Mapping academic outcomes to student routines using machine learning: a data-driven approach

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ABSTRACT

In today's environment, students often struggle with time management and dealing with emotions like frustration and anxiety, which may have an adverse impact on their academic achievement. This research aims to enhance time management and educational support for college students by leveraging demographic characteristics and performance in specific assignments to develop a predictive model for academic performance. The study evaluates various regression algorithms to identify the most accurate method for predicting students' semester grade point average (SGPA) based on their activities. This predictive model aims to optimize students' learning experiences and mitigate challenges such as frustration and anxiety. The findings highlight the potential of personalized educational assistance in improving student learning outcomes. Various machine learning algorithms, including decision trees, support vector regression (SVR), ridge regression, lasso regression, XGBoost, and gradient boosting, were implemented in Python for this study. Results show that XGBoost achieved the lowest root mean square error (RMSE) of 9.39 with a 60:40 data split ratio, outperforming other algorithms, while decision trees exhibited the highest RMSE. The findings emphasize the potential of personalized educational assistance to improve learning outcomes by helping students adjust study habits to address weaknesses and reduce anxiety. Future studies can explore integrating real-time data and additional features such as emotional well-being and extracurricular activities to further improve the model's predictive capabilities.

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1. INTRODUCTION

The dataset presented here offers a panoramic exploration into the intricate interplay between student lifestyle choices and their academic achievements. It delves deep into the fabric of a student's daily routine, capturing nuanced details such as waking habits, dedicated study durations, and leisure pursuits. With a primary focus on deciphering the intricate correlations between academic performance and various facets of student life, including academic commitments, social engagements, entertainment preferences, and physical well-being, this dataset endeavors to paint a holistic portrait of the student experience. Beyond merely presenting a collection of disparate variables, this dataset emerges as a cohesive tapestry, weaving together the myriad elements that shape a student's journey through academia. At its core lies the pivotal target variable, "Previous_Semester_Score," which serves as a cornerstone and enriches the dataset with a historical perspective on academic progress. By incorporating user-input lifestyle parameters, the dataset embarks on a quest to unveil hidden patterns, seeking to forecast academic outcomes through the lens of lifestyle analytics. In essence, this dataset emerges as a guiding beacon, offering insights into the intricacies of students' daily lives and laying the groundwork for tailored strategies aimed at fostering academic success. It stands not just as a repository of data but as a living testament to the multifaceted nature of the student experience, empowering educators and stakeholders alike to navigate the academic landscape with precision and insight. This study is significant since it tackles essential difficulties encountered by college students, like managing their time and mental health, which directly influence academic achievement. By utilizing machine learning algorithms to forecast semester grade point average (SGPA), the study offers a data-driven methodology to identify and mitigate the factors influencing academic results. The novelty lies in integrating demographic characteristics and assignment-specific performance to develop a highly accurate predictive model.

2. REVIEW OF LITERATURE

The study compares the accuracy and performance of five techniques before proposing a multi-class prediction model for imbalanced multi-class datasets. Synthetic minority oversampling and feature selection increase unbalanced dataset accuracy compared to the five methods [1]. Machine learning models from Wolkite University data predict student performance and identify low performers [2]. Another study finds that online learning, evaluation grades, and academic emotions predict academic performance [3]. Resampling strategies demonstrate that random forest (RF) and SVM-SMOTE improve unbalanced dataset performance, with RF being the best [4]. Another Indian research suggests neural networks may predict educational success despite difficulties [5]. Another article finds that course grades predict graduation better than GPAs, and sparse linear and low-rank matrix factorization increases accuracy [6], [7]. Postgraduate research showed ANN predicts CGPA well [8]. Another study uses RF and multi-class prediction models to assess first-semester grades [9], [10]. Another study found that support vector regression (SVR) best predicts Nigerian students' CGPA, with age and other characteristics less important [11]. According to publications [12]-[14], machine learning is being employed for early student performance intervention. A study demonstrates Naive Bayes categorization accurately predicts student achievement [15]. Another research found that ANN predicts computer science student results best [16]. Research shows that machine learning models predict GPA and workload with approximately 75% accuracy [17]. As a result of improving prediction accuracy and providing assistance to students with poor performance, machine learning (ML) technologies have an impact on education [18]. The analysis reveals that logistic regression accurately predicts higher education student achievement [19]. The enriched plant growth optimised ANN method predicts academic achievement better [20]. Another research compares ML workload DBMSs to common frameworks [21]. A paper shows that the RF classifier predicts computer science student performance 94% accurately [22]. Another research found critical COVID-19 student retention characteristics using data mining [23]. Historical data suggests it improves schooling [24]. College algebra success research employs k-nearest neighbours (KNN) and decision trees with 85% accuracy [25]. Another study reveals that RF and ensemble models best predict student achievement [26]. Another paper showed RBM accurately predicts electrical engineering grades [27]. Finally, an article differentiates GPA-influencing components into psychological, social, and study elements [28], while another study proposes a model that predicts final test grades with 70-75% accuracy from midterm results [29].

3. RESEARCH METHODOLOGY

A survey (G-forms) is used to gather data on a college student's activities in order to forecast their SGPA. The dataset includes many parameters pertaining to student activities, including study time, wake-up time, previous year's semester score, sleep time, over-the-top (OTT) use, TV viewing, social media engagement, online gaming, participation in social events, time spent in college, and involvement in sports. These elements have a role in deciding the students' actions and enhancing their future SGPA. The dataset has a combination of category and numerical data. Out of these eleven columns, there is one that is independent and one that is dependent. In this context, our aim is to determine the target variable, which is the SEM score from the previous year. This score is influenced by the independent factors included in the dataset. The dataset has 500 rows and 12 columns. The objective of the project is to forecast students' future SGPA by using previous semester data, machine learning algorithms, and study hours. A prognostic model is developed, providing tailored suggestions and an intuitive interface. The model undergoes continual updates, promoting the establishment of attainable objectives and providing tools to enhance study habits and time management abilities. Machine learning algorithm models include:

a) Linear regression: linear regression is a machine learning algorithm used to predict the target variable, and it builds the correlation between a target variable and one or more feature variables, considered to be linear. It tries to identify the best-fitting line through the data points:

$$y = b_0 + b_1 * x \tag{1}$$

where y is the dependent variable and the independent variable x.

Assuming a linear relationship, linear regression is a machine-learning approach that predicts the target variable by constructing a link between a dependent variable and one or more independent variables. It seeks to identify the line that fits the data points the best.

b) KNN: it calculates distances between a new data point and other training points using metrics like Euclidean distance, Manhattan distance, or Minkowski distance. The number of nearest neighbors is chosen, and the majority class is assigned to the new data point. The algorithm also uses the average value of these neighbors for regression predictions:

$$D = (x_1 - x_{11})^2 + (x_2 - x_{12})^2 + \cdots + (x_n - x_{1n})^2 \tag{2}$$

where:
x_1, x_2, x_3, x_4…..,xn are the features of the new data point you want to classify or predict $x_{11}, x_{12}, x_{13}, x_{14} \ldots . x_{1n}$ are the features of a data point in the training set that we are comparing. D is the Euclidean distance between these two data points, calculated using their respective features.

c) SVR: it is a learning method used by machines for regression problems. SVR's objective is to find the best hyperplane and classify the data points. We have considered our dataset's kernel, which is a linear function, and performed the model fitting with the five test ratios:

$$Y = w_t\, x + b \tag{3}$$

where y is the predicted value, x is the input feature vector, w is the weight vector that determines the direction of the hyperplane, and b is the bias term.

d) Bagging: it creates diverse subsets of the training data through bootstrapping and trains a base model on each subset. Bagging is effective for reducing overfitting and increasing the stability of the model, especially in high-variance algorithms like decision trees.

e) Decision tree: the decision tree is a type of bagging where it is used to handle non-dataset effectively and falls under non-parametric supervised learning.

f) Random forest: this assembles several decision trees and merges their forecasts by choosing arbitrary subsets of information and characteristics for every tree, it produces diversity. It then combines and provides a final prediction that is more accurate and less prone to overfitting.

g) Boosting: it's a method used in machine learning to reduce errors in predictive data analysis. It creates an ensemble model by combing several weak decision trees sequentially and assigning the the output of individual trees.

h) XG-Boost: XG-Boost is designed to be very efficient and can handle different types of data. It includes techniques like regularization, which helps to prevent overfitting, and parallel processing, which makes it faster to train and make predictions

i) Ada-Boost: Ada-Boost adapts and tries to self-correct, it's not as sensitive as other boosting algorithms. Combines multiple weak learners into a robust model. It assigns greater weight to data points with larger errors, focusing on areas where the model performs poorly.

j) Gradient-Boost: Gradient-Boost is a sequential training technique. It focuses on minimizing the loss function, gradually refining predictions with each iteration. By combining the strengths of multiple weak learners, such as decision trees, Gradient Boosting produces a powerful regression model capable of capturing complex relationships in the data.

k) Ridge regression: ridge regression is one of the regularization techniques used to overcome the problem of overfitting. In ridge regression, we add a penalty term equal to the coefficients' square. The mathematical equations of ridge regression are as:

$$\sum_{i=1}^{n}(y_i - \hat{y})^2 + \lambda \sum_{i=1}^{p} \beta_j^2 \tag{4}$$

where:
- n is the number of data points, p is the number of features

- y_i is the observed target value, $\hat{y}$ is the predicted target value
- λ is the regularization parameter that controls the strength of regularization
- β are the coefficients of the linear regression model

l) Lasso regression: lasso effectively shrinks less important feature coefficients to zero, allowing for feature selection and mitigating overfitting. Lasso regression minimizes the sum of squared residuals plus the sum of the absolute values of the coefficients multiplied by a regularization parameter.

$$\sum_{i=1}^{n}(y_i - \hat{y})^2 + \lambda \sum_{j=1}^{p}|\beta_j| \quad (5)$$

Where $|\beta_j|$ represents the absolute value of the coefficient β_j.

4. RESULTS AND DISCUSSIONS

The data must be evaluated after the cleansing procedure has been completed, and it is necessary to investigate the intra- and interrelationships between the dataset's characteristics and the objective variable. We have installed libraries such as Seaborn and Matplotlib from the Python programming language to examine and display the variables. Figure 1 illustrates the total number of minutes that our students spent napping. The following line chart shows that 196 students slept for 420 minutes, 142 students slept for 360 minutes, 117 slept for 480 minutes, 31 slept for 300 minutes, and 16 slept for 240 minutes. Figure 2 presents a heatmap of all independent and target variables, revealing perfect correlations among features. For instance, wake-up time is negatively correlated with online games, while study time is positively correlated with time spent in college. A value of 1 indicates a perfect correlation, with positive and negative values reflecting strong and weak correlations, respectively.

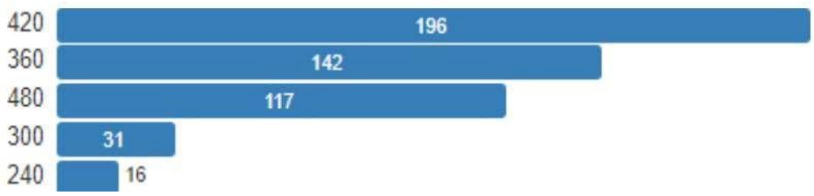

Figure 1. No. of students vs. sleeping time (in minutes)

Comparison of algorithms: Table 1 compares the RMSE of all the algorithms. We can observe that XG-Boost gives us the best result compared to other algorithms with less RMSE, i.e., 9.39 with a ratio of 60:40. From the comparison table, we find that the decision tree gives us high RMSE values compared to other algorithms. After reviewing multiple machine learning algorithms, XG Boost consistently delivered the highest performance in all the ratios, making it the top choice in our analysis. We did a forecast using XG Boost Algorithms using the different activities of the students per week. Table 2 is a prediction for college students for the upcoming semester.

Using user-provided data from Table 2, we predicted the SGPA for a group of students represented as S1, S2, and S3. The analysis considered several parameters, including wake-up time, OTT (Over-The-Top media services) time, study time, and other variables that reflect the time students allocated to different activities. These parameters were employed as inputs to a predictive model to estimate each student's SGPA.

The model's predictions for the SGPA were 6.29 for S1, 7.73 for S2, and 8.89 for S3. These predictions provide an accurate forecast of the students' potential performance in future semesters based on their current time management and activity patterns. By understanding the relationship between these parameters and academic performance, students can gain valuable insights into how their daily routines and choices may influence their SGPA. This modeling approach allows students to better comprehend the impact of their time allocation on academic outcomes. By identifying the parameters that most significantly affect SGPA, students can strategically adjust their habits and behaviors to optimize their performance, aiming for improved grades in subsequent semesters.

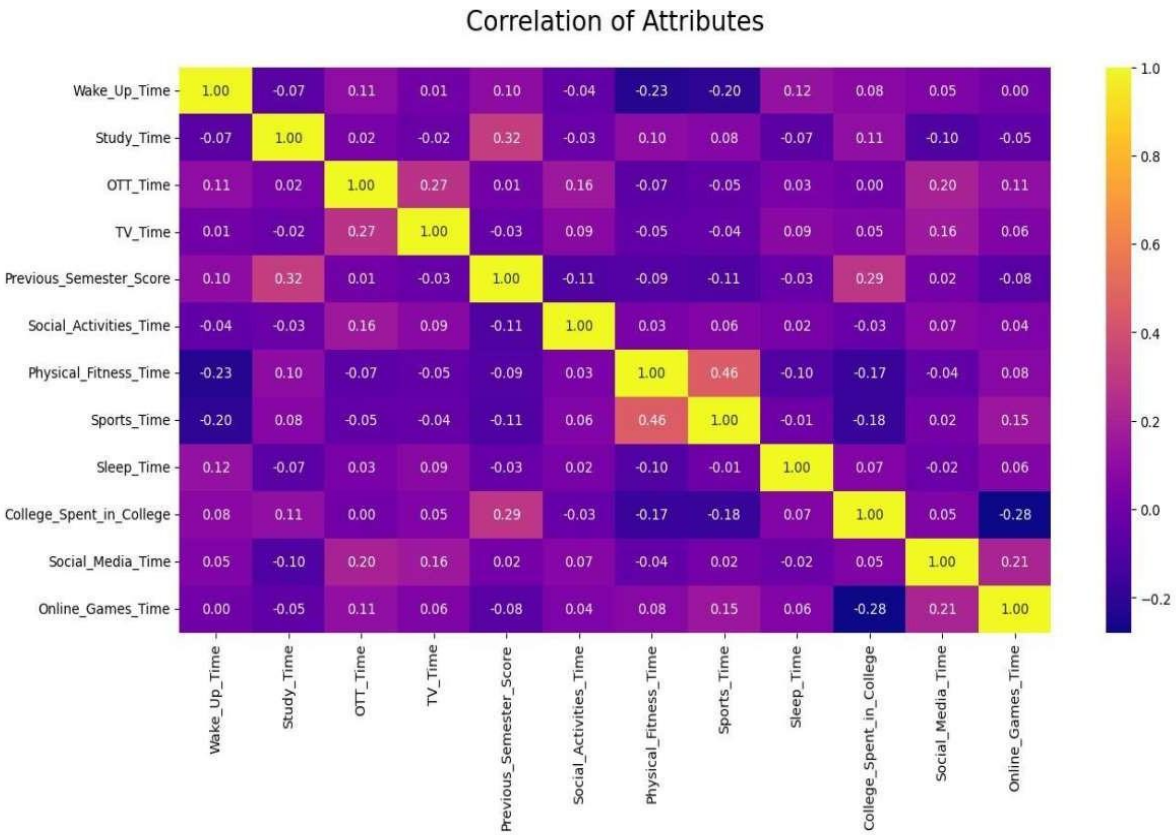

Figure 2. Heatmap of time spent

Table 1. Performance metrics: RMSE values for various Algorithms

Algorithm	80:20	75:25	70:30	65:35	60:40
Linear regression	13.07	11.73	10.96	10.25	9.42
KNN	13.07	11.76	10.79	10.16	9.45
SVR	12.99	11.67	10.7	10.13	9.4
Bagging	12.99	11.73	10.73	10.12	9.39
Decision tree	13.21	11.89	11.09	10.42	9.52
Random forest	13.01	11.67	10.75	10.22	9.43
XG boost	**12.96**	**11.64**	**10.69**	**10.09**	**9.39**
Ada boost	13.07	11.65	10.67	10.12	9.42
Gradient boosting	12.99	11.67	10.68	10.19	9.41
Ridge	12.91	11.65	10.69	9.99	9.44
Lasso	13.13	11.78	10.8	10.1	9.46

Table 2. Prediction of SGPA using XG boost Algorithms

Variables (In Mins)	Student		
	S-1	S-2	S-3
Wake up time	7.30	5.00	5.00
Study time	60	180	240
Ott time	60	30	0
Tv time	30	0	30
Social activities time	120	0	0
Physical activities time	60	60	60
Sports time	60	0	60
Sleep time	480	360	480
Spent in college	300	480	480
Social media time	30	30	30
Online games	10	0	0
Prediction of upcoming semester mark	6.29	7.73	8.89

5. CONCLUSIONS

In our analysis, we evaluated several algorithms' interpretability and computational efficiency. XGBoost emerged as the best-performing algorithm due to its high accuracy and speed, making it suitable for real-time predictions of student performance. The feature importance analysis provided by XGBoost offered valuable insights into the factors most influencing SGPA outcomes, facilitating better decision-making in educational contexts. The effective use of XGBoost highlights its versatility and capability in handling diverse data analysis and prediction tasks within the educational domain. This approach enhances SGPA prediction accuracy and helps students understand the impact of their time allocation on academic performance.

This modeling approach allows students to better comprehend the impact of their time allocation on academic outcomes. By identifying the parameters that most significantly affect SGPA, students can strategically adjust their habits and behaviors to optimize their performance, aiming for improved grades in subsequent semesters. However, this research has certain limitations, one of which is that it uses a static dataset. It may not capture all the dynamic elements, such as how people study, their emotions, or how outside influences change over time. In order to improve the prediction capabilities of the model, future research should concentrate on adding real-time data from the activities that students engage in daily. These activities could include attendance, engagement in extracurricular activities, and emotional well-being data.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [Selvakumar Venkatachalam], upon reasonable request.

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