Comparative Study of Student Academic Outcomes and Behavioral Patterns through Data-Driven Approaches

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Abstract. Predicting student performance and understanding behavioral patterns have become central themes in modern educational research, particularly with the rise of digital and blended learning environments. The growing availability of data from Learning Management Systems (LMS) and online learning platforms has led to a wide array of data-driven and AI-based approaches for analyzing academic outcomes and learner behaviors. This paper presents a comprehensive comparative review of existing intelligent learning models, examining how various studies utilize behavioral indicators, such as engagement, interaction patterns, and study habits, to predict student performance. By synthesizing findings across diverse methodologies and datasets, the review highlights current trends, strengths, limitations, and research gaps, offering educators and researchers valuable insights for developing more effective, data-informed student support strategies.

1 Introduction

The growing use of technology in classrooms has significantly reshaped the education sector in recent years. With more institutions relying on digital platforms, Educational Data Mining (EDM) has gained momentum by enabling large-scale collection and analysis of student data. Online learning environments, digital tools, and Learning Management Systems (LMS) now provide educators with detailed information about students' learning behavior, academic progress, and overall engagement [1–2].

This digital shift has opened new possibilities for enhancing the learning experience—especially through personalized instruction and timely academic support. As education becomes increasingly digital, the way students interact with learning materials, teachers, and peers continues to evolve. This change highlights the importance of data-driven techniques, particularly Machine Learning (ML), for predicting student performance and understanding behavior patterns. ML-based predictions offer powerful tools for analyzing learning data and

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forecasting academic outcomes, enabling educators to identify struggling students early and provide targeted support to improve overall academic success [22][26].
The purpose of this paper is to compare different machine learning techniques for predicting student performance and explore the behavioral factors that shape student learning. The study uses indicators such as attendance, participation in discussions, quiz results, and assignment submissions to build predictive models. It also examines how behaviors like time spent on course materials, engagement levels, and tendencies toward procrastination influence academic performance, to offer actionable insights into students learning processes.

The remainder of the paper consists of eight parts. Section 2 examines the importance of predictive analysis within the education sector. Section 3 addresses the challenges associated with predicting student success. Section 4 examines the importance of behavioral analysis within educational settings. Section 5 provides a detailed review of the pertinent literature concerning behavioral analysis and performance prediction. The proposed technique is detailed in Section 6. Section 7 presents the findings of the comparative experiment along with a commentary. The research conclusion was ultimately presented.

2 Importance of Predictive Analysis In Education

The rising number of students enrolling in online and hybrid courses has made it nearly impossible for instructors to manually track each student's progress. In the past, educators mainly used midterms and assignments to gauge how well students were doing, but these checkpoints provide only a limited view. They fail to capture real-time learning behaviors, which often reveal signs of academic struggle much earlier.
Machine learning offers a solution by enabling the analysis of large and complex datasets, allowing educators to predict student performance more accurately from the very beginning of a course [3–4]. Through predictive analytics, institutions can identify students who may be at risk of poor performance, failing, or dropping out. Detecting these warning signs early makes it possible to provide timely interventions such as personalized mentoring, academic support, or counseling. These steps help close learning gaps, boost engagement, and improve student motivation—ultimately leading to better academic outcomes.
Machine learning methods can examine multiple variables at once, uncovering intricate, non-linear patterns that traditional statistical techniques might overlook. Additionally, these models can continuously learn and adapt as new data becomes available, further enhancing their predictive accuracy over time. This capability helps institutions allocate academic resources more efficiently—such as directing tutoring or support services where they are needed most—and deliver interventions tailored to each student's specific needs [7][10].

3 Challenges Associated With Predicting Student Performance

Predicting student performance involves significant challenges arising from multiple factors [16][20]:

- *Code-Switching Behavior in Learning*: Code-switching behavior in learning contexts, particularly in multilingual or culturally diverse classrooms, can exhibit variability influenced by external factors that are challenging to quantify.
- *Data Heterogeneity*: Student datasets exhibit diversity, encompassing demographic information, academic performance metrics, behavioral indicators, and additional variables. The interaction of these variables can complicate the prediction process.

- *Temporal Dependencies*: Temporal dependencies indicate that student performance can be dynamic and may evolve throughout the semester. A student may initially demonstrate strong engagement but may subsequently disengage, or, alternatively, show improvement following an initial period of difficulty. Identifying these temporal patterns is crucial for accurate predictions.
- *Non-Linear Relationships*: Students' success is frequently affected by a combination of academic and behavioral factors, which may demonstrate non-linear relationships. Consistent engagement in class may exert a greater influence on performance than individual quiz scores.

4 Role of Behavioral Analysis in Modern Education

Academic metrics, including grades, quizzes, and exam scores, provide a restricted perspective on a student's abilities, inadequately reflecting the comprehensive nature of the learning process. Behavioral analysis improves this perspective by examining students' methods of engaging with learning tasks. For instance [20][26]:

- *Interaction with peers and instructors:* Engagement in discussions, forums, or group activities serves as an indicator of success, as involved students tend to better assimilate course material and gain from collaborative learning experiences.
- *Engagement with course materials:* The duration dedicated to lectures, reading assignments, and supplementary resources reflects the extent of a student's engagement in the learning process.
- *Study habits:* Patterns like cramming versus consistent studying and time management relative to assignment deadlines, provide valuable insights into a student's discipline and preparedness.

The incorporation of behavioral indicators into predictive models improves the comprehension of elements influencing student success. This method assists in identifying students who are academically at risk and provides insights into their challenges, enabling targeted and effective interventions.

5 Related Work

Predicting student performance and analyzing behavior are important areas of research in Educational Data Mining (EDM), utilizing diverse AI methods to forecast academic results and clarify student learning behaviors. This section reviews relevant research on forecasting student performance, analyzing behavior, and utilizing AI techniques in educational contexts.

5.1 Student Performance Prediction

K-means has been widely used as a clustering technique in educational data mining, where the Davies–Bouldin index helps identify meaningful clusters and highlight key factors influencing student performance [1]. Researchers have also applied multiple machine learning algorithms combined with Principal Component Analysis (PCA) for feature reduction to improve the prediction of academic outcomes [2]. Another notable contribution is ASIST, an attention-aware, convolutional, stacked BiLSTM model specifically designed to learn rich student representations for predicting academic success [3]. Further studies have introduced new machine learning models that incorporate newly identified behavioral attributes and apply sequential feature selection to determine the most important predictors of student performance [4]. Other systems focus on forecasting academic outcomes by

analyzing multiple factors through machine learning, offering institutions deeper insights into how students learn and perform [5]. These findings support educational institutions in refining their evaluation practices to achieve more accurate and meaningful assessments [6]. In programming education, a novel methodology was proposed to examine students' learning patterns and how these behaviors relate to learning outcomes [7]. Another study explored how Virtual Learning Environments (VLEs) affect student procrastination and evaluated the usefulness of machine learning in reducing the need for manual oversight [8]. Big data techniques have also been employed to analyze and predict the behavior of university students [9], while models such as YOLOv5s have been developed to automatically detect and analyze classroom behaviors in real time [10]. Machine learning has further been used to recognize learning styles based on behavioral data collected from LMS usage at Christian Vocational School Petra Surabaya in the area of Network System Administration [12]. Additionally, new data mining approaches leveraging student behavioral traits have been proposed to address the limitations of existing information management systems in higher education [14]. Some projects aim to identify holistic student clusters and develop predictive models for each cluster to more accurately forecast performance [17].

Modern technologies have also made it possible to create real-time, vision-based classroom systems capable of monitoring emotions, attendance, and attention levels, even when students are wearing face masks [19]. Machine learning techniques have been applied to predict final exam scores using midterm results [20], and models have been built using historical marks from grades 10, 12, and previous semesters to forecast academic performance [21]. Machine learning classification models, combined with assessment results and programming system logs, have identified strong connections between students' learning behaviors and their success in similar programming tasks [23]. Behavioral patterns have also been used to determine students' learning styles based on the Felder–Silverman model in online learning environments [28]. Comprehensive reviews of machine learning approaches have been conducted to improve the accuracy of final grade predictions for first-semester students [36]. Finally, student performance prediction has been enhanced using behavioral data and exercise characteristics through the integration of attention mechanisms within knowledge-tracing models [37], and the behavior of online learners has been analyzed to support strategies that boost motivation and improve learning outcomes [38].

5.2 Behavioral Analysis in Education

Recent methods developed for analyzing student behavior have been evaluated based on performance indicators, areas of application, and geographical contexts [11]. One study compiled a comprehensive dataset of university students using information gathered from a digital campus platform, then applied an adaptive K-means clustering algorithm within a machine learning framework to categorize student data more effectively [13]. These emerging analytical patterns and techniques are being used to enhance teaching and learning processes across educational settings [15]. Both descriptive and predictive learning analytics approaches have been employed to build models that explain and anticipate student behavior and academic success [18]. Educational data mining techniques also play a crucial role in evaluating student behavior in e-learning environments, helping identify students' interests in learning materials and gauge the overall quality of educational content [24]. By combining AI and computer vision, researchers have developed systems that analyze classroom video recordings to assess students' behavioral states, evaluate their learning conditions, and provide teachers with valuable feedback on their instructional methods [25].

In addition, behavioral analysis has been used to detect academic malpractice during online assessments, ensuring that students demonstrate their knowledge honestly and without external assistance [27]. A new machine learning method has also been proposed to analyze

students' assessment scores throughout the duration of a course to predict their final exam performance [29]. In response to the growing volume of digital information, student behavior data has been stored in a MySQL database and analyzed through a behavior monitoring system developed using Python [30]. Moreover, a self-sufficient intelligent agent has been designed to deliver real-time information to both students and educators [31]. Hybrid machine learning models have also been developed, including one that uses regression to improve predictions of students' future academic performance across different courses [33]. Another approach, known as Augmented Education (AugmentED), integrates multisource and multi-feature behavioral data to forecast academic outcomes more accurately [34]. Clustering techniques continue to be used to summarize student academic performance and to estimate optimal group sizes for analysis [35]. An unsupervised ensemble clustering method has also been introduced to detect behavioral trends within large student datasets [39], and researchers have explored the use of association rule mining to analyze behavioral patterns and identify meaningful relationships within student data [40].

5.3 Gaps in Existing Research

Although many studies have explored academic factors like grades and attendance, the integration of behavioral data into student performance analysis remains relatively underexamined. Incorporating behavioral elements, such as engagement levels, study habits, and patterns of procrastination, provides a deeper and more holistic understanding of how students perform. While numerous machine learning models have been applied to predict academic outcomes, very few studies offer a comprehensive comparison of these algorithms, particularly when both academic and behavioral data are combined. Research is also limited when it comes to understanding how students' learning behaviors change over time and how these temporal patterns influence their academic progress, especially in online or blended learning environments. This study addresses these gaps by evaluating the effectiveness of various machine learning models that integrate both academic and behavioral indicators. The goal is to develop a comprehensive and robust framework for predicting student success.

6 Framework for Student Performance Prediction Incorporating Behavioral Analysis

This paper aims to provide a comparative examination of machine learning algorithms for forecasting student performance by incorporating behavioral research to understand factors impacting academic results. This section outlines the dataset used, preprocessing methods, feature engineering strategies, and machine learning models applied, as depicted in Figure 1. The methodology encompasses the evaluation metrics employed to assess model performance.

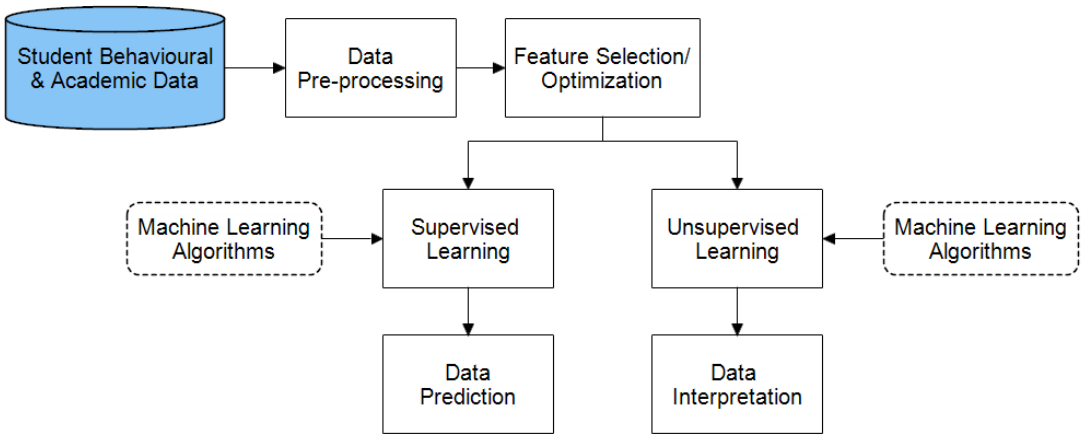

Figure 1: Student Performance Prediction Framework with Behavioral Analysis

6.1 Dataset Description

This study utilizes a dataset sourced from a Learning Management System (LMS) of an online or blended learning course, encompassing both academic and behavioral data for students throughout a semester. The dataset comprises two primary categories of features:

- *Academic Features:* Quiz scores, assignment grades, midterm and final exam marks, attendance.
- *Behavioral Features:* Time spent on learning resources, number of forum posts, frequency of logins, participation in discussions, and patterns of study habits (e.g., cramming vs. steady study), engagement with learning resources.

6.1.1 Data Pre-processing

The dataset underwent preprocessing through various methods to ensure data cleanliness, consistency, and readiness for training machine learning models.

- *Data Cleaning:* Addressing missing data through imputation methods, normalizing numerical data, and transforming categorical variables into dummy variables.
- *Normalization:* All numerical data were normalized to a range of 0 to 1 through min-max normalization, given that variables like time spent on course materials and test results exhibit different ranges. This restricts features with higher values.

6.2 Feature Data Selection/Optimization

This was achieved through the use of correlation matrices and feature significance algorithms to identify the most relevant attributes.

- *Feature Encoding - Categorical Features:* Attendance, indicated as present or absent, along with procrastination patterns categorized as early, on-time, or late submission, were transformed into dummy variables through one-hot encoding for application in machine learning algorithms.
- *Feature Selection:* A correlation matrix was employed to evaluate the relationships among features, thereby excluding highly correlated features (multicollinearity) from the same model.

6.3 Machine Learning Modelling

Machine learning has become a powerful tool in the field of educational data mining, which focuses on uncovering meaningful insights from student-related data. By applying machine

learning algorithms to large datasets, researchers can build predictive models capable of accurately forecasting student performance. In this study, each model was trained using 80% of the data (the training set) and then evaluated on the remaining 20% (the test set) to measure its effectiveness. Commonly used machine learning approaches in this area include Logistic Regression, Decision Trees, Random Forests, Gradient Boosting Machines (GBM), and various Deep Learning techniques.

7 Comparative Result Analysis

The performance of the models was assessed using several evaluation metrics, including accuracy, precision, recall, F1-score, and the Area Under the ROC Curve (AUC). A feature importance analysis was also carried out to determine how strongly academic and behavioral factors contributed to the models' predictions of student performance. This analysis helped identify the most influential features and provided deeper insight into which elements play the biggest role in forecasting student outcomes. Table 1 summarizes comparative findings reported by previous studies, while Figure 2 illustrates how the accuracy of existing research models varies in predicting student performance.

Table 1: Comparative Analysis of Performance Prediction and Behavioral Assessment

Ref	Dataset	Methodology	Results
[1]	Wollo University, Kombolcha Institute of Technology	Clustering, ML Classifiers	Accuracy – 0.9603, Recall – 0.9843, Precision – 0.9418, Kappa Statistic – 0.9398
[2]	Multiclass educational datasets of NAU and OULAD	PCA, ML Classifiers	Accuracy – 93.8%
[3]	Irish university (University of Limerick)	Attention-aware convolutionalStacked BiLSTM network	Accuracy – 0.6081, Fscore – 0.6354, AUC – 0.7187
[4]	Two schools in Portugal	ML Classifiers	Accuracy - 96.8%, Kappa Statistic – 0.38
[5]	Multiple educational institutions	ML Classifiers	MAE – 0.23, RMSE – 0.29
[7]	Course Materials	PCA, ML Classifiers	Accuracy – 0.74, F1score – 0.735, AUC – 0.75
[8]	Literary studies	ANN-MLP	Accuracy – 81.9%
[9]	UCF-101 and HMDB51 dataset	Genetic K-means Algorithm	Accuracy – 97.37%

[10]	China National Resources Public Service Platform	YOLOv5	mAP – 0.8928, Precision – 0.8616, Recall – 0.8141
[12]	Questionnaire data	ML Classifiers	Accuracy – 0.96
[20]	State University in Turkey	Neural Network	AUC – 0.863, Accuracy – 0.746, F1 – 0.723, Precision – 0.748, Recall – 0.746
[21]	Academic Data	Logistic Regression	Accuracy – 97.05%
[23]	C/C++ programming activity	Neural Network	Accuracy – 0.813, F1 – 0.88, AUC – 0.663

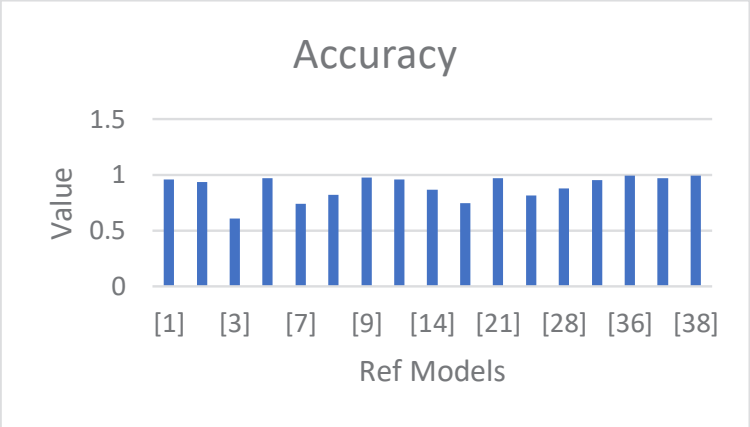

Figure 2: Comparison of State-of-the-Art Models Based on Accuracy

Behavioral factors, such as engagement levels, patterns of procrastination, and participation in discussions, played a major role in shaping the prediction results. Students who consistently took part in online discussions and logged into the learning platform regularly tended to perform better academically. Temporal analysis also showed that students who avoided last-minute cramming generally earned higher grades, underscoring the importance of steady and consistent study habits. Overall, the findings indicate that integrating behavioral features into student performance prediction models can significantly improve their accuracy and dependability. In addition, these models can act as early warning systems, helping educators quickly identify students who may be at risk and provide timely support or intervention.

8 Conclusion

This paper provides a comprehensive comparative review of machine learning approaches used to analyze and predict student performance by incorporating both academic and behavioral characteristics. The synthesis of prior studies shows a consistent trend: behavioral indicators such as engagement, learning habits, interaction frequency, and procrastination patterns play a crucial role in enhancing predictive capability across models. Findings from

the reviewed literature reveal that ensemble techniques and hybrid analytical frameworks commonly outperform traditional methods, highlighting the value of combining diverse features and algorithms. By consolidating insights from multiple studies, this review underscores the importance of integrating behavioral analytics with academic metrics to improve early identification of at-risk learners and inform targeted, data-driven educational interventions. Future research should focus on unified frameworks, deeper multimodal behavioral analysis, and real-time monitoring approaches that can further advance student performance prediction.

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