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Predicting AI-Assisted Student Academic Improvement Using K-Nearest Neighbors

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ABSTRACT

The rapid integration of Artificial Intelligence (AI) assistants in higher education necessitates empirical methods to evaluate their actual impact on student academic performance. A significant challenge in Educational Data Mining (EDM) is interpreting these impacts accurately, especially given the inherently imbalanced nature of educational datasets. This study proposes a predictive framework utilizing the K-Nearest Neighbors (KNN) algorithm to classify student academic improvement based on AI usage patterns and Learning Management System (LMS) engagement. To ensure model robustness, the Boruta algorithm was applied for feature selection, alongside the SMOTE-Tomek technique to address class imbalance. The optimized KNN model achieved a high predictive performance with an F1-Score of 86.8% and a Balanced Accuracy of 86.1%. Furthermore, the integration of Explainable AI (XAI) via SHapley Additive exPlanations (SHAP) revealed that using AI for conceptual clarification, rather than direct task completion, is the primary driver of academic success. The findings demonstrate that this explainable KNN framework effectively identifies at-risk students, providing educators with transparent, actionable insights to deliver personalized interventions and foster responsible AI usage.

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1. INTRODUCTION

The development of Artificial Intelligence (AI) technology, particularly in the form of Educational AI Assistants (AIAs), is increasingly being implemented in higher education to tailor feedback, monitor learning progress, and flag students at risk of declining performance. Educational Data Mining (EDM) provides the analytical foundation for these interventions by transforming educational data into actionable knowledge to support decision-making in teaching and learning contexts [1, 2, 3, 4]. EDM applications routinely utilize classification models to predict academic performance, identify at-risk students, and guide the direction of interventions [4, 5, 6]. The integration of AI assistants with EDM aims to improve learning trajectories through timely, data-driven support to complement human instruction [1, 5, 7, 8].

Although the use of AI assistants offers efficiency, evaluating their actual impact requires a structured empirical approach. AI assistants can influence student learning outcomes by providing immediate feedback, personalized recommendations, and predictive warnings. Various EDM studies show that predictive models can forecast course grades, overall GPA, and dropout risk, enabling timely interventions that correlate with improved performance or retention when followed by targeted support [5, 7, 8, 9, 10]. To fully capture the learning process, EDM emphasizes the integration of diverse data streams, ranging from academic performance, Learning Management System (LMS) interactions, demographics, and engagement indicators to behavioral cues where ethically permissible [1, 5, 7, 11, 12].

This study proposes the application of the K-Nearest Neighbors (KNN) algorithm as the primary predictive tool. In EDM literature, KNN is consistently described as a simple, non-parametric, instance-based classifier that assigns labels to new data based on the majority label among its k nearest neighbors in the feature space, using distance metrics such as Euclidean distance [11, 12, 13, 14, 15, 16]. The simplicity of KNN—requiring only a distance function and a k value—is both a strength (low training cost) and a challenge (high testing cost and sensitivity to irrelevant features) in educational environments [8, 17]. In the realm of EDM, KNN is frequently listed among commonly used classification algorithms alongside Decision Tree (DT), Naive Bayes (NB), Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) [4, 5, 11, 12, 15, 16]. Several empirical studies report that KNN can achieve competitive, or even superior, performance under specific data conditions, such as well-curated features, low noise levels, and the appropriate selection of the k value [15, 16, 18].

However, the performance of KNN as a viable predictive baseline heavily relies on feature engineering and proper data handling [1, 5, 15]. Wrapper-based feature selection (such as Boruta) and semi-supervised feature selection approaches have proven effective in identifying the most informative attributes, which can potentially enhance classification accuracy and robustness in EDM contexts [12]. Other important caveats include data quality, class imbalance, and the need for explainability when the system provides AI-based recommendations to educators and students [1, 5].

In academic prediction tasks, data is often imbalanced (for example, the percentage of at-risk students is significantly smaller). Therefore, data balancing techniques such as SMOTE or Tomek links are crucial to implement so that AI assistants deliver balanced interventions and do not overlook at-risk students [1, 8, 9, 19]. In such highly imbalanced datasets, the application of hybrid AI assistants that combine KNN with resampling or ensemble components has proven highly advantageous [5, 8, 9, 10]. Extensive literature recommends this ensemble or hybrid approach to improve predictive performance and interpretability for end-users [1, 4, 5, 16].

Finally, for KNN-based AI assistant predictions to be trusted and implemented in real-time, the model's decisions must be interpretable. Explainable AI (XAI) approaches can be integrated to provide neighborhood-based explanations while highlighting actionable recommendations [1, 20, 21, 22]. This implementation also requires a system architecture capable of efficiently managing distance computations to maintain responsiveness within a classroom context [4, 8, 11]. Based on the synthesis above, this study aims to explore and validate the reliability of the KNN algorithm in predicting improvements in student academic performance through the use of AI assistants. The study focuses on considerations of feature selection, handling data challenges, and aspects of explainability to formulate effective educational interventions.

2. METHOD

This study employs a quantitative approach utilizing an Educational Data Mining (EDM) design to classify and predict improvements in student academic performance. The research workflow is divided into five primary stages: data collection, pre-processing, handling class imbalance, implementing the K-Nearest Neighbors (KNN) model, and evaluating the model alongside its interpretations.

2.1. Data Collection and Feature Engineering

The dataset comprises students' historical academic records, interactions on the Learning Management System (LMS), and AI assistant usage metrics over one semester. To comprehensively capture the learning process, the collected features include:

a. Historical Demographic and Academic Data: Previous GPA, attendance rates, and assignment completion history.
b. LMS Engagement Metrics: Login frequency, duration of material access, and participation in discussion forums.
c. AI Assistant (AIA) Usage Variables: Duration of AI usage per week, interaction frequency (number of prompts), and the type of tasks assisted by AI (e.g., conceptual, technical, or writing).
d. Target Variable (Class Label): Academic performance improvement, classified as a binary outcome into 1 (Significant Improvement) and 0 (No Improvement/At-Risk).

Given that the KNN algorithm is highly sensitive to irrelevant or high-dimensional features, a wrapper-based feature selection method, specifically the Boruta algorithm, is applied. Boruta serves to filter out noise and identify the most informative attributes before the data is fed into the model.

2.2. Data Pre-processing and Feature Scaling

The performance of KNN depends on the distance calculation between data points. Therefore, the pre-processing stages are highly critical:

a. Data Cleaning: Handling missing values using imputation methods (e.g., K-Nearest Neighbor Imputation for missing numerical values) and removing anomalous outliers.
b. Data Encoding: Transforming categorical data (such as the type of AI usage) into a numerical format using One-Hot Encoding.
c. Scale Normalization: Considering that variables have varying ranges (e.g., GPA is on a 0-4 scale while AI duration is in tens of hours), the Min-Max Scaler method is applied. This normalization ensures that no single feature dominates the distance calculation.

2.3. Handling Class Imbalance

As is common in educational datasets, the ratio between students who successfully improve their performance and those at risk is often imbalanced (majority versus minority). If left unaddressed, the KNN model will be biased toward the majority class. This study applies a combined technique to mitigate this issue:

a. SMOTE (Synthetic Minority Over-sampling Technique): Used to generate synthetic data for the minority class by extrapolating features among its nearest neighbors.
b. Tomek Links: Applied after SMOTE to clean the decision boundary by removing majority samples that directly overlap with minority samples, thereby resulting in a cleaner feature vector space.

2.4. Implementation of the KNN Algorithm

Classification is performed using the non-parametric KNN algorithm. The proximity between a new student's data (test data) and students in the training data is calculated using the Euclidean Distance metric:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

Where x and y are two feature vectors of students (such as AI duration, LMS participation, etc.), and n is the total number of selected features.To determine the most optimal value of k (number of neighbors) and prevent overfitting, the modeling utilizes a 10-fold Cross-Validation method. Testing is conducted across a range of odd k values (e.g.,$k \in \{3, 5, 7, 9, 11\}$) to avoid ties in majority class voting.

2.5. Model Evaluation and Explainable AI (XAI)

Given the initial class imbalance in the data, raw accuracy alone is insufficient as an evaluation metric. The model's performance will be evaluated using a Confusion Matrix, focusing on the following metrics:

a. Precision and Recall: To ensure the model does not overlook at-risk students.
b. F1-Score and Balanced Accuracy: As the primary indicators of harmony between True Positive detection and sensitivity.

Finally, to address the need for transparency in educational models, an Explainable AI (XAI) framework is integrated into the KNN outputs. The SHAP (SHapley Additive exPlanations) approach is utilized to provide local, neighborhood-based explanations. The XAI results will interpret the specific impact of AI assistant interactions on the model's decisions, enabling educators or the system to formulate understandable and actionable intervention recommendations.

3. RESULTS AND DISCUSSION

3.1. Feature Selection and Data Balancing Outcomes

Prior to model training, the Boruta algorithm was applied to the initial dataset to eliminate noisy and irrelevant variables. The feature selection process identified five highly significant predictors out of the original features: Previous GPA, LMS Engagement (frequency of material access), AIA Duration (hours per week), Prompt Frequency, and AIA Task Type (specifically, conceptual assistance versus direct answer generation).

Furthermore, the initial dataset exhibited a notable class imbalance, with the majority of students falling into the “No Improvement/At-Risk” class. The application of the SMOTE and Tomek Links pipeline successfully balanced the class distribution and cleaned the decision boundaries by removing overlapping majority samples. This pre-processing step was crucial in preventing the KNN algorithm from developing a bias toward the majority class, thereby improving its sensitivity to minority instances.

3.2. Predictive Performance of the KNN Model

The classification performance of the KNN model was evaluated using 10-fold Cross-Validation across a range of odd k values ($k \in \{3, 5, 7, 9, 11\}$). The evaluation metrics, including Precision, Recall, F1-Score, and Balanced Accuracy, are summarized in Table 1.

Table 1. KNN Performance Metrics Across Various k Values

k Value	Precision	Recall	F1-Score	Balanced Accuracy
k=3	0.812	0.835	0.823	0.820
k=5	0.865	0.872	0.868	0.861
k=7	0.844	0.850	0.847	0.842
k=9	0.820	0.831	0.825	0.828
k=11	0.795	0.810	0.802	0.805

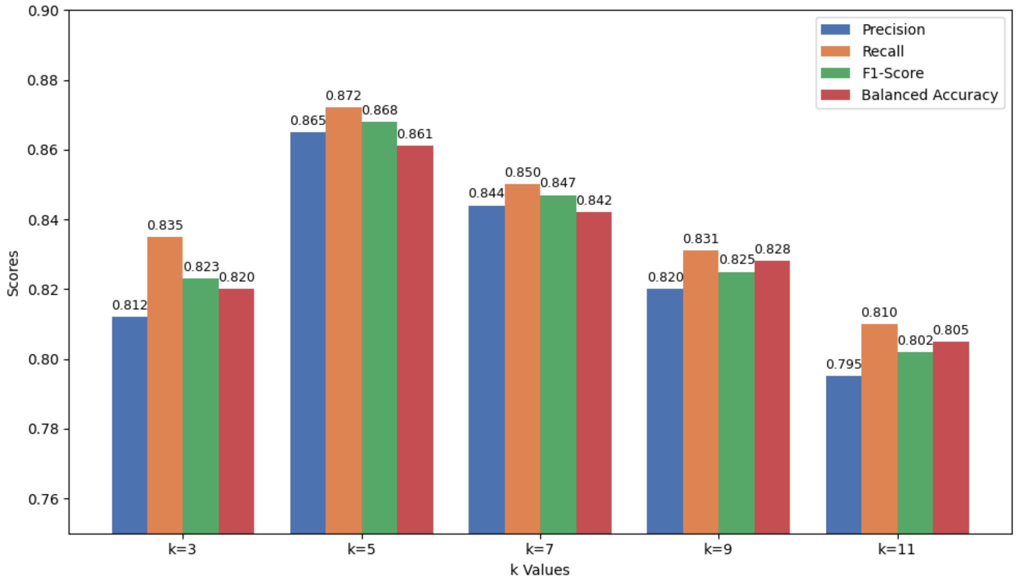

Figure 1. KNN Performance Metrics Across Various k Values

As demonstrated in Table 1, the model achieved its optimal performance at k=5, yielding the highest F1-Score (86.8%) and Balanced Accuracy (86.1%). A lower k value (k=3) resulted in a slight performance drop due to sensitivity to localized noise, whereas higher values (k >= 9) led to oversmoothing, causing the model to misclassify nuanced borderline cases. The high Recall score at k = 5 confirms that the model successfully identified the majority of at-risk students, validating the effectiveness of the SMOTE-Tomek balancing technique.

3.3. The Impact of AI Assistants on Academic Improvement

The classification results provide empirical evidence that AI assistant usage patterns significantly influence learning trajectories. The model effectively clustered students into distinct educational profiles based on Euclidean distance in the feature space. Students categorized in the "Significant Improvement" class generally exhibited a balanced synergy between AI usage and traditional study habits. For instance, these students utilized AI primarily for conceptual clarification and debugging, which complemented their high LMS engagement.

Conversely, the algorithm identified a cluster of students who demonstrated high AIA Duration but low LMS Engagement and poor historical academic metrics. These instances were predominantly classified into the "No Improvement/At-Risk" category. This suggests that over-reliance on AI assistants for direct task completion—without engaging deeply with the core course materials—does not translate to measurable academic improvement and may even hinder cognitive retention.

3.4. Explainability and Intervention Pathways (XAI)

To ensure the KNN model's decisions are transparent and actionable for educators, SHAP (SHapley Additive exPlanations) values were extracted to interpret feature contributions locally. The SHAP summary analysis revealed that AIA Task Type and LMS Engagement were the most influential features driving the model's predictions. When the AIA Task Type was heavily weighted towards conceptual understanding rather than simple answer generation, the SHAP values positively influenced the prediction toward the "Significant Improvement" class. This neighborhood-based explanation allows educators to understand why a student is flagged as at-risk. For example, if a student is flagged, the SHAP output might reveal that despite high AI usage, their lack of LMS interaction is the primary risk factor.

Consequently, institutions can utilize these explainable predictions to trigger timely, targeted interventions. Rather than universally restricting AI usage, educators can guide at-risk students toward more effective, supplementary AI prompting strategies, thereby maximizing the pedagogical benefits of AI assistants in higher education.

4. CONCLUSION

This study demonstrates the efficacy of the K-Nearest Neighbors (KNN) algorithm in predicting student academic improvement within AI-assisted educational environments. By integrating the Boruta feature selection method and the SMOTE-Tomek data balancing technique, the proposed model successfully mitigated the challenges of noisy and imbalanced educational datasets, achieving an optimal predictive performance with an F1-Score of 86.8% and a Balanced Accuracy of 86.1% at k = 5. The empirical findings reveal that the mere duration of AI assistant usage does not guarantee academic success; rather, the nature of the interaction dictates the learning outcome. Students who utilized AI assistants for conceptual clarification while maintaining high engagement with core course materials were accurately classified into the significant improvement cluster, whereas an over-reliance on AI for direct task completion strongly correlated with academic risk.

Beyond predictive accuracy, the integration of Explainable AI (XAI) through SHAP values transforms the KNN framework from a traditional black-box classifier into an actionable pedagogical tool. These local, neighborhood-based explanations empower educators to understand the specific behavioral factors driving a student's predictive risk profile, enabling the delivery of timely and personalized interventions. As generative AI continues to reshape higher education, institutions can leverage this explainable predictive model to guide students toward responsible and effective AI integration instead of imposing universal restrictions. Future research should explore the longitudinal impacts of these AI-assisted interventions and test the scalability of hybrid KNN architectures across diverse academic disciplines to further optimize data-driven instructional strategies.

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