Real-Time Student Engagement Prediction in E-Learning Platforms Using Recurrent Neural Networks and Django

Santhosh Kanna J[1], Dr. B. Kalpana[2]

[1]M. E. Computer Science Engineering, Madha Engineering College, Chennai-600069, Tamil Nadu, India
[2]Guide
B. Tech (IT), B. S. (Psychology), M. S. (Criminology), M. E. (CSE)
Head of Department (CSE), Madha Engineering College, Chennai-600069, Tamil Nadu, India

Abstract: ***Learning outcomes and academic achievement are significantly impacted by student engagement. Traditional engagement measurement techniques, such surveys and in-person observations, frequently lack scalability and objectivity. In order to automatically evaluate student engagement levels using temporal data, this study suggests a predictive model based on recurrent neural networks (RNNs). The RNN model is fed interaction logs from online learning platforms, including information on how often users check in, how long sessions last, and how they access content. To assign pupils to various involvement groups, the algorithm learns behavioral patterns. By giving teachers timely insights, this strategy seeks to enable early interventions for kids exhibiting low engagement.***

Keywords: Student engagement, Recurrent Neural Network, online learning, educational analytics, deep learning

1.Introduction

It is commonly acknowledged that academic success, retention, and general satisfaction with the educational process are all significantly predicted by student engagement. It includes participation in academic activities on a mental, emotional, and cognitive level. Teachers can frequently identify disengagement in physical classrooms by looking for visual indicators like lack of participation or inattention. However, because self-paced online learning and digital education platforms lack in-person interaction and tangible feedback, it has become more challenging to gauge student participation.

Questionnaires, self-evaluations, and instructor observations are examples of traditional approaches for evaluating involvement that are labor-intensive, subjective, and inconsistent. In addition to being time-consuming, these methods are not appropriate for continuous or extensive monitoring. Additionally, they frequently don't account for real-time engagement variations, which makes it harder for teachers to react quickly when student interest starts to decline. Massive volumes of sequential data, including login frequency, resource usage, content engagement patterns, and assignment submissions, are produced by evolving educational technology and provide valuable insights into student behavior.

In this study, an intelligent system that uses Recurrent Neural Networks (RNNs) to automatically predict engagement levels by analyzing time-based student interaction data is presented. RNNs are very good at modeling sequential behavior because they can detect temporal trends since they can preserve contextual information across time steps. Teachers can enter behavioral data and get real-time engagement forecasts by utilizing the model's user-friendly online interface, which was developed with the Django framework. In digital learning settings, this method not only improves scalability but also offers timely information for early intervention techniques, which may improve student results and learning experiences.

2.Literature Review

Shashidhara, in order to forecast student performance and participation in postsecondary institutions in developing nations such as Nigeria, Kenya, and Ghana, Ebem et al. (2024) suggest a real-time feedback evaluation system. The study emphasizes how important digital formative feedback is to fostering a positive learning environment. The K-Nearest Neighbor (KNN) machine learning technique is used by the authors to forecast student performance over time using information including attendance, personal records, and assessment history. The Django Python framework is used in the system's implementation. This method seeks to strengthen instructional techniques, raise student happiness, and support educational decision-making in environments with limited resources. The study highlights how machine learning may help students in underdeveloped nations succeed academically.

Shiri, F., Ahmadi, E., Rezaee, M., & Perumal, T. (2024) frame the problem of automatically identifying student involvement levels from e-learning films as a spatiotemporal classification problem. To study student affective states using the DAiSEE dataset, they suggest four new hybrid deep learning models that combine EfficientNetV2-L with different recurrent neural networks (GRU, Bi-GRU, LSTM, and Bi-LSTM). With an accuracy of 62.11%, the EfficientNetV2-L with LSTM model outperformed the rest. The findings show how hybrid spatiotemporal networks may be used to efficiently categorize engagement levels, which is essential for improving the caliber of online learning. With a promising method for real-time monitoring and enhanced virtual learning environments, this work adds to the expanding field of automated student involvement detection.

Brahma, S. R., Mochahari, I. D., & Maity, R. (2025) suggest a computational framework for identifying and evaluating

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2024: 7.101

ongoing student emotions in online classrooms that operate in real time. A convolutional neural network (CNN) is used in the study to predict emotional valence and arousal from student facial expressions using a WebRTC-based video conferencing system. Using the vast Affect Net dataset, which included more than 291, 000 annotated photos, the model was trained and evaluated. The following emotional states were determined by predicting valence and arousal values: neutral, bored, perplexed, hopeful, and interested. These states are relevant to online learning. The CNN model performs better in reliably identifying these emotional states than the current baseline methods, according to the results. This paradigm provides insightful information for boosting students' emotional comprehension in online learning environments, which could lead to better teaching methods and increased student involvement through real-time emotion tracking.

Hossen, M. K., & Uddin, M. S. (2025) combine computer vision with a Gradient Boosting Classifier (GBC) to create a novel method for tracking student participation in online learning settings. To measure attentiveness, the method examines multimodal behavioral signs recorded by a camera, including head postures, hand gestures, mobile phone use, and facial expressions. The GBC model outperformed conventional techniques with a high accuracy of 99.13% when tested on a dataset of 6, 000 records. Explainable AI solutions that improve model transparency, such as LIME and SHAP, aid educators in understanding what influences student engagement and build trust. Real-time monitoring and actionable insights are made possible by the scalable, resource-efficient system's user-friendly web interface, which is compatible with well-known e-learning systems. Anonymized data collecting ensures privacy. In order to enhance teaching and learning results, this method encourages data-driven interventions.

Hassan, B., Raza, M. O., Siddiqi, Y., Wasiq, M. F., & Siddiqui, R. A. (2025) introduce AfriML, a web-based platform designed to teach machine learning (ML) concepts with a focus on African cultural relevance. Implemented in Nigerian high schools, AfriML allows students to train, test, and export ML models for image, text, pose, and audio classification, incorporating African images, accents, and languages. The study used surveys, assessments, and interviews to evaluate the platform’s effectiveness, finding significant improvements in student comprehension and engagement. Despite challenges like technical limitations and resource constraints, the research emphasizes the value of culturally relevant tools in AI and ML education. It recommends expanding the platform to more schools and developing mobile applications to enhance accessibility and language processing capabilities, thereby making AI education more inclusive for African students.

3.Research Methodology

This work uses a data-driven methodology to create a predictive model based on deep learning that can categorize the degree of student participation in an online learning environment. The five main stages of the technique are: data collection, feature extraction and preprocessing, RNN model creation and training, Django system construction, and model evaluation. The pipeline as a whole is made to guarantee prediction accuracy, ease of integration, and real-time functionality.

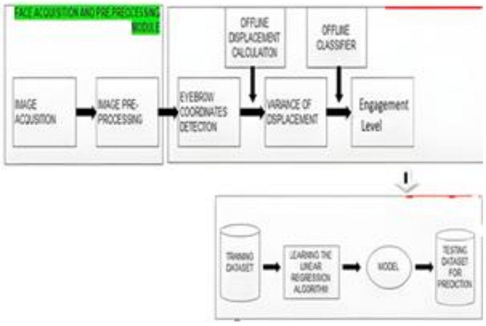

Figure 1. System Process Flow

3.1 Data Acquisition

Data The data used in this study was gathered from either synthetic activity logs that mimic actual student interactions or an online learning management system (LMS). Session-based activity data, including login/logout timestamps, session duration, clicks, quiz attempts, durations of video viewing, assignment submission records, and frequency of material access are included in the data. The foundation for comprehending how students learn over time is this sequential data. To guarantee enough sequence depth, each student's interaction records were examined for at least four weeks.

3.2 Data Preprocessing and Feature Engineering

The Missing values, erratic timestamps, and inconsistent formats are common in raw interaction data. Cleaning these discrepancies, standardizing numerical data, and encoding categorical variables were all part of preprocessing. Sliding windows were used to organize the sequences into time windows of a set duration, such as weekly parts. Temporal characteristics including average session duration, number of resources accessed, duration of inactivity, and task completion rates were taken out of each segment. A rule-based methodology developed from previous research and expert input was used to set the engagement level (goal label). For instance, students who completed assignments on time and used over 80% of the resources were classified as "Highly Engaged, " while those who did not participate were classified as "Low Engagement. " The training procedure was overseen by these labels.

3.3 Model Development

The system's fundamental component is a deep learning model based on RNNs, which was selected due to its capacity to identify temporal relationships in sequential data. Because of its ability to handle lengthy sequences without disappearing gradients, a Long Short-Term Memory (LSTM) variation of RNN was employed. One or more stacked LSTM layers, dropout regularization to avoid overfitting, an input layer for time-series information, and a final dense layer with soft max activation for multi-class classification (High, Medium, Low engagement) are all part of the design. Eighty percent of the dataset was used to train the model, while the remaining twenty percent was used for validation using the Adam optimizer and categorical cross-entropy loss. In order to improve convergence and generalization, early halting and learning rate decay approaches were used. TensorFlow and Keras, two Python libraries, were used to implement the model.

3.4 System development using Django

A web-based platform created with Django was connected with the trained model to enable real-time predictions. Faculty user authentication, a CSV log data upload mechanism, and a prediction dashboard are all included in the platform. Following an upload by an educator, the data is formatted into time-series sequences by the backend and then sent to the RNN model for inference. Together with a graphic representation of the class-wide engagement statistics, the anticipated levels of engagement are shown. Along with storing previous forecasts, the Django application enables the tracking of engagement trends over time. For scalability, it uses a PostgreSQL database and is hosted either locally or on a cloud service.

3.5 Evaluation and Validation

The model's performance was assessed using a number of classification metrics, such as F1-score, recall, accuracy, and precision. A confusion matrix was employed to examine each engagement class's performance. The system was also compared to more conventional models such as Random Forest and SVM, and the RNN showed improved accuracy and handling of sequential data. To further evaluate the Django interface's efficacy, educators participated in usability testing. According to user feedback, the tool was simple to use and the insights were helpful in identifying pupils that needed more attention.

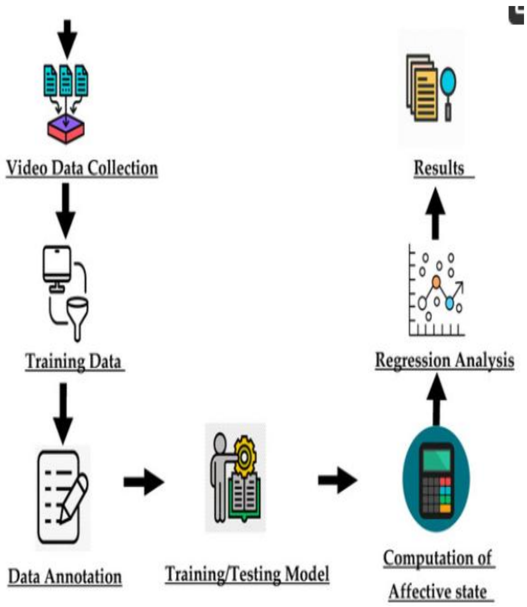

Figure 2. System Model Work Flow

4.Results and Discussion

The preprocessed student interaction dataset was used to train the Recurrent Neural Network (RNN) model, which was then assessed using a number of performance indicators. With an overall accuracy of almost 88%, the model proved to be successful in dividing student participation into three groups: high, moderate, and low. The approach is very effective at detecting highly engaged students, as evidenced by the significantly greater precision and recall scores for the high engagement class compared to the moderate and low engagement courses. The RNN's capacity to identify temporal patterns in sequential data that conventional models frequently miss is responsible for this performance advantage.

The superiority of the RNN technique was further confirmed by comparison with baseline classifiers like Random Forest and Support Vector Machine (SVM). Lower recall and precision scores were the result of traditional models' inability to adequately take use of the time-dependent character of student behavior data, despite their respectable accuracy. More complex engagement forecasts were made possible by the deep learning model's capacity to maintain contextual information over a number of time steps. Furthermore, by integrating prediction findings with an interactive web interface, the model's deployment within the Django framework enhanced accessibility for instructors.

User comments from early teacher trials demonstrated the system's usefulness in actual learning environments. Teachers said the prompt forecasts made it easier to spot distracted pupils early on, allowing for more individualized support and focused interventions. The Django application's visual analytics dashboard received recognition for its ease of use and clarity. Nevertheless, certain drawbacks were identified, such as the requirement for bigger and more varied datasets to enhance the model's generalizability across other schools and courses. To improve prediction accuracy even more, future research might concentrate on incorporating data from other sources, like sentiment analysis and discussion forum participation.

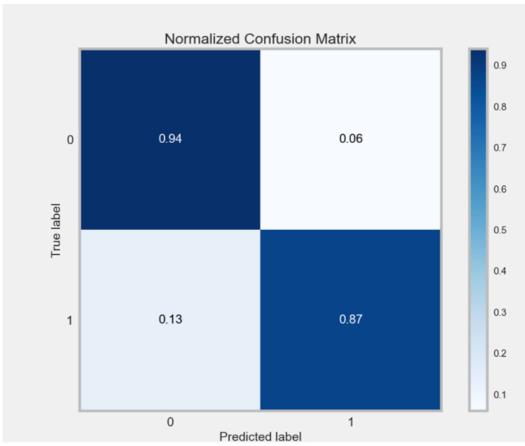

Figure 3. Trained Model Accuracy

5.Conclusion

In Using recurrent neural networks (RNNs), this study effectively created a predictive model to categorize student interest levels based on sequential interaction data from online learning environments. The model surpassed conventional machine learning classifiers in its ability to correctly identify high, moderate, and low involvement

Paper ID: SR25802064553 DOI: https://dx.doi.org/10.21275/SR25802064553

categories. The technology offers a more dynamic and objective measure of engagement than traditional survey-based techniques by utilizing temporal patterns in student behavior. The RNN model's incorporation into a Django-based web application provides instructors with an effective and user-friendly tool for tracking engagement in real time. This makes it possible to implement prompt interventions that can improve the learning outcomes and general academic achievement of students. In order to increase the model's robustness and suitability for use in a range of educational contexts, future research will concentrate on diversifying the dataset and adding more behavioral indicators.

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