Computer Vision-based AI Models for Tracking Learners' Facial Expressions and Gaze Behavior in Online Education

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ABSTRACT

Online learning faces a significant challenge: the high dropout rate caused by limitations in observing learners' behaviors. As a result, instructors often lack sufficient data to adapt teaching methods and effectively motivate learners. This research aimed to 1) develop computer vision-based AI models for analyzing online learners' facial expressions, 2) to develop computer vision-based AI models for analyzing online learners' gaze behavior, and 3) to study the potential application of the developed models in the context of online learning environments. To address the diversity of devices and computational constraints in online learning environments, a transfer learning approach was adopted to train the models. Four pre-trained models including Yolov8n, Yolov9t, Yolov10n, and Yolov11n were selected cause by their optimization for low computational resource usage, and their effectiveness was evaluated and compared. The results revealed that the Learner Emotion Detection model (LeEmo) detects academic emotions from learners' facial expressions, performed best with Yolov9t, achieving a mAP of 78.10% and an F1-Score of 76.05%. The Lerner Eye Tracking model (LeET), developed for learners' eye-tracking tasks, achieved its best performance with the Yolov11n, achieving a mAP of 94.51%, an F1-Score of 85.23%, and a performance of 93.45% for monitoring blink and closed eye activities. Lastly, the Learner Drowsiness Detection model (LeDro), which detects activeness or drowsiness from learners' facial expressions, also performs best with the Yolov11n, achieving a mAP of 85.96% and an F1-Score of 82.46%. These findings demonstrate the significant potential of computer vision-based models for detecting and monitoring online learners' behaviors, providing valuable data for instructors to enhance online learning outcomes. Furthermore, these data could be analyzed using other artificial intelligence technologies to explore various learning states of online learners, such as sustained attention levels, flow states, engagement levels, and stress levels.

Keywords: Computer vision, Gaze behavior, Facial expression

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Introduction

Online learning is an educational innovation that integrates the internet, smart devices, and software to support blended learning, enabling remote interaction between learners and instructors. It is grounded in principles such as learner-instructor interaction, teamwork, self-directed learning, timely feedback, and flexibility in time and location [1]. These features support individual differences and promote lifelong learning.

Online learning, whether asynchronous or synchronous, offers flexibility but faces challenges most notably high dropout rates due to the greater concentration, responsibility, and self-discipline required from learners compared to traditional settings [2–3]. Sustained attention is critical for engagement and deep learning [4–5] typically lasts only 10–30 minutes in conventional classrooms [6]. Limited real-time visibility in online environments makes it difficult for instructors to observe learner behavior and adjust teaching, accordingly, resulting in a lack of data to inform instructional decisions.

To address this challenge, researchers propose using artificial intelligence (AI) to analyze learners' behaviors and provide valuable insights for instructors. Recent studies have identified several learning states associated with learner behavior, including: **Engagement**, which reflects active involvement and motivation and enhances learning outcomes [7–20]; **Concentration and Flow**, immersive states where focus is intense and tasks feel effortless [21–22]; and **Attention**, the ability to suppress distractions and focus, though often limited by fatigue or task complexity [23–27]. Other relevant states include **Perception**, involving learners' self-assessment and attitudes toward tasks [28–32]; **Confusion**, a state of uncertainty that disrupts progress and increases dropout risk [33]; Mind Wandering, where thoughts drift from the task and reduce attentiveness [7,34–36]; **Boredom**, caused by monotonous or irrelevant tasks that lead to disengagement [21]; and **Anxiety**, which arises when challenges exceed skill levels, resulting in stress and reduced engagement [21]. Learning states can be extracted using two primary methods: sensor-based and computer vision-based approaches. **Sensor-based methods** analyze physiological signals such as heart rate, skin temperature, galvanic skin resistance (GSR), and brain activity [34–40]. While effective, they require specialized equipment, increasing both cost and implementation complexity. In contrast, **computer vision-based methods** analyze visual cues such as facial expressions, emotions, head and face posture, gaze behavior, and upper-body movement using standard webcams [21, 26, 41–51]. This approach is low-cost, user-friendly, and more practical for widespread use.

The literature review revealed that using computer vision to track learners' behaviors in online learning environments has significant potential to provide valuable data for instructors. This data can be utilized to adapt teaching methods, enhance learner motivation, and improve the effectiveness of online learning management, ultimately reducing dropout rates.

Objectives of the study

1. To develop computer vision-based AI models for analyzing online learners' facial expressions.
2. To develop computer vision-based AI models for analyzing online learners' gaze behavior.
3. To study the potential application of the developed models in the context of online learning environments.

Methodology

To address Objectives 1 and 2, three computer vision-based AI models were developed, including:

Learner Emotion Detection model (LeEmo): Designed to detect academic emotions from learners' facial expressions in online learning. It was trained using a supervised learning approach to classify seven emotions that influence learning: neutral, happy, surprise, angry, sad, fear , and disgust [52].

Lerner Eye Tracking model (LeET): Comprises two components: *1) Monitoring blink and closed-eye activities*, which use the Eye Aspect ratio (EAR) value to track blinked rate per minute and closed-eyes activity [53]. *2) Detecting whether the eyes are on-screen or off-screen*, by classifying learners' eyes direction and head pose into two classes: on-screen or off-screen. This component was trained using a supervised learning approach.

Learner Drowsiness Detection model (LeDro): Detects whether the learners' facial expressions indicate activeness or drowsiness. It was trained using a supervised learning approach.

Given the diversity of devices and computational constraints in online learning environments, transfer learning was used to train the models. Four pre-trained models including YOLOv8n, YOLOv9n, YOLOv10n, and YOLOv11n, optimized for low computational resource usage, were selected to evaluate and compare their effectiveness. Each model followed the development steps:

1. Data Collection and Preparation Three public datasets were used to train the proposed models.

The LeEmo model was trained using the EMOTIC dataset [54], originally labeled with 26 emotion categories. Emotions were re-categorized into 7 types (neutral, happy, surprise, angry, sad, fear, and disgust), with 3,100 images per category, totaling 21,700 images. The data were split into training (70%), validation (20%), and test (10%) sets.

The LeET model used the Columbia Gaze Dataset [55], which contains upper-body images of 56 individuals with various gaze directions and head poses. A total of 10,000 images (5,000 per class: on-screen/off-screen) were selected and divided into training (70%), validation (20%), and test (10%) sets.

The LeDro model was trained on the UTA-RLDD dataset [56], which includes 180 video clips from 60 participants. From these, 9,120 images were extracted and labeled as active or drowsy based on clip type proportions. Each class contained 4,560 images, split into training (70%), validation (20%), and test (10%) sets.

2. Training the Model. The four pre-trained models were used to train models using the same hyperparameter to evaluate their effectiveness and compare performance.

The LeEmo model was trained for 300 epochs, a learning rate of 0.01, Automatic Mixed Precision (AMP) enabled, and a batch size of 16 images. The input image resolution was set to 320 pixels.

The LeEt model consisted of two components. For the blink and closed-eye monitoring, the Eye Aspect Ratio (EAR) was calculated using the formula:

$$EAR = 2 \times \frac{|p2-p6|+|p1-p5|}{|p1-p4|}$$

where p1 to p6 = distances between specific eye coordinate points.

Euclidean distance was used to calculate these distances, with coordinate points extracted using MediaPipe's face mesh, which represents the face with 486 coordinate points. The EAR value ranged from 0 to 1, where values approaching 0 indicates closed eyes, and values approaching 1 indicates wide-open eyes. The average EAR from both eyes was calculated and compared to a default blink threshold of 0.2, which was automatically adjusted for individual learners. If the average EAR was below or equal to the threshold, the model identified closed eyes. The duration of closure was then evaluated: if the duration was less than or equal to 0.5 seconds, it was classified as a blink, while a duration exceeding 3 seconds, it indicated prolonged eyes closed.

For detecting whether the learner's eyes are on-screen or off-screen. The model was trained using transfer learning approach from four pre-trained models. It was trained for 500 epoch with a learning rate of 0.01, AMP enabled, and a batch size of 16 images. The input image resolution was set to 640 pixels.

The last model, LeDro, was trained for 500 epochs with a learning rate of 0.01, AMP enabled, and a batch size of 16 images. The input image resolution was set to 640 pixels.

3. Model evaluation. After training, the effectiveness of each model was evaluated using a confusion matrix to calculate key performance metrics: Mean Average Precision (mAP), Precision, Recall, and F1-Score. The mAP reflects the model's overall ability to accurately detect objects across all classes. Precision indicates the proportion of correct positive predictions out of all positive predictions, while Recall measures the proportion of actual positives that were correctly identified. The F1-Score, as the harmonic means of Precision and Recall, provides a balanced assessment of model performance. The results were then compared to determine which model performed best for each specific task.

Results

1. Result of LeEmo Model Training: The performance comparison of the models, in terms of mAP, Precision, Recall, and F1-score is presented in Table 1.

Table 1 Result of LeEmo Model Training.

pre-trained models	mAP@0.5	Precision	Recall	F1-Score
Yolov8n	67.59%	69.51%	73.69%	71.57%
Yolov9t	78.10%	74.23%	77.95%	76.05%
Yolov10n	75.71%	71.60%	73.76%	72.66%
Yolov11n	77.81%	70.34%	77.03%	73.53%

Based on Table 1, the YOLOv9t achieved the best performance, with a mAP of 78.10% and an F1-Score of 76.05%. The YOLOv11n followed closely with a mAP of 77.81% and an F1-Score of 73.53%. The YOLOv10n recorded a mAP of 75.71% and an F1-Score of 72.66%. Lastly, the YOLOv8n demonstrated the lowest performance, achieving a mAP of 67.59% and an F1-Score of 71.57%.

2. Result of LeET Model Training: For blink and closed-eye monitoring. The performance evaluation was conducted using 5 randomly selected video clips sourced from the internet, each with a duration of 3 minutes. Each clip featured a single individual speaking in various contexts, with diverse eye properties, such as wearing glasses. The LeEt model was used to monitor blink and closed eye activities and was compared with manual monitoring. The results are shown in Table 2.

Table 2 Result of LeET Model Training for Monitoring Blink and Closed-Eye Activities.

Clip Video	Blinking Times $_{\text{LeET}}$	Blinking Times $_{\text{Manual}}$	Closed Times $_{\text{LeET}}$	Closed Times $_{\text{Manual}}$
Clip 01	41	47	3	3
Clip 02	27	29	0	0
Clip 03	33	31	0	2
Clip 04	14	14	1	2
Clip 05	32	34	6	6
Overall	147	155	10	13

From Table 2, the LeEt model detected a total of 147 blinks and 10 closed eye times, compared to 155 and 13 detected manually. The model's performance was calculated using the formular:

$$\text{performance} = \frac{100}{\text{Blinking Times}_{\text{Manual}} + \text{Closed Times}_{\text{Manual}}} \times (\text{Blinking Times}_{\text{LeET}} + \text{Closed Times}_{\text{LeET}}) \quad \ldots\%$$

$$\text{perfomance} = \frac{100}{155+13} \times (147+10) \qquad = 93.45\ \%$$

With a performance of 93.45%, this component of the LeET model demonstrates high accuracy and reliable results in monitoring blink and closed eye activities.

For detecting whether the learner's eyes are on-screen or off-screen. The performance comparison of the models, in terms of mAP, Precision, Recall, and F1-score, is presented in Table 3.

Table 3 Result of LeET Model Training for On-Screen and Off-Screen Detection

pre-trained models	mAP@0.5	Precision	Recall	F1-Score
Yolov8n	92.72%	81.40%	86.62%	83.94%
Yolov9t	93.80%	84.70%	85.71%	85.21%
Yolov10n	91.80%	79.20%	89.32%	83.95%
Yolov11n	94.51%	80.84%	90.14%	85.24%

From Table 3, the YOLOv11n model achieved the best performance, with a mAP of 94.51% and an F1-Score of 85.24%. The YOLOv9t model closely followed with a mAP of 93.80% and an F1-Score of 85.21%. The YOLOv8n model recorded a mAP of 92.72% and an F1-Score of 83.94%. Lastly, the YOLOv10n model demonstrated the lowest performance, achieving a mAP of 91.80% and an F1-Score of 83.95%.

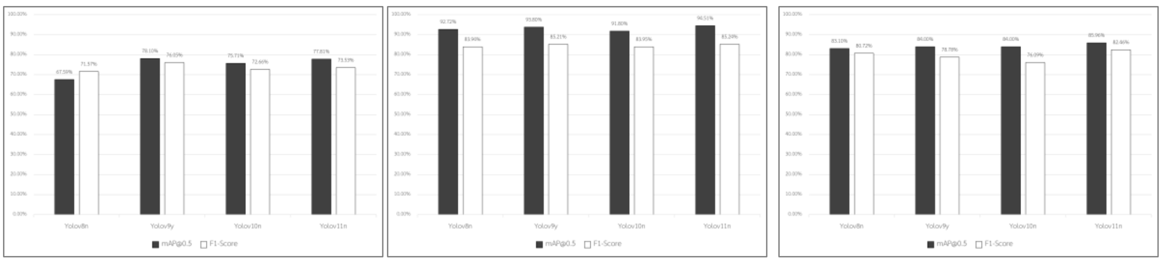
3. Result of LeDro Model Training: The performance comparison of the models presented in Table 4.

Table 4 Result of LeDro Model Training.

pre-trained models	mAP@0.5	Precision	Recall	F1-Score
Yolov8n	83.10%	78.50%	83.07%	80.72%
Yolov9t	84.00%	78.05%	79.51%	78.78%
Yolov10n	84.00%	78.82%	79.34%	79.08%
Yolov11n	85.96 %	78.74%	86.55%	82.46%

Based on Table 4, the YOLOv11n model achieved the best performance, with a mAP of 85.96% and an F1-Score of 82.46%. The YOLOv10n model closely followed, achieving a mAP of 84.00% and an F1-Score of 79.08%. The YOLOv9t model also achieved a mAP of 84.00% but recorded a lower F1-Score of 78.78.09%. Lastly, the YOLOv8n model demonstrated the lowest performance, with a mAP of 83.10% and an F1-Score of 80.72%.

The performance comparison results for all models are presented in Figure 2.



(A) LeEmo Model (B) LeET for On-Screen/Off-Screen Detection (C) LeDro Model

Figure 1 The performance comparison results for all models

Discussion and Conclusions

Based on the objectives of this study, we developed three computer vision-based models for detecting and monitoring online learner behavior including the LeEmo model for detecting learners' emotions from facial expressions, the LeET model for monitoring blink and closed eye activities and detecting whether eyes are on-screen or off-screen, and the LeDro model for detecting activeness or drowsiness based on learners' facial expressions.

All models were trained using a transfer learning approach with pre-trained models to accommodate diverse devices and computational constraints. Four pre-trained models: Yolov8n, Yolov9t, Yolov10n, and Yolov11n were selected to train each model and compare their performance. The LeEmo model achieved its best performance with the Yolov9t, which had a mAP of 78.10% and an F1-Score of 76.05%. The LeET model achieved its best performance with the Yolov11n, with a mAP of 94.51%, an F1-Score of 85.23%, and a performance of 93.45% for monitoring blink and closed eye activities. Lastly, the LeDro model also achieved its best performance with the Yolo11n, which had a mAP of 85.96% and an F1-Score of 82.46%.

These findings align with the study of Shaikh et al. [57], which demonstrated that newer YOLO versions, such as YOLOv5, achieved higher accuracy in detecting faces and emotions. Similarly, Zheng et al. [58] demonstrated that computer vision-based model for monitoring driver fatigue showed high accuracy and robust real-time performance. Therefore, this study demonstrates the potential of computer vision-based models for tracking and analyzing online learners' behaviors, providing valuable insights for instructors to enhance teaching strategies and improve online learning outcomes. Furthermore, in other studies, the behavioral data obtained in this research could be analyzed using other artificial intelligence technologies to explore various learning states of online learners, such as sustained attention levels, flow states, engagement levels, and stress levels.

Beyond its technical contributions, this study supports dropout reduction in online learning through two key approaches: instructional strategies, by using AI-generated data to adjust teaching methods; and learner behavior monitoring, through real-time attention tracking using computer vision. Together, these elements help create a more adaptive and engaging learning environment.

Limitations

This study demonstrates the potential of computer vision-based AI models for monitoring learners' behaviors in online environments; however, several limitations remain.

1. The models were trained on publicly available datasets, which may not reflect the diversity of real-world learners, potentially limiting generalizability across different contexts.

2. This approach relies solely on visual data, which may not capture deeper cognitive or emotional states. Multimodal inputs such as audio, text, or physiological signals could enhance interpretation.

3. Although YOLO-based models were chosen for efficiency, real-time classroom deployment was not tested. Further evaluation under real-world conditions is needed.

4. Ethical and privacy concerns regarding facial data collection were beyond the scope of this study and should be addressed in future work to ensure responsible use of AI in education.

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