Journal of Data-centric Machine Learning Research (2023) Submitted 9/23; Revised 10/23; Published 11/23

Benchmarking Robustness of Multimodal Image-Text Models under Distribution Shift

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Reviewed on OpenReview: *https://openreview.net/forum?id=XXXX*

Editor: My editor

Abstract

Multimodal image-text models have shown remarkable performance in the past few years. However, evaluating robustness against distribution shifts is crucial before adopting them in real-world applications. In this work, we investigate the robustness of 9 popular open-sourced image-text models under common perturbations on five tasks (image-text retrieval, visual reasoning, visual entailment, image captioning, and text-to-image generation). In particular, we propose several new multimodal robustness benchmarks by applying 17 image perturbation and 16 text perturbation techniques on top of existing datasets. We observe that multimodal models are not robust to image and text perturbations, especially to image perturbations. Among the tested perturbation methods, character-level perturbations constitute the most severe distribution shift for text, and zoom blur is the most severe shift for image data. We also introduce two new robustness metrics (MMI and MOR) for proper evaluations of multimodal models. We hope our extensive study sheds light on new directions for the development of robust multimodal models. More details can be found on the project webpage: `https://MMRobustness.github.io`.

Keywords: Multimodal, Robustness, Distribution Shift

1 Introduction

Multimodal learning has drawn increasing attention, and many datasets and models are collected and proposed to accelerate research in this field (Chen et al., 2020; Gan et al., 2020; Li et al., 2022b, 2020; Zhang et al., 2021; Radford et al., 2021; Kim et al., 2021; Li et al., 2021a, 2022a; Yang et al., 2022; Dou et al., 2021; Ramesh et al., 2022; Wang et al., 2022a; Alayrac et al., 2022; Radford et al., 2021; Yu et al., 2022). Despite the extraordinary

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Figure 1: Multimodal models are sensitive to image/text perturbations (original image-text pairs are shown in blue boxes, perturbed ones are in red). Image captioning (Top): Adding image perturbations can result in incorrect captions, e.g., the tabby kitten is mistakenly described as a woman/dog. Text-to-image generation (bottom): Applying text perturbations can result in the generated images containing incomplete visual information, e.g., the tree is missing in the two examples above.

performance and exciting potential, we find that multimodal models are often vulnerable under distribution shifts. In Figure 1, we show interesting examples of image captioning under image perturbations using BLIP (Li et al., 2022a), and text-to-image generation under text perturbations using Stable Diffusion (Rombach et al., 2022). For image captioning, we observe that by simply adding noise, blur, or pixelation to the original image, the generated captions become incorrect. For text-to-image generation, applying keyboard typos, OCR errors, or synonym replacements to the original sentence, can lead to generated images containing incomplete visual information.

There is a sizable literature on robustness evaluation of unimodal vision models (Yin et al., 2019; Zheng et al., 2016; Drenkow et al., 2021; Djolonga et al., 2021; Goyal et al., 2022; Paul and Chen, 2022; Bhojanapalli et al., 2021; Mahmood et al., 2021; Mao et al., 2021; Aldahdooh et al., 2021; Zhou et al., 2022; Wenzel et al., 2022) or unimodal language models (Wang et al., 2022b; Chang et al., 2021; Wang et al., 2020; Rychalska et al., 2019; Goel et al., 2021; Singh et al., 2021; Dong et al., 2021; Gui et al., 2021; Malfa and Kwiatkowska, 2022; Wang et al., 2021). Several recent work (Galindo and Faria, 2021; Fort, 2021; Noever and Noever, 2021; Goh et al., 2021; Daras and Dimakis, 2022) have unsystematically tested or probed a few pre-trained multimodal models, including CLIP (Radford et al., 2021) and DALL-E 2 (Ramesh et al., 2022). However, the robustness evaluation of multimodal image-text models under distribution shift has rarely been studied. To our best knowledge, there is currently no benchmark dataset nor a comprehensive study of how the perturbed data can affect their performance. Hence in this work:

- We build multimodal robustness evaluation benchmarks by leveraging existing datasets and tasks, e.g., image-text retrieval (Flicker30K, COCO), visual reasoning (NLVR2), visual entailment (SNLI-VE), image captioning (COCO), and text-to-image generation (COCO). We analyze the robustness of 9 multimodal models under distribution shifts, which include 17 image perturbation and 16 text perturbation methods.
- We introduce two new robustness metrics, one termed MMI (MultiModal Impact score), to account for the relative performance drop under distribution shift in 5 downstream applications. The other one is named MOR (Missing Object Rate), which is based on open-set language-guided object detection and the first object-centric metric proposed for text-to-image generation evaluation.
- We find that multimodal image-text models are more sensitive to image perturbations than text perturbations. In addition, *zoom blur* is the most effective attack for image perturbations, while character-level perturbations show a higher impact than word-level and sentence-level perturbations for text. In addition, we provided interpretations of performance drop by different perturbation methods using Optimal Transport alignment and attention.

2 Related Work

Multimodal Learning has advanced quickly in recent years with appealing applications in different fields, i.e., embodied learning (Bisk et al., 2020; Hu et al., 2019; Jain et al., 2022; Min et al., 2022), multimedia image/video and language understanding (Zolfaghari et al., 2021; Erickson et al., 2022; Rombach et al., 2022; Hu et al., 2022), and psychology (Liu et al., 2022b; Han et al., 2022). Thanks to the larger datasets (Radford et al., 2021; Yuan et al., 2021; Schuhmann et al., 2021, 2022; Patraucean et al., 2022) and larger transformer models (Zhai et al., 2022; Chen et al., 2022; Brown et al., 2020; Chowdhery et al., 2022; Liang et al., 2022), many powerful multimodal image-text models have been developed and shown great capability. However, unlike unimodal models, the robustness study of multimodal models under distribution shift has rarely been explored.

Robustness of Multimodal Models There is a sizable literature on robustness evaluation of unimodal vision models (Yin et al., 2019; Zheng et al., 2016; Drenkow et al., 2021; Djolonga et al., 2021; Goyal et al., 2022; Paul and Chen, 2022; Bhojanapalli et al., 2021; Mahmood et al., 2021; Mao et al., 2021; Aldahdooh et al., 2021; Zhou et al., 2022) or unimodal language models (Wang et al., 2022b; Chang et al., 2021; Wang et al., 2020; Rychalska et al., 2019; Goel et al., 2021; Singh et al., 2021; Dong et al., 2021; Gui et al., 2021; Malfa and Kwiatkowska, 2022; Wang et al., 2021). However, robustness evaluation of multimodal image-text models under distribution shift has rarely been studied (Goh et al., 2021; Daras and Dimakis, 2022). Previous works Galindo and Faria (2021); Fort (2021); Goh et al. (2021); Noever and Noever (2021) have unsystematically tested some pre-trained models, i.e., CLIP Radford et al. (2021), by attacking with text patches and adversarial pixel perturbations. Daras and Dimakis (2022) found that DALLE-2 (Ramesh et al., 2022) has a hidden vocabulary that can be used to generate images with absurd prompts. Fang et al. (2022) found that diverse training distribution is the main cause for robustness gains. Cho et al. (2022) studied the text-to-image generative models about visual reasoning skills and

social bias. For benchmarks, Li et al. (2021b) collected an Adversarial VQA dataset to evaluate the robustness of VQA models. Schiappa et al. (2022) studied the robustness of video-text models under perturbations, but they only focused on one video-text retrieval task. In this work, we conduct a systematic robustness evaluation of recent multimodal image-text models on 5 different downstream tasks based on new datasets and metrics. (More related work can be found in Appendix I).

3 Multimodal Robustness Benchmark

Distribution shift is one of the significant problems of applying models in real-world scenarios (Taori et al., 2020; Liu et al., 2022c). Distribution shift happens when the training data distribution $p_{tr}(\boldsymbol{x} \mid \boldsymbol{y})$ is different from the data distribution to which the model has applied at test time $p_{te}(\boldsymbol{x} \mid \boldsymbol{y})$. A model is said to be robust on the out-of-distribution (OOD) data, if it still produces accurate predictions on the test data. To evaluate the robustness of large pretrained multimodal models under distribution shift, we start by building several evaluation benchmark datasets via perturbing the original image-text pairs on either the image side or text side. We use these perturbations to simulate distribution shifts of various intensities and use them to stress-test the robustness of the given models.

3.1 Image Perturbation

To simulate distribution shifts for the image data, we adopt the perturbation strategies from ImageNet-C (Hendrycks and Dietterich, 2019) and Stylize-ImageNet (Geirhos et al., 2019; Michaelis et al., 2019). We include Stylize-ImageNet for its effectiveness in perturbing the original image by breaking its shape and texture (Geirhos et al., 2019). Examples of the perturbed images can be seen in Figure 7 in the Appendix. The perturbations are grouped into five categories: **noise, blur, weather, digital**, and **stylize**. Specifically, we use 17 image perturbation techniques, (1) Noise: *Gaussian noise*, *shot noise*, *impulse noise*, *speckle noise*; (2) Blur: *defocus blur*, *frosted glass blur*, *motion blur*, *zoom blur*; (3) Weather: *snow*, *frost*, *fog, brightness*; (4) Digital: *contrast*, *elastic*, *pixelate*, *JPEG compression*; and (5) *stylize*. Note that real-world corruptions can manifest themselves at varying intensities, we thus introduce variation for each corruption following (Hendrycks and Dietterich, 2019; Geirhos et al., 2019; Michaelis et al., 2019). In our evaluation setting, each category has five levels of severity, resulting in 85 perturbation methods in total. More details can be found in Appendix Sec. A. Note that these strategies are commonly considered synthetic distribution shifts and can serve as a good starting point since they are precisely defined and easy to apply.

3.2 Text Perturbation

To simulate the distribution shifts in language, we design 16 text perturbation techniques grouped into three categories: **character-level, word-level**, and **sentence-level**. Examples of the text perturbations are shown in Table 5 in the Appendix. In detail, for character-level perturbation, we adopt 6 strategies from (Ma, 2019), including *keyboard, OCR*, *character insert (CI)*, *character replace (CR)*, *character swap (CS)*, *character delete (CD)*. These perturbations can be considered as simulating real-world typos or mistakes during typing.

Table 1: Evaluation tasks, datasets, models and metrics used in our study.

Task	Datasets	Models	Evaluation metrics
Image-text Retrieval	Flicker30K, COCO	CLIP, ViLT, TCL, ALBEF, BLIP	Recall K (R@K), K = $\{1, 5, 10\}$, and RSUM
Visual Reasoning	NLVR2	ALBEF, ViLT, BLIP, TCL, METER	Prediction accuracy
Visual Entailment	SNLI-VE	ALBEF, TCL, METER	Prediction accuracy
Image Captioning	COCO	BLIP, GRIT	BLEU, METEOR, ROUGE-L, CIDEr
Text-to-image Generation	COCO	Stable Diffusion, GLIDE	FID, CLIP-FID, MOR (ours)

For word-level perturbation, we adopt 5 strategies from EDA and AEDA (Wei and Zou, 2019; Karimi et al., 2021), including *synonym replacement (SR)*, *word insertion (WR)*, *word swap (WS)*, *word deletion (WD)*, and *insert punctuation (IP)*. These perturbations aim to simulate different writing habits that people may replace, delete, or add words to express the same meaning. For sentence-level perturbation, (1) we first adopt the style transformation strategies from (Li et al., 2018; Etinger and Black, 2019; Schmidt, 2020; Schiappa et al., 2022), i.e., transferring the style of text into *formal*, *casual*, *passive*, and *active*; (2) we also adopt the *back translation* method from (Ma, 2019). These perturbations will focus more on language semantics, due to the differences in speaking or writing styles, or translation errors. Similar to image perturbations, we introduce severity levels to each strategy. For strategies within the character-level and word-level perturbations, we apply 5 severity levels similar to image perturbations, while for strategies within the sentence-level perturbations, there is only one severity level. This leads to a total of 60 text perturbation methods. More details about each text perturbation strategy can be found in Appendix Sec. A. We emphasize that these perturbation techniques cover some of the actual text distribution shifts we encounter in real-world applications (e.g., typos, word swaps, style changes, etc.). Models for text data that are deployed in real-world settings need to be robust with respect to these perturbations.

Fidelity To build a convincing benchmark, we need to ensure that the perturbed text has the same semantics as the original one. Otherwise, for image-text pairs in multimodal learning, the perturbed text will not match the original image and, hence, would no longer represent a meaningful image-text pair. In this work, we use paraphrases from pretrained sentence-transformers (Reimers and Gurevych, 2019) to evaluate the semantic similarity between the original and the perturbed sentences. Specifically, "paraphrase-mpnet-base-v2" (Reimers and Gurevych, 2019) is used to extract the original and perturbed sentence embeddings for computing similarity score α_s. Given a predefined tolerance threshold α_0, a higher score $\alpha_s > \alpha_0$ means the perturbed text still has similar semantics with the original text. However, if $\alpha_s < \alpha_0$ indicating their semantics are different, we will perturb the sentence again until the semantic similarity score meets the requirement, in a reasonable looping time $N_{max} = 100$. Beyond N_{max}, we will remove this text sample from our robustness benchmark. More details about the fidelity control process can be found in Appendix Sec. A. This procedure guarantees semantic closeness and ensures our perturbed data could serve as a valid evaluation benchmark for multimodal image-text models.

4 Experiments

Using our multimodal robustness benchmark, we are able to answer the following questions: **(1)** How robust are multimodal pretrained image-text models under distribution shift? **(2)**

What is the sensitivity of each model under different perturbation methods? **(3)** Which model architecture or loss objectives might be more robust under image or text perturbations? **(4)** Are there any particular image/text perturbation methods that can consistently show significant influence?

4.1 Evaluation Tasks, Datasets and Models

As shown in Table 1, we select five widely adopted downstream tasks for a comprehensive robustness evaluation under distribution shift, including image-text retrieval, visual reasoning (VR), visual entailment (VE), image captioning, and text-to-image generation. For each task, we perturb the corresponding datasets, i.e., Flickr30K (Young et al., 2014), COCO (Lin et al., 2014) , NLVR2 (Suhr et al., 2017), and SNLI-VE (Xie et al., 2018, 2019b), using the image perturbation (IP) and text perturbation (TP) methods introduced in Sec. 3. This leads to our 8 benchmark datasets: (1) Flickr30K-IP, Flickr30K-TP, COCO-IP, and COCO-TP for image-text retrieval evaluation; (2) NLVR2-IP and NLVR2-TP for visual reasoning evaluation; (3) SNLI-VE-IP and SNLI-VE-TP for visual entailment evaluation; (4) COCO-IP for image captioning evaluation; and (5) COCO-TP for text-to-image generation evaluation. We select 9 representative large multimodal models, which have publicly released their code and pretrained weights: CLIP (Radford et al., 2021), ViLT (Kim et al., 2021), ALBEF (Li et al., 2021a), BLIP (Li et al., 2022a), TCL (Yang et al., 2022), METER (Dou et al., 2021), GRIT (Nguyen et al., 2022), GLIDE (Nichol et al., 2022) and Stable Diffusion (Rombach et al., 2022). We appreciate the authors for making their models publicly available.

4.2 Evaluation Metrics

We adopt standard evaluation metrics for each task. To be specific, for image-text retrieval, we use recall and RSUM (i.e., the sum of recall R@K metric (Wu et al., 2019)). As for visual reasoning and visual entailment tasks, we use prediction accuracy. For image captioning, we use standard text evaluation metrics, i.e., BLEU (Papineni et al., 2002), METEOR (Denkowski and Lavie, 2014), ROUGE-L (Lin, 2004), and CIDEr (Vedantam et al., 2015). For text-to-image generation, we use FID (Heusel et al., 2017) and CLIP-FID (Kynkaanniemi et al., 2022; Parmar et al., 2022) scores, and our proposed MOR (details will be introduced later) to evaluate the quality of the generated images.

MultiModal Impact score (MMI) To evaluate the robustness of a model, it is crucial to measure the relative performance drop between the in-distribution (ID) and out-of-distribution (OOD) performance. Recall the example given by Taori et al. (2020), let d_1 be the ID dataset (where the model is trained), and d_2 be an OOD dataset, then a model m_1 should be considered more robust than model m_2 if m_1's performance drop is less significant than m_2 when evaluated from d_1 to d_2, even though m_2's absolute accuracy/recall on d_2 may still be higher than m_1's. To quantitatively measure the robustness of multimodal image-text models, we introduce a new robustness evaluation metric, termed **M**ulti**M**odal **I**mpact score (MMI). We compute MMI as the averaged performance drop compared with the non-perturbed performance ("clean"), i.e., MMI $= (s_c - s_p)/s_c$ where s_p is the perturbed score and s_c is the clean score. Here, the score can be any standard metric mentioned above, e.g., recall, RSUM, accuracy, FID, and CLIP-FID. In the following experiments, we report

Table 2: **Image-text retrieval.** [**Top**] Robustness evaluations on Flickr30k-IP and COCO-IP. [**Bottom**] Robustness evaluations on Flickr30k-TP and COCO-TP datasets. We report averaged RSUM where the most effective perturbation results are marked in bold, and the least effective perturbation results are underlined. The MMI impact score is marked in blue, the lower the better.

			Noise				Blur				Weather				Digital				Stylize		
Dataset	Method	Clean	Gauss.	Shot	Impulse	Speckle	Defocus	Glass	Motion	Zoom	Snow	Frost	Fog	Bright	Contrast	Elastic	Pixel	JPEG	Stylize	**ave**	MMI
Flickr30K	ViLT FT	522.0	413.0	419.6	396.9	387.1	417.6	489.0	388.4	236.3	332.7	453.1	455.8	496.9	372.2	461.7	**277.4**	487.6	387.1	408.7	↓ 21.7%
	CLIP ZS	533.7	501.7	504.2	481.2	515.5	502.1	530.1	509.7	457.8	470.7	495.6	519.7	530.1	515.4	510.4	469.5	524.6	**447.6**	499.2	↓ 6.5%
	CLIP FT	544.3	500.1	503.8	479.1	522.1	493.3	536.9	513.3	**444.4**	464.4	503.2	529.7	543.5	521.5	513.9	453.9	528.6	436.9	499.3	↓ 8.3%
	TCL ZS	563.8	464.9	467.0	458.4	498.0	429.8	506.6	388.5	**251.3**	407.3	449.5	434.2	509.1	473.2	434.4	247.2	502.2	343.4	427.4	↓ 24.2%
	TCL FT	573.4	529.9	532.6	527.7	551.6	504.5	566.0	513.9	397.3	521.7	551.0	554.1	568.0	557.1	421.0	**372.0**	555.4	448.7	516.2	↓ 10.0%
	ALBEF FT	577.7	533.8	538.3	532.0	557.8	528.8	569.2	516.0	**416.1**	532.0	558.1	560.4	572.0	550.6	538.7	435.9	559.8	464.1	527.3	↓ 8.7%
	BLIP FT	580.9	536.2	538.9	528.6	560.8	529.4	571.6	525.7	**412.1**	456.6	513.4	568.5	574.4	555.1	545.6	490.8	563.8	482.1	527.2	↓ 9.2%
COCO	ViLT	441.5	372.2	372.6	362.9	396.7	378.1	432.0	365.4	**193.7**	281.1	366.1	398.1	422.4	327.1	402.2	229.8	425.8	333.9	356.5	↓ 19.3%
	CLIP ZS	394.5	363.0	361.2	330.2	368.7	358.7	391.6	362.2	294.6	**294.7**	329.0	371.8	391.9	356.4	369.7	308.2	388.0	314.9	350.3	↓ 11.2%
	CLIP FT	420.5	367.2	365.3	331.7	381.5	371.0	412.2	374.4	291.0	**289.3**	337.3	389.9	413.9	371.7	379.7	306.4	402.1	310.2	358.5	↓ 14,7%
	TCL ZS	477.2	419.8	418.4	418.4	439.0	400.0	450.8	357.5	**177.3**	316.5	372.0	400.6	452.2	416.1	369.0	190.3	442.7	280.1	371.8	↓ 22.1%
	TCL FT	497.2	454.3	454.4	453.9	468.1	447.8	491.9	433.8	**259.9**	408.9	443.2	470.1	489.1	467.8	438.2	309.1	474.9	360.9	430.9	↓ 13.3%
	ALBEF FT	504.6	460.0	460.6	460.3	376.4	447.1	493.0	436.5	**282.2**	408.8	449.8	472.6	493.8	452.1	455.0	347.0	480.9	475.8	438.3	↓ 13.1%
	BLIP FT	516.6	471.9	472.1	467.7	489.5	466.1	507.2	451.7	**291.6**	432.8	471.8	494.2	506.8	470.4	472.3	404.7	499.6	402.9	458.7	↓ 11.2%

			Character-level						Word-level					Sentence-level						
Dataset	Method	Clean	Keyboard	OCR	CI	CR	CS	CD	SR	WI	WS	WD	IP	Formal	Casual	Passive	Active	Back_trans	**ave**	MMI
Flickr30K	ViLT FT	522.0	**385.3**	461.9	388.0	386.2	395.6	398.6	471.9	492.2	480.1	489.8	507.7	510.1	504.5	488.1	508.3	500.1	460.5	↓ 11.8%
	CLIP ZS	533.7	**431.8**	478.2	450.5	435.2	444.6	451.3	497.1	509.6	503.3	514.1	519.4	531.7	529.3	524.8	531.4	524.2	492.3	↓ 7.8%
	CLIP FT	544.3	**458.4**	500.1	477.6	461.6	471.1	475.5	515.4	530.4	526.0	531.1	536.4	545.8	542.1	537.9	545.1	537.3	512.0	↓ 5.9%
	TCL ZS	563.8	433.3	499.9	443.3	**428.4**	444.4	448.9	511.9	523.8	519.1	528.8	548.6	544.4	542.4	530.1	547.1	535.8	501.9	↓ 11.0%
	TCL FT	573.4	494.3	545.0	504.9	**492.8**	501.9	502.4	554.7	566.4	560.0	564.2	573.4	571.5	569.6	562.8	572.1	566.5	543.9	↓ 5.1%
	ALBEF FT	577.7	506.2	552.0	516.2	**505.0**	511.7	513.0	561.9	571.6	568.6	570.0	577.7	576.2	575.0	569.5	576.4	572.5	551.5	↓ 4.5%
	BLIP FT	580.9	**518.0**	559.5	527.3	**518.0**	526.4	525.7	565.6	576.1	572.8	573.8	580.7	579.0	578.6	574.5	579.6	574.7	558.1	↓ 3.9%
COCO	ViLT	441.5	**319.2**	386.2	327.0	321.7	333.1	334.1	397.8	417.5	404.4	413.6	433.1	436.5	433.6	423.2	437.1	426.0	390.3	↓ 11.6%
	CLIP ZS	394.5	285.5	286.4	286.1	**285.4**	285.6	285.8	347.5	363.8	355.5	368.6	374.2	393.0	391.6	379.6	393.5	381.2	341.5	↓ 13.4%
	CLIP FT	420.5	316.1	316.7	316.5	**316.4**	316.7	315.6	376.2	394.6	389.9	395.3	406.6	417.3	415.2	408.7	419.4	406.2	370.5	↓ 11.9%
	TCL ZS	477.2	**368.0**	428.4	381.3	368.4	382.0	383.4	439.3	453.4	445.7	450.9	477.2	474.4	471.8	464.7	475.7	462.0	432.9	↓ 9.3%
	TCL FT	497.2	**397.8**	455.1	412.0	398.5	408.8	410.5	463.7	481.3	471.8	477.7	497.1	494.6	493.0	487.3	496.0	483.5	458.0	↓ 7.9%
	ALBEF FT	504.6	**404.5**	461.7	418.9	406.1	414.7	415.5	471.4	488.9	483.3	486.3	504.5	503.1	502.0	496.4	503.7	491.3	465.8	↓ 7.7%
	BLIP FT	516.6	**429.1**	479.1	442.4	430.8	441.3	441.4	484.3	502.1	494.6	499.7	515.8	514.4	513.6	508.1	515.4	504.3	482.3	↓ 6.6%

both the standard evaluation metrics on the perturbed (OOD) datasets as well as their corresponding MMI variants. More details about experimental settings can be found in Appendix Sec. B.

4.3 Robustness Evaluation under Distribution Shift

Image-text retrieval We present the evaluation results under image perturbations in Table 2 [Top] and results under text perturbations in Table 2 [Bottom]. For simplicity, we only report the RSUM scores here, and the detailed results on each recall (i.e., R1, R5, and R10) and perturbation level can be found in Appendix Sec. C.

Inspecting Table 2 [Top], we observe that the performance of all models drops under image perturbation. Although different perturbation methods have various impacts on different models, we observe the following general trends. We find that most multimodal models are most sensitive to *zoom blur*. Additionally, we find that *glass blur* and *brightness* are the two "softest" perturbation methods, where the performance of all evaluated models deteriorates the least. Comparing the MMI score for both Flickr30K and COCO datasets,

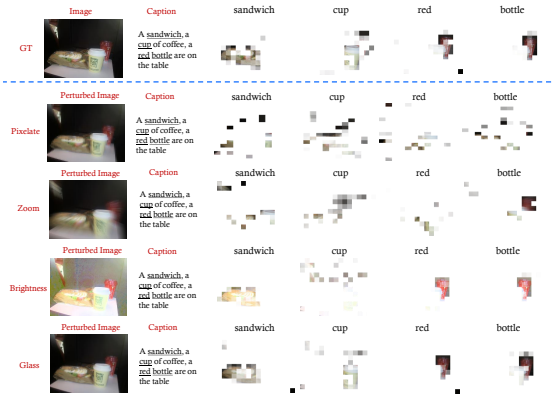

Figure 2: Optimal Transport (OT) alignment visualization between text and **perturbed images**, where *pixelate* and *zoom blur* are two high-effective image perturbation methods, *brightness* and *glass blur* are two low-effective ones.

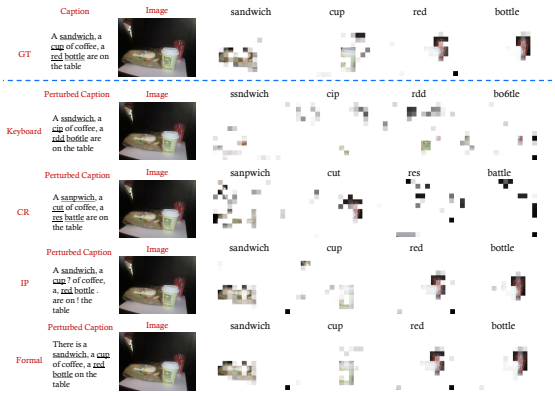

Figure 3: Optimal Transport (OT) alignment visualization between **perturbed text** and images, where *keyboard* and *character replace* are two high-effective text perturbation methods, *insert punctuation* and *formal* are two soft ones.

CLIP zero-shot (ZS) is more robust than other models, possibly due to it being trained on the large WIT400M dataset (Radford et al., 2021). As indicated in Taori et al. (2020), training models on large and diverse datasets often leads to increased robustness. For text perturbations in Table 2 [Bottom], we also find the performance of all models drop. In addition, we observe the following general trends. Character-level perturbations show more influence than word-level and sentence-level perturbations. In particular, *keyboard* and *character replace (CR)* consistently show a high impact on models' robustness, while *insert punctuation (IP)*, *formal*, and *active* are the least effective text perturbations.

For both image and text perturbations, we see that BLIP shows the best robustness performance on two datasets, i.e., the lowest MMI score. We hypothesize that using an encoder-decoder architecture and generative language modeling objective in BLIP is helpful for image-text retrieval. Given the recent paradigm shift to using generative loss objectives in pre-training multimodal models, e.g., BLIP (Li et al., 2022a), CoCa (Yu et al., 2022), SimVLM (Wang et al., 2022c) PaLI (Chen et al., 2022), Unified-IO (Lu et al., 2022), OFA (Wang et al., 2022a), we believe this observation could be generalized to other multimodal tasks.

We provide qualitative evidence by visualizing the cross-modal alignment between the image patch and word query using optimal transport (Kim et al., 2021). As shown in Figure 2, when using GT image-text pair, the retrieval model can accurately locate the image patches given word query. After image perturbations, in particular the ones with high impact like *pixelate* and *zoom blur*, we can clearly see that the model has difficulties finding the correct alignment. However, for the "softest" perturbations like *brightness* and *glass blur*, the model is still able to generate a transport plan (OT coupling matrix) between word and image patch. Similarly, in Figure 3 where the text are perturbed, we can see the retrieval model cannot locate the correct word query under *keyboard* and *CR*, but still functions well under *IP* and *formal*. Overall, the visualization of word patch alignments in

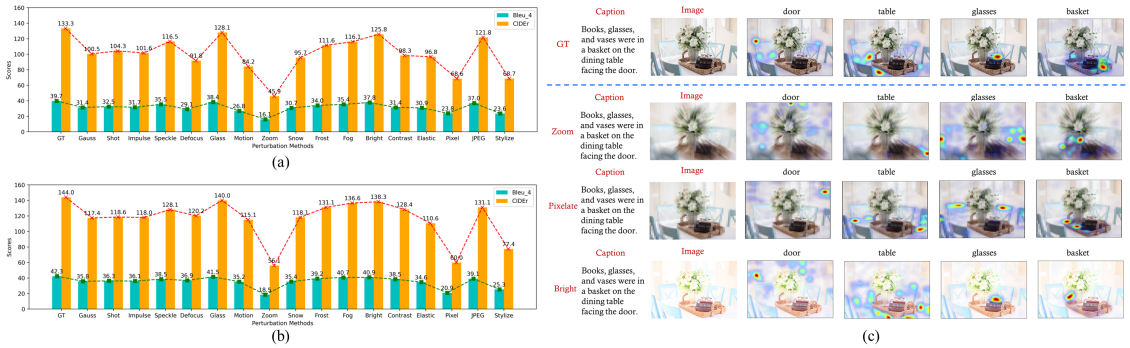

Figure 4: (a) Image captioning results of BLIP; (b) Image captioning results of GRIT; (c) Grad-CAM visualizations on the cross-attention maps corresponding to individual words under image perturbations, where *zoom blur* and *pixelate* perturbed images show worse word-image attention alignment than the *brightness* perturbed image. For example, in *zoom blur* and *pixelate*, the "door" and "glasses" words' attention maps are not matched with the correct image patches, while in *pixelate*, all words' attention maps match correctly.

Figure 2 and 3 confirm the conclusion drawn from Table 2, showing that the alignments are worst for perturbations that lead to highest performance degradation.

Visual reasoning and visual entailment These two tasks are commonly considered to be multimodal classification problems. We present the accuracy results in Tables 9 & 11, and Tables 10 & 12 (in Appendix D and Appendix E due to page limit) under image and text perturbations, respectively.

For both the visual reasoning (VR) and visual entailment (VE) task, we observe that *zoom blur* consistently impacts the model performance the most. Character-level perturbations show a stronger influence than word-level and sentence-level perturbations, which conform to the observation for image-text retrieval. Note that for visual reasoning, the most influential text perturbations are different across the different models, but they all belong to the character-level perturbation category. *Glass blur* is the "softest" image perturbation for visual reasoning and *brightness* for visual entailment. Regarding text perturbations, *insert punctuation* and sentence-level perturbations like *formal* and *active* have the least impact on the model's performance for both tasks.

Interestingly, when comparing the robustness of the different models, we make the following observation. Despite TCL is closely related to ALBEF, its robustness performance in terms of MMI score is significantly better. The major difference between both models is that TCL incorporates an intra-modal contrastive loss objective on top of ALBEF, which enforces the learned representations to be semantic meaningful. Additionally to our findings, it has been previously shown that this strategy is also useful in mitigating the noise in training data (Yang et al., 2022). Building on these observations, we recommend that we should consider both intra-modal and cross-modal relations in multimodal representation learning to improve the robustness.

Image captioning In this section, we present the image captioning results of BLIP (Li et al., 2022a) and GRIT (Nguyen et al., 2022) under image perturbations. We present the common evaluation metric Bleu_4 and CIDEr in Figure 4 and leave other metrics and more

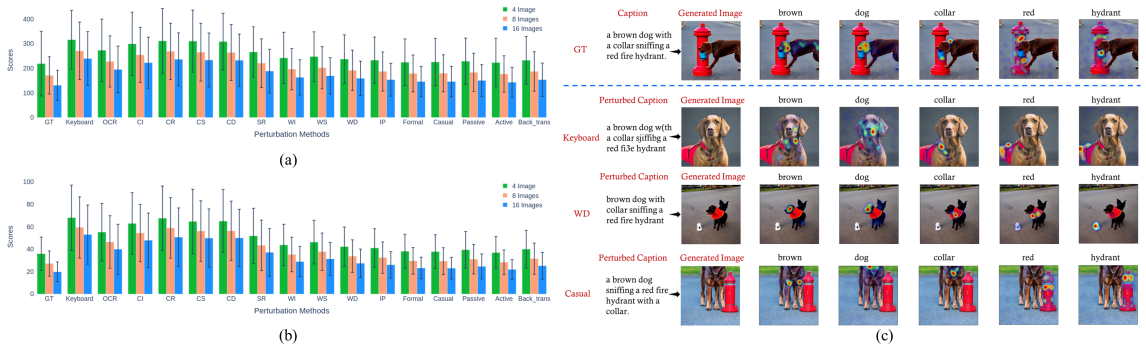

Figure 5: (a) Text-to-image generation results of Stable-diffusion in terms of (a) FID scores; (b) CLIP-FID scores. Since both scores are the lower the better, a higher bar indicates the model is less robust to a particular perturbation. (c) Grad-CAM visualizations on the cross-attention maps corresponding to perturbed captions and images generated by perturbed captions. We use the original unperturbed word query to visualize the attention map. In *keyboard*, the hydrant is missing; in *word deletion*, the color of the hydrant is incorrect, but no object is missing; in *casual*, the attention map perfectly matches the generated images, which shows character-level perturbations could be more effective than word level and sentence-level perturbations.

results to Appendix Sec. F. As shown in Figure 4, *zoom blur* consistently has the most considerable impact across all perturbations on both models. On the other hand, both models are least sensitive to *glass blur*, *brightness*, and *JPEG compression*. In addition, we find that across all considered six evaluation metrics, the CIDEr scores are most sensitive to the perturbations, which suggests it is an informative metric for robustness evaluation.

We provide further insights into the effect of the perturbations by inspecting the Grad-CAM (Selvaraju et al., 2017) visualization of BLIP in Figure 4 (c). Given an image, we expect that a robust model is able to attend to different objects according to the word query. Confirming the results shown in the bar plots of Figure 4, we find that "hardest" perturbations, including *zoom blur* and *pixelate* distract the attention of the model the most. For instance, BLIP cannot localize the table or the glasses in the perturbed images. However, for "soft" perturbations like brightness, BLIP is able to provide reasonable localization.

Text-to-image generation We present a robustness evaluation for text-to-image generation using two popular generative models, Stable Diffusion (Rombach et al., 2022) and GLIDE (Nichol et al., 2022), under text perturbations. Due to limited space, we only show results and the analysis for Stable Diffusion here and present the results for GLIDE in Appendix Sec. G. Since diversity is essential in text-to-image generation, we generate multiple images given one text for a proper analysis. To assess the diversity, we provide three evaluation settings, where each caption in the dataset is used to generate 4, 8, and 16 images. We adopt the common FID (Heusel et al., 2017) score and CLIP-FID (Kynkaanniemi et al., 2022; Parmar et al., 2022) score as evaluation metrics and report the mean and standard deviation.

As shown in Figure 5 (a) and (b), we surprisingly find that even for the generation task, character-level perturbations affect the robustness of the models the most compared to

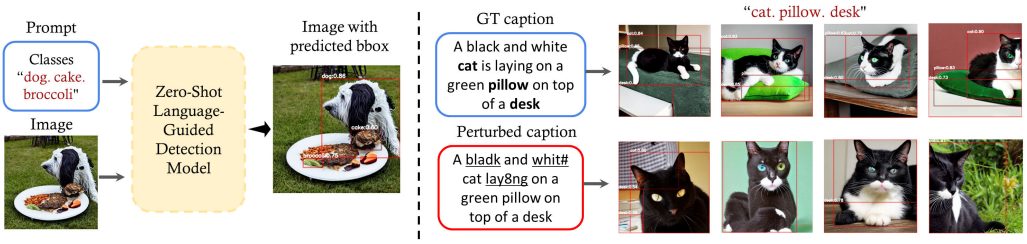

Figure 6: Left: Missing Object Rate (MOR) metric calculation. Right: Comparison of detection results between GT-caption-generated images (top) and perturbed-caption-generated images (bottom).

word-level and sentence-level perturbations. Furthermore, generating more images reduces the variance under each perturbation (e.g., comparing the green against the blue bars). Additionally, we perform a t-test on the generated images and find them to be not correlated after perturbation according to the p-value. This indicates that most text perturbations have an influence on text-to-image generation. Our finding is also corroborated by recent prompt engineering work, where well-designed prompt components can produce coherent outputs (Liu and Chilton, 2022).

Lastly, we also provide a further inspection of Stable Diffusion by Grad-CAM visualization in Figure 5 (c). We use the original unperturbed word query to visualize the attention map. *Keyboard*, *word deletion*, and *casual* are shown as character-level, word-level, and sentence-level perturbation examples, respectively. In *keyboard*, the hydrant is missing; in *word deletion*, the color of the hydrant is incorrect, but no object is missing; in *casual*, the attention map perfectly matches the generated images, which shows character-level perturbations could be more effective than word level and sentence-level perturbations. As the *word deletion* in Figure 5 (c), we found Stable Diffusion does not explicitly bind attributes to objects and the reconstructions from the model often mix up attributes and objects, similar to (Ramesh et al., 2022).

Missing Object Rate (MOR) To further provide a quantitative evaluation of the quality of the generated images, we propose a new detection-based metric to capture if the model can faithfully generate images with all the objects mentioned in the text. To achieve this goal, we leverage an open-set zero-shot language-guided object detection model, i.e., GLIP (Li et al., 2021c), to detect salient objects in the generated images. As shown in Figure 6 left, the inputs to the GLIP model are text prompt and the generated images from text-to-image generation models. Given COCO is an object detection dataset, and it has ground truth labels for the objects, we can simply use the combination of object names from the ground truth labels as the text prompt, i.e., "dog, cake, broccoli", If the ground truth object can be detected (with a detection threshold α), we assume the object is successfully generated by the text-to-image generation model, otherwise, the object is classified as missing.

In Figure 6 right, we show a visual comparison of how perturbed captions can affect the generation quality with respect to missing objects. We first use GT captions and perturbed captions to generate some images, and then perform object detection using GLIP on these images. Note that for all generated images, we always use the same ground truth COCO object names as text prompts. On the top row, we can find that the prompt "cat, pillow,

desk" can be detected successfully, which means they are faithfully generated by the Stable Diffusion model. However, for the bottom row, the perturbed prompt (*CR* in this example), some objects can not be detected and are considered as missing, i.e., pillow and desk.

Hence, similar to mean corruption error (mCE) in Xie et al. (2019a), we define our detection-based score, termed Missing Object Rate (MOR), as $\texttt{MOR} = (N_P - N_{GT})/N_{GT}$. Here N_P is the number of detected objects from images generated by perturbed captions, and N_{GT} is the number of detected objects from images generated by GT captions. A lower score indicates more objects are missing, which suggests the perturbed text has a high impact on the underlying text-to-image generation model. As shown in Table 17 in the Appendix (due to page limit), we can clearly see that MOR drops significantly for images generated by character-level perturbed captions compared to word-level and sentence-level methods.

5 Discussion

Are our findings applicable to unimodal models? Given our findings are consistent on five multimodal vision-language downstream tasks, we further investigate whether our findings still hold for unimodal models under distribution shift. The detailed results can be found in Appendix Sec. H. For image perturbations, we evaluate multiple vision models on ImageNet using the same image perturbation techniques in our multimodal setting. Interestingly, similar as in multimodal models, for unimodal vision models, *zoom blur* also has the highest impact on the model performance. For text perturbations, we evaluate several language models on IMDB (Maas et al., 2011) and MultiNLI (Williams et al., 2018) datasets, which leads to the same conclusions as for multimodal models: character-level perturbations also have more significant impacts than word-level and sentence-level perturbations. These observations can be corroborated by previous robustness studies on language models (Belinkov and Bisk, 2018; Ebrahimi et al., 2018; Liu et al., 2022a). In summary, we find that multimodal models show similar vulnerabilities to image and text perturbations as unimodal models in the corresponding modality.

Takeaway: Our main findings are as follows.
(1) Multimodal image-text models are sensitive to distribution shifts caused by image and text perturbations, especially to shifts in the image space.
(2) For image perturbations, *zoom blur* consistently shows the highest impact on the model's robustness across 5 tasks, while *glass blur* and *brightness* are the least harmful ones.
(3) For text, character-level perturbations have a higher impact than word-level and sentence-level perturbations. In particular, *keyboard* and *character replace* consistently show high impact, while *insert punctuation*, *formal*, and *active* are the three least effective ones across different settings.

Limitations and future work Given that our work is one of the early efforts in this direction, there are several promising future work directions and limitations that can be improved. First, we only adopt synthetic image and text perturbation strategies in our benchmark. Although the proposed text perturbations mimic realistic shifts, an exciting

extension of our work will be to analyze real-world distribution shifts (Taori et al., 2020; Wenzel et al., 2022). Second, we select 5 important downstream tasks, but there are more tasks, such as visual question answering and visual grounding, that could be analyzed. In addition, we have introduced the MOR metric to evaluate image generation models, but new evaluation metrics beyond existing ones might be needed for proper robustness evaluation under distribution shifts. Third, our study focuses on evaluating image-text models and highlighting failure points. Building on these insights, it is important to investigate methods that improve robustness. The next natural research direction is to study data augmentation techniques for multimodal models (Hao et al., 2022), which they have shown to be effective in improving the robustness of unimodal models (Hendrycks et al., 2020b, 2021a; Wenzel et al., 2022). Given the fact that both unimodal and multimodal models are sensitive to image *zoom blur* and character-level text perturbations, it might be a good practice to involve these data augmentations during model pre-training. Fourth, all considered multimodal models are learned from web-collected data, which likely contains multiple biases and stereotypes, e.g., w.r.t. gender, race, occupation, etc. This is particularly harmful when using large language models like GPT-3 (Brown et al., 2020), GPT-4 (OpenAI, 2023), or state-of-the-art text-to-image generation models (Saharia et al., 2022). An important research direction is to study the robustness and fairness of those models in a unified setting.

6 Conclusion

In this work, we investigate the robustness of large multimodal image-text models under distribution shifts. We introduce several evaluation benchmarks based on 17 image perturbation and 16 text perturbation strategies. We study 5 important downstream tasks, including image-text retrieval, visual reasoning, visual entailment, image captioning, and text-to-image generation, and evaluate 9 popular image-text models. We hope that our proposed benchmark is valuable for analyzing the robustness of image-text models and that our findings provide inspiration to develop and deploy more robust models for real-world applications.

7 Broader Impact Statement

Positive Societal Consequences: Our research provides a nuanced understanding of the robustness challenges faced by multimodal image-text models. By identifying weaknesses, we pave the way for the development of more robust AI systems, ensuring their reliability and effectiveness in real-world applications.

Negative Societal Consequences: Vulnerabilities identified in multimodal models could be exploited by malicious entities for harmful purposes, including deepfakes and misinformation campaigns. This underscores the urgency of addressing these vulnerabilities to safeguard individuals and communities from potential malicious activities.

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Appendix A. Perturbation Strategies

Image Perturbation Strategies The details of all the image perturbation strategies are introduced in Table 3.

Text Perturbation Strategies The details of all the text perturbation strategies are introduced in Table 4.

Magnitude of Perturbation We used the same parameters to control the magnitude of perturbation as Hendrycks and Dietterich (2019), which has been taken as the standard parameters for robustness evaluation for the community. To make a fair comparison and to be consistent with previous robustness investigation works, we used the same set of parameters as in Hendrycks and Dietterich (2019).

Image Quality Drop after Perturbation The quality drop of perturbed images has also been analyzed to make sure the model's performance drop is due to the nature of the perturbation methods, instead of the magnitude of different perturbation methods. To provide quantitative comparison results, we evaluated the perturbed images under 5 severity levels, using SSIM (structural similarity index measure (Wang et al., 2004)) and LPIPS (Perceptual Similarity Metric (Zhang et al., 2018)). The results are shown in Table 6. We can find that using SSIM and LPIPS as evaluation metrics, the image quality drop of all the imager perturbation methods are within the same level across different severities. This proved that the pre-trained models being more sensitive to some image corruptions is due to the nature of the perturbation methods themselves, instead of the quality drop not being at the same level.

Human Verification Though we designed an automatic fidelity checking mechanism to ensure the quality of the perturbed data, it would also be good to have humans verify some images/texts. In our experiments, we recruited 10 volunteers to be involved in this verification study. Each person is given one image-text pair at a time (within the pair, either the image is perturbed or the text is perturbed). The person is asked to decide whether this image and text can be considered as a pair. Each person is asked to verify 5,000 image-text pairs, which are randomly sampled from the perturbed COCO dataset (COCO-IP and COCO-TP in the paper). The results are shown in Table 8. The average correction rate is 99.00%, which shows the perturbed image-text pair still preserved the alignment relationship.

Appendix B. Experimental Settings

Evaluation Tasks We select five widely adopted downstream tasks for a comprehensive evaluation on the robustness of multimodal image-text models, including image-text retrieval, visual reasoning (VR), visual entailment (VE), image captioning, and text-to-image generation. Image-text retrieval includes two subtasks: (1) retrieve images with given text (Image Retrieval) and (2) retrieve text with given images (Text Retrieval) (Cao et al., 2022; Hao et al., 2022). Visual Reasoning (VR) requires the model to determine whether a textual statement describes a pair of images (Suhr et al., 2017). Visual Entailment (VE) is a visual reasoning task to predict whether the relationship between an image and text is entailment, neutral, or contradictory (Xie et al., 2018, 2019b). Image captioning aims at describing the

content of an image in words, resulting in textual captions (Lin et al., 2014). Text-to-image generation task is defined as taking input a natural language description and producing an image matching that description (Mansimov et al., 2016).

Perturbation Datasets For each task, we perturb the corresponding datasets i.e., Flickr30K (Young et al., 2014), COCO (Lin et al., 2014) , NLVR2 (Suhr et al., 2017), and SNLI-VE (Xie et al., 2018, 2019b), using the image perturbation (IP) and text perturbation (TP) methods introduced in Section 3 in the paper. This leads to our 8 benchmark datasets: (1) Flickr30K-IP, Flickr30K-TP, COCO-IP, and COCO-TP for image-text retrieval robustness evaluation; (2) NLVR2-IP and NLVR2-TP for visual reasoning robustness evaluation; (3) SNLI-VE-IP and SNLI-VE-TP for visual entailment robustness evaluation; (4) COCO-IP for image captioning evaluation; and (5) COCO-TP for text-to-image generation evaluation.

Evaluation Models We select 9 representative large pretrained multimodal models, which have publicly released their pretrained models (we appreciate all the authors for making the models publicly available), including CLIP (Radford et al., 2021), ViLT (Kim et al., 2021), ALBEF (Li et al., 2021a), BLIP (Li et al., 2022a), TCL (Yang et al., 2022), METER (Dou et al., 2021), GRIT (Nguyen et al., 2022), GLIDE (Nichol et al., 2022), and Stable Diffusion (Rombach et al., 2022). In order to provide a fair comparison, we adopt the model weights provided by their official repositories for either zero-shot prediction or fine-tuned results. We only perform the tasks of each model that have been studied in its original work, where their reported scores are marked as "clean" or "GT" in our Tables.

Task-Specific Experimental Settings

- For image-text retrieval, the Flickr30K dataset contains 1,000 images, and each of them has 5 corresponding captions, while the COCO dataset contains 5,000 images, and each of them also has 5 corresponding captions. We report the RSUM score averaged on five perturbation levels under each perturbation method to reveal the overall performance. More detailed results, including the recall at K (R@K) metric, K $= \{1, 5, 10\}$, can be found in Section C in this supplementary material. For CLIP and TCL, we provide the evaluation results for both zero-shot (ZS) and fine-tuned (FT) settings, while for ALBEF and BLIP, we follow their original settings and report the fine-tuned (FT) results.
- For visual reasoning, the NLVR2 dev set contains 2,018 unique sentences and 6,982 samples, while the test-P set contains 1,995 unique sentences and 6,967 samples. We report the accuracy of both the dev set and test-P set of the NLVR2 dataset under image and text perturbations. We evaluate the robustness of ALBEF, ViLT, TCL, BLIP, and METER.
- For visual entailment, the SNLI-VE val set contains 1,000 images and 6,576 sentences, while the test set contains 1,000 images and 6,592 sentences. We evaluate the accuracy of both the dev set and test set of the SNLI-VE dataset under image and text perturbations. We report the results of ALBEF, TCL, and METER.
- For image captioning, we use the COCO-IP test set as an evaluation set. We adopted standard text evaluation metrics, i.e., BLEU (Papineni et al., 2002), METEOR

(Denkowski and Lavie, 2014), ROUGE-L (Lin, 2004), and CIDEr (Vedantam et al., 2015).

- For text-to-image generation, we use the captions from the COCO-TP test set as inputs. The COCO-TP test set contains the captions for 5,000 test images, 5 captions for each image, and we select the first caption of each image as inputs, resulting in 5,000 text inputs. We take the FID (Heusel et al., 2017) and CLIP-FID (Kynkaanniemi et al., 2022; Parmar et al., 2022) scores to evaluate the quality of the generated images. We provide 3 settings, where each caption in the test set is used to generate 4,8,16 images, respectively.

Appendix C. More Results on Image-Text Retrieval

Results under Image Perturbations Detailed image-text retrieval results under image perturbations of ViLT (FT), CLIP (ZS), CLIP (FT), BLIP, ALBEF (FT), TCL (ZS), and TCL (FT), are shown in Tables 18, 19, 20, 21, 22, 23, 24, respectively.

Results under Text Perturbations Detailed image-text retrieval results under text perturbations of CLIP (ZS), CLIP (FT), BLIP, ALBEF (FT), TCL (ZS), and TCL (FT), are shown in Tables 25, 26, 27, 28, 29, 30, 31, respectively.

Visualization We show the image-text retrieval results: (1) image perturbations: in Figures 21, 22; (2) text perturbations: in Figures 27, 28. In Figures 12, 13, we show more Optimal Transport (OT) alignment visualization between images and text under image perturbations. In Figures 14, 15, we show more Optimal Transport (OT) alignment visualization between text and images under text perturbations.

Appendix D. More Results on Visual Reasoning

Results In Tables 9, 10, we show the results of the visual reasoning task under image perturbation and text perturbation, respectively.

Visualization We show image perturbation results in Figures 23, 24 and text perturbation results in Figures 29, 30.

Appendix E. More Results on Visual Entailment

Results In Tables 11, 12, we show the results of the visual entailment task under image perturbation and text perturbation, respectively.

Visualization We show image perturbation results in Figures 25, 26 and text perturbation results in Figures 31, 32.

Appendix F. More Results on Image Captioning

Results In Table 14, we show the value of image captioning results of BLIP and GRIT under image perturbations, which are the results as in Figures 8, 9 in this supplementary material, and Figure 4 in the paper. In Figures 8, 9, we show the full metrics results in the image captioning task by BLIP and GRIT.

Visualization In Figures 10, 11, we show examples of image captioning results under image perturbations by BLIP and GRIT, respectively. In Figures 16, 17, we show more Grad-CAM visualizations on the cross-attention maps under image perturbations.

Appendix G. More Results on Text-to-Image Generation

Results In Table 15, we show the value of text-to-image generation results of Stable Diffusion under text perturbations, which are the results as in Figure 5 in the paper. In Table 16, we show the value of text-to-image generation results of GLIDE under text perturbations.

Visualization In Figures 18, 19, we show more Grad-CAM visualizations on the cross-attention maps corresponding to individual words under text perturbations. In Figure 20, we show the text-to-image generation comparison on all 16 generated images. We find that though the generated images do not guarantee to perfectly show all the notions described in the captions, the probability of generating matched images by the unperturbed captions is higher than the perturbed captions, especially character-level.

Appendix H. Discussion

Unimodal Vision Model Robustness To evaluate whether the findings in our image perturbations of multimodal models are consistent with unimodal vision models, we conducted experiments on multiple unimodal vision models. The top1 classification accuracy is shown in Tables 13. In the results, we find that *zoom blur* is still very effective in most models, and brightness is the most "soft" image perturbation method, which is consistent with the findings in the multimodal setting.

Conclusion To better present the findings, we show plots on the last page. As shown in Tables 19, 20, 21, 22, 23, 24 and Tables 26, 27, 28, 29, 30, 31, we found that: (1) For image perturbations, performance drop by *zoom blur* is larger than other perturbation methods across 5 tasks, while *glass blur* and *brightness* are the least harmful ones. (2) For text, character-level perturbations are more effective than word-level and sentence-level perturbations. In particular, *keyboard* and *character replace* are the most effective ones, while *insert punctuation*, *formal*, and *active* are the three least effective ones across different settings.

Appendix I. More Related Work

Robustness of unimodal vision models is a longstanding and challenging goal of computer vision (Yin et al., 2019). Stable training, adversarial robustness, out-of-distribution, transfer learning, and many other aspects have been studied by previous works in deep learning era (Zheng et al., 2016; Drenkow et al., 2021; Djolonga et al., 2021; Goyal et al., 2022). Recently, several studies have shown that Vision Transformer (ViT) (Dosovitskiy et al., 2021) tend to be more robust than previous models, e.g., work that studied the robustness against common corruptions and perturbations (Bhojanapalli et al., 2021), robustness for distribution shifts and natural adversarial examples (Paul and Chen, 2022), robustness against different

Lp-based adversarial attacks (Mahmood et al., 2021), adversarial examples (Mao et al., 2021), and adaptive attacks (Aldahdooh et al., 2021). Several robustness benchmarks have been proposed, e.g., ImageNet-C and ImageNet-P (Hendrycks and Dietterich, 2019), Stylized-ImageNet (Geirhos et al., 2019), ImageNet-A and ImageNet-O (Hendrycks et al., 2021b), ImageNet-V2 (Recht et al., 2019). Recently, (Wenzel et al., 2022) conducted a large-scale robustness study based on natural distribution shifts. (Gupta et al., 2022) built the GRIT benchmark to evaluate the performance, robustness, and calibration of a vision system across different image tasks.

Robustness of unimodal language models under distribution shift or adversarial attack has been explored by many previous works, i.e., Chang et al. (2021); Wang et al. (2022b) provided reviews of how to define, measure and improve robustness of NLP systems, Wang et al. (2020) proposed controlled adversarial text generation to improve robustness, Goel et al. (2021) unified four standard evaluation paradigms, Singh et al. (2021) proposed a search and semantically replace strategy, Dong et al. (2021) studied robustness against word substitutions, Malfa and Kwiatkowska (2022) formalised the concept of semantic robustness, etc. In terms of benchmark, Hendrycks et al. (2020a) systematically examined and measured the out-of-distribution (OOD) generalization for seven NLP datasets. Croce et al. (2020) built a large benchmark and analyzed the impact of robustness on the performance of distribution shifts, calibration, OOD detection, fairness, privacy leakage, smoothness, and transferability. Recently, Moradi and Samwald (2021) presented empirical results achieved with a comprehensive set of non-adversarial perturbation methods for testing the robustness of NLP systems on non-synthetic text. Gui et al. (2021) proposed a multilingual evaluation platform to provide comprehensive robustness analysis. Wang et al. (2021) proposed a benchmark to evaluate the vulnerabilities of modern large-scale language models under adversarial attacks.

Table 3: Image perturbations.

Category	Perturbation	Description	Severities
Noise	Gaussian Noise	Gaussian noise can appear in low-lighting conditions.	5
	Shot Noise	Shot noise, also called Poisson noise, is electronic noise caused by the discrete nature of light itself.	5
	Impulse Noise	Impulse noise is a color analogue of salt-and-pepper noise and can be caused by bit errors.	5
	Speckle Noise	Speckle noise is the noise added to a pixel that tends to be larger if the original pixel intensity is larger.	5
Blur	Defocus Blur	Defocus blur occurs when an image is out of focus.	5
	Frosted Glass Blur	Frosted Glass Blur appears with "frosted glass" windows or panels.	5
	Motion Blur	Motion blur appears when a camera is moving quickly.	5
	Zoom Blur	Zoom blur occurs when a camera moves toward an object rapidly.	5
Weather	Snow	Snow is a visually obstructive form of precipitation.	5
	Frost	Frost forms when lenses or windows are coated with ice crystals.	5
	Fog	Fog shrouds objects and is rendered with the diamond-square algorithm.	5
	Brightness	Brightness varies with daylight intensity.	5
Digital	Contrast	Contrast can be high or low depending on lighting conditions and the photographed object's color.	5
	Elastic	Elastic transformations stretch or contract small image regions.	5
	Pixelate	Pixelation occurs when upsampling a low-resolution image.	5
	JPEG Compression	JPEG is a lossy image compression format that introduces compression artifacts.	5
Stylize	Stylize	Stylized data is generated by transferring the style information to the content images by AdaIN style transfer (Huang and Belongie, 2017).	5
Sum	**17**	—	**85**

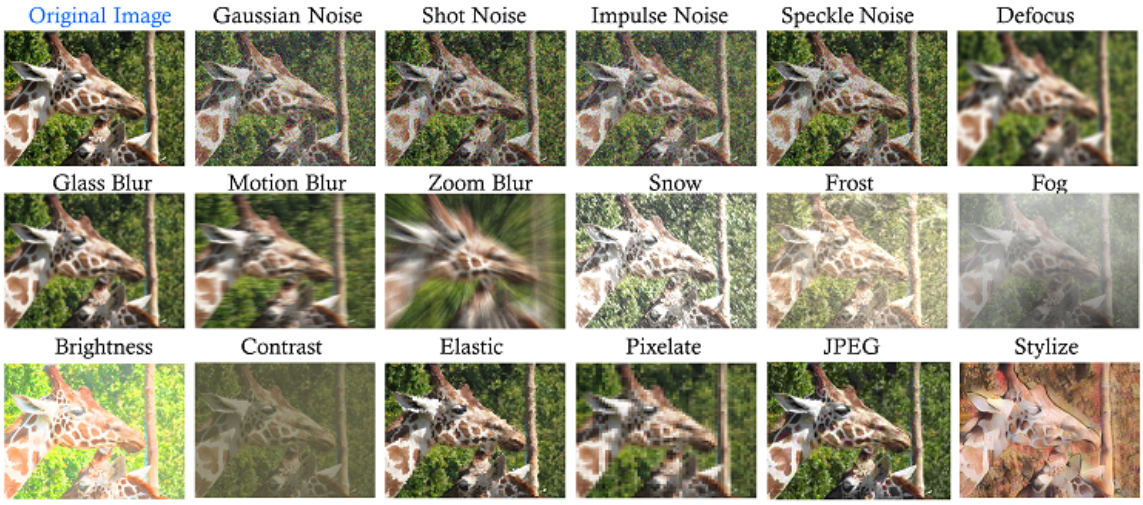

Figure 7: Examples of our 17 image perturbations. The original image is taken from the COCO dataset and shown on the top left.

Table 4: Text perturbations.

Category	Perturbation	Description	Severities
Character-level	Keyboard	Substitute character by keyboard distance with probability p.	5
	OCR	Substitute character by pre-defined OCR error with probability p.	5
	Character Insert (CI)	Insert character randomly with probability p.	5
	Character Replace (CR)	Substitute character randomly with probability p.	5
	Character Swap (CS)	Swap character randomly with probability p.	5
	Character Delete (CD)	Delete character randomly with probability p.	5
Word-level	Synonym Replacement (SR)	Randomly choose n words from the sentence that are not stop words. Replace each of these words with one of its synonyms chosen at random.	5
	Word Insertion (WI)	Find a random synonym of a random word in the sentence that is not a stop word. Insert that synonym into a random position in the sentence. Do this n times.	5
	Word Swap (WS)	Randomly choose two words in the sentence and swap their positions. Do this n times.	5
	Word Deletion (WD)	Each word in the sentence can be randomly removed with probability p.	5
	Insert Punctuation (IP)	Random insert punctuation in the sentence with probability p.	5
Sentence-level	Formal	Transfer the text style to Formal.	1
	Casual	Transfer the text style to Casual.	1
	Passive	Transfer the text style to Passive.	1
	Active	Transfer the text style to Active.	1
	Back Translation	Translate source to German and translate it back to English via (Ng et al., 2020).	1
Sum	**16**	—	**60**

Table 5: Example of our 16 text perturbations. The original text is taken from the COCO dataset and denoted as clean in the first row.

Category	Perturbation	Example
Original	Clean	An orange metal bowl strainer filled with apples.
Character	Keyboard	An orange metal bowk strainer filled witj apples.
	OCR	An 0range metal bowl strainer filled with app1es.
	CI	And orange metal bowl strainer filled with atpples.
	CR	An orange metal towl strainer fillet with apples.
	CS	An orange meatl bowl stariner filled with apples.
	CD	An orang[X] metal bowl strainer fil[X]ed with apples.
Word	SR	An orange alloy bowl strainer filled with apples.
	WI	An old orange metal bowl strainer filled with apples.
	WS	An orange metal strainer bowl filled with apples.
	WD	An orange metal bowl strainer [X] with apples.
	IP	An orange metal bowl ? strainer filled with apples.
Sentence	Formal	An orange metal bowl strainer contains apples.
	Casual	An orange metal bowl is filled with apples.
	Passive	Some apples are in an orange metal bowl strainer.
	Active	There are apples in an orange metal bowl strainer.
	Back trans	Apples are placed in an orange metal bowl strainer.

Table 6: Magnitude of perturbations.

Method	Parameters
Gaussian noise	First normalize the pixel values, then add a random normal noise scaled at values 0.08, 0.12, 0.18, 0.26, 0.38 based on severity
Shot noise	Simulate electronic noise caused by the discrete nature of light by applying a combination of salt and pepper noise with amounts ranging from 0.03, 0.06, 0.09, 0.17, 0.27
Impulse noise	Simulate corruptions caused by bit errors by applying a combination of salt and pepper noise with amounts ranging from 0.03, 0.06, 0.09, 0.17, 0.27
Speckle noise	Simulate additive noise and is similar to Gaussian but where the random value is then multiplied by the normalized pixel value
Defocus blur	Imitate a defocused lens over the entire frame, ranging from (3, 0.1), (4, 0.5), (6, 0.5), (8, 0.5), (10, 0.5)
Motion blur	Increase the radius and sigma of the kernel, ranging from (10, 3), (15, 5), (15, 8), (15, 12), and (20, 15)
Zoom blur	Increase the zoom factor based on severity, ranging from (1, 1.11), (1, 1.16), (1, 1.21), (1, 1.26), (1, 1.33)
Glass Blur	Appear with "frosted glass" windows or panels, ranging from (0.7, 1, 2), (0.9, 2, 1), (1, 2, 3), (1.1, 3, 2), (1.5, 4, 2)
Snow	Adding a visually obstructive form of precipitation, ranging from (0.1, 0.3, 3, 0.5, 10, 4, 0.8),(0.2, 0.3, 2, 0.5, 12, 4, 0.7), (0.55, 0.3, 4, 0.9, 12, 8, 0.7), (0.55, 0.3, 4.5, 0.85, 12, 8, 0.65), (0.55, 0.3, 2.5, 0.85, 12, 12, 0.55)
Frost	Simulate lenses or windows are coated with ice crystals, ranging from (1, 0.4), (0.8, 0.6), (0.7, 0.7), (0.65, 0.7),(0.6, 0.75)
Fog	Shroud objects and rendered with the diamond-square algorithm, ranging from (1.5, 2), (2, 2), (2.5, 1.7), (2.5, 1.5), (3, 1.4)
Brightness	Simulate daylight intensity, ranging from 0.1, 0.2, 0.3, 0.4, 0.5
Contrast	Simulate lighting conditions, ranging from 0.4, 0.3, 0.2, 0.1, 0.05
Elastic	Stretch or contract small image regions, ranging from (244 * 2, 244 * 0.7, 244 * 0.1), (244 * 2, 244 * 0.08, 244 * 0.2), (244 * 0.05, 244 * 0.01, 244 * 0.02), (244 * 0.07, 244 * 0.01, 244 * 0.02), (244 * 0.12, 244 * 0.01, 244 * 0.02)
Pixelate	Upsample a low-resolution image, ranging from 0.6, 0.5, 0.4, 0.3, 0.25
JPEG Compression	Convert each frame to a JPEG with quality ranging from 25, 18, 15, 10, 7

Table 7: Image Quality Drop after Perturbation.

SSIM / LPIPS	Clean	Gauss.	Shot	Impulse	Speckle	Defocus	Glass	Motion	Zoom
1	1.00/0.00	0.61/0.26	0.65/0.25	0.58/0.37	0.72/0.20	0.65/0.30	0.78/0.25	0.70/0.24	0.68/0.20
2	1.00/0.00	0.49/0.42	0.52/0.42	0.45/0.55	0.66/0.28	0.59/0.49	0.73/0.34	0.59/0.33	0.57/0.36
3	1.00/0.00	0.37/0.63	0.41/0.60	0.37/0.68	0.51/0.51	0.50/0.61	0.58/0.47	0.51/0.41	0.50/0.44
4	1.00/0.00	0.27/0.86	0.29/0.85	0.27/0.89	0.34/0.63	0.35/0.68	0.48/0.60	0.46/0.58	0.47/0.58
5	1.00/0.00	0.19/0.99	0.23/0.99	0.19/0.99	0.27/0.76	0.32/0.72	0.32/0.70	0.33/0.61	0.36/0.69

SSIM / LPIPS	Snow	Frost	Fog	Bright	Contrast	Elastic	Pixel	JPEG	Stylize
1	0.66/0.24	0.68/0.20	0.63/0.17	0.79/0.12	0.67/0.17	0.66/0.26	0.72/0.22	0.78/0.17	0.72/0.21
2	0.48/0.37	0.58/0.28	0.57/0.32	0.70/0.21	0.58/0.25	0.53/0.29	0.57/0.35	0.67/0.23	0.58/0.34
3	0.52/0.45	0.53/0.34	0.53/0.37	0.65/0.31	0.49/0.38	0.42/0.39	0.53/0.43	0.65/0.35	0.47/0.43
4	0.46/0.51	0.53/0.44	0.52/0.52	0.53/0.48	0.39/0.58	0.41/0.52	0.47/0.52	0.60/0.46	0.37/0.52
5	0.32/0.63	0.40/0.52	0.38/0.64	0.45/0.64	0.33/0.73	0.39/0.78	0.37/0.63	0.45/0.68	0.31/0.67

Table 8: Human verification of perturbed image-text pairs, where the correction rate means the percentage of given image and text can still be considered as a pair.

Correction Rate	Judge-1	Judge-2	Judge-3	Judge-4	Judge-5	Judge-6	Judge-7	Judge-8	Judge-9	Judge-10	Average
Results	98.90%	99.42%	98.80%	98.54%	99.14%	98.50%	99.02%	99.26%	99.16%	99.30%	99.00%

Table 9: **Visual reasoning:** *image robustness* evaluations for the *NLVR2-IP* dataset (averaged accuracy), where the most effective perturbation results are marked in bold and the least effective ones are underlined. Impact score is marked in blue, the lower the better.

		Noise					Blur				Weather				Digital				Stylize		
Dataset	Method	Clean	Gauss.	Shot	Impulse	Speckle	Defocus	Glass	Motion	Zoom	Snow	Frost	Fog	Bright	Contrast	Elastic	Pixel	JPEG	Stylize	**ave**	MMI
dev	ALBEF	82.55	52.80	52.46	52.61	52.63	52.22	52.44	51.78	50.79	**50.69**	52.05	52.58	52.09	51.98	52.45	50.99	52.37	51.80	52.04	↓ 37.0%
	ViLT	75.70	71.64	71.45	71.58	72.42	72.90	74.71	68.79	**63.97**	69.40	73.02	73.59	74.32	66.72	74.15	69.17	74.71	72.35	71.46	↓ 5.6%
	TCL	80.54	78.20	77.63	78.21	78.60	77.04	81.20	77.37	**66.67**	75.96	79.47	79.65	80.76	74.04	78.92	73.92	81.01	75.05	77.28	↓ 4.0%
	BLIP	82.48	85.37	78.54	72.68	76.59	80.00	73.66	78.54	**60.98**	73.66	76.59	83.90	76.10	77.07	81.46	74.63	82.93	71.71	77.42	↓ 6.1%
	METER	82.33	77.39	76.25	77.25	77.76	78.76	82.01	78.26	**69.31**	76.17	79.40	81.02	80.76	77.50	79.36	72.91	80.67	76.10	77.70	↓ 5.6%
test-P	ALBEF	83.14	53.17	52.85	53.22	53.50	52.68	53.09	52.39	**51.19**	51.60	52.98	53.49	52.78	53.13	53.12	51.72	53.10	52.95	52.76	↓ 36.5%
	ViLT	76.13	74.24	73.80	74.43	74.20	72.32	76.70	72.55	**62.34**	69.24	73.36	75.05	74.73	68.68	74.07	69.06	76.52	71.50	72.54	↓ 4.7%
	TCL	81.33	78.10	77.87	78.25	78.91	78.00	81.59	78.17	**67.81**	75.74	79.62	80.64	81.52	74.35	79.76	74.61	81.28	75.85	77.77	↓ 4.4%
	BLIP	83.08	75.39	75.39	85.10	72.31	85.64	79.49	76.92	**58.97**	80.51	75.90	81.54	76.92	81.03	77.95	73.333	78.97	73.85	77.01	↓ 7.3%
	METER	83.05	78.87	77.94	77.78	79.23	78.97	82.10	79.14	**68.89**	76.69	80.10	82.25	81.21	78.20	79.91	72.65	80.74	76.93	78.34	↓ 5.7%

Table 10: **Visual reasoning:** *text robustness* evaluations for the *NLVR2-TP* dataset (averaged accuracy), where the most effective perturbation results are marked in bold and the least effective ones are underlined. Impact score is marked in blue, the lower the better.

		Character-level							Word-level					Sentence-level						
Dataset	Method	Clean	Keyboard	OCR	CI	CR	CS	CD	SR	WI	WS	WD	IP	Formal	Casual	Passive	Active	Back_trans	**ave**	MMI
dev	ALBEF	82.55	50.64	51.02	50.81	50.66	**50.53**	50.58	51.96	51.48	51.58	51.39	51.56	50.99	51.93	51.52	51.75	51.90	51.22	↓ 38.0%
	ViLT	75.70	66.23	69.16	65.47	**64.36**	64.76	64.96	67.11	72.71	70.77	71.75	73.42	73.22	73.40	71.83	74.47	74.51	69.88	↓ 7.7%
	TCL	80.54	71.15	75.89	71.84	**70.99**	72.01	71.58	74.96	78.89	77.84	78.05	82.37	81.56	80.33	79.47	81.46	80.67	71.77	↓ 10.9%
	BLIP	82.48	70.73	**70.24**	76.59	74.63	72.68	72.20	73.17	77.56	80.00	79.51	87.81	85.37	82.93	82.93	87.81	75.61	78.11	↓ 5.3%
	METER	82.33	**72.35**	75.83	74.10	72.71	73.89	73.30	75.16	79.36	75.41	77.64	81.68	81.92	81.55	78.69	81.01	82.25	77.30	↓ 6.1%
test-P	ALBEF	83.14	51.39	51.99	**51.04**	51.26	51.05	51.24	52.69	52.95	52.95	52.88	53.30	53.39	53.06	52.68	53.26	53.23	52.40	↓ 37.0%
	ViLT	76.13	64.85	69.66	66.76	65.64	65.56	**65.14**	68.96	73.36	71.35	72.53	75.14	75.86	74.27	72.58	77.00	75.70	70.90	↓ 6.9%
	TCL	81.33	**71.16**	76.31	72.35	71.56	71.90	72.07	75.49	80.03	78.80	78.78	82.88	82.46	81.52	80.25	82.28	81.53	72.37	↓ 11.0%
	BLIP	83.08	**67.69**	85.64	67.18	67.69	75.90	74.87	69.23	72.82	78.46	83.59	83.59	79.49	87.18	82.05	82.05	74.36	76.99	↓ 7.3%
	METER	83.05	73.10	77.63	74.05	72.49	**70.64**	74.27	76.10	79.62	75.96	78.55	82.58	81.87	80.42	79.52	82.34	81.45	77.54	↓ 6.6%

Table 11: **Visual entailment:** *image robustness* evaluations for the *SNLI-VE-IP* dataset (averaged accuracy), where the most effective perturbation results are marked in bold and the least effective ones are underlined. Impact score is marked in blue, the lower the better.

			Noise				Blur				Weather				Digital				Stylize		
Dataset	Method	Clean	Gauss.	Shot	Impulse	Speckle	Defocus	Glass	Motion	Zoom	Snow	Frost	Fog	Bright	Contrast	Elastic	Pixel	JPEG	Stylize	**ave**	MMI
val	ALBEF	80.80	77.52	77.56	77.34	78.76	76.59	79.26	76.67	**71.70**	75.61	78.71	78.76	79.83	78.19	78.49	74.29	78.91	74.58	77.22	↓ 4.4%
	TCL	80.51	77.33	77.56	77.22	78.23	76.70	79.21	75.25	**70.98**	75.71	77.95	78.43	79.31	78.76	77.78	71.47	78.43	74.64	76.76	↓ 4.7%
	METER	80.86	77.05	77.19	76.76	78.37	77.14	79.72	77.04	**74.35**	77.18	79.38	80.10	80.49	79.12	78.78	73.08	78.93	75.88	77.68	↓ 3.9%
test	ALBEF	80.91	77.65	77.70	77.40	78.50	76.62	79.25	76.59	**71.70**	76.31	78.60	78.47	79.77	78.07	78.34	74.42	78.81	74.89	77.24	↓ 8.3%
	TCL	80.29	77.46	77.38	77.30	78.17	76.80	79.27	75.56	**71.07**	76.13	78.24	78.38	79.19	78.68	77.74	71.76	78.59	74.70	76.85	↓ 4.3%
	METER	81.19	77.16	77.09	76.90	78.58	77.14	80.13	77.39	**74.35**	77.79	79.84	80.18	80.46	79.18	78.91	72.67	79.32	76.08	77.79	↓ 4.2%

Table 12: **Visual entailment:** *text robustness* evaluations for the *SNLI-VE-TP* dataset (averaged accuracy), where the most effective perturbation results are marked in bold and the least effective ones are underlined. Impact score is marked in blue, the lower the better.

			Character-level						Word-level					Sentence-level							
Dataset	Method	Clean	Keyboard	OCR	CI	CR	CS	CD	SR	WI	WS	WD	IP	Formal	Casual	Passive	Active	Back_trans	**ave**	MMI
val	ALBEF	80.80	65.35	71.97	66.54	**65.17**	67.22	67.46	74.63	74.15	74.88	78.62	80.56	80.56	80.56	80.56	80.56	76.94	74.11	↓ 8.3%
	TCL	80.51	65.24	71.63	65.58	**64.72**	67.67	67.16	74.32	74.04	74.52	77.84	79.84	79.84	79.84	79.84	79.84	75.79	73.61	↓ 8.6%
	METER	80.86	**66.70**	74.17	67.99	66.41	68.64	69.53	74.65	73.19	72.55	78.28	76.24	80.72	80.49	80.76	80.72	77.43	74.28	↓ 8.1%
test	ALBEF	80.91	**64.87**	71.90	65.99	65.03	66.91	67.27	74.77	74.93	74.90	78.44	80.20	80.20	80.20	80.20	80.20	77.31	73.96	↓ 8.6%
	TCL	80.29	**65.27**	71.83	65.81	64.66	67.69	67.25	74.59	73.70	74.49	78.01	79.77	79.77	79.77	79.84	79.84	76.62	73.67	↓ 8.2%
	METER	81.19	**66.09**	74.26	67.39	66.30	68.92	69.71	74.88	73.89	72.95	78.38	76.65	80.96	80.83	81.21	81.05	77.14	74.41	↓ 8.4%

Table 13: Top1 classification accuracy of unimodal vision models. The most effective perturbation results are marked in bold and the least effective ones are underlined.

Model/corruption	**bright**	**contrast**	**defocus**	**elastic**	**fog**	**glass**	**gauss**	**impulse**	**jpeg**	**motion**	**pixelate**	**saturate**	**shot**	**snow**	**spatter**	**speckle**	**zoom**
deit_base_distilled	0.81	0.81	0.57	0.64	0.79	0.59	0.67	0.66	0.69	0.64	0.66	0.80	0.66	0.67	0.74	0.72	**0.54**
densenet169	0.72	0.61	0.41	0.45	0.60	0.41	0.42	**0.37**	0.57	0.41	0.52	0.69	0.41	0.42	0.52	0.47	**0.38**
eca_nfnet_l0	0.79	0.77	0.47	0.52	0.69	0.50	0.40	0.44	0.65	0.59	0.48	0.78	**0.39**	0.62	0.72	0.55	0.51
efficientnetv2	0.79	0.72	0.51	0.56	0.62	0.53	**0.46**	0.49	0.68	0.60	0.60	0.78	**0.46**	0.62	0.72	0.60	0.54
gmlp_s16_224	0.71	0.72	0.42	0.57	0.66	0.46	0.55	0.53	0.59	0.52	0.58	0.70	0.54	0.34	0.60	0.61	**0.39**
mixer_b16_224	0.71	0.72	0.31	0.44	0.62	0.35	0.31	**0.26**	0.44	0.41	0.48	0.63	0.29	0.35	0.50	0.38	**0.28**
mobilenetv3_large	0.71	0.46	0.35	0.47	0.51	0.38	**0.33**	0.35	0.56	0.47	0.44	0.68	0.33	0.38	0.55	0.45	0.38
pit_s_224	0.79	0.77	0.50	0.56	0.72	0.51	0.64	0.62	0.67	0.58	0.57	0.77	0.62	0.62	0.70	0.68	**0.46**
regnety_064	0.75	0.54	0.45	0.51	0.61	0.46	0.43	**0.41**	0.59	0.48	0.46	0.71	0.40	0.46	0.62	0.48	0.44
resmlp_24_224	0.76	0.73	0.48	0.57	0.61	0.51	0.56	0.54	0.60	0.56	0.54	0.75	0.54	0.56	0.64	0.62	**0.46**
resnet50d	0.78	0.77	0.44	0.46	0.71	0.47	0.41	**0.39**	0.63	0.50	0.40	0.76	0.41	0.51	0.63	0.53	0.46
resnext101_32x8d	0.74	0.53	0.48	0.52	0.60	0.47	0.42	**0.37**	0.61	0.52	0.56	0.69	0.40	0.42	0.57	0.49	0.49
swin_small_patch4	0.81	0.81	0.52	0.57	0.75	**0.52**	0.63	0.63	0.57	0.61	0.40	0.80	0.62	0.65	0.77	0.70	**0.52**
vit_small_patch16	0.62	0.73	0.45	0.50	0.67	0.47	0.34	0.31	0.55	0.52	0.58	0.56	0.31	**0.26**	0.53	0.41	0.38

Table 14: Image captioning results of BLIP and GRIT.

			Noise				Blur				Weather				Digital				Stylize		
		GT	**Gauss**	**Shot**	**Impulse**	**Speckle**	**Defocus**	**Glass**	**Motion**	**Zoom**	**Snow**	**Frost**	**Fog**	**Bright**	**Contrast**	**Elastic**	**Pixel**	**JPEG**	**Stylize**	**Ave**	**MMI**
BLIP	Bleu_1	78.9	70.9	71.9	71.1	74.8	68.5	77.5	66.5	**55.9**	70.6	73.4	75.0	77.3	71.3	69.9	62.7	76.2	63.7	66.5	↓15.7%
	Bleu_2	63.8	54.4	55.7	54.8	59.0	52.3	62.3	50.0	**37.5**	53.8	57.5	59.3	61.8	54.9	53.4	45.4	60.6	46.2	51.0	↓20.0%
	Bleu_3	50.5	41.3	42.6	41.7	45.8	39.1	49.1	36.7	**24.4**	40.5	44.3	45.9	48.4	41.6	40.6	32.6	47.4	32.9	38.6	↓23.6%
	Bleu_4	39.7	31.4	32.5	31.7	35.5	29.1	38.4	26.8	**16.1**	30.7	34.0	35.4	37.8	31.4	30.9	23.8	37.0	23.6	29.2	↓26.4%
	Meteor	31.0	26.1	26.8	26.4	28.5	24.7	30.1	23.6	**17.0**	25.7	27.7	28.8	29.8	25.7	25.7	21.3	29.3	21.1	24.4	↓21.5%
	Rouge_L	60.0	53.3	54.3	53.7	56.7	50.9	58.8	49.3	**40.5**	52.4	55.6	57.0	58.6	53.2	52.7	46.8	57.8	46.8	49.9	↓16.8%
	CIDEr	133.3	100.5	104.3	101.6	116.5	91.8	128.1	84.2	**45.9**	95.7	111.6	116.1	125.8	98.3	96.8	68.6	121.8	68.7	93.1	↓30.1%
GRIT	Bleu_1	84.2	78.6	79.1	78.8	81.1	79.4	83.6	77.9	**60.0**	78.6	81.8	83.1	83.1	81.4	77.4	64.0	81.6	68.9	73.2	↓13.0%
	Bleu_2	69.1	62.2	62.6	62.4	65.0	63.1	68.4	61.3	**40.5**	61.8	65.9	67.5	67.7	65.3	60.5	44.3	65.8	50.0	57.4	↓16.8%
	Bleu_3	54.7	47.6	48.1	47.9	50.5	48.7	53.9	46.8	**27.1**	47.2	51.4	53.0	53.2	50.7	46.1	30.3	51.2	35.5	43.8	↓19.8%
	Bleu_4	42.3	35.8	36.3	36.1	38.5	36.9	41.5	35.2	**18.5**	35.4	39.2	40.7	40.9	38.5	34.6	20.9	39.1	25.3	33.0	↓22.0%
	Meteor	30.6	27.0	27.2	27.1	28.4	27.5	30.1	26.7	**17.7**	27.0	28.8	29.6	29.9	28.5	26.2	18.7	28.9	21.2	25.0	↓18.3%
	Rouge_L	60.7	55.8	56.2	56.0	57.8	56.6	60.1	55.4	**42.6**	55.6	58.3	59.4	59.8	58.0	55.0	44.5	58.4	48.2	52.1	↓14.2%
	CIDEr	144.0	117.4	118.6	118.0	128.1	120.2	140.0	115.1	**56.1**	118.1	131.1	136.6	138.3	128.4	110.6	60.0	131.1	77.4	108.1	↓25.0%

Table 15: Text-to-image generation results of Stable Diffusion (FID and CLIP-FID), where "GT" means images generated by GT captions.

		FID									CLIP_FID								
		4 image			8 image			16 image			4 image			8 image			16 image		
		mean	std	MMI	mean	std	MMI	mean	std	MMI	mean	std	MMI	mean	std	MMI	mean	std	MMI
Character	Keyboard	315.9	131.10	↓ 44.39%	270.77	116.78	↓ 58.34%	239.27	109.41	↓ 82.80%	68.05	29.13	↓ 89.40%	59.42	27.31	↓ 118.46%	53.04	26.35	↓ 167.74%
	Ocr	272.9	119.01	↓ 24.76%	227.72	103.83	↓ 33.16%	195.25	94.93	↓ 49.17%	55.20	25.61	↓ 53.63%	46.40	23.47	↓ 70.59%	39.95	22.28	↓ 101.67%
	CI	299.1	126.80	↓ 36.70%	254.40	111.87	↓ 48.76%	222.62	103.82	↓ 70.08%	62.94	27.41	↓ 75.17%	54.41	25.45	↓ 100.04%	47.93	24.29	↓ 141.95%
	CR	311.2	129.03	↓ 42.23%	268.64	114.50	↓ 57.09%	236.27	107.73	↓ 80.51%	67.65	28.67	↓ 88.28%	58.98	26.98	↓ 116.84%	50.74	26.06	↓ 156.13%
	CS	310.3	131.50	↓ 41.85%	265.29	117.53	↓ 55.13%	233.46	109.85	↓ 78.36%	64.70	28.79	↓ 80.07%	56.17	27.03	↓ 106.51%	49.88	26.08	↓ 151.79%
	CD	308.5	125.99	↓ 40.99%	264.14	113.76	↓ 54.46%	232.46	106.40	↓ 77.60%	65.03	28.21	↓ 80.99%	56.38	26.48	↓ 107.28%	50.04	25.60	↓ 152.60%
Word	SR	266.1	115.45	↓ 21.62%	220.86	98.86	↓ 29.15%	188.45	88.97	↓ 43.98%	51.84	24.62	↓ 44.28%	43.43	22.49	↓ 59.67%	37.14	21.21	↓ 87.48%
	RI	242.0	102.38	↓ 10.60%	196.42	83.79	↓ 14.86%	163.14	71.85	↓ 24.64%	43.76	18.47	↓ 21.79%	35.28	15.42	↓ 29.71%	28.90	13.50	↓ 45.89%
	RS	247.5	104.33	↓ 13.15%	202.32	85.65	↓ 18.31%	169.39	73.77	↓ 29.41%	46.31	19.47	↓ 28.89%	37.78	16.65	↓ 38.90%	31.33	14.77	↓ 58.15%
	RD	237.3	100.41	↓ 8.44%	191.81	81.89	↓ 12.16%	158.95	69.89	↓ 21.44%	42.26	17.50	↓ 17.62%	33.80	14.56	↓ 24.26%	27.44	12.67	↓ 38.52%
	IP	233.0	98.81	↓ 6.49%	187.02	79.24	↓ 9.36%	153.63	66.62	↓ 17.37%	41.07	17.17	↓ 14.31%	32.50	13.93	↓ 19.49%	26.02	11.78	↓ 31.35%
Sentence	Formal	224.4	93.92	↓ 2.58%	178.94	74.71	↓ 4.64%	145.92	61.51	↓ 11.48%	38.15	15.20	↓ 6.18%	29.60	11.88	↓ 8.82%	23.21	9.63	↓ 17.16%
	Casual	225.6	94.97	↓ 3.14%	179.66	75.11	↓ 5.06%	146.16	61.92	↓ 11.67%	37.84	15.10	↓ 5.32%	29.40	11.90	↓ 8.09%	23.03	9.68	↓ 16.25%
	Passive	228.7	96.34	↓ 4.54%	183.60	77.26	↓ 7.36%	150.21	64.49	↓ 14.76%	39.46	16.21	↓ 9.82%	31.08	13.18	↓ 14.26%	24.65	11.14	↓ 24.43%
	Active	223.1	93.94	↓ 1.96%	176.82	73.85	↓ 3.40%	143.15	60.26	↓ 9.37%	36.94	14.36	↓ 2.81%	28.35	10.99	↓ 4.23%	21.91	8.77	↓ 10.60%
	Back_trans	232.6	98.67	↓ 6.33%	187.14	80.10	↓ 9.43%	153.64	67.80	↓ 17.38%	39.99	16.78	↓ 11.30%	31.56	13.91	↓ 16.03%	25.22	11.94	↓ 27.31%
GT	GT	218.8	96.66	—	171.01	171.01	—	130.89	61.46	—	35.93	14.85	—	27.20	11.27	—	19.81	8.79	—

Table 16: Text-to-image generation results of GLIDE (FID and CLIP-FID), where "GT" means images generated by GT captions.

		FID									CLIP_FID								
		4 image			8 image			16 image			4 image			8 image			16 image		
		mean	std	MMI	mean	std	MMI	mean	std	MMI	mean	std	MMI	mean	std	MMI	mean	std	MMI
Character	Keyboard	341.39	110.88	↓26.57%	291.92	96.54	↓34.50%	256.93	89.53	↓44.42%	69.61	25.79	↓55.10%	59.45	23.75	↓72.52%	51.97	22.83	↓95.52%
	OCR	305.16	108.71	↓13.14%	255.81	93.50	↓17.86%	219.74	85.15	↓23.51%	58.83	24.76	↓31.08%	48.81	22.44	↓41.64%	41.18	21.08	↓54.93%
	CI	333.82	110.89	↓23.76%	284.49	97.22	↓31.08%	248.06	89.42	↓39.43%	67.45	25.38	↓50.29%	57.16	23.35	↓65.87%	49.53	22.30	↓86.34%
	CR	339.82	108.85	↓25.99%	290.13	94.90	↓33.68%	254.63	88.26	↓43.12%	69.44	25.47	↓54.72%	59.17	23.57	↓71.71%	51.53	22.68	↓93.87%
	CS	339.20	110.27	↓25.76%	288.79	95.76	↓33.06%	253.56	88.69	↓42.52%	67.75	25.00	↓50.96%	57.58	22.91	↓67.09%	50.17	22.06	↓88.75%
	CD	340.87	111.23	↓26.37%	291.76	98.32	↓34.43%	252.68	87.79	↓42.03%	67.23	24.82	↓49.80%	57.07	22.75	↓65.61%	49.52	21.80	↓86.31%
Word	SR	306.08	110.11	↓13.48%	255.45	94.17	↓17.70%	254.17	88.23	↓42.86%	56.7	22.89	↓26.34%	46.65	20.27	↓35.37%	39.19	18.88	↓47.44%
	RI	286.23	106.35	↓6.12%	234.68	88.62	↓8.13%	196.88	77.27	↓10.66%	50.86	20.32	↓13.32%	40.64	17.14	↓17.93%	32.91	15.14	↓23.81%
	RS	283.53	103.71	↓5.12%	230.54	85.17	↓6.22%	195.23	77.45	↓9.74%	48.96	18.82	↓9.09%	38.61	15.33	↓12.04%	30.84	13.06	↓16.03%
	RD	286.36	106.72	↓6.17%	234.16	88.39	↓7.89%	196.08	76.79	↓10.21%	50.01	19.44	↓11.43%	39.86	16.32	↓15.67%	32.20	14.34	↓21.14%
	IP	278.34	105.05	↓3.19%	225.52	85.21	↓3.91%	189.22	74.35	↓6.36%	47.64	18.07	↓6.15%	37.21	14.32	↓7.98%	29.39	11.80	↓10.57%
Sentence	Formal	274.77	103.99	↓1.87%	222.19	84.39	↓2.37%	183.83	71.87	↓3.33%	46.5	17.87	↓3.61%	36.29	14.17	↓5.31%	28.54	11.84	↓7.37%
	Casual	275.48	103.52	↓2.13%	222.96	84.60	↓2.73%	184.38	72.27	↓3.64%	46.82	18.3	↓4.32%	36.57	14.63	↓6.12%	28.76	12.29	↓8.20%
	Passive	278.77	104.93	↓3.35%	226.95	86.19	↓4.57%	188.60	74.40	↓6.01%	48.15	19.11	↓7.29%	37.89	15.74	↓9.95%	27.21	10.56	↓2.37%
	Active	271.09	101.61	↓0.50%	218.40	82.03	↓0.63%	179.91	69.34	↓1.12%	45.42	17.01	↓1.20%	35.05	13.06	↓1.71%	30.19	13.64	↓13.58%
	Back_trans	283.70	107.07	↓5.18%	231.85	88.16	↓6.82%	190.23	73.53	↓6.92%	49.21	19.86	↓9.65%	39.13	16.59	↓13.55%	31.46	14.55	↓18.36%
GT	GT	269.73	269.73	—	217.04	81.72	—	177.91	68.55	—	44.88	16.57	—	34.46	12.47	—	26.58	9.79	—

Table 17: Quantitative results of Missing Object Rate (MOR) of Stable Diffusion. The most effective perturbation results are marked in bold, and the least effective ones are underlined. The results show that more objects are missing from the images generated by character-level perturbed captions.

Threshold	Setting	GT	Keyboard	Ocr	CI	CR	CS	CD	SR	RI	RS	RD	IP	Formal	Casual	Passive	Active	Back_trans
0.7	4-images	0.00	-12.47	-5.22	-8.41	**-13.25**	-12.15	-12.63	-8.23	-3.14	-7.33	-6.05	-2.81	-2.10	-1.42	-1.36	0.27	-0.86
	8-images	0.00	-11.00	-4.27	-6.62	**-11.79**	-11.09	-10.76	-6.77	-1.62	-6.59	-4.31	-2.83	0.01	0.69	-0.17	1.34	0.44
	16-images	0.00	-11.53	-4.29	-6.96	**-11.72**	-11.59	-10.86	-6.88	-1.65	-6.66	-4.48	-2.90	-0.16	0.17	-0.75	0.76	0.48
0.5	4-images	0.00	-5.33	-2.97	-2.96	**-6.60**	-3.97	-2.45	-1.00	0.72	-1.51	-4.63	-1.88	-0.31	-2.18	2.17	-0.30	0.65
	8-images	0.00	-4.94	-2.28	-1.18	**-5.83**	-2.48	-1.55	-0.34	1.70	-1.26	-2.72	-1.06	0.17	-1.00	3.41	0.42	1.02
	16-images	0.00	-4.95	-1.76	-1.65	**-5.02**	-2.01	-2.03	-0.62	1.41	-0.90	-2.50	-0.69	0.50	0.08	3.36	0.26	1.41

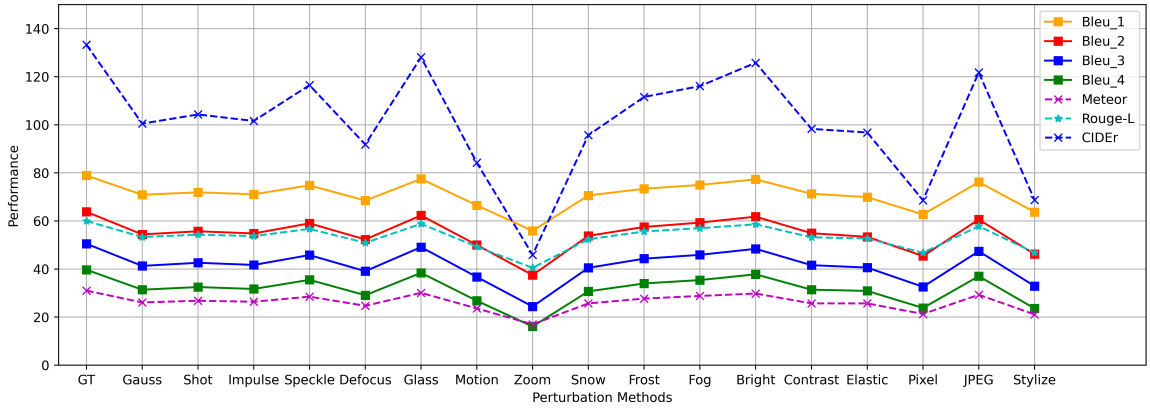

Figure 8: Image Captioning results of BLIP.

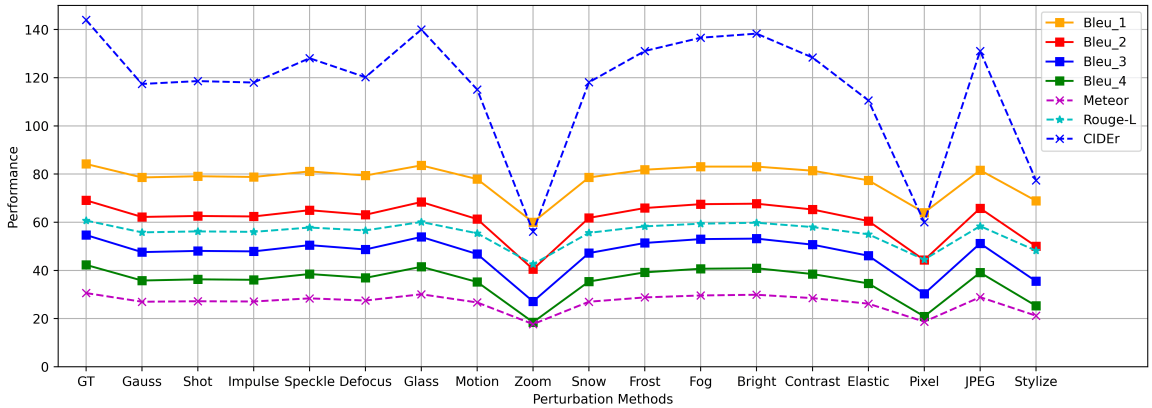

Figure 9: Image Captioning results of GRIT.

Figure 10: Examples of image captioning results under image perturbations of BLIP.

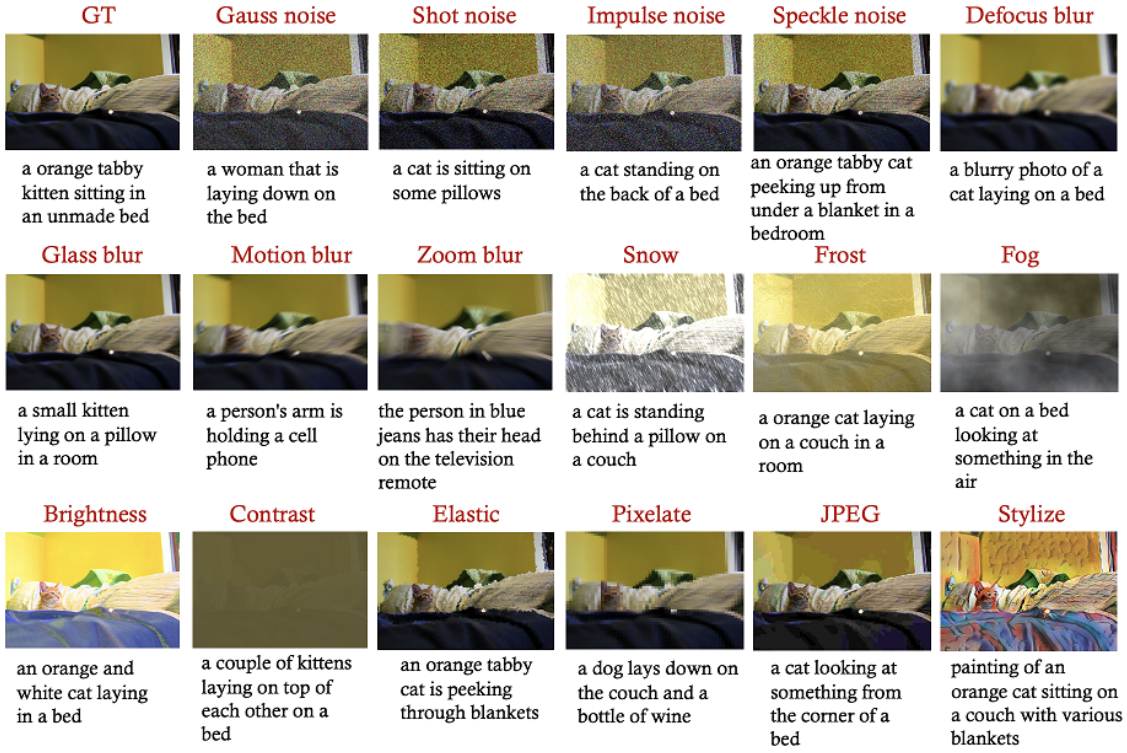

Figure 11: Examples of image captioning results under image perturbations of GRIT.

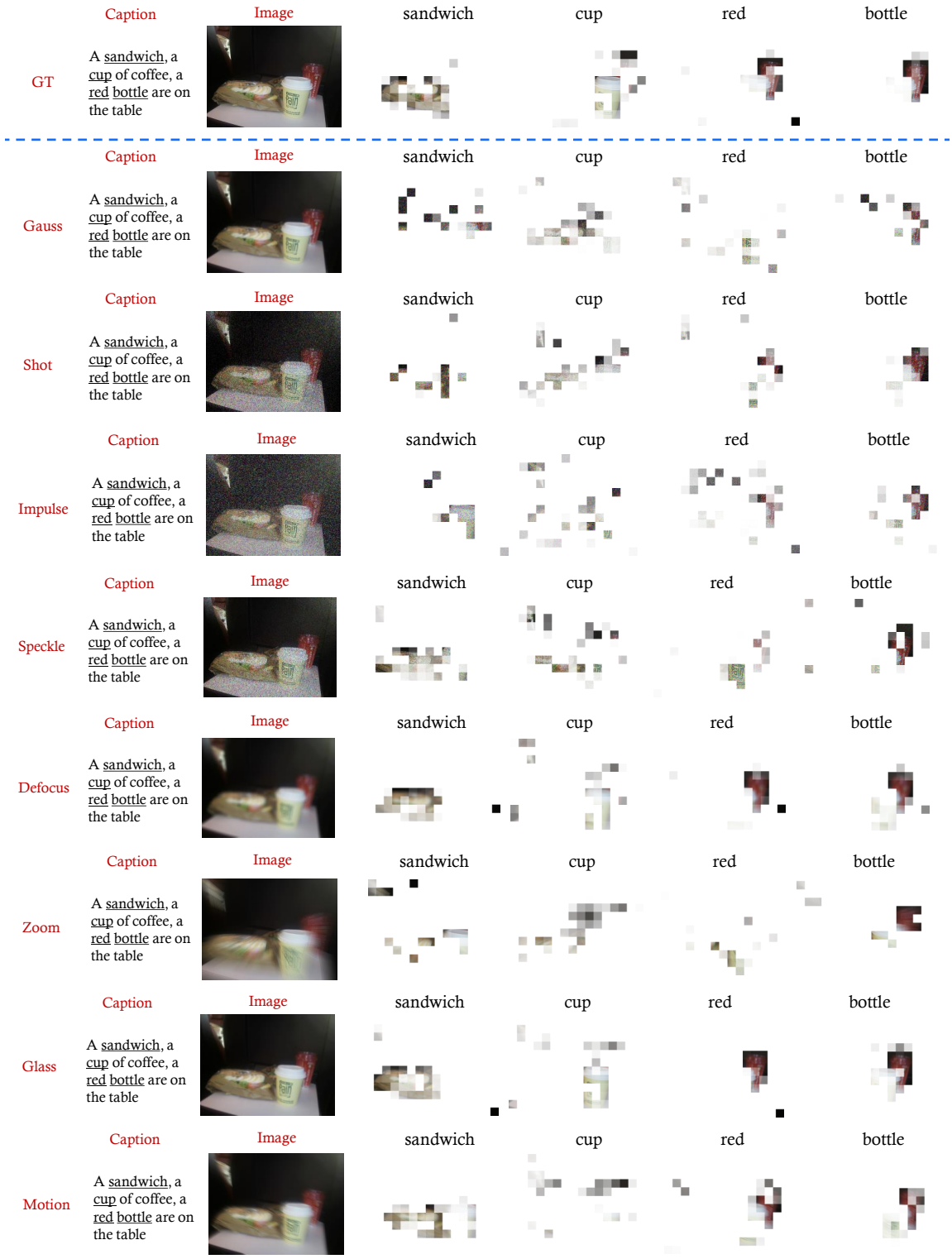

Figure 12: Optimal Transport (OT) alignment visualization between text and images under image perturbations (1/2).

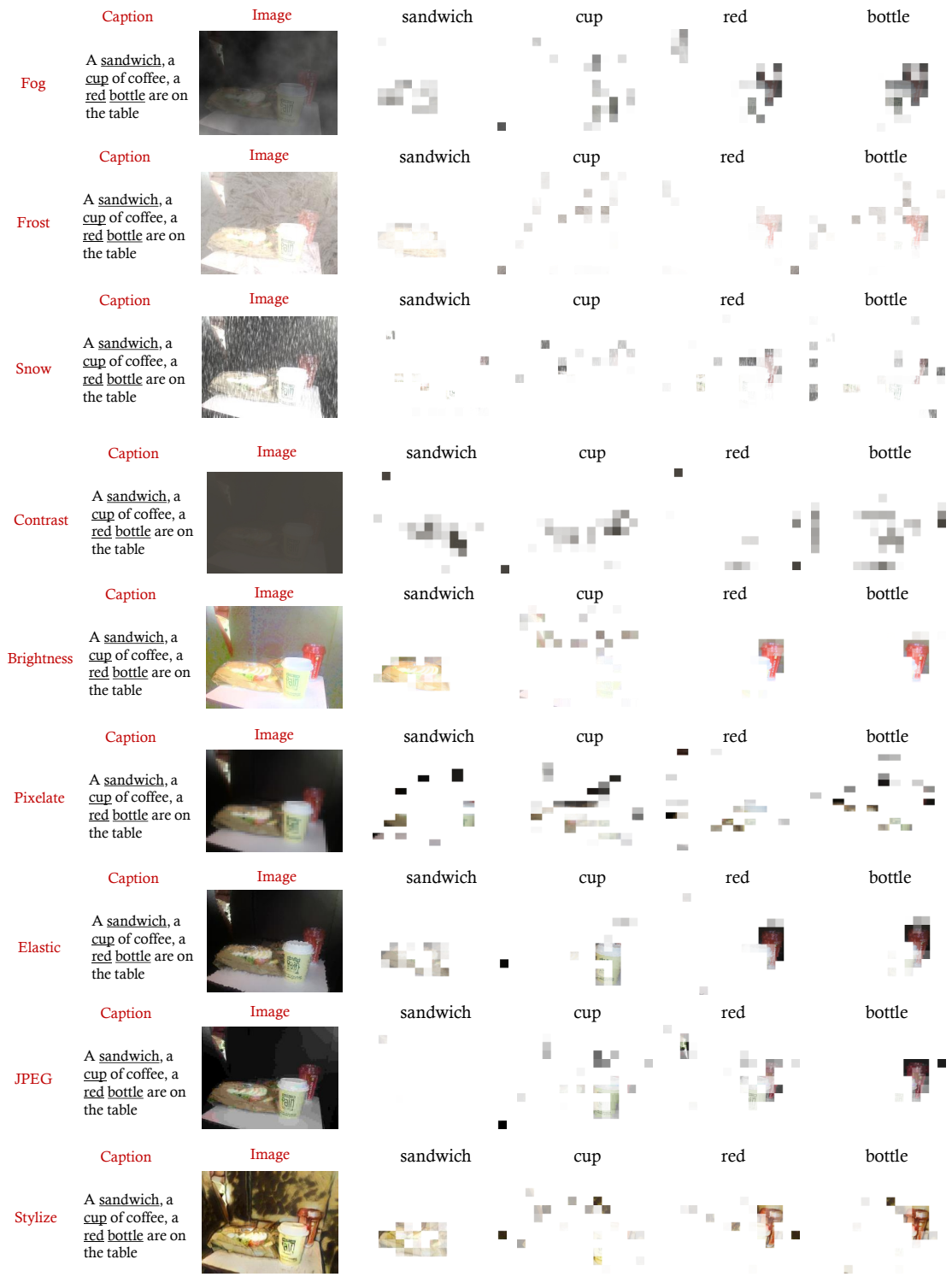

Figure 13: Optimal Transport (OT) alignment visualization between text and images under image perturbations (2/2).

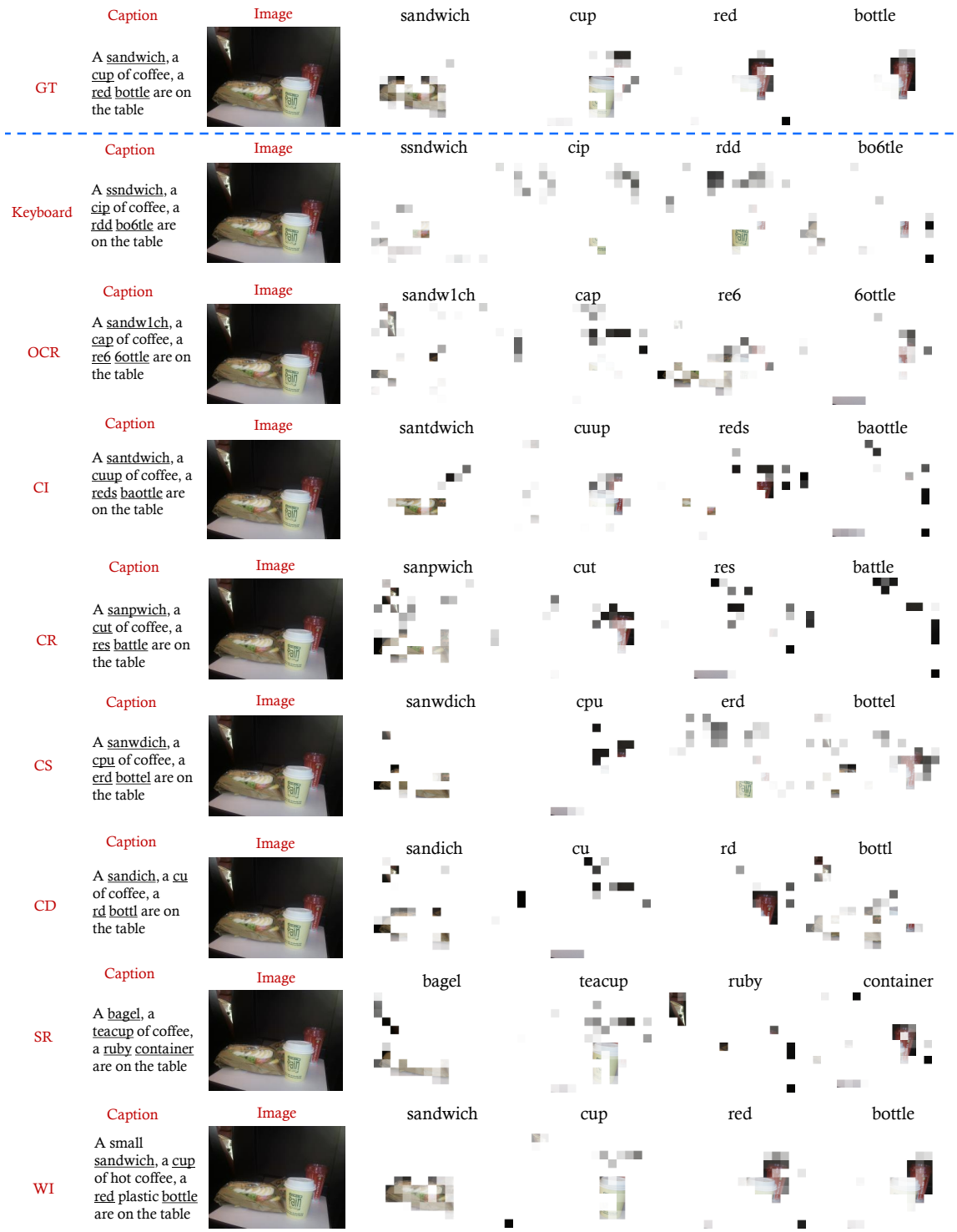

Figure 14: Optimal Transport (OT) alignment visualization between text and images under text perturbations (1/2).

Figure 15: Optimal Transport (OT) alignment visualization between text and images under text perturbations (2/2).

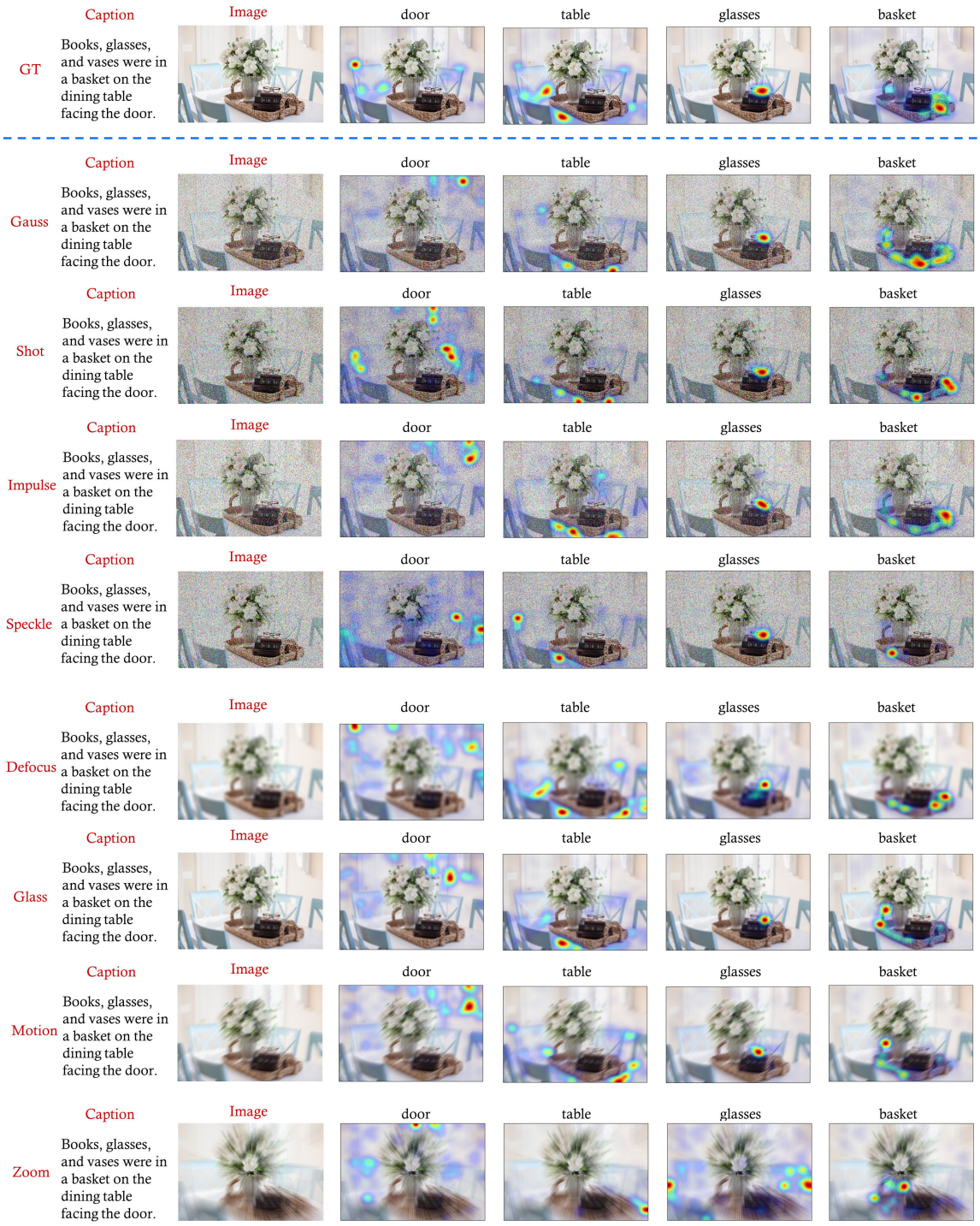

Figure 16: Grad-CAM visualizations on the cross-attention maps corresponding to individual words with image perturbations (1/2).

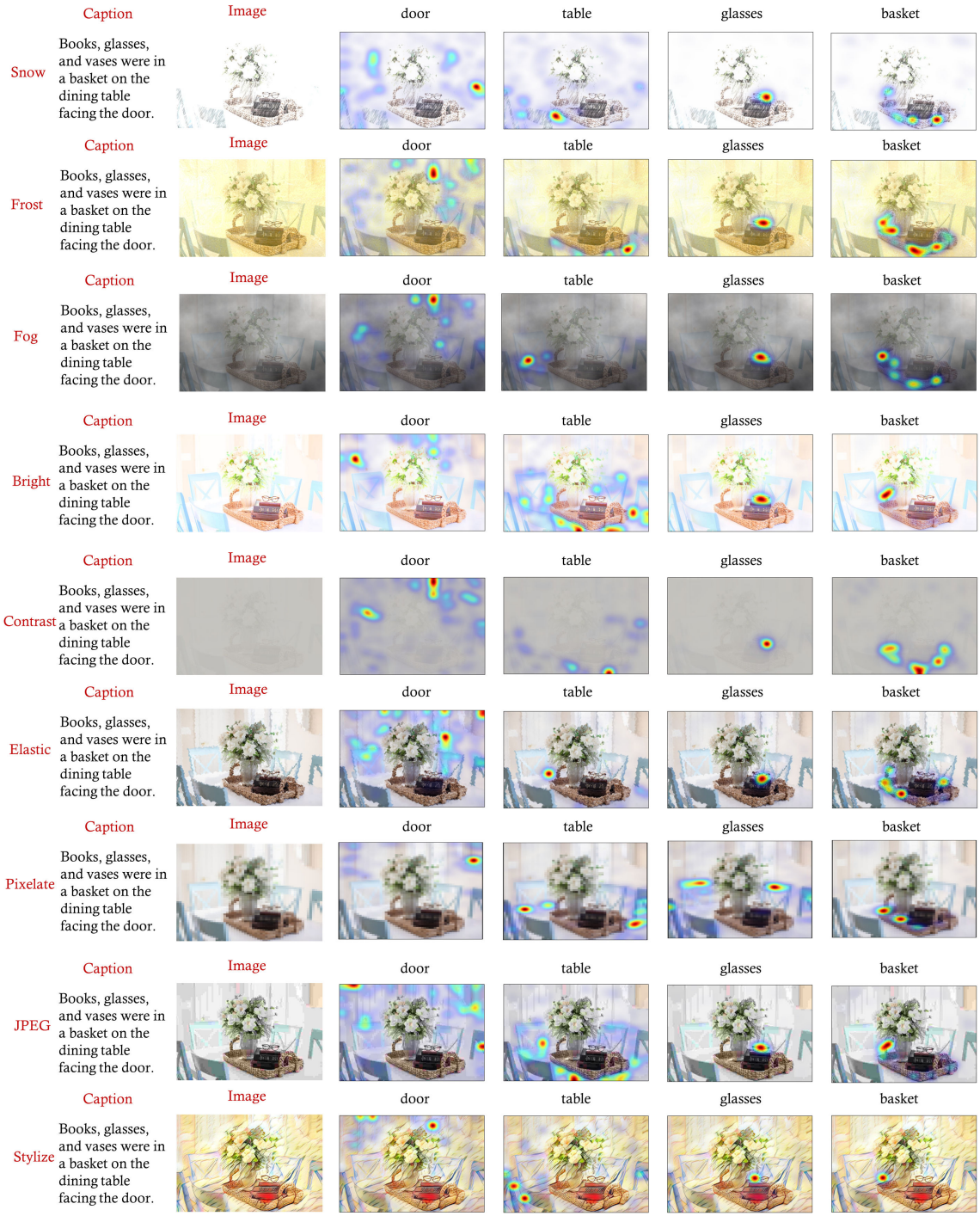

Figure 17: Grad-CAM visualizations on the cross-attention maps corresponding to individual words with image perturbations (2/2).

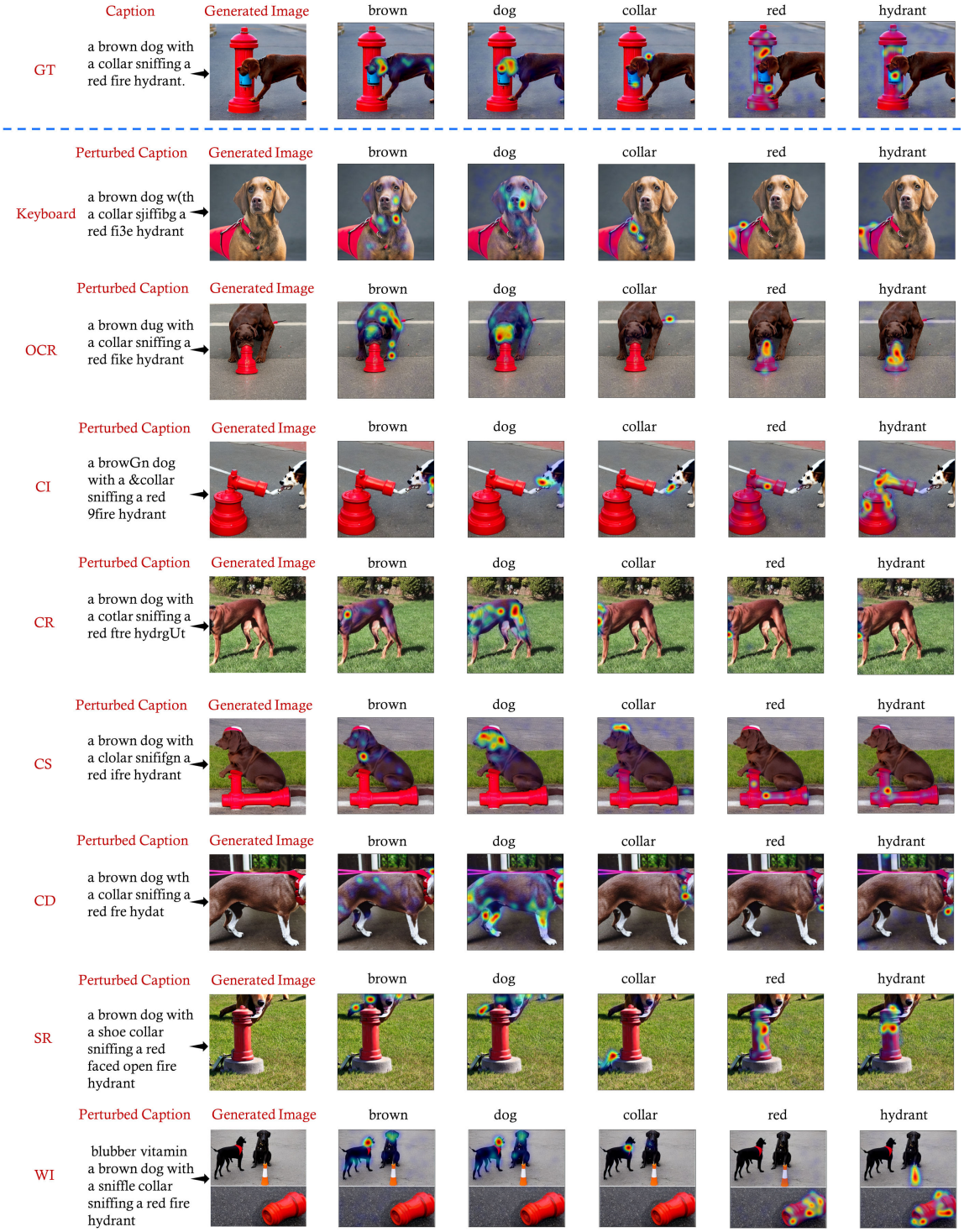

Figure 18: Text-to-image generation Grad-CAM visualizations on the cross-attention maps corresponding to individual words with text perturbations (1/2).

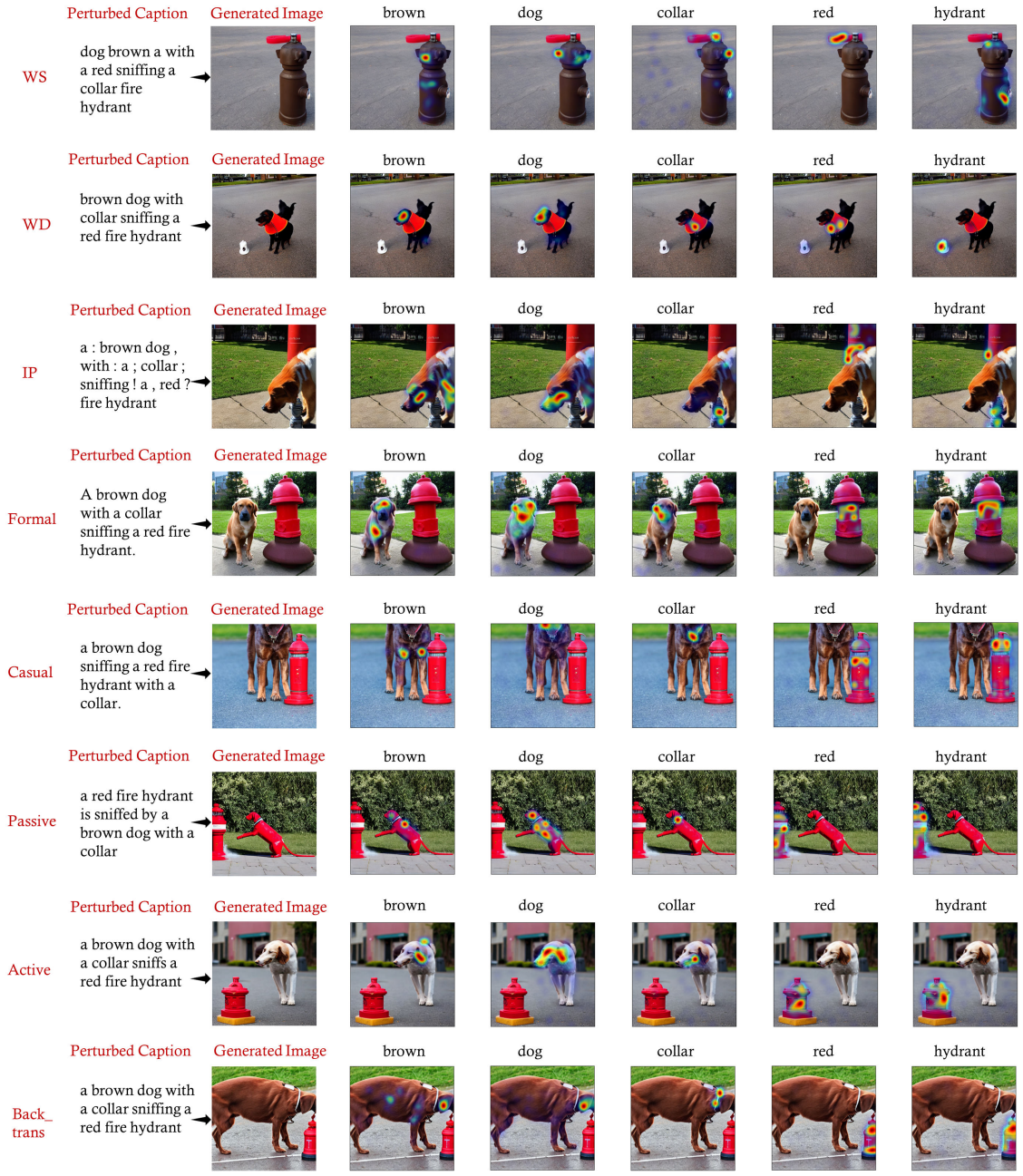

Figure 19: Text-to-image generation Grad-CAM visualizations on the cross-attention maps corresponding to individual words with text perturbations (2/2).

Figure 20: Text-to-image generation comparison on all 16 generated images. We find that though the generated images do not guarantee to perfectly show all the notions described in the captions, the probability of generating matched images by the unperturbed captions is higher than the perturbed captions, especially character-level perturbations.

Table 18: ViLT image perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	57.7	79.0	84.5	73.7	43.3	70.0	78.6	64.0	413.0	47.7	73.8	82.5	68.0	33.5	61.7	73.1	56.1	372.2
	Shot	58.9	80.4	85.7	75.0	43.9	70.9	79.7	64.8	419.6	47.9	73.9	82.6	68.1	33.3	61.7	73.2	56.1	372.6
	Impluse	54.3	76.0	82.3	70.9	40.6	67.4	76.3	61.4	396.9	45.9	71.8	80.8	66.2	32.1	60.3	71.9	54.8	362.9
	Speckle	67.9	89.0	93.5	83.4	49.4	77.8	85.6	70.9	463.2	52.2	78.7	87.0	72.6	36.2	65.7	77.0	59.6	396.7
Blue	Defocus	58.0	80.3	86.9	75.1	43.0	70.3	79.2	64.1	417.6	48.8	75.2	83.6	69.2	33.9	62.6	74.2	56.9	378.1
	Glass	74.5	92.7	95.9	87.7	55.2	81.9	88.9	75.3	489.0	58.6	84.4	91.1	79.7	40.8	70.6	81.3	63.2	432.0
	Motion	51.1	72.2	79.5	67.6	41.3	67.7	76.6	61.8	388.4	46.5	72.0	81.3	66.6	32.7	60.8	72.1	55.2	365.4
	Zoom	24.6	42.2	50.4	39.0	22.7	43.5	53.0	39.7	236.3	17.6	35.2	44.0	32.3	16.4	35.3	45.2	32.3	193.8
Weather	Snow	39.8	61.3	70.2	57.1	33.8	59.0	68.6	53.8	332.7	31.0	54.2	64.2	49.8	24.1	48.1	59.5	43.9	281.1
	Frost	65.1	87.2	92.1	81.5	47.9	76.1	84.6	69.6	453.1	46.2	72.7	81.5	66.8	32.7	60.8	72.3	55.3	366.1
	Fog	66.2	87.4	92.2	82.0	48.8	76.5	84.7	70.0	455.8	52.2	78.8	87.1	72.7	36.4	66.2	77.4	60.0	398.1
	Brightness	76.3	94.1	97.1	89.1	56.0	83.3	90.2	76.5	496.9	57.7	83.1	90.4	77.1	40.3	70.1	80.8	63.7	422.4
Digital	Contrast	53.3	70.7	75.9	66.7	39.5	62.6	70.1	57.4	372.2	41.7	64.2	72.1	59.3	29.6	54.7	64.9	49.7	327.1
	Elastic	67.2	87.3	91.8	82.1	50.8	78.5	86.1	71.8	461.7	54.0	78.7	86.5	73.1	37.9	67.1	77.9	61.0	402.2
	Pixelate	33.2	52.1	59.7	48.3	27.2	48.2	57.0	44.1	277.4	25.8	43.9	51.6	40.5	19.8	39.5	49.1	36.1	229.8
	JPEG	74.1	92.3	95.8	87.4	54.6	81.8	89.0	75.1	487.6	58.4	84.2	91.1	77.9	40.7	70.4	81.1	64.0	425.8
Stylize	Stylized	54.2	74.0	80.4	69.5	40.1	65.1	73.4	59.5	387.1	40.6	64.2	72.8	61.6	29.0	54.7	65.4	49.7	333.9

Table 19: CLIP image perturbation performance comparison of Zero-Shot (ZS) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	75.1	92.8	96.0	88.0	61.7	85.1	90.9	79.3	501.7	47.8	72.1	80.6	66.9	34.7	58.7	69.1	54.2	363.0
	Shot	75.6	93.4	96.6	88.5	61.7	85.5	91.4	79.5	504.2	47.6	71.6	80.3	66.5	34.2	58.5	69.1	53.9	361.2
	Impluse	68.2	90.2	94.3	84.2	57.4	82.1	88.9	76.2	481.2	40.1	65.6	75.4	60.4	30.1	54.1	64.8	49.7	330.2
	Speckle	80.2	95.8	98.0	91.3	62.9	86.4	92.2	80.5	515.5	49.5	73.9	82.0	68.5	34.6	59.1	69.6	54.4	368.7
Blur	Defocus	74.7	93.4	96.6	88.2	61.3	85.1	91.1	79.1	502.1	46.5	71.3	80.0	65.9	33.7	58.3	68.8	53.6	358.6
	Glass	85.5	97.8	99.0	94.1	66.1	88.4	93.4	82.6	530.1	55.6	78.9	86.4	73.6	37.3	61.7	71.7	56.9	391.6
	Motion	77.0	94.1	97.0	89.4	63.5	86.2	91.9	80.6	509.7	48.8	72.3	80.4	67.1	34.2	58.2	68.3	53.6	362.2
	Zoom	62.3	84.6	90.6	79.1	54.8	79.2	86.3	73.5	457.8	32.4	57.0	67.2	52.2	26.9	50.1	61.0	46.0	294.6
Weather	Snow	64.8	86.9	93.1	81.6	56.2	81.4	88.3	75.3	470.7	32.3	56.2	67.8	52.1	26.8	50.1	61.4	46.1	294.7
	Frost	72.8	92.6	96.5	87.3	59.4	84.0	90.4	77.9	495.6	41.1	65.6	75.6	60.8	29.4	53.2	64.1	48.9	329.0
	Fog	80.8	96.1	98.2	91.7	64.6	87.3	92.7	81.5	519.7	51.3	75.5	83.6	70.2	34.0	58.5	68.8	53.8	371.8
	Brightness	85.2	97.6	98.9	93.9	66.4	88.6	93.4	82.8	530.1	56.5	79.8	87.4	74.6	36.4	60.7	71.1	56.0	391.9
Digital	Contrast	80.7	95.9	98.0	91.5	62.7	86.2	91.9	80.3	515.4	48.0	71.5	80.1	66.5	32.5	56.9	67.4	52.2	356.4
	Elastic	79.5	94.9	97.3	90.6	61.6	85.8	91.4	79.6	510.4	50.6	74.7	83.1	69.5	33.8	58.5	69.1	53.8	369.7
	Pixelate	68.4	87.6	92.0	82.7	55.5	79.6	86.4	73.8	469.5	36.3	60.4	70.3	55.7	27.9	51.3	61.9	47.0	308.2
	JPEG	83.6	96.8	98.4	92.9	65.8	87.4	92.7	82.0	524.6	55.3	78.9	86.4	73.5	35.9	60.7	70.9	55.8	388.0
Stylize	Stylized	65.3	83.3	88.3	79.0	51.6	75.8	83.2	70.2	447.6	39.9	62.8	72.2	58.3	28.0	50.8	61.2	46.7	314.9

Table 20: CLIP image perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	72.7	91.2	95.0	86.3	63.1	86.5	91.6	80.4	500.1	43.0	70.3	80.1	64.5	35.1	63.5	75.1	57.9	367.2
	Shot	73.0	91.9	95.8	86.9	63.9	87.1	92.1	81.0	503.8	42.4	69.9	79.9	64.1	34.9	63.3	74.9	57.7	365.3
	Impluse	65.1	87.9	92.5	81.8	59.2	84.3	90.1	77.9	479.2	35.6	63.0	74.3	57.6	29.8	58.3	70.7	53.0	331.7
	Speckle	78.1	95.0	97.8	90.3	66.9	89.9	94.4	83.7	522.1	36.5	65.7	77.1	59.8	36.5	65.7	77.1	59.8	381.5
Blur	Defocus	70.1	90.2	94.5	84.9	61.6	85.6	91.4	79.5	493.4	43.7	71.7	81.5	65.6	35.2	63.8	75.2	58.1	371.0
	Glass	82.3	97.1	99.1	92.9	70.6	91.9	95.8	86.1	536.9	52.3	80.1	88.5	73.7	40.8	69.9	80.6	63.8	412.2
	Motion	76.1	93.7	96.8	88.9	65.0	88.4	93.3	82.2	513.3	44.6	71.7	81.0	65.8	36.4	64.9	75.8	59.1	374.4
	Zoom	58.7	80.9	87.8	75.8	53.0	78.5	85.5	72.3	444.3	28.4	54.1	65.1	49.2	26.6	52.3	64.4	47.8	291.0
Weather	Snow	69.6	91.3	95.7	85.5	64.2	88.8	93.4	82.1	503.0	26.6	51.7	63.9	47.4	26.4	54.0	66.6	49.0	289.3
	Frost	81.7	97.0	98.9	92.5	69.1	90.9	95.0	85.0	532.5	37.3	65.2	75.8	59.4	30.3	58.4	70.4	53.0	337.3
	Fog	80.5	95.9	98.3	91.6	69.0	90.8	95.2	85.0	529.7	47.0	75.3	84.6	69.0	37.7	67.0	78.2	61.0	389.9
	Brightness	85.9	97.8	99.3	94.3	72.3	92.3	96.1	86.9	543.7	52.8	80.1	88.4	73.8	41.2	70.4	80.9	64.2	413.9
Digital	Contrast	78.1	94.9	97.5	90.2	66.9	89.8	94.3	83.6	521.5	43.4	71.6	81.5	65.5	35.6	64.1	75.5	58.4	371.7
	Elastic	76.9	93.8	96.9	89.2	65.4	88.0	92.9	82.1	513.9	45.8	73.6	82.8	67.4	36.2	65.0	76.3	59.1	379.7
	Pixelate	62.5	83.9	88.8	78.4	54.4	78.6	85.5	72.8	453.8	32.4	58.3	68.9	53.2	27.3	53.8	65.7	48.9	306.4
	JPEG	81.5	96.2	98.3	92.0	68.2	90.1	94.2	84.2	528.5	50.4	78.1	86.8	71.8	39.2	68.2	79.4	62.3	402.1
Stylize	Stylized	59.9	80.8	86.5	75.7	51.3	76.0	82.6	70.0	437.0	33.3	59.1	69.3	53.9	28.1	54.5	65.9	49.5	310.2

Table 21: BLIP image perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	85.1	94.9	96.4	92.1	74.3	91.1	94.4	86.6	536.2	70.1	88.4	92.8	83.8	55.2	79.0	86.4	73.5	471.9
	Shot	85.4	95.0	96.8	92.4	75.1	91.6	95.0	87.3	538.9	70.1	88.2	92.8	83.7	55.2	79.2	86.5	73.7	472.1
	Impluse	83.3	93.4	95.7	90.8	72.9	89.9	93.5	85.4	528.6	68.7	87.6	92.3	82.9	54.5	78.6	86.1	73.1	467.7
	Speckle	91.3	98.2	99.1	96.2	80.2	94.8	97.2	90.7	560.8	74.4	91.5	95.0	87.0	58.4	81.6	88.5	76.2	489.5
Blur	Defocus	83.8	93.9	96.0	91.2	73.1	89.5	93.2	85.3	529.4	68.0	87.5	92.2	82.6	54.6	78.3	85.4	72.8	466.1
	Glass	94.6	99.6	99.8	98.0	83.4	96.1	98.0	92.5	571.6	79.1	94.3	97.2	90.2	62.0	84.3	90.3	78.9	507.2
	Motion	82.6	93.4	96.0	90.7	71.9	88.9	92.9	84.6	525.7	65.8	85.0	89.8	80.2	52.9	75.6	82.5	70.3	451.7
	Zoom	56.2	74.9	80.4	70.5	53.3	74.7	81.6	69.9	421.1	30.7	52.2	61.0	48.0	31.8	53.4	62.5	49.2	291.6
Weather	Snow	62.2	82.7	88.8	77.9	56.7	79.7	86.5	74.3	456.6	58.3	80.5	87.1	75.3	49.7	74.5	82.8	69.0	432.8
	Frost	79.1	93.0	96.1	89.4	66.4	86.8	91.9	81.7	513.4	69.2	88.0	92.7	83.3	55.7	79.5	86.7	74.0	471.8
	Fog	92.9	99.2	99.6	97.2	82.8	96.0	98.0	92.3	568.5	74.7	91.7	95.4	87.2	60.1	82.9	89.4	77.5	494.2
	Brightness	95.6	99.6	99.8	98.3	84.8	96.5	98.3	93.2	574.5	79.1	94.0	96.8	90.0	61.9	84.4	90.5	78.9	506.8
Digital	Contrast	90.2	97.5	98.4	95.4	79.4	93.5	96.1	89.7	555.1	69.5	87.6	92.1	83.1	56.1	79.1	86.1	73.8	470.4
	Elastic	87.3	95.4	96.8	93.2	77.5	92.8	95.7	88.7	545.6	70.4	87.9	92.4	83.6	55.9	79.3	86.4	73.9	472.3
	Pixelate	75.6	88.2	91.5	85.1	64.7	83.0	87.8	78.5	490.8	56.1	76.3	82.6	71.6	44.9	68.3	76.5	63.3	404.7
	JPEG	92.7	98.5	99.3	96.8	81.2	94.9	97.2	91.1	563.8	77.5	93.2	96.4	89.1	60.1	83.0	89.5	77.5	499.6
Stylize	Stylized	73.3	86.4	89.3	83.0	64.1	82.1	87.0	77.7	482.1	55.1	75.3	81.6	70.7	45.9	68.6	76.5	63.6	402.9

Table 22: ALBEF image perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	83.9	94.6	96.5	91.7	73.4	90.9	94.5	86.3	533.8	66.1	86.5	92.0	81.5	52.1	77.6	85.7	71.8	460.0
	Shot	84.9	95.2	97.1	92.4	74.0	91.8	95.2	87.0	538.3	66.2	86.6	92.0	81.6	52.1	77.9	85.8	71.9	460.6
	Impluse	83.7	94.4	96.3	91.5	73.0	90.5	94.1	85.9	532.0	66.0	86.8	92.1	81.6	52.1	77.6	85.7	71.8	460.3
	Speckle	90.1	98.1	99.1	95.8	78.8	94.6	97.2	90.2	557.8	69.9	89.3	94.1	84.4	54.7	80.1	87.6	74.1	475.8
Blur	Defocus	82.6	94.0	96.5	91.1	71.8	90.2	93.6	85.2	528.8	62.6	84.1	90.1	79.0	50.6	75.7	83.9	70.1	447.1
	Glass	93.8	99.2	99.7	97.6	82.3	96.3	97.9	92.1	569.2	75.1	92.1	96.2	87.8	58.1	82.2	89.2	76.5	493.0
	Motion	80.0	92.0	94.2	88.7	69.3	88.2	92.3	83.3	516.0	61.6	82.4	87.9	77.3	49.3	73.8	81.5	68.2	436.5
	Zoom	56.0	73.8	79.4	69.7	52.6	73.8	80.4	69.0	416.1	29.4	51.1	60.2	46.9	29.2	51.3	60.9	47.1	282.2
Weather	Snow	81.7	94.4	96.8	91.0	73.2	91.2	94.7	86.4	532.0	51.3	76.8	84.8	71.0	44.9	71.0	79.9	65.3	408.8
	Frost	90.4	97.5	98.8	95.5	79.5	94.7	97.2	90.5	558.1	62.1	84.7	90.7	79.2	51.0	76.7	84.6	70.8	449.8
	Fog	90.2	98.1	99.1	95.8	80.5	95.1	97.4	91.0	560.4	68.3	89.1	94.2	83.9	54.6	79.6	86.9	73.7	472.6
	Brightness	94.5	99.4	99.7	97.8	83.7	96.6	98.2	92.8	572.0	74.6	92.7	96.2	87.8	58.1	82.7	89.5	76.8	493.8
Digital	Contrast	88.2	96.7	97.9	94.3	78.3	93.4	96.0	89.2	550.6	63.8	85.0	90.8	79.9	51.7	76.5	84.3	70.8	452.1
	Elastic	85.3	94.7	96.5	92.2	75.3	91.8	95.1	87.4	538.7	65.7	85.6	91.1	80.8	51.7	76.5	84.4	70.9	455.0
	Pixelate	63.8	78.2	82.4	74.8	55.4	75.3	80.7	70.5	435.9	45.9	65.7	72.7	61.4	36.3	58.9	67.5	54.2	347.0
	JPEG	91.7	98.2	99.1	96.3	79.1	94.6	97.1	90.3	559.8	71.7	91.1	95.4	86.1	55.3	80.0	87.4	74.2	480.9
Stylize	Stylized	70.0	83.7	86.9	80.2	60.0	79.0	84.5	74.5	464.1	50.6	71.9	78.6	67.0	40.3	63.2	71.7	58.4	376.4

Table 23: TCL image perturbation performance comparison of Zero-Shot (ZS) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	69.3	86.8	90.4	82.2	55.2	78.4	84.8	72.8	464.9	57.9	80.2	87.0	75.0	44.2	70.6	79.9	64.9	419.8
	Shot	70.1	87.0	91.2	82.8	55.5	78.4	84.7	72.9	467.0	57.2	79.9	86.9	74.7	44.0	70.5	79.9	64.8	418.4
	Impluse	67.3	85.9	90.3	81.2	53.7	77.4	83.8	71.6	458.4	57.2	80.2	87.0	74.8	43.8	70.4	79.8	64.7	418.4
	Speckle	78.1	92.9	96.4	89.1	60.3	82.3	88.2	76.9	498.0	62.0	84.2	90.5	78.9	46.7	73.3	82.4	67.5	439.0
Blur	Defocus	60.0	82.0	87.3	76.4	50.2	71.6	78.7	66.9	429.8	54.7	79.1	86.5	73.4	39.9	65.2	74.6	59.9	400.0
	Glass	78.2	94.0	97.2	89.8	63.8	84.1	89.4	79.1	506.6	66.7	88.7	94.7	83.4	46.5	72.6	81.6	66.9	450.8
	Motion	51.2	72.9	80.5	68.2	43.8	66.0	74.1	61.3	388.5	47.6	72.3	80.7	66.9	33.5	57.0	66.4	52.3	357.5
	Zoom	25.0	44.5	53.5	41.0	27.5	45.9	54.9	42.8	251.3	16.7	33.5	42.7	31.0	15.3	30.5	38.7	28.1	177.3
Weather	Snow	51.7	75.4	83.3	70.1	47.6	70.5	78.8	65.7	407.3	37.1	63.8	74.7	58.5	28.5	51.2	61.2	47.0	316.5
	Frost	62.8	85.5	91.3	79.9	52.0	75.2	82.8	70.0	449.5	48.9	75.1	83.9	69.3	34.5	59.7	69.8	54.7	372.0
	Fog	59.0	81.7	89.2	76.6	49.5	73.2	81.6	68.1	434.2	55.7	81.3	89.1	75.4	38.1	63.3	73.1	58.2	400.6
	Brightness	82.4	96.2	98.6	92.4	61.3	82.5	88.1	77.3	509.1	66.8	88.7	94.3	83.3	47.1	73.3	82.0	67.5	452.2
Digital	Contrast	69.8	89.9	94.0	84.6	56.3	78.3	85.0	73.2	473.2	58.5	82.9	89.7	77.0	41.2	67.2	76.6	61.7	416.1
	Elastic	62.4	80.6	85.9	76.3	52.0	73.3	80.3	68.5	434.4	50.6	73.3	80.7	68.2	35.6	59.6	69.2	54.8	369.0
	Pixelate	30.4	46.4	53.3	43.4	25.8	42.2	49.1	39.0	247.2	21.2	36.4	43.3	33.7	17.4	32.4	39.5	29.8	190.3
	JPEG	78.2	93.8	96.6	89.5	61.2	83.4	89.0	77.9	502.2	63.1	86.0	92.0	80.3	46.5	73.1	82.1	67.2	442.7
Stylize	Stylized	44.2	64.8	71.2	60.1	38.4	58.5	66.2	54.4	343.4	33.7	55.0	63.7	50.8	26.3	46.4	55.0	42.6	280.1

Table 24: TCL image perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Noise	Gaussian	83.1	94.3	96.7	91.4	71.4	90.3	94.1	85.3	529.9	64.8	85.8	91.3	80.6	50.8	76.6	84.9	70.8	454.3
	Shot	83.3	95.1	97.1	91.8	71.9	90.7	94.5	85.7	532.6	64.8	85.7	91.3	80.6	50.7	76.8	85.1	70.9	454.4
	Impluse	82.9	94.1	96.5	91.1	70.6	89.9	93.8	84.8	527.7	64.4	85.7	91.5	80.5	50.6	76.7	85.0	70.8	453.9
	Speckle	88.8	97.8	98.7	95.1	76.3	93.5	96.5	88.8	551.6	67.9	88.1	93.4	83.2	53.0	78.8	86.8	72.9	468.1
Blur	Defocus	77.0	90.6	93.5	87.1	66.6	86.1	90.7	81.1	504.5	62.8	84.6	90.7	79.4	50.1	75.8	83.8	69.9	447.8
	Glass	92.7	99.1	99.7	97.2	81.2	95.6	97.7	91.5	566.0	74.1	92.4	96.3	87.6	57.7	82.3	89.2	76.4	491.9
	Motion	78.9	92.2	94.9	88.7	68.1	87.6	92.2	82.6	513.9	60.5	81.9	87.8	76.7	48.4	73.4	81.7	67.8	433.8
	Zoom	51.8	70.5	76.4	66.2	48.4	71.3	78.9	66.2	397.3	24.5	45.2	54.6	41.5	27.2	49.3	59.1	45.2	259.9
Weather	Snow	78.8	93.3	95.9	89.3	70.0	89.9	93.8	84.6	521.7	51.5	76.4	84.7	70.9	44.6	71.2	80.5	65.4	408.9
	Frost	88.1	97.5	98.6	94.7	76.6	93.7	96.5	88.9	551.0	61.2	83.1	89.5	77.9	49.6	75.6	84.1	69.8	443.2
	Fog	88.1	98.0	99.1	95.1	77.9	94.2	96.7	89.6	554.1	67.7	88.3	93.5	83.2	53.9	79.5	87.3	73.5	470.1
	Brightness	93.7	99.0	99.6	97.4	81.9	95.9	97.9	91.9	568.0	73.4	91.6	95.9	87.0	57.1	82.0	89.1	76.1	489.1
Digital	Contrast	90.0	97.8	99.2	95.7	78.5	94.5	97.1	90.0	557.1	67.4	87.8	93.2	82.8	53.6	79.1	86.7	73.1	467.8
	Elastic	81.3	92.4	94.7	89.5	72.1	90.1	93.8	85.3	524.4	61.3	82.4	88.4	77.4	48.9	74.4	82.8	68.7	438.2
	Pixelate	50.1	66.2	72.0	62.8	45.7	65.4	72.5	61.2	372.0	37.7	57.1	65.0	53.3	32.0	54.1	63.1	49.8	309.1
	JPEG	90.2	98.3	99.3	95.9	77.1	93.9	96.7	89.2	555.4	69.9	89.3	94.3	84.5	54.1	79.8	87.4	73.8	474.9
Stylize	Stylized	65.0	80.7	85.0	76.9	57.4	77.5	83.2	72.7	448.7	45.3	67.5	75.3	62.7	38.8	62.6	71.3	57.6	360.9

Table 25: ViLT text perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	55.6	82.9	89.3	75.9	31.8	57.7	68.0	52.5	385.3	40.3	69.6	79.9	63.3	23.1	47.3	59.0	43.1	319.2
	Ocr	71.1	92.0	96.1	86.4	45.8	74.1	82.8	67.6	462.0	51.9	80.1	88.5	73.5	32.5	60.8	72.5	55.2	386.2
	CI	55.3	83.2	90.1	76.2	31.9	58.5	68.9	53.1	388.0	41.1	70.8	81.4	64.4	24.0	48.9	60.8	44.6	327.0
	CR	55.7	82.5	90.1	76.1	31.8	57.7	68.3	52.6	386.2	40.8	69.8	80.5	63.7	23.5	47.7	59.4	43.5	321.7
	CS	57.6	83.8	90.7	77.4	33.7	59.8	70.0	54.5	395.6	42.3	72.2	82.0	65.5	24.9	49.9	61.7	45.5	333.1
	CD	57.3	84.0	90.8	77.4	34.6	60.9	71.0	55.5	398.6	42.3	71.9	82.3	65.5	25.1	50.3	62.3	45.9	334.1
Word	SR	71.0	92.4	96.1	86.5	48.9	77.4	86.0	70.8	471.9	52.8	80.9	88.9	74.2	35.2	64.3	75.7	58.4	397.8
	WI	75.0	94.0	97.3	88.8	53.9	82.4	89.5	75.3	492.2	56.5	83.4	90.9	76.9	38.6	68.4	79.7	62.2	417.5
	WS	71.6	93.0	96.8	87.1	50.4	80.2	88.1	72.9	480.1	53.7	81.4	89.5	74.9	35.8	66.0	78.0	60.0	404.4
	WD	74.3	93.9	97.3	88.5	53.0	82.0	89.3	74.8	489.8	55.6	82.5	90.3	76.2	37.8	68.0	79.4	61.7	413.6
	IP	79.5	95.7	98.0	91.1	58.1	85.0	91.3	78.1	507.7	59.9	85.4	92.0	79.1	41.8	71.6	82.3	65.2	433.1
Sentence	Formal	79.5	95.7	98.6	91.3	59.2	85.6	91.5	78.8	510.1	61.1	85.8	92.2	79.7	42.6	72.2	82.6	65.8	436.5
	Casual	78.1	95.5	97.8	90.5	57.3	84.9	90.9	77.7	504.5	60.0	85.5	91.7	79.1	42.2	71.9	82.4	65.5	433.6
	Passive	74.0	94.6	97.4	88.7	53.2	80.8	88.1	74.0	488.1	57.9	84.4	91.4	77.9	40.0	69.3	80.2	63.2	423.2
	Active	78.5	95.1	98.3	90.6	58.6	85.7	92.1	78.8	508.3	60.9	85.9	92.2	79.7	42.9	72.3	82.9	66.0	437.1
	Back_trans	78.0	94.8	98.0	90.3	56.1	83.0	90.2	76.4	500.1	59.1	84.4	91.3	78.3	40.5	69.9	80.7	63.7	426.0

Table 26: CLIP text perturbation performance comparison of Zero-Shot (ZS) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	62.4	86.9	93.1	80.8	43.5	68.8	77.0	63.1	431.8	36.8	62.1	72.8	57.2	21.0	41.2	51.6	37.9	285.5
	Ocr	73.4	93.2	96.7	87.8	52.9	77.3	84.6	71.6	478.2	37.2	62.2	72.6	57.4	21.1	41.5	51.8	38.1	286.4
	CI	66.4	89.6	94.7	83.6	47.3	72.3	80.2	66.6	450.5	37.0	62.1	72.8	57.3	21.2	41.4	51.6	38.1	286.1
	CR	63.0	88.4	93.8	81.7	44.1	68.7	77.2	63.3	435.2	36.6	62.1	72.7	57.1	21.0	41.4	51.7	38.0	285.4
	CS	65.5	89.3	94.9	83.2	45.7	70.4	78.7	65.0	444.6	36.5	62.2	72.6	57.1	21.1	41.4	51.8	38.1	285.6
	CD	66.3	90.4	95.4	84.0	47.2	71.9	80.1	66.4	451.3	36.6	62.2	73.0	57.3	21.1	41.4	51.6	38.0	285.8
Word	SR	76.0	95.1	98.0	89.7	58.0	81.7	88.2	76.0	497.1	47.0	72.8	81.8	67.2	29.2	53.0	63.6	48.6	347.5
	WI	78.3	95.7	98.3	90.8	61.6	84.9	90.9	79.1	509.6	49.9	74.9	83.5	69.4	32.1	56.5	66.9	51.8	363.8
	WS	77.2	95.1	98.0	90.1	59.7	83.6	89.8	77.7	503.3	48.9	73.6	82.3	68.3	30.6	54.7	65.3	50.2	355.5
	WD	80.9	96.8	98.5	92.1	61.4	85.4	91.1	79.3	514.1	51.7	76.4	84.6	70.9	32.3	56.5	67.1	51.9	368.6
	IP	81.8	97.1	98.8	92.6	63.8	86.1	91.6	80.5	519.4	52.4	76.6	84.5	71.2	34.1	58.2	68.4	53.6	374.2
Sentence	Formal	86.4	98.6	99.1	94.7	66.0	88.5	93.1	82.5	531.7	56.8	80.4	87.7	75.0	36.4	60.9	70.8	56.0	393.0
	Casual	84.9	97.9	99.2	94.0	66.1	88.4	92.8	82.4	529.3	57.1	79.6	87.7	74.8	35.9	60.6	70.7	55.7	391.6
	Passive	84.3	96.9	99.2	93.5	64.8	87.3	92.2	81.5	524.8	54.3	77.8	86.1	72.7	34.1	58.4	68.9	53.8	379.6
	Active	85.6	97.9	99.2	94.2	66.9	88.8	93.1	82.9	531.4	57.5	80.3	87.9	75.2	36.1	60.8	70.9	55.9	393.5
	Back_trans	83.9	97.0	98.5	93.1	65.5	87.2	92.2	81.6	524.2	55.1	78.2	85.7	73.0	34.3	58.9	69.1	54.1	381.2

Table 27: CLIP text perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	67.0	91.2	96.2	84.8	48.3	74.0	81.6	68.0	458.4	36.8	66.1	78.1	60.3	24.3	49.4	61.3	45.0	316.1
	Ocr	76.2	95.4	98.4	90.0	58.5	83.3	89.1	77.0	500.9	36.8	66.3	77.9	60.4	24.4	49.7	61.5	45.2	316.7
	CI	71.4	93.3	96.8	87.2	53.2	78.1	84.8	72.0	477.6	36.3	66.6	78.2	60.4	24.4	49.6	61.4	45.1	316.5
	CR	68.9	91.7	96.1	85.6	48.7	74.5	81.7	68.3	461.6	36.5	66.3	78.1	60.3	24.3	49.7	61.5	45.2	316.4
	CS	70.7	92.4	96.6	86.6	51.0	76.6	83.7	70.4	471.1	36.5	66.5	78.2	60.4	24.4	49.6	61.4	45.1	316.7
	CD	70.9	93.3	97.2	87.2	52.1	77.5	84.5	71.3	475.5	36.7	66.1	77.9	60.3	24.2	49.5	61.3	45.0	315.6
Word	SR	78.0	96.4	98.5	91.0	63.4	87.2	92.0	80.9	515.4	45.3	75.0	85.1	68.5	33.8	62.7	74.3	56.9	376.2
	WI	81.0	97.0	99.0	92.3	68.3	90.4	94.7	84.4	530.4	48.4	77.3	86.8	70.8	37.3	66.8	78.1	60.7	394.6
	WS	80.8	97.0	99.0	92.2	66.1	89.3	93.9	83.1	526.0	48.0	77.1	86.7	70.6	35.9	65.3	76.9	59.4	389.9
	WD	81.0	97.4	99.1	92.5	67.9	90.7	95.0	84.5	531.1	49.1	77.7	86.8	71.2	37.1	66.7	78.0	60.6	395.3
	IP	83.0	97.9	99.2	93.4	69.9	91.2	95.1	85.4	536.4	51.5	79.5	88.1	73.0	39.1	68.7	79.6	62.5	406.6
Sentence	Formal	85.2	98.4	99.5	94.4	73.3	92.9	96.4	87.6	545.8	53.5	81.0	88.9	74.5	41.7	70.8	81.3	64.6	417.3
	Casual	83.9	97.6	99.4	93.6	72.5	92.3	96.4	87.1	542.1	52.5	80.6	89.0	74.0	41.4	70.4	81.2	64.4	415.2
	Passive	82.9	97.7	99.1	93.2	71.3	91.3	95.6	86.1	537.9	51.9	80.0	88.3	73.4	39.6	68.9	80.0	62.8	408.7
	Active	85.0	97.6	99.4	94.0	73.5	92.9	96.6	87.7	545.1	54.1	81.4	89.0	74.8	42.2	71.1	81.7	65.0	419.4
	Back_trans	83.8	97.7	99.0	93.5	70.4	91.2	95.2	85.6	537.3	51.4	79.1	88.2	72.9	39.6	68.5	79.5	62.5	406.2

Table 28: BLIP text perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	84.5	97.3	98.9	93.6	63.8	84.1	89.4	79.1	518.0	64.1	86.4	91.9	80.8	42.7	67.5	76.6	62.2	429.1
	Ocr	93.6	99.5	99.8	97.6	77.5	93.1	96.0	88.9	559.5	74.3	92.2	96.0	87.5	53.6	77.7	85.3	72.2	479.1
	CI	86.6	98.0	99.3	94.7	66.3	86.1	90.9	81.1	527.3	66.7	88.1	93.4	82.7	45.0	70.2	79.0	64.7	442.4
	CR	84.6	97.5	99.0	93.7	63.9	83.8	89.2	79.0	518.0	64.5	86.7	92.1	81.1	42.9	67.7	76.9	62.5	430.8
	CS	87.4	97.9	99.3	94.9	65.9	85.4	90.5	80.6	526.4	67.0	88.1	93.2	82.8	44.6	69.7	78.6	64.3	441.3
	CD	86.8	97.7	99.2	94.6	65.9	85.7	90.4	80.7	525.7	67.0	88.1	93.3	82.8	44.8	69.7	78.6	64.4	441.4
Word	SR	93.8	99.6	99.9	97.8	80.6	94.7	97.0	90.7	565.6	74.2	92.4	96.1	87.6	55.5	79.5	86.7	73.9	484.3
	WI	96.0	99.8	99.9	98.6	85.0	96.9	98.5	93.4	576.1	78.1	94.0	97.1	89.7	60.1	83.2	89.6	77.6	502.1
	WS	94.8	99.6	100.0	98.1	83.6	96.5	98.4	92.8	572.9	75.9	93.2	96.6	88.6	58.1	82.0	88.9	76.3	494.6
	WD	95.1	99.8	100.0	98.3	83.8	96.7	98.5	93.0	573.8	77.3	93.9	97.0	89.4	59.2	82.7	89.5	77.1	499.7
	IP	97.3	99.9	100.0	99.0	87.2	97.5	98.9	94.5	580.7	81.8	95.4	97.8	91.7	63.9	85.6	91.3	80.3	515.8
Sentence	Formal	96.5	99.9	100.0	98.8	86.7	97.1	98.8	94.2	579.0	81.7	95.2	97.6	91.5	63.5	85.3	91.2	80.0	514.4
	Casual	96.8	100.0	100.0	98.9	86.0	97.1	98.7	93.9	578.6	81.3	95.0	97.7	91.3	63.4	85.1	91.1	79.8	513.6
	Passive	96.8	99.8	99.9	98.8	83.3	96.5	98.2	92.7	574.5	80.5	94.7	97.3	90.8	61.7	83.8	90.2	78.6	508.1
	Active	97.1	99.9	100.0	99.0	86.6	97.2	98.7	94.2	579.6	81.6	95.2	97.7	91.5	64.0	85.5	91.3	80.3	515.4
	Back_trans	96.0	99.9	100.0	98.6	84.5	96.1	98.2	92.9	574.7	79.9	94.2	97.0	90.4	61.0	82.9	89.3	77.8	504.3

Table 29: ALBEF text perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	82.1	96.0	98.5	92.2	59.7	82.1	87.7	76.5	506.2	57.9	82.6	89.6	76.7	38.0	63.4	73.0	58.1	404.5
	Ocr	91.3	99.2	99.6	96.7	74.6	92.1	95.1	87.3	552.0	69.3	89.9	94.8	84.7	49.5	74.9	83.3	69.2	461.7
	CI	84.4	97.2	98.6	93.4	62.5	84.2	89.2	78.6	516.2	60.8	84.7	91.0	78.8	40.6	66.2	75.6	60.8	418.9
	CR	82.1	95.9	98.4	92.1	59.9	81.6	87.2	76.2	505.0	58.3	82.9	89.9	77.0	38.3	63.6	73.1	58.3	406.1
	CS	82.9	96.8	98.8	92.8	61.6	83.2	88.4	77.7	511.7	59.9	84.1	90.8	78.3	39.8	65.3	74.8	60.0	414.7
	CD	83.6	96.7	98.5	92.9	61.9	83.6	88.7	78.1	513.0	60.0	84.1	90.8	78.3	39.9	65.7	75.1	60.2	415.5
Word	SR	92.9	99.2	99.8	97.3	78.7	94.5	96.8	90.0	561.9	70.1	90.6	95.1	85.3	52.4	77.7	85.5	71.9	471.4
	WI	94.3	99.6	99.9	97.9	82.9	96.6	98.3	92.6	571.6	73.2	92.4	96.3	87.3	56.8	81.6	88.7	75.7	488.9
	WS	93.3	99.4	99.9	97.6	81.5	96.3	98.1	92.0	568.6	72.0	91.8	96.1	86.6	55.1	80.6	88.2	74.6	483.7
	WD	93.4	99.5	99.9	97.6	82.2	96.5	98.3	92.4	570.0	72.9	92.1	96.1	87.0	55.7	81.1	88.5	75.1	486.3
	IP	95.9	99.8	100.0	98.6	85.5	97.5	98.9	94.0	577.7	77.6	94.3	97.2	89.7	60.7	84.3	90.5	78.5	504.5
Sentence	Formal	95.4	99.7	99.9	98.3	85.2	97.3	98.7	93.7	576.2	77.6	94.1	97.0	89.6	60.2	83.9	90.3	78.1	503.1
	Casual	95.1	99.7	100.0	98.3	84.6	97.1	98.5	93.4	575.0	77.1	94.1	97.4	89.5	59.7	83.6	90.1	77.8	502.0
	Passive	94.6	99.4	100.0	98.0	81.5	96.1	98.0	91.8	569.5	76.1	93.4	96.7	88.7	58.4	82.6	89.2	76.7	496.4
	Active	95.6	99.8	100.0	98.5	85.0	97.3	98.7	93.7	576.4	77.5	94.2	97.1	89.6	60.4	84.2	90.3	78.3	503.7
	Back_trans	95.9	99.7	99.9	98.5	83.0	96.1	98.0	92.3	572.5	75.2	93.0	96.4	88.2	57.4	81.0	88.3	75.6	491.3

Table 30: TCL text perturbation performance comparison of Zero-Shot (ZS) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	63.8	87.2	92.7	81.2	44.1	68.8	76.7	63.2	433.3	49.6	76.1	84.9	70.2	32.3	57.2	67.8	52.4	368.0
	Ocr	78.2	94.8	97.9	90.3	58.8	82.1	88.1	76.3	499.9	61.4	85.1	91.6	79.4	42.6	69.0	78.7	63.4	428.4
	CI	67.3	88.0	93.4	82.9	45.9	70.5	78.3	64.9	443.3	51.9	78.5	86.7	72.4	34.1	59.8	70.3	54.7	381.3
	CR	63.1	85.9	91.4	80.1	43.8	68.1	76.1	62.7	428.4	49.7	76.1	85.1	70.3	32.2	57.4	67.9	52.5	368.4
	CS	66.5	88.6	93.8	83.0	46.3	70.8	78.5	65.2	444.4	52.6	78.5	87.0	72.7	34.0	59.7	70.1	54.6	382.0
	CD	66.7	89.4	94.2	83.4	47.2	71.9	79.4	66.2	448.9	52.6	78.8	86.9	72.8	34.3	60.2	70.6	55.0	383.4
Word	SR	78.3	95.3	97.9	90.5	63.2	86.0	91.1	80.1	511.9	62.1	85.7	91.9	79.9	45.8	72.3	81.5	66.5	439.3
	WI	80.0	96.3	98.5	91.6	67.0	88.6	93.4	83.0	523.8	63.3	86.8	93.0	81.0	49.5	76.1	84.7	70.1	453.4
	WS	80.4	95.9	98.4	91.6	64.8	87.2	92.4	81.5	519.1	63.2	86.5	92.7	80.8	46.5	73.8	83.0	67.8	445.7
	WD	83.6	97.1	98.8	93.1	67.0	89.0	93.4	83.1	528.8	65.3	87.2	93.1	81.9	47.6	74.4	83.3	68.4	450.9
	IP	89.4	98.6	99.6	95.9	73.4	92.2	95.5	87.0	548.6	71.4	90.8	95.4	85.9	53.5	79.0	87.1	73.2	477.2
Sentence	Formal	88.0	98.0	99.8	95.3	72.0	91.6	95.1	86.2	544.4	70.8	90.6	95.2	85.5	52.9	78.4	86.5	72.6	474.4
	Casual	87.2	98.3	99.5	95.0	71.4	91.2	94.8	85.8	542.4	69.9	90.2	94.9	85.0	52.3	78.1	86.4	72.3	471.8
	Passive	84.5	97.1	99.4	93.7	67.6	88.6	92.9	83.0	530.1	68.6	89.1	94.4	84.0	50.5	76.9	85.2	70.9	464.7
	Active	89.3	98.3	99.9	95.8	72.9	91.5	95.1	86.5	547.1	70.9	90.6	95.3	85.6	53.1	78.9	86.9	73.0	475.7
	Back_trans	86.0	97.6	99.4	94.3	69.4	89.8	93.6	84.3	535.8	68.5	89.2	94.2	83.9	50.3	75.9	84.1	70.1	462.0

Table 31: TCL text perturbation performance comparison of Fine-tuned (FT) image-text retrieval on Flickr30K and COCO datasets (results are averaged on five perturbation levels).

	Method	Flickr30K (1K)									MSCOCO (5K)								
		Text Retrieval				Image Retrieval					Text Retrieval				Image Retrieval				
		R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM	R@1	R@5	R@10	Mean	R@1	R@5	R@10	Mean	RSUM
Character	Keyboard	79.7	95.2	97.9	90.9	57.0	79.1	85.4	73.8	494.3	55.8	81.3	88.8	75.3	36.9	62.5	72.4	57.3	397.8
	Ocr	90.0	99.1	99.7	96.3	71.7	90.4	94.0	85.4	545.0	67.6	88.9	94.0	83.5	48.0	73.9	82.6	68.2	455.1
	CI	82.2	96.2	98.3	92.2	59.6	81.4	87.2	76.1	504.9	58.5	83.5	90.4	77.5	39.3	65.3	75.0	59.8	412.0
	CR	79.3	94.8	97.8	90.7	56.7	79.1	85.0	73.6	492.8	55.6	81.5	89.0	75.4	37.2	62.7	72.5	57.5	398.5
	CS	80.7	96.0	98.2	91.6	59.0	81.2	86.8	75.7	501.9	57.6	82.9	90.2	76.9	38.7	64.8	74.6	59.4	408.8
	CD	81.4	95.7	98.3	91.8	59.1	81.2	86.7	75.7	502.4	58.1	83.0	90.0	77.0	39.2	65.3	75.0	59.8	410.5
Word	SR	91.0	99.1	99.7	96.6	76.1	93.0	95.8	88.3	554.7	67.8	89.1	94.2	83.7	51.0	76.8	84.8	70.8	463.7
	WI	93.4	99.4	99.8	97.5	80.5	95.5	97.7	91.2	566.4	70.8	91.0	95.6	85.8	55.3	80.6	88.0	74.6	481.3
	WS	91.0	99.1	99.6	96.6	78.2	94.7	97.4	90.1	560.0	69.2	90.3	94.9	84.8	52.3	78.5	86.6	72.5	471.8
	WD	92.6	99.4	99.8	97.3	79.5	95.3	97.6	90.8	564.2	70.8	90.7	95.5	85.7	53.7	79.7	87.3	73.6	477.7
	IP	94.9	99.5	99.8	98.1	84.0	96.7	98.5	93.1	573.4	75.6	92.8	96.7	88.3	59.0	83.2	89.9	77.3	497.1
Sentence	Formal	94.4	99.4	99.8	97.9	83.2	96.5	98.3	92.6	571.5	75.3	92.4	96.7	88.1	58.2	82.7	89.5	76.8	494.6
	Casual	94.0	99.5	99.9	97.8	82.1	96.0	98.0	92.1	569.6	74.6	92.1	96.5	87.8	57.9	82.5	89.4	76.6	493.0
	Passive	92.7	99.1	99.8	97.2	79.5	94.5	97.1	90.4	562.8	73.5	91.9	96.1	87.2	56.3	81.3	88.3	75.3	487.3
	Active	94.8	99.5	99.8	98.0	83.5	96.4	98.2	92.7	572.1	75.4	92.7	96.6	88.2	58.7	83.0	89.7	77.1	496.0
	Back_trans	93.9	99.5	99.9	97.8	80.6	95.3	97.3	91.1	566.5	72.7	91.6	96.0	86.8	55.5	80.3	87.3	74.4	483.5

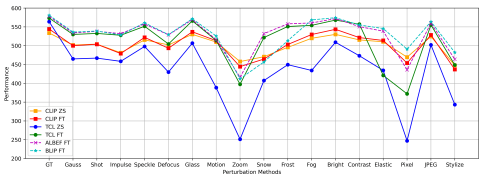

Figure 21: Image-text retrieval results on Flick30K-IP.

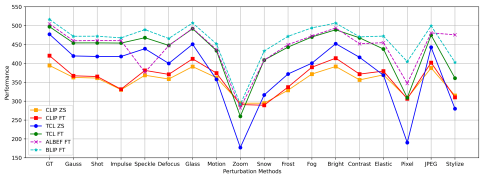

Figure 22: Image-text retrieval results on COCO-IP.

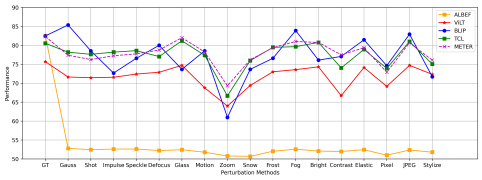

Figure 23: Visual reasoning results on NLVR-IP dev set.

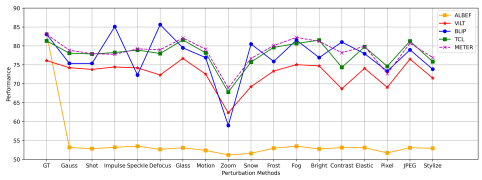

Figure 24: Visual reasoning results on NLVR-IP test set.

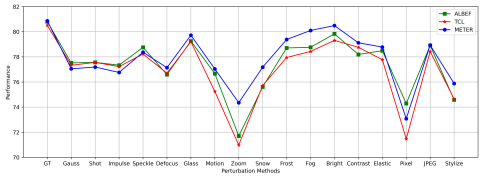

Figure 25: Visual entailment results on SNLI-VE-IP val set.

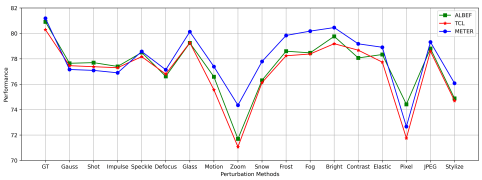

Figure 26: Visual entailment results on SNLI-VE-IP test set.

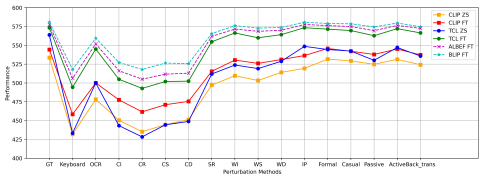

Figure 27: Image-text retrieval results on Flick30K-TP.

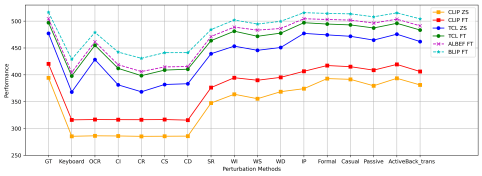

Figure 28: Image-text retrieval results on COCO-TP.

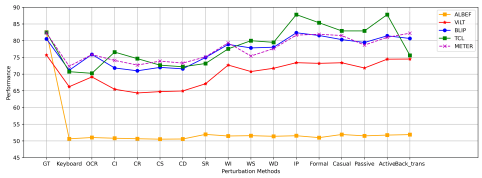

Figure 29: Visual reasoning results on NLVR-TP dev set.

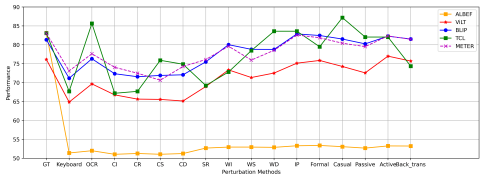

Figure 30: Visual reasoning results on NLVR-TP test set.

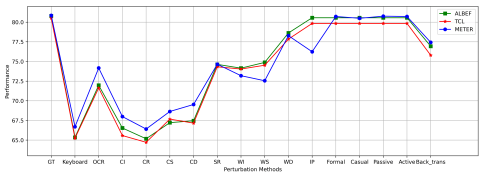

Figure 31: Visual entailment results on SNLI-VE-TP val set.

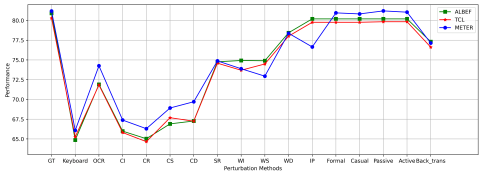

Figure 32: Visual entailment results on SNLI-VE-TP test set.