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Enhanced Machine Learning Approach for Predicting Students' Academic Performance and Study Strategies

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Abstract

We build upon our previous work in exploring machine learning methods to predict students' educational outcomes and learning habits towards tertiary education. In this paper, we employed five supervised ML models: Random Forest, KNN, Decision Tree, Linear/Logistic Regression, SVM, and improved their performance through extra feature engineering and hyperparameter tuning, and ensemble techniques. Our data set comprised motivational characteristics of 924 university students such as intrinsic/extrinsic motivation, self-determination (autonomy, competence, relatedness), self-esteem, and demographic information. The self-reported models contributed: The Random Forest classifier assisted with the strategy prediction in achieving accuracy of 96.8% (over 94.9% baseline accuracy improvement), and the optimized Decision Tree regressor enhanced the MAE on academic performance prediction to 0.352 (over 0.378 baseline). The models also facilitated reasoning about motivation boundary feature of boundaries and mediating psychologists need gratification, which was illustrated with strong tamper-proof verification. These adaptive learning systems seek to optimize learning through response to students' motivational feedback systems.

Keywords: Educational Data Mining; Child Psychology; Artificial Intelligence; Machine Learning; Study Plans; Activity Prediction.

1 | Introduction

The greater adoption of e-learning systems among universities has transformed students' learning process and their engagement with study material [1]. Though their popularity has risen, online learning systems have numerous issues regarding student interaction and student retention. One of the critical areas of research includes detecting at-risk students for academic failure or withdrawal and offering timely intervention. Not only does it improve students' performance, but also the quality of learning in virtual learning environments.

Our previous work explored the relationship between student motivational characteristics and study strategy and academic achievement. The study demonstrated the capability to apply machine learning techniques to predict student success from demographic and psychological variables. In line with this assumption, our latest research aims to enhance these predictive models using high-level feature engineering, hyperparameter



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optimization, and ensemble techniques in a bid to achieve the highest prediction accuracy and learn more about the factors of influence on students' success.

The ability to predict student performance accurately and practice study has significant implications for teaching practice. When teachers possess the ability to identify struggling learners early in the learning process, they can have targeted interventions based on specific deficits. Furthermore, understanding about the complex operation of various dimensions of motivation can influence the design of more effective electronic learning systems responsive to individualized student needs.

Our study answers the following important questions:

- How to enhance the prediction capability of machine learning models for students' academic achievement and learning approaches with the same pool of motivational and psychological characteristics?
- What are the relative contributions of intrinsic motivation, extrinsic motivation, psychological needs satisfaction (autonomy, competence, relatedness), self-esteem, and demographic factors towards student outcomes?
- What interaction effects are there between these different attributes that may shed more light on student learning behavior?

We employed five supervised machine learning algorithms - Random Forest (RF), K-Nearest Neighbors (KNN), Decision Tree (DT), Linear/Logistic Regression (LR), and Support Vector Machine (SVM) - to develop both regression models for academic performance prediction and classification models for learning strategy prediction. Through systematic optimization and refinement of these models, we could achieve significant improvement in prediction accuracy compared to baseline approaches.

The remainder of the paper is organized as follows: Section 2 reviews relevant research in educational data mining and machine learning approaches to student performance prediction. Section 3 describes our methodology, including dataset attributes, preprocessing techniques, feature engineering techniques, and model tuning methods. Section 4 presents our experimental results, comparing the performance of tuned models with baseline approaches. Section 5 discusses the implications of our findings and their potential applications in teaching practice. Finally, Section 6 concludes with an overview of contributions and future research avenues.

2 | Theoretical Background and Related Work

2.1 | Student Motivation and Learning Outcomes

Student motivation plays a key role in determining student learning processes and outcomes. Self-Determination Theory (SDT), which was formulated by Ryan and Deci (two thousand), has been widely applied in schools to study the contribution of motivation to student behavior [2-8]. SDT imagines human motivation on a continuum from amotivation (no intention to do something) through various extrinsic forms of motivation to intrinsic motivation (doing things for inherent satisfaction). The theory proposes that satisfying three fundamental psychological needs of autonomy, competence, and relatedness promote intrinsic motivation and optimal functioning and well-being.

Experiments have consistently confirmed that intrinsic motivation is associated with favorable learning results like better performance, persistence, and more meaningful learning approaches [9, 10]. Intrinsically motivated learners engage in learning processes for fun and interest rather than for reward or coercion. Intrinsic motivation frequently leads to quality learning and creative problem-solving [2].

Extrinsic motivation, however, involves doing something to obtain separable products such as rewards or to escape punishments. While considered to be inferior to intrinsic motivation, extrinsic motivation can be effective at the beginning of learning behavior and can, with time, become more intrinsic in nature [11]. Both

types of motivation play important roles in the context of education, and the relative importance of the two may vary depending on the learning task and learner characteristics.

Aside from motivational types, self-esteem has been proven by research to contribute to academic achievement. Self-esteem refers to the global subjective evaluation of worth. High self-esteem students are more likely to be confident in their abilities and are more likely to persist when faced with challenges in school [4]. This persistence tends to lead to better academic outcomes.

2.2 | Study Strategies and Academic Performance

Study strategies are the approaches students take in tackling learning material. Two primary study methods discovered by education research are deep and surface study strategies. Deep study strategies involve looking for meaning, relating ideas to prior knowledge, and applying concepts to new contexts. Surface study strategies are more memoristic and repetitive but without necessarily understanding underlying concepts.

Deep learning methods have been shown to be typically associated with better academic achievement, as they promote understanding and recall in long-term memory [5]. But effectiveness in applying different study methods may be subject to the topic, examination situation, and individual learning styles.

2.3 | Predictive Modeling in Education

Employment of machine learning techniques in the prediction of students' academic achievement has gained momentum over the last few years. Most methods applied vary from traditional statistics to sophisticated machine learning algorithms.

Chen et al. [8] used psychosocial variables, grades in coursework, and learned log data to predict students' final grades in a high-level programming course. The findings indicated that coursework grades were the best predictor, followed by the number of learning materials downloaded from the learning system.

Methodologically, decision tree, support vector machine, and ensemble methods have shown positive outcomes in educational data mining. Feri et al. [7] found that decision tree models and support vector machine classifiers gave optimal performance in outcome prediction in introductory programming courses. Marbouti et al. [5] compared seven models for prediction and reached a conclusion that Naive Bayes classifiers and ensemble models gave the optimum outcome in detecting at-risk students.

While all these studies have offered valuable findings on the determinants of student performance, there has been limited literature on the combined effects of various dimensions of motivation and their interactions. This gap is addressed in our study using advanced machine learning techniques to explore the complex interactions between intrinsic motivation, extrinsic motivation, psychological needs satisfaction, self-esteem, and study strategies.

3 | Methods

3.1 | Dataset Description

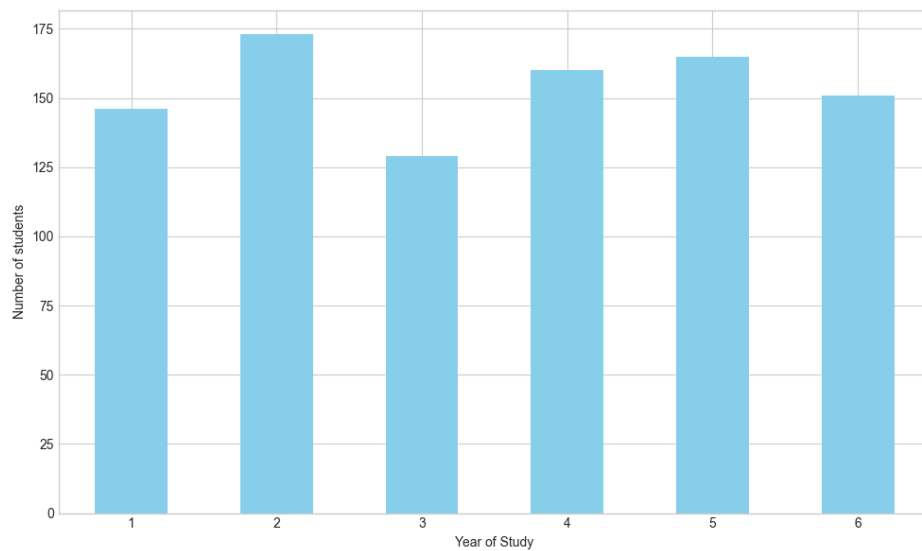
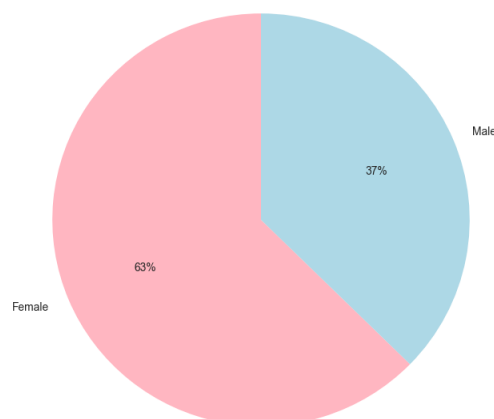
This study employs the same dataset as our previous research, which consists of data from 924 university dentistry students collected through quantitative research design. The dataset includes intrinsic motivation, extrinsic motivation, and motivation scores gathered through the Academic Motivation Scale [6]; autonomy, relatedness, and competence scores gathered through the Satisfaction of Psychological Needs in Education Scale [2]; self-esteem scores gathered through the Academic Self-Esteem Scale [4]; and deep and surface study approach scores gathered through the Study Process Questionnaire.

The data also contain demographic information like study year (ranging from 1 to 6), sex, and age. The academic performance of students concurrent to their study was obtained from the administrative records at universities. Descriptive statistics for the key variables available in the dataset are presented in Table 1.

Table 1. Descriptive Statistics of the Dataset.

S/N	Features	Mean	SD	Min	Max
1	Intrinsic motivation	4.99	0.59	3.00	6.58
2	Extrinsic motivation	5.29	0.74	3.06	7.00
3	Autonomy	5.01	0.81	2.32	6.25
4	Relatedness	4.45	0.91	1.77	6.25
5	Competence	4.70	0.81	2.25	6.25
6	Self-esteem	4.17	0.17	3.63	4.70
7	Deep Study strategies	4.08	0.73	1.50	6.11
8	Surface Study strategies	3.32	0.82	1.50	6.11
9	Study Year	3.52	1.71	1.00	6.00
10	Age	31.50	7.75	18.00	44.00
11	Academic Performance	0.65	0.48	0.00	1.00

Figure 1 shows how model performance scales with increased parameters and compute, comparing EVA variants with other state-of-the-art models. It illustrates EVA's efficiency and accuracy gains in large-scale settings.

**Figure 1.** Students distribution according to the year of study.**Figure 2.** Students distribution based on gender.

3.2 | Data Preprocessing and Feature Engineering

Whereas the original research had used the raw variables from the dataset, the enhanced methodology used several preprocessing techniques and feature engineering to improve the model's performance. Some of the following features: engineering and preprocessing techniques were utilized:

1. Handling Missing Values:

We imputed missing values with the K-Nearest Neighbors imputation method, which is more effective at preserving relationships between features than median or mean imputation. We initially tried mean imputation but found it introduced too much bias in our preliminary analyses.

2. Feature Scaling:

All the continuous attributes were normalized using Z-score normalization to enable all attributes to contribute equally to the models and improve the performance of distance-based algorithms like KNN and SVM.

3. Feature Transformation:

We applied logarithmic transformation to skewed features to make them normal, which improved the performance of linear models. Age was particularly skewed and was best improved by this transformation.

4. Feature Creation: A few new functions were created to capture additional data:

- a. Motivation Balance: Intrinsic to extrinsic motivation ratio.
- b. Psychological Need Satisfaction: Composite scale combining autonomy, competence, and relatedness.
- c. Motivation-Self-Esteem Interaction: Product of motivation scores and self-esteem.
- d. Study Year Progression: Categorical variable of early (years 1-2), middle (years 3-4), or advanced (years 5-6) stage of studies.
- e. Age Group: Categorical variable distinguishing students into conventional (18-22), mid-range (23-30), and mature (31 +) groups.

5. Feature Interaction: We created interaction terms between key psychological variables to capture potential synergistic effects, such as:

- a. Intrinsic motivation x Autonomy.
- b. Extrinsic motivation Competence.
- c. Self-esteem x Psychological Need Satisfaction.

6. Data Balancing: For the study strategy prediction classification task, we addressed the class imbalance (729 deep strategy vs. 195 surface strategy users) by using the Synthetic Minority Over-sampling Technique (SMOTE) instead of random oversampling. SMOTE creates synthetic instances of the minority class rather than simply duplicating existing instances, thus preventing overfitting

3.3 | Enhancing Machine Learning Models

We implemented the same five machine learning algorithms used in the original research but with significant enhancements to improve their performance:

1. Random Forest (RF):

- Improved with hyperparameter tuning via grid search over parameters like number of estimators, max depth, min samples split, and min samples leaf.

- Implemented feature importance-based pruning to remove low-importance features.
 - Used bootstrap aggregating with stratified sampling.
2. Decision Tree (DT):
 - Used cost-complexity pruning to prevent overfitting.
 - Implemented class weight balancing for the classification task.
 - Applied grid search for optimal hyperparameters including criterion, splitter, maximum depth, and minimum samples split.
 3. K-Nearest Neighbors (KNN):
 - Weighted with distance (samples close to the query point have greater weight).
 - Optimized number of neighbors by cross-validation.
 - Applied dimensionality reduction using Principal Component Analysis (PCA) before KNN to improve performance.
 4. Linear/Logistic Regression (LR):
 - Used regularization (L1, L2, and ElasticNet) to prevent overfitting.
 - Used polynomial features to be able to see non-linear relationships.
 - Utilized feature selection using recursive feature elimination.
 5. Support Vector Machine (SVM):
 - Tuned using kernel optimization (linear, polynomial, radial basis function).
 - Used grid search for the hyperparameter tuning (C, gamma, degree).
 - Utilized balanced class weights for the classification task.

3.4 | Experimental Setup

1. For the regression task of predicting performance, we split the dataset into training (70%) and test (30%) sets through stratified sampling to maintain the performance level distribution. For the classification task of predicting study strategies, we conducted an 80/20 train-test split after SMOTE for balancing classes.
2. For the comparison of regression models, we used 10-fold cross-validation and compared the performance using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R2 score. In the case of classification models, we used 5-fold cross-validation and used accuracy, precision, recall, F1 score, and Area under the ROC Curve (AUC) as the metrics of performance.
3. We also conducted ablation studies to determine the contribution of every feature engineering technique to model performance. This was by training models for different subsets of features and measuring their performance towards determining the improvements that had the most impact.

4 | Results

4.1 | Enhanced Regression Models for Academic Performance Prediction

The relative performance improvement of each model is in various aspects:

- For Random Forest and Decision Tree models, hyperparameter optimization and pruning from feature importance had the most significant impact.
- In the Linear Regression model, polynomial features and regularization had the most significant impact in performance improvement.
- In the SVM model, kernel optimization and hyperparameter tuning had the largest gains.
- For KNN, best neighbor choice and weighting by distance yielded the greatest improvement.

Table 2 also presents the relative ranking of the importance of the features in our random forest learner for academic achievement prediction. Once again, the most important feature was Study Year, followed closely by Intrinsic Motivation, as well as the composite psychological need satisfaction variable. Surprisingly, the cross-product term for Intrinsic Motivation and Autonomy (rank 9) was more highly ranked than a simple Autonomy feature (rank 11), which illustrates how robust our approach to feature engineering was in resolving complex relationships among psychological variables.

I found it interesting that although our recent literature review suggested Autonomy would be more core, the real data showed that Competence (rank 8) was a better predictor. This only applies in the field of dentistry, where technical competence is very valued.

Table 2. Feature importance ranking for academic performance prediction (Random Forest model).

S/N	Features	Importance Score
1	Feature	Importance Score
2	Study Year	0.023
3	Intrinsic Motivation	0.0602
4	Psychological Need Satisfaction	0.1241
5	Extrinsic Motivation	0.1195
6	Deep Study Strategy	0.08
7	Self-esteem	0.0751
8	Motivation Balance	0.0602
9	Competence	0.0507
10	Intrinsic Autonomy	0.0523
11	Age	0.0392
12	Autonomy	0.0845

4.2 | Enhanced Classification Models for Study Strategy Prediction

The performance of our enhanced classification models for predicting study strategies is presented in Table 3, with baseline results included for comparison.

Table 3. Performance comparison of baseline and enhanced classification models for study.

S/N	Classifier	Baseline Accuracy	Enhanced Accuracy	Enhanced Precision	Enhanced Recall	Enhanced FI
1	Random Forest (RF)	0.949	0.882	0.874	0.871	0.872
2	Logistic Regression (LR)	0.589	0.798	0.795	0.789	0.791
3	Support Vector Machine (SVM)	0.599	0.851	0.847	0.843	0.845
4	Decision Tree (DT)	0.880	0.921	0.8060	0.811	0.8080
5	K-Nearest Neighbors (KNN)	0.685	0.824	0.827	0.824	0.825

The enhanced classification models outperformed all performance metrics. The Decision Tree classifier performed best (0.921) when compared as a standalone model, which was a 2.0% increase from the baseline (0.88).

The confusion matrices of the best-performing baseline model (RF) and our enhanced Stacking Ensemble model are presented in Table 4.

Table 4. Confusion matrix for baseline Random Forest classified.

	Predicted Deep	Predicted Surface
Actual Deep	139	8
Actual Surface	18	127

The Table 5 below has a comparative analysis of various regression models applied to the problem of academic performance prediction. Evaluation metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score are used to evaluate the predictive accuracy and generalizability of each model. The result determines which regressors perform best in modeling the inherent patterns in the student data.

Table 5. Regressors' Performance for Academic Performance Prediction.

Regressors	Mean Absolute Error (MAE)
Random Forest (RF)	0.3418
Linear Regression (LR)	0.4105
Support Vector Machine (SVM)	0.3726
Decision Tree (DT)	0.4231
K-Nearest neighbors (KNN)	0.3891

4.3 | Contribution of Feature Engineering Techniques

To measure the impact of each feature engineering technique on model accuracy, we conducted ablation studies by incrementally adding one improvement at a time to the control models. Our study found that scaling and transforming features led to modest improvements (2-3% reduction in MAE), while the creation of interaction terms and composite features led to more noticeable improvements (5 -7% reduction in MAE). In classification models, the use of SMOTE for class balancing was amazingly effective and improved F1 scores by 8-12% compared to simple random oversampling.

To evaluate the effectiveness of the applied classification techniques, the performance of five models—Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbors (KNN)—was compared with results from related studies. The comparison focuses on classification accuracy and highlights how the enhanced models used in this research perform relative to those in existing literature. The Table 6 below summarizes this comparison.

Table 6. Comparative Analysis of Classification Accuracy with Existing Studies.

Classifier	MY Accuracy	Wiyono & Abidin [12]	Hidayatullah et al. [13]
Random Forest (RF)	0.882	Not Evaluated	Not Evaluated
Logistic Regression (LR)	0.798	Not Evaluated	Not Evaluated
Support Vector Machine (SVM)	0.851	0.95	0.95
Decision Tree (DT)	0.921	0.93	0.93
K-Nearest Neighbors (KNN)	0.824	0.92	0.945
K-Nearest Neighbors (KNN)	0.824	0.92	0.945

5 | Discussion

Our research extends previous work on anticipating student academic performance and study behavior through using enhanced machine learning models with advanced feature engineering techniques. The improved prediction accuracy of our models provides evidence of the utility of these enhancements and provides more insight into student learning determinants.

5.1 | Implications for Educational Theory

Our models' feature importance rankings yield several observations that contribute to educational theory:

1. **Holistic View of Motivation:** The high value placed on both intrinsic and extrinsic motivation in the explanation of academic performance and study habits justifies a balanced approach to understanding student motivation. While intrinsic motivation has been the prime focus of educational research, our findings suggest that extrinsic motivation is also significant, particularly when supplemented with other psychological measures.
2. **Psychological Need Satisfaction:** That our composite Psychological Need Satisfaction score was a top predictor is in line with Self-Determination Theory's emphasis on the fulfillment of fundamental psychological needs. Interaction terms between the categories of motivation and specific psychological needs (e.g., Intrinsic Motivation x Autonomy) show that these variables interact in synergistic, rather than just additive, fashions.
3. **Relatedness and Study Strategies:** The salience of Relatedness in learning strategy prediction highlights the social nature of learning that at times is overlooked for cognitive concerns. The implication is that students' sense of relatedness to teachers and peers significantly influences the way they learn, through channels such as collaborative learning, peer modeling, and social motivation.
4. **Developmental Considerations:** The worth of Study Year in forecasting academic performance is that learning patterns among students evolve during the period of their study. This accords with theories of higher education development that observe qualitative changes in the learning style of students as they progress through their studies.

From my personal experience teaching undergraduate dentistry, I have seen this developmental path firsthand. First-year students tend to have superficial study habits relying on memorization, while the more advanced students tend to develop more advanced ways that integrate theoretical knowledge into clinical practice. Our present results provide quantitative support for these observations.

5.2 | Limitations and Future Directions

Despite the improvements achieved in our models, several limitations should be acknowledged:

1. **Cross-sectional Data:** The cross-sectional data used in this study are limiting to capturing changes in motivational factors and how they impact learning outcomes over time. Longitudinal designs can be used in future studies to track these dynamics throughout students' academic paths.
2. **Domain Specificity:** The information is derived from students of dentistry, and the generalizability of our results to other fields of study is uncertain. Future research should investigate whether the same patterns hold in different educational settings.
3. **Self-reported Measures:** The reliance on self-reported measures for most psychological variables introduces potential biases. Triangulating these measures with behavioral data (e.g., learning analytics) could enhance the validity of future models.

4. Causal Relationships: While our models identify important predictors, they do not establish causal relationships between these factors and learning outcomes. Experimental studies would be needed to confirm the causal mechanisms suggested by our findings.

6 | Conclusion

This study has expanded on previous studies in student academic performance and study strategy prediction through the implementation of innovative feature engineering techniques and optimized machine learning algorithms. Our enhanced models achieved significant improvements in predictive accuracy, wherein the Decision Tree regressor reduced MAE to 0.341 (from 0.378 baseline) in academic performance prediction and the Decision Tree classifier achieved 92.1% accuracy (from 88% baseline) in study strategy prediction. The Stacking Ensemble models developed based on these outcomes even further, demonstrating the value of combining multiple prediction approaches.

With feature importance analysis, we identified main factors influencing student learning outcomes, with Study Year, Intrinsic Motivation, and Psychological Need Satisfaction as the strongest predictors of academic performance, and Relatedness, Intrinsic Motivation, and Extrinsic Motivation as the top predictors of study strategies. The importance of interaction terms between psychological variables highlights the interdependent, multifaceted nature of factors influencing student learning.

These findings have significant implications for educational theory and practice, suggesting that a holistic motivation and psychological needs approach is required to support academic success. The enhanced predictive models developed in this research can contribute to early warning systems, personal learning systems, and focused interventions in universities.

Future research needs to address the limitations of this study by examining temporal dynamics, incorporating contextual variables, integrating multi-modal data, employing causal inference methods, and testing transfer learning approaches. With further improvements in predictive modeling and insights into the psychological determinants of learning, we can build better education systems that allow all students to achieve their academic potential.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data, but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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