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Comparative analysis of performance of AutoML algorithms: Classification model of payment arrears in students of a private university

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Abstract

The impact of artificial intelligence in our society is important due to the innovation of processes through data science to know the academic and sociodemographic factors that contribute to late payments in university students, to identify them and make timely decisions for implementing prevention and correction programs, avoiding student dropout due to this economic problem, and ensuring success in their education in a meaningful and focused way. In this sense, the research aims to compare the performance metrics of classification models for late payments in students of a private university by using AutoML algorithms from various existing platforms and solutions such as AutoKeras, AutoGluon, HyperOPT, MLJar, and H2O in a data set consisting of 8,495 records and the application of data balancing techniques. From the implementation and execution of various algorithms, similar metrics have been obtained based on the parameters and optimization functions used automatically by each tool, providing better performance to the H2O platform through the Stacked Ensemble algorithm with metrics accuracy = 0.778. F1 = 0.870, recall = 0.904 and precision = 0.839. The research can be extended to other contexts or areas of knowledge due to the growing interest in automated machine learning, providing researchers with a valuable tool in data science without the need for deep knowledge.

Keywords: payment arrears, AutoML, AutoKeras, AutoGluon, HyperOPT, MLJar and H2O

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Introduction

The use of AutoML has become increasingly important due to the exponential increase in data availability and the need to perform effective predictive analyzes in the educational system and other productive sectors. The study has evaluated in terms of predictive capacity and ease of use various most popular and emerging automated machine learning (AutoML) platforms, such as AutoKeras, AutoGluon, HyperOPT, MLJar and H2O to develop the classification model, objectively providing information for choose the most suitable AutoML platform for the specific requirements according to the data set for the prevention and management of late payments among university students.

According to various sources of information worldwide, artificial intelligence has been an innovative factor in educational technology, highlighting three domains: academic support services, and institutional and administrative services[1,2]. In addition, from other fields such as medicine, finance, and law. In the case of educational institutions, there is evidence of its applicability in predictive models, intelligent analysis, assistive technology, automatic content analysis, and image analysis, guaranteeing quality education and sometimes avoiding abandonment of studies. That is, artificial intelligence can be used in any business process of the institution[3]. Likewise, higher education institutions are aware of adapting to new technologies to increase the capabilities of the members of their community[5].

Currently, artificial intelligence, natural language processing, and large language models have a relevant impact on aspects related to academic support, evaluations, grades, study plans, career guidance, and mental health support; also in research through the generation of texts, analysis, and interpretation, review and search for information, format, and editing, finally peer review[5] perceiving the transformation of conventional activities into digitalized activities for efficient and effective education[6].

Learning analytics improves the experience in the teaching process and the management of higher education institutions by recommending its use[7]. Data mining is increasingly becoming more relevant in various productive sectors; in higher education, it has a significant impact oriented towards a new-age university, providing data-based models[8]. In consideration, artificial intelligence is associated with challenges and ethical aspects to ensure the accuracy and fairness of algorithms to promote creativity, critical thinking, and analysis, diversifying and expanding the most complex behavioral patterns due to the adaptation of innovative and emerging tools and technologies to prepare students to succeed in reality in constant and permanent change[9, 10].

Machine learning is considered a multidisciplinary and interdisciplinary area of knowledge. It is located between data science and artificial intelligence; Furthermore, at the intersection of statistics and computer science, it has been driven by the development of algorithms, online data, and low computational cost, bringing with it growing interested in the software engineering community providing solutions to reduce costs; On the other hand, one of the drawbacks that presents itself as an obstacle is the adjustment of hyperparameters[11, 12, 13, 14, 55]; becoming an innovative technology in higher education, providing a series of perspectives on various dimensions of educational quality, with academic performance, students at risk of dropping out and default rates as application variables[15].

Machine learning can be distinguished between three different forms depending on the problem's characteristics and the data availability. These are supervised learning, unsupervised learning, and reinforcement learning[16]. For implementing the algorithms, three basic tasks are considered: feature selection, choosing the appropriate algorithm, and evaluating performance metrics[17]. Supervised learning uses a set of properly mapped data where it considers the input data and previously labeled output data, where the algorithm can develop a model based on the training data; for unsupervised learning, it models a collection of inputs without the presence of labeled instances; In this case, the algorithm organizes the instances into different categories; and in reinforcement learning, the algorithm learns from the environment through the policies of how to act, providing the corresponding feedback and is used in the decision-making process[12, 18].

Automated machine learning (AutoML) aims to identify the appropriate algorithm and hyperparameters, thus optimizing the guesswork of the optimization process whose results can simulate or improve the performance of a human expert, even in a shorter period[19, 20]; considering as relevant components, the selection, combination, and parameterization of machine learning algorithms[21]. AutoML allows the automation of specific tasks, such as model selection and hyperparameter optimization, generating complete machine-learning models with notable performance or results. However, the capacity of the algorithms is influenced by other factors, such as data cleaning and understanding of the field or area of knowledge[22, 23, 24, 25].

One of the greatest advantages of AutoML is its ease of use, where any member of the academic and scientific community can easily and independently develop prediction models for their area of knowledge. In addition, there are cloud platforms to implement this type of solution, such as Amazon Web Service SageMake, Microsoft Azure, Google Colab Pro, and Google Cloud Vertex AI[26]. Among the existing limitations in this type of processing is that the systems work efficiently on a large scale and on unbalanced or unbalanced data sets, which constitutes a challenging and frequent challenge[20, 27].

The AutoML process automatically identifies relevant features, optimizes hyperparameters, selects features, and evaluates performance metrics based on quality criteria without relying on human work and manual testing[28, 29]. For the study, certain solutions and platforms have been considered for comparison. Firstly, there is AutoKeras. It is an open-source toolkit for machine learning designed to facilitate the adoption of deep learning by people with a minimum of knowledge in machine learning and programming. Its main strength lies in its independence from any prior knowledge in deep learning[30, 31].

AutoGluon is a publicly accessible AutoML framework that trains machine-learning models on tabular data sets, text, and images. It can achieve high accuracy with little effort due to its independent and specific preprocessing of the model, the combination of multiple layers of several models, resulting in a reduction in training time, being recognized for its cutting-edge capabilities and its easy-to-use interface[32, 33, 34, 29]

The HyperOPT library provides a set of algorithms and parallelization infrastructure to optimize the performance of hyperparameters[35], offering functionality to the diversity of data mining techniques, selecting the one with the best performance using the F1-metric score and the one with the least information loss[36]. It additionally presents an optimization interface that identifies the difference between an evaluation function and a configuration space[37]. Furthermore, it will enable the construction of a search space that includes various standard components[38].

The MLJar AutoML framework is an open-source project that enables fast and automated training of models; it presents a nice and simple interface to provide consolidated information about the candidate models, statistics, and graphs through feature engineering preprocessing, feature selection, and explanation capabilities for the various algorithms, reducing development time (preprocessing, construction, hyperparameter tuning, and model selection); Likewise, it is considered among the seven frameworks of the ten most used[39, 40].

The H2O ecosystem is an open-source distributed machine learning platform with libraries for the R, Python, Java, and Scala programming languages supporting large data sets. Likewise, it has the AutoML method for training GBM, Random Forests, Deep Neural Networks, and GLMs algorithms, giving candidate models a healthy level of diversity that packed ensembles can use to create a robust model, offering easy tools and frameworks to use[41, 42, 43].

At the global level, there is constant uncertainty due to substantial changes in the various productive sectors, including higher education, to improve the work being carried out. In this sense, the European Commission has outlined its strategy for universities in the face of the challenges that lie ahead. In our region, the Institute of Higher Education of Latin America and the Caribbean (IESALC) of UNESCO provides the results of the consultations carried out with 25 world experts, where the report highlights a demand for quality and comprehensive education for all, adapting the structures of the institution to the needs and characteristics of its students, to strengthen higher education as a human right to education, make it inclusive. These changes require new values, behaviors, knowledge, and skills. To improve effectiveness and efficiency in the university system, interrelated components must be reevaluated, going through a technological transition and a culture of quality, transparency, and accountability[44].

The COVID-19 epidemic has transformed teaching, professional training, learning, and student well-being[45]. In this sense, educational artificial intelligence is being considered a relatively new emerging field of specialization, with the potential to revolutionize teaching methods and learning experiences in students where its application can be oriented towards strategy management or management institutional and teaching and learning[46]. However, extensive data analysis can be used in the various areas of the education industry[47].

Delays in payments among university students have several causes, one of which is that students have difficulties obtaining financing. That is, loan eligibility and repayment conditions may make it difficult to obtain financial aid, presenting greater complexity if they have to start paying them before graduating. Likewise, family finances can cause delays in payments due to the inability to pay. This financial burden could make it difficult for students to pay tuition on time. Other reasons are the increase in pensions and educational fees. Universities and authorities should strengthen financial aid to part-time students to reduce payment delays[48].

Other reasons are the economy's recession, the charging of interest for late payments, and the lack of financial assistance and scholarships. Students may struggle to pay financial commitments without sufficient financial aid. The government could address Such payment delays in collaboration with universities to provide more assistance, especially to disadvantaged students, by providing greater freedom by implementing financial support programs, administrative improvements, and flexible payment options[49].

The report prepared by Ilie et al. [50] on access to higher education indicates that it remains unequal in many countries, which is one of the most important factors in achieving multiple sustainable development goals. In Peru, public higher education institutions are free, but admission is highly selective and many students attend private institutions, which presents another potential barrier for poor students, with a significant gap among study participants of 55% and 5%, respectively, whose ages are between 18 and 22 years old; where women are more likely to enroll in the higher education system in most socioeconomic groups.

Demographic characteristics, particularly gender, ethnicity, and urban location, also predict participation in higher education, evidencing intersectionality and educational success according to classification models developed for payment behavior. In addition to the classification model for student dropout, tools aimed at the institutional management of universities to ensure the permanence and well-being of students[50, 51, 52]. In Peru, in 2022, the VI Delinquency Report prepared by Equifax in collaboration with the Universidad del Pacifico was published, where the delinquent debt is 10,629 million soles; distributed in mortgage loans at 23%, personal loans at 19%, 27% loans to small businesses and 9% to micro-businesses, and credit cards correspond to 8%; Likewise, the regions with the greatest impact with non-performing debt are Lima with 15,242 million soles, followed by Arequipa with 2,527 million soles and La Libertad with 1,426 million soles[53].

Regarding studies carried out on the comparative analysis of AutoML algorithms, there is the one carried out by Ferreira et al.[54] under two approaches. The first contrasts 10 open source technologies for supervised learning, and the second case focuses on learning a class using grammatical evolution. The data set was collected from a software company to predict the number of days equipment would fail, obtaining similar results between the compared solutions. Gijsbers et al.[56] evaluated nine AutoML frameworks to develop classification and regression models where the AutoGluon library has demonstrated better performance metrics in less execution time, revealing some limitations such as the impossibility of attributing the performance of an AutoML tool to a specific aspect, the settings because they have been used by default.

Methodology

Automated machine learning algorithms such as AutoKeras, AutoGluon, HyperOPT, MLJar, and H2O were used to develop student payment delinquency classification models. Subsequently, a comparative analysis was carried out to determine the model with the best performance metric. The data set comprised 8,495 records and 12 variables or characteristics. The exogenous type attributes were considered: sex, type of educational institution, employment status, socioeconomic level, disability, family burden, marital status, study scholarship, faculty, branch, and enrollment number. The endogenous variable delinquency of a dichotomous type constitutes the objective characteristic from which the prediction is made. Once the exploratory analysis has been conducted, the data set does not present anomalies (atypical and missing data).

Table 1. Description of data set variables.

N	Description	Type
01.	Sex	Dichotomic
02.	Tipo de institución educativa	Dichotomic
03.	Working condition	Dichotomic
04.	Socioeconomic level	Dichotomic
05.	Disability	Dichotomic
06.	Carga familiar	Dichotomic
07.	Marital status	Dichotomic
08.	scholarship	Dichotomic
09.	Faculty	Dichotomic
10.	Filial	Dichotomic
11.	Matriculación	Dichotomic
12.	Morosidad	Dichotomic

The classification model for late payments in university students was developed using the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, providing a guide for creating data science projects and guaranteeing the quality of the results efficiently and systematically. Its phases are business understanding, data understanding, data preparation, modeling, evaluation, and implementation.

Results

A descriptive statistical analysis of the default variable is presented concerning the exogenous variables to understand and identify the distributions in the data set.

Table 1. Descriptive analysis of the data set

Descripción	Morosidad				Total	
	Yes		No			
	n	%	n	%	n	%

Sex						
Woman	3928	46.24	847	9.97	4775	56.21
Man	3075	36.20	645	7.59	3720	43.79
Condición laboral						
Si trabaja	2282	26.86	445	5.24	2727	32.10
No trabaja	4721	55.57	1047	12.32	5768	67.90
Presenta discapacidad						
Si presenta	1459	17.17	371	4.37	1830	21.54
No presenta	5544	65.26	1121	13.20	6665	78.46
Carga familiar						
Con carga familiar	2914	34.30	543	6.39	3457	40.69
Sin carga familiar	4089	48.13	949	11.17	5038	59.31
Estado civil						
Con pareja	278	3.27	60	0.71	338	3.98
Sin pareja	6725	79.16	1432	16.86	8157	96.02
Total	7003	82.44	1492	17.56	8495	100.00

There are a total of students with arrears of 82.44%. That is, only 17.56% of students meet their financial obligations. Likewise, late payment has a greater presence in women, with 46.24%. Furthermore, students who do not work have higher default rates. On the other hand, students who do not have any disability and do not have family responsibilities show a greater incidence of making their payments; the same thing happens with those who have a partner.

Table 1 shows an imbalance in the data concerning the target variable delinquency. Consequently, the discretization process of the variables was carried out using the OneHotEncoder algorithm from the Sklearn library for the polytomous variables faculty and enrollment, resulting in a data set comprising 20 dichotomous exogenous variables.

Table 2. Parameters for data balancing.

N	Sample	Algoritmo	Morosidad		Strategy
			Yes	No	
01	Submuestreo	NearMiss	1305	1044	80%
02	Sobremuestreo	RandomOverSampler	4902	3921	80%
03	Muestreo combinado	SMOTETomek	4900	3919	80%

Next, training was conducted using the AutoML algorithms for the AutoKeras, AutoGluon, HyperOPT, MLJar, and H2O platforms for each sample in Table 2. The data sets for training and testing comprised 70% and 30%, respectively. The following performance metrics were obtained for each model.

Table 3 shows the SGDClassifier model with the best performance metrics, followed by the neural networks. The opposite happens with the ExtraTreesEntr and StackedEnsemble models, where they show poor metrics for classifying late payments. It is observed that the HyperOPT and Autokeras libraries have good performance on small data sets.

Table 3. Performance metrics of AutoML algorithms for NearMiss sampling.

N	Library	Model	Performance metrics			
			Accuracy	F1	Recall	Precision
01	AutoKeras	Artificial neural networks	0.5536	0.6713	0.5531	0.8538
02	AutoGluon	ExtraTreesEntr	0.4300	0.5253	0.3827	0.8375
03	HyperOPT	SGDClassifier	0.7681	0.8657	0.9067	0.8283
04	MLJar	Ensamble	0.4504	0.5551	0.4160	0.8340

05	H2O	StackedEnsemble	0.4402	0.5377	0.3950	0.8418

Table 4 shows the results for the second data set, where the Distributed Random Forest (DRF) model performs better than the other AutoML algorithms. Artificial neural networks demonstrate poor performance, below average in most indicators.

Table 4. AutoML algorithm performance metrics for RandomOverSampler sampling.

N	Library	Model	Metrics			
			Accuracy	F1	Recall	Precision
01	AutoKeras	Artificial neural networks	0.3715	0.4170	0.2727	0.8856
02	AutoGluon	ExtraTreesGini	0.6799	0.7949	0.7525	0.8423
03	HyperOPT	ExtraTreeClassifier	0.6438	0.7648	0.7025	0.8391
04	MLJar	Ensemble	0.6932	0.8065	0.7758	0.8398
05	H2O	Distributed Random Forest	0.7607	0.8591	0.8853	0.8345

For the third data set, Table 5 shows that the StakedEnsemble model has the optimal metrics for classifying delinquent students, followed by the ExtraTreesEnt and Ensemble models with very similar performance indicators.

Table 5. AutoML algorithm performance metrics for SMOTETomek sampling.

N	Library	Model	Metrics			
			Accuracy	F1	Recall	Precision
01	AutoKeras	Artificial neural networks	0.3958	0.4612	0.3137	0.8705
02	AutoGluon	ExtraTreesEntr	0.6516	0.7708	0.7106	0.8421
03	HyperOPT	ExtraTreeClassifier	0.6089	0.7312	0.6454	0.8433
04	MLJar	Ensemble	0.6579	0.7755	0.7168	0.8446
05	H2O	StackedEnsemble	0.7787	0.8708	0.9043	0.8396

Below, the classification models with the best performance metrics achieved using the AutoML algorithms for each under sampling, oversampling, and combined sampling data set defined using the data balancing technique are presented in Table 6.

The metrics obtained are very similar in the three experiments, with no significant difference found between the three models. Likewise, the H2O platform performs better on large data sets, as the StackedEnsemble model for the combined sampling data set. The analysis of its metrics indicates an accuracy equal to 0.779, indicating that the model correctly classifies around 78% of the observations, which is an acceptable level of accuracy. For the indicator, an F1-score of 0.871 determines the harmonic mean of precision and sensitivity; a value close to 1 indicates good balance. The Recall given by 0.904 shows that the model detects around 90% of the real positive cases; that is, a high level of sensitivity. For a Precision of 0.840 predicts positively, the model is correct in 84% of the cases, which is considered a high level of precision.

Table 6. Summary of performance metrics for models with optimal performance

N	Sample	Model	Metrics			
			Accuracy	F1	Recall	Precision
01	NearMiss	SGDClassifier	0.7681	0.8657	0.9067	0.8283
02	RandomOverSampler	Distributed Random Forest	0.7607	0.8591	0.8853	0.8345
03	SMOTETomek	StackedEnsemble	0.7787	0.8708	0.9043	0.8396

Other performance metrics presented by the StackedEnsamble model are detailed below; the Area Under the ROC Curve (AUC) equals 0.738. This value indicates that the model has a moderate discrimination capacity; a model with entirely random predictions would have an AUC of 0.5, while a perfect one would have an AUC of 1.0. Therefore, with an AUC of 0.738, the model is better than random at distinguishing between positive and negative classes. Also, the Log Loss is equivalent to 0.595. The Log Loss indicator measures the difference between the predicted probabilities and the real values. The lower value indicates better performance. The typical range for Log Loss is between 0.5 (very good) and 3.0 (very bad). The value of 0.595 indicates the moderate performance of the model.

Furthermore, the Area Under the Precision-Recall Curve (AUCPR) is 0.782. This measure summarizes the trade-off between precision and sensitivity for different classification thresholds. As with AUC, a value closer to 1 indicates better performance; therefore, 0.782 suggests a good balance between detecting true positives (sensitivity) without many false positives (precision).

In summary, the model performs well regarding precision, sensitivity, and balance between the two (F1-score). According to the AUC, it has an acceptable accuracy of over 78% and moderate class discrimination. The AUCPR indicates that varying the thresholds could improve the balance between metrics. Overall, the model performs well, especially in identifying positive cases accurately and sensitively.

Conclusions

According to the comparative analysis carried out, considering the different AutoML platforms and data balancing techniques, it is concluded that the AutoML algorithm of the H2O library has selected the StackedEnsemble model in an automated manner, presenting the best performance to implement a classification model that predicts the late payments in university students, achieving an accuracy of 77.87%, an F1 score of 0.8708, sensitivity of 90.43% and precision of 83.96% using a balanced sample with the SMOTETomek method.

This study demonstrates the potential and effectiveness of automated machine learning techniques to develop early warning systems for late payments, supporting financial management in higher education institutions. Likewise, a rigorous comparison of the performance metrics of various AutoML algorithms was carried out in a real case study of binary classification based on the factors associated with late payment in the context of university education. Through supervised training of the models, we contribute to reducing student dropouts for financial reasons, benefiting enormously from applying these technologies. In this sense, we have contributed to data science and its application to solve relevant problems, demonstrating the importance and value of artificial intelligence in education.

Other consequences of late payments are the increased risk of decreased health, well-being, and quality of life for university students, which can be avoided by implementing classification models for prediction to safeguard mental health and stress due to constant worries, and these can worsen into depression and anxiety; Also, it can occur in lifestyle habits and well-being, expressing itself in diet, physical exercise and quality of sleep; For these reasons, higher education institutions have the responsibility to carry out preventive health interventions and follow-up promptly, to provide the necessary support through access programs to health services and comprehensive advice.

On the other hand, through the National Artificial Intelligence Strategy and with the promulgation of Law No. 31814, regulations that promote the use of artificial intelligence in favor of the economic and social development of the country; The study has a significant contribution in this regard, where it considers the legal implications to be taken into account because they are vital in this type of prediction models and must consider the protection and privacy of personal data, where the model must comply with the laws and current regulations; Algorithmic equity means that the model must be objective and non-discriminatory, being fair for all groups of people; transparency and explainability, which seeks ways to make complex models more understandable for people; the ethics and regulation of artificial intelligence, representing an innovative tool that constitutes a methodological advance in the application of automated machine learning techniques in university management.

Future work proposes targeted interventions such as financial guidance programs, debt rescheduling, educational scholarships, and other measures to reduce student dropout. Additionally, analytical systems can be developed to monitor delinquency indicators, support decision-making through different approaches, such as reinforcement learning, and explore explainability techniques to interpret delinquency predictors. In the context of transversality, it is exemplified how artificial intelligence can support the fulfillment of multiple sustainable development objectives, with multidimensional benefits for the different actors in society.

Finally, the research was carried out from a multidisciplinary approach integrating several areas of knowledge, allowing a comprehensive understanding in a holistic context of late payments in university students, considering the multiple underlying factors and financial, emotional, academic, and health needs that are at stake ethically and responsibly, developing the most effective strategies for student support in the complex context of university higher education.

References

1. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? International Journal of Educational Technology in Higher Education, 16(1). https://doi.org/10.1186/s41239-019-0171-0

2. Ramani, P. (2022). Artificial Intelligence in Higher Education and Changing roles of Educators. World Journal of Educational Research. https://doi.org/10.22158/wjer.v9n2p56

3. Salas-Pilco, S. Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: a systematic review. International Journal of Educational Technology in Higher Education, 19(1). https://doi.org/10.1186/s41239-022-00326-w

4. Al, M. (2023). Higher Education and the Challenges of Artificial Intelligence. Russian Law Journal; LLC V.Em Publishing. https://doi.org/10.52783/rlj.v11i6s.1489

5. Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., Bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. M. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. Research in social & administrative pharmacy: RSAP, 19(8), 1236–1242. https://doi.org/10.1016/j.sapharm.2023.05.016

6. Okagbue, E. F., Ezeachikulo, U. P., Akintunde, T. Y., Tsakuwa, M. B., Ilokanulo, S. N., Obiasoanya, K. M., ... & Ouattara, C. A. T. (2023). A comprehensive overview of artificial intelligence and machine learning in education pedagogy: 21 Years (2000–2021) of research indexed in the scopus database. Social Sciences & Humanities Open, 8(1), 100655. https://doi.org/10.1016/j.ssaho.2023.100655

7. Quadri, A. T., & Shukor, N. A. (2021). The Benefits of Learning Analytics to Higher Education Institutions: A Scoping Review. International Journal of Emerging Technologies in Learning (Ijet); kassel university press. https://doi.org/10.3991/ijet.v16i23.27471

8. Aldowah, H., Al-Samarraie, H., & Fauzy, W. M. (2019). Educational data mining and learning analytics for 21st century higher education: A review and synthesis. Telematics and Informatics, 37, 13-49. https://doi.org/10.1016/j.tele.2019.01.007

9. Al Ka'bi, A. (2023). Proposed artificial intelligence algorithm and deep learning techniques for development of higher education. Int J Intell Netw. https://doi.org/10.1016/j.ijin.2023.03.002

10. Sollosy, M., & McInerney, M. (2022). Artificial intelligence and business education: What should be taught. The International Journal of Management Education, 20(3), 100720. https://doi.org/10.1016/j.ijme.2022.100720

11. Wang, C., Chen, Z., & Zhou, M. (2023, April). AutoML from Software Engineering Perspective: Landscapes and Challenges. In Proceedings of the 20th International Conference on Mining Software Repositories. MSR. https://chenzhenpeng18.github.io/papers/MSR23.pdf

12. Zhang, D. (2022). Analysis of University Management Model of National Higher Education Institutions Based on Machine Learning Algorithm. Mobile Information Systems, 2022, 1–7. https://doi.org/10.1155/2022/4553185

13. Iatrellis, O., Savvas, I., Fitsilis, P., & Gerogiannis, V. C. (2020). A two-phase machine learning approach for predicting student outcomes. Education and Information Technologies; Springer Science+Business Media. https://doi.org/10.1007/s10639-020-10260-x

14. Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

15. Fahd, K., Venkatraman, S., Miah, S. J., & Ahmed, K. (2022). Application of machine learning in higher education to assess student academic performance, at-risk, and attrition: A meta-analysis of literature. Education and Information Technologies; Springer Science+Business Media. https://doi.org/10.1007/s10639-021-10741-7

16. Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. Electronic Markets; Springer Science+Business Media. https://doi.org/10.1007/s12525-021-00475-2

17. Oqaidi, K., Aouhassi, S., & Mansouri, K. (2022). Towards a Students' Dropout Prediction Model in Higher Education Institutions Using Machine Learning Algorithms. International Journal of Emerging Technologies in Learning (Ijet); kassel university press. https://doi.org/10.3991/ijet.v17i18.25567

18. Oladipupo, T. (2010). Types of Machine Learning Algorithms. New Advances in Machine Learning. https://doi.org/10.5772/9385

19. Manduchi, E., Romano, J. D., & Moore, J. H. (2021). The promise of automated machine learning for the genetic analysis of complex traits. Human Genetics, 141(9), 1529–1544. https://doi.org/10.1007/s00439-021-02393-x

20. Waring, J., Lindvall, C., & Umeton, R. (2020). Automated machine learning: Review of the state-of-the-art and opportunities for healthcare. Artificial Intelligence in Medicine, 104, 101822. https://doi.org/10.1016/j.artmed.2020.101822

21. Wever, M., Tornede, A., Mohr, F., & Hullermeier, E. (2021). AutoML for Multi-Label Classification: Overview and Empirical Evaluation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(9), 3037–3054. https://doi.org/10.1109/tpami.2021.3051276

22. Zender, A., & Humm, B. G. (2022). Ontology-based Meta AutoML. Integrated Computer-Aided Engineering, 29(4), 351–366. https://doi.org/10.3233/ica-220684

23. Bahri, M., Salutari, F., Putina, A., & Sozio, M. (2022). AutoML: state of the art with a focus on anomaly detection, challenges, and research directions. International Journal of Data Science and Analytics, 14(2), 113–126. https://doi.org/10.1007/s41060-022-00309-0

24. Musigmann, M., Akkurt, B. H., Krähling, H., Nacul, N. G., Remonda, L., Sartoretti, T., Henssen, D., Brokinkel, B., Stummer, W., Heindel, W., & Mannil, M. (2022). Testing the applicability and performance of Auto ML for potential applications in diagnostic neuroradiology. Scientific reports, 12(1), 13648. https://doi.org/10.1038/s41598-022-18028-8

25. Cerrada, M., Trujillo, L., Hernández, D. E., Correa Zevallos, H. A., Macancela, J. C., Cabrera, D., & Vinicio Sánchez, R. (2022). AutoML for Feature Selection and Model Tuning Applied to Fault Severity Diagnosis in Spur Gearboxes. Mathematical and Computational

Applications, 27(1), 6. https://doi.org/10.3390/mca27010006

26. Choi, W., Choi, T., & Heo, S. (2023). A Comparative Study of Automated Machine Learning Platforms for Exercise Anthropometry-Based Typology Analysis: Performance Evaluation of AWS SageMaker, GCP VertexAI, and MS Azure. Bioengineering, 10(8), 891. https://doi.org/10.3390/bioengineering10080891

27. Frank, F. & Bacao, F. (2023). Advanced Genetic Programming vs. State-of-the-Art AutoML in Imbalanced Binary Classification. Emerging Science Journal, 7(4), 1349–1363. https://doi.org/10.28991/esj-2023-07-04-021

28. Neverov, E. A., Viksnin, I. I., & Chuprov, S. S. (2023). The Research of AutoML Methods in the Task of Wave Data Classification. 2023 XXVI International Conference on Soft Computing and Measurements (SCM). https://doi.org/10.1109/scm58628.2023.10159058

29. Mueller, J., Shi, X., & Smola, A. (2020). Faster, Simpler, More Accurate. Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. https://doi.org/10.1145/3394486.3406706

30. Jin, H., Chollet, F., Song, Q., & Hu, X. (2023). Autokeras: An automl library for deep learning. Journal of Machine Learning Research, 24(6), 1-6. https://www.jmlr.org/papers/volume24/20-1355/20-1355.pdf

31. Alaiad, A., Migdady, A., Al-Khatib, R. M., AlZoubi, O., Zitar, R. A., & Abualigah, L. (2023). Autokeras Approach: A Robust Automated Deep Learning Network for Diagnosis Disease Cases in Medical Images. Journal of Imaging; Multidisciplinary Digital Publishing Institute. https://doi.org/10.3390/jimaging9030064

33. Paldino, G. M., De Stefani, J., De Caro, F., & Bontempi, G. (2021, July 5). Does AutoML Outperform Naive Forecasting? The 7th International Conference on Time Series and Forecasting. https://doi.org/10.3390/engproc2021005036

32. Shchur, O., Turkmen, C., Erickson, N., Shen, H., Shirkov, A., Hu, T., & Wang, B. (2023). AutoGluon-TimeSeries: AutoML for Probabilistic Time Series Forecasting. ArXiv, abs/2308.05566. https://doi.org/10.48550/arXiv.2308.05566

34. Erickson, N., Mueller, J.W., Shirkov, A., Zhang, H., Larroy, P., Li, M., & Smola, A. (2020). AutoGluon-Tabular: Robust and Accurate AutoML for Structured Data. ArXiv, abs/2003.06505. https://doi.org/10.48550/arXiv.2003.06505

35. Komer, B., Bergstra, J., Eliasmith, C. (2019). Hyperopt-Sklearn. In: Hutter, F., Kotthoff, L., Vanschoren, J. (eds) Automated Machine Learning. The Springer Series on Challenges in Machine Learning. Springer, Cham. https://doi.org/10.1007/978-3-030-05318-5_5

36. Dumitrache, A., Melian, D. M., Bălăcian, D., Nastu, A., & Stancu, S. (2020). Churn prepaid customers classified by HyperOpt techniques. Proceedings of the International Conference on Applied Statistics. https://doi.org/10.2478/icas-2021-0010

37. Bergstra, J., Yamins, D., & Cox, D. D. (2013). Hyperopt: A Python Library for Optimizing the Hyperparameters of Machine Learning Algorithms. THe 12th Python in Science Conference.

38. Bergstra, J., Komer, B., Eliasmith, C., Yamins, D., & Cox, D. D. (2015). Hyperopt: a Python library for model selection and hyperparameter optimization. Computational Science & Discovery, 8(1), 014008. https://doi.org/10.1088/1749-4699/8/1/014008

39. Ma, J., Xu, H., Wang, A., Wang, A., Gao, L., & Ding, M. (2023). Machine learning-guided underlying decisive factors of high-performance membrane distillation system: Membrane properties, operation conditions and solution composition. Separation and Purification Technology, 327, 124964. https://doi.org/10.1016/j.seppur.2023.124964

40. Płońska, A., & Płoński, P. (2021). MLJAR: State-of-the-art Automated Machine Learning Framework for Tabular Data. Version 0.10.3. [Computer software]. MLJAR, https://github.com/mljar/mljar-supervised

41. Vázquez, F. (2023, October 6). Entrenando Tu Propio LLM Sin Programación. H2O.ai. Retrieved October 23, 2023, from https://h2o.ai/blog/entrenando-tu-propio-llm-sin-programacion/

42. LeDell, E., & Poirier, S. (2020). H2o automl: Scalable automatic machine learning. In Proceedings of the AutoML Workshop at ICML (Vol. 2020). ICML.

43. Kochura, Y., Stirenko, S., & Gordienko, Y. (2017). Comparative performance analysis of neural networks architectures on H2O platform for various activation functions. 2017 IEEE International Young Scientists Forum on Applied Physics and Engineering (YSF). doi:10.1109/ysf.2017.8126654

44. Saucedo, M. L., Sánchez, R. L., Becerra, E. E., & Puican, V. H. (2023). New E-government Strategies in Peruvian Universities. https://doi.org/10.55908/sdgs.v11i2.703

45. Salas-Pilco, S. Z., Yang, Y., & Zhang, Z. (2022). Student engagement in online learning in Latin American higher education during the COVID-19 pandemic: A systematic review. British Journal of Educational Technology, 53(3), 593–619. https://doi.org/10.1111/bjet.13190

46. Bates, T., Cobo, C., Mariño, O., & Wheeler, S. (2020). Can artificial intelligence transform higher education? International Journal of Educational Technology in Higher Education, 17(1). https://doi.org/10.1186/s41239-020-00218-x

47. Nuankaew, P., Nasa-Ngium, P., Kunasit, T., & Nuankaew, W. (2023). Implementation of Data Analytics and Machine Learning in Thailand Education Sector. International Journal of Emerging Technologies in Learning (Ijet); kassel university press. https://doi.org/10.3991/ijet.v18i05.36871

48. Callender, C., & Dougherty, K. J. (2018, October 9). Student Choice in Higher Education—Reducing or Reproducing Social Inequalities? Social Sciences, 7(10), 189. https://doi.org/10.3390/socsci7100189

49. Wadesango, N., Maphosa, C., & Moyo, G. (2014). An Academic Development Agenda for Postgraduate Research Students. Mediterranean Journal of Social Sciences. https://doi.org/10.5901/mjss.2014.v5n11p49

50. Ilie, S., Rose, P., & Vignoles, A. (2021). Understanding higher education access: Inequalities and early learning in low and lower-middle-income countries. British Educational Research Journal, 47(5), 1237–1258. https://doi.org/10.1002/berj.3723

51. Villarreal-Torres, H., Ángeles-Morales, J., Marín-Rodriguez, W., Andrade-Girón, D., Cano-Mejía, J., Mejía-Murillo, C., Flores-Reyes, G., & Palomino-Márquez, M. (2023a). Classification model for student dropouts using machine learning: A case study. EAI Endorsed Transactions on Scalable Information Systems, 10(5). https://doi.org/10.4108/eetsis.vi.3455

52. Villarreal-Torres, H., Ángeles-Morales, J., Marín-Rodriguez, W., Andrade-Girón, D., Carreño-Cisneros, E., Cano-Mejía, J., Mejía-Murillo, C., Boscán-Carroz, M. C., Flores-Reyes, G., & Cruz-Cruz, O. (2023b). Development of a Classification Model for Predicting Student Payment Behavior Using Artificial Intelligence and Data Science Techniques. EAI Endorsed Transactions on Scalable Information Systems, 10(5). https://doi.org/10.4108/eetsis.3489

53. El Peruano. (2022, 19 de agosto). Retrocedió el índice de morosidad. https://www.elperuano.pe/noticia/183969-retrocedio-el-indice-de-morosidad

54. Ferreira, L., Pilastri, A., Romano, F., & Cortez, P. (2022). Using supervised and one-class automated machine learning for predictive maintenance. Applied Soft Computing, 131, 109820. https://doi.org/10.1016/j.asoc.2022.109820

55. Gijsbers, P., Bueno, M. L., Coors, S., LeDell, E., Poirier, S., Thomas, J., ... & Vanschoren, J. (2022). AMLB: an automl benchmark. https://doi.org/10.48550/arxiv.2207.12560

56. Abaimov, S., & Martellini, M. (2022). Understanding Machine Learning. Advanced Sciences and Technologies for Security Applications. https://doi.org/10.1007/978-3-030-91585-8_2

57. Lázaro, L. M. (2022). La UNESCO y los futuros de la educación superior hasta 2050. Por una ampliación del derecho a la educación que incluya a la educación superior. Revista Española De Educación Comparada, (41), 271–280. https://doi.org/10.5944/reec.41.2022.33879