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Leveraging Machine and Ensemble Learning Techniques to Timely Predict Student Academic Achievements and Performance

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Abstract: Student achievement analysis and prediction seems to be the most helpful when used to assist instructors and students enhance their pedagogical practices. The use of various analytical tools to forecast student performance has been looked at in recent studies on this topic. Researchers have most frequently employed two data sets: internal evaluation and external evaluation that gives Cumulative Grade Point Average (CGPA). Techniques of machine learning such as Logistic Regression, Random Forest, Support Vector Machine, K-Nearest Neighbors, Naive Bayes, Decision Tree, Multi-Layer Perceptron, AdaBoost, or Ensemble learning are suggested for this study. Support Vector Machine, Random Forest, Decision Trees, and Ensemble Learning all acquire a Precision, Recall and F1 score of **100**, while Naive Bayes achieves a Precision, Recall and F1 score **of 68, 65, and 66**, respectively, according to the performance evaluation for Models with Matrices. Also included is a performance evaluation of the models that consider the metrics accuracy, the macro average accuracy and the weighted average accuracy. The most accurate models have a weighted average, with K-Nearest Neighbors, Naive Bayes or AdaBoost being the least accurate. Support Vector Machine, Random Forest, Decision trees Multi-Layer Perceptron and Ensemble learning Models are **100** percent accurate which provide the highest accuracy, macro average accuracy and also weighted average accuracy.

Keywords: Student Performance Analysis and Prediction, Machine Learning, Ensemble Learning, SMOTE, ENN and Voting Classifier.

Introduction

Effective teaching relies on clear behavior definitions. The success of the learning process is enhanced by the ability to specify behavior. In common parlance, actions are what constitute behavior [1]. Actions that can be observed and quantified are considered part of a person's behavior. Definitions of conduct often focus on the individual's behavior or the teacher's expectations for the student's future behavior [2]. Explaining someone's actions by focusing on their motivations is not the norm. Determining a person's mental state before acting is irrelevant to understanding their behavior [3]. The findings which are demonstrated brings a significant relationship between personality traits and students' academic achievement [4]. As a result, pupils who exhibited poor behavior received low grades, while those who showed excellent behavior received high ones.

Students are required to act maturely and respectfully at all times. No loud noises, jogging, or playing around [5] [6]. Students are not allowed to insult instructors or other students, touch the mirrors, or hang from the barres. Peer conflict and prosocial behavior are two types of conduct that have been associated with students' academic success [7].

There has been research linking these two activities directly to the academic based abilities that mainly includes study techniques, classroom conduct, and peer interaction processes. They have repeatedly found a strong link between doing well in school and giving to others a recent study of information from a thorough Italian poll. They demonstrated that prosocial behavior was a powerful predictor for academic performance even when personality and intellect were taken into account [8]. In a similar vein, a thorough twin study discovered that altruistic behavior significantly increased genetic and environmental predictability [9] [10]. The reduced achievement was also linked to poor social skills, and problems with peers were found to have a comparable impact [11]. Recent research has shown that pupils who have problems with their peers are more likely to have difficulties in the classroom. Difficult behavior includes reclusive traits including shyness, gazing, shaking, trembling, fear of school, absenteeism, social isolation, or hand flapping. Disruptive behavior such as chatting during class, moving around while seated, having fits, swearing, or disobeying teachers' directions to behave [12]. There are several ways to gauge academic progress, including grades and achievement scores [4], but these techniques are not interchangeable. Achievement tests are less strongly related to a variety of non-cognitive

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characteristics, such as social behavior, than grades. Despite being an indirect predictor, social behavior can generally forecast future academic success. However, given their indirect nature, sufficient large-scale studies are needed to determine the specific association that social behaviors have with both academic performance and accomplishment scores [13]. A rare chance to investigate these connections is provided by the National Education Panel Study (NEPS), a significant longitudinal study of numerous cohorts of German students [14] [15]. To determine which academic metrics (grades vs. achievement scores) connect with social behavior, we model the link between social behavior's (particularly prosocial behavior and peer difficulties), competency, and grades in this research using data from NEPS [16].

For example, grades have been proven to reflect a variety of personality traits in addition to academic proficiency, and many educators now incorporate behavior assessments into their grading. For instance, the kindergarten theory of mind predicted grades in grades 1 and 2, but they did not investigate any link to achievement test results. Additionally, the theory of mind is a particular feature of social development, and PR sociality and peer issues require further study [17].

Despite this, there aren't many extensive studies that look at social conduct, grades, and achievement testing together. Several factors including students' learning capabilities, parents' overall background, peer extended pressure, instructors' qualifications, and learning infrastructure have a direct impact on students' overall academic achievements [18]. Educators have always worked to boost their pupils' academic performance so that they can enter the workforce as fully equipped individuals. Students interested in pursuing engineering jobs need to possess more than just a head for numbers; they need to be able to think critically, analyze situations, and make decisions. Identifying the critical parameters that affect engineering students' performance in a given classroom setting is a pressing concern [19]. Predicting how well a pupil will do in school is also helpful for improving methods of instruction. Given the large variety of variables that could affect performance prediction results [20], this is a challenging goal to pursue (For instance, educational background, demographics, or cultural, social, & economic factors). Educational systems have not completely appreciated the usefulness of DL approaches and how data can be turned into valuable insights, despite the methods' promising aptitude in forecasting student success [21]. Instead, several researchers have turned to statistical and other traditional approaches.

As a result, there is a pressing need to implement a variety of DL techniques to spread innovative teaching and learning practices [22]. Data on what students have learned can be gathered using direct and indirect approaches. Direct measures include, for instance, homework assignments, exams, quizzes, essays, research papers, case study studies, and performance grading rubrics [23]. There is enormous educational potential in anticipating a team's performance before games, but this hasn't been fully examined in the relevant literature [24]. The effectiveness of the team or its members is a relevant factor to consider while investigating team performance [25]. According to the writers, one of the most telling indicators of a student's knowledge is their participation in a team's performance. Knowledge acquisition may be more accurately reflected in data collected on team performance as opposed to the performance of an individual student [26].

Literature Review

Nasser Alsubaie 2023 et. al [12] The foundation of this study's methodology is the Kingdom of Saudi Arabia's standards for online learning training, and its suggested remedy is an approach which is solely the Machine Learning (ML) based that anticipates the performance of the Students with a view to improve the quality assurance and relevant factors of online training programs provided through the platform of Maharat located in Taif University (KSA). Predicting student success considering their use of an online learning environment is the primary focus of this paper. Once hybrid optimization was used to extract the necessary features, classification was performed. The supported vector machine method was used to make the forecasts and further analyzed the views of a cross-section of Taif University learners and Professors on the Maharat online training quality assurance platform using a descriptive-analytical approach. Rodrigues 2022 et.al [27] It was recognized that the popularity of research in predicting academic success in colleges has sparked interest in the subject among both high and middle school students. The use of deep neural networks to investigate semi-structured data, a frequent issue in the academic setting, is, nonetheless, in its early stages. Together with the presented models and the primary criteria used to predict students' achievement, the authors also highlighted the limitations of previous prior studies on the subject. Future research directions were finally discussed.

Mildawani 2022 et. al [28] utilized a survey questionnaire to gather data, which was then examined using structural equation modelling. According to the study, the empirical data and theoretical model are in agreement (NNFI = 1.00, RMSEA = 0.00), proving the fact that the data of the sample is actually representing the entire population. It is impossible to foresee competing behaviors that are mediated by social comparison using critical thinking. This study contributes to the expanding body of information showing how competitive behavior is complex and intricately linked to one's cognitive, self, or adaptive abilities.

Walid 2022 et al. [29] has been prepared with the fewest significant attributes possible to keep the model simple. After collecting 343 observations, eleven attributes were collected, and the operation was terminated. Six widely known ML approaches are employed to make the predictions. In order to assess the model effectiveness, the Precision, Recall, F-Score or the Area under the Curve (AUC) score matrices are computed. As a means to gauge how well the proposed method performs on unobserved data, Stratified K-fold cross-validation is strongly suggested. The results of this in-depth analysis make it abundantly evident that the technique developed based on resampling from the blend of the Edited Nearest Neighbor (ENN) with the borderline Support Vector Machine based SMOTE as well as the Support Vector Machine model produced observably excellent results. Performance-wise, the Support Vector Machine based SMOTE and AdaBoost models are tied for second place.

Atlam 2022 et al. [30] It is composed primarily of two parts. The first component of the survey asks questions about the demographics and academic history of participants, while the second component of the survey asks questions about their utility of various digital devices, habits related to sleeping, media and social interactions, emotional -cum- mental health, and success in academia. The poll was completed by students at universities and colleges in Saudi Arabia, Jordan, and Egypt. We received 1766 replies in total and used machine learning and statistical methods to assess them. According to the results, there is a direct link between the mental health of the students' and the popularity of online education during the years surrounding the pandemic of COVID-19.

The results of COVID-19 also indicated a positive relationship between students' general academic success and their usage of digital technologies for online learning. The studies ultimately highlighted the detrimental consequences of COVID-19 on educational institutions. Finally, the research ends with suggestions for improving the current online education system. Furthermore, Universities has the responsibility to execute and active role in assisting the learners in coping with the pandemic psychological effects.

Table 1: Data Set, Method/Model and Relevant Parameters

Author/ Year	Data Set	Method / Model	Parameter	Reference
Al - Zawahri/ 2022	OULAD	**Multilayer Perceptron (MLP)**	**Accuracy = 81%**	[31]
Mai/ 2022	Course#1-2018, Course#2-2018	**Louvain Method**	**Accuracy = 74%, F1-Score - 73.5%.**	[32]
Chen /2022	---	**Negative Response Method**	**F = 109.986**	[33]
Waldeyer/ 2022	---	**Diagonally Weighted Least Square**	**CFI=0.97 RMSEA = 0.03, TLI=0.96.**	[34]
Legette /2021	Pre-K	**Faculty Appraisal of Impulsive Reactions**	**M = 4.11, SD = 1.23**	[35]

3 Proposed Methodology

The proposed methodology mainly covers Data Collection, Exploratory Data Analysis, Pre-processing, Machine Learning and Modeling,

A) Data Collection:

The total of 21 columns, including "Program of study," "Aggregate% Marks in Class-X," "Aggregate% Marks in Class-XII," "CGPA," "SGPA," "Highest_SGPA" and "Student Behavior," are included in the data used in this work. These data were collected using student mark sheets and behavior and included various student performances based on marks and behavior. You registered in the program by, "Self-Study per day (In Hours)," "Time spent in extracurricular activities (In Hours)," "Do you regularly access virtual learning platforms," "Do you smoke," "Do you drink alcohol," "Are you exposed to social media," "Do you have regular access to virtual learning platforms." Several siblings, Father and Mother qualifications, Father and Mother employment, Annual Family Income (In Lacs), and Current Health Status are all required [36]. These columns are available in the data and are utilized to determine student performance. The following figure step-by-step outlines the Proposed Flowchart as per the Proposed Methodology.

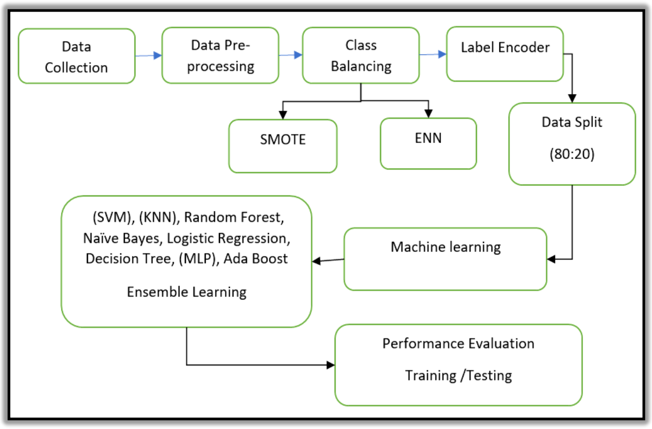

Fig. 1: Proposed Flowchart

B) Exploratory Data Analysis:

Exploratory Data Analysis (EDA) is the systematic way followed to spot the patterns and abnormalities (outliers) in the dataset and then formulating hypotheses based on what we have learned about it. A picture is worth thousand words and in this direction to help the users in understanding the data, EDA provides summary statistics of the numerical data in the dataset, producing a variety of graphical representations [37]. EDA is an essential part of any data analysis, regardless of whether the queries are handed to you on a silver platter. This is because you should constantly verify the accuracy of your data. One of the many applications of EDA is data cleaning, which entails determining whether the data support the assumptions. must undertake data purification using all EDA techniques, including modelling, transformation, and visualization [38].

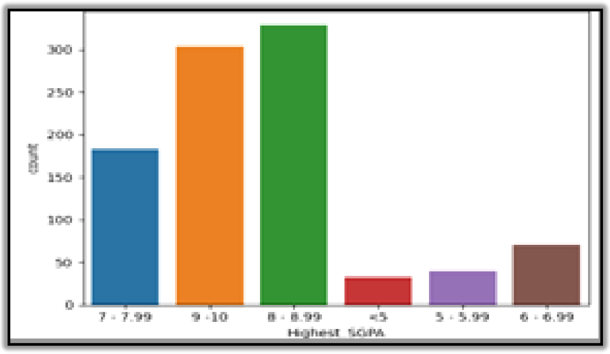

Fig. 2(a). Highest SGPA

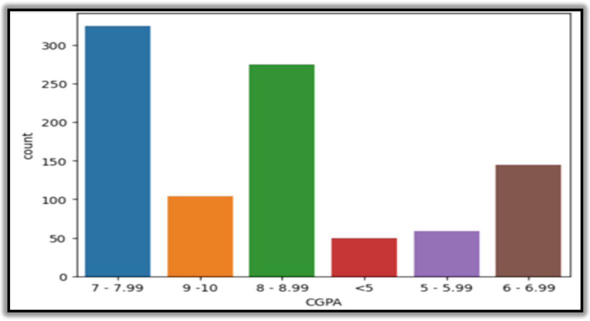

Fig. 2(b). CGPA

The highest SGPAs and CGPAs are shown in Fig. 2(a) and 2(b). The different SGPA levels are shown in Fig. 2(a), with an 8–8.99 achieving a rating of above 300. Orange, blue, green, and red are used to denote the numbers 9 through 10, 7-7.99, and 5, respectively. Purple represents the price range of 5–5.99 and brown the price range of 6–6.99. The CGPA is shown in Fig. 2(b) with 9–10 being represented by orange, 7–7.99 by blue, 8–8.99 by green, and 5 being represented by red. Purple and brown are used to represent the numbers 5–5.99 and 6–6.99, respectively; the greatest number is 7–799, which is over 300.

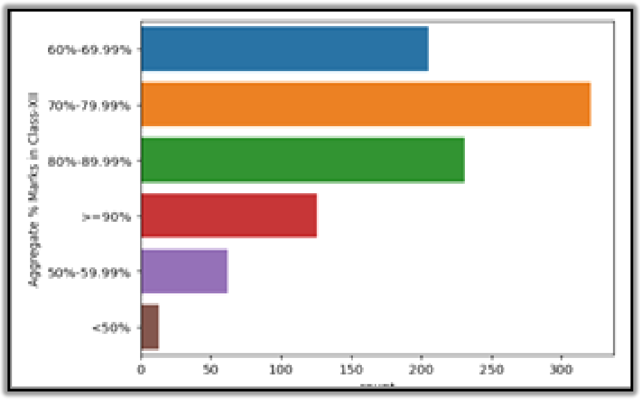

Fig. 3(a). Aggregate % Marks in Class-XII

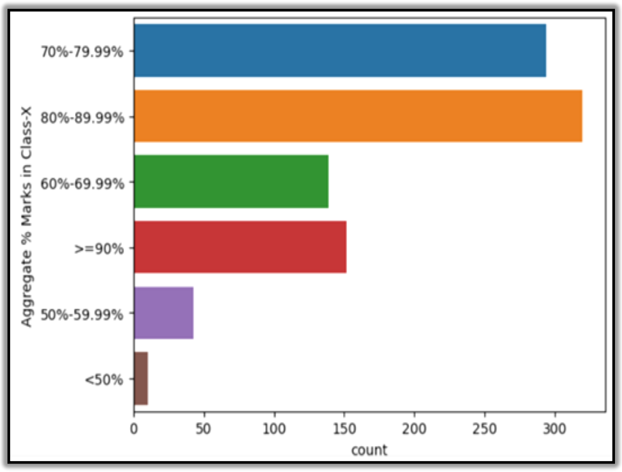

Fig. 3(b). Aggregate % Marks in Class-X

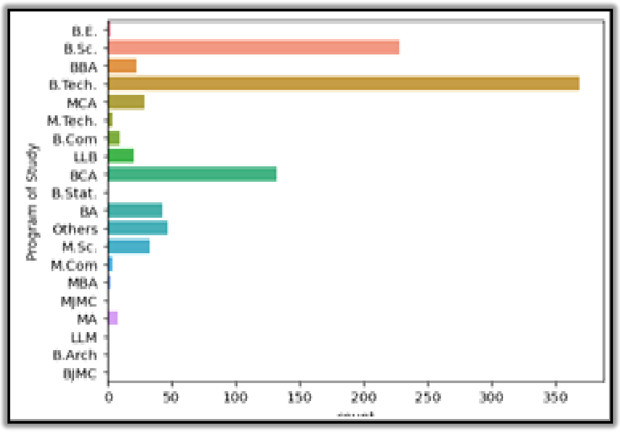

Fig. 3(c). Program of Study

The Aggregate% Marks in Class-XII, Aggregate % Marks in Class-X, and Program of Study are displayed in Fig. 3(a), 3(b) and 3(c). Aggregate% Marks in Class XII into various levels are shown in Fig. 3(a), where 70–79.99% of the more than 300 received in orange. Blue indicates 60-69.99%, green represents 80-89.99%, orange represents 70-79.99%, and red represents >=90%. Purple represents 50-59% and brown represents 50%. The Aggregate% Marks in Class-X are displayed in Fig. 3(b), where orange marks obtained of more than 300 are represented by 80-89.99%. Blue represents 70-79.99%, Green represents 60-69.99%, Orange represents 80-89.99%, Red represents >=90%, Purple represents 50-59%, and Brown represents 50%. The program of study where B.Tech., B.Sc., MCA, and LLB are included, with the greatest value gained from B.Tech. being more than 350, is shown in Fig. 3(c).

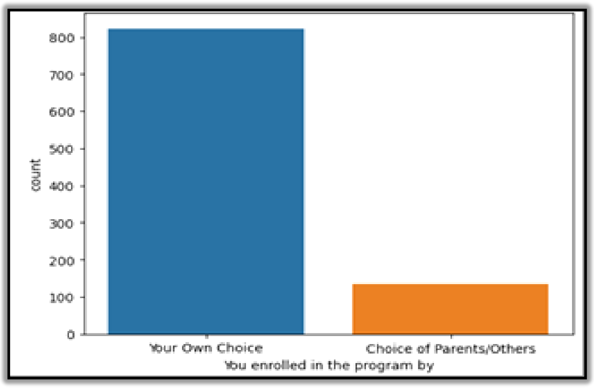

Fig. 4(a). You enrolled in the program.

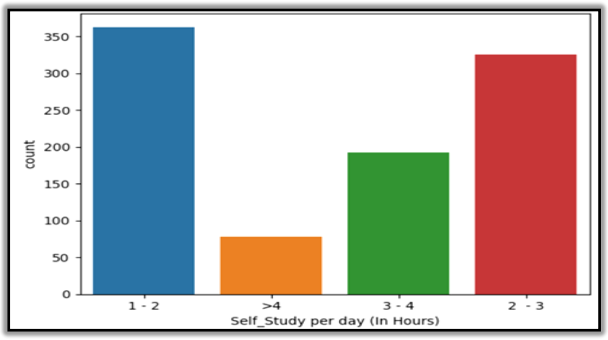

Fig. 4(b). Self-study per day (in Hours)

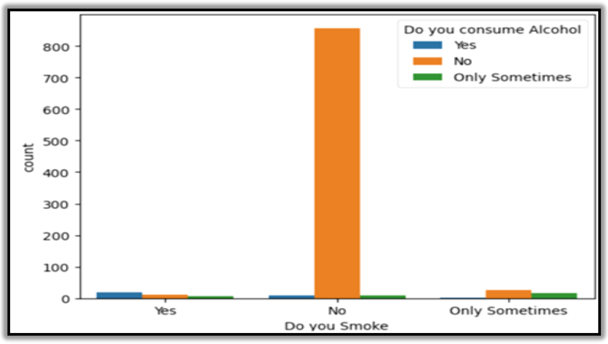

Fig. 4(c). Do you Smoke.

Fig. 4(a), 4(b) and 4(c) depicts -You signed up for the course, how many hours a day do you spend for the self-study, and do you smoke? Fig. 4(a) displays “You signed up for the program”. There are two variables: the first is your own choice, and the second is the option of your parents or others. "Your own choice" had the highest value at almost 800. Self-study hours per day (in Fig. 4(b)) greatest value received from 1-2, greater than 350, is represented by blue. The "Do you smoke" graph is shown in Fig. 4(c), with "yes" denoting blue, "no" denoting orange, and "green" denoting occasionally the greatest value received by No, which is denoted by orange. Program of study, Aggregate% Marks in Class X, Aggregate% Marks in Class XII, CGPA, SGPA, Highest SGPA, Student Behavior, and other variables available in the dataset are shown in Fig. 7's correlation matrix.

The Class Imbalancing Feature: Class imbalance in machine learning refers to an uneven distribution of classes in a dataset, where one class greatly outnumbers the others as shown in Fig. 8. This may cause the model to exhibit bias towards the majority class, impacting its accuracy in predicting minority class cases. Imbalanced datasets present issues since models tend to favor the dominant class, resulting in subpar performance on minority classes. Strategies such as oversampling, under sampling, or utilizing specialized algorithms for imbalanced data can help mitigate this problem. Ensuring equitable class distribution is essential for developing unbiased and efficient machine learning models that encompass all classes.

Need to make and use final_performance variable: Utilizing analytical techniques is crucial for improving teaching methods in the field of analyzing and predicting student progress. As shown in Fig. 5, current research frequently utilizes two primary datasets: internal and external assessments, resulting in the calculation of Cumulative Grade Point Average (CGPA). Use of machine learning techniques including ensemble learning, AdaBoost, K-Nearest Neighbors, Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, and Naive Bayes is advised. The results of the performance tests show that Ensemble Learning, Random Forest, Decision Trees, and Support Vector Machine all received flawless ratings.

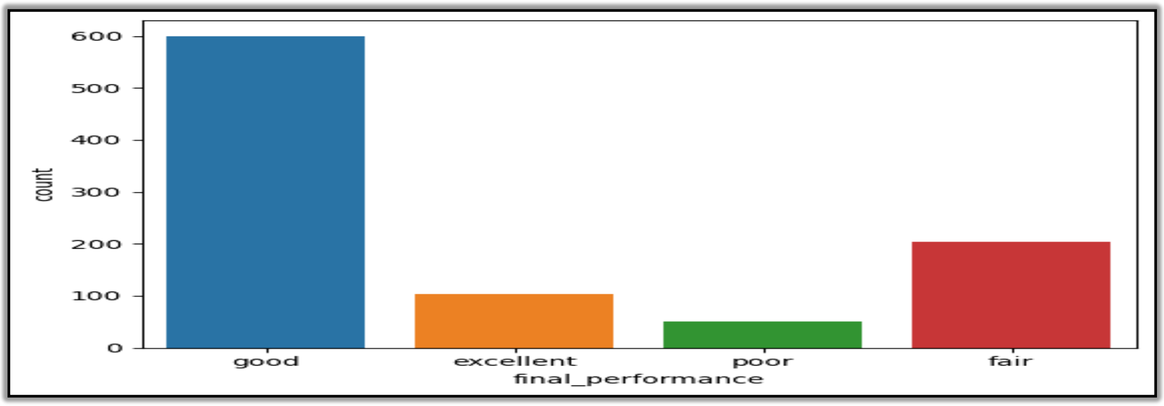

Fig. 5. Graph showing final_performnace as Categorical Values

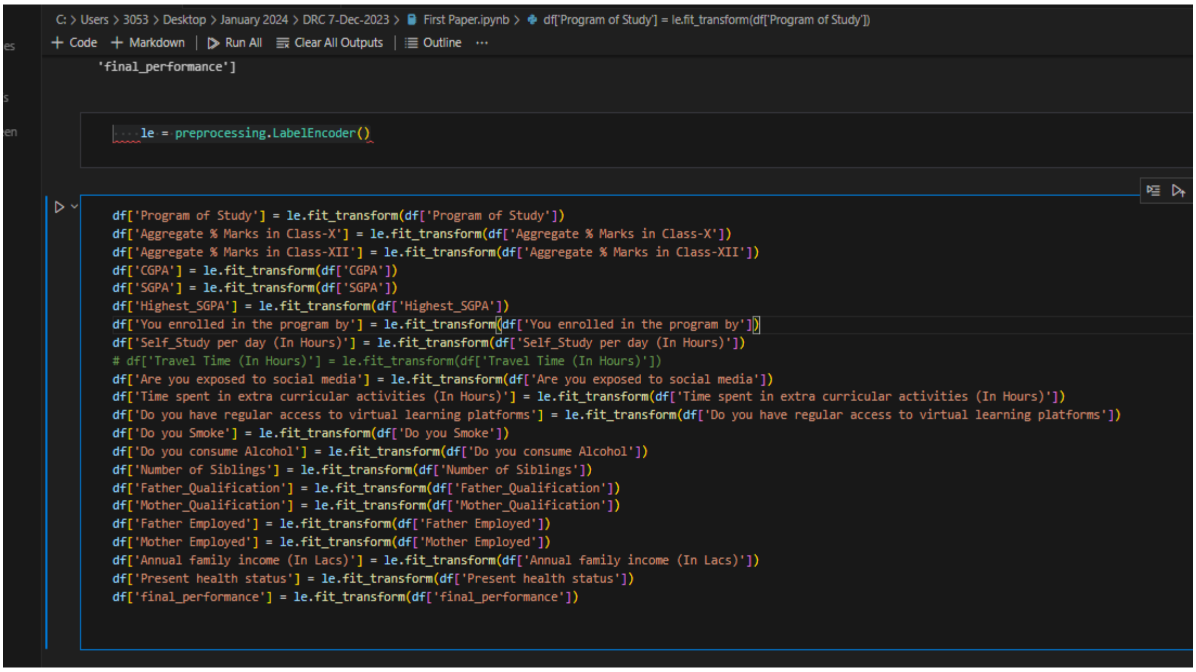

Fig. 6. Pre-processing Label Encoder

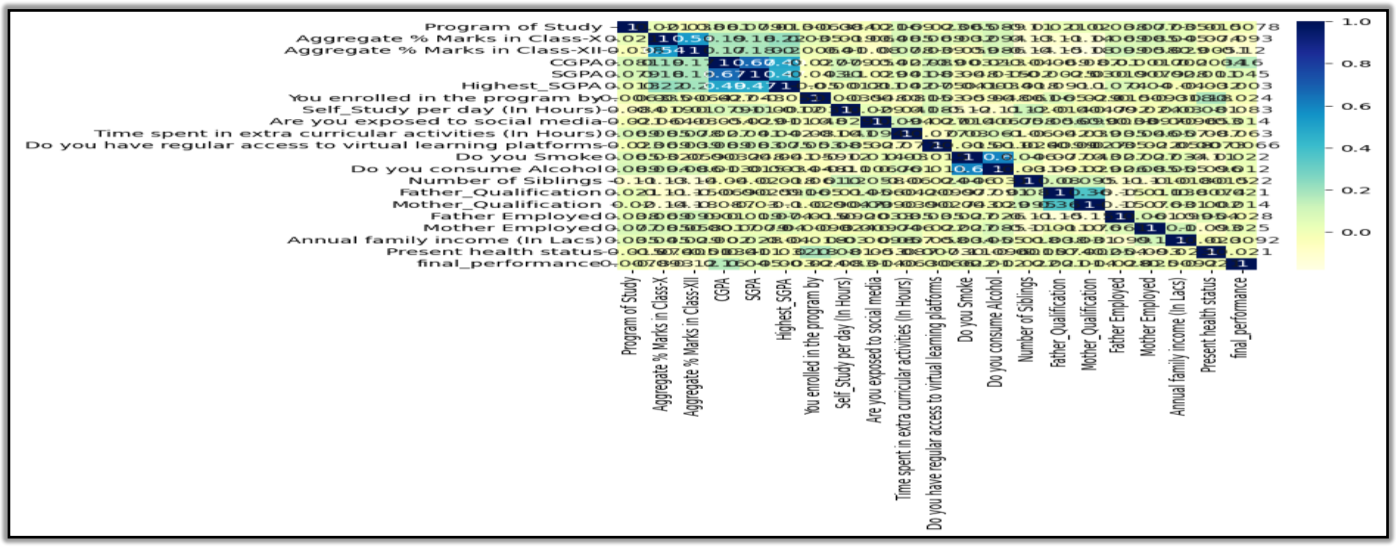

Fig. 7. Correlation Matrix of Dataset

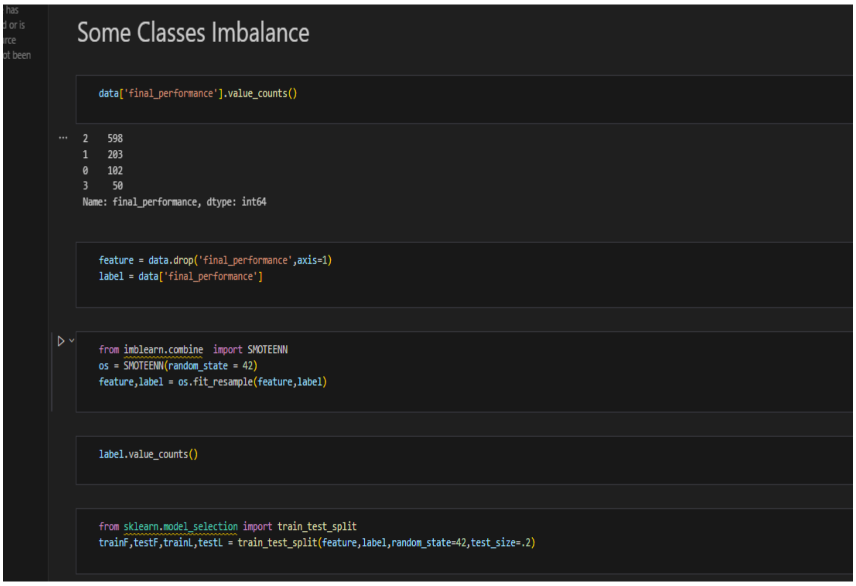

Fig. 8. Python Code to perform Class Imbalancing

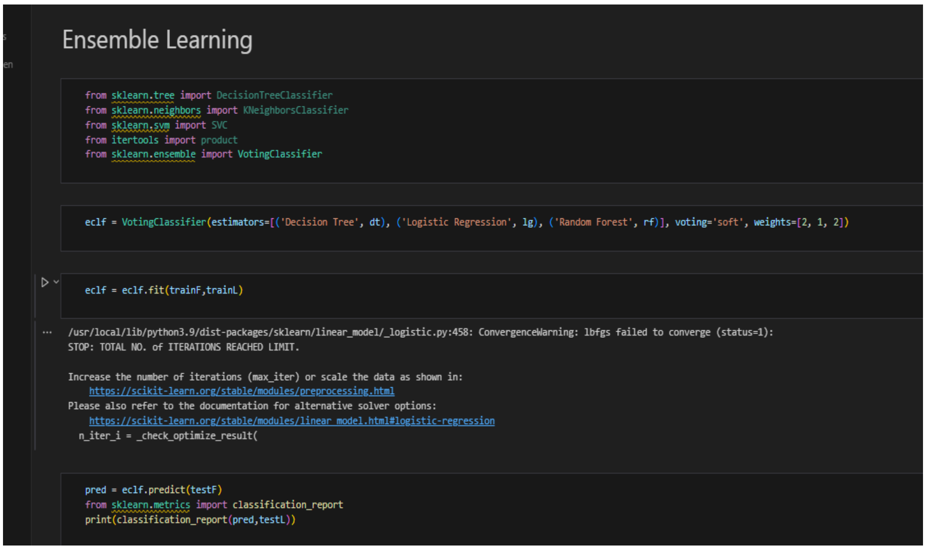

Fig. 9. Python Code for Ensemble Learning and application of Voting Classifier

Fig. 10. Results of Proposed Model

C) Pre-processing:

Pre-processing entails balancing the classes, label encoding, eliminating duplicate values, and eliminating inactive categories in the dataset. To analyze and analyze raw data, "data preparation" entails transforming and cleaning up the data. The cleaning, accuracy checking, and integrating of the data with additional datasets that provide greater detail are all actions that fall within the preparation phase. In this section, the SMOTE & ENN algorithms were used to pre-process the data. Change the category value in label encoding to a numeric value between 0 and 1 and reduce the number of classes to 1. In the scenario when the category variable's value falls into one of five categories (0, 1, 2, 3, or 4). The ability of ENN and SMOTE is to exclude some observations from both the discovered classes. This is done to finally to have a class which differs from both- the observation’s class and its K-Nearest Neighbor majority class.

D) Machine Learning & Modelling:

With an objective to predict student academic performance, the concept of predictive modelling is commonly employed with various educational data mining techniques. Predictive modelling is created using a number of processes, such as classification, regression, and categorization. The most popular task for predicting student progress is classification. Numerous methods have been employed to predict student success in the categorization job. Voting Classifier Decision Tree, Ada Boost, Naive Bayes, Random Forest, MLP, KNN, Support Vector Machine and Logistic Regression are a few of the result-oriented approaches used.

- **Ensemble Learning and Use of Voting Classifier**

To enable precise and better decisions, machine learning ensemble approaches aggregate the insights from various learning models. These techniques adhere to the same fundamentals as the previously mentioned air conditioner purchase example. In this context, it is worth to learn that a voting classifier is a machine learning estimator (Fig. 9). It is mainly used for developing a number of base models or estimators. The voting classifier makes appropriate and well accepted predictions by taking an average of the results produced from each base estimator. The choice of voting for the output of each estimator can include the aggregating factors. Here, there are two categories of voting parameters that is available: “Hard Voting” is the voting which is based on the expected outcome class whereas the “Soft Voting” is the voting which is based on the output class's projected probability.

- **Logistic Regression**

Logistic regression is regarded as the supervised learning method. Its principal use is to point or forecast the likelihood of a binary (yes/no) occurrence. To assess a person's likelihood of having the COVID-19 virus by making the use of machine learning is one good example of the logistic regression.

- **Multi-Layer Perceptron (MLP)**

Multi-Layer Perceptron (MLP) is a type of feed forward Artificial Neural Network (ANN) and it is fully linked. The term "MLP" is confusing; it is sometimes used broadly to refer to any feed forward ANN and other times solely to networks made up of several layers of perceptron.

• **Decision Tree**

The family of supervised learning algorithm has many members, and the decision tree algorithm is one of them. Unlike the other supervised learning algorithms, we can use the approach of the decision tree for the resolution of classification and regression issues in a result-oriented way.

• **Support Vector Machine (SVM)**

Support Vector Machine is considered as the most powerful supervised algorithm which can perform and generate excellent results on smaller datasets. This algorithm can serve the purpose of both -classification and regression tasks, however it has been observed that they often lead in classification related activities.

• **K-Nearest Neighbor (KNN)**

The term "K-Nearest Neighbor" is denoted by the acronym KNN. An algorithm is well suggested for supervised machine learning purposes. Regression as well as classification issue statements can be resolved using this approach. The letter "K" represents closest neighbors’ number to a new unidentified variable which has to be forecasted or categorized.

• **Random Forest**

Random Forest algorithm is mainly based on the idea of ensemble learning, which is the process of combining multiple classifiers with a view to solve a challenging problem. It also enhances the performance of the model, very well-known machine learning algorithm that belongs for the supervised learning technique. Random Forest can be utilized to solve both – regression problems and classification problems in the Machine Learning platforms.

• **Naive Bayes**

The Naive Bayes classifier, a supervised machine learning method, is employed for various classification tasks such as the classification of the text. Being a member generative learning algorithms family, it also helps to represent the distribution of inputs inside a certain class or category. It is to be noted that unlike discriminative classifiers to say like the logistic regression, it does not figure out which features are most crucial for the class differentiations.

• **AdaBoost**

If we talk about various boosting algorithms, then AdaBoost was one of the first to be applied in various problem-solving techniques. You can combine numerous "weak classifiers" with AdaBoost with a view to create a single "strong classifier

Table 2: Model Performance Assessment Using Metrics – Precision, Recall and F1-Score.

Models	Accuracy	Macro Average Accuracy	Weighted Average Accuracy
Support Vector Machine (SVM)	**100**	**100**	**100**
K-Nearest Neighbour (KNN)	**97**	**96**	**97**
Random Forest	**100**	**100**	**100**
Naïve Bayes	**74**	**72**	**74**
Logistic Regression	**98**	**98**	**98**
Decision Tree	**100**	**100**	**100**
Multi-Layer Perceptron (MLP)	**100**	**100**	**100**
AdaBoost	**87**	**71**	**92**
Ensemble Learning	**100**	**100**	**100**

4 Results and Discussion

In this section, various pre-processing steps explained together with the outcomes, include class imbalance, label encoding, deleting values with the same value, & removing inactive categories from the dataset. Data that has not been processed must be transformed and cleaned up before it can be used for the study. When data is divided into an **80:20** training ratio: testing ratio and used to train the suggested model, text documents are said to have an n-gram if there are n successive objects, such as words, numbers, symbols, and punctuation. The evaluation metrics are listed below.

A) TN/TP/FN/FP

In the Truly Positive (TP) value, better results are anticipated, and they are obtained. A False Positive (FP) value is a result that is expected to be the positive result but comes out as the negative result. In the True Negative (TN) value, the things that have occurred or are anticipated to happen are the consequences. False Negative (FN) value are the things that, in contrast to assumptions that they would be the negative, actually turn out to be the positive.

B) The Confusion Matrix

A confusion matrix serves as a table representation that can be presented to for evaluating a classification system's effectiveness. A confusion matrix is usually drawn to summarize the performance and the efficiency of an algorithm.

C) Accuracy

Accuracy is one parameter used to gauge the effectiveness of classification models. Informally, accuracy refers to the proportion of predictions that our model successfully made. According to formal definitions, accuracy is as follows.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{1}$$

D) Precision

Precision, or in other words the bar for a correct prediction made by the model, is one form of an indicator of a machine learning model's worthiness. Precision is the ratio of true positives number to the whole of positive predictions, or the summation of the true positives and the false positives.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

E) Recall

The data samples proportion that a machine learning model appropriately identifies as being part [39] of an interesting class called the "positive class, out of every sample used for that particular class is known as the True Positive Rate (TPR), and also known by the term 'Recall'.

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

F) F- Score

We know that we can create F1-Score with the help of Precision and Recall scores which is considered a very important machine-learning evaluation statistics [40]. When to use it and how to use it correctly is considered a very important learning to effectively monitor the accuracy of the proposed model.

$$F - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \tag{4}$$

Table 3: Performance Assessment of Models Using Metric - Accuracy, Macro Average Accuracy, and Weighted Average Accuracy.

Models	Precision	Recall	F1-Score
Support Vector Machine (SVM)	100	100	100
K-Nearest Neighbor (KNN)	98	93	95
Random Forest	100	100	100
Naïve Bayes	68	65	66
Logistic Regression	94	98	96
Decision Tree	100	100	100
Multi-Layer Perceptron (MLP)	98	100	99
AdaBoost	100	70	82
Ensemble Learning	100	100	100

Table-2 displays a Performance Evaluation of Models sing Matrices of Precision, Recall and the F1- Score. Support Vector Machine, Random Forest, Decision Tree, and Ensemble Learning can all attain a maximum - Precision, recall, and F1-Score of 100, but Naive Bayes can only manage 68, 65, and 66 for these metrics, respectively. Support Vector Machine, K-Nearest Neighbor, Random Forest, Naive Bayes, Logistic Regression, Decision Tree, Multi-Layer Perceptron, AdaBoost, and Ensemble Learning models are all included in Table 3's Performance Evaluation for Models with Matrices -Accuracy, Macro Average Accuracy, and Weighted Average Accuracy. It is to be noted that Naive Bayes and AdaBoost have the lowest Accuracy, Macro Average Accuracy and Weighted Average Accuracy respectively. However, Support Vector Machine, Random Forest, Multi-Layered Perceptron, Ensemble Learning and Decision Trees have the best Accuracy, Macro Average Accuracy, and Weighted Average Accuracy which is exactly 100.

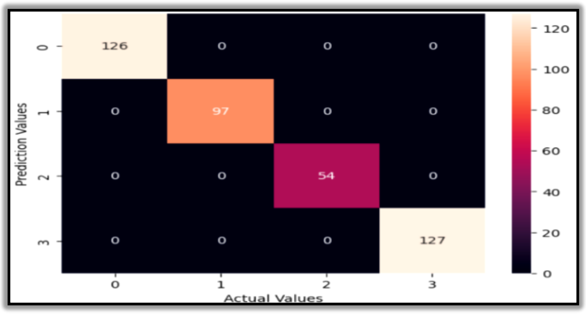

Fig. 11(a). Confusion Matrix of Support Vector Machine

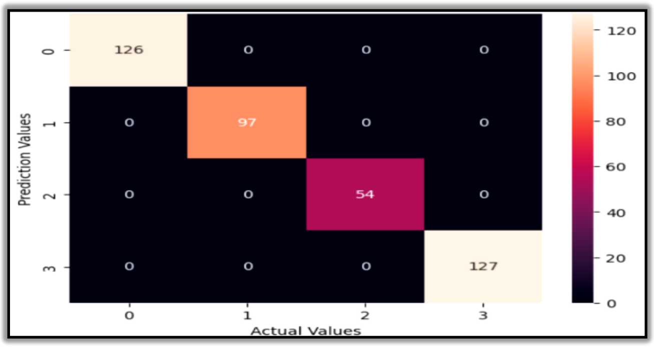

Fig. 11(b). Confusion Matrix of Random Forest

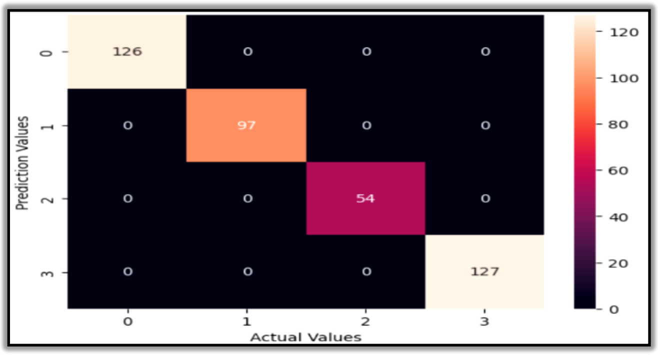

Fig. 11(c). Confusion Matrix of Decision Tree

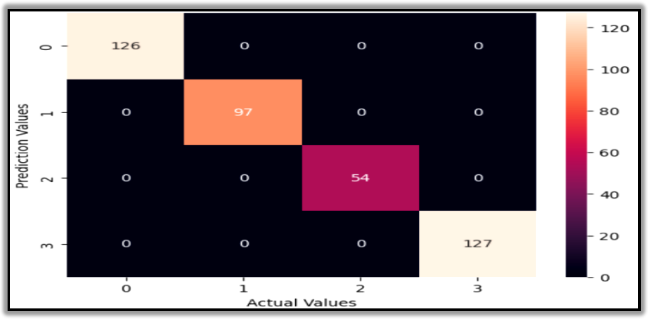

Fig. 11(d). Confusion Matrix of Ensemble Learning

5 Conclusion

When utilized to assist teachers and students in analyzing and improving their teaching and learning methods, student achievement prediction is most beneficial. Recent studies on the use of various analytical methods to forecast student performance have been explored in this post. The most often used data sets by researchers have been internal evaluation and the cumulative grade point average (CGPA). This study strongly suggests various machine learning methods such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest, Naive Bayes, Logistic Regression, Decision Tree, Multi-Layered Perceptron (MLP), AdaBoost, or Ensemble Learning. The results of the Performance Evaluation of Models with Matrices such as Precision, Recall, and F1 Score show that Support Vector Machine, Random Forest, Decision Trees & Ensemble Learning all obtain the Precision, Recall and F1-Score of 100, whereas Naive Bayes earns Precision, Recall and the F1-Score of **68, 65, and 66**, respectively.

Moreover, a performance evaluation of the models is provided, which takes into an account the Weighted Average, the Macro Average, and the Accuracy of the metric. The least accurate models are Naive Bayes and the AdaBoost with the most accurate models having a weighted average. The best Accuracy, Macro Average Accuracy, and Weighted Average Accuracy are achieved by the application of Support Vector Machine, Random Forest, Multi-Layer Perceptron, Ensemble Learning and Decision Trees, all of which are **100**.

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Conflicts of interest

The authors declare **no** conflicts of interest.

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