

Supplementary Material of MIP-GAF: A MLLM-annotated Benchmark for Most Important Person Localization and Group Context Understanding

S. Madan¹, S. Ghosh², L. R. Sookha¹, M.A. Ganaie¹, R. Subramanian^{1,3}, A. Dhall⁴, T. Gedeon²
¹IIT Ropar, ² Curtin University, ³ University of Canberra, ⁴ Monash University
 {surbhi.19csz0011, lownish.23csz0010, mudasir, s.ramanathan}@iitrpr.ac.in,
 {shreya.ghosh, tom.gedeon}@curtin.edu.au, abhinav.dhall@monash.edu.au







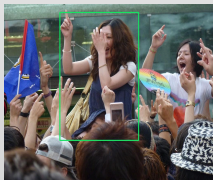






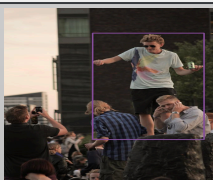
Negative					
	The most important person in the image is the mother, as she is the primary caregiver for the child. She is the one who is responsible for providing the child with the necessary care, guidance, and support.	The most important person in the image is the person in the blue shirt. This person is likely a leader, activist, or a person who has a significant impact on the community. Their actions and contributions can significantly impact the lives of others, and their actions can be seen as valuable in the context of the image.	The most important person in the image is a woman. She is selling fruits and vegetables on a market, which is a common activity for her. Her box is the most valuable, as it is the largest and most valuable of all the items she sells.	The most important person in the scene is the person holding a rifle, as they are the main characters in the film. They are the ones responsible for the safety of the group and the overall plot of the film, as well as the main protagonists.	The most important person in this image is the woman holding a sign that says "She won, but he will govern. SAD" in the crowd of women at the Women's March in Denver, Colorado. She is a role model for other women. Her presence and her sign contribute to the overall message of the Women's March.
					
	The most important person in the image is most likely the president of the United States.	The most important person in the image is the groom, who is being held by his bride. They are important because they are the couple who are about to get married. The bride is the one who is bounding in the box, while the groom is the man who is about to be married.	The most important person in the image is a woman who is standing in the middle of a crowd, holding up her hands and dancing. She is the center of attention, and her actions are likely to attract attention and admiration from the crowd. Her actions can be seen as a form of entertainment or an expression of her personality.	Ariana Grande is the most important person in the image. She is a pop star, singer, songwriter, and actress. Her music has sold over 100 million records worldwide, and she has won multiple awards, including two Grammys. Her performances have been highly praised, and her fans have been loyal to her. ble.	The most important person is most likely a teacher, coach, or a leader in a school or sports team. They are responsible for guiding and motivating the students, ensuring their safety, and ensuring their success in various activities.
					
The most important person in the image is a woman, who is holding a microphone and reading from a piece of paper. She is standing in front of a group of people, holding signs and banners. The group is protesting against the war in Syria, and the woman is holding a microphone to amplify their voices. This person is likely the most important figure in the scene, as they are the one who is leading the protest and communicating	The most important person in the scene is a teacher. She is the one who is supervising the students and is responsible for their education.	The most important person in the image is Narendra Modi, the Prime Minister of India. He is the leader of the Bharatiya Janata Party (BJP), and is the current Prime Minister. Modi is the most important person in India, as he is the head of the government and the leader who is responsible for the country's policies and the development of the country.	The most important person in the image is most likely the CEO of the company. They are the person responsible for overseeing the company's operations, ensuring that the company is meeting its goals and objectives.	The most important person in the scene is the young man standing on a rock. He is the center of attention, and he is holding a beer in his hand. This person is likely the main focus of the gathering. The presence of other people around him also indicates that the event is likely a social gathering.	

Figure 1. *More Sample Images from the MIP-GAF Dataset.* Additional examples from the MIP-GAF dataset along with their corresponding MIPs. Row (1) represents negative emotion images, row (2) represents positive emotion images, and row (3) represents neutral emotion images. These examples illustrate the diversity and complexity of scenes, emphasizing the varying contexts in which MIPs must be identified.

1. MIP-GAF: Additional MIP Examples

We have presented additional example images from the MIP-GAF dataset (Figure 1) to illustrate the diversity in scenes and the complexity involved in identifying the MIP in real-world scenarios. These examples are categorized into three emotional settings: Positive, Negative, and Neutral (**Note:** Emotion information is not used anywhere in the paper but has been kept as meta-data for future work).

- For the Negative emotion images, we have a scene where a mother scolds her child, with the mother marked as the MIP since she is the primary caregiver. Another example is a protest scene featuring a central figure who could be the leader or activist, marked as the MIP. Additionally, there is a roadside scene showing two poor women selling vegetables, with the woman whose face is visible marked as the MIP. Further, we include a movie scene where the person holding a rifle is marked as the MIP, suggesting he could be the main character. Lastly, we present another march scene where a woman holding a banner is marked as the MIP, as her presence and the banner contribute significantly to the image’s message.
- For the Positive emotion images, we have an image featuring a politically dominant personality, marked as the MIP due to being the President of the United States. Another example is a wedding scene where the groom sitting on the chair is marked as the MIP, with his bride standing beside him. We also show a stage performance scene where pop star and singer Ariana Grande is marked as the MIP. Additionally, there are group images where the person at the center is marked as the MIP for being the center of attention.
- For the Neutral emotion images, we have a rally scene where Indian Prime Minister Narendra Modi is marked as the MIP due to his political prominence. Another example is a protest scene against the war in Syria, where a girl giving an interview is marked as the MIP because the microphone is close to her, and she is reading something in front of a group of people. Additionally, there is a classroom scene where a teacher standing behind the students is marked as the MIP. We also show a business meeting setup where multiple people are looking at a central figure, marking that person as the MIP for being the center of attention.

2. Experiments and Results

2.1. More Details on MIP-CLIP: Stage 1

Given an input image I and a text description of MIP as L (Figure 2), the process begins by encoding the visual features (V_I) using a vision encoder [1] and the textual

features (T_L) using a text encoder [4]:

$$V_I = ResNet50(I)$$

$$T_L = BERT(L)$$

Since we are working with visual features, the image features are down-sampled by a factor of k in both the width and height of the image:

$$Height = Height_I/k$$

$$Width = Width_I/k$$

Next, both the visual and textual embeddings are projected into a common latent space with dimension d termed C_d , using a projection layer.

To align the domain differences, we enhance the visual features using text features and the text features using visual features. This enhancement facilitates the classification process: enhancing text features with visual information helps in classification, while enhancing visual features with textual information aids in localization [2]. An affine transformation is then applied to both the visual (A_v) and text features (A_t) using the following equations:

$$A_t = SoftMax((VW_1^v) \otimes (TW_2^t)^T) / \sqrt{C_d}$$

$$A_v = SoftMax((TW_1^t) \otimes (VW_2^v)^T) / \sqrt{C_d}$$

Where, W_*^v and W_*^t are learnable parameters. These affine transformations are used to create the final vision and textual features as described by the following equations:

$$Text_{Final} = A_t^T \otimes (VW_3^v)$$

$$Vision_{Final} = Re(A_v^T \otimes (TW_3^t))$$

This stage is trained in a contrastive classification manner, where positive and negative descriptions associated with the image are classified. A response map is generated for each description (both positive and negative, denoted as R_p and R_N), and an image-level score (y_j) is computed for each description in a contrastive manner. The goal is to make $y_j = 1$ for positive image-description pairs and $y_j = 0$ for negative image-description pairs.

2.2. More Qualitative Evaluations

Figure 3 presents a performance comparison of various state-of-the-art models on the MIP-GAF, MS, and NCAA datasets. In the figure, the dotted line represents the predicted bounding box, while the solid line indicates the ground truth. The results reveal that our MIP-GAF dataset poses significant challenges, necessitating the development of more robust algorithms. Unlike other datasets, the MIP in MIP-GAF is rarely positioned at the center, and the largest

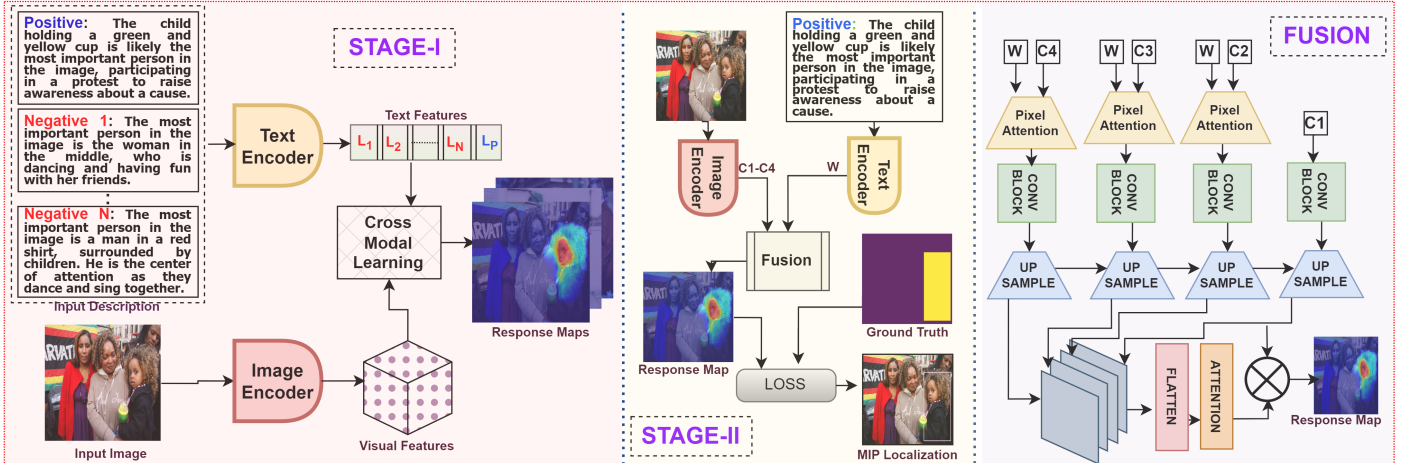


Figure 2. Our proposed MIP-CLIP framework. Stage 1: It learns to classify text inputs and uses positive expressions to locate the MIP on response maps. Stage 2: Trained image and text encoders generate feature maps, and a fusion model localizes MIP using response maps.

face is not always marked as the MIP. Additionally, the POINT model frequently struggles to accurately identify the MIP. In contrast, our MIP-CLIP method demonstrates superior performance by effectively utilizing contextual information and scene descriptions to locate the MIP. This highlights the complexity of our dataset and the difficulties inherent in identifying MIPs within real-world images.

3. Other Details

3.1. MLLM Failed Cases

We employ the KOSMOS-2 [3] model as a Multimodal Large Language Model (MLLM) to annotate MIP in the first round. However, the MLLM encountered considerable confusion in various complex scenarios, some of which are depicted in Figure 4. Below are detailed examples of where the MLLM struggled:

1. **Multiple Individuals in Similar Attire:** The MLLM is unable to accurately identify MIP when there are several people in the image wearing similar formal attire or the same type of sash. This situation often occurs in professional meetings or celebratory events, where distinguishing between individuals can be difficult due to the uniformity of their attire or accessories.
2. **Meeting Setup with Focused Person Not Visible:** The model has difficulty when the image depicts a meeting setup where all participants are looking at a particular person, but that person is not visible in the frame. This creates ambiguity for the MLLM, as it relies on visual cues that are absent.
3. **Hands Prominently Positioned:** In images where hands are prominently positioned towards the camera,

the MLLM gets confused. The focus on hands instead of faces or bodies disrupts the model’s ability to correctly identify and annotate the MIP.

4. **Group Photos with Uniform Poses:** The model encounters issues in group photos where all participants are looking at the camera in the same way. This uniformity in pose and direction makes it challenging for the MLLM to single out and annotate the MIP accurately.

These examples clearly illustrate the limitations of the MLLM in handling complex visual contexts. Such scenarios underscore the necessity for human intervention to ensure accurate annotation and identification of MIP, highlighting the complementary role of human oversight in conjunction with automated models.

3.2. Face-API

Face-api.js [5] is a powerful, browser-based face recognition library built on TensorFlow.js, designed for seamless integration into web applications. It offers a comprehensive suite of features, including face detection for single and multiple faces, providing precise bounding box coordinates, and face recognition with matching capabilities against known faces using unique face descriptors. The library also supports facial landmarks detection with a 68-point model, aiding in face alignment, and can recognize various facial expressions and emotions in real-time video streams. Additionally, it predicts age and classifies gender of detected faces. Optimized for performance, Face-api.js utilizes WebGL for real-time processing and works efficiently across modern web browsers on desktops, laptops, tablets, and smartphones. It includes pre-trained models for different tasks and supports fine-tuning or training

		Ground Truth		Prediction	
MS					
NCAA					
MIP-GAF (Ours)					
	Most-Center	Max-Face	Max-Scale	POINT	MIP-CLIP

Figure 3. *Qualitative Analysis*. We compare the output of different off-the-shelf methods on MS, NCAA, and MIP-GAF datasets. Here, the dotted line (green) indicates the predicted bounding box and the solid line (red) bounding box indicates the ground truth.



Figure 4. *MLLM Failed Cases*. Instances where MLLM failed to annotate the MIP. These scenarios include: multiple individuals in similar attire or wearing the same sash, meeting setups where the focused person is not visible, hands prominently positioned, and group photos with uniform poses. Different colors of bounding boxes (bboxes) indicate that MLLM marked all of these bboxes as MIP in the given figures. The colors of the bboxes are random and hold no significance.

custom models using TensorFlow.js, ensuring customization and extensibility.

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