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Analysis of Facial Expression to Estimate the Engagement Level of Students in Online Lectures

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Abstract

Student engagement is a critical factor in educational effectiveness, particularly in remote and hybrid learning environments. This project presents an AI-based Student Engagement Detection system that utilizes facial analysis and eye tracking to monitor student attention levels in real images. Facial features were analyzed to predict RT to a task-irrelevant stimulus, which was assumed to be an index of the level of attention. We applied a machine learning method. We re-analyzed the data while excluding RT data with sleepy faces of the students to test whether decreased general arousal caused by sleepiness was a significant factor in the RT lengthening observed in the experiment. The results were similar regardless of the inclusion of RTs with sleepy faces, indicating that facial expression can be used to predict learners' level of attention to video lectures.

Keywords: *Attention, affective computing, engagement, facial features, online lecture.*

1. Introduction

Understanding students' engagement levels while studying is important for improving learning outcomes. To improve the quality of education, it is crucial to estimate learners' level of engagement with their studies. However, it is difficult for teachers to pay attention to all students, particularly in online classes. Automated measurement of engagement levels may be helpful for improving learning conditions. For online learning, webcams can be used to capture learners' facial expressions, which can be used to estimate their mental states [1-3]. In recent years, online learning has become an essential mode of education, especially with the rise of digital platforms. However, one major challenge in virtual classrooms is understanding the engagement level of students. Unlike traditional classrooms where teachers can observe students directly, online education [4].

1.1. Methods of Sign Language:

Methods of sign- language-based facial expression analysis focus on interpreting non-manual cues—such as eyebrow movements, eye openness, lip shape, and head motion—which play an important role in sign languages and emotional communication. These methods often use the Facial Action Coding System (FACS) to break down expressions into measurable Action Units and analyze subtle emotional changes like confusion, interest, or boredom [5, 6]. Facial landmark detection is also commonly used to track key points on the eyes, brows, and mouth, helping identify engagement levels in online classes. Additionally, head pose estimation, inspired by sign-language interpretation, helps detect whether a student is attentive or distracted by observing nods, tilts, or gaze direction. Deep learning techniques, including CNNs, LSTMs, and transformer-based models, further enable automatic recognition of non-manual signals and emotion patterns [7]. Together, these sign- language-inspired methods offer an effective approach for analyzing facial expressions and understanding student engagement during online learning.

2. Tables and Figures

The analysis of facial expressions during online

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classes involves several important techniques that help understand a student's engagement level [8]. It begins with facial landmark detection, which identifies key points on the eyes, eyebrows, and mouth to capture subtle expression changes. Tables 1 and Figures 1 are presented center, as shown below and cited in the manuscript.

Table 1 Facial Expressions and Their Possible Interpretation

Facial expressions	Indicators	Interpretation
Happy	Smile, raised cheeks	interest
Confused	Frowning, eye brow squeeze	Needs clarification
Sad	Dropped mouth corners	Low motivation
Neutral	Relaxed face	Normal attention
Angry	Tight lips, narrowed eyes	Frustration
Bored	Dropping eyelids	Low engagement

2.1. Tables

A table for analyzing facial expressions during online classes helps systematically observe and record students' emotional and behavioral responses. It usually includes columns such as the student's name or ID, timestamp, type of facial expression (e.g., happy, neutral, confused, bored, surprised), and observed behavior such as attention level or engagement. Additional fields like frequency of expression, duration, and remarks by the observer help capture patterns over time. This flexibilit enables adjustments and improvements tailored to individual research objectives and various application scenarios. Fourthly, OpenFace supports processing large datasets of facial images and videos. this is particularly valuable for research projects that involve handling extensive data, such as facial recognition in video surveillance systems or the establishment of facial image databases.

2.2. Figures

Figure for analyzing facial expressions during online classes visually represents how students' emotions and engagement levels are monitored throughout a virtual session. It typically includes sample images or graphical outputs that show different detected expressions such as happiness, neutrality, confusion, boredom, or surprise. The figure may also display the output of an AI model or facial expression recognition system, highlighting key facial landmarks, emotion labels, or confidence scores generated during detection.

Figure 1 Facial Expressions

3. Results and Discussion

3.1. Results

Target presentations without responses within 10 sec were excluded from the reaction time (RT) analysis. Such target presentations occurred on 5.5% of trials on average across all participants. The average RT over all sessions of all participants was 1.1 sec, with a standard deviation of 2.3 sec. Because average RT varied among participants, we normalized RT as Z-scores after taking the logarithm. The horizontal axis shows RT measured in the experiment and the vertical axis shows the prediction from LightGBM. Each point represents each target presentation from all sessions of all participants and different colors indicate different training-test combinations (15 different combinations with different colors).

3.2. Discussion

Discussion should be an interpretation of the results rather than a repetition of the Results. Our approach was to predict the response time under assumption

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that the response time would become longer when more attention was paid to the lecture, reducing attention to a target that was irrelevant to the lecture [9]. By applying computer vision and deep learning techniques, educators can automatically detect these expressions and evaluate student participation in real time. This analysis helps instructors adjust teaching strategies, improve content delivery, and identify students who may need additional support. However, challenges such as varying lighting conditions, camera quality, individual facial differences, and privacy concerns can affect accuracy Shown in Figure 2.

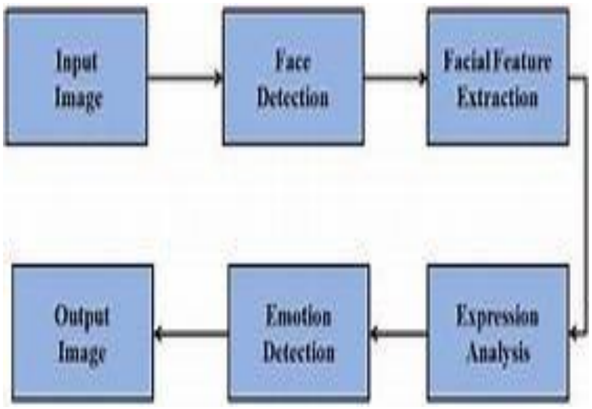

Figure 2. Activity Diagram

Conclusion

The Conclusion should contain the confirmation of the problem that has been analyzed in result and discussion section. The Conclusion should contain the confirmation of the problem that has been analyzed in result and discussion section. The Conclusion should contain the confirmation of the problem that has been analyzed in result and discussion section. Secondly, significant individual differences have been observed. Customizing the model may be one possible solution.

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