Naturalistic Emotion Recognition Using EEG and Eye Movements

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Abstract. Emotion recognition in affective brain-computer interfaces (aBCI) has emerged as a prominent research area. However, existing experimental paradigms for collecting emotional data often rely on stimuli-based elicitation, which may not accurately reflect emotions experienced in everyday life. Moreover, these paradigms are limited in terms of stimulus types and lack investigation into decoding naturalistic emotional states. To address these limitations, we propose a novel experimental paradigm that enables the recording of physiological signals in a more natural way. In our approach, emotions are allowed to arise spontaneously, unrestricted by specific experimental activities. Participants have the autonomy to determine the start and end of each recording session and provide corresponding emotion label. Over a period of three months, we recruited six subjects and collected data through multiple recording sessions per subject. We utilized electroencephalogram (EEG) and eye movement signals in both subject-dependent and cross-subject settings. In the subject-dependent unimodal condition, our attentive simple graph convolutional network (ASGC) achieved the highest accuracy of 76.32% for emotion recognition based on EEG data. For the cross-subject unimodal condition, our domain adversarial neural network (DANN) outperformed other models, achieving an average accuracy of 71.90% based on EEG data. These experimental results demonstrate the feasibility of recognizing emotions in naturalistic settings. The proposed experimental paradigm holds significant potential for advancing emotion recognition in various practical applications. By allowing emotions to unfold naturally, our approach enables the future emergence of more robust and applicable emotion recognition models in the field of aBCI.

Keywords: Affective Brain-computer Interfaces · Naturalistic Emotion Recognition · EEG · Eye Movements

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1 Introduction

In the field of mental illness diagnosis, scale tests and empirical judgments by physicians are often considered the gold standard. However, patients may provide false answers and conceal their true condition for various reasons. As a result, there is a growing interest in objective methods for determining emotional and mental states based on patients' physiological signals [1]. With the rapid advancement of artificial intelligence technology, emotional intelligence (EI) has shown great potential in medical and other domains, offering the possibility of emotion recognition based on physiological signals [2].

In recent studies, EEG and eye movement signals have played a significant role in capturing human emotions [3–5]. In the field of aBCI, existing emotion recognition paradigms based on physiological signals typically rely on passive elicitation, which can place a considerable burden on subjects [6]. These paradigms involve collecting signals in controlled laboratory environments while evoking emotions through specific stimuli. Subjects are immersed in emotional stimuli such as pictures, audio, and videos to induce specific emotional states corresponding to the stimuli. The limited experimental settings are due to the lack of technology for collecting high-quality labeled emotion data in daily life, limiting the experimentation to specific tasks conducted in a laboratory. While these experiments fall under the emotion elicitation experiment paradigm and have demonstrated that EEG and eye movement signals can detect human emotions, they still have two limitations: 1) Emotions are passively evoked in unnatural states, and 2) The stimuli are limited to pictures and videos, with the paradigm reliant on stimuli.

To address these limitations, we propose a novel paradigm for emotion recognition that operates in natural states without relying on passive stimuli. Our paradigm introduces several key innovations: 1) Emotions are actively evoked rather than relying on stimuli, aiming to closely resemble daily life experiences; 2) There are no limitations on the forms of stimuli used; 3) The data collection process does not require consistency across subjects, allowing for a diversity of data; and 4) The emotion labels in our collected data are more accurate as they are provided by the subjects themselves.

To validate the feasibility of recognizing emotions in naturalistic settings using our paradigm, we collected EEG and eye movement signals from six subjects engaged in daily emotional activities. Subsequently, we conducted a series of experiments using commonly used models in aBCI. The results demonstrated the viability of recognizing emotions in a naturalistic manner.

2 Methods

2.1 Paradigm Design

The EEG signals were recorded using the DSI-24 Dry Electrode EEG Cap, while eye movement signals were recorded with the Tobii Screen-based Eye Tracker. To ensure that our experiments closely resembled the daily lives of the subjects, we selected six graduate students (three males and three females; Avg. of ages: 24.33, Std. of ages: 1.97). The experiments took place in proximity to their workplaces. The start and end of the experiments were determined by the subjects themselves. The objective of the experiments was to record the subjects' natural emotional states during their daily activities, which included watching movies, reading, playing games, etc.

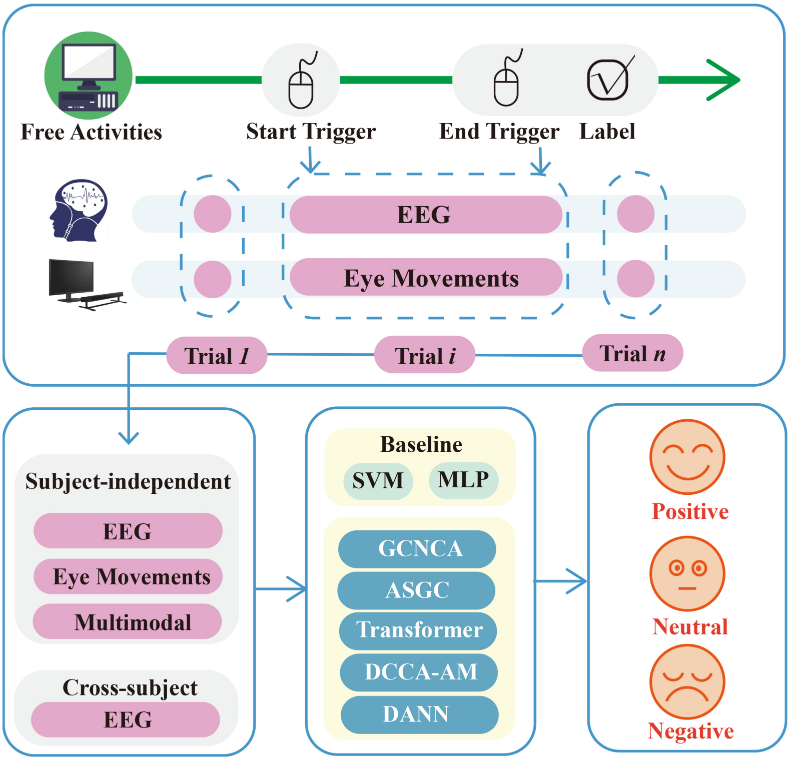

Fig. 1. The procedure of data collecting and emotion recognition from collected signals.

Each experiment consisted of multiple trials. The subjects initiated each trial by clicking the mouse to send triggers. When the subjects perceived a significant change in their emotions, they would click the mouse to send the start trigger, and they would label the trial after sending the end trigger. Several trials were recorded within a single experiment, corresponding to the subjects' emotional states. The subject would also retrace the entire experiment and refine the emotion labels at the end of each experiment. A brief illustration of the procedure is provided at the top of Fig. 1, while the bottom shows the models used for emotion recognition (Sect. 2.3) and our experiment settings (Sect. 3.1). After the experiment, the information of each trial included the start and end time, EEG and eye movement signals, emotion labels, and the activities performed.

We utilized the 2-D valence and arousal space [7] as a popular method for dimensional emotion representation. Based on the 2-D Emotion Wheel [8,9], we selected several common typical emotions as our emotion labels, including astonished, excited, delighted, happy, pleased, satisfied, relaxed, calm, sleepy, tired, droopy, bored, depressed, sad, miserable, frustrated, distressed, annoyed, angry, afraid, tense and alarmed. We defined the point at 0 arousal and 0 valence as neutral emotion, representing a state without positive or negative emotions. The subjects categorized their emotional states and rated the intensity of their emotions on a scale from 0 to 5, with 5 indicating the strongest intensity.

2.2 Data Preprocessing

For EEG signals, we extracted the differential entropy (DE) features [10] in the five frequency bands (δ: 1–3 Hz, θ: 4–7 Hz, α: 8–13 Hz, β: 14–30 Hz, and γ: 31–50 Hz) with non-overlapping 4-s time window from every sample. The DE feature on a one-dimensional signal X drawn from a Gaussian distribution $N(\mu, \delta^2)$ is defined as

$$h(X) = -\int_{-\infty}^{\infty} P(x)\log(P(x))dx = \frac{1}{2}\log(2\pi e\sigma^2), \tag{1}$$

where $P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$.

For eye movement signals, we extracted 23 features, including pupil diameter, fixation duration, saccade duration, blink duration and other event statistics. Detailed information of eye movement features is shown in Table 1.

Table 1. Details of the extracted eye movement features.

Eye movement parameters	Extracted features
Pupil diameter	Mean, standard deviation, DE features in four bands (0–0.2 Hz, 0.2–0.4 Hz, 0.4–0.6 Hz, 0.6–1 Hz)
Fixation duration	Mean, standard deviation, maximum
Saccade duration	Mean, standard deviation
Blink duration	Mean, standard deviation
Event statistics	Fixation frequency, saccade frequency, saccade latency, blink frequency

We carried out the emotion classification tasks with positive (emotions on the right side of the Emotion Wheel), negative (emotions on the left side of the Emotion Wheel) [8,9] and neutral emotions. Since the emotions were generated under the natural states of subjects, statistical results have shown an obvious data imbalance. Specifically, the numbers of neutral and negative trials were significantly less than that of positive ones. The statistics of different emotions for six subjects are shown in Table 2.

Table 2. The number of trials for EEG and eye movement data over six subjects. Each row represents statistic for each subject. Each column represents the statistic for positive, neutral and negative emotions.

Subject	EEG				Eye Movement			
	Positive	Neutral	Negative	Total	Positive	Neutral	Negative	Total
01	12	4	2	18	6	1	2	9
02	13	2	8	23	13	2	8	23
03	7	3	10	20	7	3	10	20
04	7	5	5	17	7	4	5	16
05	18	5	6	29	17	5	6	28
06	13	6	1	20	5	4	1	10

2.3 Models

We carefully selected several classification models commonly employed in emotion recognition based on EEG and eye movement signals, and we created appropriate training and test data sets tailored to their characteristics.

To effectively capture the interdependencies between input channels, we employed a graph convolutional network (GCN) that utilizes an adjacency matrix as a weight representation. This approach helps prevent overfitting among the channels of features and allows us to examine the significance of each channel. We treated the EEG and eye movement signals as graphs and applied a graph convolutional network with channel attention (GCNCA) model [11]. This model achieved notable performance in classifying three emotions: anger, surprise, and neutrality.

Similarly, we utilized an attentive simple graph convolutional network (ASGC) [12], a graph neural network-based model for processing EEG signals in tasks related to measuring human decision confidence. ASGC incorporates a learnable adjacency matrix and a simple graph convolutional network (SGC) to capture the coarse-grained relationships between EEG channels. It then employs a self-attention mechanism to capture the fine-grained relationships between channels. Finally, a confidence distribution loss is used to calculate the discrepancy between the predicted class distribution and the true confidence distribution. ASGC leverages the topological structure of EEG signal channels through graph neural networks, dynamically adjusts channel weights for each sample using self-attention, and addresses the challenges of limited training samples and ambiguous labels using a confidence distribution loss, as opposed to relying solely on simple one-hot encoding. The main process of the model is as follows.

Considering each EEG channel as a graph node, a feature matrix $\mathbf{X} \in \mathbb{R}^{n \times d}$ is constructed, where n denotes the number of channels and d denotes the feature dimension of each channel. Using the learnable adjacency matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ in SGC to capture the coarse-grained relationships between EEG channels, a high-dimensional feature matrix $\mathbf{Z} \in \mathbb{R}^{n \times h}$ is obtained, where h denotes the hidden layer size. Specifically, $\mathbf{Z}$ can be expressed as follows

$$\mathbf{Z} = \mathbf{S}^K \mathbf{X} \mathbf{W} = \tilde{\mathbf{X}} \mathbf{W}, \tag{2}$$

where $\mathbf{S} = \tilde{\mathbf{D}}^{-\frac{1}{2}} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-\frac{1}{2}}$, which is a normalized adjacency matrix. Meanwhile, $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}_n$, $\tilde{\mathbf{D}}_{ii} = \sum_j \tilde{\mathbf{A}}_{ij}$, $\mathbf{W} \in \mathbb{R}^{d \times h}$, and K represents the number of graph convolution layers. Then, the fine-grained relationships between EEG channels are captured by a self-attentive mechanism to obtain a weighted feature matrix $\hat{\mathbf{X}} \in \mathbb{R}^{n \times d}$. Specifically, $\hat{\mathbf{X}}$ can be denoted as

$$\hat{\mathbf{X}} = \text{softmax}\left(\mathbf{Z}\mathbf{Z}^T\right) \tilde{\mathbf{X}}, \tag{3}$$

where the softmax operation is normalized along each row so that each row sums to 1. Finally, the features of all nodes in $\hat{\mathbf{X}}$ are stitched into a vector, and the final class distribution is obtained by a fully connected layer and a softmax activation function.

Transformer and attention-based fusion have been employed to extract complementary properties of EEG and eye movements, which proved the effectiveness of Transformer on interpreting temporal resolution for both modalities [13]. Besides improving the performance of emotion recognition, Transformer achieves better parallelism than sequential models like recurrent neural networks (RNN).

For multimodal approaches, by extending deep canonical correlation analysis (DCCA) model, Liu *et al.* [14] introduced deep canonical correlation analysis with attention mechanism (DCCA-AM), which added an attention-based fusion module assisting the representations of multiple modalities by passing them to multiple nonlinear transform layers for better emotion recognition. Through adaptive weighted-sum fusion, attention-based fusion produced no worse results than weighted-sum fusion since the weights computed by attention-based fusion can be the same as the weighted-sum fusion. In addition, DCCA-AM can handle different dimensions, different distributions, different sampling rates, etc. It is worth mentioning that the loss function of DCCA-AM consists of two parts,

$$\mathbf{L} = \alpha \mathbf{L}_{cca} + \beta \mathbf{L}_{classification}, \tag{4}$$

where $\mathbf{L}$ is the final loss, α and β are trade-offs that control the synergy of the two loss terms. Let $\mathbf{X_1} \in \mathbb{R}^{N \times d_1}$ and $\mathbf{X_2} \in \mathbb{R}^{N \times d_2}$ be the instance matrices for two modalities respectively, where d_1 and d_2 represent the dimensions of two different features and N represents the number of instances. By constructing two deep neural networks f_1, f_2 with parameters W_1, W_2 respectively, we can obtain $\mathbf{L}_{cca}$ which represents the opposite number of correlations between EEG and eye movement signals.

$$\mathbf{L}_{cca} = -\operatorname{corr}(f_1(X_1; W_1), f_2(X_2; W_2)), \tag{5}$$

where $f_1(X_1; W_1)$ and $f_2(X_2; W_2)$ represent the outputs of the neural networks and corr represents the correlation between them. $\mathbf{L}_{classification}$ represents the cross entropy generated by fusing the EEG and eye movement signals into the fully connected layer.

For cross-subject models, domain adversarial neural network (DANN) [15] can extract the shared representations between the source domain and the target domain. It utilizes an ingenious gradient reversal layer (GRL) to bridge differences between domains, resulting in learning domain-independent features. In cross-subject emotion recognition, DANN can eliminate the differences across subjects and achieve better generalization performance.

3 Experiments and Results

3.1 Experiment Settings

In the field of emotion recognition in aBCI, two paradigms are commonly used: subject-dependent and cross-subject [14]. Previous studies have demonstrated that both EEG and eye movement modalities are effective in measuring the emotional state of subjects [4]. Furthermore, combining multiple modalities can provide a more comprehensive understanding of human emotions by capturing different aspects. Additionally, research has shown that different modalities can complement each other in emotion measurement [16]. However, collecting multimodal signals can be costlier due to the various types of signals involved. To ensure fair and comprehensive results, we conducted experiments using both unimodal and multimodal approaches.

In this study, we designed four experimental settings that constructed different training and test data: subject-dependent emotion recognition (including EEG-based, eye movement-based, and multimodal) and cross-subject emotion recognition based on EEG to testify our paradigm under different conditions. We utilized stratified K-fold cross-validation technique for the subject-dependent experiment settings, while leave-one-subject-out validation was applied for the cross-subject experiment setting. Notably, Table 2 indicates that there is only one trial in eye movement signals of *Subject 01* and both EEG, eye movement signals of *Subject 06* under neutral or negative emotion. For these three cases, we performed binary classification tasks, which are marked with stars in the result tables. The average and standard deviation of accuracies reported in the results do not include the binary classification tasks. In all four settings, we used traditional support vector machine (SVM) and multilayer perceptron (MLP) as the baseline classifiers.

Table 3. Results of different models on EEG-based subject-dependent unimodal emotion recognition task.

Model	SVM	MLP	GCNCA	Transformer	ASGC
01	60.53	58.99	67.16	72.69	83.79
02	77.53	77.02	71.20	64.63	72.21
03	67.35	72.01	69.55	91.81	90.54
04	46.45	38.21	40.15	58.81	55.94
05	79.77	70.98	64.58	89.01	79.11
*06	64.49	72.00	64.70	83.64	90.55
Avg.	66.33	63.44	62.53	75.39	**76.32**
Std.	12.13	13.94	**11.41**	13.06	11.82

* Binary classification due to the number of trials

3.2 Experimental Results

Subject-Dependent Emotion Recognition. In the subject-dependent unimodal EEG-based emotion recognition, we further evaluated the performance of GCNCA [11], Transformer [13], and ASGC [12]. From the results presented in Table 3, we can observe that ASGC and Transformer achieved the highest average accuracies of 76.32% and 75.39%, respectively, across the three classification tasks. When focusing on the subject-dependent unimodal eye movement-based emotion recognition, we considered GCNCA and Transformer as well. Table 4 illustrates that Transformer outperformed the other algorithms with an accuracy rate of 75.65%. Notably, the average accuracy of eye movement signals using Transformer was higher than that of EEG signals.

Table 4. Results of different models on eye movement-based subject-dependent unimodal emotion recognition task.

Model	SVM	MLP	GCNCA	Transformer
*01	97.12	99.74	97.38	99.19
02	44.22	54.57	70.62	72.76
03	72.51	71.29	77.04	84.09
04	39.32	62.80	50.73	57.99
05	71.67	69.27	77.09	87.75
*06	82.79	70.29	92.44	87.47
Avg.	56.93	64.48	68.87	**75.65**
Std.	15.26	**6.53**	10.80	11.60

* Binary classification due to the number of trials

For the multimodal setting, we fused EEG and eye movement signals and used Transformer and DCCA-AM [14] additionally. From Table 5, an average accuracy of 74.91% is obtained using DCCA-AM which achieves the best performance.

Table 5. Results of different models under subject-dependent multimodal setting.

Method	SVM	MLP	Transformer	DCCA-AM
*01	89.96	94.19	81.41	99.74
02	56.38	52.61	57.54	68.16
03	77.92	75.22	84.24	76.99
04	52.60	41.05	45.62	60.55
05	80.28	67.90	72.69	93.93
*06	64.49	80.83	81.77	74.62
Avg.	66.80	59.20	65.02	**74.91**
Std.	**12.41**	13.28	14.67	12.43

* Binary classification due to the number of trials

Cross-Subject Emotion Recognition. For the cross-subject emotion recognition task, we adopted leave-one-subject-out validation, where signals from one subject were used as the test set, and signals from the remaining subjects served as the training set. The corresponding results are displayed in Fig. 2. In this evaluation, we solely utilized EEG data, which aligns with the prevailing trend in current emotion recognition tasks based on physiological signals [17]. We also assessed the performance of GCNCA, Transformer, and DANN [15] models. Among these models, DANN with transfer learning techniques demonstrated the best performance, achieving an average accuracy of 71.90%. The success of DANN can be attributed to the effective utilization of the Gradient Reversal Layer (GRL) to minimize subject-related differences and extract domain-independent features. This approach eliminates the negative impact caused by inter-subject variations [18]. It is worth noting that the lowest performance was observed when the test set exclusively contained data from *Subject 04*.

Based on the aforementioned results, it is evident that the performance of *Subject 04* is consistently poor across all settings. The confusion matrices depicting the performance of *Subject 04* and *Subject 05* using ASGC, Transformer, and DCCA-AM models under the subject-dependent setting can be seen in Fig. 3. We can see that the results for *Subject 05* exhibit a significant effect across all three emotions, particularly positive emotion. Conversely, *Subject 04* demonstrates proficiency in recognizing neutral emotion but struggles with differentiating between positive and negative emotions when relying on EEG signals.

Upon closer examination of the source data, we discovered that, except for *Subject 04*, the remaining subjects actively or consciously engaged in activities

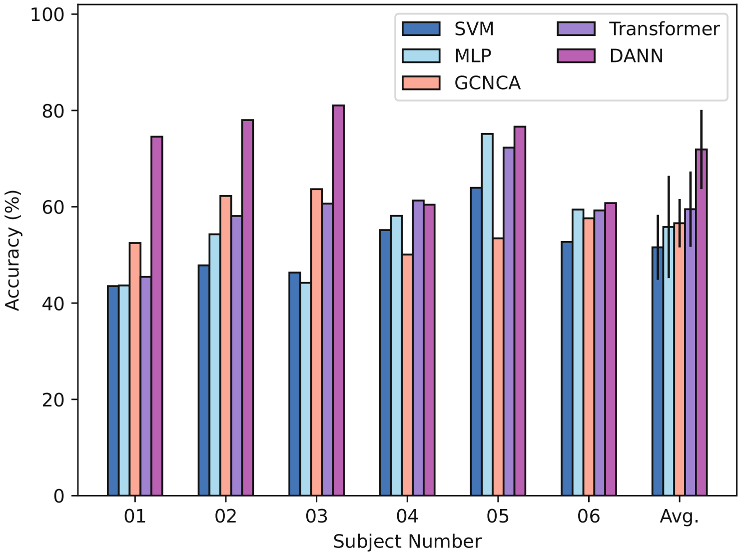

Fig. 2. The accuracies for each subject of each model and the averages under the cross-subject setting.

that evoked or elicited emotions, albeit in varying forms. Analyzing the activities among the subjects reveals that the other participants engaged in a wider range of behaviors, some of which led to noticeable changes in emotion, such as watching movies. In contrast, *Subject 04* predominantly participated in less emotionally stimulating activities, such as reading papers and performing official work. During these activities, emotions such as distress or calmness naturally

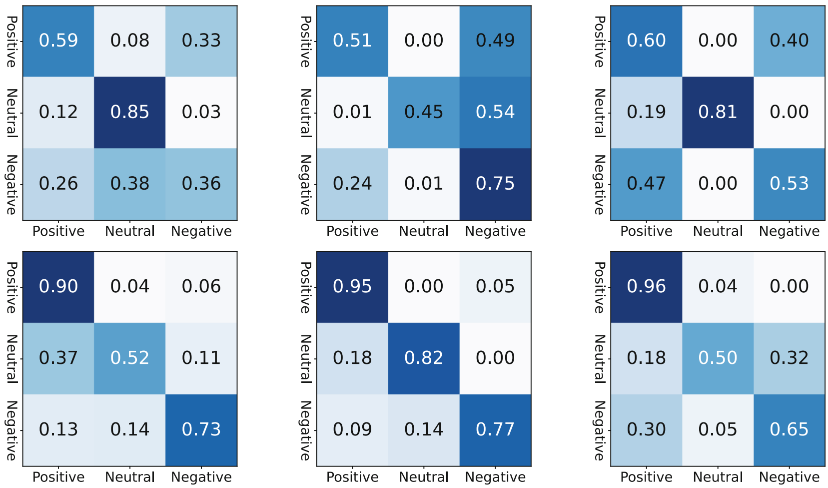

Fig. 3. Confusion matrices of *Subject 04* (top) and *Subject 05* (bottom) under subject-dependent experimental setting. Each column includes matrices under settings of EEG, eye movement and multimodal signals, respectively.

arise, but they are discontinuous and less apparent due to the subjects' primary focus on thinking or cognitive tasks.

4 Conclusions

In this paper, we have introduced a novel paradigm for emotion recognition and conducted a series of experiments to demonstrate its feasibility. Our approach involved recording various physiological signals while minimizing the influence of external stimuli, allowing us to capture naturally occurring emotions rather than relying on passively induced responses. The results obtained from our current models have shown promising performance, indicating the potential for non-passive stimuli-based emotion recognition in future applications, particularly in everyday contexts.

Moving forward, we plan to expand our dataset by collecting emotional data from a larger number of subjects under natural conditions. This will enable us to enhance the diversity and representativeness of our dataset, leading to more robust and reliable emotion recognition models. Additionally, we aim to develop efficient annotation tools that facilitate the continuous and natural collection of emotion labels, further improving the quality and granularity of our data.

By advancing our understanding of emotion recognition through non-passive stimuli and continuously refining our methodology, we believe our research will contribute to the development of more accurate and practical emotion recognition systems in various real-world applications.

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