Education Data Mining: Students' Performance in Statistics Class Using Machine Learning

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ABSTRACT

This study aims to investigate student performance in the Statistics Course, using machine learning, at ACLEDA University of Business, so that students at risk of academic failure can be identified. The study employs a dataset comprised of the academic records of 1,074 students. The records include final exam scores, ongoing assessments (homework and quizzes), and midterm grades. Orange software is a tool used to process data and train models using a number of machine learning algorithms, including K-nearest neighbors, Random Forest, Logistic Regression, Support Vector Machine, and Naïve Bayes. The findings indicate that midterm performance and continuous assessments are powerful predictors of final exam success, and that difficulties on final exams are associated with subpar performance in these domains. Equal-width discretization was used to classify the data in order to control for outliers and examine non-linear relationships. Classification accuracy, precision, recall, F1 score, and AUC were used to assess the model's effectiveness. This study demonstrates how machine learning can give teachers information about how well their students are performing, allowing for more focused interventions and a more encouraging learning environment.

Keywords: Education Data Mining, Predictive Modeling, Machine Learning Algorithms, Academic Performance, Risk Identification, Intervention Strategies

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1. Introduction

Background of the study

Statistics is known as an essential subject across a wide range of academic disciplines including social sciences, health sciences, and business. A solid understanding of statistics equips students with the ability to analyze data, interpret results, and make evidence-based decisions. Despite its significance, students frequently underperform in statistics courses, with challenges linked to factors such as math anxiety, lack of foundational knowledge, and ineffective teaching methods (Sutter et al., 2024; Yağcı, 2022). This persistent difficulty not only undermines academic performance but also limits students' preparedness for data-driven professions.

To address these challenges, educators and researchers are increasingly leveraging Educational Data Mining (EDM) and Machine Learning (ML). These approaches enable the analysis of large-scale educational data, uncover patterns of student behavior, and facilitate early prediction of academic performance (Yağcı, 2022). For example, EDM techniques such as regression models, decision trees, and clustering can be used to detect at-risk learners, while ML methods provide predictive accuracy that can guide timely interventions (Xiong et al., 2024).

Given the persistent struggle of students in statistics and the growing potential of EDM and ML for education, this study seeks to identify key predictors of student success in statistics courses. It will provide insights that can support innovative teaching strategies and improve student learning outcomes.

Research objective

This study aims to investigate student performance in the Statistics Course, using machine learning at ACLEDA University of Business. This study focuses on the use of six machine learning algorithms, namely Random Forest, Support Vector Machine, Logistic Regression, KNN, Naïve Bayes, and Neural Network to predict students' performance in the 2023-2024 academic year in Statistics courses I & II. Early identification of students who may be at risk of academic failure allows for timely interventions, which can enhance their learning experiences and outcomes (Ujkani et al., 2024).

Research scope

In this study, we draw a comprehensive dataset comprised of the academic records of 1,074 students. The dataset encompasses various performance indicators, with ongoing assessments accounting for 40% of the total grade, midterm exams contributing 20%, and final exams making up 30%. By analyzing these components, the study seeks to identify the significant predictors of final exam performance. The research employs a range of machine learning algorithms, including k-nearest neighbors, random forest, logistic regression, support vector machine, and naïve Bayes, to build predictive models capable of accurately forecasting student outcomes.

Significance of the study

By employing advanced data mining techniques, educators can move beyond traditional qualitative assessments and gain a deeper understanding of student behavior and performance. Students are able to receive any special support, such as personal discussions with at-risk students about the barriers to learning statistics. Students who lack prior knowledge in statistics or foundational mathematics may require additional support.

The finding also contributes to the creation of a nurturing learning environment that encourages academic achievement for all students by identifying those who are at risk and offering prompt interventions. The lecturers have enough time to assist students in concentrating on the upcoming assessment, such as quiz II and the final exam, if the results of the ongoing assessment and midterm exam fall short of the average score. Teachers can benefit greatly from the knowledge gathered from this study, which will help them make wise decisions that will increase their effectiveness as teachers and raise student achievement.

2. Literature Review

In recent years, there has been a growing attention to the application of data mining and machine learning techniques in educational settings, especially when it comes to forecasting student performance (Xiong et al., 2024). The study looks at a number of studies that demonstrate how well these approaches work to improve learning outcomes and identify students who are at risk.

Papadogiannis et al. (2024) emphasizes the importance of utilizing diverse data sources within educational contexts to gain a comprehensive understanding of learners and their behaviors. The combination of both enables educators to develop more effective strategies for performance prediction and the identification of students who may require additional support (Chen et al., 2025). The field of education data mining has been transformed by the development of big data techniques, which enable teachers to obtain timely insights into the behaviors of their students (Baig et al., 2020). This point is further developed by (Yadav et al., 2012), who point out that data mining is crucial for pinpointing particular student groups in need of focused interventions, going beyond conventional qualitative evaluations.

Koedinger et al. (2015) have investigated diverse approaches to assessing statistics learning, incorporating measures of cognition, metacognition, motivation, affect, language, and social discourse. Drawing on data from intelligent tutoring systems and massive open online courses, their study demonstrates that these techniques significantly enhance the prediction of students' responses to tasks involving intelligent tutoring. The findings also show how data-driven models can strengthen cognitive understanding and foster meaningful dialogue in online learning environments, such as discussion forums and chat rooms. This highlights the potential of applying machine learning collaboratively in educational settings to improve student engagement and learning outcomes.

Francis and Babu (2019) have introduced a novel prediction algorithm designed to evaluate student performance across various academic disciplines. By combining clustering and classification methods, this hybrid data mining approach makes it possible to conduct assessments in real time using student datasets. The study has proved that their algorithm could successfully spot pupils who might perform poorly, allowing for prompt interventions to help them along their academic paths.

Romero and Ventura (2013) focus on developing techniques to investigate the diverse kinds of data generated in learning settings. their research sought to better understand how students learn and the environments in which learning occurs. They maintained that each educational issue has unique goals and traits that call for customized data mining strategies. This viewpoint has remained essential for educators looking to put data-driven insights into practice through successful interventions.

Makhtar et al. (2017) further contributed to the literature by predicting various levels of student performance, from outstanding to poor, using the Naïve Bayes algorithm. Their study demonstrates how machine learning methods can provide detailed insights into student performance, enabling educators to identify high achievers as well as those in need of additional support.

Hoffait and Schyns (2017) have confirmed the efficacy of machine learning models in forecasting student performance, pointing out that more sophisticated models are typically more accurate in identifying students who are having difficulty than more conventional approaches. Their study highlights how crucial it is to choose the best machine learning approaches depending on the data at hand and the particular analysis goals (Hoffait & Schyns, 2017). Diekuu et al. (2025) have emphasized that utilizing longitudinal records of students' past performance enhances the accuracy of predicting their academic outcomes in future semesters. These studies have led to the conclusion that machine-learning methods can greatly improve student performance prediction, especially in difficult subjects like statistics.

According to Tapio (2025), Random Forest and Neural Networks are particularly adept at handling the complex, non-linear relationships found in educational data, which often leads to better performance than traditional statistical models. Instruments for generating these forecasts are models like Random Forest and Neural Networks are useful for predicting student performance (Alyahyan & Düştegör, 2020). Their ability to detect patterns in student data allows educators to identify learners who may require additional support at an early stage, enabling timely interventions to enhance learning outcomes (Alyahyan & Düştegör, 2020).

Wu et al. (2024) emphasized the importance of developing personalized support systems for students based on the insights gained from machine learning analyses. By focusing on the key factors influencing student success, educators can create tailored learning experiences that cater to individual needs (Idowu, 2024). This approach not only benefits struggling students but also fosters a more supportive and effective learning environment for all.

In summary, the literature indicates that applying data mining and machine learning techniques in education holds significant potential for improving the prediction of student performance. By leveraging these advanced methodologies, educational institutions can gain valuable insights into student behavior and performance trends, ultimately leading to interventions that are more effective and enhance academic outcomes. The ongoing exploration of data-driven methods in educational contexts is essential for fostering a culture of continuous improvement and student success.

3. Methodology

Research design

This study employed a predictive modeling approach using educational data mining (Batool et al., 2023). A comprehensive dataset of 1,074 students' academic records from the ACLEDA University of Business, including ongoing assessments, midterm grades, and final exam scores, were utilized. The research design involves processing and training this data using Orange software and several machine learning algorithms: K-nearest neighbors, Random Forest, Logistic Regression, Support Vector Machine, and Naïve Bayes (Dayyeh et al., 2025). Equal-width discretization was applied to the data to handle outliers and non-linear relationships. Model performance was evaluated using metrics such as classification accuracy, precision, recall, F1 score, and the AUC-ROC curve to identify the most effective predictive model for student performance.

Data set

ACLEDA University of Business (AUB) regularly stores all the available students' information, including demographic and study records, in a modern system, which is developed by an AUB programmer called University Resource Management Systems (URMS). The records of students' achievements are really beneficial for lecturers and researchers. In this study, the researcher aims to investigate students' progress in Statistics I and II (STA 106 and STA 207) over the course of the semester and predict their academic outcomes. This approach enables educators to provide timely support to students with lower performance levels.

Table 1: Data set

Academic performance	Number of students
Statistics for Business and Economics (STA 106)	501
Quantitative Analysis for Management (STA 207)	573
Total	1074

At AUB, a full semester is 16 weeks, while ongoing assessments are the performance of students during the semester, including homework, quizzes, and any participation. It can be flexible depending on the subject and lecturers; however, the weighted average is 40%. For STA 106 and STA 207, Homework I, II, and Quiz I will be done before the midterm, and Homework III, IV, and Quiz II will be done after the midterm. The midterm was done around 7-8 weeks after the class started, and the full score was 20%. Students with an achievement below 12% were considered unsuccessful, and those above were considered successful. Similarly, the final exam accounted for 30% of the grade and was conducted at the end of the semester. Those with a score below 18% were considered unsuccessful, while those with a score above it were considered successful. The total assessment scores from lecturers are 90%, while 10% is automatically generated in the system if they were absent and permission was granted for fewer than six sessions. The duration from midterm to final was 8 to 9 weeks, which would provide sufficient time for high-risk students (those at risk of failure) to prepare for the final exam. The results of ongoing assessments and midterm examinations serve as strong indicators for predicting students’ performance on the final exam. In other words, students who perform poorly on these assessments are likely to be predicted to achieve lower final exam scores.

Data collection

The study utilized achievement records from 1,074 students enrolled in Statistics I and II, obtained from the URMS for the academic year 2023–2024. Students’ performance was evaluated based on ongoing assessments, midterm examinations, and final examinations, which served as the criteria for prediction.

The implementation of the Algorithm and Model Establishing Machine

Machine learning algorithms are useful tools to predict students' performance in many studies since these tools can predict the factors, including qualitative and quantitative, together (Zhao et al., 2023). Moreover, it can train and learn from the data and produce an accurate model to predict students 'performance. In this study, some machine learning algorithms such as k-nearest neighbors, Random Forest, Logistic regression, Support Vector Machine, and Naïve Bayes were employed to predict the students' performance.

Experiments

In the experiment session, data sets were completely trained and processed by Orange (machine learning software) based on data mining. Orange software is convenient and powerful for training data for developing model prediction, and it produces more accurate prediction models by combining different components in workflows that exist in terms of qualitative and quantitative variables (Popchev & Orozova, 2023).

The data sets included midterm exam grades and ongoing assessment grades, which included homework I and II; quizzes I, II, and the final exam were employed as features. All variables are the data associated with students' information that were taken from 1074 students who took STA I & II courses during the 2023-2024 semester. Detailed information about the datasets is provided in the attached file and corresponding tables.

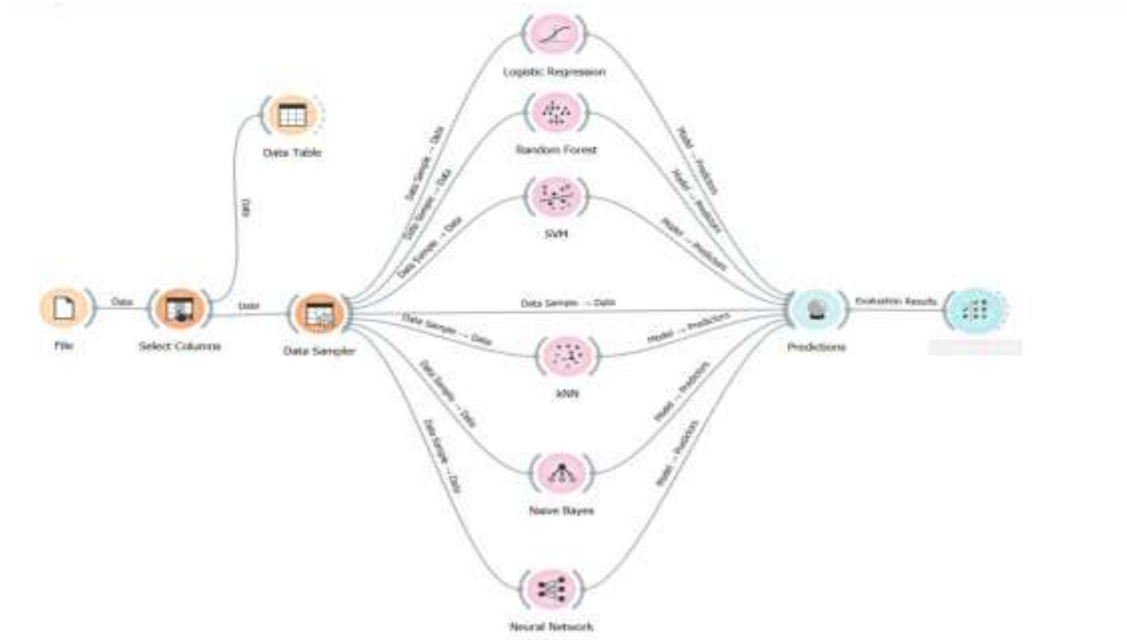

Figure 1: Design Model

Table 2: Dataset

N0	Name	On Going Ass 40%	Midterm 20%	Final Exam 30%
1	St ID 0001	29.69	15.20	23.70
2	St ID 0002	32.72	9.20	8.70
3	St ID 0003	32.88	13.60	3.60
4	St ID 0004	28.97	14.20	15.90
5	St ID 0005	35.97	15.00	19.20
6	St ID 0006	33.25	13.60	17.70
7	St ID 0007	35.22	15.00	15.30
8	St ID 0008	31.09	14.20	20.70
…	…	…	…	…
1072	St ID 1072	33.00	9.40	14.70
1073	St ID 1073	33.33	9.60	20.10
1074	St ID 1074	38.75	14.80	24.30

After the variable model was determined, ongoing assessment scores, midterm exam, and final exam grades were categorized according to the equal-width discretization model, since some data are outliers, and the researcher aims to predict a non-linear relationship between the data, it is important to convert those into a category format.

Evaluation of the model performance

The performance of the model was evaluated with a confusion matrix, classification accuracy (CA), precision, recall, f-score (F1), and Area under the ROC curve (AUC) metrics.

Table 3: The Model Variables

Features	Target variable	Meta Attributes
Midterm		
On Going Assessment	Final	stdID

Confusion Matrix

The confusion matrix displayed the current state of the dataset and the number of correct and incorrect predictions made by the model. Table 4 shows that the number of correctly classified instances and incorrect instances calculate the model's performance. The row shows the real numbers of the sample in the test set, and the column represents the estimation of the proposed model.

Table 4: The Confusion Matrix

	Predicted	
	Positive (1)	Negative (0)
Actual	TP	FP
	FN	TN

In Table 4, true positives and true negatives show the number of correctly classified instances. False positives show the number of instances predicted as positive (1) while they should be in the negative (0) class. False negative shows the number of instances predicted as negative (0) while it should be positive (1) class.

Classification Accuracy: CA is the ratio of the correct predictions $TP + TN$ to the total number of instances: $(TP + TN + FP + FN)$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision is the ratio of the number of positive instances that are correctly classified to the total number of instances that are predicted positive. Gets the value in the rang $[0,1]$.

$$Precision = \frac{TP}{TP + FN}$$

Recall: Recall is the ratio of the correctly classified number of positive instances to the number of all instances whose actual class is positive. The recall is also called the *F - criterion*.

$$F - criterion = \frac{2 \times Duyarlilik \times Ke\sin lik}{Duyarlilik + Ke\sin lik}$$

Receiver operating characteristics (ROC) curve

The AUC-ROC curve describes how well a model predicts and is used to assess how well machine learning algorithms perform, particularly when dealing with unbalanced datasets.

AUC: Area under the ROC curve

The Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) is a critical metric used to evaluate the performance of machine learning models, particularly in binary classification tasks. The AUC provides a single scalar value that summarizes the model's ability to distinguish between positive and negative classes across various threshold settings.

In Table 5, the AUC values for different machine-learning models are presented as follows:

- Random Forest: AUC = 0.964
- Neural Network: AUC = 0.999
- Support Vector Machine (SVM): AUC = 0.996
- Logistic Regression: AUC = 0.999
- Naïve Bayes: AUC = 0.969
- k-Nearest Neighbors (kNN): AUC = 0.978

Table 5 also shows the values of classification for different machine-learning models are presented as follows:

- Random Forest: CA = 0.930
- Neural Network: CA = 0.972
- Support Vector Machine (SVM): CA = 0.956
- Logistic Regression: CA = 0.963

- Naïve Bayes: CA = 0.888
- k-Nearest Neighbors (kNN): CA = 0.953

In general, if the AUC and CA values are closer to 1.00, it indicates a better-performing model, while a value of 0.5 suggests no discriminative ability (equivalent to random guessing).

According to the results, as demonstrated in Table 5, the Neural Network results in a high accuracy of 97.2%, and the models are particularly effective for predicting student performance based on the data analysis.

4. Results and Discussions

The results of our study show that different machine-learning models can predict student performance with varying levels of success. Among the models we tested, the Neural Network models performed the best, both achieving a classification accuracy of 97.2% and an AUC of almost 100%. This means that this model was able to correctly predict whether students would do well or poorly in their courses more than 97% of the time. The Logistic Regression model is the second best, with an area under the curve (AUC) score of 0.999, the same as the Neural Network. A higher AUC score indicates that the model is better at distinguishing between students who are likely to succeed and those who are at risk of failing.

On the other hand, the Random Forest model had a lower classification accuracy of 93.0% and an AUC of 96.4%. Neural Network models are the best predictors, while other models are still useful since these models achieve student performance with an accuracy of over 90% accuracy. However, their AUC values suggest that they might not be as reliable in identifying students who are struggling compared to the more advanced ones.

Table 5: Performance Metrics (AUC, CA, F1-Score) for Different Machine Learning Models.

Model	AUC	Classification Accuracy (CA)	F1 score (%)
Knn	0.978	0.953	0.953
Logistic Regression	0.999	0.963	0.962
Random Forest	0.964	0.93	0.93
SVM	0.996	0.956	0.955
Naiv Bayes	0.969	0.888	0.89
Neural Network	0.999	0.972	0.972

These results highlight how crucial it is to choose the best machine-learning methods based on the data at hand and the particular goals we hope to accomplish. With a 90% confidence level, 12.2% of students were found to be at a very high risk of failing, which highlights the necessity of providing these students with early support. By leveraging the predictive power of these models, schools and universities can develop targeted support programs to assist students who are most in need.

5. Conclusion and recommendation

Conclusion

The study demonstrates that machine learning techniques can be highly effective in predicting students' performance in their courses, particularly in subjects such as statistics. The Neural Network models stood out as the most effective tools for making these predictions. Their ability to analyze multiple factors influencing student performance enables educators to identify learners who may require additional support at an early stage.

The insights from this research can guide schools in developing personalized support systems for students. By focusing on the key factors that influence student success, educators can create tailored learning experiences that meet the individual needs of each student. This approach not only helps students who are struggling but also promotes a more supportive and effective learning environment for everyone.

Overall, the use of machine learning in education has great potential. By implementing these advanced techniques, educational institutions can better understand their students' needs and improve academic outcomes. This study underscores the need for further research on how data-driven approaches can improve teaching and learning, ultimately fostering higher levels of student success.

Recommendation

Enhance Data Collection Practices

To ensure comprehensive and accurate records of student performance, institutions should strengthen both quantitative and qualitative data collection methods. Robust data practices provide the foundation for effective analysis and informed decision-making.

Integrate Machine Learning into Educational Strategies

Educators should incorporate machine learning tools into their instructional approaches. Providing faculty with training on how to interpret predictive analytics can empower them to make data-informed decisions that address the diverse learning needs of their students.

Implement Targeted Interventions

Educational institutions should use predictive models to identify students at risk of academic failure early in the semester. By offering timely support, such as tutoring or mentoring programs, institutions can enhance student engagement and improve overall academic performance.

References

Alyahyan, E., & Düştegör, D. (2020). Predicting academic success in higher education: literature review and best practices. *International Journal of Educational Technology in Higher Education*, *17*(1), 3.

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2020). Big data in education: a state of the art, limitations, and future research directions. *International Journal of Educational Technology in Higher Education*, *17*(1), 44.

Batool, S., Rashid, J., Nisar, M. W., Kim, J., Kwon, H.-Y., & Hussain, A. (2023). Educational data mining to predict students' academic performance: A survey study. *Education and Information Technologies*, *28*(1), 905-971.

Chen, Y., Sun, J., Wang, J., Zhao, L., Song, X., & Zhai, L. (2025). Machine Learning-Driven Student Performance Prediction for Enhancing Tiered Instruction. *arXiv preprint arXiv:2502.03143*.

Dayyeh, R., AlSawareah, W., Kasasbeh, B., Qaddoura, R., & Kamal, S. (2025, 2023). Comparative Analysis of Decision Trees, Random Forest, and k-Nearest Neighbors in Predictive Analytics for Orange Telecom's Customer Complaint Data.

Diekuu, J.-B., Mekala, M. S., Abonie, U. S., Isaacs, J., & Elyan, E. (2025). Predicting student next-term performance in degree programs using AI-based approach: a case study from Ghana. *Cogent Education*, *12*(1), 2481000.

Francis, B. K., & Babu, S. S. (2019). Predicting academic performance of students using a hybrid data mining approach. *Journal of medical systems*, *43*(6), 162.

Hoffait, A.-S., & Schyns, M. (2017). Early detection of university students with potential difficulties. *Decision support systems*, *101*, 1-11.

Idowu, E. (2024). Personalized Learning: Tailoring Instruction to Individual Student Needs.

Koedinger, K. R., D'Mello, S., McLaughlin, E. A., Pardos, Z. A., & Rosé, C. P. (2015). Data mining and education. *Wiley Interdisciplinary Reviews: Cognitive Science*, *6*(4), 333-353.

Makhtar, M., Nawang, H., & Wan Shamsuddin, S. N. (2017). ANALYSIS ON STUDENTS PERFORMANCE USING NAÏVE BAYES CLASSIFIER. *Journal of Theoretical & Applied Information Technology*, *95*(16).

Papadogiannis, I., Wallace, M., & Karountzou, G. (2024). Educational data mining: A foundational overview. *Encyclopedia*, *4*(4), 1644-1664.

Popchev, I., & Orozova, D. (2023). Algorithms for Machine Learning with Orange System. *International Journal of Online & Biomedical Engineering*, *19*(4).

Romero, C., & Ventura, S. (2013). Data mining in education. *Wiley Interdisciplinary Reviews: Data mining and knowledge discovery*, *3*(1), 12-27.

Sutter, C. C., Givvin, K. B., & Hulleman, C. S. (2024). Concerns and challenges in introductory statistics and correlates with motivation and interest. *The Journal of Experimental Education*, *92*(4), 662-691.

Tapio, R. (2025). Comparative Analysis of Multiple Linear Regression and Random Forest Regression in Predicting Academic Performance of Students in Higher Education. *Asian Research Journal of Mathematics*, *21*(4), 170-181.

Ujkani, B., Minkovska, D., & Hinov, N. (2024). Course success prediction and early identification of at-risk students using explainable artificial intelligence. *Electronics*, *13*(21), 4157.

Wu, S., Cao, Y., Cui, J., Li, R., Qian, H., Jiang, B., & Zhang, W. (2024). A comprehensive exploration of personalized learning in smart education: From student modeling to personalized recommendations. *arXiv preprint arXiv:2402.01666*.

Xiong, Z., Li, H., Liu, Z., Chen, Z., Zhou, H., Rong, W., & Ouyang, Y. (2024). A review of data mining in personalized education: Current trends and future prospects. *Frontiers of Digital Education*, *1*(1), 26-50.

Yadav, S. K., Bharadwaj, B., & Pal, S. (2012). Mining Education data to predict student's retention: a comparative study. *arXiv preprint arXiv:1203.2987*.

Yağcı, M. (2022). Educational data mining: Prediction of students' academic performance using machine learning algorithms. Smart Learning Environments, 9, doi.org/10.1186/s40561-022-00192-z

Zhao, L., Ren, J., Zhang, L., & Zhao, H. (2023). Quantitative analysis and prediction of academic performance of students using machine learning. *Sustainability*, *15*(16), 12531.

Author's Biography

Chanrey Pang is a Lecturer at the Department of Business Economics in Faculty of Law and Economics at ACLEDA University of Business (AUB). She received a Bachelor degree in Science, Majoring in Mathematics at Royal University of Phnom Penh in 2014 and Master degree of Economics at National University of Management in 2021. She has been lecturing some courses: Principles of Economics, Statistics for Business and Economics, Quantitative Analysis for Management. Before presenting at AUB, she had been an English teacher at Sovannaphumi School for four years. After that, at the early of 2014, she had moved to Zaman International School for a position as Teacher Assistant and worked there until 2015. In late 2015, she was employed by ACLEDA Bank plc., as a cashier, and had been working there for three years and was promoted to be a Lecturer at AUB in 2018 until present.

Pisith Hok has obtained a Master degree of Finance and Business Economics from the University of Adelaide, Australia. He also has had a strong educational background from Cambodia, including a Bachelor of Arts in English (TEFL-Teaching English as a Foreign Language), a Bachelor of Business Administration in Accounting, a Certificate of Teacher with Higher Education Degree (CTHED) in English and Educational Psychology and a Master of Business Administration in Finance and Banking. He has extensive experience of more than 18 years in the educational field, from ESL teaching to tertiary lecturing at various institutes and universities, mostly Accounting, Finance, Banking and Economics subjects. In addition to his teaching, he also has had more than 4-year practical experience in Accounting and Finance work, including more than 2 years of employment in public accounting at the Provincial Treasury and about 2 years in budgeting at the Ministry of Economy and Finance. He is a qualified tertiary educator with a Professional Certificate in Pedagogy, endorsed by the Ministry of Education, Youth and Sport, and with expertise in the development of the curriculum of Accounting, Finance and Banking, Economics, and other majors, both at undergraduate and graduate levels. He has been working for the ACLEDA University of Business (AUB) since 2016, starting as a Consultant to an Assistant Professor and to a Technical Team Leader. He is currently a Dean of Faculty of Law and Economics (FLE).

Bun Khem is currently Head of Department of Law, Faculty of Law and Economics, ACLEDA University of Business (AUB). He has obtained Master of Arts in Indian

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Sinit To has joined the Faculty of Law and Economics and worked as a lecturer of Business at ACLEDA University of Business (AUB), since January 2022. He is presently working in a Department of Supply Chain Management and Logistics (DSL). He has been lecturing a wide range of courses including Introduction Business, Principles of Marketing, Global Marketing, Doing Business in Digital Era, and other courses related to business disciplines. He had previously worked at NathThananmanpower. Co., Ltd., in a position of an Administrative Manager in Chonburi City, Thailand in 2017. In 2019, he moved to work as an Assistant Director of Administration at Paññásástra University of Cambodia (PUC). Before he had joined AUB, he worked with an NGO as an Oral Interpreter and worked as a Part-time Lecturer at several universities. In 2010-2014, he has successfully completed a Bachelor's Degree of English Literature in the major of Teaching English as a Foreign Language (TEFL) at Cambodia International Cooperation Institute (CICI). In 2016-2018, he also has successfully completed a Master's Degree of Business Administration International Program at Bangkok University (BU), Thailand.

Socheat Hoeung is a Lecturer "B" at ACLEDA University of Business (AUB). He graduated with a Master's Degree in Public Administration from Preah Sihamonyraja Buddhist University (PSBU) in 2022. He graduated a Bachelor of Law from Preah Sihamonyraja Buddhist University (PSBU) in 2020 and a Bachelor's Degree in Management from the National University of Management (NUM) in 2020. In 2017-2022, he was the Vice President of the Ideal Association of Khmer Children and the Director of Buddhist Studies in Kampong Thom Province. In 2019, He is the president of the volunteer club teaching law at Preah Sihamoni Reach University (PSBU). He has been working for the AUB since 2023.

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