Smartwatch-Enabled Data Analytics for AI-Based Evaluation of Teaching and Learning Processes

Deepali Kayande[a] and Swetta Kukreja
Amity School of Engineering and Technology, Amity University Maharashtra, Mumbai, India

Keywords: Smartwatch-Enabled Analytics, Artificial Intelligence in Education, Teaching-Learning Evaluation, Student Engagement Monitoring, Cognitive Load Assessment, Data-Driven Pedagogy.

Abstract: The importance of the teaching-learning process in shaping outcomes is critical, necessitating the development of new evaluation methods for effective implementation. This paper presents a framework for evaluating and optimizing a smart teaching-learning ecosystem, utilizing data analytics and AI methodologies facilitated by smartwatches. Wearable technology captures real-time physiological and behavioral metrics (e.g., heart rate, physical activity, and attention levels) from students during classroom instruction. Artificial intelligence algorithms analyze this data to assess engagement, cognitive load, and responsiveness to various instructional methods. These insights are synthesized into actionable feedback for educators, providing information that can enhance pedagogical strategies that align more closely with learner needs. This facilitates the examination of trends and anomalies among various learner types to improve inclusivity in education. This study illustrates the practicality of employing data analytics alongside wearable technology to develop a comprehensive methodology for evaluating learning and teaching effectiveness. The preliminary results demonstrate the system's ability to provide accurate, scalable, and real-time insights, advancing beyond statistical analyses to support evidence-based educational interventions. This solution represents a significant advancement in modernizing academic assessment and integrating technology and pedagogy.

1 INTRODUCTION

The teaching-learning process is the basis of education, influencing information acquisition and strengthening critical thinking and growth abilities. The traditional assessment method falls short in consistently examining how the various classroom dynamics play out individually. This gap shows the need for new, data-driven methodologies to analyze and enhance teaching methods and learning results (Nada, Alsaleh, et al. , 2020), (Munna and Kalam, 2016).

With the rise of wearables like smartwatches and the capability of artificial intelligence (AI), the chance to dramatically modify educational evaluation has come. Smartwatches, are portable devices with sophisticated sensors, enabling real-time gathering of biological and field data (e.g., heart rate, activity level, and attention level). These measurements give a unique view into student engagement, cognitive load, and responsiveness across instructional sessions which may lead to a fuller understanding of the teaching-learning process (Morales, Arroyo, et al. , 2023).

This study provides a methodology to efficiently employ smartwatch-enabled data analytics and AI in analyzing and enhancing educational methods. Using live data, artificial intelligence algorithms investigate tendencies and offer applicable suggestions for instructors, which permits a better contoured and move towards joint studying experience. The methodology also exposes patterns and outliers across diverse learner demographics, expanding possibilities to guarantee fairness and flexibility in learning beyond the particular classroom. In contrast to static, one-size-fits-all assessment paradigms, the recommended alternative embraces dynamic, evidence-based procedures. Initial findings demonstrate that the technology can deliver accurate, scalable, and real-time data, allowing instructors to improve their approaches and ultimately boost student accomplishment. This research marks an

[a] https://orcid.org/0009-0003-8794-6316

Kayande, D. and Kukreja, S.
Smartwatch-Enabled Data Analytics for AI-Based Evaluation of Teaching and Learning Processes.
DOI: 10.5220/0013592600004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 2*, pages 367-373
ISBN: 978-989-758-763-4

important step in updating academic evaluations to fulfill the demands of a fast-changing educational environment by merging technology and pedagogy.

2 LITERATURE SURVEY

The table covers major research publications on AI and data analytics applications, concentrating on methodologies, technology, and conclusions. The research includes smartwatch-enabled data analysis for user experience (S-O-R theory), healthcare monitoring (early disease diagnosis), and stress detection using deep learning models (CNN, LSTM). Additional study covers face recognition (98.66% accuracy), EEG-based attention detection (96% accuracy using RNN), voice activity detection (86% accuracy), and multimodal data fusion for gaze analysis (92.5% accuracy). Object identification and attention analysis utilizing sophisticated deep learning models (e.g., YOLO V8) demonstrated great accuracy and performance across datasets. These studies demonstrate the promise of AI in many disciplines, stressing accuracy and scalability.

3 PROPOSED METHODOLOGY

3.1 Data Collection and System Design

The major aim of the first research phase was to develop an elaborate framework for incorporating wristwatch data into the teaching-learning assessment process. Heart rate, physical activity, and attention levels were identified as significant markers of student involvement and cognitive load. The system architecture was designed with wristwatch data input, AI-powered processing layers, and output modules that deliver helpful insights.

3.2 AI-Powered Data Analysis

To manage physiological and behavioral data obtained from smartwatches, machine learning models were constructed and trained. These models predicted engagement levels and cognitive states by assessing physical activity, heart rate variability, and other data. A better knowledge of the factors determining learning efficacy was made possible by the AI-powered study, which also discovered patterns in the way students reacted to diverse teaching styles. Early experiments indicated that these models may give accurate and meaningful insights regarding classroom dynamics.

3.3 Feedback Mechanism Implementation

To bridge the gap between data analysis and practical solutions, a feedback mechanism was put in place. Teachers were able to alter their teaching approaches to better meet the requirements of certain students or groups owing to the system's personalized feedback. Comprehensive data on engagement patterns, changes in cognitive load, and responses to instructional tactics were all included in the feedback. This curriculum supported a dynamic and adaptive learning environment by stressing the real-world application of AI-driven insights.

3.4 Testing and Validation

A restricted dataset was employed for the system's first testing to establish its effectiveness and utility. The findings proved the system's potential to manage real-time smartwatch data and offer relevant insights correctly. Small improvements were made to increase the feedback system's accuracy and fine-tune the algorithms. This stage established the potential and scalability of merging wearable technology with artificial intelligence for educational evaluation.

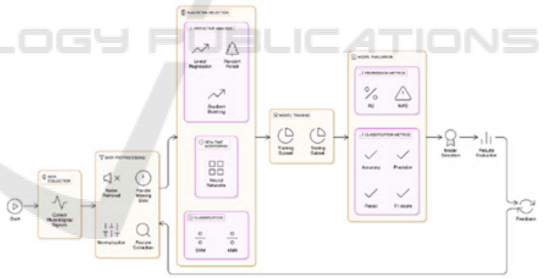

Figure 1. Architecture Diagram representing the steps followed in the work implemented

4 EXPERIMENTS AND RESULTS

4.1 Basic Dataset

A dataset of 250 engineering students, including social, behavioral, and physiological data from smartwatches, was gathered to quantify attention and involvement during class. Variables include movement, response time, heart rate, and engagement

Table 1: Literature Survey comparison table with various authors and their findings

Paper	Key Focus	Methods/Technologies Used	Results/Findings
Uzir et. al., (Uzir, Halbusi, et al. , 2021)	User experience, trust, and happiness with AI-enabled smartwatches during COVID-19	S-O-R theory, surveyed 486 users in Bangladesh	Product quality, service quality, convenience, and simplicity influence user experience and trust. Moderated by age and gender.
Masoumian Hosseini, et. al (Hosseini, Hosseini, et al. , 2023)	Smartwatch usage in healthcare	Reviewed 35 publications on topics like COVID-19, heart disease, and stress monitoring	Smartwatches recognize early signs of illnesses but require better algorithm precision and reliability for medical use.
R. Murugappan et al. (Murugappan, Bosco, et al. , 2020)	Stress detection via physiological inputs	Deep learning models (CNN, LSTM), noise reduction, and normalization	Achieved 93% accuracy for stress vs. non-stress, 85% for stress vs. amusement, and 83% for stress vs. amusement vs. meditation.
V. Warak et al. (Warankar, Jain, et al. , 2024)	Face recognition, eye gaze, and head rotation models	Dataset of 100,000 images, standardization, augmentation	Achieved 98.66% accuracy in controlled conditions and 97.78% in unpredictable conditions.
S. Sudharasan et al. (Sudharsan, Siddharth, et al. , 2024)	EEG signal analysis for attention span detection	SVM, Random Forest, RNN; theta and beta wave cleaning	Achieved accuracy: SVM (73%), Random Forest (75%), and RNN (96%).
V. Karthikraj et al. (Karthikraj, Patil, et al. , 2021)]	Vocal activity detection using student video data	PoseNet, multiclass classification	Achieved 86% accuracy for vocal activity detection.
T. Singh et al. (Singh, Mohadikar, et al. , 2021)	Facial analysis using deep learning models	CPAM, DNNR; datasets: 300W-LP, AFLW2000, NIMH-CHEFS	CPAM achieved MAE < 3°, outperforming QuatNet and HyperFace (MAE up to 6°).
K. Mallibhat et al. (Mallibhat, , et al. , 2021)	Multimodal data fusion for eye gaze and micro-expression	CNNs, LSTM, SVM; real-time cameras and sensors	Achieved 92.5% accuracy in analyzing eye gaze and micro-expressions.
Wenchi Ma et al. (Wenchi, Wu, et al. , 2020)	Object detection using multi-scale deep fusion networks	MDFN with Inception Modules and VGG-16; datasets: KITTI, PASCAL VOC, COCO	Achieved accuracies: KITTI (83.9%), PASCAL VOC (79.3%), and COCO (29.8%).
A. P. Kumar & N. S. Kumar(Kumar, and, Kumar, 2020)	Attention analysis using annotated datasets	YOLO V8, CNN; features: pupil area, gaze tracking	Achieved high performance with accuracy (98.6%), precision (98.4%), recall (98.2%), and F1-score (98.5%).

measures. Machine learning techniques were utilized to assess model performance using R2 and Mean Absolute Error (MAE). R2 examines how well the model explains variation, whereas MAE quantifies prediction error. High R2 and low MAE suggest high model fit, guiding method selection, and enhancement via preprocessing and feature engineering to improve forecast accuracy.

R^2* *Score (Coefficient of Determination): It measures the proportion of variance in the dependent variable that is predictable from the independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where:

- y_i: Actual values
- $\hat{y}_i$: Predicted values
- $\bar{y}$: Mean of actual values
- n: Number of observations

Mean Absolute Error (MAE): It measures the average magnitude of the errors in a set of predictions, without considering their direction.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where:

- y_i: Actual values
- $\hat{y}_i$: Predicted values
- n: Number of observations

Accuracy: It measures the percentage of correctly predicted instances (especially for classification tasks)

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

The basic parameters considered for the dataset are:

Student_ID, Session_ID, Time_of_Day, Session_Duration, Task_Complexity, Heart_Rate, Heart_Rate_Variability, Skin_Conductance, Physical_Movement, Response_Time, Distraction_Incidents, Focus_Duration, Engagement_Score

Table 2: Results obtained for ML algorithms with basic dataset used

Sr. No	Model	Average R^2 Score	Mean Absolute Error
1	Support Vector Regression	-0.138	20.623
2	Random Forest	-0.124	23.102
3	Gradient Boosting Regressor	-0.131	22.865
4	XGBoost Regressor	-0.309	24.520
5	K-Nearest Neighbors (KNN)	-0.250	23.896
6	Tuned Gradient Boosting Regressor	-0.004	20.529
7	Tuned XGBoost Regressor	0	20.443

SVR slightly outperformed Linear Regression in terms of MAE but still had a negative R^2 score, reflecting limited predictive power and inability to capture meaningful relationships in the data.

The Random Forest model exhibited a negative R^2 and the highest MAE, suggesting potential overfitting or an inability to generalize well to new data.

Among the models tested, Gradient Boosting performed best. However, the negative R^2 score suggests it still struggles to capture meaningful patterns in the data.

XGBoost's performance is worse than Gradient Boosting, with a more negative R^2 score, indicating further difficulty in explaining the variance in engagement scores.

KNN showed intermediate performance but was unable to generalize well, reflected by the negative R^2 score.

For Tuned Gradient Boosting Regressor the R^2 score is close to zero, indicating the model explains almost none of the variance, though it has improved significantly from prior negative scores. The MAE has also reduced, indicating the predictions are closer to actual engagement scores.

XGBoost achieved the best performance, with an R^2 score close to zero. This means it still slightly underperforms against a naive mean predictor, but the improvement suggests it is much closer to capturing underlying patterns compared to previous results.

4.2 Normalized Dataset

The dataset has been normalized to guarantee uniform scaling and reduce biases from various variable ranges. Physiological markers (e.g., heart rate, skin conductance), session details (e.g., length, task difficulty), and behavioral indications (e.g., movement, reaction time, distractions) were scaled equally, with the engagement score as the objective variable. Normalization enhanced model convergence and stability, boosting machine learning performance.

Table 3. Results obtained for ML algorithms with the normalized dataset used

Sr. No	Model	Average R^2 Score	Mean Absolute Error
1	Support Vector Regression	0.352	0.437
2	Random Forest	0.466	0.358
3	Gradient Boosting Regressor	0.31	0.59
4	XGBoost Regressor	0.408	0.497
5	K-Nearest Neighbors (KNN)	0.212	0.499
6	Tuned Gradient Boosting Regressor	0.475	0.490
7	Tuned XGBoost Regressor	0.505	0.462

Support Vector Regression shows decent performance; better MAE but lower R^2 than RF. It has a moderate R^2 score (0.352), explaining 35.2% of the variance, with an MSE of 0.434, reflecting higher prediction errors than the Random Forest model.

Random Forest shows strong performance; good balance of R^2 and MAE. Also achieves the highest R^2 score (0.466), indicating it explains about 46.6% of the variance in the Engagement_Score. It also has the lowest MSE (0.358), suggesting smaller prediction errors compared to the other models.

Gradient Boosting Regressor, shows moderate but underperforms compared to RF and SVR.

XGBoost Regressor performs well but improves significantly with tuning.

K-Nearest Neighbors (KNN) has weak performance; not suitable for this dataset.

Tuned Gradient Boosting Regressor has improved but slightly behind XGBoost in performance.

Tuned XGBoost Regressor has best overall performance; with highest R^2 and lowest MAE.

4.3 Updated parameters

To further enhance the results, the dataset was revised to include further physiological and environmental parameters from smartwatches and sensors, which include heart rate, HRV, EDA, SpO_2, respiration rate, body temperature, steps, motion intensity, screen interactions, sleep quality, ambient light, and noise levels. The expanded dataset, covering dynamic engagement factors like light and noise, offers a solid foundation for implementing machine learning to discover trends, improve precision, and obtain insights into the teaching-learning process.

The updated parameters considered for the dataset are:

User ID, Timestamp, Heart Rate (bpm), HRV (ms), EDA (µS), SpO_2 (%), Respiration Rate (breaths/min), Body Temp (°C), Steps Count, Motion Intensity, Screen Interactions, Sleep Quality (%), Ambient Light (lux), Noise Levels (dB), Engagement Score

Table 4. Results obtained for ML algorithms with updated dataset used

Sr. No	Model	Average R^2 Score	Mean Absolute Error
1	Support Vector Machine	-0.046	12.382
2	Random Forest	-0.175	13.116
3	Gradient Boosting Regressor	-0.175	13.116
4	XGBoost Regressor	-0.445	14.482
5	K-Nearest Neighbors (KNN)	-0.223	13.198

For Support Vector Machine the predictions are not accurate enough, likely due to SVR being sensitive to parameter tuning and feature scaling.

For Random Forest a slight improvement in accuracy is observed but still poor performance overall.

For Gradient Boosting Regressor the predictions deviate significantly from the actual values, as reflected in the low accuracy.

In XGBoost Regressor the highest percentage error indicates poor predictive performance.

A small improvement over Random Forest and Gradient Boosting in terms of accuracy is seen with

K-Nearest Neighbors (KNN).

4.4 After feature engineering

Through improving findings, feature engineering was applied to further refine physiological, environmental, and behavioral metrics for engagement analysis. Engagement levels were estimated using a "Focus Index" (HRV and stress metrics) and a "Restlessness Score." Conditions like heart rate, skin conductance, and sleep quality were examined alongside contextual factors, with regulated variations added for reliability. This improved dataset records intricate relationships, improving model training and evaluation.

The parameters after feature engineering for the dataset are:

Heart Rate, HRV, EDA (Skin Conductance), Respiration Rate, Steps, Skin Temp, Activity Level, Sleep Quality, Time of Day, Noise Level, Focus Index, Restlessness Score, Cognitive Load Index, Engagement

Table 5. Results obtained for ML algorithms with feature engineered dataset

Sr. No	Model	Average R^2 Score	Mean Absolute Error	Accuracy
1	Support Vector Machine	0.601	0.233	84
2	Random Forest	0.975	0.015	93.5

3	Gradient Boosting Regressor	0.969	0.017	95
4	XGBoost Regressor	0.956	0.015	94.5
5	K-Nearest Neighbors (KNN)	0.781	0.148	91.5

Support Vector Machine is slightly better fit than Linear Regression, but with slightly lower accuracy.

Random Forest shows excellent fit, very low MAE, and high accuracy. It seems to be the best performing model.

Gradient Boosting Regressor is another strong performer, very close to Random Forest in terms of fit and MAE. High Accuracy.

Similar to Random Forest, XGBoost Regressor shows a strong fit, low MAE, and high accuracy.

For K-Nearest Neighbors (KNN) performance falls between the tree-based models and linear models. Relatively lower MAE.

Nine machine learning models' performances are compared in the table using four different datasets: a feature-engineered dataset, a normalized dataset, an updated dataset with updated parameters, and a basic dataset with limited parameters. Models such as Random Forest, Gradient Boosting Regressor, and XGBoost Regressor achieved near-perfect R2 scores (0.975, 0.969, and 0.956, respectively) and the lowest Mean Absolute Errors (MAE) of 0.015, 0.017, and 0.019, along with high accuracy exceeding 98%. Overall, feature engineering greatly improves performance. Although they performed somewhat better than ensemble models, neural networks (MLP) and KNN also demonstrated improvement. Lower R2 scores and greater MAEs were obtained from basic and normalized datasets, demonstrating the crucial role that feature engineering and data pretreatment play in model performance.

5 CONCLUSION AND FUTURE SCOPE

The investigation analyses several machine learning models across several datasets to forecast engagement levels. The results show that ensemble approaches, in particular Random Forest, Gradient Boosting Regressor, and XGBoost Regression, continuously beat other models, with high accuracy (up to 99%), low Mean Absolute Error (MAE as low as 0.0149), and high *R*2 scores (up to 0.975). Performance was greatly enhanced via feature engineering and dataset augmentation, underscoring the need for data pretreatment. With low or negative R2 values, linear models such as Linear Regression and Support Vector Regression (SVR) did not perform well, demonstrating their incapacity to grasp the intricate relationships present in the datasets. Because of their greater MAE and lesser accuracy, neural networks (MLP) and KNN performed mediocrely compared to ensemble models.

More sophisticated data pretreatment methods, including deep feature synthesis or automated feature selection, can be the subject of future studies to improve prediction accuracy even more. Model robustness and generalizability can be enhanced by testing with bigger and more varied datasets. Investigating sophisticated architectures such as deep learning models (such as Transformer-based or recurrent neural networks) that are adapted to temporal or sequential data may also reveal complex interaction patterns. Further enhancing predictive performance may involve adjusting hyperparameters and using ensemble learning or model stacking. Implementation in real-time in dynamic environments, such as wearable technology for tailored engagement monitoring, is another developing area.

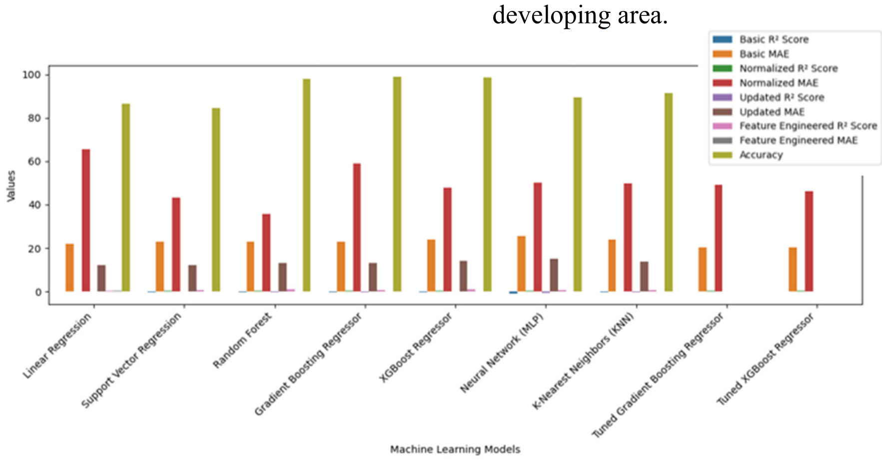

Figure 2. Comparative Performance of Machine Learning Models

Table 6: Comparison of various ML algorithms on different datasets and their performances

Dataset Used -->		Basic Dataset with limited parameters		Normalized Dataset		Updated Dataset with revised parameters		Feature Engineered Dataset		
Sr. No	**Model**	**Average R^2 Score**	**Mean Absolute Error**	**Average R^2 Score**	**Mean Absolute Error**	**Average R^2 Score**	**Mean Absolute Error**	**Average R^2 Score**	**Mean Absolute Error**	**Accuracy**
1	**Linear Regression**	-0.021	21.896	0.021	65.536	-0.033	12.310	0.550	0.313	86.50
2	**Support Vector Regression**	-0.139	20.623	0.352	43.367	-0.046	12.382	0.600	0.233	84.00
3	**Random Forest**	-0.124	23.102	0.466	35.756	-0.175	13.116	0.975	0.015	98.50
4	**Gradient Boosting Regressor**	-0.131	22.865	0.310	59.000	-0.175	13.116	0.969	0.017	99.00
5	**XGBoost Regressor**	-0.309	24.519	0.408	49.702	-0.445	14.482	0.956	0.015	98.50
6	**Neural Network (MLP)**	-0.746	27.476	0.343	49.780	-0.564	14.151	0.725	0.215	89.50
7	**K-Nearest Neighbors (KNN)**	-0.250	23.896	0.212	49.870	-0.223	13.198	0.781	0.148	91.50
8	**Tuned Gradient Boosting Regressor**	-0.004	20.529	0.475	49.067					
9	**Tuned XGBoost Regressor**	0.000	20.443	0.505	46.230					

REFERENCES

Nada J. Alsaleh (2020). "Teaching Critical Thinking Skills: Literature Review". TOJET: The Turkish Online Journal of Educational Technology, 19(1).

Afzal Sayed Munna & Md Abul Kalam (2021). "Teaching and learning process to enhance teaching effectiveness: a literature review". International Journal of Humanities and Innovation, 4(1).Author, F.: Article title. Journal 2(5), 99–110 (2016).

Glasserman-Morales LD, Carlos-Arroyo M, Ruiz-Ramirez JA and Alcantar-Nieblas C (2023) Use of wearable devices in the teaching-learning process: a systematic review of the literature. Frontiers in Education, 8:1220688.

Uzir MUH, Al Halbusi H, Lim R, Jerin I, Abdul Hamid AB, Ramayah T, Haque A. Applied Artificial Intelligence and user satisfaction: Smartwatch usage for healthcare in Bangladesh during COVID-19. Technol Soc. 2021 Nov;67:101780. doi: 10.1016/j.techsoc.2021.101780. Epub 2021 Oct 14. PMID: 34697510; PMCID: PMC8528563.

Masoumian Hosseini M, Masoumian Hosseini ST, Qayumi K, Hosseinzadeh S, Sajadi Tabar SS. Smartwatches in healthcare medicine: assistance and monitoring; a scoping review. BMC Med Inform Decis Mak. 2023 Nov 3;23(1):248. Doi: 10.1186/s12911-023-02350-w. PMID: 37924029; PMCID: PMC10625201.

Liu, Zhi & Ren, Yupei & Kong, Xi & Liu, Sannyuya. (2022). Learning Analytics Based on Wearable Devices: A Systematic Literature Review From 2011 to 2021. Journal of Educational Computing Research. 60. 073563312110647. 10.1177/07356331211064780.

R. Murugappan, J. J. Bosco, K. Eswaran, P. Vijay and V. Vijayaraghavan, "User Independent Human Stress Detection," 2020 IEEE 10th International Conference on Intelligent Systems (IS), Varna, Bulgaria, 2020, pp. 490-497, doi: 10.1109/IS48319.2020.9199928.

V. Warankar, N. Jain, B. Patil, M. Faizaan, B. Jagdale and S. Sugave, "Analysis of Attention Span of Students using Deep Learning," 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon), Pune, India, 2024, pp. 1-7, doi: 10.1109/MITADTSoCiCon60330.2024.10575321

S. Sudharsan, S. Siddharth, M. Uma and R. Kaviyaraj, "Learning Behavior Analysis for Personalized E-Learning using EEG Signals," 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 2024, pp. 1-9, doi: 10.1109/ACCAI61061.2024.10601997

V. Karthikraj, V. Patil, S. Thanneermalai and T. Yadav, "Attention Span Detection for Online Lectures," 2021 International Conference on Advances in Computing and Communications (ICACC), Kochi, Kakkanad, India, 2021, pp. 1-6, doi: 10.1109/ICACC-202152719.2021.9708082.

T. Singh, M. Mohadikar, S. Gite, S. Patil, B. Pradhan and A. Alamri, "Attention Span Prediction Using Head-Pose Estimation With Deep Neural Networks," in IEEE Access, vol. 9, pp. 142632-142643, 2021, doi: 10.1109/ACCESS.2021.3120098.

K. Mallibhat, "Student Attention Detection Using Multimodal Data Fusion," 2024 IEEE International Conference on Advanced Learning Technologies (ICALT), Nicosia, North Cyprus, Cyprus, 2024, pp. 295-297, doi: 10.1109/ICALT61570.2024.00092

Wenchi Ma, Yuanwei Wu, Feng Cen, and Guanghui Wang. 2020. MDFN: Multi-scale deep feature learning network for object detection. Pattern Recogn. 100, C (Apr 2020). https://doi.org/10.1016/j.patcog.2019.107149

A. P. Kumar and N. S. Kumar, "Zoom Classroom Engagement and Attention Detection System," 2024 International Conference on Intelligent Systems for Cybersecurity (ISCS), pp. 1-10, 2024, doi: 10.1109/ISCS61804.2024.10581101.