Anatolian Journal of Computer Sciences

Volume:3 No:2 2018 © Anatolian Science

pp: 15-23 ISSN:2548-1304

EXTREME LEARNING MACHINES BASED ANALYSIS OF THE IMPACT OF ACTION LEARNING ON DECISION-MAKING STYLES OF SCHOOL ADMINISTRATORS

Dönüş Şengür[1], Muhammed Turhan[2], Songül Karabatak[3]*

*[*1] Şht.Pyd. Bnb. Zafer KILIÇ Anadolu İmam Hatip Lisesi, Elazig, Turkey, (kdksengur@gmail.com)*

[2] Fırat University, Faculty of Education, Elazig, Turkey (muhammedturhan66@gmail.com)

[3] Fırat University, Department of Informatics, Elazig, Turkey (skarabatak@firat.edu.tr)

Received:12.08.2018
Accepted: Sep. 2018
Published:Sep. 2018

Abtract—School administrators need to be trained by using practice-based training approaches to make right decisions. Action learning (AL) is one of the approaches to serve this aim. But, there is a need for empirical evidences to show the impact of learning action on school administrators' decision-making styles. In this paper, a novel framework is proposed for determination of the school administrators who trained through an AL course where they improved their decision-making skills for various conditions and environments. To this end, a popular single layered feed forward neural network structure namely extreme learning machine (ELM) is used to distinguish the trained and non-trained school administrators based on their Melbourne Decision Making Questionnaire (MDMQ) output. The MDMQ output is a data set where it was constructed based on a pre-test and post-tests. The pre and post-tests were applied to a number of school administrators and school administrator candidates in Elazig providence in Turkey. MDMQ was used to collect data before and after the AL course. A series of computer simulations were carried out on MATLAB environment. 5-fold cross validation technique is used in evaluation of the proposed method. The achievements were measured by accuracy, sensitivity and specificity criteria. The computer simulations show that ELM produced reasonable results in distinguishing trained and non-trained school administrators. We further compare the ELM results with several support vector machines (SVM) classifiers. In comparisons, it is seen that both ELM and SVM methods performed better in three different simulations. Results showed that AL based training course has a measurable impact on school managers' decision-making styles.

Keywords : *Decision-making, action learning, school administrators, MDMQ, ELM and SVM.*

1. Introduction

In recent years, criticism about school administrators training programs has increased. These criticisms are mostly related to the link between theory and practice in the breeding programs has not been sufficiently established (Hallinger & Bridges, 2007; Karabatak & Turhan, 2015). Theoretical weighted training programs provide school administrators with theoretical knowledge of school management, but they are inadequate about the reflection of the theory to practice (Cardno & Piggot-Irvine, 1996). The gap between the theory and practice in the training programs is not sufficiently effective in the development of school administrators' decision making skills.

The decision making is defined as a set of actions and factors that begin with the identification of a stimulus for action, and end with the specific commitment to action (Mintzberg, Raisinghani, & Théorêt, 1976). In recent years, school administrators often encounter various problems while teaching, counseling, promoting and providing other services which convey them to take some decisions. The development of effective decision-making skills is one of the key objectives of school administrators training programs. AL is an effective way to train school administrators in order to improve their decision making styles (Dilworth & Boshyk, 2010). AL is defined as an approach that can provide learning and problem solving skills for the change of individual, the team, the organization, and even the whole system (Pedler, 2012). It is also defined as a process in which a group of volunteer colleagues who come together to work on unclear and real problems reflect their continuous learning and learning (Brockbank & McGill, 2003).

Experimental and quasi-experimental designs are frequently used in social science research. Particularly in the field of educational sciences, the effectiveness of education or training programs is evaluated by comparing pretest and post-test scores. Determining the differences in perception, attitude, or skills before and after participating in a training program is considered necessary for making training programs more effective. *t*-test as parametric test or Mann Whitney U test as non-parametric test are used in analyzing pretest and post-test scores of the individuals participating in the training programs. The use of new statistical methods and data mining techniques in experimental research has not attracted much attention of researchers. The main purpose of this research is to classify the pre-test and post-test scores of decision-making styles of school administrators participating in an AL course by using extreme learning machines. This research brings important contributions to related literature from two perspectives. First, the effectiveness of AL approach in development of school administrators' decision-making styles is examined. Second, the usability of extreme learning machines in experimental researches is shown.

In this work, extreme learning machine (ELM) is used to analyze if an AL experience had a positive impact on school administrators decision-making skills. Recently, artificial intelligence (AI) methods have been densely used in educational applications (Turhan, Şengür, Karabatak, Guo, & Smarandache, 2018; Şengür & Tekin, 2013). In this work, 38 volunteer administrators from Elazig/Turkey were administered a pre and a post-tests of the MDMQ (Mann, Burnett, Radford, & Ford, 1997). The pre-test was applied to the administrators before AL experience and post-test was applied after the experience. The MDMQ is composed of two parts. The first part of MDMQ aims to determine the self-esteem level in decision-making by using six items and one sub-scale. The second part of MDMQ aims to determine the decision-making styles by using 22 items and four sub-scales namely Vigilance, Buck Passing, Procrastination, and Hypervigilance. In the AI perspective, we approach the problem if ELM can determine whether AL program affects the participated administrators positively. Moreover, we investigate if MDMQ questions are capable to reflect the improvement in decision-making skills after training. To do so, the pre-test participates are labeled as non-trained and the managers who participated in the training and have post-test are labeled as trained. Various computer simulations are handled to evaluate the proposed idea based on the two scenarios. In the first one, all MDMQ factors are used to predict if a school administrator is trained or not with an AL program. In the second scenario, the each MDMQ factor is used individually to predict if a school administrator is trained or not with an AL program. In the first scenario, ELM obtained 97.32% accuracy, 100% sensitivity and 95.25% specificity scores. The obtained results for second scenario are also presented accordingly. We further compared the ELM achievement with several SVM techniques and the related comparisons are presented.

The organization of the paper is as following. In next section, the related theories are given briefly. ELM, MDMQ and data set collection is introduced in section 2. In section 3, the computer simulations and results are given. The paper is concluded in section 4.

2. Related Theories

In this section, we briefly review related theories. The reader may refer to related references for detailed information about those theories.

2.1. Extreme Learning Machine (ELM)

Extreme learning machine (ELM), which was constructed as a single layer feed-forward neural networks (SLFN) structure, aims to learn a classification or regression problem with zero error by calculating the hidden layers weight analytically (Huang, Zhu, & Siew, 2006; Alcin, Sengur, Ghofrani, & Ince, 2014; Alcin, Sengur, & Ince, 2015). Thus, it alleviates the deficiencies (slow convergence and stuck in the local minimum) of the standard back-propagation learning algorithm.

The output of the ELM o_i can be calculated as;

$$o_i = \sum_{j=1}^{L} \beta_j g(a_j, b_j, x_i), i = 1,2, \ldots, N \qquad (1)$$

where L is the number of neurons in the hidden layer and $\beta_j = [\beta_{j1}, \beta_{j2}, 2\beta_{jn}]^T$ is the output weight vector, b_j is the bias of the j^{th} hidden node, $g(.)$ is the activation function, x_i is the i^{th} input data, $a_j = [a_{j1}, a_{j2}, \ldots, a_{jn}]^T$ is the weight vector of input layer and N shows the number of samples.

Thus, if ELM learns these N samples with zero error as it aims, then Eq. (1) can be re-written follows;

$$t_i = \sum_{j=1}^{L} \beta_j g(a_j, b_j, x_i), i = 1,2, \ldots, N \qquad (2)$$

where t_i shows the actual output. Moreover, Eq. (2) can be arranged as shown in Eq. (3);

$$H\beta = T \qquad (3)$$

where $H = \{h_{ij}\} = g(a_j, b_j, x_i)$ is the hidden-layer output matrix. The analytical calculation of the hidden layer weights is given as in Eq. (4).

$$\hat{\beta} = H^{+T} \qquad (4)$$

where H^+ is the Moore-Penrose generalized inverse of matrix H and T is the actual output vector.

2.2. Melbourne Decision-Making Questionnaire (MDMQ)

The MDMQ, which is known as one of the efficient decision making assessment tools, was designed by Mann et al. in 1997 (Dilworth & Boshyk, 2010). The main aim of the MDMQ was to assess the individual's decision making styles in various situations. To this end, authors proposed a comprehensive study which covers university students from six countries namely US, Australia, New Zealand, Japan, Hong-Kong and Taiwan, to compare the university student's self-esteem as decision-making and decision-making styles. The MDMQ was translated in Turkish by Deniz (2011) to determine decision-making styles of Turkish university students and to carry out comparative studies with students from other countries.

The MDMQ is composed of two parts. The first part of MDMQ aims to determine the self-esteem level in decision-making by using six items and one sub-scale. The second part of MDMQ aims to determine the decision-making styles by using 22 items and four sub-scales namely Vigilance, Buck Passing, Procrastination, and Hypervigilance. The vigilant decision maker carefully searches the necessary information and evaluates the alternatives carefully, before making a decision. Buck passing decision maker rejects to making a decision and tends to leave it to others. Thus, it is aimed to get rid of the decision by transferring responsibility to another person. Procrastination decision maker generally delays or abandonments a decision without any valid reason. Hypervigilance decision maker feels him/herself under the time pressure and shows hasty behaviors and aims to reach quick solutions. In other words, hypervigilance is a `panic'-like state in which the decision maker vacillates between unpleasant alternatives (Dilworth & Boshyk, 2010).

2.3. Study Groups and Data Collection

An experimental study was constructed where experimental groups were used. The statement on ethics for this study was approved by Firat University ethical commission with protocol number 05/04/2017-195525. The experimental studies are also defined as intervention studies or group comparison studies that experimental researchers test an idea (or practice or procedure) to determine its effect on an outcome (Creswell, 2012). The repeated measures design is considered as the experimental designs. Repeated measures design has the advantage of employing only a single group. Thus, all participants in a single group participate in all experimental treatments, with each group becoming its own control. The researcher compares the group's performance under one experimental treatment with its performance under another experimental treatment (Creswell, 2012). The appearance of the experimental design is presented in Table 1.

Table 1. Repeated measures design

Group	Pre-test	Process	Post-test
Experimental group	MDMQ	AL experiences	MDMQ

The participants constituting the experimental group of the research were determined by the purposeful sampling method. To access the further information is provided by purposeful sampling especially in accordance with the purpose of the Büyüköztürk, Çakmak, Akgün, Karadeniz, & Demirel, 2011). Thus, the study was carried out with the participants who were most appropriate to the purpose of the research. Volunteerism was taken as a criterion when participants were determined. Experimental study was constructed with 38 school administrators and administrator candidates from Elazig/Turkey province center. Attention has been paid to the fact that the participants in the group are experienced and inexperienced. 15 (39.5%) participants were experienced, and 23 (60.5%) of them were inexperienced administrators.

3. Computer Simulations and Results

The ELM technique was used to analyze if an AL experience resulted in school administrators more productive to extend their decision making skills. Various computer simulations were constructed where a pre and post-tests were used to the school administrators before and after AL experience in MATLAB environment. The pre-test participates were labelled as non-trained and the administrators who participated in the training and have post-test were labelled as trained. 5-fold cross validation test was used in the evaluation of the employed ELM technique. The accuracy, sensitivity and specificity values were recorded. The sigmoid function was considered for the activation function of the ELM. The input dataset was normalized according to zero mean and unit variance criterion. It is worth to mentioning that the other activation functions such as "sine", "hardlim" and "radbas" were also used in the experiments. The best results were obtained with the sigmoid function and the sigmoid function results were given in the paper.

During the simulation works 5-fold cross validation method was adopted and two scenarios were analyzed and the results were evaluated based on accuracy, sensitivity and specificity values. In the first scenario, whole scale items were considered to predict if AL course had a positive impact on school administrators decision making styles based on their MDMQ answers. In the second one, each factor of MDMQ was used to determine trained and non-trained school administrators in order to determine the relationship between the factors and the trained and non-trained clusters. Table 2 shows the obtained accuracy values for the first scenario.

Table 2. Prediction results for the first scenario

Method	Accuracy	Sensitivity	Specificity
ELM	97.32%	100%	95.25%

As seen in Table 2, ELM technique achieved 97.32% accuracy, 100% sensitivity and 95.25% specificity, respectively. 100% sensitivity shows that all non-trained labelled samples were determined correctly.

In the first simulation of the scenario 2, the first part of the MDMQ was used. As it was mentioned earlier, the first part of MDMQ measures the self-esteem level in decision making. As self-esteem level covers 6 items, the input of ELM is 6-dimensional. The obtained evaluation scores are given in Table 3.

Table 3. Prediction results for the second scenario. The self-esteem level was used as input to ELM.

Method	Accuracy	Sensitivity	Specificity
ELM	97.32%	100%	95.25%

As seen in Table 3, the obtained results were dropped dramatically when compared with results depicted in Table 2. The calculated accuracy, sensitivity and specificity scores were 60.61%, 59.01% and 66.90%, respectively.

In the second simulation of the scenario 2, the hypervigilance factor was used as input to ELM. The hypervigilance factor covers 5 items and obtained results were tabulated in Table 4.

Table 4. Prediction results for the second scenario. The hypervigilance was used as input to ELM.

Method	Accuracy	Sensitivity	Specificity
ELM	81.81%	76.49%	90.95%

As seen in Table 4, hypervigilance factor performed better than self-esteem level in determination of the trained and non-trained school administrators. The calculated accuracy was 81.81%, sensitivity was 76.49% and specificity was 90.95%, respectively.

In the third simulation of the scenario 2, the vigilance factor, which covers 6 items, was used as input and the obtained achievements were given in Table 5.

Table 5. Prediction results for the second scenario. The vigilance was used as input to ELM.

Method	Accuracy	Sensitivity	Specificity
ELM	90.89%	94.92%	88.89%

As seen in Table 5, the calculated accuracy score was 90.89% and the calculated sensitivity and specificity scores were 94.92% and 88.89%, respectively. When Tables 5 and 6 are compared, it is seen that calculated vigilance factor’s accuracy and sensitivity scores are higher than the hypervigilance factor’s accuracy and sensitivity scores. On the other hand, the hypervigilance factor’s specificity score is higher than the vigilance factor’s specificity score.

Table 6. Prediction results for the second scenario. The Buck Passing was used as input to ELM.

Method	Accuracy	Sensitivity	Specificity
ELM	94.64%	93.33%	97.78%

In table 6, the obtained scores for buck passing factor are given. The buck passing factor contains 6 items and the obtained results are better than the other results that were obtained in the second scenario coverage. 94.64% accuracy, 93.33% sensitivity and 97.78% specificity scores were obtained as shown in Table 6.

Table 7. Prediction results for the second scenario. The Procrastination was used as input to ELM.

Method	Accuracy	Sensitivity	Specificity
ELM	56.50%	56.78%	55.77%

Finally, Table 7 shows the obtained prediction results for procrastination factor which has 5 items. As seen in Table 7, the calculated accuracy, sensitivity and specificity scores were the worst ones in all second scenarios' prediction results (Tables 3-6). The obtained accuracy, sensitivity and specificity scores were 56.50%, 56.78% and 55.77% respectively.

We further compared the obtained accuracy scores with Support Vector Machine (SVM) techniques for both scenarios. SVM is an important and efficient supervised classification algorithm which searches the best hyperplane where the separation of data points of one class from others is guaranteed (Vapnik, 1995; Burges, 1998). The MATLAB classification learner application was used which enables the user to explore various SVM classifiers. The classification learner application presents six different SVM algorithms such as linear (l), quadratic (Q), cubic (C), fine Gaussian (FG), medium Gaussian (MG) and coarse Gaussian (CG), respectively. The produced all results were tabulated in Table 8.

Table 8. Prediction accuracies obtained with SVM and ELM techniques for the first scenario. The bold case shows the highest accuracy.

Classifier Type	Accuracy (%)
L SVM	97.1
Q SVM	**98.1**
C SVM	97.1
FG SVM	59.2
MG SVM	96.1
CG SVM	93.4
ELM	97.3

As seen in Table 8, except Fine Gaussian SVM, all SVM techniques produced reasonable achievements. Quadratic SVM technique yielded the best achievement where the calculated accuracy score was 98.1%. ELM method obtained the second best accuracy score with 97.3% value and the third best results were obtained by Linear and Cubic SVM techniques. The worst accuracy was produced by the Fine Gaussian SVM where the calculated accuracy was 59.2%.

Table 9. Prediction accuracies obtained with SVM and ELM techniques for the second scenario. The self-esteem level was used as input. The bold case shows the highest accuracy.

Classifier Type	Accuracy (%)
L SVM	59.2
Q SVM	59.2
C SVM	57.9
FG SVM	60.1
MG SVM	48.7
CG SVM	55.3
ELM	**60.6**

We also compared the SVM and ELM methods on the second scenario where the self-esteem level was used as input. The obtained results were given in Table 9. As seen in Table 9, the ELM method achieved the best accuracy score. The calculated accuracy was 60.6% and the second best accuracy was performed by Fine Gaussian SVM technique where the recorded accuracy was 60.1%.

In the second comparison of the scenario 2, the hypervigilance factor was used as input to both ELM and SVM techniques and obtained results were tabulated in Table 10.

Table 10. Prediction accuracies obtained with SVM and ELM techniques for the second scenario. The hypervigilance factor was used as input. The bold case shows the highest accuracy.

Classifier Type	Accuracy (%)
L SVM	78.9
Q SVM	81.0
C SVM	78.9
FG SVM	76.3

MG SVM	81.3
CG SVM	80.3
ELM	**81.8**

As seen in Table 10, ELM method outperformed for hypervigilance factor with 81.8% accuracy score. The Medium Gaussian SVM achieved the second best performance with 81.3% accuracy score. ELM's accuracy score is 0.05% better than the Medium Gaussian SVM's accuracy score.

Table 11. Prediction accuracies obtained with SVM and ELM techniques for the second scenario. The vigilance factor was used as input. The bold case shows the highest accuracy.

Classifier Type	Accuracy (%)
L SVM	**93.1**
Q SVM	91.7
C SVM	91.7
FG SVM	85.2
MG SVM	89.1
CG SVM	90.4
ELM	90.9

The comparisons for vigilance factor are given in Table 11. As seen in Table 11, with 93.1% accuracy score the linear SVM method achieved the highest accuracy score. In addition, Quadratic and Cubic SVM techniques were also produced better accuracy scores than the ELM method. ELM method only produced better accuracy score than Fine Gaussian, Medium Gaussian and Coarse Gaussian SVM techniques, respectively.

In Table 12, we show the comparison results for the Buck Passing factor. As seen in Table 12, ELM method achieved the highest accuracy score. It is also worth to mentioning that all SVM techniques produced reasonable accuracy scores. Quadratic, Cubic and Medium Gaussian SVM techniques produced accuracy scores over 94.0% which are quite close to ELM achievements.

Table 12. Prediction accuracies obtained with SVM and ELM techniques for the second scenario. The Buck Passing factor was used as input. The bold case shows the highest accuracy.

Classifier Type	Accuracy (%)
L SVM	93.1
Q SVM	94.4
C SVM	94.1
FG SVM	86.3
MG SVM	94.5
CG SVM	93.1
ELM	**94.6**

The last comparisons were done on the Procrastination factor and the related results were tabulated in Table 13. As seen in Table 13, all SVM techniques obtained higher accuracy scores than the ELM technique. The best accuracy was obtained by linear SVM technique where the accuracy was 73.7%. This score is almost 17% higher than the ELM's achievement. Coarse Gaussian SVM also produced 72.4% accuracy score, which is the second highest accuracy score.

Table 13. Prediction accuracies obtained with SVM and ELM techniques for the second scenario. The Procrastination factor was used as input. The bold case shows the highest accuracy.

Classifier Type	Accuracy (%)
L SVM	**73.7**
Q SVM	63.2
C SVM	59.2
FG SVM	59.2
MG SVM	69.7

CG SVM	72.4
ELM	56.5

4. Conclusions

In this paper, we used an artificial intelligence technique namely ELM to determine if an AL experience resulted in school administrators more productive to extend their decision making skills. There have been so many works that have been carried out with ELM. To this end, MDMQ and MATLAB software is used. The MDMQ is composed of two parts and MATLAB software is used to construct several computer simulations for classification purposes. The computer experiments (simulations) are carried out with 5 fold cross validation technique and the classification accuracy, sensitivity and specificity scores are calculated to evaluate the classification performance. The computer experiments are conducted based on the two scenarios. In the first one, all MDMQ factors are used to predict if a school administrator is trained or not with an AL program. In the second scenario, the each MDMQ factor is used individually to predict if a school administrator is trained or not with an AL program. In the first scenario, ELM obtained 97.32% accuracy, 100% sensitivity and 95.25% specificity scores. In the second scenario, vigilance and buck passing factors obtained accuracy scores over 90.0%, but other factors such self-esteem level, hypervigilance and procrastination produced low accuracy scores than other. Especially, self-esteem level and Procrastination factors achievements were around 60%. In the comparisons with SVM techniques, it was seen that SVM technique produced better accuracy score than ELM method for scenario 1. In addition for second scenario, SVM method outperformed for vigilance and procrastination factors. ELM method also outperformed for self-esteem level, hypervigilance and buck passing factors respectively.

This study has contributions for both educational research and educational administration field. Firstly, results have shown that extreme learning machines can be used in experimental research in the field of education to measure the difference between pre-test and post-test scores by using classification accuracy. Secondly, considering the accuracy level of classification between before and after the course, it can be said that AL approach has a remarkable effect on school administrators' decision making skills. Therefore, AL approach can be used to develop decision-making skills of school administrators.

5. References

Alcin OF, Sengur A, Ghofrani S, Ince MC (2014) GA-SELM: greedy algorithms for sparse extreme learning machine. *Measurement* 55:126–132.

Alcin OF, Sengur A, Ince MC (2015) Forward–Backward Pursuit Based Sparse Extreme Learning Machine. *Journal of The Faculty of Engineering and Architecture of Gazi University* 30(1):111–117.

Brockbank A, McGill I (2003) The Action Learning Handbook: Powerful Techniques for Education, Professional Development and Training, Routledge.

Burges C (1998) A Tutorial on Support Vector Machines for Pattern Recognition. *Data Mining and Knowledge Discovery* 2(10): 121–167.

Büyüköztürk Ş, Çakmak EK, Akgün ÖE, Karadeniz Ş, Demirel, F (2011) Bilimsel Araştırma Yöntemleri, PegemA Publishing, Ankara.

Cardno C, Piggot-Irvine, E (1996) Incorporating Action Research in School Senior Management Training. *International Journal of Educational Management* 10(5): 19-24.

Creswell JW (2012) Educational Research: Planning, Conducting, and Evaluating Quantitative, Fourth Edition, Upper Saddle River, New Jersey.

Deniz ME (2011) An Investigation of Decision Making Styles and the Five-Factor Personality Traits with Respect to Attachment Styles. *Kuram ve Uygulamada Egitim Bilimleri* 11(1): 105.

Dilworth RL, Boshyk Y (Eds.) (2010) Action Learning and its Applications, Palgrave Macmillan, London.

Hallinger P, Bridges EM (2007) A Problem-based Approach for Management Education: Preparing Managers for Action, Springer Science+Business Media B.V., London, New York.

Huang GB, Zhu QY, Siew CK, (2006) Extreme Learning Machine: Theory and Applications. *Neurocomputing* 70: 489–501.

Mann L, Burnett P, Radford M, Ford S (1997) The Melbourne Decision Making Questionnaire: An Instrument for Measuring Patterns for Coping with Decisional Conflict. *Journal of Behavioral Decision Making* 10(1): 1-19.

Mintzberg H, Raisinghani D, Théorêt A (1976) The Structure of "Unstructured" Decision Processes. *Administrative Science Quarterly* 21: 246 - 275.

Pedler MM (2012) Action Learning for Managers. Gower Publishing Ltd.

Şengür D, Tekin A (2013) Öğrencilerin Mezuniyet Notlarının Veri Madenciliği Metotları ile Tahmini. *Bilişim Teknolojileri Dergisi* 6(3): 7-16.

Turhan M, Karabatak, S (2015) Okul Liderlerinin Web Tabanlı Yetiştirilmesinde Problem Temelli Öğrenme: Teorik Bir Model Önerisi. *Kuram ve Uygulamada Eğitim Yönetimi* 21(3): 395-424.

Turhan, M, Şengür D, Karabatak S, Guo Y, Smarandache F (2018) Neutrosophic Weighted Support Vector Machines for the Determination of School Administrators Who Attended an Action Learning Course Based on Their Conflict-Handling Styles. *Symmetry* 10: 176.

Vapnik VN (1995) The Nature of Statistical Learning Theory; Springer, New York, USA.