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Application of Artificial Neural Networks for Prediction of Learning Performances

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***Abstract*—Artificial neural networks (ANNs) have rarely been used in the field of medical education, especially in the prediction of learning performances. This study aims to evaluate the potential application of ANN models for predicting learning performances, in comparison with multivariate logistic regression models. The predictor variables included demographics, high-school backgrounds, first-year grade-point averages, and composite scores of examinations during the course. Medical student learning performances were represented by their normalized T-scores of the total examination score. Three ANN models, including a support vector machine, were used to predict performance. A comparison between the models, based upon areas under the receiver operating characteristic curve values, showed no significant differences between the ANNs and logistic regression models ($p > 0.05$ for all pairs in the comparison). This work thus reveals the promising potential for the application of ANNs in the prediction of learning performances, in the field of medical education.**

***Keywords*— RBF; MLP; PNN; SVM**

I. INTRODUCTION

Artificial neural networks (ANNs) have been rarely utilized in the field of medical education, especially for predicting learning performances. ANNs had been used to predict the test selection patterns of students' successful solutions for computer based simulations [1-4]. One study has shown that, by using an ANN, the national science placement test-score at high-school level is a most powerful predictor of successful study in medical school, and such analysis can predict medical student performances with as close to 100% accuracy [5]. ANNs have been used as a teaching tool for the learning about structure-function relationships, and the results show that first-year medical students can develop a more dynamic and integrated vision of biological systems and can gain greater insight into the use of theoretical models [6].

ANNs can detect implicit and complex relationships between predictor variables. ANNs are a type of multivariate statistics which extends multivariate regression analysis and clustering systems to non-linear multivariate models [7]. ANNs incorporate high-order interactions between predictive variables and have proven to be superior over linear modeling in a number of areas of medical research [8,9], such as predicting patient survival [10,11], disease complications [12], drug response and pharmacodynamics [13,14], and modeling parts of the human body from various imaging [15]. ANNs are also widely applied in other fields [16-21]. Each ANN model may have different accuracy, sensitivity and specificity when processing the same clinical information. Thus, using only one model of ANN may mislead such predictions [12]. Well-known ANN models include radial bias function (RBF), multilayer perceptron (MLP), and probabilistic neural network (PNN), including support vector machine (SVM), a new generation of learning algorithm.

The authors hypothesize that ANN models would yield a more accurate classification of subjects than logistic regression analyses using the same input variables. Thus, this study aims to predict student learning performances as being represented by their normalized T-scores of the total examination score on the medical neuroscience course, using three ANN models, including SVM. The research questions addressed within the study are: Which models between ANNs and logistic regression analysis are more superior at predicting medical student performances? And among the ANN models, to what extent is each model more accurate than others, and therefore suitable for further application?

II. METHODS

A. Study Design

Data collection was performed with regard to second-year medical student learning performances in the medical neuroscience course, in two academic years, with the ethical approval of Mahidol University Institutional Review Board. Records of sex, high-school location backgrounds, first-year GPA scores, composite scores in examinations, and normalized T-scores of the total examination scores after completing the course, for students registered at the Faculty of Science, Mahidol University, were all collected. As a common criticism of ANN analyses is the failure to replicate the model with new or modified data sets [16], data corrected from a different group of students, which was belonged to a separate academic year, was therefore included in a separate analysis for comparison. Examination items for each examination component between these two academic years were also different. Thus, replicatability of ANN analyses is subjected to

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TABLE I. CHARACTERISTICS OF INPUT VARIABLES FOR GOOD LEARNING PERFORMANCE

Variable	Academic year A			Academic year B		
	< 95th (n = 345)	≥ 95th (n = 23)	p value	< 95th (n = 344)	≥ 95th (n = 24)	p value
Sex, n (%)						
Female	175 (51)	8 (35)		177 (51)	12 (50)	
Male	170 (49)	15 (65)		167 (49)	12 (50)	
High-school, n (%)						
Capital	232 (67)	23 (100)		237 (69)	21 (88)	
Non-capital	113 (33)	0 (0)		107 (13)	3 (13)	
1st-year GPA						
Mean ± SD	3.0 ± 0.3	3.4 ± 0.3	< 0.0001	3.1 ± 0.3	3.6 ± 0.2	< 0.0001
Range	2.1-3.9	2.6-3.8		2.0-3.9	3.3-3.9	
MCQ score						
Mean ± SD	48.3 ± 9.0	68.8 ± 4.1	< 0.0001	48.2 ± 8.8	68.7 ± 4.3	< 0.0001
Range	20-70	64-80		20-66	61-80	
Lab exam						
Mean ± SD	48.4 ± 9.2	65.3 ± 7.7	< 0.0001	48.3 ± 9.2	64.8 ± 7.1	< 0.0001
Range	20-70	47-80		20-72	49-80	
Lab posttest						
Mean ± SD	48.9 ± 9.8	52.2 ± 8.5	< 0.0001	48.9 ± 9.9	57.2 ± 7.2	< 0.0001
Range	20-76	44-76		20-76	44-71	
Group posttest						
Mean ± SD	48.7 ± 9.3	55.8 ± 8.7†	0.0005	49.0 ± 9.8	56.8 ± 9.0	0.0003
Range	20-64	35-64		20-74	39-74	

be demonstrated.

B. Study Protocol

Collected data consisted of independent (predictor) and dependent (target) variables. Independent variables included: sex, high-school location backgrounds, first-year GPAs, and composite scores of examinations. High-school backgrounds were categorized into 'the capital and vicinity' and 'non-capital and vicinity'. Composite scores include unweighted raw scores of MCQ examinations, laboratory examinations, laboratory post-tests, and post-tests of small-group/PBL/TBL sessions. There were two target variables based upon normalized T-scores of the total examination score, and these were: 'good' and 'poor'. A performance in the 95th percentile or more was classified as 'good' performance, and in the 5th percentile or less was classified as 'poor' performance.

C. Artificial Neural Networks

The software package, namely Decision Tree and Regression (DTREG), was used for predictive modeling [17]. This software accepts a dataset containing a number of rows for each column for variables. The value of the 'target variable' is modeled and predicted as a function of the 'predictor variable'. DTREG analyzes the data and generates a model showing how best to predict the values of the target variable based on values of the predictor variables. The software includes a full data transformation language (DTL) for transforming variables. DTL makes it easy to generate new variables, transform and combine input variables and select which rows to be used in the analysis. In this study, DTREG was used to generate RBF, MLP, PNN, and SVM. Details of how each model works have been described [12]. Each network was compared based on the accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), F-measure, and areas under the receiver operating characteristic (ROC) curves (AUC). F-measure combines precision (or PPV) and recall (or sensitivity) to give an overall measure of the quality of the classification and is calculated using the formula: 2 x [PPV x sensitivity]/[PPV + sensitivity].

D. Validation of the Networks

Cross-validation was used to determine the statistically optimal tree size for RBF, MLP, PNN, and SVM. The dataset is partitioned into 10 groups called "folds" in 10-fold cross classification. The process is repeated 10 times, building 10 separate trees. In each case, 90% of the data are used to build a tree and 10% are held back for independent testing. A different 10% is held back for each tree. Once the 10 trees have been built, their classification error rate as a function of

TABLE II. CHARACTERISTICS OF INPUT VARIABLES FOR POOR LEARNING PERFORMANCE

Variable	Academic year A			Academic year B		
	> 5th (*n = 248*)	*≤ 5th* (*n = 20*)	*p value*	*> 5th* (*n = 350*)	*≤ 5th* (*n = 18*)	*p value*
Sex, n (%)						
Female	175 (50)	8 (40)		181 (52)	8 (44)	
Male	173 (50)	12 (60)		169 (48)	10 (56)	
High-school, n (%)						
Capital	248 (71)	7 (35)		252 (72)	6 (33)	
Non-capital	100 (29)	13 (65)		98 (28)	12 (67)	
1st-year GPA						
Mean ± SD	3.1 ± 0.3	2.6 ± 0.2	< 0.0001	3.1 ± 0.3	2.7 ± 0.3	< 0.0001
Range	2.1-3.9	2.3-3.0		2.0-3.9	2.2-3.2	
MCQ score						
Mean ± SD	50.1 ± 9.0	29.3 ± 3.6	< 0.0001	50.6 ± 9.0	29.7 ± 4.2	< 0.0001
Range	32-80	20-34		30-80	20-35	
Lab exam						
Mean ± SD	50.5 ± 9.2	31.9 ± 5.9	< 0.0001	50.3 ± 9.2	31.4 ± 5.4	< 0.0001
Range	29-80	20-41		27-80	20-39	
Lab posttest						
Mean ± SD	50.0 ± 9.7	39.9 ± 9.7	< 0.0001	49.9 ± 9.7	40.3 ± 9.2	0.0002
Range	20-76	24-54		20-76	27-56	
Group posttest						
Mean ± SD	49.2 ± 9.4	48.4 ± 8.1	0.6298	49.8 ± 9.9	42.2 ± 8.3	0.0014
Range	20-64	36-57		20-74	24-57	

tree size is averaged. The cross validation cost for each size of the trees is then computed. DTREG prunes the tree by removing the least important nodes during each pruning cycle to the size that produces the absolutely minimum cross-validated classification error.

E. Relative Importance of Predictors

Relative importance of each predictive variable was automatically calculated for RBF, MLP, PNN, and SVM using sensitivity analysis where the values of each variable were randomized and the effect on the quality of the model was measured. The scores are computed with information about how variables are used as both primary splitters and surrogate splitters. A variable that is selected as a primary splitter early in the tree is important. If a primary splitter is slightly better than a surrogate, then the primary splitter may mask the importance of the other variable. By considering surrogate splits, the importance measure calculated by DTREG gives a more accurate measure of the actual and potential value of a predictor. The importance score for the most important predictor is scaled to a value of 100.00. Other predictors will have lower scores. Only predictors with scores greater than zero are shown.

F. Statistical Analyses

Categorical variables were described by proportions and continuous variables were expressed by mean ± SD. Comparison among models was performed based on the area under the ROC curve (AUC) using one-way ANOVA, with $\alpha = 0.05$, followed by the post-hoc Bonferroni test.

III. RESULTS

A. Characteristics of Students with Good and Poor Performances

The statistics of predictive variables are shown in Tables 1 and 2. There were 368 students registered on the course each year, of which 6-7% were ranked > 95th percentile, thus suggesting 'good' performance on the course. A Better first-year GPA score and higher scores in composite examinations and post-tests were more common in students with a ranking > the 95th percentile, whereas the poorly performance students (ranking < the 5th percentile) were more likely to have a lower first-year GPA and lower examination scores. Similar patterns were observed in both academic years.

B. Artificial Neural Nnetwork Analyses of Predictive Variables

To determine the variables that are good potential predic-

TABLE III. COMPARISON OF ANN MODELS FOR PREDICTION OF GOOD LEARNING PERFORMANCE

	RBF		MLP		PNN		SVM	
	Training	Test	Training	Test	Training	Test	Training	Test
Year A								
Accuracy	98.9	98.6	100	99.2	100	99.5	98.4	98.1
Sensitivity	95.6	91.3	100	91.3	100	95.6	91.3	82.6
Specificity	99.1	99.1	100	99.7	100	99.7	98.8	99.1
PPV	88.0	87.5	100	95.4	100	95.6	84.0	86.4
NPV	99.7	99.4	100	99.4	100	99.7	99.4	98.8
F-measure	0.92	0.89	1.00	0.93	1.00	0.96	0.87	0.84
AUC	0.998	0.997	1.000	0.998	1.000	0.997	0.999	0.994
Year B								
Accuracy	98.9	98.1	99.7	99.5	100	98.4	99.2	98.4
Sensitivity	91.7	83.3	100	91.7	100	75.0	87.5	83.3
Specificity	99.4	99.1	99.7	100	100	100	100	99.4
PPV	91.7	87.0	96.0	100	100	100	100	90.9
NPV	99.4	98.8	100	99.4	100	98.3	99.1	98.8
F-measure	0.92	0.85	0.98	0.96	1.00	0.86	0.93	0.87
AUC	0.999	0.995	0.999	0.998	1.000	0.995	0.999	0.997

TABLE IV. COMPARISON OF ANN MODELS FOR PREDICTION OF POOR LEARNING PERFORMANCE

	RBF		MLP		PNN		SVM	
	Training	Test	Training	Test	Training	Test	Training	Test
Year A								
Accuracy	99.7	99.5	99.2	99.2	99.7	99.5	99.7	98.9
Sensitivity	95.0	95.0	85.0	90.0	95.0	95.0	95.0	85.0
Specificity	100	99.7	100	99.7	100	99.7	100	99.7
PPV	100	95.0	100	94.7	100	95.0	95.0	94.4
NPV	99.7	99.7	99.1	99.4	99.7	99.7	100	99.1
F-measure	0.97	0.95	0.92	0.92	0.97	0.95	0.97	0.89
AUC	0.999	0.999	0.999	0.998	1.000	0.998	1.000	0.997
Year B								
Accuracy	99.2	97.5	98.9	98.1	100	97.5	98.4	97.0
Sensitivity	88.9	66.7	83.3	72.2	100	55.6	66.7	61.1
Specificity	99.7	99.1	99.7	99.4	100	99.7	100	98.9
PPV	94.1	80.0	93.7	86.7	100	90.9	100	73.3
NPV	99.4	98.3	99.1	98.6	100	97.8	98.3	98.0
F-measure	0.91	0.73	0.88	0.79	1.00	0.69	0.80	0.67
AUC	0.998	0.989	0.995	0.952	1.000	0.930	0.996	0.986

tors of both good or poor learning performances, and to evaluate the classification results of ANN modeling, the accuracy, sensitivity, specificity, positive and negative predictive values (PPV and NPV), F-measure, and AUC of RBF, MLP, PNN, and SVM were all analyzed (Tables 3 and 4). These values were calculated at the thresholds used to minimize weighted misclassification of training or test data. Based upon the AUC values, in which area values closer to 1.0 represented a better model, all models had an AUC value > 0.90. Comparison between models was performed based on AUC values, and showed no significant differences between RBF, MLP, PNN, and SVM models ($p > 0.05$ for all pairs of the comparison), for each data set (year) of both good and poor performance prediction. Accuracies of 98.1 to 99.5% and 97.0 to 99.5% were consistent for all ANN models, for each data set of good (Table 3) and poor (Table 4) learning performance prediction, respectively.

TABLE V. RELATIVE IMPORTANCE SCORES OF VARIABLES FOR PREDICTION OF GOOD LEARNING PERFORMANCE

Variable	Academic year A				Academic year B			
	RBF	***MLP***	***PNN***	***SVM***	***RBF***	***MLP***	***PNN***	***SVM***
Sex	0	0	0	0	0.1	0	0	0
High-school	0	5.5	0	0	0	4.2	0	30.4
1^{st}-year GPA	1.7	10.8	0	5.0	1.5	4.9	0	17.4
MCQ score	100	100	100	100	100	100	100	100
Lab exam	3.4	12.4	0	50.0	4.4	31.8	30.2	26.1
Lab posttest	6.7	9.3	0	0	0.4	3.6	4.8	0
Group posttest	2.3	15.2	22.8	5.0	2.1	11.0	2.9	17.4

TABLE VI. RELATIVE IMPORTANCE SCORES OF VARIABLES FOR PREDICTION OF POOR LEARNING PERFORMANCE

Variable	Academic year A				Academic year B			
	RBF	***MLP***	***PNN***	***SVM***	***RBF***	***MLP***	***PNN***	***SVM***
Sex	0	0.1	0	0	0	5.8	0.7	0
High-school	0	0.3	0	4.0	1.0	4.3	0	15.4
1^{st}-year GPA	1.7	2.4	0.6	12.0	5.2	4.1	11.7	7.7
MCQ score	100	100	100	100	100	100	100	100
Lab exam	5.4	53.4	48.3	52.0	24.3	67.0	33.7	61.5
Lab posttest	1.2	19.5	14.2	4.0	6.3	6.2	2.4	15.4
Group posttest	1.0	4.2	0.5	4.0	0.7	0.7	0.1	0

Next, importance scores of the predictor variables for all neural network models were considered. With a maximum score of 100, MCQ examination scores were ranked the most important variables, from all the neural network models used for the prediction of both good and poor learning performance (Tables 5 and 6). Arbitrarily, with a minimum score of 50, together with an AUC value > 0.90, lab examination scores displayed high importance for scores derived from the SVM model for predicting good performance, in the year A (Table 5). This variable was ranked second with importance scores of about 30% derived from the two models (MLP and PNN). Using the same criteria of a minimum score of 50 applied to poor performance prediction, MLP and SVM displayed high importance scores for lab examination scores for both data sets (Table 6).

C. *Comparison of logistic regression and ANN models*

To evaluate the classification results of multivariate logistic regression and ANN modeling, the rates of true and false positives predicted by the respective models were compared. Representations, in graphical charts, for those rates of prediction for good performance in year A are shown in Fig. 1. The logistic regression model showed slightly better classification (at > 0.5 probability threshold) than ANN models, as suggested by its superior rates of true positives. Similar results were observed in other data sets for good and poor performance prediction (data not shown).

A graphical comparison between the multivariate logistic regression and ANN models, using receiver-characteristic (ROC) plots, for the prediction of good performance in year A is shown in Fig. 2. The area under the ROC curve reflects the predictive power of the model, and the ROC plots indicate that the logistic regression model is not significantly superior to the ANN models. The AUC values of the logistic regression model for the data sets of good and poor performance prediction are ranged between 0.981-0.999. A comparison between models, based upon AUC values, showed no significant differences between RBF, MLP, PNN, SVM, and the logistic regression models ($p > 0.05$ for all pairs in the comparison).

IV. DISCUSSION

A. *Which models between ANNs and logistic regression analysis are more superior at predicting learning performances?*

The results are supported by previous statistical studies showing that academic marks are better predictors of study success than non-cognitive variables [18]. The advantage of ANNs over logistic regression models lies in their hidden layers of nodes. In fact, a particular ANN with no hidden node has been shown to be identical to a logistic regression model [19]. Although this study does not show that ANN models are superior to multivariate logistic regression, it implies the great potential for the application of ANNs in predicting learning performances in the field of medical education. One intrinsic advantage of ANN is that it can detect implicit and complex relationships between the predictor variables [20]. To clearly visualize the benefits of ANN, more input variables shall be required. One drawback of this work is its limitation in its number of predictor variables. Other factors which may affect

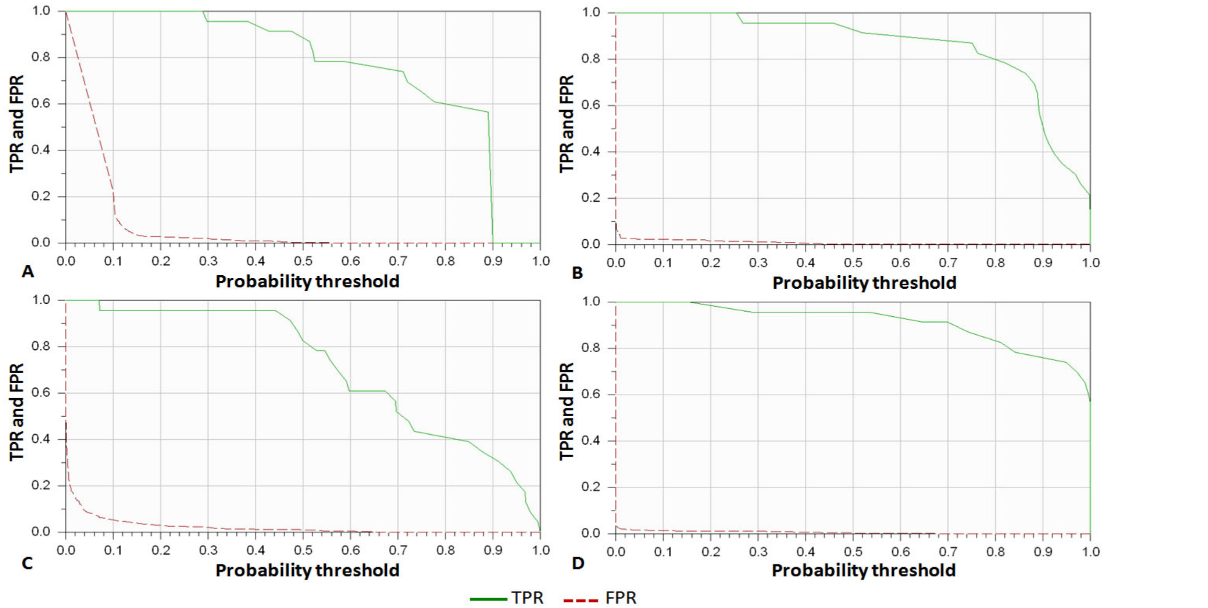

Fig. 1. Representatives of graphical charts for true and false positive rates from ANN models and logistic regression model as a function of classification threshold for the prediction of good learning performance (A) MLP, (B) PNN, (C) SVM, and (D) LR. TPR = true positive rates; FPR = false positive rates.

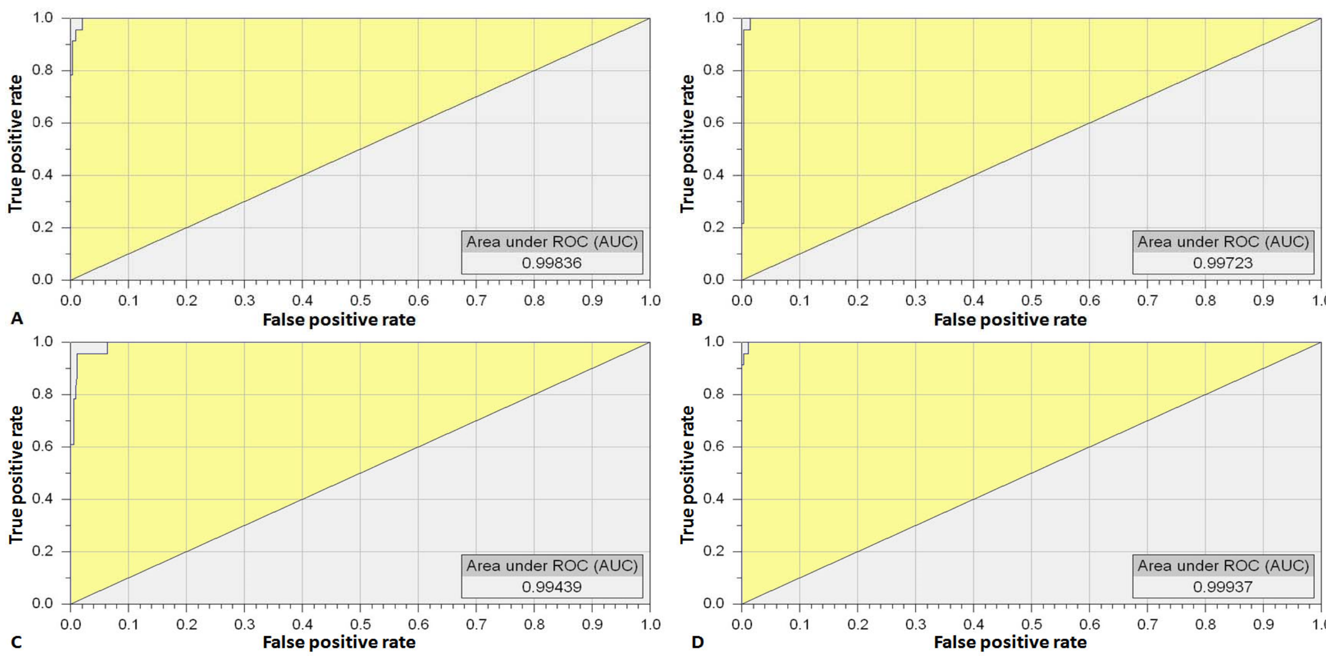

Fig. 2. resentatives of graphical ROC charts for the prediction of good learning performance (A) MLP, (B) PNN, (C) SVM, and (D) LR.

learning performance, and should be included in analysis are, for example: learning behaviors, economic status, existing psychological stress, and other non-cognitive factors.

B. Among ANN models, to what extent is each model more accurate than others, and therefore suitable for further application?

ANNs have been rarely used in the field of medical education [2,3,5,6], especially for the prediction of learning performances. A previous study has shown that ANN analysis can predict medical student performances with as close to 100% accuracy [5]. In the present study, the accuracy of all ANNs was between 97.5% and 99.7%, and the F-measure, which combined PPV and sensitivity to evaluate the overall quality of the classification, showed that the values were mostly close to 1.00 for all neural network models used in the analysis of all data sets. Based upon the AUC values, a comparison between ANN models showed no significant differences between RBF, MLP, PNN, and SVM models ($p > 0.05$ for all pairs in the comparison), for each data set of both good and poor performance prediction. These findings suggest that all ANN models can be used for prediction, with a similar power of model performance.

A common criticism of ANN analyses is the failure to replicate the model with new or modified data sets [22]. The authors replicated the models by the training data set with a second sample randomly selected from the original data set, and validated the findings with an independent data set. We have supported the replicatability of utilizing ANN models.

V. CONCLUSION

The potential for application of ANNs in predicting the learning performances of medical students was evaluated. The evaluation showed similar results for predicting performances, when analyzing the two data sets for the prediction of both good and poor learning performances. The advantage of ANN is not only its direct identification of the most important predictor variable, but it also suggests an implicit relationship between the predictor variable and the target variable. Future work will be needed to validate these results using more input data, including both cognitive and non-cognitive factors. This study could also be expanded to a larger scale of learning performance prediction, such as yearly GPA scores and learning performances after all years of having completed medical training.

References

[1] R. H. Stevens, and K. Najafi, “Can artificial neural networks provide an "expert's" view of medical students performances on computer based simulations?,” Proceedings of the Annual Symposium on Computer Application in Medical Care, pp. 179-183, 1992.

[2] R. H. Stevens, and K. Najafi K, “Students' use of prior problem representations when performing computer-based simulations: an artificial neural network perspective,” Academic Medicine, vol. 67, no. 10, pp. S51-53, October 1992.

[3] R. H. Stevens, and K. Najafi K, “Artificial neural networks as adjuncts for assessing medical students' problem solving performances on computer-based simulations,” Computers and Biomedical Research, vol. 26, no. 2, pp. 172-187, April 1993.

[4] R. H. Stevens, and A. C. Lopo AC, “Artificial neural network comparison of expert and novice problem-solving strategies,” Proceedings of the Annual Symposium on Computer Application in Medical Care, pp. 64-68, 1994.

[5] B. van Heerden, C. Aldrich, and A. du Plessis, “Predicting student performance using artificial neural network analysis,” Medical Education, vol. 42, no. 5, pp. 516-517, May 2008.

[6] D. G. Salinas, C. Acevedo, and C. R. Gomez, “Modeling a neural network as a teaching tool for the learning of the structure-function relationship,” Advances in Physiology Education, vol. 34, no. 3, pp. 158-161, September 2010.

[7] J. J. Valdes, and G. Bonham-Carter, “Time dependent neural network models for detecting changes of state in complex processes: applications in earth sciences and astronomy,” Neural Networks, vol. 19, no. 2, pp. 196-207, March 2006.

[8] Z. H. Khan, S. K. Mohapatra, P. K. Khodiar, and S. N. Ragu Kumar, “Artificial neural network and medicine,” Indian Journal of Physiology and Pharmacology, vol. 42, no. 3, pp. 321-342, July 1998.

[9] M. Frize, and C. Frasson, “Decision-support and intelligent tutoring systems in medical education,” Clinical and Investigative Medicine, vol. 23, no. 4, pp. 266-269, August 2000.

[10] D. Delen, G. Walker, and A. Kadam, “Predicting breast cancer survivability: a comparison of three data mining methods,” Artificial Intelligence in Medicine, vol. 34, no. 2, pp. 113-127, June 2005.

[11] F. Jaimes, J. Farbiarz, D. Alvarez, and C. Martinez, “Comparison between logistic regression and neural networks to predict death in patients with suspected sepsis in the emergency room,” Critical Care, vol. 9, no. 2, pp. R150-156, April 2005.

[12] P. Dharmasaroja, and P. A. Dharmasaroja, “Prediction of intracerebral hemorrhage following thrombolytic therapy for acute ischemic stroke using multiple artificial neural networks,” Neurological Research, vol. 34, no. 2, pp. 120-128, March 2012.

[13] A. Serretti, P. Olgiati, M. N. Liebman, H. Hu, Y. Zhang, R. Zanardi, C. Colombo, and E. Smeraldi, “Clinical prediction of antidepressant response in mood disorders: linear multivariate vs. neural network models,” Psychiatry Research, vol. 152, no. 2-3, pp. 223-231, August 2007.

[14] S. Yamamura, “Clinical application of artificial neural network (ANN) modeling to predict pharmacokinetic parameters of severely ill patients,” Advanced Drug Delivery Reviews, vol. 55, no. 9, pp. 1233-1251, September 2003.

[15] J. A. Scott, “Artificial neural networks and image interpretation: a ghost in the machine,” Seminars in Ultrasound, CT and MRI, vol. 25, no. 5, pp. 396-403, October 2004.

[16] F. Fazayeli, L. P. Wang, and W. Liu, “Back-propagation with chaos,” Proc. 2008 IEEE International Conference on Neural Networks and Signal Processing (ICNNSP2008), Zhenjiang, China, June 7-11, pp.5-8, 2008.

[17] V. Mitra, Chia-Jiu Wang, and S. Banerjee, "Lidar detection of underwater objects using a neuro-SVM-based architecture," IEEE Trans. Neural Networks, no.17, pp.717-731, 2006.

[18] L.P. Wang and X.J. Fu, Data Mining with Computational Intelligence, Springer, Berlin, 2005.

[19] Raymer, M.L., Punch, W.F., Goodman, E.D., Kuhn, L.A., Jain, A.K., "Dimensionality reduction using genetic algorithms," IEEE Trans. Evolutionary Computation 4 (2000) 164-171.

[20] V. Kecman, Learning and Soft Computing, Support Vector machines, Neural Networks and Fuzzy Logic Models, The MIT Press, Cambridge, MA, 2001.

[21] Y. Frayman and L. P. Wang, "Data mining using dynamically constructed recurrent fuzzy neural networks," Research and Development in Knowledge Discovery and Data Mining, vol. 1394, PAKDD’98, pp. 122-131, 1998.

[22] T. G. Buchman, K. L. Kubos, A. J. Seidler, and M. J. Siegforth, “A comparison of statistical and connectionist models for the prediction of chronicity in a surgical intensive care unit,” Critical Care Medicine, vol. 22, no. 5, pp. 750-762, May 1994.

[23] P. H. Sherrod, “DTREG predictive modeling software,” P. H. Sherrod. http://www.dtreg.com, 2010.

[24] E. Ferguson, D. James, and L. Madeley, “Factors associated with success in medical school: systematic review of the literature,” British Medical Journal, vol. 324, no. 7343, pp. 952-957, April 2002.

[25] K. A. Spackman, “Maximum likelihood training of connectionist models: comparison with least squares back-propagation and logistic regression,” Proceedings of the Annual Symposium on Computer Application in Medical Care, pp. 285-289, 1991.

[26] J. Trujillano, J. March, and A. Sorribas, “Methodological approach to the use of artificial neural networks for predicting results in medicine,” Medicina Clínica (Barcelona), vol. 122, no. Suppl 1, pp. 59-67, 2004.