Feathers dataset for Fine-Grained Visual Categorization

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Abstract—This paper introduces a novel dataset FeatherV1, containing 28,272 images of feathers categorized by 595 bird species. It was created to perform taxonomic identification of bird species by a single feather, which can be applied in amateur and professional ornithology. FeatherV1 is the first publicly available bird’s plumage dataset for machine learning, and it can raise interest for a new task in fine-grained visual recognition domain. The latest version of the dataset can be downloaded at https://github.com/feathers-dataset/feathersv1-dataset. We also present feathers classification task results. We selected several deep learning architectures (DenseNet based) for categorical crossentropy values comparison on the provided dataset.

Index Terms—Image classification; Dataset; FeathersV1; Convolutional neural networks; Deep learning; DenseNet; Categorical crossentropy

I. INTRODUCTION

Feathers remained out of computer vision focus, despite a sufficient amount of unstructured data available on the Internet. The lack of high-quality datasets may limit the research progress of the community in this domain. Bird species categorization can be called a classic fine-grained visual recognition task [1]–[3]. However, as far as we know, there were no previous attempts to categorize bird species by an image of a single feather. In this paper, we introduce our on-going dataset project called FeathersV1, aimed at studying the problem of fine-grained classification and recognition of bird species by a feather. The dataset contains 28,272 feather images of 595 bird species. Several enthusiasts provided initial images, a full list of authors can be found at the GitHub page of the dataset. We manually divided every image into multiple images with a single feather and constructed the result dataset. Several examples of the dataset images are provided in Fig. 1.

Our contributions are three-fold. First, we introduce a new dataset of feather images with species annotations. Second, we describe how data was collected using online-resources and the work of hobbyists and enthusiasts. Third, we present baseline classification results on species identification using several DenseNet convolutional neural networks (CNN) architectures. Sect. II describes the content of the FeathersV1 dataset, and it is properties. The following Sect. III describes the dataset construction and preprocessing. In Sect. IV we examine the performance of a baseline classifier on the data. Finally, Sect. V contains a results summary and future research plans.
II. DATASET

FeathersV1 contains 28,272 images of feathers annotated with their species. Images are organized in a two-level hierarchy:

• **Species.** This is the most specific class label with Latin names of bird species. The dataset contains 595 species of birds.

• **Order.** This level represents the biological order of bird species. It is not used in the classification task but provides a more organized structure. The dataset contains 23 orders of birds.

One of the main challenges of this dataset is its very uneven diversification of images per class. It may vary between 2 and 620, and depends on species’ abundance and popularity among collectors. Due to this aspect, it requires a high augmentation level on some of the classes to exclude their imbalance. To make the dataset more even, we split the dataset into three datasets, containing Top-50, Top-100, and all classes ordered by images number. Quantitative distribution of images per species is shown in Fig. 3.

Image quality also varies because of the different nature of images. They are collected from several enthusiasts and were made at different times.

Dataset is divided into train and test subsets. We define classification tasks - bird species recognition. The performance is evaluated as class-normalized average classification accuracy, obtained as the average of the diagonal elements of the normalized confusion matrix [12].

The dataset is published for non-commercial purposes.
III. DATASET CONSTRUCTION

Identifying the species of a bird from a feather image is challenging for anyone, but ornithology experts, and collecting 28,272 such annotations is daunting in general. Sect. III-A explains how feather data was collected by feather enthusiasts. Sect. III-B explains how data was preprocessed.

A. Initial data

Feather images can be found at various sites across the Internet, where collectors publish their feather collections. Although research purposes can be considered as a fair use of images, nevertheless, we contacted collectors to ask permission to use images. We contacted several collectors, and five of them gave us permission. Also, three sites had open licenses: Creative Commons BY 4.0, Copyleft, and GNU Free Documentation License. To maximize a variety of images, we added images from minor collectors published on social networks. Most of these images are made for sale, and they may have some text or other objects. Example of initial images is presented in Fig. 4. This allowed to add images with different lighting, angles, and background, although minor collectors usually have less variety of species and have a higher percent of incorrect recognition of feathers. The initial dataset contained a total of 2561 images, and the vast majority of images had many feathers, the average number of feathers per image is 11.03.

B. Images preprocessing

After collecting images, we manually cropped every image into individual feather images to prevent the classification model from training based on feathers arrangement instead of visual patterns of individual feathers. All the images were annotated with bounding boxes via the VOTT Annotating tool. After converting annotations to JSON format, we wrote a script to save bounding boxes into individual images. Each image contains a cropped image of a single feather, sometimes with part of adjacent feathers of the same species. Dataset contains 28,272 images of 595 bird species. Not all the feathers from initial images were annotated, we filtered out down, semiplume and contour feathers if it considered not meaningful for classification, an example of bounding box annotations is presented in Fig. 5. Also, we filtered out some of the highly overlapping feathers if they were unrecognizable for classification.

IV. BASELINE

In this section, we study fine-grained feather classification using DenseNet models. We select 78,126 images from the FeathersV1 dataset and divide them into three subsets. The first subset (Top-50) contains 50 classes with a total of 10,314 images of bird species ordered by the number of images per class. The second subset (Top-100) consists of 100 classes with 14,941 images in total. The last subset (All) contains the entire dataset of 595 species with 28,272 images. We compare the recognition performance of three DenseNet models: DenseNet121, DenseNet169 and DenseNet201 [10].

| Orders            | Images | Species | Num. images per species |
|------------------|--------|---------|-------------------------|
| Passeriformes    | 8,480  | 252     | 33.7                    |
| Anseriformes     | 4,555  | 62      | 73.5                    |
| Charadriiformes  | 3,908  | 45      | 86.8                    |
| Accipitriformes  | 2,783  | 41      | 67.9                    |
| Strigiformes     | 1,650  | 24      | 68.8                    |
| Galliformes      | 1,104  | 28      | 39.4                    |
| Piciformes       | 872    | 22      | 39.6                    |
| Ciconiiformes    | 800    | 18      | 44.4                    |
| Caprimulgiformes | 658    | 8       | 82.3                    |
| Columbiformes    | 656    | 19      | 34.5                    |
| Gruiformes       | 557    | 14      | 39.8                    |
| Coraciiformes    | 415    | 11      | 37.7                    |
| Apodiformes      | 411    | 9       | 45.7                    |
| Procellariiformes| 272    | 7       | 38.9                    |
| Phoenicopteriformes | 259 | 2  | 129.5                  |
| Gaviiformes      | 239    | 4       | 59.8                    |
| Psittaciformes   | 234    | 10      | 23.4                    |
| Bucerotiformes   | 161    | 6       | 26.8                    |
| Cuculiformes     | 128    | 4       | 32.0                    |
| Pelecaniformes   | 73     | 7       | 10.4                    |
| Trogoniformes    | 26     | 1       | 26.0                    |
| Pterocliformes   | 19     | 1       | 19.0                    |
| Coliiformes      | 12     | 1       | 12.0                    |

Fig. 3. Quantitative distribution of images per species.

| Table II | Test and validation split |
|----------|---------------------------|
| Category | Train split | Validation split |
| Top-50 classes | 8,251 | 2,063 |
| Top-100 classes | 11,953 | 2,988 |
| All classes | 22,618 | 5,654 |

only at https://github.com/feathers-dataset/feathersv1-dataset.
models show great results for fine-grained classification tasks [11]. The performances of these nine models are summarized in Table III. Models trained on the entire dataset show the best performance, although the dataset is very imbalanced. Including into dataset many rare species with a small number of images has led to better performance, although it made the dataset more imbalanced. Fig. [11] shows the confusion matrix for DenseNet169 trained at Top-50 classes. This model is not one with the best performance but allows us to see results better. The model is less confident at genera of Acrocephalus and Larus because feathers of different species of those genera vary very slightly, and it is hard to recognize species manually. Recognition of Accipiter Nisus and Accipiter Gentilis is significantly more accurate because those species have 619 and 437 images, respectively, which is significantly more than other species in the dataset. The full code of our research can be found at https://github.com/feathers-dataset/feathersv1-classification.

V. SUMMARY

We have introduced the FeathersV1 dataset, a new dataset for fine-grained visual categorization. The data contains 28,272 feather images of 595 bird species. We believe that FeathersV1 has the potential of introducing a new kind of object to a fine-grained visual recognition domain. Feathers have interesting aspects for visual recognition. With further development, the dataset can be used in real-world applications for professional and amateur ornithologists. In the future, we plan to increase the size of the FeathersV1 dataset by organizing image crowd-sourcing among collectors.

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TABLE III
FINE-GRAINED CLASSIFICATION RESULTS.

| Subset | Model     | Sparse Categorical Crossentropy | Sparse Top 1 Categorical Accuracy | Sparse Top 5 Categorical Accuracy |
|--------|-----------|---------------------------------|----------------------------------|----------------------------------|
| Top-50 | DenseNet121 | 1.4597                           | 0.6394                           | 0.8871                           |
|        | DenseNet169 | 1.3592                           | 0.6684                           | 0.9186                           |
|        | DenseNet201 | 1.9363                           | 0.5700                           | 0.8740                           |
| Top-100| DenseNet121 | 0.6771                           | 0.7989                           | 0.9709                           |
|        | DenseNet169 | 0.7131                           | 0.7979                           | 0.9695                           |
|        | DenseNet201 | 1.0256                           | 0.7266                           | 0.9491                           |
| All    | DenseNet121 | 0.8549                           | 0.7642                           | 0.9482                           |
|        | DenseNet169 | 1.0586                           | 0.7181                           | 0.9360                           |
|        | DenseNet201 | 0.7689                           | 0.7978                           | 0.9586                           |

Fig. 5. Initial images annotations.
Fig. 6. Confusion matrix of DenseNet169 model at Top-50 classes.