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Measuring Student Attentiveness Using Eye-tracking and Visual-spatial Data Analytics

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Abstract

With the increasing trend toward e-learning, accurately assessing student attentiveness has become a critical need for effective education. In traditional classrooms, teachers rely on nonverbal cues to gauge student engagement, but online environments limit this ability, hindering real-time feedback that can help adapt instructional methods. To address this challenge, we proposed a student eye movements-based model to assess the student's attentiveness more effectively.

For the student's attentiveness, the data is directly collected using ETVision glasses, and the features of eye movements are selected and preprocessed. To detect students' attentiveness and drowsiness, we propose a modified version of the Closed Eye Aspect Ratio (CEAR) model. Although the traditional model requires six eye landmark positions, in this paper, the proposed model requires only four eye landmark positions for the vertical dimension's eye landmarks. However, as virtual vision-mapped-to-real vision relation can be exposed in the Pixel Per Inch (PPI) measurement, the essential eye aspect ratio can be obtained from the vertical to the horizontal dimensions. The proposed approach is deployed in our experiments to analyze the students' eye-movement tracking and distraction behaviors. The analysis of the results has testified that the proposed model effectively detects students' attentiveness and drowsiness.

Keywords
Attentiveness, E-learning, Eye-tracking, Close Eyes Aspect Ratio (CEAR), Education

1. Introduction
With the increasing adoption of e-learning, accurately assessing student attentiveness has become critical for improving instructional methods and learning outcomes. Traditional in-person classrooms enable teachers to rely on nonverbal cues such as eye contact and facial expressions to gauge engagement, but online learning environments limit these observational capabilities [1]. Consequently, there is a growing need for computational models that can quantify student attentiveness in virtual settings.

Recent research suggests that eye-tracking technology, particularly methods based on the Eye Aspect Ratio (EAR), is a promising approach for measuring attentiveness by detecting blink patterns and eyelid movements [2]. The EAR method has been extensively used in applications such as driver drowsiness detection and fatigue monitoring [3]. In e-learning, real-time tracking of eye behavior provides valuable insights into student focus and cognitive load, as spontaneous blink rates and eyelid distance variations have been linked to levels of attention [4].

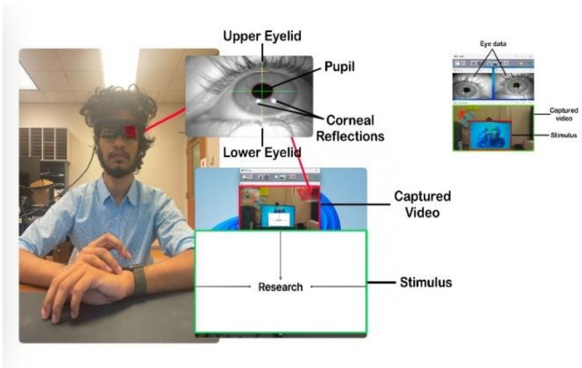
Building upon these findings, our study employs a refined Close Eye Aspect Ratio (CEAR) model, which minimizes reliance on multiple eye landmarks while maintaining accuracy. Unlike traditional models that require six eye landmark positions, our approach only utilizes four, optimizing computational efficiency while ensuring reliable assessment of attentiveness [5].

This paper presents an approach to student attentiveness detection, emphasizing the effectiveness of eye-tracking technology in online education. Through empirical experiments using the ETVision system [6], we demonstrate how our model enhances real-time attentiveness measurement, offering a viable solution for improving personalized learning experiences and adaptive instructional design.

2. Methodology

2.1 Experimental Setup

The team collected eye-tracking data using the ETVision system which is a wearable 180Hz binocular eye-tracking system from Argus Science [6]. The position data is measured in pixels relative to the origin. Figure 1 shows the experimental setup and a student wearing the ETVision glasses. A calibration procedure was implemented to align gaze data with the observed environment, ensuring precision in eye movement tracking. This setup facilitated the assessment of attentiveness and drowsiness by capturing relevant eye movement metrics and providing a field-of-view recording through a scene camera as shown in Figure 1. The experiment included four stimuli: two reading tasks and two videos. Each subject was offered one reading task and a video to watch. The order and content of the stimuli were randomized to address any effect of these factors.



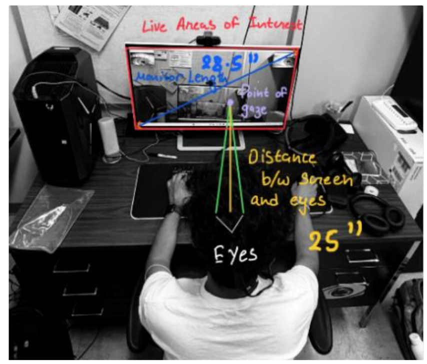


Figure 1: Experimental Setup.

2.2. Proposed Approach

Feature Selection

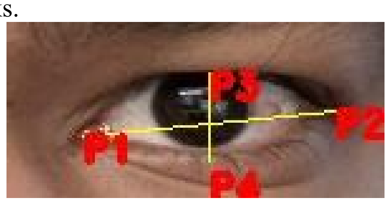
The device can collect up to 57 features such as the start of record, Gaze LAOI (Live Area of Interest), left pupil position horizontal, right pupil position horizontal, etc. Of these 57 features, the research team selected five features: the start of record, left and right eyelid upper vertical positions, and left and right eyelid lower vertical positions. The start of record is a timestamp in seconds.

Pixel Per Inch (PPI)

The ETVision system measures the upper eyelid and lower eyelid position in pixels. We measured the width of the eye in inches. To accommodate the differences in the measurement units, we calculated the ratio, K (pixel/inch), i.e., pixels per inch (PPI). For example, we measured the distance between the upper and lower eyelids of a student to be 7/16 and 6/16 inches for the left and right eyes, respectively. In addition, we measured the width of the left and right eyes to be 1.5 inches. As an example for the same student, the vertical distance between the upper and lower eyelids is 119 pixels. Thus, the K is calculated as $K = \frac{119}{(6.5/16)} = 292.923 = 293$ pixels per inch. We believe that the impact of the differences between individuals' dimensions will be trivial since we are using the PPI as the aspect ratio between the eye's height and width, which will be almost the same for different individuals.

Proposed Model

The traditional close-eye aspect ratio (CEAR) model requires six eye landmark positions. Unlike the traditional CEAR model, the proposed model needs four eye landmark positions only. Figure 2 shows the positions (P1, P2, P3, & P4) of these landmarks.



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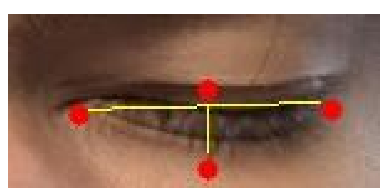


b)

Figure 2: a) Open-eye measurements with four eye landmarks; b) Closed-eye landmarks

The proposed CEAR model is shown below:

$$CEAR_{proposed} = \frac{||P3-P4||}{||P1-P2||} \quad 1)$$

Compared to the original CEAR model in [1], [4], two vertical eye landmarks are needed instead of four. The calculated ratio, K, can be used to calculate the width of the eye in pixels. As an example for the same student, the student's eye width in pixels can be calculated to be 293 PPI x 1.5 inches = 439.5 pixels. Thus, the CEAR value is 119/439.5 = 0.271. Figure 3 shows the pseudocode of the proposed approach.

Algorithm: The proposed approach
Input: The data collected from the ETVision glasses (.CSV file)
Output: Data visualization resulted from the proposed model
Specification: 1. Get the data from .CSV files. 2. Select features from the data and convert them to the numerical type. 3. Calculate the proposed CEAR values. 1) Use the vertical measurements to calculate the K $K = \left(pixel(\lVert upper\ eyelid - lower\ eyelid\rVert)\right)/\left(inch(\lVert upper\ eyelid - lower\ eyelid\rVert)\right)$ 2) Use K to calculate the eye width in pixels $pixel(\lVert eye\ width\rVert) = K \cdot inch(\lVert eye\ width\rVert)$ 3) Calculate the proposed CEAR value $CEAR_{proposed} = \left(pixel(\lVert eye\ length\rVert)\right)/\left(pixel(\lVert eye\ width\rVert)\right)$ 4. Average the CEAR values over each second. In the loop: • Sum the CEAR values in each second timestamp and count the length of the proposed CEAR in a second. • Average the proposed CEAR is calculated: $CEAR_{proposed} = \frac{\sum_{i=1}^{n} CEAR_{proposed}^{ti}}{n},\ i \in Z$ End loop 5. Create an image of the proposed CEAR values over time.

Figure 3: The pseudocode of the proposed approach

Attentiveness Peak Levels

To evaluate the proposed model's performance using students' data, the distance of human eyelids from both vertical and horizontal perspectives is considered. The human eyelid measures between 1.10236 - 1.1811 inches wide and around 0.354331 - 0.393701 inches in height [5], [7], [8]. Thus, according to these ranges, the CEAR ranges can be calculated to be 0.3 and 0.3571. Therefore, the threshold value should not be beyond these values, if the proposed model provides the maximum ratio when the attentiveness is at its peak.

Drowsiness Thresholds

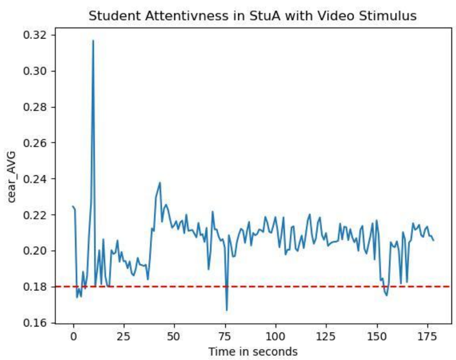
While the proposed model can detect students' peak attentiveness, a drowsiness threshold is another critical measure.

According to studies, the drowsiness threshold for a car driver can be in the discrete range between 0.18, 0.2, 0.225, and 0.25 [1]. In addition, the constant threshold of 0.2 is used for the CEAR model for the student's drowsiness as described in [4]. We considered these thresholds in our experiments to evaluate the performance of the proposed model.

3. Results and Discussions

3.1 The Proposed CEAR Using the Data of Individual Students with a Video Stimulus

Figures 4 a, b, c, & d present the proposed CEAR values over time for four students using a video stimulus. The values were calculated using the proposed model in Figure 3.



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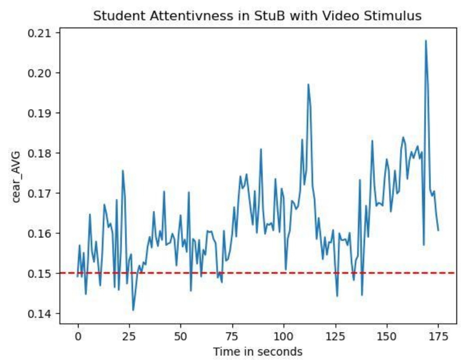

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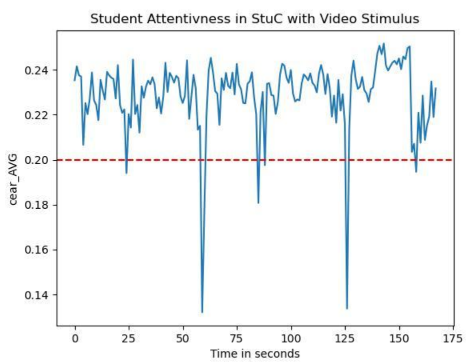

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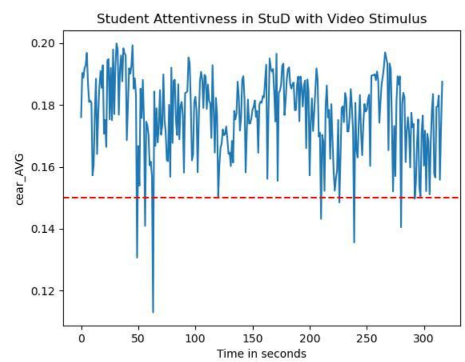


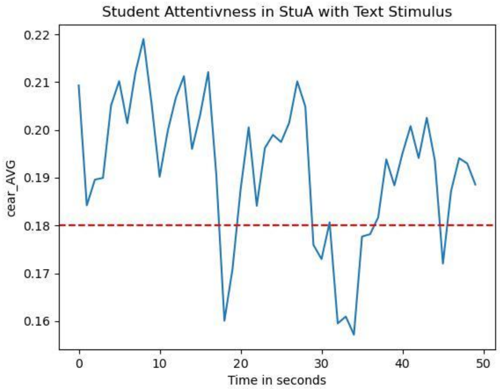
d)

Figure 4: Student CEAR average values for students a) A, b) B, c) C, & d) D with video stimulus.

The proposed CEAR values fall within the range (0, 0.32], validating the accuracy of the approach, as it does not exceed the peak student attentiveness level of 0.3571. Individual threshold values set for different students—0.18 for Student A, 0.15 for Student B, 0.2 for Student C, and 0.15 for Student D—demonstrate effective outcomes. In addition, the spikes at specific timestamps, such as 0, 75, and 150 seconds in Student A's data in Figure 4 a, vary in individual plots but consistently reflect distraction behaviors. As the experiment is videotaped, these spikes align with observable student behaviors, including eye blinking, pupil movement, head movement, and loss of focus on the screen.

3.2 The Proposed CEAR Using the Data of Individual Students with a Text Stimulus

Figures 5 a, b, c, & d present the proposed CEAR values over time for four students using a text stimulus. The values were calculated using the proposed model in Figure 3.



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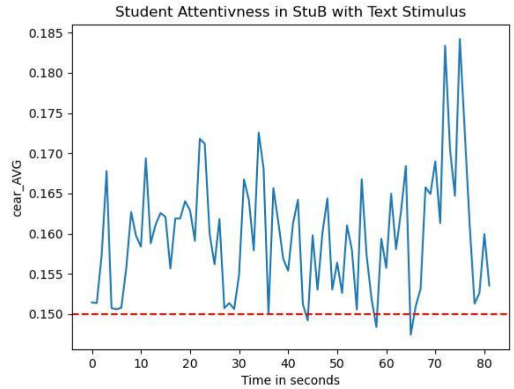

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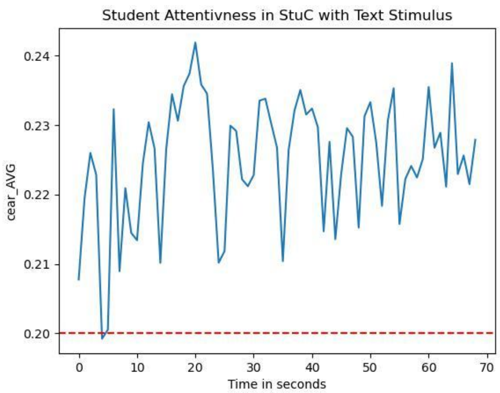

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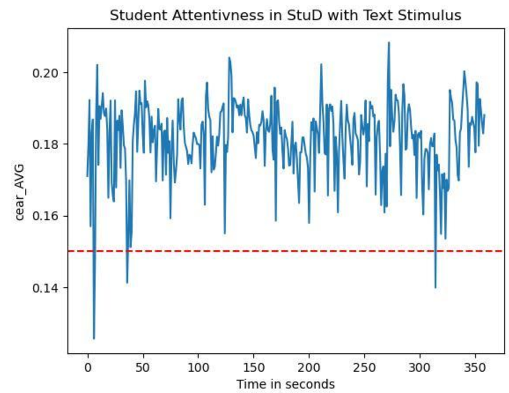

d)

Figure 5: Student CEAR average values for students a) A, b) B, c) C, & d) D with Text Stimulus

The proposed CEAR values fall within the range (0, 0.25], validating the accuracy of the approach. Although both stimuli 1 and 2 utilize the same constant threshold for each student, they produce spikes at different timestamps, indicating that different stimuli impact student attentiveness in distinct ways. Furthermore, the CEAR value is directly proportional to attentiveness, meaning higher CEAR values correspond to increased student attentiveness. Conversely, the CEAR value is inversely proportional to drowsiness, implying that lower CEAR values indicate a higher likelihood of distraction.

4. Conclusion

This study demonstrates the effectiveness of eye-tracking and visual-spatial data analytics in assessing student attentiveness in e-learning environments. By leveraging the Close Eye Aspect Ratio (CEAR) model with a reduced set of eye landmarks, our approach enhances the accuracy and efficiency of attentiveness detection while minimizing computational complexity. The integration of blink analysis and eyelid position monitoring provides a comprehensive framework for real-time engagement assessment, addressing a critical challenge in remote education. As digital learning continues to expand, such objective measures of attentiveness can support adaptive instructional strategies, ultimately improving student outcomes and personalized learning experiences. Future research can explore refining the model with additional behavioral indicators, such as head movements and facial expressions, to further enhance the robustness of attentiveness detection systems.

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References
[1] M. Elbawab and R. Henriques, "Machine Learning applied to student attentiveness detection: Using emotional and non-emotional measures," *Educ Inf Technol (Dordr)*, vol. 28, no. 12, pp. 15717–15737, Dec. 2023, doi: 10.1007/S10639-023-11814-5/TABLES/4.

[2] C. Dewi, R. C. Chen, C. W. Chang, S. H. Wu, X. Jiang, and H. Yu, "Eye Aspect Ratio for Real-Time Drowsiness Detection to Improve Driver Safety," *Electronics 2022, Vol. 11, Page 3183*, vol. 11, no. 19, p. 3183, Oct. 2022, doi: 10.3390/ELECTRONICS11193183.

[3] A. Kuwahara, K. Nishikawa, R. Hirakawa, H. Kawano, and Y. Nakatoh, "Eye fatigue estimation using blink detection based on Eye Aspect Ratio Mapping(EARM)," *Cognitive Robotics*, vol. 2, pp. 50–59, Jan. 2022, doi: 10.1016/J.COGR.2022.01.003.

[4] N. A. Shah, K. Meenakshi, A. Agarwal, and S. Sivasubramanian, "Assessment of Student Attentiveness to E-Learning by Monitoring Behavioural Elements," *2021 International Conference on Computer Communication and Informatics, ICCCI 2021*, Jan. 2021, doi: 10.1109/ICCCI50826.2021.9402283.

[5] A. H. Fathi, F. A. Mohammadi, and M. T. Manzuri, "The eyelids distance detection in gray scale images," *2006 International Symposium on Communications and Information Technologies, ISCIT*, pp. 937–940, 2006, doi: 10.1109/ISCIT.2006.339914.

[6] "Argus Science Products - ETVision." Accessed: Jan. 18, 2025. [Online]. Available: https://www.argusscience.com/ETVision.html

[7] K. M. Price, P. K. Gupta, J. A. Woodward, S. S. Stinnett, and A. P. Murchison, "Eyebrow and eyelid dimensions: An anthropometric analysis of African Americans and Caucasians," *Plast Reconstr Surg*, vol. 124, no. 2, pp. 615–623, Aug. 2009, doi: 10.1097/PRS.0B013E3181ADDC98.

[8] W. A. Van den Bosch, I. Leenders, and P. Mulder, "Topographic anatomy of the eyelids, and the effects of sex and age," *British Journal of Ophthalmology*, vol. 83, no. 3, pp. 347–352, Mar. 1999, doi: 10.1136/BJO.83.3.347.