Enhancing learning outcomes in smart education: a supervised machine learning predictive analytics model for course completion

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ABSTRACT

Predictive analytics have become increasingly capable of delivering actionable and accessible feedback to enhance teacher performance to enhance student outcomes in higher education. This study introduces a supervised machine learning predictive model designed to forecast the duration required to complete a course in a video learning environment using a dataset of 8,665 statements from 490 students from National Higher School of Art and Design at Hassan II University in Casablanca over six academic years (2019-24). This paper analyzes decision trees (DT), random forest (RF), support vector machines (SVM), gradient boosting (GB), and linear regression (LR) techniques. The CMI-5 standard and JSON format are used to automatically transfer learning activity data from the learning management system (LMS) to the learning record store (LRS). The results indicate that DT, RF, and GB achieved 100 percent predictor accuracy.

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1. INTRODUCTION

In a rapidly evolving educational and digital learning environment, it is essential for effective teaching to be able to anticipate and influence the learning experience of learners. Artificial intelligence (AI) is a force that has transformed the educational landscape by trying to create intelligent agents [1] that have cognitive capabilities similar to those of humans. In computer science, AI is defined as systems that can perceive their environment and make decisions that optimise their chances of achieving their goals, mimicking the learning and problem solving process of humans [2]. Since the 1950s, machine learning, the most fundamental branch of AI, has made great strides in creating systems that can not only learn from data, but also adapt and improve over time. Deep learning, a kind of AI employing neural networks to analyze extensive datasets and uncover intricate patterns beyond human detection, is a major development.

As interest in machine learning in the educational field continues to grow, significant amount of research is being done to predict student performance in areas such as problem solving and course completion [3]. The use of learning data mining tools and AI in learning environment has been the subject of a number of studies [4] focusing on AI-based strategies, such as artificial neural networks (ANN), which effectively classify diverse educational outcomes, surpass traditional methods [5], [6] to improve learner engagement and virtual learning outcomes [7], [8]. Strong AI models are now needed to develop new strategies in this area [9]. Although machine learning has made great progress in predicting academic performance in online environments, there are different points of view from different studies. For example, Iqbal *et al.* [10] used data from the Department of Electrical Engineering to study academic performance prediction using machine learning techniques such as matrix factorization, collaborative filtering and Boltzmann's constrained computing. An approach [11] was proposed wherein the performance prediction of individual classification algorithms was improved by leveraging them within ensemble methods, including both homogeneous (bagging, boosting) and heterogeneous (voting, stacking) techniques. Bakhouyi *et al.* [12] proposes a hybrid system that leverages several machine learning modeling techniques—namely, decision trees (DT), support vector machines (SVM), and naïve Bayes (NB) classifiers—for the dual purpose of analyzing student data and predicting course completion success. A summary and comparison of these related studies are presented in Table 1.

Table 1. Comparison of related studies

Reference/Year	Dataset size	Data source	Attribute	Machine learning algorithm	Best model
Iqbal *et al.* [10]	225	Undergraduate Electrical Engineering students (2013–2015), ITU Lahore	Grades, GPA	User-based collaborative filtering (UBCF), singular value decomposition (SVD), non-negative matrix factorization (NMF), and restricted Boltzmann machine (RBM)	RBM
Anderson and Anderson [11]	683	Students from Craig School of Business, California State University, Fresno (2006–2015)	Historical grade data (18 semesters)	NB, k-nearest neighbors (kNN), SVM	SVM
Zohair [13]	50	Master's graduates	Student ID, age, bachelor’s degree info, course details, grades, instructor names	Multi-layer perceptron (MLP)-ANN, NB, SVM, kNN, linear discriminant analysis (LDA)	SVM
Das and Marek [14]	227	Electrical Engineering Students, Eastern Washington University (2007–2016)	Demographic & academic: gender, income, SAT/ACT, GPA, grades in math and physics	kNN, NB, SVM	kNN
Adekitan and Salau [15]	1841	Covenant University, Nigeria (2002–2014), 7 engineering departments	First 3 years GPA, final CGPA	Probabilistic neural network (PNN), random forest (RF), DT, NB, tree ensemble, logistic regression (LogReg)	LR
Abana [16]	133	Computer Engineering students (4-year program)	Research method & project grades, gender, backlog, programming proficiency	Random tree (RT), Reptree, J48	RT
Tsiakmaki *et al.* [17]	592	Business Administration Department, TEI Western Greece (2013–2017)	Final grades of first-semester courses	Linear regression (LR), RF, SVM, DT, M5 Rules, kNN	RF
Fernández *et al.* [18]	335	Computer Systems Engineering students, Ecuadorian university (2016–2018)	Subject details, final grades, academic and semester information	DT	DT
Bujang *et al.* [19]	489	ICT students, northwestern Malaysian polytechnic (2016–2019)	Year, class group, cohort, gender, assessment components (CAM, FEM), final grade	LR, RF, SVM, LR	DT

In addition, Das and Marek [14] developed a predictive model to increase academic achievement and reduce dropout rates among electrical engineering students at the University of Eastern Washington. The accuracy of the model to predict GPA using machine learning techniques was approximately 85 percent. More sophisticated, Adekitan and Salau [15] at Covenant University in Nigeria predicted cumulative grade point average (CGPA) using regression techniques in addition to konstanz information miner (KNIME). According to their findings, LR outperformed other techniques such as DT, PNN, and tree assemblies, with a maximum accuracy of 89 percent. In another study, Abana [16] predicted student grades for 133 cases over a 4-year period using DT classification models (RT RepTree, J48). Although the study stressed the need for more samples and more elements to improve accuracy, the RT algorithm was the most accurate (75 points 19 percent). Similarly, regression models have been tested [17].

2. METHOD

Recent advances in machine learning and learning analytics can now improve the forecasting of learning time in courses. The adoption by the European Commission of standards such as CMI-5 [20] has made it easier to develop more sophisticated predictive models, which have greatly improved the capacity to collect and evaluate a wealth of data on learner-to-learner interactions and learning outcomes. Combining machine learning and CMI-5 allows for accurate prediction of how long a course will take to complete, and provides teachers with more information about the learning rate and progress of their students. By analysing historical interaction data, these predictive models can estimate the time it will take for individual learners to complete specific modules or courses. Providing students with reasonable expectations for the duration of the course can increase motivation and engagement, fostering a more stimulating and productive learning environment. Consequently, machine learning and the integration of CMI-5 are not exclusive.

Moodle is the main platform for user administration, course delivery and communication between students and course materials. A learning record store (LRS) is built into Moodle to enhance its embedded capabilities and record a variety of learning activities that are performed on the platform [21]. Data on learning experiences can be managed, stored and analyzed in a specialized storage facility called LRS [22]. The LRS guarantees full compatibility and interoperability with a wide range of digital teaching tools and platforms, as it has been developed in accordance with the CMI-5 specification. The LRS combines data streams and provides teachers and administrators with comprehensive insight into student performance, progress and behavior through seamless integration with the LRS, which connects the Moodle and assignable units (AUs). Assignable units are those that represent different components of learning activities or content, which are necessary for the LRS to function. The proposed model for collecting learning experience data by using the integration of CMI-5 specifications to to enable the accurate prediction of time to course completion is shown in Figure 1.

The predictive analytics component of this study is represented by the learning record consumer (LRC), which uses supervised machine learning techniques to predict how long it will take to complete a course based on the structured data stored in The Learning Record. For the accurate prediction of the time to course completion, our methodology uses a structured process which includes data collection, pre-treatment, analysis and modelling. To estimate the course completion time (CCT) of individual learners, supervised learning algorithms such as RF, gradient boosting (GB), SVM, DT and LR are used in the predictive model, as illustrated in Figure 2.

We propose a methodical and structured approach to collect, prepare, analyze and model learner data for accurate CCT prediction. Figure 2 shows the different stages of the predictive analytics framework. For the estimation of CCT for individual learners supervised machine learning models were used; DT, GB, RF, SVM, and LR. The methodology is composed of a number of key steps, as illustrated in Figure 2.

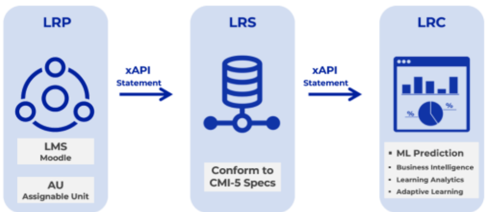


Figure 1. Proposed model for collecting learning experience data through the integration of CMI-5 specifications

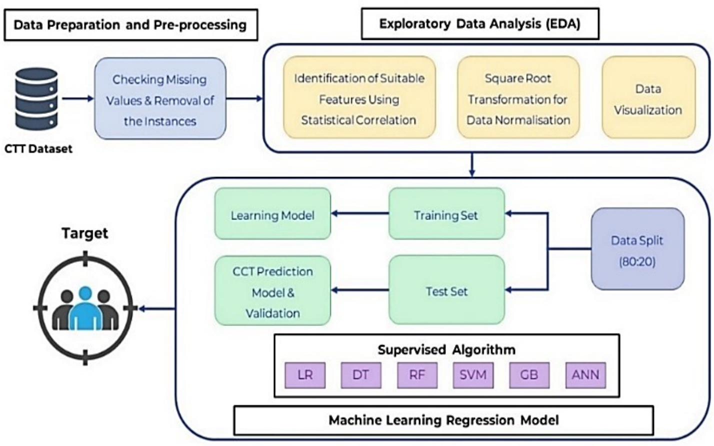


Figure 2. Proposed supervised machine learning predictive analytics model

2.1. Identifying data sources

Data collection is the first step from the LRS, which is provided by the learning record provider (LRP) and is linked to the learning management system (LMS) which is compliant with CMI-5. These systems record many data points, such as student demographics, test performance, module progress, and student's understanding of the material. In order to ensure the universality and robustness of the prediction model, the CCT data set should cover a wide range of courses and learners.

2.2. Data preparation and pre-processing

To ensure the quality and analytical potential of the data, they undergo a thorough pre-processing phase after collection. This step involves the processing of missing values, encoding of categorical variables and the processing of ambiguous data, normalization of numerical characteristics, and detection and treatment of possible outliers. For the prediction of CCT, machine learning models are trained using the features taken from the CMI-5 declaration. Transforming CMI-5 commands into machine learning-ready data sets requires parsing JSON structures to extract basic elements such as actor details, actions performed, learning sources, results, context information, and time stamps, as illustrated in Figure 3. The model input data set contains these extracted elements as features.

In Waikato Knowledge Analysis Environment, version 3.8 (WEKA), techniques for selecting features were used to remove redundant or irrelevant attributes and to improve the set of features [23]. To be more precise, the WrapperSubsetEval method was used in combination with BestFirst to determine which attributes are most relevant for predictive accuracy. The performance of the model was further improved by using engineering techniques to modify or add new variables. Attributes associated with actor, verb, store, ID, authority, and other non-contributory fields have been removed. The nine main variables retained in the final dataset were time spent, progress, state of completion, duration of sessions and activities, threshold for completion, number of interactions, types of interactions, and metadata selected. Then they were subdivided into five categories of characteristics: i) verb-related features, ii) object-related features, iii) context-related features, iv) interaction-related features, and v) other metadata.

The following specific actions were used to further categorize interaction types in order to efficiently track course progression and completion times: “Initialized”, “Launched”, “Played”, “Paused”, “Interacted”, “Seeked”, “Terminated”, and “Completed”. By choosing pertinent features from CMI-5 statements, a refined dataset was created for the purpose of training the predictive models. Numerous facets of student interaction and context are captured by these features, such as session length, progress, activity kinds, interaction counts, and metadata. The final set of attributes utilized in the model is compiled in Table 2, where they are categorized into groups like object features, verb-related features, contextual information, interaction data, and extra metadata. CCT can be accurately modeled thanks to this structured feature set.


```json
{
    "actor": {
        "mbox": "mailto:Guest 103.255.106.10@learnlab.ma",
        "name": "Guest 103.255.106.10",
        "objectType": "Agent"
    },
    "verb": {
        "id": "http://adlnet.gov/expapi/verbs/completed",
        "display": {
            "en-US": "completed"
        }
    },
    "object": {
        "id": "https://www.youtube.com/watch?v=rdguWcRqBBc",
        "definition": { ···
        },
        "objectType": "Activity"
    },
    "result": {
        "duration": "PT35.17S",
        "completion": true,
        "extensions": {
            "https://w3id.org/xapi/video/extensions/time": 36.219,
            "https://w3id.org/xapi/video/extensions/progress": "0.702",
            "https://w3id.org/xapi/video/extensions/played-segments":
            "1.048[.]5.068[,]5.068[.]10.108[,]10.108[.]15.172[,]15.172[.]36.219"
        }
    },
```


Figure 3. Representation JSON of a CMI-5 statement

Table 2. Characteristics that the dataset uses

Categories	Attribute name	Description	Type	Possible values
Verb-related features	Actor ID	Unique identifier of the learner interacting with the content.	Nominal	userID@domain.edu
	Time spent	Total time the learner interacted with the activity, measured in seconds.	Numeric (measured in seconds)	36.464 seconds
	Progression	Percentage of activity completed (e.g., how much of a video has been viewed).	Numeric (percentage)	70.3%
	Completion status	Indicates whether the activity was completed (binary or categorical).	Numeric	1 = Completed, 0 = Not Completed
	Session duration	Length of the session during which the interaction occurred.	Numeric (measured in seconds)	35.17 seconds
Object features	Activity type	Type of activity interacted with (e.g., video, course, quiz).	Nominal	Video, Course
	Activity length	Total duration of the activity content.	Numeric (measured in seconds)	49.683 seconds
Contextual features	Session ID	Unique identifier of the session during which interaction occurred.	Nominal (unique identifier)	63bb18d8-37af-40f8-911c-eb6a2ab5d6a2
	Completion threshold	Minimum required progression percentage to mark the activity as completed.	Numeric (threshold percentage)	70%
Interaction features	Number of interactions	Total count of learner interactions during the session.	Numeric (count)	5 interactions
	Types of interactions	Specific actions taken by the learner during the session.	Nominal	Initialized, launched, played, paused, seeked, completed
Additional metadata	Metadata	Supplementary data from CMI-5 statements relevant for analysis (e.g., demographics, environment, device).	Nominal	Age: 25–30, Gender: Female, Browser: Chrome, Location: Casablanca

2.3. Exploration data analysis

To gain a thorough understanding of data set structure and properties, exploration data analysis (EDA) was performed prior to running predictive models. This analytical phase was necessary to identify statistical trends, possible outliers and the fundamental correlations between input properties and the target variable, CCT. Various visualization tools, such as charts, summaries, correlation charts and histograms, have been used to assist in this process. These methods have allowed the evaluation of variable distributions and the detection of correlations which guide the selection of features and the training of models [24].

The dataset analyzed consisted of 8,665 learner interaction reports collected between the years 2019 and 2024. Based on a CMI-5 compliant learning environment, these assessments provided a deep insight into the interaction patterns and learner engagement behavior. Significant patterns, representing different levels of commitment and development of learners during the learning process, have been identified by examining specific types of interaction. Observed in 670 interviews, the played activity was associated with an average of 20-70 minutes and 2-47 interactions per session, which indicates a regular and significant involvement in the material of the course. On the other hand, the 'Pause' action was used in 677 commands, with an average session duration of 6:87 minutes and no additional interaction. This suggests that learners may have paused for a moment, most likely to reflect, to take notes, or to temporarily shift their attention.

The interaction “Terminated” was detected in 218 reports. As shown in Figure 4, this represents a sustained effort prior to disengagement, with an average interaction duration of 3.20 in Figure 4(a) and an average duration of 42.22 minutes in Figure 4(b). This behavior may be an indication of content difficulty, cognitive overload, or external distractions that caused the learning session to be interrupted prematurely. Finally, 168 statements that included the “Completed” action showed an average engagement time of 36.23 minutes with 3.36 interactions, indicating a high level of persistence and commitment by learners to completing tasks. These descriptive insights, illustrated graphically in Figure 4, help to create more accurate and effective predictive models for predicting course completion and to advance a more nuanced understanding of learner behavior.

2.4. Data preparation and pre-processing

The study evaluates six machine learning models for the estimation of student learning completion rates: LR, gradient enhancement (GB), support vector regression (SVR), RF, DT and ANN. The choice of the model took into account the readability, complexity of the task and the characteristics of the dataWeKA used a five-fold cross-validation to divide the dataset into 20 percent testing and 80 percent training. The performance of the model was evaluated by using the metric R-squared (R^2).

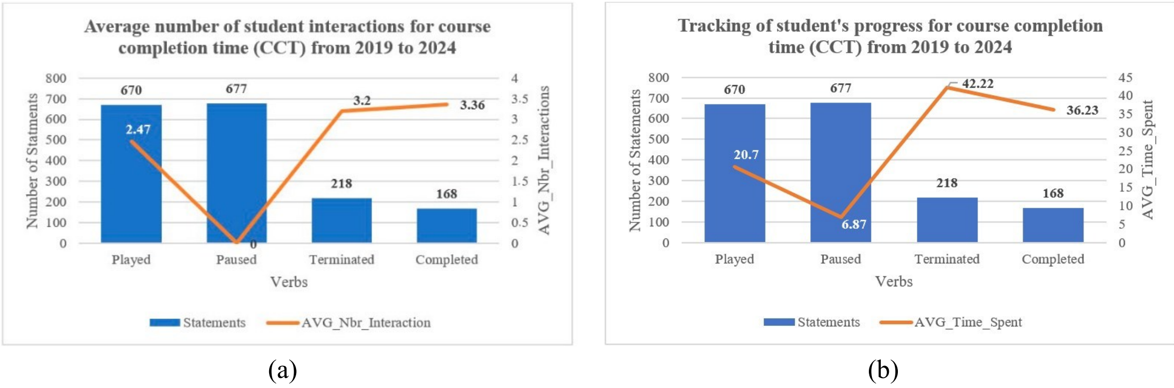


Figure 4. Student interactions and progress for CCT from 2019 to 2024 (dataset: 8,665 statements): (a) average number of interactions by activity verb and (b) average time spent by activity verb.

2.5. Model training and evaluation

To assess the predictive power of the algorithms selected, they were trained and evaluated on different subsets of the dataset. The regression measures such as the root mean square (symmetric) and the mean absolute error (MAE). The evaluation used explained variance score (EVS), root mean squared error (RMSE), relative absolute error (RAE), and median absolute error (MedAE) as measures of the explanatory variability [25]. A k-fold cross validation has been used to improve resistance and reduce overfitting. EVS calculates the percent of the deviation explained by the model, MedAe calculates the average deviation between expected and observed values, and RAE quantifies the error in relation to the mean of the observed values [26].

3. RESULTS AND DISCUSSION

In regression analysis, it is important to compare and contrast different models to understand their generalizability and prediction ability in different data situations [27]. The goal was to predict CCT using learner interaction data that met CMI-5 requirements. Using learner interaction data that met the CMI-5 requirements, six machine learning techniques were used to predict the time to completion of the course: RF, DT, LR, SVR, ANN, and gradient boosting regression (GBR).

The R^2 metric was used to compare expected CCT values with actual results to assess the predictive performance of each model. According to the results, DT and RF both achieved R2 scores of 1,000, indicating perfect fit, but also raising concerns about possible overfitting, especially for a DT model that is known to be sensitive to training data. Although it also has a similar risk of overfitting, the ANN model has shown exceptional performance, capturing most of the variance of the dataset with a R2 of 0.998. With a R^2 of 0.999, the GBR model demonstrated good generalizability and predictive power. With an R^2 of 0.993, the LR model shows a strong linear relationship and is less likely to be oversimplified. By contrast, the SVR model with a R^2 of 0.890 performed worst, indicating that it was only partially successful in identifying the underlying patterns in the data.

A broad range of regression performance metrics, such as the RAE, the MAE, and the RMSE. EVS and MedAE were used to further assess the performance and robustness of the model. Table 3 summarises the predictive results for each model. It is noteworthy that ANN and LR also achieved high precision, while DT, RF and GBR all achieved flawless or near flawless performance. The relatively weaker performance of SVR highlights the importance of model selection and parameter optimization in educational predictive analytics. These results highlight the importance of rigorous evaluation and cross validation processes to maintain the reliability of models and avoid overfitting, particularly when used to predict learner outcomes in an online learning environment.

The predictive accuracy of the algorithms tested varies depending on the performance assessment of the model using standard regression techniques. For example, mean squared error (MSE) of 0.0004808 and MAE of 0.0047437 demonstrate that LR models are highly accurate. The ability of the model to capture linear data trends is confirmed by the R^2 of 0.9937, which means that the model explains approximately 99.37 percent of the variance of the target variable. In addition, the RMSE of 0.02193 underlines the robustness of the model in real-world applications, as it shows that the prediction deviations remain within 2.19 percent of the average target value. RF, gradient boosting regression (GBR), and DT are examples of ensemble methods that achieved perfect scores for all the major metrics, including R^2, MAE, MSE, and RMSE. Although these findings initially point to a better predictive performance, they also raise eyebrows.

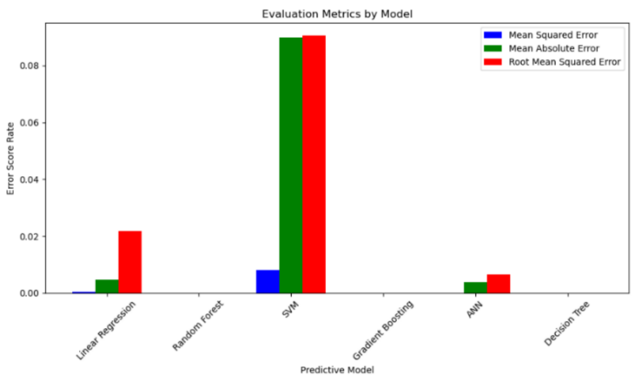
Table 3. Comparison of algorithms performance

Models	MSE	MAE	RMSE	RAE	R^2 score (%)	EVS	MedAE
DT	0.0	0.0	0.0	0.0	100	1.0	0.0
ANN	9.018	0.005	0.009	2.349	99.8	0.998	0.004
GBR	5.423	4.438	7.364	0.002	99.9	0.999	2.663
LR	0.0	0.0	0.02	3.096	99.3	0.993	0.001
SVR	0.008	0.089	0.090	58.678	89	0.975	0.092
RF	0.0	0.0	0.0	0.0	100	1.0	0.0

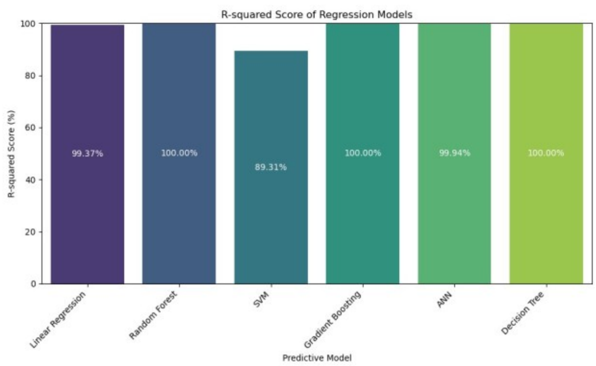
Although it performed relatively well, the SVR model generated higher error values than the LR model. Its relatively poorer performance, with a R^2 of 0.8931, MSE of 0.0082, and MAE of 0.0899, suggests that it may not be able to fully capture the underlying structure of the data set, possibly due to insufficient hyperparameter tuning or its sensitivity to nonlinearities. On the other hand, ANNs have shown extraordinary predictive power. The ANN model successfully identified complex non-linear patterns in the data with an MSE of 4.368 times $10.^5$, MAE of 0.00392, and R^2 of 0.9994. These results highlight the strong learning capacity and versatility of the model. However, in order to ensure the robustness and applicability of the model in real-world situations, due to the possibility of overfitting of neural nets, continuous validation and assessment of generalisation performance is required.

The advantages and disadvantages of each regression model are unique. LR and ANN are good at modelling linear and non-linear patterns, but due to their tendency to overfit, they should be applied with caution in an ensemble approach. Ultimately, a deeper understanding of the performance of the model, supported by a thorough analysis of metrics and rigorous validation, is necessary to make a wise choice of models and to implement them effectively in both applied and research contexts.

The results of the evaluation of the prediction models are shown in Figure 5. A performance comparison based on MAE, MSE, and RMSE is presented in Figure 5(a), highlighting the accuracy of the predictions of each machine learning algorithm. The R^2 score of each model is shown in Figure 5(b) to show how well each model explains the change in the CCT.



(a)



(b)

Figure 5. Performance evaluation of the predictive analytics models for CCT: (a) comparison of MAE, MSE, and RMSE scores for each model, and (b) R^2 score rates of the CCT prediction models

The ability of machine learning models to predict is dependent on how well they perform, measured by metrics such as RMSE. The consistency and reliability of the model predictions are revealed by looking at the RMSE score for each fold and the RMSE average for the cross validation, which divides the dataset into several training and testing folds [28]. The DecisionTreeRegressor successfully captures the underlying data patterns, as shown by its consistently low RMSE score across all folds. This conclusion is further supported by the RMSE average cross-validation, which shows consistent and reliable performance across different subsets of data. This robustness can be explained by the inherent simplicity and adaptability of DT models, which allow them to work well with different data distributions and relationships.

However, as shown by the relatively higher RMSE score for fold 1 compared to other folds, the ANN model shows greater variability in performance across folds. Its higher average RMSE after cross-validation reflects less reliable predictive performance. This variability may be due to the complexity of neural networks, which are more sensitive to changes in training data due to their many parameters and the risk of overfitting [29]. Although the gradient enhancement model shows a low mean RMSE for cross-validation, its RMSE score in fold 1 is slightly higher than the RMSE score in the subsequent folds. The iterative nature of gradient reinforcement and its sensitivity to the order of the low-performing learners may contribute to this initial variability in performance. However, the low mean RMSE of the model suggests that it has good overall predictive power in LR and both.

To assess the consistency and robustness of models, we used 5-fold cross-validation and testing the RMSE across all folds. The results of the cross-validation of each model are shown in Figure 6, which also shows the corresponding mean RMSE and RMSE obtained at each of the two fold rates. This visualization allows a comparative assessment of model stability and generalisation performance across dataset subsets.

The SVM model has a higher average RMSE score for cross-validation, but a relatively low RMSE score for all folds, compared to other models. Due to the sensitivity of SVMs to the selection of kernel and regularisation parameters, this difference implies a certain variation in performance between folds. Adjusting these parameters may help to increase model coherence and reduce variability of performance between different subsets of data. In summary, all models show predictive capability, but consistency and reliability of their performance varies according to the data subset. It is necessary to understand these details in order to select the best model for a specific task and to ensure accurate and consistent predictions in the application of the procedure.

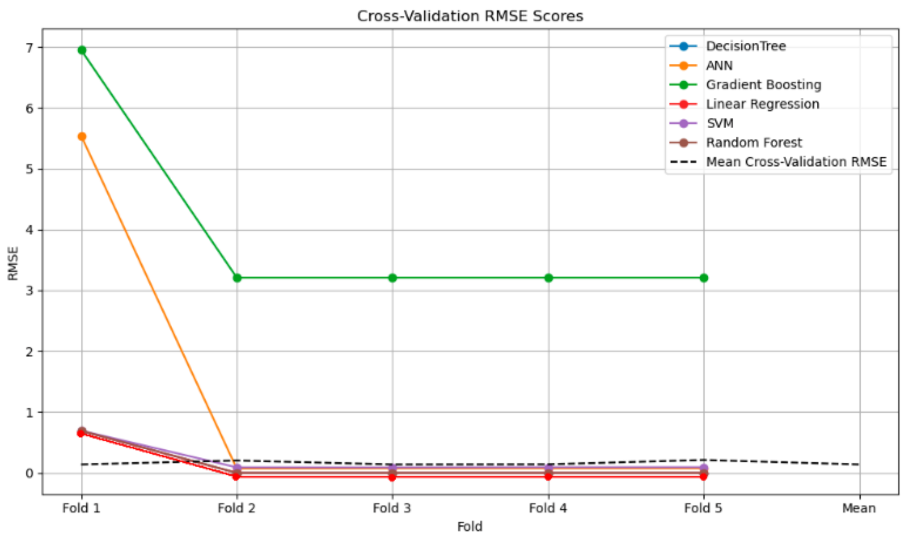


Figure 6. Visualizing the cross-validation techniques with 5-fold cross-validation

4. CONCLUSION

This study shows how well different machine learning models predict the time to finish for high achievers in video-based learning environments. Models generate instructions in JSON format and are automatically transferred from the LMS to the LRS using data from the Hassan II University of Casablanca and CMI-5 specification. Despite their almost perfect accuracy (R^2 of 100 percent), models such as DT, RF, and gradient grading regression (GGR) are prone to overfitting. ANNs performed equally well (R^2 99.8), although with comparable problems of overfitting. LR was the most reliable choice, with a lower probability of overfitting and strong performance (R^2 99.3). SVM performed worse, with an R^2 of 89. Nevertheless, the overall results of the ensemble methods are high.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available at https://e-learning.univh2c.ma/

REFERENCES

[1] D. Saba, Y. Sahli, R. Maouedj, A. Hadidi, and M. B. Medjahed, "Towards artificial intelligence: concepts, applications, and innovations," in *Artificial Intelligence and Digital Systems Engineering*, 2020, pp 103–146, doi.org/10.1007/978-3-030-52067-0_6.

[2] A. Konar, *Artificial intelligence and soft computing: behavioral and cognitive modeling of the human brain,* Boca Raton: Taylor & Francis, 2018.

[3] F. Galbusera, G. Casaroli, and T. Bassani, "Artificial intelligence and machine learning in spine research," *JOR Spine*, vol. 2, no. 1, Mar. 2019, doi: 10.1002/jsp2.1044.

[4] M. Hussain, W. Zhu, W. Zhang, S. M. R. Abidi, and S. Ali, "Using machine learning to predict student difficulties from learning session data," *Artificial Intelligence Review*, vol. 52, no. 1, pp. 381–407, Feb. 2018, doi: 10.1007/s10462-018-9620-8.

[5] M. F. Musso, C. F. R. Hernández, and E. C. Cascallar, "Predicting key educational outcomes in academic trajectories: a machine-learning approach," *Higher Education*, vol. 80, no. 5, pp. 875–894, Mar. 2020, doi: 10.1007/s10734-020-00520-7.

[6] F. Ouyang, L. Zheng, and P. Jiao, "Artificial intelligence in online higher education: a systematic review of empirical research from 2011 to 2020," *Education and Information Technologies*, vol. 27, no. 6, pp. 7893–7925, Feb. 2022, doi: 10.1007/s10639-022-10925-9.

[7] J. Cowin, B. Oberer, J. Lipuma, C. Leon, and A. Erkollar, "Accelerating higher education transformation: simulation-based training and AI coaching for educators-in-training," *Towards a Hybrid, Flexible and Socially Engaged Higher Education (ICL 2023)*, pp. 532–541, Jan. 2024, doi: 10.1007/978-3-031-51979-6_55.

[8] K. Seo, "The impact of artificial intelligence on learner–instructor interaction in online learning," *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, pp. 1–23, Oct. 2021, doi: 10.1186/s41239-021-00292-9.

[9] N. D. -Rodríguez, J. D. Ser, M. Coeckelbergh, M. L. de Prado, E. H. -Viedma, and F. Herrera, "Connecting the dots in trustworthy Artificial Intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation," *Information Fusion*, vol. 99, Nov. 2023, doi: 10.1016/j.inffus.2023.101896.

[10] Z. Iqbal, J. Qadir, Mian, Adnan Noor, and F. Kamiran, "Machine learning based student grade prediction: a case study," *arXiv:1708.08744*, 2017.

[11] T. Anderson and R. Anderson, "Applications of machine learning to student grade prediction in quantitative business courses," *Global Journal of Business Pedagogy*, vol. 1, no. 2, pp. 13–22, 2017, doi: 10.33423/gjbp.v1i2.123.

[12] A. Bakhouyi, A. Dehbi, L. Amhaimar, S. Broumi, M. Talea, and A. Khalidi, "Improving SMART learning: Course completion via AI-driven hybrid system integration in big data," *Telematics and Informatics Reports*, vol. 18, 2025, doi: 10.1016/j.teler.2025.100199.

[13] L. M. A. Zohair, "Prediction of Student's performance by modelling small dataset size," *International Journal of Educational Technology in Higher Education*, vol. 16, no. 1, Aug. 2019, doi: 10.1186/s41239-019-0160-3.

[14] A. K. Das and E. R. -Marek, "A predictive analytics system for forecasting student academic performance: insights from a pilot project at Eastern Washington University," *2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR)*, 2019, pp. 255-262, doi: 10.1109/ICIEV.2019.8858523.

[15] A. I. Adekitan and O. Salau, "The impact of engineering students' performance in the first three years on their graduation result using educational data mining," *Heliyon,* vol. 5, no. 2, 2019, doi: 10.1016/j.heliyon.2019.e01250.

[16] E. C. Abana, "A decision tree approach for predicting student grades in research project using Weka," *The Science and Information Organization (SAI)*, vol. 10, no. 7, 2019, doi: 10.14569/IJACSA.2019.0100739.

[17] M. Tsiakmaki, G. Kostopoulos, G. Koutsonikos, C. Pierrakeas, S. Kotsiantis, and O. Ragos, "Predicting university students' grades based on previous academic achievements," *2018 9th International Conference on Information, Intelligence, Systems and Applications (IISA)*, May 2018, pp. 1-6, doi: 10.1109/IISA.2018.8633618.

[18] D. B. -Fernández, D. Gil, and S. L. -Mora, "Application of machine learning in predicting performance for computer engineering students: a case study," *Sustainability*, vol. 11, no. 10, May 2019, doi: https: 10.3390/su11102833.

[19] S. D. A. Bujang, A. Selamat, O. Krejcar, P. Maresova, and N. T. Nguyen, "Digital learning demand for future education 4.0—case studies at malaysia education institutions," *Informatics*, vol. 7, no. 2, Apr. 2020, doi: 10.3390/informatics7020013.

[20] A. Bakhouyi, A. Dehbi, and S. Broumi, "Performance evaluation of JSON2RDF TransLRS semantic solution in smart education by using CMI-5 specification," *2022 2nd International Conference of Smart Systems and Emerging Technologies (SMARTTECH), Riyadh, Saudi Arabia*, 2022, pp. 20-25, doi: 10.1109/SMARTTECH54121.2022.00020.

[21] A. Bakhouyi, R. Dehbi, and M. Talea, "A new web service architecture for enhancing the interoperability of LMS and mobile applications using the next generation of SCORM," *Advances in intelligent systems and computing*, pp. 719–726, Jan. 2019, doi: 10.1007/978-3-030-11928-7_65.

[22] A. Bakhouyi, R. Dehbi, M. Talea, and O. Hajoui, "Evolution of standardization and interoperability on E-learning systems: An overview," *2017 16th International Conference on Information Technology Based Higher Education and Training (ITHET)*, Ohrid, Macedonia, 2017, pp. 1-8, doi: 10.1109/ITHET.2017.8067789.

[23] E. O. Omuya, G. O. Okeyo, and M. W. Kimwele, "Feature selection for classification using principal component analysis and information gain," *Expert Systems with Applications*, vol. 174, Jul. 2021, doi: 10.1016/j.eswa.2021.114765.

[24] M. G. Majumder, S. D. Gupta, and J. Paul, "Perceived usefulness of online customer reviews: A review mining approach using machine learning & exploratory data analysis," *Journal of Business Research*, vol. 150, pp. 147–164, Nov. 2022, doi: 10.1016/j.jbusres.2022.06.012.

[25] N. V. Thieu, "PerMetrics: a framework of performance metrics for machine learning models," *The Journal of Open Source Software*, vol. 9, no. 95, May 2024, doi: 10.21105/joss.06143.

[26] A. A. -Zadeh, J.-P. Calliess, D. Kaiser, and S. Roberts, "Machine Learning-Based Financial Statement Analysis," *SSRN Electronic Journal*, 2020, doi: 10.2139/ssrn.3520684.

[27] Z. M. Yaseen, "An insight into machine learning models era in simulating soil, water bodies and adsorption heavy metals: Review, challenges and solutions," *Chemosphere*, vol. 277, Aug. 2021, doi: 10.1016/j.chemosphere.2021.130126.

[28] F. Cabitza *et al.*, "The importance of being external. methodological insights for the external validation of machine learning models in medicine," *Computer Methods and Programs in Biomedicine*, vol. 208, Sep. 2021, doi: 10.1016/j.cmpb.2021.106288.

[29] V. Asghari, Y. F. Leung, and S.-C. Hsu, "Deep neural network based framework for complex correlations in engineering metrics," *Advanced Engineering Informatics*, vol. 44, Apr. 2020, doi: 10.1016/j.aei.2020.101058.

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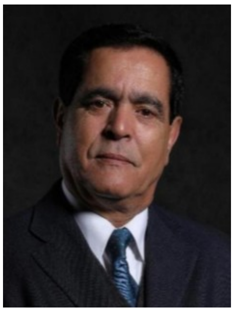

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