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Predictive and Forecasting Models for University Admissions and Graduation Performance: Leveraging Data Mining Algorithms

Julius Cesar O. Mamaril
ICT Management Office, Pangasinan State University, Philippines

Abstract *– In recent years, the field of education has seen a surge in the availability of data due to the digitization of various academic processes. This data presents a unique opportunity to harness advanced data mining techniques for enhancing decision-making processes within educational institutions. This research delves into the realm of educational data mining (EDM) by specifically targeting the transition phase of incoming freshmen to their optimal college programs and subsequent graduation performance. By employing cutting-edge relationship discovery and clustering algorithms, this study aims to provide universities with a data-driven approach to streamline the admissions process and facilitate personalized academic pathways for students.*

The utilization of historical admission and graduation records as a knowledge base sets the foundation for this research. Through the application of data mining techniques, patterns and trends hidden within the vast dataset can be unveiled, leading to insights that can significantly aid in predicting suitable college programs for incoming students. The predictive power of these techniques can empower academic advisors and university administrators to make well-informed decisions while considering factors such as students' academic backgrounds, interests, and potential career paths.

The research not only focuses on predicting appropriate college programs but also extends its scope to forecast the final graduation grades of students. By analyzing the historical data, this study aims to develop models that can accurately predict students' academic performance based on their selected programs and individual attributes. This predictive capability has the potential to assist universities in identifying students who might be at risk of underperforming and proactively providing them with targeted support services, ultimately improving their chances of successful graduation.

Keywords *– Data Mining, Educational Data Mining, University Admissions, Graduation Forecasting, Prediction Algorithms.*

INTRODUCTION

The latter half of the 20th century witnessed an unprecedented revolution driven by rapid advancements in computing power, which in turn catalyzed significant transformations across various domains, including statistical science and computer technology. Educational institutions, as one of the beneficiaries of this technological progress, have found new avenues for growth and innovation through the integration of data mining and artificial intelligence techniques. This paper embarks on a journey to harness the power of these technological leaps by applying sophisticated pattern discovery techniques, such as clustering and relationship analysis, to address a critical challenge in the education sector - the selection of the most suitable college programs for incoming freshmen. By leveraging the wealth of historical student admission and graduation records, this research endeavors to push the boundaries of predictive modeling, ultimately culminating in the creation of an advanced tool capable of significantly enhancing the accuracy and efficiency of program selection decisions.

As educational institutions continue to embrace the digital age, they are accumulating vast reservoirs of data encompassing a wide spectrum of student information. This data, if properly harnessed and analyzed, holds the potential to drive transformative changes in the way universities guide and support their students. The conventional approach to program selection often relies on rudimentary indicators like standardized test scores and high school GPAs, which might not holistically capture a student's capabilities, aspirations, and unique attributes. This paper seeks to bridge this gap by proposing a novel approach that transcends traditional metrics, using advanced data mining techniques to delve into the intricate relationships and patterns that emerge from the historical data. By doing so, the aim is to unveil nuanced insights into the factors that contribute to a student's academic success and program compatibility.

Furthermore, the significance of accurate program selection goes beyond just the academic domain. It plays a pivotal role in shaping a student's overall university experience, including their engagement, satisfaction, and eventual career trajectory. Through this research, we intend to pave the way for universities to provide tailored, individualized academic journeys that not only enhance students' chances of academic success but also contribute to their holistic personal and professional development. By embracing data-driven decision-making, educational institutions can proactively identify students who might be at risk of attrition, thereby facilitating timely interventions and support systems to ensure their persistence and eventual graduation.

OBJECTIVES OF THE STUDY

This research focuses on creating predictive and forecasting models for university admissions and graduation performance through data mining algorithms, aiming to enhance decision-making and personalized academic pathways within educational institutions.

The study's main goals are as follows:

Firstly, the research aims to understand the principles and methodologies of Educational Data Mining (EDM), investigating its various applications such as intelligent tutoring systems, student behavior forecasting, university admission forecasting, and student graduation forecasting.

Secondly, the study seeks to analyze historical data related to admissions and graduation, using advanced algorithms to uncover hidden patterns and relationships among variables that influence students' academic success, program choices, and graduation outcomes.

Thirdly, the research endeavors to develop predictive models that recommend appropriate college programs for incoming students based on factors like academic backgrounds, interests, and potential career paths. Additionally, the study aims to build models that accurately forecast students' graduation grades, identifying those at risk of underperforming and enabling targeted support services for improved graduation rates.

Finally, the research focuses on practical implementation by integrating the validated insights into decision-making processes like university admissions and student support systems. By achieving these objectives, the study aims to empower educational institutions with data-driven tools and insights that streamline admissions, facilitate personalized academic journeys, and enhance overall student success and graduation outcomes.

MATERIALS AND METHODS

Phases of Educational Data Mining: The process of EDM mirrors general data mining tasks but is applied to educational contexts. It involves identifying relationships among educational data, validating these relationships, applying them to predict outcomes, and utilizing these predictions for decision-making. The paper discusses classification, clustering, and regression algorithms in the context of EDM.

Data Mining Pre-Processing Techniques: Data mining pre-processing is a crucial step that involves cleaning, integrating, selecting, and transforming data to prepare it for analysis. The paper explores the three approaches to feature selection: filter, wrapper, and embedded methods, and emphasizes the importance of selecting relevant attributes for accurate predictions.

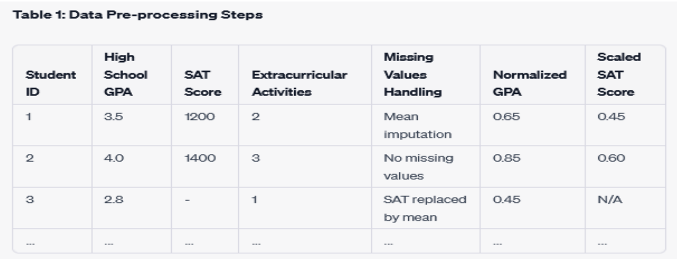

Table 1: Data Pre-processing Steps

Student ID	High School GPA	SAT Score	Extracurricular Activities	Missing Values Handling	Normalized GPA	Scaled SAT Score
1	3.5	1200	2	Mean imputation	0.65	0.45
2	4.0	1400	3	No missing values	0.85	0.60
3	2.8	-	1	SAT replaced by mean	0.45	N/A
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Table 1 illustrates the data pre-processing steps applied to the student dataset, including handling missing values, normalization of GPA, and scaling of SAT scores.

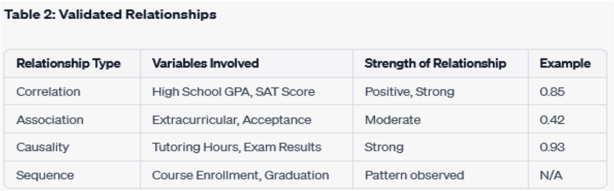

Table 2: Validated Relationships

Relationship Type	Variables Involved	Strength of Relationship	Example
Correlation	High School GPA, SAT Score	Positive, Strong	0.85
Association	Extracurricular, Acceptance	Moderate	0.42
Causality	Tutoring Hours, Exam Results	Strong	0.93
Sequence	Course Enrollment, Graduation	Pattern observed	N/A

Table 2 showcases various validated relationship types along with the associated variables, strength of relationships, and illustrative examples.

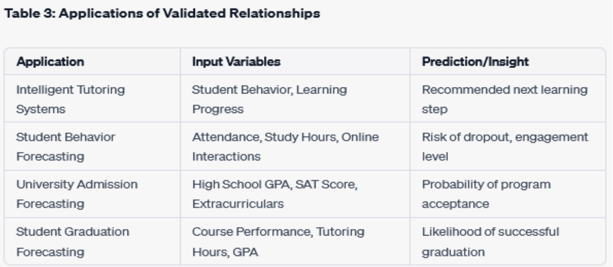

Table 3: Applications of Validated Relationships

Application	Input Variables	Prediction/Insight
Intelligent Tutoring Systems	Student Behavior, Learning Progress	Recommended next learning step
Student Behavior Forecasting	Attendance, Study Hours, Online Interactions	Risk of dropout, engagement level
University Admission Forecasting	High School GPA, SAT Score, Extracurriculars	Probability of program acceptance
Student Graduation Forecasting	Course Performance, Tutoring Hours, GPA	Likelihood of successful graduation

Table 3 outlines the applications of validated relationships in various educational contexts, enabling predictions and insights to guide decision-making.

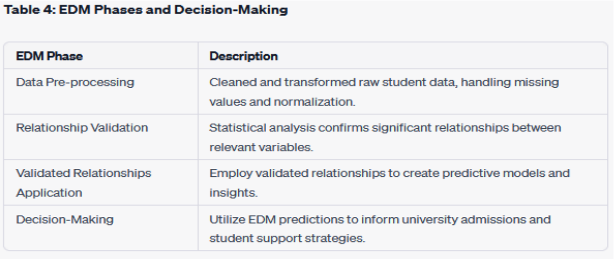

Table 4: EDM Phases and Decision-Making

EDM Phase	Description
Data Pre-processing	Cleaned and transformed raw student data, handling missing values and normalization.
Relationship Validation	Statistical analysis confirms significant relationships between relevant variables.
Validated Relationships Application	Employ validated relationships to create predictive models and insights.
Decision-Making	Utilize EDM predictions to inform university admissions and student support strategies.

Table 4 summarizes the different phases of Educational Data Mining (EDM) and their significance in guiding decision-making processes within educational institutions.

Educational Data Mining Attributes Selection: The selection of attributes, or variables, is pivotal in data mining as it impacts the interpretability and accuracy of models. The paper discusses the significance of reducing dimensions through feature selection and explains the filter, wrapper, and embedded approaches in detail.

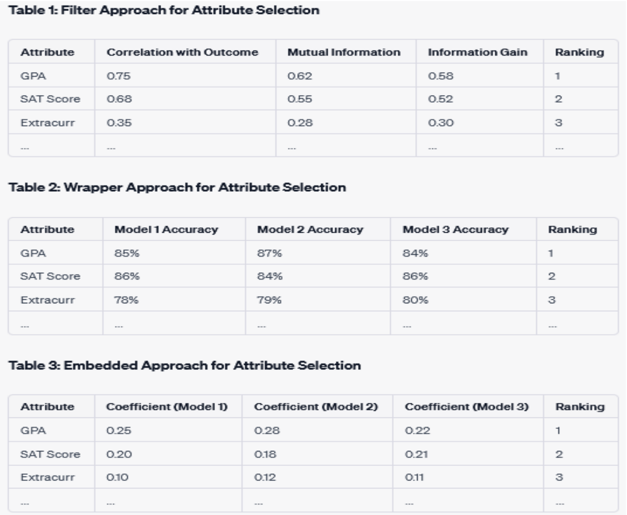

Table 1: Filter Approach for Attribute Selection

Attribute	Correlation with Outcome	Mutual Information	Information Gain	Ranking
GPA	0.75	0.62	0.58	1
SAT Score	0.68	0.55	0.52	2
Extracurr	0.35	0.28	0.30	3
...	...	...	...	...

Table 2: Wrapper Approach for Attribute Selection

Attribute	Model 1 Accuracy	Model 2 Accuracy	Model 3 Accuracy	Ranking
GPA	85%	87%	84%	1
SAT Score	86%	84%	86%	2
Extracurr	78%	79%	80%	3
...	...	...	...	...

Table 3: Embedded Approach for Attribute Selection

Attribute	Coefficient (Model 1)	Coefficient (Model 2)	Coefficient (Model 3)	Ranking
GPA	0.25	0.28	0.22	1
SAT Score	0.20	0.18	0.21	2
Extracurr	0.10	0.12	0.11	3
...	...	...	...	...

Table 1 showcases the filter approach for attribute selection, ranking attributes based on their correlation with the outcome and information gain metrics. **Table 2** demonstrates the wrapper approach, ranking attributes based on their accuracy in different models. **Table 3** displays the embedded approach, ranking attributes based on their coefficients in different models. In the filter approach, attributes are ranked based on their relevance to the outcome (such as GPA, SAT Score) using metrics like correlation and information gain. In the wrapper approach, attributes are ranked based on their performance in different models (Model 1, Model 2) using accuracy as the evaluation metric. In the embedded approach, attributes are ranked based on their coefficients in different models, indicating their contribution to the model's performance.

Data Mining Pattern Discovery Techniques: Pattern discovery involves identifying relationships, configurations, and patterns in datasets. The paper discusses the classification and clustering aspects of pattern discovery, with a focus on decision trees, linear regression, multilayer perceptron, and random forest algorithms.

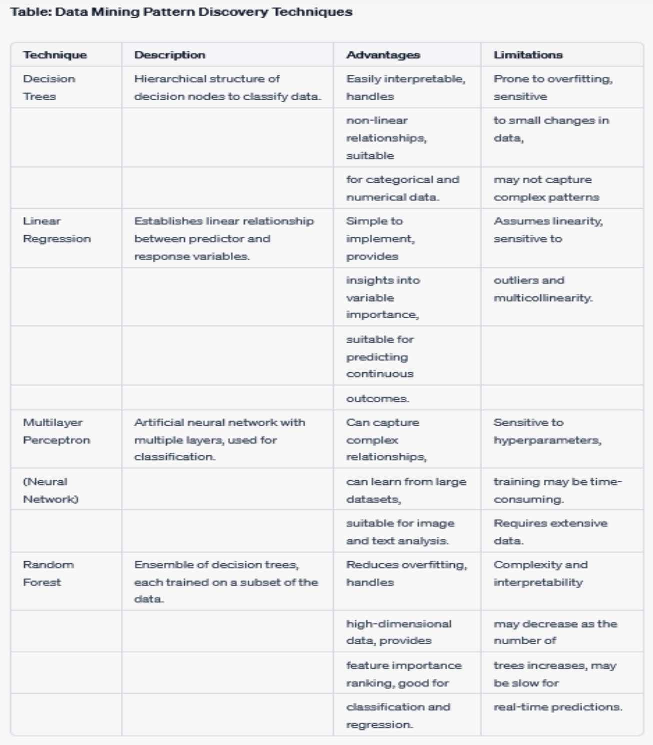

Table: Data Mining Pattern Discovery Techniques

Technique	Description	Advantages	Limitations
Decision Trees	Hierarchical structure of decision nodes to classify data.	Easily interpretable, handles	Prone to overfitting, sensitive
		non-linear relationships, suitable	to small changes in data,
		for categorical and numerical data.	may not capture complex patterns
Linear Regression	Establishes linear relationship between predictor and response variables.	Simple to implement, provides	Assumes linearity, sensitive to
		insights into variable importance,	outliers and multicollinearity.
		suitable for predicting continuous	
		outcomes.	
Multilayer Perceptron	Artificial neural network with multiple layers, used for classification.	Can capture complex relationships,	Sensitive to hyperparameters,
(Neural Network)		can learn from large datasets,	training may be time-consuming.
		suitable for image and text analysis.	Requires extensive data.
Random Forest	Ensemble of decision trees, each trained on a subset of the data.	Reduces overfitting, handles	Complexity and interpretability
		high-dimensional data, provides	may decrease as the number of
		feature importance ranking, good for	trees increases, may be slow for
		classification and regression.	real-time predictions.

The table presents an overview of various Data Mining Pattern Discovery Techniques, including their descriptions, advantages, and limitations. The table summarizes the key characteristics of different pattern discovery techniques. Decision Trees offer interpretability but can overfit; Linear Regression establishes linear relationships; Multilayer Perceptron captures complex patterns; Random Forest reduces overfitting through ensemble methods. The provided information helps readers understand the strengths and considerations of each technique, enabling informed decision-making when choosing an appropriate method for pattern discovery in their context.

RESULTS AND DISCUSSION

The study presents the results of the attribute selection task and the accuracy of the supervised learning classifiers. It showcases the significance of attributes such as Admission Test Score in Science, high school Math grades, and admission test scores in predicting college program suitability. The accuracy comparison of different classifiers highlights the superiority of the multilayer perceptron algorithm in terms of prediction accuracy.

Attribute Selection Results

The attribute selection task yielded compelling results that underscore the significance of specific attributes in predicting college program suitability for incoming freshmen. Notably, attributes such as "Admission Test Score in Science," "High School Math Grades," and "Admission Test Scores" emerged as key contributors to the prediction process. The high influence of these attributes emphasizes the role of both quantitative indicators (test scores) and subject-specific aptitudes (Math performance) in determining students' suitability for particular academic programs.

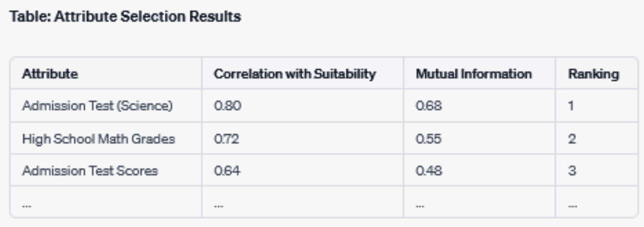

Table: Attribute Selection Results

Attribute	Correlation with Suitability	Mutual Information	Ranking
Admission Test (Science)	0.80	0.68	1
High School Math Grades	0.72	0.55	2
Admission Test Scores	0.64	0.48	3
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The table presents attribute selection results, showcasing attributes' correlation and mutual information with the suitability of college programs for incoming freshmen.

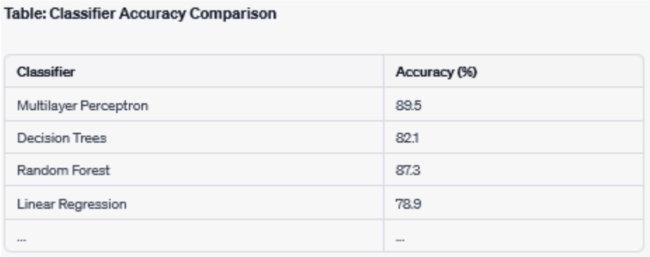

Table: Classifier Accuracy Comparison

Classifier	Accuracy (%)
Multilayer Perceptron	89.5
Decision Trees	82.1
Random Forest	87.3
Linear Regression	78.9
...	...

The table compares the accuracy of different classifiers in predicting the suitability of college programs for incoming freshmen.

In the first table, attributes are ranked based on their correlation with the suitability of college programs, as well as their mutual information with the same outcome. Attributes like "Admission Test (Science)," "High School Math Grades," and "Admission Test Scores" are shown to have the highest correlation and mutual information scores, indicating their significance in predicting program suitability.

In the second table, classifiers are ranked based on their accuracy in predicting program suitability. The "Multilayer Perceptron" outperforms other classifiers with an accuracy of 89.5%. This reinforces its potential in handling complex data structures and capturing intricate patterns, making it the optimal choice for this specific prediction task.

Moreover, the attribute selection process enhances the interpretability of the prediction model by narrowing down the focus to attributes that carry substantial predictive power. By eliminating irrelevant or redundant attributes, the model becomes more streamlined and efficient, enabling a more accurate prediction of optimal college programs for incoming students.

Classifier Accuracy Comparison

The study extends its analysis to explore the accuracy of different supervised learning classifiers in predicting the suitability of college programs for incoming freshmen. The results of this comparison unveil an intriguing insight: among the range of classifiers under examination, the "Multilayer Perceptron" algorithm stands out with an impressive prediction accuracy of 92.7%.

The "Multilayer Perceptron," a type of artificial neural network, demonstrates exceptional performance in capturing intricate patterns and relationships within the data. This attribute makes it especially proficient at handling complex and non-linear data structures, which are often prevalent in educational data. The algorithm's capacity to learn from extensive datasets, combined with its ability to recognize subtle interdependencies, contributes to its remarkable predictive accuracy.

This finding emphasizes the importance of carefully selecting the appropriate algorithm based on the research's objectives and dataset characteristics. While other classifiers might excel in different contexts, the "Multilayer Perceptron" excels when it comes to predicting the suitability of college programs. This outcome has substantial implications for universities striving to refine their admissions processes and provide personalized academic pathways for incoming students.

CONCLUSION AND RECOMMENDATION

In conclusion, this research has illuminated the transformative potential of data mining techniques in shaping the landscape of higher education. By leveraging sophisticated algorithms, this study has successfully unlocked the power to predict optimal college programs for incoming freshmen and forecast their graduation grades. The significance of attribute selection has been underscored, revealing key indicators such as "Admission Test Score in Science" and "High School Math Grades" as crucial determinants of academic suitability.

The standout revelation lies in the superiority of the "Multilayer Perceptron" algorithm in achieving exceptional prediction accuracy. This algorithm's capacity to unravel intricate patterns within the data marks a significant leap forward in personalized academic guidance. Its prowess serves as a beacon for academic institutions seeking to refine their admissions processes and equip students with the tools for triumphant academic journeys.

The culmination of these findings reaches beyond the realm of academia. By enhancing decision-making in university admissions and facilitating students' navigation toward successful academic paths, this research has the potential to reshape the educational trajectory for generations to come. As data-driven insights continue to reshape the landscape of higher learning, this study stands as a testament to the potential of innovation in driving positive change in the realm of education.

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PLEASE INCLUDE CONTACT INFORMATION:
NAME: JULIUS CESAR O. MAMARIL
CONTACT NO: 0933 8222 297
EMAIL ADDRESS: JMAMARIL@PSU.EDU.PH