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TOWARD IMPROVING STUDENT PERFORMANCE IN AN ONLINE ENVIRONMENT USING EDUCATIONAL DATA MINING APPROACH

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ABSTRACT

As online learning grows increasingly popular; there is an increasing demand for practical strategies for enhancing student performance. Analyzing Student performance is one of the most significant issues for decision-makers. Educational data mining techniques are useful for exploring hidden data inside data, finding a pattern, and analyzing student performance. In this paper, we present a hybrid methodology for improving prediction and optimizing student learning outcomes by combining educational data mining (EDM) techniques with ensemble methods. We performed experiments with an online dataset to compare the performance of our proposed model to classic EDM and ensemble approaches. The results demonstrate that our model outperformed the other techniques and obtained a considerable increase in accuracy. Our findings imply that integrating EDM approaches with ensemble methods can increase student performance in online learning environments. This research has significant implications for educators and researchers who want to improve the performance of students and optimize the use of data-driven approaches in online education.

Keywords: *Student Performance; Data Mining; E-Learning; Ensemble Techniques*

1. INTRODUCTION

Education is a crucial aspect of our lives, and academic performance plays a vital role in shaping our future. The performance of students in their academic pursuits not only affects their immediate future but also has long-term implications. Therefore, it is essential to ensure that students are performing well in their studies [1]

Academic performance is a reflection of a student's ability to learn and apply knowledge. It is an indicator of their understanding of the subject matter and their capacity to use that knowledge to solve real-world problems. Good academic performance is also an essential factor in determining a student's future career prospects. Employers tend to take into account one's academic performance when hiring, as it is seen as a measure of an individual's discipline, dedication, and work ethic. It is crucial to monitor students' academic performance in E-learning to identify areas of weakness and provide support to help them improve. Teachers and parents are responsible for keeping track of students' performance and providing assistance to help them excel. In addition, technology can also play a vital role in monitoring and improving students' academic performance. Data mining techniques can analyze students' performance data and provide personalized recommendations based on their learning needs [2]. All of these data can be analyzed to address a wide range of academic issues, such as the provision of recommendations and automated project assessment. This data has been analyzed using a number of methods based on machine learning over the years, but data mining and deep learning techniques are only now gaining popularity in educational data mining [3].

The goal of this paper is to investigate the student performance by developing a model that combines traditional data mining techniques and ensemble methods. The experiments were carried out using an E-learning dataset.

Researchers have been using ensemble methods with traditional data mining techniques [7,8,9]. Typically, they integrate ensemble methods and a single classifier. The objective of our research was to provide various combinations of these techniques by adding more than one classifier to ensemble methods in order to observe an accuracy enhancement.

The paper is structured as follows: The second section provides an overview of related work, the third section presents the methodology of this study, followed by displaying the results of our findings in the fourth section. The final section is devoted to discussion and future work.

2. OVERVIEW OF RELATED WORK

This study attempts to create a comprehensive review for evaluating data from online courses in order to assist education institutions in predicting student achievement. Several researches have been conducted to investigate learners' prediction of achievement using past learning outcomes to forecast outcomes in the future at the exact same level. Furthermore, several researchers have looked into the aspects that influence student success. It is widely believed that the combination of traditional data mining techniques and ensemble methods will improve the accuracy of student performance predictions [3,4.7].

A summary of pervious research studies is provided below.

In [4], the authors attempted to forecast the student's exam performance. They used the K-nearest neighbor and decision tree and to model the experiment. The study revealed that the decision tree accurately predicts whether or not a learner will be successful or unsuccessful in their courses. In [5], in the field of analyzing student performance, researchers examined different classification techniques: REP-tree, J48, Naive-Bayes, multilayer perceptron, and SMO. The data set was created from 300 student records from a college's computer science department. WEKA was the study's tool of choice. According to the findings, Multilayer perceptron performance is the most accurate method to forecast student success. Multilayer perceptron accuracy was higher than other classifiers when compared to other techniques. In [6], the authors were trying to identify the fundamental characteristics that have a major impact on secondary student performance. This was accomplished by integrating single and ensemble-based classifiers to generate an appropriate classification approach, which was subsequently applied to predict student achievement. Initially, some of data mining techniques were applied: multilayer perceptron, decision tree, and PART; additionally, bagging, multi-boost, and voting were employed separately. In order to improve the accuracy of the previous classifiers, one classifier and an ensemble method were merged to generate additional models. Based on the results of the experiment, multi-boost with multilayer perceptron is more accurate than other methods. In [7], researchers attempted to predict student dropout using data mining techniques. The results showed that dropout was possible, In the majority of instances, false-positive rates range between 0.10 and 0.15 on the average, with an accuracy values of greater than 0.80. Among the methods, they select the following methods to conduct their experiment, logistic regression, random forest, support vector machines, naive Bayes, decision trees, and K-nearest neighbors. In terms of accuracy, F-measure, and precision, random forest succeeded other machine learning algorithms.

In this study [8], the researchers intended to conduct investigations into educational data mining to predict student achievement in E-learning. Classifiers such as decision tree, KNN, and support vector machine were applied to evaluate the proposed model. Ensemble methods such as Random Forest, Boosting, and Bagging were

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employed to improve the efficacy of the classifiers. Using the voting method, the three techniques were integrated. The suggested model enhanced Nave Bayes' accuracy. The study demonstrated that the use of ensemble methods is enhancing accuracy and will result in classifying student performance effectively. In [9], researchers focused on anticipating student performance in various interactive online sessions by analyzing data collected with the E-learning. The data set records student engagement in classes, such as the amount of text modification, keystrokes, and time expended on every task. The classifiers utilized were support vector machine, logistic regression, multi-layer perception, random forest, and naive Bayes logistic regression. Fivefold cross-validation and randomized data partitioning for training and assessment were used as evaluation methods. Except for the testing session, the model was trained in all sessions. The RF classifier model had the highest accuracy.

In this study [10], the authors were exploring the non-academic parameters and their influence on student performance. Eight data mining approaches and ensemble methods were used to develop the proposed model. They are respectively, Support Vector Machine, Multi-Layer Perceptron, Logistic Regression, Decision Tree, and Random Forest, Bagging, and Voting. They concluded that academic characteristics such as final grades have an impact on their graduation, but so do non-academic parameters such as demography. They believed that combining academic and non-academic parameters would result in better prediction of student achievement.

In this study [11], the authors built a model utilizing ensemble techniques to investigate the characteristics that lead to student dropout. Various attributes were explored such as academic achievements, behavior features, and social traits were used. The performance of students throughout their early years has the greatest influence on their graduation. Ensemble methods, according to the researchers, are the best techniques for investigating student performance.

In order to determine whether students' learning behaviors were important, researchers examined an E-learning data set [12]. They used the ensemble methods, voting, bagging, and boosting, alongside with four data mining techniques, which are Decision Tree, Naive Bayes, K-Nearest Neighbor, and Support vector machines. Using the voting process, the highest accuracy was achieved.

In [13], the relationships between students and online learning have been investigated. A combination of ensemble methods with traditional data mining was used: Decision Trees, K- Nearest Neighbors, and Support Vector Machines. It was discovered that student behavior was highly correlated with academic achievement. In contrast, ensemble techniques increased accuracy.

This paper [14] investigates various factors that influence student performance. The researchers provide a model that combines traditional techniques as well as ensemble methods. They specifically use three DM techniques, MLP, Random Forest, and PART, before introducing three ensemble methods, Bagging, Logitboost, and Voting, to each unique DM technique. The major goal of integrating these techniques is to improve the model's performance. In terms of accuracy, the results indicated that Logitboost with Random Forest outperforms the other models. The model is evaluated by using four metrics: accuracy, precision, recall, and F-measure

In [15], the authors used two different educational data set to compare different EDM techniques. Random Forest, Naive Bayes, K-nearest-neighbor, Logistic Regression, , Artificial Neural Network, XGboost, Support Vector Machine, and Decision Tree classifications have been applied. They observed that random forest outperformed other classifiers.

3. METHODOLOGY

We detail the data set utilized to conduct this study in this section, followed by a description of the proposed approach and the evaluation metrics.

3.1 Data Set

3.1.1 data collection

The data was gathered from a second-year undergraduate science course taught in a hybrid format at a North American university [16]. The raw dataset is made up of 486 enrolled students' event logs, with a total of 305933 records acquired from the university's learning management system (LMS). As we can see in Table 1, the dataset has fourteen attributes represent the students' interaction in the courses.

Table 1 Dataset Description

Attribute	Description	Type
Student Id	University ID	Nominal
Number of Logins	The number of times a student entered the	Numeric

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	LMS course site	
Number of Content Reads	The number of times a student entered the course material	Numeric
Number of Forum Reads	The number of times a student read posts on the discussion section	Numeric
Number of Forum Posts	The number of times a student post on the discussion section	Numeric
Number of quiz review	The number of times a student checked their quiz solution before submitting it	Numeric
Assignment 1 lateness indicator	Whether or not a student submits Assignment 1 late	Numeric
Assignment 2 lateness indicator	Whether or not a student submits Assignment 2 late	Numeric
Assignment 3 lateness indicator	whether or not a student submits Assignment 3 late	Numeric
Assignment 1 duration to submit(in hours)	The time between posting Assignment 1 and submitting it	Numeric
Assignment 2 duration to submit(in hours)	The time between posting Assignment 2 and submitting it	Numeric
Assignment 3 duration to submit(in hours)	The time between posting Assignment 3 and submitting it	Numeric
Average Assignment duration to submit(in hours)	The average time between posting and submitting Assignments	Numeric
Engagement Level	Level of student involvement	Nominal

The features can be numerical or nominal. They look into how the student interacts with the assignments, posts, and quizzes.

3.1.2 Data Cleaning

It is crucial to delete unnecessary values and missing objects from a collection of the data as part of preprocessing. The data collection has no missing values.

3.2 Feature Selection

Feature selection refers to the procedure of selecting the appropriate characteristics from a dataset using established requirements. Data reduction techniques fall into two categories: wrapper methods and filter methods. The filter approach employs variable-ranking methods to rank the attributes, with the most highly ranked attributes being included in the machine learning method [17].

Both the information gain ranking filter and the correlation-ranking filter were utilized in this study. At each node of the decision tree, the information gain metric is considered to select the test feature. The information gain (IG) metric identifies attributes with major values. It is calculated using the next formula:

$$IG(T,a)=H(T) - H(T|a)$$

When T is a random variable and $H(T|a)$ represents T's entropy while considering the value of the feature a.

The correlation coefficients is a statistical indicator of how strongly two variables are linearly related [18]. It is calculated using the next formula:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

Where:

- n = *Number of data points*
- $\sum x$ = *Total of the 1st data List*
- $\sum y$ = *Total of 2nd data list*
- $\sum xy$ = *Total of the product of the first and second values*
- $\sum x2$ = *Total of 1st values' squares*
- $\sum y2$ = *Total of 2nd value's squares*

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Figure 1 shows the results of applying correlation ranking. We observe that the amount of time students devote to submitting their assignments has an important influence on their academic achievement. When students continuously submit their assignments late or at the very last moment, it could represent a sign that they are experiencing academic difficulties that reduce their ability to complete their work on time. As a result, their academic performance might drop and students may become at risk of failing. Instructors can gain useful knowledge about student behavior and provide help to support their academic performance by monitoring the amount of time students spend submitting assignments.

```
       Correlation Ranking Filter
Ranked attributes:
 0.8896   11 Assignment 2 duration to submit (in hours)
 0.825    13 Average time to submit assignment (in hours)
 0.7545   10 Assignment 1 duration to submit (in hours)
 0.711    12 Assignment 3 duration to submit (in hours)
 0.1786    7 Assignment 1 lateness indicator
 0.1357    9 Assignment 3 lateness indicator
 0.1207    8 Assignment 2 lateness indicator
 0.1121    5 # Forum Posts
 0.107     4 # Forum Reads
 0.0765    2 # Logins
 0.0443    1 Student ID
 0.0421    3 # Content Reads
 0.0355    6 # Quiz Reviews before submission
```

Figure 1 Correlation Ranking

3.3 Data Mining Tool

In this study, we used the WEKA software, which is a well-known Java-based machine-learning program, and New Zealand's University of Waikato devised it. [19]. The WEKA package offers graphical user interfaces for easier access to this capabilities, data analysis and predictive modeling algorithms, and visualization tools. It contains several machine learning and data mining methods.

3.4 Proposed Model

This study's objective is to assess the efficacy and outcomes of each model of prediction using ensemble methods and traditional data mining techniques. The proposed model that will be used with the data set is shown in Figure 3. We first gather the data set and preprocess it for the investigation. To create a performance model, three data mining techniques: Random Forest (RF), Decision Tree (DT), and Naive Bayes (NB) will be used. Three ensemble approaches, Boosting, Bagging, and Voting, are utilized in addition to the classifiers already described to enhance their performance. Both boosting and bagging are used to increase the effectiveness of the student prediction model. For a more precise prediction, Using the voting process, two to three data mining techniques have been included in every ensemble method. The final stage of the model will involve analyzing and evaluating the outcomes. The data was split into training and test sets. The effectiveness of each prediction model has been examined using K-fold cross-validation. This method resolves the variance issue when testing a model. K-fold cross-validation, in essence, folds the training set into ten folds. Before the final fold is tested during training, nine folds are applied. This more accurately depicts the model performance because an average of the various accuracy levels is taken. We ran the method ten times. The default settings for the WEKA program were used to run each model.

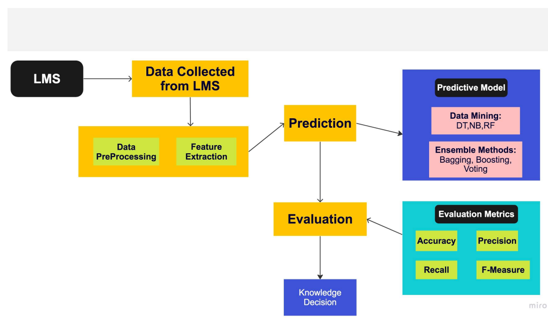

Figure 2 Proposed Model

3.4 Overview of Traditional Data Mining

3.4.1 Decision Tree

The decision tree method is a member of the supervised learning algorithm family. In numerous disciplines, including machine learning, image processing, and pattern recognition, decision trees are one of the most effective techniques. The decision tree algorithm can tackle both classification and regression problems. Researchers can build models for training that determine the group of a variable. by learning basic decision rules from training data. Every tree contains nodes and branches. Each node is identified by a feature within the classification category, and each subset identifies a possible value for the node [20].

3.4.2 random forest

Random forest is a supervised algorithm in machine learning that predicts output through the integration of multiple decision trees into a forest. By applying

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ensemble learning to the predictions of all decision trees, a reliable forecast can be obtained [20].

3.4.3 naive Bayes

Naive Bayes is a Bayesian classifier that uses the probability theory theorem of Bayes. The Naive Bayes method uses Bayes' theorem for each pair of features, taking the value of the class variable into consideration and assuming that the features are conditionally independent. In naive Bayes, it indicates that the classification of every pair of features is not dependent on the classification of the other pairs [21].

3.5 Overview of Ensemble Methods

3.5.1 Bagging

Bagging is the most popular independent technique for improving accuracy by combining the results of various classifiers that have been trained into one prediction, resulting in a more accurate hybrid classifier. This technique trains classifiers using replacements on subsets of instances from the training set, ensuring that the population sizes of the initial training set and each sample are similar [22]. By constructing a composite classifier and integrating the outcomes of various models of classification into a single prediction, bagging aims to enhance the accuracy of unreliable classification models. This method guarantees that each data has a similar likelihood of being chosen [23].

3.5.2 Boosting

Boosting is a group of methods that transform weakness learners into strong learners. Boosting operates by training various Boosting operates by training multiple classification algorithms, obtaining their predictions, and then modifying the weights of the weaker classifier to reduce its error rate, gaining their predictions, and then adjusting the weighting of the weakest classifier to decrease its errors. Boosting was exclusively utilized for binary classification. This adaptive limitation is avoided by the AdaBoost algorithm. Boosting determines instances' weights according to their potential size [24].

3.5.3 Voting

A voting method is a model developed using machine learning that predicts the class by using the output with the highest probability derived from multiple base models. Learning classifiers are voted on by the majority (for classification) and average (for regression) in the voting process. At last, the greatest vote total or class average will be predicted [25].

3.6 Evaluation Measures

In this study, the WEKA Data Mining tool was used to conduct the experiments. In this investigation, data were uploaded into the WEKA software. Then, various data mining techniques and ensemble methods were examined to identify which provided the most accurate predictions, and a decision was made based on this comparison. Accuracy, precision, recall, and F-measure are common metrics applied for evaluation the results of the performance.

3.6.1 Accuracy

Accuracy is the degree to which a predictor correctly forecasts the effect of a predicted attribute on new data. This indicates the capacity and efficacy of the classifier. Accuracy equals the proportion of accurate predictions divided by the overall sum of the forecasts. [27]. It is calculated using the next formula

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

Where:

- True positives (TP): cases predicted to be positive.
- True negatives (TN): cases predicted to be negative.
- False positives (FP): cases that are predicted to be positive but are in fact positive.
- False negatives (FN) are cases that are predicted to be negative but are in fact positive.

3.6.2 Precision

Precision is the percentage of correctly identified positive predictions to the total number of positive predictions, whether correctly or incorrectly identified [26]. It is calculated using the next formula

$$Precision = TP/(TP + FP)$$

3.6.3 Recall

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The recall is calculated by dividing the number of correctly classified positive predictions by the total number of positive predictions [26]. It is calculated using the next formula:

$$Recall = TP/(TP + FN)$$

4.6.4 F-measure

F-measure is integrating both precision and recall into one individual measurement [26]. It is calculated using the next formula:

$$F-measure = (2 * Recall * Precision)/(Recall + Precision)$$

4. EXPERIMENTAL RESULTS

In this section provides the outcomes for every one of these models of prediction (traditional data mining without and within ensemble methods).

4.1 Data Mining Techniques

As indicated in the earlier section, the experiments were conducted using the WEKA software. Figure 3 explains the implantation of the data mining techniques model. In the beginning, the data was fed applying the CSVLoader operator to initiate the establishment of models. In the last section, the selected dataset's description and features were described. The entire set of 14 attributes from the dataset was selected for the experiments. By connecting the "CSVLoader" to a text viewer in WEKA, a table of all features will be displayed. Second, an operator had been assigned the data. named "ClassAssigner" in order to identify which feature to be described as a class. Third, when the class had been assigned, the data will linked to the WEKA "CrossValidationFoldMaker" cross-validation operator. There were two components: training and testing. In each cross-validation iteration, there were nine subsets trained the model and one for testing. Consequently, training and validation of the model were conducted sequentially in a single step, which was acknowledged as an appropriate test as the outcome of testing data is unidentified. As illustrated in Figure 3, cross-validation was then applied to each method. The data has been split into two categories: training and testing. The training data were used to train the method, while the testing data were used to evaluate the method. The "Classifier PerformanceEvaluator" was then used to determine the model's efficacy. On the other hand, all of the models in Figures 4 and 5 were created using same procedure as in Figure 3.

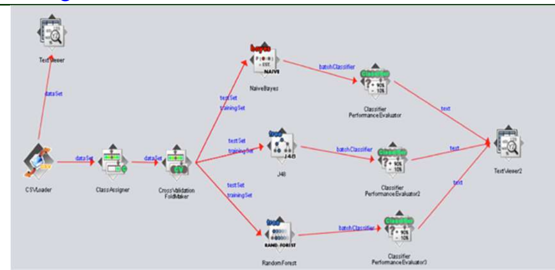

Figure 3 Traditional DM technique implementation using WEKA

4.2. Ensemble Methods

4.2.1 boosting

The exact same steps will be applied to the model for boosting. Uploading the data set, connecting the data to a class, linking it to the cross-validation in order to link the data to a method, and then employing the model are the steps involved in building a machine-learning model. As shown in Figure 4, number of experiments has been conducted using boosting method. At first, three separate experiments utilizing every data mining technique have been performed. Boosting was then conducted with two algorithms simultaneously using voting methods, which are boosting with random forest and decision trees and boosting with naive Bayes and random forest. Finally, an experiment was performed by using boosting with all three data mining methods using the voting method. The aim was to determine if there is an enhancement in performance when we modify the model.

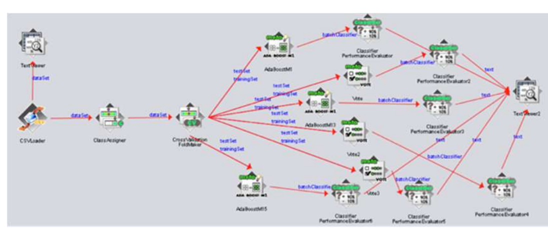

Figure 4 Boosting Implementation Using WEKA

4.2.2 bagging

Figure 9 illustrates the procedure that will be utilized for the bagging model, which is identical to the one described in the subsection on boosting implementation.

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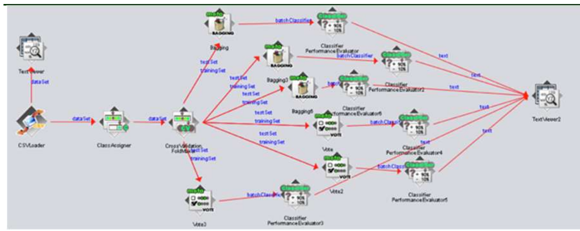
Figure 5 Bagging Implementation Using WEKA

4.3 Results

4.3.1 Tradition Data Mining

Table 2 demonstrates the four different metrics that used to evaluate the performance of data mining techniques. The accuracy of the decision tree is 99.1%, its precision is 0.99, its recall is 0.99, and its F-measure is 0.99. For naive Bayes, the accuracy is 97.7%, the precision is 0.98, the recall is 0.97, and the F-measure is 0.97. Random forest had an accuracy of 98.9%, a precision of 0.99, a recall of 0.99, and an F-measure of 0.99.

Table 2 Results of Evaluation Metrics For DM Techniques

Evaluation Measure	DT	NB	RF
Accuracy	99%	97%	98%
Precision	0.99	.98	0.99
Recall	0.99	.97	0.99
F-Measure	0.99	.97	0.99

4.3.2 Boosting

The evaluation metrics for boosting using traditional data mining techniques are displayed in Table 3. Accuracy is 99%, precision is 0.96, recall is 0.96, and F-measure is 0.96 when boosting was combined with decision trees. Boosting with random forest produced results of 98% accuracy, 0.98 precisions, 0.98 recall, and final the F-measure is 0.98. When applying boosting and naive Bayes: the accuracy is 98.7%, the precision is 0.98, the recall is 0.98, and the F-measure is 0.98. Boosting with decision trees and naive Bayes achieved the following results: the accuracy is 99%, the precision is 0.99, the recall is 0.99, and the F-measure is 0.9. Finally when boosting was combined with decision trees, naive Bayes and random forest methods, their evaluation results as follows: the accuracy is 99%, the precision is 0.99, the recall is 0.99, and the F-measure is 0.9.

Table 3 Results of Evaluation Metrics For Boosting

Evaluation Measures	Boosting					
	DT	NB	RF	DT+NB	RF+DT	All
racy	99%	98.7%	98%	99%	99%	99%
ision	.96	0.98	0.98	0.99	0.99	0.99
ll	.96	0.98	0.98	0.99	0.99	0.99
easure	.96	0.98	0.98	0.99	0.99	0.99

4.3.3 Bagging

The evaluation metrics for bagging with traditional data mining are shown in Table 4. The Accuracy is 98%, precision is 0.99, recall is 0.99, and F-measure is 0.98 when boosting was combined with decision trees. Bagging with random forest yields an accuracy of 97%, the precision is 0.98, the recall is 0.97, and F-measure is 0.97. When applied bagging to naive Bayes, the accuracy is 98%, the precision is 0.98, the recall is 0.98, and the F-measure is 0.98. Bagging with naive Bayes and decision trees obtains 98% accuracy, 0.98 precision, 0.98 recall, and 0.98 F-measure. The accuracy is 97%, the precision is 0.98, the recall, is 0.98 and the F-measure is 0.98 when are the outcomes of applying the bagging method to decision trees and random forest. Using bagging with all three data mining techniques produces an accuracy of 98.9%, precision of 0.99, recall of 0.799, and F-measure of 0.989.

Table 4 Results of Evaluation Metrics For Bagging

Evaluation Measures	Bagging					
	DT	NB	RF	Dt+NB	RF+DT	ALL
Accuracy	98%	98%	97%	98%	99%	98.9%
Precision	0.99	0.98	0.98	0.98	0.99	0.99
Recall	0.99	0.98	0.97	0.98	0.99	0.99
F-Measure	0.98	0.98	0.97	0.98	0.99	0.989

5. EVALUATION RESULTS AND DISCUSSION

In this section, outcomes of all methods will be evaluated and discussed. As pointed out previously, four different metrics will be utilized for evaluations, which are: accuracy, precision, recall, and F-measure.

5.1 Accuracy

In every experiment we performed using traditional data mining techniques and ensemble approaches, the accuracy results have been greater than 97%. We found that naive Bayes had the lowest average accuracy among traditional data mining techniques. As depicted in Table 2, the decision tree has a significantly higher accuracy of 99.1% than other methods, indicating that 482 of 486 students were effectively classified with the appropriate class labels, while 4 were not. Furthermore, when ensemble methods are applied, an improvement in

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accuracy is achieved. In terms of Naïve Bayes, the accuracy increased from 97.7% (without ensemble) to 98.7% (with boosting) and 98% (with bagging) as we can see in Figure 6. Moreover, Figure 6 demonstrates how combining multiple classifiers (NB+ DT+ Boosting) and (NB+DT +Bagging) with the help of voting techniques improved the accuracy of naive Bayes. In term of random forest, the model increased the accuracy from 98% to 99% when combine the classifiers (Boosting +RF +DT) and also the combination of (Bagging+ RF+ DT). These finding indicate that the proposed model improved the accuracy and supports the belief that the ensemble methods enhance the accuracy of traditional data mining techniques.

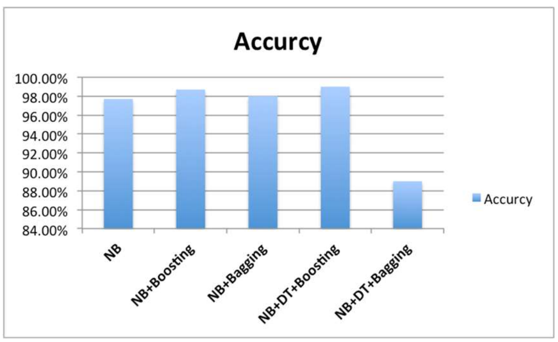

Figure 6 The Accuracy of Naive Bayes and Ensemble Methods

5.2 Precision

In every experiment we performed using traditional data mining techniques and ensemble approaches, the precision outcomes have been greater than 0.96. In terms of traditional data mining, random forest and decision trees achieved the highest value, 0.99 precisions. Figure 7 demonstrates that the ensemble methods scenarios enhanced the precision of naive Bayes from 0.98 to 0.99.

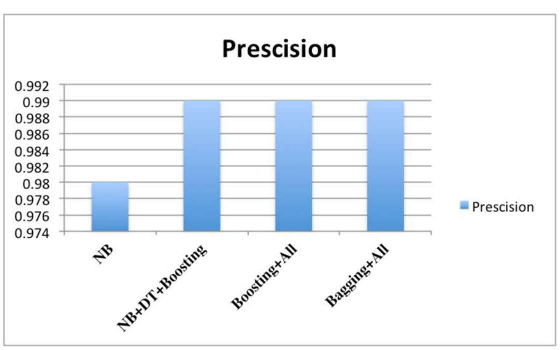

Figure 7 The Precision Of Naive Bayes and Ensemble Methods

5.3 Recall

In every experiment we've conducted utilizing traditional data mining techniques and ensemble methods, the recall results have exceeded 0.95.
In terms of traditional data mining, random forest and decision trees obtained 0.99 recall, the highest value. Ensemble methods (Boosting +NB) and (Bagging +NB) enhanced the recall of naïve Bayes respectively from 0.97 to 0.98. The combination of several classifiers also increased the recall of naïve Bayes as Figure 8 shows.

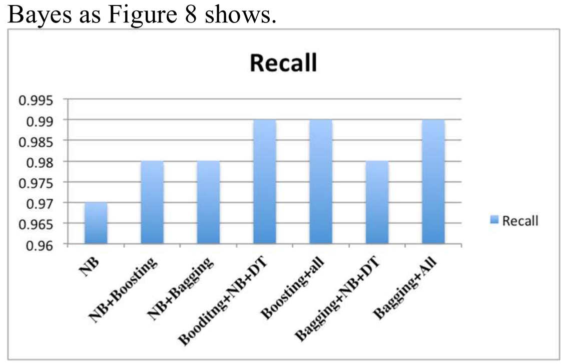

Figure 8 The Recall of Naive Bayes and Ensemble Methods

5.4 F-Measure

In every experiment using traditional data mining techniques and ensemble methods, the recall was above 0.95. Among the traditional data mining, random forest and decision trees achieved 0.99 of recall. Ensemble techniques (Boosting +NB) and (Bagging +NB) improved the F-measure of naive Bayes from 0.97 to 0.98, respectively. Figure 9 indicates that the combination of multiple classifiers increased the recall of naive Bayes.

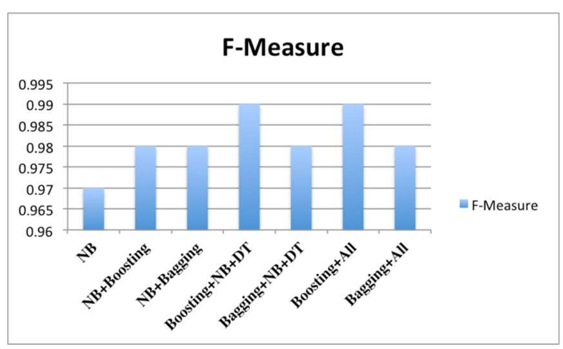

Figure 9 The F-Measure of Naïve Bayes and Ensemble Methods

At the end, the experiments demonstrated that the performance of traditional data mining techniques could be substantially enhanced by combining ensemble methods with them. Ensemble methods are capable of overcoming the limitations of

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individual models and delivering more precise and accurate predictions by combining the strengths of multiple algorithms [27]. In particular, our findings indicate that ensemble methods can improve the accuracy, precision, recall, and F1 score of traditional data mining techniques in the field of educational data. To validate our findings, we implemented the same model to a second E-learning dataset and discovered that combining traditional data mining and ensemble methods enhanced performance [27]. Despite the fact that the outcomes of our experiments improved performance, the authors intend to modify the model by introducing additional classifiers in order to observe any modifications in the results. This allows us to compare the results of different classifiers. To confirm the efficacy of the model, additional E-learning data sets will be tested with the precise model.

5. CONCLUSION AND FUTUREWORK

All over the world, colleges and universities are concerned with the achievement of students. As the prevalence of learning management systems increases, a vast quantity of data regarding the interaction between the teachings and learning processes is gathered. The objective of this paper was accomplished by designing a model that incorporates traditional data mining techniques and ensemble methods in terms of student performance. The results improved the accuracy of the classifiers, making the model suitable for use with educational data. In addition to optimizing the predictive model, the study revealed a correlation between online student interaction and performance. This indicates that encouraging students to engage in such interactions will enhance their academic performance. We applied the model to a dataset of online student interactions, containing how many post students read; quizzes review and the time spend to submit an assignment.

By applying ensemble methods, which integrate multiple models to make forecasts, the authors were able to enhance the predictive model's accuracy, precision, recall, and F-measure. This indicates that a combination of methods can be more efficient than a single technique by itself.

Besides optimizing the predictive model, the study discovered a significant correlation between online student interaction and performance. This suggests that encouraging students to participate in such interactions will result in improved academic outcomes. In the future work, the proposed model will be evaluated using a number of online datasets in order to verify that its performance is trustworthy and consistent. Thus, the generality and adaptability of the model to an extensive range of real-world scenarios can be evaluated. In addition, different algorithms will be utilized and their findings will be compared to the performance of the proposed model in order to gain a better understanding of the advantages and disadvantages of the different approaches. By analyzing the results, they can determine which techniques are best suitable for certain tasks or highlight the areas of the proposed model that could be improved.

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