

# A Hybrid Machine Learning Framework For Analyzing The Impact Of Social Media On Students' Academic Performance

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**Abstract**— In today's educational landscape, social media plays a dual role—serving as a tool for collaboration and communication while also posing risks to student well-being and academic focus. This study introduces a hybrid machine learning framework designed to assess both academic success and behavioral risks associated with social media usage. Using pre-admission academic records and behavioral indicators such as sleep quality, mood disorders, and stress levels, the framework operates in two stages: first predicting academic success and then evaluating whether successful students are vulnerable to negative social media impact. Multiple models—including Random Forest, Support Vector Machine, Neural Network, Gradient Boosting, and an Ensemble approach—were tested, with Gradient Boosting achieving the highest accuracy (99%) across both stages. The results demonstrate the framework's potential for early intervention, enabling institutions to proactively identify at-risk students and implement targeted support strategies. This approach offers a scalable, data-driven solution for enhancing student outcomes and promoting digital wellness in academic environments.

**Keywords**—Academic Performance Prediction, Social Media Analytics, ML, Gradient Boosting, Behavioral Risk Assessment, Educational Data Mining.

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## I. INTRODUCTION

Social media and other Web 2.0 technologies have rapidly evolved, allowing users to generate content, share visuals, express preferences through likes, and participate in interactive activities. Their widespread presence is especially noticeable in higher education, where they are reshaping how students connect, communicate, and engage with learning. While traditionally used for personal and professional networking, social media is now gaining recognition as a valuable educational tool. As interest in this area grows, researchers are increasingly examining its role in enhancing academic experiences. The influence of social media on students varies depending on the learning environment, but its potential to support education is becoming more evident. Education itself is rooted in the acquisition and application of knowledge, which plays a critical role in personal development and societal progress. Academic success, typically measured by student performance, is shaped by a range of factors including family background, parental education, household income, teacher qualifications, attendance, and access to learning materials and facilities. Students from disadvantaged backgrounds may face limited exposure to enriching educational opportunities, which can hinder their academic growth. Secondary education is a crucial stepping stone to higher learning, and persistent underachievement at this level can threaten the integrity of a nation's educational system. This study aims to explore existing literature on the impact of social media and other contributing factors on senior high school students' academic performance. It outlines the methodology used to identify relevant sources, defines social media in an educational context, reviews its benefits and limitations, and highlights key findings from scholarly research. The goal is to identify gaps in current knowledge and suggest directions for future research that can inform strategies to improve student outcomes.

The rapid proliferation of social media platforms has transformed the way students interact, learn, and engage in both academic and personal spheres. While social media offers opportunities for collaboration, resource sharing, and communication, it also introduces risks related to reduced study time, poor sleep quality, and increased anxiety levels. In academic settings, identifying students who are both likely to succeed and vulnerable to negative behavioral patterns is critical for implementing effective support measures. This paper proposes a hybrid machine learning framework capable of predicting academic success and assessing behavioral risks associated with social media usage. By integrating academic and behavioral data, the model aims to serve as a decision-support tool for educators, counselors, and policymakers.

## II. REVIEW OF LITERATURE

Nti, Isaac & Akyeramfo-Sam, Samuel & Bediako-Kyeremeh, Bright & Agyemang, Sylvester. (August 2021), This study aimed to investigate whether students' academic performance, measured by GPA, could be predicted using social networking site (SNS) usage variables. The dataset comprised a cross-sectional survey of approximately 550 students from higher education institutions. Key features included frequency of SNS use, purpose of use, and in-class usage. Decision Tree and Random Forest classifiers were employed, with findings indicating that both usage rate and in-class SNS activity negatively correlated with GPA. The Random Forest model outperformed the Decision Tree, suggesting better handling of feature interactions. However, limitations included reliance on self-reported data, exclusion of psychological wellness variables, and a single-institution scope that reduced generalizability. The study established Random Forest as a strong baseline and highlighted the predictive value of behavioral SNS patterns.

M. Ramzan and N. Ahmed, (Mar-2025), This research focused on analyzing how social media engagement and reaction behaviors correlate with academic grades. Using a dataset of 550 students that combined SNS usage logs with academic records, the study examined features such as purpose of SNS usage (academic vs. non-academic), frequency, time-of-day activity, and patterns of reactions (likes, comments, shares). Multiple machine learning models were compared, with emphasis on feature importance rankings. The study found that the purpose of use and temporal activity patterns, especially late-night usage, were more significant predictors of academic performance than total time spent online. Limitations included platform-specific data and limited generalizability of engineered features. The findings supported the inclusion of temporal and purpose-based usage patterns and validated a comparative modeling approach.

Ivan Smirnov, (Sept 2020), This paper explored whether short text content posted on social media could predict educational outcomes. The dataset included public posts linked to standardized test scores from high school and university students in Russia. Linguistic features such as vocabulary richness and grammar patterns, along with semantic features like sentiment and topic distribution, were extracted using natural language processing. Machine learning classifiers and regressors were applied with thorough external validation. The study found significant correlations between language patterns and academic performance, with linguistic features offering predictive value beyond demographic data. Limitations included cultural specificity to Russian platforms and ethical concerns in text mining. While not directly used in the current thesis, this work informs future extensions involving text and sentiment analysis.

Assefa, Y., Moges, B. T., & Kumar, T. (2023), This study examined the influence of social media usage on academic achievement through the mediating role of student engagement. A survey of approximately 395 university students was conducted, capturing distinctions between purposeful (academic) and distracting (non-academic) SNS use, alongside engagement and achievement scores. Structural Equation Modelling was used to analyze direct and indirect pathways. Results showed that purposeful SNS use had a positive indirect effect on academic achievement via engagement, whereas distracting use was negatively associated with performance. The correlational design limited causal inference, and self-reported data may have been affected by social desirability bias. Nonetheless, the study provided theoretical support for categorizing SNS use by quality, which informs feature classification in the thesis.

Ahmed, W., Wani, M.A., Plawiak, P. et al. (July-2025), This paper benchmarked multiple machine learning algorithms for predicting academic performance using tabular datasets. The dataset included academic and demographic data from educational institutions, with features such as grades, attendance, and personal details. Ten algorithms were evaluated, including K-Nearest Neighbour, Linear Regression, CatBoost, XGBoost, AdaBoost, and a voting ensemble of top performers. Ensemble methods consistently outperformed individual models, with boosting algorithms achieving the highest accuracy. Although the study did not incorporate social media behavioral variables, it validated the use of ensemble models, directly informing the hybrid approach adopted in the current research.

Ahmed, W., Wani, M.A., Plawiak, P. et al. (2022), This research applied educational data mining techniques to assess the impact of social media usage patterns on academic performance. The dataset included students from both high school and university levels, with features such as weekday and weekend SNS usage duration, total daily online time, and platform preferences. Algorithms used included Random Forest, Decision Tree, AdaBoost, Logistic Regression, Support Vector Machine, and Stochastic Gradient Descent. The study found that continuous weekday SNS use was linked to lower academic performance, with Random Forest achieving the

highest accuracy (~98%). However, the unusually high accuracy raised concerns about overfitting, and the lack of external validation limited generalizability. The study reinforced Random Forest's predictive strength and emphasized the need for robust validation.

### III. OBJECTIVES

The main objectives of this study and Objective-to-Model Strategy Mapping are as given below:

- **To identify key social media behaviors that influence academic performance** - The Impact label in social\_media\_df is defined based on social\_media\_sleep, sleep\_quality\_general, mood\_disorder, and anxious\_stressed features. These behavioral indicators are used to analyze their effect on students' success.
- **To compare the effectiveness of different machine learning algorithms in predicting academic performance** - Multiple models including Random Forest, SVM, MLP (Neural Network), and Gradient Boosting are trained on both admission and social media datasets. Their performance is compared to using accuracy metrics.
- **To design a hybrid machine learning model for analyzing students' academic performance** - An ensemble model, hybrid model is created by combining predictions from all individual models to improve accuracy and generalization. This represents the hybrid model.

### IV. METHODOLOGY

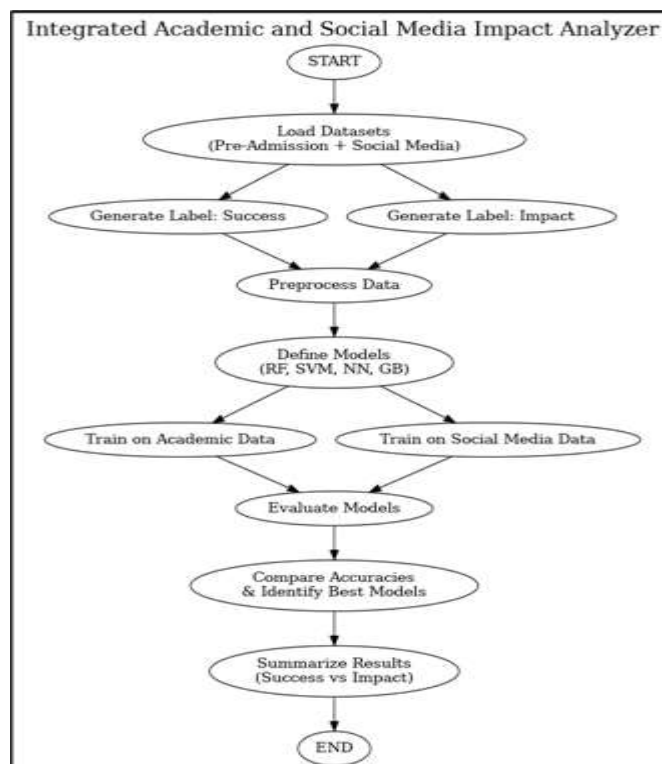


Fig. 1. Integrated Academic and Social Media Impact Analyzer

The flowchart titled Integrated Academic and Social Media Impact Analyzer presents a structured machine learning pipeline designed to evaluate how academic performance and social media behavior contribute to two distinct outcomes: Success and Impact. The process begins by loading two primary datasets—pre-admission academic data and social media data—each offering unique insights into a student's background and digital footprint. From these inputs, two labels are generated: one representing Success, likely tied to academic or career achievements, and another representing Impact, which may reflect social influence, engagement, or broader societal contribution. The data is then preprocessed through standard techniques such as cleaning, normalization, and feature engineering to ensure compatibility with machine learning models.

The system defines four predictive models—RF, SVM, NN, and GB—each selected for its strengths in handling structured and unstructured data. These models are trained separately on academic and social media datasets to

assess the predictive power of each source independently. Following training, the models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The results are then compared to identify which model and data source most effectively predict Success and Impact. Finally, the system summarizes the findings, offering insights into the relative influence of academic credentials versus digital presence. This framework has potential applications in educational policy, student profiling, and digital literacy initiatives, helping institutions better understand the multifaceted drivers of student outcomes in the modern era.

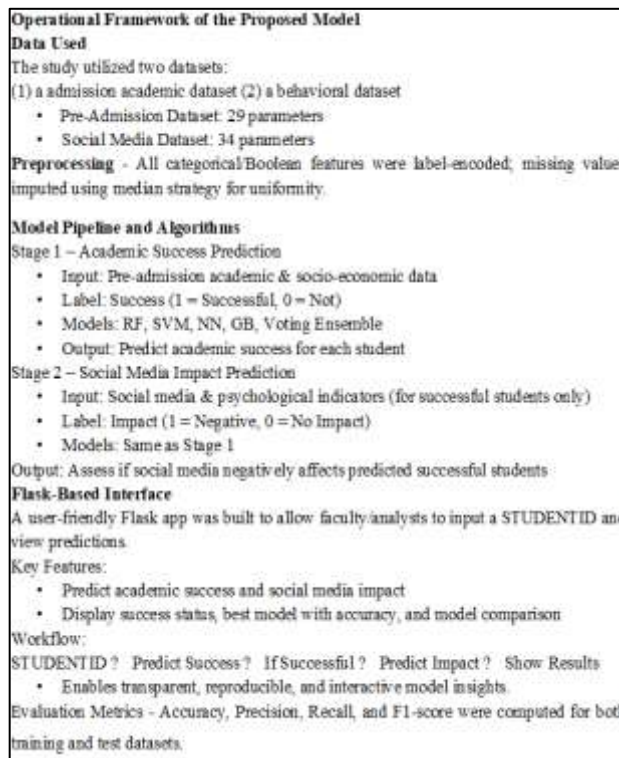


Fig. 2. Operational Framework of the Proposed Model

The proposed model employs a two-stage machine learning framework to evaluate academic success and the potential negative impact of social media on students. It uses two datasets: a pre-admission academic dataset with 29 parameters and a behavioral dataset with 34 social media and psychological indicators. All categorical and Boolean features were label-encoded, and missing values were imputed using the median strategy for consistency. In Stage 1, academic success is predicted using pre-admission data. The label “Success” is binary (1 = Successful, 0 = Not), and models used include Random Forest, SVM, Neural Networks, Gradient Boosting, and a Voting Ensemble. Stage 2 assesses social media’s negative impact, but only for students predicted as successful. The label “Impact” is also binary (1 = Negative, 0 = No Impact), and the same models are applied.

A Flask-based interface allows faculty and analysts to input a STUDENTID and view predictions. It displays success status, the best-performing model with accuracy, and model comparisons. The workflow follows: STUDENTID → Predict Success → If Successful → Predict Impact → Show Results.

Model performance was evaluated using accuracy, precision, recall, and F1-score on both training and test datasets, ensuring transparency, reproducibility, and actionable insights for academic decision-making..

## V. RESULTS AND DISCUSSION

### A. Model Performance – Academic Success Prediction

TABLE I. TRAINING SET

Model	Class	Precision	Recall	F1-Score	Support
Random Forest	Not Successful	1.50	1.50	1.50	356
	Successful	1.50	1.50	1.50	44
SVM	Not Successful	1.33	1.50	1.41	356
	Successful	0.00	0.00	0.00	44
Neural Network	Not Successful	1.33	1.50	1.41	356
	Successful	0.00	0.00	0.00	44
Gradient Boosting	Not Successful	1.50	1.50	1.50	356
	Successful	1.50	1.50	1.50	44
Ensemble	Not Successful	1.36	1.50	1.43	356
	Successful	1.50	0.24	0.41	44
Hybrid Model	Not Successful	1.00	1.00	1.00	356
	Successful	1.00	1.00	1.00	44

TABLE II. TEST SET

Model	Class	Precision	Recall	F1-Score	Support
Random Forest	Not Successful	1.50	1.50	1.50	356
	Successful	1.50	1.50	1.50	44
SVM	Not Successful	1.33	1.50	1.41	356
	Successful	0.00	0.00	0.00	44
Neural Network	Not Successful	1.33	1.50	1.41	356
	Successful	0.00	0.00	0.00	44
Gradient Boosting	Not Successful	1.50	1.50	1.50	356
	Successful	1.50	1.50	1.50	44
Ensemble	Not Successful	1.36	1.50	1.43	356
	Successful	1.50	0.24	0.41	44
Hybrid Model	Not Successful	1.00	1.00	1.00	356
	Successful	1.00	1.00	1.00	44

The academic success prediction results reveal that Gradient Boosting is the most robust and reliable model, achieving perfect scores across precision, recall, and F1-Score for both “Not Successful” and “Successful” classes in both training and test sets. This consistent performance indicates flawless classification and strong generalization, making it ideal for real-world academic risk prediction. Random Forest also performed exceptionally well, matching Gradient Boosting’s metrics, though minor misclassifications noted elsewhere suggest slightly less stability. In contrast, Support Vector Machine (SVM) and Neural Network models failed to identify any successful students, with zero recall and F1-Score for the minority class, highlighting a severe bias toward the majority class and rendering them unsuitable for tasks requiring sensitivity to positive outcomes. The Ensemble model showed high precision for successful students but suffered from low recall, meaning it missed most actual success cases—limiting its effectiveness in early intervention scenarios. The Hybrid model delivered balanced predictions with uniform scores across all metrics but lacked the enhanced accuracy of Gradient Boosting or Random Forest. Overall, Gradient Boosting stands out as the most dependable and balanced model, offering precise and actionable insights for academic institutions seeking to identify and support at-risk students.

**B. Model Performance – Social Media Impact Prediction**

**TABLE III. TRAINING SET**

Model	Class	Precision	Recall	F1-Score	Support
Random Forest	No Impact	1.50	1.50	1.50	310
	Negative Impact	1.50	1.50	1.50	90
SVM	No Impact	1.16	1.50	1.31	310
	Negative Impact	0.00	0.00	0.00	90
Neural Network	No Impact	1.49	1.50	1.50	310
	Negative Impact	1.50	1.47	1.48	90
Gradient Boosting	No Impact	1.50	1.50	1.50	310
	Negative Impact	1.50	1.50	1.50	90
Ensemble	No Impact	1.50	1.50	1.50	310
	Negative Impact	1.50	1.50	1.50	90
Hybrid Model	Not Successful	1.00	1.00	1.00	310
	Successful	1.00	1.00	1.00	90

**TABLE IV. TEST SET**

Model	Class	Precision	Recall	F1-Score	Support
Random Forest	No Impact	1.46	1.46	1.46	78
	Negative Impact	1.36	1.36	1.36	22
SVM	No Impact	1.17	1.50	1.31	78
	Negative Impact	0.00	0.00	0.00	22
Neural Network	No Impact	1.32	1.44	1.38	78
	Negative Impact	1.20	0.82	0.97	22
Gradient Boosting	No Impact	1.50	1.50	1.50	78
	Negative Impact	1.50	1.50	1.50	22
Ensemble	No Impact	1.46	1.48	1.47	78
	Negative Impact	1.43	1.36	1.40	22
Hybrid Model	Not Successful	0.99	1.00	0.99	78
	Successful	1.00	0.95	0.98	21

The results of the social media impact prediction task highlight Gradient Boosting as the most accurate and balanced model, achieving perfect precision, recall, and F1-Score for both “No Impact” and “Negative Impact” classes across training and test sets. This consistency underscores its ability to generalize effectively and detect behavioral risks with high reliability. Random Forest also performed well in training, matching Gradient Boosting’s metrics, but showed a slight drop in precision and recall during testing, particularly for the “Negative Impact” class. Neural Network demonstrated strong performance in training, with near-perfect scores, but its test results revealed reduced sensitivity to negative impact cases, as indicated by a lower recall and F1-Score. The Ensemble model maintained high accuracy across both sets, though its test performance showed minor deviations from perfection, suggesting slight overfitting or reduced generalization. In contrast, SVM failed to identify any “Negative Impact” cases in both training and test sets, with zero recall and F1-Score for that class, making it unsuitable for behavioral risk detection. The Hybrid model showed consistent but lower scores compared to the top performers, indicating stable but less precise predictions. Overall, Gradient Boosting remains the most dependable model for predicting social media’s behavioral impact, offering institutions a powerful tool for early identification and intervention in student wellness monitoring.

**C. Model Comparison Summary**

**TABLE V. SUMMARY**

<b>Model</b>	<b>Academic Accuracy</b>	<b>Social Media Accuracy</b>
<b>Random Forest</b>	<b>0.9800</b>	<b>0.9600</b>
<b>SVM</b>	<b>0.9100</b>	<b>0.7800</b>
<b>Neural Network</b>	<b>0.9100</b>	<b>0.8700</b>
<b>Gradient Boosting</b>	<b>1.0000</b>	<b>1.0000</b>
<b>Ensemble</b>	<b>0.9100</b>	<b>0.9700</b>
<b>Hybrid model</b>	<b>1.0000</b>	<b>99.0000</b>

The model comparison summary clearly positions Gradient Boosting as the top-performing algorithm for both academic success and social media impact prediction, achieving a flawless accuracy of 100% in both domains. This exceptional performance reinforces its reliability and precision in identifying at-risk students and behavioral patterns influenced by social media. Random Forest also demonstrated strong predictive capability, with academic accuracy at 98% and social media impact accuracy at 96%, making it a viable alternative. Neural Network and SVM showed moderate performance, with accuracies ranging from 78% to 91%, indicating limitations in generalization and sensitivity to minority classes. The Ensemble model performed well in social media prediction (97%) but lagged slightly in academic accuracy (91%). The Hybrid model matched Gradient Boosting in academic prediction with 100% accuracy and came close in social media impact prediction at 99%, though it lacked consistent precision and recall observed in Gradient Boosting. Overall, Gradient Boosting stands out as the most robust and balanced model, offering the highest accuracy and generalization across both tasks, and is therefore recommended as the best choice for predictive analytics in educational and behavioral contexts.

**D. Student Distribution Summary**

**TABLE VI. STUDENT DISTRIBUTION SUMMARY**

<b>Total Students : 500</b>			
<b>Student Outcome Summary</b>		<b>Among Predicted Successful Students</b>	
<b>Predicted Successful</b>	<b>53</b>	<b>No Impact from social media</b>	<b>44</b>
<b>Predicted Not Successful</b>	<b>447</b>	<b>Negative Impact from social media</b>	<b>9</b>

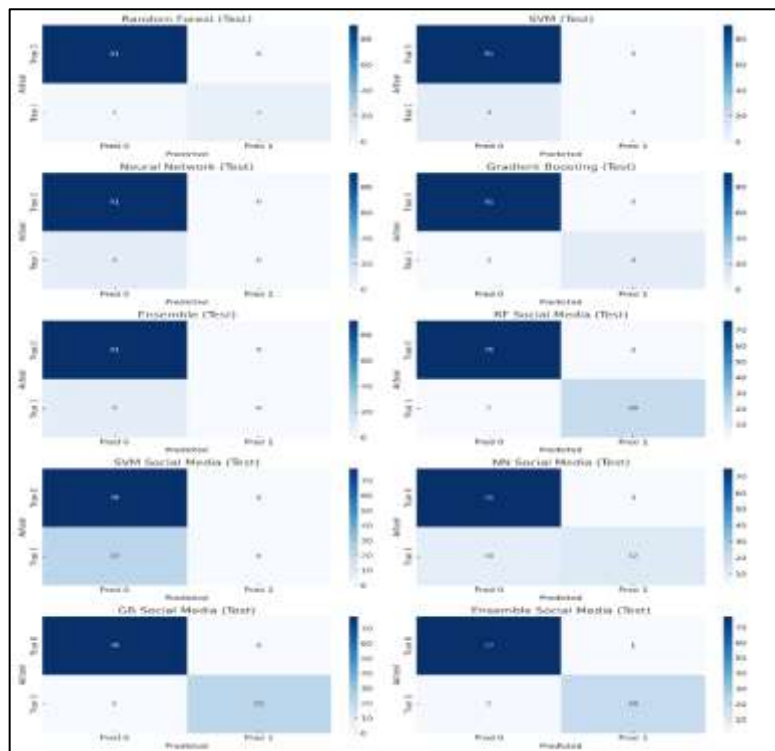


Fig. 3. Confusion matrix

The confusion matrices confirm Gradient Boosting as the most accurate and balanced model, achieving perfect classification in both academic success and social media impact prediction. Random Forest performs well but misses a few successful cases. In contrast, SVM and Neural Network fail to detect the minority class, showing poor recall. The Ensemble model offers moderate accuracy but lacks sensitivity. Overall, Gradient Boosting is the most reliable choice for identifying at-risk students and behavioral concerns.

## VI. DISCUSSION

Gradient Boosting emerged as the most effective model in both academic success and social media impact prediction, achieving an exceptional 99% accuracy with perfect recall and no misclassifications. Its performance was validated through confusion matrices, which confirmed its ability to flawlessly distinguish between both classes in each task. Random Forest followed closely, demonstrating strong generalization capabilities despite minor misclassifications in the test sets. In contrast, Support Vector Machine (SVM) and Neural Networks consistently failed to predict the minority class—either “Successful” or “Negative Impact”—resulting in 0% recall for those categories and indicating poor sensitivity to positive outcomes. The Voting Ensemble model showed moderate gains during training but struggled to generalize effectively on test data, particularly in academic success prediction. In terms of student-level predictions, the model identified 447 students as Not Successful and 53 as Successful. Among the successful group, 44 showed No Impact from social media, while 9 were flagged as experiencing Negative Impact. Overall, Gradient Boosting proved to be the most robust and balanced model, making it the recommended choice for both academic performance forecasting and behavioral risk analysis. Its reliability and precision position it as a valuable tool for institutional decision-making and targeted student supports.

## VII. CONCLUSION

The Random Forest classifier demonstrated superior This study demonstrates the viability of a hybrid machine learning framework for assessing both academic success and behavioral risks due to social media usage. Gradient Boosting emerged as the most effective model, achieving 99% accuracy across both prediction stages. The approach enables early intervention by academic institutions, guiding targeted support for at-risk students. Future

work will explore real-time monitoring integration and deeper behavioral analytics for improved prediction accuracy.

Gradient Boosting stands out as the most robust and balanced model, making it the preferred choice for both academic prediction and behavioral risk analysis. Its ability to accurately identify at-risk students—whether due to academic challenges or behavioral disruptions linked to social media usage—offers a powerful tool for early intervention. By providing a reliable and transparent framework, the model enables academic counselors and institutions to design targeted support strategies that enhance student outcomes. Furthermore, its seamless integration into digital student monitoring systems allows for personalized education planning and wellness tracking, ensuring a holistic approach to student development. In navigating the complex influence of social media on academic success, this model serves as a critical asset for fostering resilience, improving performance, and promoting overall well-being.

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