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Predicting Outcomes of Aerospace and Mechanical Engineering Students via Artificial Intelligence

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Predicting Outcomes of Aerospace and Mechanical Engineering Students via Artificial Intelligence

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Abstract

Academic intervention in underrepresented students during the early years of their engineering program plays a crucial role in improving program retention and academic success. These issues are particularly prominent in Science, Technology, Engineering, and Mathematics (STEM) fields, where many students opt to change majors due to difficulties in their programs. Artificial Intelligence (AI) has emerged as a powerful tool for predicting student outcomes and has the potential to revolutionize education. By leveraging AI, we aim to develop a framework that utilizes historical student data to predict future outcomes. The predictor dataset used includes demographic and educational performance information of students in the Aerospace and Mechanical Engineering (AME) program at The University of Texas at El Paso (UTEP). The majority of the AME student population in this minority serving institution are Hispanic males. Our research question focuses on identifying the factors that contribute to an accurate prediction of student outcomes in AME students. The two outcomes this work exhibits are whether or not the students graduated and if they completed the AME program or switched to another one. We employ the use of MATLAB's Statistics and Machine Learning Toolbox and Deep Learning Toolbox to train and test our neural networks. The Fitcnet command was selected to create a feed-forward neural network classifier. Initial results display a minimum level of accuracy of 92 percent for our trained models with variable predictor selection. The models not only successfully predict the program outcomes but also provide insight onto what predictor parameters are important and which ones do not affect the outcome. The initial work aims to identify key predictors for high-accuracy predictions using a reduced dataset available, as well as help identify and test more prediction factors used in the literature. Through future iterations of our model, we aim to further improve prediction accuracy by incorporating additional predictor data and increasing the student pool available for such analyses. Early identification of students at risk of changing or dropping from the program will enable targeted intervention and improve their chances of success. These initial iterations will serve as benchmarks, with the ultimate validation of our project relying on the performance of the AI model with data from current AME students upon their completion of the program.

Keywords — Student Outcomes, Artificial Intelligence, Prediction, Neural Networks

Introduction

There continues to be a historical gap in STEM programs for both women and ethnic minorities, despite the progress made toward bridging this gap. Research has shown that underrepresented students who receive academic intervention within the first few years are more likely to persist in STEM programs [1, 2]. This highlights the importance of identifying students at a higher risk of dropping from these programs. In this paper, we aim to address this issue by leveraging the power of AI algorithms, specifically Neural Networks (NNs). The study performed aims to identify trends for educational performance in a population of students where 79% are Hispanic and 84% Male. We hope to identify and predict the patterns related to the student outcomes in minority serving institutions, specifically in STEM programs.

Previous studies utilizing machine learning and classification techniques have demonstrated their potential in predicting and understanding student performance in academic programs [3, 4, 5, 6]. Using these methodologies, along with key predictor groups such as Academic Achievement, Demographics, Environmental, and Psychological Variables, we seek to expand on this existing research [7, 8, 9, 10, 11, 12]. We will analyze institutional data divided into student demographics, academic preparation, outcomes, and additional data to be collected. Our ultimate goal is to develop a predictive model that can identify students in need of academic improvement, allowing educational institutions to monitor student performance and offer targeted support programs.

We believe that our research will contribute to the overall objective of promoting student success in STEM programs. This algorithm will provide help to students after each semester, but by applying it throughout each course, we can foster a more inclusive and supportive learning environment. Also, we draw upon the work of Al-Doulat [13] to emphasize the need for collaborative efforts among all members of the institution and program leadership, as well as the research by Ramesh [14] that highlights the potential for intervention at an individual course level. This work focuses on the effect student demographics and personal data has on their performance and does not address the effect instruction quality and instructor training has on such performance. Efforts are being made to increase the amount of predictor data available for each student.

Methods

Neural Networks

The data variables used in this study pertain to 1091 individuals who are former AME students. The outcomes of these students fall into two categories, graduation and AME program completion, with either positive or negative results in each of the two categories. This project has been IRB approved and the student data was collected by the Institution's Center for Institutional Evaluation. This paper aims to provide a method for predicting student success using AI, precisely using NNs within the realm of Machine Learning (ML). This will help determine what variables contribute the most to students who are considered successful by graduating in 12 semesters or less and have a high GPA.

MATLAB is the chosen software for this research because the information and code are stored locally, which enhances the security and privacy of the student's information and research results. MATLAB was also selected to employ its different toolboxes for AI and

Classification. There are two main toolboxes in use, the Statistics and Machine Learning Toolbox along with the Deep Learning Toolbox. The Fitcnet command was chosen to train and test our neural networks. Fitcnet, also known as Fast Iterative Shrinkage-Thresholding Covariance-Net, is a type of neural network primarily used for regression and classification tasks [15]. It is specifically designed to handle large datasets efficiently. Fitcnet incorporates both ridge and lasso regularization, both techniques used in regression analysis to mitigate overfitting and stabilize the model's predictions. This allows for effective feature selection, reducing the complexity of the model, and preventing overfitting. In the context of predicting a student's success in an engineering program using demographics and other predictors, Fitcnet leverages the provided information to train the network. Using various parameters such as gender, ethnicity, and educational background, the network learns to establish correlations and patterns within the data. Through its training process, Fitcnet aims to build a model that accurately predicts or classifies a student's success in the program based on the provided predictors.

The first set of NNs have been trained and validated using institutional data of students from an Aerospace and Mechanical Engineering program. A variety of models have been trained and tested with small variations between them. The differences are the use of certain predictors to identify the level of accuracy each predictor combination produces. The specifics of these combinations are discussed in the next section.

The second-generation networks will include variables from institutional data and data collected from students in the program that is not yet available. These networks will be trained and tested using the data from current students. Data will be collected periodically throughout the program, allowing academic intervention before the student becomes at risk. All the NNs will be fully validated once the current students have completed their degrees and the program.

Predictors and Predictor Combinations

The institutional data obtained for each student was used as predictors for our NNs. The student data used for this study had missing data on some predictors, for this initial phase, those predictors were overlooked. The incomplete predictors include name of high school attended before registration in the program, participation in early college, high school ranking at graduation, high school percentile, age at registration, English as Second Language (ESL), number of transferred credits, and SAT score. The complete predictors include demographic data such as gender and ethnicity along with educational background. Grade data for introductory courses such as Calculus 1, Chemistry 1, and Statics are available, but more student data is desired to increase the understanding each of those course outcomes have on the student performance. We did not employ incomplete predictors in this initial phase but we plan on segmenting the total student population to use these predictors in a future analysis. Perhaps more information such as number of repeat attempts at each course might also prove fruitful.

Individual student performance was predicted using an array that contains the predictor data for each student. Originally, this array was made up of alpha-numeric data, but it was decided only numerical data was needed to allow MATLAB to run more efficiently. Therefore, all the data were preprocessed to convert to numerical values only. For an accurate prediction, the number of classes should exceed 20. For these preliminary results only the available data containing eight predictor classes was used.

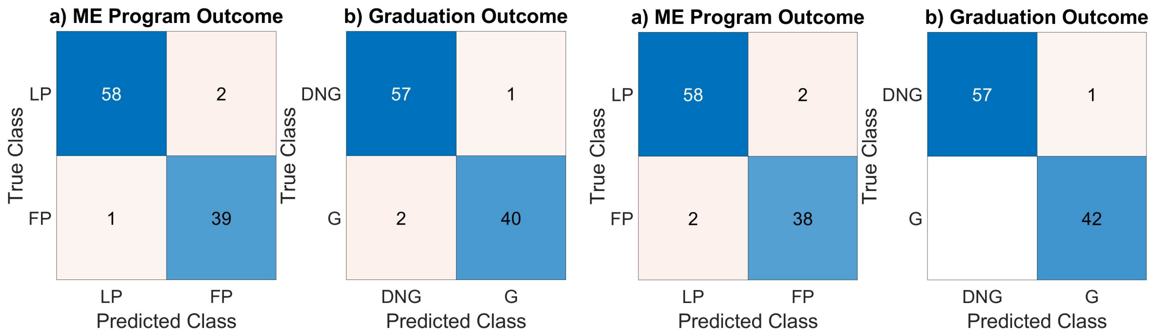
Table 1 depicts all the available predictors for this study. Different networks were tested, each containing a different predictor combination. This was done in an attempt to better understand which data class combinations provide better predictions. The main difference is the use of gender and race within the different predictor combinations. We performed this test in an attempt to identify whether or not gender and race have a high impact on a student's performance.

Table 1: **Predictors available for network training and evaluation.**

Data Predictors
Gender, Race, Early College, # of Failed Courses, # of Passed Courses, Calculus 1 Grade, Statics Grade, Chemistry 1 Grade

Results

Figure 1 displays classification results of two separate networks developed. In the confusion matrices, the blue squares represent the correct predictions, while the white squares indicate incorrect predictions made by the networks. In this context, "LP" stands for "Left Program" and "FP" for "Finished Program". Meanwhile, in the Graduation outcome section, "DNG" refers to "Did Not Graduate", and "G" represents "Graduated".



(a) Classification with All Predictors (b) Classification without Gender or Race Predictors

Figure 1: Classification Results

The results were generated using different classifier selections for different neural network training and testing. Figure 1a shows the results of the network that uses all the classifiers available in Table 1. Figure 1b shows the results with the removal of the gender and ethnicity classifiers. This provides a more general prediction without taking into account some demographic data. We noticed that there were no major differences in the results obtained for each combination.

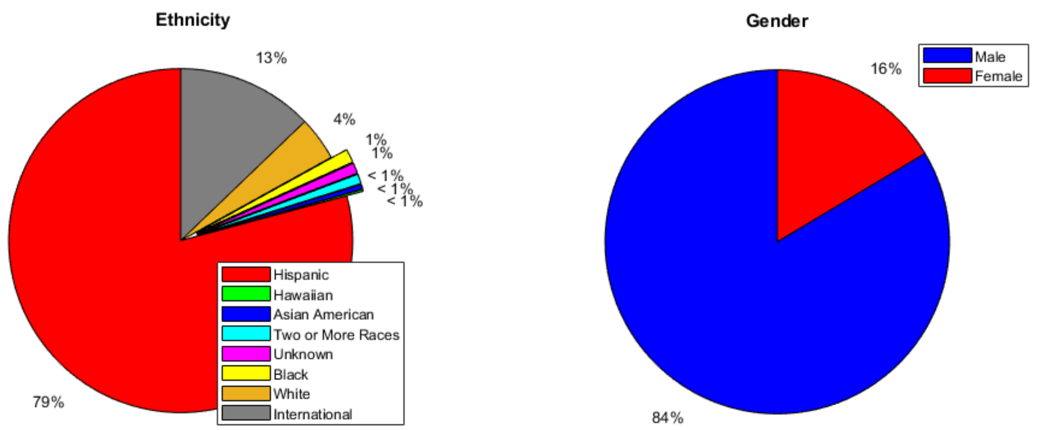
It is important to note that the algorithm randomly divides all test subjects into training and testing data sets. Various ratios of data sectioning for training and testing are used in practice for neural networks, they range from 90:10 all the way to 60:40 for training and testing respectively. Our networks were trained and tested using random samples of 100 students for testing, where the total number of students in the study is 1,091. For that reason, when each network is tested multiple times, the results vary slightly, but the error yielded between each test is always 3 or less for any class in the confusion matrices. This training was essential to provide the most accurate results, where an accuracy rate of over 92 percent was achieved for all networks.

Discussion

Testing of various networks with varying classifiers is important to understand which classifiers have a significant impact on the prediction. Despite well-documented gender and minority gaps in STEM fields, these factors do not always play a crucial role in research. Therefore, we decided to focus on the difference between selecting race and ethnicity as classifiers for our research.

Results that do not consider gender and ethnicity remain highly accurate when compared to models that do consider these predictors. This suggests that personal student data does not significantly impact the AI results for our student population. Although student performance can be influenced by factors such as gender, ethnicity, and socioeconomic background, our algorithm can consistently provide accurate performance predictions without some of those predictors. Baashar et al. [16] do a great job of addressing the many options of predictors and outcome variables selected in related research.

Because of the close results between our networks, we decided to perform statistical analysis of our student population. We generated a demographic breakdown of the student population by ethnicity and gender. We identified a heavy concentration in the gender and race of our test subjects that is depicted in Figure 2. The majority of the test subjects in the study are Hispanic males. When we analyzed the breakdowns between the entire student population in this study and compared it to the breakdown of only the students who did not graduate, we observed the same percentages in ethnicity and gender concentrations. That is, no specific class of student, whether in race or gender, is more prone to graduate.



(a) Demographic Breakdown by Ethnicity.

(b) Demographic Breakdown by Gender

Figure 2: Demographic Breakdown of Test Subjects.

This observation combined with the heavily homogeneous concentration of student population produces no major effects on the accuracy of our model when we remove those two classifiers from our algorithms. This concentration bias is present at our institution and should not be a generalization made to all institutions where the demographics in their student population might be more balanced. Although ethnicity and race were removed from our networks, any findings in our research will automatically apply to minorities as the vast majority of our student demographic is Hispanic.

Future Work

We have information on the students' grade classification at enrollment, we plan to use that in future iterations of the models. We aim to increase the number of predictor data we have available and grade the effect of each of these predictors in guiding the outcome of our students in the program. Such predictors include nationality, first-generation status, socioeconomic status, employment, scholarship status, military participation, and first language. We are working closely with university administrators and student offices to obtain more student data for our efforts. We are also making plans to administer surveys to the students in the AME program consistently throughout their academic journey to upkeep their progress and update our algorithms.

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