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ORIGINAL ARTICLE

An Analysis of MARS and Logistic Regression Methods in Educational Data Mining in Light of Some Performance Indicators

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No conflict of interest is present in the conduction or the reporting of this study.

ABSTRACT

This study aims to compare the MARS method and Logistic Regression (LR) methods from the family of nonlinear regression methods regarding correct classification rate, type I error, type II error and area under the ROC curve (AUC) metrics according to sample sizes using ABIDE data. For this purpose, Turkish achievement scores of 5000 randomly selected eighth grade students who participated in ABIDE 2016 and various demographic variables were used. The analyses show that in terms of correct classification rate, the LR method is more accurate in small sample size and the MARS method is more accurate in large sample size. With respect to the area under the ROC curve, the LR method performs better at small sample sizes and the MARS method performs better at large sample sizes. In terms of Type I error rate, LR has less error rate at small sample size and more error rate at large sample size, while MARS has more error rate at small sample size and less error rate at large sample size. In terms of Type II error rate, the MARS method has less error rate than the LR in all other sample sizes except 1500 sample size. The MARS method yields better results than the LR in both error types. In order to obtain robust and error-free results in educational studies, using the LR method for small sample sizes and the MARS for large sample sizes is recommended.

Keywords: ABİDE, Logistic Regression, MARS, Correct Classification Rate.

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INTRODUCTION

Countries conduct various studies to monitor and evaluate education systems. Internationally, large-scale studies such as PISA, TIMMS, and PIRLS are implemented. In addition to participating in these studies that measure high-level thinking skills, Türkiye has implemented the Monitoring and Evaluation of Academic Skills (ABIDE) survey to monitor student achievement on a national basis. This study aims to have some data at the national and provincial level through monitoring, research and evaluation of educational activities. The application enables the measurement of student skills and achievements in terms of student, teacher, school and instructional qualities (Şevgin & Öner, 2022). Based on the data of this study, which allows the education system to be monitored regularly, it will be possible to identify the deficiencies of our education system (MEB, 2017; Reyhanlıoğlu & Tiryaki, 2021).

ABIDE is similar to large-scale international practices. The application, which measures the ability of eighth grade students to apply the knowledge they have learned in school life to daily life, is carried out in two-year periods. Unlike international applications, ABIDE also reveals the specific situation of provinces. In the study, affective, family and school environment-related characteristics, which are factors affecting students' achievement, are also addressed. The relationship between these variables and students' possession of high-level cognitive skills is examined (MEB, 2017). ABIDE implementation was carried out for the first time in 2016. The application, whose second cycle was carried out in 2018, could not be carried out in 2020 due to the pandemic. The last cycle was conducted in 2022. In ABIDE research, Turkish, Mathematics, Science and Social Studies fields are included. For each of these areas, students are divided into five categories according to their achievement levels: below basic, basic, basic, intermediate, advanced and above advanced. The separation process is performed by taking into account the standard cut-off scores determined by field experts (Güre et al., 2022).

Reviewing the related literature reveals many studies using ABIDE data (Doğru, 2019; Kılıç, 2019; Özgürlük, 2019; Ülkü, 2019; Akıncı, 2020; Çalık, 2020; Elkonca, 2020; Göktentürk et al.., 2021; Uysal & Doğan, 2021; Yılmaz, 2021; Doğan, 2022; Güre et al., 2022; Kaya, 2022; Şevgin & Önen, 2022). There is one study in which the MARS method was used (Şevgin & Önen, 2022), and the LR method was used in three others (Göktentürk et al., 2021; Uysal & Doğan, 2021; Yılmaz, 2021). However, there are no studies examining the performance of both methods. In the field of education, there are some studies using the MARS method (Binadari et al., 2015; Martis et al., 2015; Hasyim & Prastyo, 2018; Kılıç Depren, 2018; Zurimi, 2020; Hasanah, 2021; Hasyim et al., 2021; Addini et al., 2023) and LR method (Cabero-Almenara et al., 2021; Eratlı et al., 2020; Kumar et al., 2019; Negricea, 2022; Niu, 2020; Peng et al., 2002; Singh & Alhulail, 2022). The current study compares the MARS and LR regression methods by correct classification rate, Type I error, Type II error and AUC metrics according to sample sizes using ABIDE data.

Regression analysis is a statistical analysis method used to model and examine the relationship between two or more variables and explain it with a mathematical equation. The method is among the analyses that deal with the relationships between dependent and independent variables on the basis of cause and effect. If certain assumptions such as normality, homogeneity of variances and linearity are met, parametric regression methods can be used, and if these assumptions are not met, nonparametric or semi-parametric regression methods can be used. If the relationship between variables is linear, it is called linear regression analysis; if not, it is called nonlinear (curvilinear) regression analysis. Although linear models are quite simple, due to the nonlinearity of some real-life examples, the MARS method, a more flexible statistical method, can be used as an alternative to identify and characterize nonlinear regression effects. The logistic regression model does not assume a linear relationship between the dependent and independent variables, but since it assumes a linear relationship between the logits of the explanatory variables and the response, this study aims to compare it with the MARS analysis method. Since both analysis methods are regression-based methods, it is important to compare and evaluate regression methods in this context and to compare their results.

In line with this purpose, the answer to the following question was sought in the study;

Is there a difference when the results obtained through the estimation of the variables thought to affect the Reading Skills of the eighth-grade students participating in ABIDE 2016 are compared with MARS and LR by correct classification rate, type I and II error rate, and area under the ROC curve?

METHOD

Research Design

This study was conducted using the descriptive relational survey design, one of the general survey methods. This research design tries to describe the past and present situation as it is (Karasar, 2009).

Dataset

The dataset consists of Turkish achievement scores of 5000 eighth grade students randomly drawn from ABIDE 2016 and various demographic variables. After missing data deletion and assignment procedures, this number was obtained as 4148. The dependent variable, which has a continuous structure, was categorized under two clusters with a cut-off point of 514.75 as a result of Two-Stage Clustering Analysis, which is homogeneous within clusters and heterogeneous between clusters. The first cluster (between 241.90 and 514.74) was labeled as unsuccessful (2270 students) and the second cluster (between 514.76 and 731.33) was labeled as successful (1878 students).

Data Analysis

Within the scope of the study, 5 samples were randomly selected from the dataset with samples of 250, 500, 1500, 3000 and 4148, and analyses were performed using these samples. The analysis process of the methods was carried out by using the demo version of SPM 7.0 program for the MARS method, and SPSS 25 program for the LR method.

MARS

Multivariate Adaptive Regression Splines (MARS), a nonparametric method, was developed by Friedman. It is a non-linear method used to find the relationship between dependent and independent variables (Goh et al., 2017). The method is very suitable for problems with a large number of independent variables (Austin, 2007).

MARS can be defined as a piecewise multivariate regression analysis method, also known as a basis function, which can model the complex nonlinear relationship between variables without making strong model assumptions (Freidman, 1991; Park & Abdel-Aty, 2015; Zhang et al., 2016; Ghasemzadeh & Ahmed, 2018). The method provides unbiased parameter estimates with powerful algorithms that take into account the effects of independent variables on the dependent variable besides the interactions of independent variables with each other (Kartal et al., 2018). Since the method uses forward and backward step processes, robust and unbiased parameter estimates are made (Kayri, 2010). The MARS method completes the training process in large data sets in a short time and has the feature of easy interpretation (Lee & Chen, 2005).

In MARS, the space of predictors is divided into multiple nodes. A linking function consisting of several Basis Functions is placed between the nodes. Each basis function can be either a basis or a function of interactions of different variables (Ghasenadeh & Ahmed, 2018). The MARS model is given in the following equation.

$$\hat{y} = \alpha_0 + \sum_{f=1}^{F} \alpha_f \beta_f(x) \quad (1)$$

In the equation, $\hat{y}$ denotes the estimated dependent variable, α_0 denotes the constant coefficient of the base function, α_f denotes the coefficient of the fth percentile function, $\beta_f(x)$ denotes the base function, and F denotes the number of base functions in the model (Haleem, Gan, & Lu, 2013). The coefficients in the model are calculated using the least squares method (Park et al., 2017).

The MARS model has two steps. The first is the construction, in which the basis functions are introduced in various regions of the estimators using a forward step selection procedure. In this step, the basis functions keep being generated until the maximum number of nodes and estimators with significant contributions in the model is reached (Haleem et al., 2013; Park & Abdel-Aty, 2015; Kartal et al., 2018). An adaptive regression algorithm is used to select the nodes (Goh et al., 2017). Here, interactions are included to improve model fit. In the second stage, pruning, the functions with the least contribution to the model are deleted by backward deletion. Generalized cross validity (GCV) criterion is used to overcome overfitting and remove redundant basis functions in the MARS model (Haleem et al., 2013; Park & Abdel-Aty, 2015; Park et al., 2017). In the method, the GCV criterion should be minimum and the R2 value should be maximum (Kartal et al., 2018). Variable significance can be evaluated by observing a decline in the GCV values calculated in case of deleting a variable from the model (Kuhnert et al., 2000). GCV Generalized cross validity criterion is given by the following equation;

$$GCV(M) = \frac{1}{n}\frac{\sum_{i=1}^{n}(y_i-\hat{y})^2}{(1-C(M)/n)^2} \quad (2)$$

$$C(M) = M + dM \quad (3)$$

y_i is the dependent variable of observation i, n is the number of observations, C(M) is the penalty function, d is the cost defined for the optimization of each basis function (Park & Abdel-Aty, 2015). The number of nodes can be small if the penalty value is high. The optimal penalty value is considered to be between 2 and 4 (Goh et al., 2017; Park et al., 2017).

Logistic regression method

The LR method is preferred by researchers because it can be applied to nominal and ordinal variables as well as continuous variables and it does not have assumptions as in classical regression (Tatlıdil, 2002; Tatlıdil & Demirağ, 2014). The aim of the method is to determine a model that establishes the relationship between dependent and independent variables in a way that has the best fit with the use of the fewest variables (Çokluk, 2010).

Logistic regression analysis can be used when the dependent variable has two or more categories. The method specifies the effects of the independent variable on the dependent variable as probability (Özdamar, 2002). The aim of the logistic regression method is to define the linear relationship between the independent variables and the logit of the dependent variable (Hosmer & Lemeshow, 2000; Rotigliano et al., 2018). The equation for logistic regression is given below.

$$y = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (4)$$

Here, $\pi(x)$ is the mean of x values, α is the constant term, and β is the coefficient of the independent variables. Maximum likelihood is used to determine α and β values (Şevgin, 2013; Rotigliano et al., 2018).

Performance Criteria

The methods were compared by using the correct classification rate, type I and type II error rate and area under the ROC curve metrics.

Table 1. Confusion matrix

		Predicted class		
	Unsuccessful	Unsuccessful	Successful	Total
True class	Unsuccessful	TN	FP	TN+FP
	Successful	FN	TP	FN+TP
	Total	58	504.48	TN+FN+FP+TP

In the table above, TN indicates a True Negative, FP indicates a False Positive, FN indicates a False Negative, and TP indicates a True Positive.

Correct Classification Rate: It gives the correct classification rate of the analysis method used for classification on the total samples in a dataset. In this study, the correct classification rate is a ratio of the extent to which students are correctly assigned to the actual class they are in. Its formulaic representation is as follows:

$$Correct\ Classification\ Rate = (TP + TN)/(TP + FP + TN + FN) \quad (5)$$

Type I error: expressed as a false positive and also known as α error (Cohen, 1988). It gives a proportion of the error that occurs when a student who actually fails is positioned in the successful class as a result of the analysis (Tan, 2016). Its formulaic representation is as follows:

$$\alpha = FP/(TN + FN + FP + TP) \quad (6)$$

Type II error: It is expressed as a false negative and is also known as β error (Cohen, 1988). It gives a proportion of the error that occurs when a student who is actually successful is positioned in the unsuccessful class as a result of the analysis (Tan, 2016). Its formulaic representation is as follows:

$$\beta = FN/(TN + FN + FP + TP) \quad (7)$$

Area Under Curve-AUC: The value, which is expressed as a measure of the accuracy of the model or the ability to predict whether an event will occur or not, shows the balance between true positive and false positive rate (Yeşilnacar & Topal, 2005; Şevgin & Önen, 2022). The AUC value varies between 0.5 and 1, and if it is close to 1, it indicates high accuracy, and if it is close to 0.5, it indicates low accuracy (Fawcett, 2006).

RESULTS AND DISCUSSION

In the first stage, students' Turkish scores were classified as successful and unsuccessful through two-stage clustering analysis. In this way, the continuous dependent variable was transformed into a two-category structure. Then, for various sample sizes (250, 500, 1500, 3000 and 4148), MARS and LR analyses were compared in terms of classification performance according to CCR, AUC, type I error, and type II error rates respectively.

The results regarding the students classified as successful and unsuccessful by the MARS and LR analysis methods on the basis of Turkish score is given in Table 1.

Table1. MARS and LR Regression analysis Values obtained for Predicted Class range

		MARS		LR	
		Predicted Class		Predicted Class	
True Class	250	101	43	110	34
		20	86	22	84
	500	211	76	218	69
		51	162	58	155
	1500	608	227	591	244
		197	468	189	476
	3000	1153	480	1151	482
		349	1018	390	977
	4148	1639	631	1604	666
		529	1349	542	1336

Table 1 consists of the sum of confusion matrices obtained as 2x2 for each sample size. In the first stage, the values obtained for the metrics of CCR and AUC for each sample size are as presented in Table 2.

Table 2. Metric values obtained for CCR and AUC from MARS and LR Regression analyses

Sample size	Method	CCR	AUC
250	MARS	74,80%	81,29%
	LR	77,60%	87,72%
500	MARS	74,60%	82,96%
	LR	74,60%	84,39%
1500	MARS	71,73%	79,58%
	LR	71,13%	79,58%
3000	MARS	72,37%	80,34%

	LR	70,93%	79,27%
4148	MARS	72,04%	79,71%
	LR	70,88%	78,86%

As seen in Table 2, the values obtained from MARS and LR methods for CCR and AUC metrics for each sample size are given. These values are also shown in Figure 1 and Figure 2.

Figure 1. Correct classification rate (CCR)

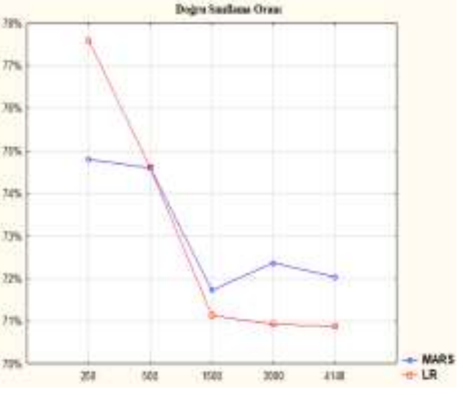
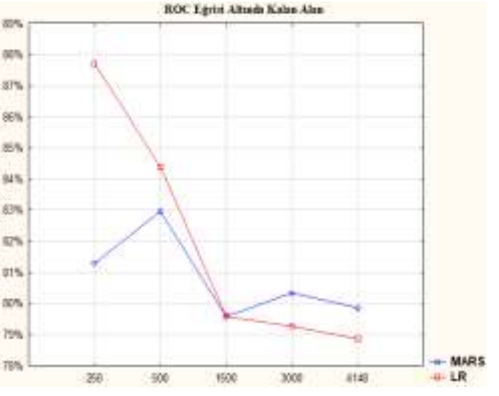


Figure 2. Area under the ROC curve (AUC)



As seen in Table 2 and Figures 1 and 2, the LR method performs better than the MARS method in terms of CCR and AUC values for sample size 250. For sample size 500, both methods are observed to perform the same in terms of CCR value and LR method performs better than MARS method as regards the AUC values. For sample size 1500, both methods perform the same regarding the AUC value, and MARS performs better than LR considering the CCR values. For sample size 3000, it is clear that MARS performs better than LR with regards to CCR and AUC values. For sample size 414, MARS clearly performs better than LR regarding the CCR and AUC values.

The values obtained for the metrics of type I error and type II error for each sample size in the second step are as presented in Table 3.

Table 3. MARS and LR Regression analysis metric values obtained for Type I and Type II Error

Sample size	Method	Type I Error	Type II Error
250	MARS	0,172	0,080
	LR	0,136	0,088
500	MARS	0,152	0,102
	LR	0,138	0,116
1500	MARS	0,151	0,131
	LR	0,163	0,126
3000	MARS	0,160	0,116
	LR	0,161	0,130
4148	MARS	0,152	0,128
	LR	0,161	0,131

As seen in Table 3, the values obtained from MARS and LR methods for type I error and type II error metrics for each sample size are given. These values are also shown in Figure 3 and Figure 4.

Figure 3. Type I error

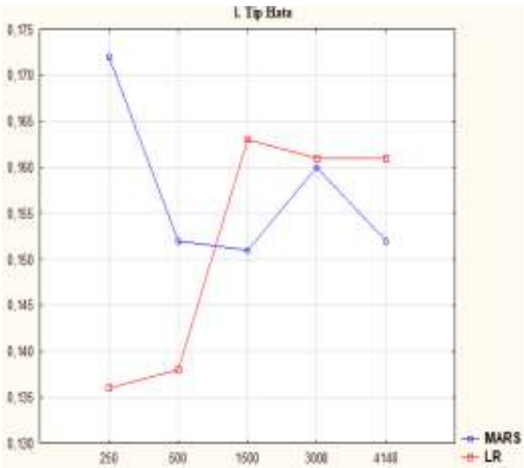
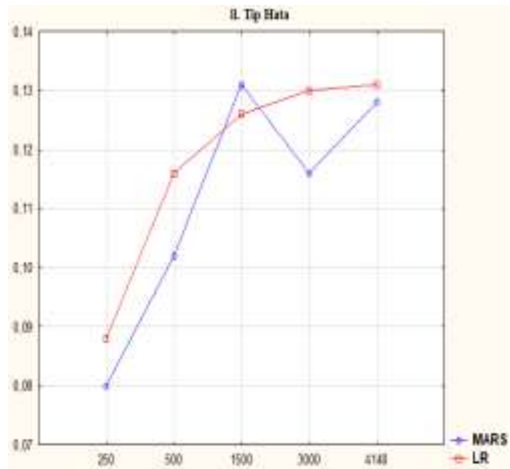


Figure 4. Type II error



As seen in Table 3 and Figures 3 and 4, for sample size 250, LR has lower error values in terms of type I error rate and MARS has lower error values in terms of type II error rate. Therefore, LR performs better for type I error and MARS performs better for type II error for a sample size of 250. For sample size 500, LR has less error values in terms of type I error rate and MARS has less error values in terms of type II error rate. Therefore, LR performs better for type I error and MARS performs better for type II error in 500 samples. For sample size 1500, MARS has less error values in terms of type I error rate and LR has less error values regarding the type II error rate. Therefore, MARS performs better for type I error, and LR performs better for type II error in 1500 samples. For sample size 3000, MARS has less error values than the LR method in terms of type I error and type II error rates. Therefore, MARS performs better than LR for type I and type II error in 3000 samples. For sample size 4148, MARS has less error values than LR with regard to type I error and type II error rates. Therefore, MARS is observed to perform better than LR for type I and type II error in 4148 samples.

CONCLUSION AND RECOMMENDATIONS

This study compared the classification performances of the LR and MARS methods on the data obtained in the field of education. Four classification criteria were determined to compare the classification performances of both analysis methods. The literature review conducted at the beginning of the study revealed that the MARS method is biased for very small sample sizes and that it produces more successful results for large sample sizes (Şevgin & Önen, 2022). Therefore, in the current study, very low sample sizes such as 50 or 100 were not considered and the maximum sample size was determined as 4148 (the number remaining after data cleaning). The relevant literature was also taken into consideration in determining the sample numbers in between.

A review of the literature reveals many studies comparing the classification performance of MARS and LR methods (Austin, 2007; Lin et al., 2008; Jalaluddin, 2009; Felicísimo et al., 2013; Miguéis et al., 2013; Demir, 2014; Conoscenti et al., 2015; Zhang & Goh, 2016; Goh et al., 2017; Park et al., 2017; Ghasemzadeh & Ahmed, 2018; Rotigliano et al., 2018). However, there are no studies that are similar to the current study in terms of both sample size and performance criteria used in these studies. In this sense, the findings obtained from the metrics considered in the current study are discussed in terms of providing clues as to which method researchers will choose according to the sample sizes they can reach.

In our analyses, the LR method showed better classification accuracy in small sample size and the MARS method showed better classification accuracy in large sample size in terms of correct classification rate. In parallel with our study results, studies conducted by Conoscenti et al., 2015, Hasanah et al., 2014, Lee et al., 2006, Miguéis et al., 2013, Park et al., 2017, Tatlıdil & Demirağ, 2009, Wang et al., 2015 and Wibowo & Ridha, 2020 have also reported that the MARS method perform better at large sample sizes. On the other hand, some studies indicate that the LR method performs better than the MARS method at large sample sizes (Austin, 2007; Tollenaar & van der Heijden, 2013). In addition, Rotigliano et al. (2018) state that there is no significant difference between the methods in terms of accuracy and AUC values, but the MARS method is relatively more sensitive and discriminates better, while Weingarten (2023) found no difference between the methods.

In the current study, when analyzed in terms of the AUC value used as a performance indicator, the LR method performed better in small sample size and the MARS method performed better in large sample size. Park et al. (2017) also obtained similar results. On the other hand, there are also studies indicating that the LR method shows better predictive performance in large sample sizes. Austin (2007), Demir (2014) and Ennis et al. (1998) reported that the LR method shows better predictive performance.

With respect to Type I error rate, the LR method has less error rate at small sample size and more error rate at large sample size, while the MARS method has more error rate at small sample size and less error rate at large sample size in the current study. When analyzed in terms of Type II error rate, MARS method has less error rate than LR method in all other sample sizes except 1500 sample size. It was observed that the MARS method gave better results in both error types compared to the LR method. The study conducted by Lee et al. (2006) also supports our results. On the other hand, Afrilia et al. (2021) used the MARS method in a study consisting of 3309 samples, where type I error was 0.00% and type II error was 0.54%. On the other hand, Chuang and Lin (2009) used LR method in a study consisting of 600 samples and found 11% type I error and 52% type II error.

The MARS method has the capacity to model complex relationships without the need for assumptions required in the LR method. Especially in the field of education, the MARS method can be considered as an alternative option instead of the LR method in analyzing data where the dependent variable consists of two categories. The LR method is recommended for small sample sizes, and the MARS method is recommended for large sample sizes to obtain robust and error-free results.

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