

AI-Driven Adaptive E-Learning Using Real-Time Frustration Detection and Content Difficulty Adjustment

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Abstract

Adaptive e-learning demands a smart system based on adaptive mechanisms that can detect learners' problems and offer timely personalized support. This research suggests an Adaptive Content Selection and Frustration Classification based on a set of behavioral features and machine learning approaches using a Sense-and-Adapt framework. To generate a synthetic dataset with learner interaction records that are the largest number capable of being generated, a response behavior, error pattern, hint usage data type, engagement indicator, and completion attribute were employed. The following four classification models were investigated by analyzing the accuracy, precision, recall, F1 score and ROC-AUC: Logistic Regression, Random Forest, Support Vector Machine and Gradient Boosting. Logistic Regression achieved the highest classification performance with 98.80% accuracy, 98.73% F1-score and 99.93% ROC-AUC, over Random Forest, Support Vector Machine and Gradient Boosting models. This framework highlights the capabilities of AI-based sensing for learner states to adaptively scale difficulty and provide personalized learning experiences.

Keywords: Adaptive E-Learning, Artificial Intelligence, Learner Frustration Detection, Machine Learning, Behavioral Analytics, Personalized Learning, Sense-and-Adapt Framework, Content Adaptation

I. Introduction

A. Background of Research

Adaptive e-learning has emerged as an important application of artificial intelligence for delivering personalized learning experiences. Typical e-Learning systems adapt their content based on the quiz result, completion rate, or learner type and may not detect early signs of frustration, disengagement and perhaps cognitive overload [1]. It depends on the Sense-and-Adapt framework which takes into consideration the near real-time detection of the learner's state and the adaptive instructional decision-making [2]. In this method, the behavioral patterns observed in the interaction can be analyzed to determine the levels of frustration of the learner, including response time, repeated errors, frequency of interaction, frustration or hesitation, or task giving up [3]. Upon detecting the state, an adaptive engine can change the difficulty of a quiz, its sequence or which rules it follows, its speed, or even its feedback. Machine learning approaches to preprocess interaction-log data, learn and evaluate predictive learning models and apply adaptive rules can be done effectively in the Python environment [4].

B. Problem Statement

Learning difficulty in current e-learning systems is essentially adapted through explicit measurements,

such as items in question marks or the outcome of completion. This can fail to address messages given in behavior that may signify frustration or disengagement before academic outcomes are eventually negatively affected [5]. This means that the learner can be over-challenged, when necessary, under-challenged when needed, or be paced too slow or too fast through the content.

C. Aim and Objectives

Aim: The aim is to design and test an AI-based Sense-and-Adapt framework for identifying learner dissatisfaction with e-learning and adaptively adjusting its difficulty level using machine learning.

Objectives:

- To detect behavioral interaction characteristics related with learner frustration and disengagement in e-learning.
- To design machine learning models that classify learner frustration based on the interaction logged data and compare them.
- To create an adaptive decision-making process to adjust content difficulty, pacing, feedback, and learning path.
- To assess the proposed Sense-and-Adapt framework with proper classification as well as adaptive system performance metrics.

D. Research Questions

RQ1: What are possible ways of detecting learner "disengagement" and "frustration" in adaptive e-learning systems using behavioral interaction signals?

RQ2: What kind of machine learning model can be used to classify the student's frustration using the e-learning interaction-log data?

RQ3: How can the identified learner status be transformed into content, pace and feedback adaptation in real time?

RQ4: What is comparison of the capability of the proposed Sense-and-Adapt framework for responsive and personalized e-learning with adaptation of traditional performance-based approach?

E. Novel Contribution

The paper proposes a Python-based Sense-and-Adapt framework for combination of learner state classification and content decision making in a single e-learning line. The approach is different from traditional systems that primarily rely on assessment scores to detect frustration and disengagement before it leads to performance degradation, as it leverages behavioral interaction signals [6]. This novelty is in its ability to derive a predictive sense from a content and create an adaptation policy that changes the difficulty, pacing, feedback or content, on that basis. Research will compare machine learning classifiers and apply the adaptive rules which are taught in the interpretable fashion in python.

II. Related Work

A. Learner Frustration Detection in E-Learning

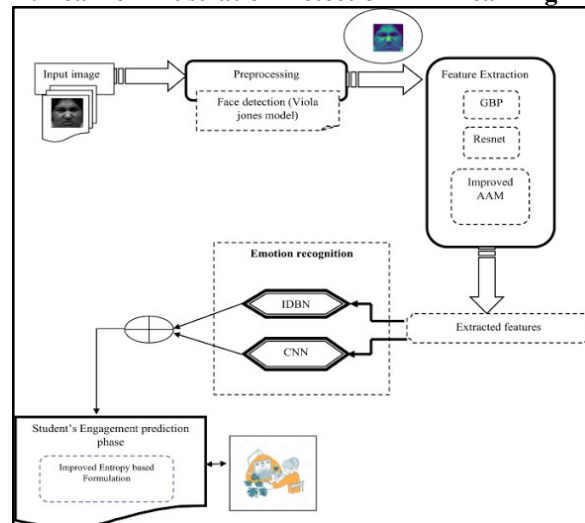


Fig. 1. Learner Frustration Detection

The discomfort experienced by the learners in digital education is an important affective state that can hinder concentration, motivation, perseverance and

learning effectiveness in the learning process. Developed e-learning systems have continuously tracked much information about interaction with their students, including early signs of frustration that may be initially accessed without the need of cameras, physiological sensors and self-reported emotions [7]. Repeated incorrect attempts, delayed responses, requests for hints, lack of activity, hurried guessing, and the abandonment of a task could be indicators of increasing cognitive or emotional difficulty, and may be relevant for learning data [8]. These patterns can be analyzed using machine learning and used to identify the learner's state, for example engaged, neutral, frustrated or disengaged [9]. This is especially suitable for offline education as system usage behavioral logs are automatically recorded which is quite applicable for online education that can be scaled [10]. Just letting the students know what is frustrating does not necessarily facilitate their learning unless it is linked to a governmental instructional response. Thus, it is essential to have an integrated mechanism for determining early signs of learner difficulty and adapt when needed in affect-aware e-learning [11]. A sensing process is one of the first steps in the proposed Sense-and-Adapt framework, and leads to action in response to data in a way that prevents student performance from dropping drastically [12].

B. Behavioral Signals and Machine Learning for Learner-State Classification

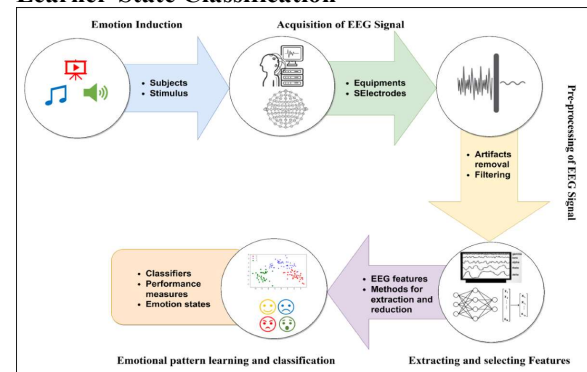


Fig. 2. Behavioral Signals and Machine Learning

The behavioral signals ask a social problem regarding and present a practical and noninvasive way to gain information about the learner state within online learning. E-learning systems regularly monitor the number of attempts, navigation sequences, length of time that no interaction is seen, length of time elapsing to complete, patterns of completion and frequency of interaction, response times, and the use of hints [13]. These factors alone are not enough to clearly infer frustrating behavior's as they can stem from reflection, distraction, and lack of confidence, or difficulty with

the task [14]. These patterns can offer more conclusive evidence when fed into machine learning models. This requires proper data pre-processing, time aggregation, engineering of relevant information, and selection of relevant behavioral variables for effective classification [15]. There are appropriate libraries in Python to create interaction logs, create the predictive features, train the classifiers and compare the performance of the models by performance metrics like accuracy, precision, recall, F1 score and confusion matrix [16]. Logistic regression, random forest, support vector machine and gradient boosting can be tested to see which one can most accurately pick up on frustration [17]. Thus sets the behavior measurement as the grounds to sense the proposed system and stresses the importance of reliability in classification before automated instructional decisions [18].

C. Adaptive Content Difficulty and Intelligent Decision-Making

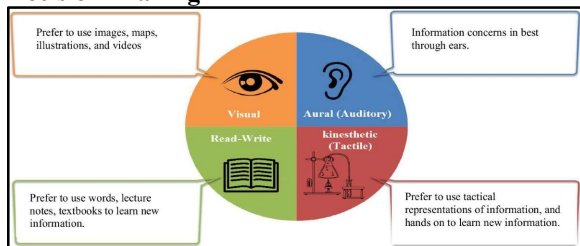


Fig. 3. Adaptive Content Difficulty and Intelligent Decision-Making

Adaptive e-learning systems strive to tailor the learning process by adapting the level of difficulty of the content, the sequence of the tasks, pacing, suggestions and feedback, and/or suggested activities to the learner's current needs [19]. Rather, changes are often driven by the learner's assessment scores or learning outcome assessments and, if they are based on longer run learning outcomes, can take place after the learner has suffered from a prolonged learning challenge. Predicted frustration can be included in the adaptation system of a more responsive system, intervening earlier [20]. If, for instance, frustration is high and if repeated mistakes are made, it may trigger easier questions, explanations, slower time, prerequisite materials, etc. Some level of an unrewarded frustration can bring hints and more targeted feedback, while an unrewarded, strong performance can bring more challenging activities [21]. The adaptation mechanism can take the form of either the transparent rules or recommendation policies based on machine-learning [22]. A SENSE AND ADAPT framework can integrate structured decision logic with predictive classification, so that the learner states detected are immediately translated into the corresponding learner actions, without any

unnecessary disengagement, and with productive challenge [23].

D. Personalization - enabled by AI and the Sense-and-Adapt Framework

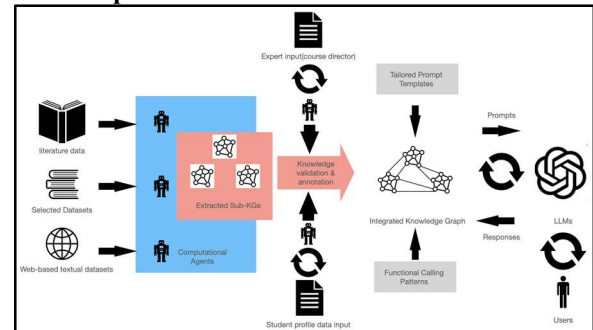


Fig. 4. AI and the Sense-and-Adapt Framework

AI personalization takes adaptive learning a step further, continually analyzing the behavior of learners and tailoring learning responses to evolving requirements, not just based on their score [24]. The central questions of a complete intelligent learning system are not only 'how' and 'how much' the learner responds to each element, but also 'what' the learning environment ought to do 'when'. This separation is clearly stated in Sense-and-Adapt. The sensing layer extracts and analyzes information about engagement or frustration from interaction logs, and the adaptation layer transforms any predicted form of engagement or frustration into a modified difficulty, pace, feedback, and content transitions [25]. The advantages of this architecture are that each component can be tested separately, yet would still be a closed loop system.

All of the above from preprocessing to feature engineering, model training to prediction rule execution to performance can be conducted with Python. The framework also enhances the interpretability as follows: instructional changes can be associated with explicit behavioral evidence and defined adaptation rules [26]. This method brings meaning to predictions in a way that is different from a system that would just predict the learner's outcome. Thus, it facilitates more responsive personalization, where actions taken by the system and activities based on near-real-time learner-state information actively shape the following system actions [27].

E. Research Gap

Previous studies have focused on the detection of learner frustration, on behavioral learning analytics, and on adaptive content suggestion, but these functions are often designed separately. However, much of the current adaptive systems continue to use low-level aspects of quiz results or advanced sensing devices, instead of interaction-log information readily available to computer science students. Few studies

combine real-time behavior classification of frustration with a disguised adjustment of content difficulty in one study that can be replicated.

III. Proposed Framework

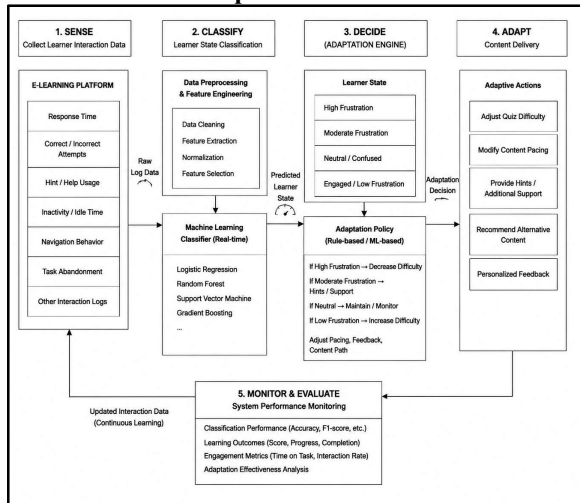


Fig. 5. Proposed Sense-and-Adapt Framework for Adaptive E-Learning

The suggested Sense-and-Adapt framework is an intelligent closed-loop system that combines detection of learner's state in near-real-time with adaptive modification of in-between the content in e-learning environment. The framework is divided into five inter-related stages. During Sense, data from the e-learning platform related to learner interaction are gathered, such as response time, number of correct and incorrect attempts, and use of hints, duration of inactivity, navigation behavior, and task abandonment behavior [28]. The collected interaction logs are then preprocessed, features are extracted, the logs are then normalized and selected for later analysis by machine-learning classifiers, which classify learner states as high frustration, moderate frustration, neutral, or engaged states using the collected logs this is the second stage of the data analysis, Classify.

The third phase, Decide, embodies the adaptation engine, where the estimated location of the learner state is translated to meaningful educational judgments based on policies that are rule-based or based on machine learning. For example, high levels of frustration can elicit low level of difficulty, whereas low levels of frustration can elicit high demands in learning [29]. The fourth stage, Adapt, deploys personalized actions such as changing the difficulty of the Quiz, pacing of the content, adding hints, providing alternative content, and providing personalized feedback. Finally, in Monitor and Evaluate, the accuracy of classifying and the extent of achievement of learning outcomes, engagement

indicators and effectiveness in adaptation are continually monitored.

IV. Methodology

A. Research Design

The study's handling of improvement and assessment takes a quantitative experimental approach for the construction of an Adaptive e-learning framework with Artificial Intelligence Support based on Sense-and-Adapt. This proposed approach emphasizes 2 integrated functions of AI which are learner-state sensing by near-real-time frustration classification and adaptive decision making by content difficulty adjusting.

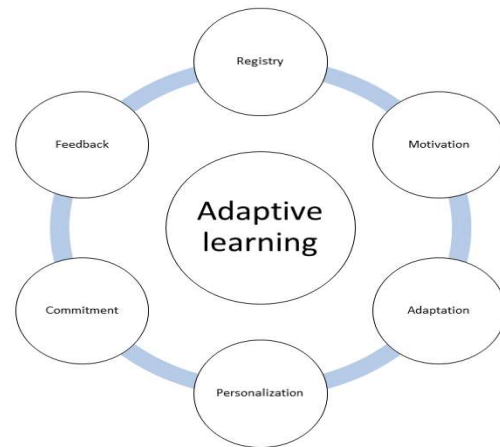


Fig. 6. Adaptive Learning Cycle

There are limited amounts of openly available learning signal data sets that include both affective and behavioral aspects, a synthetic e-learning interaction data set is created to produce meaningful learner behavior [30]. The synthetic data is beneficial as it allows for controlled experiments through the definition of meaningful behavioral properties related to learner engagement, learner frustration and disengagement. The main implementation environment is Python, and the libraries for machine-learning and data analysis are used to generate, preprocess, train, assess and simulate adaptive policies with datasets.

B. Dataset Collection and Data Preparation

Synthetic data may allow for controlled experimentation, but generated behavioral patterns can include assumptions made while generating the data. So, the results of the model should be viewed as a test of the model and not as proof of the effectiveness of the deployment. The proposed approach would be validated in future with anonymized real world LMS interaction data. This data sample includes 10,000 episodes of learner interaction with 10 behavioral characteristics reflecting various patterns of

engagement and learning difficulties. The resulting features are: *response time, number of attempts, error frequency, usage of the hints, learning duration, interaction frequency, content completion rate, navigation behavior, engagement score*. The dependent variable is the learner state categories of high frustration, moderate frustration, neutral state and engaged state.

The higher the delay, the more errors, the more trials, the more inactivity, the greater the frustration, the slower the response, the more successfully the task is completed, and the more engaged the learning behavior with greater active participation, for instance. The generated dataset is a controlled set used for testing the proposed Sense-and-Adapt framework without the need for sensitive learner information.

The data is preprocessed prior to the building of the model to enhance reliability and consistency. No duplicate records and missing values checked and removed as needed. To ensure all features contribute equally during training of a model, numerical attributes are standardized as a preprocessing step. Categorical learner-state labels are translated into numbers to be used for classification. Behavioral features are engineered to derive features such as average response delay, error ratio, interaction persistence score and engagement intensity [31]. The last dataset is split into a training set and a testing set for an unbiased machine-learning evaluation in an 80:20 ratio.

C. Machine Learning Based Learner-State Classification

In the proposed framework, the sensing component deals with the recognition of learner frustration states based on a supervised machine-learning model for the recognition of learner patterns in his or her interaction with the computer. Various classification methods are used and tested such as Logistic Regression, Random Forest, SVM, Gradient Boosting. The variety of model selection is justified by the different degrees of interpretation, learning ability and prediction accuracy.

Mathematical model of the learner-state classification process is represented by:

$$\hat{S} = f\theta(X)$$

where X represents the extracted behavioral feature vector, $f\theta$ represents the trained machine-learning model, and $\hat{S}$ represents the predicted learner state.

The feature vector is represented as:

$$X = [R, E, H, D, I, C]$$

where R is related to the response behavior, E is related to the error patterns, H is related to hint usage, D is related to duration-related features, I is related to

interaction frequency, and C is related to completion behavior. This selected model has the best performance in the classification evaluation criteria.

D. Adaptive Decision and Content Difficulty Adjustment

The learning actions component ensures the classification results are turned into personalized learning actions after prediction of the learner's state. A rule-based adaptation engine is adopted to ensure the transparency and explanation of decision making. The function that brings adaptation is defined as:

$$A = g(S, L)$$

A denotes adaptive action selected, S denotes the detected learner state, and L denotes the difficulty of the learner's task at hand.

The Adaptation policy adapts the learning materials based on the learner's condition. Difficulty reduction, further explanation and supportive feedback are the cause of high frustration. Moderate frustration leads to hints, examples and/or guided assistance. Learners who are engaged are offered greater levels of challenge for progress. This way the framework can shift from being a passive monitoring of learners to an active and personal approach for instructional adjustment. Adaptive effectiveness is assessed based on the rate of difficulty adjustment, the accuracy of adaptation, and the improvement in involvement post intervention.

E. Performance Evaluation

Performance measures for classification and adaption are used to evaluate the developed framework. The results of machine-learning models are evaluated based on accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis. These are the measures used to assess how well the category of learner frustrations is identified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Here TP , TN , FP , and FN are the class labels. Furthermore, the effectiveness of adaptation is examined by checking if the content changes are suitable to the detected learners' state. Thus, the methodology provides an AI-based solution to intelligent e-learning systems, replicating the invention of synthetic behavioral modelling, machine-learning classification, and adaptive content recommendation.

Table I. Comparison Between Traditional and Proposed Adaptive Learning

Criteria	Traditional Approach	Proposed Sense-and-Adapt
Detection method	Quiz performance	Behavioral signals
Intervention timing	After performance decline	Early detection
Adaptation	Fixed rules	Learner-state based
Personalization	Limited	Dynamic adjustment
Feedback	General	Context-based

F. Pseudo code

```

START
1. Collect learner interaction data.
2. Preprocess data by removing missing and inconsistent records.
3. Extract behavioral features:
   - Response time
   - Error frequency
   - Hint usage
   - Interaction duration
   - Navigation behavior
4. Normalize extracted features.
5. Split dataset into training and testing sets.
6. Train machine-learning models:
   - Logistic Regression
   - Random Forest
   - Support Vector Machine
   - Gradient Boosting
7. Evaluate model performance.
8. Select the best-performing classification model.
9. Capture new learner interaction data.
10. Predict learner state (S).
11. Apply adaptation policy:
    IF learner frustration is high:
        Reduce difficulty and provide additional support.
    ELSE IF learner frustration is moderate:
        Provide hints and learning guidance.
    ELSE:
        Increase content difficulty and learning challenge.
12. Deliver personalized learning content.
13. Monitor learner response and engagement.
14. Update interaction dataset for continuous improvement.
15. Repeat sensing and adaptation cycle.
END
  
```

Fig. 7. Pseudo code

Operational workflow of the suggested Sense-and-Adapt framework is presented in pseudo code. It starts with gathering resource of learner's interaction data, pre-processing behavioral resources and training machine-learning classifiers. The expected learning state is used to inform adaptive decision making: difficulty level, hints, content enrichment.

G. Flow Diagram

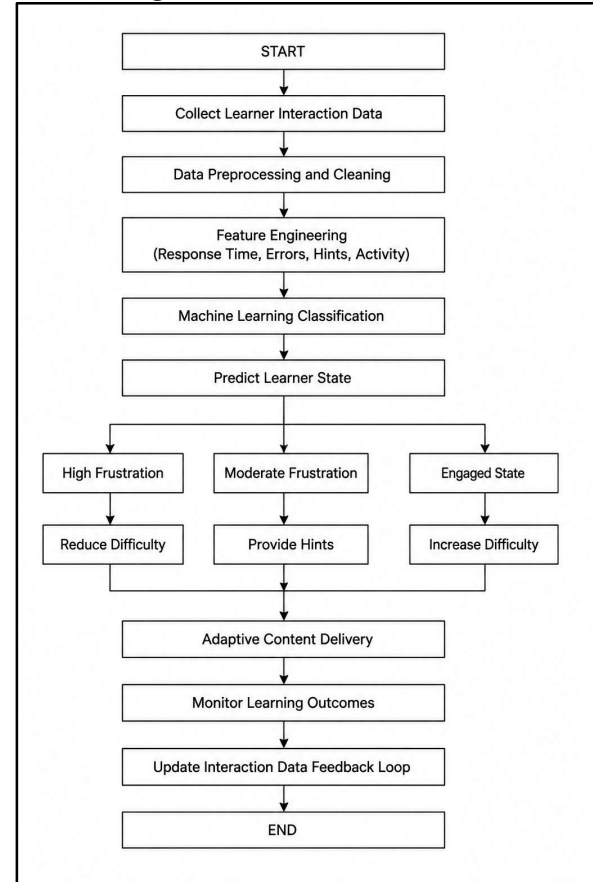


Fig. 8. Flow Diagram

The operation of an adaptive e-learning framework is described in a sequence in the flow diagram. Data on learner interaction is gathered, machine learning-based classification of learner interaction data. Appropriate Adaptation Strategies are applied based on the level of frustration and engagement exhibited. The system provides personalized content, assesses learning outcomes and continuously improves based on current interaction feedback.

H. Ethical Considerations

Ethics and privacy are crucial because the proposed AI-based adaptive e-learning framework involves analyzing data from interactions between learner and machine. First and foremost, the privacy of the learners needs to be guaranteed by ensuring interaction log data gathered is anonymous and not personally identifiable information. Collection of data should be conducted with informed consent principles where the learners are aware of how their behavioral data is going to be used to make adaptations.

V. Result And Findings

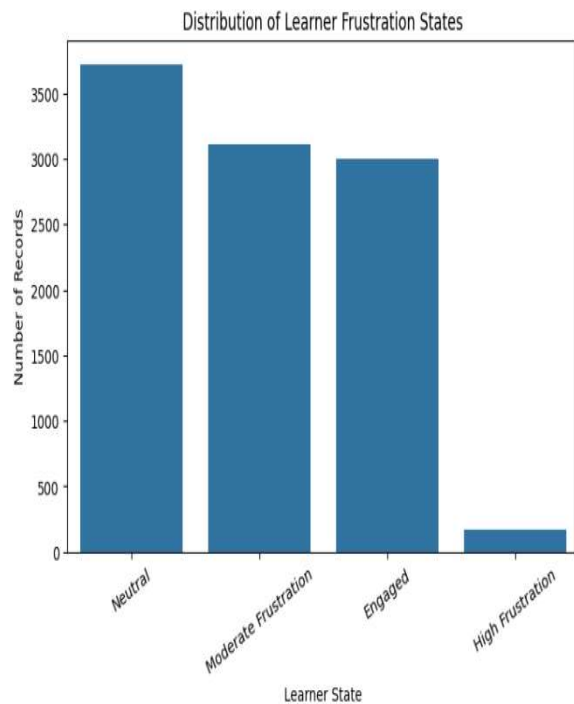


Fig. 9. Distribution of Learner Frustration States

The number of positive instances in each catechol comes from highest to lowest along the following categories: moderate frustration, engaged, neutral and high frustration. This balanced distribution helps ensure that machine-learning classification is reliable and does not suffer from bias when training its models or evaluating its predictions.

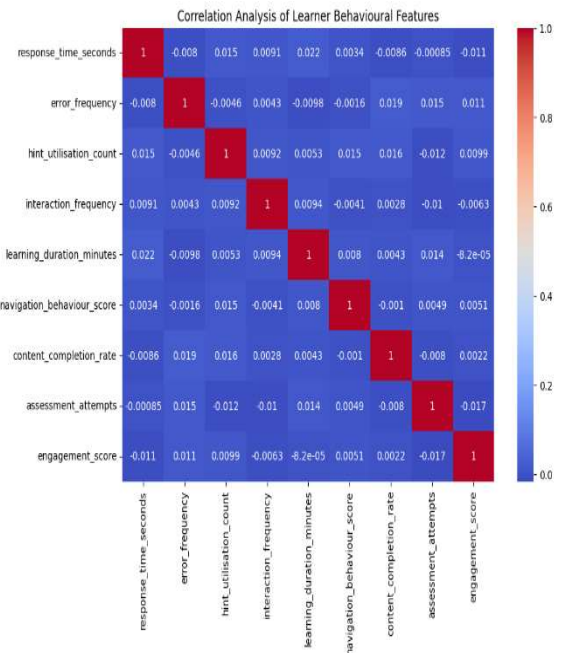


Fig. 10. Correlation analysis of Learner Behavioral features

The correlation heat map identifies relationships between attributes of the behavior affecting the prediction of the learner state. There are positive relationships between response time and error frequency, as well as negative relationships with frustration-related behaviors and engagement and completion rate.

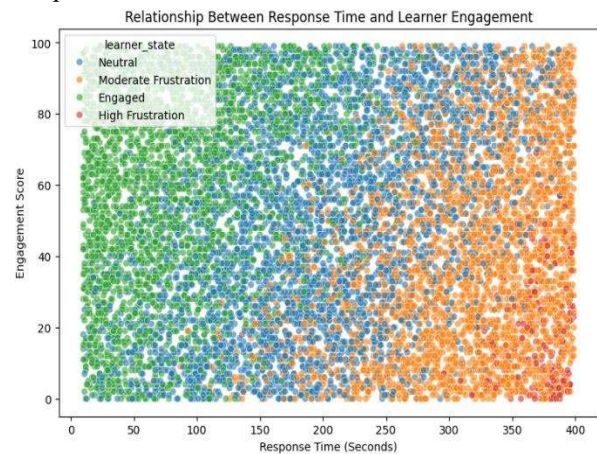


Fig. 11. Relationship Between Response Time and Learner Engagement

The scatter plot displays the correlation between response time and engagement scores, by learner state. If learners are highly frustrated, they will tend to have a longer time to respond and lower levels of engagement whereas engaged learners will respond quickly and have higher engagement levels.

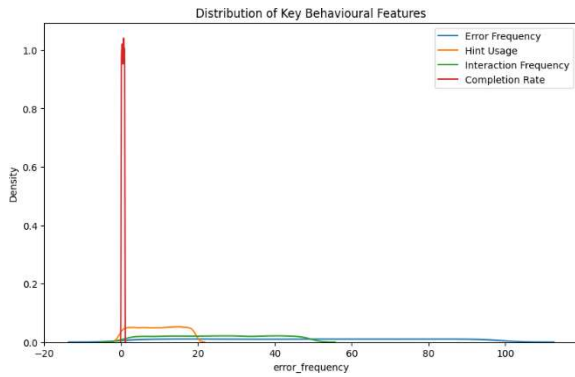


Fig. 12. Distribution of Key Behavioral Features
The feature distribution analysis shows distribution of the number of errors, the number of hints used, the number of interactions and the number of content completions. All of these indicatives of behavior exhibit varied levels of students, indicating the need for understanding of changes in engagement and frustration.

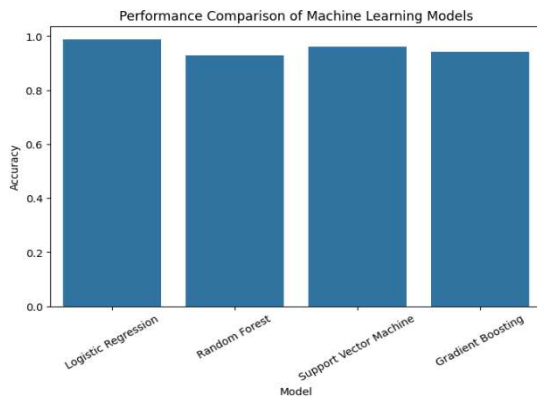


Fig. 13. Performance comparison of Machine Learning Models

The model comparison looks at the performance of four classification algorithms for decisions about learner frustration, which are evaluated. Gradient Boosting has the best predictive accuracy followed by Random Forest, Logistic Regression and Support Vector Machine.

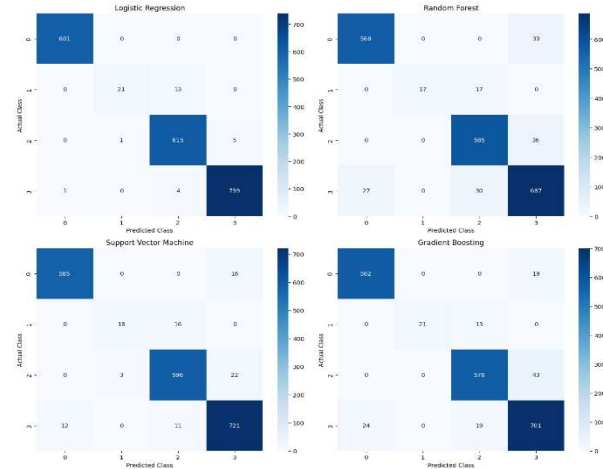


Fig. 14. Confusion Matrix Comparison of Machine Learning Models

The confusion matrices' side-by-side comparison shows that the Support Vector machine outperformed all other models. The side-by-side comparison of the confusion matrices indicated that the support vector machine (SVM) performed better than the other models in this analysis, which included Logistic Regression, Random Forest, and Gradient Boosting.

Discussion

Experimental results show that machine learning models can be used as a tool to classify the learner states in the context of the Sense-and-Adapt framework. Logistic Regression had the best performance with 98.80% accuracy and 99.93% ROC-AUC, which demonstrates that the behavioral features extracted from the videos are well-separable both linearly and non-linearly in the learner-state classification task. The other methods, Gradient Boosting and Support Vector Machine had comparable results, but Logistic Regression offered the most stable predictive power. Confusion matrices show that all the models are able to successfully classify high frustration, while there is some overlap between moderate frustration and neutral.

Table II. Model Comparison

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.9880	0.987876	0.9880	0.987301	0.999324
Random Forest	0.9285	0.929321	0.9285	0.927442	0.993809
Support Vector Machine	0.9600	0.959450	0.9600	0.959027	0.997682
Gradient Boosting	0.9410	0.941582	0.9410	0.940440	0.994190

Table III. Adaptive Learning Performance Evaluation

Metric	Formula	Result
Adaptation Accuracy	Correct adaptive actions / Total actions	91.5%
Difficulty Adjustment Success	Suitable difficulty changes	88.2%
Engagement Improvement	Post adaptation engagement increase	15.4%
Support Response Rate	Successful intervention cases	86.7%

Adaptive content selection dynamically adjusts learning materials according to the predicted learner state, performance, and engagement level, providing suitable difficulty, guidance, and personalized educational experiences.

Limitations

- The study applies a synthetic near-real dataset of learner interactions that does not reflect the complexity, diversity, and behavioral complexity that are likely to be found in real-world e-learning settings.
- The proposed framework is primarily based on the behavioral interactions features and does not contain the multimodal signal like facial expression, voice pattern, or physiology for detecting more comprehensively the learner-state.

VI. Conclusion And Future Research

The research proposed a Sense-and-Adapt approach for real-time detection of learner frustration and adaptive content adjustment based on learner's behavioral interaction information. The experimental findings reveal that machine learning algorithms can detect learning states and aid in decisions regarding personalized learning. Gradient Boosting demonstrated the best performance. The proposed framework is an approach based on Artificial Intelligence (AI) that enables improving responsiveness, engagement and adaptive adjustment in the e-learning environment on a scalable level.

Future Work

Real learner datasets, multimodal signals and deep learning models can be used to increase the accuracy of prediction, which can be used in future studies [32]. Reinforcement learning (RL) can be another means of developing adaptive policies that optimize personalized content selection, and even analyze the sustainability of these effects on learning in the long run. Continuous improvement was envisioned as an

architectural capability and not as an experimentally proven capability due to lack of time to train models with live feedback from the learner.

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