Personalized Learning Management System using a Machine Learning Technique

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***Abstract* – Learning Management System (LMS) is a traditional tool for E-learning. Combined with Machine Learning (ML), such technology has unprecedentedly allowed teachers to observe and understand students' behaviors and performance. This research aims to enhance individual learning results by classifying a risk group and offering a self-tutoring program. This paper adopts a machine-learning model and proposes a new algorithm named "RSU-ML-PL," which enables a personalized and self-tutoring system. Overall, the experiment revealed good progress in student marks on their final examinations. The final examination results show that 606 (79%) students in the risk group passed their exams.**

***Keywords* – machine learning (ML); e-learning; personalized education; learning management system.**

1. Introduction

The recent pandemic, such as COVID19, has not only overwhelmed healthcare systems worldwide but also affected the global economy and people's way of life. Due to the restricted physical distances as well as the limited number of people within a class, it has become more challenging for schools and institutions to provide teaching and learning.

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Higher institutions worldwide have tried to cope with these issues by providing online teaching and learning or adopting innovative technology to enhance student's learning experiences. Nevertheless, organizing online classrooms during the outbreak is still challenging for teachers and students. Teachers are unable to observe the students' performance and attention in order to guarantee their success in learning and academic results.

Learning Management System (LMS) is a traditional tool for E-learning. Machine Learning (ML) has been used to understand data from many sources. It also allows teachers to view and understand students' behaviors and performance. We propose a classification model in section 4.4. This model can classify the data according to its class label. Five algorithms are implemented to construct a classification model in Section 4.

The basic premise of Personalized Learning (PL) emphasizes that each student is unique and learns in different ways. This research paper proposes a new algorithm named "RSU-ML-PL" enabling a personalized and self-tutoring system in Section 3. Tracking activity data was gathered from the E-learning system and the registration system, as shown in Figure 1. All data were integrated and analyzed to identify a risk group. Finally, the prediction of student attrition has been visualized.

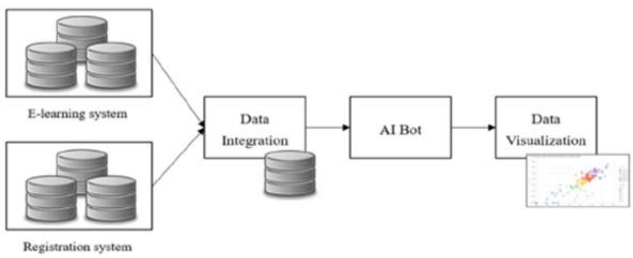

Figure 1. Research framework

Moddle stands for "Modular Object-Oriented Dynamic Learning Environment." Moddle is a famous open-source LMS that is used and modified by adding "The RSU-ML-PL machine learning module demonstrated in sections 4 and 5. Five algorithms are used in this research to construct a classification model to perform a model evaluation.

A classification model is a model that can categorize data into a given number of classes. In this case, we know exactly a class label but do not know which features caused a class. The five algorithms in this research are discussed as follows.

1. Logistic regression.
2. K-nearest neighbors.
3. A decision tree.
4. Random forest classifier.
5. Support vector machine.

Five algorithms are required to construct a model to identify a risk group, as shown in Section 4.

The present paper is structured as follows. In Section 2, the author reviewed the literature and relevant academic papers. In Section 3, the author presented the implemented research methodology. The results of the experiments are discussed in Section 4. Finally, the author presented a conclusion of the study in Section 5.

2. Literature Review

Acheson and Ning [1] suggested a method of analyzing students' online behaviors using ML approaches. In this regard, a software tool was created to monitor students' behaviors. The teachers will be informed directly in the light of the application about the declining performance of the students and the possible corrective recommendations. Therefore, students can make immediate improvements.

Araque et al.[2] have proposed a personalized model that illustrates the risk of students who may abandon their degree and analyzes the profile of those who abandon the degree.

Cakula and Sedleniece [3] proposed four basic factors of personalization: student personality, knowledge level, course content, and technologies. They concluded that machine learning-based personalization could rapidly and accurately match each user's needs.

Chafouleas et al. [4] presented the framework for determining the types of behavioral data, selecting appropriate measures, and interpreting and organizing the results.

Jetinai [5] developed the ontology-based approach and recommended suitable learning resources in E-learning systems. Ontology rule-based reasoning adoption was suggested. However, such an approach focuses mainly on how to cope with the problem of heterogeneous E-learning systems.

Limongelli et al. [6] proposed the approach to selecting a learning pathway in personalized adaptive learning by formulating the problem as an optimization problem. Such an approach is modeled as a Markov decision process based on students' competencies and learning outcomes. The results can be used as a basis for applying data analytics to improve student's learning outcomes.

Pane [8] proposed a framework that discusses school design features and implementations, including learner profiles, individual learning routes, adaptable learning environments, and preparedness for college and the workplace.

Loftin et al.,[7]; Rafferty,[9]; and Zajac, [14] focus on self-monitoring strategies showed how individualized planning could improve academic results.

Sampson et al. [10] studied the shift towards personalized learning by investigating several important aspects, including education, technology, and standardization. The study revealed that the instructional process had been changed from instruction dominated to student-centered environments. The study suggests that adaptive E-learning systems are needed to provide just-in-time (JIT) learning and learning-on-demand for life-long learning situations.

Wongwatkit et al. [11] developed the learning mechanism via an online personal learning support system to monitor students' understanding. Such a mechanism is effective during the learning process. The study further suggests suitable learning activities by considering the students' current understanding level and learning styles.

The study of Xue [12] focuses on personalization education. His model is a human-oriented personalized education platform.

Xue-jun et al. [13] have examined how to evaluate the features of educational contexts by using Machine learning to analyze and model both knowledge level and learning to push learning content, resources, and activity sequences accurately.

Chourishi, Dharmendra et al.[15] proposed Moddle LMS software to provide a better effective e-learning system. They presented how to use Moodle to facilitate instructors and used tutors to provide better communication interactively.

Panagiotis Stasinakis, Michail Kalogiannakis [16] introduced and implemented Moddle LMS as a pilot project for the Greek educational system in 2015. The result is an outstanding improvement. Students can submit written projects online and then get feedback quicker than submitting by hand to teachers in person. The efficiency of interactivity between teachers and students is higher and obviously noticed.

S. Kumar, A. K. Gankotiya, and K. Dutta [17] s compared the performance between Moddle and other e-learning systems. The result showed that Moddle is much more flexible in terms of user-friendly and custom-modified ability.

Moussawi, Ali & Ibrahim, Pierre & Said, Bilal & Mershad, Khaleel. [18] introduced a novel learning management concept in 2020. They proposed automatically evaluating laboratory assignments online using a trained Machine Learning model. Due to human physical limitations, they argued that a number of teachers compared to thousands of assignments could not be done within a short period, but machines could do it easily.

All reviewed research papers are in the same direction that machine learning can improve the learning process. The main advantage of it is to respond to students who help much more quickly. Computer-aided learning systems such as LMS alone are not enough to track and improve the student performance individually.

3. Proposed Algorithm

From [15,16,17] reviewed research papers, Moddle freeware is chosen as our LMS. Since it is written by PHP, it; therefore, is easily modified by regular programmers. Besides, Moddle is designed to be modified by learning institutes. That is a reason why a lot of learning institutes, such as schools and universities, implemented Moddle as their LMS for a decade. It was also enhanced with our add-in machine learning module. This research paper proposes a new algorithm named "RSU-ML-PL"; enabling a personalized and self-tutoring system. RSU-ML-PL module is added into Moddle as a custom module.

In this paper, Python is chosen as a programing language because it coped with machine learning very well and also can interface with Moddle LMS. In addition, it is widely accepted as a programming arm for machine learning. Many good machine learning algorithms have been developed in Python for decades.

Our algorithm aims to identify a risk group. As described in this section, we employed a machine learning model in order to identify a risk group. Accordingly, the ability to customize the machine learning model for a specific purpose is the key factor. Therefore, this study chose Moodle LMS as a learning management system. Courseware was customized to each student based on his or her behaviors.

3.1. Pseudo-Code of the Algorithm

Table 1 demonstrates the pseudo-code of our algorithm. Starting from line 1 and 2. We collected students' activities from the E-learning system and students' grades from the registration system for the selected courses respectively.

Thereafter, we combined these two datasets in line 3 to explore the correlation between students' activities and grades. In line 4, we grouped students into two clusters. Subsequently, the authors applied a clustering algorithm to obtain a list of students who needed help and attention. Finally, we were able to provide personalized learning for the students.

Table 1. Pseudo code of our algorithm

Line No.	Pseudocode
1.	Activities = Sourcing (e-Learning)
2.	Grades = Sourcing (Registration)
3.	Students = Merging (Activities, Grades)
4.	Clusters Model (Student Data, 2)
5.	Personalized and Self-Tutoring System
6.	Predictive Model and Evaluation

3.1.1. Step 1: Students with good performance in Cluster 1

Students are able to withdraw from a class after the midterm if they need. A drop-off rate is a general problem in every university.

To prevent this problem, identifying a risk group is urgently required [2]. According to our historical data, students who got very low scores on the midterm exam were more likely to drop off or withdraw from the course. Some of them may decide to retire from the university.

The first step is to identify the students who need help. This step intends to categorize students with high-class attendance but low midterm scores. By using the K-Means, the students can be grouped into two clusters:

1) Cluster 1: those students who have participated intensively in E-Learning activities or had a high frequency of online interaction and academic achievement.
2) Cluster 2: those students who have participated intensively in E-Learning activities or had a high frequency of online interaction but did not have a good score in the midterm examination. i.e., his/her midterm score is less than means of a midterm score.

According to these clusters, students from the Cluster 2 need the most help. Once Cluster 2 is identified, a tutorial system can be implemented. At this stage, a teacher assistant will be assigned to help students in this group.

This step shows that the students from the Cluster 2 need the most help. Figure 2 and 3 illustrate the number of students who got lower than the means of midterm scores on the midterm exam but then studied on the courseware. The results revealed that 768 predicted students were gathered in Cluster 2.

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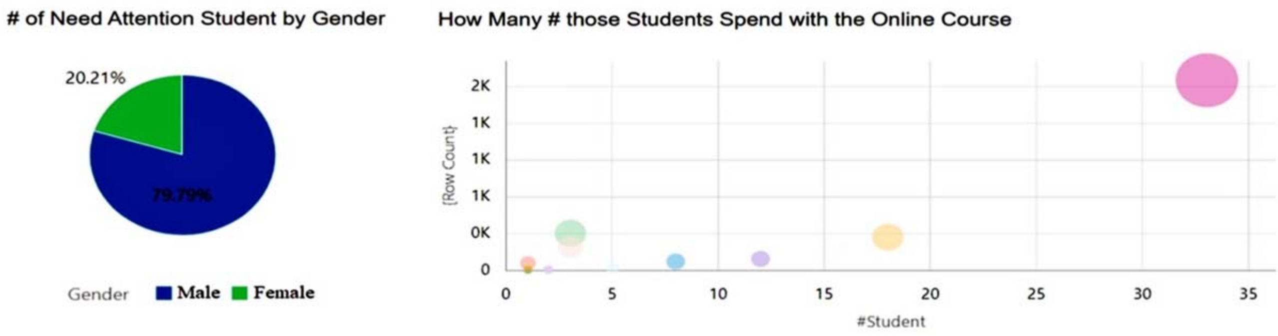

Figure 2. Students who need attention (1)

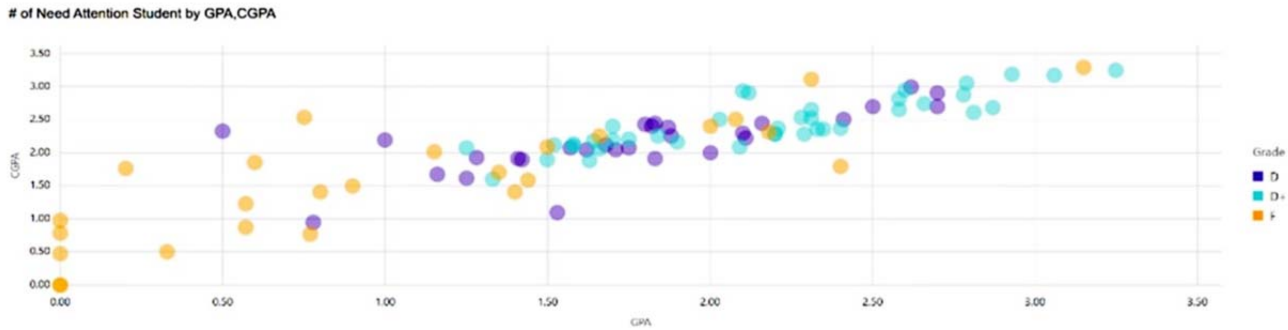

Figure 3. Students who need attention (2)

3.1.2. Step 2: Predict the likely good grade or the student attrition

A serious problem of university business around the world is the drop-off rate. The higher rate of drop-off, the lower income to the university. However, every student has a right to drop out or withdraw from a class after the midterm if needed. Due to a large group of students, machine learning can detect and respond faster than humans. In our case, it is more than a thousand enrolled students.

From cluster 2 in Step 1, a classification model in section 4.4 was applied to predict "Student attrition" or "Risk group."

3.1.3. Step 3: Tutoring a risk group

To establish a pattern, all electronic courses have been monitored and analyzed. From these statistics, patterns were created. Some online quizzes were fed to all learners periodically to measure students' ability levels and their competencies. Their usage behaviors were also monitored. Furthermore, diving intensely into the performance report of the students highly assisted the teachers in understanding students' improvements as well as their strength and weakness points. We used the reports on big data analytics to recommend the regions in which the students were interested. By doing this, we could know whether the students sought professional assistance and in which field. A Custom LMS was used to feed suitable courseware to learners based on their interests.

4. Experiment

When the COVID-19 pandemic started, higher institutions were requested to refrain from providing education activities taking place at the institution. The government announced that all classes in Thailand must be fully online in 2021. Since online activities were arranged throughout the year, a lot of data has been collected by nature. To provide a better service, data has been analyzed by our algorithm and also has been developed and used accordingly.

4.1. Front-end Platform

Videoconference platforms and Learning Management Systems are part of the front-end platform (LMS).

4.1.1. Videoconference platform

Videoconferencing technology was an effective tool for teaching and learning when the COVID-19 pandemic started. Zoom Meetings is one of the videoconferencing platforms which generates online meetings professionally. It provides several features such as audio, video, and wireless screen sharing which are suitable for conducting online classes. Google Classroom can be used on PCs, Macs, and mobile devices.

4.1.2. Learning management systems (LMS) and collaboration tools

Learning Management Systems (LMS) refer to software that runs on the Internet. It helps teachers connect to students from anywhere. LMS is widely used in an institution to set up online courses. Any type of content, such as text, document, image, video, quiz, assignment, the topic of discussion, and more, can be added in LMS. In addition, it allows teachers to track the detailed progress of each student. Google Classroom is one type of LMS that provides the features mentioned. However, an additional collaboration tool such as Slack might be needed for teachers and students when group works, or software projects are required. Slack allows a group of students to build their virtual workspace to plan and monitor their project progress.

4.2. A Back-End platform

In this study, we reported on 1,980 students who registered for the THAI106 course as a general education course in 2021.

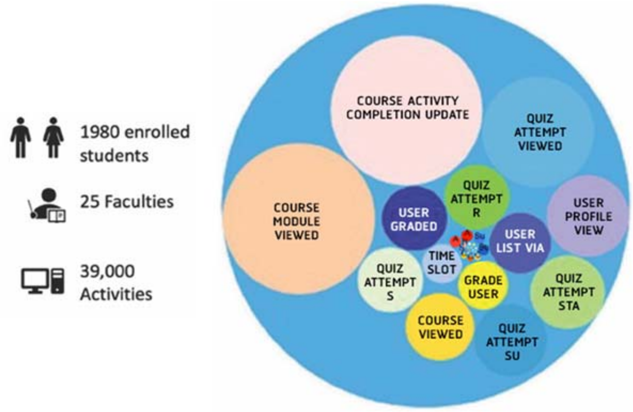

Figure 4. An overview of all transactions

Figure 4 demonstrates an overview of course transactions. Within the course, there were 39,000-course activities, such as quiz attempts, the number of courses viewed, etc.

The THAI106 course was offered fully online during the COVID-19 crisis in 2021. All activities and behavioral patterns were tracked and analyzed. This study aims to identify a new Algorithm that can be used to help students who tend to fail, as well as to help them possibly obtain a better grade. Two common ML algorithms, including supervised learning (a decision tree) and unsupervised learning (K Means) are described in Section 3.

By using ML, some incidents and failure factors can be measured. Thus, we used LMS to feed customized courseware to each student based on their interests and behaviors.

ML is implemented in this research. Overall, the experiment revealed good students' progress, especially on the final examination. More than 50 percent of the students had higher final exam scores than their midterm ones.

Figure 8 shows the number of students who tended to fail but obtained good grade after participating in the tutoring program by LMS.

4.3. Data Preparation and Data Cleansing

The section is to create a model to evaluate a risk group. According to the data, several failed cases were found, such as dropped-off students or students who failed the exam. Five algorithms were used for the comparison. The data contained 12 columns and 768 rows with the header row.

Table 2 shows the attributes, such as 1. Student ID, 2. Student name, 3. E-Learning-Activity-Count, 4. Faculty, 5. Gender, 6. CGPA, 7. Age, 8. Midterm score, 9. Login timestamps, 10. Logout timestamps, 11. IP addresses, and 12. Class (Fail/Pass). Student names were blind using the number starting from 1 to 768 for data privacy reasons.

Table 2. Excerpt of prediction results for student attrition

```
import pandas as pd
df=pd.read_excel('Table2.xlsx')
df
```

	Student-Name	E-Learning-Activity-Count	Faculty	Gender	CGPA	Age	Midterm	Class
0	1	180	17	1	2.962	22	75	Pass
1	2	100	17	1	3.893	22	67	Fail
2	3	162	17	1	2.551	22	73	Pass
3	4	147	17	0	2.454	22	63	Fail
4	5	118	15	1	2.600	22	66	Pass
...	...	...	...	...	...	...	...	...
763	764	76	19	0	2.652	23	53	Fail
764	765	175	30	0	2.235	22	54	Pass
765	766	100	25	1	2.299	20	57	Pass
766	767	136	32	1	2.233	19	57	Pass
767	768	163	11	1	2.741	20	61	Pass

768 rows × 8 columns

Table 2 also presents an excerpt of prediction results for student attrition. For example, student number 768 is a male student with a CGPA of 2.652. He participated in the E-learning activities only 76 times.

According to the data, our algorithm recommended that this student needed more attention to successfully pass the course.

In addition, we dropped attributes such as student ID, student name, login and logout timestamps, and IP addresses because they were irrelevant to our model.

Figure 5 shows that there is no relationship between a student's name and a class variable. Hence, we dropped out those attributes from our analysis from the beginning.

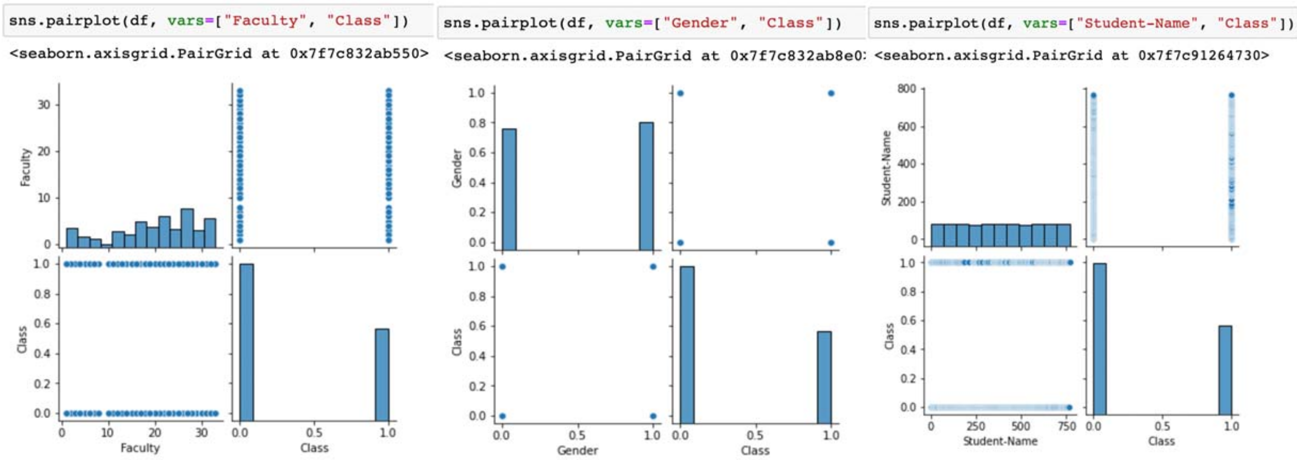

Figure 5. Excerpt of the correlation between class and attributes

4.4. Predictive Model and Evaluation

To construct a predictive model, a classification model reads input and generates an output that classifies the data into a specific category. In this study, a class label that was used is "Class" in Table 2. A class labeled "0" means that the student failed the final examination and got an F.

We adopt a classification model to identify a risk group.

As shown in Figure 6, the program was developed by Python (Sklearn software) using the data from 768 rows and 12 columns. In this study, the student performance is evaluated by using five algorithms, namely: Random Forest, K-Nearest Neighbors, Decision Tree, Logistic Regression, and SVC (Support Vector Machine).

We adopt a classification model to identify a risk group. As shown in Figure 6, the program was developed by Python (Sklearn software) using the data from 768 rows and 12 columns.

```
from sklearn.neighbors import KNeighborsClassifier
#The plot suggests that we should choose n_neighbors=9. Here we are:
knn = KNeighborsClassifier(n_neighbors=9)
knn.fit(X_train, y_train)
print('Accuracy of K-NN classifier on training set: {:.2f}'.format(knn.score(X_train,y_train)))
print('Accuracy of K-NN classifier on training set: {:.2f}'.format(knn.score(X_test,y_test)))

Accuracy of K-NN classifier on training set: 0.75
Accuracy of K-NN classifier on test set: 0.72

from sklearn.neighbors import LogisticRegression
#logreg = LogisticRegression().fit(X_train, y_train)
logreg = LogisticRegression(max_iter=200).fit(X_train, y_train)))
print('Training set score: {:.3f}'.format(logreg.score(X_train,y_train)))
print('Test set score: {:.3f}'.format(logreg.score(X_test,y_test)))

Training set score: 0.745
Test set score: 0.776

tree = DecisionTreeClassifier(max_depth=3, random_state=0)
tree.fit(X_train, y_train)
print('Accuracy on training set: {:.3f}'.format(tree.score(X_train,y_train)))
print('Accuracy on test set: {:.3f}'.format(tree.score(X_test,y_test)))

Accuracy on training set score: 0.755
Accuracy on test set score: 0.740

from sklearn.ensemble import RandomForestClassifier
rf1 =  RandomForestClassifier(max_depth=9, n_estimators=100 random_state=0)
rf.fit(X_train, y_train)
tree.fit(X_train, y_train)
print('Accuracy on training set: {:.3f}'.format(rf1.score(X_train,y_train)))
print('Accuracy on test set: {:.3f}'.format(rf1.score(X_test,y_test)))

Accuracy on training set score: 0.957
Accuracy on test set score: 0.719
```

Figure 6. Excerpt of lab results

In this study, a python program was run on a Jupiter notebook. To construct a decision tree, export_graphviz was used as a drawing tool.

Figure 7 shows that midterm score and E-Learning-Activity-Count are the main factors used to classify the result.

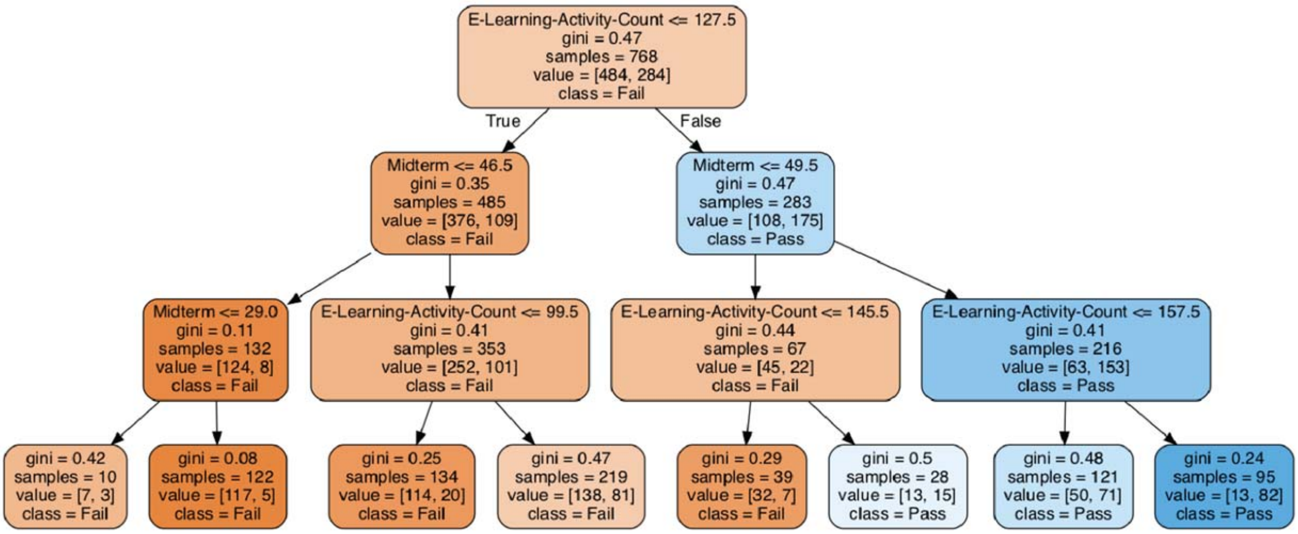

Figure 7. A decision tree model

4.5. Evaluating a model

In this research paper, we used confusion matrix to evaluate the model.

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y, y_pred))
print(classification_report(y, y_pred))

[[483   1]
 [ 38 246]]
              precision    recall  f1-score   support

        Fail       0.93      1.00      0.96       484
        Pass       1.00      0.87      0.93       284

    accuracy                           0.95       768
   macro avg       0.96      0.93      0.94       768
weighted avg       0.95      0.95      0.95       768
```

Figure 8. Correlation matrix

All algorithms are evaluated using a confusion matrix. Performance comparison is shown in Table 3 and Figure 9.

Table 3. Performance Comparison

Algorithm	Precision	Recall	F1-Score	Accuracy on Training Data	Accuracy on Test Data
Random Forest	0.80	0.95	0.87	0.957	0.719
K-Nearest Neighbors	0.66	0.93	0.77	0.75	0.72
Decision Tree	0.93	1.00	0.96	0.755	0.740
Logistic Regression	0.68	0.91	0.78	0.745	0.776
SVC (Support Vector Machine)	0.68	0.91	0.78	0.730	0.760

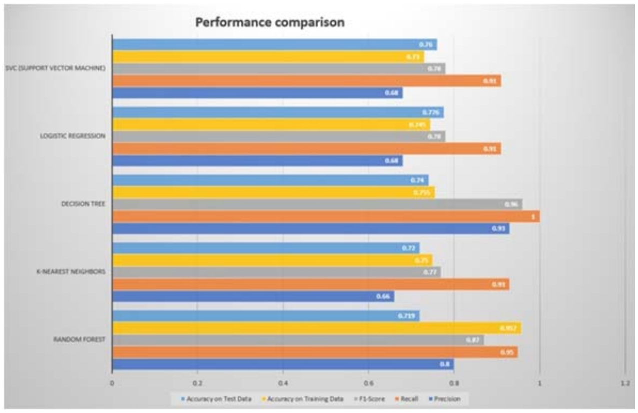

Figure 9. Performance comparison

4.6. Experiment

This study intends to enhance individual learning results by classifying a risk group and offering a self-tutoring program. The authors adopted a machine-learning model and proposed a new algorithm named "RSU-ML-PL." According to the data, 768 students who tended to fail the course were tutored by our algorithms and mentored by human tutors. The content on the LMS was adapted to each student based on their weaknesses and personal interests.

5. Conclusion

RSU-ML-PL algorithm was designed to provide each student with a personalized and self-tutoring system. The results of the experiment are presented as follows.

1. Figure 9 shows that the decision tree outperforms other algorithms. Precision and recall are the highest, as presented in Table 3.
2. The random forest algorithm is also an interesting choice because of its performance.

The training data has a maximum accuracy of (95.7%), while the test data is highly accurate (71.9%). Despite the fact that a random forest on the training data has the maximum accuracy, the accuracy of the test data shows a significant drop to 71.9%. This might be a sign of an overfitting problem.

3. Precision on K-Nearest Neighbors, Logistic Regression, and SVC (Support Vector Machine) are lower than others. We, therefore, conclude that they are not a good choice for students.

Therefore, the authors chose the decision tree algorithm as a classification model for this research. Figure 7 shows that midterm score and E-Learning-Activity-Count are the main factors used to classify the result.

There are three steps in the RSU-ML-PL algorithm for implementing this framework, as presented in Section 4. A predictive model becomes a rule-based method for future use. A confusion matrix will be an indicator for adjusting a model for the next round of implementation.

Overall, the experiment revealed good progress, and students got better scores on the final examination. After participating in the tutoring program by LMS, 768 students were in the risk group. The final Examination results show that 606 (79%) students in the risk group passed their examination.

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