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Analysis of Facial Expression to Estimate the Levels of Engagement in the Online Lectures

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Abstract: In online education, understanding students' engagement is essential for improving learning outcomes. This paper proposes a method to estimate students' attentional states through facial expression analysis. By recording reaction times (RT) to an irrelevant auditory stimulus during online lectures, we gauge students' focus levels. Facial features were extracted using OpenFace, and LightGBM models were trained to predict RT from these features. The findings indicate a significant relationship between facial expressions and attentional states, highlighting potential applications in adaptive online learning environments.
Keywords: Facial Expression Analysis, Engagement Detection, Online Learning, LightGBM, Attention Estimation.

I. INTRODUCTION

Monitoring student engagement during online lectures poses significant challenges for educators. Traditional methods relying on subjective assessments often fail to capture internal attentional states accurately. Recent advancements in affective computing and facial expression analysis offer promising alternatives. In this study, we propose an objective, real-time approach that uses facial action units (AUs) to estimate students' attention during lectures by predicting their reaction times (RT) to task-irrelevant auditory stimuli.

II. RELATED WORK

Prior research has utilized facial expressions, heart rate monitoring, and self-reporting to assess engagement levels. Shioiri et al. demonstrated that facial expressions could reflect subjective preferences, while Thomas and Jayagopi predicted engagement levels through facial cues. However, subjective evaluations often miss unconscious mental processes, emphasizing the need for objective, non-invasive measurements

III. METHODOLOGY

A. Experimental Design

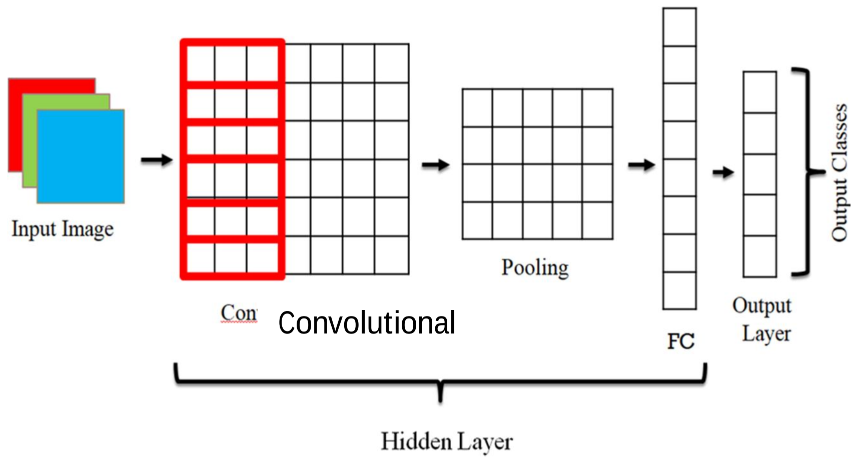
Fifteen participants (average age 23.1 years) watched nine PHP tutorial videos while wearing headphones that played continuous white noise. The disappearance of the noise, randomly occurring every 25–35 seconds, served as the secondary task target. Participants pressed a key when they detected the sound disappearance. Reaction times (RTs) were recorded alongside facial video data.

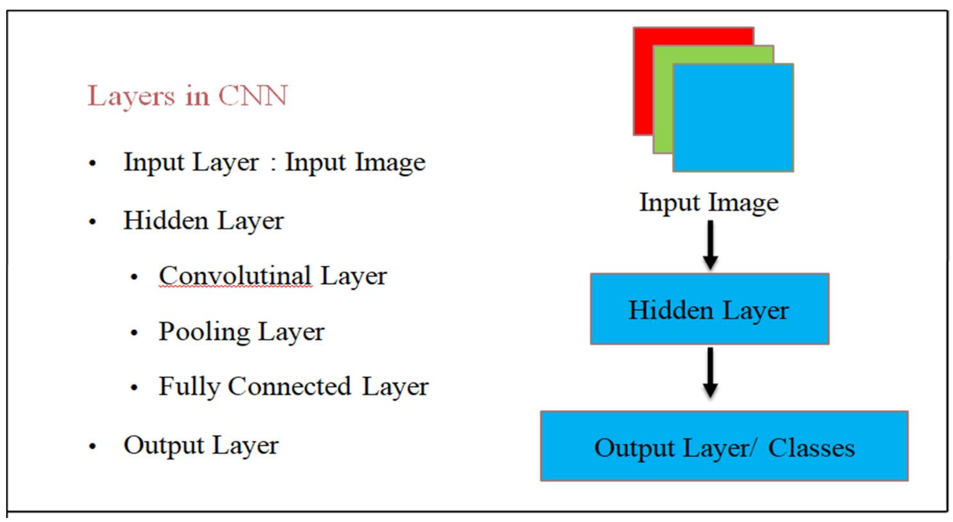
B. Facial Feature Extraction

Facial videos were processed using OpenFace, extracting 17 continuous (AUr) and 18 binary (AUc) facial action units based on the Facial Action Coding System (FACS). Features such as the mean, maximum, minimum, standard deviation, and percentiles of the AU intensities were calculated for the 3-second window before each auditory target event.

C. Machine Learning Model

The Light Gradient Boosting Machine (LightGBM) was employed for RT prediction based on the extracted features. Two models were built: a Pooled Data Model and an Across- Individual Model. Model performance was evaluated using Root Mean Square Error (RMSE) and Pearson’s correlation coefficient.





IV. IMPLEMENTATION DETAILS

1) Hardware Setup: A standard webcam is used for real-time video capture. All components operate on a personal computer with Intel i3/i5 processor, ensuring sufficient computational resources for live emotion detection.
2) Face and Emotion Detection: Face regions are detected using Haar-Cascade classifiers implemented in OpenCV. Emotion recognition is carried out by a lightweight Convolutional Neural Network (CNN) trained on publicly available datasets.
3) Preprocessing Techniques: Input frames are converted to grayscale, filtered for noise removal using median filters, and resized for uniformity before being fed into the neural network.
4) Engagement Estimation: Recognized emotions are mapped to engagement levels based on predefined rules. The system classifies attention status into high, moderate, or low engagement categories.
5) Data Storage and Reporting: Attendance and engagement results are logged in structured CSV files using Pandas, which can later be exported or visualized for analysis.
6) Software Environment: The solution is developed in Python using libraries like OpenCV, Keras, NumPy, and Pandas. Keras with TensorFlow backend enables efficient deep learning inference.

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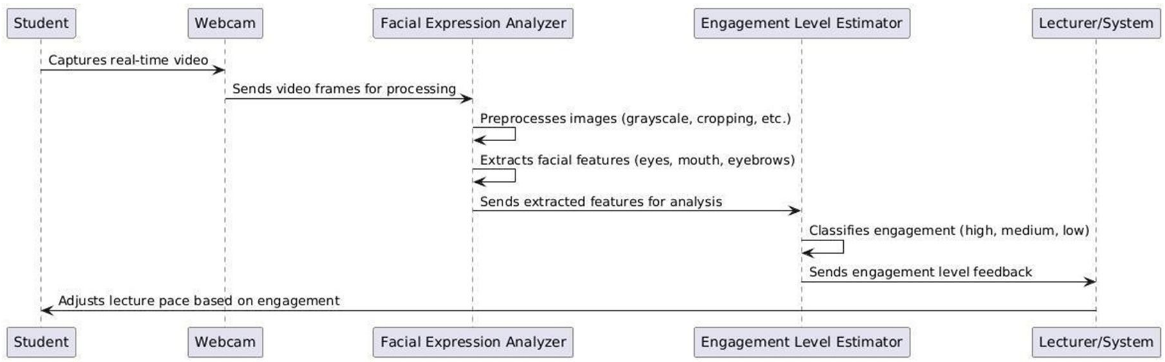
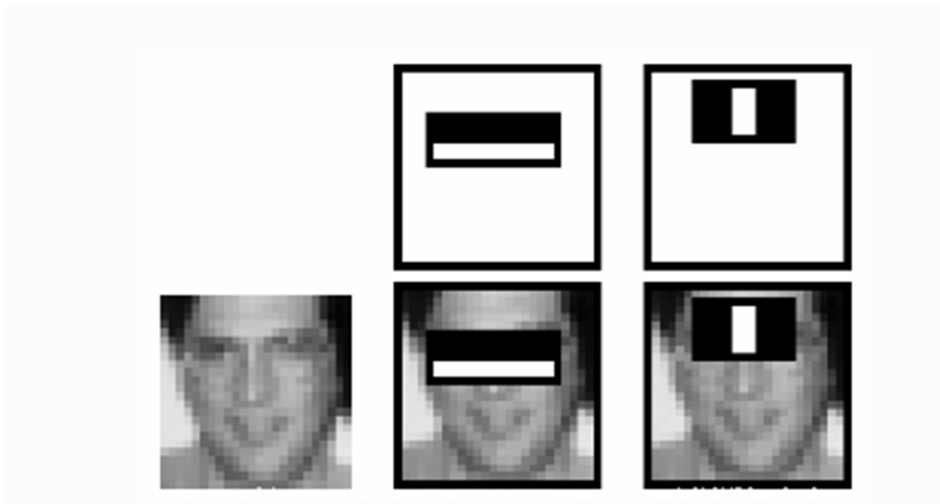
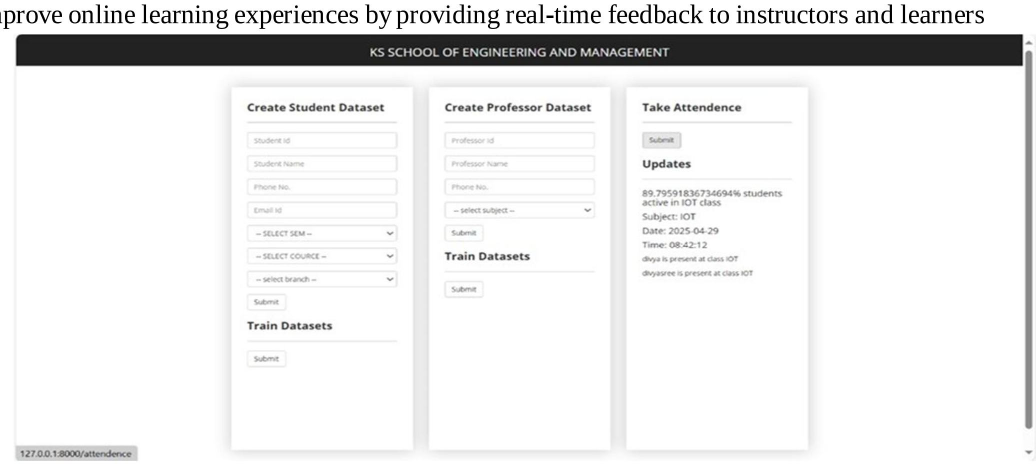




V. RESULTS AND DISCUSSION

The pooled model achieved a correlation coefficient of 0.66 and an RMSE of 0.75, indicating a strong predictive relationship between facial features and attentional states. Key contributing features identified through SHAP analysis included AU9 (Nose Wrinkler), AU45 (Blink), AU15 (Lip Corner Depressor), and AU7 (Lid Tightener). Exclusion of sleepy faces maintained prediction accuracy, reinforcing that facial features can reflect attentional states independently of general arousal levels. However, across-individual models failed to predict RTs accurately, revealing substantial individual differences in engagement-related facial expressions.

The findings confirm that facial features provide valuable insights into engagement levels. The observed individual variability suggests that personalized models or group-specific models may enhance prediction accuracy. Customized engagement monitoring systems could improve online learning experiences by providing real-time feedback to instructors and learners



VI. CONCLUSION

Facial expression analysis, paired with machine learning, can objectively estimate student engagement during online lectures. Future work should focus on refining feature extraction methods, handling individual variability, and exploring integration into real-world educational platforms.

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