



RESEARCH ARTICLE

Student's Academic Performance Improvement Using Adaptive Ensemble Learning Method

G. Vijayalakshmi*, M. V. Srinath

Abstract

Online learning platforms have transformed education by offering flexible, accessible, and interactive learning experiences. With advancements in technology and the increasing need for remote learning, these platforms empower students to study from anywhere at their own pace, offering various resources such as video lectures, assignments, quizzes, and discussion forums. These tools facilitate both self-paced learning and collaborative activities, allowing students to interact with peers, engage in group discussions, and work on joint projects. Big data analytics, in particular, plays a critical role in understanding student behaviour and cognitive processes, providing educators with valuable insights to personalize learning experiences more effectively. This study focuses on analysing student performance on online collaborative platforms through big data analytics, utilizing an ensemble model that integrates multiple Machine Learning (ML) algorithms to predict student outcomes more accurately. The proposed ensemble model achieved an accuracy of 98.87%, outperforming traditional classifiers in both accuracy and precision, particularly in identifying cognitive traits and predicting academic performance. These findings underscore the value of ensemble of ML in big data optimizing student engagement and success.

Keywords: Big data, Ensemble model, Adaptive voting classifier, Machine learning, students' academic performance.

关键词：大数据 · 集成模型 · 自适应投票分类器 · 机器学习 · 学生学业表现。

Introduction

The fast-paced development of digital learning environments has greatly altered the delivery of education, enhancing its flexibility and accessibility. Modern online platforms allow learners to engage with educational materials in a

flexible manner, breaking down traditional barriers to time and location. These platforms offer a wide array of tools that support both individual learning and collaborative efforts, encouraging interactive participation in various forms of group activities and peer engagement. Learning management systems are now widely used by businesses and educational organisations. Online learning has several benefits as a teaching approach (Choudhury, S., & Pattnaik, S. 2020). However, it still has to overcome a number of obstacles. Some examples include the challenges associated with assessing students in major classes, reducing academic dropout, forecasting student success, and redefining the responsibilities of educators. These issues also frequently arise in other contexts, such as intelligent tutoring systems that use intelligent algorithms to support students in learning certain skills on their own (Mousavinasab, E., *et al.*, 2021).

An educational approach known as Online Collaborative Learning (OCL) enables students to communicate with one another, share ideas, and use what they have learnt to work together to solve issues at anytime, anyplace (Zheng, L., *et al.*, 2023). OCL now demonstrates a significant deal of promise for enhancing academic performance in the areas of social skills (Ouyang, F., *et al.*, 2021), critical thinking (Koşar, G. 2021), and problem-solving abilities (Li, S., *et al.*, 2022). As

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a result, it is more widely used in higher education (Ye, J., & Zhou, J. 2022; Zhang, S., *et al.*, 2021). On the other hand, OCL learners could have a number of difficulties, including low cognitive engagement (Lin, Y.-T., *et al.*, 2021). The purpose of this study is to analyse online learning performance in order to identify potential patterns of cognitive involvement in distinct performance groups. Based on these findings, recommendations are made for enhancing the instructional design and encouraging student cognitive engagement.

Students' learning behaviour is captured by the online learning platform, providing useful data that may be utilised to examine a variety of aspects, including the students' learning preferences, speed, and progress. Students can receive individualised learning help from this analysis, which will enhance their learning results. To help detect learning issues early and offer focused tutoring and treatments, the examination of students' learning behaviours can also be used to forecast their academic success (Liu, Y. G. 2020). In order to achieve personalised learning, enhance teaching techniques, implement early interventions into practice, and advance educational research, it is crucial to analyse students' learning behaviour and anticipate their success.

Furthermore, it makes use of the most recent developments in technology by integrating modern big data ecosystem technologies into online learning platforms. Together with massively parallel computing power and distributed storage capabilities, big data offers advanced ML techniques and algorithms for analysing and obtaining information gathered from the various forms of data generated by online learning systems, such as learner profiles, activities, preferences, outcomes, etc. This work established the most widely used big data application in the world, a recommendation engine, to assist and direct the learner in quickly identifying and choosing the most appropriate educational resources by providing an intelligent system that can create a catalogue of courses tailored to their interests and cognitive level by analysing the learning activities.

Data volume, diversity, and speed all coexist together in higher education. Every day, a vast amount of educational data is collected and generated from many sources and in various formats in the university environment. Learning objectives, teaching materials, activities, exam results, and other types of data related to education and quality improvement processes and procedures comprise educational data, which ranges from what results from students' use. Due to the weak support for big data in learning and the amount and type of this data in higher education, special methods need to be used to find valuable additional clues that are currently hidden in the information (Baig, M. I., *et al.*, 2020). ML might be a subfield within the AI. ML aims to understand the intricacy of various types of gathered data and, via testing several models, determine

which model best fits the data. This can be efficiently systematised for simpler human understanding and utilisation. While ML is a branch of engineering science, it is not the same as the simple computer methods employed in problem solving. ML involves the construction of algorithms that enable the computer or system to interpret input data, generate training sets, and use statistical estimates to produce the desired output within a given range.

In ML, the algorithms are designed to allow systems to process input data, create training sets, and generate a specified range of outputs using statistical estimation. Unlike traditional classifiers that rely on single models, the proposed ensemble adaptive voting classifier combines the strengths of multiple classifiers. This approach aggregates predictions from several models and adapts over time, often yielding superior performance compared to traditional classifiers. By leveraging multiple perspectives and dynamically adjusting to the data, this ensemble method offers more robust and accurate results, making it a more effective solution for complex data scenarios.

This paper is structured as follows: Section 1 introduces the transformative impact of online learning platforms on education, focusing on their flexibility and interactivity. Section 2 reviews related works in the field, particularly in collaborative learning and ML applications. Sections 3 and 4 outline the research gap concerning current models' limitations and the proposed methodology that utilizes an ensemble approach to analyse student performance. Section 5 & 6 analyses various ML techniques, emphasizing the effectiveness of the adaptive voting classifier in predicting student outcomes. Section 7 presents the results of the research, showcasing the ensemble model's accuracy. Finally, Section 8 concludes the study, emphasizing the potential of ensemble ML methods in optimizing educational strategies.

Literature Review

Anthony, B., *et al.*, (2020) stated that there is currently a renewed discussion on the effectiveness of online learning, particularly in light of the ongoing pandemic. Modern educational institutions must offer creative, time- and space-independent methods of instruction. They must create interesting learning environments and approaches in order to meet these expectations for e-learning (Okronipa, A. Q., *et al.*, 2024; Balakrishnan, B., & Parivara, S. A. 2023), mobile learning, and online learning. It is also advised that academic staff offer assignments that allow students to actively research and expand their understanding of a certain topic. They must perform well in their virtual classes. Teachers must also give feedback and set up tasks and educational objectives in an adaptable manner to allow students to grow at their own faster rates (Willison, J. 2020; Chen, W. S., & Tat Yao, A. Y. 2016).

Alonso-Fernández, C., *et al.*, (2020) have demonstrated the efficacy of using serious games-based learning analytics to inspire, engage, and support students' learning. In order to forecast changes in knowledge, they specifically suggested combining data mining methods with game learning analytics based on student interactions inside the game. Chui, K. T., *et al.*, (2020) have employed a statistical prediction model based on Support Vector Machines (SVM) to identify students at risk of dropping out of school early in a virtual learning environment. They also combined the results of previous studies that used various ML techniques and a variety of datasets as benchmarks. Moreno-Marcos, P. M., *et al.*, (2020) have used educational analytics tools to identify the key factors influencing student performance.

According to Azar, A. S., *et al.*, (2021) collaborative learning is a group learning technique that can be a suitable and successful way to prepare students for the 21st-century abilities needed to solve problems, finish tasks, or produce a product. The concept of collaborative learning stems from the idea that learning is an inherently social process where participants discuss ideas, meanings, and/or solutions with one other, or develop a workable answer in the form of a feasible product. According to Koretsky *et al.*, (2021) individuals who engage in collaborative learning engage on significant tasks and are more comfortable in sharing knowledge, coming up with ideas, and solving problems as a group.

According to Dewi, C. A., *et al.*, (2021) people rely on one another to acquire new knowledge, so they don't feel alone in the learning process. McHugh, D., *et al.*, (2020) stated that collaborative learning enhances students' comprehension of course content and helps them retain more knowledge when they work in groups. As a result, group learning becomes more purposeful and engaging. From the study of Warsah, I., *et al.*, (2021) collaborative learning has the potential to improve performance for individuals who are falling behind in their studies over time.

Liu, Z., *et al.*, (2020) have employed a combination of statistical analysis and text mining techniques to examine learners' implicit post contents and cognitive behaviours. They then used content analysis to manually encode the learners' cognitive activities. Citrawathi, D. M., *et al.*, (2020) have looked into the biological research projects of the College of Mathematics and Natural Sciences at Ganesha University of Education. The research aims to validate the effectiveness of problematic model-based perception on sharing learning and improve student engagement and educational results in gastrointestinal research. Along with knowledge assessments on cognitive learning outcomes, their tools include observation forms and questions concerning learning participation as well as solutions.

Cacciamani, S., *et al.*, (2019) have investigated whether providing an individual tutor to every student enrolled

in online college courses enhances peer engagement in online discussions, advancement of social awareness, and productive learning. An online system for managing courses was presented by Thuku, J., *et al.*, (2019). Its features include adding subjects or issues for counselling, configuring courses, scheduling classroom demos, keeping an eye on group activities, and assessing group performance. Students may use the system to post their term papers, choose research topics, collaborate on papers, sign up for counselling groups, and share their work with others. Enormous learner data, including behaviour inside LMSs, must be readily available for Big Data to function. Big data may help higher education institutions handle a variety of issues related to education, such as maintaining student achievement over time and reducing the dropout rate. As stated by Saeed, M. M., *et al.*, (2020), it is imperative to shift from concentrating exclusively on the average student to providing customised attention that is informed by students' interactions in the digital setting. According to Binsawad, M., *et al.*, (2022) by using big data analytic technology to make prompt, data-driven choices, Learning Management Systems (LMSs) can optimise their advantages while also improving the learning process.

Sandra, L., *et al.*, (2021) have discussed the process of developing these learning as well as evaluation models relies heavily on ML techniques. The example student data should, nonetheless, be sufficient and instructive. When analysing data for prediction analysis to examine student performance, ML models seem to be advantageous. This feature of ML that predicts the future helps students perform better and offers early intervention for learning and test achievement.

Numerous scholars have examined diverse methodologies, including the amalgamation of two or more prediction models about the efficacy of performance. In order to overcome the shortcomings in ML algorithms, ensemble approaches have gained popularity recently as a means of transforming weak ML learners into strong learners. Phyto, P. P., *et al.*, (2022) have used the ensemble approach to merge five ML models in order to reduce forecast errors. The stacking ensemble-based smart ML model proposed by Gupta, A., *et al.*, (2022) may serve as a model for forecasting the influence of environmental factors on crop health and productivity.

Research Gap

Previous studies on how students learn on online platforms have looked at ML models like factorisation machine classifiers, which work well with sparse data, have not provided satisfactory results when applied to complex and dynamic educational data. When it comes to clickstream data, text-based communications, and engagement patterns, these models find it difficult to represent the variety of interactions, particularly as student behaviours

fluctuate between platforms and subjects. This research suggests using ensemble models rather than factorisation machines to overcome these constraints since ensemble techniques are better able to integrate diverse data sources and can adjust over time to changing student behaviours. The objective of this change is to provide a more customised and flexible framework that addresses the limitations of previous models and yields more reliable and accurate student learning patterns.

Research Methodology

The research methodology for analysing student cognitive behaviour on online learning platforms utilising ensemble techniques is a systematic one and its overall flow diagram is shown in Figure 1. The first step in the data collecting process involves compiling data from several sources, such as the platform itself. This includes engagement metrics, assessment results, interaction logs, and demographic data. The data is prepared by applying preprocessing techniques such encoding, feature extraction, normalisation, and data cleaning. A variety of basic models, including Factorisation Machine (FM) classifiers, Navie Bayes (NB), and Decision Tree (DT), are trained on subsets of the data. These models are then combined using ensemble approaches such as

bagging, boosting, and stacking, thereby utilising their complimentary capabilities to increase total prediction accuracy.

Factorisation Machine Classifier

An effective ML technique for capturing and modelling feature interactions in sparse, high-dimensional datasets is the Factorisation Machine (FM) classifier. FMs effectively reflect pairwise feature interactions by factorising these interactions into low-dimensional latent vectors, in contrast to typical linear models, which only take individual feature contributions into consideration. This technique makes FMs especially helpful in contexts with scarce user-item interactions, such as recommendation systems, and in classification tasks where feature correlations are critical. FM classifiers give a systematic approach to modelling complicated interactions without requiring deep neural networks, while also balancing interpretability and performance.

Adaptive Voting Classifier

An Adaptive Voting Classifier is an Ensemble Learning (EL) method that combines predictions from several classifiers to make a final decision, with the ability to adjust the influence of each classifier based on their performance.

Table 1: Dataset of various students as an input source

Attribute	Description	Example
Timestamp	Timestamp of the action	14:42:57 17-02-2021
Author	Student ID	a.l6ZFAmhSZ4KY2HU1
Group	Group ID	1
Char_Bank	Characters added during this action	How many access points do you have throughout the hotel?
Source_length	Length of the text before performing the action	2352
Operation	Type of operation (>: writing, >:deleting)	>
Difference	The difference in number of characters caused by the current action and source length	56
Text	Text from the document at the current time.	Have you contacted your Internet service provider, i.e your operator? [...]
Timestamp	Timestamp of the action	16/02/2021 22:40:00
User ID	The User ID, it can represent a student or a teacher.	a.WCpdVcSKpEcVM13V
User involved	If the teacher does an action it can involve other teachers or students.	a.l6ZFAmhS4KY2HU1
Event Context	The Section in Moodle in which the event occurred.	Course: TRAFFIC ENGINEERING IN TELEMATIC NETWORKS (1-211-460-45033-1-2020)
Component	The type of resource in Moodle	Questionnaire.
Event name	The name of the event	Course module viewed.
Description	The description of the action	The user with id 'a.WCpdVcSKpEcVM13' viewed the 'resource' activity with course module id '974963'
Source	The source from where Moodle has been accessed and the action has been performed.	Web
IP Address	The IP address from which the action was performed.	83.58.29.136

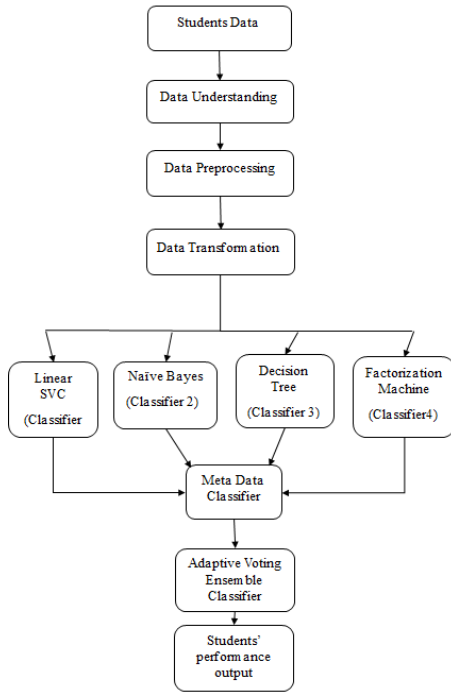


Figure 1: Overall flow diagram for adaptive ensemble learning model

Unlike traditional voting classifiers, which weigh all models equally (in hard voting) or based on fixed probabilities (in soft voting), an adaptive voting classifier dynamically changes the weighting of each model's vote, giving more influence to better-performing models. This adaptability helps improve prediction accuracy and robustness over time, especially in changing data environments.

The primary goal of the method is to determine the weight w_{ij} of a classifier algorithm for a particular kind of data, which represents the probability (credibility) of detecting the detection result in that particular case. When every data set has different properties, the voting weight may also be manually modified by checking the weight value to get the optimum results. The algorithm for adaptive voting is as follows:

Adaptive Voting Algorithm

Input:

$$T = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}, x_i \in X, y_i \in Y$$

$$Y = \{1, \dots, c\}; F = \{f_1, f_2, \dots, f_m\};$$

Output: $H(x)$

1) Set the class weights at initial value.

$$w_{ij} = 1; i = \{1, \dots, m\}; j = \{1, \dots, c\}$$

2) For each i between 1 and m ,

(a) Fit a classifier $f_i(x)$ to the training data

(b) Calculate possibility for $f_i(x|c=j)$, $w_{ij} =$

$$\frac{\sum_0 f_i(x) == \hat{y} \&\& (y == j)}{N}$$

3) To predict, use all classifiers: classifier. Predict (Test_x),

4) Determine the probability of single record belonging to class C , $p_i = \sum_1^m w_{ij} (f_i(x) = c)$

5) Output:

$$H(x) = \operatorname{argmax} \left(\sum_{i=1}^{i=c} p_i (f_i(x) = \hat{y}) \right)$$

Description of an algorithm:

- Improve the ML algorithms (classifiers) in F. Next, train and assess them on training and verification sets.
- Determine each algorithm's training accuracy as the weight cardinality w_{ij} for various attack instances.
- The [0–4] type is used to determine each classifier's predicted results for each test record.
- Select the class that received the greatest number of votes as the record's final predictor.
- Produce the whole set of five-category test findings.

The weighted voting algorithm's operation is demonstrated using an example.

Result and Discussion

In this experimental research, the ensemble approach was able to capitalize on the strengths of each classifier, thereby mitigating their weaknesses. The experimental setup performed as follow the Jupiter notebook environment using python language with libraries of scikit-learn, Pyspark and tensorflow on Win11 as operating system. The test PC has an Intel(R) Core i7 CPU running at 1.8GHz and 8.0GB of RAM. The goal of this study was to analyse student cognitive behavior and performance using an ensemble method of adaptive voting classifiers. The ensemble included classifiers such as NB, DT, and FM. In this section, the results are discussed by applying this method and how it compares to individual classifiers used in previous research. The adaptive voting classifier demonstrated improved accuracy over individual classifiers such as NB, DT and FM. This adaptive voting mechanism adjusts weights during voting based on the performance of each model in real-time, enhancing overall performance.

Evaluation Metrics

The four fundamental characteristics of the confusion matrix that show the actual and anticipated classes are the basis for all of these assessment metrics, which are as follows.

- True Positive (TP): It refers to attack data that has been accurately identified as an attack.
- False Positive (FP): Normally occurring data that is mistakenly categorised as an attack.
- True Negative (TN): Normal data that is appropriately categorised as normal.

- False Negative (FN): Data from attacks that is mistakenly categorised as normal.

The following measures will be used to evaluate the efficacy of the proposed solution:

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

The accuracy calculates the percentage of all correctly classified cases.

$$\text{Precision} = \frac{TP}{TP+FP}$$

The precision calculates how many right classifications are deducted from the total number of wrong classifications.

$$\text{Recall} = \frac{TP}{TP+FN}$$

Recall, also known as detection rate, quantifies how many accurate classifications are deducted from the total number of incorrect inputs.

Figure 2 & 3. Illustrates the confusion matrix heat map for FM classifier and adaptive ensemble model respectively. and Table 3 illustrate the accuracy of different ML classifiers which can be determined through four parameters of confusion matrix is TP, TN, FP and FN in which the predicted model performs better is determined.

The proposed ensemble model produces higher precision and recall values than other classifiers. DT and NB perform with both Precision and Recall around 80%, the FM and Ensemble models demonstrate significantly better results, achieving near-perfect Precision and Recall values close to 100%. Notably, the proposed Ensemble method outperforms all other models by consistently maintaining high Precision and Recall, showcasing its strength in combining multiple classifiers to deliver superior and balanced performance compared to individual models.

Figure 5 illustrates the accuracy of ML classifiers whereas the proposed adaptive ensemble method has high accuracy with 98.87% which is comparatively higher than FM, NB

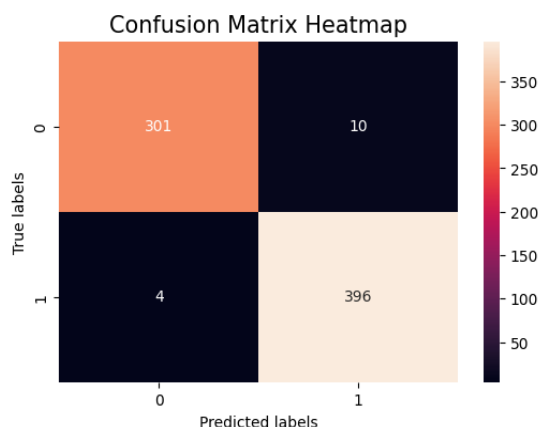


Figure 2: Confusion matrix heatmap of FM classifier

Table 2: Parameters of confusion matrix

MODEL	TP	TN	FP	FN
DT	290	248	84	89
NB	302	351	81	77
FM Classifier	396	301	4	10
Ensemble Method	396	307	4	4

and DT are 98.03%, 77.78% and 75.67% respectively. The accuracy performance is high in adaptive ensemble method that assist in improve the student's academic performance identification precisely. Therefore, this proposed method is beneficial for the exact prediction in identifying the student academic performance.

The prediction analysis in this study used 711 student samples in total. The most accurate findings were obtained by taking into account a number of criteria. For comparison, NB, FM, DT, and the suggested ensemble model were used. Among these, the ensemble model that was suggested performed better and predicted student outcomes with more accuracy. Institutions can categorise students into high-performing and low-performing groups by using this model to assess and anticipate student performance in an efficient manner. As a result, institutions can focus on supporting underperforming students, which eventually improves overall academic outcomes.

Ensemble Model Confusion Matrix Heatmap

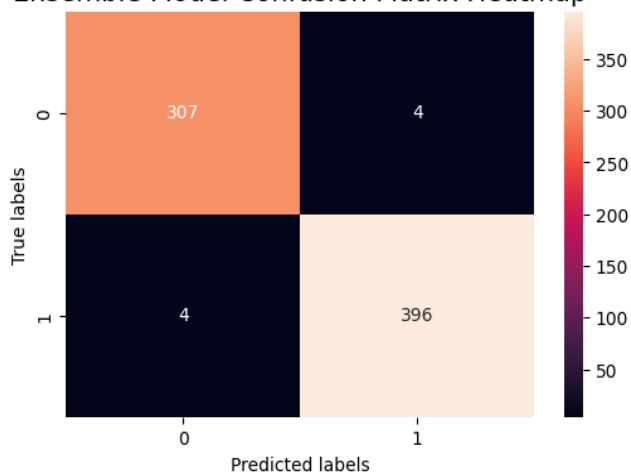


Figure 3: Confusion matrix heatmap of adaptive ensemble model

Table 3: Accuracy of various ML classifiers

Classifiers	Accuracy (%)	Precision	Recall
DT	75.67	77.54	76.52
NB	77.78	78.85	79.68
FM	98.03	99	97.54
Ensemble AV	98.87	99	99

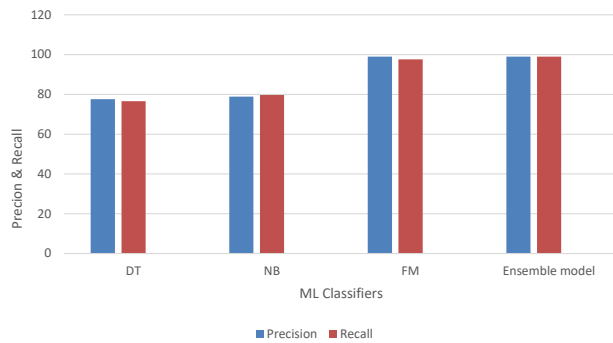


Figure 4: Precision and recall for ML classifiers

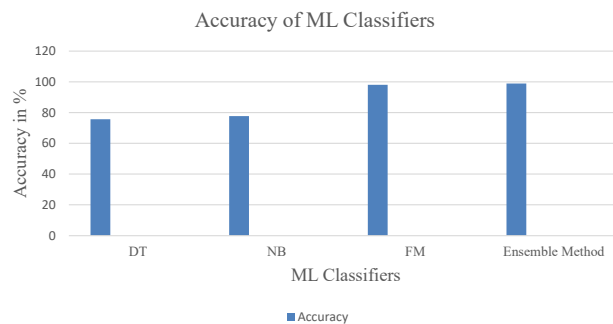


Figure 5: Accuracy of ML classifiers

Conclusion

This study has demonstrated the substantial potential of ensemble ML approaches, notably the adaptive voting classifier, for predicting student performance and cognitive behaviour on online collaborative learning platforms. The ensemble model outperformed individual classifiers with a noteworthy high accuracy of 98.87%, obtained by combining numerous classifiers, including FM, DT and NB. The adaptive voting classifier's better predictive power was aided by its dynamic nature, which modifies weights in response to real-time performance. These results underscore how important it is to use ensemble methods and big data analytics in educational contexts in order to maximise instructional tactics, increase student outcomes, and promote personalised learning.

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References

- Alonso-Fernández, C., Martínez-Ortiz, I., Caballero, R., Freire, M., & Fernández-Manjón, B. (2020). Predicting students' knowledge after playing a serious game based on learning analytics data: A case study. *Journal of Computer Assisted Learning*, 36(3), 350–358. <https://doi.org/10.1111/jcal.12405>
- Anthony, B., Kamaludin, A., Romli, A., Raffei, A. F. M., Phon, D. N. A. E.,

- Abdullah, A., & Ming, G. L. (2020). Blended learning adoption and implementation in higher education: A theoretical and systematic review. *Technology, Knowledge and Learning*, 1–48. <https://doi.org/10.1007/s10758-020-09477-z>
- Azar, A. S., Keat, O. B., & Arutus, J. S. (2021). Collaborative learning in the classroom: The study of Malaysian university students' attitude. *Ilkogretim Online - Elementary Education Online*, 20(4), 272–284. <https://doi.org/10.17051/ilkonline.2021.04.30>
- 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), 1–23. <https://doi.org/10.1186/s41239-020-00223-0>
- Balakrishnan, B., & Parivara, S. A. (2023). E-HRM: Learning approaches, applications and the role of artificial intelligence. *The Scientific Temper*, 14(4), 1367–1373. <https://doi.org/10.58414/SCIENTIFICTEMPER.2023.14.4.45>
- Binsawad, M., Abbasi, G. A., & Sohaib, O. (2022). People's expectations and experiences of big data collection in the Saudi context. *PeerJ Computer Science*, 8, e926. <https://doi.org/10.7717/peerj-cs.926>
- Cacciamani, S., Cesareni, D., Perrucci, V., Balboni, G., & Khanlari, A. (2019). Effects of a social tutor on participation, sense of community and learning in online university courses. *British Journal of Educational Technology*, 50(4), 1771–1784. <https://doi.org/10.1016/j.bjete.2019.04.007>
- Chen, W. S., & Tat Yao, A. Y. (2016). An empirical evaluation of critical factors influencing learner satisfaction in blended learning: A pilot study. *Universal Journal of Educational Research*, 4(7), 1667–1671. <https://doi.org/10.13189/ujer.2016.040719>
- Choudhury, S., & Pattnaik, S. (2020). Emerging themes in e-learning: A review from the stakeholders' perspective. *Computers & Education*, 144, 103657. <https://doi.org/10.1016/j.compedu.2019.103657>
- Chui, K. T., Fung, D. C. L., Lytras, M. D., & Lam, T. M. (2020). Predicting at-risk university students in a virtual learning environment via a machine learning algorithm. *Computers in Human Behavior*, 107, 105584. <https://doi.org/10.1016/j.chb.2018.06.032>
- Citrawathi, D. M., Widiyanti, N. P. M., & Adnyana, P. B. (2020). The effectiveness of the think pair share model based on questions to improve students' participation and learning outcomes about histology structure of the digestive system. *Journal of Physics: Conference Series*, 1503(1), 012040. <https://doi.org/10.1111/bjet.12656>
- Dewi, C. A., Erna, M. M., Haris, I., & Kundera, I. N. (2021). The effect of contextual collaborative learning based on ethnoscience to increase student's scientific literacy ability. *Journal of Turkish Science Education*, 18(3), 525–541. <https://doi.org/10.36681/tused.2021.88>
- Gupta, A., Jain, V., & Singh, A. (2022). Stacking ensemble-based intelligent machine learning model for predicting post-COVID-19 complications. *New Generation Computing*, 40(4), 987–1007. <https://doi.org/10.1007/s00354-021-00144-0>
- Koretsky, M. D., Vauras, M., Jones, C., Iiskala, T., & Volet, S. (2021). Productive disciplinary engagement in high- and low-outcome student groups: Observations from three collaborative science learning contexts. *Research in Science Education*, 51(1), 159–182. <https://doi.org/10.1007/s11165-019-9838-8>

- Koşar, G. (2021). Online collaborative learning: Does it improve college students' critical reading skills? *Interactive Learning Environments*, 1–13. <https://doi.org/10.1080/10494820.2021.1998137>
- Li, S., Pöysä-Tarhonen, J., & Häkkinen, P. (2022). Patterns of action transitions in online collaborative problem solving: A network analysis approach. *International Journal of Computer-Supported Collaborative Learning*. <https://doi.org/10.1007/s11412-022-09369-7>
- Lin, Y.-T., Wu, C.-C., Chen, Z.-H., & Ku, P.-Y. (2020). How gender pairings affect collaborative problem solving in social-learning context: The effects on performance, behaviors, and attitudes. *Journal of Educational Technology & Society*, 23(4), 30–44. <https://www.jstor.org/stable/26981742>
- Liu, Y. G. (2020). Analysis and research on early warning of college students' achievements based on big data. *Digital Technology & Application*, 38, 95–96. <https://doi.org/10.5194/isprs-archives-XLII-3-W10-659-2020>
- Liu, Z., Liu, S., Zhang, C., Su, Z., Hu, T., & Liu, S. (2020). Investigating the relationship between learners' cognitive participation and learning outcome in asynchronous online discussion forums. In *CSEDU 2020* (pp. 26–33). <https://doi.org/10.5220/0009338900260033>
- McHugh, D., Hall, J. M., McLeod, K. M., Kovelowski, C. J., & Payne, A. M. (2020). Twelve tips for developing and implementing curriculum in dedicated 'collaborative classroom'. *Medical Teacher*, 42(3), 266–271. <https://doi.org/10.1080/0142159X.2018.1551992>
- Moreno-Marcos, P. M., Pong, T. C., Muñoz-Merino, P. J., & Kloos, C. D. (2020). Analysis of the factors influencing learners' performance prediction with learning analytics. *IEEE Access*, 8, 5264–5282. <https://doi.org/10.1109/ACCESS.2019.2963503>
- Mousavinasab, E., Zarifsanaiy, N., Niakan Kalhori, S. R., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, 29(1), 142–163. <https://doi.org/10.1080/10494820.2018.1558259>
- Ochronipa, A. Q., Asampana, I., & Nyame, J. Y. (2024). Exploring e-learning system loyalty: The role of system quality and satisfaction. *The Scientific Temper*, 15(4), 3205–3213. Doi: 10.58414/SCIENTIFICTEMPER.2023.14.4.45
- Ouyang, F., Chen, S., & Li, X. (2021). Effect of three network visualizations on students' social-cognitive engagement in online discussions. *British Journal of Educational Technology*, 52(6), 2242–2262. <https://doi.org/10.1111/bjet.13126>
- Phyo, P. P., Byun, Y. C., & Park, N. (2022). Short-term energy forecasting using machine-learning-based ensemble voting regression. *Symmetry*, 14(1), 160. <https://doi.org/10.3390/sym14010160>
- Saeed, M. M., Al Aghbari, Z., & Alsharidah, M. (2020). Big data clustering techniques based on Spark: A literature review. *PeerJ Computer Science*, 6, e321. <https://doi.org/10.7717/peerj-cs.321>
- Sandra, L., Lumbangaol, F., & Matsuo, T. (2021). Machine learning algorithm to predict student's performance: A systematic literature review. *TEM Journal*, 10, 1919–1927. <https://doi.org/10.18421/tem104-56>
- Thuku, J., Henry, A. Y. O. T., Ondigi, S., & Maina, E. (2019). Cloud based tutorial management system to enhance student participation in learning. In *2019 IST-Africa Week Conference (IST-Africa)* (pp. 1–8). IEEE. <https://doi.org/10.23919/ISTAfrica.2019.8764858>
- Warsah, I., Morganna, R., Uyun, M., Hamengkubuwono, & Afandi, M. (2021). The impact of collaborative learning on learners' critical thinking skills. *International Journal of Instruction*, 14(2), 443–460. <https://doi.org/10.29333/iji.2021.14225a>
- Willison, J. (2020). Blended learning needs blended evaluation. In *Critical Perspectives on Teaching, Learning and Leadership* (pp. 87–106). Springer. https://doi.org/10.1007/978-981-15-6667-7_5
- Ye, J., & Zhou, J. (2022). Exploring the relationship between learning sentiments and cognitive processing in online collaborative learning: A network analytic approach. *The Internet and Higher Education*, 55, 100875. <https://doi.org/10.1016/j.iheduc.2022.100875>
- Zhang, S., Chen, J., Wen, Y., Chen, H., Gao, Q., & Wang, Q. (2021). Capturing regulatory patterns in online collaborative learning: A network analytic approach. *International Journal of Computer-Supported Collaborative Learning*, 16(1), 37–66. <https://doi.org/10.1007/s11412-021-09339-5>
- Zheng, L., Zhong, L., & Fan, Y. (2023). An immediate analysis of the interaction topic approach to promoting group performance, knowledge convergence, cognitive engagement, and coregulation in online collaborative learning. *Education and Information Technologies*. <https://doi.org/10.1007/s10639-023-11588-w>