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AN ENSEMBLE-BASED MACHINE LEARNING APPROACH TO PREDICTING STUDENTS' PERFORMANCE

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Decision Tree, Logistic Regression, Machine Learning, Random Forest, Student Performance, Support Vector Machine, Voting Ensemble.

ABSTRACT

In this paper, advanced machine learning models are investigated for their ability to predict student academic performance, focusing on key features termed "important features." The study thoroughly compares data mining techniques to categorize student performance and predict grades, utilizing a diverse array of classifiers including Bayes Network, Logistic Regression, Random Forest, Support Vector Machine, and Decision Tree. Additionally, ensemble method like Voting was employed to enhance classifier performance. Exploring an ensemble-based machine learning method to predict students' performance is driven by the desire to improve learning. Notably, the results showed exceptional performance by the voting classifier, achieving impressive accuracy rates of 86% in the online dataset and 100% in the local dataset compared to other classifiers. This research significantly contributes to the evolution of predictive modeling within educational settings, offering insights into the comparative effectiveness of different classifiers and ensemble approaches. By identifying important features and exploring ensemble methods, the study provides valuable insights for personalized education, resource allocation, and informed decision-making in educational policies. Educators and institutions of learning can leverage these findings to develop targeted interventions and support systems tailored to individual student needs, ultimately promoting academic success.

1. INTRODUCTION

In the current era, institutions of higher education, both public and private entities, are engaged in intense competition to attract students (Olukoya, 2020). The overarching goal is not only to elevate the quality of education but also to foster student development, given the profound impact of academic achievements and prospects (Rizvan, 2019; Yagci, 2022). Timely identification and prediction of student performance are deemed critical for providing proactive support and facilitating personalized learning experiences (Johnson, 2014).

A rising trend in educational research involves the application of machine learning to educational data, a discipline known as educational data mining (Sharma, 2019). This approach has gained prominence for its effectiveness in predicting learning outcomes and assessing students' academic progress through various tasks such as prediction, classification, clustering, and anomaly detection.

Ensemble methods, which involve combining multiple models, emerge as promising avenues for enhancing predictive capabilities (Wang et al., 2018). The optimization of model parameters is identified as a crucial aspect to prevent overfitting and enhance overall performance (Rizvan, 2019). Additionally, the integration of hybrid approaches, which amalgamate different techniques, offers both flexibility and improved performance (Rashmi et al., 2021). Despite prior research in this domain, there remains ample room for refining the application of machine learning algorithms, particularly in accurately predicting student learning outcomes. Key challenges include algorithm selection, feature identification, data preparation, and addressing imbalanced datasets.

Furthermore, numerous researchers have explored diverse machine learning methods in predicting students' performance. For instance, (Yagci, 2022) employed random forest and a support vector machine, with the latter exhibiting superior performance. (Oyelade et al., 2021) proposed a hybrid model that merges neural networks and decision trees to enhance prediction accuracy (Bai et al., 2021) applied Naïve Bayes and logistic regression to predict student dropout, with Naïve Bayes yielding better results. While these studies have contributed significantly to the field, there is still considerable room for improvement. Techniques such as ensemble, parameter tuning, and hybridization hold promise in advancing the predictive capabilities of machine learning models. While these models prove valuable in predicting student performance, this study seeks to innovate further by focusing on parameter fine tuning to provide better student support and elevate the overall quality of education.

2. RELATED WORKS

Recent academic investigations have significantly advanced the prediction of students' academic performance through diverse machine learning and data mining approaches. Notable studies highlight the potential of these methods in accurately forecasting outcomes and detecting at-risk students early enough. This section presents few of the related studies in the problem domain with respect to the methods adopted.

In the studies conducted by (Juli et al., 2021; Meizer et al., 2019) machine learning models were developed to predict students' academic outcomes. The work of (Juli et al., 2021) applied a spectrum of algorithms, including decision trees, Logistic regression, and ensemble methods like boosting and random forest classifiers. The study reported that ensemble techniques notably achieved a commendable 75% prediction accuracy, underscoring the importance of exploring advanced machine learning approaches, including deep learning and reinforcement learning, to enhance predictive capabilities and adapt to evolving methodologies. Likewise, in the work of (Meizer et al., 2019) a model incorporating Gaussian, Decision Tree Classifier, Linear Support Vector Machine, Multi-Layer Perceptron Classifier, and Random Forest Classifier was developed. Particularly, noteworthy was the linear support vector machine model, which demonstrated 80% accuracy in predicting overall academic performance and an impressive 84% accuracy in predicting English proficiency. These combined studies underscore the significance of employing diverse algorithmic approaches and highlight the effectiveness of specific models, such as the linear support vector machine, in accurately forecasting various dimensions of student academic performance. The findings collectively contribute to the evolving landscape of machine learning applications in predicting academic outcomes. The studies outcomes could be improved further probably if the classical model can be enhanced through ensemble approach.

In their study, (Oyedeji, et al., 2020) explored various models, including neural networks, linear regression with deep learning, and linear regression for supervised learning. Notably, linear regression for supervised learning achieved the highest prediction accuracy, as indicated by the mean average error (MAE). However, these models encountered challenges in accurately predicting future outcomes due to a limited number of available data points for training. In a separate investigation conducted by (Olukoya 2020), the focus shifted to leveraging data mining techniques, specifically emphasizing Students' Essential Features (SEF) associated with their interactions within an e-learning system. The research revealed a significant correlation between learner behaviors and academic achievement. Particularly impressive were the results from the Reduced Error Pruning (REP) Tree Classifier, which demonstrated accuracy rates of 83.33% when used independently or as part of an ensemble, especially when incorporating SEF. Overall, this research underscores the importance of integrating data mining techniques and highlighting specific features related to learner interactions to enhance predictions regarding academic performance.

A novel approach was introduced by (Imran et al., 2019), to forecast academic performance in the first year of study, addressing the challenge of class imbalance through various classification methods and balancing techniques. The most notable success was achieved by combining Support Vector Machine (SVM) and the Synthetic Minority Oversampling Technique (SMOTE), resulting in an impressive overall accuracy of 90.24%. This research emphasizes the crucial role of utilizing machine learning methodologies, especially for balancing data, in addressing challenges posed by imbalanced class distributions when predicting learning outcomes. The use of SVM and SMOTE significantly improved accuracy, providing valuable insights for the early identification of freshmen who may require additional support.

In another study carried out by (Yang et al., 2018) the authors used a comprehensive set of analytical tools to evaluate student performance, progress, and potential. Employing the Back Propagation Neural Network (BP-NN) method for assessment, the tools included progress indicators, causal relationship predictors, and a student potential function. The evaluation using real academic performance data demonstrated the efficiency of these tools in assessing student performance and potential, offering valuable insights for decision-making, and positively impacting student outcomes.

Furthermore, (Oyelade et al., 2021) suggested a system to evaluate students' learning outcomes through cluster analysis and statistical algorithms, aiming to track student progress at higher institutions. Utilizing the k-means clustering algorithm on performance data tailored for a private institution in Nigeria, the model, combined with a deterministic approach, and empowered university planners to make informed decisions on interventions, curriculum adjustments, and resource allocation. This system serves as a valuable tool for academic institutions, enabling data-driven decision-making to track and understand students' progress and support student success.

(Kashif, 2020) investigated the application of data mining techniques in the educational area, introducing a model grounded in a fuzzy neural network (FNN) trained through the Henry Gas Solubility Optimization (HGSO) algorithm. The study provided compelling evidence of the model's efficacy, surpassing conventional methods in predicting student academic learning outcomes.

(Thaer, 2020) presented an effective model anchored in Educational Data Mining (EDM) principles, employing a Multi-Layer Perceptron (MLP) with the synthetic minority oversampling technique (SMOTE) to tackle the challenge of imbalanced data. The research conducted a meticulous comparison of MLP models with various classifiers, elucidating the exceptional performance of the MLP method in predicting student outcomes.

(Shouq, 2021) introduced a hybrid model that ingeniously combined machine learning techniques with binary teaching-learning based optimization (TLBO) for feature selection. Employing logistic regression (LR) and linear discriminant analysis (LDA), the model demonstrated augmented precision in the Area Under the Curve (AUC) metric, underscoring its effectiveness in accurately predicting student performance.

According to (Jalota, 2023) educational data mining (EDM) elevates educational quality and predicts the academic performance of secondary-level students. The study evaluated different classification algorithms, including MLP, Random Forest, Bagging (BAG), LogitBoost (LB), and Voting (VT), revealing that the combination of Logitboost and Random Forest stood out by achieving an exceptional accuracy of 99.8%.

Several researchers have created models using different datasets related to student performance, leading to challenges in direct comparisons due to dataset variations. Thus, this study focuses on refining the accuracy of existing models by utilizing benchmark datasets from the Kaggle website and local datasets, ensuring thorough validation. The evaluation process will involve precision, recall, and F-measure metrics, providing a comprehensive understanding of model performance.

2.1 Data Mining Perception

Data mining acts as a potent tool, transforming raw data into meaningful insights that empower institutions to make informed decisions and comprehend their data more deeply. It involves systematically scrutinizing extensive data stores to uncover undiscovered models and insights, enhancing decision-making processes (Rokach, 2005). The goal is to analyze large data sets from diverse sources, unveiling patterns and correlations not easily discernible through traditional analysis. Leveraging data mining capabilities enables higher education institutions to extract valuable insights, discover hidden opportunities, mitigate risks, and generate actionable information for substantially improved performance and competitive advantage.

Steps involve in Knowledge Discovery

Knowledge discovery involves several key steps collectively known as the KDD (Knowledge Discovery in Databases) process. This research work will look at the following steps in the knowledge discovery process.

i. Discovering Relevant Data: This journey begins by carefully selecting and identifying the data most relevant to the knowledge discovery process. This data serves as a valuable resource for uncovering hidden insights and patterns (Fayyad et al., 1996)
ii. Data preparation: Once the data is selected, a preprocessing phase takes place. This step cleans the data by removing unwanted noise, handling missing values, and fixing discrepancies and errors. The data are then transformed into a format suitable for analysis (Han et al., 2011)
iii. Data transformation: This step transforms the preprocessed data into a format more suitable for knowledge discovery. Various techniques such as normalization, aggregation, feature selection, and dimensionality reduction can be used to improve data quality and relevance (Han et al., 2011)
iv. Mining for Knowledge: The core of the process lies in the data mining phase. Advanced algorithms and techniques are applied to the transformed data to extract hidden patterns, relationships, and knowledge. Based on specific analytical goals, Different data mining techniques, including clustering, association rules, classification, regression, and sequential pattern mining, are under consideration.
v. Evaluating Patterns: After the data mining process, the patterns and insights discovered should be carefully evaluated. This step involves assessing the quality of patterns, measuring their interestingness, and determining their potential value in achieving specific goals of knowledge discovery projects (Fayyad et al., 1996).
vi. Presenting Knowledge: The final step is to present the acquired knowledge in a meaningful and understandable way. This may include the use of visualizations, reports, or summaries to effectively communicate insights and results to stakeholders and decision makers.

2.2 Classification Algorithm Problem

Classification is a key task in machine learning that involves assigning predefined labels or classes to input data based on their attributes. Its objective is to develop a classification model or classifier capable of learning from labeled training examples and accurately predicting the classes of new, unseen instances. Machine learning provides a variety of classification algorithms, each with distinct strengths, assumptions, and applications. Frequently used classification algorithms include:

2.2.1 Logistic Regression

Logistic regression, a commonly used supervised learning method in machine learning for binary classification, distinguishes itself from linear regression. Unlike linear regression, which predicts continuous values, logistic regression focuses on estimating the chance that a particular instance falls within a certain class. It does so by employing a logistic or sigmoid function to convert the linear combination of input features into a probability, ranging from 0 to 1. During training, logistic regression determines the optimal weights that reduces the gap between the predicted probabilities and the real class assignments. These weights represent how crucial each feature is in determining the classification. Logistic regression is a top choice in machine learning for its simplicity, efficiency, and interpretability, making it a favorite among practitioners. It serves as a foundational technique that helps researchers and practitioners make informed decisions in various domains.

$$y = e^\wedge ((b_0 + b_1 * x) / (1 + e^\wedge (b_0 + b_1 * x)) \quad (1)$$

x is the input, y is the prediction, b_0 stands for the bias or intercept term, and b_1 represents the coefficient for the single input (x). Each column in your input data holds a specific b coefficient, a fixed real value that's learned from your training data and is integral to the equation.

2.2.2 Decision Tree

Decision tree, a prevalent algorithm in machine learning, is frequently employed to predict student performance in classification tasks. They utilize a structure that represents a tree, where internal nodes correspond to features and branches correspond to decision rules based on those attributes. The end nodes within the tree showcase the predicted labels of the predicted class. In the domain of student academic prediction, Decision trees have been extensively researched and applied. For instance, (Rashmi, 2019) conducted a study that employed Decision Trees to forecast the academic performance of students at a Turkish university. The researchers considered multiple factors such as high school GPA, university entrance exam scores, and demographic information to construct the Decision Tree model. The research results have shown the effectiveness of decision trees in predicting student learning outcome. This research demonstrates the utility of Decision Trees as a valuable tool for student academic prediction. By leveraging various input features, Decision Trees can effectively analyze and classify students based on their academic outcomes.

2.2.3 Random Forest

Random Forest, an ensemble learning algorithm, harnesses the combined knowledge of several decision trees to improve accuracy and reinforce reliability in predictive modeling. It constructs distinct decision trees using random subsets of training data and features, and clusters their predictions to yield a better outcome (Rosende, 2018). This method of classification utilizes multiple Classification and Regression Trees (CART) to achieve greater accuracy than a single decision tree.

2.2.4 Support Vector Machines (SVM)

Support Vector Machines (SVM) is a robust algorithm widely utilized in machine learning for tasks involving classification and regression. It excels at handling complex data sets that lack a linear separation between classes. The objective of SVM is to identify an optimal hyperplane that efficiently divides data points into distinct classes, maximizing the margins between these classes. In SVM, data points are depicted as vectors in a high-dimensional space. The hyperplane search algorithm works to distinctly separate vectors, representing the data points near the decision boundaries of various classes.

3. METHODS

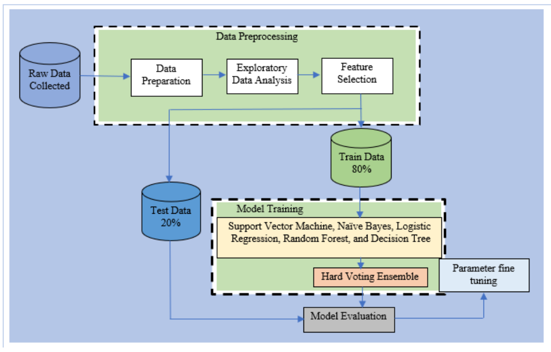

Figure 3.1: Proposed model

3.1 Proposed Model for Student Learning Activities

The student learning model involves stages of data gathering on students' performance, preprocessing, model selection, training, and evaluation. It uses classifiers and ensemble model to predict student performance, preceded by dataset preprocessing and feature selection, and concludes with model assessment.

3.2 Development of Ensemble Model and Data Acquisition

The research was conducted using Python 3.11 as the programming language within an open-source Jupyter notebook. Tabular manipulation was facilitated using Pandas, Seaborn, and Scikit-learn libraries. The computational tasks were performed on a system equipped with an Intel(R) Core (TM) i9-12900HK processor running at 2500Mhz, 32GB of RAM, and operating on the Microsoft Windows 11 Pro operating system.

For data acquisition, publicly available datasets were utilized. The main dataset, compiled by (Cortez et al., 2018) and accessible through the article titled "Student's Academic Performance Prediction in Academic using Data Mining Techniques on the Social Science Research Network (SSRN), contains information on the educational achievements of students from two schools in Portugal. This dataset used in the study comprises 31 columns and 1044 rows, encompassing various attributes such as student grades, demographic details, social factors, and school-related features, all identified by alphabet letters (A-Z). Additionally, a supplementary dataset was administered locally by extracting significant features (demographic, school characteristics, social, etc) from the Kaggle dataset in a Senior Secondary School in Jabi, Abuja. This additional dataset consists of 20 columns and 45 rows.

3.3 Exploratory Data Analysis

In this study, Exploratory Data Analysis (EDA) was carried out to investigate factors influencing the results. Utilizing descriptive and multivariate analyses, it reveals insights into elements such as study habits and socio-economic status.

3.4 Evaluation and Measurement Terms

In machine learning, the assessment of model performance is conducted using a test dataset. An algorithm builds a model based on training dataset. To assess its effectiveness, the model's performance is evaluated against a distinct set of data called the test dataset, which was not utilized in building the model. Employing a technique called 10-fold cross-validation, the dataset is repeatedly divided into training data (90%) and a distinct test dataset (10%) across ten cycles. In this approach, each part of the dataset is tested, allowing the algorithm to make predictions for assessment. To measure the model's performance, a confusion matrix, showed in table 1, is used. This matrix summarizes predictions for two categories, labelled Positive and Negative, where the rows indicate actual outcomes, and the columns indicate predicted classes. As stated by (Vijayalakshmi et al., 2019) key evaluation parameters in classification include accuracy, precision, recall, F1-Score, Receiver operating characteristic curve (ROC) and Precision-Recall curve (PR curves), specificity, and the confusion matrix. The metric chosen varies depending on the nature of the problem and the balance between false positives and false negatives as highlighted by (Vijayalakshmi et al., 2019)

Table 1: Confusion Matrix

		Prediction	
		Positive	Negative
Actual	+	True Positive (T_P)	False Negative (F_N)
	-	False Positive (F_P)	True Negative (T_N)

Accuracy represents the percentage of correct predictions out of the total predictions made. Precision measures the ratio of correctly classified cases to the sum of misclassified and correctly classified cases. Recall quantifies the ratio of correctly classified cases to the total of unclassified and correctly classified cases. Furthermore, the F-measure combines both precision and recall, offering a comprehensive assessment of their interplay. Meanwhile, the ROC Area, derived from plotting the true positive rate against the false positive rate across different threshold adjustments, serves as a valuable metric. Accuracy assessment typically involves calculating the area under the ROC curve.

$$\text{Accuracy} = \frac{(T_P + T_N)}{(T_P + F_N + F_P + T_N)} \quad (2)$$

$$\text{Precision} = \frac{T_P}{(T_P + F_P)} \quad (3)$$

$$\text{Recall} = \frac{T_P}{(T_P + F_N)} \quad (4)$$

$$\text{F.Measure} = \frac{\text{Precision x Recall}_c}{\text{Precision + Recall}_c} \quad (5)$$

4. *RESULTS AND DISCUSSION*

Table 2: Analyzing the online dataset: Individual classifier performance and ensemble method.

Name of the classifier	Accuracy	Precision	Recall	F-Measure
Voting	0.84	0.85	0.99	0.91
Logistic Regression	0.86	0.87	0.98	0.92
Naïve Bayes	0.81	0.89	0.89	0.89
Support Vector Machine	0.84	0.84	1.00	0.91
Decision tree	0.83	0.86	0.56	0.91
Random Forest	0.85	0.85	1.00	0.92

After data preprocessing, the base classifier (Voting) is applied to the datasets. Among the five base classifiers used, it is clearly visible from table 2 that Logistic Regression and Random Forest stand out as top performers in overall accuracy across multiple metrics. Naïve Bayes demonstrates balanced precision and recall despite slightly lower accuracy. Decision Tree exhibits good precision but lower recall. The Voting ensemble method shows balanced precision and recall at 99%.

Table 3: Result of single classifier performance and ensemble method on a local dataset

Name of the classifier	Accuracy	Precision	Recall	F-Measure
Voting	1.00	1.00	1.00	1.00
Logistic regression	1.00	1.00	1.00	1.00
Naïve Bayes	0.78	0.78	0.78	0.88
Support vector machine	1.00	1.00	1.00	1.00
Decision tree	1.00	1.00	1.00	1.00
Random forest	1.00	1.00	1.00	1.00

Just as in the section above, the experiment was repeated using a local dataset. Metrics like accuracy, precision, recall, and F-measure evaluate model effectiveness. From table 3, most classifiers achieve perfect scores in these metrics, except for Naïve Bayes. While Naïve Bayes shows slightly lower scores, suggesting it may have missed some positive instances, its overall performance remains satisfactory. Naïve Bayes still demonstrates reasonably good performance compared to other classifiers.

Conclusion

This research focused on creating an ensemble model using a voting classifier to predict students' academic performance. Machine learning has proven highly effective in analyzing and forecasting student outcomes. The ensemble model combined decision trees, logistic regression, random forest, and support vector machine techniques to analyze student data and make predictions. By combining these methods with the voting approach, prediction accuracy was enhanced using real-world data. Leveraging diverse data sources and algorithms, machine learning models identified patterns and relationships among factors such as attendance, age, and past failures to make precise predictions about student performance. The results showed exceptional performance by the Voting classifier, achieving impressive accuracy rates of 86% in the online dataset and 100% in the local dataset compared to other classifiers. This study can guide educators and institutions in developing targeted interventions and support systems to help students achieve academic success. Overall, machine learning holds great promise in reshaping education and ensuring students' academic progress.

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