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Original Article

Different machine learning methods based prediction of mild cognitive impairment

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Abstract

Aim: In this study benefits from different machine learning methods to analyze factors which affect young person's scores of cognitive assessment.

Material and Methods: This study was performed among 144 persons aged between 18 and 24 who study at Kahramanmaras Sutcu Imam University. Boosted Tree Regression (BTR), Random Forest Regression (RFR) and Support Vector Machine (SVM), which are among machine learning methods, were used in order to determine the factors affecting the score of cognitive assessment. K-10 fold cross validation method was also used. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Correlation coefficients (R) metrics were used in order to measure prediction performances of machine learning methods.

Results: MSE values were calculated as 9.66 for BTR, 9.78 for RFR, and 6.43 for SVM. MAE values were calculated as 2.06 for BTR, 2.05 for RFR, and 1.97 for SVM. RMSE values were calculated as 3.10 for BTR, 3.12 for RFR, and 2.53 for SVM. Finally, correlation coefficients were calculated as 0.289 for BTR, 0.371 for RFR and 0.546 for SVM. In addition, it was also found out that the most important variables which affected the scores of cognitive assessment were anti-depressant use, depression and obsession.

Conclusion: It was demonstrated in this study that SVM displayed the lowest error rates and highest prediction performance in terms of determining the score of cognitive assessment. Therefore, SVM can be stated that it is the most suitable method for the prediction of cognitive impairment.

Keywords: Machine learning; support vector machine; random forest; boosted tree; cognitive impairment

INTRODUCTION

Disorders of perception and attention deficit disorder are usually observed in persons aged over 65 along with mild cognitive impairment and dementia, and affect their social lives negatively. Studies on mild cognitive impairment predicted the prevalence of mild cognitive impairment at a range of 5.0%-36.7% (1). The prevalence of mild cognitive impairment without dementia in persons aged over 71 was reported as 22.2% (2). It is argued that the prevalence of mild cognitive impairment in developed countries will continue to increase in the upcoming years (3-4). Disorders of perception and attention deficit disorder occur in aged persons as a result of physiological aging and are accompanied by mild cognitive impairment, dementia and Alzheimer (5). The reasons for disorders of perception and attention deficit disorder vary in young persons. Cognitive impairment is widely observed in young person's suffering from depression and anxiety (6). It was observed that cognitive abilities such as attention, visual learning and perception malfunction in major depression patients. A significant correlation was found between depression severity and memory and learning performance (7). Meanwhile, young person's lifestyles are heavily influenced by technological developments, which bring about news sources of stress for them. Young persons usually suffer from stress due to their problems in school environment, family members and social circle. These problems cause them to suffer from stress and depression (8). Young people suffering from stress and depression resort to different treatment methods in order to reduce these problems. One of these treatment methods is anti-depressant drug treatments which help reduce

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stress and depression problems. However, it also leads to several cognitive impairments such as attention deficit, perception difficulties and weak memory performance (9). In addition to anti-depressant use, genetic, physiological and psychiatric disorders may sometimes lead to mild cognitive impairment in young persons. Young people suffering from obsession may encounter long-term unobserved cognitive impairments (10). Apart from individual factors, cognitive impairment may also stem from a number of environmental factors such as socio-economic status, level and field of education, traumas, social environment and personal experiences. While the reasons for cognitive impairment in elderly persons can be determined, it may be associated with quite different reasons in young persons. In short, cognitive impairment is an important health problem that affects young person's life quality in a negative way. The first step to treat cognitive impairment is the determination of various factors leading to cognitive impairment.

Linear regression analysis can be used in the prediction of cause and effect relationship among certain variables when the dependent variable and predictor variables are continuous. However, logistic regression analysis can be used when the dependent variable is categorical and predictor variables are either continuous or categorical. Finally, regression trees or machine learning algorithms can be used when the dependent is continuous and predictor variable is categorical.

Machine learning involves artificial intelligence models which perform various tasks such as information extraction, pattern recognition, prediction and diagnosis thanks to data based learning (11). In recent years, machine learning methods have been more widely used compared to conventional prediction models. Various studies in the literature have employed machine learning methods to perform successful predictions using medical data. For instance, Meer et al. used Random Forest Regression (RFR) in order to determine factors which affect the severity of attention deficit and hyperactivity disorder (12). Lee et al. compared the performances of some machine learning methods and logistic regression methods in weighted scores and pointed out that Boosted Tree Regression (BTR) method offers an effective alternative for a high prediction performance (13). Mannson et al. employed Support Vector Machine (SVM), a machine learning method, in order to predict the performance of cognitive behavioral therapy in patients suffering from social anxiety disorder and suggested that SVM could prove to be a useful method in the prediction of treatment performance (14). O'Dwyer et al. classified mild cognitive impairments using SVM method (15). Arslan et al. compared the performances of machine learning methods in order to identify the algorithm that displayed the highest performance in the prediction of ischemic stroke (16). Dreiseitl et al. compared the performance of machine learning methods for the diagnosis of skin lesion related diseases using K-NN algorithm, SVM, Artificial Neural Network (ANN), decision trees and logistic regression (17). Machine learning methods have not only been used in the comparison of prediction and diagnosis performances. These methods also lay the foundation of numerous medical diagnosis models. Nahar et al. focused on machine learning methods based on medical knowledge approach for the diagnosis of cardiac diseases through artificial intelligence (18). Asri et al. benefited from machine learning methods in order to predict breast cancer risk and diagnose breast cancer (19). Machine learning methods are widely used in the diagnosis of cognitive disorders or early diagnosis, too. These methods are often used in the classification of MRI images as far as the diagnosis of cognitive disorders is concerned. Munteanu et al. used ANN method for the classification of Alzheimer and mild cognitive impairment, and classified MRI images using ANN (20). Chen and Herskovits dealt with different machine learning algorithms and MRI images to create a diagnosis model for mild cognitive impairment and Alzheimer (21). So et al. analyzed the machine learning method with the highest performance in the early diagnosis of cognitive impairment and dementia based on the clinical data, and reported that SVM method displayed the highest performance in the early diagnosis of cognitive impairment (22). Weakley et al. stated that machine learning methods could be used to reduce the number of neuropsychological tests in the diagnosis of cognitive impairment and thus offer a time-saving approach for the diagnosis process (23).

Many studies have so far been conducted on the analysis of factors leading to cognitive impairment in adult and elderly persons. However, the number of studies on the factors causing cognitive impairment in young persons is limited. The effects of modern day problems on the cognitive impairment are seldom analyzed. In this respect, the present study aims to compare the performances of different machine learning methods in the prediction of various factors leading to cognitive impairment in young persons.

MATERIAL and METHODS

Data Set

In this study was carried out on 144 young persons aged between 18 and 24 and studying at Kahramanmaras Sutcu Imam University. For this purpose, an ethical approval dated 2018/05 and numbered 23 was obtained from the Kahramanmaras Sutcu Imam University Clinical Research Ethics Committee. α: 0.05 type I error (alpha), 0.20 type II error (beta), 0.80 test power and 0.5 effect size and power analysis in order to determine sample size. The data set consists of predictor variables and a dependent variable. Independent (predictor) variables contain variables affecting an individual's cognitive state, and demographic information defining an individual such as gender, age, area of study, mental disability in family history, Alzheimer in family history, trauma in history, obsession, smoke, sleep disorder, depression and use of anti-depressant. The dependent variable consists of scores obtained from Turkish version of Moca cognitive assessment test used to determine individual's cognitive state (24-25). This test is widely used to mental diseases such as diagnose mild cognitive impairment and Alzheimer. It assesses an individual's attention, visual construction, memory, concentration, calculation, abstraction, orientation and executive functions. The maximum test score is 30. The dependent and predictor variables in the data set are given in Table 1.

Pre-analysis of Data Set

Outliers in the quantitative variables of the data set were identified using Local Outlier Factor (LOF) and removed from the study. Feature selection was performed in order to determine important features that affect cognitive state, and these features were found as gender, use of anti-depressant, obsession, depression and area of study.

Table 1. Definition of predictor and dependent variables

Variables	Variable Type	Definition	Role
Cognitive Test Score	Numerical	Natural Number	Target(Dependent)
Age	Numerical	Natural Number	Input(Predictor)
Mental disability in family history	Categorical	Present/Absent	Input(Predictor)
Alzheimer in family history	Categorical	Present/Absent	Input(Predictor)
Sleep Disorder	Categorical	Present/Absent	Input(Predictor)
Trauma in history	Categorical	Present/Absent	Input(Predictor)
Smoke	Categorical	Use/No use	Input(Predictor)
Gender	Categorical	Female/Male	Input(Predictor)
Obsession	Categorical	Present/Absent	Input(Predictor)
Antidepressant	Categorical	Use/No use	Input(Predictor)
Depression	Categorical	Present/Absent	Input(Predictor)
Area of Study	Categorical	Engineering Science/ Social Science/ Health Science/ Educational Science	Input(Predictor)

Boosted Tree for Regression

Boosted Tree for Regression was designed as a combination of regression trees and boosted techniques in order to improve prediction performances. In this method, the data sub-clusters are iteratively and randomly selected in order to minimize loss function. Tree based models in this algorithm perform iterative tasks until they reach a minimum deviation value (26). Boosted tree for regression consists of four parameters: learning rate, number of trees, tree complexity and bag fraction. Parameter optimization is recommended in order to maximize the prediction performance. The ideal parameter values for number of trees, learning rate, tree complexity and bag fraction are 1000, 0.0025, 9 and 0.75, respectively (26).

Random Forest for Regression

A supervised learning algorithm, Random Forest algorithm performs predictions using a number of decision trees for regression problems. It calculates a mean of the predictions obtained from each tree. There are two main parameters in this algorithm as the number of variables to be used in each node for splitting (m) and the number of trees (n). There is an f bagging consisting of h_1 (x),… ,h_j (x) tree learners which are combined to create a f(x) predictor. The following equation is used to mean of learners' predictions (Eq.1) (27-28):

$$f(x) = \frac{1}{J}\sum_{j=1}^{J} h_j(x)$$

Support Vector Machine

Support vector machine is a powerful Kernel function based machine learning algorithm for classification and regression problems. It aims to find a regression function in a hyperspace. Each input in the training data set of the support vector machine predicts y values with a minimum deviation. It aims to minimize the distance between two planes within the training data sets (29).

Modeling and Performance Assessment

K-10 fold cross validation method was used to eliminate any overfitting problems in the model. The seed number was randomly set. 70% of the data set was used for training and the remaining 30% was used for testing and validation in boosted tree and random forest methods. Weka, R 3.3.2 software and IBM SPSS version 22 (IBM

SPSS for Windows version 22, IBM Corporation, Armonk, New York, United States) were used for data modeling and analysis. Grid search algorithm was used for parameter optimization. Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), R^2 and R metrics were used in order to analyze the prediction performances of the models and algorithms. Error of Machine Learning Methods for train and test datasets is shown in Figure 1.

In this model, the error is defined by $e_i=(P_i-O_i)$ when predictions are denoted by P_i $(i=1,2,\ldots,n)$, and observations are represented by O_i $(i=1,2,\ldots,n)$. Other equations are as follows:

$$\text{Mean Squared Error (MSE)} = \frac{1}{n}\sum_{i=1}^{n} e_i^2$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{n}\sum_{i=1}^{n} |e_i|$$

$$\text{Root Mean Squared Error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$$

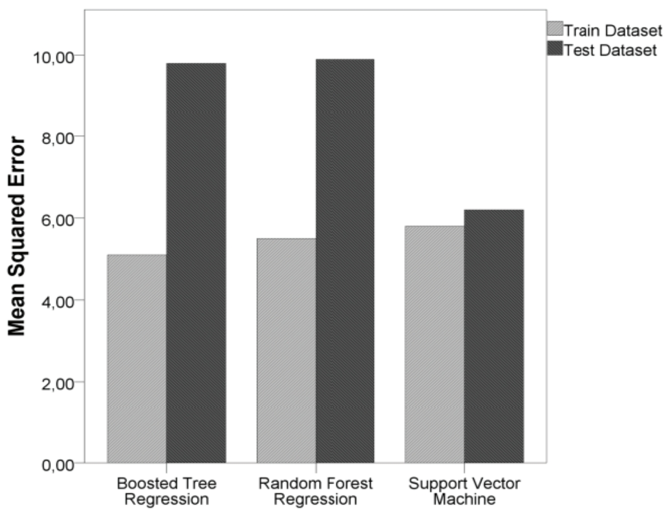

Figure 1. Error of machine learning methods for train dataset and test dataset

RESULTS

First, the outliers in the present study were analyzed, no outliers were found in the data set. While male comprise 34.7% of 144 participants, female comprise 65.3% of them. 14.58% of the participants have used anti-depressants in the past. Mean age of the participants was calculated as 20.58±3.50.

MSE, MAE and RMSE metrics were used in order to analyze the performances of machine learning methods used in the analysis of factors affecting young persons' scores of cognitive impairment. MSE, MAE and RMSE values were calculated 2.06, 9.66 and 3.10 for BTR method, respectively. MSE, MAE and RMSE values were calculated 2.05, 9.78 and 3.12 for RFR method, respectively. MSE, MAE and RMSE values were calculated 1.97, 6.43 and 2.53 for SVM method, respectively. It can be understood from these values that the lowest error rates and highest performance was displayed by SVM method. When correlation coefficients (r) between prediction values (p_i) and observation (o_i) values are analyzed, they were calculated as r= 0.289, r= 0.371 and r= 0.546 for BTR, RFR and SVM, respectively. It can be thus stated that SVM displayed the highest performance in the prediction of young persons scores of cognitive assessment. Error rates and correlation coefficients for each method are given in Table 2. Performance Metrics of Machine Learning Methods are shown in Figure 2.

Table 2. The performance metrics of machine learning methods

	MAE	MSE	RMSE	R	R^2
Boosted Tree Regression	2.06	9.66	3.10	0.289	0.083
Random Forest Regression	2.05	9.78	3.12	0.371	0.138
Support Vector Machine	1.97	6.43	2.53	0.546	0.298

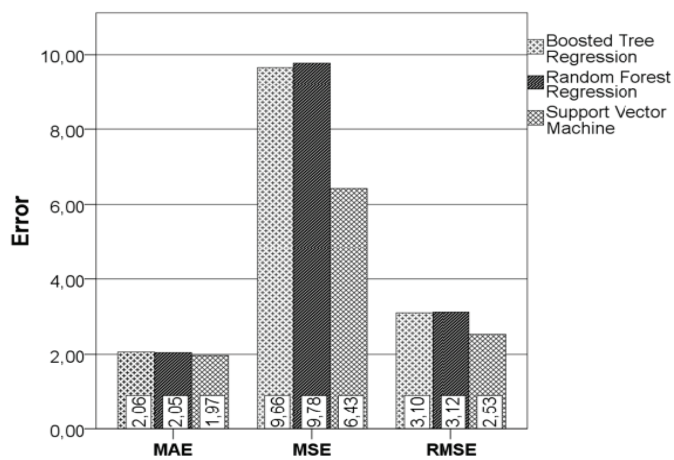

Figure 2. Performance metrics of machine learning methods

Taking SVM which displays the highest prediction performance for young persons' cognitive assessment into account, it was observed that the most significant factor affecting score of cognitive assessment was anti-depressant use, followed by obsession and depression. The values regarding the significance of each variable are given in Table 3. Moca test results were taken into account

Table 3. Importance of predictor variables for SVM

Predictor Variables	Importance (Normalized)
Antidepressant	100.00
Obsession	78.75
Depression	72.65
Area of Study	36.55
Gender	24.41

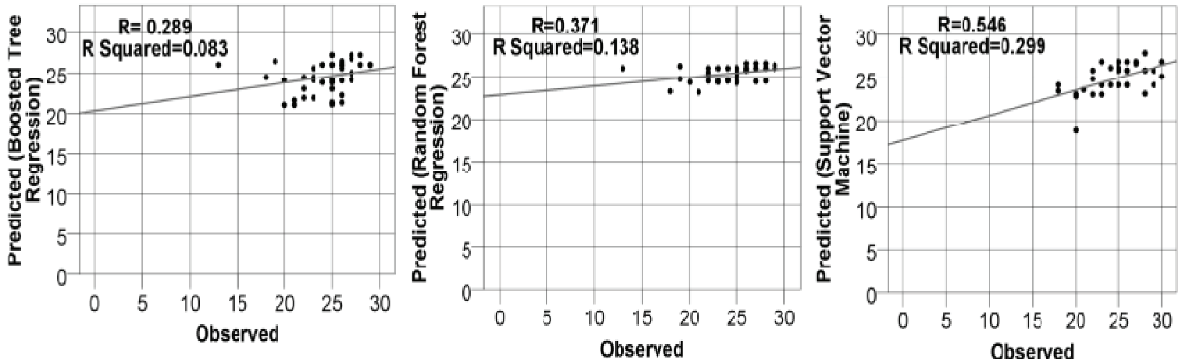

Figure 3. Prediction performances of machine learning methods

to measure the scores of cognitive assessment based on each factor. It was found out that individuals with the lowest score of cognitive assessment were those using anti-depressants and suffering from depression and obsession. While individuals using anti-depressants had an mean score of 22.66±3.16 in the test, those who did not use anti-depressants had an mean score of 25.21±2.79, which was a statistically significant difference (p<0.001). The performance of each machine learning method for training and testing datasets is shown in Figure 1. In addition, the prediction performances of machine learning methods are shown in Figure 3. Finally, the importance of each predictor variable is shown in Figure 4.

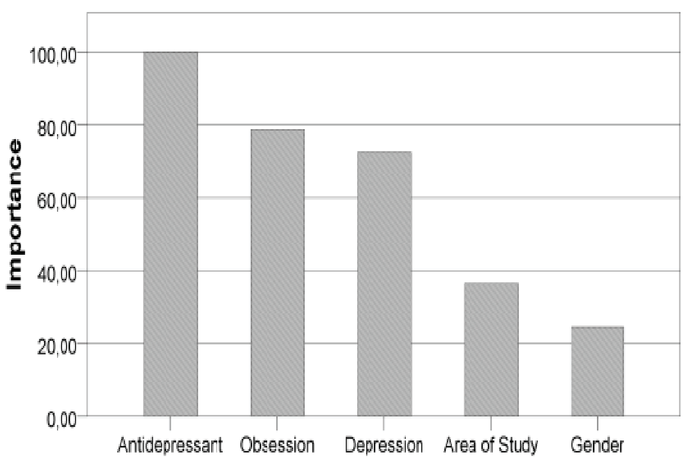

Figure 4. Importance of predictor variables for SVM

DISCUSSION

In recent years, machine learning methods have been widely used in the field of medicine. When predictor variables are categorical and the dependent variable is continuous, machine learning algorithms can display high performance predictions. Shirmohammadi-Khorram et al. compared the performances RFR, SVM and MARSs methods to predict brucellosis surveillance in the upcoming periods (30). The findings of this study demonstrated that RFR displayed the highest performance in terms of predicting brucellosis surveillance on a monthly basis. While the performances of RFR and SVM were closer, MARSs display a relatively lower performance. On the other hand, the findings of the present study indicated that SVM displayed the highest performance, while the performance of RFR was closer to it. Khalid et al. compared BTR, multiple linear regression and SVM methods in order to predict blood pressure and reported that BTR displayed the highest performance in terms of predicting blood pressure (31). Valizadeh and Sohrabi compared SVM and ANN methods in order to determine the ideal amount of eye drop and suggested Radial basis function based SVM method because it displayed the highest performance (32). Guo et al. compared different machine learning methods in order to predict the development of Dengue virus in China, and reported that the lowest error value was obtained from SVM model (33). Liu et al. analyzed the performances of 9 different machine learning algorithms in a study focusing on pharmacogenetics dosing of Warfarin, and reported that Bayesian additive regression tree, MARS and SVM algorithms displayed the highest performances (34). The findings of the present study overlap the above-mentioned studies since it was demonstrated that SVM displayed the highest prediction performance.

When the present study is analyzed in terms of clinical findings, it was observed that different factors affected young persons' scores of cognitive assessment. It was found out that young individuals who used anti-depressants and suffered from depression and obsession had the lowest score of cognitive assessment. Swardfager and MacIntosh analyzed the relationship between Type 2 diabetes and stroke and scores of cognitive assessment and cognitive impairment, and found a correlation between Type 2 diabetes following stroke and depression and cognitive impairment (35). Studies on cognitive impairment and level of cognitive assessment have been generally conducted on elderly persons because they usually emerged prior to Alzheimer and dementia (36-38). In young persons, on the other hand, depression is considered as one of the main reasons for cognitive impairment. Similarly, the findings of the present study indicated that depression was one of the main reasons for cognitive impairment. In addition, depression was also a significant factor causing a low score of cognitive assessment and use of anti-depressant.

CONCLUSION

As a result, SVM, RFR and BTR machine learning algorithms used in the model can be effectively used to predict score of cognitive assessment. It was demonstrated that SVM method displayed the highest performance in terms of predicting score of cognitive assessment. In addition, it was observed that anti-depressant, depression and obsession affected score of cognitive assessment in young persons.

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