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PROPOSING A COMPUTER VISION-BASED FRAMEWORK FOR CLUSTERING ENGAGEMENT LEVEL ASSESSMENT IN THE CONTEXT OF E-LEARNING

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ABSTRACT
The rapid growth of e-learning platforms has led to an increased need for effective methods to assess and analyze learner engagement. Engaging learners in online educational environments is crucial for promoting effective learning outcomes. Traditional approaches to engagement assessment often rely on self-reported measures, which can be subjective and prone to biases. To overcome these limitations, this paper proposes a computer vision-based framework for clustering engagement level assessment in the context of e-learning.
The proposed framework leverages computer vision techniques to analyze visual cues, such as face detection, facial landmark detection, and head pose estimation, to estimate the engagement levels of learners. By employing machine learning algorithms and data clustering techniques, the framework aims to identify distinct patterns of engagement across a collected dataset of recorded videos for e-learning interactions. This clustering approach allows for a more objective and fine-grained assessment of engagement levels, enabling educators and researchers to gain deeper insights into learner behavior and tailor instructional strategies accordingly.

Keywords:
Engagement Level Assessment, Clustering Engagement Level, Computer Vision, Fuzzy C-Mean

INTRODUCTION
In the realm of e-learning, the assessment and understanding of learner engagement play a pivotal role in evaluating the effectiveness of online educational experiences [1][2]. Learner engagement, encompassing cognitive, emotional, and behavioral involvement, directly influences knowledge acquisition, retention, and overall learning outcomes [3][4]. As the demand for e-learning continues to surge, there is an increasing need for robust and effective methods to assess and measure learner engagement in this digital context.
Traditional approaches to engagement assessment in e-learning primarily rely on self-reported measures and quantitative metrics derived from interaction logs or clickstream data [5][6]. While these methods provide valuable insights, they have limitations in capturing the nuanced and multidimensional nature of learner engagement [7]. Consequently, researchers and practitioners have turned their attention to advanced techniques, such as computer vision, to enhance engagement assessment and gain a more holistic understanding of learner behaviors.
Computer vision techniques, involving the analysis of visual cues and non-verbal behaviors, have demonstrated promise across various domains, including education [8][9]. By integrating computer vision into the assessment of learner engagement, researchers can tap into a rich source of information, encompassing facial expressions, gaze patterns, and body postures, to glean deeper insights into learner engagement states [10] [11]. These visual cues can complement traditional metrics and provide a more comprehensive understanding of learners' cognitive and affective states during the learning process.
However, clustering the results of engagement level assessment poses unique challenges given the complex and multidimensional nature of the data.
Researchers have explored diverse clustering techniques to identify underlying patterns and groups within engagement assessment data [12]. Traditional clustering algorithms, such as k-means and hierarchical clustering, have been widely employed in this context. Additionally, advanced techniques, including spectral clustering and density-based clustering, have been proposed to address the intricacies inherent in engagement assessment data [13].
the primary objective of this paper is to propose a comprehensive framework that integrates computer vision techniques

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into the clustering process of engagement level assessment in e-learning. By leveraging computer vision, we aim to capture and analyze the rich visual cues that provide valuable insights into learner engagement. Furthermore, we endeavor to address the challenges associated with clustering engagement assessment results, encompassing the selection of appropriate clustering algorithms, determination of the optimal number of clusters, and handling of high-dimensional data.

Literature review

A. Engagement Level Assessment in E-Learning:

The assessment of engagement levels in e-learning environments has garnered significant attention from researchers and practitioners due to its pivotal role in evaluating the effectiveness of online educational experiences [1][2]. Various approaches and methodologies have been proposed to assess and measure learner engagement in the e-learning context. These approaches encompass diverse data sources, including interaction logs, clickstream data, forum participation, and self-reported measures, which aim to capture and quantify the multifaceted nature of learner engagement [5][6]. To analyze engagement data, researchers have employed various techniques, including machine learning algorithms, sentiment analysis, and statistical modeling, to derive meaningful insights and patterns [7] [14].

B. Challenges in Clustering Engagement Level Assessment Results:

Clustering engagement level assessment results presents unique challenges due to the complex and multidimensional nature of engagement data. The identification of meaningful patterns and the selection of appropriate clustering algorithms are critical aspects in clustering engagement data effectively [15] [16]. Challenges also arise in determining the optimal number of clusters, handling high-dimensional data, and addressing the heterogeneity of engagement metrics in terms of scales and types [15] [16]. These challenges necessitate the development of specialized clustering techniques capable of accommodating the intricacies inherent in engagement-level assessment data.

C. Existing Clustering Techniques for Engagement Level Assessment:

A multitude of clustering techniques have been explored to analyze engagement level assessment results in the context of e-learning. Traditional clustering algorithms such as k-means, hierarchical clustering, and DBSCAN have been widely employed to segment learners based on their engagement patterns [1] [2]. Probabilistic models, such as Gaussian mixture models, have also been investigated to capture the latent structure underlying engagement data [4]. In addition to these traditional techniques, advanced clustering methods such as spectral clustering, self-organizing maps, and density-based clustering have been utilized to address specific challenges associated with engagement level assessment [13] [14].

D. Incorporating Computer Vision Techniques in Engagement Level Assessment:

Recent research has witnessed a growing interest in integrating computer vision techniques to augment engagement level assessment in e-learning. Computer vision offers the potential to analyze visual cues and non-verbal behavior exhibited by learners, thereby providing supplementary insights into engagement levels [8] [9].
Techniques such as facial expression recognition, gaze tracking, and body posture analysis have been employed within the realm of computer vision to extract visual features that can be integrated into the clustering process [6] [8]. These computer vision-based approaches hold promise for capturing rich and nuanced information, complementing traditional engagement assessment methods.

Methodology

Overview of the Proposed Framework:

To address the challenges associated with clustering engagement level assessment results in e-learning, we propose a comprehensive framework that integrates computer vision techniques into the clustering process. Our framework aims to leverage the power of computer vision to capture visual cues and non-verbal behaviors exhibited by learners, providing valuable insights into their engagement levels. By incorporating these visual features into the clustering analysis, we strive to enhance the accuracy, depth, and granularity of engagement assessment. The proposed framework will be implemented using appropriate programming languages and libraries for computer vision, data processing, and clustering analysis as shown in figure 3.1. The framework can be deployed as a standalone software tool or integrated into existing e-learning platforms to facilitate real-time engagement analysis and provide personalized feedback to learners.

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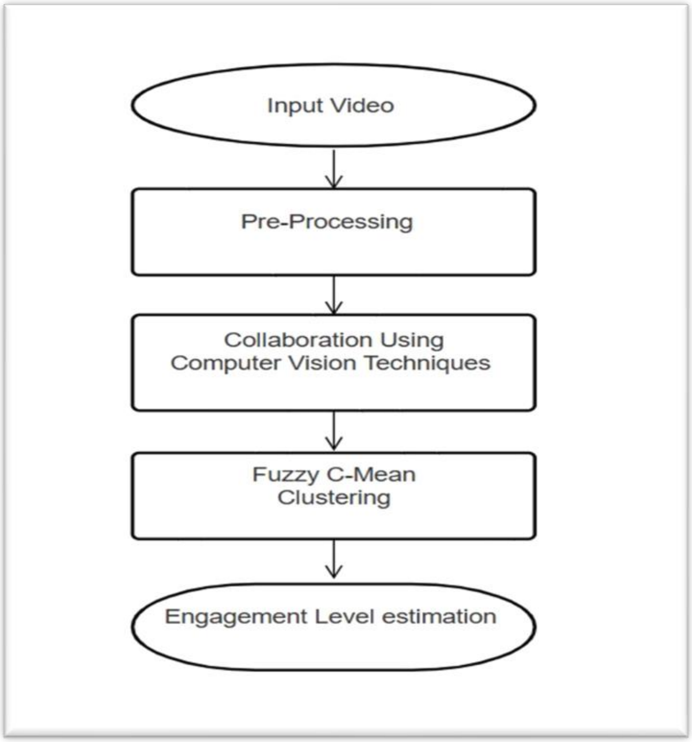

Figure 3.1: Framework for the proposed model

The initial step of the model involves acquiring recorded video input from the Webcam. The video frames are extracted from the threaded video file stream. Before proceeding further, each frame undergoes a pre-processing step. This particular model incorporates two image pre-processing techniques, namely image resizing and grayscale conversion. Once the frame is appropriately resized and converted to grayscale, it enters the Collaboration stage, where computer vision techniques can be applied for face detection. The Haar Cascade Classifier from the Open Source Computer Vision Library (OpenCV) is employed to achieve this. The output of this process displays a bounding box around the detected face. Subsequently, the model performs facial landmark detection on the identified face, accurately determining the facial features by detecting and localizing 68 coordinates on the face.

To estimate the rotation and translation vectors for head pose estimation, the model leverages the head shape defined by the 68 facial landmark points. The Perspective-n-Point problem is solved using the solvePnP function from the OpenCV library. The sequence of operations involves face detection, followed by facial landmark detection, and ultimately determining the direction of the head pose to establish the engagement threshold. By combining the results of these steps, the initial engagement level can be estimated. To ensure more accurate results clustering of engagement levels, fuzzy C-mean clustering is applied. The final outcomes, derived from applying the fuzzy C-mean algorithm, provide estimates of the final engagement level. The instructor receives feedback only when the student's engagement level is low.

In this way, we were able to identify valuable information that allows us to assist the instructors in monitoring any low-engagement student who may need to interfere with further activities using the computer vision technique. In a clustering evaluation, the metric is used to measure the better-defined cluster and the separation between the clusters using a fuzzy C-mean algorithm that can influence policy change in undergraduate education.

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Result and Discussion

The Fuzzy C-means clustering model was utilized in this study, employing a three-cluster configuration. To prevent the model from running indefinitely, the MAX_ITER parameter was set to 20. Additionally, a value greater than 1 was assigned to the m parameter to prevent the model from operating akin to K-nearest neighbors. Subsequently, the model was fitted with the given parameters, and the resulting cluster labels were stored in a separate variable. In order to examine the dispersion of the data and clusters, a scatter plot was employed as a visualization tool as shown in Figure 4.1.

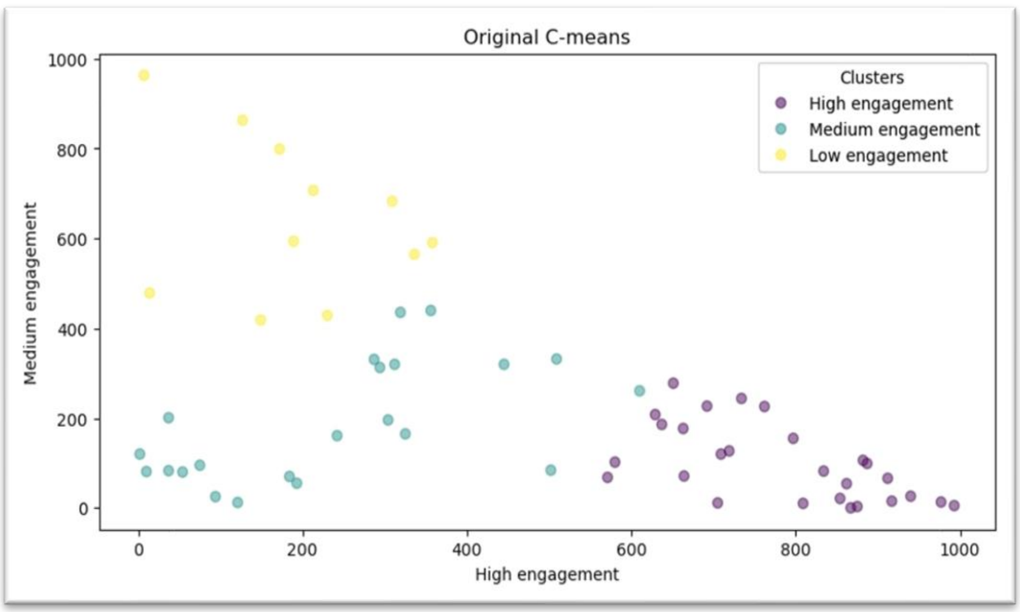

Figure 4.1: Student engagement level results after utilizing the g Fuzzy C-Mean algorithm.

In this section, we present the results and visualizations obtained from the experiments conducted to evaluate the performance of fuzzy C-means, the algorithm for measuring student engagement levels.
It achieved more precise clustering by effectively capturing the nuances and variations in student engagement. The evaluation of the Davies-Bouldin (Figure 4.2: Equation 4.1) score further confirmed the algorithm's effectiveness (85%), demonstrating its ability to create well-defined and distinct clusters.

$$\bar{D} = \frac{1}{N}\sum_{i=1}^{N} D_i$$

Figure 4.2: The Davies-Bouldin Equation

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Which is simply the average of the similarity measures of each cluster with a cluster most similar to it.
Note: The best choice for clusters is where the average similarity is minimized, therefore a smaller $\bar{D}$ represents better-defined clusters.
The proposed model demonstrated increased robustness to noise present in the data set. It effectively handled outliers and noisy data points, leading to improved performance in challenging scenarios.
The proposed model's higher accuracy, precise clustering, and robustness to noise make it an invaluable tool for educators and researchers seeking to gain comprehensive insights into student behaviors and tailor instructional strategies accordingly.
Overall, the experimental results affirmed that our proposed model using the fuzzy C-means algorithm offers significant improvements in accurately assessing and categorizing student engagement levels, further highlighting its potential as a reliable and effective solution in educational settings.

CONCLUSION

In this study, our experiments have demonstrated the superiority of our proposed model using a fuzzy C-means algorithm in measuring student engagement levels. These findings have important implications for educators, as the proposed model offers a more reliable and precise tool for understanding student behaviors and tailoring instructional strategies accordingly. It has the potential to enhance educational practices and improve learning outcomes by providing valuable insights into student engagement levels more accurately and robustly.

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