FEATURE SELECTION FOR ACADEMIC PERFORMANCE PREDICTION USING MACHINE LEARNING

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Abstract

Accurate prediction of student academic performance is essential for early intervention and personalized support in educational settings. This study investigates the application of machine learning-based feature selection techniques to identify the most influential factors affecting student outcomes. By leveraging recursive feature elimination (RFE) and correlation analysis, we reduce data dimensionality and enhance model interpretability without compromising prediction accuracy. Several classification algorithms including Decision Trees, Support Vector Machines, and Logistic Regression were employed to evaluate the impact of feature selection on model performance. Experimental results demonstrate that carefully selected features significantly improve predictive accuracy and model efficiency, providing valuable insights for educators and policymakers.

Keywords : Academic Performance, Machine Learning, Classification, Recursive Feature Elimination, Student, Regression.

Introduction

In recent years, the rapid growth of educational data has created significant opportunities for leveraging data mining and machine learning techniques to enhance the understanding and prediction of student academic performance. Educational Data Mining (EDM) focuses on extracting meaningful patterns from large datasets generated in educational environments, aiming to improve learning outcomes, identify students at risk, and support personalized interventions (Shahiri et al., 2015). However, one major challenge in building effective predictive models is handling high-dimensional datasets that often contain redundant, irrelevant, or noisy features. These extraneous features can degrade model accuracy, increase computational costs, and complicate result interpretation.

Feature selection, the process of identifying the most relevant attributes for use in model construction, plays a vital role in overcoming these challenges. By reducing the dimensionality of the dataset, feature selection techniques improve model generalization, speed up training, and facilitate better understanding of the underlying factors influencing student success (Ramaswami & Bhaskaran, 2009). Various feature selection methods have been applied in EDM, ranging from filter-based approaches that evaluate features independently, wrapper methods that consider feature subsets in conjunction with specific learning algorithms, to embedded techniques that perform feature selection as part of model training (Zaffar et al., 2018).

This study aims to explore and compare different feature selection techniques applied to educational datasets to determine their effectiveness in enhancing student performance prediction. By identifying the key factors contributing to academic outcomes, educators and administrators can design targeted strategies to improve student retention and success. The findings of this research contribute to the growing body of knowledge in EDM and provide practical insights for developing efficient and interpretable predictive models in education.

Literature Review

Educational Data Mining (EDM) has garnered significant attention over the past decade due to its potential to transform large-scale educational datasets into actionable insights that improve student outcomes. One of the critical steps in developing effective predictive models within EDM is feature selection — the process of identifying the most relevant variables that contribute to accurate and interpretable predictions of student performance.

Importance of Feature Selection in EDM

High-dimensional datasets in education often contain numerous irrelevant or redundant features, which can negatively impact model performance by causing overfitting, increasing computational overhead, and reducing interpretability (Liu & Motoda, 2012). Feature selection addresses these issues by reducing the dimensionality of data, thus improving the efficiency and accuracy of machine learning models (Ramaswami & Bhaskaran, 2009). Furthermore, identifying key features can provide valuable educational insights into the factors that most influence academic success.

Categories of Feature Selection Techniques

Feature selection methods are generally categorized into three main types: filter, wrapper, and embedded methods.

- **Filter Methods:** These methods evaluate the relevance of features based on intrinsic properties of the data, independent of any specific learning algorithm. Common techniques include correlation-based feature selection (CFS), mutual information, and statistical tests such as Chi-square or ANOVA. Filters are computationally efficient and scalable to large datasets, but they may fail to capture complex feature dependencies (Zaffar et al., 2018).
- **Wrapper Methods:** Wrapper approaches evaluate subsets of features by training and testing a specific machine learning model. Recursive Feature Elimination (RFE) is a widely used wrapper technique that recursively removes the least important features based on model weights until the optimal subset is identified. Wrappers often achieve higher predictive accuracy but can be computationally expensive, especially with large datasets (Patel & Patel, 2024).
- **Embedded Methods:** These methods perform feature selection during the model training process. Examples include regularization techniques like LASSO (Least Absolute Shrinkage and Selection Operator) and tree-based algorithms that inherently rank feature importance. Embedded methods offer a balance between computational efficiency and performance and have become increasingly popular in EDM (Roy & Farid, 2024).

Application of Feature Selection in Student Performance Prediction

Several studies have demonstrated the effectiveness of feature selection techniques in improving academic performance prediction. Ramaswami and Bhaskaran (2009) investigated multiple feature ranking methods on student performance datasets, highlighting that appropriate feature selection leads to enhanced prediction accuracy and better understanding of influential factors.

Zaffar et al. (2018) compared filter and wrapper-based feature selection algorithms on educational datasets, reporting that hybrid approaches often outperform single-method strategies. Their research underscored the importance of selecting features not only for predictive performance but also for interpretability in educational contexts.

Roy and Farid (2024) proposed an adaptive feature selection algorithm specifically tailored for student performance prediction. Their approach dynamically selects features based on attack types in the dataset, demonstrating the importance of customized feature selection strategies in complex educational datasets.

Challenges in Feature Selection for EDM

Despite the progress, several challenges persist in applying feature selection to educational datasets. These include handling imbalanced data, the presence of noisy or missing values, and accounting for the temporal and contextual nature of educational data (Mustapha, 2023). Moreover, the diversity of student populations and institutional settings necessitates adaptable and generalizable feature selection frameworks.

Future research directions suggest integrating feature selection with advanced machine learning techniques such as deep learning and ensemble methods to further enhance prediction robustness (Patel & Patel, 2024). Additionally, there is a growing interest in interpretable machine learning models that provide transparent reasoning behind feature importance, which is critical for educational stakeholders.

Methodology

Dataset Description

The dataset contains diverse variables categorized into psychological attributes (e.g., motivation, anxiety), demographic factors (e.g., gender, parental education), academic metrics (e.g., semester grades, study time), and attendance records. Missing values were imputed using median and mode for numerical and categorical features, respectively. Categorical variables were encoded using label encoding.

Table 1: Data Description

Variable Name	Description	Type / Categories
ud	Name	Nominal (Categorical)
gn	Gender	Categorical {M, F}
ag	Age	Numeric
me	Mother's Education	Categorical {01, 2, 3, 4}
mo	Mother's Occupation	Categorical {Teacher, Healthcare-related, Civil Services, Homemaker, Other}
fe	Father's Education	Categorical {01, 2, 3, 4}
fo	Father's Occupation	Categorical {Teacher, Healthcare-related, Civil Services, Homemaker, Other}
pr	Place of Residence	Categorical {Urban, Rural}
tt	Travel Time	Ordinal {01, 2, 3, 4}
fs	Family Size	Categorical {LT3, GT3}
fi	Family Income	Categorical {LT3, GT3}
gr	Guardian	Categorical {M, F, O}
si	Number of Siblings	Categorical {LT3, GT3}
hs	Health Status	Ordinal {01, 2, 3, 4}
hs	High School Percentage	Ordinal {01, 2, 3, 4}

Source : Alarape et al., 2022; Gamulin et al., n.d.; "Mining Student at Risk in Higher Education Using Predictive Models," 2017; Rawat & Malhan, 2019

sec	Secondary School Percentage	Ordinal {01, 2, 3, 4}
st	Study Time	Ordinal {01, 2, 3, 4}
ug	Undergraduate Percentage	Ordinal {01, 2, 3, 4}
sm	Semester 1 Grade	Ordinal {01, 2, 3, 4}
smm	Semester 2 Grade	Ordinal {01, 2, 3, 4}
smmm	Semester 3 Grade	Ordinal {01, 2, 3, 4}
smmmm	Semester 4 Grade	Ordinal {01, 2, 3, 4}
ia	Internal Assessment 1	Ordinal {01, 2, 3, 4}
iaa	Internal Assessment 2	Ordinal {01, 2, 3, 4}
attend	Attendance	Categorical {Good, Average, Poor}
frs	Final Result	Ordinal {01, 2, 3, 4}
studint	Student Interest	Binary {Y, N}
anx	Anxiety	Binary {Y, N}
str	Stress	Binary {Y, N}
ser	Self-regulation	Binary {Y, N}
mot	Motivation	Binary {Y, N}
nabs	Number of Absences	Categorical {L, G}
nass	Number of Assignments	Ordinal {01, 2, 3}
nta	Number of Tests Attended	Ordinal {01, 2, 3}
ntp	Number of Tests Passed	Ordinal {01, 2, 3}
lab	Label	Ordinal {01, 2, 3}

Feature Selection Techniques

Based on extensive review of literature, it was observed that – RFE and correlation were most suited for this type of data. Hence these 2 methods were employed for feature selection- Two primary methods were employed

- **Recursive Feature Elimination (RFE):** A wrapper-based technique that iteratively removes less important features based on model weights. RFE was implemented with Logistic Regression and Support Vector Machine as base estimators.
- **Correlation Analysis:** Pearson correlation coefficients were calculated for numerical features, and features with correlation above 0.85 were candidates for removal to prevent multicollinearity.

Machine Learning Models

The selected features were used to train and evaluate several classification algorithms:

Out of the 10 classification algorithms used by most of the researcher, the performance of following 4 classification algorithm were found to be promising and hence it was decided to eliminate other 6 algorithms and to consider the following 4 for detailed performance evaluation

- Decision Tree (DT)
- Support Vector Machine (SVM)
- Logistic Regression (LR)
- K-Nearest Neighbors (KNN)

Performance was measured using accuracy, precision, recall, and F1-score via 10-fold cross-validation.

Results

Feature Selection Outcomes

RFE reduced the original feature set from 40 to 15 key features, including student interest, mother's education level, number of absences, semester 1 grade, and motivation. Correlation analysis identified highly correlated semester grades, leading to retention of only one representative grade per semester.

Table 2 : Model Performance

Model	Accuracy (All Features)	Accuracy (Selected Features)	F1-Score (Selected Features)
Decision Tree	78.3%	81.5%	0.80
SVM	82.1%	85.4%	0.84
Logistic Regression	79.4%	83.2%	0.82
KNN	75.0%	78.6%	0.77

Models trained with the reduced feature set consistently outperformed their full-feature counterparts, demonstrating improved generalization and reduced overfitting.

Discussion

Feature selection plays a pivotal role in the development of predictive models for student academic performance by improving both the accuracy and interpretability of machine learning algorithms. This study confirms that reducing the number of input variables to the most relevant subset not only enhances model efficiency but also facilitates better understanding of the critical factors influencing student outcomes.

Consistent with findings by Ramaswami and Bhaskaran (2009), the application of feature selection techniques significantly reduces dimensionality without compromising, and often improving, prediction accuracy. Their work highlighted that irrelevant or redundant features can introduce noise, leading to overfitting and reduced generalizability of models. Similarly, our results demonstrate that applying Recursive Feature Elimination (RFE) and correlation-based filters effectively identifies key predictors, such as attendance, parental education, and prior academic performance.

The balance between computational efficiency and predictive power is a recurring theme in feature selection research. Filter methods, which rely on intrinsic data properties, offer computational simplicity and scalability but may overlook feature interactions important for model accuracy (Zaffar et al., 2018). Conversely, wrapper methods like RFE provide superior accuracy by evaluating feature subsets using a learning algorithm but are computationally intensive for large datasets (Patel & Patel, 2024). The hybrid use of these methods, as shown in recent studies, optimizes both accuracy and efficiency, supporting our methodology of combining correlation analysis with RFE.

Moreover, the interpretability gained through feature selection is critical in educational settings, where stakeholders such as educators and policymakers require clear, actionable insights. Roy and Farid (2024) emphasize that adaptive feature selection algorithms not only boost model performance but also help in tailoring interventions by highlighting context-specific influential factors. This aligns with our findings that psychological factors like motivation and stress, alongside demographic and academic variables, are among the top predictors influencing student success.

Nevertheless, challenges remain, including handling imbalanced datasets and the temporal nature of educational data, which can affect the stability of feature selection outcomes (Mustapha, 2023). Future work could focus on integrating

feature selection with deep learning models and developing dynamic feature selection techniques that adapt over time as new data become available.

In summary, the study underscores that thoughtful feature selection is indispensable for robust academic performance prediction. It supports the growing consensus in the literature that combining multiple feature selection strategies can yield better predictive models that are both accurate and interpretable, ultimately benefiting educational decision-making and personalized learning pathways.

Conclusion

Feature selection is essential for improving the accuracy and efficiency of student performance prediction models. By focusing on the most relevant factors, these techniques help uncover the complex influences on academic success, enabling better-informed interventions. This study underscores the importance of integrating diverse features and adopting adaptive methods to enhance educational data mining outcomes. Ultimately, effective feature selection is key to transforming raw data into actionable insights that support student achievement.

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