

VLLMs Provide Better Context for Emotion Understanding Through Common Sense Reasoning

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Abstract. Recognising emotions in context involves identifying the apparent emotions of an individual, taking into account contextual cues from the surrounding scene. Previous approaches to this task have involved the design of explicit scene-encoding architectures or the incorporation of external scene-related information, such as captions. However, these methods often utilise limited contextual information or rely on intricate training pipelines. In this work, we leverage the groundbreaking capabilities of Vision-and-Large-Language Models (VLLMs) to enhance in-context emotion classification without introducing complexity to the training process in a two-stage approach. In the first stage, we propose prompting VLLMs to generate descriptions in natural language of the subject’s apparent emotion relative to the visual context. In the second stage, the descriptions are used as contextual information and, along with the image input, are used to train a transformer-based architecture that fuses text and visual features before the final classification task. Our experimental results show that the text and image features have complementary information, and our fused architecture significantly outperforms the individual modalities without any complex training methods. We evaluate our approach on three different datasets, namely, EMOTIC, CAER-S, and BoLD, and achieve state-of-the-art or comparable accuracy across all datasets and metrics compared to much more complex approaches. The code will be made publicly available on github: <https://github.com/NickyFot/EmoCommonSense.git>.

Keywords: Contextual Emotion Recognition, Vision-Language Models

1 Introduction

Recognising apparent emotion in human subjects is a primary task of affective computing, with several applications [1, 2]. While a considerable amount of research effort has been directed towards discerning apparent emotion from facial expressions, these approaches often overlook the crucial contextual information

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inherent in human emotional expression and perception [3,4]. In-context emotion recognition is a task that has seen some rise in popularity in recent years [5–9]; however, when compared to more established tasks like Facial Expression Recognition (FER), in-context recognition remains relatively unexplored even though it is more reflective of real-world settings. This imbalance may be attributed, in part, to the inherent complexity of the task, which can be challenging even for human experts. More specifically, emotions can be subjective both in expression and understanding; Ekman’s [10] basic emotions identify the universal human emotions but focus on facial expressions, completely disregarding other cues.

Context plays a pivotal role in identifying apparent emotion; a facial expression that may indicate surprise in one context might be read as fear in another. However, the physical environment, which may provide some contextual cues, can also vary significantly. This raises a challenge and introduces noise or bias to the emotion recognition problem, as it becomes harder for automated methods to identify meaningful patterns in the visual context. This challenge is further compounded by the typically limited number of samples available for affective tasks. Previous works mainly relied on heavy pipelines to effectively recognise emotion while isolating only relevant information from the context. Either using prior knowledge about emotional expression [6] or by leveraging prior information to create a context dictionary [9], these works include limited context information and may require more time and resources to train. Vision and Language have been explored generally in emotion recognition [11–14]; however, these have relied on existing sample level descriptions and are trained in a retrieval setting, where text descriptions do not inform the classification.

In this work, we propose a novel yet simple approach to predicting emotions in context by generating descriptions of the visual context in natural language. This approach leverages the generative capabilities of VLLMs to include relevant context information. More specifically, we propose a two-stage approach; first, we instruct LlaVa [15, 16]—a state-of-the-art VLLM—to describe the subject’s emotional state relative to the visual context. The generated responses contain information regarding emotions (*e.g.*, “smiling”) and contextual cues (*e.g.*, “two men discussing”). In the second stage, we use the image sample and the generated text to train a transformer-based architecture that fuses visual and text features before performing the final classification. In the ablation studies, we show that the two have complementary information, as the fused architecture performs better than the individual modalities. Finally, we evaluate our work on three popular emotions-in-context datasets and show that our method outperforms



Fig. 1: Example of an ambiguous facial expression from the EMOTIC [5] dataset. On the left, the apparent emotion of the cropped image is not clear and can be confused for discomfort. On the right, the context provides more cues to the ground truth: Pain, Sadness, Suffering

previous works and achieves state-of-the-art results, thus making our approach effective and novel without bells and whistles.

Our main contributions can be summarised as follows:

- We propose a two-stage approach to address predicting emotions in context. In the first stage, we leverage the vast amount of knowledge encoded implicitly inside the parameters of VLLMs for common sense reasoning for emotion recognition in the wild. Specifically, we propose generating contextual information in natural language of the image or video input. In the second stage, the generated text, along with visual features from the images or videos, are used to train a multi-modal architecture in the task of recognising emotions in context. Generating captions using VLLMs and using them as context is novel in the domain of affect and, specifically, in-context emotion recognition.
- Through extensive experimentation, we show that our approach achieves superior performance to individual modalities of text and image. We also show that our proposed method yields results comparable to or outperforming previous state-of-the-art (SOTA) using a simpler pipeline compared to previous works and without bells and whistles.
- Specifically, we conduct experiments on two static and one video in-context emotion recognition benchmarks, namely, the EMOTIC [5], CAER-S [7] and BoLD [17] datasets. We achieve performance comparable to previous SOTA on EMOTIC and outperform previous works on CAER-S and BoLD by 2% in terms of accuracy and over 4% in terms of mAP, respectively.

2 Related Work

2.1 Context Aware Emotion Recognition

Recognising emotions in context is relatively unexplored compared to the related task of FER. However, the task has seen some rise in popularity in recent years. The approaches can be roughly split into three main groups: (a) separating the image input into subject and context through cropping and masking, respectively [9, 18–23], (b) extracting features based on prior knowledge regarding emotional expression [6, 24, 25] or (c) examining label relationships [24, 26, 27]. All see an improvement when compared to uni-modal methods, where the input is either just the subject [28] or the entire image [29]; however, they also face several limitations. More specifically, it may be difficult for Machine Learning (ML) models to identify meaningful patterns when using the visual context without any constraint. Yang *et al.* [9] addresses this issue by essentially building a context dictionary based on clusters of visual features. However, such an approach may result in very coarse-grained features that do not adequately represent the visual context. On the other hand, features such as body pose [6] may omit interactions of the subject with others and the environment. Finally, Graph Neural Networks (GNN) [26, 27] and models that rely on label relationships [24] may result in poor generalisation due to the variable definitions of emotions.

2.2 Vision and Language Models

VLLMs have seen a rise in popularity for several vision-language tasks, such as Visual Question Answering (VQA) [30–36] and image-to-text retrieval [37, 38]. The idea behind such works is to represent the image input through natural language, which is more rich semantically. With the robust zero-shot capabilities of LLMs today, these captions can directly serve as a basis for reasoning about visual content, eliminating the need for visual features. Several works [31, 33, 35] leverage LLMs such as ChatGPT to improve the answer options of the VLLM, which in turn improves the VQA performance of the baseline architecture. Furthermore, works that do generate captions for image and video [31, 35–37] achieve good performance in terms of natural language generation on their respective tasks. However, the common sense and reasoning ability of VLLMs is relatively unexplored in the problem of in-context emotion recognition.

In an image-to-label retrieval setting, VLM has been used in emotion recognition with more focus on FER [11–14]. However, these so far have heavily relied on humans creating sample-level descriptions. In addition, only Zhang *et al.* [14] evaluate their method outside of FER and show some zero-shot generalisation capabilities that are, however, still lacking compared to supervised methods in in-context emotion recognition.

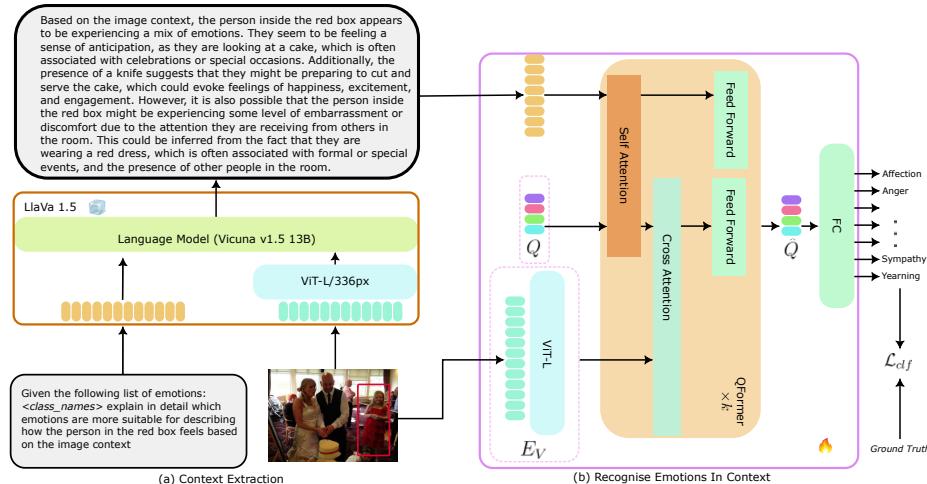


Fig. 2: An overview of our proposed method. We first use LlaVa-1.5 [16], a pre-trained VLLM, to extract language descriptions about the subject’s apparent emotion and context (left). The image-description pairs then train our architecture, consisting of a vision encoder (E_V), a set of learnable queries (Q), a Q-Former module and a Fully Connected layer that performs the final classification on the emotion prediction task. When bounding boxes are available in the annotations, we draw them on the input image so that the model differentiates the subjects and so that the image and generated description are aligned.

3 Methodology

An overview of the proposed method can be seen in Fig. 2. In a nutshell, we first use a large pre-trained VLLM, specifically LlaVa-1.5 [16], to extract subject-level descriptions of apparent emotion in natural language. Leveraging the common sense reasoning of VLLMs is a straightforward approach, which we consider a key strength of our method. We then use the image along with the text descriptions to train our architecture, which consists of a vision encoder (E_V), a set of learnable queries (Q) and a Q-Former module that performs: 1. cross-attention between the queries and the image tokens and 2. self-attention between the queries and the text tokens. Finally, a fully connected layer performs the final classification. The details of our generation method are outlined in Sec. 3.1, and the details of our architecture can be seen in Sec 3.2.

3.1 Building Context Descriptions in Natural Language

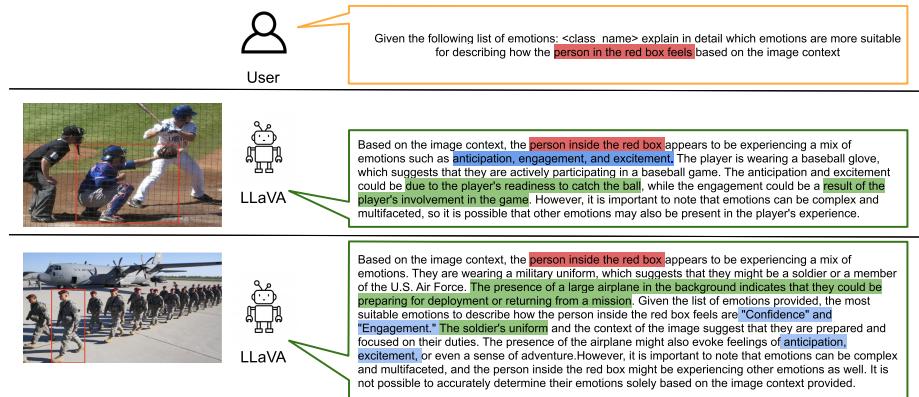


Fig. 3: Examples of contextual descriptions generated for the EMOTIC [5] dataset using LLaVa-1.5 [16]. The responses are typically person-specific, referring to “the person inside the red box,” with guesses regarding the person’s apparent emotion (marked with blue) and explanations for these guesses (marked with green).¹

Our proposed method is based upon incorporating context in the form of natural language to recognise emotion in the wild. However, such an annotation effort would be very labour-intensive for human annotators and impractical during inference. For this, we instruct LlaVa-1.5 [16] to generate sample-level descriptions that describe the apparent emotion of the subject in the given image context. We draw the bounding box on the image to specify for whom the description should be and formulate the prompt given to the VLLM as:

¹ Please refer to Supplementary material for more examples

```

USER: <image>
Given the following list of emotions: {class names},
please explain in detail which emotions are more suitable
for describing how the person in the red box feels
based on the image context.
ASSISTANT:

```

where {class names} are substituted for the list of class names available in each dataset. The intuition behind the proposed method is to generate emotionally aware descriptions of the subject and context. That is, rather than generating a generic text description that may be influenced by the input noise (*e.g.* irrelevant background objects), we guide the VLLM to provide descriptions and context relevant to the apparent emotion. When bounding boxes are not available, the prompt is modified as follows:

```

USER: <image>
Given the following list of emotions: {class names},
please explain in detail which emotions are more suitable
for describing how the person feels based on the image
context.
ASSISTANT:

```

Fig. 3 shows examples of generated sample-level descriptions. The descriptions often cover details about the emotional state of the subject as well as their interaction with others and the environment. We observe that these can include information regarding facial expressions (*e.g.*, “smiling”) and body pose (*e.g.*, “pointing at something”) or more generic context descriptions (*e.g.* “holding cards” or “having a conversation”) but ignore irrelevant details (*e.g.* detailed descriptions of clothing). While VLLMs are not trained specifically to recognise emotional cues, the large corpus of image-text pairs used to train them provides a strong basis to infer context.

The proposed method to extract sample-level descriptions can be adjusted for video input. In Fig. 2 (a), we see that LlaVa, similar to most VLLMs, is composed of a Large Language Model (LLM) that generates a response given language tokens (the prompt) and image tokens taken from a vision encoder –in this case, a Vision Transformer architecture (ViT) [39]. To extract a single description for each video sample, we propose averaging the visual tokens of the frames along the temporal dimension before forwarding them to the LLM. As the LLM module expects a set of spatial representations, we average the representations of the sampled frames for each spatial position.

3.2 Multi-modal In Context Emotion Prediction

Our architecture consists of four key components: a vision encoder (E_V), a set of learnable queries (Q), a Q-Former module [40], and finally, a fully connected layer that performs the final classification.

Vision Encoder The vision encoder consists of a ViT [39] module that is used to extract visual features. Given an image $X_v \in \mathbb{R}^{H \times W \times C}$, where $H \times W \times C$ represent the height, width and channels respectively, the image is first divided into $P \times P \times C$ non-overlapping flattened patches. The vision encoder E_V first maps the patches into visual tokens using a linear embedding layer so that each image is represented as a set of $\frac{H}{P} \times \frac{W}{P} \times D$ dimensional tokens, where D is the output dimension of the embedding layer. The visual tokens and a prepended learnable classification token are fed into a standard Transformer encoder layer. The last hidden state of the visual tokens is used as the visual features in the Q-Former module. More formally, we can express this as:

$$\hat{X}_v = E_V(X_v) \in \mathbb{R}^{(\frac{H}{P} \times \frac{W}{P} + 1) \times D} \quad (1)$$

Text Encoder To obtain the text features $X_t \in \mathbb{R}^{L \times d}$, the description generated as described in Sec 3.1 is tokenized to obtain L tokens which are then passed to a linear embedding layer to obtain a vector representation $\mathbf{t}_i \in \mathbb{R}^d$ representing each (sub)-token

$$\mathbf{t}_i = E_T(t_i), \mathbf{t}_i \in \mathbb{R}^d, \quad (2)$$

where d is the dimension of the text embedding layer and $X_t = \{\mathbf{t}_0, \dots, \mathbf{t}_L\}$.

Query Tokens The model is initialised with a set of learnable query tokens $Q \in \mathbb{R}^{N \times d}$, that match the dimensions of the text embeddings.

Q-Former The query tokens and the text features $X_t \in \mathbb{R}^{L \times d}$ are concatenated to form a single sequence:

$$Z = \text{Cat}[Q; X_t] \in \mathbb{R}^{(N+L) \times d} \quad (3)$$

This sequence is then fed to the Q-Former module. The Q-Former comprises of k self-attention layers and $k/2$ cross-attention layers (inserted every other transformer block). In each self-attention layer, the queries interact with each other and the description tokens via standard Multihead Self-Attention (MSA) [41]. The l -th Transformer layer processes the tokens $Z^{l-1} \in \mathbb{R}^{(N+L) \times d}$ of the previous layer using a series of MSA, Layer Normalization (LN), and MLP ($\mathbb{R}^d \rightarrow \mathbb{R}^{4d} \rightarrow \mathbb{R}^d$) layers as follows:

$$Y^l = \text{MSA}(\text{LN}(Z^{l-1})) + Z^{l-1}, \quad (4)$$

$$Z^l = \text{MLP}(\text{LN}(Y^l)) + Y^l \quad (5)$$

A single Self-Attention (SA) head is given by

$$y_t^l = \sum_{t'=0}^{N+L} \sigma \left\{ \frac{(q_t^l k_{t'}^l)}{\sqrt{d_h}} \right\} v_{t'}^l, t = 0, \dots, N+L, \quad (6)$$

where $\sigma(\cdot)$ is the softmax activation, $q_t^l, k_t^l, v_t^l \in \mathbb{R}^{d_h}$ are the query, key, and value vectors computed from z_t^l using embedding matrices $W_q, W_k, W_v \in \mathbb{R}^{d \times d_h}$, d_h is the scale factor in self-attention. Finally, the outputs of the h heads are concatenated and projected using embedding matrix $W_h \in \mathbb{R}^{h_{d_h} \times d}$. In each cross-attention layer, the queries (Q) interact with the image features through Multihead Cross-Attention (MCA), which is similar to MSA, but Q are the attention queries and \hat{X}_v are the keys and values.

The attended query vectors \hat{Q} and text tokens are further processed by 2 small feed-forward networks before the next Q-Former block. The output of the Q-Former – the last state of the attended query vectors – $\hat{Q} \in \mathbb{R}^{N \times d}$ is averaged pooled to obtain a single d -dimensional representation and fed to one fully connected layer that performs the final classification so that

$$\hat{y} = \text{Act}(\hat{Q}^T W_{cls}), \quad (7)$$

where $\hat{y} \in \mathbb{R}^C$ is the predicted class vector for C number of classes, W_{cls} is the weight matrix of the prediction layer, and $\text{Act}(\cdot)$ is the activation function.

4 Experimental Results

4.1 Experimental Setup

Datasets and Evaluation Metrics We evaluate the performance of our method on three different recently published challenging benchmarks, including two image datasets and a video dataset. **CAER-S** consists of 70k static images from clips of 79 TV shows. Each image is annotated for the seven basic emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. The dataset is randomly split into training (70%), validation (10%) and testing (20%). **EMOTIC** is composed of 23,571 images of 34,320 subjects in the wild. The annotations include bounding boxes and the annotation for 26 categorical emotions. The dataset is randomly split into training (70%), validation (10%) and testing (20%). **BoLD** is a video dataset of in-context human emotion recognition in the wild. It consists of 9,827 video clips and 13,239 subjects. Each subject annotation includes bounding boxes and labels for the 26 discreet categories of EMOTIC. For **evaluation**, we adhere to the metrics established by each respective dataset and report mean Average Precision (mAP) on EMOTIC and Bold. For the CAER-S, the standard classification accuracy is used for evaluation.

Implementation Details We initialise our backbone with the publicly available weights of InstructBLIP [42]² without the weights of the LLM. For training, we use the AdamW [43] optimiser. Our framework is trained for a maximum of 50 epochs with early stopping and a linear rate scheduler. For experiments on CAER-S and BoLD, we use weight decay of 0.1. Experiments in EMOTIC use

² We used the Salesforce/instructblip-flan-t5-xl checkpoint from huggingface. <https://huggingface.co/>

a weight decay of 0.0005 and a frozen vision encoder. As the weights of the backbone are initialised using a pre-trained network, we use variable learning rates for the classification layer and the backbone. Specifically, for CAER-S, we use an initial learning rate of 10^{-3} , and for Emotic and BoLD, we use an initial learning rate of 10^{-4} . The Q-Former and vision encoder learning rates are then adjusted by a factor of 0.1. For BoLD, the vision encoder learning rate is lower and is adjusted by a factor of 0.01. Finally, for experiments on BoLD, which is a video dataset, we sample 8 frames from each video and average pool their representations before passing them to the Q-Former. The batch size is set to 64 for all static datasets and 4 for dynamic datasets due to hardware constraints. As affective datasets are typically small and large models have a tendency to overfit, we add dropout in the attention layers with a probability of 0.4 on the Q-Former and 0.3 on the vision encoder. We pad the language descriptions to the longest in the batch. All models are trained end-to-end on a single NVIDIA Tesla A100 GPU using a PyTorch framework.

Generated Description Statistics We set the maximum number of new tokens to 300 during generation. The generated descriptions for the EMOTIC [5] training set have a mean of 157 tokens and a standard deviation of 45.52. Of all the samples, 25% have less than 124 tokens, and 75% have less than 183.

4.2 Ablation Studies

We perform a series of ablation studies to assess the effectiveness of our approach. Specifically, we systematically study the impact of individual components within our model architecture using the Emotic dataset [5]. Firstly, we examine the impact of different types of text descriptions in our pipeline. Then, we assess the impact of the bounding boxes in our setting in Tab. 1a (upper and bottom splits correspondingly). Additionally, given that our method integrates both text and visual modalities, we investigate the impact of each input modality independently (visual features, text features) as well as their fusion in Tab. 1b. Finally, for the Bold dataset [17], which is a video dataset, we conduct a separate investigation on the effect of the number of frames sampled as well as on the impact of the temporal modelling strategy in Tab. 2.

Generic vs Emo-Aware descriptions. We test if generic context (*i.e.* detailed description of an image) can serve as better contextual information than instructing LLaVa-1.5 to generate context based on the emotion recognition task. To this end, we compare emotion-aware descriptions, as described in Section 3.1, with generic descriptions generated from LLaVa-1.5 using the prompt:

“Please provide a detailed description of the image.”

Our results, detailed in Tab. 1a (upper split), reveal that emotion-aware text descriptions perform slightly better than the generic ones without significant differences. Finally, we employed a mixture (concatenation) of text from both generic and emotionally aware descriptions. For the concatenation in particular,

Input	Train	Vision	Train	Text	mAP↑
Ours(Emo-aware Desc.)	x		✓		38.52
Ours(Emo-aware Desc.)	✓		✓		38.09
Ours(General Descriptions)	x		✓		38.30
Ours(General+Emo-aware Desc.)	x		✓		38.28
Ours (No bounding Box)	x		✓		37.61
Ours (Subject)	x		✓		37.88

(a) Ablation on the quality of text descriptions (upper split) and the impact of the bounding box (bottom split) in our pipeline. "Train vision" and "Train text" indicate whether the train and/or text modality is trained.

Architecture	Input type	mAP↑
E_V (whole image)	Vis.	29.19
E_V^* (whole image)	Vis.	27.17
E_V (subject)	Vis.	25.55
LlaVa-1.5 [16], zero-shot†	Text	16.98
RoBERTa [44]‡	Text	34.25
$Cat(E_V, RoBERTa)$ ‡	Text, Vis.	34.66
$Cat(E_V^*, RoBERTa)$ ‡	Text, Vis.	34.29

(b) Ablation on the impact of the text input, visual input, and their fusion. "Text" and "Vis" indicate whether text and/or vision inputs are used.

* denotes a frozen model.

†Zero-shot evaluation of the generation method

‡As our architecture lacks a text modality, we use RoBERTa as a text backbone in the ablations.

Table 1: Ablation Study of Model Components on the Multi-Label Emotion Classification of the EMOTIC [17] Dataset

we use the first 100 tokens from the emotion-aware descriptions and concatenate them with the first 100 tokens from generic descriptions. The concatenated descriptions slightly hurt the performance (38.52 vs 38.28 mAP).

Bounding Boxes. To differentiate between individuals in a contextual image, a) we prompt the VLLM specifically regarding the person within the red bounding box, and b) we overlay a bounding box around the subject of interest in each sample. To assess the influence of localising a person using a bounding box, we conduct two experiments: a) We simply use as input the images without any drawn bounding boxes, and b) we employ bounding boxes to crop the subject of interest and use the cropped subject as our visual input for training under the same setting as in our method. Our findings, illustrated in Tab. 1a, reveal that utilising the red bounding box enhances our pipeline, increasing the mAP from 37.88 to 38.52. However, when employing the bounding box to crop the image, performance significantly decreases (38.52 vs 37.88 mAP), underscoring the importance of aligning the text descriptions with the visual input; both modalities contain bounding box information.

Visual Features. We investigate the effectiveness of the vision modality using a standard linear probe approach, *i.e.* by adding a single classification layer over our vision encoder modality, namely E_V in our pipeline. Within this framework, we investigate three cases; firstly, we train the entire pipeline end-to-end (first-row in Tab. 1b; secondly, we freeze the backbone and only train the classifier (second-row in Tab. 1b) and thirdly we train the whole pipeline end-to-end, but the model is fed the image of the subject of interest cropped without any additional visual context (last row in Tab. 1b). Our results indicate that the visual features alone are not enough to achieve good performance on this task with the use of a simple uni-modal vision encoder. We believe this is due to the noise and bias contained in the image context.

Text Features. We investigate whether our description extraction model, LlaVa-1.5 [16], can directly predict emotion categories in a zero-shot manner. Specifically, we prompt LlaVa to predict the apparent emotion of the subject given the available classes while considering contextual cues. To measure accuracy, we follow the approach of [45], evaluating whether the response contains the class name or not. As depicted in Tab. 1a, our proposed method, which achieves an mAP of 38.52, significantly outperforms the zero-shot capabilities of LlaVa, which gets an mAP of 16.98 in Tab. 1b, hence showcasing the need for a task-specific model. We attribute this to the challenges that occur when prompting Llava to respond on a multi-label task and the noisy label definitions in emotion prediction tasks. To further investigate whether text descriptions alone are sufficient for in-context emotion prediction, we employ RoBERTa [44] as a language baseline as our architecture does not have a text modality; the Q-Former directly takes the text embeddings as input. We use the text descriptions as input to RoBERTa and then pass the last hidden state of the class token through a classifier. As shown in Tab. 1b, text features in isolation perform worse than in our pipeline. Still, they significantly outperform the visual modality (34.25 Vs 29.19 mAP), enhancing our argument for the need for contextual LLM-generated descriptions for the task of in-context emotion recognition.

Fusion. To investigate the fusion method *i.e.* a Q-Former module, we compare our method with a fusion baseline model, in which we concatenate the text features and the visual features ($Cat(\cdot)$) extracted from RoBERTa and our vision encoder E_v respectively, before feeding them into the classifier. Our results, depicted in Tab. 1b, underscore that our approach using Q-former as a fusion mechanism is more suitable for this task (38.52 Vs 34.66 mAP). We also train the same pipeline, keeping the visual modality frozen. We note that in this setting, fine-tuning the visual modality does not have a significant impact.

Method	mAP ↑	AUC ↑	#Frames (T)	mAP ↑	AUC ↑
Ours (w Transformer & frozen E_V)	22.74	66.54	4	23.40	67.74
Ours (frozen E_V)	23.53	67.62	8	23.53	67.62
Ours	26.66	69.83	16	23.50	67.67

(a) Temporal Strategy

(b) Effect of number of frames T (frozen E_V)

Table 2: Ablation Study of Model Components on the Multi-Label Emotion Classification of the BoLD [17] Dataset

Temporal Dimension As the BoLD [17] dataset contains video clips, we compare our proposed method of averaging the visual tokens before forwarding them to the Q-Former with an architecture that employs two Transformer Encoder layers as a temporal module. The Q-Former uses all visual tokens, not just the classification token; therefore, the temporal module also needs to be able to handle the multiple tokens per frame. To achieve this, we replicate the temporal module for each $\frac{H}{P} \times \frac{W}{P} + 1$ tokens, with shared weights. The results can be seen in Table 2a. Finally, we compare the number of frames used in Table 2b.

4.3 Comparison with Other State-Of-The-Art

We compare our proposed methodology with other state-of-the-art models in three emotions in context datasets, namely CAER-S [7], EMOTIC [5] and BoLD [17]. Table 3 shows the overall performance of our model across all datasets.

As shown in Table 3a, for the BoLD dataset, our method substantially outperforms the state-of-the-art on the challenging 26-class emotion classification task in terms of both mean Average Precision and AUC metric. Specifically, our proposed method achieves a mAP of 26.66% – over 4% the previous state-of-the-art [14]. For the CAER-S dataset, [9] stood as the prior SOTA with an accuracy of 91.17%. Our method outperformed it substantially by a margin of nearly 2%. In Emotic, our method performs comparably to previous state-of-the-art [9].

Method	mAP ↑	AUC ↑
TSN-ResNet101 [17]	17.04	62.29
I3D [17]	15.37	61.24
TSN [17]	17.02	62.70
Filntsis <i>et al.</i> [22]	16.56	62.66
Pikoulis <i>et al.</i> [46]	19.29	66.82
EmotionCLIP [14]	22.51	69.30
Ours (E_V frozen)	<u>23.53</u>	67.62
Ours	26.66	69.83

(a) BoLD [17]

Method	mAP ↑	Method	Acc (%) ↑
EMOTNet [5]	27.93	CAER-Net [7]	73.47
GCN-CNN [26]	28.16	EMOT-Net [5]	74.51
CAERNet [7]	23.85	GNN-CNN [26]	77.21
RRLA [24]	32.41	SIB-Net [47]	74.56
VRD [21]	35.16	RRLA [24]	84.82
EmotiCon [6]	35.28	EmotiCon [6]	88.65
EmotiCon+CCIM [9]	39.13	EmotiCon+CCIM [9]	91.17
Ours	38.52	Ours	93.08

(b) Emotic [5] (c) CAER-S [7]

Table 3: Comparisons to the state-of-the-art across datasets.

4.4 Qualitative analysis and discussion

To qualitatively assess our model’s predictions, we compare its output with that of the ViT vision encoder (E_V) trained under two conditions: first, without any context on subject images ($E_V(\text{cropped})$), and second, with the entire image including all visual context ($E_V(\text{whole})$), and the drawn bounding box. Fig. 4 shows some examples from the EMOTIC [5] test set, along with our model predictions and the predictions of the two ViT architectures.

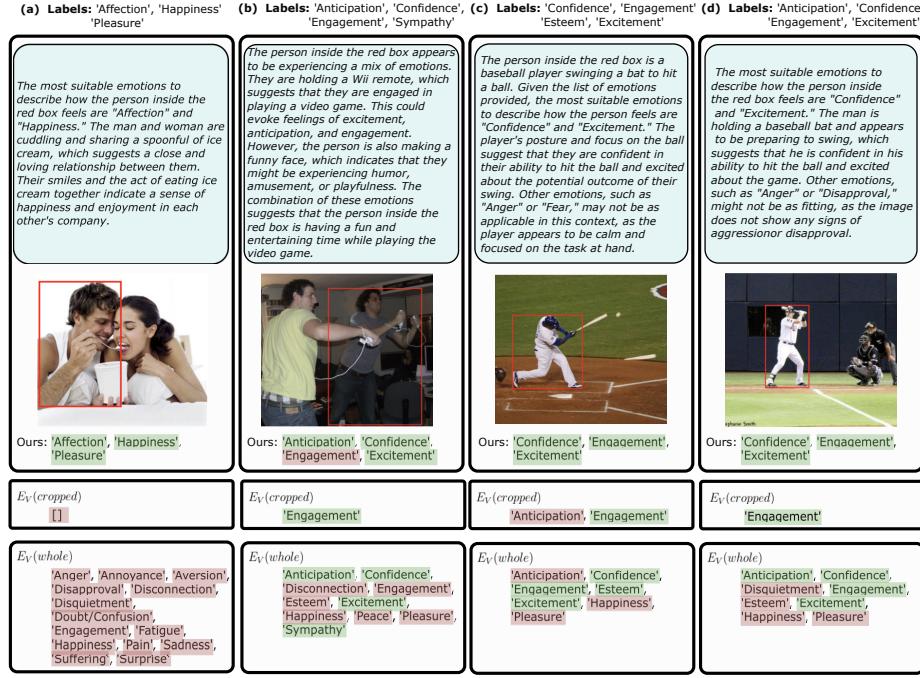


Fig. 4: Qualitative comparison of predictions made by our proposed method vs a ViT [39] vision encoder trained on the cropped image of the subject ($E_V(\text{cropped})$) and whole images ($E_V(\text{whole})$) –including the bounding box and visual context, from the test set of the EMOTIC [5] dataset.

Some initial observations are with regard to the number of classes above the threshold each network predicts.³ More specifically, we can observe that the network trained on the whole image –*i.e.* subject and visual context– confidently predicts a large number of classes for each sample, resulting in many False Positives for each class. On the contrary, it appears that the vision encoder trained only on the subject has a large number of False Negatives and, on some occasions, *e.g.* Fig. 4(a), does not confidently predict any classes. From a visual inspection of the dataset, we can observe that the visual context of the samples contains rich information, which may result in input noise. The input noise, without a signal to ground this pattern, may lead to a high number of classes being predicted as the network is unable to find a meaningful pattern in the visual context. This seems to corroborate the findings of our ablation –that text and visual context have complementary information.

A second observation is with regard to the consistency of the prediction; we can see in Fig. 4 examples (c) and (d) have very similar content, that is, a baseball player ready to swing a bat with limited facial expression information.

³ We used the standard 0.5 prediction threshold.

However, there is a different set of ground truth labels for very similar contexts. Our proposed method and the ViT trained on the entire image appear to have more consistent predictions, while the subject-only ViT defaults to majority class prediction. Some of the failures of all models can be attributed to annotation noise present in the dataset; however, we see that the combination of visual and text features as context information aids the network to learn better.

Finally, we examine the attention maps of the Vision Encoder-only architecture trained on the whole image – that is, the image of the subject and the visual context – and our proposed method. Specifically, we select the last self-attention layer of the vision-only architecture and qualitatively compare the maps to those of the last cross-attention layer in our proposed method. The results can be seen in Fig 5. We can see that while our proposed architecture is not trained explicitly to localise the subject, the cross-attention mechanism between the learnable queries and image tokens has concentrated the areas of importance over the subject, while the attention of the vision encoder seems to be too spread out.

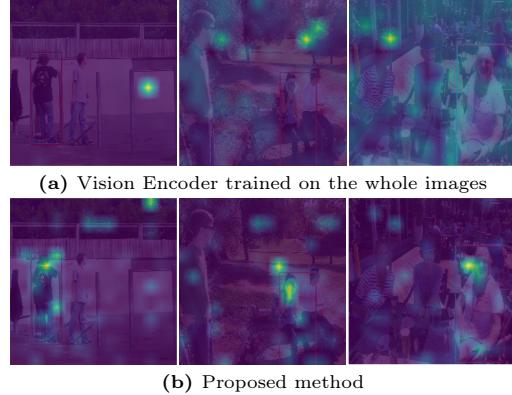


Fig. 5: Examples of Attention Maps of the last attention layer of the Vision Encoder only trained on the whole image –*i.e.* subject and context (top), and the last Q-Former cross-attention in our proposed method (bottom).

5 Conclusion

In this work, we proposed a simple yet effective pipeline to address the task of in-context emotion recognition in the wild. Our method leverages the common sense knowledge and reasoning ability of powerful VLLMs such as Llava 1.5 and shows that this knowledge can be transferred effectively to the problem of emotion recognition. Specifically, we proposed a two-stage architecture, where initially, we generate context descriptions for each image (or video) sample, and then we fuse the visual and text features using a Q-Former-based architecture for the final emotion recognition classification. We showed that the fused architecture vastly outperforms the individual modalities and that our description generation strategy is optimal among those examined. Finally, we qualitatively analysed the output and attention maps of our proposed fused method against those of the vision-only modalities. Our method achieves SOTA results on two static and one video in-context emotion recognition datasets, namely, EMOTIC, CAER-S and BoLD.

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Appendix

In this supplementary document, we present additional quantitative and qualitative results that complement and extend the findings outlined in the main text. More specifically, in Appendix A, we show the per-class metrics our method achieves on each dataset we use for evaluation and compare them with previous works. Then, in Appendix B, we show additional samples of the generated descriptions from all datasets.

A Per-class analysis

	EMOTNet [5]	GCN-CNN [26]	CAERNet [7]	RRLA [24]	VRD [21]	EmotiCon [6]	EmotiCon +CCIM [9]	Ours
Affection	26.47	47.52	22.36	37.93	44.48	38.55	40.77	51.78
Anger	11.24	11.27	12.88	13.73	<u>30.71</u>	14.69	15.48	34.62
Annoyance	15.26	12.33	14.42	20.87	<u>26.47</u>	24.68	24.47	27.69
Anticipation	57.31	<u>63.2</u>	52.85	61.08	59.89	<u>60.73</u>	95.15	59.52
Aversion	7.44	6.81	3.26	9.61	12.43	11.33	19.38	11.10
Confidence	80.33	74.83	72.68	<u>80.08</u>	79.24	68.12	75.81	79.90
Disapproval	16.14	12.64	15.37	<u>21.54</u>	24.54	18.55	23.65	24.93
Disconnection	20.64	23.17	22.01	28.32	<u>34.24</u>	28.73	31.93	40.01
Disquietment	19.57	17.66	10.84	22.57	24.23	22.14	26.84	26.37
Doubt/Confusion	31.88	19.67	26.07	33.5	25.42	38.43	34.28	28.53
Embarrassment	3.05	1.58	1.88	4.16	4.26	<u>10.31</u>	16.73	3.99
Engagement	86.69	87.31	73.71	88.12	88.71	86.23	97.41	91.03
Esteem	17.86	12.05	15.38	20.5	17.99	<u>25.75</u>	27.44	19.38
Excitement	78.05	72.68	70.42	80.11	74.21	<u>80.75</u>	81.59	75.99
Fatigue	8.87	12.93	6.29	17.51	<u>22.62</u>	19.35	15.53	28.17
Fear	15.7	6.15	7.47	15.56	13.92	<u>16.99</u>	15.37	18.81
Happiness	58.92	72.9	53.73	76.01	83.02	<u>80.45</u>	83.55	85.07
Pain	9.46	8.22	8.16	14.56	16.68	14.68	<u>17.76</u>	26.36
Peace	22.35	30.68	19.55	26.76	28.91	<u>35.72</u>	38.94	34.04
Pleasure	46.72	48.37	34.12	55.64	55.47	67.31	64.57	56.04
Sadness	18.69	23.9	17.75	30.8	42.87	40.26	<u>45.63</u>	54.33
Sensitivity	9.05	4.74	6.94	9.59	15.89	13.94	17.04	15.24
Suffering	17.67	23.71	14.85	30.7	46.23	<u>48.05</u>	21.52	55.97
Surprise	22.38	8.44	17.46	17.92	16.27	<u>19.6</u>	26.81	18.08
Sympathy	15.23	19.45	14.89	15.26	15.37	16.74	47.6	21.44
Yearning	9.22	9.86	4.84	10.11	10.04	15.08	12.25	13.16
mAP	27.93	28.16	23.85	32.41	35.16	35.28	39.13	38.52

Table 4: Performance of the Proposed Method on the EMOTIC [5] 26-Class Multi-Label Emotion Classification Against Other SOTA Methodologies in terms of Average Precision

	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Total
CAER-Net [7]	-	-	-	-	-	-	-	73.47
EMOT-Net [5]	-	-	-	-	-	-	-	74.51
GNN-CNN [26]	-	-	-	-	-	-	-	77.21
SIB-Net [47]	-	-	-	-	-	-	-	74.56
RRLA [24]	-	-	-	-	-	-	-	84.82
EmotiCon [6]	-	-	-	-	-	-	-	88.65
EmotiCon+CCIM [9]	-	-	-	-	-	-	-	91.17
Ours	94.33	98.23	99.33	88.83	79.83	95.87	95.13	93.08

Table 5: Performance of the Proposed Method on the CAER-S [7] Multi-Class Emotion Classification Against Other SOTA Methodologies in terms of Accuracy

We show the per-class metrics of each dataset used for evaluation. In Tab. 4, we present the per-class performance of our method on EMOTIC [5] dataset against that of [5–7,9,21,24,26]. For each class, we compute the average precision. Our approach demonstrates improvements in 11 out of the 26 categories, notably increasing in categories like “Pain” with an +8% mAP increase and “Sadness” with a large +9% mAP improvement. It is worth noting that the performance trends across categories remain consistent between our method and most of the previous works, suggesting a) a shared understanding of the complexities of the task and b) that our approach provides a good solution to advancing the task.

	ResNet101 [17]	I3D [17]	TSN [17]	Filntisis <i>et al.</i> [22]	Pikoulis <i>et al.</i> [46]	EmotionCLIP [14]	Ours
Affection	-	-	-	-	-	42.06	52.47
Anger	-	-	-	-	-	15.24	15.63
Annoyance	-	-	-	-	-	18.78	18.65
Anticipation	-	-	-	-	-	32.23	35.74
Aversion	-	-	-	-	-	9.08	9.93
Confidence	-	-	-	-	-	40.33	44.32
Disapproval	-	-	-	-	-	14.12	18.36
Disconnection	-	-	-	-	-	11.08	18.99
Disquietment	-	-	-	-	-	23.75	24.41
Doubt/Confusion	-	-	-	-	-	22.82	20.38
Embarrassment	-	-	-	-	-	2.29	22.57
Engagement	-	-	-	-	-	44.54	46.13
Esteem	-	-	-	-	-	20.66	19.47
Excitement	-	-	-	-	-	28.04	32.43
Fatigue	-	-	-	-	-	13.17	23.51
Fear	-	-	-	-	-	19.41	24.41
Happiness	-	-	-	-	-	48.59	52.59
Pain	-	-	-	-	-	14.58	15.03
Peace	-	-	-	-	-	28.09	35.63
Pleasure	-	-	-	-	-	37.87	34.23
Sadness	-	-	-	-	-	25.85	35.02
Sensitivity	-	-	-	-	-	14.81	16.08
Suffering	-	-	-	-	-	26.61	31.66
Surprise	-	-	-	-	-	11.91	13.68
Sympathy	-	-	-	-	-	12.6	17.61
Yearning	-	-	-	-	-	6.66	14.32
mAP	17.04	15.37	17.02	16.56	19.29	22.51	26.66

Table 6: Performance of the Proposed Method on the BoLD [17] 26-Class Multi-Label Emotion Classification Against Other SOTA Methodologies in terms of Average Precision

Similarly, in Tab. 5, we show the per-class accuracy on the CAER-S [7] dataset. We note that our model demonstrates consistently high accuracy across the majority of classes, exceeding 98% accuracy for classes such as “Fear” and “Disgust”. Previous state-of-the-art methods do not provide per-class accuracy; therefore, we cannot compare individual categories. However, we can see that our proposed method achieves very high performance across all categorical emotions.

Finally, in Table 6, we compare the mean Average Precision (mAP) of our method on the BoLD dataset [5] against that of EmotionCLIP [14]. We report the per-class mAP as well as the average mAP. We observe that across the 26 class categories, our method outperforms EmotionCLIP in 23. Overall, our method surpasses prior work in most of the categories, with some classes (*e.g.* “Fatigue”, +9 mAP and “Sadness”, +9 mAP) showing a large performance improvement.

B Generated Text Examples

We present several examples of the generated text descriptions for each dataset. Overall, LlaVa-1.5 [16] appears to have sound common sense reasoning when it comes to describing emotional states and providing context. A qualitative investigation of the descriptions across all three datasets showed no clear sign of hallucination from the Large Language Model (LLM), which would introduce noise to the downstream task.

However, the information in the generated context largely relies on the availability of visual context. We see in Tab. 8 that as the samples of CAER-S [7] have limited visual context, the descriptions are also quite limited to the subject and their facial expressions. As BoLD [17] and EMOTIC [5] have noticeably more noisy context, the descriptions are more verbose and appear to contain more environmental and contextual cues as seen in Tab. 9 & 7 respectively.

Please rotate for easier reading.

Image	Text Context	Ground Truth
	<p>Based on the image context, the person inside the red box appears to be experiencing a mix of emotions. They seem to be in a state of anticipation, as they are looking at their luggage and possibly preparing for a journey. The presence of multiple suitcases and backpacks around them suggests that they might be travelling or waiting for their luggage at an airport or train station. Their emotions could also be influenced by their surroundings, such as the presence of other people in the area, which might evoke feelings of disconnection or disquietment. Additionally, the person might be experiencing some level of fatigue or pain, as travelling can be physically and mentally Engaged exhausting.</p> <p>In summary, the person inside the red box might be experiencing a mix of emotions, including anticipation, disconnection, disquietment, fatigue, or pain, depending on the context and their surroundings. However, it is important to note that emotions can be complex and multifaceted, and it is difficult to pinpoint a single emotion based solely on the image.</p>	<p>Based on the image context, the person inside the red box is a woman playing tennis on a clay court. She is holding a tennis racket and appears to be walking on the court. Given the list of emotions provided, the most suitable emotions to describe her feelings would be "Confidence" and Confidence, Engagement. These emotions suggest that she is actively participating in the game and feels engaged confident in her abilities. Other emotions, such as "Anger" or "Disapproval," might not be as fitting since there is no clear indication of negative emotions in the image.</p>
		<p>Based on the image context, the person inside the red box appears to be experiencing a mix of emotions such as surprise, annoyance, and engagement. The person is sitting in the front row of a classroom, surrounded by other students who seem to be attentive to the ongoing lecture. The presence of a laptop on the table in front of the person suggests that they might be using it for note-taking, research, or other class-related activities.</p>
		<p>The emotions of surprise, annoyance, and engagement are more suitable for describing how the person inside the red box feels, as these emotions can be inferred from their facial expression, body Engagement language, and the context of the classroom setting. The surprise could be due to an unexpected event or question during the lecture, while the annoyance could be a result of the person feeling overwhelmed, bored, or frustrated with the content being taught. The engagement, on the other hand, suggests that the person is actively participating in the class and paying attention to the ongoing lecture.</p>

Table 7 continued from previous page

Image	Text Context	Ground Truth
	<p>Based on the image context, the person inside the red box appears to be experiencing a mix of positive and negative emotions. They are smiling, which suggests that they are experiencing happiness or pleasure. However, they are also holding up a cell phone, which might indicate that they are experiencing frustration, annoyance, or disconnection due to technology-related issues. Additionally, they are surrounded by other people holding up their cell phones, which could imply that they are engaged in a social activity or event. Overall, the person inside the red box seems to be experiencing a combination of happiness, frustration, and social engagement.</p>	
	<p>Based on the image context, the person inside the red box appears to be experiencing a mix of emotions. They are looking at their cell phone, which suggests that they might be engaged in an activity such as texting, browsing, or using an app. However, their facial expression and body language do not provide enough information to confidently determine their exact emotions. It is important to note that emotions can be complex and multifaceted, and a single image may not capture the full range of a person's emotions. Therefore, it is not possible to definitively determine which emotions are more suitable for describing how the person inside the red box feels.</p>	Engagement
	<p>Based on the image context, the person inside the red box appears to be experiencing a mix of emotions. They seem to be engaged in a creative activity, such as drawing or painting, which could evoke feelings of excitement, anticipation, and engagement. Additionally, the presence of a cell phone suggests that they might be connected to the outside world or communicating with others, which could contribute to feelings of disconnection, disquietment, or even annoyance if they are interrupted or distracted from their work.</p> <p>However, it is also possible that the person inside the red box is experiencing a range of negative emotions, such as fear, sadness, or pain, depending on the specific context of the image. Without more information, it is difficult to determine which emotions are more suitable for describing how the person inside the red box feels.</p>	Engagement

Table 7: Examples of descriptions generated for the EMOTIC [5] dataset.

Image	Text Context	Ground Truth
	Based on the image context, it is more likely that the man in the yellow shirt is experiencing a mix of emotions, such as surprise, disgust, or even a hint of sadness. He appears to be staring at something off-camera, which might have caught his attention or caused an unexpected reaction. His facial expression and body language suggest that he could be reacting to a surprising or unpleasant situation.	
	Based on the image context, it appears that the woman is feeling angry or disgusted. She is sitting on a bed and pointing at something, which suggests that she is expressing negative emotions.	Disgust
	In the image, a woman with curly hair is smiling and appears to be happy. Her facial expression and body language suggest that she is experiencing positive emotions such as happiness, joy, or contentment. It is unlikely that she is feeling angry, disgusted, fearful, sad, or surprised, as her Happy smile and overall demeanor convey a sense of positivity and well-being.	Happy
	Based on the image context, it appears that the man with long hair is experiencing a mix of emotions. He seems to be surprised, as indicated by his raised eyebrows and open mouth. Additionally, he appears to be angry or disgusted, as he is pointing his finger at the other man. The facial Angry expressions and body language of the two men suggest that they might be engaged in a heated discussion or disagreement.	Surprise
	Based on the image context, the most suitable emotions to describe how the person in the image feels are "Angry" and "Surprise." The woman is holding a deck of cards and appears to be staring intently at the camera. Her facial expression and body language suggest that she might be upset Angry or surprised about something related to the cards or the situation they are in.	Angry

Image	Text Context	Table 8 continued from previous page	Ground Truth
	In the image, a man and a woman are having a conversation while sitting at a dining table. The man is wearing a suit and tie, which suggests a formal or professional setting. Given the context, it is more likely that the man is experiencing emotions such as "Neutral" or "Sad". The neutral Fear emotion could be due to the seriousness of the conversation, while the sad emotion could be inferred from the	In the image, a man and a woman are having a conversation while sitting at a dining table. The man is wearing a suit and tie, which suggests a formal or professional setting. Given the context, it is more likely that the man is experiencing emotions such as "Neutral" or "Sad". The neutral Fear emotion could be due to the seriousness of the conversation, while the sad emotion could be inferred from the	
	In the image, a man is wearing a red shirt and standing in front of a mirror. He has a smile on his face, which suggests that he is feeling happy or content. There is no indication of anger, disgust, fear, sadness, or surprise in his facial expression or body language. Therefore, the most suitable Happy emotion to describe how the person in the image feels is "Happy."	In the image, a man is wearing a red shirt and standing in front of a mirror. He has a smile on his face, which suggests that he is feeling happy or content. There is no indication of anger, disgust, fear, sadness, or surprise in his facial expression or body language. Therefore, the most suitable Happy emotion to describe how the person in the image feels is "Happy."	
	In the image, a woman with red hair is wearing a green shirt and standing in a room. She appears to be staring into the distance with a serious expression on her face. Based on her facial expression and body language, it is more likely that she is experiencing a mix of emotions such as sadness, Angry surprise, or even a hint of disgust.	In the image, a woman with red hair is wearing a green shirt and standing in a room. She appears to be staring into the distance with a serious expression on her face. Based on her facial expression and body language, it is more likely that she is experiencing a mix of emotions such as sadness, Angry surprise, or even a hint of disgust.	

Table 8: Examples of descriptions generated for the CAER-S [7] dataset.

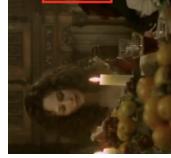
Image	Text Context	Ground Truth
	<p>Based on the image context, the person in the red box appears to be experiencing a combination of emotions such as anticipation, engagement, and excitement. The presence of a microphone suggests that they might be preparing to sing or perform, which can evoke feelings of anticipation and excitement. Additionally, their posture and facial expression indicate that they are actively engaged. Happiness, Excitement, further supporting the idea that they are experiencing these positive emotions. However, it is important to note that emotions can be complex and multifaceted, so it is possible that other emotions may also play a role in the person's experience.</p>	
	<p>Based on the image context, it appears that the person in the red box is experiencing a mix of emotions. The presence of a book suggests that they might be engaged in reading or studying, which can evoke feelings of anticipation, excitement, and curiosity. The fact that they are holding a musical instrument, such as a cello, indicates that they might be passionate about music and could be experiencing a range of emotions related to their artistic pursuits, such as happiness, pleasure, and confidence. However, the presence of a bottle in the scene might suggest that the person is also experiencing some negative emotions, such as fatigue, annoyance, or even sadness. It is important to note that interpreting emotions from a single image can be subjective, and the emotions experienced by the person in the red box may vary depending on the viewer's perspective.</p>	
	<p>Based on the image context, it appears that the person in the red box is experiencing a mix of emotions. The presence of a wine glass and a dining table suggests that they might be attending a social gathering or enjoying a meal with friends or family. However, their facial expression and body language indicate that they may also be experiencing some negative emotions such as discomfort, annoyance, or even sadness. It is important to note that interpreting emotions from a single image can be subjective, and Disapproval the person's emotions could be influenced by various factors beyond what is visible in the image. Nonetheless, the emotions that seem most suitable for describing how the person in the red box feels are discomfort, 'annoyance', and 'sadness'.</p>	
	<p>Based on the image context, it is difficult to determine the exact emotions the person in the red box is experiencing. However, we can make some educated guesses based on their facial expression and body language. The person appears to be staring intently into the distance, which could suggest that they are Anticipation, experiencing a range of emotions such as anticipation, engagement, or even surprise. Their facial Surprise, expression might also indicate a mix of emotions like happiness, pleasure, or excitement. Doubt/Confusion It is important to note that interpreting emotions from a single image can be subjective, and the actual emotions experienced by the person in the red box may vary.</p>	

Table 9 continued from previous page

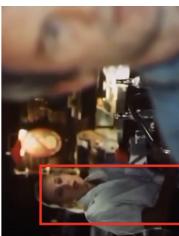
Image	Text Context	Ground Truth
	<p>Based on the image context, it is difficult to determine the exact emotions that the person in the red box is experiencing. However, we can make some educated guesses based on their facial expression and surroundings.</p> <p>The person appears to be looking at a man in a blue shirt, which suggests that they might be Sympathy, Sadness, experiencing curiosity, engagement, or anticipation. Their facial expression indicates that they could be experiencing a range of emotions, such as surprise, excitement, or even discomfort. It is important to note that interpreting emotions from a single image can be subjective and may not provide a complete understanding of the person's feelings.</p>	
	<p>Based on the image context, it appears that the person in the red box is experiencing a mix of emotions. While it is difficult to pinpoint a single emotion, we can infer that they might be experiencing some level of engagement or anticipation, as they are sitting at a desk with a book and a glass of wine. The presence of the wine glass suggests that they might be enjoying a leisurely activity, such as reading or relaxing.</p> <p>However, there are also indications of negative emotions, such as sadness or discomfort. This could be inferred from the person's facial expression, posture, or body language. It is important to note that interpreting emotions from a single image can be subjective, and multiple interpretations may be valid depending on the viewer's perspective.</p>	

Table 9: Examples of descriptions generated for the BoLD [17] dataset.

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