Camera traps enable the automatic collection of large quantities of image data. Biologists all over the world use camera traps to monitor animal populations. We have recently been making strides towards automatic species classification in camera trap images. However, as we try to expand the geographic scope of these models we are faced with an interesting question: how do we train models that perform well on new (unseen during training) camera trap locations? Can we leverage data from other modalities, such as citizen science data and remote sensing data? In order to tackle this problem, we have prepared a challenge where the training data and test data are from different cameras spread across the globe. For each camera, we provide a series of remote sensing imagery that is tied to the location of the camera. We also provide citizen science imagery from the set of species seen in our data. The challenge is to correctly classify species in the test camera traps.

1. Introduction

In order to understand the effects of pollution, exploitation, urbanization, global warming, and conservation policy on our planet’s biodiversity, we need access to accurate, consistent biodiversity measurements. Researchers often use camera traps – static, motion-triggered cameras placed in the wild – to study changes in species diversity, population density, and behavioral patterns. These cameras can take thousands of images per day, and the time it takes for human experts to identify species in the data is a major bottleneck. By automating this process, we can provide an important tool for scalable biodiversity assessment.

Camera trap images are taken automatically based on a triggered sensor, so there is no guarantee that the animal will be centered, focused, well-lit, or at an appropriate scale (they can be either very close or very far from the camera, each causing its own problems). See Fig. 2 for examples of these challenges. Further, up to 70% of the photos at any given location may be triggered by something other than an animal, such as wind in the trees. Automating camera trap labeling is not a new challenge for the computer vision community [3, 5, 7–9, 12, 16, 17, 17–20, 23–26]. However, most of the proposed solutions have used the same camera locations for both training and testing the performance of an automated system. If we wish to build systems that are trained to detect and classify animals and then deployed to new locations without further training, we must measure the ability of machine learning and computer vision to generalize to new environments [6, 20]. This is central to the 2018 [6], 2019 [4], and 2020 iWildCam challenges.

The 2020 iWildCam challenge includes a new component: the use of multiple data modalities (see Fig. 1). An ecosystem can be monitored in a variety of ways (e.g. camera traps, citizen scientists, remote sensing) each of which has its own strengths and limitations. To facilitate the exploration of techniques for combining these complementary data streams, we provide a time series of remote sensing imagery for each camera trap location as well as curated subsets of the iNaturalist competition datasets matching the species seen in the camera trap data. It has been shown that species classification performance can be dramatically improved by using information beyond the image itself [8, 10, 15] so we expect that participants will find creative and effective uses for this data.
Illumination: Animals are not always well-lit. (2) Motion blur: common with poor illumination at night. (3) Size of the region of interest (ROI): Animals can be small or far from the camera. (4) Occlusion: e.g. by bushes or rocks. (5) Camouflage: decreases saliency in animals’ natural habitat. (6) Perspective: Animals can be close to the camera, resulting in partial views of the body.

2. Data Preparation

The dataset consists of three primary components: (i) camera trap images, (ii) citizen science images, and (iii) multispectral imagery for each camera location.

2.1. Camera Trap Data

The camera trap data (along with expert annotations) is provided by the Wildlife Conservation Society (WCS) [2]. We split the data by camera location, so no images from the test cameras are included in the training set to avoid overfitting to one set of backgrounds [7].

The training set contains 217,959 images from 441 locations, and the test set contains 62,894 images from 111 locations. These 552 locations are spread across 12 countries in different parts of the world. Each image is associated with a location ID so that images from the same location can be linked. As is typical for camera traps, approximately 50% of the total number of images are empty (this varies per location).

There are 276 species represented in the camera trap images. The class distribution is long-tailed, as shown in Fig. 3. Since we have split the data by location, some classes appear only in the training set. Any images with classes that appeared only in the test set were removed.

2.2. iNaturalist Data

iNaturalist is an online community where citizen scientists post photos of plants and animals and collaboratively identify the species [1]. To facilitate the use of iNaturalist data, we provide a mapping from our classes into the iNaturalist taxonomy. We also provide the subsets of the iNaturalist 2017-2019 competition datasets [22] that correspond to species seen in the camera trap data. This data provides 13,051 additional images for training, covering 75 classes.

Though small relative to the camera trap data, the iNaturalist data has some unique characteristics. First, the class distribution is completely different (though it is still long tailed). Second, iNaturalist images are typically higher quality than the corresponding camera trap images, providing valuable examples for hard classes. See Fig. 4 for a comparison between iNaturalist images and camera trap images.

2.3. Remote Sensing Data

For each camera location we provide multispectral imagery collected by the Landsat 8 satellite [21]. All data comes from the the Landsat 8 Tier 1 Surface Reflectance dataset [13] provided by Google Earth Engine [14]. This data has been been atmospherically corrected and meets certain radiometric and geometric quality standards.

Data collection. The precise location of a camera trap is generally considered to be sensitive information, so we first obfuscate the coordinates of the camera. For each time point when imagery is available (the Landsat 8 satellite images the Earth once every 16 days), we extract a square patch centered at the obfuscated coordinates consisting of 9 bands of multispectral imagery and 2 bands of per-pixel metadata. Each patch covers an area of 6km × 6km. Since one Landsat 8 pixel covers an area of 30m², each patch is 200 × 200 × 11 pixels. Note that the bit depth of Landsat 8 data is 16.

The multispectral imagery consists of 9 different bands.
ordered by descending frequency / ascending wavelength. Band 1 is ultra-blue. Bands 2, 3, and 4 are traditional blue, green, and red. Band 5-9 are infrared. Note that bands 8 and 9 are from a different sensor than bands 1-7 and have been upsamled from 100m²/pixel to 30m²/pixel. Refer to [13] or [21] for more details.

Each patch of imagery has two corresponding quality assessment (QA) bands which carry per-pixel metadata. The first QA band (pixelqa) contains automatically generated labels for classes like clear, water, cloud, or cloud shadow which can help to interpret the pixel values. The second QA band (radsatqa) labels the pixels in each band for which the sensor was saturated. Cloud cover and saturated pixels are common issues in remote sensing data, and the QA bands may provide some assistance. However, they are automatically generated and cannot be trusted completely. See [13] for more details.

3. Baseline Results

We trained a basic image classifier as a baseline for comparison. The model is a randomly initialized Inception-v3 with input size 299 × 299, which was trained using only camera trap images. During training, images were randomly cropped and perturbed in brightness, saturation, hue, and contrast. We used the rmsprop optimizer with an initial learning rate of 0.0045 and a decay factor of 0.94.

Let $C$ be the number of classes. We trained using a class balanced loss from [11], given by

$$L'(p, y) = \frac{1 - \beta}{1 - \beta n_y} L(p, y)$$

where $p \in \mathbb{R}^C$ is the vector of predicted class probabilities (after softmax), $y \in \{1, \ldots, C\}$ is the ground truth class, $L$ is the categorical cross-entropy loss, $n_y$ is the number of samples for class $y$, and $\beta$ is a hyperparameter which we set to 0.9.

This baseline achieved a macro-averaged F1 score of 0.62 and an accuracy of 62% on the iWildCam 2020 test set.

4. Conclusion

The iWildCam 2020 dataset provides a test bed for studying generalization to new locations at a larger geographic scale than previous iWildCam competitions [4, 6]. In addition, it facilitates exploration of multimodal approaches to camera trap image classification and pairs remote sensing imagery with camera trap imagery for the first time.

In subsequent years, we plan to extend the iWildCam challenge by adding additional data streams and tasks, such as detection and segmentation. We hope to use the knowledge we gain throughout these challenges to facilitate the development of systems that can accurately provide real-time species ID and counts in camera trap images at a global scale. Any forward progress made will have a direct impact on the scalability of biodiversity research geographically, temporally, and taxonomically.

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