EALD-MLLM: Emotion Analysis in Long-sequential and De-identity videos with Multi-modal Large Language Model

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ABSTRACT

Emotion AI is the ability of computers to understand human emotional states. Existing works have achieved promising progress, but two limitations remain to be solved: 1) Previous studies have been more focused on short sequential video emotion analysis while overlooking long sequential video. However, the emotions in short sequential videos only reflect instantaneous emotions, which may be deliberately guided or hidden. In contrast, long sequential videos can reveal authentic emotions. 2) Previous studies commonly utilize various signals such as facial, speech, and even very sensitive biological signals (e.g., electrocardiogram). However, due to the increasing demand for privacy, it is becoming important to develop Emotion AI without relying on sensitive signals. To address the aforementioned limitations, in this paper, we construct a dataset for Emotion Analysis in Long-sequential and De-identity videos called EALD by collecting and processing the sequences of athletes' post-match interviews. In addition to providing annotations of the overall emotional state of each video, we also provide Non-Facial Body Language (NFBL) annotations for each player. NFBL is an inner-driven emotional expression and can serve as an identity-free clue to understanding the emotional state. Moreover, we provide a simple but effective baseline for further research. More precisely, we propose a Multimodal Large Language Models (MLLMs) based solution for long-sequential emotion analysis called EALD-MLLM and evaluate it with de-identity signals (e.g., visual, speech, and

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NFBLs). Our experimental results demonstrate that: 1) MLLMs can achieve comparable, even better performance than the supervised single-modal models, even in a zero-shot scenario; 2) NFBL is an important cue in long sequential emotion analysis. EALD will be available on the open-source platform.

CCS CONCEPTS

• Applied computing → Psychology.

KEYWORDS

Multi-modal Large Language Model, Emotion Understanding, Affective Computing, Social Signal Processing, Human-Computer Interaction, Identity-free

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1 INTRODUCTION

Emotion analysis [21, 24] is one of the most fundamental yet challenging tasks. For humans, emotions are present at all times, such as when people talking, thinking, and making decisions. Therefore, emotion analysis plays an important role in human-machine communication, such as in e-learning, social robotics, and healthcare [7, 23, 25]. In the past decades, emotion analysis has attracted a lot of attention from the research community [13, 14, 27, 38, 42]. Various modalities of signals have been explored for emotion analysis. Biological signals such as electrocardiogram (ECG) [22], electroencephalogram (EEG) [28], and galvanic skin response [30] have been used for emotion analysis. Another research direction is static facial

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signals emotion analysis. For example, dataset EmotionNet [15] and AffectNet [36] were proposed to identify emotions from facial images. Nowadays, video and multimodal (video + audio) emotion analysis has become a dominant research direction. AFEW [10], AFEW-VA [11] and LIRIS-ACCEDE [3] provided emotional annotation from the movie clip. VAM [20] collected visual and speech data from the speech and interview. Similarly, MOSEI [45] comprised 23,453 annotated video segments featuring 1,000 distinct speakers discussing 250 topics. The Youtube dataset [37] included product reviews and opinion videos sourced from YouTube. SEWA [26] recorded video and audio of subjects who watched adverts and provided detailed facial annotation. The summary of existing video and multimodal datasets for emotion analysis is present in Table. 1.

Previous datasets have successfully improved research in emotion analysis from various aspects. However, two major limitations remain to be addressed: 1) Regardless of the modality used, all of the above studies are highly correlated with sensitive biometric data. This is because biometric data (e.g., facial, speech, and biological signals) plays a critical role in various applications, such as telephone unlocks and mobile payment. While every coin has two sides, biometric information is so sensitive that it is particularly prone to being stolen, misused, and unauthorized tracking. As the risk of hacking and privacy violations increases, the protection of personal biometric data is receiving increasing attention; 2) Existing datasets are more focused on short sequential video emotion analysis while overlooking long sequential video emotion analysis. As shown in Table 1, most datasets only provide videos that are shorter than one minute. The emotions depicted in short sequential videos merely capture fleeting moments, which could be intentionally directed or concealed. In contrast, long sequential videos have the capacity to unveil genuine emotions. For example, when an athlete who lost the game is interviewed after the game, although he or she may have expressed positive emotions in the middle of the interview, his or her overall emotion may still be negative. While iMiGUE [31] is close to our dataset, it lacks audio data. Moreover, as depicted in Fig. 2, the majority of videos in iMiGUE are shorter than 5 minutes, some even lasting only 3 minutes. Therefore, iMiGUE [31] may not be suitable for long-sequential emotion analysis.

To solve the aforementioned limitations of the existing datasets, we construct and propose a dataset for Emotion Analysis in Longsequential and De-identity videos called EALD. More precisely, we collect videos containing "post-match press" scenarios in which a professional athlete is given several rounds of Q&A with reporters after a tough match. As a result of the match, winning or losing is a natural emotion trigger, leading to positive or negative emotional states of the player being interviewed. In addition, we annotated the Non-Facial Body Language (NFBL) of athletes during the interview. Because NFBL has been proven that it can be a crucial clue for understanding human hidden emotions in psychological studies [1, 2, 33]. Then, We use McAdams [41] and face detection ¹ for speech and facial de-identification. Finally, we evaluate various single models (e.g, video and audio) and the Multimodal Large Language Model (MLLM) (e.g., Video-LLaMA [46]) on the proposed dataset EALD. The experimental results demonstrate that MLLM



Figure 1: Selected samples of non-facial body language with the masked face of the proposed dataset *EALD*.



Figure 2: The comparison of the duration of videos of iMiGUE and *EALD*. The X-axis denotes the length of the videos, and Y-axis denotes the number of videos.

surpasses other supervised single-modal models, even in the zeroshot scenario. In summary, the contributions of this paper can be concluded as follows:

- We construct and propose *EALD* dataset. It bridges the gap in existing datasets in the aspect of de-identity long sequential video emotion analysis.
- We provided a benchmark evaluation of the proposed dataset for future research.
- We validate that NFBL is an effective and identity-free clue for emotion analysis.

2 EALD DATASET

In this section, we will present the construction and detailed information of the proposed dataset *EALD*.

¹http://dlib.net/python/

Dataset	Modality	Duration in total (hours)	Duration in avg. (mins)	NFBL annota.?	Identity free?
HUMAINE [12]	V+A+L	4.18	5.02	\checkmark	×
VAM [20]	V+A	12.00	1.449	×	×
IEMOCAP [5]	V+A+L	11.46	<1	×	×
Youtube [37]	V+A+L	0.50	<1	×	×
AFEW [10]	V+A	2.46	<1	×	×
AM-FED [35]	V	3.33	<1	×	×
AFEW-VA [11]	V+A	0.66	<1	×	×
LIRIS-ACCEDE [3]	V+L	-	<1	\checkmark	×
EMILYA [17]	V+L	-	<1	\checkmark	×
SEWA [26]	V+A	4.65	<1	×	×
CMU-MOSEI [45]	V+A+L	65.88	1.68	×	×
iMiGUE [31]	V+L	34.78	5.81	\checkmark	\checkmark
EALD (Ours)	V+A+L	32.15	7.02	\checkmark	\checkmark

Table 1: Comparison of the different video and multimodal emotion understanding datasets.

Note: V, A, and L denote video, audio, and language, respectively.

2.1 Motivation

As shown in Table 1, there is a gap between existing datasets and real-life applications: 1) sensitive biological signals involved in their datasets, such as facial and speech. It is hard for the existing datasets to meet the needs for privacy protection in real life; 2) pay more attention to short sequential video emotion analysis but overlook long sequential video. In fact, long sequential video is crucial to emotion analysis. Next, we will show how to construct the proposed dataset *EALD*. And later, we will demonstrate how *EALD* can effectively bridge this gap.

2.2 Dataset Construction

Data collection. The videos of athletes participating in post-game interviews are a suitable data source. First, the outcome of the game, whether it's a victory or a loss, serves as a natural catalyst for emotions, eliciting either positive or negative states in the interviewed player. Second, the players had no (or very little) time to prepare because the press conference would be held immediately after the game, and he or she needed to respond to the questions rapidly. Unlike acting in movies or series, athletes' NFBL is natural. Third, the duration of the post-game interview videos is commonly relatively long, which meets the need of our target, namely, long sequential emotion analysis. Therefore, we collect videos of post-game interviews in a total of 275 from the Australian Open² and BNP Paribas Open³ from YouTube.

Data de-identification. As aforementioned, one of the aims of the proposed dataset is to provide identify-free data for emotion analysis. As one may see, the majority of identity information exists in facial and speech signals. Therefore, we perform video and audio de-identification to remove the identity information. Specifically, for video de-identification, we utilize pre-trained face detection Convolutional Neural Network (CNN) model $m_{face_detection}$ from Dilb⁴ to implement facial masking for de-identification. Formally, give a video $\mathbf{V} = \{v_1, v_2, ..., v_{Nsample}\}$ where v_i denote the each frame of video V. Then, we can get the coordinates *C* by

 $C = m_{face_detection}(v_i)$. Finally, we mask the face with Gaussian blur according to the coordinates *C* of the face. The examples are presented in Fig. 1.

Regarding audio de-identification, our goal is to remove the identity information in the audio while preserving the emotions. Therefore, we follow the method described in [43] and utilize the McAdams coefficient-based approach [34] to ensure broad applicability and ease of implementation. Specifically, the process of anonymization using the McAdams coefficient is as follows. For an input audio signal $\mathbf{A} = \{a_1, a_2, ..., a_{N_{sample}}\}$ with a sampling frequency f_s , we divide it into overlapping frames of length T_{win} milliseconds and step size T_{shift} milliseconds, denoted as $\hat{A} = \{\hat{a}_1, \hat{a}_2, ..., \hat{a}_{N_{frame}}\}$. These frames are then processed with a Hanning window, resulting in windowed frame signals $\hat{S}^w = \{\hat{a}_1^w, \hat{a}_2^w, ..., \hat{a}_{N_{frame}}^w\}$. Then, we utilize Linear Predictive Coding (LPC) analysis and Transfer Function to Zeroes, Poles, and Gain (tf2zpk) to obtain the corresponding poles $P = \{p_1, p_2, ..., p_{N_{frame}}\}$.

$$c_i, r_i = \text{LPC}(\hat{s}_i^w, lp_order), \tag{1}$$

$$z_i, p_i, k_i = \text{tf2zpk}(c_i), \tag{2}$$

where lp_order is the order of the LPC analysis, c_i, r_i represent the LPC coefficients and the residuals. Then, we adjust the angle θ_i of the poles p_i using the McAdams coefficient λ to obtain the new angle $\theta_i^{new} = \theta_i^{\lambda}$. Then, based on the new angle θ_i^{new} and the original amplitude of the poles, we calculate the new poles p_i^{new} . Then, following the reverse process, A^{new} is reconstructed. The waveform example of de-identity audio is presented in Fig. 3.

Data annotation. After data collection and de-identification, each video sequence needs to be annotated with NFBL. According to a study on human behavior [39], NFBL includes self-manipulations (e.g., scratching the nose and touching the ear), manipulation of objects (e.g., playing with rings, pens, and papers), and self-protection behaviors (e.g., rubbing the eyes, folding arms, or rhythmically moving legs). The defined NFBL classes are presented in Fig. 4. The annotation job is carried out in the following stages: First, the NFBL is identified from the collected videos, including start and end times, as well as the NFBL type (clip-level) by trained annotators. We consider "positive" and "negative" as two emotional categories

²https://www.youtube.com/@australianopen

³https://www.youtube.com/@bnpparibasopen

⁴http://dlib.net/

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(c) spectrogram of original audio (d) spectrogram of de-identity audio

Figure 3: Comparison of the waveform of original with deidentity audio of a sample (sample id 275) of *EALD*

to start with, and the labels are based on the objective fact that the game is won (positive emotion) or lost (negative emotion). After the initial annotation, we perform a review to ensure the accuracy of the labels.

Table 2: Properties of the proposed EALD.

Properties	EALD
Number of videos	275
Number of annotated NFBL	16180
Resolution	1280×720
Frame rate	32
Subjects	40 Male, 42 Female
Nationality	30
Total duration	32.15 hours
Average duration	7.02 mins

2.3 Dataset Statistics and Properties

In the proposed dataset *EALD*, we collect 275 (74 Lost, 201 Won) post-game interview videos as shown in Table. 2. The difference between the proposed dataset and existing datasets can be summarized as follows: 1) long sequential data. To meet our needs for long sequential emotion analysis, the average duration of collected videos is 7.02 minutes. Each video has a resolution of 1280×720 of 32 Frame Per Second (FPS); 2) identity-free: We remove the identity information for the video and audio as described in Sec. 2.2; 3) diversity: The expression for different people may be different because of cultural background, particularly in body language. It is worth emphasizing that the proposed *EALD* is well diverse in the aspects of gender and nationality. For example, the athletes in the collected video from different countries around the world (e.g., Australia, China, Japan, Slovak, South Africa, USA). More importantly, the gender of the athletes is well-balanced (40 Male, 42 Female).

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Regarding the annotation of NFBL, we provide 16,180 clips of various NFBL with timestamps in the proposed dataset. The clips range from 0.08 seconds to 184.50 seconds. The distribution of different NFBL is shown in Fig. 4. As one may observe, the proportion of N9 (Biting nails) and N5 (Covering face) is significantly higher than that of other categories.

3 EALD-MLLM

with 40 males and 42 females.

For humans, it is possible to identify the emotions of others through the visual system, the auditory system, or by combining both. Recently, Multimodal Large Language Models (MLLM) have shown their robust performance in many sub-stream tasks. MLLM combines the capabilities of large language models with the ability to understand content across multiple modalities, such as text, images, audio, and video. Next, we will introduce an MLLM-based solution for emotion analysis.

3.1 Framework

The framework of the proposed EALD-MLLM solution for emotion analysis is illustrated in Fig.5. As we can see, the proposed solution consists of three stages. Formally, given a video V, corresponding audio A and corresponding NFBL N. In stage one, we perform de-identification to remove the identity information. Thus, the de-identity video \hat{V} and audio \hat{A} can be obtained. More details of de-identification can be found in Sec.2.2.

MLLM inference. In stage two, we employ Video-LLaMA [46] as our MLLM for emotion analysis inference, utilizing de-identity video $\hat{\mathbf{V}}$, audio $\hat{\mathbf{A}}$, and NFBL *N* as inputs. We chose Video-LLaMA because it aligns different modality data (e.g., video, audio, and text), meeting our requirements. Specifically, Video-LLaMA incorporates a pre-trained image encoder into a video encoder known as the Video Q-former, enabling it to learn visual queries, and utilizes ImageBind [19] as the pre-trained audio encoder, introducing an Audio Q-former to learn auditory queries. Finally, it feeds visual and auditory queries to the pre-trained large language model LLaMA [44] to generate responses.

Since **MLLM** is determined, we simply input de-identity video $\hat{\mathbf{V}}$ and audio $\hat{\mathbf{A}}$ into **MLLM**. Specifically, we uniformly sample M frames from $\hat{\mathbf{V}}$ to form visual input $\bar{\mathbf{V}} = {\hat{v}_1, \hat{v}_2, ..., \hat{v}_m}$, where \hat{v}_i denotes a frame in $\hat{\mathbf{V}}$. For audio, we sample S segments of 2-second audio clips. Next, we convert each of these 2-second audio clips into spectrograms \bar{a}_i using 128 mel-spectrogram bins to form audio



Figure 4: The distribution of various non-facial body language in *EALD*. The y-axis represents the frequency, and the x-axis represents the NFBL. The orange, green, and blue colors represent different types of NFBL, namely, Self-manipulations, Manipulation (touching) objects, and Self-protection behaviors, respectively. Viewed digitally and zoom-in may be better.



Figure 5: The pipeline of the proposed EALD-MLLM.

Video	Audio	NFBL	Accuracy(%)↑	F-score(%)↑	Precision(%)↑	Confidence score↑
\checkmark			49.09	63.91	66.31	6.08
\checkmark	\checkmark		53.45	67.51	68.91	6.83
\checkmark	\checkmark	\checkmark	58.54	70.77	68.65	7.29

Table 3: Ablation study of the EALD-MLLM on full EALD.

input $\bar{\mathbf{A}} = \{\bar{a}_1, \bar{a}_2, ..., \bar{a}_s\}$. Regarding NFBL *N*, we utilize it as text input. Finally, the response *R* is **MLLM**($\bar{\mathbf{V}}, \bar{\mathbf{A}}, N$). It is noted that proposing another new MLLM model is not our goal; instead, we

aim to utilize MLLM for long-sequential emotion analysis. Therefore, we choose to use the existing model Video-LLaMA instead of proposing a new MLLM model. Additionally, although the current selection of MLLM may not be optimal, it still achieved satisfactory

Method	Pretraining dataset	Modality	Zero-shot?	Accuracy(%)↑	F-score(%)↑	Precision(%)↑
SlowFast [16]	K400	Video	×	52.70	42.62	54.10
TSM [29]	ImageNet+K400	Video	×	51.35	60.87	50.91
TimeSformer [4]	ImageNet+K400	Video	×	48.65	61.22	49.18
Video-Swin [32]	ImageNet+K400	Video	×	51.35	63.27	50.82
BEATs [8]	AudioSet	Audio	×	50.00	66.67	50.00
EALD-MLLM (ours)	Webvid+VideoChat	Video + Audio + NFBL	\checkmark	58.10	66.67	55.35

Table 4: Comparative experiment on part of EALD.

results, as shown in Table. 4. Thus, we stop further optimizing it. If one may interested in MLLM, please refer to [47].

LLM judgement. Although we can get a reasonable response $R = \text{MLLM}(\bar{\mathbf{V}}, \bar{\mathbf{A}}, N)$, MLLM's response is more about descriptive content than emotion analysis. We think the response is related to the instruction dataset. Because Video-LLaMA is instruction-tuned on Visual Question Answering (VQA) datasets while not on emotion analysis datasets. However, the generated response R is still helpful for emotion analysis because it contains descriptive information about visual, audio, and body language. Therefore, we opt for ChatGPT [40] from emotion estimation based on the given response R. More precisely, we utilize gpt-3.5-turbo-0125 to generate a response that includes the estimation of emotion and the confidence score. The used prompt for ChatGPT is present in Fig.5 (Stage 3).

4 EXPERIMENTAL RESULT

In this section, we will introduce the ablation study and comparative study of the proposed MLLM solution EALD-MLLM.

4.1 Experimental settings

Metrics. As the emotion analysis *EALD* can be regarded as a binary classification problem, we employ accuracy, precision, and F-score as metrics to assess the performance of different models, as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN},$$
(3)

$$\text{Recall} = \frac{TP}{TP + FN},\tag{4}$$

$$Precision = \frac{TP}{TP + FP},$$
(5)

$$F1\text{-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}},$$
(6)

where True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) represent the instances accurately predicted as positive, instances correctly predicted as negative, indicate instances inaccurately predicted as positive, and instances inaccurately predicted as negative respectively.

Inference. As described in Sec.3.1, the proposed EALD-MLLM solution for emotion analysis utilizes Video-LLaMA [46] and Chat-GPT [40] without training. For the inputs of Video-LLaMA, we uniformly sample 32 frames for each video and sample audio clips every 2 seconds for each audio. As for NFBL, we directly use the annotation of NFBL and input it as the text form for Video-LLaMA.

4.2 Ablation Study

Before comparing the EALD-MLLM with other approaches, three key questions need to be addressed: 1) Do we need multimodal data for long-sequential video emotion analysis? 2) Is NFBL helpful for long-sequential video emotion analysis? 3) Does long sequential emotion analysis more accurately reflect genuine emotions? Thus, we conduct an ablation study to investigate these three questions. Since all experiments in the ablation study are conducted under the zero-shot scenario, we use the full data of the proposed *EALD*.

Dose multimodal data beneficial for emotion analysis? We begin with video input alone as the base model, then gradually integrate audio and NFBL. As shown in Table 3, relying solely on visual cues for detecting emotions proves challenging, with an accuracy below 50%. In contrast, incorporating audio data significantly improves the model's accuracy by about 4%. Therefore, we believe that both video and audio are crucial modalities as they can provide rich information for long-sequential emotion analysis. Utilizing multimodal techniques that combine the features of video and audio is advantageous for emotion analysis.

Dose non-facial body language Helpful? As shown in Table 3, combining NFBL can significantly improve performance (by 5% in accuracy). Additionally, it enhances the confidence score, which represents the descriptive content generated by Video-LLaMA and provides more informative insights for emotion analysis.

Does emotion analysis over a long sequential period more accurately reflect people's genuine emotions? As shown in the supplementary materials, when we compare instantaneous (short sequence) and long sequential video emotion analysis, longterm analysis is better able to reflect people's actual emotional states comprehensively. Short-term recognition may be influenced by specific moments, whereas long-term observation can better capture emotional fluctuations and trends, thus providing more accurate emotional analysis. Long-term emotion recognition also allows for a deeper understanding of the context and underlying factors influencing individuals' emotional states. This contextual richness further enhances the accuracy and depth of the emotional analysis over time. Due to limited space, please refer to the details in the supplementary materials.

4.3 Benchmark Evaluation

To validate the effectiveness of the proposed EALD-MLLM solution, we selected several single-modal models for comparison: 1) for video-based models, we chose Video-Swin-Transformer (Video-Swin) [32], TSM [29], TimeSformer [4], and SlowFast [16]; 2) for





audio-based models, we selected BEATs [8]. Typically, these methods require training before they can be tested on the proposed dataset. Thus, we randomly selected data from the dataset for the comparative experiment to reduce the impact of data imbalance. Specifically, we used 72 videos (36 Negative, 36 Positive) for training and 74 videos (37 Negative, 37 Positive) for testing. The video IDs of the selected dataset can be found in the Appendix. Considering the size of the training dataset is relatively small, we opted for linear probing to train these models. Thus, we only trained the last classification layer and froze the rest of the pre-trained layers. Video-Swin [32], TSM [29], TimeSformer [4] and are pre-trained on the Kinetics-400 [6] and ImageNet [9]. SlowFast [16] is pre-trained on the Kinetics-400 [6]. Then, we employ an AdamW optimizer for 30 epochs using a cosine decay learning rate scheduler and 2.5 epochs of linear warm-up. The audio recognition model BEATs [8] is pre-trained on the AudioSet [18]. Then, we employ an AdamW optimizer for 30 epochs with EarlyStopping. It is noted that our audio files typically have a duration of about 10 minutes, which can be unacceptable for conventional audio classification models to handle. To enhance the feasibility of training, we resample the original audio from a sampling rate of 16,000 Hz to 320 Hz.

The results displayed in Table 4 indicate that classic video or audio recognition models exhibit relatively poor performance, achieving an accuracy of approximately 50%. This also proves that using only one modality is not suitable for long-sequential emotion analysis. In contrast, our proposed solution, EALD-MLLM, achieves superior performance, boasting a 5% increase in accuracy. The qualitative results are present in Fig. 6 and Fig. 7.

5 LIMITATION

As one can see, although the proposed EALD-MLLM outperforms other models, its performance is not very high, as shown in Table 4. This also proves that the proposed EALD dataset designed for longsequential emotion analysis in this paper is challenging. In Table 3, we validate that Non-Facial Body Language (NFBL) is an important clue for long-sequential emotion analysis. However, we use the annotation of NFBL directly. To our knowledge, detecting these NFBLs in real applications is not a simple task, as they often occur quickly and are difficult to recognize. Therefore, we plan to study the detection of NFBLs in the future. Furthermore, the EALD-MLLM approach follows a two-stage methodology. Because the employed MlLM (Video-LLaMA) is specifically designed for general purposes

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User: Please play the role of human praxeology expert. We will provide you with a video, audio and body languages (give in json) of an athlete who attending a post-game interview. Please only focus on his or her series of body languages and voice of tone. You must to infer the emotion of this athlete (Positive or Negative) of the athlete. + <mark>video</mark> + <mark>audio</mark>

👔 Response: In this video, a young woman is seen talking to a reporter on a blue couch. Her body language is calm, with her arms relaxed and her legs crossed. Her voice tone is serious and professional as she answers questions. The young woman seems very focused, giving clear answers to each question. Her body language remains calm, with only occasional movements of her leas or arms to punctuate her words. In terms of visual content, the young woman is seen sitting on a blue couch in front of a large microphone. There is a large black microscope in front of her, and there are also other objects, such as a large brown bag and a white and black cup with a red stripe on it, in the background. The room is also decorated with a large, blue wall with various other objects in it, such as a large picture frame, a large book, and several other books. In terms of audio content, the young woman's voice is heard clearly and confidently answering the reporter's questions. There are also sounds of the reporter's voice asking questions and the camera clicking as it takes photos of the interview. The video is in 4k and has clear audio and visuals throughout.

User: Please play the role of an emotion recognition expert. Please recognize the sentiments evoked. Please sort the provided categories from high to low according to the similarity. Here are the optional categories: {Positive, Negative}. Give the confidence score (1 - 10) of your answer. + Response

Based on the provided description, the sentiments evoked from the video could be categorized as follows: Positive: The young woman appears focused, calm, and professional throughout the interview, giving clear and confident answers to the reporter's questions. Confidence Scores: Positive: 8 Neutral: 7

Figure 7: Example case of without Non-facial Body Language.

м 👔 Response: The video opens with a young man wearing a red shirt speaking at a podium in front of a microphone. The camera captures a close-up of his face as he speaks, revealing his facial expressions and tone of voice. The young man sits at a table, talking at a podium while at the conference. He stands at a podium, his face visible in the shot, before taking a seat at the microphone. The young man wears a red shirt and black pants throughout the video. In the second part of the video, the young man is speaking at a podium, his face in the frame. He stands behind a microphone, his face visible in the shot, talking at a podium. His red shirt is visible, as is a black microphone he holds in his hand. At the third part of the video, the young man sits at a table, holding a microphone while speaking. He stands at a podium, talking to the press, his red shirt visible. He sits at a table, wearing a red shirt, while talking at a podium. The young man takes a seat, wearing a red shirt and black pants, at the podium while talking to the press

Figure 8: Example case of failure MLLM response. The response lacks the information for emotion analysis.

and is not optimized for emotion analysis. As shown in Fig.8, in some cases, the generated response by MLLM does not provide useful information for emotion analysis while paying more attention to the environment information. Therefore, we have to use another LLM (ChatGPT) to refine the response and estimate the final emotion. We plan to propose an end-to-end MLLM model for long-sequential emotion analysis in the future.

6 CONCLUSION

In this paper, we introduce a novel dataset for Emotion Analysis in Long-sequential and De-identified termed EALD to solve the limitations of the existing datasets: 1) lack of long sequential video for emotion analysis; 2) sensitive data (e.g., de-identity facial, speech, and ECG signals) involved. The EALD dataset comprises 275 videos, each with an average duration of 7 minutes. It is worth emphasizing that we perform de-identification processing on all videos and audio. In addition to providing annotations of the overall emotional state of each video, we also provide the Non-Facial Body Language (NFBL) annotations for each player. Furthermore, we propose a solution utilizing a Multimodal Large Language Model (MLLM) called EALD-MLMM. Experimental results demonstrate: 1) MLLMs can achieve comparable performance to supervised single-modal models, even in zero-shot scenarios; 2) NFBL serves as an important identity-free cue in the analysis of emotions over long-sequential.

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Supplementary Materials: EALD-MLLM: Emotion Analysis in Long-sequential and De-identity videos with Multi-modal Large Language Model

1 EXPERIMENTS

Does emotion analysis over a long sequential period more accurately reflect people's genuine emotions? As aforementioned, we propose the *EALD* dataset for long sequential emotion analysis because short sequential videos or audios may not reflect authentic emotions. Therefore, we conduct an experiment to verify our assumption. Specifically, we randomly extracted sequences of varying lengths from videos, audio, and Non-Facial Body Language (NFBL). The length of the sequence is determined by the extraction proportion and the duration of the data. Then, we evaluated the different sequence data using the proposed EALD-MLLM. It is noted that we repeated this experiment five times with different seeds, except for the experiment with 100% proportion sequences. The average results are shown in Table 1.

Table 1: Ablation study on videos of different sequentiallengths for emotion analysis on full EALD.

Sequence length (%)	Accuracy(%)↑	F-score(%)↑	Precision(%)↑	Score↑
20	54.25	68.76	68.54	6.98
50	55.27	69.17	69.69	7.05
70	56.72	70.47	70.29	7.11
100	58.54	70.77	68.65	7.29

As one may observe, when comparing short sequence (20% proportion length) and long sequential (100% proportion length) video emotion analyses, long-term analysis is better able to comprehensively reflect people's actual emotional states, with an accuracy boost of at least 4%. Short-term emotion analysis may be influenced by particular moments, whereas long-term observation can better capture emotional fluctuations and trends, thus providing a more accurate emotional analysis. Long-term emotion analysis fosters a profound comprehension of contextual nuances and underlying factors shaping individuals' emotional states. This contextual richness significantly amplifies the accuracy and depth of emotional analysis over time. For example, in early childhood mental health consultation [6], long sequential emotional analysis can help counselors better understand children's emotional states. Because children's emotional states are more easily triggered by environments or other factors. Therefore, it is necessary to estimate their emotion comprehensively. For instance, in the field of early childhood mental health consultation [6], conducting long sequential emotional analyses can assist counselors in gaining a better understanding of children's emotional states, as environmental or other factors can easily trigger changes in children's emotions. Therefore, it is necessary to assess their emotions comprehensively.

Does MLLMs work better? In this paper, we introduce EALD-MLLM, which is a Multimodal Large Language Model (MLLM) solution for analyzing long sequential emotions. We utilize the existing

MLLM (Video-LLaMA [9]) to generate responses by feeding Video-LLaMA with de-identity inputs (video, audio, and NFBL) for further emotion analysis. In addition to evaluating Video-LLaMA, we also conduct an experiment on different MLLM backbones, such as PandaGPT [7].

The experimental results are presented in Table 2 and Table 3. Video-LLaMA and PandaGPT exhibit different performances on various protocols. We believe this discrepancy stems from the utilization of different LLMs as backbones, such as Vicuna [10] and LLaMA [8], as well as variations in pre-training datasets. It is worth emphasizing that our goal is not to propose another MLLM model but to evaluate the effectiveness of MLLMs in a zero-shot way for emotion analysis. As shown in Table 3, regardless of which MLLM is used, the proposed MLLM solution performs better than other single-modal models.

As aforementioned, one of the aims of

2 EXPERIMENT PROTOCOL

We propose two protocols for evaluating *EALD*. Specifically, we utilize all available data from *EALD* to evaluate MLLMs in a zero-shot manner. This experimental protocol is called *full EALD*. Additionally, to compare supervised models, we extract balanced data (where the number of negative and positive labeled data is equal) from the proposed dataset to mitigate potential bias for supervised models. This experimental protocol is called *part of EALD*. The data IDs of the training set and testing set of *part of EALD* are as follows:

- training set: [2, 7, 10, 12, 13, 16, 22, 29, 31, 38, 45, 47, 48, 49, 51, 60, 61, 66, 67, 70, 78, 83, 87, 88, 92, 97, 114, 115, 119, 120, 121, 123, 125, 130, 131, 132, 133, 136, 139, 145, 146, 148, 149, 150, 153, 154, 157, 169, 175, 176, 180, 183, 189, 194, 195, 199, 203, 204, 213, 214, 215, 235, 245, 246, 247, 248, 253, 256, 265, 269, 272, 274]
- testing set: [0, 1, 6, 15, 17, 23, 30, 32, 35, 41, 42, 50, 52, 53, 62, 71, 72, 76, 82, 84, 85, 86, 90, 93, 96, 99, 100, 101, 105, 107, 109, 112, 113, 116, 117, 122, 124, 129, 134, 135, 155, 160, 177, 179, 187, 191, 192, 193, 197, 198, 201, 206, 208, 217, 224, 227, 229, 234, 236, 241, 242, 243, 244, 250, 251, 252, 257, 260, 261, 263, 266, 268, 270, 273]

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Table 2: Ablation study of different MLLM of EALD-MLLM on full EALD.

Method	MLLM	Accuracy(%)↑	F-score(%)↑	Precision(%)↑	Score↑
EALD-MLLM	PandaGPTL	64.00	76.25	73.61	8.89
EALD-MLLM	Video-LLaMA	58.54	70.77	68.65	7.29

Table 3: Comparative experiment on part of EALD.

Method	MLLM	Pretraining dataset	Modality	Zero-shot?	Accuracy(%)↑	F-score(%)↑	Precision(%)↑
SlowFast [3]	-	K400	V	×	52.70	42.62	54.10
TSM [4]	-	ImageNet+K400	V	×	51.35	60.87	50.91
TimeSformer [1]	-	ImageNet+K400	V	×	48.65	61.22	49.18
Video-Swin [5]	-	ImageNet+K400	V	×	51.35	63.27	50.82
BEATs [2]	-	AudioSet	Α	×	50.00	66.67	50.00
EALD-MLLM (Ours)	PandaGPT	llava-instruct + cc-sbu-align	V+A+L	\checkmark	55.41	65.26	53.44
EALD-MLLM (Ours)	Video-LLaMA	Webvid+VideoChat	V+A+L	\checkmark	58.10	66.67	55.35

Note: V, A, and L denote video, audio, and non-facial body language, respectively.

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