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Integration between Deep Neural Network and Predictive Learning Analytics (PLA): to Improve Student's Performance in Online Exam

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Abstract: In this paper we discussed the Predicting performance of university students has become an important necessity among education experts, as it helps rationalize spending and invest efforts correctly. The current study sheds light on the best techniques for predicting the performance of university students in an online exam conducted over the Internet. The study used the integration between Deep Neural Network and Predictive Learning Analytics (PLA) to improve students' performance in these e-exams. The study was applied to a sample of students from the Faculty of Engineering at Damietta University through their scores in the electronic exam during the years from 2019 to 2022. The dataset was divided into train (687 instances (50%)) and exam (686 instances (50%)). Besides, the dataset includes four features, such as year, score, percent, and grade. Five ML algorithms were selected to examine high prediction accuracy. "The ML algorithms are Random Forest (RF), Naive Bayes (NB), Support Vector Machine (SVM), Decision Table (DT), and K-Nearest Neighbors (KNN). Besides, evaluation metrics were applied to compare ML algorithms such as confusion matrix, accuracy, recall, precision, and F-measure. According to the results, the Random Forest, Decision Table, and K-Nearest Neighbors classifiers were the best, as they correctly classified 685 instances during the prediction of the student's performance. For other metrices of evaluation (recall, precision, and F-measure), concerning the Random Forest, Decision Table, and K-Nearest Neighbors classifiers, precision, recall, and F-measure achieve 0.99."Our finding also revealed the successful achievement of high accuracy in predicting the performance of students at the Faculty of Engineering, Damietta University, in online exams using ML algorithms.

Keywords: Deep Neural Network, Learning, Online exams, University students, Machine Learning.

1 Introduction

The use of learning analytics (LA) has recently emerged in the field of education. This is due to the many advantages it provides, as it works on the quality of learning and helps in managing educational institutions by predicting at-risk students. The importance of machine learning in different industries stems from its ability to extract valuable insights and patterns from massive amounts of data, automate processes, and provide accurate predictions or recommendations. Machine learning models excel at making predictions based on historical data. Machine learning plays a crucial role in cybersecurity by identifying patterns of malicious activity and detecting anomalies in network traffic. It helps in fraud detection, spam filtering, malware detection, intrusion detection, and enhancing security infrastructure. By training models on historical data, organizations can predict future trends, behavior, and outcomes. Predictive analytics is valuable in areas such as sales forecasting, demand forecasting, fraud detection, risk assessment, and customer behavior analysis. Despite these advantages, there are many problems in applying LA, including the difficulty of collecting and analyzing data, as well as the problem of ethics and conducting the evaluation process [1]. Learning analytics relies on reinforcement learning technology and the mining and visualization of educational data, so it is used to provide predictive and actionable information [2]. The topic of forecasting academic achievement among students has been extensively researched due to its importance for any educational institution aiming to improve the performance and retention of its students. However, because it depends on so many traits and factors, predicting student performance is still a challenging and complex problem. Most studies were concerned with researching the effect of different characteristics on students' academic performance, and few of them focused on the effect of students' evaluation scores in the online exam. These techniques include the integration between Deep Neural Network and Predictive Learning Analytics (PLA) to improve students' performance in online exams. The current paper aims to predict student performance at the Faculty of Engineering, Damietta University, in an online exam during the years 2019 to 2022.

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2 Literature review

2.1 Learning Analytics (LA) in education

LA is a tool for customizing educational opportunities according to the abilities and needs of learners through several actions, such as providing feedback and educational content or intervening with at-risk students. It focuses on applying known methods and models to address problems that affect student learning and the organizational learning system. While data mining automates responses and creates a methodology for learners, it focuses on developing new methods for computational data analysis [3]. LA focused-on data about learners' interactions with peers, content, and teachers. It is considered the result of integrating analysis techniques relevant to data visualization, machine learning (ML), data mining, learning sciences, psychology, social network analysis, artificial intelligence, semantics, social aspects, and e-learning [4]. The goal of using LA in MOOCs is to increase student success and participation. Teachers can also use it to gather information about their students, and use that information to make changes, and give them more personalized feedback. In this paper, the authors examine the many forms of online criticism and catalog the corresponding data sets. Two tools are used for data analysis and visualization: Analyzing qualitative data with Many Eyes and quantitative data with Tableau [5]. "LA is a significant subfield of technology-enhanced education that has developed significantly over the past ten years. Cogitating the technological, educational, and political reality walk that prompted it to contribute to enlightening environments is how this is accomplished. The birth of perspectives that are focused on discrimination, the development of analytics that are driven by data, and the relationships between learning analytics, educational data mining, and learning analytics. It investigates the aspects of learning analytics that serve as checkpoints for progress and identifies the challenges that lie ahead at the destination"[6]. Analytics is the field that aims to uncover new patterns of information by bringing together large sets of data found in previously distinct sources. Some studies have focused on the challenges facing the use of learning analytics, including the challenges of applying analytics to the academic and ethical reliability of data control. Another challenge is the disruption of the educational process at the present time, and the main challenge is collecting a large amount of data, protecting it, and using it appropriately. This is to provide a big data model for the higher education system. [7]. In 2011, a study was conducted to enhance the learning process using learning analytics, where student data was collected and analyzed to measure and evaluate student performance and understand the context [8]. Learning analytics has also been used to improve learning environments by collecting, analyzing, and measuring learner data within these environments [9]. Through previous studies, LA can be defined as “systematically collecting and analyzing a huge amount of data from online sources to improve learning processes” [10]. Given the assistance that learning analytics brings to educational institutions, it works to keep students in these institutions because of the tools it provides through which it is possible to monitor and predict student performance, enhance the success of students, and decrease the burden of accountability. This makes it an important tool for faculty members in higher education institutions [11]. In 2012, some researchers used data from learning management systems to predict student performance by tracking students through the frequency of logging into the system, the student’s speed in the course, sharing sites, and the student’s grades in the tasks assigned to them [12]. Macfadyen and Dawson also used a learning management system to predict student performance in a course by using the number of discussion messages read and the number of responses to them to predict the student’s grade in this course [13]. There is also a study in which a student's performance was predicted by tracking the number of attempts to solve homework assignments and the time spent on solving them to predict his final grade in this course [14].

2.2 Neural Networks and Deep Learning

This form of learning is a category of ML that is considered an artificial intelligence (AI) technology, which relies on neural networks and is applied in many fields such as education, health, modern technological industries, and scientific research. It is in a continuous process of development as a result of recent developments in the field of neural networks and algorithms [15].

As a result of the importance of deep learning in addressing complex problems through ANN-based systems, it has attracted the attention of scientific research. Some research has focused on the knowledge tracking methodology, which is used to predict the student’s performance in solving specific exercises by looking at his previous performance in solving the exercises. Through knowledge tracking (KT), it is possible to predict student behavior over time, which is why it can be used by teachers to know which students are at risk and to benefit from it to warn a student who has not mastered the performance of a certain skill. For this reason, it can be used to intervene in real time to support students. It also helps the teacher modify the content or change the teaching method used so that students can acquire the greatest amount of knowledge and acquire skills well, and the knowledge tracking methodology is considered effective in online and direct learning [16]. Deep learning is synonymous with machine learning, but not all machine learning is classified as deep learning, and because deep learning techniques are superior to machine learning techniques, computational models allow learning features gradually from data at multiple levels and dealing with big data, so there are many studies that address methods Different types of deep learning, their developments, and their applications [17].

There are many studies that aim to determine the efficacy of transferring learning from deep neural networks for the task of predicting student performance in higher education. This is because the models used in data mining for prediction give inaccurate results. Therefore, neural networks have been deployed to forecast students at risk of academic failure, and the result of this prediction can be accurately determined provided that data sets of students who attended relevant courses are available [18]. In this study, deep learning models were used and a new and ongoing line of research known as (deep knowledge traceability), through which student performance is predicted using information in the collected data, has been proven to be capable of predicting student performance [16]. In addition, this study used LSTM through a set of features extracted from video clickstream data to predict learners' weekly performance and enable teachers to set measures for timely intervention. The results showed the superiority of the LSTM model over ANNs and SVMs with an accuracy of up to 93% [19].

2.3 Predicting students' performance

X. Wang and M. Gao Confirmed that understanding cognitive processes and measuring the online testing process has received great attention. In their study used data on students' cognitive styles and eye movements collected in an online testing environment and used the C5.0 decision tree algorithm to predict student performance. And The results show that it is practical and the prediction accuracy is over 87% [20].

Brahim affirmed that A great deal of research has been done on predicting students' success during their years of academic education. It provides significant insights that can assist and direct organizations in making prompt decisions and adjustments that improve student outcomes. Since the end of the COVID-19 epidemic, e-learning has become more popular and there is more online learning material available. This has prompted academics to create models based on machine learning to forecast how well students will succeed in virtual classrooms. The goal of Brahim's work is to forecast student performance in a sequence of online interactive sessions by utilizing a dataset gathered through the usage of digital electronics education and design software. 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. His study's suggested machine learning algorithm seeks to forecast whether a student will do well or poorly. The model's best classification accuracy performance of 97.4% was attained with the RF classifier, according to the results [21].

3 Materials and methods

In the current research, data was collected on the electronic exam score during the academic year (2019-2022) for Faculty of Engineering students at Damietta University. The data was extracted into frames and processed. The data was cleaned by removing noise, selecting features, and then classifying the data into datasets. Training and test data, creating models and training, and finally analyzing the data and interpreting the results. As shown in Figure 1.

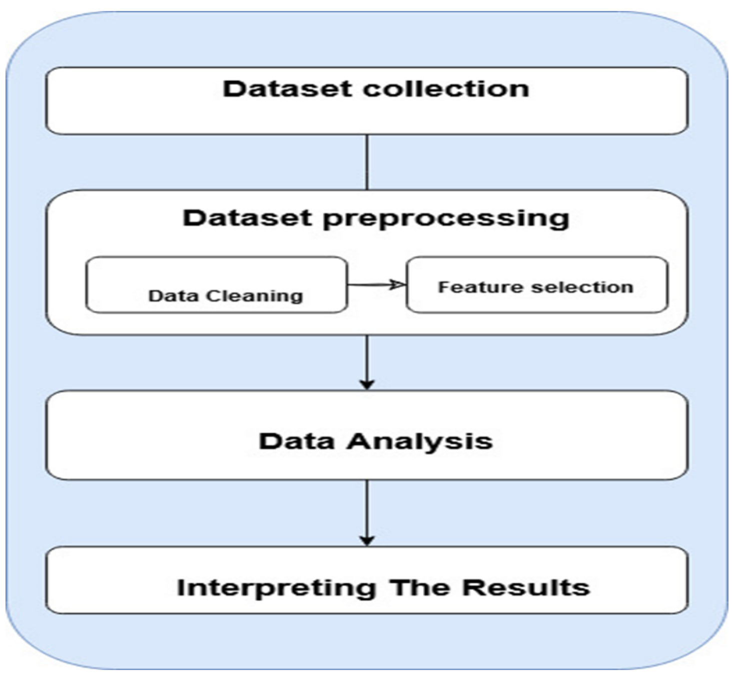

Fig. 1: Proposed methodology

3.1 Dataset collection

The dataset was obtained from the Faculty of Engineering at Damietta University. Degree students of the online exam through the academic year (2019-2022). The dataset contains 1373 instances after excluding 4 instances of missing values. The dataset was divided into train (687 instances (50%)) and exam (686 instances (50%)). Also, the dataset included four features.

3.2 Dataset pre-processing

In the process of preprocessing a data set, the first step is data cleaning. The collected data is cleaned to avoid any errors occurring while analyzing the resulting data and drawing conclusions. This stage is regarded as one of the most crucial ones when conducting data analysis because the data cleaning process effectively contributes to drawing high-quality results that serve the set goals. Data cleaning is the process of eliminating all irrelevant attributes. The dataset consists of 1373 instances after excluding 4 instances for missing values. Then some records were removed from the dataset after missing values from different features were discovered. After completing the data cleaning process, the second step in the pre-processing stage of the data set is selecting the distinctive features. To obtain better classification results, we reduce the dimensions in the feature space. So as not to lead to overfitting of the model. This is done by selecting a subset of original features and removing redundant and obsolete features without losing any important information. The dataset included 4 features as shown in Table 1, such as year, score, percentage, and grade. The features, their values, and descriptions are shown in Table 1.

Table 1: List of features of dataset

No.	Features	Description	Value
1	Year	Academic year	From 2019 to 2022
2	Score	Degree of the online exam through academic year	(0:20)
3	Percent	The percentage of the online exam score	(0:100)
4	Grade	Grades obtained from the online exam score A: degree range [85:100] B: degree range [75:84] C: degree range [65:74] D: degree range [50:64] F: degree range [0:49]	(A, B, C, D, E or F).

3.3 Data analysis

After completing the previous two stages of the data preprocessing process, the data is ready for analysis. There are several different ways to analyze data. Including using data visualization to examine it in a graphical format and analyzing statistical data models to determine relationships between data variables in order to interpret, understand, and draw conclusions based on requirements. The analysis process may require repeating several operations to clean the data or collect additional data.

3.4 Interpreting the results

The stage of interpreting the results is one of the most important stages, as researchers interpret the results extracted from the data analysis process, and through these interpretations, the best results are determined. By examining reports, tables, or diagrams.

4 Machine learning algorithms training

The evaluation matrices were applied to compare among ML algorithms (Random Forest (RF), "Support Vector Machine (SVM), Naive Bayes (NB), Decision Table (DT), K-Nearest Neighbors (KNN)) such as precision, accuracy, F- measure, Recall, were calculated from the TP, TN, FP, and FN values."

Jayaprakash et al. (2020) proposed the random forest algorithm and an in-house variation, the improved random forest algorithm. These algorithms yielded 91 and 93% accuracy, respectively,

When predicting academic performance [22]. Kumar et al. (2020) also proposed using algorithm a decision tree algorithm, to predict student performance. For this, as a result, they obtained 81% accuracy [23]. Rincon-Flores et al. (2020) forecast academic student performance using different algorithms. mentioned several models, such as Random Forest and K-nearest neighbors (KNN), to achieve 80% accuracy [24]. In their study, Hasan et al. (2019) present a model that tries to predict final exam results for a given student. For this, they used a dataset of 1,170 students in 3 courses. Then, the authors reprocessed the dataset by removing unnecessary columns such as Student ID. They used the KNN algorithm and a decision tree classifier (the ID3 algorithm) for their predictions, thereby obtaining 94.44% accuracy based on the decision tree classifier algorithm [25]. Daud et al. (2017), used a supervised learning model to predict whether students will complete or abandon their study programs. Specifically, they used the SVM model, wherein the best result was obtained with 86% in the F1-score test [26]. Ma et al. (2018) also used the SVM supervised learning model to predict online student passing rates. Using the grid search algorithm at 50% pass / 50% fail data, this model achieved 95% accuracy [27]. Shafiq et al. (2022) reviewed 100 papers on student prediction from 2017–2021. They also found that nearly 50% used supervised machine learning and RF, LR, normal decision tree, and NB was the top four algorithms. This was followed by deep learning at 28% (artificial neural network (ANN) and MLP) [28]. Xiao, Ji & Hu (2022) found that almost all (77 studies) of the 80 selected studies used supervised machine learning classification algorithms to predict students' performance, and some (19) used ensemble method. More than one classifier was used in 69% of the selected models. Among them, the machine learning (ML) classifiers with more than 10 times are decision tree (DT), naive Bayes (NB), multi-layer perception (MLP), support vector machine (SVM), random forest (RF), K-nearest neighbor (KNN) and logic regression (LR), while the most used ensemble methods are classical boosting, bagging and voting [29]. Dutt, Ismail & Herawan, 2017; Rimpy, Dhankhar & Solanki, (2022) For our study, we need consider these prediction models to validate our dataset. This is because the difference of datasets often leads to different accuracy of the prediction models. In light of the researches above, these commonly used algorithms will also appear in our experiments to predict performance students [30].

A. K-Nearest Neighbors (KNN)

The KNN algorithm is considered one of the most important and simplest supervised machine learning algorithms. It is used in classification and forecasting operations. It deals with data and outliers efficiently. The KNN algorithm determines the value of a new sample based on its location from the closest training set samples.

The nearest neighbor's algorithm works by calculating the Euclidean distance or Manhattan distance between points, where the closer together two points are, the higher the likelihood that those two points are within the same set of coordinates. K indicates the number of samples through which a point will be classified based on the distances between it and its neighbors [31]. As shown in Fig. 2:

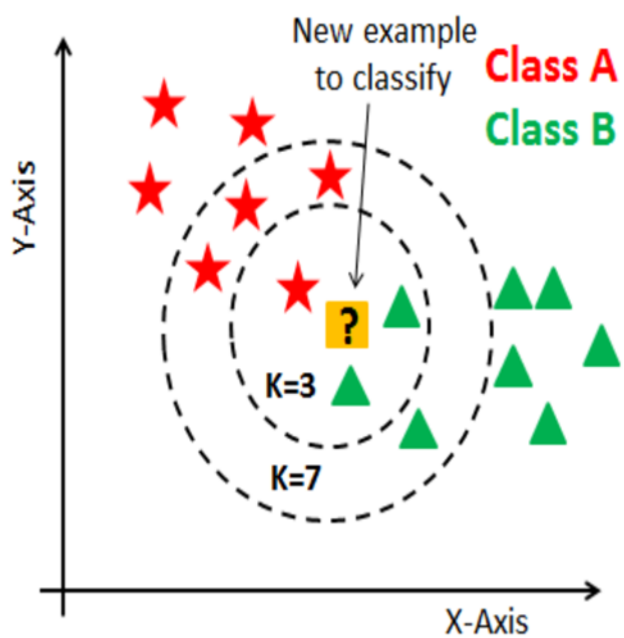

Fig. 2: K-nearest neighbor algorithm [32]

The working idea of the KNN algorithm is as follows:

First, preprocessing is done, preparing the training data set by converting the data into an appropriate format, such as a matrix or data frame. Then normalize the features, to ensure that each feature has the same scale. After that, separate the data into two distinct sets—a training set and a test set—so that you can analyze how well the algorithm is working.

The second step is the calculation of the distance between each sample and every other sample that is included in the training data set. This is accomplished by making use of an appropriate distance metric, such as: B. "The Euclidean distance, which is the square root of the sum of squared differences between points; the Manhattan distance, which is the distance between vectors by using the sum of their absolute differences; and the Hamming distance, which is used for categorical variables". The third step is to look for the closest neighbors. The distances are listed in descending order, and the user is responsible for determining the value of the parameter K. A decision that is unstable may result from using a small value of K; consequently, it is recommended that a large value of K be used.

Fourth: Determine the class or value. In classification, the class of the new sample is found through the majority class of the K-nearest neighbors. In prediction, the value is then found as per the average value of the K-nearest neighbors. Fifth: Evaluate the performance of the algorithm by comparing the expected class A for the new sample with the actual class or value. These steps are repeated for all samples in the test set, calculating accuracy or other performance metrics to evaluate the algorithm's performance [33].

$$Euclidean \sqrt{\sum_{i=1}^{k} (x_i - y_i)2}$$

Manhattan distance. (34)

$$D = \left(\sum_{i=1}^{n} |\mathbb{p}_{i-} \ \mathbb{q}_i| \ p \right) 1 \, / \, p$$

B. Support Vector Machine (SVM)

This is essentially a supervised machine learning algorithm specifically deployed for classification or prediction. The value of each data element is an integrated value, and each element can be seen as a single point in an n-dimensional space (where n is the number of elements). Classification is done by finding the highest level that separates the categories. SVM finds a hyper layer that separates different classes at a higher level in the feature space. The super layer is responsible for increasing the distance between the closest points in each category [34].

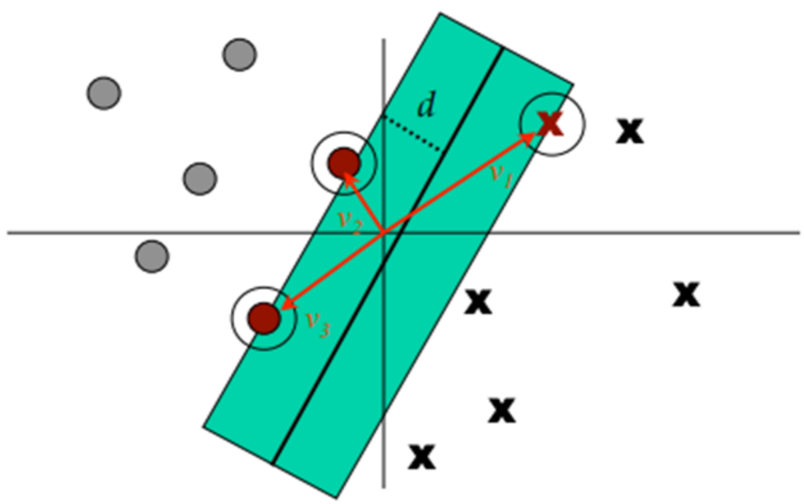

Fig. 3: Support vector machine margin [35]

The SVM algorithm is able to process data that is not linearly separable by mapping the input data to a higher dimension using the kernel method. It is a tool that converts small-dimensional spaces into multi-dimensional spaces (for example, converting two-dimensional planes into three- or four-dimensional planes); that is, it converts data that cannot be separated into separable data. This is useful for non-linear classifications. "It contains some functions: radial basis function (RBF), linear, polynomial, and sigmoid kernels [35]."The SVM algorithm has a number of benefits, including the ability to process high-dimensional data and resistance to overfitting. These are just two of its many strengths. It functions admirably when there is a distinct margin for separation; it is efficient in areas that have high dimensions; and it is useful if they possess greater features than specimens.

Despite these advantages, it has some drawbacks, including the fact that it does not work well with a large data set because it requires a lot of training time. It also does not give accurate results with a data set that contains many extreme values. It does not provide direct probability estimates.

C. Decision Tree (DT)

A decision tree algorithm is a machine learning algorithm that analyzes data and divides it into categories using a series of decisions based on values in a set of variables.

These decisions are represented in the form of a tree structure, branches, and classifications, and decisions are made based on specific criteria and are used in conducting classification and prediction, as they are used to classify elements into different categories. " And to solve classification and regression issues that arise from conducting data analysis and finding relationships between the variables. One of the main goals of using a decision tree algorithm is to build a training model that can be used to guess the class or value of target variables. Learning inferred decision rules from training data—previous data—accomplishes this. The decision tree algorithm utilizes a tree representation to resolve the problem, with each inner node representing an attribute and each leaf node representing a class label. The decision tree algorithm works by analyzing data and extracting relationships between variables to reach a classification decision. This is done as follows:

- Select variables that affect the result and are used to classify the data. The best feature of the data set is placed at the root of the tree.
- Divide the training group into subgroups. Each subset contains data with the same attribute value. The data is divided into a small set of sections (subsets) using the selected variables. The different values of each variable are analyzed, and the data is divided into different branches based on the values of the variables.
- Calculating the differences between different branches of data and choosing the branch that gives the best representation of the data.
- Create a decision tree as before, so that the data is divided into different subgroups, and this is represented in the form of a tree consisting of branches and leaves.
- The created decision tree is used to classify new data, where the appropriate branches in the tree are followed and the classification to which the data belongs is determined.

The process of creating a decision tree relies on statistical analysis and logical rules, which are some of the most common tools for analyzing and classifying data. Start at the very top of the tree if you want to use this information to predict variables for records of any class using a decision tree. Analyze how the value of the log attribute compares to the value of the root attribute. Following the comparison, you should go down the branch that corresponds to this value and then continue on to the following node. until a leaf node is found that has the expected value for the class it belongs to. When working with decision trees, there are a lot of assumptions that need to be made. At the beginning, the entire training set is taken into consideration when determining the root set. The distribution of records is done in a recursive manner based on the attribute values. Several different tools that use statistical methods are combined to arrive at the conclusion that the attribute should be placed at the tree's root or an internal node. There are multiple algorithms that make decision trees, such as CART, C4.5, CHAID, MARS, and ID3. The decision tree separates nodes into all possible variables before selecting the split that produces the sub nodes with the highest homogeneity. The algorithm's choice is influenced by the type of target variable [36]." The way the algorithm works is shown in Fig. 4:

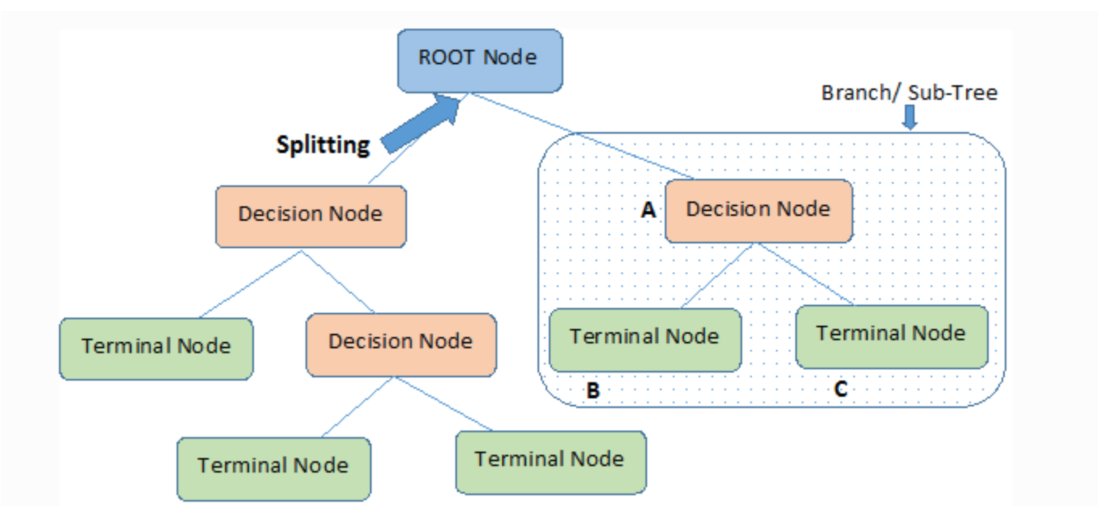

Fig. 4: Decision Tree [37]

To create a decision tree, we must calculate two types of entropy using frequency tables as indicated below [37]:"

a) Entropy by deploying one attribute's frequency table:

$$\mathrm{E}(\delta) = \sum_{i=1}^{c} -p_i \ log_2 \, p_i$$

b) Entropy using the frequency table of two attributes:

$$\mathrm{E(T,X)} = \sum_{c \in \mathrm{X}} \mathrm{P(C)\ E(C)}$$

A. Random Forest (RF)

A random forest algorithm is comprised of numerous individual decision trees. Each tree generates a class prediction. Thereafter, this receives the greatest number of votes and is considered the model forecast. The introductory principle of the Random Forest algorithm is public opinion. We can see that essentially, the success of the arbitrary timber algorithm in data wisdom is caused by the huge number of fairly unconnected models (trees) that perform the function of a commission. It'll outperform any single-decision tree model. Also, the low correlation measure between decision tree models.

Uncorrelated models can provide more accurate population vaccinations than individual vaccinations. This is because the trees protect each other from individual violations (unless they always err in the same direction). Some trees may be wrong, but many others are right, so the trees as a group may be on the right track. The basic requirements for Random Forest to function properly are as follows:

- "There must be some real signal for the models built using those features to perform better than random guesses."
- Individual trees were the basis of predictions, wherein we can see that a low correlation coefficient was present herein.

Such algorithms have many advantages. This reduces overfitting of the decision tree and improves accuracy and efficiency. Flexible classification and prediction operations. Works well with both categorical and continuous values. Handles missing values in your data nicely.

The random forest algorithm has its advantages, but also has some drawbacks: Lack of interpretability of its results. Computational complexity: Random forests can be computationally intensive, especially if you have a large number of features or trees in the forest. Overfitting: One of the benefits was reducing overfitting of decision trees, but random forests can be prone to overfitting, especially if they use a large number of trees or if they have high-dimensional features. This can lead to models that perform well on training data but poorly on test data, bias toward features with multiple levels, and difficulty dealing with imbalanced data [38].

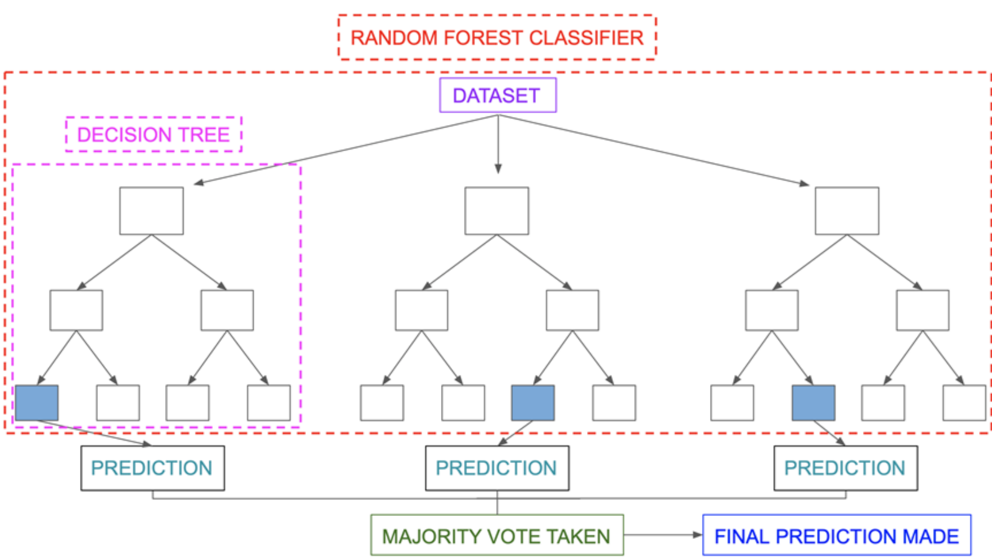

Fig. 5: A Simplified View of a Random Forest algorithm [39].

5 Results and discussion

5.1 Dataset description

Table 2 in indicates the dataset contains 1373 instances after excluding 4 instances of missing values. The dataset was divided into train (687 instances (50%)) and exam (686 instances (50%)). Table 2 shows categories of grade (A, B, C, D, and F) and the number of students in each category in academic years (2019–2022) and their percentage. Fig. 6 shows the categories of the grades (A, B, C, D, F) and number of students in each category in the academic years [2019-2022].

Table 2: number of students in each category in academic years [2019-2022] and their percentage

Academic year	A	%	B	%	C	%	D	%	F	%	Total
2019	40	12.94%	51	16.5%	60	19.42%	84	27.18%	74	23.95%	309
2020	102	25.37%	106	26.37%	79	19.65%	67	16.67%	44	10.95%	398
2021	121	37.93%	74	23.2%	54	16.93%	56	17.55%	14	4.39%	319
2022	92	26.51%	100	28.82%	69	19.88%	71	20.46%	15	4.32%	347

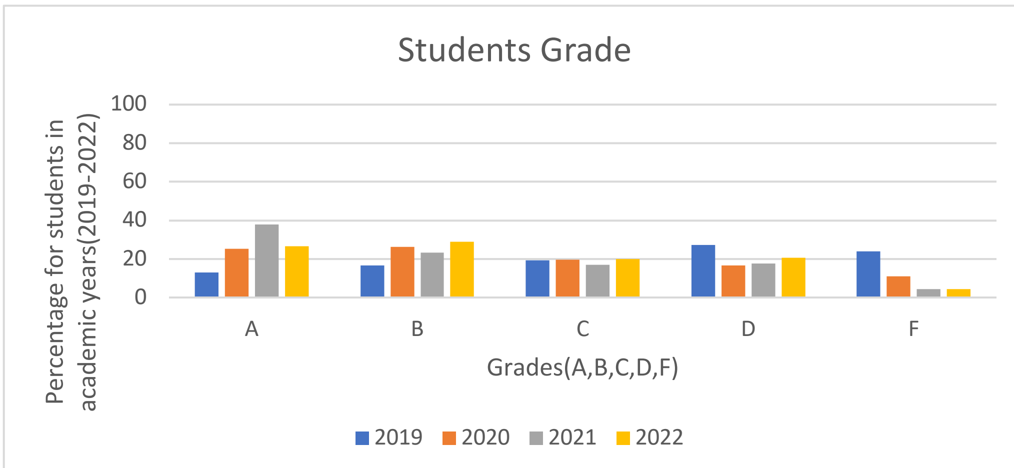

Fig. 6: Students Grade (A, B, C, D, F) in academic years (2019-2022)

The grade in the dataset is divided into 5 categories (A, B, C, D, and F), and the number of students in each category in academic years (2019–2022) is shown in Fig. 7. Whereas the number of students who obtained grade A is 355. Also, the number of students obtaining grade B is 331. In addition, the number of students obtaining grade C is 262. Meanwhile, the number of students obtaining grade D is 278. Finally, the number of students who obtained grade F is 147.

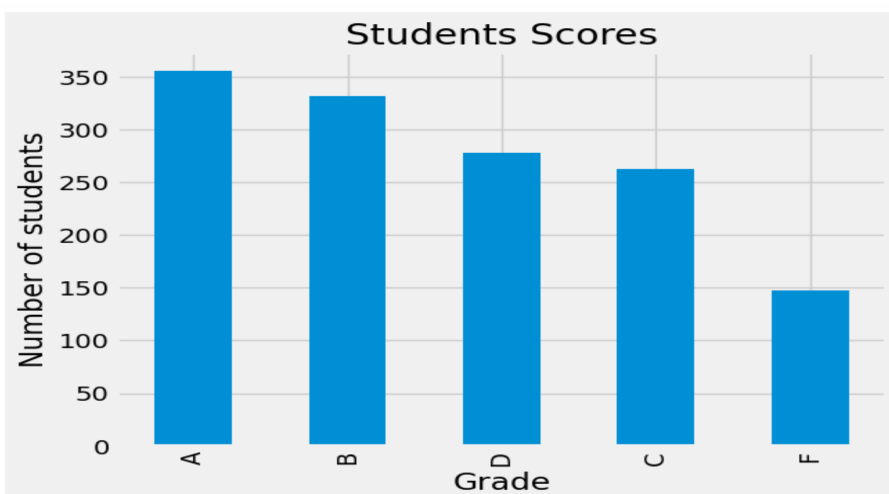

Fig. 7: Number of students in each category of grade (A, B, C, D, F) in academic years (2019-2022)

5.2 Evaluation of the best selected trained ML algorithms

Fig. 8 shows the confusion matrix for students in each category of grade (A, B, C, D, F) in academic years (2019-2022).

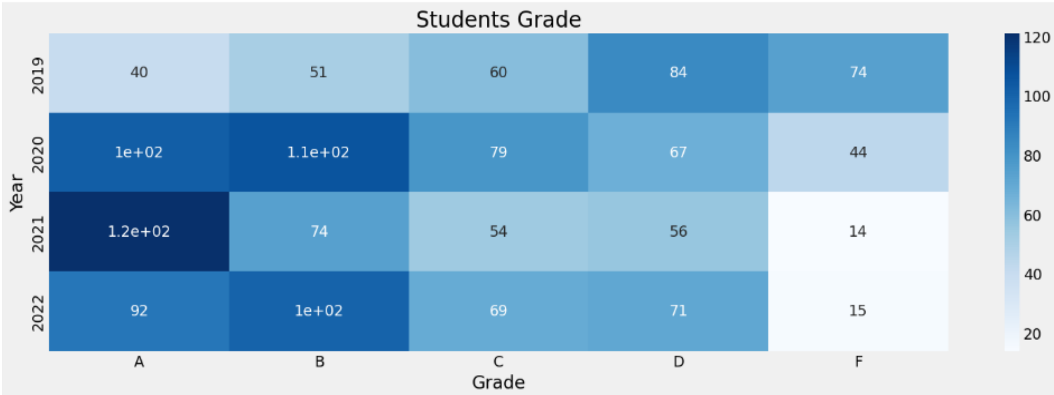

Fig. 8: Confusion matrix for students in each category of grade (A, B, C, D, F) in academic years (2019-2022)

The evaluation metrices were "applied to compare among ML algorithms (Random Forest (RF), Decision Table (DT), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)) such as accuracy, precision, Recall, F- measure were calculated from the TP, TN, FP, and FN values. Table 3 shows evaluation metrices such as the number of each correctly and incorrectly classified instances. Accuracy (is the rate of correct prognostications out of all prognostications made by an algorithm) of each classifier by the following equation (1), Precision (is the rate of true cons over the sum of false cons and true negatives) by the following equation (2), Recall (is the rate of rightly prognosticated issues to all prognostications) by the following equation (3), and F-measure (combines these three criteria into one single metric that ranges from 0 to 1 and takes into account both Precision and Recall) by the following equation (4)."

Table 3: Evaluation metrices (correctly and incorrectly classified instances, accuracy of each classifier, precision, recall, and F-measure)

No.	ML. Algorithms	Correctly classified instances	Incorrectly classified instances	Precision	Recall	F-measure	Accuracy
1	**RF**	685	1	0.99	0.99	0.99	99.8%
2	**DT**	685	1	0.99	0.99	0.99	99.8%
3	**NB**	671	15	0.98	0.97	0.97	97.4%
4	**SVM**	569	117	0.85	0.83	0.82	79.4%
5	**KNN**	685	1	0.99	0.99	0.99	99.8%

$$Accuracy = \frac{T_{p+T_n}}{T_{p+T_{n+F_{p+F_n}}}} \quad (1)$$

$$Precision = \frac{T_p}{T_{p+F_p}} \quad (2)$$

$$Recall = \frac{T_p}{T_{p+F_n}} \quad (3)$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

where T_p "*(True Positive*) is the proportion of positive states that were correctly classified as positive, T_n (*True Negative*) is the proportion of negative states that were correctly classified as negative, F_p *(False Positive)* is the proportion of positive states that were incorrectly classified, and F_n (*False Negative*) is the proportion of negative states that were incorrectly classified as positive [40]."

Fig. 9 presents the number of correctly classified instances and incorrectly classified instances for each classifier (RF, DT, NB, SVM, and KNN). The Random Forest, Decision Table, and K-Nearest Neighbors classifiers were the best, as they correctly classified 685 instances during the prediction and incorrectly classified only 1 instance out of 686 instances from the testing set. Correspondingly, the Naive Bayes classifier correctly classified 671 instances and 15 instances incorrectly. Likewise, the Support Vector Machine classifier correctly classified 569 instances and 117 instances incorrectly.

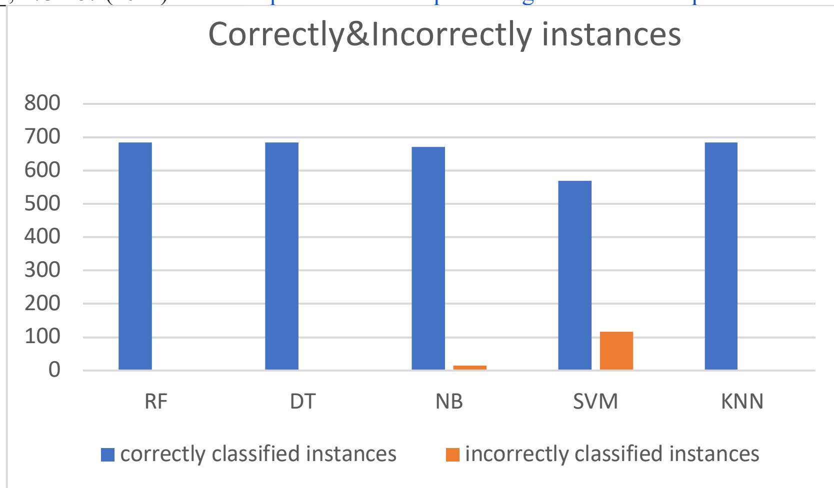

Fig. 9: Correctly & incorrectly classified instances for each classifier

Also, Fig. 10 shows the accuracy of each classifier. The accuracy during testing for the Random Forest classifier was like that of the Decision Table classifier, where K-Nearest Neighbors equals 99.8%. In addition, the Naive Bayes classifier achieves an accuracy of 97.4%. Meanwhile, the Support Vector Machine achieves accuracy of 79.4%.

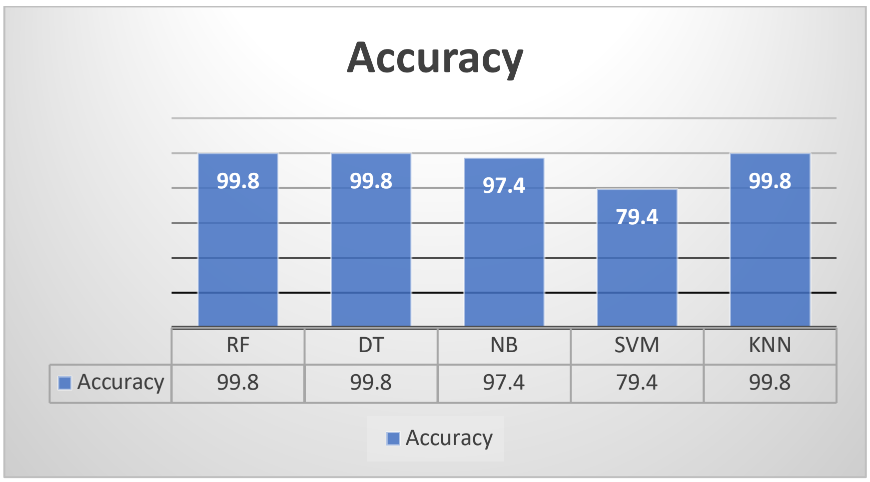

Fig. 10: Accuracy of each classifier

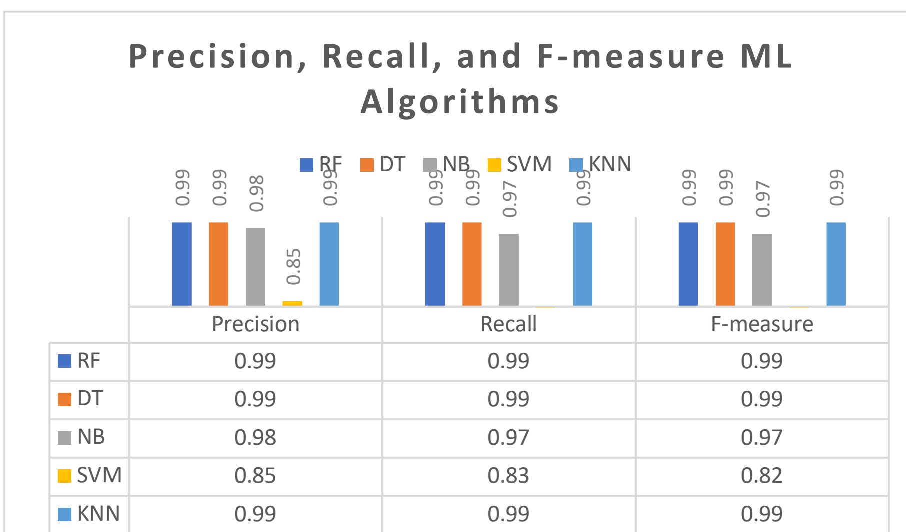

Fig. 11: Precision, recall and F-measure metrices ML classifier

Fig. 11 shows other metrices of evaluation such as precision, F-measure, and recall. The Random Forest classifier, Decision Table, and K- Nearest Neighbors the metrices precision, recall, and F- measure achieves 0.99. Likewise, Naive Bayes classifier the metrices precision achieves 0.98, recall, and F- measure achieves 0.97. Besides, Support Vector Machine classifier the metrices precision achieves 0.85, recall achieves 0.83, and F- measure achieves 0.82.

6 Conclusion and Future Work

This paper presents techniques for predicting students' performance in online tests. These techniques include the integration of deep neural networks and predictive learning analytics to improve students' performance in online testing. These techniques have benefited students in online testing environments by predicting which results in better performance to improve the academic level of students, and this has been done in many studies, most of which we will review. In this study, the study period and students' graduation on time are predicted through (C4.5, K-Nearest Neighbor, Naive Bayes, and Random Forest) techniques. Universities can reduce the failure of students to graduate by conducting more planning and guidance. The application was done on a database consisting of 2022 graduates from undergraduate programs in information engineering and information systems at STMIK Mikroskil Medan from 2011 to 2014, and the results were evaluated using a confusion matrix to determine a more accurate data mining classification algorithm to predict students' graduation on time, where the K-Nearest Neighbor and Random Forest algorithms have the highest accuracy of 72,651%, followed by the C4.5 algorithm of 72,453%, and the Naïve Bayes algorithm of 71,860% [41]. Additionally, this study aimed to understand and predict students' performance based on features extracted from electronic learning management systems. The database presented a number of features from learning management systems that predict student performance. The proposed model consists of five traditional machine learning algorithms, which are further enhanced by applying four collective techniques: bagging, boosting, stacking, and voting. The overall F1 scores for the individual models are as follows: DT (0.675), RF (0.777), GBT (0.714), NB (0.654), and KNN (0.664). The proposed model can be useful for predicting student performance and helping educators to make informed decisions by proactively notifying the students [42]. Also, this study used machine learning techniques to understand and overcome the basic challenges students face, predict at-risk students, and predict dropout students. The study also emphasized the importance of machine learning methods in prediction to improve student performance [43]. Additionally, this study also emphasized the importance of evaluating student knowledge in order to measure student progress and provide feedback to improve and enhance student performance. The results showed accuracy of predictions regarding student performance, as they found that DT, RF, and SVM achieved 98% and emphasized their importance in the prediction process [44]. In the same study, the importance of using machine learning techniques to use students' historical data to predict unknown or future performance [45]. Also, this study discussed one of the main problems, which is predicting the future achievements of students before taking final exams in order to help students achieve better performance and prevent dropout. Machine learning techniques were used to predict student performance and extract data [46]. In addition, this study proposed a machine learning-based framework for early detection of students at risk of poor performance in higher education institutions in Rwanda, where machine learning models were trained and tested from data of graduates of secondary schools and higher institutions, where the decision tree DT achieved high accuracy, as the results helped to monitor students for better performance [47]. This paper aims to predict the performance of students at the Faculty of Engineering, Damietta University, in online exams during the years 2019 to 2022. The dataset contains 1373 instances after excluding 4 instances of missing values. The dataset was divided into train (687 instances (50%)) and exam (686 instances (50%)). Besides, the dataset includes four features, such as year, score, percent, and grade.

This paper includes five ML algorithms that were selected to achieve high prediction accuracy. The ML algorithms are Random Forest (RF), Decision Table (DT), Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Besides, evaluation metrics were applied to compare ML algorithms such as confusion matrix, accuracy, precision, Recall, and F-measure. According to this paper, it is clear that the Random Forest, Decision Table, and K-Nearest Neighbors classifiers were the best, as they correctly classified 685 instances during the prediction of students' performance in the statistics course and incorrectly classified only 1 instance out of 686 instances from the testing set. Correspondingly, the Naive Bayes classifier correctly classified 671 instances and 15 instances incorrectly. Likewise, the Neural Network classifier correctly classified 244 instances and 96 instances incorrectly, and the Support Vector Machine algorithm correctly classified 569 instances and 117 instances incorrectly. This is because neural networks usually need to be trained on a larger number of instances to improve its performance, and this can be achieved if a larger dataset is available for the training process. This has been confirmed by many studies[48][49].

Also, the accuracy during testing for Random Forest, Decision Table, and K-Nearest Neighbors classifiers equals 99.8%. Similarly, the Naive Bayes classifier achieves an accuracy of 97.4%. Likewise, the Support Vector Machine classifier achieves an accuracy of 79.4%. For other metrics of evaluation such as recall, precision, and F-measure. Concerning the Random Forest, Decision Table, and K-Nearest Neighbors classifiers, the metrics recall, precision, and F-measure achieved 0.99. Likewise, the Naive Bayes classifier for recall, precision, and F-measure achieves 0.96. Furthermore, the

Naive Bayes classifier achieves 0.98 metric precision, 0.83 recall, and 0.97 F-measure, while the support vector machine achieves 0.85 metric precision, 0.83 recall, and 0.82 F-measure. Therefore, the paper has been successfully achieving high accuracy in predicting the performance of students at the Faculty of Engineering, Damietta University, in an online exam using ML algorithms. In the future, we intend to collect significant data on students' performance on online exams to predict the performance of many online courses. In addition, we use other machine learning classifiers. And using many different algorithms that can predict students' performance, as the results of each algorithm differ and vary depending on the size and type of data it processes. More learning analytics processes and techniques can also be used to develop many skills. Learning analytics can also be applied through various e-learning management systems in order to improve the educational process practices in higher education institutions. Conduct learning analyzes in different educational environments to verify the impact of its use in the educational process.

Conflicts of Interest Statement

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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References

[1] Y. S. Mian, F. Khalid, A. W. C. Qun, and S. S. Ismail, "Learning Analytics in Education, Advantages and Issues: A Systematic Literature Review," Creat. Educ., vol. 13, no. 09, 2022, doi: 10.4236/ce.2022.139183.

[2] M. Scheffel, H. Drachsler, S. Stoyanov, and M. Specht, "Quality Indicators for Learning Analytics: EBSCOhost," J. Educ. Technol. Soc., vol. 17, no. 4, 2014.

[3] M. Bienkowski, M. Feng, and B. Means, "EDM-00: Enhancing teaching and learning through educational data mining and learning analytics," in USA 2018-01-11 77p, 2012.

[4] S. Dawson and G. Siemens, "Analytics to literacies: The development of a learning analytics framework for multiliteracies assessment," Int. Rev. Res. Open Distance Learn., vol. 15, no. 4, 2014, doi: 10.19173/irrodl.v15i4.1878.

[5] F. Martin and A. Ndoye, "Using learning analytics to assess student learning in online courses," J. Univ. Teach. Learn. Pract., vol. 13, no. 3, 2016, doi: 10.53761/1.13.3.7.

[6] R. Ferguson, "Learning analytics: Drivers, developments and challenges," International Journal of Technology Enhanced Learning, vol. 4, no. 5–6. 2012. doi: 10.1504/IJTEL.2012.051816.

[7] D. T. Tempelaar, A. Heck, H. Cuypers, H. Van Der Kooij, and E. Van De Vrie, "Formative assessment and learning analytics," in ACM International Conference Proceeding Series, 2013. doi: 10.1145/2460296.2460337.

[8] S. K. Banihashem, K. Aliabadi, S. Pourroostaei Ardakani, M. Nili Ahmadabadi, and A. Delaver, "Investigation on the Role of Learning Theory in Learning Analytics," 2019. doi: https://doi.org/10.30476/ijvlms.2019.84294.1001.

[9] G. Siemens and P. Long, "Penetrating the Fog: Analytics in Learning and Education," Educ. Rev., vol. 46, no. 5, 2011.

[10] J. T. Avella, M. Kebritchi, S. G. Nunn, and T. Kanai, "Learning analytics methods, benefits, and challenges in higher education: A systematic literature review," J. Asynchronous Learn. Netw., vol. 20, no. 2, 2016, doi: 10.24059/olj.v20i2.790.

[11] B. Dietz-Uhler and J. E. Hurn, "Using learning analytics to predict (and improve) student success: A faculty perspective," J. Interact. Online Learn., vol. 12, no. 1, 2013.

[12] V. C. Smith, A. Lange, and D. R. Huston, "Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses," J. Asynchronous Learn. Netw., vol. 16, no. 3, 2012, doi: 10.24059/olj.v16i3.275.

[13] L. P. Macfadyen and S. Dawson, "Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan," Educ. Technol. Soc., vol. 15, no. 3, 2012.

[14] B. Minaei-Bidgoli, D. A. Kashy, G. Kortemeyer, and W. F. Punch, “Predicting student performance: An application of data mining methods with an educational web-based system,” in Proceedings - Frontiers in Education Conference, FIE, 2003. doi: 10.1109/FIE.2003.1263284.

[15] H. Wang, R. Czerminski, and A. C. Jamieson, “Neural Networks and Deep Learning,” in The Machine Age of Customer Insight, 2021. doi: 10.1108/978-1-83909-694-520211010.

[16] G. Casalino, L. Grilli, P. Limone, D. Santoro, and D. Schicchi, “Deep learning for knowledge tracing in learning analytics: An overview,” in CEUR Workshop Proceedings, 2021.

[17] A. Mathew, P. Amudha, and S. Sivakumari, “Deep learning techniques: an overview,” in Advances in Intelligent Systems and Computing, 2021. doi: 10.1007/978-981-15-3383-9_54.

[18] M. Tsiakmaki, G. Kostopoulos, S. Kotsiantis, and O. Ragos, “Transfer learning from deep neural networks for predicting student performance,” Appl. Sci., vol. 10, no. 6, 2020, doi: 10.3390/app10062145.

[19] A.A. Mubarak, H. Cao, and S. A. M. Ahmed, “Predictive learning analytics using deep learning model in MOOCs’ courses videos,” Educ. Inf. Technol., vol. 26, no. 1, 2021, doi: 10.1007/s10639-020-10273-6.

[20] X. Wang and M. Gao, “Predicting Students’ Performance in an Online Testing Environment Using Eye-movement Behavior and Cognitive Styles,” in Proceedings - 2023 International Conference on Artificial Intelligence and Education, ICAIE 2023, 2023. doi: 10.1109/ICAIE56796.2023.00028.

[21] G. Ben Brahim, “Predicting Student Performance from Online Engagement Activities Using Novel Statistical Features,” Arab. J. Sci. Eng., vol. 47, no. 8, 2022, doi: 10.1007/s13369-021-06548-w.

[22] S. Jayaprakash, S. Krishnan, and J. Jaiganesh, “Predicting Students Academic Performance using an Improved Random Forest Classifier,” in 2020 International Conference on Emerging Smart Computing and Informatics, ESCI 2020, 2020. doi: 10.1109/ESCI48226.2020.9167547.

[23] V. U. Kumar, A. Krishna, P. Neelakanteswara, and C. Z. Basha, “Advanced Prediction of Performance of a Student in an University using Machine Learning Techniques,” in Proceedings of the International Conference on Electronics and Sustainable Communication Systems, ICESC 2020, 2020. doi: 10.1109/ICESC48915.2020.9155557.

[24] E. G. Rincon-Flores, E. Lopez-Camacho, J. Mena, and O. O. Lopez, “Predicting academic performance with Artificial Intelligence (AI), a new tool for teachers and students,” in IEEE Global Engineering Education Conference, EDUCON, 2020. doi: 10.1109/EDUCON45650.2020.9125141.

[25] H. M. R. Hasan, A. K. M. S. A. Rabby, M. T. Islam, and S. A. Hossain, “Machine Learning Algorithm for Student’s Performance Prediction,” in 2019 10th International Conference on Computing, Communication and Networking Technologies, ICCCNT 2019, 2019. doi: 10.1109/ICCCNT45670.2019.8944629.

[26] A.Daud, M. D. Lytras, N. R. Aljohani, F. Abbas, R. A. Abbasi, and J. S. Alowibdi, “Predicting student performance using advanced learning analytics,” in 26th International World Wide Web Conference 2017, WWW 2017 Companion, 2017. doi: 10.1145/3041021.3054164.

[27] X. Ma, Y. Yang, and Z. Zhou, “Using machine learning algorithm to predict student pass rates in online education,” in ACM International Conference Proceeding Series, 2018. doi: 10.1145/3220162.3220188.

[28] D. A. Shafiq, M. Marjani, R. A. A. Habeeb, and D. Asirvatham, “Student Retention Using Educational Data Mining and Predictive Analytics: A Systematic Literature Review,” IEEE Access, vol. 10. 2022. doi: 10.1109/ACCESS.2022.3188767.

[29] W. Xiao, P. Ji, and J. Hu, “A survey on educational data mining methods used for predicting students’ performance,” Engineering Reports, vol. 4, no. 5. 2022. doi: 10.1002/eng2.12482.

[30] A.Dutt, M. A. Ismail, and T. Herawan, “A Systematic Review on Educational Data Mining,” IEEE Access, vol. 5. 2017. doi: 10.1109/ACCESS.2017.2654247.

[31] V. B. S. Prasath et al., “Effects of Distance Measure Choice on KNN Classifier Performance - A Review,” arXiv:1708.04321v3, 2019.

[32] R. Shah, “Introduction to k-Nearest Neighbors (kNN) Algorithm.” Accessed: Sep. 15, 2023. [Online]. Available: https://ai.plainenglish.io/introduction-to-k-nearest-neighbors-knn-algorithm-e8617a448fa8

[33] D. Subramanian, “K-Nearest Neighbor Algorithm: An Introduction.” Accessed: Sep. 15, 2023. [Online]. Available:

https://builtin.com/machine-learning/nearest-neighbor-algorithm

[34] S. Salcedo-Sanz, J. L. Rojo-Álvarez, M. Martínez-Ramón, and G. Camps-Valls, "Support vector machines in engineering: An overview," Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, vol. 4, no. 3. 2014. doi: 10.1002/widm.1125.

[35] R. B. V. Idiot, "An Idiot's Guide to Support Vector Machines (SVMs)." Accessed: Sep. 16, 2023. [Online]. Available: https://web.mit.edu/6.034/wwwbob/svm-notes-long-08.pdf

[36] S. B. Kotsiantis, "Decision trees: A recent overview," Artificial Intelligence Review, vol. 39, no. 4. 2013. doi: 10.1007/s10462-011-9272-4.

[37] N. S. Chauhan, "Decision Tree Algorithm, Explained." Accessed: Sep. 12, 2023. [Online]. Available: https://www.kdnuggets.com/2020/01/decision-tree-algorithm-explained.html

[38] G. Biau and E. Scornet, "A random forest guided tour," Test, vol. 25, no. 2, 2016, doi: 10.1007/s11749-016-0481-7.

[39] K. Kashyap, "Machine Learning- Decision Trees and Random Forest Classifiers." Accessed: Sep. 16, 2023. [Online]. Available: https://medium.com/analytics-vidhya/machine-learning-decision-trees-and-random-forest-classifiers-81422887a544

[40] J. Huang, "Performance measures of machine learning," Univ. West. Ontario, 2008.

[41] Gunawan, Hanes, and Catherine, "C4.5, K-Nearest Neighbor, Naïve Bayes and Random Forest Algorithms Comparison to Predict Students' On Time Graduation," Indones. J. Artif. Intell. Data Min., vol. 4, no. 2, 2021.

[42] F. Saleem, Z. Ullah, B. Fakieh, and F. Kateb, "Intelligent decision support system for predicting student's e-learning performance using ensemble machine learning," Mathematics, vol. 9, no. 17, 2021, doi: 10.3390/math9172078.

[43] B. Albreiki, N. Zaki, and H. Alashwal, "A systematic literature review of student' performance prediction using machine learning techniques," Educ. Sci., vol. 11, no. 9, 2021, doi: 10.3390/educsci11090552.

[44] N. Alruwais and M. Zakariah, "Evaluating Student Knowledge Assessment Using Machine Learning Techniques," Sustain., vol. 15, no. 7, 2023, doi: 10.3390/su15076229.

[45] A. R. F. Al-Shaikhli, "Estimation Of Students' Performance in Distance Education Using Ensemble-Based Machine Learning," Karabuk University, 2023. [Online]. Available: http://acikerisim.karabuk.edu.tr:8080/xmlui/handle/123456789/2545

[46] S. Batool, J. Rashid, M. W. Nisar, J. Kim, H. Y. Kwon, and A. Hussain, "Educational data mining to predict students' academic performance: A survey study," Educ. Inf. Technol., vol. 28, no. 1, 2023, doi: 10.1007/s10639-022-11152-y.

[47] E. Masabo et al., "Early detection of students at risk of poor performance in Rwanda higher education using machine learning techniques," Int. J. Inf. Technol., vol. 15, no. 6, 2023, doi: 10.1007/s41870-023-01334-3.

[48] S. Feng, H. Zhou, and H. Dong, "Using deep neural network with small dataset to predict material defects," Mater. Des., vol. 162, 2019, doi: 10.1016/j.matdes.2018.11.060.

[49] A. Alwosheel, S. van Cranenburgh, and C. G. Chorus, "Is your dataset big enough? Sample size requirements when using artificial neural networks for discrete choice analysis," J. Choice Model., vol. 28, 2018, doi: 10.1016/j.jocm.2018.07.002.