MLLM-Protector: Ensuring MLLM's Safety without Hurting Performance

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The deployment of multimodal large language models (MLLMs) has brought forth a unique vulnerability: susceptibility to malicious attacks through visual inputs. This paper systematically investigates the novel challenge of defending MLLMs against such attacks. We discovered that images act as a "foreign language" that is not considered during alignment, which can make MLLMs prone to producing harmful responses. Unfortunately, unlike the discrete tokens considered in text-based LLMs, the continuous nature of image signals presents significant alignment challenges, which poses difficulty to thoroughly cover the possible scenarios. This vulnerability is exacerbated by the fact that open-source MLLMs are predominantly fine-tuned on limited image-text pairs that is much less than the extensive text-based pretraining corpus, which makes the MLLMs more prone to catastrophic forgetting of their original abilities during explicit alignment tuning. To tackle these challenges, we introduce MLLM-Protector, a plug-andplay strategy combining a lightweight harm detector and a response detoxifier. The harm detector's role is to identify potentially harmful outputs from the MLLM, while the detoxifier corrects these outputs to ensure the response stipulates to the safety standards. This approach effectively mitigates the risks posed by malicious visual inputs without compromising the model's overall performance. Our results demonstrate that MLLM-Protector offers a robust solution to a previously unaddressed aspect of MLLM security. Code and data will be made public in this link.

## 1 Introduction

The emergence of Large Language Models (LLMs) has marked a significant milestone in the field of artificial intelligence, revolutionizing natural language processing and understanding (Geng and Liu, 2023; OpenAI, 2023; Touvron et al., 2023; Scao

[^0]et al., 2022; Chowdhery et al., 2022; Taori et al., 2023; Chiang et al., 2023). These models, trained on vast datasets, excel in generating coherent and contextually relevant text, making them invaluable for a myriad of applications. With the advancement of technology, Multimodal Large Language Models (MLLMs) have seen rapid improvements (Liu et al., 2023a; Zhu et al., 2023; Su et al., 2023; Dai et al., 2023b; Li et al., 2023; OpenAI, 2023; Bai et al., 2023), extending the capabilities of LLMs to engage in conversations with image inputs, which enables more potential applications.

Despite their success, LLMs are prone to attacks. In text-based models, malicious attacks typically involve inputting crafted text that induces the model to generate inappropriate or harmful content. The defense against such attacks has been an area of active research, leading to the development of various strategies. These include input detection (Robey et al., 2023), in-context learning (Xie et al., 2023), and explicitly aligning models with adversarial examples (Ouyang et al., 2022; Stiennon et al., 2020; Nakano et al., 2021; Bai et al., 2022a,b; Glaese et al., 2022; Ziegler et al., 2019; Wu et al., 2021; Scheurer et al., 2023). The core challenge lies in maintaining the balance between robust defense mechanisms and the preservation of the model's functionality and performance.

Recently, in the realm of MLLMs, a new observation has been made: images can inadvertently induce these models to produce malicious content (Liu et al., 2023c), as illustrated in Figure 1. This weakness, if not properly handled, could potentially lead to serious consequences. To gain a deeper understanding of this issue, we experimentally find that the likelihood of generating harmful responses is significantly higher given image inputs than text input (Table 3). We assume this is because the LLMs such as Vicuna (Chiang et al., 2023) are extensively aligned with textual inputs, but were not well aligned with human values given


Figure 1: State-of-the-art MLLMs become more prone to generating harmful response when using images as input. On the other hand, our MLLM-Protector is able to effectively detect such harmful content and make the response safe.
image inputs. We point that images, in the context of MLLMs, may act as a "foreign language", which may have related or similar semantics with textual queries, but are able to trick the model into a generating harmful content.

For state-of-the-art LLMs, Supervised FineTuning (SFT) and Reinforcement Learning from Human Feedback (RLHF) are commonly employed to calibrate the model's outputs to align with human preferences. However, these techniques become more challenging when applied to MLLMs that involve images as inputs. The continuous nature of images result in vastly more variation compared to the discrete text tokens, which presents a substantial challenge. This increased variation in images results in a much larger input space to consider and align, making the tuning process more intricate and demanding in terms of capturing a diverse range of human preferences and interpretations. Given that the MLLMs are typically aligned with much less image-text pairs than pre-training textual corpus, this exhaustive alignment could further result in catastrophic forgetting of the MLLM's original capability.

In response to this unique challenge, we propose MLLM-Protector. Our approach consists of a harm detector, which is lightweight classifier that assesses the harmfulness the response generated by the MLLM. Should the output be deemed potentially harmful, a response detoxifier is then activated to modify the output, such that it stipulates to the safety standards. Our MLLM-Protector
is a plug-and-play approach that could be trained independently and incorporated with any MLLMs, which effectively counters the risk of harmful outputs triggered by malicious image inputs without compromising the overall performance of the MLLM.

Our contribution through this paper is threefold. Firstly, we provide analysis on the previously under-explored vulnerability in MLLMs related to image inputs. Secondly, we introduce MLLM-Protector, a plug-and-play defense mechanism designed for MLLMs. Lastly, we demonstrate through empirical evidence that our approach effectively mitigates the risk of harmful outputs in response to malicious image inputs, while maintaining the model's original performance.

## 2 Related Work

Multi-Modal Large Language Model. Recent years have witnessed transformative advancements in the development of large language models (LLMs), characterized by a series of pioneering studies (Brown et al., 2020; Scao et al., 2022; Chowdhery et al., 2022; Smith et al., 2022; Hoffmann et al., 2022; Ouyang et al., 2022; Touvron et al., 2023; Bai et al., 2022a). These breakthroughs have significantly elevated the capabilities of language understanding and generation, showcasing near-human proficiency across diverse tasks. Concurrently, the success of LLMs has inspired explorations into vision-language interaction, leading to


Figure 2: The overall framework of our MLLM-Protector, which serves as a plug-and-play module that ensures the safety of MLLM's responses. During inference, the output from the MLLM is first passed to the harm detector to identify whether it contains harmful content. If the response is identified as harmful, it will then be passed to the response detoxifier, which will remove the harmful content from the response.
the emergence of multi-modal large language models (MLLMs) (Liu et al., 2023a; Li et al., 2023; Dai et al., 2023b; Zhu et al., 2023; Dai et al., 2023b; OpenAI, 2023; Bai et al., 2023; Su et al., 2023; Gao et al., 2023c; Pi et al., 2023a,b; Ding et al., 2022, 2023; Gao et al., 2023b). These models have exhibited remarkable capabilities in engaging in dialogue based on visual inputs. However, we observe that current state-of-the-art MLLMs become more prone to be affected by malicious visual inputs.

Attack and Defense. Attacks on LLMs and MLLMs can be categorized into two primary categories: malicious utilization by users (Perez and Ribeiro, 2022; Liu et al., 2023d; Xie et al., 2023) and attacks by third parties targeting regular users (Yi et al., 2023; Greshake et al., 2023). Malicious utilization by users encompasses various techniques, such as jailbreak attacks (Kang et al., 2023; Xie et al., 2023; Shayegani et al., 2023), prompt leakage attacks (Perez and Ribeiro, 2022), and prompt injection attacks (Perez and Ribeiro, 2022; Liu et al., 2023d). These attacks are designed to exploit these models by providing maliciously crafted inputs to produce outputs that deviate from ethical alignment. Such outputs can be harmful, misleading, or privacy-compromising. In response to these attacks, defense mechanisms have been
proposed, particularly for LLMs. These defense strategies include self-reminders (Xie et al., 2023), input detection (Robey et al., 2023), and in-context learning (Wei et al., 2023), which aim to mitigate the impact of malicious user utilization. On the other hand, attacks by third parties targeting regular users are another category, typified by indirect prompt injection attacks (Yi et al., 2023; Greshake et al., 2023; Liu et al., 2023d). In these attacks, a third party inserts prompts into external content, which may be erroneously interpreted as a user query, thereby affecting the user experience. To defend against such attacks, strategies have been proposed to assist LLMs in distinguishing between a user's genuine query and external content (Yi et al., 2023). This work specifically focuses on addressing the former category of attacks for MLLMs to defend against malicious utilization by users.

Alignment of Large Language Model. Alignment in agent behavior, initially proposed in Leike et al. (2018), ensures actions conform to human intentions, a concept enhanced in models like InstructGPT (Ouyang et al., 2022), Claude (Bai et al., 2022b), and Sparrow (Glaese et al., 2022). Through scalable reward learning (Leike et al., 2018; Christiano et al., 2018; Irving et al., 2018) from communication-based supervised signals (Ziegler et al., 2019), Reinforcement Learn-


Figure 3: We showcase a few examples of our MLLM-Protector's effectiveness with various MLLMs. MLLMProtector is able to effectively remove the harmful contents in the MLLM's response without affecting the model's original capability.
ing from Human Feedback (RLHF) (Ouyang et al., 2022; Stiennon et al., 2020; Nakano et al., 2021; Bai et al., 2022a,b; Glaese et al., 2022; Ziegler et al., 2019; Wu et al., 2021; Scheurer et al., 2023) employs methods like proximal policy optimization (PPO) (Schulman et al., 2017) to maximize the outputs' reward. InstructGPT's successful alignment in GPT-3 (Brown et al., 2020) also involves supervised finetuning (SFT). In visual models, alignment studies (Hao et al., 2022; Lee et al., 2023; Wu et al., 2023) focus on interpreting specific visual signals (Lee et al., 2023), with ongoing challenges in balancing human preferences and image fidelity. RRHF (Yuan et al., 2023) and RAFT (Dong et al., 2023; Diao et al., 2023) leverage the LLM to bootstrap responses, and then finetune the model on the high-reward subset of these collected samples. Rafailov et al. (2023) propose direct preference optimization (DPO), which directly utilizes the human preference as sample weights during finetuning. Liu et al. (2023b) and Xiong et al. (2023) also found that the quality of proposal offline distribution matters in RLHF literature. More recently, (Chen et al., 2024) finds that learning from mistake analysis improve the model's alignment. Despite the promising results achieved by alignment strategies for text-based LLMs, their effectiveness for defending against adversarial user inputs remains questionable for MLLMs.

## 3 Observation

We have observed that when state-of-the-art open-source multi-modal large language models (MLLMs), such as LLaVA (Liu et al., 2023a), are presented with relevant input images that have malicious content, they become prone to generating sensitive or potentially harmful responses. This is despite the model's ability to recognize and refuse to provide advice on such topics when the input is purely text-based. A recent study by (Liu et al., 2023c) also supports this observation, as they found that both related natural images, and OCR images containing the relevant phrase, can mislead the model into generating harmful content.

We make further analysis on the MLLM's outputs, and observe the following: For MLLMs that are based on instruction-tuned LLMs (e.g., Vicuna (Chiang et al., 2023), LLaMA-Chat (Touvron et al., 2023)), given related images that contain malicious content as inputs, the likelihood for generating harmful responses becomes markedly higher compared to scenarios where only text inputs are used as inputs. Specifically, as demonstrated Table 3, the perplexity for harmful responses is significantly higher than that of the harmless ones for text-only inputs, while it is not the case for inputs containing images.

We hypothesize that for image-text aligned MLLMs, images might act as a sort of "foreign
language", offering semantic parallels to textual inputs. However, unlike their textual counterparts, image-based inputs have not been subject to the same level of instruction tuning or alignment. This discrepancy appears to be a contributing factor to the models' increased susceptibility to generating harmful content in response to image inputs.

## 4 Vanilla Alignment Tuning

In our preliminary investigation, we adopted the supervised fine-tuning (SFT) alignment strategy, which represents the conventional approach for aligning text-based Language Model (LM) systems. To construct our image-text paired SFT dataset, we followed the subsequent steps. Initially, we leveraged an existing text-based dataset (Dai et al., 2023a) that comprises malicious user queries, each paired with two responses generated by the LM model. These responses are accompanied by annotations indicating their harmfulness.

For each user query, we generated two types of images, as outlined in (Liu et al., 2023c). Firstly, we created stable-diffusion-generated images, which visually represent the content associated with the user query. Secondly, we produced OCR images that contain the keywords present in the user query. To maintain consistency, we only retained the responses that were labeled as "harmless". Consequently, we successfully curated a substantial collection of approximately 60,000 image-text pairs.

Subsequently, we employ this collected imagetext paired dataset to perform supervised finetuning on the LLaVA-7B model (Liu et al., 2023a). We demonstrate the results evaluated on the benchmark proposed by (Liu et al., 2023c) in Table 1, which shows that the performance gain achieved by the SFT approach is marginal. In addition, in some scenarios, SFT even elevates the attack success rate (ASR). We assume this is due to the continuous nature of image inputs, which makes alignment more difficult. Furthermore, we observe that alignment tuning also deteriorates the original capability possessed by the MLLM.

We summarize the disadvantages of tuningbased alignment methods in the context of MLLMs as follows:

- The intrinsic nature of images, being continuous as opposed to the discrete nature of text, poses a substantial challenge for alignment tuning. Achieving a comprehensive range of

| Scenarios | OCR |  | SD+OCR |  |
| :---: | :---: | :---: | :---: | :---: |
|  | wo SFT | w SFT | wo SFT | w SFT |
| Illegal Activity | $\mathbf{7 9 . 3 8}$ | 82.47 | $\mathbf{7 7 . 3 2}$ | 81.44 |
| Hate Speech | $\mathbf{3 9 . 8 8}$ | 46.01 | 47.85 | $\mathbf{4 7 . 2 4}$ |
| Malware Generation | 65.91 | $\mathbf{5 9 . 2 5}$ | 70.45 | $\mathbf{6 4 . 3 1}$ |
| Physical Harm | 60.42 | $\mathbf{5 6 . 9 4}$ | $\mathbf{6 2 . 5 0}$ | 63.19 |
| Economic Harm | $\mathbf{1 4 . 7 5}$ | 51.64 | $\mathbf{1 5 . 5 7}$ | 53.28 |
| Fraud | $\mathbf{7 2 . 7 3}$ | 77.92 | $\mathbf{6 6 . 8 8}$ | 79.87 |
| Pornography | $\mathbf{5 3 . 2 1}$ | 66.06 | $\mathbf{5 3 . 2 1}$ | 67.89 |
| Political Lobbying | 94.77 | $\mathbf{1 5 . 0 3}$ | 96.73 | $\mathbf{1 9 . 6 1}$ |
| Privacy Violence | 55.40 | $\mathbf{4 9 . 6 4}$ | $\mathbf{5 1 . 0 8}$ | 53.96 |
| Legal Opinion | 94.62 | $\mathbf{4 9 . 2 3}$ | 96.92 | $\mathbf{5 1 . 5 4}$ |
| Financial Advice | 99.40 | $\mathbf{8 4 . 4 3}$ | 100.00 | $\mathbf{8 9 . 8 2}$ |
| Health Consultation | 100.00 | $\mathbf{7 5 . 2 3}$ | 100.00 | $\mathbf{7 7 . 9 8}$ |
| Gov Decision | 99.33 | $\mathbf{4 3 . 6 2}$ | 99.33 | $\mathbf{4 2 . 9 5}$ |
| Average | 71.52 | $\mathbf{5 8 . 2 6}$ | 72.14 | $\mathbf{6 1 . 0 1}$ |

Table 1: The attack success rate (ASR) achieved by different inputs w/o supervised fine-tuning (SFT). OCR stands for OCR images with corresponding content; $\mathrm{SD}+\mathrm{OCR}$ refers to the combination of the previous inputs. We follow (Liu et al., 2023c) to conduct experiment with their constructed benchmark. We observe that SFT only results in marginal gains in safety. Furthermore, in many scenarios, the ASR even reaches higher after SFT.
input images that can cover all potential scenarios is considerably more complex.

- Open-source MLLMs suffer from a certain fragility: image inputs are aligned with large language models (LLMs) during the finetuning stage, using substantially less training data and shorter training durations compared to the extensive text-based pre-training processes. The conventional method of aligning based of supervised fine-tuning (SFT) or RLHF may compromise the model's efficacy in executing standard tasks.
- The safety standard should often be customized to different scenarios and be agnostic to MLLMs: in some scenarios, the model should be able to provide certain content, which are prohibited in other scenarious, e.g., advice on sexual-related topics should be allowed for medical purposes, but should be prohibited for children. Therefore, a plug-andplay approach could be more desirable than tuning the model itself.


## 5 MLLM-Protector

In this section, we introduce our proposed method termed MLLM-Protector, which serves as a plug-and-play component that works in conjunction with
any MLLMs. Notably, the components of MLLMProtector can be trained independently, then be used directly during inference, which prevents hampering the MLLM's original capability while ensuring their safety.

In this section, we will first elaborate the model architecture of MLLM-Protector. Then, we introduce the objective and data used during training. Lastly, we illustrate how our MLLM-Protector can be incorporated with any MLLM during inference.

```
Algorithm 1 Inference with MLLM-Protector
    Initialize: isFirstRound = True
    while True do
        \(\operatorname{Img}_{\text {in }}\), Text \(_{\text {in }} \leftarrow\) ReceiveInput()
        if isFirstRound then
            Input \(\leftarrow\) Concat \(\left(\operatorname{Img}_{\text {in }}\right.\), text \(\left.{ }_{\text {in }}\right)\)
            isFirstRound \(=\) False
        else
            Input \(\leftarrow\) Concat \(\left(\right.\) Input \(_{\text {prev }}, \operatorname{Img}_{\text {in }}\), Text \(\left._{\text {in }}\right)\)
        end if
        Output \(\leftarrow\) MLLM-Generate(Input)
        if HarmDetector(Output) then
            Output \(\leftarrow\) Detoxify(Input, Output)
        end if
        Input \(_{\text {prev }} \leftarrow\) Concat(Input, Output)
    end while
```


### 5.1 Model Components

Harm Detector To identify whether the output from the model contains harmful content, we train a binary classifier. Specifically, we adopt the pretrained LLM for the backbone architecture of harm detector. To adapt the model to the binary classification task of identifying harmful content, we replace the last layer to a linear layer with one-dimensional output. LLMs with various sizes can be utilized to trade-off between efficiency and effectiveness. The Harm-Detector takes a response as input, and predicts a score that indicates the harmfulness of the generated response.

Response Detoxifier One straightforward approach is to leverage a fixed sentence to replace the original harmful response, such as "Sorry, I can not answer this question". However, this may result in inconsistency of the generated results and hamper the user experience. It is more promising if the responses can be harmless and related to the query at the same time. Therefore, we finetune a language model targeted at correcting the response
from the MLLM if it contains harmful contents.

### 5.2 Training and Inference

Training Data The data used to train our MLLMProtector main comes from two sources: 1) We utilize the pre-existing QA data that have annotations of both accepted and rejected answers for each question, e.g., SafeRLHF (Dai et al., 2023a); 2) Inspired by previous works that leverage LLM to generate training data (Liu et al., 2023a; Zhu et al., 2023; Ye et al., 2022; Gao et al., 2023a), we resort to the powerful ChatGPT to generate new QA pairs with accepted and rejected answers that cover more diverse scenarios.

The combined training dataset has the form of: $D=\left\{\left(q^{i}, a_{a c c}^{i}, a_{r e j}^{i}\right)\right\}_{i=1}^{N}$, where $q_{i}, a_{a c c}^{i}$ and $a_{r e j}^{i}$ stand for the $i^{\text {th }}$ question, accepted answer and reject answer, respectively. Naturally, the accepted answer $a_{a c c}^{i}$ is associated with harmlessness label $h=1$, and for rejected answer $a_{r e j}^{i}$, the label is $h=0$.

Training Harm Detector We use the conventional binary cross entropy (BCE) loss to train the Harm Detector. We reformulate the dataset into the following format: $D_{H D}=\left\{\left(q^{i}, a^{i}, h^{i}\right)\right\}_{i=1}^{2 N}$

$$
\begin{align*}
\mathcal{L}_{H D}(\mathbf{h}, \mathbf{x}) & =-\frac{1}{N} \sum_{i=1}^{2 N} h^{i} \log \left(\phi\left(\mathrm{a}^{i}\right)\right)  \tag{1}\\
& \left.+\left(1-h^{i}\right) \log \left(1-\phi\left(\mathrm{a}^{i}\right)\right)\right]
\end{align*}
$$

where $h^{i} \in\{0,1\}$ is the harmfulness label associated with the answer $a^{i}, \phi$ represents the harm detector. Note that we only use the MLLM's response as input to the harm detector.

Training Detoxifier To train the detoxifier, we use the auto-regressive language modeling loss, which aims at enabling the detoxifier to remove the harmful content from the original response. The training objective has the following formulation:

$$
\begin{align*}
& \mathcal{L}_{\text {Detox }}\left(\mathbf{a}_{a c c}, \mathbf{a}_{r e j}, \mathbf{q}\right)= \\
& \quad-\frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{L} \log p\left[a_{a c c}^{i, t} \mid \mathcal{F}\left(a_{c o r r}^{i,(<t)}, a_{r e j}^{i}, q^{i}\right)\right], \tag{2}
\end{align*}
$$

where $\mathcal{F}$ is the detoxifier; $\mathbf{a}_{a c c}$ and $\mathbf{a}_{r e j}$ are the accepted and rejected answer, respectively. $a_{\text {corr }}$ is the corrected answer generated by the detoxifier. The training aims at enabling the detoxifier to generate the harmless answer given the user query and

| Scenarios | Text-only |  | SD |  | OCR |  | SD+OCR |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | w/o Guard | w/ Guard | w/o Guard | w/ Guard | w/o Guard | w/ Guard | w/o Guard | w/ Guard |
| Illegal Activity | 5.25 | $\mathbf{0 . 0 0}$ | 22.68 | $\mathbf{4 . 1 2}$ | 79.38 | $\mathbf{2 . 0 6}$ | 77.32 | $\mathbf{0 . 0 0}$ |
| Hate Speech | 3.78 | $\mathbf{0 . 5 8}$ | 16.56 | $\mathbf{3 . 0 6}$ | 39.88 | $\mathbf{0 . 0 0}$ | 47.85 | $\mathbf{3 . 0 7}$ |
| Malware Generation | 26.32 | $\mathbf{6 . 8 2}$ | 20.45 | $\mathbf{2 . 2 7}$ | 65.91 | $\mathbf{6 . 8 2}$ | 70.45 | $\mathbf{9 . 0 9}$ |
| Physical Harm | 13.17 | $\mathbf{7 . 6 4}$ | 20.14 | $\mathbf{6 . 9 4}$ | 60.42 | $\mathbf{7 . 6 4}$ | 62.50 | $\mathbf{1 0 . 4 2}$ |
| Economic Harm | 3.03 | $\mathbf{2 . 2 7}$ | 4.10 | $\mathbf{3 . 7 9}$ | 14.75 | $\mathbf{9 . 0 2}$ | 15.57 | $\mathbf{1 1 . 3 6}$ |
| Fraud | 9.24 | $\mathbf{5 . 8 4}$ | 20.13 | $\mathbf{4 . 5 5}$ | 72.73 | $\mathbf{4 . 5 5}$ | 66.88 | $\mathbf{7 . 7 9}$ |
| Pornography | 18.91 | $\mathbf{1 4 . 4 3}$ | 11.93 | $\mathbf{1 0 . 1 9}$ | 53.21 | $\mathbf{7 . 3 4}$ | 53.21 | $\mathbf{4 2 . 2 0}$ |
| Political Lobbying | 84.27 | $\mathbf{2 4 . 1 8}$ | 73.86 | $\mathbf{1 1 . 1 1}$ | 94.77 | $\mathbf{1 1 . 1 1}$ | 96.73 | $\mathbf{2 4 . 1 8}$ |
| Privacy Violence | 11.34 | $\mathbf{1 0 . 7 9}$ | 12.95 | $\mathbf{1 1 . 5 1}$ | 55.40 | $\mathbf{1 9 . 4 2}$ | 51.08 | $\mathbf{1 6 . 5 5}$ |
| Legal Opinion | 79.38 | $\mathbf{6 . 1 5}$ | 92.31 | $\mathbf{2 3 . 0 8}$ | 94.62 | $\mathbf{1 3 . 8 5}$ | 96.92 | $\mathbf{3 1 . 5 4}$ |
| Financial Advice | 92.16 | $\mathbf{5 0 . 3 0}$ | 97.00 | $\mathbf{8 2 . 6 3}$ | 99.40 | $\mathbf{7 7 . 8 4}$ | 100.00 | $\mathbf{7 8 . 4 4}$ |
| Health Consultation | 90.89 | $\mathbf{6 5 . 4 2}$ | 99.08 | $\mathbf{6 9 . 3 7}$ | 100.00 | $\mathbf{7 2 . 5 1}$ | 100.00 | $\mathbf{7 5 . 3 8}$ |
| Gov Decision | 95.35 | $\mathbf{2 8 . 1 9}$ | 98.66 | $\mathbf{2 0 . 8 1}$ | 99.33 | $\mathbf{2 6 . 8 5}$ | 99.33 | $\mathbf{2 9 . 5 3}$ |
| Average | 41.01 | $\mathbf{1 7 . 1 2}$ | 45.37 | $\mathbf{1 9 . 4 9}$ | 71.52 | $\mathbf{1 9 . 9 2}$ | 72.14 | $\mathbf{2 6 . 1 1}$ |

Table 2: The attack success rate (ASR) achieved by different inputs w/ or w/o using our MLLM-Protector for LLaVA7B model. "SD" stands for stable-diffusion generated images; OCR stands for OCR images with corresponding content; SD+OCR refers to the combination of the previous inputs. We follow (Liu et al., 2023c) to conduct experiment with their constructed benchmark. We observe significant decline of ASR after equipping the model with MLLM-Protector. Specifically, for typical scenarios, such as illegal activity and hate speech, our method is able to almost completely prevent all harmful outputs.
the harmful answer. It is worth noting that $\mathbf{q}$ only consists of the textual queries.

Inference During inference, the output from the MLLM is first passed to the harm detector to identify whether it contains harmful content. If the response is identified as harmful, it will then be passed to the response detoxifier, which will remove the harmful content from the response. The overall algorithm is illustrated as in Algorithm 1.

## 6 Experiments

### 6.1 Implementation Details

For the harm detector, we adopt Open-LLaMA3B model from (Geng and Liu, 2023). For the detoxifier, we utilize LLaMA-7B (Touvron et al., 2023). For the harm detector, we perform tuning for 3 epochs using LoRA with rank 32, batch size is set to 32 , and the learning rate is set to $2 e^{-5}$; For the detoxifier, we finetune the model for 3 epochs using LoRA with rank 128 , batch size is set to 32 , and the learning rate is set to $1 e^{-4}$. The components are both trained on 8 A40 GPUs using deepspeed with bfloat 16 .

### 6.2 Main Experiment

We conduct our main experiments on the recently proposed MM-SafetyBench, which contains examples of 13 common scenarios containing malicious intent. Each question is associated four types of inputs: 1) text-only, which refers to using only textual

| Scenarios | Text-only |  | SD+OCR |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Harmful | Harmless | Harmful | Harmless |
| Illegal Activity | 1.87 | $\mathbf{1 . 2 3}$ | $\mathbf{1 . 6 2}$ | 2.17 |
| Hate Speech | 2.06 | $\mathbf{1 . 2 3}$ | $\mathbf{1 . 6 5}$ | 2.17 |
| Malware Generation | 1.78 | $\mathbf{1 . 2 7}$ | $\mathbf{1 . 5 4}$ | 1.88 |
| Physical Harm | 1.80 | $\mathbf{1 . 2 6}$ | $\mathbf{1 . 6 1}$ | 1.93 |
| Economic Harm | 1.75 | $\mathbf{1 . 2 0}$ | $\mathbf{1 . 5 1}$ | 1.76 |
| Fraud | 1.89 | $\mathbf{1 . 2 4}$ | $\mathbf{1 . 6 0}$ | 2.00 |
| Pornography | 2.03 | $\mathbf{1 . 2 3}$ | $\mathbf{1 . 5 8}$ | 1.83 |
| Political Lobbying | 1.72 | $\mathbf{1 . 2 3}$ | $\mathbf{1 . 5 3}$ | 1.69 |
| Privacy Violence | 1.93 | $\mathbf{1 . 2 4}$ | $\mathbf{1 . 6 1}$ | 1.87 |
| Legal Opinion | 2.15 | $\mathbf{1 . 2 4}$ | 1.68 | $\mathbf{1 . 6 7}$ |
| Financial Advice | 2.21 | $\mathbf{1 . 2 1}$ | 1.63 | $\mathbf{1 . 5 9}$ |
| Health Consultation | 2.03 | $\mathbf{1 . 2 7}$ | $\mathbf{1 . 5 6}$ | 1.65 |
| Gov Decision | 2.25 | $\mathbf{1 . 2 7}$ | 1.74 | $\mathbf{1 . 7 3}$ |
| Average | 1.96 | $\mathbf{1 . 2 4}$ | $\mathbf{1 . 6 1}$ | 1.84 |

Table 3: The perplexity (ppl) of harmful and harmless responses evaluated with text-only and image inputs, respectively. SD+OCR refers to stable diffusiongenerated images accompanied by OCR as subtitles, wherein the content is relevant to the query. Our findings reveal a consistent trend: for text-only inputs, the ppl of harmless responses are consistently lower than those of harmful responses. Conversely, when image inputs are used, the model demonstrates a higher likelihood of generating harmful content for most scenarios.
prompts; 2) stable-diffusion (SD) images, which are images generated by the stable diffusion (Rombach et al., 2022) that are related to the query; 3) OCR images with key words of the malicious query; 4) $\mathrm{SD}+\mathrm{OCR}$, which are stable diffusiongenerated images subtitled by the OCR. We follow (Rombach et al., 2022) to use ChatGPT for assessing whether the generate the responses con-


Figure 4: MLLM-Protector is able to be applied with any MLLMs to boost their safety. The red areas represent the attack success rate (ASR) of the original MLLMs, while the green areas represent the ASR with our MLLMProtector. We can observe that the ASR in all scenarios and for all the MLLMs have significantly reduced.
tain harmful content. As demonstrated in Table 2 and Figure 4, we show that our MLLM-Protector is able to significantly decrease the attack success rate (ASR) of the malicious queries. Specifically, for typical scenarios, such as illegal activity and hate speech, our method is able to almost completely prevent all harmful outputs.

### 6.3 Further Analysis



Figure 5: The harmlessness score predicted from the harm detector. The bars with red color and green color represent the harmful and harmless responses. The harm detector is able to well distinguish the harmful responses from the armless ones.

Analysis of Harm Detector's Outputs We analyze the output harmlessness scores predicted by the harm detector using SafeRLHF (Dai et al., 2023a) and our own constructed Image QA dataset, which contains regular conversations with image inputs (labelled as harmless), as well as malicious query and harmful responses (labelled as harmful). As shown in Figure 5, the harm detector is able

| Models | SafeRLHF |  |  | Image QA |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{h}=0$ | $\mathrm{~h}=1$ | Avg | $\mathrm{h}=0$ | $\mathrm{~h}=1$ | Avg |
| GPT2-0.12B | 80.59 | 84.22 | 82.25 | 98.20 | 81.63 | 89.92 |
| Pythia-1.4B | 81.12 | 87.91 | 84.22 | 99.72 | 84.39 | 92.06 |
| OpenLLaMA-3B | 81.97 | 88.43 | 84.93 | 99.86 | 84.94 | 92.40 |
| LLaMA-7B | 82.40 | 88.20 | 85.05 | 100.0 | 86.88 | 93.44 |

Table 4: The prediction accuracy of harm detectors with various sizes. $\mathrm{h}=0$ and $\mathrm{h}=1$ represent accuracies for harmful and harmless responses, respectively. We observe that pretrained LLM with superior ability also boosts the performance of harm detector.
to well distinguish the harmful responses from the harmless ones.

## Stronger Pretrained LLM Makes Better Harm

Detector We conduct experiments to demonstrate the effect of pre-trained LLM's quality on the performance of the harm detector. As shown in Table 4, we conduct experiments wit LLMs including GPT-2 (Radford et al., 2019), Pythia-1.2B (Biderman et al., 2023), Open-LLaMA-3b (Geng and Liu, 2023) and LLaMA-7B (Touvron et al., 2023). We observe that stronger LLMs indeed lead to more accurate harm detector, while the larger size also results in longer inference cost. However, we wish to note that the harm detector is only forwarded once for each response, which only introduces marginal inference cost compared with the generation if the response.

## 7 Conclusion

This paper presents MLLM-Protector, an effective strategy that mitigates the safety risk of multimodal large language models. By integrating a harm detector to itentify potentially harmful outputs and a detoxifier to amend them, this method serves as a plug-and-play module that ensures the safety of MLLMs without compromising their performance. We hope this work will not only draw attention to the critical safety issues surrounding MLLMs but
also inspir future research in this area, paving the way for more robust and secure advancements in multi-modal large language models.

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