# MV-Debate: Multi-view Agent Debate with Dynamic Reflection Gating for Multimodal Harmful Content Detection in Social Media

Rui Lu<sup>1,2</sup>, Jinhe Bi<sup>3</sup>, Yunpu Ma<sup>3,4</sup>, Feng Xiao<sup>5</sup>, Yuntao Du<sup>1</sup>, Yijun Tian<sup>6</sup>

<sup>1</sup>Shandong University
<sup>2</sup>Ping An Technology
<sup>3</sup>Ludwig Maximilian University of Munich
<sup>4</sup>Munich Center for Machine Learning
<sup>5</sup>Computility Lab, Beijing EB Technology Co.LTD
<sup>6</sup>AWS AI

ruilu42@outlook.com, bijinhe@outlook.com, yunpu.ma@ifi.lmu.de, fengx@ebtech.com, yuntaodu@sdu.edu.cn, yijunt@amazon.com,

#### **Abstract**

Social media has evolved into a complex multimodal environment where text, images, and other signals interact to shape nuanced meanings, often concealing harmful intent. Identifying such intent, whether sarcasm, hate speech, or misinformation, remains challenging due to cross-modal contradictions, rapid cultural shifts, and subtle pragmatic cues. To address these challenges, we propose MV-Debate, a multi-view agent debate framework with dynamic reflection gating for unified multimodal harmful content detection. MV-Debate assembles four complementary debate agents, a surface analyst, a deep reasoner, a modality contrast, and a social contextualist, to analyze content from diverse interpretive perspectives. Through iterative debate and reflection, the agents refine responses under a  $\Delta$ -gain criterion, ensuring both accuracy and efficiency. Experiments on three benchmark datasets demonstrate that MV-Debate significantly outperforms strong single-model and existing multi-agent debate baselines. This work highlights the promise of multi-agent debate in advancing reliable social intent detection in safety-critical online contexts.

#### Introduction

The rapid growth of social media platforms as multimodal communication channels—integrating images, short videos, emojis, and stylized texts—has significantly increased the complexity and ambiguity of online messages, posing critical challenges for effective multimodal harmful content detection. For example, multimodal ambiguity occurs when a seemingly neutral caption paired with an ironic image or exaggerated visual cues expresses hidden ridicule, undetectable from text alone; similarly, memes or edited videos frequently amplify emotional or persuasive meanings beyond their literal content, complicating harmful intent detection. Accurately identifying the underlying social intent, whether a post ridicules (sarcasm), vilifies (hate speech), or misleads (misinformation), is thus critical not only for content moderation and community safety, but also for opinion mining, public-discourse analysis, and manipulation-campaign detection. The challenge is heightened by the creative ways users blend modalities, often relying on cultural references,

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irony, or ambiguity to veil harmful messages. Consequently, effective detection requires integrating linguistic cues, visual semantics, and contextual knowledge to uncover the true communicative intent of multi-modal content, ensuring reliable performance in safety-critical applications across increasingly complex online environments.

Yet such intent remains challenging to discern because cues are often (i) *cross-modal*: an image can invert or reinforce a caption's meaning; (ii) *context-dependent*: memes, slang, and cultural references evolve rapidly; and (iii) *subtle or sparsely distributed*: harmful intents may be concealed subtly within predominantly benign content. Empirical studies confirm these obstacles: state-of-the-art multimodal classifiers struggle with culturally grounded irony (Lu et al. 2025), while single-stream text-only models like BERT variants become brittle when visual evidence contradicts textual sentiment (Hee, Chong, and Lee 2023).

Recently, with the development of LLM agents, multiagent-based frameworks have achieved remarkable progress in many fields (Guo et al. 2024; Chan et al. 2023). Among them, multi-agent debate (Chan et al. 2023; Madaan et al. 2023) is an effective manner of utilizing the debate among multiple agents to promote the reasoning performance, which can compensate for individual blind spots. Representative methods include opinion-holding (Estornell and Liu 2024) and free-form method (Chan et al. 2023), where the former assigns a predefined opinion (e.g., true for sarcasm task), while the latter performs free-form prediction. Multi-agent debate mechanisms have improved performance on complex reasoning tasks, such as zero-shot stance detection and value-sensitive decision-making, by encouraging agents to expose, defend, and contest alternative interpretations (Du et al. 2023a; Zhang et al. 2024). Although achieving significant performance, few work has explore multi-agent debate for multimodal harmful content detection.

Current multi-agent debate-based systems typically have the following shortcomings for this scenario: (i) In multiagent debate settings, existing methods often employ identical LLM prompts across roles, resulting in similar reasoning patterns and repeated errors due to pre-training biases. (ii) The General MAD strategy is designed for general question

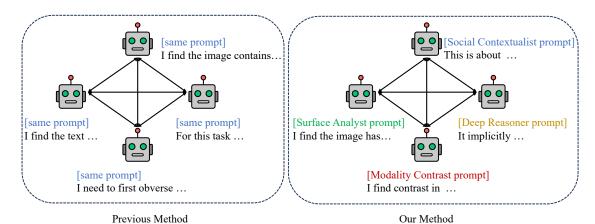


Figure 1: Comparison between existing MAD and our method.

answering tasks, which often overlooks task-specific design and leads to sub-optimal performance. (iii) Existing methods focus on a *single pragmatic category*, which needs multiple different methods for different tasks.

To address these gaps, we propose MV-Debate, a Multi-View agent Debate framework with dynamic reflection gating for unified multimodal harmful content detection. MV-Debate reformulates three historically siloed tasks—sarcasm (Benchekroun et al. 2022), hate speech (Kiela et al. 2020), and misinformation detection (Shu et al. 2020), under a broader Harmful Content Detection objective. Inspired by the intuition that diverse ways of thinking (Liu et al. 2025) can promote mutual inspiration, during the debate, our architecture assembles four different view-based vision-language agents, namely Surface Analyst, Deep Reasoner, Modality Contraster, and Social Contextualist. Each agent adopts a different reasoning perspective and combines insights from the perspective of others. By comparing these perspectives and extracting valuable insights, agents refine their answers to reach the correct result.

Specifically, in the first round, given an image and text pair, each agent generates an individual response with a unique given prompting. Then, a judge agent is introduced to score different competing responses, with the better response leading to a higher score. Next, to better stimulate the potential of each agent, a reflection agent proposes to reflect the topscoring agents. The new response is adopted only when a measurable  $\Delta$ -gain criterion (e.g.,  $\Delta \geq 0.1$  in judge scoring) is met, thus improving the reflection quality. At the second round, each agent reviews and critiques the highest score response selected from the last round, incorporating this feedback to produce its own response. Then, we perform a similar process as the first round. This whole debate process is repeated over several rounds. MV-Debate promotes diversity by introducing diverse views, leading to more robust solutions.

We conduct extensive experiments on three public benchmarks from three tasks. The Experimental results on these benchmarks demonstrate that: (i) MV-Debate consistently outperforms strong single-model and existing multi-agent debate baselines across all three intent types; (ii) MV-Debate with heterogeneous agents achieves better results than that of homogeneous agents; (iii) Large model size and more de-

bate rounds often lead to better performance, while they also require more cost and time.

To sum up, the contributions of this work are as follows:

- We introduce MV-Debate, a multi-agent debate framework that guides agents to employ diverse reasoning views for multi-modal harmful content detection in social media.
- We design four view-specific debate agents with a dynamic reflection gating mechanism to improve the performance.
- We empirically validate the effectiveness of the proposed method on multiple multi-modal harmful content benchmarks.

## **Related Work**

#### **Harmful Content Detection in Social Media**

Early multimodal studies addressed sarcasm, hate speech, and misinformation as *separate* problems, each with its own dataset and model design. Recent years have shifted toward LMMs and agentic frameworks.

- (i) Sarcasm: Tang et al. (Tang et al. 2024) adapt LMMs via visual instruction templates with in-context demonstrations. S³ Agent (Wang et al. 2024) integrates multiple LMMs from semantic, superficial, and sentiment views, while Commander-GPT (Zhang et al. 2025) decomposes sarcasm into six subtasks and aggregates rationales through a central "commander."
- (ii) **Hate speech**: Van & Wu (Van and Wu 2023) show that prompting LLaVA and GPT-4V with crafted instructions achieves strong zero-shot hateful-meme detection. Yamagishi (Yamagishi 2024) finds simple prompts outperform complex ones for event detection. Lin (Lin et al. 2024a) offers an explainable method by reasoning over conflicting harmless and harmful rationales.
- (iii) Misinformation: To tackle scarce and noisy supervision, LVLM4FV (Tahmasebi, Müller-Budack, and Ewerth 2024) combines GPT-ranked evidence retrieval with an InstructBLIP verifier, while SNIFFER (Qi et al. 2024) employs two-stage instruction tuning with entity extraction and imagebased web search. LEMMA (Xuan et al. 2024) enhances reasoning via multi-query retrieval and distillation. Cekinel et al. (Cekinel, Karagoz, and oltekin 2025) probe VLM embeddings with a lightweight classifier.

Toward unification of these tasks, MM-SOC (Jin et al. 2024) integrates ten tasks, including sarcasm, hate, and misinformation, revealing LMMs' fragility in socially nuanced harmful content.

## **Multi-Agent Debate**

Multi-agent debate was first shown to improve factual accuracy in open-domain QA (Du et al. 2023a) and later operationalised through open-source frameworks such as AUTO-GEN (Wu et al. 2023). Following works studied MAD from different perspectives. Some assign different agents to play different roles (Wang et al. 2023). There are also other methods improving MAD through embeddings (Pham et al. 2023). RECONCILE arranges a round-table "conference" among LLMs to reach consensus (Chen, Saha, and Bansal 2024), while CAF-I tailors role-specialised agents to irony detection (Liu, Zhou, and Hu 2025). These successes confirm that agent heterogeneity and structured interaction benefit hard reasoning tasks.

However, most of them debate with a single thinking which may lead to similar output patterns. Instead, we propose MV-Debate to encourage different agents to think with distinct reasoning views, which can prompt mutual inspiration. Similarly, (Gao et al. 2024a) dynamically selects the most suitable reasoning method to solve the problem.

# Large Multimodal Model

Large Multimodal Models (LMMs) have achieved progress in integrating vision and language, enabling cross-modal understanding and reasoning. A typical LMM comprises three components: a language encoder, a vision encoder, and a cross-modal interaction module (Caffagni et al. 2024; Balauca et al. 2025; Bi et al. 2025; Jinhe et al. 2025b,a). The cross-modality module bridges the two, allowing effective processing of visual inputs.

Building on this architecture, models such as Qwen2.5-VL (Bai et al. 2025), InternVL2.5 (Chen et al. 2024), and LLaVA series (Liu et al. 2023; Li et al. 2025) adopt different design choices and training strategies. These advances have significantly improved vision-language alignment, yielding strong performance across multimodal benchmarks (Kil et al. 2024; Huang and Zhang 2024). Additionally, closed-source models such as GPT-4v, GPT-4o (Hurst et al. 2024), Gemini(Comanici et al. 2025), and Claude-Sonnet have demonstrated excellent results in diverse multimodal tasks. Besides, agent-based method (Gao et al. 2024b; Fan et al. 2024; Wang et al. 2025) also achieved remarkable progress.

#### **Reflection in LMMs**

Prompt-level *self-reflection* has proven to boost test-time reasoning. Self-Refine (Madaan et al. 2023) lets a model iteratively critique and rewrite its own answer, improving seven diverse tasks without extra training. Renze & Guven (Renze and Guven 2024) systematically evaluate eight reflection variants and report significant gains across public question banks. Beyond prompting, Bansal (Bensal et al. 2025) introduces Reflect-Retry-Reward, a reinforcement-learning framework that rewards tokens produced during successful reflections. Taken together, these

studies confirm that reflection is powerful but costly when applied indiscriminately, underscoring the importance of *gated* or selective reflection strategies.

## Methodology

This section describes our proposed reflection-gated multiagent debate framework (**MV-Debate**) for multimodal harmful content detection in social media.

#### **Problem Formulation**

Given a multimodal social-media post composed of text  $x^{text}$  and associated visual content  $x^{img}$ , the goal is to predict its underlying *social intent* label  $y \in \mathcal{Y}$ , where  $\mathcal{Y} = \{Yes, No\}$  indicates whether there are sarcasm, hate content, or misinformation. The objective is to maximize predictive accuracy.

## **System Architecture**

Inspired the intuition that diverse reasoning methods could lead to better cooperation results in multi-agent debates. This method could avoid the analogous phenomenon in existing LMMs, that MAD with a fixed prompting strategy may always produce similar answers to a problem. Thus, we argue the importance of utilizing different reasoning views in debate to promote diverse thinking and propose a multi-view-based debate method for multimodal harmful content detection. We employ a variety of prompting reasoning techniques to produce distinct modes of thought, which do not need training or fine-tuning. We endeavor to design reasoning methods with significant divergence to avoid the issue of similar reasoning processes.

Specially, the MV-Debate system consists of four types of specialized debate agents, alongside three additional control agents. Each debate agent is required to answer the question with the corresponding assigned view, and the control agent aims to score and reflect the reasoning path, and eventually, make a final prediction.

#### 1. Specialized Debate Agents:

- Surface Analyst agent (SA): This agent focuses exclusively on explicit textual and visual cues to detect.
- Deep Reasoner agent (DR): This agent uncovers implicit meanings and hidden intents to detect.
- Modality Contrast agent (MC): This agent assesses alignment or contradictions between textual and visual modalities to detect.
- Social Contextualist agent (SC): This agent leverages external cultural and social-contextual knowledge to detect.
- Judge Agent: This agent evaluates arguments generated by the debate agents. It assigns scores based on logical coherence, consistency, and plausibility, where a better response would get a higher score.
- Reflection Agent: This agent generates structured feedback highlighting logical flaws and improvement suggestions.
- 4. **Summary Agent**: This agent aggregates the debate history and delivers the final prediction.

Algorithm 1: Reflection-Gated Multi-View Debate

```
Require: Input: (x^{\text{text}}, x^{\text{img}}), Max rounds R, Reflection
      threshold \tau, Top-k
Ensure: Predicted social intent label: \hat{y}
 1: Initialize debate history: H \leftarrow \emptyset
 2: for t = 1 to R do
         Agent responses generation (parallel)
 3:
 4:
         for each agent i \in \{SA, DR, MC, SC\} in parallel do
            \mathbf{r}_{i,t} \leftarrow a.\mathsf{GENERATE}(x^{\mathsf{text}}, x^{\mathsf{img}}, H)
 5:
         end for
 6:
 7:
         if \mathsf{CONSENSUS}(\{\mathbf{r}_{i,t}\}) then
 8:
            return SUMMARY(H \cup \{\mathbf{r}_{i,t}\})
 9:
         end if
         \mathbf{s}_{i,t} \leftarrow \texttt{Judge}(\{\mathbf{r}_{i,t}\})
10:
         Update best response: i^* \leftarrow \arg\max_i s_{i,t}
11:
         Append to history: H \leftarrow H \cup \{(\mathbf{r}_{i^*,t}, s_{i^*,t})\}
12:
         Calculate reflection gain:
13:
             \Delta \leftarrow \text{COMPUTEDELTA}(x^{\text{text}}, x^{\text{img}}, k)
14:
15:
         if \Delta \geq \tau then
            \phi_t \leftarrow \text{Reflect}(H)
16:
17:
            Append reflection feedback:
            H \leftarrow H \cup \{\phi_t\}
18:
19:
20: end for
21: return SUMMARY(H)
```

#### **Multi-View Debate**

**Initial Response Generation** At the first round of debate, given an image-text pair, each specialized debate agent generates its response  $r_{i,1}$ , where the subscript "1" means the first round, guided by the corresponding task view prompt  $p_i$ :

$$r_{i,1} = M_i(x^{text}, x^{img} | h_i, p_i), i = 1, 2, ..., 4.$$
 (1)

where  $h_i$  is the history messages for i-th agent and is initialized as an empty list.  $r_{i,1}$  is output as a structured JSON object comprising a binary decision ('YES' or 'NO') and a brief reasoning. Their role-specific prompts strictly enforce distinct analytical perspectives, ensuring diversity and complementarity in the overall reasoning process.

Consequently, the judge agent collects the solving processes and answers to the questions of all debate agents, and it assigns a score  $s_{i,1}$  for each agent's response, with a better response leading to a higher score.

**Top-**k  $\Delta$ **-Reflection Gating** As the initial response from these agents may contain incorrect information, following previous work, we introduce a reflection mechanism to self-improve the response quality.

To reduce computational overhead, we introduce a Top-k  $\Delta$ -reflection gating strategy. At each round, the reflection agent would receive all the debate agents' responses and check the reasoning process of each agent. Then, it would point out the reasoning error and provide a revision suggestion. Next, the top k highest responses scored by the judge agent are selected. Then, each selected original debate agent would generate a new response  $\hat{r}_{i,1}$  with the query instance, initial response, and revision suggestions. After that, the judge agent would rescore the new response, denoted as  $\hat{s}_{i,1}$ .

Then, we estimate the expected utility of reflection by comparing the scores of the agents with and without reflection feedback. Formally, reflection gain  $\Delta_{i,1}$  is calculated as follows:

$$\Delta_{i,1} = \frac{1}{k} \sum_{i \in \text{Top}_k} (\hat{s}_{i,1} - s_{i,1})$$
 (2)

Reflection is only triggered when  $\Delta_{i,1}$  surpasses a predefined threshold  $\tau$ , i.e.,  $\Delta_{i,1} \geq \tau$ . Otherwise, we would use the original response.

In our experiments, we empirically set k=2 and  $\tau=0.1$  to achieve efficiency improvements. As it could reduce redundant reflection calls by over 60% compared with reflecting all debate agents, while maintaining or improving accuracy compared to the unconditional reflection baseline.

**History Update** After reflection, if the newer response is not adopted, the judge agent would collect highest highest-scoring response, and append it to the history. Otherwise, we will additionally append the reasoning error and revision suggestions  $\phi_1$  into the history.

**Debate Loop** Starting from the second round, the best-scoring response from the last round, including both the reasoning processes and the answers, is incorporated into each agent's history  $h_i$ . In the following round, each agent leverages these reasoning traces and solutions as additional input, selectively extracting useful information from the diverse perspectives to refine its own answer. This iterative debate process follows the same process as described above, until either the maximum number of rounds N is reached or the agents converge on the same judgment. In our experiments, we set N=3. Finally, at the end of the debate, the summary agent would aggregate the debate history and deliver the final prediction  $\hat{y}$ . Algorithm 1 summarizes the iterative debate and reflection procedure.

#### **Discussion**

The proposed reflection-gated multi-view debate framework (MV-Debate) offers three main advantages for multimodal harmful content detection. First, assigning specialized roles to debate agents enforces diverse reasoning perspectives. Unlike single-view prompting, this design combines surface-level, deep semantic, cross-modal, and social-cultural analyses, reducing the risk of missing implicit or context-specific harmful cues

Second, the Top-k  $\Delta$ -reflection gating mechanism enhances reliability while maintaining efficiency. By adaptively triggering reflection only when substantial improvement is expected, the framework avoids redundant computation yet achieves accuracy comparable to or better than unconditional reflection. This is relevant for real-world deployment where scalability and cost-efficiency are critical.

Third, the iterative debate loop encourages cumulative reasoning. Agents refine their predictions by integrating high-quality responses and structured feedback into their histories, promoting both inter-agent diversity and intra-agent improvement while mitigating repeated errors.

Table 1: The comparison results on three multimodal harmful content detection datasets.

Method	Model	MMSD		HatefulMeMe		GossipCop		Avg	
		Acc	F1	Acc	F1	Acc	F1	Acc	F1
	Closed-source								
Single Model	GPT o4-mini	77.5	78.0	70.8	63.7	72.8	66.9	73.7	69.5
	GPT 4o	78.5	75.4	75.2	71.5	73.4	75.8	75.7	74.2
	Gemini-Flash-2.5	73.9	80.1	77.4	67.5	76.5	72.7	75.9	73.4
	Claude-4-Sonnet	82.5	84.9	72.2	64.2	76.6	73.9	77.1	74.3
	Open-source								
	InternVL3-14B	74.5	78.6	68.2	64.1	72.2	68.7	71.6	70.5
	Gemma-3-12B	68.5	70.9	67.2	67.8	74.8	68.2	70.2	69.0
	Qwen2.5-VL-7B-Instruct	56.1	54.7	59.1	42.3	68.8	63.7	61.3	53.6
	LLaMA-4-Maverick-17B	75.4	77.4	67.8	65.5	72.4	64.2	71.9	69.0
	MAD	78.6	77.0	69.1	66.5	75.0	70.3	74.2	71.3
Multi-Agent Debate	DMAD	81.1	81.8	72.5	69.2	77.1	72.0	76.9	74.4
(Heterogeneous)	ChatEval	81.9	88.5	71.3	68.3	77.6	72.9	77.0	76.6
	DebUnc	79.6	72.1	68.6	63.2	73.8	69.6	74.0	68.3
Ours (Homogeneous)	Open-source								
	Qwen2.5-VL-7B-instruct	65.7	62.3	61.7	61.5	71.1	65.6	66.2	63.1
	InternVL3-14B	81.4	75.5	72.5	72.5	74.4	62.3	76.1	70.1
	LLaMA-4-Maverick-17B	82.1	83.5	74.4	76.1	77.6	64.7	78.0	74.8
	Gemma-3-12B	80.4	79.1	68.3	67.5	78.1	69.8	75.6	72.1
	Closed-source								
	Claude-4-Sonnet	90.2	86.1	80.4	70.5	78.3	69.2	82.9	75.3
Ours	Ours (Open-source)	86.1	82.5	76.0	64.5	79.4	72.3	80.5	73.1
(Heterogeneous)	Ours (Closed-source)	92.3	93.1	80.8	70.9	81.7	70.1	84.9	<b>78.0</b>

## **Experiment**

#### Setup

**Datasets** Following previous work (Lin et al. 2024b; Liang et al. 2022), in this section, we conduct comprehensive experiments on three widely-used multimodal social context datasets, including the MMSD dataset (Benchekroun et al. 2022) for the sarcasm detection task, the HatefulMeMe dataset (Kiela et al. 2020) for the hate speech task, and the GossipCop dataset (Shu et al. 2020) for the misinformation detection task. As our method and baseline multi-agent debate methods need many tokens for a given instance, following previous works (Du et al. 2023a; Liu et al. 2025). We do not use the whole dataset and instead randomly select a subset for evaluation. The number of MMSD, HatefulMeMe, and GossipCop dataset is all 500.

**Baseline Methods** To show the effectiveness of the proposed method, we compare MV-Debate with several types of methods.

The first type of method is the state-of-the-art large multimodal models. For these models, we perform zero-shot prediction with the corresponding task prompt. The selected models includes closed-source models: GPT 40 (Hurst et al. 2024), GPT o4-mini (OpenAI 2025), Gemini-Flash-2.5 (Comanici et al. 2025), Claude-4-Sonnet. Besides, we also select some representative open-source models: Qwen2.5-

VL (Bai et al. 2025), InternVL3 (Chen et al. 2024), LLaMA-4-Maverick, and Gemma-3 (Team et al. 2025).

The second type of method is existing general multiagent debate methods, including MAD (Du et al. 2023b), DMAD (Liu et al. 2025), ChatEval (Chan et al. 2023), and DebUnc (Yoffe, Amayuelas, and Wang 2024). It is noted that these methods are proposed based on LLM and replace the corresponding debate agent with LMMs.

The third type of method is our proposed method and its variants. We implement our methods with both homogeneous and heterogeneous agent scenarios, where the former means that all the debate agent adopts the same LMMs, and the latter adopt different LMMs as the debate agents. For these two scenarios, we test the model on both open-source and closed-source LMMs.

Implementation Details We implement our method based on PyTorch and Huggingface Transformer for the experiments. As for evaluation, we adopt the accuracy and F1 score as metrics, and all the reported metrics were computed by scikit-learn. We utilize closed-source LMMs as our control agents (Judge Agent, Reflection Agent, and Summary Agent) in MV-Debate, including Claude-4-Sonnet, GPT o4-mini, and GPT 40, respectively. We set the temperature to 0 and greedy-search to ensure reproducibility. For the Specialized Debate Agents, we use both closed-source and open-source LMMs in our experiments. We use the same model (e.g., LLaMA-4-

Maverick-17B) for the multi-view specialized agents in the homogeneous experiments. For the heterogeneous settings, we use four unique LMMs as our multi-view specialized agents. We leveraged API interfaces to invoke closed-source LMMs and implemented an asynchronous strategy to execute specialized debate agents in parallel, significantly enhancing runtime efficiency. The experimental hyperparameters in the code fall into three main categories: (i) Randomness: We set the random seed to 42 in all experiments. (ii) Debate process control: we set max rounds N=3, reflection-gain threshold  $\tau=0.1$ , and  $k=\lfloor\frac{L}{2}\rfloor$  (where L represents the number of multi-view specialized agents) as the top-k agents selected for the computation of reflection gain. (iii) API scheduling: we set max retries p=5 times and retry delay q=3 seconds for all the closed-source LMM agents in our experiments.

#### **Main Results**

The comparison with baseline methods is shown in Table 1. Based on the results, we have the following findings.

**Single-model baselines.** Closed-source models generally outperform open-source counterparts. Claude-4-Sonnet achieves the best overall performance among single models, while GPT 40 and GPT 04-mini trail slightly behind. In contrast, open-source models show a notable performance gap, with Qwen2.5-VL variants performing poorly. These results indicate the difficulty of applying off-the-shelf open-source LMMs to harmful content detection.

**Existing multi-agent debate baselines.** We implement the existing multi-agent debate baseline in an heterogeneous setting with SOTA open-source LMMs (including Qwen2.5-VL-7B-instruct, InternVL3-14B, LLaMA-4-Maverick-17B, and Gemma-3-12B). The results show that existing multi-agent debate frameworks (e.g., DMAD, ChatEval) demonstrate clear advantages over single models. ChatEval, for example, achieves 76.6% of F1 score, confirming that multi-agent collaboration with a debate manner improves robustness.

Our homogeneous MV-Debate. In a homogeneous scenario, we implement MV-Debate with four kinds of open-source LMMs. The results show that our homogeneous framework consistently improves over its base models. For instance, the accuracy of Gemma-3-12B increases from 70.2 (single) to 75.6 with MV-Debate, while InternVL3-14B improves from 71.6 to 76.1. LLaMA-4-Maverick-17B achieves the best open-source results with an accuracy of 78.0. These gains validate the effectiveness of enforcing multi-view reasoning and reflection even without heterogeneous agents.

Our heterogeneous MV-Debate. We implement MV-Debate in a heterogeneous scenario with both open- and closed-source LMMs, and our heterogeneous framework achieves the highest performance. Besides, the open-source variant yields an accuracy of 80.5, which outperforms existing multi-agent debate methods. The closed-source variant reaches an accuracy of 84.9, surpassing all baselines. This demonstrates that reflection-gated multi-view debate establishes new state-of-the-art results. Besides, the heterogeneous agent achieves better results than a homogenous agent under open-source models, which implies that different models could also lead to diverse thinking.

In summary, MV-Debate effectively integrates diverse rea-

Table 2: Ablation study about the debate agent.

Settings	LLaMA	-4-Maverick-17B	Claude-4-Sonnet			
	Acc	F1	Acc	F1		
Ours	82.1	83.5	90.2	86.1		
w/o SA	80.4	87.2	87.6	85.1		
w/o DR	78.4	69.8	86.3	84.4		
w/o MC	75.7	72.5	85.7	83.5		
w/o SC	77.5	74.5	86.1	82.5		
Zero-shot	75.4	77.4	82.5	84.9		

soning views with adaptive reflection, achieving superior accuracy and efficiency. The results highlight its promise as a scalable and reliable framework for multimodal harmful content detection.

# **Insightful Analysis**

Ablation study of debate agents We conduct an ablation study to evaluate the contribution of each specialized debate agent in the homogeneous scenario, as the heterogeneous scenario would couple the effect of different LMMs. We evaluate four agents: Surface Analyst (SA), Deep Reasoner (DR), Modality Contraster (MC), and Social Contextualist (SC). The results are shown in Table 2.

For LLaMA-4-Maverick-17B, removing any agent leads to a performance drop compared with the full MV-Debate. The most significant decline occurs when excluding the Modality Contrast. This confirms the critical role of assessing consistency and contradictions between modalities. Removing the deep reasoner also causes a large drop, highlighting the importance of capturing implicit meanings and hidden harmful intents that are often overlooked by surface-level cues. Excluding the Social Contextualist results in a moderate decline, suggesting that external sociocultural knowledge is essential to interpret nuanced harmful signals. In contrast, removing the Surface Analyst causes only a minor drop, as explicit cues may be partly covered by other agents. Besides, a similar trend is observed for Claude-4-Sonnet. These consistent patterns across both open- and closed-source models validate the necessity of combining diverse reasoning views.

Ablation Study of reflection mechanism Table 3 demonstrates the impact of incorporating reflection in our method in both homogeneous and heterogeneous scenarios. Across all models, reflection consistently improves both accuracy and F1. For example, for Claude-4-Sonet, the accuracy increases from 85.1 to 90.2 (+5.3), highlighting its effectiveness in correcting reasoning errors and enhancing the detection of implicit harmful cues. In summary, reflection plays a pivotal role in maximizing the effectiveness of multi-agent debate. By selectively guiding agents to revise their reasoning, it stabilizes outputs and improves consistency, making the framework more reliable and scalable for real-world harmful content detection tasks.

**Ablation Study of the best history** During the debate, we would select the best-scoring response of the debate agents instead of that of all agents. To show the effectiveness, we compare these two settings in both homogeneous and heterogeneous scenarios. The results of the ablation study of the

Table 3: Ablation study about reflection. "homo" and "hete" mean homogeneous and heterogeneous, respectively.

		w/o R	eflection	with Reflection		
		Acc	F1	Acc	F1	
Ours	LLaMA-4-maverick-17B	80.4	78.2	82.1	83.5	
(homo)	Claude-4-Sonnet	85.1	82.3	90.2	86.1	
Ours	Ours(Open-source)	84.3	79.5	86.1	82.5	
(hete)	Ours(Closed-source)	88.2	<b>87.5</b>	<b>92.3</b>	<b>93.1</b>	

best history are shown in Table 4. Our method with LLaMA-4-Maverick-17B shows notable sensitivity to data quality, with its accuracy improving from 70.1 ("All History") to 82.1 ("Best History"), suggesting it benefits substantially from filtered or higher-quality data. A consistent trend across all models is the superior performance in the "Best History" setting compared to "All History," highlighting the importance of data quality and curation. This effect is most pronounced for LLaMA-4-Maverick, suggesting it is particularly vulnerable to noisy or suboptimal data.

Table 4: Ablation study about history. "homo" and "hete" mean homogeneous and heterogeneous, respectively.

		All History		Best History	
		Acc	F1	Acc	F1
Ours	LLaMA-4-Maverick(17B)	70.1	62.8	82.1	83.5
(homo)	Claude-4-Sonnet	80.4	78.6	90.2	86.1
Ours	Ours (Open-source)	72.0	63.5	86.1	82.5
(hete)	Ours (Closed-source)	<b>82.2</b>	<b>80.1</b>	<b>92.3</b>	<b>93.1</b>

Ablation about debate round The effect of varying the number of debate rounds from 1 to 4 in a homogeneous scenario based on LLaMA-4-maverick-17B is shown in Figure 2. We observe that increasing the debate rounds generally enhances performance. Specifically, accuracy rises from 76.6 at one round to 82.1 at four rounds. Notably, the transition from one to three rounds yields the most substantial gains. The fourth round brings marginal improvements, suggesting that iterative debate allows agents to progressively refine their reasoning by integrating complementary perspectives, though performance gains tend to saturate after three rounds. These results highlight the effectiveness of multi-round debate in enhancing both robustness and precision, while indicating a practical trade-off between performance gains and additional computational overhead. Thus, considering both efficiency and effectiveness, set the debate round to be 3 in our experiments.

Ablation about model size The results of the impact of model size on sarcasm and hate detection in a homogeneous scenario on Qwen2.5-VL series models are shown in Table 3. As the parameter scale increases from 7B to 72B, the accuracy consistently improves across tasks. For sarcasm detection, accuracy rises from 66% to 81%, indicating a substantial gain of over 15 percentage points. Similarly, for hate detection, accuracy increases from 62% to 79%. These results suggest that larger models possess a stronger capacity for capturing subtle multimodal cues and complex pragmatic signals, leading to more accurate social intent classification.

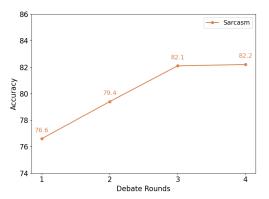


Figure 2: Ablation about debate round.

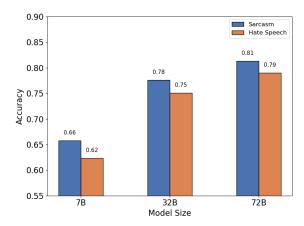


Figure 3: Ablation about model size on Qwen2.5-VL.

## Conclusion

In this work, we introduced MV-Debate, a novel multi-view debate framework for multimodal harmful content detection on social media. By orchestrating four view-specific agents with complementary reasoning strategies and a dynamic reflection gating mechanism, MV-Debate effectively integrates cross-modal evidence and contextual cues to identify complex social intents such as sarcasm, hate speech, and misinformation. Extensive experiments across multiple benchmarks confirm its superior accuracy, efficiency, and interpretability compared with strong baselines. Beyond performance gains, MV-Debate also generates transparent debate transcripts, supporting model debugging, auditing, and user trust. Looking forward, our framework provides a foundation for extending multi-agent debate approaches to broader safety-critical multimodal reasoning tasks.

As for the limitation, the framework's performance depends on the underlying LMMs, which may inherit biases or struggle with culturally nuanced content such as sarcasm. The current design also fixes the number of reasoning views, which may not always balance accuracy and efficiency.

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