

Student Engagement Level Prediction in Online Education

Author 1 S. REVATHI

Student, Department of Master of

Computer Applications

AVS Engineering College, Salem, India

revathisiva2412@gmail.com

Author 2 Mrs. K. DEEPIKA

Assistant Professor, Department of Master of

Computer Applications

AVS Engineering College, Salem, India

kdeepikabca@gmail.com

Abstract—Given the increasing importance of online education, this research seeks to provide a solution to more accurately predict the level of student engagement in these environments. The proposed method consists of three key steps: first, data preprocessing to prepare and refine a set of indicators related to the level of student engagement in online education environments. Analytic Hierarchy Process (AHP) is used to rank and weight the features, and then an iterative process is used to determine an appropriate number of these ranked features. A Multilayer Perceptron (MLP) model as a meta-learner makes the final prediction based on the results of the predictions made by the first-level models. The proposed stacking ensemble approach integrates AHP feature weighting with MLP meta-learning to produce more accurate, adaptive, and interpretable predictions of student engagement, enabling educators to take timely and data-driven interventions.

Keywords—Student Engagement Prediction, Online Education, Analytic Hierarchy Process (AHP), Multilayer Perceptron (MLP), Machine Learning, Stacking Ensemble, Feature Selection, E-Learning.

I. INTRODUCTION

Online education has emerged as a transformative paradigm in modern academic environments, enabling learners to access educational content from diverse geographical locations and at flexible times. However, the absence of physical classroom interaction introduces significant challenges in monitoring and maintaining student engagement. Unlike traditional in-person settings where instructors can observe behavioral cues directly, online platforms must rely on data-driven methods to assess learner involvement and motivation.

Predicting student engagement in e-learning systems is crucial for early identification of at-risk students and enabling timely pedagogical interventions. Traditional engagement prediction approaches, which often rely on simple statistical analyses or rudimentary machine learning models, lack the ability to model the multiple complexities of student engagement. Furthermore, existing studies ignore the qualitative and subjective factors affecting engagement, leading to research gaps in accurately predicting student engagement.

This paper proposes a comprehensive framework that addresses these limitations through a three-stage pipeline: (1) data preprocessing to standardize and clean engagement-related indicators; (2) feature ranking and weighting using the Analytic Hierarchy Process (AHP) to prioritize the most influential variables; and (3) a stacking ensemble model where a Multilayer Perceptron (MLP) serves as a meta-learner that synthesizes predictions from multiple first-level base classifiers.

The proposed system leverages advanced ensemble learning techniques to exploit the complementary strengths of different classifiers, such as Decision Trees, Random Forest, and Gradient Boosting, before combining their outputs into a final prediction. By applying AHP to guide feature selection objectively, the model reduces noise and computational overhead while improving prediction reliability. The dataset employed includes behavioral features such as raised hands, visited resources, viewed announcements, participation in discussions, and parent engagement indicators.

The rest of this paper is organized as follows: Section II presents a survey of related works, Section III details the proposed methodology including the algorithmic workflow, Section IV discusses the experimental results and performance metrics, and Section V concludes the paper with future research directions.

II. LITERATURE SURVEY

In recent years, researchers have explored a wide range of approaches to predict and improve student engagement in online learning environments. The following table summarizes representative works across different methodological perspectives:

S.No	Title	Description	Existing Work	Proposed Work	Performance
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1	The Role of Stakeholders Participation, Goal Directness and Learning Context	Identify antecedents of students' academic performance.	Academic Performance (AP) is multidimensional. Empirical measurement remains a point of debate.	Antecedents of academic engagement positively relate to academic performance and student engagement.	Contextual and social network designs used for determining academic performance.
2	A Motivational Perspective on Engagement and Disaffection	Emphasizes constructive, focused, enthusiastic participation; distinguishes engagement from disaffection.	Accurate assessment made difficult if students conceal disaffection by masking compliant behaviors.	Student engagement as observable manifestations of motivation; direct observations are optimal indicators.	Based on conceptualization of engagement incorporating behavior, emotion, engagement, and disaffection.
3	Application of Deep Learning on Student Engagement in e-learning	Importance of emotion detection for determining engagement during online classes.	Digital learning sessions must ensure students are properly engaged during online classes.	Unique weights assigned to different emotions. Mean Engagement Score (MES) calculated.	Observed real-time facial emotions and engagement concentration during eclasses.
4	The Educational Power of Humor on Student Engagement in Online Learning	Investigates effect of humor on behavioral, emotional, and cognitive engagement in online learning.	Humorous elements did not contribute to behavioral engagement for quizzes.	Use of humor created significant difference and improved emotional engagement.	Positive influence of humorous elements in course materials, discussions, and assignments was observed.

Table 1: Literature Survey Summary

The literature review reveals that while prior studies have tackled individual aspects of engagement detection — such as facial emotion recognition, behavioral analysis, and motivational assessment — a unified framework integrating principled feature weighting with ensemble learning remains underexplored. This gap motivates the proposed AHP-MLP stacking approach.

III. EXISTING SYSTEM

Existing systems for predicting student engagement in online environments often rely on traditional survey-based methods or simple statistical techniques, which may lack the precision and adaptability needed to analyze complex relationships within educational data. Traditional methods involve questionnaires where students self-report their engagement levels, academic performance, and behavioral patterns.

Some systems use basic classification algorithms such as Logistic Regression (LR) or Naive Bayes to examine the correlation between behavioral indicators and engagement levels. These approaches are often limited in handling non-linear relationships or high-dimensional data. Additionally, existing methods frequently ignore the relative importance of different features, treating all input variables as equally significant.

A. Disadvantages of Existing Systems

- Limited handling of non-linear relationships negatively affects prediction accuracy.
- Struggles with high-dimensional data, reducing model efficiency and interpretability.
- Fails to integrate dynamic technological and behavioral influences on student engagement.
- Self-reported data introduces inaccuracy due to social desirability biases.
- Absence of principled feature weighting mechanisms leads to suboptimal model performance.

IV. PROPOSED SYSTEM

The proposed system aims to provide a more accurate and comprehensive prediction of student engagement in online education by utilizing a stacking ensemble learning approach integrated with the Analytic Hierarchy Process (AHP) for feature selection and weighting. The system is structured into three principal components:

A. Data Preprocessing Module

Raw student engagement data is cleaned to handle missing values, outliers, and inconsistencies. Features are normalized to ensure uniformity across different scales. The dataset includes both behavioral indicators (raised hands, resource visits, discussion participation, announcement views) and parent engagement indicators (parent satisfaction, parent survey responses).

B. AHP-Based Feature Selection Module

The Analytic Hierarchy Process (AHP) is applied to assign relative weights to the input features based on domain expert knowledge and pairwise comparisons. Features are ranked according to their weight scores, and an iterative selection process

identifies the optimal subset of top-ranked features to feed into the model. This step ensures that the most influential predictors are retained while reducing dimensionality.

C. Stacking Ensemble with MLP Meta-Learner

The stacking ensemble framework consists of two levels. In the first level, multiple base classifiers — including Decision Tree, Random Forest, K-Nearest Neighbors, and Gradient Boosting — are trained on the selected features. Their predictions are collected and used as input to the second level, where a Multilayer Perceptron (MLP) acts as the meta-learner to generate the final engagement level prediction (High, Medium, or Low).

D. Advantages of the Proposed System

- Handles complex non-linear feature interactions through ensemble learning and neural meta-learning.
- AHP-guided feature selection reduces noise and improves model interpretability.
- Stacking architecture combines strengths of diverse classifiers for superior predictive accuracy.
- Provides personalized engagement alerts enabling timely teacher intervention.
- Scalable to large datasets with high-dimensional behavioral and parental engagement indicators.

V. SYSTEM ARCHITECTURE AND MODULES

The proposed system is designed as a modular pipeline ensuring clean separation of concerns across data ingestion, preprocessing, feature engineering, model training, and prediction. The following modules constitute the full architecture:

A. Data Collection Module

This module collects student behavioral and engagement data through structured questionnaires and learning management system (LMS) logs. Parameters include frequency of resource access, discussion participation, announcement view rates, assignment submission patterns, and parental involvement metrics.

B. Preprocessing Module

Raw data is cleaned to address missing values, outliers, and class imbalance. Feature normalization ensures that all input variables contribute equitably to model learning. Label encoding is applied to categorical variables such as parent relationship type and student absence categories.

C. Feature Selection Module

Using AHP, the relative importance of each feature is computed via pairwise comparison matrices. The resulting weight vector is used to rank features. An iterative forward selection process then determines the minimum feature subset that preserves maximum predictive information.

D. Model Building Module

Base classifiers (Decision Tree, Random Forest, Gradient Boosting, KNN) are trained on the selected feature set using 5-fold cross-validation. Their prediction probabilities are compiled into a meta-feature matrix for training the MLP meta-learner. Hyperparameter tuning is performed via grid search to optimize each classifier.

E. Evaluation Module

Model performance is assessed using accuracy, precision, recall, F1-score, and ROC-AUC metrics. Confusion matrices are generated to analyze per-class prediction accuracy. The evaluation ensures the model generalizes well across unseen data.

F. Integration and Intervention Module

The trained stacking model is integrated into a web-based dashboard. Educators can input student activity parameters and receive real-time engagement level predictions. Automated alerts are generated for students classified as Low Engagement, facilitating early intervention.

VI. IMPLEMENTATION ALGORITHM

The algorithmic workflow of the proposed AHP-MLP Stacking Ensemble for Student Engagement Level Prediction is described below:

Algorithm: AHP-MLP Stacking for Engagement Prediction

Step 1: Data Collection — Gather student behavioral features (raised_hand, visited_resources, announcements_view, discussion) and parent engagement features (parent_relationship, parent_satisfaction, parent_survey).

Step 2: Preprocessing — Handle missing values via mean/mode imputation. Normalize continuous features using MinMax scaling. Encode categorical labels.

Step 3: AHP Feature Weighting — Construct pairwise comparison matrices for each feature pair. Compute priority weights and consistency ratio ($CR < 0.1$ required). Rank features by normalized weight.

Step 4: Feature Selection — Apply iterative forward selection using ranked AHP weights to identify optimal top-k features that maximize validation accuracy.

Step 5: Base Classifier Training — Train Level-1 classifiers (DT, RF, GB, KNN) on selected features using 5-fold cross-validation. Collect out-of-fold predictions to form meta-feature set.

Step 6: MLP Meta-Learner Training — Train a Multilayer Perceptron on the meta-feature matrix. Architecture: Input layer → 2 Hidden Layers (ReLU activation) → Output Layer (Softmax). Optimize with Adam optimizer, cross-entropy loss.

Step 7: Prediction — For new student records, extract features → apply AHP weighting → obtain base model predictions → pass through MLP meta-learner → output engagement level (High/Medium/Low).

Step 8: Alert Generation — If predicted engagement = Low, trigger alert to educator dashboard for targeted intervention.

VII. RESULTS AND DISCUSSION

The proposed AHP-MLP Stacking Ensemble model was implemented and evaluated on the Student Performance and Engagement dataset. The dataset comprised 480 student records with 16 behavioral and parental engagement features labeled with three engagement levels: High, Medium, and Low. The dataset was split 80:20 into training and testing sets.

The proposed system was compared against standalone classifiers: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and a standard MLP. The AHP-guided feature selection consistently reduced the effective feature set from 16 to 10 top-ranked features while improving overall accuracy.

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	72.4	0.71	0.72	0.71	0.79
Decision Tree	78.1	0.77	0.78	0.77	0.83
Random Forest	82.3	0.82	0.82	0.82	0.88
Standard MLP	83.7	0.83	0.84	0.83	0.89
Proposed AHP-MLP Stack	91.2	0.91	0.91	0.91	0.96

Table 2: Performance Comparison of Classification Models

The proposed AHP-MLP Stacking Ensemble achieved the highest accuracy of 91.2%, outperforming all baseline models. The integration of AHP feature weighting contributed to a reduction in irrelevant features, allowing base classifiers to train on more discriminative signals. The MLP meta-learner effectively leveraged the diverse predictions of base classifiers to resolve ambiguous cases, particularly for the Medium engagement class which historically exhibited the highest misclassification rate in standalone models.

The ROC-AUC score of 0.96 further confirms the model's strong discriminative ability across all three engagement levels. Notably, the proposed approach achieved balanced precision and recall across all classes, indicating robust generalization without overfitting to any single engagement category.

VIII. CONCLUSION AND FUTURE SCOPE

This paper presented a novel framework for predicting student engagement levels in online education environments using an AHP-guided Stacking Ensemble model with an MLP meta-learner. By combining principled feature weighting through AHP with the complementary predictive strengths of multiple base classifiers, the proposed approach achieves superior accuracy, interpretability, and scalability compared to conventional methods.

The experimental evaluation demonstrated that the proposed system achieves 91.2% accuracy and a ROC-AUC of 0.96, substantially outperforming Logistic Regression, Decision Trees, Random Forest, and standard MLP baselines. The integration of parent engagement features alongside behavioral indicators further enriched the predictive model, capturing holistic dimensions of student engagement.

In future work, the system can be extended by incorporating real-time LMS log data streams for continuous engagement monitoring. Deep learning architectures such as Long Short-Term Memory (LSTM) networks could be explored to model temporal engagement patterns over the course of a semester. Additionally, natural language processing techniques can be applied

to analyze discussion forum posts and assignment submissions to capture cognitive engagement dimensions. Expanding the framework to support multilingual and multicultural learner populations will further enhance its global applicability.

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