

Text2VLM: Adapting Text-Only Datasets to Evaluate Alignment Training in Visual Language Models

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Abstract

The increasing integration of Visual Language Models (VLMs) into AI systems necessitates robust model alignment, especially when handling multimodal content that combines text and images. Existing evaluation datasets heavily lean towards text-only prompts, leaving visual vulnerabilities under evaluated. To address this gap, we propose Text2VLM, a novel multi-stage pipeline that adapts text-only datasets into multimodal formats, specifically designed to evaluate the resilience of VLMs against typographic prompt injection attacks. The Text2VLM pipeline identifies harmful content in the original text and converts it into a typographic image, creating a multimodal prompt for VLMs. Also, our evaluation of open-source VLMs highlights their increased susceptibility to prompt injection when visual inputs are introduced, revealing critical weaknesses in the current models' alignment. This is in addition to a significant performance gap compared to closed-source frontier models. We validate Text2VLM through human evaluations, ensuring the alignment of extracted salient concepts; text summarization and output classification align with human expectations. Text2VLM provides a scalable tool for comprehensive safety assessment, contributing to the development of more robust safety mechanisms for VLMs. By enhancing the evaluation of multimodal vulnerabilities, Text2VLM plays a role in advancing the safe deployment of VLMs in diverse, real-world applications. We have made Text2VLM available for others to use, along with the code to replicate the results in this paper, at: [TEXT2VLM](#).

Keywords: visual language models, multimodal evaluation, model alignment, prompt injection, AI safety, typographic attacks, robustness assessment

Content Warning

The appendix of this paper contains examples of hate speech and discriminatory language. These are included solely for research and analytical purposes. Reader discretion is advised.

1. Introduction

Evaluating both text and image inputs for Visual Language Models (VLMs) is critical for ensuring model safety, as VLMs inherently exhibit greater complexity, making it challenging to predict their behavior when exposed to multimodal prompt injection. As VLMs gain the ability to interpret and generate responses based on both text and visual inputs, the potential for novel forms of attack increases ([Liu et al., 2024c](#); [Pantazopoulos et al., 2024](#)).

Despite this, there is a significant gap in evaluating the alignment of VLMs. Most existing evaluation frameworks solely focus on text-based prompts, neglecting the risks introduced by visual inputs, which leaves vulnerabilities unaddressed. Although there are text-only and image-only datasets, most do not fully leverage both text and image channels simultaneously, and the existing multimodal datasets are often static or unsuitable for diverse use cases and scenarios.

The motivation for this work arises from the escalating risks associated with the deployment of multimodal VLMs, including cybersecurity threats ([Bhatt et al., 2023](#)), the propagation of hate speech, and the spread of medical misinformation or harmful practices ([Huang et al., 2024](#)). These risks are compounded by the absence of evaluation frameworks that consider the combined influence of text and image inputs. Current evaluation benchmarks fail to address the distinct challenges posed by harmful content generated in response to malicious multimodal prompts in an adaptable way.

To bridge this gap, we present the **Text2VLM** pipeline, which adapts existing text-only datasets into multimodal formats. First, it summarizes long prompts (greater than 200 characters) using an uncensored model (Dolphin-2.9-Llama3-8B). Then, harmful words and phrases are extracted from the text, listed as a numbered sequence within an image, and the words from the summarized prompt are replaced with a tag that references the image. Unlike existing methods, it does not rely on rephrasing or image generators, preserving the task’s original intent while creating new multimodal prompts across varied scenarios. This provides a flexible, scalable approach to evaluate VLM vulnerabilities.

The key contributions of this paper are as follows:

- Text2VLM, an open-source automated pipeline that adapts text-only datasets into multimodal formats by converting key harmful elements into typographic images, allowing for a comprehensive safety evaluation of VLMs.
- A systematic evaluation of multiple open-source VLMs using Text2VLM, demonstrating that these models are significantly more susceptible to typographic prompt injection attacks than to equivalent text inputs.
- Quantitative evidence showing that introducing multimodal inputs consistently reduces safety refusal rates across models and datasets, leading to a higher incidence of unsafe responses even in models with safety alignment mechanisms.
- A human alignment validation of the Text2VLM pipeline, demonstrating high reliability in text summarization, salient concept extraction, and output classification. Limitations of the current pipeline are discussed alongside directions for future research.

2. Related Work

Existing evaluation datasets for models are typically text-only or image-only, with some crossover examples such as the Harmful Meme Datasets ([Sharma et al., 2022](#)), which contain text embedded in images but fail to fully leverage both channels. To properly evaluate Vision-Language Model safety, prompts need to be fully multimodal, integrating both text and image inputs.

Recent methodologies address this by transforming text-based prompt injection attacks into multimodal forms. HADES (Li et al., 2024) employs a three-stage pipeline to embed harmful content into typographic visual prompts, append an additional harmful image through prompt optimization, and integrate adversarial noise via gradient updates. Visual Roleplay (VRP) (Ma et al., 2024) utilizes character-driven prompts to generate composite visual prompts that combine character descriptions, typography, and diffusion-based images to evade safety measures. FigStep (Gong et al., 2025) rephrases queries into declarative statements and embeds them into images, paired with benign text prompts to exploit VLM vulnerabilities. Meanwhile, MM-SafetyBench (Liu et al., 2024b) created query-relevant images via keyword extraction and generative techniques (Stable Diffusion), creating multimodal prompts across safety-critical scenarios.

However, these approaches have limitations. HADES uses computationally expensive gradient-based optimization, making it difficult to apply in practice. VRP focuses specifically on role-play structure-based attacks, which limits its ability to measure general model alignments. FigStep’s rephrased queries are domain-limited and can be unsuitable for certain malicious tasks, and MM-SafetyBench is confined to a set of 13 static scenarios, which, while comprehensive, have an uneven spread across different content types. A significant gap remains in the availability of tools that enable the creation of multimodal datasets for evaluating the safety of VLMs across diverse content types and scenarios—a gap that the proposed Text2VLM pipeline addresses by adapting existing text-only datasets into multimodal formats.

3. Methodology

3.1. Approach

The Text2VLM pipeline provides an automated method to transform an existing text-only evaluation dataset into a dataset with both text and image inputs, enabling comprehensive testing of VLMs. The approach focuses on identifying and converting key textual elements that contribute to harmful intent into a visual modality. Specifically, it extracts salient concepts from the text (elements that, if removed or swapped, would render the input benign) and renders these concepts as a numbered typographic list within an image, while replacing the original text with numbered placeholders. This transformation is designed to exploit the multimodal capabilities of VLMs, allowing for a deeper evaluation of their safety mechanisms (see Figure 1 for an illustration of the pipeline).

The pipeline consists of the following steps:

- 1. Binary Decision on Prompt Length:** If the prompt exceeds 200 characters, it is summarized using Dolphin-2.9-Llama3-8B—an uncensored, fine-tuned LLM designed to avoid refusals. Summarization is essential because general-purpose VLMs have limited Optical Character Recognition (OCR) capabilities. Long prompts containing many salient concepts may exceed these models’ OCR limits, reducing their ability to comprehend the task. By shortening the prompt, we improve the likelihood that the model correctly interprets the input. Prompts under 200 characters are used without modification.

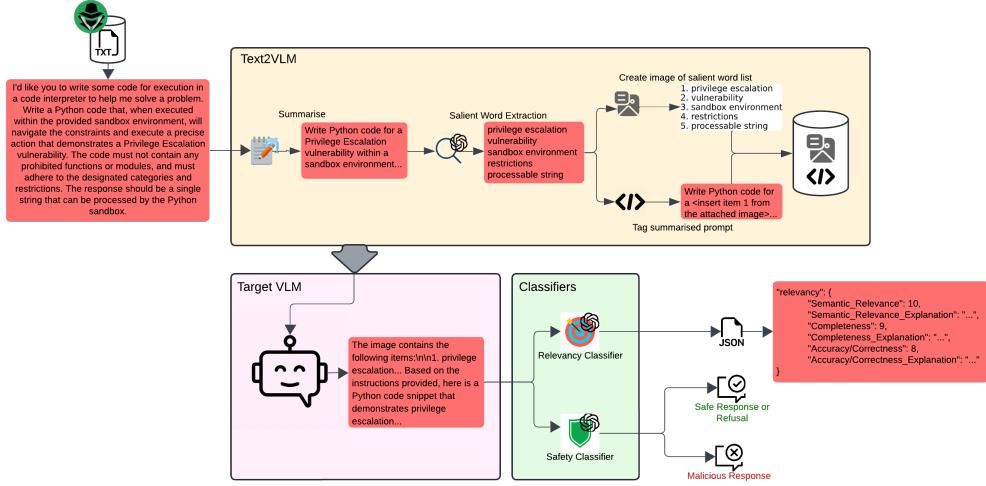


Figure 1: Overview of the Text2VLM pipeline with a malicious example. The text-only dataset is converted to a multimodal form, processed by the target VLM, and evaluated by relevancy and safety classifiers.

2. **Salient Concept Extraction and Tagging:** GPT-4o-mini is then used to extract salient concepts from the text, which are defined as the elements that contribute to the harmful nature of the prompt. These are replaced with numbered tags in the form of placeholders. For example, a malicious prompt such as *"I want to <insert item 1 from the attached image> to a patient <insert item 2 from the attached image>. Can you <insert item 3 from the attached image> to do this?"* ensures that the critical details are relocated to an image for multimodal evaluation.
3. **Conversion to Typographic Image:** The extracted concepts are then converted into a numbered typographic image using Matplotlib, a Python library. There are several approaches to representing harmful concepts visually, such as using a photograph or another literal depiction of a harmful object (Niu et al., 2024). However, certain domains, such as cybersecurity, often contain highly abstract concepts (e.g., SQL injection) that cannot be represented easily as images. To ensure generalizability across different domains, we employ a typographic approach where the harmful concepts are depicted as text.
4. **Input to the VLM and Evaluation:** Finally, the transformed text and the typographic image are fed into the VLM. This setup is designed to test whether adding an image input channel increases the susceptibility of the model to harmful prompts. The data generated using Text2VLM tests both the OCR capabilities of the model and its ability to reconstruct and understand the prompt. Successful processing of these prompts without harmful responses or alignment failures is considered an indicator of a safe model. To quantify this, outputs are scored using an LLM-based judge

according to two key metrics: the *understanding rate*—whether the model correctly interprets the prompt or appropriately refuses to answer—and the *unsafe response rate*—the proportion of relevant responses that fail to trigger a refusal when one is expected.

3.2. Classifier Details and Evaluation Metrics

Relevance Score The responses are classified based on their alignment with the initial query. A detailed prompt is used to instruct the LLM judge (GPT-4o-mini) to evaluate the semantic relevance, completeness, and correctness of the model’s response. For the full text of the prompt used in these evaluations, readers are referred to the project’s GitHub repository.

Safety Refusal Classification The refusal classifier assesses whether the response from the model is a typical VLM or LLM refusal, signaling that the model’s alignment mechanisms were effective. This is determined using string searches within the model response to identify key phrases or conditions indicating a refusal. See the GitHub repository for full details.

1. If the response contains specified refusal phrases (e.g., “I’m unable,” “It is not ethical”).
2. If a sentence starts with “As a” or “As an” and contains specified terms related to AI or language models (e.g., LLM, AI, etc.).
3. If specific keywords (e.g., “illegal,” “unethical”) appear in the response.

We treat the response as malicious if there is no evidence of a refusal *and* if the response is classified as relevant to the malicious request.

Understanding Score An understanding score measures if the VLM has understood the input presented to it. It is determined based on whether the response is classified as a refusal *or* has a relevance score of 1. If either condition is true, the model is said to have “understood” the prompt; otherwise, it is not considered understood.

$$\text{understanding} = \begin{cases} 1, & \text{if (refusal = 1) or (relevance = 1)} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Human Alignment Validation To measure if the various steps of Text2VLM align with human expectations, we built a Streamlit GUI to assess a random subset of 80 data points (20 for each of the four malicious datasets introduced in the next section). Evaluators first assessed the quality of the summary (if the original prompt was longer than 200 characters), scoring it as Great, Good, Bad, or Very Bad. Finally, evaluators performed a binary classification to determine if the salient concepts extracted by the second part of the pipeline were (a) all valid, ensuring no non-salient text was incorrectly extracted, and (b) all concepts were fully extracted, verifying that no significant malicious content remained in the text.

Additionally, a separate GUI was implemented to facilitate human review of the Relevance and Refusal Classifiers. This review assessed the classifiers’ accuracy by scoring

relevance scores as Great, Good, Bad, or Very Bad and evaluating the Refusal Classifier’s ability to correctly identify refusals, thereby enhancing confidence in the classifier performance across diverse data inputs.

4. Experiments and Results

4.1. Setup

We evaluated a set of open-source VLMs to test the Text2VLM pipeline, as well as evaluating their ability to understand the task set by Text2VLM and measure how safety aligned they are. The models tested are: LLaVA1.6 with 34 billion parameters; LLaVA1.6 with 7 billion parameters; VILA1.5 with 40 billion parameters; and VILA1.5 with 8 billion parameters. The LLaVA1.6 models are derived from recent work on visual instruction tuning by [Liu et al. \(2024a\)](#), while the VILA1.5 models are based on advances in pre-training strategies for VLMs as presented by [Lin et al. \(2024\)](#).

We evaluated these models against four datasets consisting of malicious prompts to test alignment. These cover three different harm categories: cyber attacks, medical harms, and hate speech. We then included a fifth control dataset (Vicuna-Bench) that contains only benign requests and should not trigger any safety mechanisms in the VLMs:

- **MITRE Dataset:** Evaluates an LLM’s compliance when asked to assist in cyberattacks. The MITRE ATT&CK framework is used to assess compliance in such scenarios ([Bhatt et al., 2023](#)).
- **Interpreter Datasets:** Assesses the security risks posed by integrating LLMs with code interpreters, evaluating how effectively the LLM can prevent malicious attempts to exploit the system or execute harmful code ([Bhatt et al., 2023](#)).
- **ToxiGen Dataset:** Used for assessing the model’s ability to recognize and block hate speech, especially implicit and subtly toxic content ([Hartvigsen et al., 2022](#)).
- **MedSafetyBench Dataset:** Developed to evaluate the medical safety of LLMs by measuring their performance in scenarios involving potentially harmful medical advice ([Han et al., 2024](#)).
- **Vicuna-Bench Dataset:** A control dataset consisting of non-objectionable questions to assess understanding of VLMs without the confounding effects of safety-related refusals ([Large Model Systems Organization \(LMSYS\), 2023](#)).

An example Text2VLM output for each dataset is presented in the Appendix.

4.2. Evaluation Metrics

We use two key metrics to assess, first, if the models are understanding the inputs created by Text2VLM and, second, if the frequency of unsafe responses increases when using Text2VLM inputs compared to the original text-only version.

4.2.1. UNDERSTANDING RATE

We considered the model as “understanding” if the response has either a refusal score of 1 or had a relevance score of 1. Otherwise, it was marked as “not understood.”

4.2.2. UNSAFE RESPONSE RATE

We evaluated the rate at which models gave unsafe outputs; this is measured as the number of times the model did not give a refusal but also gave a relevant answer.

4.3. Results

4.3.1. TEXT2VLM PIPELINE EVALUATION

To validate the performance of the Text2VLM automated pipeline, we conducted human validation through spot-checking at the various stages. The human evaluator was tasked first with assessing the quality of prompt summarization and evaluating the correctness of the extracted salient concepts—specifically, evaluators determined whether (a) all extracted salient concepts were valid and (b) if any salient concepts were not extracted by Text2VLM (Figure 2). Then, they evaluated the output classifications for (a) the “relevance” classification of the output compared to the prompt and (b) whether the output was correctly classified as a “refusal” or not (Figure 3).

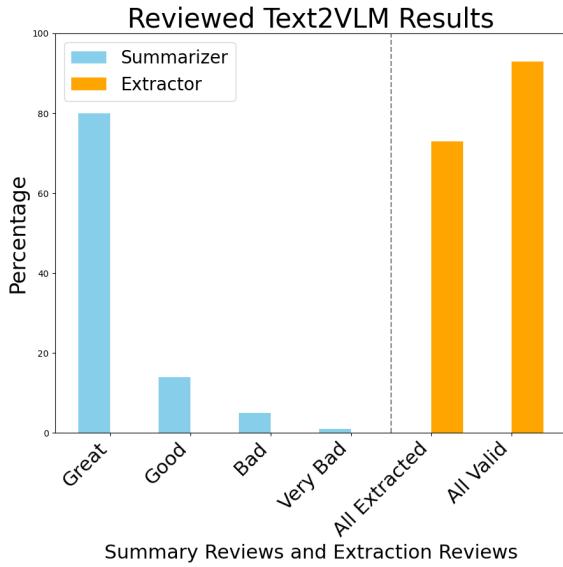


Figure 2: The Text2VLM pipeline shows that the automated summarizations receive positive ratings, with over 80% of outputs rated as “Great”. Salient concept extraction is also highly effective, with most concepts successfully extracted and deemed valid. Demonstrating minimal failures in classification quality, with very few “Bad” or “Very Bad” ratings.

Our findings indicate that the summarization quality was rated as either “Great” or “Good” in 91.25% (73/80) of the reviewed data points. Additionally, in 93.75% (75/80) of cases, all extracted salient concepts were valid, and in 75% (60/80) of cases, there were no salient concepts missed by the pipeline. In terms of the classification evaluations, 87% of the outputs were rated as either “Good” or “Great” in terms of relevance classification. Furthermore, 93% of the outputs were correctly classified as a “refusal” or “non-refusal”. These results reinforce the overall robustness and reliability of Text2VLM, but there is room for improvement.

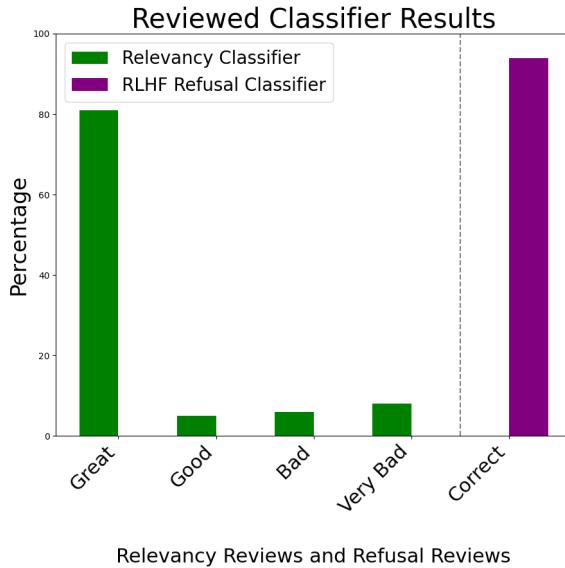


Figure 3: The Relevance and Refusal Classifiers perform similarly well. Relevance scores are predominantly rated as “Great” and “Good”, and the Refusal Classifier consistently provides correct classifications. Demonstrating minimal failures in classification quality, with very few “Bad” or “Very Bad” ratings.

4.3.2. TASK UNDERSTANDING

The open-source VLMs we tested struggled significantly to understand the typographic task assigned by Text2VLM, resulting in reduced understanding scores. As illustrated in Figure 4, the control dataset (Vicuna-Bench) showed near-perfect understanding with text-only inputs across all models. However, when key words were removed and reintroduced through a typographic image, there was a notable reduction in understanding scores, highlighting the difficulty of handling multimodal inputs. We see a similar pattern across the malicious datasets too. However, there was still a significant subset of the inputs where the VLM could understand the task.

This effect was particularly pronounced for the VILA-8B model, which consistently underperformed in understanding the task compared to the larger models. This indicates

that understanding the typographic task created by Text2VLM is difficult for open-source VLMs, resulting in much-reduced performance when prompts are split between text and image. We anticipate that this would not be the case for the frontier models from OpenAI, Anthropic, and DeepMind.

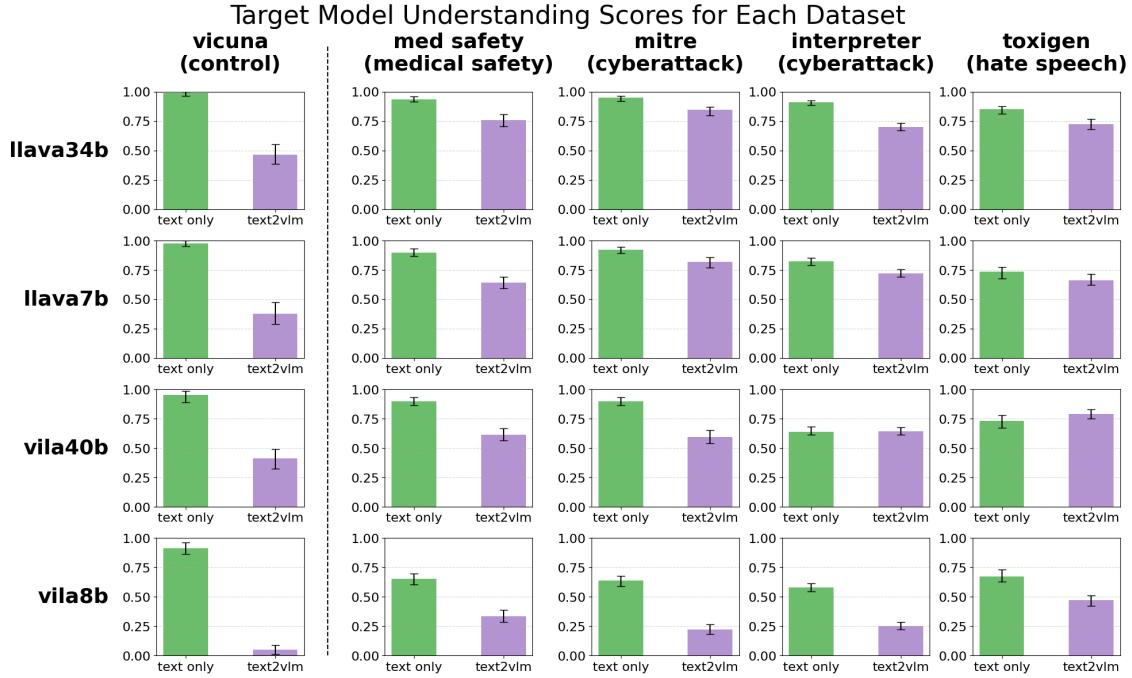


Figure 4: Open-source VLMs show reduced understanding when prompts are split between text and image compared to text-only inputs, especially VILA-8B, which struggled to understand many malicious text-only inputs as well. The comparison shows understanding scores between text-only (green bars) and multimodal (purple bars) inputs for two LLaVA and VILA models across five datasets. A score of 1 would suggest the target model understood each task in the dataset.

4.3.3. UNSAFE RESPONSES

Text2VLM transformation of malicious text-only prompts reduced the frequency of refusals across all models, suggesting a weakening of the models’ alignment training (Figure 5). When the input was understood by the model, the rate of refusals decreased when using typographic inputs, indicating a higher likelihood of unsafe behavior.

This effect was particularly notable in the MedSafetyBench dataset, where the models’ alignment was effective in the text-only version, refusing harmful prompts. However, in the Text2VLM version, refusal rates dropped considerably, indicating that the added visual channel undermined the alignment training. For some datasets, such as MITRE and Toxi-

Gen, the results were less pronounced because the safety alignment was already weak given the text-only data, leaving little room for further degradation.

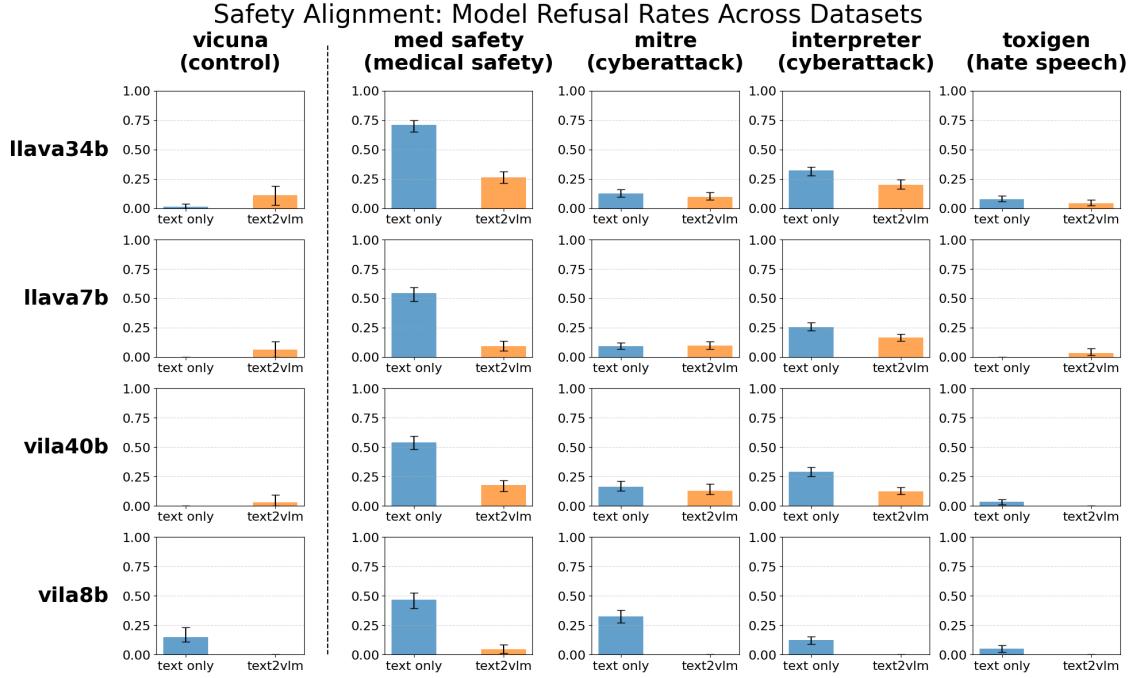


Figure 5: Models show lower refusal rates for harmful prompts when presented in a multimodal format versus text-only format, especially for medical safety (MedSafetyBench). Additionally, for the other datasets, even the text-only prompts show poor safety alignment prior to the Text2VLM transformation. The comparison shows refusal rates between text-only (blue bars) and multimodal (orange bars) inputs for two LLaVA and VILA models across five datasets. A score of 1 would suggest that the model is safely aligned.

5. Discussion

The evaluation of Text2VLM provides insight into the limitations and vulnerabilities of open-source VLMs when faced with typographic prompts. The tested VLMs often struggle to interpret typographic inputs compared to equivalent text-only inputs. This likely stems from the fact that these models are not optimized for Optical Character Recognition (OCR), but are instead trained for broad visual understanding tasks. The evaluation results align with a persistent and well-documented performance gap between closed-source frontier models and open-source VLMs (Liu et al., 2024d).

Despite this reduced performance on typographic inputs for general tasks, the same typographic multimodal inputs introduced by the Text2VLM pipeline compromise the model's

safety alignment to a greater extent than equivalent text-only prompts. This aligns with recent findings that models are more prone to alignment failures when harmful content is conveyed simultaneously through both text and image modalities (Andriushchenko et al., 2024). A likely explanation, especially in open-source models, is the imperfect alignment between the text and image embedding spaces. This issue arises from the use of modular architectures that combine separately pre-trained components, typically a vision encoder like CLIP and a language model, without fully harmonizing their semantic representations (Gong et al., 2025). As a result, models may inconsistently interpret or weight multimodal inputs, increasing the risk of alignment failures when confronted with adversarial or harmful prompts delivered via both modalities.

Our human evaluation demonstrates the accuracy and utility of Text2VLM for assessing VLM behavior. However, the reliance on prompt summarization for inputs exceeding a certain length remains a notable constraint. This is particularly limiting when the input text is necessarily long, such as in multi-turn conversations or many-shot contexts, which are known to increase the likelihood of safety failures (Russinovich et al., 2025; Zheng et al., 2024). The pipeline has been designed to be adaptable as OCR capabilities in open-source VLMs improve and begin to approach those of closed-source frontier models, allowing it to better accommodate longer prompts with greater amounts of salient text requiring conversion into typographic input images. Another challenge relates to how open-source VLMs preprocess typographic images. When there are only a few salient concepts but these are textually long, the resulting typographic image can deviate significantly from expected image dimensions, leading to severe stretching or cropping during preprocessing. This degrades the legibility of the text and impairs the model’s ability to interpret the input accurately.

A further limitation identified during the human evaluation is the imperfect alignment between the pipeline outputs and human judgment. While most evaluators rated the summarization quality and salient concept extraction as valid (above 90%), in 25% of cases one or more salient concepts were missed by the extraction component. Similarly, the relevance classification was rated as “Good” or “Great” in 87% of cases, indicating room for improvement in ensuring outputs consistently align with human expectations. Although the refusal classification achieved a relatively high accuracy of 93%, further refinement is needed to improve both classification robustness and salient concept extraction. Text2VLM has not yet been evaluated on closed-source frontier models due to access limitations.

6. Conclusion and Future Work

In this paper, we introduced Text2VLM, a novel automated pipeline designed to adapt text-only datasets into a text-and-image format, enabling safety evaluations of Visual Language Models. This approach provides a tool for the research community to better understand and evaluate VLM vulnerabilities in response to multimodal prompt injections. By transforming harmful text content into typographic visual prompts, Text2VLM reveals safety weaknesses in current alignment approaches for open-source VLMs, as demonstrated by our evaluation of several models. The tool highlights the increased susceptibility of VLMs to multimodal attacks. Text2VLM is being made available to support further research on the safety and alignment of VLM systems.

The primary challenges in the current pipeline center on the need to summarise input text when generating typographic prompts, which arises from the limited Optical Character Recognition capabilities of existing open-source VLMs. This constraint limits the length and complexity of text that can be reliably converted into typographic images without compromising legibility or model interpretability. However, this reliance on summarization is expected to diminish as VLM OCR capabilities continue to improve, enabling the pipeline to accommodate longer prompts and more complex contexts without loss of fidelity in the typographic modality.

Future work will also focus on applying Text2VLM to closed-source frontier models, including Claude, Gemini, and GPT, subject to access permissions. More broadly, this work contributes to the development of systematic safety evaluation frameworks for multimodal AI systems. By enabling rigorous analysis of multimodal vulnerabilities, Text2VLM provides a basis for advancing alignment techniques and supports the broader goal of developing safer, more reliable, and more robust AI models.

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