# Towards Generative Class Prompt Learning for Fine-grained Visual Recognition


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## Motivation, Challenges, and Contributions

### Limitations of CLIP-based representations

- Fine-grained category names are often highly dataset-specific that ***lack in semantic visual cues***
- CLIP's knowledge is about natural visual content, *cannot be adopted directly to* ***unseen domains***
- Visual concepts that are ***hard to describe by language*** (e.g. fractal patterns, abstract imagery) yield spurious representations from CLIP during prompting

Core underlying issue: ***Suboptimality of raw CLIP representations, which often lack fine-grained visual semantic awareness.*** We use *Generative Models to capture fine-grained visual information!*

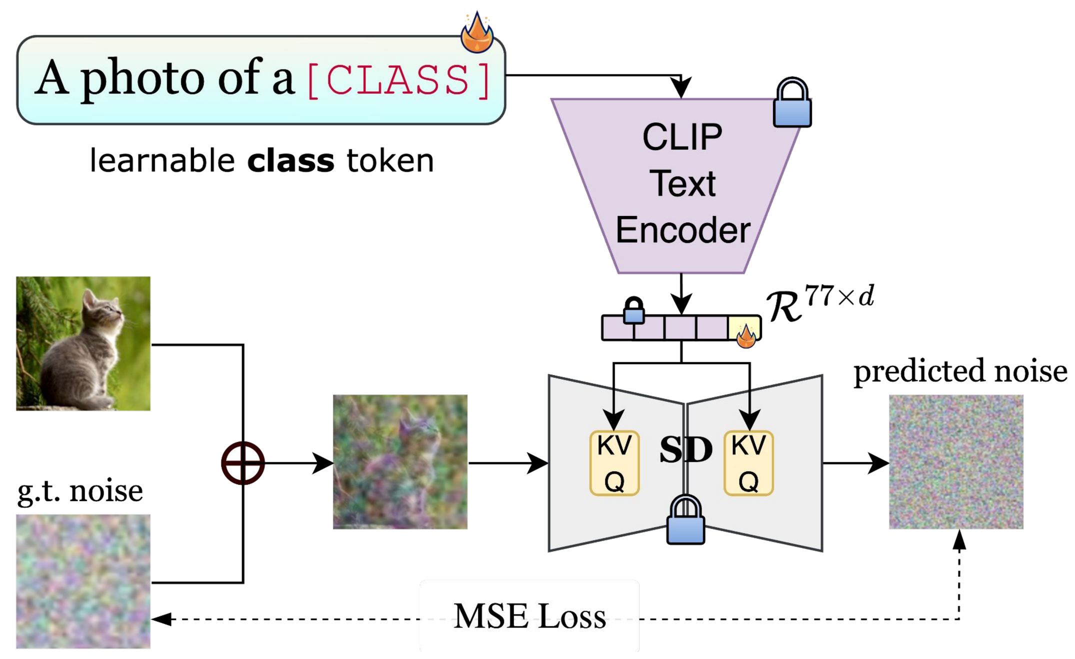
### Contributions

- We propose a *generative class prompt learning (GCPL)* baseline, leveraging pre-trained diffusion models to tackle CLIP's limitations.
- GCPL explicitly conditions CLIP class embeddings with *fine-grained visual semantic knowledge* via **generation-aided learning**.
- We further extend it, advocating for learning stronger vision-induced textual representations with ***inter-class discriminative knowledge.***

*To our best knowledge – one of the first attempts to introduce* ***generation guided prompting*** *for few-shot VLM adaptation!*

## GCPL: Generative Class Prompt Learning

- Inject learnable `[CLASS]` token via handcrafted prompt into CLIP *(only this token is* ***trainable!****)*
- Use it to condition a T2I LDM, optimizing **L2 loss** w.r.t. the few-shot support set.

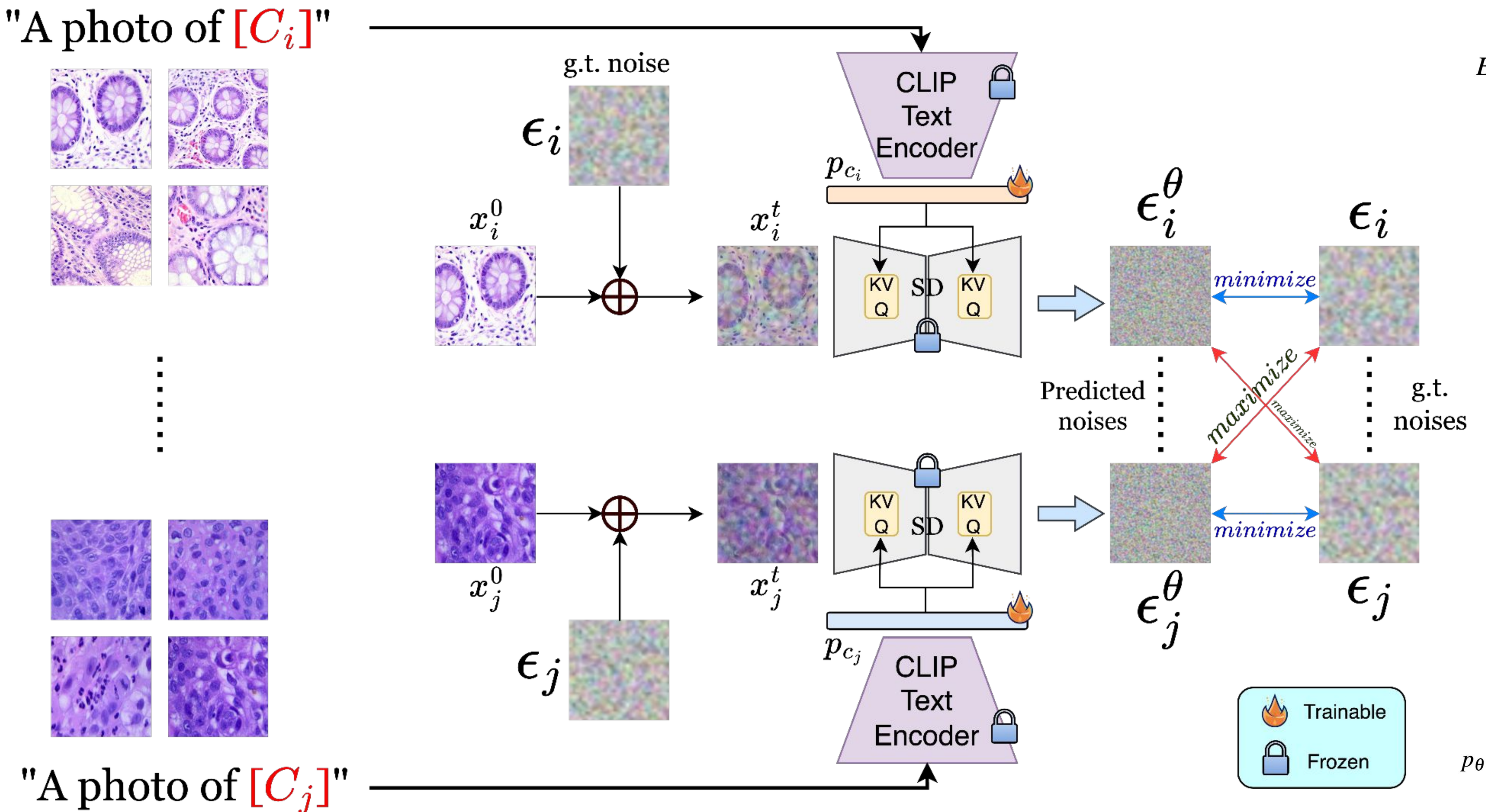



$$\mathcal{L}_{GCPL} = \mathbb{E}_{x\sim\mathcal{E}(x),p_c,\varepsilon\sim\mathcal{N}(O,1),t}\left[\|\varepsilon_c - \varepsilon_c^{\theta}(x_t,t,c_\theta(p_c))\|_2^2\right]$$

$$p_c^* = \arg\min_{p_c} \mathbb{E}_{x\sim\mathcal{E}(x),p_c,\varepsilon\sim\mathcal{N}(O,1),t}\left[\|\varepsilon_c - \varepsilon_c^{\theta}(x_t,t,c_\theta(p_c))\|_2^2\right]$$

## CoMPLe: Contrastive Multi-Class Prompt Learning

**Extends GCPL to multi-class setting – all class prompts are jointly optimized by additionally enforcing divergence of the noise predictions across other classes.**




$$\mathcal{L}_{CoMPLe} = \frac{1}{B}\sum_{i=j}^{B}\mathbb{E}_{x\sim\mathcal{E}(x),p_{c_j},\varepsilon\sim\mathcal{N}(O,1),t}\left[\|\varepsilon_{c_i} - \varepsilon_{c_j}^{\theta}(x_t^j,t,c_\theta(p_{c_j}))\|_2^2\right] - \lambda\cdot\frac{1}{B(B-1)}\sum_{i\neq j}^{B}\mathbb{E}_{x\sim\mathcal{E}(x),p_{c_j},\varepsilon\sim\mathcal{N}(O,1),t}\left[\|\varepsilon_{c_i} - \varepsilon_{c_j}^{\theta}(x_t^j,t,c_\theta(p_{c_j}))\|_2^2\right]$$

## Few-shot Diffusion Classifier

### Inference pipeline after training

- ELBO approximation for LDMs:

$$ELBO = -\mathbb{E}_\varepsilon\left[\sum_{t=2}^{T} w_t\|\varepsilon-\varepsilon_\theta(x_t,c)\|_2^2 - \log p_\theta(x_0\mid x_1,c)\right]+C$$
$$= -\mathbb{E}_{\varepsilon,t}\left[\|\varepsilon-\varepsilon_\theta(x_t,c)\|_2^2\right]+C$$

- Bayes' theorem gives us:

$$p_\theta(c_i\mid x) = \frac{p(c_i)p_\theta(x|c_i)}{\sum_j p(c_j)p_\theta(x|c_j)}$$

- Simplifying using ELBO:

$$p_\theta(c_i\mid x) = \frac{\exp\{-\mathbb{E}_{\varepsilon,t}\left[\|\varepsilon-\varepsilon_\theta(x_t,c_i)\|_2^2\right]\}}{\sum_j\exp\{-\mathbb{E}_{\varepsilon,t}\left[\|\varepsilon-\varepsilon_\theta(x_t,c_j)\|_2^2\right]\}}$$

- Conditioning signal *c* is derived from *few-shot learned [CLASS] prompts* ⇒ **few-shot diffusion classifier!**

$$c_i = c_\theta(p_{c_i})$$

$$p_\theta(c_i\mid x) = \frac{1}{\sum_j exp\{\mathbb{E}_{\varepsilon,t}\left[\|\varepsilon-\varepsilon_\theta(x_t,c_\theta(p_{c_i}))\|_2^2 - \|\varepsilon-\varepsilon_\theta(x_t,c_\theta(p_{c_j}))\|_2^2\right]\}}$$

(please refer to paper for details.)

## Quantitative Results: Few-shot Classification

### Medical imaging datasets

- Zero-shot methods *completely fail* on the unseen domain.
- **GCPL** and **CoMPLe** *significantly boosts* performance over prior SoTA.
- **Prompt learning** is very noisy for unseen domain (i.e. medical datasets) – as seen from **high variances.**
- **GCPL** and **CoMPLe** are lot consistent and robust across unseen domains.

| Method | CRC5k | ISIC2018 | LC25000 |
|---|---|---|---|
| **Zero-Shot** | | | |
| CLIP | 21.49 | 14.43 | 25.40 |
| Diffusion Classifier | 24.16 | 10.41 | 17.29 |
| **Adapter** | | | |
| Tip-Adapter | 59.90±2.18 | 33.88±7.26 | 80.48±1.93 |
| Tip-Adapter-F | 71.44±2.46 | 40.32±5.19 | 86.02±1.59 |
| **Prompt learning** | | | |
| CoCoOp | 60.91±2.98 | 24.67±6.54 | 73.86±4.19 |
| KgCoOp | 59.90±5.17 | 29.16±6.82 | 75.87±3.88 |
| MaPLe | 40.56±16.12 | 30.33±13.67 | 71.96±5.22 |
| PromptSRC | 56.45±18.28 | 44.18±7.02 | 77.54±1.51 |
| **Ours** | | | |
| Ours-GCPL | 74.76±1.94 | 48.84±2.13 | 93.44±0.78 |
| Ours-CoMPLe | **76.36**±1.82 | **49.27**±2.59 | **94.83**±0.28 |

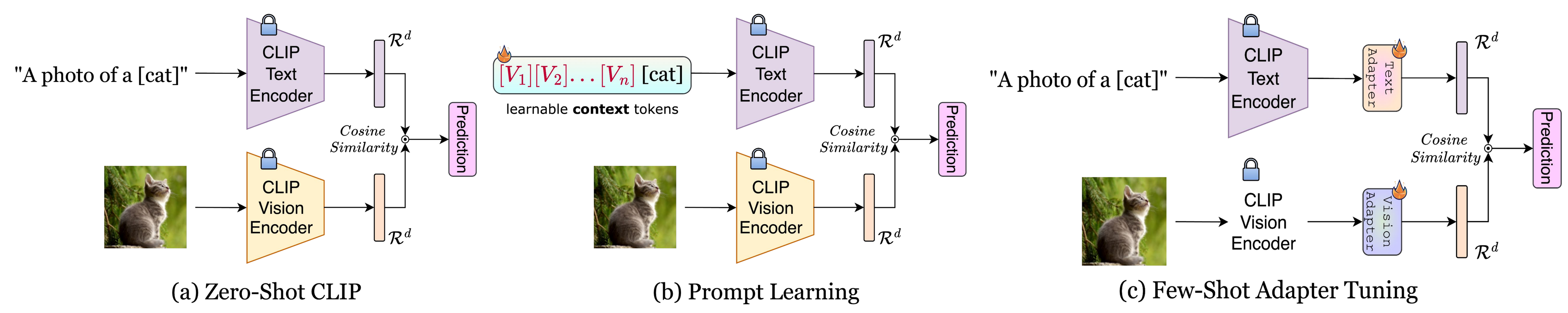
### Fine-grained natural image datasets

- Mostly observe *high gains* over prior few/zero-shot methods.

| Method | StanfordCars | Cornseeds | Flowers102 | Fractals |
|---|---|---|---|---|
| **Zero-Shot** | | | | |
| CLIP | 65.56 | 18.47 | 70.73 | 9.25 |
| Diffusion Classifier | 76.77 | 17.77 | 54.21 | 6.25 |
| **Adapter** | | | | |
| Tip-Adapter | 65.82±0.51 | 34.27±3.97 | 89.28±0.55 | 81.49±1.22 |
| Tip-Adapter-F | 75.14±0.35 | 39.61±2.88 | 94.25±0.43 | 86.16±0.54 |
| **Prompt learning** | | | | |
| CoCoOp | 71.57±0.76 | 36.56±5.42 | 87.84±0.48 | 67.89±1.29 |
| KgCoOp | 78.76±0.61 | 38.45±4.84 | 91.97±0.44 | 72.84±0.93 |
| MaPLe | 74.39±0.43 | 34.37±15.44 | 93.96±0.61 | 76.91±6.55 |
| PromptSRC | 83.33±0.35 | 33.69±4.55 | **97.06**±0.27 | **93.45**±0.52 |
| **Ours** | | | | |
| Ours-GCPL | **88.47**±0.27 | 43.42±2.84 | 93.45±1.39 | 90.76±2.23 |
| Ours-CoMPLe | 87.69±1.47 | **45.79**±2.12 | 90.73±1.05 | 88.83±1.57 |

## Experimental Setup

**Competitors:** existing VLM adaptation paradigms

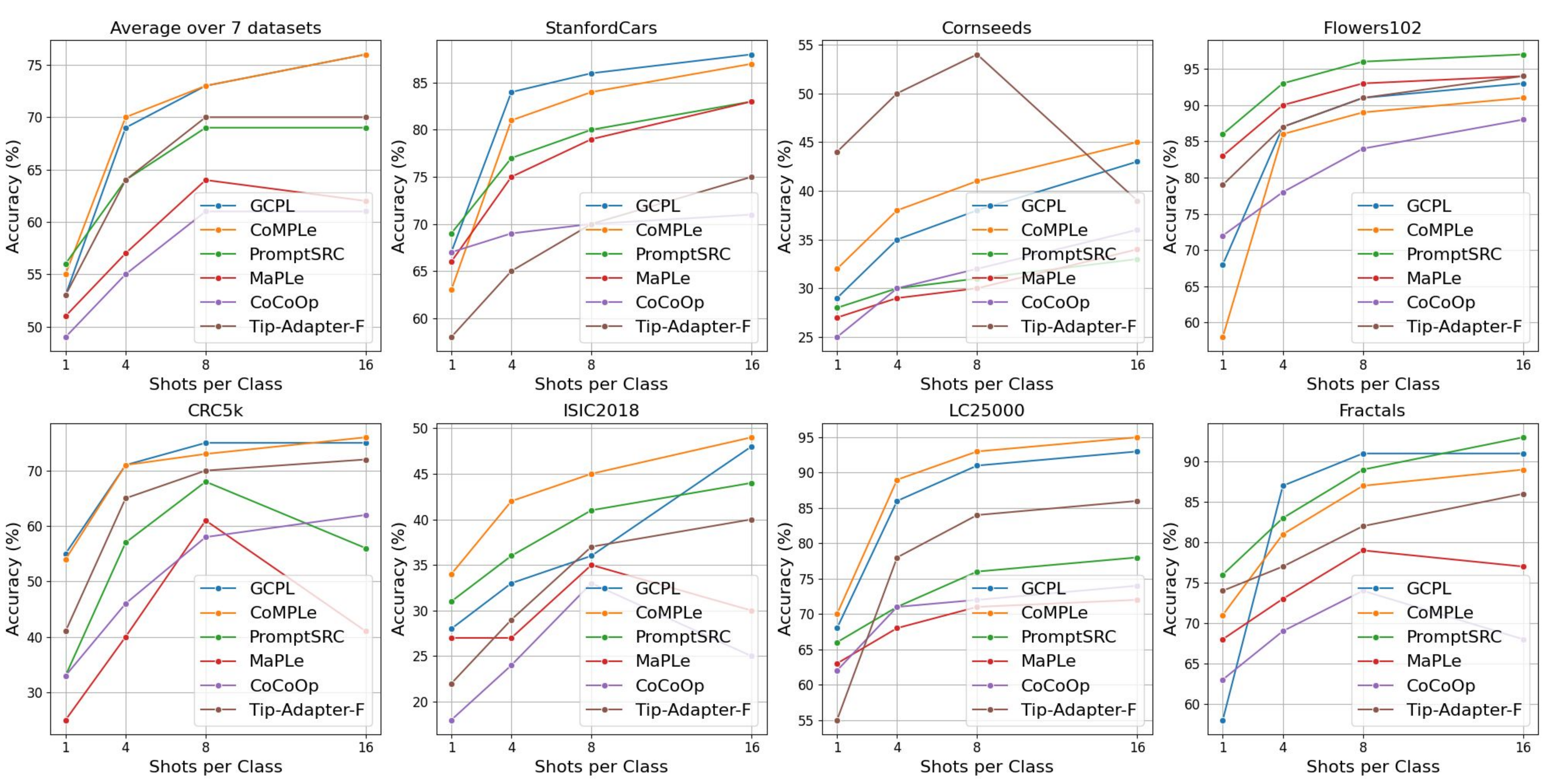



(a) Zero-Shot CLIP (b) Prompt Learning (c) Few-Shot Adapter Tuning

**Datasets:** (a) fine-grained natural images; (b) medical images; (c) abstract patterns

| Dataset | Visual concept | Prompt template | Initializer word |
|---|---|---|---|
| StanfordCars | Vehicular variants | "A photo of `[CLASS]`, a type of car." | car |
| Cornseeds | Natural images, agriculture | "A photo of `[CLASS]` corn seed." | seed |
| CRC5k | Histopathology | "`[CLASS]` tissue." | tissue |
| ISIC2018 | Dermatology | "`[CLASS]` skin lesion." | skin |
| LC25000 | Histopathology | "`[CLASS]` tissue." | tissue |
| Fractals | Abstract imagery | "`[CLASS]` fractal." | fractal |

## Ablation Study: Varying number of shots per class





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For more details, please refer to the arXiv version of our paper at: https://arxiv.org/abs/2409.01835 or email authors at: soumitri@cs.unc.edu | sbiswas@cvc.uab.es | evivoli@cvc.uab.es. Thanks for visiting!