

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

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Team ID	PNT2022TMID43253
Project Name	Digital Naturalist –AI Enabled Tool for Biodiversity Researcher.
Maximum Marks	8 Marks

## **EMPATHIZE:**

In this techniques have profoundly transformed our ability to extract information from visual data. AI techniques have been applied for a long time in security and industrial domains, for example, in iris recognition or the detection of faulty objects in manufacturing.

They were nevertheless only recently made more widely accessible after their use in smartphone apps for face recognition and song identification.

Combined with increasing access to cloud-based computation, AI techniques can now automatically analyze hundreds of thousands of visual data every day.

## **APPLICATION OF AI:**

To biological recording have to date typically focused on active sampling, that is, images collected specifically for the purpose of recording wildlife (e.g., wildlife recording apps or camera traps). However, this has neglected large

amounts of image data that are not collected for the purposes of biological recording, but which nonetheless may contain useful information about biodiversity.

This includes social media imagery(e.g., Flickr and Instagram), CCTV, and imagery collected along linear infrastructure (e.g., Google StreetView). These unexploited image data could be rapidly analyzed using “AI naturalists” designed to locate potential images of biodiversity and classify what they see.

## **HIGHLIGHTS:**

- AI image classifiers can create biodiversity datasets from social media imagery.
- Flickr hosts many images of plants; some can be accurately classified to species by AI.
- Images are spatially aggregated around tourist sites and under-represent native species.
- Images focused on a single, non-horticultural, plant are most reliably identified.

## **DISCOVER:**

By combining social media APIs with AI classifiers, we were able to build an AI naturalist capable of creating biodiversity datasets from previously unexploited data sources. However, we demonstrate that there are a number of biases in the data produced, some of which may be able to be mitigated against, that must be carefully considered before the data could be used in certain types of analyses.

## **SAMPLE IMAGES DISCOVER:**

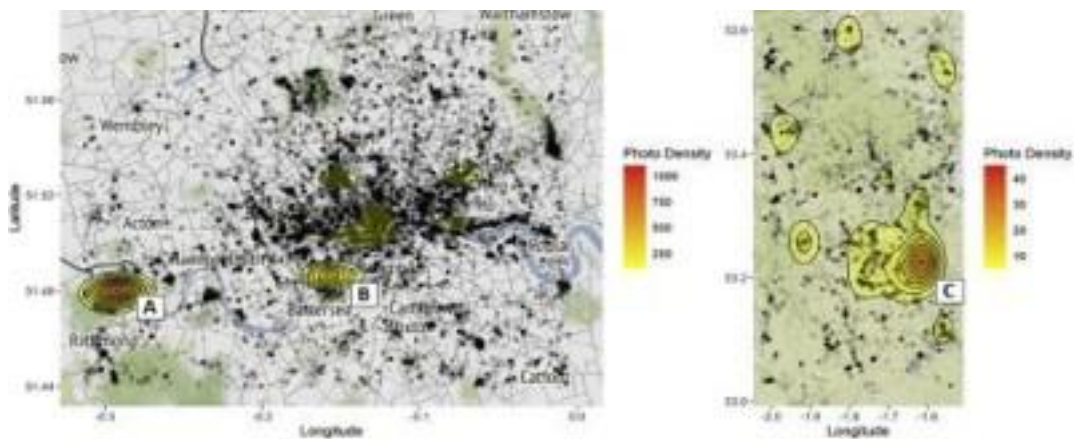
### **1. Randomly Selected Example Images:**

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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