Leveraging Textures in Zero-shot Understanding of Fine-Grained Domains

Chenyun Wu
UMass Amherst
chenyun@cs.umass.edu

Subhransu Maji
UMass Amherst
smaji@cs.umass.edu

Abstract

Textures can be used to describe the appearance of objects in a wide range of fine-grained domains. Textures are localized and one can often refer to their properties in a manner that is independent of the object identity. Moreover, there is a rich vocabulary to describe textures corresponding to properties such as their color, pattern, structure, periodicity, stochasticity, and others. Motivated by this, we study the effectiveness of large-scale language and vision models (e.g., CLIP) at recognizing texture attributes in natural images. We first conduct a systematic study of CLIP on texture datasets where we find that it has good coverage for a wide range of texture terms. CLIP can also handle compositional phrases that consist of color and pattern terms (e.g., red dots or yellow stripes). We then show how these attributes allow for zero-shot fine-grained categorization on existing datasets.

1. Introduction

There has been significant progress on training large-scale models such as ResNet [15] on ImageNet [9] for vision, and BERT [10], GPT3 [6] trained on WebText [21] for natural language understanding. However for a long time large-scale models that jointly understand multiple modalities, such as language and vision, have been lacking in comparison. Therefore the common strategy for language and vision tasks was to align pre-trained models for each modality using domain-specific aligned data. This allows the benefit of transfer learning but requires collecting training data and fine-tuning for each cross-modal task in each domain.

Recently, this has changed with the publication of models that can have a common understanding of language and vision such as CLIP [20], ALIGN [17], and UNITER [7]. These models are trained on massive data of images paired with text to embed language and vision input into a common space. They provide a basis for zero-shot recognition through the names of categories. However, as seen in Figure 1, the scientific names of bird species are domain-specific and the terms are often unfamiliar to the pre-trained language encoders of CLIP and other models as they are trained on generic image descriptions. This limits their capability to generalize to novel fine-grained domains without extra training data.

Textures, on the other hand, provide a common basis for describing the appearance of various visual domains. Textures including local patterns, colors, materials, and styles that can be described by similar vocabularies across domains because they often refer to localized properties of surfaces in a manner independent of the object category. Textures also exhibit rich variations and are discriminative across categories, which play an important role in many recognition tasks. Motivated by this, we aim to leverage texture descriptions to improve the zero-shot understanding of fine-grained domains.

We first demonstrate the capability of CLIP on understanding texture attributes by comparing its image and phrase retrieval on texture datasets against models trained on domain-specific texture datasets. Second, we show that CLIP can understand compositional phrases such as combi-
nation of two colors or combination of colors with patterns better than domain-specific models (Table 4). We further apply CLIP to retrieve bird images with texture phrases, where CLIP is able to recognize localized textures on the birds. Finally we add attributes to category descriptions of bird species which improves Top 10 classification accuracy on scientific names from 24.89% to 56.61% (Table 6).

In §2, we discuss related works on large-scale pre-trained image and text models and textures. In §3, we introduce the models and datasets we use in more detail. In §4, we present experiments on understanding texture attributes as well as zero-shot classification on different datasets and we conclude in §5.

2. Related Work

2.1. Joint Representations of Image and Text

With the availability of large datasets of paired image and text, advanced image and text encoders, and the growth of computing resources, it now becomes possible to train large-scale representation learning models for jointly understanding images and texts. These models can be applied to various tasks such as zero-shot classification, image-text retrieval, visual question answering, etc.

For example, UNITIER [7] applies a transformer on top of image and text encoders to better align image regions with words through mining and combining multiple vision and language datasets. WenLan [16] constructs a Chinese image-text paired dataset containing 30 million pairs and applies a two-tower structure on top of the image and text encoders for better contrastive learning. ALIGN [17] leverages a noisy dataset of over one billion image-text pairs, obtained without expensive filtering or post-processing steps from the Conceptual Captions dataset.

CLIP [20] trains an image encoder and a text encoder jointly on 400 million image-text pairs from the Internet. Radford et al. demonstrate the quality of image representations through training linear classifiers on top of image embeddings. They have also applied the encoders in downstream tasks including geo-localization, optical character recognition, facial emotion recognition, and action recognition. In this paper, we select CLIP as an example to analyze the effectiveness of large-scale pre-trained models, especially on their understanding of texture attributes, and improve their zero-shot application to fine-grained classification through describing textures.

2.2. Texture Recognition and Description

Studies into recognizing and describing textures can be traced back to efforts on classifying terrains based on texture features in the 1970s. Some early works [12, 23] design texture features based on lower-level statistics such as gray level run lengths. Other works [1, 3] describe textures as measurements on several aspects such as “coarseness, contrast, directionality, line-likeness, regularity, and roughness”. Bhusan et al. [4] links English words with texture visual attributes. Based on that, the Describable Texture Dataset (DTD) [8] is introduced with zoomed-in texture images of 47 categories. It is then further improved into the Describable Textures in Detail Dataset (DTD2) [26] in which natural language descriptions are used to describe more details of textures. In this paper, we compare CLIP with models trained on DTD2 on various tasks of texture recognition as well as generalization to novel domains.

2.3. Textures in Classification Tasks

Before the era of deep learning, texture features have played a key role in object recognition and image classification in various domains including aerial photographs, satellite images, and also medical imaging [14, 22]. More recently it is also shown that deep neural networks rely heavily on textures for image classification [5, 13, 18]. Leveraging texture as intermediate representations, deep learning models can achieve better performance especially in fine-grained domains [2, 19]. Inspired by the importance of textures for classification, we propose to encode texture attributes into the representation of categories, thus improving the classification performance of general-purpose models on fine-grained domains.

3. Models and Datasets

We use the Describable Textures in Detail Dataset [26] (DTD2) to evaluate CLIP’s capability on understanding texture attributes, and choose the Caltech-UCSD Birds (CUB) Dataset to evaluate CLIP on recognizing the fine-grained domain of bird species.

To provide a baseline comparison, we experiment with the metric learning model trained on DTD2, which achieves best performance as reported in [26] and has a similar architecture with CLIP: both models contain an image encoder and a text encoder to encode images/texts into a shared embedding space, and provide a distance function such that relative/paired images and texts have smaller distances in the embedding space than irrelevant images and texts.

In the remainder of this section, we introduce these models and datasets in further detail.

3.1. Overview of CLIP

CLIP [20] was introduced by OpenAI with the overall model design consisting of an image and text encoder jointly trained on 400 million image-text pairs collected from the Internet1. The training objective is to score the image and text pairs to be higher than other text and other

1The dataset is not yet publicly available.
images in each sampled batch. They experimented with various image and text encoding architectures to conclude that Transformer [24] text encoder and vision Transformer [11] as the image encoder yield the best performance in zero-shot classification. Our experiments are based on the model with transformer text encoder and “ViT-B/32” transformer image encoder.

CLIP is also shown to be useful as a zero-shot classifier. In the zero-shot setting, the goal is to learn an image classifier given descriptions of the categories. Their work showed the category can be encoded by its name alone, and the text encoder of CLIP can map input in the format of “A photo of a [Category]” to an embedding that is compatible with the image embeddings. For a given image, one can therefore search for its nearest category embedding as its predicted category. The authors experimented on 27 datasets to demonstrate that CLIP is competitive with fully supervised baselines, suggesting that CLIP has a strong understanding of common categories. In Section 4.4, we investigate if the performance can be further improved using more detailed descriptions of categories.

3.2. Metric Learning Model on Texture Dataset

We choose the metric learning model using DTD$^2$ as its mere training set to compare against CLIP on understanding textures and generalizing to novel domains.

This model adopts the standard metric learning approach with triplet-loss to train the image and text encoder. Given a pair of associated image and phrase, a negative image and a negative phrase are randomly sampled. The training objective is to have the squared Euclidean distance between the positive image-phrase pair smaller than the distances from negative pairs by a certain margin.

Selecting the model with best performance in [26], we run all our experiments on the model with BERT [10] text encoder and ResNet101 [15] image encoder (noted as “DTD2-ML”). The BERT text encoder is trained on “BookCorpus” [27] and “English Wikipedia” and does not get updated when training on DTD$^2$. Only a linear layer on top of BERT is trained on DTD$^2$. The ResNet-101 image encoder is pre-trained on ImageNet and fine-tuned on DTD$^2$.

Table 1 compares the size of the two models and their training datasets. CLIP has a comparable size of training data to the size of ImageNet and BERT but it sees much more paired data than DTD2-ML has seen. It allows CLIP to train more complicated encoding models from scratch.

3.3. Describable Textures in Detail Dataset

DTD$^2$ contains 5369 images that show various textures without shapes of objects. Each image is annotated with attribute phrases parsed from natural language descriptions of the texture. In total there are 655 distinctive phrases with their frequency above 10 and on average 11.6 phrases are labeled on each image. In this paper, we only use the validation and test splits which take up 15% and 25% respectively of the whole dataset.

Along with DTD$^2$, a set of synthetic texture images and descriptions is also introduced in [26] which allows for systematic analysis on understanding compositional phrases of two colors (e.g., “red and blue”), color+pattern (e.g., “yellow square”), as well as foreground/background colors (e.g., “gray background”). We conduct the same experiment as in Section 5.3 of [26] using CLIP without any training.

3.4. Caltech-UCSD Birds Dataset

CUB [25] Dataset contains 11,788 images across 200 bird species labeled with 312 binary attributes on each image. We only use the test split of 5794 images roughly equally distributed across the 200 categories. CUB Dataset provides the common names for the bird species and we also use scientific names from their hierarchical categorization of species, genus, family, and order.

The 312 binary attributes describe the color, shape, and pattern of a certain part of the bird (e.g., is the wing blue or not). Figure 7 in [26] shows that color and pattern attributes play an essential role for categorization, and the adjectives describing color and pattern align with attributes in DTD$^2$ (as shown in the x axis of Figure 6).

4. Experiments and Analysis

4.1. Phrase and Image Retrieval on DTD$^2$

We first compare CLIP with DTD2-ML on phrase and image retrieval on DTD$^2$. For phrase retrieval, we rank the 655 frequent phrases in DTD$^2$ according to their embedding distances to the input image; For image retrieval, we rank all images in the test split by their distances to the query phrase. DTD2-ML directly encodes the phrases without prompt sentences, which is the same setting as it’s trained with. CLIP on the other hand has varied performance with different prompts. We experiment various
Figure 2. Image retrieval examples on DTD² test set from CLIP and DTD2-ML. For each query attribute phrase, we display 5 random ground-truth images labeled with the given attribute, and the top 5 retrieved images from CLIP and DTD2-ML.

Figure 3. CLIP and DTD2-ML phrase retrieval examples from DTD² test set. We display the ground-truth phrases labeled in DTD² and top 20 retrieved phrases from CLIP and DTD2-ML. The retrieved phrases in bold are the ones included in the ground truth.

prompts on the validation set (as shown in Table 2) and decide to encode text in the format of “An image of [P] texture”, where [P] is the input texture phrase. It outperforms directly using the phrase by a large margin.

In Table 3 we list the retrieval metrics from CLIP and DTD2-ML. Compared with DTD2-ML, CLIP gets similar performance on image retrieval but worse on phrase retrieval. As shown in examples in Figure 2, both models retrieve reasonable images. “Zigzagged” is a very specific pattern that CLIP makes mistakes on but DTD2-ML is able to understand accurately. “Equally spaced” is a failure case for CLIP that it looks for galaxy space.

The performance gap between CLIP and DTD2-ML on phrase retrieval may come from incomplete annotation and over-fitting of DTD2-ML on phrase frequency distribution in DTD². Looking at the first example in Figure 3, the phrases retrieved by CLIP are reasonable although the retrieval metrics for CLIP are low in Table 3. Both CLIP and DTD2-ML retrieve “striped”. DTD2-ML also retrieves “lined” and “lines”, while CLIP retrieves “striated” and “strips”, which are all synonyms to “striped”. However, “striated” and “strips” are rare in DTD² and DTD2-ML.
Table 2. Image and phrase retrieval mean average precision of CLIP on DTD$^2$ validation split using different prompt templates. Considering both image and phrase retrieval performance, we select “An image of [Phrase] texture” as our template for further experiments.

| Prompt Template               | Image Retrieval | Phrase Retrieval |
|------------------------------|-----------------|------------------|
| [Phrase]                     | 13.53           | 9.34             |
| A [Phrase] image             | 13.54           | 9.93             |
| [Phrase] texture             | **14.15**       | 11.57            |
| A photo of [Phrase] texture  | 13.82           | 11.98            |
| An image of [Phrase] texture | 13.93           | **12.31**        |
| An image with [Phrase] texture| 12.88           | 10.65            |

Figure 4. Cloud of phrases with the best and worst performance of image retrieval on DTD$^2$ test set for CLIP and DTD2-ML. The blue (red) cloud is sampled from the top 80 phrases with the highest(lowest) average precision. On the right, we also display 80 phrases with the maximum difference in average precision between CLIP and DTD2-ML. Font sizes are proportional to phrase frequencies in DTD$^2$.

4.2. Understanding Compositional Phrases on Synthetic Texture Images

We conduct the compositionality modeling analysis on synthetic texture images the same as described in Section 5.3 of [26]. Given a compositional query phrase such as “blue and red”, the task is to calculate its distance to positive images as well as hard negative images (which are “blue” or “red” but not both), retrieve the top k nearest images where k is the number of true positives, and report the R-precision as listed in Table 4. Note that DTD2-ML is not trained on synthetic images but the domain is very similar to the training set of DTD2-ML.

CLIP achieves a huge improvement on “Two-colors” and a slight improvement on “Color+Pattern”. CLIP is trained on much more language data, therefore during training it may have seen plenty of examples of the combinations that are rare or novel in DTD$^2$. While the DTD2-ML model needs to infer the language composition, CLIP can simply learn the exact bi-gram or tri-gram phrases from training.

We also see a slight improvement for CLIP on “Background” compared against DTD2-ML but it performs lower than random guesses on “Foreground”. Our interpretation is that background usually takes more area than the foreground. CLIP tends to recognize more of the majority color and fails to distinguish the foreground and background.

4.3. Phrase and Image Retrieval of Texture Phrases on CUB Dataset

We further compare the two models on CUB [25] Dataset which DTD2-ML hasn’t been trained on and poses a huge domain shift to DTD2-ML. We select 17 attributes that both occur in DTD$^2$ and CUB as listed in Figure 6. For example, images from CUB with a positive attribute “blue” on wing, upper-parts, or back, etc. are all counted as positive for “blue”.

In Table 5 we list retrieval metrics of two models. CLIP performs better than DTD2-ML on image retrieval and they perform similarly on phrase retrieval. In Figure 5 we show image retrieval examples. CLIP is able to focus on the main object while DTD2-ML recognizes attributes from the background. For example, CLIP can retrieve “blue” birds, while DTD2-ML retrieved images with a “blue” background. On the other hand, DTD2-ML can retrieve from different categories but CLIP tends to return images of the same category, which implies that CLIP image features are highly related to categories such that images of the same
category are close to each other in the embedding space. In Figure 6 we compare each attribute in terms of image retrieval average precision. CLIP outperforms DTD2-ML on almost all attributes, especially “blue”, “yellow” and “red”.

It is challenging to apply DTD2-ML to a novel domain of bird images because there is very limited overlapping of attributes and “bird” is an unseen concept for DTD2-ML. CLIP can perform reasonably on both DTD$^2$ and CUB Dataset without any extra training. This demonstrates the strength of CLIP in generalizing to novel domains.

### 4.4. Zero-Shot Classification with Attribute Phrases

As introduced in [20], CLIP can work as a zero-shot classifier on novel categories. Each category $C$ is converted to a sentence “A photo of a $[C]$” and encoded by the text encoder. Given an image, one can encode it with the image encoder and retrieve the nearest category as its prediction.

One concern of such a zero-shot classification mechanism is that the category names can be special proper nouns or rare words especially in fine-grained domains, which may lead to compromised classification performance. Here we extend the idea to improve fine-grained zero-shot classification through using attributes mostly on textures to construct more informative category descriptions.

#### Texture Classification

We first apply CLIP to classify 45 texture types in DTD$^2$. We count the most frequent attributes for each category in the training set, choose the top 20 attributes for each category that have a higher frequency than the average for that category, and construct the phrases as “An image of [xxx] texture”, where [xxx] are the 20 phrases. For example, the “gauzy” class is described as “An image of gauzy, sheer, transparent, light, thin, white, translucent, soft, see through, delicate, netted, meshed, airy, silky, fabric, see-through, folded, wavy, curtains, cloth texture.” On DTD$^2$ test set, we achieve a classification accuracy of 54.84%, compared to 41.06% when only including the category names.

This experiment verifies the effectiveness of CLIP for zero-shot classification for texture understanding. One can add a novel category to the CLIP classifier and achieve reasonable performance with only a description of the category name and most distinguishing attributes, which is much easier to collect than a set of images for this novel category.

#### Bird Species Classification

On CUB Dataset, we first count the percentage of images within a given category $C$ in CUB that are positive for attribute $A$ and compare it with the positive percentage of $A$ across all categories. Based on such statistics, we gather a sorted list of attributes for each category that distinguishes it from other categories and add these attributes into the category description. The attributes from CUB contain adjectives describing the whole bird, e.g., “has wing color: brown”, and we construct the category description in the format of “An image of a [P_0] [C] with [P_1] [N_1], [P_2] [N_2], ...” where $C$ is the category name, $P_0$ contains adjectives describing the whole bird, $N_i$ are nouns of bird body parts (such as “belly”, “tail”) and $P_i$ are adjectives modifying $N_i$. We use different levels of category names to construct the descriptions.

Figure 7 shows three examples of constructed descriptions. The attributes reflect subtle differences among the three similar species, e.g., “Rhinoceros Auklet” is more “duck-like” with “buff leg”, “Parakeet Auklet” has “white eye” and “white belly”, “Crested Auklet” has “crested head” and “black nape”.

Classification results are listed in Table 6. We report the top-k accuracy, i.e., we consider a test image to be correctly classified if the ground-truth category is ranked within top-k among all the 200 categories. When no attribute is added, we construct the description simply as “An image of a [C]” where [C] can be the common name, species, genus, family, or order. In such case, species from the same genus, family or order may have the same category description, resulting in

### Table 3. Phrase and image retrieval performance of DTD2-ML and CLIP on DTD$^2$ test set. We report the mean average precision (MAP), mean reciprocal rank (MRR), as well as top-k precision (P@k) and recall (R@k) of both models.

| Task                   | Model   | MAP  | MRR  | P@5  | P@20 | R@5  | R@20 |
|------------------------|---------|------|------|------|------|------|------|
| Phrase Retrieval       | DTD2-ML | 31.68| 72.59| 40.67| 22.96| 20.23| 44.50|
|                        | CLIP    | 12.20| 16.52| 14.57| 5.24 | 17.32|
| Image Retrieval        | DTD2-ML | 13.50| 31.12| 16.32| 5.49 | 14.57| 27.45|
|                        | CLIP    | 12.74| 32.15| 16.95| 7.40 | 6.16 | 17.31|

### Table 4. R-Precision of image retrieval on texture compositional tasks with DTD2-ML and CLIP. CLIP has a better understanding of compositional terms despite not being trained on this dataset. For example, on the “two-colors” the performance is significantly better.

| Model      | Foreground | Background | Color+Pattern | Two-colors |
|------------|------------|------------|---------------|------------|
| DTD2-ML    | 46.55 ± 20.65 | 52.00 ± 6.32 | 41.73 ± 22.77 | 27.45 ± 15.13 |
| CLIP       | 38.00 ± 14.94 | 60.18 ± 5.49 | 45.23 ± 23.51 | 55.18 ± 16.18 |
| Random guess | 50.00      | 50.00      | 7.40          | 5.26       |
| Task            | Model   | MAP  | MRR  | P@5  | P@20 | R@5  | R@20 |
|-----------------|---------|------|------|------|------|------|------|
| Phrase Retrieval| DTD2-ML | 52.58| 68.65| 46.36| -    | 45.80| -    |
|                 | CLIP    | 54.06| 75.93| 43.21|- 43.43| -    | -    |
| Image Retrieval | DTD2-ML | 35.33| 53.71| 44.71| 43.82| 0.17 | 0.75 |
|                 | CLIP    | 50.14| 91.71| 72.94| 71.76| 0.46 | 1.60 |

Table 5. Phrase and image retrieval with DTD2-ML and CLIP on CUB test set. We experiment with 17 attributes that are included in both CUB and DTD as input queries.

Figure 5. Image retrieval examples on CUB test set from CLIP and DTD2-ML. For each query attribute phrase, we display 5 randomly selected ground-truth images labeled with the given attribute, and the top 5 retrieved images from CLIP and DTD2-ML. CLIP tends to associate color and texture attributes with the foreground objects – in part due to training on datasets with category labels as the source of text annotations which focus on the canonical object. For example, the query “blue” is only associated with blue birds, while the DTD2-ML picks up blue birds and background water.

in multiple tied nearest classes, and a random class will be selected from the nearest ones as the final prediction.

Each of the 200 categories has a unique species name, but there is a significant performance gap when using the common names compared to using the scientific names of the species. This shows that the CLIP classification performance depends on how familiar the text encoder is with the category names. CLIP has learned plenty about the common names during pre-training, even overfitting to the commonly used datasets available on the web, but fails when using species names.

Adding attributes to the descriptions improve the accuracy by a large margin, especially on the Top 5/10 accuracy. With the help of attributes, we achieve similar performance when we replace the species names with the word “bird”. This provides a more robust way to construct zero-shot fine-grained classifiers when we don’t have category names but are able to provide coarse attribute descriptions.

5. Conclusion and Limitations

We analyze how well CLIP understands texture in natural images and texture terms in natural languages. Without any fine-tuning, CLIP achieves comparable performance on texture image and phrase retrieval compared to the baseline model specialized in the domain of textures. CLIP is capable of understanding various compositional texture descriptions and recognizing localized texture features in bird images. By including texture attributes in category descriptions, CLIP demonstrates its capability of constructing reliable zero-shot classifiers on fine-grained categories even with unknown or coarse category names.

We presented experiments in the domain of bird species mainly because of the availability of localized texture attribute annotations as well as the hierarchical taxonomy of category names from the CUB dataset. But the models might apply to other fine-grained domains such as fashion, Fungi, and Butterflies.

All our reported results apply CLIP in a zero-shot manner. Our preliminary experiments did not lead to improvements by fine-tuning, but fine-tuning large-scale language-vision models is currently an open question. We notice a foreground bias in the CLIP model which might not be desirable in some settings. Overall a better understanding of accuracy and biases of CLIP would encourage better adoption of these enormously popular pre-trained models.

Acknowledgements The project was supported in part by grants from the National Science Foundation #1749833 and #1617917, and grants from Adobe. Our experiments were performed in the UMass GPU cluster funded by the MassTech Collaborative.
Figure 6. **Image retrieval average precision of each query attribute on CUB test set from CLIP and DTD2-ML.** The gray line shows the accuracy difference between CLIP and DTD2-ML. CLIP outperforms DTD2-ML on all attributes except “plain”.

- **Rhinoceros Auklet** | **Cerorhinca monocerata** | **Aethia** | **Alcidae** | **Charadriiformes**
- “An image of a duck-like shape medium size black **Rhinoceros Auklet** with buff leg, orange bill, black nape, solid wing, black upper tail, black solid back, black crown, grey underparts, grey breast, solid tail, grey throat.”

- **Parakeet Auklet** | **Aethia psittacula** | **Aethia** | **Alcidae** | **Charadriiformes**
- “An image of a medium size black **Parakeet Auklet** with white eye, specialized red short bill, white belly, black nape, white underparts, black back, black crown, black forehead, grey leg, white breast, black upper tail.”

- **Crested Auklet** | **Aethia cristatella** | **Aethia** | **Alcidae** | **Charadriiformes**
- “An image of a medium size **Crested Auklet** with white eye, crested head, specialized orange bill, solid wing, black nape, black forehead, black upper tail, black throat, black solid back, black crown, black under tail, black upperparts.”

Figure 7. **Examples of category names, attributes and constructed descriptions for zero-shot classification on CUB Dataset.** We show the “common name | species | genus | family | order” for each of the categories, as well as the input descriptions containing the common name and the attributes. The bolded common names can be replaced by other category names such as species.

| Category | common name(200) | species(200) | genus(115) | family(39) | order(12) | “bird”(1) |
|----------|------------------|--------------|------------|------------|-----------|----------|
| #Attribute | 0 | 15 | 0 | 15 | 0 | 15 | 0 | 15 | 0 | 15 |
| Top1 | 51.78 | 50.24 | 6.58 | 14.33 | 15.48 | 14.43 | 10.87 | 12.93 | 6.59 | 12.46 | 12.08 |
| Top5 | 82.59 | 81.65 | 19.23 | 40.97 | 18.78 | 40.54 | 11.55 | 36.00 | 6.73 | 35.40 | 35.78 |
| Top10 | 90.97 | 91.34 | 24.89 | 56.61 | 20.80 | 53.32 | 17.33 | 51.92 | 11.34 | 51.52 | 52.28 |

Table 6. **Zero-shot classification top-k accuracy on CUB test set using CLIP with different levels of category names and attributes.** In the brackets we show the number of categories for each level. *e.g.*, there are 115 different genus names.
References

[1] Moses Amadasun and Robert King. Textural features corresponding to textural properties. *IEEE Transactions on Systems, Man, and Cybernetics*, 19(5):1264–1274, 1989. 2

[2] R. Arandjelović, P. Gronat, A. Torii, T. Pajdla, and J. Sivic. NetVLAD: CNN architecture for weakly supervised place recognition. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2016. 2

[3] Ruzena Bajcsy. Computer description of textured surfaces. In *Proceedings of the 3rd international joint conference on Artificial intelligence*, pages 572–579, 1973. 2

[4] Nalini Bhushan, A Ravishankar Rao, and Gerald L Lohse. The texture lexicon: Understanding the categorization of visual texture terms and their relationship to texture images. *Cognitive Science*, 21(2):219–246, 1997. 2

[5] Wieland Brendel and Matthias Bethge. Approximating CNNs with Bag-of-Local-Features Models works surprisingly well on ImageNet. In *Int. Conf. Learn. Represent.*, 2019. 2

[6] Mark Chen, Alec Radford, Rewon Child, Jeffrey Wu, Heewoo Jun, David Luan, and Ilya Sutskever. Generative pretraining from pixels. In *ICML*, pages 1691–1703. PMLR, 2020. 1

[7] Yuqi Huo, Manli Zhang, Guangzhen Liu, Haoyu Lu, Yizhao Gao, Guoxing Yang, Jingyuan Wen, Heng Zhang, Baogui Xu, Weihao Zheng, et al. Wenlan: Bridging vision and language by large-scale multimodal pre-training. *arXiv preprint arXiv:2103.06561*, 2021. 2

[8] Mary M Galloway. Texture analysis using grey level run lengths. *NASA STI/Recon Technical Report N*, 75:18555, 1974. 2

[9] Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness. *arXiv preprint arXiv:1811.12231*, 2018. 2

[10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018. 1, 3

[11] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*, 2021. 1, 2, 6

[12] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020. 3

[13] Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness. *arXiv preprint arXiv:1811.12231*, 2018. 2

[14] Robert M Haralick, Karthikeyan Shanmugam, and Its’ Hak Dinstein. Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, 6:610–621, 1973. 2

[15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *IEEE Conf. Comput. Vis. Pattern Recog.*, 2016. 1

[16] Tsung-Yu Lin, Aruni RoyChowdhury, and Subhransu Maji. Visualizing and understanding deep texture representations. In *IEEE Conf. Comput. Vis. Pattern Recog.*, pages 2791–2799, 2016. 2

[17] Tsung-Yu Lin and Subhransu Maji. Bilinear CNN models for fine-grained visual recognition. In *Int. Conf. Comput. Vis.*, 2015. 2

[18] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019. 1

[19] E Sali and H Wolfson. Texture classification in aerial photographs and satellite data. *International Journal of Remote Sensing*, 13(18):3395–3408, 1992. 2

[20] Hideyuki Tamura, Shunji Mori, and Takashi Yamawaki. Textural features corresponding to visual perception. *IEEE Transactions on Systems, Man, and Cybernetics*, 8(6):460–473, 1978. 2
[24] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Adv. Neural Inform. Process. Syst., pages 5998–6008, 2017. 3

[25] Catherine Wah, Steven Branson, Peter Welinder, Pietro Perona, and Serge Belongie. The Caltech-UCSD Birds-200-2011 Dataset. Technical Report CNS-TR-2011-001, California Institute of Technology, 2011. 3, 5

[26] Chenyun Wu, Mikayla Timm, and Subhransu Maji. Describing textures using natural language. In Eur. Conf. Comput. Vis., August 2020. 2, 3, 5

[27] Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In Int. Conf. Comput. Vis., pages 19–27, 2015. 3