Enhancing learner performance prediction on online platforms using machine learning algorithms

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Article Info

ABSTRACT

E-learning has emerged as a prominent educational method, providing accessible and flexible learning opportunities to students worldwide. This study aims to comprehensively understand and categorize learner performance on e-learning platforms, facilitating timely support and interventions for improved academic outcomes. The proposed model utilizes various classifiers (random forest (RF), neural network (NN), decision tree (DT), support vector machine (SVM), and K-nearest neighbors (KNN)) to predict learner performance and classify students into three groups: fail, pass, and withdrawn. Commencing with an analysis of two distinct learning periods based on days elapsed (≤120 days and another exceeding 220 days), the study evaluates the classifiers' efficacy in predicting learner performance. NN (82% to 96%) and DT (81%-99.5%) consistently demonstrate robust performance across all metrics. The classifiers exhibit significant performance improvement with increased data size, suggesting the benefits of sustained engagement in the learning platform. The results highlight the importance of selecting suitable algorithms, such as DT, to accurately assess learner performance. This enables educational platforms to proactively identify at-risk students and offer personalized support. Additionally, the study highlights the significance of prolonged platform usage in enhancing learner outcomes. These insights contribute to advancing our understanding of e-learning effectiveness and inform strategies for personalized educational interventions.

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1. INTRODUCTION

The performance of learners on online platforms refers to their ability to effectively engage with and achieve learning outcomes in an online environment. Online platforms provide opportunities for learners to access educational content, interact with instructors or peers, and participate in assessments [1]. The performance of learners in online platforms can be influenced by a variety of factors. These may include the design and functionality of the online platform, the quality of instructional content. Also the level of learner engagement and motivation, the availability of support and resources, and the learner's prior knowledge and skills [2], [3]. Additionally, factors such as internet connectivity, device compatibility, and technical skills can

also impact learner performance on online platforms. Some learners may thrive in online environments, while others may face challenges due to different learning styles, distractions, or other external factors. Providing appropriate support, feedback, and resources can help learners optimize their performance in online platforms and achieve successful learning outcomes [4], [5]. So, it is important for educators and institutions to continually assess and adapt their online learning strategies to support learner success. As online learning continues to evolve, it presents both opportunities and challenges. Understanding learner performance in this context is key to maximizing the potential of online education [6]. The performance of learners in online platforms is a complex phenomenon that requires ongoing research, assessment, and pedagogical strategies [7]. With the right support, resources, and pedagogical strategies, learners can excel in online platforms and achieve their educational objectives. So, it is essential to continually assess, adapt, and optimize online learning environments to support learner performance and success [8]. One of the key aspects of learners' performance in online platforms is their ability to navigate and utilize the features of the platform, such as accessing content, submitting assignments, participating in discussions, and engaging in collaborative activities [9].

In recent years, the field of education has witnessed a significant growth in the use of machine learning algorithms to predict learners' performance. These algorithms leverage the vast amount of educational data available to develop models that can accurately forecast how well a learner will perform in a given academic task or course. This literature review aims to explore the current state of research on the prediction of learners' performance using machine learning algorithms and provide insights into the various approaches and techniques employed in this domain. The reviewed studies highlighted the machine learning algorithms employed for predicting learners' performance, including decision tree (DT), random forest (RF), K-nearest neighbors (KNN), support vector machine (SVM), and neural network (NN). For instance, [10]–[14] applied machine learning algorithms to predict learner performance. One particularly notable study as stated in [15] used a DT algorithm to predict learners' academic performance in a computer science course. The authors collected data on learners' prior knowledge, learning styles, and demographic characteristics. The DT algorithm achieved an accuracy of 83.09% in predicting learners' final course grades, demonstrating its effectiveness in this context.

Several studies also explored the use of ensemble methods, which combine multiple machine learning algorithms to improve prediction accuracy. Kotsiantis *et al.* [10], the authors applied a stacked generalization ensemble model that combined SVM, RF, and logistic regression to predict learners' performance in an online learning platform. The ensemble model outperformed individual algorithms, achieving an accuracy of 71% in predicting learners' final exam scores (NN with 70.51% and NB 72.48%). Furthermore, the reviewed studies emphasized the importance of feature selection and engineering in improving prediction performance. Butcher and Smith [16] proposed a feature selection approach based on information gain and genetic algorithms to identify the most relevant features for predicting learners' performance. Their study demonstrated that using a reduced set of informative features led to better prediction results compared to using all available features. Additional studies have also contributed to this field, investigated the prediction of student academic performance using the RF algorithm, while as stated in [17] this work explored the use of deep learning for predicting student performance in online learning environments [18]–[21].

This research paper aims to address the issue of learner performance on online platforms by proposing a machine learning-based prediction model. By highlighting the power of data analytics and classification algorithms, this model seeks to categorize learners into distinct groups based on their performance, namely fail, pass, and withdrawn. The prediction model will explore various classification methods, including RF, NN, DT, SVM, and KNN, to identify the most effective approach in assessing learner achievements [22]. Furthermore, individual learning styles and preferences can impact learners' performance in online platforms. Some learners may prefer visual or auditory learning, while others may prefer more interactive or hands-on approaches. Online platforms that offer diverse learning modalities and opportunities for personalized learning can better accommodate different learning styles and preferences, leading to improved performance [23], [24].

2. MATERIALS AND METHOD
2.1. Proposed model

The proposed method for analyzing learner performance on online platforms begins with a log file containing raw data and follows a systematic workflow. In order to facilitate further analysis, the unprocessed data are converted into a CSV file using an algorithm. Next, the data are preprocessed to ensure their integrity and dependability. To prepare the data for subsequent analysis, techniques such as data cleaning, removal of duplicate entries, management of missing values, standardization of variables, addressing outliers, normalization, and data transformation are utilized. Once the data has been preprocessed, feature selection identifies a subset of pertinent features within the preprocessed data. This subset is then used as input for multiple classifier algorithms, including NN, RF, KNN, DT, and SVM. These classifiers utilize the chosen features to discover patterns and relationships within the data, allowing them to make predictions and classify

new instances. The preprocessed data is divided into two subsets the training set and the testing set to evaluate the performance and generalization ability of the trained models. The training set is used to train classification algorithms, whereas the testing set is used to evaluate unseen data.

Prediction results are derived from the output of classifier algorithms. Various metrics, including accuracy, precision, recall, and F1-score, are calculated to evaluate the performance of each classifier. In addition, confusion matrices are constructed for each classifier, considering both data durations longer than 220 days and shorter than or equal to 120 days. Separate ROC curves are also generated to illustrate the performance of the classifier in these duration categories. Various instruments have been utilized throughout the analysis procedure to facilitate and streamline the workflow (Excel, Jupyter Notebook, and Python). To achieve the goals of this study, we adhered to the procedures depicted in Figure 1.

Figure 1. The workflow processes

2.2. Dataset

In this work, the dataset was collected from the open University platform as stated in [25]. The collected dataset provided a comprehensive snapshot of user interactions. The utilization of this dataset offered valuable insights into online learning behavior and paved the way for a comprehensive study in this research domain. Table 1 provides a description of the dataset attributes.

Table 1. Description of dataset attributes

Feature	Description	Type	Values
Id_stud	The unique identifier for each learner.	Numeric	Numeric value
Gender	the gender of the learner.	Nominal	M or f
Age_band	the age group or band.	Nominal	0-30, 30-50 or =>50
Num_of_prev Attempts	Represents the number of previous attempts the learner.	Numeric	From 0 to 3
Disability	Indicates whether the learner has a disability or not	Nominal	"yes" or "no"
Date	The number of days since the start of the module-presentation.	Numeric	Numeric value
Sum_of click	The number of times a learner interacts with platform	Numeric	Numeric value
Score	Indicates the date when each assessment was submitted.	Numeric	From 0 to 100
Final_result	The final result of the course for the learner.	Nominal	"pass," "fail," or "withdrawn."

We employed a novel feature called "learner productivity" or "engagement" to enhance the predictive power of our model. To quantify this feature for each learner, we calculate the ratio between the total number of activities they performed on the platform and the total number of days they spent engaging with the platform, which is then multiplied by 100 to obtain a percentage. This metric allows us to measure the learner's productivity in terms of activities completed per day on the platform. Here is the mathematical formula to calculate this feature (1).

$$Learner\_eng = \frac{Total\ number\ of\ activities}{Total\ number\ of\ days\ spent\ on\ the\ platform} * 100 \qquad (1)$$

This (1) expresses the ratio between the total number of activities carried out by the learner on the platform and the total number of days he spent using the platform, multiplying it by 100 to obtain a percentage. This feature allowed the quantify of learner productivity in terms of activities completed per day on the platform. In the dataset, we observed a noticeable number of learners who withdrew from a course even before

it commenced. Consequently, as a next step, we plan to exclude these learners from our dataset due to the absence of any academic performance data for them.

To determine the importance of features in our dataset, as depicted in Figure 2, we adopt the technique of permutation importance. This method involves systematically shuffling the values of each feature in the dataset and observing the resulting impact on the model's performance metric, such as accuracy or mean squared error.
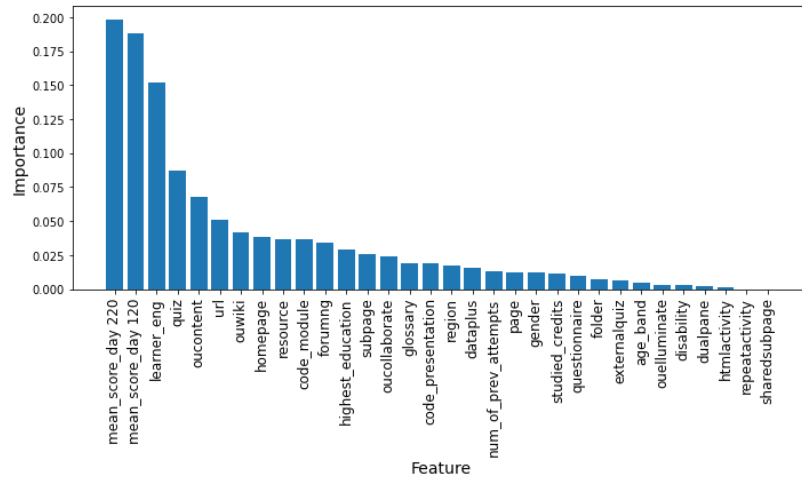

Figure 2. Dataset feature importance

The dataset we analyze contains crucial information, including learner demographics, such as gender (male or female). It also likely encompasses various attributes such as attendance records, test scores, course grades, and other relevant details. Our primary objective in this data analysis is to examine and predict learners' final results, which are typically classified into three categories: fail, pass, and withdrawn Figure 3. Machine learning classification algorithms, used to build a predictive model that can accurately determine whether a learner is likely to fail, pass, or withdraw from a particular online course. These predictive models hold the potential to offer valuable insights to educational institutions, enabling them to identify at-risk learners, tailor support and intervention strategies, and ultimately enhance overall learner achievement.
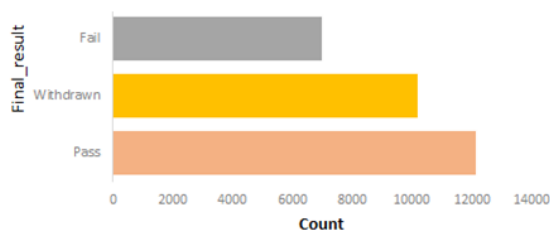

Figure 3. Learners' results: fail, pass, or withdraw

2.3. Classification algorithms

In this section, we explore the application of various classification algorithms to predict learner performance on online platforms. The selected classifiers include: RF is an ensemble learning technique that builds multiple decision trees during training and combines their predictions to make final classifications. It is known for its ability to handle complex datasets and reduce overfitting. NN are deep learning models inspired by the human brain's structure. They consist of interconnected layers of artificial neurons and can learn intricate patterns from data, making them suitable for complex classification tasks. DT are hierarchical structures that use if-else conditions to make decisions based on features and their values. They are interpretable and useful for gaining insights into how the classifier arrives at its decisions. SVM is a powerful binary classification algorithm that finds the optimal hyperplane to separate data points belonging to different classes in a

high-dimensional feature space. KNN is a simple and intuitive algorithm that classifies an instance based on the majority class among its KNN in the training data.

2.4. Evaluation metrics

For evaluation, we use performance metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified instances over the total number of instances, providing an overall assessment of the classifier's correctness. Precision quantifies the ratio of true positive predictions to the total predicted positive instances, focusing on the classifier's ability to avoid false positives. Recall, also known as sensitivity or true positive rate, calculates the proportion of actual positive instances correctly identified by the model. The F1-score is the harmonic mean of precision and recall, offering a balanced measure of the classifier's performance [26], [27]. The following equations were used to compute the performance metrics, including accuracy, precision, recall, and F1-score, for each classification algorithm.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \tag{2}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

$$\text{F1-score} = 2 * \frac{\text{Precision*Racall}}{\text{Precision+Recall}} \tag{5}$$

The comparison of the performance metrics for each classifier is done at two distinct periods based on the number of days in the data. We partition the dataset into two subsets, one with data spanning less than or equal to 120 days and the other with data exceeding 220 days. This stratification allows us to evaluate the classifiers' performance under different time intervals, providing insights into their effectiveness over shorter and more extended durations on the online platform.

3.   RESULTS AND DISCUSSION

In this section, we provide a comprehensive overview of our experimental configuration, detailing the specific parameters, and tools employed to conduct a rigorous assessment of our proposed model. Subsequently, we present the results of the performance evaluation. Following this, a detailed discussion of the results obtained from the performance evaluation, highlighting the model's effectiveness in predicting learner performance within the dynamic context of online platforms.

3.1. Experiment configuration

In this section, we present the results of our experiments related to performance prediction. The experimental models are implemented in the Google Colab open cloud environment, utilizing a Tesla K80 GPU with 12 GB of GDDR5 VRAM. Python 3.7, along with diverse libraries like TensorFlow and Scikit-learn, is employed for building these models.

During this research, we conducted three distinct sets of experiments, each with a distinct objective. Objective 1 entailed evaluating the efficacy of the proposed model using all extracted features. Utilizing an entropy-based ranking methodology, Objective 2 aimed to determine the significance of each extracted feature in the classification process. Objective 3 was to evaluate the performance of our model.

During the training and evaluation phase, three sets of experiments were conducted. The first experiment utilized random distribution, allocating 80% of the data for training and 20% for evaluation. The second experiment utilized fivefold cross-validation, and the third experiment evaluated the performance of the model independently for each session. We selected the most accurate classifier from among RF, NN, DT, SVM, and KNN. The configuration parameters for the classifiers, including Batch size, learning rate, and loss, were fine-tuned.

3.2. Model performance assessment

The effectiveness of the proposed classification model was determined using four metrics: accuracy, precision, recall (sensitivity), and F1-score. Based on true positive (TP), true negative (TN), false positive (FP), and false negative (FN) testing cases, these metrics were analyzed. To assessing learner performance, we conducted an in-depth analysis of our model's ability to distinguish between performance categories. To achieve this, we employed the receiver operating characteristic (ROC) metric, a valuable tool in evaluating the discriminative power of our model.

In Figure 4, we offer a visual representation of our model's effectiveness in distinguishing learner performance across two specific platform engagement periods. Figures 4(a) and (b) of Figure 4 present ROC curves for learner performance during platform engagement periods of Figure 4(a) less than or equal to 120 days and Figure 4(b) greater than 220 days, respectively. These two distinct periods are characterized by the number of days in the dataset, where the first period encompasses data with a duration less than or equal to 120 days, and the second period comprises data greater than or equal to 220 days. The ROC curves serve as a visual representation of our model's effectiveness in distinguishing learner performance across these varying timeframes, providing valuable insights into the model's capabilities and performance under different conditions.

Analyzing the ROC curves permits us to compare the performance of the classifiers in differentiating between learner performance categories for both brief and extended platform engagement periods. The curves provide valuable information for selecting the most appropriate classifier based on its capacity to make accurate predictions and minimize incorrect classifications. These insights are essential for educational platforms and institutions to deploy appropriate predictive models and support systems, thereby enhancing the performance and success of learners.
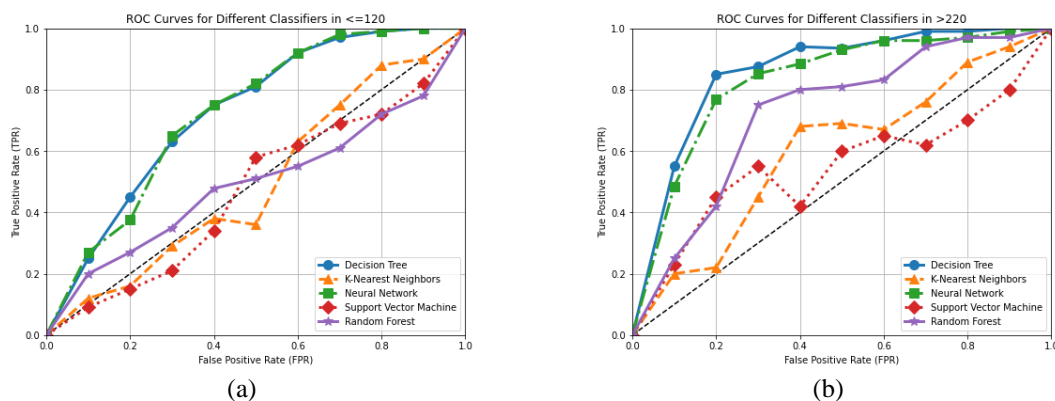

(a)   (b)

Figure 4. ROC curves for learner performance (a) platform engagement <=120 days and (b) of platform engagement >220 days

Figures 5 to 9 illustrate the performance of various classifiers (DT, NN, RF, SVM, and KNN) in predicting learner performance for two distinct time periods: when the number of days in the data is either less than or equal to 120 or greater than 220. These matrices provide an exhaustive evaluation of the classifiers' predictive abilities and their efficacy in classifying students into the correct performance groups: fail, pass, and withdrawn. Each confusion matrix consists of a grid that depicts the five potential classification outcomes. By analyzing the confusion matrices, we can determine the strengths and weaknesses of each classifier in predicting the performance of learners. The number of instances that were correctly classified (TP and TN) reflects the classifier's accuracy and its ability to accurately identify learners' performance levels. On the other hand, the misclassifications (FP and FN) emphasize areas in which the classifier may have difficulty differentiating between performance categories. Comparing the confusion matrices of various classifiers permits us to determine which algorithm performs best during each time interval. By analyzing the distribution of TP, TN, FP, and FN values, we can evaluate the classifiers' precision, recall, and overall F1-score, allowing us to select the most appropriate algorithm for accurate prediction of learner performance on the online learning platform.

Table 2 presents the performance metrics of five classification algorithms (DT, NN, RF, SVM, and KNN) in the context of two distinct time periods less than or equal to 120 days and greater than 220 days. The metrics evaluated include accuracy, precision, recall, and F1-score. In the case of RF, it achieved an accuracy of 55% for the less than or equal to 120 days period and 81% greater than 220 days. The precision values were 0.65 and 0.87, respectively. The recall values for the two periods were 0.6 and 0.845. The F1-scores, combining precision and recall, were 0.666 and 0.863. NN demonstrated higher performance with an accuracy of 82% for less than or equal to 120 days and 96% for greater than 220 days. The precision values were 0.82 and 0.93. NN exhibited recall values of 0.83 and 0.941. The F1-scores for the two periods were 0.813 and 0.92. DT achieved an accuracy of 81% for less than or equal to 120 days and 99.5% for greater than 220 days. The precision values were remarkably high at 0.83 and 0.83. DT showed recall values of 0.809 and 0.96. The F1-scores for the two periods were 0.82 and 0.96.

SVM exhibited an accuracy of 61% for less than or equal to 120 days and 65% for greater than 220 days. The precision values were 0.61 and 0.73. SVM's recall values were 0.42 and 0.45. The F1-scores for the two periods were 0.40 and 0.46. KNN achieved an accuracy of 62.2% for less than or equal to 120 days and 71.2% for greater than 220 days. The precision values were 0.671 and 0.81. KNN exhibited recall values of 0.61 and 0.69. The F1-scores for the two periods were 0.457 and 0.52.
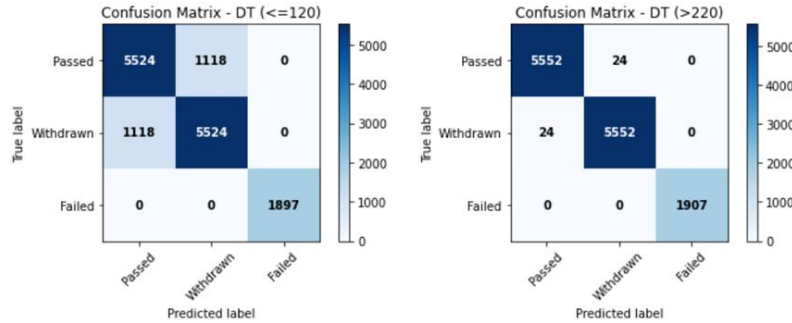
Figure 5. Confusion matrix for learner performance using DT classifier (<=120 and >220 days)
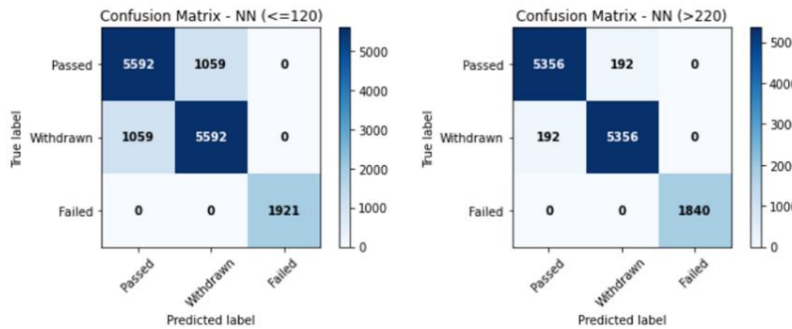
Figure 6. Confusion matrix for learner performance using NN classifier (<120 and >220 days)
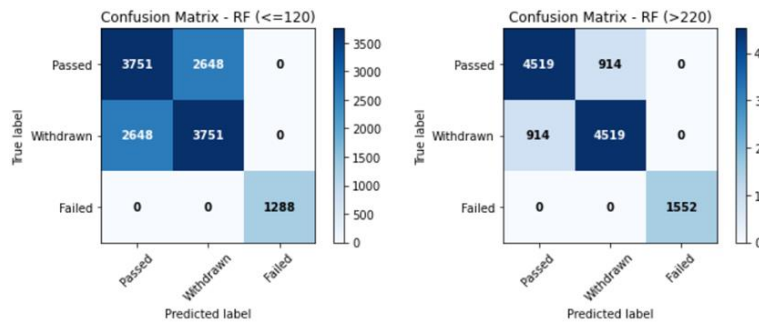
Figure 7. Confusion matrix for learner performance using RF classifier (<=120 and >220 days)
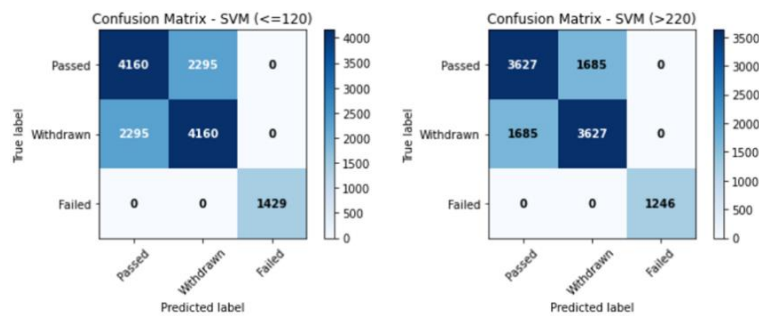
Figure 8. Confusion matrix for learner performance using SVM classifier (<=120 and >220 days)
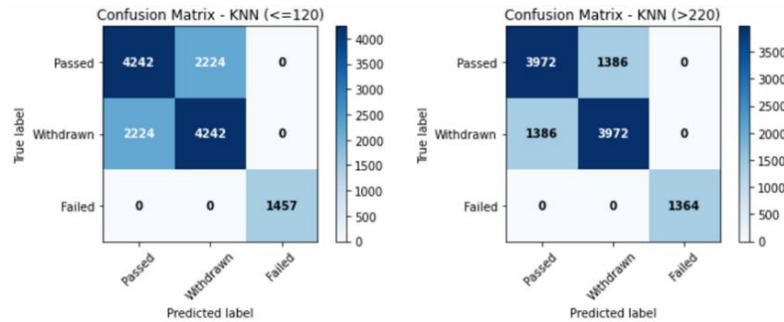
Figure 9. Confusion matrix for learner performance using KNN classifier (<=120 and >220 days)
Performance of classification algorithms RF, NN, DT, SVM, and KNN

Table 2. Performance of classification algorithms RF, NN, DT, SVM and KNN

Classifier	Accuracy		Precision		Recall		F1-score	
	<=120 days	>220 days	<=120 days	>220 days	<=120 days	>220 days	<=120 days	>220 days
RF	55%	81%	0.65	0.87	0.6	0.845	0.666	0.863
NN	82%	96%	0.82	0.93	0.83	0.941	0.813	0.92
DT	81%	99.5%	0.83	0.83	0.809	0.96	0.82	0.96
SVM	61%	65%	0.61	0.73	0.42	0.45	0.40	0.46
KNN	62.2%	71.2%	0.671	0.81	0.61	0.69	0.457	0.52

3.3. Discussion

In this study, we compared various classification algorithms for predicting learner performance on online platforms. Based on our evaluation of the algorithms, the NN and DT classifiers consistently outperformed the others in terms of accuracy, precision, recall, and F1-score. DT and NN demonstrated robustness by maintaining stable performance and obtaining the highest accuracy, making them the top-performing classifiers for both shorter (=120 days) and longer (>220 days) durations of platform engagement. In addition, we found that the amount of data had a substantial effect on classifier performance. The performance of the DT, NN, and KNN classifiers improved significantly as the data size increased from =120 days to >220 days. On the other hand, RF and SVM demonstrated comparatively consistent performance regardless of the size of the dataset, indicating their robustness.

The analysis of the ROC curve shed additional light on the classifiers' capacity to differentiate between distinct performance categories for both shorter and extended platform engagement periods. The DT attained an impressive area under the curve (AUC) of 0.987% for >220 days, demonstrating excellent discrimination abilities. With an AUC of 0.93, the NN demonstrated its efficacy in differentiating between performance categories. In contrast, for =120 days, the AUC values for the RF, KNN, and SVM were moderate, indicating their moderate discrimination capabilities between performance categories. In addition, the results indicated a general correlation between accuracy and AUC scores, with classifiers attaining a higher level of accuracy tending to have greater discrimination capabilities.

In Table 3, we have provided a list of papers along with their respective applied techniques and results. In the presented comparative analysis, our proposed model, with using NN and DT techniques, emerges as a clear standout. Its sustained high accuracy, reaching 96% and 99.5% over a significant period of more than 220 days, underscores its exceptional performance. Our proposed model consistently ranks at the top in terms of accuracy, making it the preferred choice for predicting learners' performance on online platforms. Its superiority is particularly evident when compared to models with varying accuracy rates.

Our study's findings have significant implications for augmenting the predictability of learner performance on online platforms. The proposed predictive performance model has the potential to play a pivotal role in determining the success or standing of learners on the learning platform. Educational institutions and adaptive learning platforms can provide opportune interventions and support by identifying students who may encounter difficulties or drop out of school early on. This information enables educators to provide additional resources, individualized assistance, or academic counseling, which can improve the academic performance of struggling students and reduce attrition rates.

In addition, our proposed model functions as a valuable instrument for proactive decision-making and targeted interventions, resulting in increased learner success rates. By basing decisions on objective data as opposed to subjective evaluations, educational institutions can make educated decisions that have a direct impact on learner outcomes, thereby maximizing the efficacy of their efforts.

Table 3. Evaluating the precision of our model in comparison to existing approaches

Work	Applied techniques	Main results
[10]	Generalization ensemble method	Accuracy NN: 70.51%, NB 72.48%
[15]	Data mining	Accuracy: 83.09%
[17]	Deep learning	Accuracy: 84%-93%
[28]	data-driven using genetic algorithm	Accuracy: 75.55%
[29]	NN, DT and linear regression	Accuracy: 80%.
[30]	Logistic regression, RF, SVM, and NB,	F1 measure :71.31%
Proposed model	NN and DT (For more than 220 days)	Accuracy: 96% and 99.5%

4. CONCLUSION AND PERSPECTIVES

In this comprehensive study on e-learning platforms, we employed a variety of machine learning algorithms, including RF, NN, DT, SVM, and KNN, to predict learner performance. Our findings demonstrate that these classifiers effectively categorize learners based on their platform engagement. Notably, the analysis of two distinct learning periods (≤120 days and >220 days) revealed varying performances among classifiers, emphasizing the critical need for selecting the most suitable algorithm for precise classification. Specifically, DT and NN consistently emerged as top-performing models, showcasing superior accuracy and discrimination, particularly for engagements exceeding 220 days. The observed enhancement in model performance with increased data suggests potential benefits associated with prolonged platform engagement. The implications of our results are substantial for educational institutions and learning platforms, facilitating proactive identification of at-risk students and optimal resource allocation. Furthermore, our study underscores the significance of prolonged platform usage in positively influencing learner outcomes. Future research in online education could explore the integration of social and emotional learning (SEL) elements, offering a holistic approach to enhance both well-being and academic success.

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