TEXT MEETS VISION: A DEEP DIVE INTO CLIP PERFORMANCE

DATA586 Group 12
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BACKGROUND

CLIP stands for Contrastive Language–Image Pretraining. It's a powerful vision-language model developed by OpenAI. It can be instructed in natural language to predict the most relevant text snippet, given an image, without directly optimizing for the task.

Why CLIP?

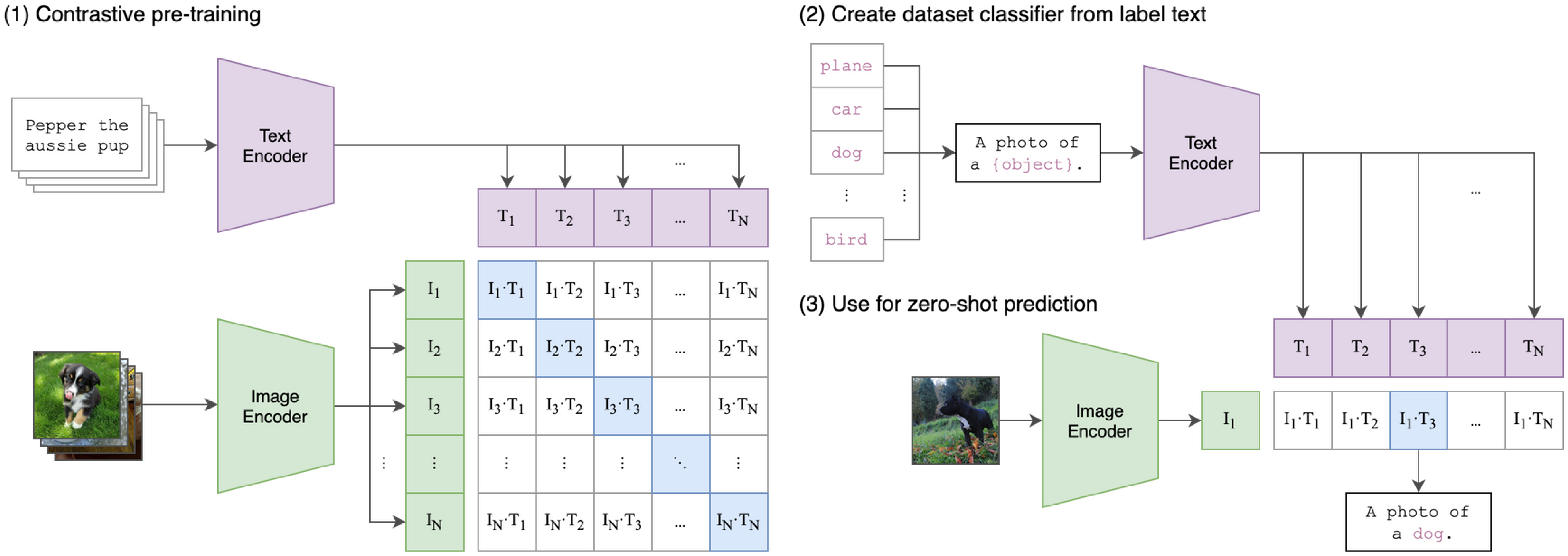
- bridging vision and language without task-specific training.
- align images and text in the same embedding space.

Project Goal

- Explore how well CLIP performs across multiple datasets
- Image-to-Text
  - Compare zero-shot **VS** linear probe **VS** Openclip
  - ResNET50 **VS** VIT32 **VS** VIT16
- Text-to-Image
  - prompt style change？
  - Subject noun change？
  - Descriptive adj. change?

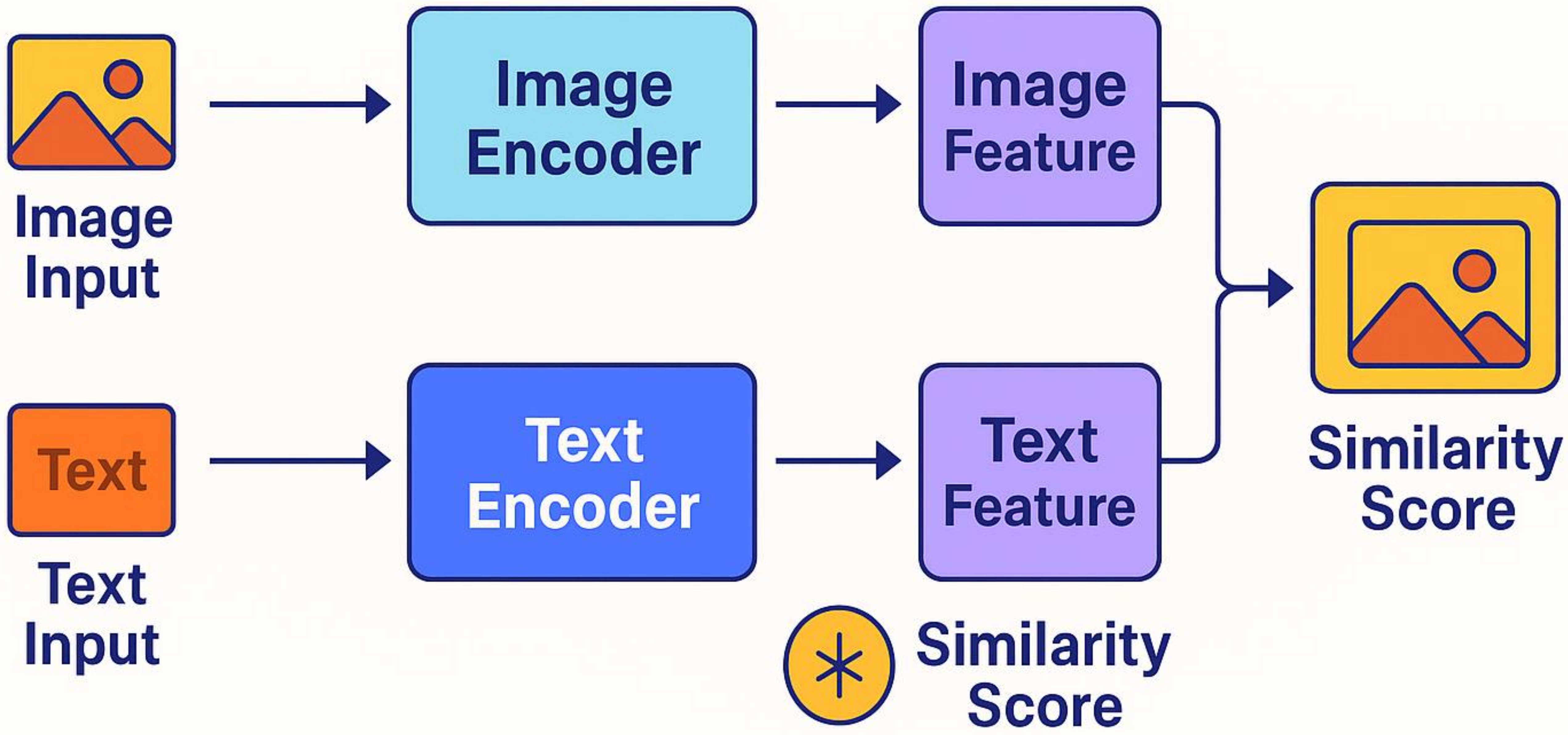
MODEL ARCHITECTURE

“A Vision + Language Model”



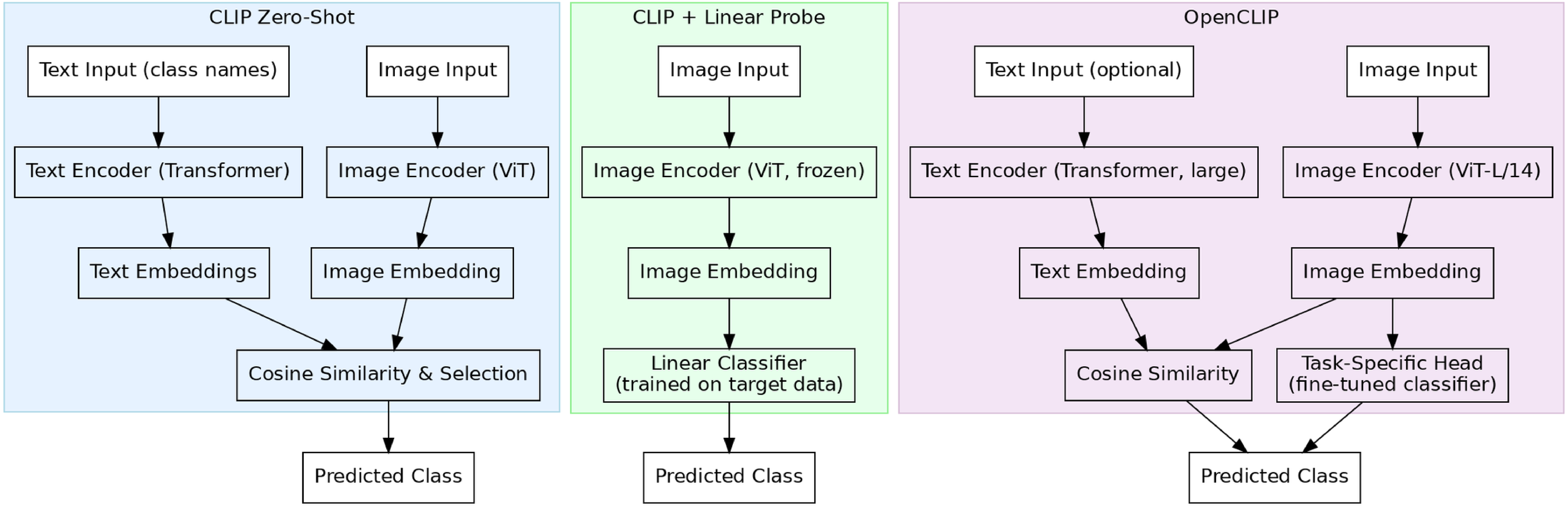
https://github.com/openai/CLIP

$$\text{similarity score} = \cos(\theta) = \frac{v_{img} \cdot v_{text}}{\|v_{img}\| \, \|v_{text}\|}$$



MODEL ARCHITECTURE

- CLIP Zero-Shot, CLIP + Linear Probe, and OpenCLIP

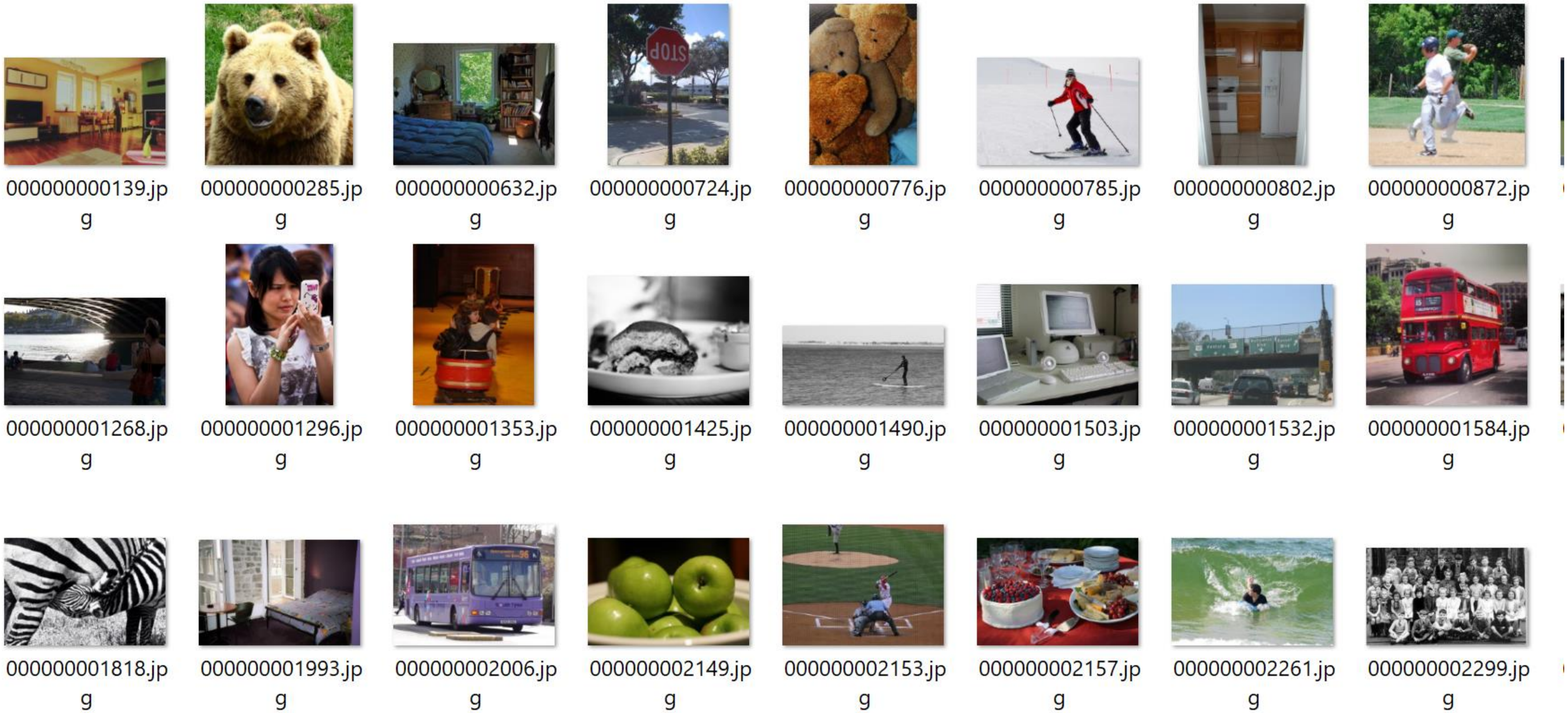


DATASETS

Dataset	Why we chose it
CIFAR100	General-purpose, small resolution, many classes
ImageNet-Mini	Benchmark-like, high diversity, test generalization
Food101	Fine-grained → test CLIP's zero-shot limit
EuroSAT	Remote sensing → test out-of-distribution generalization

DATASETS

Coco



DATASETS

ImageNet-mini

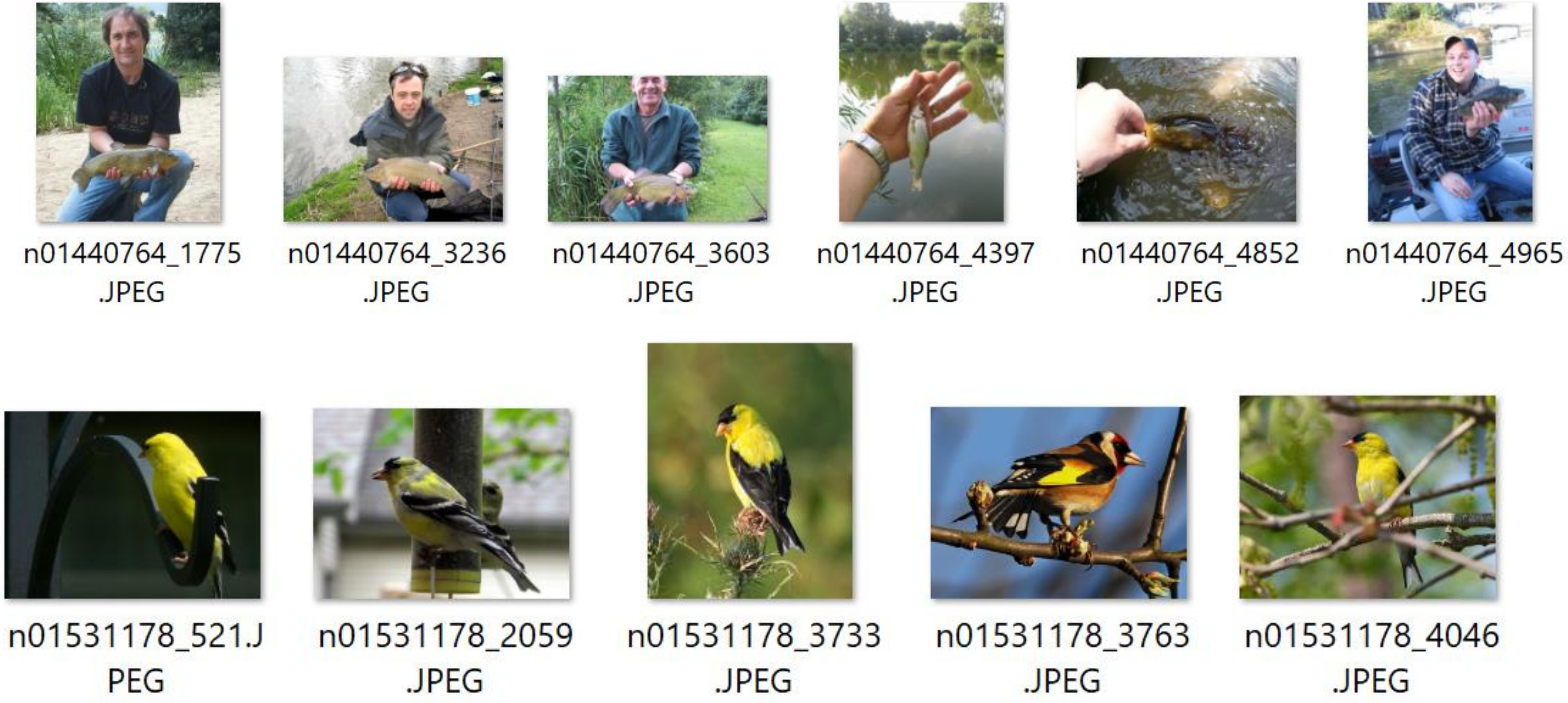


IMAGE-TO-TEXT CLASSIFICATION

Experiments- Image-to-text

Hyperparameter tuning: Image Encoder

Model	Architecture	Patch/Kernal Size	Pre-training (OpenAI CLIP / OpenCLIP)
ViT-B/32	Vision Transformer (Base)	32×32 patches	WIT (WebImageText, 400 M pairs) LAION-2B (2B pairs)
ViT-B/16	Vision Transformer (Base)	16×16 patches	WIT (WebImageText, 400 M) LAION-400M (400 M pairs)
Resnet50	ResNet-50 CNN	7×7 kernels	WIT (WebImageText, 400 M)
ViT-L-14	Vision Transformer (Large)	14×14 patches	LAION-2B
ConvNeXt-Base	ConvNeXt-Base CNN	7×7 kernels	LAION-400M

Experiments- Image-to-text

CIFAR100

	CLIP - Zero shot	CLIP - Linear Prob	OpenCLIP - Zero shot
ViT-B/32	Top1: 64.18% Top5: 88.15%	Train: 99.35% Test: 73.20%	Top1: 75.89% Top5: 93.86%
ViT-B/16	Top1: 68.04% Top5: 89.14%	Train: 98.90% Test: 78.05%	Top1: 71.61% Top5: 92.47%
Resnet50	Top1: 40.62% Top5: 72.30%	Train: 67.95% Test: 58.75%	
ViT-L-14			Top1: 82.39% Top5: 96.47%
ConvNeXt-Base			Top1: 46.50% Top5: 73.79%

Experiments- Image-to-text

ImageNet-mini

	CLIP - Zero shot	CLIP - Linear Prob	OpenCLIP - Zero shot
ViT-B/32	Top1: 61.89% Top5: 85.24%	Train: 100% Test: 37.96%	Top1: 61.89% Top5: 85.24%
ViT-B/16	Top1: 62.17% Top5: 87.48%	Train: 100% Test: 44.59%	Top1: 62.22% Top5: 85.44%
Resnet50	Top1: 54.45% Top5: 81.01%	Train: 74.86% Test: 16.82%	
ViT-L-14			Top1: 70.20% Top5: 90.39%
ConvNeXt-Base			Top1: 49.27% Top5: 74.28%

Experiments- Image-to-text

FOOD101

	CLIP - Zero shot	CLIP - Linear Prob	OpenCLIP - Zero shot
ViT-B/32	Top1: 82.06% Top5: 96.89%	Train: 99.43% Test: 86.79%	Top1: 82.10% Top5: 96.62%
ViT-B/16	Top1: 87.78% Top5: 98.44%	Train: 99.75% Test: 91.19%	Top1: 85.91% Top5: 97.62%
Resnet50	Top1: 77.57% Top5: 95.41%	Train: 89.76% Test: 84.10%	
ViT-L-14			Top1: 90.78% Top5: 98.76%
ConvNeXt-Base			Top1: 70.74% Top5: 89.68%

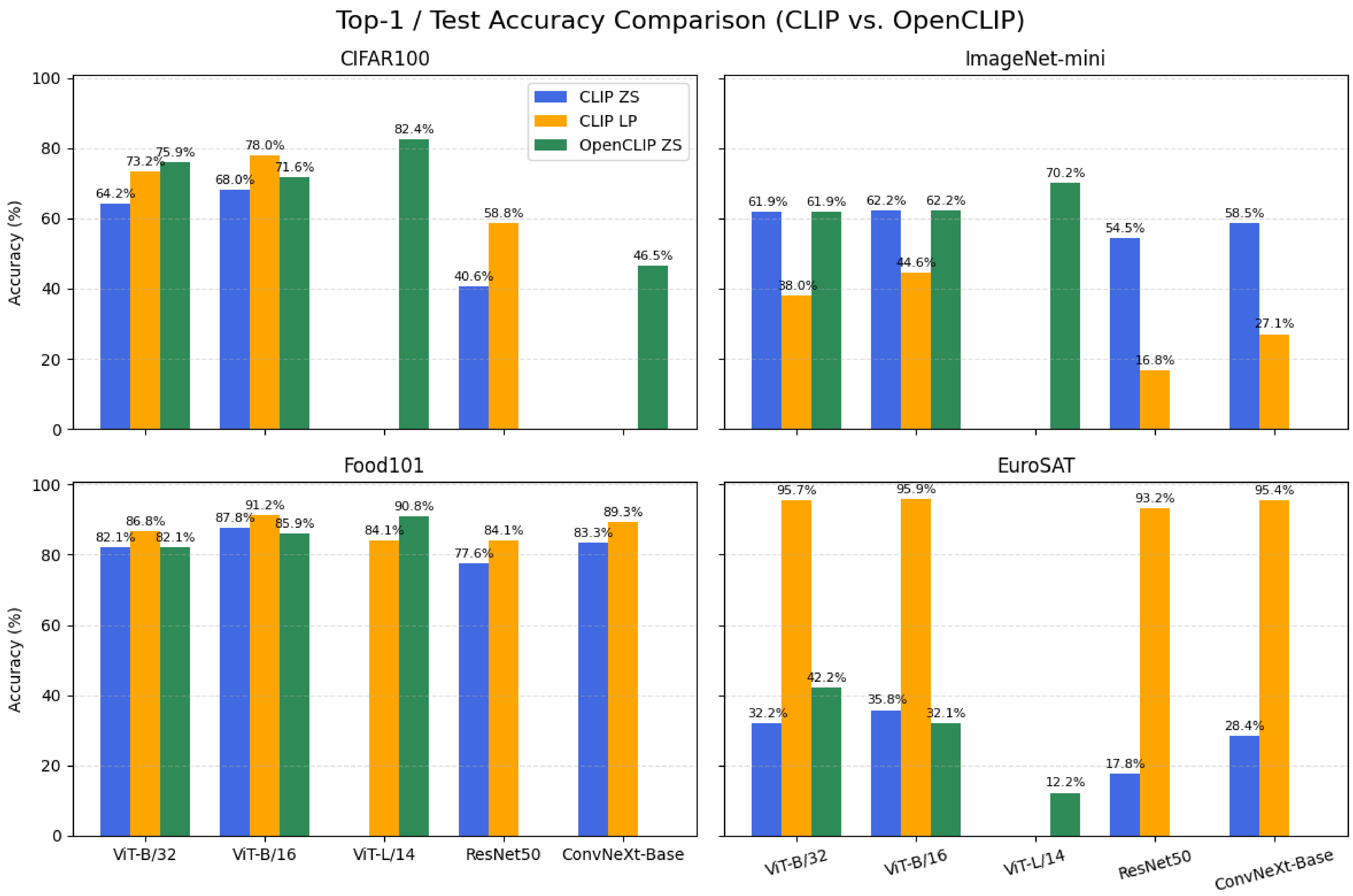
Experiments- Image-to-text

EuroSAT

	CLIP - Zero shot	CLIP - Linear Prob	OpenCLIP - Zero shot
ViT-B/32	Top1: 32.18% Top5: 82.87%	Train: 98.14% Test: 95.65%	Top1: 42.24% Top5: 90.03%
ViT-B/16	Top1: 35.80% Top5: 80.89%	Train: 98.23% Test: 95.94%	Top1: 32.12% Top5: 83.49%
Resnet50	Top1: 17.75% Top5: 76.40%	Train: 93.88% Test: 93.20%	
ViT-L-14			Top1: 12.25% Top5: 88.29%
ConvNeXt-Base			Top1: 26.53% Top5: 74.33%

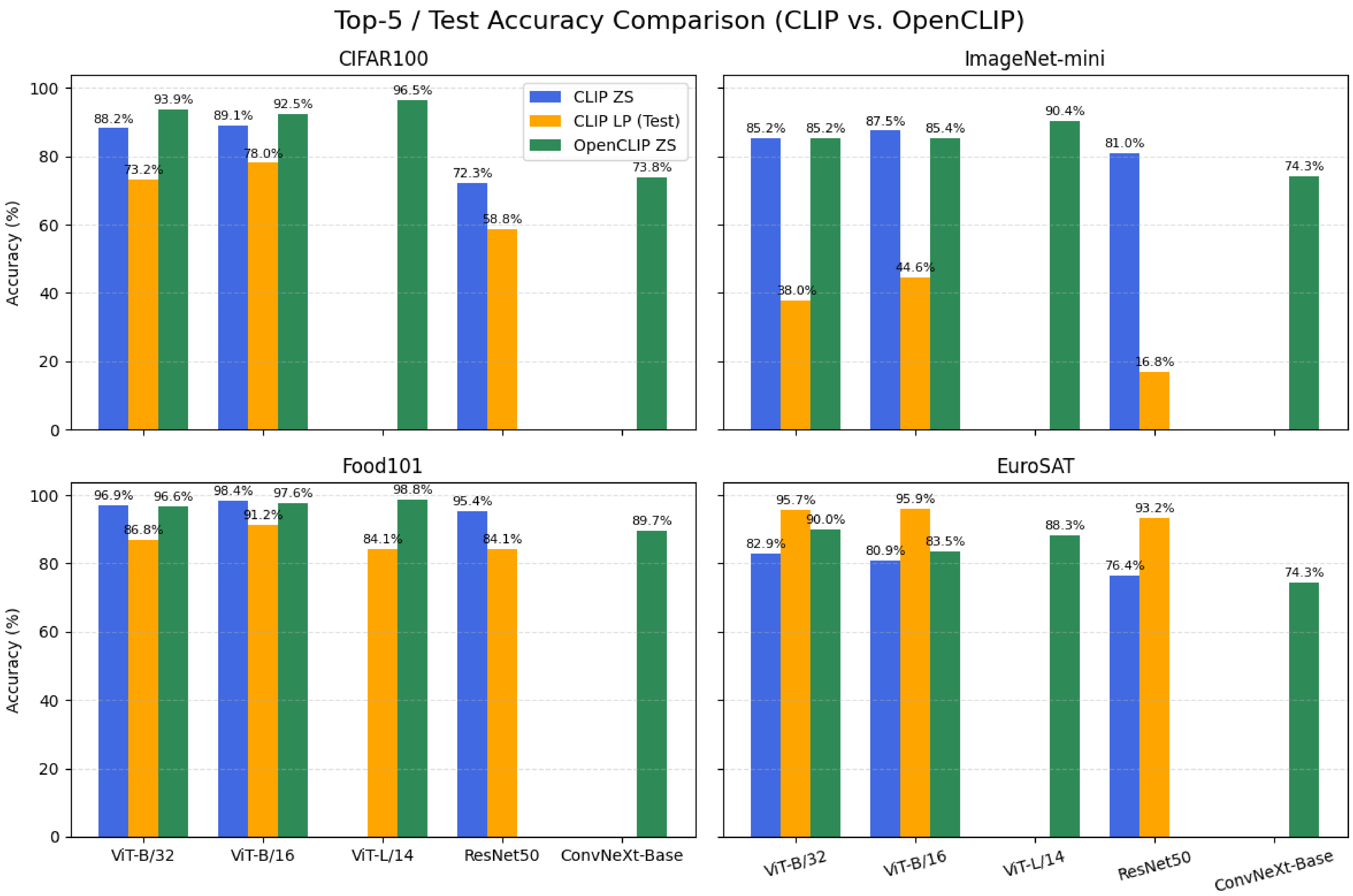
Experiments- Image-to-text

Comparison



Experiments- Image-to-text

Comparison



Experiments- Image-to-text

Key findings:

- **Robust zero-shot performance**: The top5 accuracy matches or outperforms linear-probe baselines across multiple tasks without task-specific fine-tuning
- **Dataset-dependent accuracy:** Perform better on general object datasets but shows reduced performance on specialized or fine-grained domains (e.g., satellite image in EuroSAT)
- **Pre-training impacts behavior:** Different pre-training data (WIT vs. LAION) affect output accuracy, even under the same natural-language prompts

GET PICTURES FROM PROMPTS

Research Questions

1. Does prompt style (adjective: photo vs. drawing) affect retrieval results?

- Example: "a photo of an orange" vs. "a drawing of an orange" .

2. What is the impact of changing the subject noun?

- Example: "apple" vs. "orange".

3. How do descriptive adjectives refine retrieval?

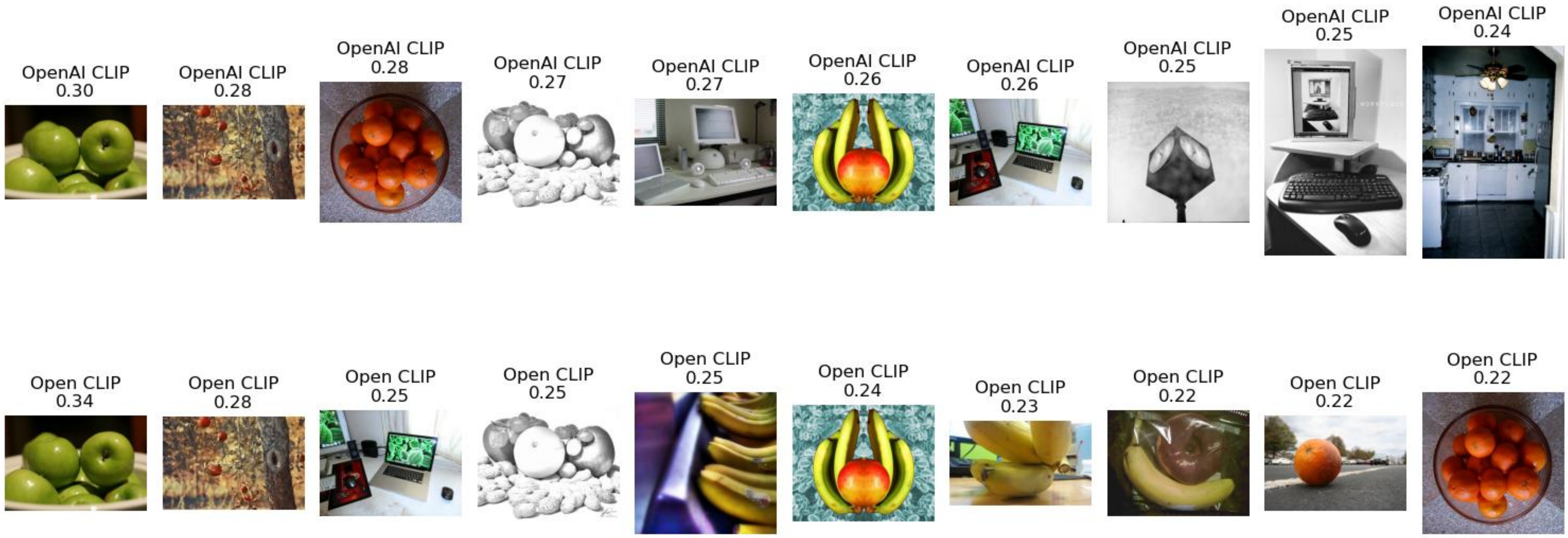
- Example:
  - "a photo of a bird"
  - "a photo of a white bird"
  - "a photo of a flying white bird"

4. Can CLIP find the original image from its human caption?

- Use COCO captions as prompts and see if the correct image is top-1.

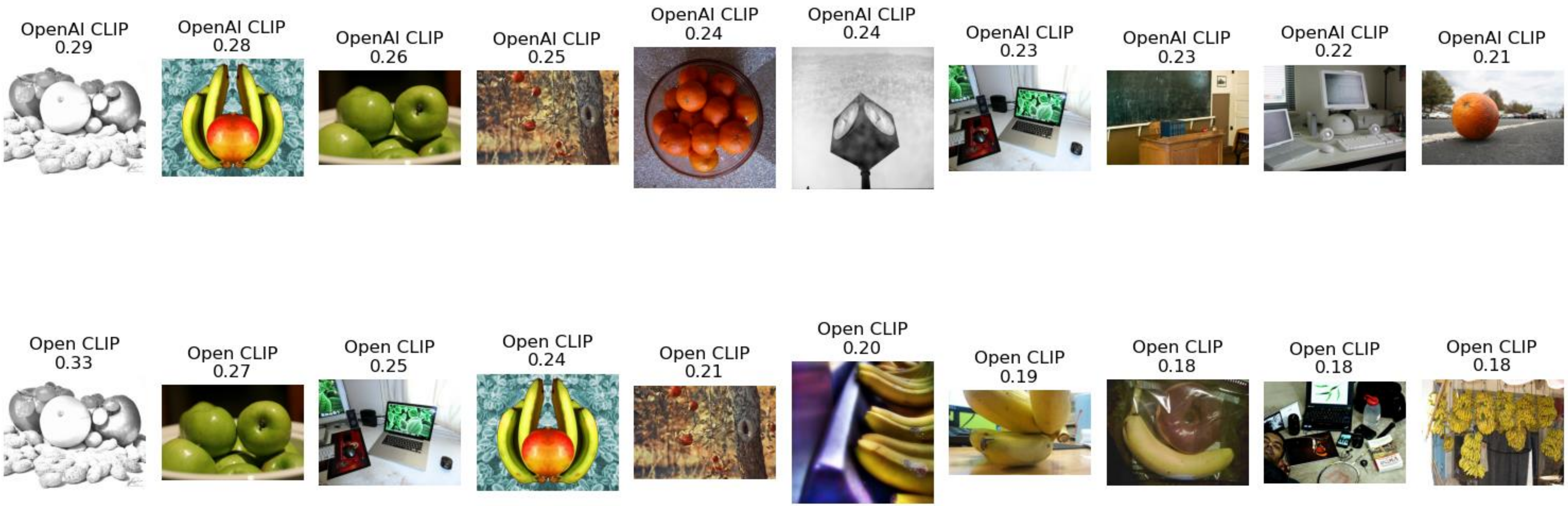
1. DOES PROMPT STYLE AFFECT RETRIEVAL RESULTS?

1. a photo of apples



Coco

2. a drawing of apples



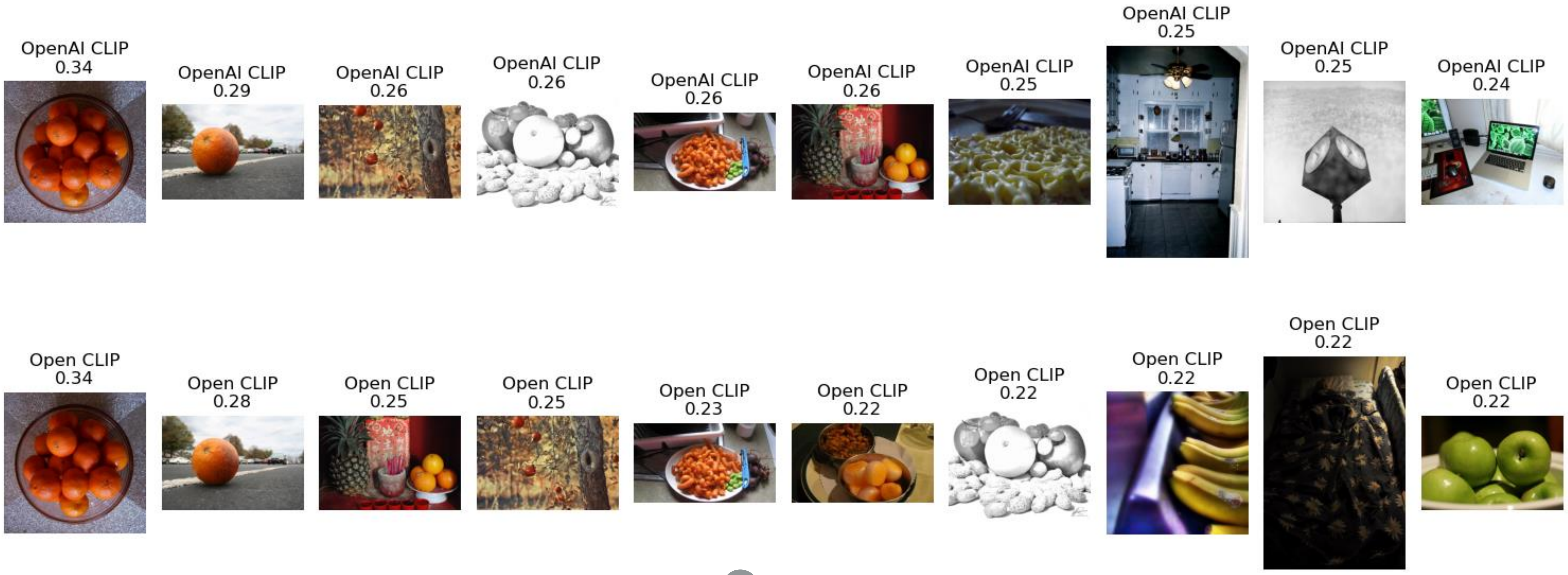
Coco

3. Different prompts on satellite dataset

```
Evaluating: 'a photo of a {}': 100%|██████████| 157/157 [13:00<00:00,  4.97s/it]
Prompt: 'a photo of a {}' -> Accuracy: 61.71%
Evaluating: 'a sketch of a {}': 100%|██████████| 157/157 [13:00<00:00,  4.97s/it]
Prompt: 'a sketch of a {}' -> Accuracy: 58.91%
Evaluating: 'a drawing of a {}': 100%|██████████| 157/157 [13:06<00:00,  5.01s/it]
Prompt: 'a drawing of a {}' -> Accuracy: 61.10%
Evaluating: 'a cartoon of a {}': 100%|██████████| 157/157 [13:46<00:00,  5.27s/it]
Prompt: 'a cartoon of a {}' -> Accuracy: 61.82%
Evaluating: 'an artistic rendering of a {}': 100%|██████████| 157/157 [13:02<00:00,  4.98s/it]
Prompt: 'an artistic rendering of a {}' -> Accuracy: 63.17%
Evaluating: 'a low-resolution photo of a {}': 100%|██████████| 157/157 [13:01<00:00,  4.98s/it]
Prompt: 'a low-resolution photo of a {}' -> Accuracy: 63.23%
Evaluating: '{}': 100%|██████████| 157/157 [13:02<00:00,  4.98s/it]
No prompt (only category name) -> Accuracy: 55.15%
```

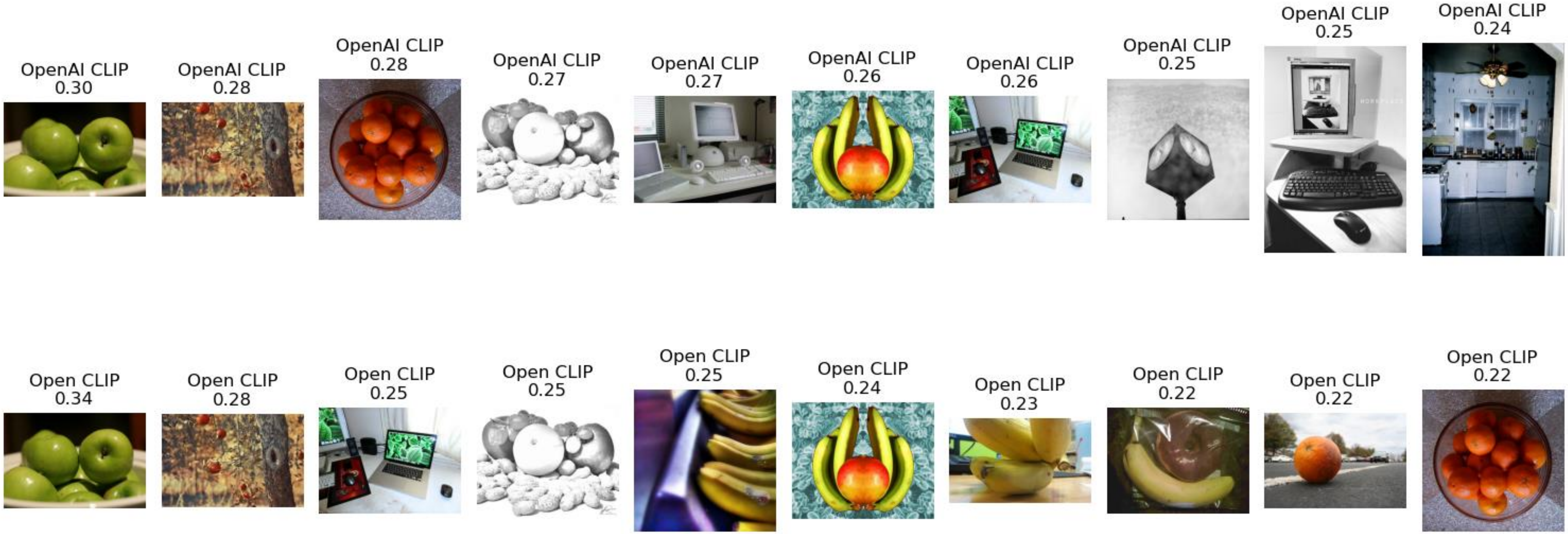
2. WHAT IS THE IMPACT OF CHANGING THE SUBJECT NOUN?

1. a photo of oranges



Coco

2. a photo of apples

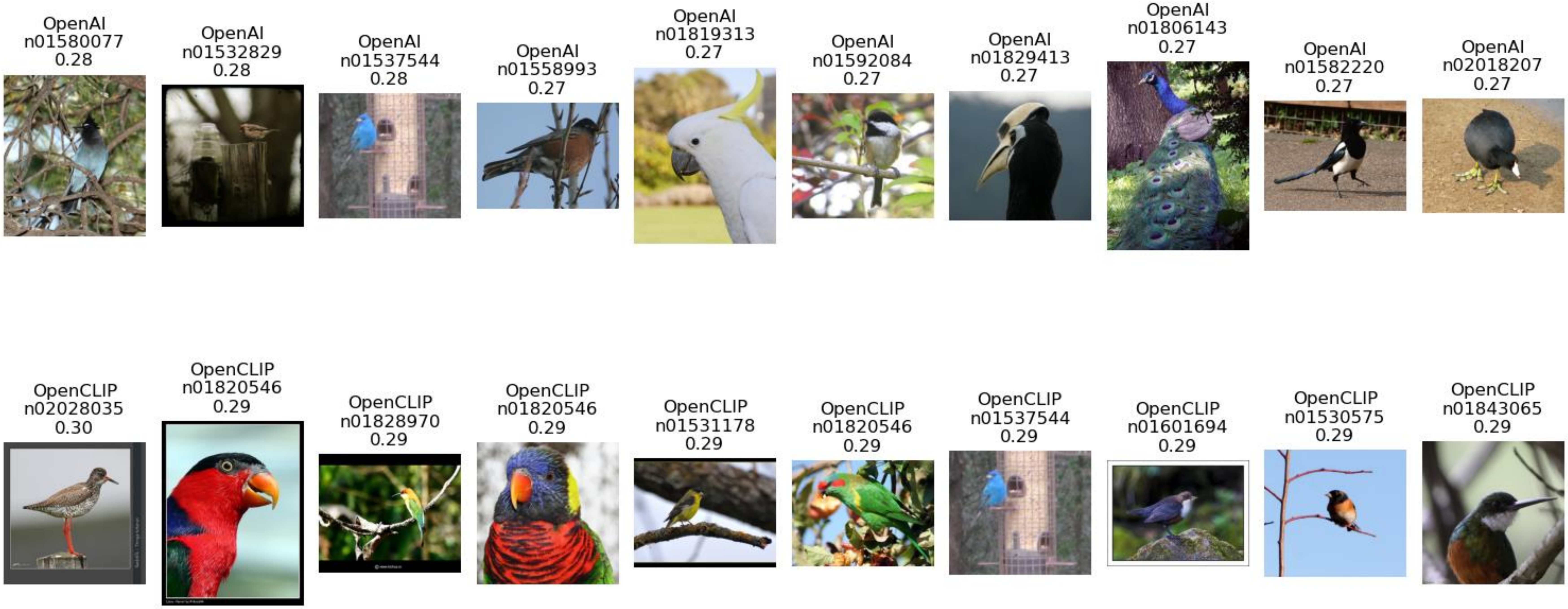


Coco

3. HOW DO DESCRIPTIVE ADJECTIVES REFINE RETRIEVAL?

BIRDS

1. a photo of bird

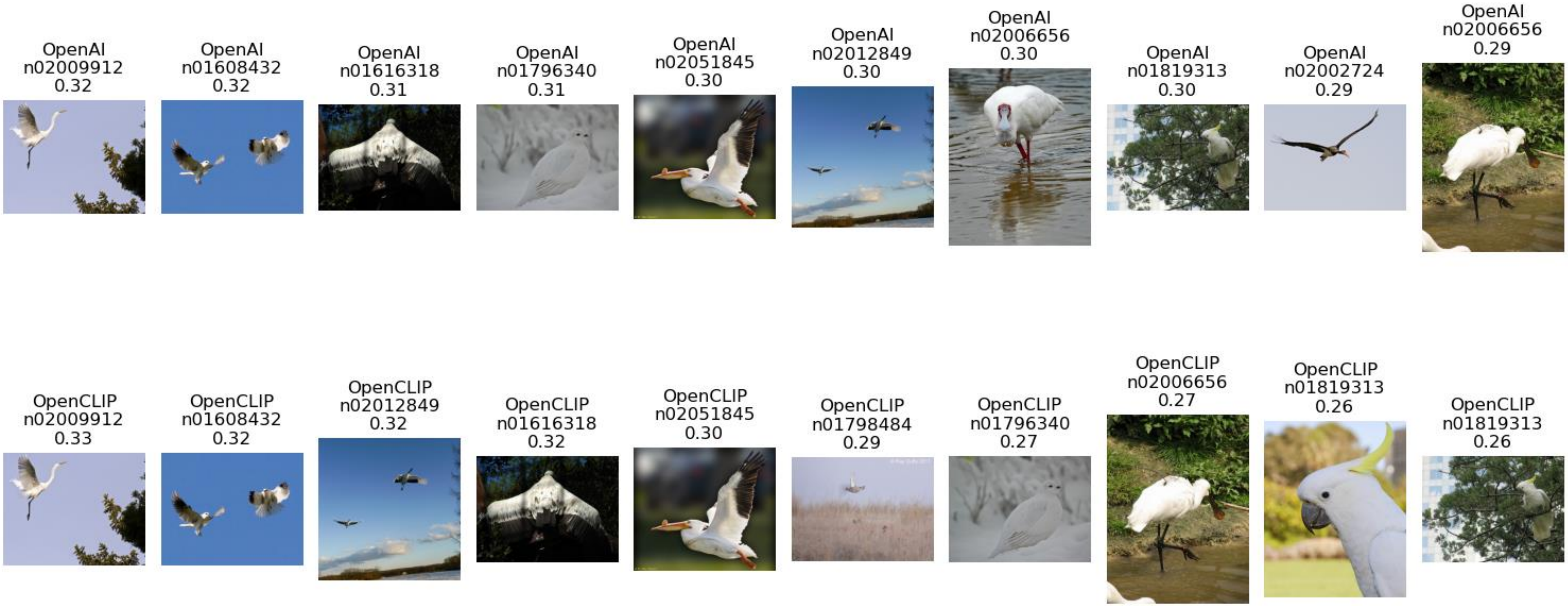


ImageNet-Mini

2. a photo of white bird

ImageNet-Mini

3. a photo of flying white bird



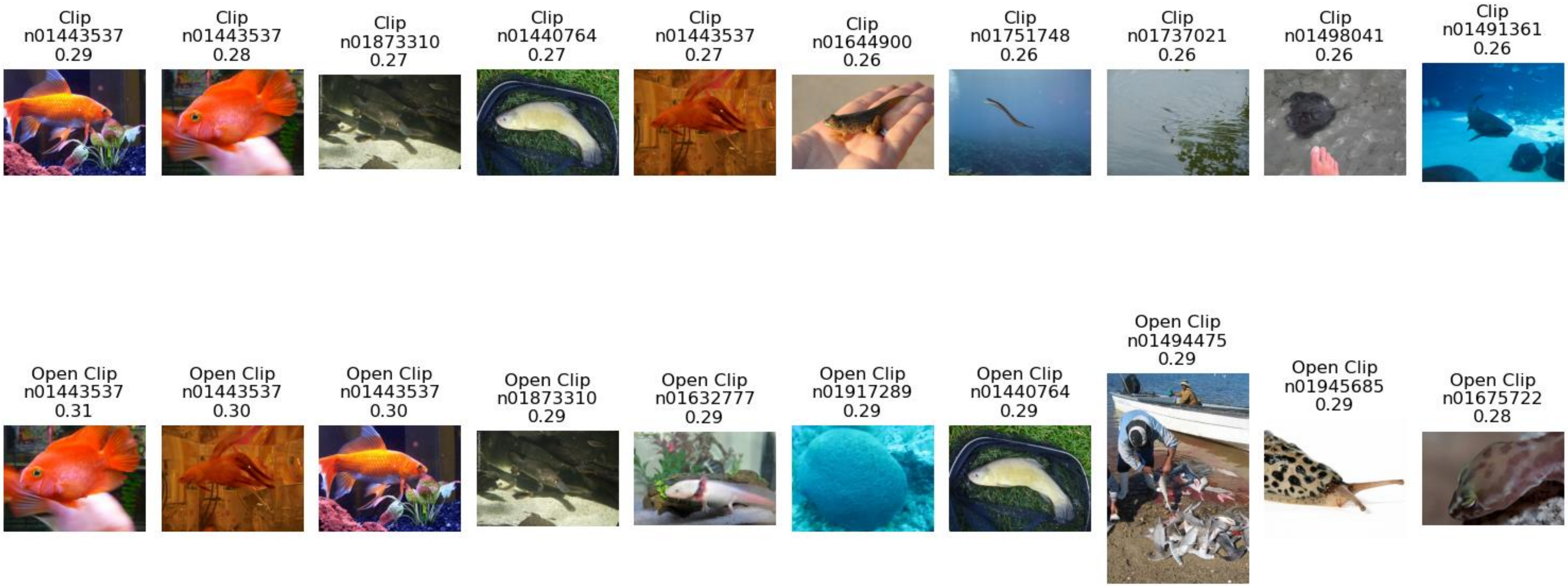
ImageNet-Mini

4. bird, white, flying

ImageNet-Mini

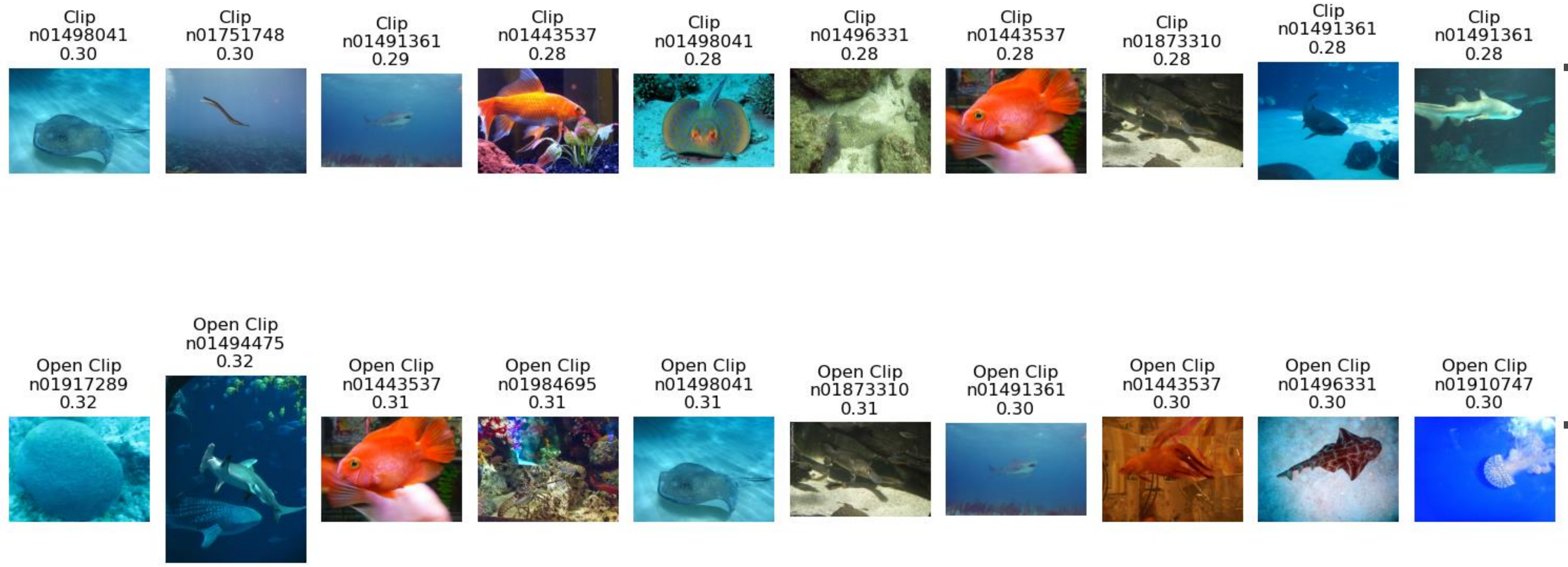
FISH

1. fish



ImageNet-Mini

2. a photo of ocean fish



ImageNet-Mini

3. a photo of river fish

ImageNet-Mini

4. CAN CLIP FIND THE ORIGINAL IMAGE FROM ITS HUMAN CAPTION?

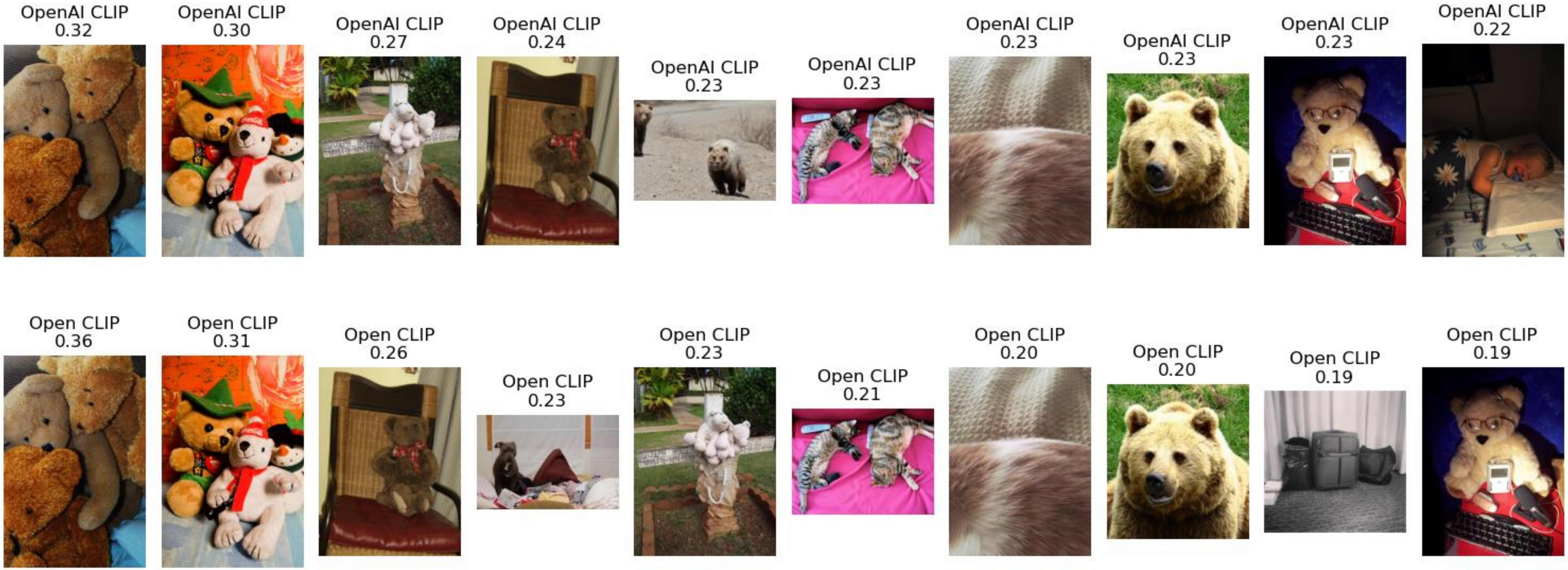
1. Three teddy bears, each a different color, snuggling together.

Original:

Coco

1. Three teddy bears, each a different color, snuggling together.

Results:



Coco

1. Three teddy bears, each a different color, snuggling together.

Addition: Teddy bear

Coco

HOWEVER, IF YOU HAVE MANY SIMILAR PICTURES...

2. The people are posing for a group photo.

Original:

Coco

2. The people are posing for a group photo.

Results:

OpenAI CLIP
0.26

OpenAI CLIP
0.26

OpenAI CLIP
0.26

OpenAI CLIP
0.26

OpenAI CLIP
0.25

OpenAI CLIP
0.25

OpenAI CLIP
0.25

OpenAI CLIP
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OpenAI CLIP
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Open CLIP
0.23

Open CLIP
0.23

Open CLIP
0.22

Open CLIP
0.22

Open CLIP
0.22

Coco

3. A meal is lying on a plate on a table.

Original:

Coco

3. A meal is lying on a plate on a table.

Results:

Coco

Key findings:

- **Prompt engineering is powerful:** Small changes in prompt wording can dramatically affect results.
- **Model differences:** OpenCLIP and OpenAI CLIP sometimes favor different image styles or concepts.
- **Practical:** Good prompts yield high accuracy in image search without any fine-tuning.

Summary:

- CLIP models transfer well across tasks with minimal training.
- Zero-shot is effective, but **linear probe offers significant gains**.
- Prompt design & model size are key to performance.

Future Improvements:

- Current datasets are **not large or diverse enough** to fully test generalization.
- **No numerical metrics** were used for retrieval tasks; evaluation was **manual**.
- Explore **few-shot tuning** strategies for better adaptation.
- Investigate **automatic prompt optimization** techniques.

REFERENCE

- **CLIP**

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., Krueger, G., & Sutskever, I. (2021). *Learning transferable visual models from natural language supervision. In Proceedings of the International Conference on Machine Learning (ICML)*.
https://github.com/openai/CLIP

- **OpenCLIP**

Ilharco, G., Wortsman, M., Wightman, R., Gordon, C., Carlini, N., Taori, R., Dave, A., Shankar, V., Namkoong, H., Miller, J., Hajishirzi, H., Farhadi, A., & Schmidt, L. (2021).. *OpenCLIP* (Version 0.1) [Computer software]. Zenodo.
https://github.com/mlfoundations/open_clip

THANK YOU