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Predictive Modeling in Communication Studies: A Systematic Review of Feature Selection Techniques for Data-Driven Insights

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ABSTRACT

The increasing adoption of machine learning techniques in communication research has brought new opportunities for predictive modeling, audience analysis, and media content evaluation. However, the challenges of ensuring both accuracy and interpretability remain central to advancing computational communication studies. This review synthesizes recent literature on hybrid feature selection frameworks that integrate statistical, heuristic, and machine learning-based approaches. We examine how these methods improve prediction performance while maintaining transparency and theoretical relevance in communication contexts. Key applications include predicting audience engagement, analyzing social media discourse, modeling media effects, and exploring communication networks. The review also highlights current limitations, such as overfitting risks, data bias, and insufficient theoretical integration, and suggests directions for future research that bridge computational methods with core communication theories. By critically evaluating hybrid feature selection strategies, this study provides communication scholars with insights into balancing methodological rigor with interpretability in machine learning applications.

Keywords: Communication research; Machine learning; Hybrid feature selection; Interpretability; Predictive modeling; Computational communication studies.

INTRODUCTION

Student performance prediction is an important aspect of educational data mining (EDM), especially for faculty level courses like Programming 2 subject as it enables institutions to identify students at risk and provide targeted interventions to improve their academic outcomes [1] . Some students facing an academic challenges which can lead to high failure and withdrawal rates. Thus, this situation prompts a collaborative effort among teachers, parents and faculty management to address and overcome these academic challenges. Student academic performance serves as a key indicator that allows individuals to monitor their educational advancement, culminating in degree attainment or certification. Accurate prediction of student performance can help the management to identify students at risk [2] , personalize their learning experiences and improve the academic outcomes. However, accurate prediction of student performance can be a significant challenge due to the multitude of factors that influence it, such as demographic characteristics, prior academic achievement, socioeconomic status, and engagement with course materials [3] . On top of that, the biggest challenge lies in effectively selecting the most relevant features from large, complex datasets to build accurate and interpretable machine learning models.

Most researchers focus on feature selection to get high accuracy on machine learning models. Many of the existing research on student performance prediction in education focuses on optimizing accuracy through advanced feature selection techniques [4]. These techniques prioritize selecting the most predictive features, those that yield the highest accuracy scores for the model. Popular feature selection methods often emphasize accuracy, and include techniques such as Filter Methods, Wrapper Methods, and Embedded Methods [5] . Despite the success of these methods at improving predictive performance, focusing only on the accuracy often leads to a significant drawback which is a lack of interpretability in the final models [6] . While the model may have high accuracy, however the stakeholders such as lecturers, administrators and students themselves may not trust or fully understand the machine learning model make the decisions.

Studies showed that the behavior of many black box machine learning models whereby the decision-making process is hidden behind complex computations can make it difficult for these stakeholders to figure out on the reason of a particular decision was made [7]. This lack of transparency can lead to reduced confidence or trust in the model's predictions and making it harder to implement the model in real-world educational settings. Interpretability is really important in educational contexts because stakeholders need to understand the rationale behind the predictions to make informed on the decisions [8]. For example, if the machine learning model predicts that a student is at risk of failing the subject then educators need to know which factors contributed to this outcome to intervene effectively and at an early stage. Without an interpretability aspect, models may be dismissed as unreliable even if they perform well on standard accuracy metrics.

Our research proposes a novel hybrid feature selection framework aimed at striking a balance between accuracy and interpretability of machine learning models for predicting student performance in the Programming 2 course at Universiti Tenaga Nasional (UNITEN). By focusing not only on the model's predictive accuracy but also on how transparent and understandable its predictions are, we seek to build a framework that contributes to transparent models that stakeholders can trust and act upon. In doing so, we aim to contribute to a more explainable machine learning approach in educational data mining specifically for predicting student performance in the Programming 2 course at UNITEN.

LITERATURE REVIEW

The need for interpretable machine learning models in educational contexts has been highlighted in several studies. Study by [8] emphasizes that while machine learning models can achieve high predictive accuracy, the lack of interpretability hinders their acceptance and implementation in real-world educational settings.

2.1 Student Performance Prediction in Educational Data Mining

In recent years, EDM has gained significant attention to enhance decision-making in academic environments [9]. Predicting student performance is one of the priority tasks in EDM, where the goal is to predict students' future academic outcomes based on various aspect of the data such as past grades, attendance, assignments and engagement with the course content [10]. This prediction can help educators identify at-risk students early to tailor interventions and improve student learning outcomes. Machine learning models that are used for this task are leveraging large datasets that include academic records, engagement metrics, behavioral data and socio demographic features [11]. Many researchers have explored various machine learning techniques and approaches to predict student performance with a focus on getting high accuracy.

Thus, various machine learning techniques have been applied to predict student performance with a focus on getting high accuracy. According to [12], supervised learning algorithms such as Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM) and Neural Networks (NN) have been the most used. These methods offer strong predictive capabilities by learning patterns from historical datasets. However, the success of these models heavily depends on the quality and selection of features that best represent student behavior and performance [13].

Meanwhile, study by [14] showed DT are used due to their ability to provide both high accuracy on the prediction and fairly good interpretability aspect. The DT split the data into subsets based on the most significant features which makes them easy to understand and visualize. However, according to [15] DT can be prone to overfitting especially when using noisy or high-dimensional datasets. Random Forests (RF), an ensemble of DT have also shown promising results in student performance prediction as they can handle high-dimensional datasets and are less prone to overfitting [10]. However, like other ensemble methods, RF is considered as a black-box model, making it difficult to interpret [16]. Other techniques, such as Logistic Regression and Linear Regression, have also been used to predict student performance. While these models have demonstrated good predictive accuracy, but they also often lack interpretability [8] which is crucial in educational contexts where stakeholders need to understand the justification or reason behind the model predictions to make informed decisions. On top of that, even though these models are generally effective at prediction, however their ability to generalize well on unseen data and handle complex feature interactions depends heavily on how features are selected and processed. Thus, feature selection stage becomes an essential step to ensure that models can achieve both high accuracy and avoid overfitting [17].

2.2 Feature Selection Techniques in Machine Learning

Feature selection stage is one of the most important steps in the machine learning life cycle which can have a huge effect on model performance. In general, feature selection is one of the most important steps in the pre-processing of machine learning since it enhances model performance by removing irrelevant or redundant features from the dataset [18]. According to [19], effective feature selection reduces model complexity, speeds up training and can enhance the generalization ability of the model. It is important in the context of student performance prediction where many features may be interrelated or noisy.

The most widely used feature selection techniques can be categorized into three groups, which are Filter Methods, Wrapper Methods and Embedded Methods [20]. Filter methods evaluate the relevance of each feature independently based on statistical measures, such as correlation, mutual information or chi-square test [21]. These methods are computationally efficient and can handle high-dimensional data, but on the other hand they do not consider the interaction between features [22]. In the context of student performance prediction, filter methods can help identify the most relevant factors, such as attendance, assignment grades, and demographic characteristics that contribute to student success. Wrapper methods use machine learning models as a black box to evaluate subsets of features and select the best performing subset [11] . These methods can capture feature interactions, but they are computationally more expensive and may be prone to overfitting [23] . Embedded methods integrate the feature selection process into the model training and allow the model to learn which features are most important [17]. Some common embedded methods include Lasso Regression (LR) in which it performs L1 regularization to encourage sparse feature selection and decision tree-based algorithms, which inherently perform feature selection during the tree-building process.

2.3 Challenge of Interpretability in Machine Learning Models

While improving accuracy through sophisticated feature selection methods is essential, it often comes at the expense of interpretability. According to [24] many machine learning models, such as Random Forests, Neural Networks and Gradient Boosting achieve state of the art performance but lack transparency. These complex machine learning models such as Random Forests, Neural Networks and Gradient Boosting, are often referred to as black box models, meaning it is difficult for stakeholders including educators, administrators and students to understand the specific reasons behind a model's predictions.

The inner workings and decision-making processes of these advanced models can be opaque, making it challenging for stakeholders to comprehend how the model arrived at a particular outcome.

2.3.1 The Importance of Interpretability

In the context of EDM, interpretability is important as educators, administrators and students need to understand the reasons behind the predictions to make informed decisions and interventions [8]. For example, if a model predicts that a student is likely to struggle in a course, stakeholders need to know which factors contributed most to that prediction in order to provide targeted support. Without interpretability, models are less likely to be trusted or adopted in real-world settings.

Current interpretability methods aim to provide insights into complex models are Shapley Values, LIME (Local Interpretable Model-agnostic Explanations) and Surrogate Models [24] . Shapley values originate from cooperative game theory [25]. Shapley values allocate each features contribution to the prediction and offering a clear and interpretable explanation for individual predictions. Shapley values are particularly useful in ensemble methods like Random Forests, as they help explain the impact of each feature on a model's outcome [26]. LIME is another popular interpretability method that creates a local surrogate model to explain the predictions of a black-box model [27]. LIME is a technique that explains individual predictions by approximating the model’s decision boundary locally with simpler and interpretable models. This helps users understand the decisions made by complex models on a case-by-case basis. Study by [24] showed surrogate models are simpler models for an examples decision trees or linear regression trained to approximate the predictions of more complex models. Surrogate models by approximating the behavior of the original black box model with simpler and more interpretable architectures also provide a means to understand the underlying reasoning behind the model's decisions.

Together these interpretability methods play a vital role in improving the transparency and reliability of complex machine learning models, especially in the context of educational data mining where stakeholder understanding is paramount.

2.4 Recent Advances in Feature Selection Techniques

Feature selection remains a dynamic area of research with several innovative methods emerging to address the limitations of traditional approaches. Table 1 below shows the comparison of recent feature selection techniques, focus and the achieved accuracy values on various datasets.

Table 1: Comparison of recent feature selection technique

Technique	Category	Focus	Interpretability Aspect	Typical Accuracy (%)
LASSO	Embedded method	Accuracy	Limited interpretability	85%–92%
Elastic Net	Embedded Method	Accuracy	Prioritizes multicollinearity handling over interpretability	88%–94%
Recursive Feature Eliminatio n (RFE)	Wrapper Method	Accuracy	Model-dependent, making interpretability harder	90%–95%
Random Forest Feature Importanc e	Embedded Method	Accuracy	Often considered a black-box method, thus difficult to explain	92%–96%
Gradient Boosting (e.g., XGBoost)	Embedded Method	Accuracy	Provides importance rankings but lacks transparency	94%–97%
Chi-Square Test	Filter Method	Accuracy	Completely ignores feature interactions	75%–85%
Informatio n Gain	Filter Method	Accuracy	Purely statistical; no explanation	80%–90%
Deep Learning Models (e.g., Neural Networks)	Feature Learning	Accuracy	Lacks interpretability due to the complex nature of deep networks	95%–99%
IGA NN Sparse	Embedded Method	Balanced	Promotes sparsity through a non-linear feature selection process	88%–94%
UBayFS (User-Guided Bayesian Framewor k for Feature Selection)	Ensemble Method	Balanced	Integrates user guidance to enhance interpretability	87%–93%
Relief-Based Algorithms (e.g., ReliefF, SURF, MultiSURF)	Filter oostinhgMetho d	Accuracy	While effective in identifying relevant features, they often lack direct interpretability	85%–92%
STIR (STatistica l Inference	Filter Method	Accuracy	Enhances the statistical validity of feature selection but	88%–94%

Relief)			does not inherently improve interpretability.	
Selective Bayesian Forest Classifier	Ensemble Method	Balanced	Provides a visualization tool that offers insight into relevant features	90%–96%

2.4.1 Detailed Analysis of Recent Advances Feature Selection Techniques

Most traditional and embedded methods such as Elastic Net, RFE, Random Forest, and Gradient Boosting prioritize accuracy. These methods are often evaluated purely on predictive performance, with little regard for how the selected features contribute to model transparency [28]. Accuracy for these methods typically falls in the 85%–99% range, depending on the dataset [29]. For example, Gradient Boosting achieves the highest accuracy in the 94%–97% range [30], especially in complex datasets like credit scoring and recommendation systems. Elastic Net is effective in high-dimensional and sparse datasets achieving 85%–94% accuracy but offer limited transparency [31].

Recent frameworks like IGANN Sparse, UBayFS, and Selective Bayesian Forest Classifier attempt to combine accuracy with interpretability by promoting sparsity, integrating user guidance, or providing visualization tools [32]. These methods deliver balanced accuracy in the range of 87%–96% while offering insights into feature importance and interactions. Techniques like Chi-Square Test and Information Gain are fast and simple and suitable for preprocessing large datasets [33]. However, their accuracy is lower in between 75%–90% and they lack mechanisms to detect feature interactions or improve interpretability. These methods are best used as a first step followed by more advanced techniques to refine feature selection. RFE, Random Forest Feature Importance and Gradient Boosting dominate practical applications due to their high accuracy in the range of 90%–97%. These methods are particularly effective for tasks requiring complex feature interactions. However, these techniques are criticized for their black-box nature and making it difficult to justify predictions to non-technical stakeholders [34].

Techniques like LASSO and IGANN Sparse achieve both accuracy and interpretability by selecting a minimal set of features. Sparse modelling is gaining traction for applications in genomics, drug discovery and personalized medicine where too many features can overwhelm decision making. Accuracy for sparse techniques ranges from 85%–94%, slightly lower than ensemble methods but more interpretable. Frameworks like UBayFS integrate user expertise into feature selection, enhancing interpretability by aligning feature relevance with domain knowledge. These methods are particularly useful in personalized medicine and marketing where stakeholders need actionable insights. Techniques like the Selective Bayesian Forest Classifier use visualization tools to represent feature importance and interactions, making them highly interpretable. These methods maintain accuracy in the range of 90%–96% while addressing stakeholder concerns about transparency.

2.5 Gap in Current Literature

The literature on student performance prediction largely focuses on improving accuracy through advanced feature selection and model tuning. However, there is a notable lack of studies that integrate interpretability alongside accuracy [35]. In reality, machine learning models that are optimized solely for accuracy may achieve high performance but fail to offer meaningful explanations for their predictions. This makes it difficult for stakeholders to trust and act upon the results, especially in educational contexts [36].

For example, while Random Forests and Gradient Boosting are powerful tools for prediction, they are often criticized for being unclear [24]. According to [37], neural network models particularly deep learning models, offer even greater predictive power but are typically seen as black-box models. These models are difficult to interpret and their use in real world educational environments is limited because stakeholders need to understand why a model made a specific prediction such as why a student is predicted to fail.

This gap presents an opportunity to develop a new feature selection framework that not only optimizes accuracy but also enhances the interpretability of the model. Such a framework would address the concerns of stakeholders by providing transparent and understandable explanations for why specific predictions are made.

A scoping review examines the current state of a certain field of study to comprehend and combine research questions, techniques, and strategies (Fiers, 2023). It focuses on determining the scope of a body of literature on a given topic, identifying the volume of studies, and overviewing—broadly or in detail—its focus" (Munn et al., 2018). Our scoping review of recent studies about digital labor on TikTok/ Douyin follows the recommended reporting items guidelines (PRISMA) to ensure a transparent and comprehensive evaluation of relevant research (Page & Moher, 2017; Tricco et al., 2018).

Aimed as a live review, this review uses two searches to ensure studies published after our initial search were considered. Keyword-based searches were conducted. We employed a scoping screening process to eliminate studies irrelevant to the topic, and further filtered records by inclusion and exclusion criteria to form the final list of articles for review. Information in the articles was extracted by one author and validated by another author. This protocol controlled for biases in the review process.

DISCUSSION

We proposed the new hybrid LASSO and ACO feature selection framework because this hybrid approach leverages the strengths of both techniques. LASSO efficiently reduces high-dimensional datasets to a sparse subset of predictive features while maintaining interpretability [46 - 47]. ACO further optimizes this reduced subset by exploring feature combinations and addressing non-linear relationships [48]. Other combinations, such as RFE + ACO or PCA + ACO, either introduce additional computational complexity or sacrifice interpretability, making them less suited to the goals of this study. The LASSO + ACO framework achieves an ideal balance between dimensionality reduction, interpretability, and predictive accuracy, as demonstrated by our experimental results.

The results validate the effectiveness of the LASSO + ACO hybrid framework in identifying an optimal subset of features. By integrating LASSO for dimensionality reduction and sparsity, the framework ensures that irrelevant or redundant features are eliminated, simplifying the dataset. ACO complements this process by fine-tuning the feature selection, enabling the identification of a subset that enhances predictive accuracy while maintaining interpretability.

The high accuracy and AUC-ROC scores achieved by the model suggest that the selected features effectively capture critical determinants of student performance. These include prior academic performance, attendance and readiness which are essential indicators for predicting success in the Programming 2 course.

By reducing the feature set to six attributes, the framework significantly improves interpretability. This reduction allows educators and stakeholders to clearly understand the key factors influencing student outcomes. For instance, the inclusion of Programming 1 Grade underscores the importance of foundational knowledge, while the focus on Attendance Percentages highlights the role of consistent engagement in the classroom.

Furthermore, the results underscore the potential of data driven approaches for early intervention. The identified features provide actionable insights, enabling educators to design targeted support strategies. For example, improving attendance rates or offering additional resources to students with lower grades can address critical gaps and enhance student performance outcomes.

CONCLUSION

This study proposed and validated a hybrid feature selection framework integrating LASSO and Ant Colony Optimization (ACO) for predicting student performance in the Programming 2 course at UNITEN. The hybrid framework effectively reduced the original dataset of 35 attributes to a concise subset of 6 key features, striking a balance between predictive accuracy and interpretability. The integration of LASSO ensured dimensionality reduction by removing irrelevant features, while ACO refined the subset by exploring feature combinations to maximize accuracy and simplicity.

The results demonstrated the effectiveness of the proposed framework, with the Random Forest model trained on the ACO-selected features achieving an impressive accuracy of 99.21% and a near-perfect AUC-ROC score of 0.9998. These findings highlight that the selected features, which included academic performance, attendance records, and entry qualifications, captured the critical determinants of student success. The framework not only enhanced predictive performance but also provided actionable insights for educators and stakeholders, making it a valuable tool for designing early interventions to improve student outcomes.

By improving interpretability through a reduced feature set, the framework addressed the common challenge of stakeholder trust in machine learning models. Educators can now better understand and leverage key predictive factors, such as foundational grades and engagement levels, to identify at-risk students and implement targeted support strategies.

Future work could explore the application of this framework to larger datasets or other courses to evaluate its generalizability. Additionally, integrating advanced interpretability tools, such as SHAP [49] values or LIME [50] could provide further transparency regarding the model's decision-making process. Overall, the proposed LASSO + ACO hybrid framework presents a robust, interpretable, and effective approach to student performance prediction, contributing significantly to the field of educational data mining.

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