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A web-based learning platform to assess student performance using online session activity engagement

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ABSTRACT

Predicting students' performance and engagement is crucial for academic eLearning partners in colleges and universities as well as students themselves considering post-COVID-19 pandemic and university grant commission (UGC) dual degree regulation era. An educational system's data on students' engagement in taking courses that are a significant component of an institution of higher learning with a cogent vertical syllabus can be used to make predictions. By examining how closely a student's course-taking actions correspond with the requirements of the syllabus, one can utilize the student's conduct in the classroom and online eLearning web tool as a predictor of future achievement. This paper presents a study that uses an eLearning web-based dataset to predict students' success throughout a series of online interactive sessions. The dataset records how students engage with each other during online lab work, including how many keystrokes they make, how long they spend on each task, and how well they perform on exams overall. The current methods lack accuracy to assess student performance and engagement with high precision. In addressing this paper introduces novel multi-label ensemble learning (MLEL) using XGBoost (XGB) and K-fold cross validation. Experiment outcome shows the proposed (MLEL-XGB) achieves much improved outcome than other existing models.

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1. INTRODUCTION

The widespread use of the internet and the development of information technology have had an impact on how businesses and academics gain knowledge, moving away from standard offline models to virtual ones through the use of eLearning web-based/application-based platforms [1]. The entire curriculum has switched to an online format, particularly during the COVID-19 epidemic, emphasizing the importance of eLearning platforms. Alongside, university grant commission (UGC) allows student to enroll for two degrees considering one conventional offline and other through online portal. Thus, it is important to assess the student engagement level and their performance by employing artificial intelligence techniques. Nonetheless, there are a lot of obstacles in the way of developing a legitimate and precise model to forecast student engagement level and performance [2]. By offering individualized information, an efficient evaluation technique for comprehending student behavior via eLearning platform student engagement session streams can help improve students' academic performance.

One of the main problems of the twenty-first century is delivering personalized content to students in an e-learning platform based on their unique behavior of student by assessing their engagement [3]. The use of adaptive personalization techniques to comprehend learner profiles has been highlighted [4], [5]. In recent years, models for analyzing student engagement level and predicting student performance are being created using data mining and machine learning [6]. Through the establishment of behavior patterns from engagement session data [7], [8], data mining has been utilized for enhancing predictive model efficiency [9] and to gain valuable insights from student engagement session information of eLearning web-based tools. The approaches of data mining [10] and machine learning [11]–[13] show great promise in a variety of fields, including enterprises and information security, which includes education data mining (EDM) [14]–[16]. In the next sub-section this research work studies the various recent methodologies designed to analyze the performance student using machine learning and deep learning have been studied and highlight the problem and motivation of the research work.

EDM [17] has emerged a new concept for enhancing learning style [18], understanding behavior, engagement level [19], and improving student performance [20]. The EDM data is composed of different information [21] such as administration data, student session stream activity [22], and student academic performance and engagement information. Using the results of their midterm exams as primary data, the study aims to predict undergraduate students' final exam marks. To generate predictions, it uses a variety of machine learning techniques, including as random forest (RF), support vector machine (SVM), naïve Bayes (NB), K-nearest neighbors (KNN), and logistic regression (LR). The academic accomplishment grades of 1854 students enrolled in a Turkish language-I course make up the dataset. With just three parameters—midterm exam grades, department data, and faculty data—the suggested model was able to classify objects with an accuracy of between 70 and 75 percent. Establishing a learning analysis framework in higher education and supporting decision-making processes—particularly in identifying high-risk students for failure—are made possible by the findings of this study. In accordance with Saudi Arabian online learning training regulations, this study presents a machine learning strategy to forecast student performance in an online learning environment via the Maharat platform at Taif University. Hybrid optimization is used for feature extraction, while the SVM method is used for prediction. Predicting academic success and evaluating the quality control of online training courses are the main goals. Sample views regarding quality assurance are analyzed using descriptive-analytical techniques. By bridging the gap between student performance prediction and online learning requirements, this work improves the caliber of online learning. Grubov *et al.* [22] suggested a multi-output hybrid ensemble model that makes use of information from the superstar learning communication platform (SLCP) to forecast grades. It predicts midterm and final grades using the XGBoost (XGB) model, outperforming comparable models with an accuracy of 78.37%. Furthermore, the gradient boosting model outperforms comparable models in mean squared error when used to forecast grades for homework and experiments. This multi-output hybrid ensemble model sheds light on how grade predictions can enhance the caliber of student learning and the efficacy of teacher instruction.

Aldalur [23] provided EDM dataset collected from different databases and e-learning systems. Here ensemble learning combining multiple machine learning model mechanism is constructed for predicting student performance during the course. The outcome shows ensemble model outperforms other model in terms of prediction accuracy. Similarly, predicting student performance in online interactive sessions using a dataset gathered from digital electronics education and design suites was the main goal of the project. The dataset records text editing, keystrokes, activity duration, exam results per session, and student interactions during online lab work. The study presents a prediction model made up of 86 statistical parameters that can be broadly grouped into three categories: peripheral activity count, timing statistics, and activity type. Five well-known classifiers are used, including RF and SVM, for feature selection, which helps preserve important features. The model's goal is to forecast whether a student will do well or poorly. The model is evaluated in three different circumstances, and the results show remarkable classification accuracy, with RF exhibiting the best performance at 97.4%. However, when data is imbalanced in nature these model fails to establish feature impacting in identifying the engagement level and performance; thus, provides poor classification accuracies [24].

The focus of the current work is developed a novel ensemble learning model that is efficient in solving both binary and multi-label classification problem in attaining higher prediction accuracy considering both student engagement and performance dataset in online student eLearning web portal. Multiple machine learning models are combined by existing models to create ensemble learning. Nonetheless, these models work well for binary classification problems. However, they perform poorly when applied to multi-label classification problems that take data imbalance into account [25]. The drawbacks drive this study's efforts to enhance ensemble approach to create a better student performance and engagement prediction model. This paper first presents an eLearning web portal framework employing artificial intelligence technique leveraging novel ensemble learning namely multi-label ensemble learning (MLEL) model to assess student engagement and performance. The ensemble model is created using refined XGB algorithm. Later, feature ensemble is

created to identify the useful feature employing K-fold cross validation and finally, the multi-label classifier is constructed. Research significance:
– The work introduced MLEL leveraging refined XGB model and K-fold cross validation.
– The work analyzed both performance and engagement dataset. No prior work has analyzed both datasets together. This shows robustness of proposed model.
– The result shows the proposed model achieves much better performance than existing methods.

This paper organize as follows: section two, the proposed web-based learning tool to assess student performance using online session activity engagement. In section three, the outcome of proposed MLEL model is studied on different dataset and methodologies. The last section the contribution of work is provided, followed by future enhancement.

2. PROPOSED METHOD

In this section, a web-based learning tool designed is introduced to evaluate student performance through their engagement in online sessions, as illustrated in Figure 1. To enhance the accuracy of performance assessment and gauge engagement levels, we propose a novel ensemble learning model that refines XGB through K-fold cross-validation (CV). By integrating these techniques, we aim to provide a robust and comprehensive approach for analyzing student engagement and performance in online learning environments.

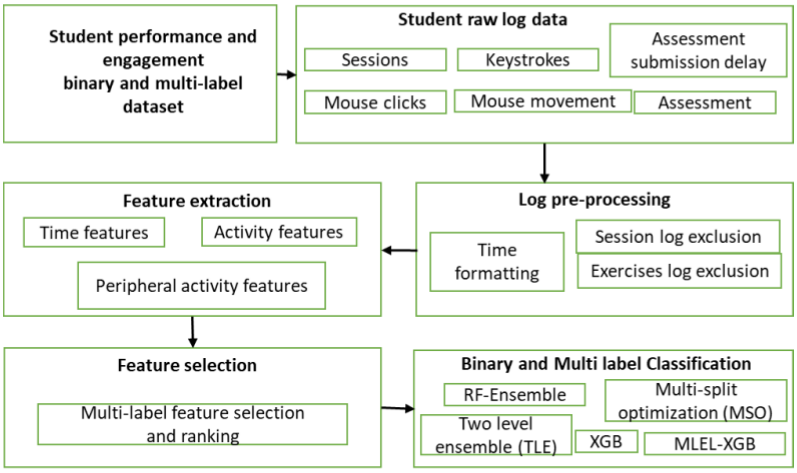

Figure 1. eLearning web portal to assess student performance and engagement using MLEL XGB model

2.1. Refined XGBoost model

The XGB tree algorithm represents an enhanced version of the previous gradient-boosting approach [25]. It involves the aggregation of less effective classifiers to form a robust classifier, resulting in improved classification results. Let us consider a dataset denoted as E, that represents an ongoing stream of learning session information. This dataset consists of o examples, where each sample is represented by a pair (y_j, z_j). Here, y_j represents a vector of n features, and z_j represents a label associated with the example. The variable $\hat{z}_j$ is utilized to denote the expected result generated by the approach in (1).

$$\hat{z}_j = \sum_{l-1}^{L} g_l(y_j),\ g_l \in G \tag{1}$$

The term g_l refers to an independent regression-tree, while $g_l(y_j)$ denotes the corresponding prediction results generated by the l^{th} tree for the j^{th} sample as shown in (2). In the context of this study, it is observed that for each tree, denoted as g(y), there exists some agreement regarding the leaf-weight, represented by x, and the structure variable, denoted as t. The regression-tree, denoted as g_l, alongside its corresponding function can both be acquired by minimizing the objective-function presented in (3).

$$G = \{g(y) = x_{t(y)}\} \tag{2}$$

$$O = \sum_{j=1}^{o} m(z_j, \hat{z}_j) + \sum_{l=1}^{L} \beta(g_l) \tag{3}$$

In this study, the variable m is defined to be the initial training-loss function, which is utilized to quantify the difference between the predicted outcome, denoted as $\hat{z}_j$, along with the actual outcome, denoted as z_j. To mitigate the issue of over-fitting, researchers often employ a variable denoted as β to penalize the complex nature of a predictive approach. This approach seeks to achieve a balance between approach complexity and generalization performance. By introducing a penalty term, the approach's ability to fit noise or irrelevant features in the data is reduced, thus improving its ability to make accurate predictions on unseen data. The evaluation of β is given as shown in (4).

$$\beta(g_l) = \delta U + \frac{1}{2}\mu||x||^2 \tag{4}$$

The regularization-variable is denoted by δ and μ, while the leaf's-size is represented by U. Additionally, the ranking for various leaves is denoted by x. The construction of any ensemble-tree is achieved by means of a summation method. The anticipated results for the j^{th} sample during the u^{th} iteration, denoted as $\hat{z}_j^{(u)}$, necessitates the inclusion of g_u in order to minimize the specified function as shown in (5). The aforementioned equation can be reduced by employing the technique of removing the stable variable using the second-order Taylor's expanding, which can be expressed in (6).

$$O^{(u)} = \sum_{j=1}^{o} m\left(z_j, \hat{z}_j^{(u-1)} + g_u(y_j)\right) + \beta(g_l) \tag{5}$$

$$O^{(u)} = \sum_{j=1}^{o} \left[h_j g_j(y_j) + \frac{1}{2} i_j g_u(y_j)^2\right] + \beta(g_l) \tag{6}$$

The variable h_j is used to denote the initial order-gradient with regard to m, and its defined is given as shown in (7). The variable i_j is used to denote the next order-gradient with regard to m, and its defined is given as shown in (8). Hence, the objective-function parameters of the predicting approach are mathematically represented by the subsequent equation as in (9).

$$h_j = \partial_{\hat{z}_j^{(u-1)}} m\left(z_j, \hat{z}_j^{(u-1)}\right) \tag{7}$$

$$i_j = \partial^2_{\hat{z}_j^{(u-1)}} m\left(z_j, \hat{z}_j^{(u-1)}\right) \tag{8}$$

$$O^{(u)} = \sum_{j=1}^{o} \left[h_j g_j(y_j) + \frac{1}{2} i_j g_u(y_j)^2\right] + \delta U + \frac{1}{2}\mu \sum_{k=1}^{U} x_k^2 \tag{9}$$

The formula mentioned above is represented in its simplest form as shown in (10). The sample collection of leaf k, denoted as J_k, is represented in the following manner as shown in (11). The tree-size, denoted by r, is assumed to be fixed. In order to determine the ideal weights, x_k^*, for leaf j, the following equation is employed as shown in (12). The ideal weight values for each tree-size are then derived in (13). The variable H_k is denoted in the following manner as shown in (14). The variable I_k is denoted in (15).

$$O^{(u)} = \sum_{j=1}^{U} \left[\left(\sum_{j\in J_k} h_j\right)x_j \frac{1}{2}\left(\sum_{j\in J_k} i_j + \mu\right)x_k^2\right] + \delta U \tag{10}$$

$$J_k = \{r(y_j = k)\} \tag{11}$$

$$x_k^* = \frac{H_k}{I_k + \mu} \tag{12}$$

$$O^* = \frac{1}{2}\sum_{k-1}^{U} \frac{H_k^2}{I_k + \mu} + \delta U \tag{13}$$

$$H_k = \sum_{j\in J_k} h_j \tag{14}$$

$$I_k = \sum_{j\in J_k} i_j \tag{15}$$

The O^* metric is utilized to evaluate the characteristics of tree r, with a lower value indicating a more favorable tree organization. While XGB approach are known for their efficiency in achieving excellent forecasting accuracy, it is important to note that they may encounter challenges in scenarios where feature selection is inadequate or whenever dealing with imbalanced information considering multi-label classification problem. In such cases, the prediction accuracy of XGB approaches may experience a decrease in performance. The subsequent subsection will focus on the modeling of an efficient feature selection technique throughout the training information, as a means of solving the multi-label classification problem.

2.2. Multi-label ensemble learning model

In this study, we propose a modification for the feature-selection method of the conventional XGB approach in order to perform classification on multi-label dataset. Our aim is to enhance the feature-importance result, thereby leading towards an enhanced prediction approach. In this work a novel K-fold cross validation approach is introduced by modifying the below standard K-fold cross validation considering grid size of l as shown in (16).

$$\mathrm{CV}(\sigma) = \frac{1}{M}\sum_{k=1}^{K} \sum_{j\in G_{-k}} P\left(b_j, \hat{g}_{\sigma}^{-k(j)}(y_j, \sigma)\right) \tag{16}$$

Nevertheless, it is important to note that the aforementioned equation does not explicitly specify the particular feature(s) that exert influence on the correctness of the predictive approach. This study aims to investigate the implementation of a robust CV technique coupled with an efficient feature-selection method to enhance predictive accuracy. The proposed approach is designed to incorporate features that have a significant effect on the predictive performance. This is evaluated using (17).

$$\mathrm{CV}(\sigma) = \frac{1}{SM}\sum_{s=1}^{S} \sum_{k=1}^{K} \sum_{j\in G_{-k}} P\left(b_j, \hat{g}_{\sigma}^{-k(j)}(y_j, \sigma)\right) \tag{17}$$

In (17), the process of selecting the optimal value for $\hat{\sigma}$ in order to optimize the learner's predictive approach is achieved through the following as given (18). In (18), M represents the size of the training-set under consideration. The function $P(\cdot)$ is used for defining the loss-function, while the function $\hat{g}_{\sigma}^{-k(j)}(\cdot)$ is employed for calculating the coefficients. The selection of effective features in developing a learner's performance predictive approach is accomplished using the technique of ranking $r(\cdot)$, as indicated in (19).

$$\hat{\sigma} = \mathrm{CV}_s(\sigma) \tag{18}$$

$$r(a) = \{0 \text{ if } n_j \text{ is not selected } 1 \text{ if } n_j \text{ is selected as optimal prediction model } j = 1,2,3,\dots,n \tag{19}$$

The following equation is used for construction of the feature-subset as shown in (20). The optimal features, which achieves the highest rank, is determined by considering multiple instances of $K-$folds. This is evaluated using (21). Next, the calculation is performed to determine the frequency of a specific feature being chosen within K feature-subsets that have the highest rank. The finalized feature-subset can be derived using the (22). The function $f_s(\cdot)$ represents a scenario in which the n^{th} feature is either chosen or not. This is scientifically denoted as (23).

$$F_s = \{r(n_1), r(n_1), \dots, r(n_n)\} \tag{20}$$

$$F_{s_k} = \{r(n_1), r(n_1), \dots, r(n_n)\} \tag{21}$$

$$F_{s_{final}=\{f_s(p_1), f_s(n_2), \dots, f_s(n_n)\}} \tag{22}$$

$$\begin{aligned} &F_s(a) = \{0 \text{ if } q_j \text{ is chosen lesser than } \tfrac{K}{2} \text{ times} \\ &j = 1,2,3,\dots,n\ 1 \text{ if } q_j \text{ is chosen greater or equal to } \tfrac{K}{2} \text{ times}, j = 1,2,3,\dots,n \end{aligned} \tag{23}$$

The preceding equation is utilized to generate a group of n' chosen features, in which n^{th} represents the frequency of feature selection. The training set used in this study is a group that has been carefully chosen to include only relevant features. This approach aims to construct a learner's predictive approach that is both efficient and accurate. To mitigate the impact of variability throughout the training stage, the $K-$folds technique is employed by iteratively repeating the steps S numerous times. Additionally, with the goal to minimize variability, a particular group of features will be chosen based on the equations outlined. The dataset E is reduced to E' by selectively retaining features based on the criteria defined in (23). The resulting dataset, denoted as E', is obtained by including only the instances from E that satisfy the conditions specified by n'. The K-folds method is analyzed in the same way as (17). The EPM dataset, denoted as ${E'}^{(-k)}$, is utilized for training purposes by eliminating the k^{th} section. The remaining section, ${E'}^{(k)}$, is reserved as the testing information set. This process is repeated for each value of k from 1 to K. The following phases are executed in a continual way, through a predetermined size denoted as S. In order to optimize variables, we iterate over a grid of size L, denoted by the variable l, ranging from 1 to L. The development of a prediction approach is achieved through the utilization of the (24).

$$\hat{g}_{\sigma_l} = \hat{g}\left(E'^{(-k)}; \sigma_l\right) \tag{24}$$

In order to calculate the error, use the loss-function equations given below for a variety of l values and implement $\hat{g}_{\sigma_l}$ to the training dataset $E'^{(-k)}$ as shown in (25). Calculate the $K-$fold CV-error with varying values of the optimization variable L as shown in (26). Utilizing a sequential CV method, the calculation of CV error is as shown in (27). Use the subsequent equation to determine the optimum value for the optimization variable for a given range of l values as shown in (28).

$$E_{\sigma_l} = P\left(b_j, \hat{g}\left(E'^{(-k)}; \sigma_l\right)\right) \tag{25}$$

$$CV(\hat{g}; \sigma_l) = \frac{1}{M}\sum_{k=1}^{K} \sum_{j \in E'^{(-k)}} P\left(b_j, \hat{g}\left(E'^{(-k)}; \sigma_l\right)\right) \tag{26}$$

$$CV_S(\hat{g}; \sigma_l) = \frac{1}{KS}\sum_{s=1}^{S} \sum_{k=1}^{K} \sum_{j \in E'^{(-k)}} P\left(b_j, \hat{g}\left(E'^{(-k)}; \sigma_l\right)\right) \tag{27}$$

$$\hat{\sigma} = CV_S(\hat{g}; \sigma_l) \tag{28}$$

The final prediction approach is obtained by configuring the optimum values of improving parameters as an objective-function and then minimizing it using a gradient-decent approach. To reduce the amount of unpredictability in the prediction approach while taking into account distinct folds, stage 1 of training involves building K-folds and iterating on them S times. Stage 2 incorporates a select group of features into the final forecasting approach, helping to lower variation in the process. Thus, when compared to state-of-the-art ensemble and ML-based student performance and engagement predictive approaches, the presented MLEL-based student performance and engagement predictive approach greatly enhances accuracy as proved in following section.

3. RESULTS AND DISCUSSION

The section studies the classification performance achieved using proposed MLEL using XGB over other existing approaches like XGB-based, and multi-split optimization (MSO), RF-ensemble, and two-layer ensemble (TLE). Experiments are conducted on multi-label performance and engagement dataset. More details of dataset can be obtained. The following metrics are used for validating models. The accuracy is computed as shown in (29). Where TP defines true positive, FP defines false positive, TN defines true negative, and FN defines false negative. The recall is computed as shown in (30). The precision is computed as shown in (31). The F1-score is computed as shown in (32).

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \tag{29}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{30}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{31}$$

$$\text{F1} - \text{score} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision} \times \text{Sensitivity}} \tag{32}$$

3.1. Student performance analysis

The student performance analysis is done using performance-oriented dataset obtained. Various models like XGB-based, and MSO, RF-ensemble, and TLE are used to compare with classification outcome of proposed MLEL-XGB. The Figure 2 shows the accuracy outcome achieved using different models. The result shows the proposed MLEL-XGB achieves an accuracy of 0.9995 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.971, TLE with 0.85, and MSO with 0.65.

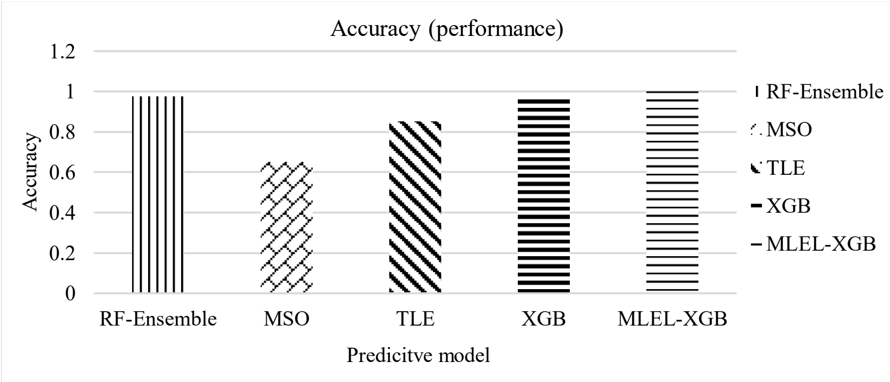

Figure 2. Accuracy outcomes to assess student performance using session activity

Figure 3 shows the precision outcome achieved using different models. The result shows the proposed MLEL-XGB achieves an accuracy of 0.9989 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.97, MSO with 0.867, and TLE with 0.86. Figure 4 shows the recall outcome achieved using different models; the result shows the proposed MLEL-XGB achieves an accuracy of 1 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.974, TLE with 0.94, and MSO with 0.857.

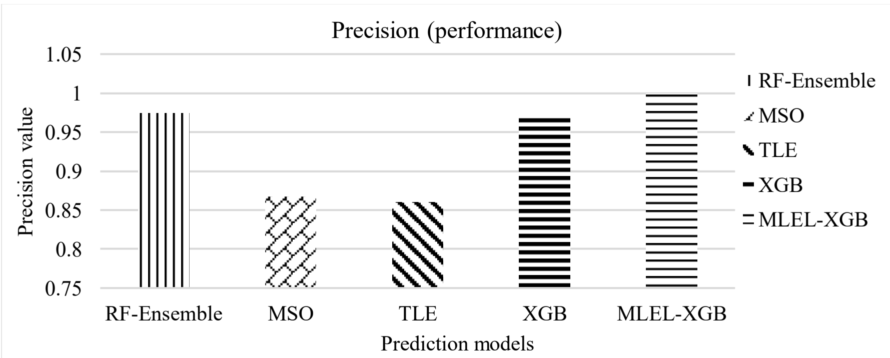

Figure 3. Precision outcomes to assess student performance using session activity

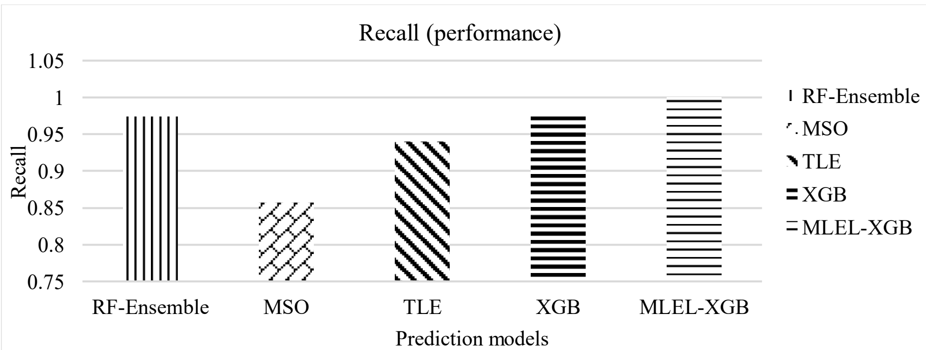

Figure 4. Recall outcomes to assess student performance using session activity

Figure 5 shows the F1-score outcome achieved using different models. The result shows the proposed MLEL-XGB achieves an accuracy of 0.9991 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.97, TLE with 0.9, and MSO with 0.857. Table 1 shows the comparative study of all metrics of different classification model testing on performance related dataset. The overall results achieved show the proposed model achieves much higher accuracy, precision, recall, and F1-score in comparison with XGB-based, MSO, RF-based, and TLE.

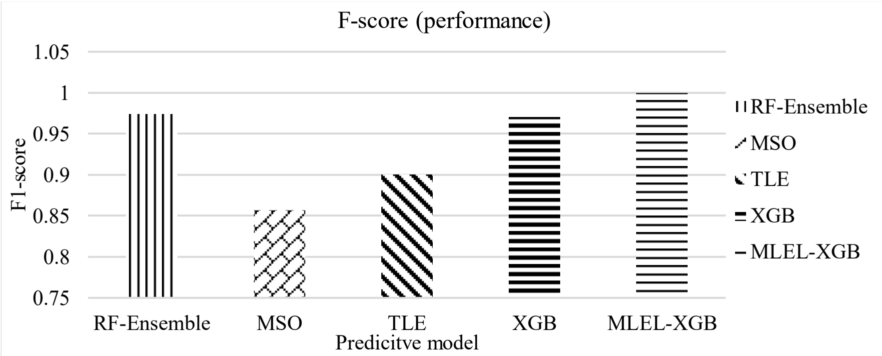

Figure 5. F1-score outcomes to assess student performance using session activity

Table 1. Comparative study for performance dataset

Predictive model	Accuracy	Precision	Recall	F1-score
RF-ensemble	0.974	0.974	0.974	0.974
MSO	0.8	0.917	0.353	0.857
TLE	0.86	0.86	0.95	0.9
XGB	0.967	0.972	0.97	0.971
MLEL-XGB	0.9992	0.999	0.9992	0.9991

3.2. Student engagement analysis

The student engagement analysis is done using engagement-oriented dataset obtained. Various models like XGB-based, MSO, RF-based, and TLE are used to compare with classification outcome of proposed MLEL-XGB. The Figure 6 shows the accuracy outcome achieved using different models; the result shows the proposed MLEL-XGB achieves an accuracy of 0.9992 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.967, TLE with 0.86, and MSO with 0.8.

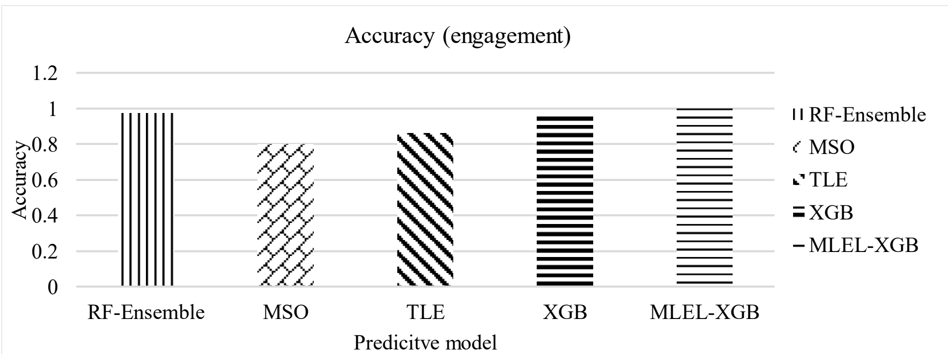

Figure 6. Accuracy outcomes to assess student performance using session activity

Figure 7 shows the precision outcome achieved using different models. The result shows the proposed MLEL-XGB achieves an accuracy of 0.999 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.972, MSO with 0.917, and TLE with 0.86. Figure 8 shows the recall outcome achieved using different models; the result shows the proposed MLEL-XGB achieves an accuracy of 0.9992 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.97, TLE with 0.95, and MSO with 0.353.

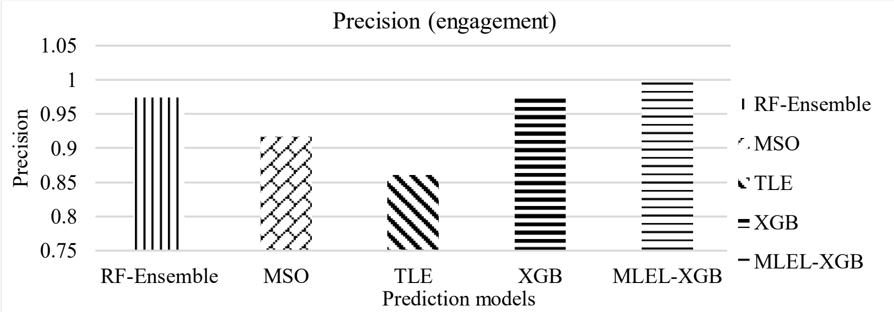

Figure 7. Precision outcomes to assess student performance using session activity

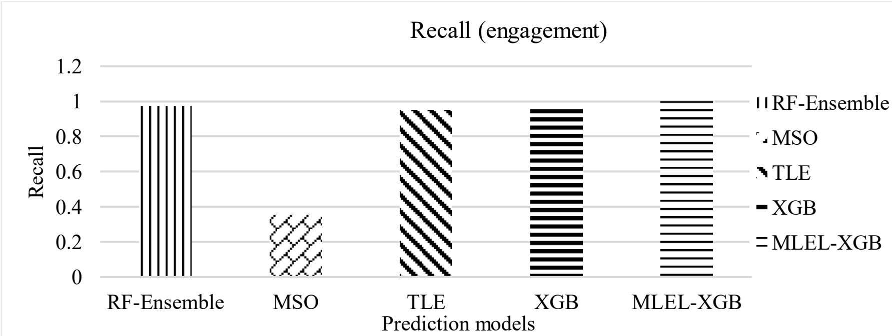

Figure 8. Recall outcomes to assess student performance using session activity

Figure 9 shows the F1-score outcome achieved using different models. The result shows the proposed MLEL-XGB achieves an accuracy of 0.9991 and the next best result is achieved using RF-ensemble with 0.974, XGB with 0.971, TLE with 0.9, and MSO with 0.857. Table 2 shows the comparative study of all metrics of different classification model testing on performance related dataset. The overall results achieved show the proposed model achieves much higher accuracy, precision, recall, and F1-score in comparison with XGB-based, MSO, RF-based, and TLE.

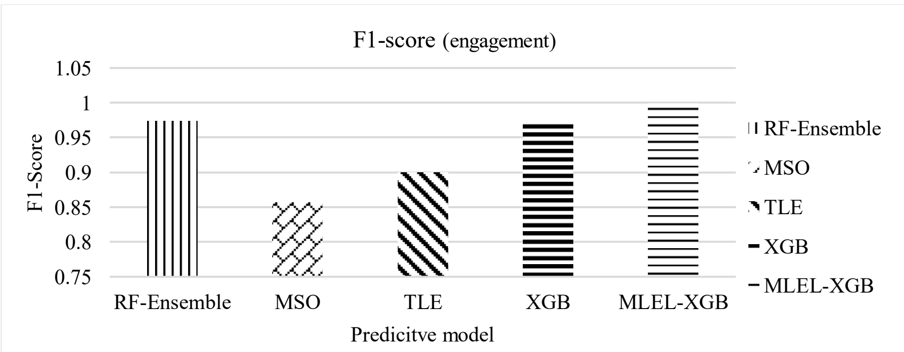

Figure 9. F1-score outcomes to assess student performance using session activity

Table 2. Comparative study for engagement dataset

Predictive model	Accuracy	Precision	Recall	F1-score
RF-ensemble	0.974	0.974	0.974	0.974
MSO	0.8	0.917	0.353	0.857
TLE	0.86	0.86	0.95	0.9
XGB	0.967	0.972	0.97	0.971
MLEL-XGB	0.9992	0.999	0.9992	0.9991

4. CONCLUSION

This paper introduced a novel ensemble model namely MLEL-XGB to accurately assess student performance and engagement level for designing effective eLearning-based web-based tool. The proposed model is studied using a performance-oriented dataset; the results achieved are very promising. Further, the proposed model is validated using an engagement-oriented dataset; a very good performance is achieved. Considering both the dataset the proposed MLEL-XGB model achieves much better performance than XGB-based, MSO, RF-ensemble, and TLE. The result shows robustness of proposed classifier in handling multi-label classification dataset. The future work would focus on analyzing more different kind of dataset to assess the performance of proposed classifier.

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Shashirekha Hanumanthappa	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Chetana Prakash	✓	✓			✓	✓		✓	✓	✓	✓	✓		

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

The authors state no conflict of interest.

DATA AVAILABILITY

Dataset is utilized in this research in reference [23].

REFERENCES

[1] B. Flanagan, R. Majumdar, and H. Ogata, "Early-warning prediction of student performance and engagement in open book assessment by reading behavior analysis," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, 2022, doi: 10.1186/s41239-022-00348-4.

[2] A. Al-Zawqari, D. Peumans, and G. Vandersteen, "A flexible feature selection approach for predicting students' academic performance in online courses," *Computers and Education: Artificial Intelligence*, vol. 3, 2022, doi: 10.1016/j.caeai.2022.100103.

[3] G. B. Brahim, "Predicting student performance from online engagement activities using novel statistical features," *Arabian Journal for Science and Engineering*, vol. 47, no. 8, pp. 10225–10243, 2022, doi: 10.1007/s13369-021-06548-w.

[4] K. Jawad, M. A. Shah, and M. Tahir, "Students' academic performance and engagement prediction in a virtual learning environment using random forest with data balancing," *Sustainability*, vol. 14, no. 22, 2022, doi: 10.3390/su142214795.

[5] M. Yağcı, "Educational data mining: prediction of students' academic performance using machine learning algorithms," *Smart Learning Environments*, vol. 9, no. 1, 2022, doi: 10.1186/s40561-022-00192-z.

[6] H. Xue and Y. Niu, "Multi-output based hybrid integrated models for student performance prediction," *Applied Sciences*, vol. 13, no. 9, 2023, doi: 10.3390/app13095384.

[7] M. N. Injadat, A. Moubayed, A. B. Nassif, and A. Shami, "Systematic ensemble model selection approach for educational data mining," *Knowledge-Based Systems*, vol. 200, 2020, doi: 10.1016/j.knosys.2020.105992.

[8] S. C. M. Sundararajan, G. U. Maheswari, P. Kaur, and A. Kaushik, "Heart diseases diagnosis using chaotic Harris Hawk optimization with E-CNN for IoMT framework," *Information Technology and Control*, vol. 52, no. 2, pp. 500–514, 2023, doi: 10.5755/j01.itc.52.2.32778.

[9] P. Pujar, A. Kumar, and V. Kumar, "Efficient plant leaf detection through machine learning approach based on corn leaf image classification," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 13, no. 1, pp. 1139–1148, 2024, doi: 10.11591/ijai.v13.i1.pp1139-1148.
[10] S. H. Sreedhara, V. Kumar, and S. Salma, "Efficient big data clustering using adhoc fuzzy C means and auto-encoder CNN," in *Inventive Computation and Information Technologies*, Singapore: Springer, 2023, pp. 353–368, doi: 10.1007/978-981-19-7402-1_25.
[11] Z. Zheng, Z. Wu, Z. Tari, J. Zhu, and K. Deng, "CeKT: knowledge tracing for predicting collective performance on exercise sequence," *IEEE Transactions on Computational Social Systems*, vol. 11, no. 6, pp. 7244–7256, 2024, doi: 10.1109/TCSS.2024.3406048.
[12] K. Park and P. Kang, "Detection and defense: student-teacher network for adversarial robustness," *IEEE Access*, vol. 12, pp. 82742–82752, 2024, doi: 10.1109/ACCESS.2024.3412890.
[13] Y.-W. Chu *et al.*, "Multi-layer personalized federated learning for mitigating biases in student predictive analytics," *IEEE Transactions on Emerging Topics in Computing*, vol. 13, no. 2, pp. 451–466, 2025, doi: 10.1109/TETC.2024.3407716.
[14] M. Abinaya and G. Vadivu, "Identification of social anxiety in high school: a machine learning approaches to real-time analysis of student characteristics," *IEEE Access*, vol. 12, pp. 77932–77946, 2024, doi: 10.1109/ACCESS.2024.3407885.
[15] M. Chahardoli, N. O. Eraghi, and S. Nazari, "Namib beetle optimization algorithm: A new meta-heuristic method for feature selection and dimension reduction," *Concurrency and Computation: Practice and Experience*, vol. 34, no. 1, 2022, doi: 10.1002/cpe.6524.
[16] F. Guo, X. Sun, A. Zhou, Q. Tan, and K.-H. Lai, "Entrepreneurial motivations, entrepreneurial persistence, and academic entrepreneurship performance: moderating effects of innovation and entrepreneurship support institutions and female entrepreneurs," *IEEE Transactions on Engineering Management*, vol. 71, pp. 11091–11104, 2024, doi: 10.1109/TEM.2024.3407093.
[17] W. Villegas-Ch, J. G.-Ortiz, and S. S.-Viteri, "Application of artificial intelligence in online education: influence of student participation on academic retention in virtual courses," *IEEE Access*, vol. 12, pp. 73045–73065, 2024, doi: 10.1109/ACCESS.2024.3403758.
[18] Y. P. Tsang, C. Ka Man Lee, C. Ho Wu, and Y. Li, "Gamified blockchain education in experiential learning: an analysis of students' cognitive well-being," *IEEE Transactions on Education*, vol. 67, no. 4, pp. 620–628, 2024, doi: 10.1109/TE.2024.3395617.
[19] P. De and M. Bakhshi, "Managing uncertainties in technology-mediated communication: a qualitative study of business students' perception of emoji/emoticon usage in a business context," *IEEE Transactions on Professional Communication*, vol. 67, no. 2, pp. 211–228, 2024, doi: 10.1109/TPC.2024.3382788.
[20] Z. Fan, J. Gou, and S. Weng, "A feature importance-based multi-layer CatBoost for student performance prediction," *IEEE Transactions on Knowledge and Data Engineering*, vol. 36, no. 11, pp. 5495–5507, 2024, doi: 10.1109/TKDE.2024.3393472.
[21] F. Xiang *et al.*, "Using pupil diameter for psychological resilience assessment in medical students based on SVM and SHAP model," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 7, pp. 4260–4268, 2024, doi: 10.1109/JBHI.2024.3390390.
[22] V. V. Grubov *et al.*, "Open-loop neuroadaptive system for enhancing student's cognitive abilities in learning," *IEEE Access*, vol. 12, pp. 49034–49049, 2024, doi: 10.1109/ACCESS.2024.3383847.
[23] I. Aldalur, "Introducing students to web engineering topics by teaching web augmentation," *Journal of Web Engineering*, vol. 23, no. 1, pp. 1–26, 2024, doi: 10.13052/jwe1540-9589.2311.
[24] H. Ma *et al.*, "Personalized early warning of learning performance for college students: a multilevel approach via cognitive ability and learning state modeling," *IEEE Transactions on Learning Technologies*, vol. 17, pp. 1414–1427, 2024, doi: 10.1109/TLT.2024.3382217.
[25] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, pp. 785–794, doi: 10.1145/2939672.2939785.

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