rUSGsIa&sig=CTAvmOwlwJTqxYOIZxlS2e0Q8Ww&redir_esc=y#v=onepage&q=Quinlan%2C%20J.R.%2C%20(1993)%2C%20C4.5%3A%20Programs%20for%20Machine%20Learning&f=false

Raczko, E., & Zagajewski, B. (2017). Comparison of support vector machine, random forest and neural network classifiers for tree species classification on airborne hyperspectral APEX images. *European Journal of Remote Sensing, 50*(1), 144-154. doi:10.1080/22797254.2017.1299557

Saarela, M., Yener, B., Zaki, M. J., & Karkkainen, T. (2016). Predicting math performance from raw large-scale educational assessments data: A machine learning approach. In *33rd International Conference on Machine Learning, MLR Workshop and Conference Proceedings* (pp. 1-8). New York City, USA.

Sadıç, A., & Çam, A. (2015). 8. sınıf öğrencilerinin epistemolojik inançları ile PISA başarıları ve fen ve teknoloji okuryazarlığı. *Bilgisayar ve Eğitim Araştırmaları Dergisi, 3*(5), 18-49. Retrieved from http://www.dergipark.ulakbim.gov.tr/jcer

Satıcı, K. (2008). *PISA 2003 sonuçlarına göre matematik okuryazarlığını etkileyen faktörler: Türkiye ve Hong Kong-Çin* (Unpublished master's thesis). Balıkesir University, Balıkesir.

Savaş, E., Taş. S., & Duru, A. (2010). Factors affecting students' achievement in mathematics. *Inonu University Journal of The Faculty of Education, 11*(1), 113-132. Retrieved from http://dergipark.gov.tr/download/article-file/92276

Seyman, M. N., & Taşpınar, N. (2009). Çok katmanlı yapay sinir ağları kullanarak OFDM sistemlerinde kanal dengeleme. *5. Uluslararası İleri Teknolojiler Sempozyumu (IATS'09),* 13-15 Mayıs 2009 içinde (630-633). Karabük: Türkiye.

Shah, A. S., Shah, M., Fayaz, M., Wahid, F., Khalid Khan, H., & Shah, A. (2017). Forensic analysis of offline signatures using multilayer perceptron and random forest. *International Journal of Database Theory and Application, 10*(1), 139-148. doi:10.14257/ijdta.2017.10.1.13. Retrieved from https://www.researchgate.net/profile/Abdul_Salam_Shah/publication/313477318_Forensic_Analysis_of_Offline_Signatures_Using_Multilayer_Perceptron_and_Random_Forest/links/589c0e13aca2721ae1b7b20c/Forensic-Analysis-of-Offline-Signatures-Using-Multilayer-Perceptron-and-Random-Forest.pdf

Shaw, M. J., Subramaniam, C, Tan, G. W., & Welge M. E. (2001). Knowledge management and data mining for marketing. *Decision Support Systems, 1*(31), 127-137. doi:10.1016/S0167-9236(00)00123-8. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.87.1196&rep=rep1&type=pdf

Shichkin, A. V, Buevich, A. G., & Sergeev, A. P. (2018). Comparison of artificial neural network, random forest and random perceptron forest for forecasting the spatial ımpurity distribution. In *Mathematical Methods and Computational Techniques in Science and Engineering II AIP Conference Proceedings* (pp. 020005-1-020005-7). doi:10.1063/1.5045411. Retrieved from https://aip.scitation.org/doi/abs/10.1063/1.5045411

Şentürk, B. (2010). *İlköğretim beşinci sınıf öğrencilerinin genel başarıları, matematik başarıları, matematik dersine yönelik tutumları ve matematik kaygıları arasındaki ilişki* (Unpublished master's thesis). Afyon Kocatepe University, Afyon.

Tanju, E. H. (2010). Çocuklarda kitap okuma alışkanlığına genel bir bakış. *Aile ve Toplum, 11*(6), 31-39. Retrieved from https://dergipark.org.tr/en/download/article-file/197991

Tatar, E., & Soylu, Y. (2006). Okuma-anlamadaki başarının matematik başarısına etkisinin belirlenmesi üzerine bir çalışma. *Kastamonu Eğitim Dergisi, 14*(2), 503-508.

Tepehan, T. (2011). *Türk öğrencilerinin PISA başarılarının yordanmasında yapay sinir ağı ve lojistik regresyon modeli performanslarının karşılaştırılması* (Unpublished doctoral dissertation). Hacettepe University, Ankara.

Toprak, E. (2017). *Yapay sinir ağı, karar ağaçları ve ayırma analizi yöntemleri ile PISA 2012 matematik başarılarının sınıflandırılma performanslarının karşılaştırılması* (Unpublished doctoral dissertation). Hacettepe University, Ankara.

Türkan, A., Üner S. S., & Alcı, B. (2015). 2012 PISA matematik testi puanlarının bazı değişkenler açısından incelenmesi. *Ege Eğitim Dergisi, 16*(2), 358-372. doi:10.12984/eed.68351. Retrieved from https://www.researchgate.net/publication/290958106_2012_Pisa_Matematik_Testi_Puanlarinin_Bazi_Degiskenler_Acisindan_Incelenmesi

Uysal, E., & Yenilmez, K. (2011). Sekizinci sınıf öğrencilerinin matematik okuryazarlığı düzeyi. *Eskişehir Osmangazi Üniversitesi Sosyal Bilimler Dergisi, 12*(2), 1-15. Retrieved from http://dergipark.gov.tr/ogusbd/issue/11000/131632

Ünal Çoban, G., & Ergin, Ö. (2008). İlköğretim öğrencilerinin bilimsel bilgiye yönelik görülerini belirleme ölçeği. *İlköğretim Online, 7*(3), 706-716. Retrieved from http://ilkogretim-online.org.tr/

Üredi, I., & Üredi, L. (2005). İlköğretim 8. sınıf öğrencilerinin öz-düzenleme stratejileri ve motivasyonel inançlarının matematik başarısını yordama gücü. *Mersin Üniversitesi Eğitim Fakültesi Dergisi, 1*(2), 250-260. Retrieved from http://dergipark.gov.tr/download/article-file/161017

Yeh, I. C. (1998). Modeling of strength of high-performance concrete using artificial neural networks. *Cement and Concrete Research, 28*(12), 1797-1808. doi:10.1016/S0008-8846(98)00165-3. Retrieved from https://www.researchgate.net/publication/222447231_Modeling_of_Strength_of_High-Performance_Concrete_Using_Artificial_Neural_Networks_Cement_and_Concrete_research_2812_1797-1808

Yıldız, A., & Baltacı, S. (2016). İlköğretim matematik öğretmen adaylarının geometrik olasılık problemlerini çözme süreçlerinin analitik düşünme bağlamında incelenmesi. *Mehmet Akif Ersoy Üniversitesi Eğitim Fakültesi Dergisi, 1*(39), 91-111. Retrieved from https://dergipark.org.tr/en/pub/maeuefd/issue/24654/260770

Yılmaz, E. T. (2006). *Uluslararası öğrenci başarı değerlendirme programı (PISA)'nda Türkiye'deki öğrencilerin matematik başarılarını etkileyen faktörler* (Unpublished master's thesis). Hacettepe University, Ankara.

Yücel, Z., & Koç, M. (2011). The relationship between the prediction level of elementary school students' math achievement by their math attitudes and gender. *Elementary Education Online, 10*(1), 133-143. Retrieved from http://ilkogretim-online.org.tr/

Ziya, E. (2008). *Uluslararası öğrenci başarı değerlendirme programına (PISA 2006) göre Türkiye'deki öğrencilerin matematik başarılarını etkileyen bazı faktörler* (Unpublished master's thesis). Hacettepe University, Ankara.