

Digital Naturalist - AI Enabled tool for Biodiversity Researchers...

Team ID	PNT2022TMID49396
Project Name	Digital Naturalist - AI Enabled tool for Biodiversity Researchers

PROJECT OBJECTIVES:

EMPATHIZE:

These methods have significantly improved our capacity to glean information from visual input. For example, iris identification and the detection of defective manufacturing products are only two examples of the security and industrial domains where AI approaches have been used extensively.

Despite this, they were only recently made more generally available after being used in smartphone apps for song and facial recognition. Now that cloud-based computing is more widely available, AI approaches can automatically evaluate hundreds of thousands of visual data points daily.

APPLICATION OF AI:

Active sampling, or photos taken especially with the intention of documenting animals, has always been the emphasis of biological recording up until this point (e.g., wildlife recording apps or camera traps). Large volumes of image data, which are not collected for the goal of biological recording but which yet may include significant information on biodiversity, have been overlooked as a result of this.

Images from social media (such as Flickr and Instagram), CCTV, and photographs gathered along linear infrastructure are included in this (e.g., Google StreetView). These untapped image data might be quickly studied utilising "AI naturalists" that are created to find potential biodiversity images and categorise what they observe.

HIGHLIGHTS:

- Biodiversity datasets can be produced from social media pictures by AI image classifiers.
- There are several plant photographs on Flickr, some of which can be precisely categorised to species by AI.
- Images underrepresent native species and are spatially gathered around tourist attractions.
- Images with a single, non-horticultural plant in focus can be identified most accurately.

DISCOVER:

We developed an AI naturalist capable of generating biodiversity datasets from previously untapped data sources by fusing social media APIs with AI classifiers. However, we show that there are a number of biases in the data generated, some of which may be avoidable, that need to be carefully taken into account before the data could be used in particular types of analyses.

SAMPLE IMAGES DISCOVER:

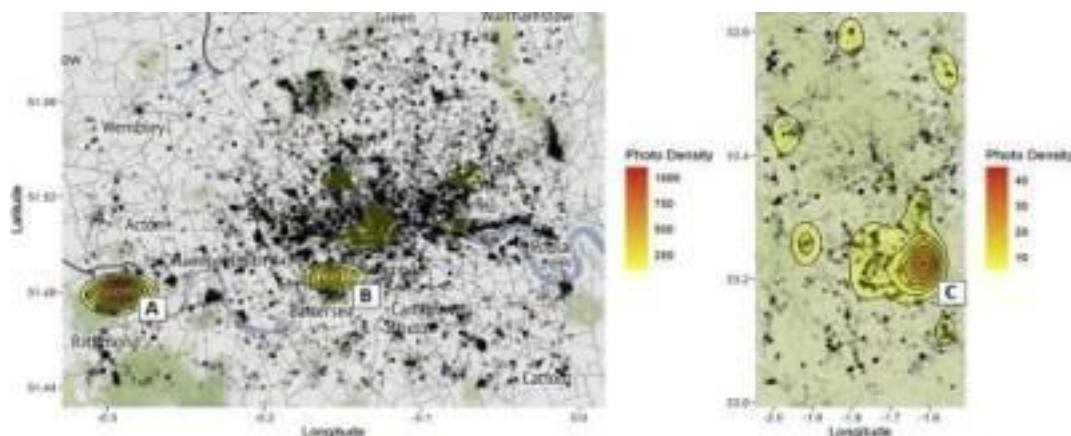
1. Randomly Selected Example Images:

The top row (1–3) were all correctly identified to species by the AI classifier; 4 and 5 were classed as unidentifiable by our expert botanist, with 4 additionally classified as a representation; 6 was classed as identifiable, but as not being focused on a single species. Credits clockwise from top left: Karen Roe, “Its No Game,” William Warby, “SamJKing.co.uk,” Dmitry Djouce, Matt Brown (all shared under CC BY 2.0).



2. Spatial Distribution of Images:

The spatial distribution of Flickr images returned when searching with the term “flower” in (A) London (urban) and (B) the Peak District (rural). Gray/black dots show the location of individual images. Colored areas show regions of particularly high densities of images. Hotspots correspond to: (A) Kew Gardens (a botanic garden), (B) the Chelsea Flower Show (an annual horticultural show), and (C) Chatsworth House (a large country house and gardens open to the public).



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