Making LVLMs Look Twice: Contrastive Decoding with Contrast Images

Anonymous ACL submission

Abstract

Large Vision-Language Models (LVLMs) are becoming increasingly popular for text-vision tasks requiring cross-modal reasoning, but often struggle with fine-grained visual discrimination. This limitation is evident in recent benchmarks like NaturalBench and D3, where closed models such as GPT-4o achieve only 39.6%, and open-source models perform below random chance (25%). We introduce Contrastive decoding with Contrast Images (CoCI), which adjusts LVLM outputs by contrasting them against outputs for similar images (Contrast Images - CIs). CoCI demonstrates strong performance across three distinct supervision regimes: First, when using naturally occurring CIs in benchmarks with curated image pairs, we achieve improvements of up to 98.9% on NaturalBench, 69.5% on D3, and 37.6% on MMVP. Second, for scenarios with modest training data (∼5k samples), we show that a lightweight neural classifier can effectively select CIs from similar images at inference time, improving NaturalBench performance by up to 36.8%. Third, for scenarios with no training data, we develop a caption-matching technique that selects CIs by comparing LVLM-generated descriptions of candidate images. Notably, on VQAv2, our method improves VQA performance even in pointwise evaluation settings without explicit contrast images. Our approach demonstrates the potential for enhancing LVLMs at inference time through different CI selection approaches, each suited to different data availability scenarios.

1 introduction

Large Vision-Language Models (LVLMs) are becoming increasingly popular for text-vision tasks that require reasoning over both modalities. However, they often struggle with fine-grained visual discrimination — that is, the ability to tell two similar yet distinct images apart — a crucial capability for real-world applications such as multimodal search, manufacturing, and robotics. Recent benchmarks have exposed this limitation: on NaturalBench (Li et al., 2024a), which tests visual question answering over closely related images, state-of-the-art closed models like GPT-4o (OpenAI et al., 2024) achieve only 39.6% accuracy. Similarly, on the D3 benchmark (Gaur et al., 2024), which requires describing differences between paired images, open-source models perform below random chance (25%).

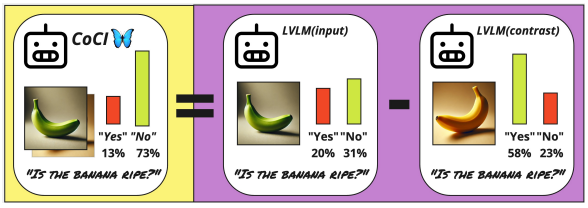

Figure 1: CoCI penalizes target image logits using those from a contrast image, weighted by hyperparameter α.

Efforts to address fine-grained visual discrimination in LVLMs are still under-explored. Current strategies addressing other LVLM shortcomings often rely on fine-tuning with specialized datasets (Wang et al., 2023; Chen et al., 2023; Liu et al., 2024a; Sarkar et al., 2024), multi-step correction pipelines (Yin et al., 2023; Zhou et al., 2023), or inference-time methods (Leng et al., 2023; Manevich and Tsarfaty, 2024; Liu et al., 2024b; Huang et al., 2023). Inference-time methods are particularly appealing as they do not require expensive model training and are less prone to compounding errors that can affect multi-step systems.

Building on the advantages of inference-time methods, we propose Contrastive decoding with Contrast Images (CoCI), an approach specifically designed to improve fine-grained visual discrimination in LVLMs. CoCI penalizes LVLM next-token probabilities with those obtained by feeding a different, contrasting image input (See Figure 1).

We evaluate CoCI across three different supervision regimes. First, using naturally occurring

Contrast Images in curated benchmarks like NaturalBench, D3 and MMVP, we demonstrate improvements up to 98.9%, 69.5%, 37.6% respectively. This establishes a performance ceiling for CoCI when ideal CIs are available. For applications where natural CIs are unavailable but training data exists, we show that a lightweight classifier can effectively select CIs from visually similar images at inference time, improving NaturalBench performance by up to 36.5%. In settings without training data, we propose a caption-matching technique that selects CIs at inference time by comparing LVLM-generated descriptions of candidate images.

Experiments with leading LVLMs — Qwen2-VL, LLaVA-OneVision, and Llama 3.2 (Wang et al., 2024a; Li et al., 2024b; Grattafiori et al., 2024) — establish the potential of contrastive decoding strategies with contrastive images for improved multimodal reasoning in real-world tasks.

2 Contrastive Decoding with Contrast Images (CoCI)

We present CoCI, a method to improve LVLM outputs by penalizing token probabilities that are likely under a contrast image. The choice of contrast image is crucial: e.g., when querying about fruit ripeness with an input image of an unripe banana, contrasting against an image of a ripe banana provides strong contrastive signal, while an image of a ripe pear offers weaker contrast and an image of a bus provides no useful signal and may degrade performance. This intuition guides our CI selection strategies across different scenarios. Before formalizing this intuition, we first review key concepts in LVLM text generation.

2.1 Preliminaries: Text Generation in LVLMs

LVLMs extend LLMs by conditioning next-token prediction on both text and images.[1] Generation proceeds by iteratively sampling tokens from the model's predicted distributions until reaching an EOS token or length limit. The LVLM next-token prediction is:

$$\text{LVLM}t(y{<}\,t, I) = P(y|y{<}\,t, I) \quad \forall y \in \mathcal{V} \quad (1)$$

where $y_{<t}$ is the token prefix, I is the input image, and $\mathcal{V}$ is the model's vocabulary.

2.2 Contrastive Decoding

Following Li et al. (2023), various Contrastive Decoding approaches have emerged (Sennrich et al., 2024; Jin et al., 2024; Phan et al., 2024). We implement CoCI based on Sennrich et al. (2024)'s minimal variant:

$$\text{CoCI}_t(y_{<t}, I, I') = \log\Big(P(y|y_{<t}, I) - \alpha P(y|y_{<t}, I')\Big) \quad \forall y \in \mathcal{V} \quad (2)$$

CoCI penalizes token probabilities from the target image distribution $P(y|y_{<t}, I)$ with those from the contrast image distribution $P(y|y_{<t}, I')$. The parameter α controls penalty strength.[2]

2.3 Obtaining Contrast Images

We propose three approaches for obtaining CIs:

Naturally occurring CIs. Many tasks naturally provide pairs of images that can serve as contrast images (CIs). For instance, a home assistant robot searching for "the blue ceramic mug with a chip on the handle" needs to distinguish between similar cups to find the exact match. We evaluate this scenario using LVLM benchmarks with curated image pairs designed to test fine-grained discrimination capabilities. These paired images serve as natural CIs in our experiments.

Classifier-obtained CIs. For cases without natural CIs, we train an MLP classifier to select them during inference. Given LVLM L and training triplets $\langle q, I, I' \rangle$ (binary question and image pairs with different answers), we: (a) Extract LVLM hidden states $h_{q,i} \in R^{d_L}$ per image-question pair. (b) Concatenate states for image pairs: $h_{q,i,i'} \in R^{2*d_L}$. (c) Create negative samples using the j least similar images from top-k similar images to I in dataset D[3]. (d) Train a three-layer MLP classifier.[4] We train on NaturalBench (60% split) augmented with GPT-4-generated question paraphrases. At inference, we select the CI maximizing classifier score among k most similar images.[5]

Caption-matched CIs. For scenarios without training data, we select CIs by comparing LVLM-generated image descriptions. Given an input image, we (a) Retrieve k similar images[6]. (b) Generate LVLM descriptions for all $k+1$ images. (c)

[1] In this work, we focus on single image inputs.

[2] We use $\alpha = 0.5$ for VQA and $\alpha = 0.8$ for open-ended generation.

[3] $j = 5, k = 100$. Using flickr30k (Young et al., 2014) and open-clip (Ilharco et al., 2021; Cherti et al., 2023; Radford et al., 2021a; Schuhmann et al., 2022) with cosine similarity.

[4] See appendix A.1 and A.3 for implementation details.

[5] See table 2 for k value comparisons. Inference uses identical retrieval setup as training.

[6] We set $k = 5$ without tuning.

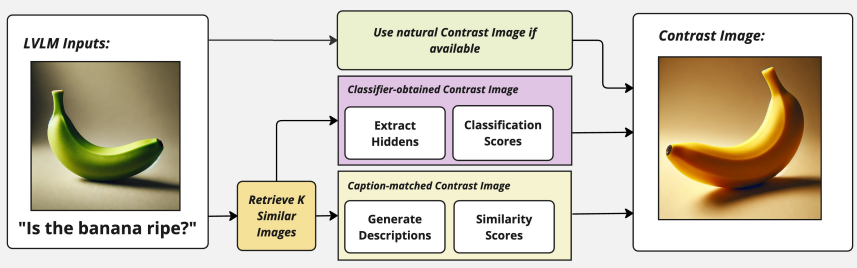

Figure 2: Illustration of the approaches we explore for obtaining a Contrast Image (CI).

Embed descriptions using a text encoder. (d) Select the image whose description is most similar to the input image's description

2.4 Research Hypothesis

We test whether: (a) Contrastive decoding with CIs improves LVLM fine-grained reasoning, (b) A lightweight classifier trained on LVLM hidden states can effectively select CIs, and (c) Images with similar LVLM descriptions can serve as CIs.

3 Experiments

We evaluate CoCI using three leading LVLMs[7] on four benchmarks, three specifically targeting fine-grained visual discrimination:

NaturalBench (Li et al., 2024a) evaluates similar image discrimination through yes/no and multiple-choice questions, with different answers for paired images. The benchmark contains 1900 image pairs (two questions per pair), split into train (60%), dev (20%), and test (20%) sets. We measure image accuracy (both questions correct), question accuracy (per-question), and group accuracy (all four image-question combinations correct).

MMVP (Multimodal Visual Patterns) (Tong et al., 2024) evaluates visual difference detection through multiple-choice questions on 150 image pairs. Each pair differs in specific visual aspects (object state, position, or orientation). Success requires correct answers for both images in a pair.

D3 (Detect, Describe, Discriminate) (Gaur et al., 2024) assesses models' ability to generate discriminative descriptions between similar images across 247 pairs. We adapt D3 for CoCI by treating it as a single-input task, generating separate descriptions per image. Evaluation follows the original self-retrieval protocol, measuring whether an image-text encoder correctly matches descriptions to their images.

[7] See appendix A.2 for details on the checkpoints we used.

Model	Method	D3 (self-ret.)	MMVP (acc.)	NB (g-acc.)	VQAv2 (acc.)
Qwen2-VL	Baseline	30.8	46.0	30.8	72.66
	CoCI_{CAP}	34.8	48.7	31.3	**74.33**
	CoCI_{NAT}	**52.2**	**63.3**	**46.6**	-
LLaVA-OV	Baseline	25.1	52.7	28.2	61.66
	CoCI_{CAP}	31.6	57.3	31.6	**73.66**
	CoCI_{NAT}	**38.1**	**66.7**	**56.1**	-
Llama 3.2	Baseline	28.7	39.3	21.1	58
	CoCI_{CAP}	33.6	41.3	22.4	58
	CoCI_{NAT}	**35.6**	**43.3**	**29.2**	-

Table 1: CoCI performance comparison with provided CIs across benchmarks, with natural CIs (CoCI_{NAT}) and caption-matched CIs (CoCI_{CAP}).

VQAv2 (Goyal et al., 2017) serves as our general-purpose visual question answering benchmark. While not focused on fine-grained discrimination, we include it to demonstrate CoCI's broader applicability. We evaluate on 300 validation set image-question pairs using exact match accuracy.

4 Results and Discussion

In Table 1 we can see that using natural CIs yields substantial improvements: up to 21.4 points on D3 (Qwen), 17.3 points on MMVP (LLaVA), and 27.9 points on NaturalBench (LLaVA). Caption-matched CIs show moderate but consistent gains, particularly on D3 where LLaVA improves from 25.1% to 31.6%, suggesting that contrasting against images with similar captions effectively guides visual discrimination. CoCI with caption matching improves performance on VQAv2 for two of the three tested models while maintaining baseline performance for Llama 3.2, demonstrating that CoCI enhances general-purpose VQA abilities beyond fine-grained visual discrimination tasks.

Throughout our experiments, Llama exhibits different behavior compared to other models - showing lower performance and reduced responsiveness

Model	Method	Q-acc	I-acc	Acc	G-acc
Qwen2-VL	Baseline	55.3	59.3	76.8	30.8
	$Cls_{k=4}$	55.5	58.8	76.4	32.1
	$Cls_{k=8}$	56.3	58.9	76.7	32.4
	$Cls_{k=16}$	57.4	60.1	77.2	33.7
	$Cls_{k=32}$	57.8	60.1	77.4	**34.2**
	$Cls_{k=64}$	**58.2**	**60.8**	**77.9**	33.9
LLaVA-OV	Baseline	53.8	56.1	74.6	28.2
	$Cls_{k=4}$	59.2	59.6	77.6	35.3
	$Cls_{k=8}$	57.8	60.1	77.5	34.5
	$Cls_{k=16}$	57.6	58.7	77.0	33.4
	$Cls_{k=32}$	**60.3**	**62.1**	**78.5**	**38.4**
	$Cls_{k=64}$	59.7	62.1	78.2	37.6
Llama 3.2	Baseline	46.3	50.5	71.8	21.1
	$Cls_{k=4}$	**49.2**	**52.8**	**73.2**	**23.2**
	$Cls_{k=8}$	49.1	52.2	73.1	21.8
	$Cls_{k=16}$	48.8	52.4	73.1	22.4
	$Cls_{k=32}$	49.9	52.5	73.7	22.1
	$Cls_{k=64}$	49.7	52.5	73.6	22.1

Table 2: CoCI accuracy metrics on the NaturalBench test set with CIs chosen using a lightweight classifier. $k = j$ denotes the classifier ran on the j most similar images to the input image.

to our methods. This pattern is evident in Table 2, where Qwen and LLaVA's performance improves with larger candidate pools (k), peaking around k=32, while Llama performs best with small pools (k=4). This behavior could be attributed to two factors: First, while the hyperparameters worked well for Qwen and LLaVA, they may not be optimal for Llama without model-specific tuning. Second, Llama's architectural differences, particularly its use of cross-attention, could lead to different behaviors in our contrastive decoding context. While exploring these architecture-specific considerations could be valuable, it is beyond the scope of this work.

In NaturalBench, G-Acc shows particularly strong improvement with natural CIs as it requires consistency across all image-question combinations. This pattern persists with classifier-selected CIs, where G-Acc improves by up to 10.2 points while other metrics show modest gains. The substantial gap between natural CIs and other methods suggests that classifier-selected and caption-matched CIs, while beneficial, don't yet capture all aspects that make natural pairs effective. [8]

5 Related Work

Inference-time methods for enhancing multimodal reasoning. Recent work has focused on hallucination reduction through confidence-based adjustments (Huo et al., 2024), semantic references (Yang et al., 2024), and contrastive decoding with perturbed inputs (Leng et al., 2023; Manevich and Tsarfaty, 2024). Our work extends these approaches to fine-grained visual discrimination.

Alignment and grounding in LVLMs. Prior work has enhanced visual-textual alignment through object-level synthesis (Wang et al., 2024b), targeted fine-tuning (Lu et al., 2024), and dataset construction (Li et al., 2024c). While these methods improve foundational capabilities, they don't directly address fine-grained discrimination.

Contrastive examples in multimodal models. CLIP (Radford et al., 2021b) established contrastive learning for modality alignment. Recent works leverage contrast pairs: (Le et al., 2023) and (Zhang et al., 2024) generate synthetic datasets using text-to-image models, while (Abbasnejad et al., 2020) and (Zhou et al., 2024) use contrastive examples to address dataset biases. Unlike these approaches requiring data generation or training, our method operates at inference time.[9]

6 Conclusion

We introduced Contrastive decoding with Contrast Images (CoCI), demonstrating its effectiveness in improving LVLMs' fine-grained visual discrimination capabilities in both VQA and long-form generation tasks. While naturally occurring contrast pairs yielded the strongest gains, both classifier-based and caption-matching approaches provide meaningful improvements without requiring dataset curation or model training. We validated the generality of our method through experiments with caption-based contrast selection, showing that CoCI does not rely on pre-curated pairs but can leverage them when available. Notably, CoCI improves performance even on tasks that don't explicitly measure fine-grained discrimination.

Our results show that contrastive decoding algorithms, when combined with strategic contrast image selection, improve LVLMs' ability to make fine-grained distinctions and their overall VQA abilities, opening new avenues for improving multimodal reasoning through inference-time techniques.

[8] See appendix A.3 for ablation tests with different CI selection strategies.

[9] Classifier-selected CIs require minimal preprocessing compared to model finetuning or dataset curation.

7 Limitations

CoCI has several limitations worth noting. While we demonstrate its effectiveness with classifier-based and caption-matching approaches, the substantial performance gap between natural and automatically selected CIs indicates significant headroom for finding more effective contrast images. We tested simple selection methods to establish the viability of the approach, leaving the exploration of more sophisticated CI selection strategies to future work. Additionally, our evaluation focuses primarily on VQA and self-retrieval protocols; exploring additional evaluation methods could reveal other aspects of how CoCI affects LVLM generations.

The method introduces additional computation at inference time, running the LVLM twice per generation step and requiring CI selection overhead. While this aligns with the growing trend of leveraging test-time compute for improved performance, the current implementation could be optimized. Future work could explore more efficient implementations of contrastive decoding and investigate fusing operations like hidden state extraction with the generation procedure to reduce computational overhead.

Our implementation uses Flickr30k as the image database for CI selection - using larger, more diverse image collections could improve performance. Alternative image retrieval models and similarity scoring methods could also enhance CI selection. Additionally, our approach does not address cases where multiple contrasts might be informative - we only use a single contrast image, while some scenarios might benefit from multiple contrasting viewpoints.

The experiments use a fixed contrastive weight (α) across tasks within each category (VQA/generation). A more nuanced approach to setting this parameter, dynamically per sample or per token, based on the specific input or task, could yield better results.

While CoCI improves visual discrimination, it could potentially amplify biases present in contrast image databases or introduce new failure modes when inappropriate contrast images are selected. These risks should be carefully evaluated before deployment in sensitive applications.

Finally, our experiments focus exclusively on English-language benchmarks. Extending CoCI to multilingual settings and investigating how contrastive decoding approaches perform across different languages represents an important direction for future research.

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A Appendix

A.1 Lightweight Classifier Implementation Details

Below is the PyTorch code of the lightweight classifier.

```
class Classifier(torch.nn.Module):
    def __init__(self, input_dim: int):
        super(Classifier, self).__init__()
        # factor of 2 due to concatentaion of target and candidate features
        self.linear1 = torch.nn.Linear(input_dim * 2, input_dim)
        self.linear2 = torch.nn.Linear(input_dim, input_dim)
        self.linear3 = torch.nn.Linear(input_dim, 1)
        self.dropout = torch.nn.Dropout(p=0.3)

    def forward(self, x) -> torch.Tensor:
        x = self.dropout(self.linear1(x))
        x = F.relu(x)
        x = self.dropout(self.linear2(x))
        x = F.relu(x)
        x = self.linear3(x)
        return x
```

We trained a classifier per tested LVLM, all with the following parameters, using the AdamW (Loshchilov and Hutter, 2019) optimizer.

```
batch_size=256
num_epochs=13
learning_rate=3e-4
weight_decay=1e-6
```

A.2 LVLM Checkpoints Tested

The following are the LVLM checkpoints we tested CoCI with:

```
Qwen/Qwen2-VL-7B-Instruct
llava-hf/llava-onevision-qwen2-7b-ov-hf
meta-llama/Llama-3.2-11B-Vision-Instruct
```

We used *laion/CLIP-ViT-L-14-DataComp.XL-s13B-b90K* as the open-clip model for both image and text encoding throughout this work.

A.3 Effect of Choosing a Contrast Image on NaturalBench Performance

Method	Setting	Q-acc	I-acc	Acc	G-acc
CoCI ablations	Baseline	51.6	55.4	75.1	25.6
	CI ←Random (out of top-5 most similar to input)	49.6	52.1	73.8	23.2
	CI ←Natural	**71.8**	**70.8**	**84.3**	**51.6**
	CI ←Most similar to input	49.7	52.5	73.6	23.9
	CI ←Most similar to Natural	60.3	60.7	78.9	35.0
	CI ←Least similar to Natural	46.7	48.9	72.6	21.8
Classifier	$k = 4$	51.7	54.3	74.5	26.6
	$k = 8$	53.0	55.4	75.3	26.6
	$k = 16$	54.3	56.8	76.1	29.2
	$k = 32$	52.2	54.6	75.1	25.8
	$k = 64$	51.8	53.9	74.7	26.3
	$k = 100$	52.1	54.1	74.8	25.5
$\text{Classifier}_{\text{+augmentations}}$	$k = 4$	52.0	54.3	74.6	27.1
	$k = 8$	52.8	55.9	75.0	27.9
	$k = 16$	54.5	57.8	76.1	29.2
	$k = 32$	54.9	58.2	75.9	30.0
	$k = 64$	54.7	57.9	76.1	30.3
	$k = 100$	54.7	58.0	76.1	30.0

Table 3: CoCI performance on the NaturalBench dev set with different CI selection methods, using Qwen2-VL. $\text{Classifier}_{\text{+augmentations}}$ indicates training data augmentation with GPT-4o paraphrased questions and standard image augmentations. Using natural CIs provides the strongest performance gains, with a 26-point improvement in group accuracy over baseline (51.6% vs 25.6%). Selecting CIs by similarity to natural CIs improves performance significantly (35.0% G-acc), while using the least similar images performs worse than baseline (21.8%), validating the importance of CI selection strategy. Random CI selection hurts performance (23.2% G-acc) even when restricted to similar images, highlighting that similarity alone is insufficient. Training with augmented data provides modest but consistent improvements across all metrics, with G-acc increasing by about 4 points compared to the non-augmented classifier. The augmented classifier also demonstrates more robust performance, maintaining consistent scores across different k values compared to the higher variance seen in the non-augmented version.

A.4 Examples of Image Pairs and Their Descriptions from D3

The following pairs of images with their respective captions are sampled from D3 results, obtained using CoCI with Natural Contrast Images and Qwen 7B.

Baseline: The image shows a person holding a banana in front of their mouth. The person is wearing a green shirt and is standing against a plain wall. The banana is positioned in such a way that it appears to be covering the person's mouth, creating a humorous or playful effect. The background is simple and uncluttered, which helps to focus attention on the person and the banana.
CoCI: The image shows a person holding a banana close to their face. The person appears to be making an exaggerated facial expression, with their eyes wide open and eyebrows raised. The background is a plain, light-colored wall.

Baseline: The image shows a person holding a banana in front of their mouth, creating the illusion of a smile. The person is wearing a green shirt and is standing against a plain wall. The banana is positioned in such a way that it covers the lower part of the person's face, mimicking a smile. The lighting in the image is even, and the background is simple and uncluttered.
CoCI: The image depicts a man with a light complexion wearing a green shirt. He is leaning against a wall, which appears to be a combination of light and dark shades, possibly indicating a corner or a wall with different sections. The man is holding a banana in his right hand, and he has placed the banana horizontally across his mouth, creating a playful expression that resembles a mustache. The banana has some dark spots on it, suggesting it is ripe. The background is relatively plain, with no visible decorations or objects, focusing the viewer's attention on the man and the banana.

Figure 3: Comparison of baseline and CoCI captions. The baseline captions are very similar and provide no information that allows to discriminate between the images, while the left CoCI caption mentions the raised eyebrows.

Baseline: The image depicts the iconic Elizabeth Tower, commonly known as Big Ben, located in London, England. The tower is a prominent example of Gothic Revival architecture and is part of the Palace of Westminster. The photograph captures the upper portion of the tower, focusing on its clock face and the ornate details of its structure.
CoCI: The image showcases a close-up view of a prominent clock tower, which is characterized by its Gothic architectural style. The tower is adorned with intricate details and features two large, circular clock faces, one on each visible side of the structure. Both clocks are encased in ornate frames, which are embellished with decorative patterns and motifs.

Baseline: The image depicts the iconic Elizabeth Tower, commonly known as Big Ben, located in London, England. The tower is a prominent example of Gothic Revival architecture and is part of the Palace of Westminster. The clock face is visible in the center of the tower, displaying the time. The clock is encased in a decorative frame with intricate designs, and the hands of the clock are clearly visible. The tower is topped with a spire and a weathervane, which adds to its historical and architectural significance. The sky in the background is clear, providing a sharp contrast to the detailed stonework of the tower.
CoCI: The image depicts the iconic clock tower known as Big Ben, located in London, England. The tower is part of the Palace of Westminster and is one of the most recognizable landmarks in the world.

Figure 4: Comparison of baseline and CoCI captions. The left CoCI caption mentions the two visible clock faces.

Baseline: The image depicts a person engaged in windsurfing, a water sport that combines elements of surfing and sailing. The individual is standing on a windsurfing board, which is partially submerged in the water. ... The individual appears to be in a standing position, holding onto the sail with both hands, indicating that they are actively maneuvering the board.
CoCI: The image depicts a person engaging in the water sport of windsurfing near a beach. The individual is wearing a black wetsuit and appears to be holding onto the sail of the windsurfing board ... The person appears to be standing in shallow water, with their upper body and arms visible above the waterline.

Baseline: The image depicts a person engaged in windsurfing, an activity that combines elements of surfing and sailing. The windsurfer is standing on a surfboard, which is partially submerged in the water ... The individual's posture suggests they are actively maneuvering the sail, likely using their body weight and the wind to control the direction and speed of the board.
CoCI: The image depicts a windsurfer riding a wave in the ocean. The windsurfer is captured from the side, showing their body leaning back as they navigate the wave ... The windsurfer is wearing dark clothing and appears to be in motion, with the water splashing around their feet as they ride the wave. ...

Figure 5: Comparison of baseline and CoCI captions. The CoCI captions describe the state of the windsurfer: standing in the shallow water vs. riding the wave.