HVGuard: Utilizing Multimodal Large Language Models for Hateful Video Detection

Anonymous ACL submission

Abstract

The rapid growth of video platforms has transformed information dissemination and led to an explosion of multimedia content. However, this widespread reach also introduces risks, as some users exploit these platforms to spread hate speech, which is often concealed through complex rhetoric, making hateful video detection a critical challenge. Existing detection methods rely heavily on unimodal analysis or simple feature fusion, struggling to capture cross-modal interactions and reason through implicit hate in sarcasm and metaphor. To address these limitations, we propose HVGuard, the first reasoning-based hateful video detection framework with multimodal large language models (MLLMs). Our approach integrates Chain-of-Thought (CoT) reasoning to enhance multimodal interaction modeling and implicit hate interpretation. Additionally, we design a Mixture-of-Experts (MoE) network for efficient multimodal fusion and final decision-making. The framework is modular and extensible, allowing flexible integration of different MLLMs and encoders. Experimental results demonstrate that HVGuard outperforms all existing advanced detection tools, achieving an improvement of 6.88% to 13.13% in accuracy and 9.21% to 34.37% in M-F1 on two public datasets covering both English and Chinese.

Disclaimer: This paper contains harmful content, which has the potential to be offensive and may disturb readers.

1 Introduction

In recent years, video platforms like YouTube (Google, 2005), Bilibili (Kuanyu, 2009), and TikTok (ByteDance, 2016) have transformed information dissemination and fueled multimedia growth. However, this also brings risks, as some users exploit these platforms to spread false information, extremist content, and hate speech (Ottoni et al., 2018). Hate speech, which demeans, attacks, or marginalizes individuals or groups based on characteristics like race, religion, or gender (Hee et al., 2024b; Fortuna and Nunes, 2018). It may not only incite social conflicts but also cause real-world harm to individuals and groups. Thus, effectively detecting hate speech on video platforms (Alcântara et al., 2020; Das et al., 2023; Wu and Bhandary, 2020) has become an urgent challenge.

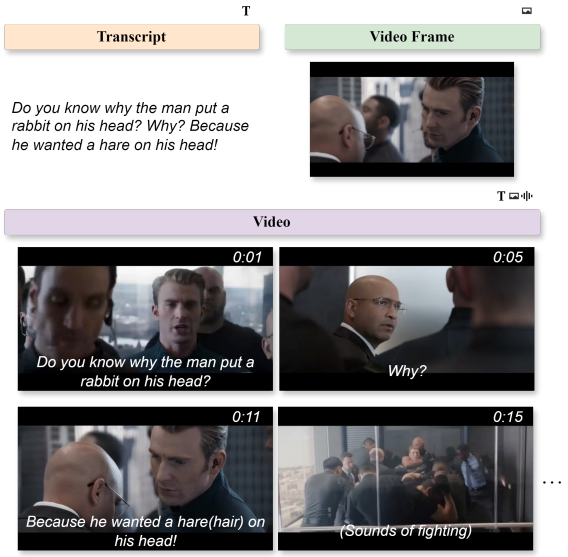


Figure 1: A typical example of hateful video

Compared with traditional text-based forms, the spread of hate speech in videos is more concealed and has a broader impact. Since video content typically includes multimodal information including text, audio, and visual elements, hate message is often embedded in a more subtle manner, making it difficult for single-modality detection methods to identify effectively. Figure 1 shows an offender joking with a bald victim: "Do you know why the man put a rabbit on his head?" "Because he wanted a hare on his head!" This uses the phonetic similarity between "hair" and "hare" to offend bald individuals. It highlights a challenge in detecting subtle hate speech and the need for inference. Fur-

thermore, content that appears harmless in a single modality may reveal its offensive nature when visual, auditory, and contextual cues are considered together. Effective hateful video detection thus requires an integrated understanding of multimodal interactions and rhetorical devices such as metaphor and wordplay.

Current hateful video detection methods mainly use modality encoders to extract features and then classify them (Yu et al., 2022; Wu and Bhandary, 2020; Wang et al., 2024; Das et al., 2023). However, these methods either use single modality or simply concatenate features from multiple modalities which is limited because it does not take into account the interaction between different modalities. At the same time, hateful videos often involves rhetorical devices such as metaphors, irony, and sarcasm (Xu et al., 2024; Ge et al., 2023), which cannot be addressed by simple modality feature extraction methods without some form of reasoning (Prystawski et al., 2022). Moreover, online hateful videos are increasing rapidly and are often related to specific cultural contexts (Ottoni et al., 2018). This requires the integration of rich world knowledge to enhance reasoning capabilities to address this issue. Therefore, research on hateful video detection has important practical significance and can provide more precise technical support for the content moderation mechanisms of social platforms.

Recent advancements in multimodal large language models (MLLMs) (Bai et al., 2023; Team et al., 2024; Liu et al., 2024; Wang et al., 2023) have demonstrated strong video understanding capabilities by leveraging extensive world knowledge and deep semantic comprehension (Tang et al., 2023). This makes them promising for tackling the challenges of hateful video detection. To enhance their effectiveness in this domain, we incorporate Chain-of-Thought (CoT) reasoning, which enables MLLMs to break down complex reasoning tasks into intermediate steps. This structured approach allows for a more systematic analysis of multimodal information—spanning audio, visual, and textual components—while capturing their interactions to form a coherent understanding of the video's overall semantics.

In this work, we first explore the effectiveness of MLLMs and CoT reasoning in understanding hateful videos, particularly their role in handling multimodal interactions and rhetorical devices such as metaphors. Building on these insights, we propose the first reasoning-based hateful video detection framework, HVGuard[1]. Our approach leverages MLLMs to generate multimodal rationales and incorporates a CoT strategy that explicitly models cross-modal interactions and rhetorical elements, addressing the challenges of implicit hate detection. Additionally, we design a Mixture-of-Experts (MoE) network (Jacobs et al., 1991) to effectively integrate diverse multimodal information. The MoE model fuses multimodal representations with MLLM-derived rationales, optimizing the decision-making process. This integration enables our framework to combine low-level feature extraction with high-level semantic reasoning, ultimately improving the accuracy and robustness of hateful video detection. Experimental results demonstrate that HVGuard achieves a detection accuracy of up to 0.86, outperforming existing state-of-the-art methods.

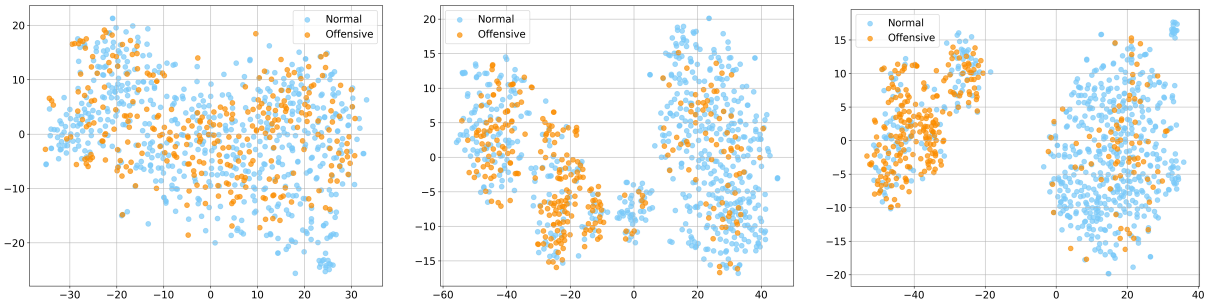
The key contributions of this paper are as follows:

- **First Exploration of MLLMs and CoT in Hateful Video Understanding.** This is the first work to explore the potential of MLLMs and CoT reasoning for hateful video understanding, demonstrating their effectiveness in managing multimodal interactions and complex rhetorical devices, such as metaphors.

- **Novel Reasoning-Based Hateful Video Detection Framework.** We propose the first reasoning-based hateful video detection framework, integrating MLLMs with CoT reasoning to enhance multimodal interaction modeling and implicit hate interpretation. Additionally, we introduce a MoE network to efficiently fuse multimodal representations and MLLM-generated rationales, optimizing the decision-making process.

- **Extensive Evaluation of HVGuard.** Experimental results show that HVGuard achieves up to 0.86 accuracy, outperforming all existing detection tools with accuracy gains of 6.88% to 13.13% and M-F1 improvements of 9.21% to 34.37%. Extensive experiments on two public datasets, covering both English and Chinese, further validate its effectiveness in binary and ternary classification settings against five state-of-the-art baselines, including advanced MLLMs and existing detection tools.

[1]We will open-source our framework for future research.



(a) Embeddings from BERT. (b) Embedding from GPT-4o. (c) Embedding from GPT-4o with CoT.

Figure 2: Visualization of features used by different methods. (a) Embedding of video titles, transcripts. (b) Embedding of MLLM rationale. (c) Embedding after incorporating the CoT prompts.

2 Preliminary Study

With the advancement of artificial intelligence, MLLMs have become the focal point of the latest developments. The complementarity of LLMs and VLMs has given rise to MLLMs, such as Gemini 1.5(Team et al., 2024) and GPT-4 series (Achiam et al., 2023). They can receive, reason, and output multi-modal information, showing impressive capabilities in various multi-modal tasks, including image reasoning and video understanding (Wu et al., 2023; Fu et al., 2024), thus opening up new ways to solve complex and novel challenges in the multi-modal field.

To more clearly demonstrate how the reasoning capability of MLLMs aids in understanding of hateful content in videos, we conducted a visual analysis of embedding representations on the hateful video dataset Multihateclip (Wang et al., 2024). Figure 2a visualizes the embeddings of pure textual information (video title and transcript) extracted using the pre-trained text encoder BERT (Devlin, 2018), which exhibit significant overlap with no discernible class separability. This indicates the insufficiency of traditional approaches with single modality. However, when analyzing videos with MLLMs (Figure 2b), a certain degree of class separability becomes observable. By further incorporating the CoT prompting strategy (detailed in Section 3.4), we guide the MLLM to clarify rhetorical devices such as metaphors and puns in the videos, ultimately achieving sharper classification boundaries (Figure 2c). Thus, MLLMs provide effective rationale for hateful video understanding, and the CoT prompting strategy further amplifies this capability.

3 Method

3.1 Task Definition

The goal of hateful video detection is to extract features from videos and classify them based on these features. The video dataset is represented as $\mathcal{V} = \{v_1, \ldots, v_i, \ldots, v_{|\mathcal{V}|}\}$, where $|\mathcal{V}|$ is the number of videos. The task can be expressed as:

$$\arg \max_{c \in \{1,2,\ldots,|C|\}} P(c|v_i) \quad (1)$$

where $c \in \{1, 2, \ldots, |C|\}$ represents the classification categories. Our work focuses on utilizing rationale generated by MLLM and multimodal information from the video itself for hateful video detection. Therefore, this task can be re-expressed as:

$$\arg \max_{c \in \{1,2,\ldots,|C|\}} P(c|v_i^T, v_i^A, v_i^F, v_i^M) \quad (2)$$

where v_i^T represents the text information in the video (such as title, subtitles, or transcript), v_i^A represents the audio information of the video, v_i^F represents the frame information of the video, and v_i^M represents MLLM-derived rationales.

3.2 Overview

The overview of our framework, HVGuard, is shown in Figure 3. Based on preliminary study, we design this novel framework for hateful video detection, leveraging MLLM-derived rationales to address challenges in multimodal interaction and the interpretation of metaphors and rhetorical devices. This framework extracts text, audio, and video frames from the input video, providing a comprehensive semantic representation of the video. A

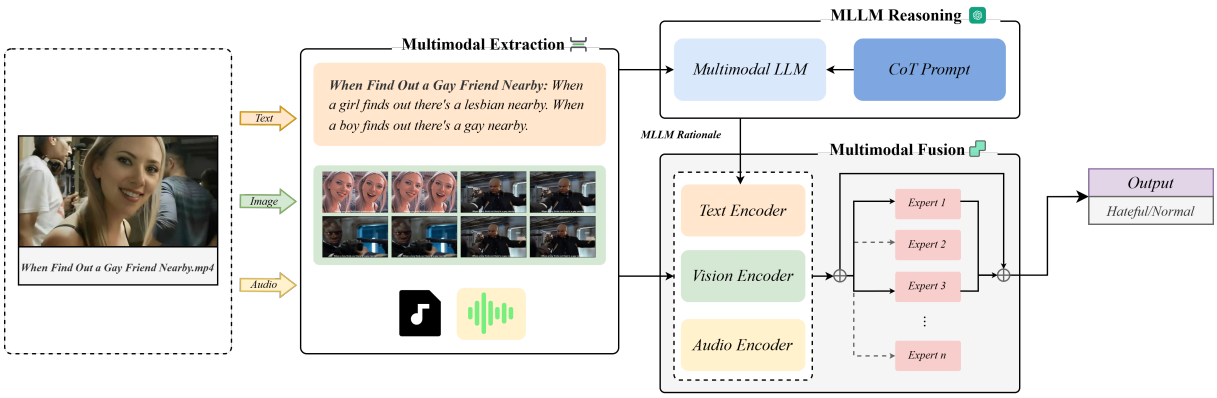


Figure 3: Overview of the proposed framework.

CoT-based reasoning approach is then applied, progressively reasoning through the individual modalities and their interactions, to generate rationale from MLLM. In the final stage, these embeddings are ultimately integrated using a MoE network to yield the final classification results.

3.3 Multimodal Extraction Module

Considering that hateful videos encompass multiple modalities, we first extract feature information from the three main modalities of the video: text, audio, and video frames. We process audio signal v_i^A as a combination of semantic information and emotional information. We use FunASR (Gao et al., 2023), an open-source audio processing tool, to transcribe the audio into transcript v_i^{trans} and extract the emotion of the spoken content v_i^{emo}. Subsequently, following the approach of Vivit (Arnab et al., 2021), the video is uniformly sampled into 32 frames, with a fixed interval between consecutive frames to ensure equal temporal spacing throughout the video.

$$\begin{aligned} v_i^A, v_i^F &= extract(v_i), \\ v_i^{trans}, v_i^{emo} &= trans(v_i^A) \end{aligned} \tag{3}$$

where v_i^A represents the original audio signal, v_i^F represents the video frames, and v_i^{title} represents the video title.

Next, we construct the textual content v_i^T using the video title and transcript:

$$v_i^T = \{v_i^{title}, v_i^{trans}\} \tag{4}$$

3.4 MLLM Reasoning Module

To address the challenges in hateful video detection, such as metaphors, cultural contexts, and the complexity of multimodal interactions, it is necessary to leverage MLLMs to extract deep semantic information from the video. Based on preliminary study (Chapter 2), we find that hateful video detection is a complex process, requiring the extraction of key cues from multiple modalities, including text, visuals, and audio. Inspired by the works of (Xu et al., 2024; Vishwamitra et al., 2024), we employ carefully designed CoT prompts to decompose this complex task, thereby enabling the understanding of multimodal hateful content within the video. Specifically, our CoT prompt is as follows:

Adaption Prompt. In the field of hateful content detection, domain alignment, role description and task-specific adaptation is critical, as it equips MLLMs with essential cultural context and contextual comprehension. This focuses the model's capabilities on addressing the specific challenges of understanding both nuanced and overt hateful content, thereby improves its performance and reliability (Csurka, 2017; Qi et al., 2024). We employ the prompt:

> *This is a video that may contain harmful content, such as hate speech, explicit violence, discrimination, or other forms of harmful behavior. You are a content moderation specialist. Your task is to identify any instances of hate speech, violent imagery, discriminatory actions, or any other content that could be considered harmful, abusive, or offensive. Ensure the answer's accuracy while keeping it concise and avoiding over-explanation.*

Visual Meaning Understanding. To guide the model to analyze the video progressively, starting

with the visual information while ignoring the subtitles in the video frames. The focus is placed on analyzing the characters and scenes in the frames. To achieve this, we employ the following prompt:

> *Describe the video content based on {video frames}, ignoring subtitles in the frames. Pay attention to any special characters or scenes.*

Given the video frames v_i^F and this prompt X_{prompt}^F , the output computation is as follows:

$$res1 = MLLM(v_i^F, X_{prompt}^F) \quad (5)$$

Textual Meaning Understanding. We guide the model to focus on textual information by analyzing the video titles and transcripts, paying special attention to the presence of rhetorical devices such as puns and homophonic wordplay used as promotional strategies. Based on this, we employ the following prompt:

> *The video title is {video title}. The text in the video is {video transcript}. Please analyze the meaning of this text. Note that there may be homophonic memes and puns; distinguish and explain them.*

Given the textual input v_i^T and the prompt X_{prompt}^T , the output computation is as follows:

$$res2 = MLLM(v_i^T, X_{prompt}^T) \quad (6)$$

Fusion Meaning Understanding. Given the complex relationships between semantics across different modalities, it is essential to comprehensively consider the meaning conveyed by the video after multimodal fusion. As illustrated by figure 1, some videos may contain no obvious offensive content in their text or visuals individually, yet their combination can give rise to new meanings. Therefore, we aim for the model to synthesize the results from the first two steps and further integrate the video's raw information, including video frames, text, and extracted emotions of spoken content. This approach seeks to uncover deeper cross-modal interactions and analyze potential new metaphors. We employ the following prompt:

> *Please combine the {video title}, {video transcript}, {video frames}, {voice emotion}, {response1}, {response2} and analyze both the visual, textual and audio elements of the video to detect and flag any hateful content. No need to describe the content of the video, only answer implicit meanings and whether this video expresses hateful content further.*

The MLLM rationale is as follows:

$$v_i^M = MLLM(v_i^T, v_i^F, v_i^{emo}, res1, res2) \quad (7)$$

3.5 Multimodal Fusion Module

After obtaining rationale generated by MLLM reasoning module, we designed a multimodal fusion module to fuse information from the aforementioned modalities. We employ modality-specific encoders for each type of modality to obtain their respective embedding representations:

$$\begin{aligned} E_i^T &= f_T(v_i^T), \\ E_i^A &= f_A(v_i^A), \\ E_i^F &= f_F(v_i^F) \end{aligned} \quad (8)$$

where f_T, f_A, and f_F represent the text, audio, and vision modality encoders, while E_i^T, E_i^A, and E_i^F represent corresponding embeddings. To reduce the inference burden, we designed an embedding cache, allowing the above process to be executed only once on the dataset.

The rationale v_i^M generated by the MLLM is presented in textual form. We treat it as additional textual input and feed it into the text modality encoder to obtain embeddings:

$$E_i^M = f_T(v_i^M) \quad (9)$$

To fuse the embeddings from different modalities, we designed a mixture of experts network. First, all embeddings are concatenated into a single long vector as the representation embedding E_i for the entire video:

$$E_i = concat(E_i^T, E_i^A, E_i^F, E_i^M) \quad (10)$$

Next, we constructed n identical expert networks and one gating network, where n is the number of experts. These experts and the gating network share the same input E_i. Each expert network extracts high-level information specific to certain feature.

The output of the k-th expert is denoted as O_k and is computed as follows:

$$O_k = f_k(E_i; \theta_k), \quad k \in \{1, 2, \ldots, n\} \tag{11}$$

where f_k represents the mapping function of the k-th expert network, and θ_k denotes its parameters.

Simultaneously, the gating network $g(E_i; \phi)$ dynamically generates weights w_k to adjust the contribution of each expert's output. To prevent weight polarization, dropout is applied to the gating network's output weights. The gating network computes these weights as:

$$w_k = \text{Dropout}\left(\frac{\exp(g_k(E_i;\phi))}{\sum_{j=1}^{n}\exp(g_j(E_i;\phi))}\right), \quad k \in \{1, 2, \ldots, n\} \tag{12}$$

where $g_k(E_i; \phi)$ is the unnormalized weight produced by the gating network, and ϕ represents the parameters of the gating network.

The final fused output O_{fusion} is obtained by combining the weighted outputs of all experts:

$$O_{fusion} = \sum_{k=1}^{n} w_k \cdot O_k \tag{13}$$

3.6 Final Decision

During training, we optimize the parameters of the expert and gating networks by minimizing a loss function. Assuming the ground truth labels are y and the final decision outputs are $\hat{y}$, we use a cross-entropy loss function:

$$\mathcal{L} = -\frac{1}{m}\sum_{i=1}^{m}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{14}$$

where m denotes the number of samples.

4 Experiments

Dataset	Language	Total	H	O	N
HateMM	English	1,066	427	0	639
Multihateclip	English	891	72	218	601
	Chinese	897	112	180	605

Table 1: Overview of datasets. H:hateful, O:offensive, N:normal

In this chapter, we first introduce the two datasets used to validate our method, the experimental setup, and the selection of baselines. Then, we present the experimental results and provide a detailed analysis.

4.1 Dataset

In our study, we employ two high-quality, up-to-date public datasets for hateful video detection: the HateMM dataset and the MultiHateClip dataset.

HateMM(Das et al., 2023). The HateMM dataset consists of 1,083 videos sourced from BitChute, a platform with lenient content moderation, resulting in a higher prevalence of hateful content. Videos are labeled as either Hate or Non-Hate.

MultiHateClip(Wang et al., 2024). The MultiHateClip dataset is a multilingual benchmark dataset for hateful video detection, including 2,000 videos from YouTube and Bilibili, with 1,000 videos in English and 1,000 in Chinese. Each video is classified as Hateful, Offensive, or Normal.

To enhance data reliability, we filtered out corrupted and blurry videos. Additionally, to ensure high-quality textual information, we re-annotated the video transcripts using the speech transcription tool FunASR (Gao et al., 2023), improving the accuracy of multimodal analysis. The dataset we use is summarized in Table 1.

4.2 Experiment Settings

We randomly split all datasets into training, testing, and validation sets with a 7:2:1 ratio. For the ternary classification task on the MultiHateClip dataset, the labels used are Hateful, Offensive, and Normal. For binary classification on both the MultiHateClip and HateMM datasets, we combine Hateful and Offensive into a single category, keeping the Normal label unchanged.

All models are trained with a learning rate of 1e-4, a batch size of 32, and early stopping after 100 epochs. Experiments are conducted on three Tesla V100-32G GPUs. Model performance is primarily evaluated using macro-averaged F1 score (M-F1) and accuracy (acc). We employ GPT-4o(Achiam et al., 2023), XLM(Conneau, 2019), Vit(Dosovitskiy, 2020), and Wav2Vec(Baevski et al., 2020) as the fundamental MLLM and modality encoders.

4.3 Baseline Models

We evaluate HVGuard with five baselines, including three advanced MLLMs and two state-of-the-art methods in hateful video detection: (1) **GPT-4o** (Achiam et al., 2023): An advanced MLLM by OpenAI, with high-level reasoning capabilities. (2) **Gemini-1.5-pro** (Team et al., 2024): A sophis-

Dataset	Number of categories	Model	Acc	M-F1	F1(H)	R(H)	P(H)	F1(O)	R(O)	P(O)
Multihateclip(English)	3	GPT-4o	0.7326	0.3280	0.2957	0.2361	0.3953	0.4923	0.4486	0.5455
		Gemini-1.5-pro	0.6319	0.4458	0.2143	0.2000	0.2308	0.3409	0.3488	0.3333
		Qwen-VL	0.5618	0.4060	0.2051	**0.6154**	0.1231	0.2258	0.1556	0.4118
		HateMM	0.6966	0.4894	0.1333	0.1667	0.1111	0.5217	0.5516	0.5345
		Multihateclip	0.7079	0.4946	0.1667	0.1667	0.1667	0.4928	0.5780	0.4750
		HVGuard	**0.8090**	**0.6646**	**0.4556**	0.4722	**0.5000**	**0.6488**	**0.6270**	**0.6994**
	2	GPT-4o	0.7989	0.5019	/	/	/	0.6455	0.5699	0.7443
		Gemini-1.5-pro	0.7198	0.6020	/	/	/	0.3855	0.2759	0.6400
		Qwen-VL	0.6573	0.6549	/	/	/	0.6258	**0.9273**	0.4722
		HateMM	0.7191	0.6646	/	/	/	0.5421	0.4722	0.6548
		Multihateclip	0.7416	0.6806	/	/	/	0.5544	0.4861	0.7269
		HVGuard	**0.8539**	**0.7714**	/	/	/	**0.6308**	0.5819	**0.7619**
Multihateclip(Chinese)	3	GPT-4o	0.6444	0.4460	0.2326	0.1852	0.3125	0.2941	0.3448	0.2564
		Gemini-1.5-pro	0.6648	0.4393	0.2069	0.1500	0.3333	0.2985	0.2703	0.3333
		Qwen-VL	0.5719	0.4472	0.3333	**0.6875**	0.2200	0.2491	0.1889	0.3656
		HateMM	0.6889	0.4163	0.0741	0.0476	0.1667	0.3667	0.3889	0.4722
		Multihateclip	0.7111	0.4573	0.1667	0.1111	0.3333	0.3778	0.3889	0.4167
		HVGuard	**0.8045**	**0.5643**	**0.3563**	0.2917	**0.5278**	**0.4417**	**0.4190**	**0.6139**
	2	GPT-4o	0.7389	0.6900	/	/	/	0.5766	0.5714	0.5818
		Gemini-1.5-pro	0.7443	0.6188	/	/	/	0.4000	0.2632	0.8333
		Qwen-VL	0.6704	0.6684	/	/	/	0.6424	**0.9298**	0.4907
		HateMM	0.7444	0.6908	/	/	/	0.5694	0.5694	0.5826
		Multihateclip	0.7778	0.6904	/	/	/	0.5299	0.4028	0.7833
		HVGuard	**0.8603**	**0.8219**	/	/	/	**0.7408**	0.6905	**0.8274**
HateMM	2	GPT-4o	0.7308	0.7306	0.7238	0.8806	0.6144	/	/	/
		Gemini-1.5-pro	0.7874	0.7872	0.7933	0.8554	0.7396	/	/	/
		Qwen-VL	0.7089	0.7089	0.7075	**0.8824**	0.5906	/	/	/
		HateMM	0.7500	0.7454	0.7430	0.7259	0.7614	/	/	/
		Multihateclip	0.7614	0.7594	0.7611	0.7537	0.7690	/	/	/
		HVGuard	**0.8563**	**0.8597**	**0.8479**	0.8228	**0.8809**	/	/	/

Table 2: Results of different methods on the task of hateful video detection. H:hateful, O:offensive, Acc:accuracy, M-F1:macroF1, R:recall, P:precision.

ticated multimodal model by Google DeepMind, capable of handling diverse reasoning tasks and understanding multiple modalities, including audio, images, videos, and text. (3) **Qwen-VL-7B** (Bai et al., 2023): An open-source vision-language model by Alibaba Cloud, excelling in tasks like image captioning, question answering, and visual localization. (4) **HateMM** (Das et al., 2023): A multimodal hateful video detection model that combines text, audio, and visual pretrained models through a trainable fusion layer to make final predictions. (5) **MultiHateClip** (Wang et al., 2024): A model that processes each modality's features through independent fully connected layers, concatenates them, and performs final classification to determine whether the video contains hate speech.

For the MLLMs used, we employ a generalized prompt to detect hateful videos: "*Analyze whether the video contains hateful content.*" To ensure test consistency, we reproduced all the baselines and conducted a unified evaluation.

4.4 Evaluation Results

To verify the effectiveness of HVGuard, experiments were conducted on the dataset shown in Table 2. The Multihateclip dataset includes both English and Chinese videos, which are used to evaluate the generalization ability of the detection tools in cross-lingual environments. The binary and ternary classification tasks aim to assess the performance of the detection tools in tasks with varying levels of granularity. In real-world scenarios, the binary classification task aids platforms in quickly identifying and blocking hateful videos, while the ternary classification task enables more precise content moderation. The additional "Offensive" category in the ternary task allows for further differentiation, thereby reducing false positives.

Overall, HVGuard outperformed all other baselines, with an improvement of 6.88% to 13.13% in accuracy and 9.21% to 34.37% in M-F1 compared to existing SOTA detection tools. We then explored further conclusions through the following analysis.

HVGuard achieved SOTA performance on both English and Chinese hateful video datasets, demonstrating its multilingual adaptability. Additionally, it outperformed other baselines in both ternary and binary classification tasks.

We also achieved superior performance on most metrics for the crucial labels of "Hateful" and "Offensive," demonstrating the HVGuard ability for hateful video detection. Notably, Qwen-VL

Model	Ternary		Binary	
	Acc	M-F1	Acc	M-F1
w/o Vision encoder	0.7865	0.4760	0.8202	0.7397
w/o Text encoder	0.7753	0.5633	0.8258	0.7090
w/o Audio encoder	0.7697	0.5807	0.8258	0.7413
w/o Modal features	0.7584	0.4816	0.8146	0.7126
w/o CoT	0.7416	0.4715	0.7921	0.5512
w/o MoE	0.7809	0.5936	0.8371	0.7466
HVGuard	**0.8090**	**0.6646**	**0.8539**	**0.7714**

Table 3: Ablation study for the components in HVGuard.

achieved the highest recall rate for the "Hate" category, but performed poorly in accuracy and M-F1. This suggests that Qwen-VL tends to classify videos as "Hate", leading to the misclassification of some normal videos. In practical applications, an excessively high false positive rate may negatively impact the normal information flow within online communities.

To more clearly demonstrate the effectiveness of the proposed framework, we present a case study in Appendix A.

4.5 Effectiveness of Components in HVGuard

Table 3 summarizes the results of the ablation study on the MultiHateClip(English) dataset using HVGuard. Removing the visual, text, or audio components individually resulted in performance declines, indicating that each modality plays a crucial role in hate detection. Furthermore, ablation of all modal features, relying solely on MLLM rationale—led to a noticeable decrease in performance. These findings underscore the importance of integrating comprehensive multimodal information for accurate detection.

Moreover, removing the CoT guidance for the MLLM and relying solely on generalized prompt templates resulted in a significant performance drop. This demonstrates that the CoT approach generates more informative supplementary features, enabling the multimodal fusion module to make more accurate predictions.

Furthermore, replacing the MoE in the model with a standard MLP also led to a performance decline. This indicates that MoE is crucial for the multimodal tasks in this context. MoE leverages information from different modalities, along with the rationale provided by the MLLM, to enhance hateful video detection.

In addition, we conducted comprehensive experiments on different combinations of MLLMs, Text encoders, Vision encoders, and Audio encoders, demonstrating the deployment flexibility of HVGuard. Details are shown in Appendix B.

4.6 Hyper-parameter Study

To investigate the effects of the hyper-parameters in HVGuard, we show the impact of hyper-parameters on the performance trend. Details can be found in Appendix C.

5 Related Work

Hate speech detection includes unimodal (text, image, audio) and multimodal methods. Most current methods focus only on a single modality. However, multimodal detection, especially in hateful video detection, integrates these modalities to achieve more comprehensive understanding. Our research not only explores the integration of modalities but also analyzes their interactions to enable a deeper analysis. For more detailed information, please refer to the Appendix D.

6 Conclusion

In this work, we propose a hateful video detection framework named HVGuard, which is the first reasoning-based hateful video detection framework with MLLMs. This framework carefully designs a CoT reasoning strategy to fully leverage the reasoning ability of MLLMs and introduces a MoE network for the efficient utilization of rationale and multimodal features. Experiments demonstrate that the proposed framework achieves SOTA performance on two public datasets, containing both English and Chinese videos. In the future, we aim to improve the framework by incorporating larger, more diverse, and multilingual datasets to enhance its performance and adaptability across different contexts and languages. This expansion will help address the complexities of detecting hateful content in a broader range of scenarios.

Limitations

We only evaluated HVGuard on the Chinese and English datasets and did not evaluate other languages. This limits our further exploration of the language generalizability of the framework.

Moreover, we believe that fine-grained detection of hateful videos is of great importance. Although we have considered both binary and ternary classification scenarios, more refined categorization may be more beneficial for the application of such research in real-world contexts.

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A Case Study

To provide a more comprehensive demonstration of HVGuard's effectiveness, we present a detailed case study in Figure 4. In this example, a video titled "*When Find Out a Gay Friend Nearby.mp4*" is processed, where understanding the reactions of different gender groups to homosexuality requires analyzing both visual and textual modalities. In HVGuard, MLLM leverages CoT prompts to guide

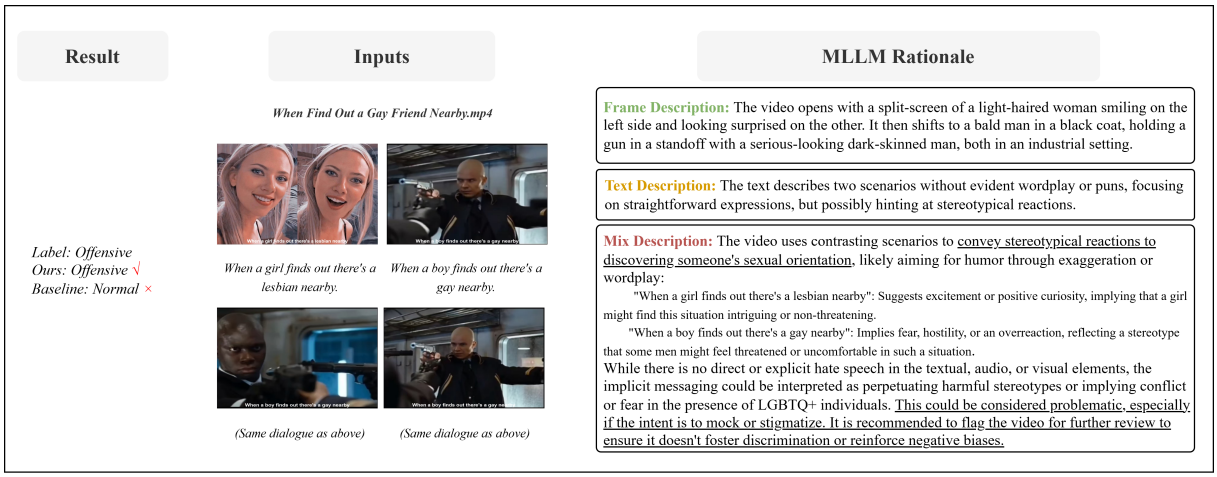


Figure 4: Example of case study.

reasoning from both video frames and transcripts, with the analysis from these modalities integrated to accurately interpret the video content. In contrast, baseline methods lacking MLLM reasoning fail to capture the complementary information between the visuals and the text, leading to incomplete analysis and misclassification.

B Flexibility of framework component

Table 4 shows the impact of different combinations of MLLMs and Encoders. We conducted tests on the ternary classification scenario of Multihateclip(English). The combination of GPT-4o(Achiam et al., 2023), XLM(Conneau, 2019), Vit(Dosovitskiy, 2020), and Wav2Vec(Baevski et al., 2020) achieved the highest M-f1 value, while the combination of Qwen-VL(Bai et al., 2023), Bert(Devlin, 2018), ViViT(Arnab et al., 2021), and Wav2Vec achieved the highest accuracy. MFCC as an Audio Encoder significantly lowered the results, indicating that excellent modality encoders are necessary.

We found that different combinations have varying impacts on performance, with the capabilities of the MLLM being the most significant factor. However, even the least effective combination significantly outperformed the baseline, demonstrating the flexibility and generalizability of our proposed HVGuard framework.

C Hyper-parameter Analysis

Figure 5 illustrates the impact of varying numbers of experts, learning rate and batch size on the performance through a line chart, showing that the model achieves optimal performance when the number of experts is eight, and the learning rate and batch size have little to no impact on the performance. Despite experimenting with different values for these hyperparameters, the model's performance remained relatively stable across the variations, indicating that the performance is primarily influenced by the number of experts rather than the learning rate or batch size.

MLLM	Text Encoder	Vision Encoder	Audio Encoder	Acc	M-F1
GPT-4o	XLM	Vit	Wav2Vec	0.8090	**0.6646**
			MFCC	0.7809	0.4762
		ViViT	Wav2Vec	0.7921	0.5881
			MFCC	0.7865	0.5604
	Bert	Vit	Wav2Vec	**0.8202**	0.5562
			MFCC	0.7978	0.5590
		ViViT	Wav2Vec	0.8034	0.6175
			MFCC	0.8146	0.5384
Qwen-VL	XLM	Vit	Wav2Vec	0.7865	0.6276
			MFCC	0.7640	0.4759
		ViViT	Wav2Vec	0.7809	0.5744
			MFCC	0.7697	0.5637
	Bert	Vit	Wav2Vec	0.7921	0.5652
			MFCC	0.7753	0.5022
		ViViT	Wav2Vec	0.7978	0.5282
			MFCC	0.7809	0.4835

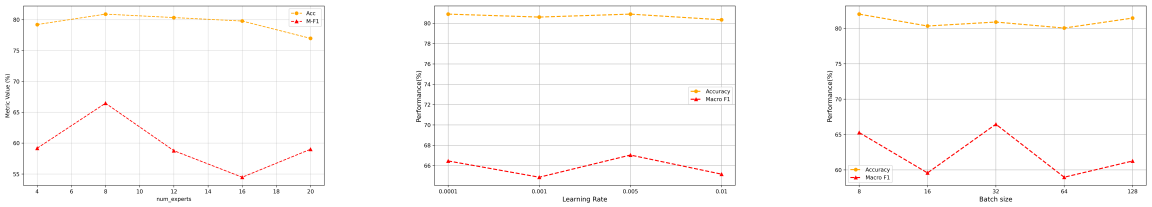
Table 4: Results of different model combinations on Multihateclip(English)

D Related Work

D.1 Hate Speech Detection

Hate speech detection can be divided into unimodal hate speech detection and multimodal hate speech detection, based on the type of data used. Unimodal hate speech detection is further categorized into text-based, image-based, and audio-based approaches.

Text hate speech detection: This primarily ad-



(a) number of experts (b) learning rate (c) batch size

Figure 5: (a) Number of experts hyper-parameter study. (b) Learning rate hyper-parameter study. (c) Batch size hyper-parameter study.

dresses binary classification tasks, with some studies expanding to three categories: hate speech, offensive speech, and normal speech. Notable studies, such as those by (Davidson et al., 2017) and (Founta et al., 2018), have made significant contributions in classifying hate speech from text. More recently, researchers have explored the subtleties of black humor (Hee et al., 2024a) and discourse context (Yu et al., 2022) to better understand the complexities of text-based hate speech.

Image-based hate speech detection: This area focuses on visual content, such as memes, with studies investigating methods to detect hate speech in images and build appropriate datasets (Gasparini et al., 2022; Bhandari et al., 2023). Approaches like Pro-Cap (Cao et al., 2023) and MR.HARM (Lin et al., 2023) attempt to address challenges in implicit hate speech detection.

Audio-based hate speech detection: Techniques in this domain often involve the use of CNNs to process audio features, such as spectrograms. Works like (Medina et al., 2022) and (Yousefi and Emmanouilidou, 2021) explore methods to enhance audio feature extraction for better detection.

Multimodal hate speech detection: This approach integrates text, image, and audio modalities to enhance hate speech detection, particularly in video content. Studies such as (Das et al., 2023) and (Wang et al., 2024) demonstrate the potential of multimodal techniques in capturing complex context, thereby improving detection performance.

In our study, we focus on multimodal hate speech detection, particularly in videos. While existing research typically concatenates modality information, our approach delves deeper into the interactions between different modalities, improving the understanding of hate speech videos and their intricate patterns.

D.2 Multimodal Large Language Models (MLLMs)

The emergence of large language models (LLMs) has led to significant advances in natural language processing, enabling models like Gemini (Team et al., 2024) to handle multimodal inputs, such as images and text. While LLMs excel at reasoning and world knowledge, they lack the ability to "see" images, making them less effective at understanding multimodal data. Conversely, large visual models (VLMs) excel in image recognition but are limited in reasoning and world knowledge (Kirillov et al., 2023; Shen et al., 2024). The combination of LLMs and VLMs in MLLMs allows for more robust multimodal understanding, making them highly effective in tasks like image reasoning and video understanding (Wu et al., 2023). In our research, we leverage MLLMs to analyze and understand the complex interaction patterns in hate speech videos, providing valuable insights for reasoning models.