



Article title: Improving Students' Retention Using Machine Learning: Impacts and Implications

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Improving Students' Retention Using Machine Learning: Impacts and Implications

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Abstract

Traditional statistical tools and qualitative techniques were employed in the literature to discover and forecast characteristics/factors that impact student retention the most. Modeling the links between these early available indicators and a student's future status of engineering persistence can be very useful in improving student retention in engineering. For some years, machine learning approaches have been used in education to predict retention and discover factors impacting retention rates, with better outcomes since 2010. This study focuses on different machine learning techniques used in literature for improving students' retention; we have identified various factors that might affect the students' retention and employed SVM and Neural Networks for predicting students' retention rates.

Keywords: Data Mining, retention, Machine Learning, Neural Networks, SVM

INTRODUCTION

THE COVID-19 pandemic is often known as the coronavirus recession which has casted a severe impression on education as well and without improvements in education to address the requirements of the workforce, the skill gap in our workforce will only expand. Today's professions require greater technical skills and higher degrees than in previous generations, [1]. Today's industries need greater technical skills and higher degrees than in previous generations. Jobs that fill a void often demand a college diploma, while individuals without additional skills have struggled, [2].

These forces drive the higher education system to look inward for answers to problems such as rising costs, inequalities, retention, and completion rates. According to statistics by The National Student Clearinghouse Research Center, 65.7% of students at four-year public universities graduate in six years, whereas a dramatic decrease with 39.2% of students at two-year public institutions graduates in three years, [3]. Dropouts are nearly twice as likely to be unemployed as college graduates, and they are four times more likely to default on student loans, damaging their credit and limiting their employment possibilities.

To fulfill the potential of an educated and technically skilled workforce, higher education must assess its methods. The growing number of students who attend community colleges, or two-year schools, during their first two years has necessitated the inclusion of this significant factor in the study. Machine learning techniques have been used to evaluate student data in recent years, which corresponds with the goal of enhancing data processing through data mining, using methods such as neural networks (NN) and support vector machines, [4]. Delen, [5] shows, through several comparison studies, NN, SVM, and decision trees (DT) have better prediction results than other statistical techniques such as logistic regression (LR) and discriminant analysis (DA). Because of their capacity to predict a result using both quantitative and qualitative/categorical data, these approaches have attracted a lot of attention in the literature.

Supervised learning is a machine learning approach that uses training data to construct a computer model through repeated changes to eliminate error. SVM is a supervised learning model that can be used to predict and classify data. A training algorithm is created, which categorizes updated data. SVM is especially effective for determining data clustering in groups. Another predictive modeling method is DT, which uses classification trees to form judgments about a target value based on observations. When the objective

is a classification, DTs are employed; however, when the target is a continuous variable, a regression tree is used. When the target is a binary dependent variable, LR is also employed to create a statistical model. Finally, as DA examines data to predict a categorical, dependent variable, it is widely employed in retention research.

Alkhasawneh and Hargraves, [6] created a paradigm that included both qualitative and quantitative research. The factors affecting retention rates were discovered in each research. The essential parameters were then put into a NN model to predict first-year retention rates for students pursuing degrees in science, technology, engineering, and mathematics (STEM). The first research was a quantitative model designed to identify characteristics that have the greatest influence on student retention. The dataset included 1,996 registered students who were divided into two groups: 1,468 registered students and 498 registered minority students. To improve learning time and reduce repetition while feeding the cohorts, the genetic algorithm was utilized to pick factors that had a greater influence on retention. The second research was qualitative, with data gathered through an eight-question survey from a focus group. Content analysis was employed in this section since it is a methodology that is commonly used for textual content. The findings of the two trials were combined into a NN that was run independently to predict GPA and identify whether or not students would be retained.

When employing datasets including all students, the majority of students, and under-represented students, the NN demonstrated overall classification accuracy of 74 percent, 79 percent, and 60 percent, respectively. Furthermore, in the quantitative model, reducing the number of variables for each database enhanced classification accuracy. The research concluded the following factors were useful for predicting performance and retention: first math course grade, high school rank, the impact of pre-college intervention programs, and SAT math score.

This research gives a thorough review of machine learning strategies for improving educational institution retention rates. This study provides a research perspective related to the identification of student retention using Machine Learning through previous studies and approaches used for prediction. We have investigated the use of SVM and Neural networks for predicting students' performance and improving retention. Different Machine Learning classifiers are studied for evaluating students' retention, [6].

Various studies have been proposed in literature for improving students' retention. Table.1 shows the methodologies have been employed for predicting retention over years.

Method	Study	Performance
Decision trees	Raju & Schumacker (2015)	73.50% 73.75%
Bayesian belief network	Slim et al. (2014)	MSE curves
Support vector machines	Dissanayake et al. (2016)	76%
	Miranda & Guzman (2017)	Accuracy was not reported
	Uddin & Lee (2017)	
	Slim et al. (2014)	MSE curves
	McAleer & Szakas (2010)	79.5%
SVM+DT+NN (ensemble)	Oztekin (2016)	77.6%
	Babic (2017)	57.6%
K-nearest neighbor	Adejo & Connolly	81.6%
	Dissanayake et al. (2016)	83.3%
Logistic regression	Iam-On & Boongoen (2017)	93.3%
	Delen (2011)	74.3%
Neural Networks	Kondo et al. (2017)	75%
	Delen (2011)	79.8%
	Raju & Schumacker (2015)	77.7%
	Miranda & Guzman (2017)	83%
	Adejo & Connolly	73%

Table.1 Methodologies employed for prediction over years

2. PREDICTING STUDENT RETENTION USING SUPPORT VECTOR MACHINES (SVM)

SVM is categorized as a supervised learning algorithm that performs regression or classification for numeric responses and categorical variables. It creates a mapping space to separate the input data into different classes. SVM maps both linear and non-linear data by using kernel functions to transform the inputs to a higher-dimensional space, which allows for a linear separability. The usage of kernels, therefore, lowers the cost.

By separating the data into parallel hyperplanes, you can reduce the problem's complexity. The optimum condition is found by minimizing the Euclidean norm of the weight vector, which is a constrained optimization problem that can be solved using the method of LaGrange multipliers.

The program aims to optimize the margin between parallel hyperplanes, which limits misclassification. As the distance between the hyperplanes grows, it is predicted that the generalization error decreases.

Research methodology using SVM

The research process is conducted in the following phases, i.e., 1) data description and preparation, 2) data modeling, application of SVM, and 3) model assessment.

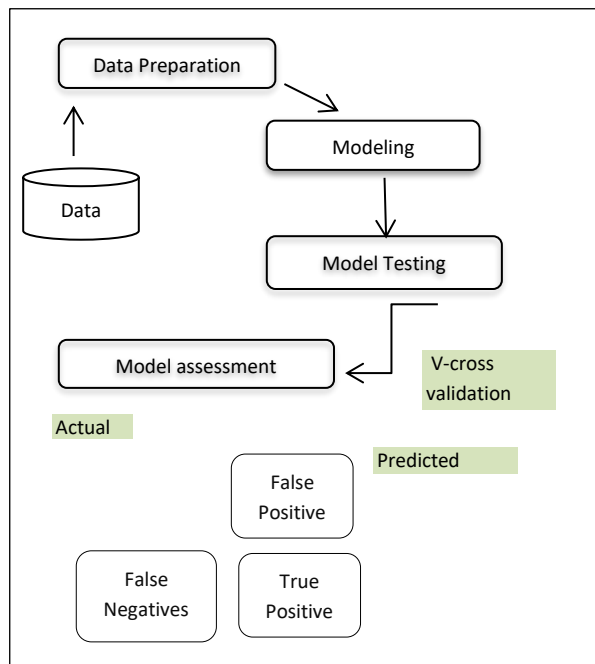


Figure.1. Methodology using SVM

The dataset was made up of 904 students who were pursuing degrees in chemistry, biology, or engineering over five years. Based on this information, 177 students were found to have completed their degree in less than

three years, which is 150 percent of the usual time for completion as defined by the 1990 Student Right-to-Know Act for postsecondary institutions. The other 727 students did not complete their degree within that time frame, owing to causes such as college dropout or changing their major to something other than STEM. Due to a large amount of missing data and inconsistent data, the data set was cleansed. Some students' standardized test scores, for example, were absent since this information is not necessary for community college entrance. After cleansing the data to remove any duplicates.

INITIAL INPUT VARIABLES

X ₁	Degree
X ₂	Gender
X ₃	Age
X ₄	1 st student
X ₅	1 st generation
X ₆	ACT English
X ₇	ACT composite
X ₈	ACT Math
X ₉	ACT Reading
X ₁₀	High school GPA
X ₁₁	Plans to work
X ₁₂	College GPA
X ₁₃	FT student

Table 2. Initial input variables

INPUT VARIABLES (after filtering)

X ₁	Degree
X ₂	Gender
X ₃	Age
X ₄	1 st generation
X ₅	ACT composite
X ₆	High school GPA
X ₇	Plans to work
X ₈	College GPA

Table 3. Variables used in the model

Model

SVM type 2 classification was used as the model. For a discrete target variable, this approach classifies binary data. The classifier uses the radial basis function (RBF), which is also known as the kernel for dimensional transformation. The prediction model was trained and validated using k-fold cross-validation. A 0.01 error objective and a maximum number of iterations of 10,000 were defined as a halting criterion.

Model Specification	Value
SVM type	Classification type-2
Kernel type	Radial basis function
No. of SVs (0)	34
No. of SVs (1)	48
No. of independent variables	8

Table. 4 Model summary

Model assessment

In the validation set, precision and recall metrics were used to test the model, as well as overall accuracy. By avoiding possible misinterpretations, the last phase provides a more comprehensive study of the data. The model must be accurate in predicting non-completers (low error type II) because the data will be used to enhance and build retention tactics, which will cost the institution money if they invest in students who are a false negative for completion risk. The overall performance was calculated as the proportion of correctly classified values from the training, testing, and validation subsamples obtained from the k-fold cross validation application.

Results

Because the model employed soft bounds, bounded vectors are placed within the margin area. Only 9% of the categorized vectors are bounded, which indicates a solid model implementation since data generalization is better when the number of bounded vectors is low concerning the total cases. Table 5. Summarizes the results and shows that the model can classify with an accuracy of above 70% with modest misclassification (false positive). In addition, the model is more accurate when it comes to predicting non-completers.

Class	0	1	Total	Recall
0	39	8	47	0.82
1	7	17	24	0.70
Total	46	25	71	
Precision	0.84	0.68		

Table 5. Confusion matrix, recall, and precision measures

Despite the lack of weights used to prioritize class categorization, the results are more accurate in identifying students who are in danger of dropping out. This is vital to keep in mind while developing retention tactics that depend on purposeful counseling, as correcting false-positive misclassifications can be costly. This is why the recall measure is the focus of the model study.

The model's overall accuracy is high, as seen in Table 6. However, there is a clear distinction between training and testing results.

Classification Accuracy (%)	
Train	94.3
Test	78.8
Overall	90.4

Table 6. Accuracy

The testing accuracy provides more information about the prediction performance in this scenario since it eliminates misinterpretations due to data over fitting. The model then has a strong prediction performance when the testing accuracy is greater than 78 percent, which is a sufficient metric for the problem's prediction aims.

3. Neural Networks

Neural networks (NN) have been widely employed in technical applications involving prediction and categorization in recent decades, particularly in engineering, business, and medicine. Because of its importance and effectiveness, the neural network model is particularly appealing for modeling complex systems: universal function approximation capacity, accommodation of several non-linear variables with unknown interactions, and strong generalization ability, [6].

Few studies have been published on the application and accuracy of data-mining tools in institutional research, [8], [9]. The use of neural networks and decision tree analysis in predicting community college students transfer to four-year colleges was shown, with the conclusion that a classification and regression tree (C&RT) method achieved overall better accuracy than decision trees, [10]. Byers González and DesJardins [7] found that neural networks outperformed binary logistic regression in predicting the application behavior of potential freshmen who submitted admission test results to a prominent research university.

Although cumulative research on time to degree (TTD) completion is less spectacular, regression and route analysis models have contributed significantly to our knowledge of student retention, [11, 12, 13]. The more complicated nature of the road to graduation, which has stretched significantly over the previous thirty years for a bachelor's degree, is a plausible cause.

Methodology

The neural network model is particularly

interesting for modeling complex systems because of its importance and effectiveness: universal function approximation capability, accommodation of numerous non-linear variables with unknown interactions, and excellent generalization ability. The *overall college GPA* is the response variable in this research.

In this study, two different models were created utilizing a multilayer feed-forward backpropagation network (as illustrated in Figure.2) to 1) predict incoming freshmen retention and 2) predict incoming freshmen retention. 2) Divide the same group into three groups: at-risk, intermediate, and advanced. At-risk students have a lower GPA and are more likely to drop out of an S&E major, whereas advanced students have a better GPA and are less likely to drop out. Students were split into three categories depending on their total GPA: at-risk, intermediate, and advanced. At-risk students had a GPA of less than 2.7; intermediate students had a GPA of 2.7–3.4, and advanced students had a GPA of more than 3.4. The average GPA categorization in higher education was used to create this classification.

The network contains a six-element input layer, an eleven-element hidden layer, and a single-element output layer.

The network that solves non-linear least squares problems was trained using the Gauss-Newton learning approach. S&E majors were modeled separately using 8 and 6 elements, respectively.

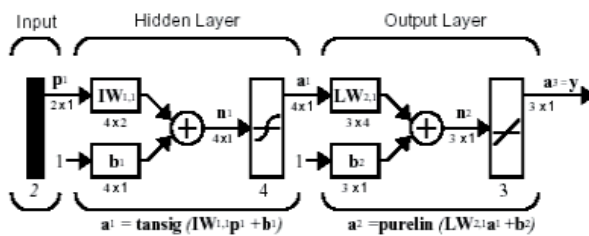


Figure.2. Multilayer Feed-Forward Backpropagation Network [14]

RESULTS

To minimize overfitting, the 10-fold cross-validation technique was proposed for all S&E majors.

The absolute GPA prediction model has an r-value of 0.54 and an accuracy range of [-0.5, 0.5]. The margin of error for [0.5] is 68%.

The actual predicted GPA plot is shown in figure.3.

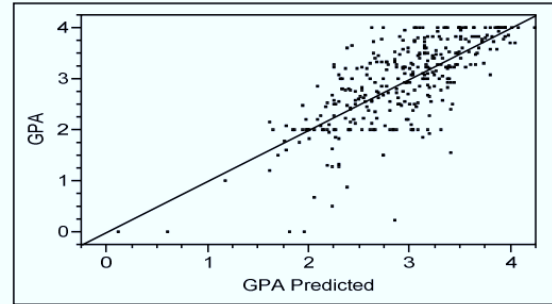


Figure.3 Regression analysis of actual GPA by Predicted GPA plot

Table 7. shows that predicting the absolute GPA for science majors alone yielded better results than predicting both science and engineering or engineering alone. The mean for forecasting S&E is roughly 0.42, 0.40 for predicting science, and 0.41 for engineering, according to an analysis of the model's error within the [-0.5, 0.5] margin of error. This is a good indication of the model's accuracy.

Variable	S&E	Science	Engineering
R value	0.54	0.57	0.59
Accuracy	68%	70.5%	68.9%
Total	338	190	148

Table.7 Accuracy by Major and outcomes by r

Variable	S&E	Science	Engineering
Min	0.002808	0.000519	8.06E-05
Max	2.6238	1.6528	2.7725
Mean	0.427	0.407178	0.41065

Table.8 Summary of the result of errors

In terms of the classification model, 70.1% of the output was properly categorized, with an R-value of 0.41. The Receiver Operating Characteristics (ROC) graph (Figure. 4) shows that the concept of dividing incoming freshmen into three categories: at-risk, moderate, and advanced appears to be a viable test. For advanced, intermediate, and at-risk pupils, the area under the curve is 91.5 percent, 87.2 percent, and 85.8%, respectively. In addition, 10-fold cross-validation was employed.

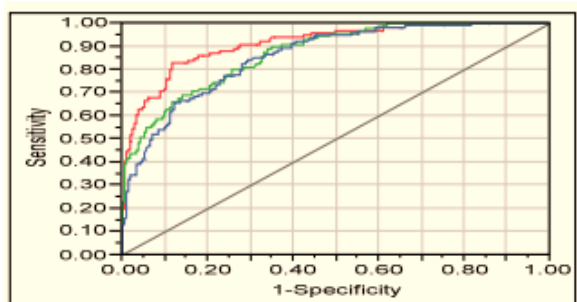


Figure.4 Regression analysis of actual GPA by Predicted GPA plot

When it comes to forecasting incoming freshman retention at VCU S&E disciplines, the findings of the two models shown above are highly encouraging. The outcomes of neural networks might be greatly improved with big data sets (i.e. more than 500 students), according to the literature [4]. For our sample size and constrained parameters, prediction accuracy of 68 percent for absolute GPA is reasonable. Furthermore, the ROC curve provided a solid indicator of how well our classification model worked, and it is thought that results might be enhanced with a bigger data set and additional associated criteria like arithmetic performance.

In this data collection, 70 pupils were identified as African American, Hispanic American, or Native American minorities. Due to the small number of minority students in this data set and the restricted number of variables available, the race was used as an input variable rather than comparing the performance of minority and majority groups. The research was also confined to the 2008 academic year. Future research might incorporate a more diversified data collection with a higher proportion of minority students.

When predicting the success of science students, the results were marginally better than when predicting the performance of engineering students. There is no adequate rationale for this disparity at this moment, although it is speculated that it is connected to the variety in input factors for scientific students.

CONCLUSION

For decades, many scholars have been concerned about attracting more students to scientific and engineering areas. This paper gives a thorough assessment of the research on using machine learning algorithms to predict student retention in higher education using variables such as dropout risk, attrition risk, and completion risk.

We have investigated SVM and Neural networks in predicting students' retention. At epoch 2919, the SVM's best performance was attained with an error of 0.01. In other words, the model achieved its error objective and terminated training. SVM can classify with an accuracy of above 70% with modest misclassification (false positive). In addition, the model is more accurate when it comes to predicting non-completers.

Neural network approaches will be used to model S&E incoming freshmen retention, paving the door for a greater understanding of student retention characteristics. The models established here are intended to forecast absolute GPA and to categorize students into three groups depending on their total GPA: at-risk, intermediate, and advanced. We have observed that Neural Networks' accuracy is more than SVM and hence it can classify the performance of students, or students' retention more precisely.

The study had a small sample size and a small population, and it was intended to predict college retention in general. Future research will be tailored to the student's grade level (freshman, sophomore, etc.) and race/ethnicity.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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