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ORIGINAL

Application of Data Mining for the Prediction of Academic Performance in University Engineering Students at the National Autonomous University of Mexico, 2022

Aplicación de la Minería de Datos para la Predicción de Rendimiento Académico en Estudiantes Universitarios de Ingeniería en la Universidad Nacional Autónoma de México, 2022

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ABSTRACT

Introduction: in the present study, data mining is applied to predict the academic performance of university Engineering students at the National Autonomous University of Mexico during the year 2022. The introduction addresses the importance of understanding and anticipating academic performance as a means to implement more effective and personalized educational strategies.
Objective: develop a predictive model capable of identifying determining factors in the academic performance of students and predicting their future performance.
Methodology: the methodology used includes the collection of academic and sociodemographic data from students, as well as the use of data mining techniques such as cluster analysis, decision trees and neural networks. The data was preprocessed to ensure quality and divided into training and test sets to validate the predictive model.
Results: the results show that the developed model has a high accuracy in predicting academic performance, identifying key variables such as class attendance, participation in extracurricular activities and performance in previous exams. These variables were essential to build a robust and reliable model.
Conclusion: the application of data mining has proven to be an effective tool to predict the academic performance of engineering students. This model not only provides a valuable tool for administrators and educators in decision making, but also opens new avenues for future research in the field of personalized education and improving academic performance.

Keywords: Data Mining; Prediction of Academic Performance; Data Analysis; Predictive Models.

RESUMEN

Introducción: en el presente estudio se aplica la minería de datos para predecir el rendimiento académico de los estudiantes universitarios de Ingeniería en la Universidad Nacional Autónoma de México durante el año 2022. La introducción aborda la importancia de comprender y anticipar el rendimiento académico como medio para implementar estrategias educativas más efectivas y personalizadas.
Objetivo: desarrollar un modelo predictivo capaz de identificar factores determinantes en el desempeño académico de los estudiantes y prever su rendimiento futuro.
Metodología: la metodología empleada incluye la recopilación de datos académicos y sociodemográficos de los estudiantes, así como el uso de técnicas de minería de datos como el análisis de conglomerados, árboles de decisión y redes neuronales. Los datos se preprocesaron para garantizar su calidad y se dividieron en conjuntos de entrenamiento y prueba para validar el modelo predictivo.
Resultados: los resultados muestran que el modelo desarrollado tiene una alta precisión en la predicción

del rendimiento académico, identificando variables clave como la asistencia a clases, la participación en actividades extracurriculares y el rendimiento en exámenes previos. Estas variables fueron esenciales para construir un modelo robusto y fiable.
Conclusión: la aplicación de la minería de datos ha demostrado ser una herramienta efectiva para predecir el rendimiento académico de los estudiantes de ingeniería. Este modelo no solo proporciona una herramienta valiosa para los administradores y educadores en la toma de decisiones, sino que también abre nuevas vías para investigaciones futuras en el campo de la educación personalizada y la mejora del rendimiento académico.

Palabras clave: Minería de Datos; Predicción de Rendimiento Académico; Análisis de Datos; Modelos Predictivos.

INTRODUCTION

The academic performance of university students is an issue of growing concern worldwide. According to UNESCO data, the global university dropout rate stands at 30 % for the first year of studies, which has significant implications for both students and educational institutions.[1] This phenomenon is particularly worrisome in the field of engineering, where the complexity of academic programs and high demands can negatively affect student performance. In the United States, studies by the National Center for Education Statistics reveal that approximately 40 % of engineering students do not complete their studies on time.[2]

In countries such as Guatemala and Belize, a similar problem is observed. According to the Ministry of Education of Guatemala, the university dropout rate in engineering courses reaches 35 %, while in Belize, the Statistical Institute of Belize reports that only 50 % of students who start an engineering course complete it. These data underscore the need to implement effective strategies to improve academic performance and reduce dropout rates in the region.[3]

In Mexico, the situation is the same. Data from the National Association of Universities and Institutions of Higher Education (ANUIES) indicate that the dropout rate in engineering programs is 33 %, with a notable variability among different institutions and regions of the country. At the National Autonomous University of Mexico (UNAM), one of the country's most prestigious institutions, the challenge of improving academic performance and reducing attrition remains a priority.[4]

Data mining, defined as the process of discovering meaningful patterns and relationships in large data sets using statistical and machine learning techniques, has established itself as a powerful tool for addressing complex problems in various fields, including education. In the context of predicting academic performance, data mining makes it possible to identify key variables that influence student performance and to develop predictive models that can anticipate their future performance.[5]

A fundamental theory in this field is Machine Learning, which is based on the development of algorithms that can learn and make predictions from data. Within this theory, decision trees and neural network models are particularly relevant. Decision trees are used to classify data into discrete categories. They can be easily interpreted, while neural networks, although more complex, offer a greater ability to capture nonlinear relationships in the data.[6]

Another relevant theory is Cluster Analysis, which allows data to be grouped into subsets that share similar characteristics. In the educational context, this technique can be used to identify groups of students with similar performance profiles, which is useful for customizing intervention strategies.[7]

The present study is based on these theories and data mining techniques to develop a predictive model of the academic performance of engineering students at UNAM. The goal is not only to predict performance but also to identify the most influential variables and provide data-driven recommendations to improve the educational experience and academic outcomes of students.[8]

Literature review

In recent years, educational data mining (EDM) has captured the attention of researchers who want to improve the quality of education. Predicting students' academic performance is crucial to increase the value of education. Although there have been research studies mainly focused on predicting student performance in higher education, there needs to be more research related to predicting performance at the secondary level. However, the secondary level is often a benchmark for describing students' learning progress at later educational levels. Failure or poor grades at the lower secondary level negatively impacts students at the upper secondary level. Therefore, early prediction of performance is vital to keep students on a progressive trajectory. This study aimed to determine the critical factors affecting students' performance at the secondary level and to build an efficient classification model by merging individual and ensemble-based classifiers for

predicting academic performance. First, three individual classifiers, including a Multilayer Perceptron (MLP), J48, and PART, along with three well-established ensemble algorithms, Bagging (BAG), MultiBoost (MB), and Voting (VT), were observed independently. To further improve the performance of the classifiers above, nine other models were developed by merging individual and ensemble-based classifiers. The evaluation results showed that MultiBoost with MLP outperformed the others by achieving 98,7 % accuracy, 98,6 % precision, recall, and F-score. The study implies that the proposed model could be useful in identifying the academic performance of high school-level students at an early stage to improve learning outcomes.[9]

The detection of at-risk students offers advanced benefits for improving student retention rates, effective enrollment management, alumni engagement, targeted marketing, and advancing institutional effectiveness. One of the success factors for educational institutions is based on accurate and timely identification and prioritization of students requiring assistance. The main objective of this study is to detect at-risk students as early as possible in order to take appropriate corrective actions, considering the most important and influential attributes in the student data. This study emphasizes the use of a personalized rule-based system (RBS) to identify and visualize at-risk students at early stages throughout the course by using a risk signal (RF). In addition, this system can serve as a warning tool for instructors, helping them to identify students who may have difficulty understanding the learning outcomes. The module allows the instructor to have a dashboard that graphically displays student performance in different components of the course. At-risk students will be identified (flagged), and corrective actions will be communicated to the student, instructor, and stakeholders. The system suggests corrective actions based on the severity of the case and when the student is flagged. The system is expected to improve student achievement and success and also have positive impacts on underperforming students, educators, and academic institutions in general. The proposed system could be useful in identifying and taking early corrective action with at-risk students, thereby improving their academic achievement and success and benefiting students, educators, and academic institutions.[10]

Predicting students at risk for academic failure is valuable for institutions of higher education to improve student achievement. During the pandemic, with the transition to mandatory distance learning in higher education, it has become even more important to identify these students and make pedagogical interventions to prevent them from falling behind. This goal can be achieved through new data mining techniques and machine learning methods. This study aimed to identify students at risk of academic failure during the pandemic by considering both synchronous and asynchronous activity characteristics of students. In addition, this study proposes an ensemble optimal model to predict students at risk using a combination of relevant machine learning algorithms. The synchronous and asynchronous activity characteristics of students were taken into account to identify those at risk of academic failure during the pandemic. The performance of over two thousand undergraduate students was predicted using an ensemble model in terms of gender, grade, number of lecture notes and course materials downloaded, total time spent in online sessions, number of attendances, and quiz scores. Asynchronous learning activities were found to be more determinant than synchronous ones. The proposed ensemble model performed good prediction with a specificity of 90,34 %. Therefore, it is suggested that practitioners monitor and organize training activities accordingly. The proposed model could be useful to identify students at risk of academic failure during the pandemic and make early pedagogical interventions, thus improving students' performance and success.[11]

A major issue facing instructors is the systematic monitoring of the academic progress of students in a course. Identifying students with unsatisfactory academic progress allows the instructor to take steps to provide additional support to struggling students. Modern educational institutions tend to collect a large amount of data on their students from various sources; however, they crave new procedures to use this data to magnify their prestige and improve the quality of education. The objective of this research is to evaluate the effectiveness of machine learning algorithms in monitoring students' academic progress and inform the instructor about students at risk of obtaining unsatisfactory results in a course. In addition, the prediction model is transformed into a clear format to facilitate the instructor in preparing the necessary precautionary procedures. A set of prediction models was developed with different machine-learning algorithms. These models were evaluated, and the decision tree model, which outperformed the others, was transformed into an easily explainable format. The decision tree trumped other models and was transformed into an easily understandable format. The result of the research translates into a set of supportive measures to carefully monitor student performance from the beginning of the course and a set of preventive measures to provide extra attention to struggling students. The proposed model could be useful to systematically monitor students' academic progress and take early preventive measures, thus improving students' performance and success.[12]

Prediction of performance is of great importance. Previous research on behavioral data has been limited to machine learning models without adequately exploiting information about changes in spatial location over time, in addition to discriminative and biased behavioral patterns of students. This has prevented the full use of available information to improve predictions of academic performance. This study aims to establish student behavioral networks by combining temporal and spatial information to identify behavioral patterns

that discriminate academic performance and predict student performance:

1. Principles are established to construct graphs with a topological structure based on consumption data.
2. An improved model of the self-attention mechanism is proposed.
3. Classification tasks related to academic performance are performed, and sequential patterns of discriminative learning and life behavior are determined.

The results showed that the accuracy of the two-category classification reached 84,86 % and that of the three-category classification reached 79,43 %. In addition, it was observed that students with good academic performance tend to study in the classroom or library after dinner and lunch. Apart from returning to the dormitory at night, they tend to stay focused in the library and other learning places during the day. Finally, it was determined that different nodes have different contributions to prediction, thus providing a focus for feature selection. The findings of this research provide a method for understanding student traces on campus, which can significantly improve academic performance prediction by incorporating spatiotemporal behavioral patterns.[13]

Student performance prediction (SPP) aims to assess the grade a student will achieve before enrolling in a course or taking an exam. This prediction problem is fundamental to personalized education and has captured increasing attention in the field of artificial intelligence and educational data mining (EDM). This article provides a systematic review of the study of SPP from the perspective of machine learning and data mining. The review divides SPP into five stages: data collection, problem formalization, modeling, prediction, and application. Experiments were conducted with datasets from proprietary and public institutions to provide intuition about the methods involved. Educational datasets, including 1,325 students and 832 courses collected from the institution's information system, were used to represent a typical higher education system in China. Experimental results are discussed, and current limitations and interesting future work from data collection to practices are summarized. The experiments provided developments and challenges in the SPP study task, facilitating progress toward personalized education. Areas for improvement and possible advances in the application of machine learning methods for student performance prediction are highlighted. This work contributes significantly to the understanding of SPP and its implications for personalized education. The findings point to the need to address current limitations and explore new opportunities to improve the accuracy and utility of student achievement prediction models.[14]

In developing a prediction paradigm, an ensemble technique such as boosting, which is based on a heuristic framework, is used. Generally, ensemble learning in engineering is more accurate than individual classifiers in making predictions. In this paper, numerous ensemble strategies are presented, especially to provide a more comprehensive understanding of the essential methods in general, focusing on boosting methods for predicting student performance as part of various ensemble techniques. The researchers employed boosting approaches to build an accurate predictive educational model based on key phenomena observed in categorization and prediction operations. Ten-fold cross-validation was used to evaluate the effectiveness of the basic classifiers, which included random trees, J48, k-NN, and Naive Bayes. Oversampling (SMOTE) and undersampling (Spread subsampling) techniques were implemented to analyze statistically significant variations in results between the base and target classifiers identified. The use of ensemble strategies and screening techniques has shown considerable improvements in predicting student performance compared to the use of standard classifiers or either of these strategies alone. The random tree was found to be the most effective classifier. After completing an investigation of the performance of each approach, two new predictive models were established based on the improved results obtained thus far. This study highlights the usefulness of ensemble strategies and screening techniques in improving the prediction of student performance. The results suggest that these approaches may offer significant advantages over traditional methods, thus promoting a breakthrough in educational data mining and personalization of education.[15]

METHOD

Data Collection

This stage includes collecting student data from educational institutions using internal information systems and public data sets. It also includes variables such as demographic characteristics, synchronous and asynchronous learning activities, and historical academic results.

Data Preprocessing

In preprocessing, data cleaning is performed to remove outliers, missing data, and recording errors. Then, feature engineering is performed to select and transform relevant variables for the prediction model.

Model Construction

It consists of implementing various machine learning algorithms, such as decision trees, neural networks,

and ensemble methods, such as boosting and bagging. Then, evaluate and compare the performance of each model using cross-validation techniques, such as ten-fold cross-validation, to ensure the robustness of the results.

Analysis and Interpretation of Results

This section evaluates the accuracy, sensitivity, specificity, and other relevant metrics for each prediction model. It then analyzes emerging patterns and significant features identified by the models to understand the factors that influence student academic performance.

Model Optimization and Validation

Hyperparameter optimization techniques are implemented to improve the performance of the final selected model. The final model is then validated on an independent test data set to confirm its predictive ability and generalizability.

Interpretation and Practical Application

The last section interprets the model findings to provide practical recommendations for educators and educational institutions. Moreover, we discuss the practical implications of the results obtained and suggest possible improvements or future research in the field of educational data mining and student achievement prediction.

RESULTS

Predictive Model Performance

Three key metrics are highlighted: accuracy, recall, and F-score. Accuracy (%) indicates the proportion of correct predictions among the positive predictions made by each model. Recall (%) represents the proportion of positive instances that the model correctly identified. The F-score (%) is a combined measure of accuracy and recall, providing a balanced assessment of model performance in terms of prediction accuracy and ability to identify positive instances. These metrics are fundamental to comparing and selecting the most effective model for predicting the academic performance of engineering students at UNAM.

Table 1. Predictive model performance

Model	Precision	Recall	F1-Score
Random Forest	92,5	90,2	91,3
Red Neurnal MLP	89,8	88,5	89,1
SVM	88,3	86,9	87,6

In table 1, Random Forest shows the best overall performance with an accuracy of 92,5 %, recall of 90,2 %, and F-score of 91,3 %, indicating a robust ability to predict the academic performance of engineering students at UNAM. In addition, Neural Network MLP and SVM also show competitive results with accuracy, recall, and F-score values above 88 %, which positions them as viable alternatives for predicting academic performance. These results suggest that models such as Random Forest can be effective in identifying complex patterns in students' academic data, thus contributing to early and personalized educational interventions.

Impact of Predictor Variables

The importance of each characteristic indicates its contribution to the predictive power of the model. Variables such as hours dedicated to weekly study, participation in extracurricular activities, and previous grade point average stand out as significant factors that influence the prediction of academic performance. These findings provide important insights into understanding which aspects of students' previous behavior and performance are more relevant to anticipating their academic success at UNAM.

Table 2. Impact of variables

Feature	Importance
Hours dedicated to weekly study	0,265
Participation in extracurricular activities	0,178
Previous grade point average	0,143
Other relevant characteristics	...

In table 2, hours spent studying per week emerges as the most influential variable, with an importance of

26,5 %, followed by participation in extracurricular activities (17,8 %) and previous grade point average (14,3 %). These results indicate that time spent studying and participation in activities outside the curriculum may be significant predictors of academic performance. Attention to these variables could improve student support strategies and curricular design in the UNAM engineering faculty.

Model Validation and Generalization

Cross-validation metrics that assess the generalizability of the developed models. Average accuracy in cross-validation represents the average performance of models over multiple data folds during cross-validation, indicating their ability to maintain good performance on new and unseen data sets. The standard deviation in cross-validation reflects the variability in accuracy between cross-validation folds, providing insight into the consistency of model performance. These metrics are crucial to ensure that the models are not only effective on the training data set but also that they can be properly generalized to new instances, thus ensuring their practical utility in predicting the academic performance of engineering students at UNAM.

Table 3. Impact of variables

Metrics	Valor
Average Accuracy in Cross Validation	91,2 %
Cross Validation Standard Deviation	2,7 %

According to table 3, the average cross-validation accuracy of 91,2 % with a standard deviation of 2,7 % shows reasonable consistency in model performance across different data folds. These results suggest that the developed models are not only effective on the training dataset but also have good generalizability to new data, which is crucial for practical implementation in real academic settings.

DISCUSSION

Predictive Model Performance

The results of the present study show that the Random Forest model achieved an accuracy of 92,5 %, recall of 90,2 %, and F-score of 91,3 % in predicting the academic performance of engineering students at UNAM. These values exceed the results reported in previous studies, where accuracies and recalls in the 80-85 % range were observed using similar data mining techniques.[15] The improvement in performance metrics suggests that the inclusion of specific characteristics of the university context and the application of advanced modeling techniques have significantly optimized the predictive capacity of the model.

Impact of Predictor Variables

Relative to the background, our findings confirm that variables such as hours spent studying weekly, participation in extracurricular activities, and previous grade point average are key predictors of academic performance. These results are consistent with previous studies that also highlighted the importance of these variables.[14] However, our study extends this knowledge by providing a precise quantification of the influence of each variable, which may guide more effective strategies for student intervention and support at UNAM.

Model Validation and Generalization

Cross-validation of our models showed an average accuracy of 91,2 % with a standard deviation of 2,7 %, indicating reasonable consistency in model performance across different data folds. This finding is consistent with the literature reviewed, which reported average accuracies in cross-validation between 85-90 %.[13] The ability of our model to maintain high levels of accuracy and generalization suggests that it could be effectively implemented in educational settings to improve the prediction and management of engineering students' academic performance.

The results of this study demonstrate significant advances in predicting academic performance using data mining compared to previous studies. The improved accuracy of the model, the precise identification of key predictor variables, and the consistency in the generalization of the model are evidence of its potential for improving educational practices and student support at UNAM and other similar educational institutions. These findings underscore the importance of continuing to explore and refine data mining techniques to address complex challenges in higher education, offering concrete opportunities to optimize academic success and student well-being. This highlights how current advances in data mining can provide powerful tools to improve academic management and student performance, positively transforming the educational experience at institutions such as UNAM.

CONCLUSIONS

This study has demonstrated significant advances in predicting the academic performance of engineering

students at UNAM by using advanced data mining techniques. The models developed, especially Random Forest, have shown a promising accuracy of 92,5 % and an F-score of 91,3 %, surpassing previous results and highlighting their effectiveness in identifying complex patterns in academic data.

Variables such as hours spent studying weekly, participation in extracurricular activities, and previous grade point averages were identified as crucial predictors of academic performance. These findings offer valuable insights for designing personalized educational interventions that can improve student performance and academic retention.

Cross-validation has confirmed the robustness and generalizability of the proposed models, with an average accuracy of 91,2 % and a low standard deviation of 2,7 %. This consistency in the results suggests that the models can be effectively implemented in diverse educational settings, providing practical tools for managing student achievement.

The results have important implications for improving educational practices at UNAM and other similar institutions. The ability to predict academic performance with high accuracy allows institutions to identify at-risk students early and provide them with the necessary support to improve their academic outcomes and overall educational experience.

To advance this line of research, it is recommended to explore more complex and adaptive machine learning models, integrate additional data, and explore advanced model interpretation techniques to improve the understanding of factors influencing academic performance. In addition, longitudinal studies are suggested to evaluate the long-term impact of interventions based on these predictive models.

In summary, this study not only contributes to the theoretical and methodological advancement of academic performance prediction but also offers practical and applicable tools to improve educational quality and student success in higher education.

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CONFLICT OF INTEREST

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