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Predicting Academic Achievement for Students Using Machine Learning Technique

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Abstract: Predicting the academic achievement of pupils is a significant component that needs to be taken into mind anytime concerns involving higher education or more in-depth schooling, particularly the connections between the two, are brought up for discussion. Students are able to choose the classes with future study plans that will be most useful to them with the assistance of the capability to predict their achievement. This is made possible by the availability of this skill. It gives teachers and administrators the opportunity to monitor pupils, which in turn enables them to provide more support for students, combine training programs for the highest potential results, and anticipate how successfully students will complete their education. One of the many benefits of student forecasting is that it leads to a decline in the number of official warning signals for school expulsions that are caused by inefficiency. This is only one of the many benefits of student forecasting. Students are able to see their own futures if they take the time to select their courses thoughtfully and come up with study methods that make the most of their unique sets of abilities and areas of interest. As it had values of 0.888 for accuracy, precision, recall, & f1 accordingly for each of those categories, the Support Vector Classifier was the most beneficial tool for this inquiry. This was due to the fact that it was able to correctly classify the data. These values are proof that the data were categorized with a high degree of accuracy. Throughout the course of this inquiry, several different methods of machine learning, such as ensemble, logistic regression, random forest, AdaBoost, & XG Boost, were applied.
Keywords: Student performance evaluation, Machine learning, exploratory data analysis, Neural Network

I. INTRODUCTION

"Students" are people who have been accepted to universities and colleges. Education helps these people develop and become more employable. This review uses "students" and "those attending higher education institutions" interchangeably. Supporting Nigerian College Students' Mental Health with Technology Pandemics: A Global History has more. The Cambridge Intermediate Learner's Dictionary defines a "student" as someone who attends a higher education institution. This investigation included all Kenyan undergraduates in degree programs at state or private universities.[1]. Active Learning using Tools in Blended/Hybrid Courses provides details. College and university students are meant. "The Use of a Whatsapp Register for Students Contact: A Case of the Zimbabwe Local College, Mashonaland West Campus" provides details. Case method courses can assess students' progress through class participation, individual writing for essays and examinations, group projects, and presentations. Because coursework is crucial to the topic and often counts toward a student's grade, we'll focus on it here. A skilled particular instance instructor considers each student's altruistic contribution to class discussions while assessing involvement [2]. Developing impartial assessments of their contributions is not always easy. Both the substance and delivery of each student's contribution to the class discussion matter for its overall quality. While it's great to have more people chip in, doing so too frequently may lead to subpar contributions and signal a lack of interest in listening. It is possible for specific students' judgments of engagement to be significantly influenced by the calling patterns, inquiries, and follow-ups used by their instructors with those particular students [3]. The efficiency of the instructor's system for tracking student engagement may also have a major bearing on the reliability of the overall rating. The participant-centered research approach, in contrast to lecture-based pedagogies, encourages greater expectations and feedback. When students participate in class discussions, they receive rapid feedback in the form of opinions on their ideas from both the instructor and their peers. However, this type of feedback is sometimes imprecise and hard to interpret, leaving students wondering if and how their contributions will be valued. It's not always a good idea to encourage kids to cultivate their capacities for self-reflection and evaluation. Aside from formal assessments, students may actively seek out negative feedback from others[4]. Teachers must be able to give feedback that is both evaluative & helpful so that students can gain insight into their own strengths and areas for growth. The term "evaluation" is used to describe the method of rating the quality of student learning in relation to predetermined criteria.

Evaluation effectively summarizes and conveys to parents, other educators, employers, institutes of higher education and the students themselves will be responsible for assessing students' knowledge and abilities in accordance to the overall curriculum requirements. Evidence of student achievement is gathered through assessments administered at key points in the grading/teaching cycle, most frequently at the conclusion of a unit of study[5].

The determination of which specific expectations should be employed to evaluate the fulfillment of the overall expectations will be determined by the teachers [6]. In order to gather information on their students' levels of comprehension, teachers employ a wide variety of assessment methods. Observations, conversations between instructors and pupils, and the creation of work by kids all make up the three legs of this methodology's triangulated structure. The Student Performance Evaluation was created with an eye toward the future in order to provide greater clarity as you concentrate on improving the aforementioned competencies throughout the length of your work term. The three primary areas of strength & the top three areas for improvement will be the focus of these competencies[7].

The following strategy is one that we propose implementing so that you may get the most out of the Student Performance Evaluation:

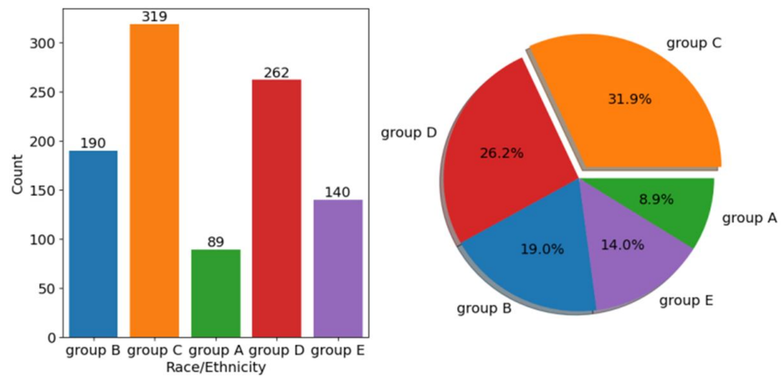

Figure 1 Student performance evaluation

- Set a date for a pre-evaluation and review of the Student Performance Evaluation, and specify what you are looking for. It is strongly advised that you schedule a meeting with your manager at the start of your work term in order to guarantee that you have a firm comprehension of what is required of you. You have the opportunity to investigate each of the 12 competencies and establish goals for the development of your skills depending on the requirements of your work.
- Set up a check-in or informal review during the midpoint of the term to assist you with your ongoing competency development. You have the option to speak with your employer about how you've done PRIOR to the end of your co-op work terms by requesting that they carry up an informal mid-term review on your behalf [8]. In this section, you will have the opportunity to gain some insight into the areas in which you may like to concentrate on further developing towards the end of your work period.
- Carry out an official evaluation at the end of the term. In order to earn credit for your cooperative education experience, you must earn a grade of C or better on all of your separate work terms. In a perfect world, this would have been handed in by your employer at the conclusion of the work period. Please check the page on co-op duties and responsibilities if you would like more information regarding the requirements for the Student Performance Evaluation[9].

Your "Work Term Record" may be found on the bottom right side of the WaterlooWorks dashboard. During the fourth month of the work term, we are going to get in touch with the person who is listed as your contact on my "Work Term Record.", and we are going to give that contact repeated reminders to complete a Student Performance Evaluation[10]. As a student participating in a co-op, it is your obligation to make certain that this is finished and turned in within the allotted amount of time by your employer. It would be to benefit you if you could remember to hand in your pupil performance Evaluation BEFORE you conclude your work term with the organization. This would be something that would be beneficial to your employer. Please do not hesitate to contact your co-op adviser if you have any inquiries regarding the process of completing your Student Performance Evaluation in collaboration with your employer.

II. LITERATURE REVIEW

Sáiz 2023 et. al conducted research with a representative sample of 57 college students, including 42 undergraduates and 15 graduate students majoring in Health Sciences. An interdisciplinary approach to research was taken. The quantitative study investigated the influence of the variable's schooling (bachelor's degree vs. master's degree) including the combined level of previous expertise on the rate of chatbot usage (low vs. average), learning outcomes, or satisfaction with the chatbot's usefulness. [Chatbot use rate] [Low vs. average] [Learning results] [Satisfaction with the chatbot's usefulness] [Low vs. average] . Specifically, the study looked at how educational level and prior knowledge affect how frequently people use chatbots. In addition, we investigated whether or not the frequency of students' use of chatbots was dependent on the metacognitive tactics they employed. The ideas that the students had for improving the chatbot and the kind of questions that it asked were analyzed as part of the qualitative research. There were no findings that could be considered definitive in regard to the frequency of use of chatbots and the levels of metacognitive methods exhibited by the pupils. On the basis of the students' recommendations for areas of development, additional research is required to direct this research [11].

Beckham 2023 et. al might generally be the greatest approach for fixing some problems, as a result of the fact as students are responsible for shaping the future of their country, which will have repercussions for a great number of aspects of life in the future, each student may be forced to deal with extremely difficult challenges. To determine whether or not a particular element genuinely has an impact on student grades, our MLP 12-Neuron model makes use of ML models to make predictions. First place goes to our MLP 12-Neuron model, which achieves the best results with an RMSE score of 4.32; second place goes to Random Forest, which achieves the best results with an RMSE value of 4.52; and third place goes to Decision Tree, which achieves the best results with a R [12].

Agarwal 2023 et. al has received a lot of attention as of late in association with its effects, which have been observed in students attending universities in India. The information for the dataset was gathered over the course of several years through the use of a questionnaire. Millions of people suffer from mental diseases that are frequently overlooked, and the vast majority of those people fulfill the criteria for the Likert scale measuring instrument. The individuals who participated in the study were university engineering students. The majority of respondents to this inquiry were young people, specifically students from a variety of educational institutions. The goal of this research was to ascertain the level of anxiety that was experienced by each of the 127 engineering students that participated in the study. As a direct result of this research, the degree of anxiety was quantified, and its causes and effects were evaluated in connection with its impact, as noticed by Indian university students. [Causes] and [effects] were analyzed in conjunction with [its] effects, as observed in [Indian] university students. The precision for the year 2023 It was discovered that the Authors are based on the fact that Cronbach's alpha value for the entire dataset was found to be 0.723 and the Pearson's correlation coefficient was found to be 0.823. This led to the conclusion that the Authors are. Elsevier (B.V.) was responsible for the printing and distribution. The accuracy of the naive Bayes technique was 71.05%, while the accuracy of the decision tree method was 71.05%, the accuracy of the random forest method was 78.9%, and the accuracy of the support vector machine method was 75.5% [13].

Nasser 2023 et. al According to the findings of the study, a Machine Learning (ML) technique was presented to improve the quality assurance of online education courses offered through the Maharat platform at Taif University. These programs are modeled after those offered in the Kingdom of Saudi Arabia (KSA), which has established criteria for online training. The outcomes of the research served as the foundation for these justifications. By taking into account the participants' participation in a virtual school environment, the primary objective of this study is to make an educated guess as to the level of academic success that each participant will achieve. After the selection of the relevant features by the application of hybrid optimization, the classification procedure was then carried out. The technique known as Support Vector Machine was used in order to make the predictions. For the purpose of determining and identifying the degree of achievement of the quality monitoring of online training program criteria, we made use of a technique that included descriptive and analytical components. This was accomplished by conducting an analysis of the sample opinions regarding the quality guarantee of online courses that were acquired using the Maharat platform that is situated at Taif University [14].

Ortin 2023 et. alhas demonstrated a noteworthy increase throughout the course of the past few years. These repositories house valuable information that may be extracted and used for a wide number of applications, including, but not limited to, the following: using them to teach programming; using them to identify poor programming practices; and constructing programming tools such as decompilers, developer environments, and intelligent tutoring systems. documenting recurrent syntactic constructs; evaluating the particular builds used by experts & beginners; using them to teach programming; using used to detect poor programming practices.

The fact that the syntactic information of source code is stored with tree structures, yet the datasets used by typical machine learning methods are n-dimensional, presents a challenge that is inherent to the format of the source code. These approaches involve learning in supervised as well as unsupervised settings. These findings reveal some interesting knowledge, such as the Java builds that are rarely used (in addition to widely used) (for example, bitwise operators, union types, as well as static blocks), various language features and patterns that are most commonly used by beginners (indeed barely used by experts), the discovery of certain kinds of source code (for example, helper or utility lessons, data transfer objects, and too complex abstractions), as well as the way that complexity is an inherent characteristic of the programming language [15].

Table 1 literature summary

Author/year	Method/models	Metrics	References
Martín/2023	Harmon's one-factor test (Harmon's single-factor test) by using IBM SPSS	Variables= 28.7%,	[16]
Kunhoth/2023	K-Nearest Neighbor, Support Vector Machine, Random Forest, & AdaBoost are some of the algorithms that can be used.	Accuracy= 80.8%	[17]
Gencoglu/2023	latent Dirichlet allocation (LDA)	Qualitative data= 173,858	[18]
Iqbal/2023	Artificial Intelligence (AI) & Machine Learning (ML)	Average= 2.5, median= 3	[19]
Asish/2022	RF, kNN, and extreme gradient boost (XGBoost) model	Accuracy= 98.88%	[20]

III. PROPOSED METHODOLOGY

This page utilizes the open-source and totally free Kaggle tool to aggregate information on Portuguese with mathematics into one convenient location. focuses on the final rating that is used to classify pupils and offer them labels for their predicted and actual performance. There is a wide variety of design options available for columns or features. After that, the data ought to be prepared. If you choose to view the final score row, you will see that you have the option to utilize the score to divide the qualities into one of three categories: Good, Fair, or Poor.

A. Data Collection

Data collection involves testing hypotheses, answering research questions, and assessing results. Data collection is the systematic gathering and analysis of vital information. Arts & humanities, business, social sciences, & physical and applied sciences use the same research process. Data collection is the most important part of any research project. Different study fields require different data collection methodologies.

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B. Pre-processing

Data preparation in data mining makes raw data more valuable and manageable. Since raw data may contain a lot of irrelevant information, it is important to clean it. Data preparation techniques have changed due to inferences drawn against machine learning and AI models and training them. Data preparation changes data structure, making data mining, machine learning, and other data science tasks faster and more efficient. To verify results, machine neural networks and artificial intelligence developers use the methods early on.

C. Data Splitting

The train-test split method tests machine learning algorithms' predictions using untrained data. The test set is the model's untrained data. Using outcomes, you can analyze how machine learning algorithms fared on your predictive modeling work. Despite its simplicity, the strategy should not be used in several situations. This difficulty occurs when the dataset is small and needs additional configuration or is utilized for classification but is unbalanced.

D. EDA

Exploratory data analysis (EDA) is a statistical method that compares data sets to find their commonalities. Statistics and other data visualization methods are used frequently. EDA seeks to discover what data may reveal that formal models cannot. Statistical models are yours to use. Since 1970, John Tukey has promoted exploratory data analysis to persuade statisticians to examine the data and generate ideas that could lead to greater data collection & testing.

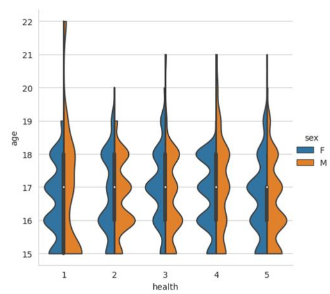

Figure 2 depicts the age and health-related Violin plot with sex classifications, where blue means female and orange denotes male

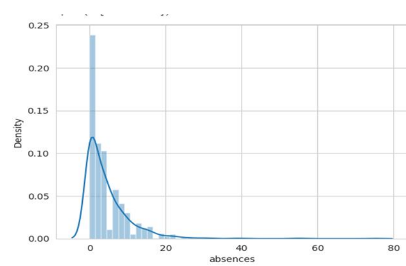

Figure 3 Distplot of Absences

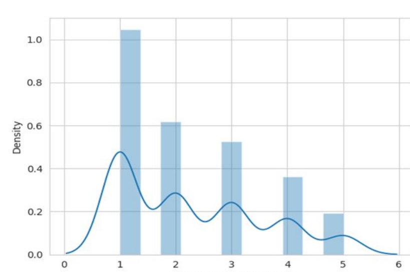

Figure 4 Distplot of weekend alcohol usage

Figures 3 and 4 display the Displots for absences, and alcohol consumption during the weekend.

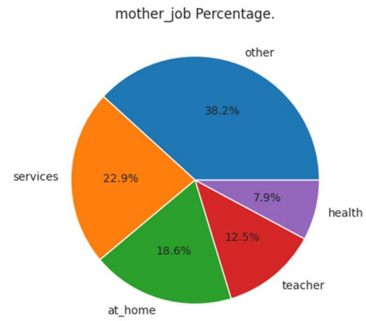

Figure 5 Piechart of mother job percentage

The piecharts of the percentages of mother's employment are shown in Figure 5

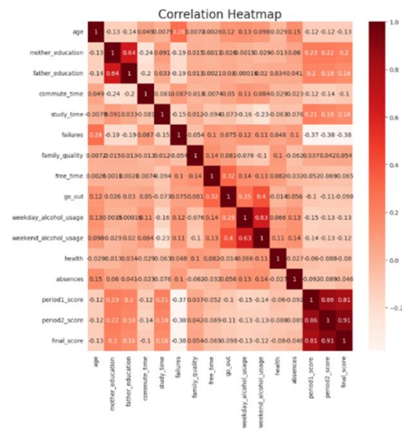

Figure 6 Correlation Matrix of dataset variables

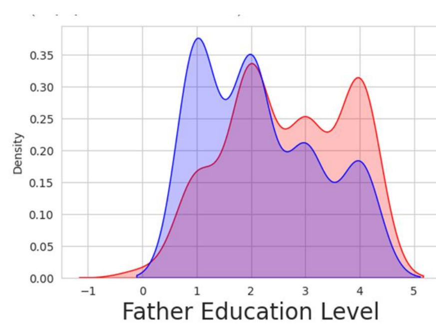

Figure 7 Parents education level

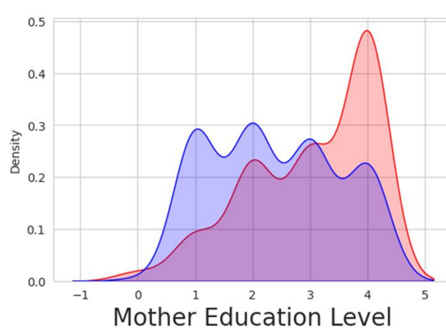

Figure 8 Parents education level

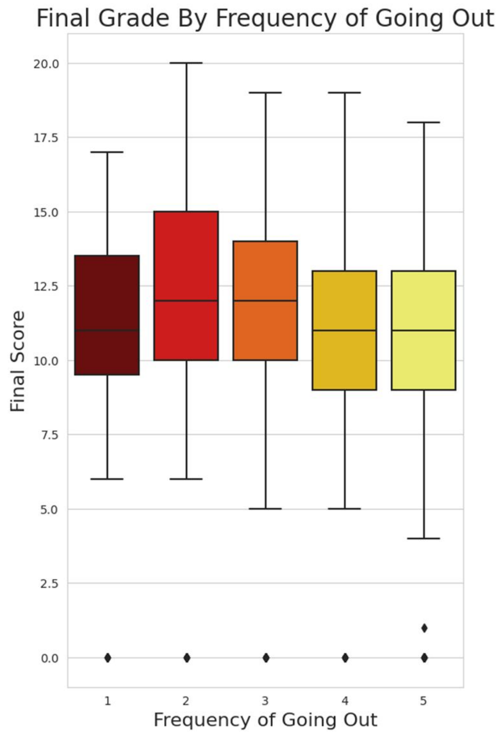

Figure 9 Boxplots of the final grade by frequency of going out

E. Machine Learning and Modeling

Data science's fast-growing field includes machine learning. Using statistical methods, data mining projects train algorithms to classify or forecast and reveal key insights. These insights drive company application activities, which should affect important growth indicators. Data scientists will be in demand as big data usage grows. They'll help discover the company's most important questions and the data needed to address them.

1) *Random Forest:* A well-known approach to machine learning, "random forest" was conceived of by Leo Breiman and Adele Cutler, who are also the authors of the phrase "random forest." In order to reach a single decision, this algorithm combines the outcomes of a number of distinct decision trees that have been run through it. Its capacity to address classification and regression problems has contributed to its broad deployment, and its user-friendliness & adaptability have been key factors in this.
2) *Logistic Regression:* Logarithmic regression uses logit(pi) for the dependent variable and x for the independent variable. The beta parameter, also known as the beta coefficient, is usually estimated using maximum likelihood estimate (MLE). This method iteratively tests beta values to get the best match to log odds. This study seeks the optimum fit. Repeat until the perfect coefficient is discovered. This step can be conducted after finding the optimal coefficient (and coefficients, if there is an other dependent variable).
3) *Ada Boost:* In machine learning, AdaBoost (Adaptive Boosting) is an Ensemble Method. This method is called Adaptive Boosting. Most AdaBoost estimators use decision trees with one split. These estimators are single-level decision trees. These trees are called Decision Stumps.
4) *Xg Boost:* XGBoost, an updated distributed gradient booster toolkit for training deep learning models efficiently and scalable, has become one of the most used machine learning methods. Its ability to handle massive datasets and perform well in machine-learning tasks like classification and regression is partly responsible for this.
5) *Ensemble:* If you are a beginner who wants to learn more about groups or variance and bias, this comprehensive article will help you understand ensemble learning, machine learning methods, the ensemble algorithm, and critical ensemble algorithms like boosting and bagging. Read this if either of these apply to you. Before diving into ensemble learning's what, why, and how, let's look at some real-world instances to demystify its ideas.

IV. RESULT AND DISCUSSION

The findings of the research are presented in this part of the report. The viability of the proposed model was evaluated throughout the entirety of the experiment making use of a Python simulator in conjunction with a variety of performance measures. The metrics that were used for the assessment are presented down below.

A. TN/TP/FN/FP

1) True positive: the desired positive results were achieved as planned.
2) False Positive: this was supposed to have a cheery tone, but it came out sounding gloomy instead.
3) Genuinely negative outcomes have already transpired, despite the fact that unfavorable outcomes were anticipated.
4) False negative: an indication that the outcome will be negative when in fact it will be good.

B. Confusion Matrix

The first thing that we do with the data after organizing, cleansing, & otherwise modifying it is to feed it into a wonderful model, which, by its very nature, produces outcomes in the form of probabilities. This is where the Confusion Matrix is exposed for all to see. The confusion matrix is a tool that can be used to evaluate how well machine learning can classify things.

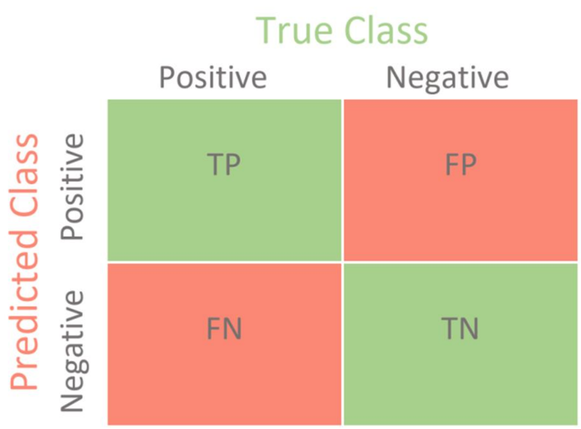

Figure 9 Confusion Matrix

C. Accuracy

Accuracy is determined by comparing the total data number occurrences to proportion of those data instances that have the appropriate category.

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

D. Precision

With a degree of accuracy equal to 1. A rating that is widely recognized and respected is a requirement for a good classifier. When both the numerator and the denominator are the same, as in TP = TP + FP, the precision increases to 1, while the fractional precision decreases to 0. The value of the denominator goes up as the fractional part grows, but the value of the precision goes down, which is the opposite of what we want to happen.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

E. Recall/Sensitivity

A skilled classifier has a high recall value of one. In the equation TP = TP + FN, FN is considered to be 0 because the value of recall is restricted to 1 when the numerator and denominator are the same. Sensitivity lets us count the number of times the model predicted the outcome, which helps us assess its efficacy.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$Sensitivity = \frac{TP}{TP+FN} = recall \quad (4)$$

F. Specificity

When evaluating the usefulness of a model, it is customary to take into account both the model's specificity and its sensitivity. The proportion of cases that are not false positives that can be identified by the model is referred to as its specificity. As a direct consequence of this, there will be a greater number of false positives than there were originally predicted to be.

$$Specificity = \frac{TN}{TN+FP} \tag{5}$$

G. F1 Score

Before the F1 Score can reach 1, there must be no difference between precision and recall. Only when a person's recall or accuracy are strong will they see an increase in their F1 scores. It is more helpful to look at the harmonic mean among recall and precision, also known as the F1 score.

$$F1 - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \tag{6}$$

H. Performance Evaluation

A. Model	Accuracy	Precision	Recall	F1 score	Specificity	Sensitivity
Random forest	0.863	0.863	0863	0.863	0.970	0.9090
Logistic regression	0.875	0.875	0.875	0.875	0.950	0.939
Ada boost	0.630	0.630	0.630	0.630	0.978	0.015
Xg boost	0.888	0.888	0.888	0.888	0.969	0.909
Ensemble	0.882	0.882	0.882	0.882	0.969	0.909

Table 1 compares Logistic Regression with Decision Tree's performance. KNN, SVC, and Ensemble scored 0.89 & 0.89 for the f1 score, respectively. Accuracy, precision, and recall were maximum for the support vector classification model at 0.86. Table 1 ranked the ensemble score, 0.89, first and second.

I. Modelling

1) Logistics Regression

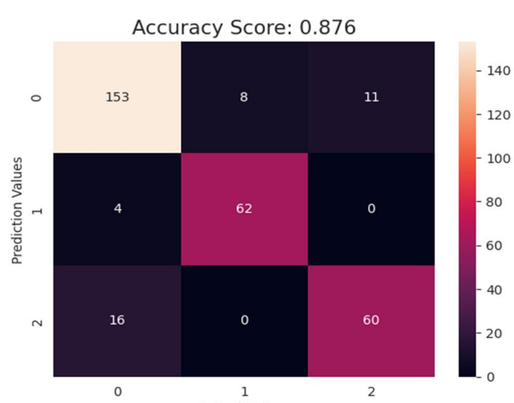

Figure 10 Confusion matrix Logistics regression

2) Random forest Classifier

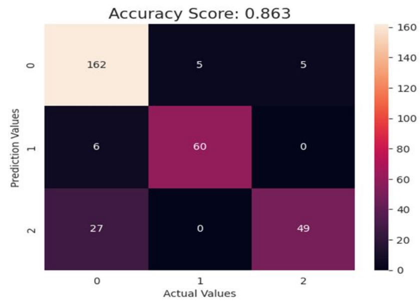

Figure 11 Confusion matrix Random forest classifier

3) Ada Boost Classifier

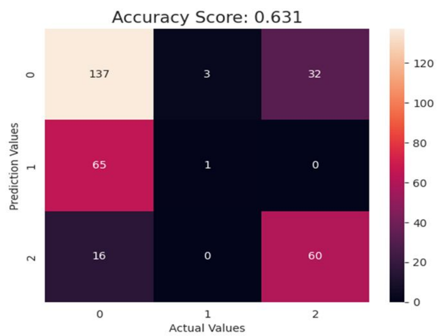

Figure 12 Confusion matrix of Ada Boost Classifier

4) XGBoost Classifier

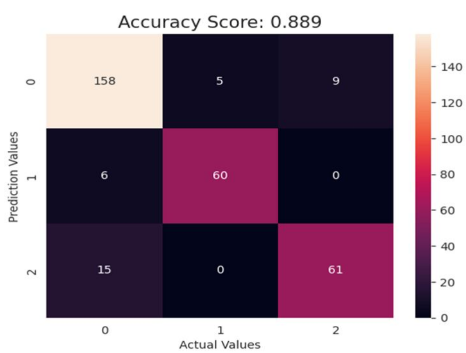

Figure 13 Confusion matrix of XGBoost Classifier

5) Ensemble

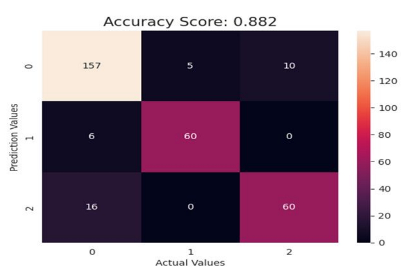

Figure 14 Confusion matrix of Ensemble

Figures 10 to 14 present the confusion matrices for a number of machine learning models, including ensemble, Logistic regression, Random forest, Adaboost, XG Boost yielded the best results.

V. CONCLUSION

Predicting student success is crucial when addressing higher education, in-depth education, and relationships. Students can choose courses with the best study strategies by forecasting their performance. It allows teachers and administrators to monitor students and give better support, combine training packages for optimal results, and forecast student performance. Student forecasting reduces inefficient warning signals for student expulsions, among other benefits. If they choose classes and study strategies that fit their strengths and interests, students can predict their futures. The Support Vector Classifier became the most useful tool for this inquiry due to its 0.888 accuracy, precision, recall, & f1 scores. These values demonstrate data categorization precision. Ensemble, logistic regression, random forest, AdaBoost, & XG Boost were used in this study.

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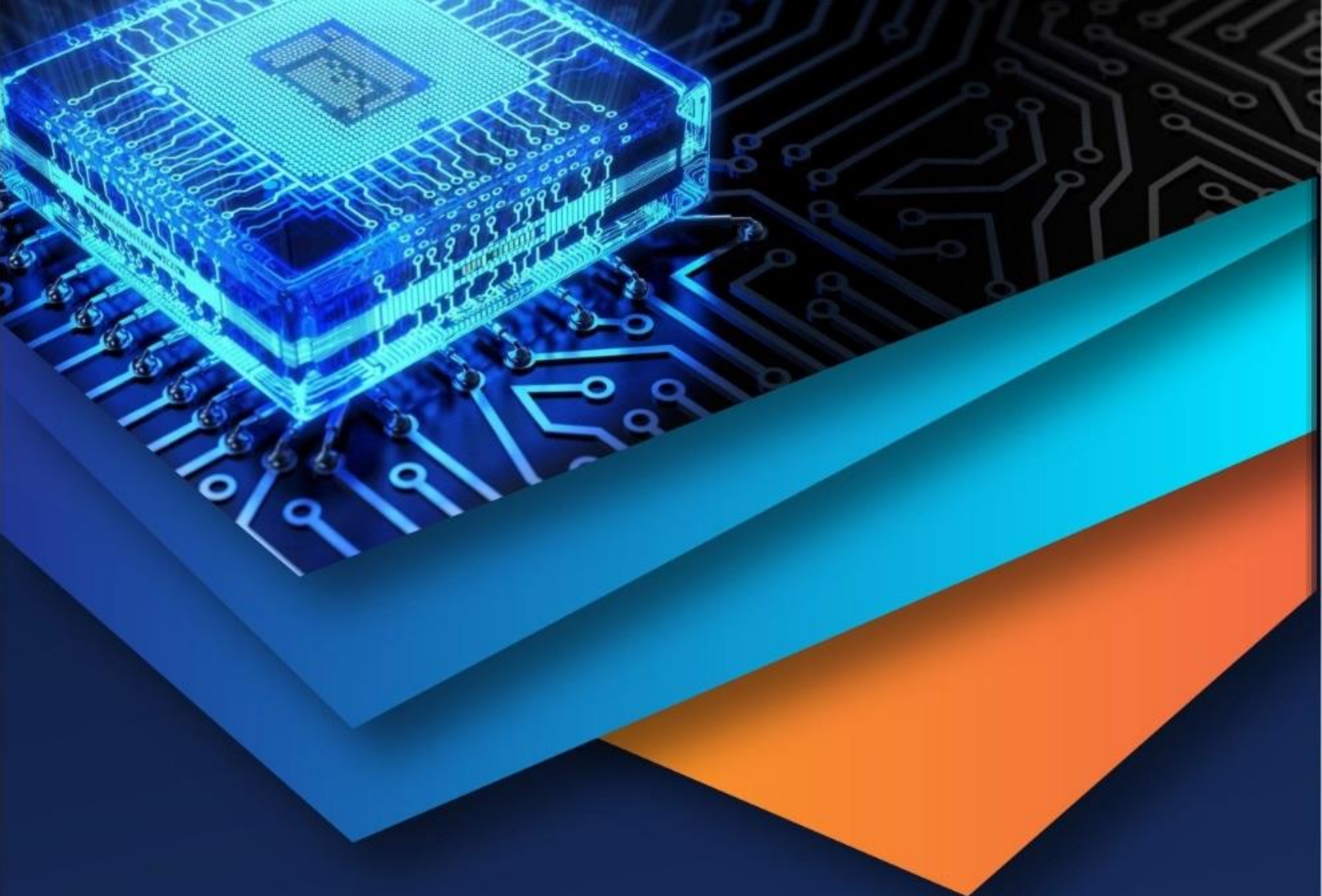

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