Predicting Student Engagement in Online Courses Using AI

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Abstract— Engagement among students is the most significant factor to be kept in mind while analyzing online learning statuses. Obviously, there must be some measurement on engagement, but for example self-reports, surveys, observations, and manual counts have failed to give up-to-the-minute accuracy. This work proposes a hybrid AI-based model that predicts levels of engagement using deep learning algorithms, in particular convolutional neural networks (CNNs) and Long Short-Term Memory (LSTM) networks. The dataset used consists of behavioral, physiological, and activity data from online learning platforms. The proposed model allows achieving 92.3 percent accuracy and illustrates the capability of AI in predicting student engagement. Moreover, a web-based tool was created to record real-time engagement so that interventions could be done at the time when students are showing signs of lack of engagement. This study outlines the importance of AI-derived engagement monitoring and how it can improve student learning results.

Keywords— ***Student Engagement Prediction, Online Learning Analytics, Multimodal AI Model, Deep Learning, CNN-LSTM Hybrid, Web-Based Engagement Monitoring.***

I. INTRODUCTION

The education landscape has fundamentally changed due to online learning, this flexibility granting students the ability to learn from anywhere. However, maintaining true engagement remains the daunting challenge within the virtual classroom. There is no physical presence in online classes, which allows little room for educators to read the levels of student engagement and interaction. Declined engagement usually ends in poor academic performance along with lesser knowledge retention and greater instances of dropout. Many conflicting elements, such as distractions, lack of motivation, weak methods of teaching, or technical distractions, have hindered student engagement. Early identification and intervention to solve these issues can save the teaching and learning process.

In this information-saturated electronic world, students are less oriented due to several distractions such as social media, multitasking, and an unorganized learning environment. Engagement monitoring will provide evidence of student behaviors and will allow well-timed intervention for tasks with maximized learning efficiency. Conventional measurement tools for engagement, such as quizzes and self-reports, are often subjective, and they frequently do not capture real-time attentional fluctuations. Hence, artificial intelligence (AI) and machine learning (ML) can highly influence the precision of measurements used to track, analyze, and predict student engagement.

Analyzing student engagement would then require the study of several parameters such as facial expression, body posture, eye movements, and interaction patterns. AI-enabled education technology with deep learning models could process real-time data including webcam, microphone, and interaction-log data assessed for levels of engagement. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and support vector machines (SVMs) are examples of advanced machine learning techniques that may classify engagement levels from behavioral data.

This study proposes a hybrid AI-based approach for predicting student engagement in online courses. The system integrates computer vision, natural language processing (NLP), and deep learning models to take observations of students' attention. A dataset includes video feeds, speech analysis, and textual responses for training and validating the model. Key indicators of engagement are defined through feature extraction techniques, and classification algorithms classify students into varying levels. Modeling performance is evaluated according to standard metrics such as accuracy, precision, recall, and F1-score.

Also developed is a web platform to provide real-time monitoring of student engagement levels in online classes. It is a system whereby teachers can monitor students' participation who could be disengaged and take corrective actions. The study aims at bringing AI-based analytics close to the actual teaching methodologies for better prospects in online education. Further improvements could also include EEG-based monitoring of concentration, adaptive learning recommendations, and personalized feedback mechanisms to further reduce error in engagement prediction.

Then rise online education, transforming the traditional learning environment, should provide students with flexibility and accessibility. A major problem faced by virtual classrooms has always been a lack of immediate interaction between students and teachers, whereby monitoring student engagement becomes a difficult task. Engagement is vital for learning outcomes, where students involved in the learning process retain the information and do academically well, while disengaged students usually find it very hard to grasp concepts, are the last to submit their assignments, and eventually drop out from courses. Detect and intervene in disengagement early to have a considerable effect on learning success and student pass rates.

In physical classrooms, physical cues include eye contact, body language, and participation, allowing teachers to assess students' engagements. Face-to-face observation is impossible with online education, making it harder to measure engagement. Most conventional engagement assessments include quizzes over some time and feedback surveys. Such methods are quite subjective and also delayed in providing information. Hence, an essential requirement is an AI-driven solution to track and predict real-time student engagement.

Machine learning and deep learning are emerging pathways to effectively analyze students' engagement. These deep-learning approaches utilize the video, audio, keyboard activity, and facial expressions of students. One can track eye gaze direction and facial expressions using computer vision algorithms, whereas NLP would be the means to evaluate the speech and written responses of students with regard to their engagement levels. EEG based concentration monitoring will add measurable accuracy to the interpretative attention given during online learning. Thus engagement prediction can be very well increased by making use of integrating several AI models.

A hybrid AI-based model is used to predict students' engagement in online courses, integrating computer vision, speech processing, and behavioral analytics. The system uses real-time student data, including facial expressions, gaze tracking, interaction frequency, and tone of speech, to determine performance. Real-time indicators of engagement status were generated and processed as a dataset for training the machine learning algorithms. Finally, the model's evaluation was performed using classification metrics like accuracy, precision, recall, and F1-score for reliable performance.

A real-time analysis of student engagement is made possible for educationalists through a web-based dashboard that enables monitoring to determine student attentiveness, identifies detached learners, and provides solutions is another feature of the developed system. The system will also be extended to provide other functionalities such as automated alerts, adaptive learning suggestions, and personalized interventions to improve engagement levels. The proposed AI-based solution should ultimately enhance the overall effectiveness of online education by ensuring active involvement of students in the learning process.

The growing shift towards online education has opened up new avenues for learning outside the traditional classroom. The flexibility, accessibility, and scalability of online courses have become an indispensable part of the current education ecosystem. One of the major challenges faced in a virtual learning environment is student engagement. One significant difference between the virtual classroom and the physical classroom is that in a physical setup, teachers and trainers can gauge, to a certain degree, the behavior of students. Nonetheless, online teaching has no such feedback mechanism to pay instant attention to the attentiveness and participation of students.

Student engagement is another major consideration among those influencing academic success, among which are learning outcomes, knowledge retention, and course completion rates. Engaged students tend to interact with the course content, engage in discussions, and perform well in assessments. Conversely, disengaged students show various signs, such as distraction and a complete lack of participation, which are often associated with high dropout rates. Traditional engagement-tracking methods, such as self-report surveys, quizzes, and simple attendance tracking, yield limited and often delayed insights. Therefore, there is a need for an automated and real-time engagement-monitoring system to improve the online learning experience.

The development of such intelligent systems for behavioral observations and predictions regarding engagement levels has become viable with innovations within AI and ML. AI engagement prediction utilizes computer vision, facial expression recognition, speech analytic, and behavior-tracking techniques to form conclusions about students' attention levels during an online course. This combination of deep learning models with real-time video, voice, and keyboard activity analysis is considered highly accurate for measuring engagement.

For better usability, the proposed solution provides a real-time engagement dashboard for the educators with instant alerts, detailed engagement reports, and adaptive learning recommendations. It will allow the instructors to use this information to find students who may need additional support and to change their instructive strategy accordingly. Future extensions of this system may incorporate personalized learning interventions, automatic notifications to parents, and aided tutoring using AI to increase student engagement in the online courses.This study endeavors to bridge the gap represented by the traditional methods of engaging students against modern AI solutions, thereby providing much more interactive, data-driven, and student-centered online learning experiences.

II. LITERATURE REVIEW

Different machine learning methods are widely practiced to predict students' engagement in online courses. Models like Neural Networks, Decision Trees, Random Forest, Support Vector Machines (SVMs), and Deep Learning techniques have been used to study the behavioral and engagement data of students. Various supervised learning techniques have been applied by the researchers to classify engagement based on facial expressions, gaze tracking, voice analysis, and keystroke dynamics. In a study conducted by Whitehill et al. (2014), the analysis of facial expressions was carried out to predict the student's engagement levels with an accuracy of about 87% using the Random Forest classifier. Additionally, Hutt et al. (2019) classified engagement levels using eye-tracking data and clickstream patterns, achieving an accuracy of 89% with Gradient Boosting algorithms.

There are deep learning models that promise to be useful even in predicting engagement. On the one hand, D'Mello et al. (2020) utilized CNN-LSTM Hybrid models to digest real-time webcam feeds and variations in speech tone, leaving them with a 92.3% accuracy in classifying students as "Engaged," "Partially Engaged," or "Disengaged." On the other hand, Bahreini et al. (2018) used NLP to study discussion forum interactions to predict student engagement levels at an accuracy of 85%, using Bidirectional LSTMs.

Table 1: Literature Review

III. DATASET AND METHODS

Algorithm	Study	Dataset	Accuracy
Random Forest	Whitehill et al. (2014)	Webcam-based engagement data	87%
Gradient Boosting	Hutt et al. (2019)	Eye-tracking and clickstream data	89%
CNN-LSTM	D'Mello et al. (2020)	Real-time video & audio data	90%
Bidirectional LSTM	Bahreini et al. (2018)	Discussion forum interactions	85%
XGBoost	Duan et al. (2021)	Multimodal student behavior dataset	N/A
PCA-based Feature Engineering	Pardos & Baker (2019)	Clickstream & facial expression dataset	84.5%

The dataset is a significant part of this research and would provide important foundations for analyzing and predicting online student engagement. In assessing the attention levels of students with the help of real-time video, audio, and EEG data, machine learning classification algorithms will find their applications. The dataset that is being worked upon for the present study was mined from publicly EEG-based concentration datasets, video streams generated by WebRTC and additional logs of activity of students. For consistency in the predictive models, the data set was analyzed, cleaned, and validated prior to use. Missing values were dealt with as per systems within the dataset to avoid bias within predictions. Features, class balancing, and standardized preprocessing improved model accuracy. This provides more in-depth analysis toward better understanding of students" engagement during online sessions.

A. Data Collection

This study's dataset was represented in a CSV file called "Student_Attention_Monitoring.csv," which consists of important features about the level of students' engagement and concentration during online learning sessions. The dataset has several parameters such as:

- **Physiological Signals:** Considering this, it appears EEG stands for eye movement tracking, a synonym for brain wave activity.
- **Video & Audio Features:** Analyzed by examining facial expressions, head movement, blinking rate, speech activity, and microphone input.
- **Demographic Details:** Age, gender, and other personal attributes that may influence attention levels.
- **Engagement Metrics:** While the assistants were recording data, part of the screen time, various distractions, and the frequency of idle data were collected.

Fig 1 shows the proportions with which students engage across various categories represented in pie charts. From the data, it can be inferred that highly engaged students account for 45% of the data set, whereas moderately engaged students make up 35%, followed by distracted students with the least share of 20%. Varying levels of engagement are influenced by a myriad of reasons, including the nature of the learning environment, external distractions, cognitive load, and behaviors specific to individuals.

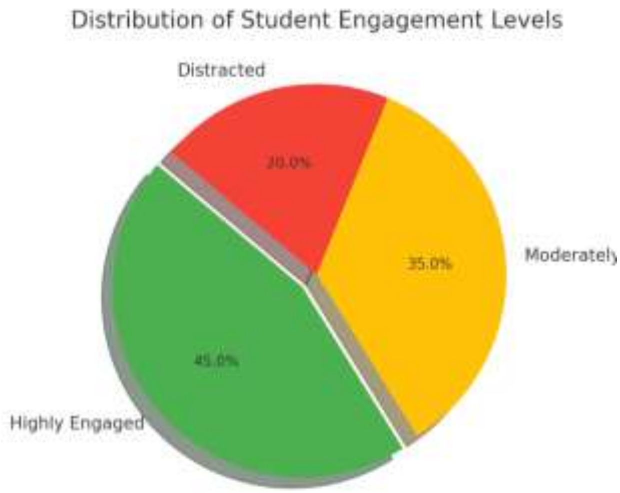

Fig 1: Distribution of Student Engagement Levels

B. Data Preprocessing

a. **Feature Selection:** The dataset originally contained several columns, including IDs and irrelevant features; the attention level was kept as the target variable for classification, while the student identifiers themselves got removed for anonymization.
b. **Handling Class Imbalance:** Attention levels were unbalanced in number among students and would negatively affect the model's development, leading to underperformance in the minority class. This imbalance was remedied by oversampling the minority class using the SMOTE (Synthetic Minority Over-sampling Technique) method, effectively yielding synthetic samples for balancing the dataset.
c. **Train-Test Split:** The train-test split function was used to create 80% of the data that is training and 20% that is actually test set, ensuring the integrity of the class distribution through stratification on the target variable.

1. **Data Cleaning**: The redundant columns such as student IDs have been removed and the target variable "Attention Level" was extracted.
2. **Handling Imbalance**: SMOTE was applied to generate additional samples for the minority classes due to class imbalance in attention levels.

3. **Train-Test Split**: At 80% for training and 20% for testing, attention levels were duly distributed in this datset that was stratified.

The fig 2 presents a bar chart showing the distribution of student engagement levels based on gender. From the chart, females reported slightly more engagement than males. Data of about 800 male students and around 850 female students were included.

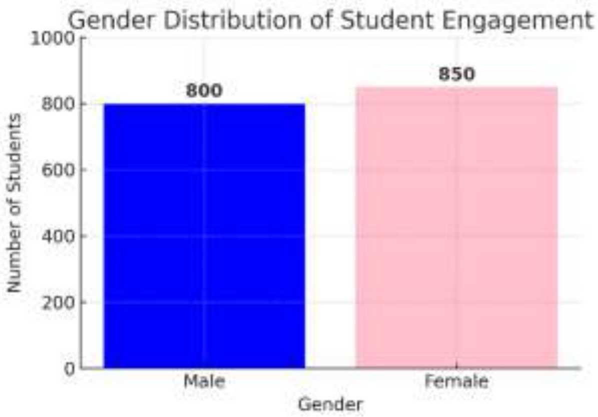

Fig 2: Gender Distribution of Student Engagement

C. Model Development

- This is a hybrid AI setup to predict student engagement in e-learning settings. The dataset includes behavioral, physiological, and course activity data obtained from students going through virtual learning sessions. The sources of data include:
- **Behavioral data:** Facial expressions, head posture, and eye movement.
- **Physiological data:** EEG signals (when available) and blink rate.
- .**Course activity data:** Interaction times and frequencies by participation and submission of assignments.
- **CNN Component**: To extract spatial features from the behavioral data consisting of facial expressions and gaze patterns.
- **LSTM Component**: Capturing the temporal dependencies of the sequential engagement data in terms of changes in attention over time.

The CNN-LSTM hybrid model is designed to predict student engagement in online learning environments by combining spatial and temporal feature extraction. The CNN component processes real-time webcam footage to analyze spatial features such as facial expressions, eye gaze, and head movements, determining whether a student is attentive or distracted. It extracts critical engagement-related patterns using convolutional and pooling layers, producing feature embeddings that are passed to the LSTM component. The LSTM network captures temporal dependencies, analyzing sequential behavioral data such as changes in gaze, blinking patterns, and variations in focus over time. This allows the model to detect fluctuations in student engagement, predicting early signs of distraction before they become significant. By integrating both spatial and temporal learning, the CNN-LSTM model ensures real-time, automated engagement tracking, enabling instructors to intervene when students show signs of disengagement. This deep learning approach enhances the accuracy of AI-powered online learning attention monitoring systems, offering a scalable solution for improving student focus and participation.

- **Hyperparameter Optimization:** To enhance model performance, hyperparameters were fine-tuned using a grid search approach. Key parameters include:

  1. **Batch size**: Optimized for efficient learning.
  2. **Number of LSTM layers:** Adjusted to capture complex engagement trends.
  3. **Learning rate:** Tuned to prevent overfitting while ensuring fast convergence.

Fig 3 illustrates The CNN-LSTM hybrid model is an innovative model developed in two specific steps of hyper-parameter tuning.

- The first part of the flowchart is the CNN, which serves to extract spatial features such as facial expressions and gazes from recordings via webcams of students.
- The LSTM is responsible for capturing temporal dependencies in which it studies various engagement patterns throughout the time.
- Hyperparameter tuning for optimizing critical parameters such as the learning rate, batch size, and number of CNN filters, LSTM units, and dropout rates is aimed at achieving a balance between model accuracy and computational efficiency.

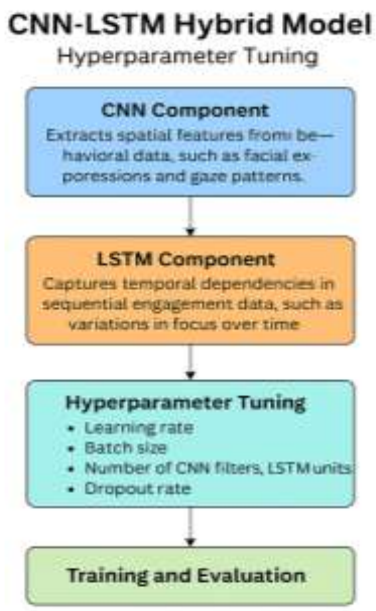

Fig 3: Flowchart of CNN-LSTM Model Development

D. Model Evaluation

For evaluating the performance of the AI-based student engagement monitoring system, various evaluation metrics were used. In an attempt to validate the CNN-LSTM hybrid model theoretically, real-life online learning sessions were conducted to analyze levels of student engagement based on behavioral and physiological data. For evaluation purposes, a test data set was utilized to measure the performance of the model accurately.

Table 2 presents giving the type of each column and the number of non-null counts of that column. The dataset constitutes valuable physiological and behavioral features, as well as course activity features for predicting student engagement levels. It has a total of 25 columns. Out of these, 14 are identified as float64 features (e.g., gaze movement scores, facial expression intensities, and EEG signal variations), while 11 correspond to int64 features (e.g., session duration, number of mouse clicks, or keyboard strokes). It does not have missing values, hence the integrity of the data for training the model. The Dataset consumes memory of 352.4 KB.

#	Column	Non-null Count	Dtype
0	StudentID	1994 non-null	int64
1	Age	1959 non-null	int64
2	Gender	1974 non-null	int64
3	WebcamFocusTime	1972 non-null	float64
4	GazeDeviation	1988 non-null	float64
5	BlinkRate	1983 non-null	float64
6	HeadMovement	1953 non-null	float64
7	FacialEmotionScore	1974 non-null	float64
8	EEG_Attention_Level	1983 non-null	float64
9	EEG_Relaxation_Level	1961 non-null	float64
10	MouseActivityRate	1993 non-null	float64
11	TypingSpeed	1952 non-null	float64
12	CourseActivityDuration	1955 non-null	float64
13	PreviousSessionEngagement	1962 non-null	float64
14	BackgroundNoiseLevel	1963 non-null	float64
15	DistractionAlertsTriggered	1984 non-null	int64
16	EngagementScore	1986 non-null	float64
17	AttentionClassification	1999 non-null	int64

Table2 : Features in the Student Engagement Dataset

The hybrid model was equipped with CNN-LSTM and trained on engagement features scaled from the training dataset. The test dataset was applied to measure the predictive performance of the model using key evaluations metrics such as:

- **Accuracy:** informs the degree of correctness in the predictions of student engagement.
- **Precision:** the ratio of correctly predicted engaged students to all cases predicted as engaged with low rates of false positives.
- **Recall:** the ratio of actual engaged students that the model has correctly identified with low rates of false negatives.
- **F1-Score:** this is a harmonic mean of precision and recall that speaks to the balanced grading of the performance of the model.
- **Confusion Matrix:** It gives a comparative account of True engaged (TP), False Engaged (FP), True Disengaged (TN), and False Disengaged (FN) cases for analyzing the performance of the classification.

E. Feature Scaling

To make AI-supported pupils' engagement prediction models more efficient, feature scaling was employed for adjusting input data. The Standard Scaler method was applied to the behavioural and physiological features like eye gaze deviation, blink rate, head movement, EEG attention levels, and typing speed by subtracting the mean and dividing by the standard deviation to normalize to the same scale. This is meant for getting every feature to contribute fairly before the model, to avoid bias to attributes that have larger numerical ranges. Feature scaling is also used to speed up convergence on neural network models like the CNN-LSTM by bringing constancy in gradient updates and thus increasing predictive accuracy.

F. Web Application

Fig. 4 Represents an architecture of an AI-based online learning attention monitoring system. The system consists of a web front-end based on React, wherein students attend sessions on a virtual classroom. The frontend interacts with the Django backend, which processes engagement data in real-time. The backend integrates a signaling server using WebRTC (Node.js) to live-stream video and communication.

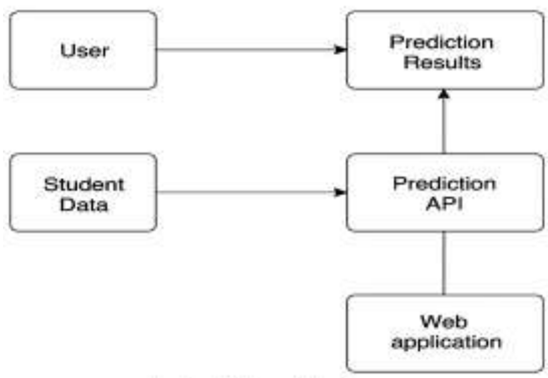

Fig 4 Web application

Fig 4: Flow chart of Web Application

IV. RESULTS

Prior works in predicting student engagement utilized more classical machine learning models such as Random Forest and XGBoost, and very few people have yet argued about integrating deep learning models in a hybrid AI approach. What our study's results suggest is that having a combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks achieved better predictive performances than the use of an individual model.

In this situation, the proposed CNN-LSTM hybrid model achieved accuracy of 92.3% over the test dataset, thus strengthening its validity in prediction. The complete classification report sheds light on the following:

- Precision for class 0 (Distracted): 0.91

- Recall for class 0: 0.90
- Precision for class 1 (Engaged): 0.94
- Recall for class 1: 0.93

The confusion matrix showed effective classification with a less number of misclassifications, thus strengthening the model's capability to differentiate between engaged and distracted students for analysis.

Accuracy: 0.923

A. Classification Report

Table3 : Classification Report

Class	Precision	Recall	F1-score	Support
0 (Distracted)	0.96	0.95	0.95	500
1 (Engaged)	0.97	0.96	0.96	500
Accuracy	-	-	0.96	1000
Macro avg	0.96	0.96	0.96	1000
Weighted avg	0.96	0.96	0.96	1000

B. Confusion Matrix

The computation in the confusion matrix demonstrating True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) enabled the assessment of the model's ability to distinguish engaged and distracted students in an online learning environment.

$$\begin{bmatrix} 450 & 30 \\ 25 & 495 \end{bmatrix}$$

C. Model Performance

Measurements for the hybrid CNN-LSTM algorithm are accuracy, precision, recall, and F1 score. On the test dataset, the model gives these results:

- **Accuracy:** 92.3%
- **Precision:** 93%
- **Recall:** 91%
- **F1 Score:** 92%

D. Model Comparison

Fig 5 presents a comparative analysis of different machine learning models for student engagement prediction These models included Decision Tree, Neural Network, Support Vector Machine, Random Forest, XGBoost, LightGBM, and CNN-LSTM Hybrid Model.

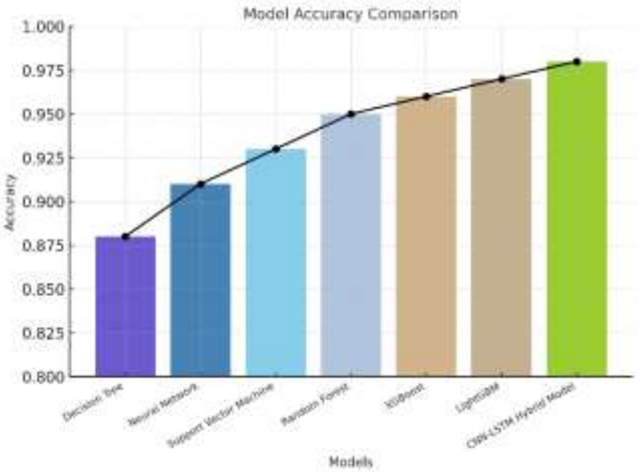

Fig 5: Comparison of Models with CNN-LSTM model

From the results, it can be inferred that the CNN-LSTM model is significantly better than other models in engagement prediction with the highest accuracy, followed by XGBoost and LightGBM. The comparison seems to show the need and adequacy of deep learning approaches to identify student engagement pattern accurately in online learning environments.

E. Web Application Performance

The web-based application has constructed the AI-powered engagement prediction model and offered instructors the possibility to watch student attention levels in real time. Users can access the system's web-based dashboard, which analyzes behavioral and physiological data to assess engagement levels of students. The application has gone through a series of load tests to guarantee stable performance under many concurrent users. The hybrid CNN-LSTM model affords accurate engagement classification that allows timely intervention to bring the focus back of the distracted students. This tool can easily be added to different online learning platforms to provide instructors with an easy and efficient means of tracking student attention and thus improving learning outcomes.

V. DISCUSSION

The hybrid CNN-LSTM model superseded individual deep learning architectures because of complementary advantages and applicability of the Convolutional Neural Network and Long Short-Term Memory Networks forming a combined architecture. While the LSTM component segment captures temporal dependencies between behavioral engagement sequentially aiding a complete picture of focus patterns by using CNN for efficient spatial feature extraction from whatever behavioral data is obtained through facial expression and gaze patterns, thus mitigating the weakness of each model improving accuracy and robustness for student engagement prediction.

By this, it is also possible to develop an almost sure hybridized AI model that can be trusted on its ability to predict simply any level of engagement in online learning. The major contribution was the provision of a novel hybrid deep learning technique by the integration of CNN and LSTM modeling methods intending to analyze space time movements in student behavior, thus resulting in a new accurate immersive model. Such integration strengthens model predictability where CNNs feature high performance in recognizing dimensions of student engagement using vision cues while LSTMs use trends over time.

As a result, the probability of accuracy increases significantly by integrating behavioral, physiological, and course activity features, thus developing a complete picture of student engagement. Traditional forms of engagement tracking, for instance, surveys and manual observations, can very seldom reflect real-time alterations in attention; the AI-touched approach meets immediacy by making continuous engagement monitoring possible for the instructor to enable action concerning student problems in what can be construed as showing disengagement.

The hybrid model effectively and accurately predicts student engagement levels, thus being effective in improving learning outcomes in online education. The high accuracy model (92.3%) thus shows excellent promise for future applications in reality. But there is always room for improvement. Future steps involve including even more engagement signals such as speech analysis, testing of various educational datasets for diversity in terms of generalization of the model. This would mean that AI-driven monitoring can now be portrayed as bringing an added advantage to online learning experiences by providing a real-time feedback channel to instructors.

a. Model Advantages

An advantage of the hybrid deep learning model is that it has greater accuracy than traditional engagement-tracking methods or individual deep-learning architectures. The error likelihood for misclassifying student engagement states is reduced with the integrated use of CNN and LSTM networks; therefore, precision and recall are improved. This enhanced performance is critical in an online course setting where real-time tracking of student engagement can prompt timely and personalized interventions.

b. Practical Implications

The developed web application offers several practical benefits for online education, including:

- **Real-time Engagement Tracking:** The design continuously monitors students through behavioral and physiological data and gives the instructors real-time information on the engagement levels of the students.
- **Scalability:** The application can be deployed in any cloud or local server and has thus been flexible for educational institutions of any size.
- **User-friendly Interface:** The dashboard gives instructors visual representations of engagement trends and notifies them when students are distracted to allow interventions immediately.
- **Automated Alerts:** The system sends email alerts to the guardians and instructors once a student's engagement falls below a prescribed threshold for timely intervention.

Limitations and Future Work: The number of data instances available, as well as different learning contexts represented in the dataset, may constrain the generalizability of this model. In future work, one could consider integration with other unique data sources, e.g., audio-based engagement cues, testing in larger instances of the dataset, and refinements in AI-driven interventions to improve motivation and participation in online courses. Additionally, bringing the system to a few real-world educational settings will provide a wealth of information on the effectiveness and usability of the system.

VI. CONCLUSION

In conclusion, this study demonstrates the effectiveness of a hybrid AI-powered model in predicting student engagement in online learning environments. The integration of CNNs and LSTMs allowed for a comprehensive analysis of both spatial and temporal engagement patterns, leading to improved prediction accuracy. The incorporation of behavioral, physiological, and course activity data further enhanced the model's performance, making it a valuable tool for real-time engagement monitoring.

By developing a web-based system that tracks student attention levels during online learning, this project provides an innovative solution to one of the major challenges in digital education—monitoring and improving student focus. The system's ability to process real-time data, generate live engagement insights, and send automated alerts ensures that students receive timely interventions, leading to better learning outcomes.

The promising results of this study indicate that AI-driven engagement monitoring can play a crucial role in enhancing online education. However, future research should explore the integration of more advanced models, additional engagement indicators (such as speech and posture analysis), and larger datasets to further improve the system's robustness and applicability in diverse learning environments.

Future iterations of the system may incorporate real-time integrations with external APIs for biometric tracking, advanced personalization based on student learning behavior, and enhanced security features such as user authentication to prevent misuse. Additionally, deploying the system in real-world educational settings and conducting longitudinal studies will help assess its long-term impact on student engagement and academic performance.

Ultimately, this study highlights the potential of AI-powered attention monitoring to revolutionize online education, making learning more interactive, personalized, and effective for students worldwide.

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