RESEARCH ARTICLE

Rapid literature mapping on the recent use of machine learning for wildlife imagery

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Short title: Machine learning and wildlife imagery

Abstract

1. Machine (especially deep) learning algorithms are changing the way wildlife imagery is processed. They dramatically speed up the time to detect, count classify animals and their behaviours. Yet, we currently lack a systematic literature survey on its use in wildlife imagery.

2. Through a literature survey (a 'rapid' review) and bibliometric mapping, we explored its use across: 1) species (vertebrates), 2) image types (e.g., camera traps, or drones), 3) study locations, 4) alternative machine learning algorithms, 5) outcomes (e.g., recognition, classification, or tracking), 6) reporting quality and openness, 7) author affiliation, and 8) publication journal types.

3. Typically, studies have focused on single large charismatic or iconic mammalian species and used neural networks (i.e., deep learning). Additional taxa or alternative machine learning algorithms were rarely used, with limited sharing of code. There were considerable gaps, and therefore there is a great promise for deep learning to transform behavioural detection, classification, and tracking of wildlife.

4. Much of the published research and focus on animals came from India, China, Australia, or the USA. There were relatively few collaborations across countries. Given the power of machine learning, we recommend increasing collaboration and sharing approaches to utilise increasing amounts of wildlife imagery more rapidly and transform and improve understanding of wildlife behaviour and conservation.

5. Our survey augmented with bibliometric analyses provide valuable signposts for future studies to resolve and address shortcomings, gaps, and biases.

KEYWORDS

Conservation biology, field biology, big data, research weaving, drone imagery, systematic maps, evidence synthesis, deep learning

1 | INTRODUCTION

1.1 | Background

Camera-trap, surveillance-video, and drone imagery are producing a deluge of digital data on wildlife (Koh & Wich, 2012; Meek *et al.*, 2014; Allan *et al.*, 2018; Weinstein, 2018; Tuia *et al.*, 2022). Processing these digital images typically requires a substantial outlay of resources and time. However, machine learning algorithms for computer vision are revolutionising the field. A type of machine learning, deep learning algorithms using neural networks, have contributed to the recent rise of efficient computer visions (LeCun, Bengio & Hinton, 2015; Webb, 2018; Christin, Hervet & Lecomte, 2019; Lamba *et al.*, 2019; Tuia *et al.*, 2022). For example, a well-trained deep learning model can process video recordings and camera trap data extremely efficiently, reducing ten years of manual human work to less than one week (Norouzzadeh *et al.*, 2018).

This rapid and efficient processing opens possibilities for obtaining critical and detailed information on species' ecology, demography, life history and behaviour at previously impossible temporal and spatial scales (Villa, Salazar & Vargas, 2017; Christin, Hervet & Lecomte, 2019; Lamba *et al.*, 2019; Tuia *et al.*, 2022). This is increasingly useful for both *in-situ* and *ex-situ* conservation. This is especially because the number of endangered species surges in the Anthropocene (Emer *et al.*, 2019; Turvey & Crees, 2019; Wyner & DeSalle, 2020). Conservation biologists and wildlife biologists are progressively employing machine (deep) learning algorithms to process image data, often collaborating with computer scientists (e.g., Tabak *et al.*, 2019; Willi *et al.*, 2019). Review articles are also appearing on how machine (deep) learning can help in species recognition, individual recognition, behaviour detection and classification and animal tracking (e.g., Christin, Hervet & Lecomte, 2019; Lamba *et al.*, 2019; Nazir & Kaleem, 2021).

Yet, there is no systematic survey of this emerging and important field (cf. Caravaggi *et al.*, 2017). There are two major and effective ways to map literature: systematic mapping and bibliometric mapping. Systematic mapping covers the state of knowledge, revealing the knowledge clusters and research gaps (Haddaway *et al.*, 2016). A bibliometric map augments this approach, providing information on the location of research (Cobo *et al.*, 2011). This 'research weaving' can reveal differences between locations of wildlife research (field) and affiliation (Nakagawa *et al.*, 2019); highlighting discrepancies in international collaboration, inequalities in study opportunities and field access (cf. Trisos, Auerbach & Katti, 2021).

1.2 | Objectives

We use a 'rapid' review approach, which abbreviates the process of systematic maps by not being comprehensive but being representative (Lagisz *et al.,* 2022). Therefore, we cut down some of the systematic-map processes to be comprehensive by, for example, focusing on more recent articles and using one database. Such a rapid review (mapping) is useful especially for a rapidly moving fields like the topic of this article. Importantly, we also use a 'research weaving' approach. First, we map the content of recent studies (published between 2017 and 2021) utilising machine learning to process wildlife imagery. Using these studies, we attempt to find answers to the following questions:

1. What species and how many species were studied?
2. What was the source of wildlife images (e.g., camera traps, surveillance cameras)?
3. Where was the location (country) from which the wildlife image originated?
4. What machine (deep) learning algorithms were used?
5. What was the purpose or outcome of the study (e.g., individual recognition, behaviour detection)?
6. Was analysis code open and available?

With these questions, we aim to elucidate research trends, practices, gaps, and biases in the relevant literature, revealing future needs in this research area.

Then, we augment the above questions with bibliometric analyses, which ask two additional questions:

7. In which country was the study conducted? (Is it different to where images originated?)
8. In what type of journal was the study published? (Biological sciences, computer science or multi-disciplinary journals?)

These two additional questions relate to the aspects of diversity in this research area. The first question reveals internationality, while the second question indicates cross-disciplinary diversity. Overall, our research weaving of the literature aims to create some guideposts for future work.

2 | MATERIALS AND METHODS

We followed the ROSES (RepOrting standards for Systematic Evidence Syntheses) checklist for Systematic Maps (Haddaway *et al.*, 2018) for rigorous reporting of our data collection process. Search string development, validation, piloted screening and data extraction process were pre-piloted but not registered due to the rapid nature of this scoping-like review. Therefore, this is not a systematic map, but I can be considered more as a 'rapid' map or literature survey on a group of sample articles. This article is also intended to show how to conduct such a rapid review or survey, which will be especially useful for scoping a topic of interest or summarising evidence base in a limited time (Lagisz *et al.,* 2022).

2.1 | Eligibility criteria

We included publications in the last five years (2017-2021), where all criteria within an adapted PICO/PECO framework were fulfilled (Guyatt *et al.*, 2011; Morgan *et al.*, 2018):

P – Population: study subjects (in images) were wild or semi-wild vertebrate species (excluding domestic or farmed animals, invertebrates, and museum specimens). Datasets that included the target population but also contained images of other species (eg. domesticated species or humans) were also allowed, however the non-target population species were not included in the analysis.

I – Intervention / Innovation: use of computer vision machine learning algorithms (including deep neural-networks ,, Support Vector Machines, Random Forests; Nacchia *et al.*, 2021) for automated or semi-automated processing of image data (e.g., from camera traps, video tracking, thermal imaging; Nazir & Kaleem, 2021), at a scale where individual animals are visible (including aerial and drone images but excluding images gathered from satellites, biologging, X-ray, MRI images or equivalent).

C – Comparator / Context: images from the wild or semi-wild (including zoo enclosures, but excluding lab-based or agricultural / aquaculture / pet studies).

O – Outcomes: analyses focus on individual animal / species recognition / classification or animal behaviour recognition / classification.

2.2 | Searches

For a representative sample of multi-disciplinary literature, we ran a literature search using Scopus search engine on 2021/10/10 with a pre-piloted search string: (TITLE-ABS-KEY ((*automatic* OR "machine learning" OR "computer learning" OR "deep learning" OR "neural network*" OR "random forest*" OR "convolutional neural" OR "convolutional network*" OR "learning algorithm*" OR "Support Vector*") AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR "species identif*" OR "species label*" OR "species richness" OR (behavio* AND within/ 10 classif*) OR (behavio* AND within/ 10 recogn*)) AND NOT ("natural language" OR "sign language" OR accelomet* OR clinical* OR industr* OR agricult* OR farm* OR leaf OR husbandry OR food* OR tissue* OR cell* OR cultur* OR wildfire* OR "tree growth" OR forestry OR hydrolog* OR engineer* OR "oxygen species" OR molec* OR bacteria* OR microb* OR chemi* OR spectrom* OR brain* OR drug* OR patient* OR cancer* OR smoking OR disease OR diabet* OR landsat* OR sentinel OR satellite* OR "land cover" OR "land use" OR "vegetation map*" OR galax* OR "Google Earth" OR scan* OR "X-ray" OR "health care" OR participant* OR emotion* OR employee* OR speech OR proceedings))) AND PUBYEAR > 2016. We did not use language filters to ensure we captured literature from multiple countries. We chose Scopus as their bibliometric information was easy to handle than other databases such as the Web of Science (note that bibliometric information form two databases are usually not compatible to each other).

2.3 | Article screening

We used Rayyan QCRI software (Ouzzani *et al.*, 2016) to screen bibliographic records downloaded from Scopus. Three researchers (ML, JT, RF) independently performed the screening, assessing titles, abstracts, and keywords of each article. This screening resulted in articles included for full-text assessment and data extraction. We excluded publications without full text available, after contacting study authors via ResearchGate.

2.4 | Data extraction and coding

For data extraction from the articles with full text, we used a two-part custom questionnaire (details in Supplementary Materials) implemented as a Google Form. We used the first part of the form to re-assess the fulfilment of the inclusion criteria and the second part of the form to extract key data on the study content. At least two assessors extracted the first 6% of the papers independently during the piloting round. One assessor (ML) extracted the remaining, and another assessor (RF) independently cross-checked extracted data. Assessors authoring articles considered within the review were not involved in decisions regarding inclusion, extraction, or critical appraisal of their work. Apart from the data extracted via the questionnaire, we derived additional variables such as whether the full-text publication was included or excluded from the final dataset and the main reason for exclusion, extracted geographic coordinates for field-based studies. We coded whether location information was relatively precise or unclear. We also categorised publication journals into ecological, computer science-related and multidisciplinary. Details of data extraction and coding are provided in Supplementary File 1.

2.5 | Critical appraisal

As an indicator of reporting quality, we coded when we could not extract or infer information on key variables, such as sources of animal images (type of hardware and settings / locations), number of animal species / classes studied, and general types of machine learning algorithms used. We also coded whether the analysis code used in the study was available for checking or reuse.

2.6 | Data synthesis and presentation

We collated manually coded data in a single data table (Supplementary File 2) and supplemented it with bibliographic information from downloaded Scopus records. All data wrangling and visualisations were conducted in an R environment (R Development Team, 2022). Counts of articles within specific categories for each variable are presented as bar plots or stacked area plots, while spatial information (location of origins of animal images, first author affiliation country) is plotted as global distribution maps and alluvial plots using the ggplot2 (Wickham, 2016), rworldmap (South, 2011), and ggalluvial (Brunson, 2020), R packages. Species identities from single-species individual recognition studies are presented on a phylogenetic tree derived using the rotl package (Michonneau, Brown & Winter, 2016). Given that our data coding categories were pre-defined, knowledge gaps and clusters were identified via visual inspection of the plots. The narrative synthesis of our findings follows our key review questions.

3 | RESULTS

3.1 | Searches, screening, and a database

Our initial screening of 2,259 unique bibliographic records downloaded from Scopus resulted in 225 articles for full-text assessment and data extraction. Of these 225 articles, we obtained full text for 215 articles. Out of the 215 full-text articles assessed, 23 were excluded (Supplementary File 1, Table S2), and 192 were eligible for data extraction (Supplementary File 1, Table S3). The final dataset consists of 19 papers from 2017, 21 from 2018, 46 from 2019, 63 from 2020, and 43 from 2021.

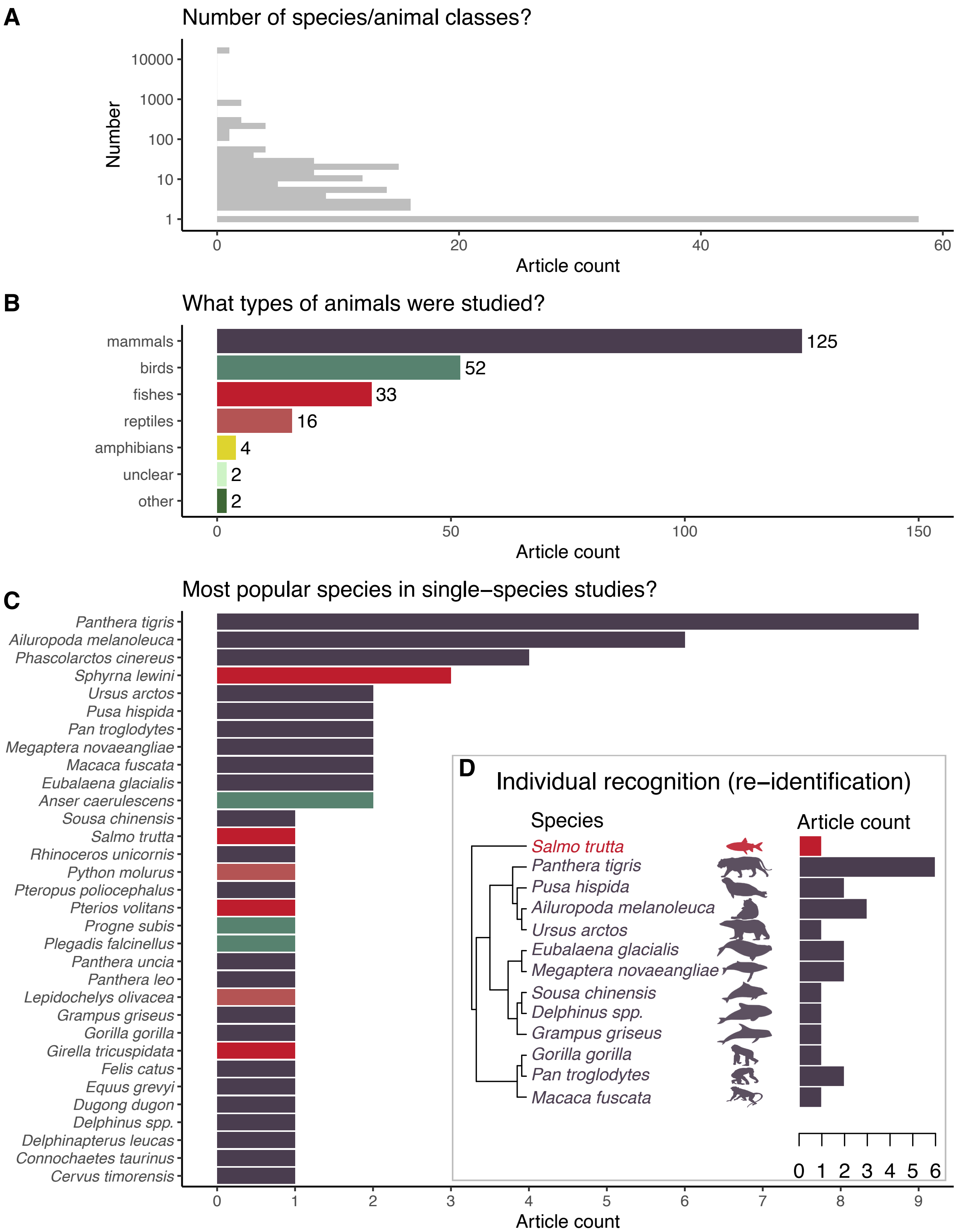

FIGURE 1. Diversity of the vertebrate species studied in the included machine learning studies. A – numbers of species / animal classes per study. B – counts of articles that studied each vertebrate class, C – counts of articles focused on a given species from one-species studies only (bar colours

are referring to vertebrate class from panel B). D - counts of articles focusing on a given species in one-species individual recognition (individual identification) studies only (bar colours referring to vertebrate classes from 1B) and a phylogenetic tree of the focus species.

3.2 | Study characteristics

3.2.1 | Study species and image types

Most studies (58 studies, 30%) only examined one species ('single-species' studies) with one study dealing with 16,583 species (mean = 118, SD = 1,241, median = 3; Fig. 1 A). The most popular biological group among vertebrates was mammals (65% studies), followed by birds (27%), fish (17%), reptiles (8%) and amphibians (2%); Fig. 1 B; some studies studied more than one class so that percentages do not total 100%. Thirty-five species were used in single-species studies. Here, the most popular study species were tigers (*Panthera tigris*), pandas (*Ailuropoda melanoleuca*) and koalas (*Phascolarctos cinereus*). In single-species studies, images of 13 species were used for individual recognition (re-identification) analyses, and these studies were dominated by mammals, especially large carnivores, cetaceans and primates (Fig. 1 D).

Nearly half of included studies used wildlife images from fixed cameras (52%), such as camera traps and surveillance cameras, while 28% of studies used images from hand (mobile) cameras, and 16% of studies used aerial images from drones or aircraft (Fig. 2 A). Over the last five years, the use of images from fixed cameras and mobile cameras has markedly increased, while the use of aerial images remained stable (Fig. 2 B). Note that in this and similar time-trend graphs, the apparent decrease in the relevant papers in 2021 is an artifact, because we conducted our literature search in October 2021, meaning that we did not cover the entire year 2021 period.

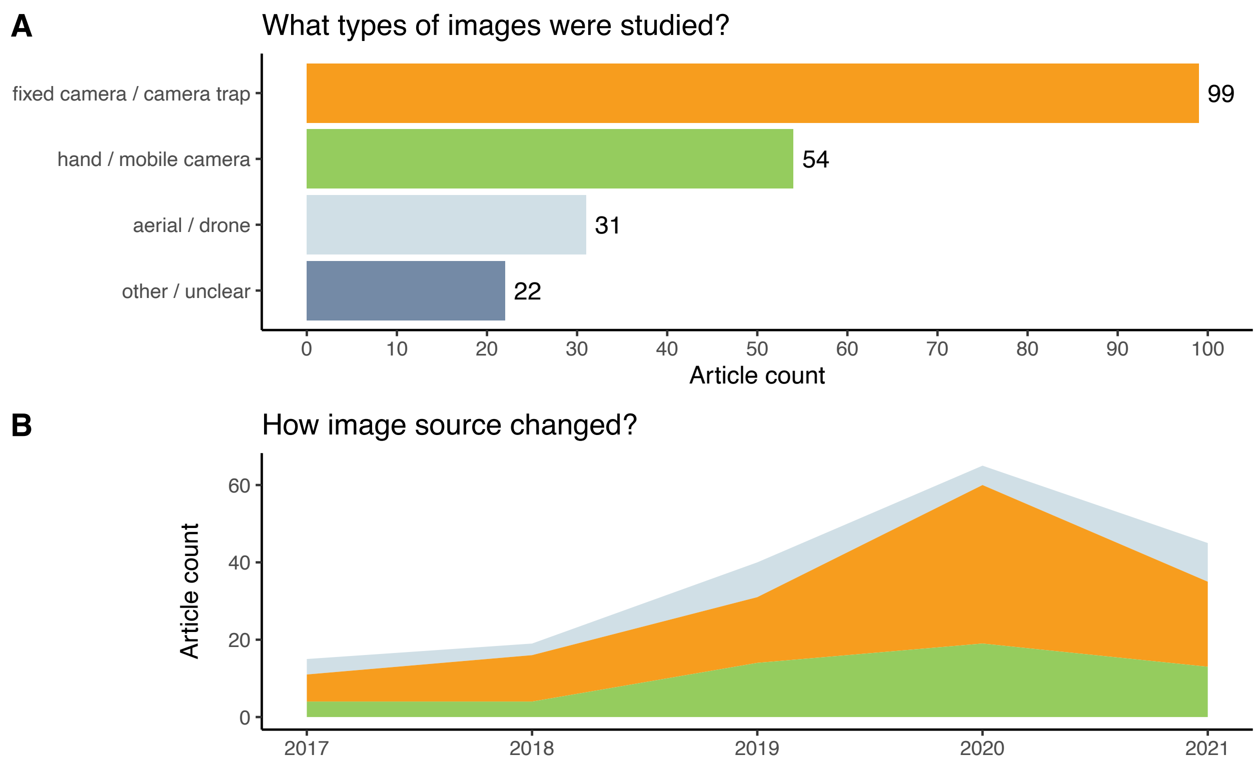

FIGURE 2. Diversity of the wildlife imagery analysed in machine learning studies. A - article counts by image source hardware type (one study could use more than one image type), B - temporal trends (annual counts) across the last five years. Year 2021 is included only up to October; colours are corresponding to image source hardware types shown in panel A; "other/unclear" category not shown.

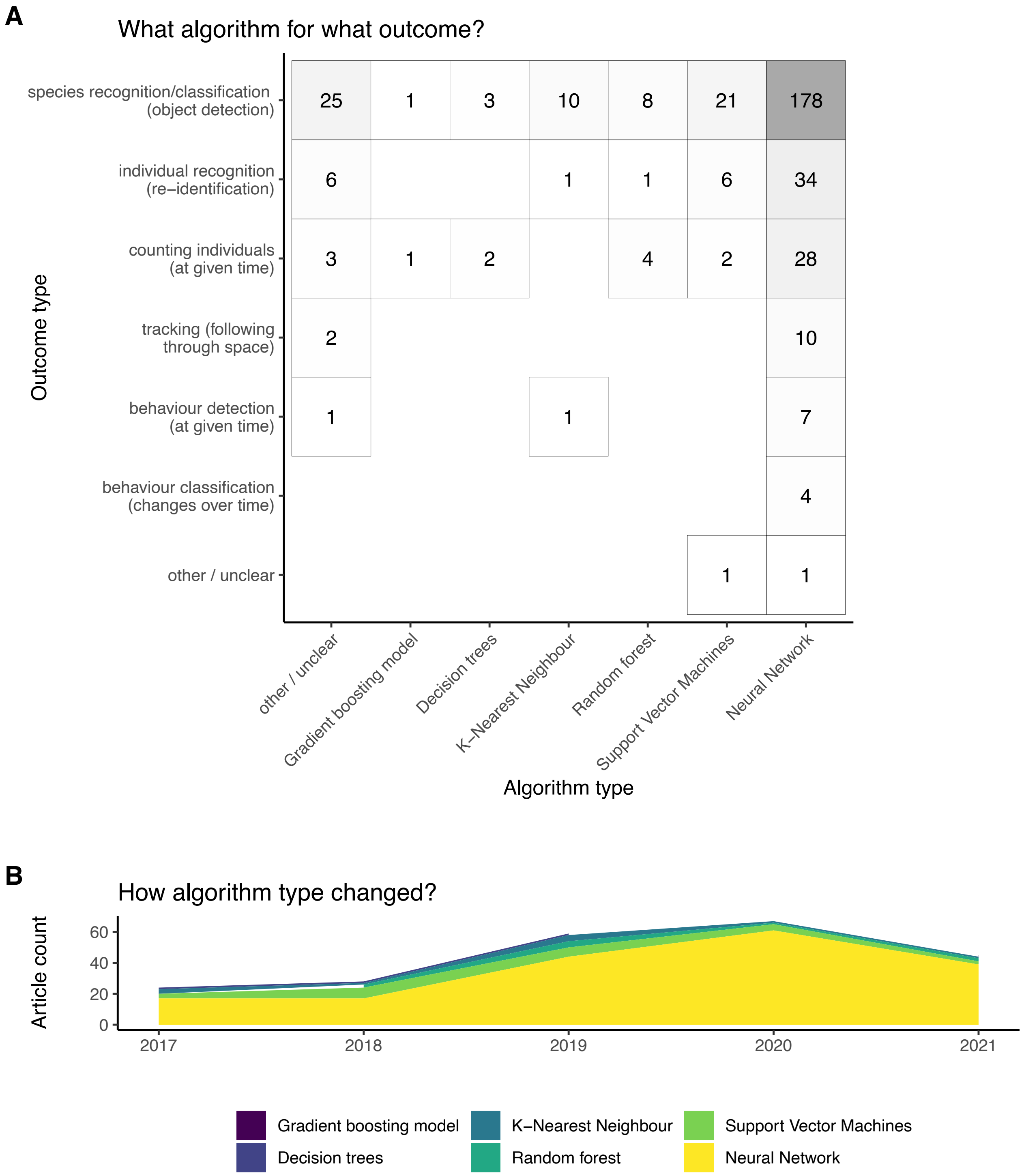

FIGURE 3. Machine learning algorithm types and wildlife outcome types analysed in the included studies. A – article counts by algorithm type and outcome type (one study could use more than one type of each), B – temporal trends (annual counts) in types of algorithms used across the last five years; "other/unclear" category not shown (Year 2021 is included only up to October).

3.2.2 | Algorithms and outcomes

Neural-network-based analyses were easily the most popular machine learning algorithms (93% of studies), followed by Support Vector Machines (11% of studies), K-Nearest Neighbours (5%), and Random Forests (5%). The use of the other algorithms was relatively low (14% of studies) and included Naïve Bayes, Bag of Visual Words, Histogram of Colors, Local Binary Patterns Histograms, Multi-class Logistic Regression, Principal Component Analysis, Linear Discriminant Analysis, and other statistical approaches. The primary use of machine learning was for species recognition / classification (99% of studies), followed by individual recognition (19% of studies) and counting the numbers of individuals (18% of studies), with the latter being implemented as an extension to species recognition / classification. Few studies attempted to conduct behaviour detection, classification, and tracking (10% of studies). The combination of species recognition / classification using neural networks was most frequent with neural networks used for all types of outcomes (Fig. 3 A). Fig 3 B shows the dominance of neural network algorithms and how this trend is increasingly apparent over time (note that 2021 literature was included only up to October of that year).

FIGURE 4. Geographic distributions and overlaps in the affiliations of first study authors and the locations of the wildlife imagery. A – connecting author's countries (in alphabetical order) and image source geographic locations; only countries / locations with more than one study are shown. B – Visualisation of the relative number of articles that use images from the same country as the

first author and where other sources of wildlife images are located (arrows pointing from the source towards the countries of the first authorship); "global" and "unclear" image source location categories not shown.

3.2.3 | Geographical origin, affiliations, and journal types

We analysed the countries of affiliation of the first authors of the included studies and locations of wildlife images used in the studies. The authors came from 40 different countries, but only 17 countries had more than one study (Fig. 4 A; left column), using images from 38 countries and 10 other location types, including 'global' and Antarctica (Fig. 4 A; right column). Three countries, Australia, China, and the USA, dominated the literature in terms of author affiliations and wildlife images. Datasets from the Antarctic, Africa and Southeast Asia were commonly analysed by researchers from other geographical areas (Fig. 4 B). There was especially strong international use of images by the United States, compared to Australia, the two largest generators of articles (Fig. 4 B). While all papers had more than one author, only 3 out of 173 papers with complete bibliographic data on affiliations had authors from more than one country (Supplementary Table S4).

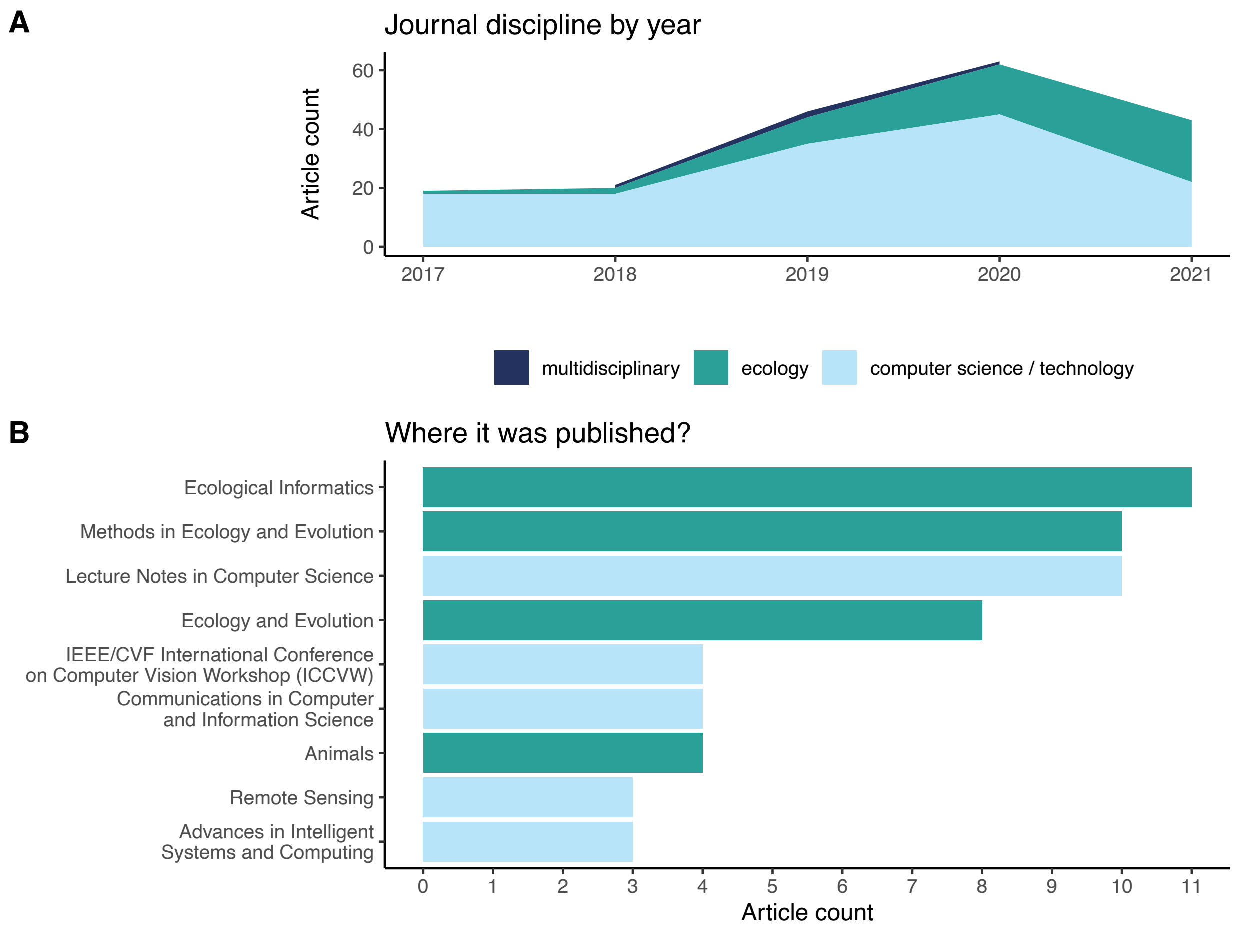

FIGURE 5. Diversity of the journals publishing machine learning studies on wildlife imagery. A – temporal trends (annual counts) in three main journal subject disciplines across the last five years. Year 2021 is included only up to October . B – article counts for journals with at least three articles included in our survey data set.

Although in 2017 most publications were in 'computer science' journals (mostly computer science conference proceedings, but also more traditional journals such as Lecture Notes in Computer Science, Remote Sensing), increasing numbers of studies were published in 'ecological' journals over the last few years (Fig. 5 A). Indeed, the top two destinations of the surveyed papers were ecological journals: Ecological Informatics and Methods in Ecology and Evolution (Fig. 5 B).

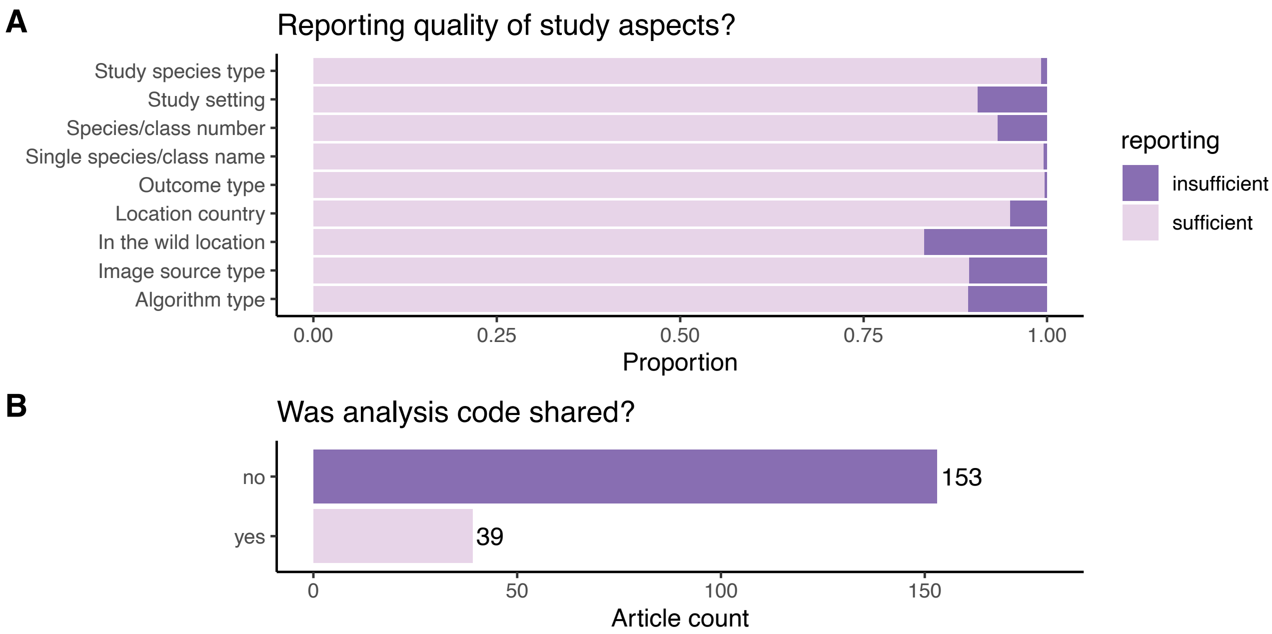

FIGURE 6. Aspects of reporting quality and openness of the included machine learning studies. A – percentages of relevant articles providing sufficient or insufficient information to code a given variable. B – article counts for studies that shared or did not share their analysis programming code.

3.2.4 | Reporting and open practices

Reporting quality was usually sufficient for nine survey questions (> 80% of studies; Fig. 6 A) to allow us to collect the basic information for our survey. However, few studies published their analysis code (i.e., shared links to computer scripts used in a study; ~20%, Fig. 6 B).

4 | DISCUSSION

We characterised recent use of machine learning to process wildlife imagery, using systematic and bibliometric mapping techniques. We had eight questions regarding: 1) study species, 2) image types (e.g., the use of fixed camera / camera trap, hand / mobile camera, or aerial / drone), 3) study location, 4) machine learning algorithms, 5) study outcomes (e.g., species / individual recognition or counting), 6) reporting quality and openness, 7) author affiliation, and 8) journal types (see

Section 1.2). We have profiled some clear patterns for each of these questions (Fig. 1 – 6). We discuss these patterns in four subsections below: i) Questions 1 & 2, ii) Questions 4 & 5, iii) Questions 3, 7 & 8, and iv) Question 6.

4.1 | Study species and image types

Studies mainly focused on large charismatic or iconic mammals such as the top three (tigers, pandas, and koalas), other big cats, cetaceans and primates, reflected in single-species studies and individual-recognition studies (Fig. 1 C, D). Birds were the second most popular taxon (Fig. 1 B), but only two species, snow geese, *Anser caerulescens* (Bowley *et al.*, 2017; Bowley *et al.*, 2018) and purple martins, *Progne subis* (Williams & DeLeon, 2019), were represented in single-species studies (Fig. 1 C). This is because multiple-species studies often focused on mammalian species, while occasionally also including large bird species (e.g., images from African savanna including ostrich; Rey *et al.*, 2017; Loos, Weigel & Koehler, 2018). The paper with 16,583 species included an exceptionally wide range of species, as it tried to utilise all the species recorded in GBIF (the Global Biodiversity Information Facility; Mo, Frank & Vetrova, 2017). Other papers with over 100 species often dealt with a particular taxon, such as birds (Ragib *et al.*, 2020), fish (Sayed *et al.*, 2018), and snakes (Picek *et al.*, 2021).

Researchers' preference for certain taxa is known as taxonomic bias (Bonnet, Shine & Lourdais, 2002; Donaldson *et al.*, 2016), well known in the research literature, including conservation, behavioural ecology and ecotoxicology (Rosenthal *et al.*, 2017; Troudet *et al.*, 2017; Prosser *et al.*, 2021). The distribution of study species in our literature survey supports the anthropomorphic stimuli hypothesis that we humans are more attracted to species phylogenetically closer to us (Miralles, Raymond & Lecointre, 2019). This hypothesis explains the widespread use of mammals and primates (Fig. 1 B, C). Indeed, a recent comprehensive study, including 7,521 mammalian species, showed that phylogenetic relatedness was closely related to research interest, as reflected by the number of publications and citations (Tam *et al.*, 2021), with primates overrepresented among the most popular species. In our survey, among the 13 species used for individual recognition, brown trout (*Salmo trutta*) appeared to be the 'odd one out', not fitting categories of iconic species or phylogenetic relatedness. However, the motivation behind the study was related to human economic values – helping aquaculture and fishing tourism by tracing fish migration and distribution, (Zhao *et al.*, 2019).

Given the affordability and accessibility of fixed cameras (i.e., camera traps and surveillance cameras), it was not surprising that fixed cameras were most used among the surveyed studies (52% studies). Indeed, many machine learning applications have focused on camera traps in ecology and environmental sciences (cf. Caravaggi *et al.*, 2017), with the dedicated book titled "Camera traps: wildlife management and research" (Meek *et al.*, 2014). Notably, a combined total of the usage of hand cameras (including mobile phones) and aerial (drone) wildlife images was nearly as high as that of fixed cameras (85 vs. 99 studies). However, the use of the fixed camera (especially camera traps) has been increasing rapidly, and this trend is likely to continue (Fig. 2 B; tailing off in 2021 is caused by our survey not capturing all images from that year, as literature searches were run in October 2021). This trend may be driven by increasing availability of images from fixed cameras and camera traps via freely available biodiversity collections (e.g., GBIF and iNaturalist) and computer vision programming challenge platforms (e.g., ImageNet and Kaggle).

4.2 | Algorithms and outcomes

Most (~92%) algorithms applied a neural network approach to classify or recognise animals. Neural networks or deep leaning algorithms were used for all six different tasks: 1) species recognition/classification, 2) individual recognition, 3) counting the number of individuals, 4) tracking individuals, 5) detecting behaviour at a given time and 6) classifying behaviours over time (in order of the usage; Nazir & Kaleem, 2021). On the other hand, the use of the traditional machine learning algorithms was limited, with the second most popular, Support Vector Machines, only found in 30 studies (Fig 3 A). However, the observed dominance of the literature by deep learning was not surprising. This is due to the recent resurrection of deep neural networks, initially proposed in 1943 (Mcculloch & Pitts, 1990), associated with the increased processing power provided by GPU, the availability of big data for training (LeCun, Bengio & Hinton, 2015; Webb, 2018) and the development of more advanced algorithms in the field of computer vision.

Our mapping effort elucidated future directions in the use of deep learning in wildlife imagery. The clear next step is to increase the use of deep neural networks to detect and track animals and classify their behaviour, with relevant algorithms already developed for human behaviour detection and tracking (e.g., Al-Faris *et al.*, 2020; Bendali-Braham *et al.*, 2021). Therefore, a challenge for ecologists and environmental scientists is to co-opt such algorithms for wildlife imagery. This challenge requires cross-disciplinary collaborations between computer and environmental scientists, which we discuss further in the next section.

4.3 | Geographical origin, affiliations, and journal types

In many studies, the geographical origin of wildlife images and the first author affiliation country are congruent (Fig. 4 A, B). Australia, China, India and the USA are four clear hot spots in both origins of wildlife images and authors, reflected in the top three species, tigers, koalas and pandas (Fig. 1 C). However, many wildlife images from Africa were usually analysed elsewhere (apart from South Africa; e.g., Butgereit & Martinus, 2018). Such incongruence could be related to scientific colonialism, initiating discussions on the ways to decolonise science (Baker, Eichhorn & Griffiths, 2019; Trisos, Auerbach & Katti, 2021). Building capacity and involving local collaborators including indigenous peoples could be a first step towards resolving this incongruence, increasing representation of underrepresented nations and their wildlife imagery. There is also considerable scope for more international collaborations, given only three studies had authors from multiple countries.

This field was entirely dominated by computer scientists five years ago (in 2017), reflected in almost all articles published in computer science journals or conference proceedings. Later, numbers shifted dramatically towards more ecological / environmental journals (Fig. 5 A). As a result, the top two highest-ranked journals most recently represent these disciplines (the third-ranked was a 'computer science' journal, Fig. 5 B). Disciplinary diversity is increasing, along with the accessibility of deep learning for non-computer scientists (Christin, Hervet & Lecomte, 2019; Lamba *et al.*, 2019) and interdisciplinary collaborations between ecologists and computer scientists are also on the rise (e.g., Tabak *et al.*, 2019; Willi *et al.*, 2019).

4.4 | Reporting and open practices

Although we could identify basic study information for our survey, about 10 – 20% of the papers lacked critical information, required for replication, such as study species (not just taxa), and details of image sources or locations (Fig. 6 A). This may still be underestimated, with generally poor reporting, exemplified by much of the coded survey information based on example images provided in figures and dataset descriptions from other publications or the Internet (e.g., when the study only mentioned the use of publicly available datasets, often not even naming which dataset). With an increasing number of studies applying machine learning to wildlife images, creating formal reporting guidelines may be useful. Reporting guidelines are common in (bio)medical research (e.g., du Sert *et al.*, 2020; Page *et al.*, 2021) and can improve reporting quality (Sun *et al.*, 2018). In our literature survey, we were particularly surprised that research (analysis) code was not published in approximately 80% of the studies, given the importance of computational reproducibility and code sharing within computer sciences (Cadwallader *et al.*, 2021). Where code was shared, researchers often used GitHub repositories (e.g., classification accuracy; Akcay *et al.*, 2020; Allken *et al.*, 2021). We recommend that the code and relevant data be made available according to the FAIR principles (findable, accessible, interoperable & reusable; Wilkinson *et al.*, 2019).

4.5 | Limitations and future opportunities

Our work had three notable limitations. First, we focused on vertebrate species, although we were aware that machine learning has been used to process images of invertebrates in the wild (e.g., Hoye *et al.*, 2021). Detecting small animals, such as many invertebrates, is more difficult with camera traps, especially with variations in light conditions. Future deep learning algorithms may resolve this by techniques such as small object detection (Liu, Yang, et al., 2021) and low-light detection (Chen and Shah, 2021). Second, we excluded satellite imagery since we focused on wildlife images where individual-level recognition was possible. For some large wildlife species, such as whales and elephants, individuals could be detected and followed using satellite images (Guirado *et al.*, 2019; Duporge *et al.*, 2021). As the quality of images increases, satellite imagery will become an increasingly important tool for wildlife conservation (Tuia *et al.*, 2022). Finally, we acknowledge that the relevant literature is rapidly increasing and changing: our map will inevitably be obsolete in a few years. However, this study provides some current insights, providing new perspectives.

4.6 | Conclusions

In this study, we revealed the recent trends, knowledge clusters and gaps in the use of machine learning in processing wildlife imagery. Future applications could aim to mitigate the current taxonomic bias, the limited use of deep learning in behaviour detection and tracking, and collaborate internationally to tackle incongruency between image origins and author affiliations. We hope our knowledge maps will guide future studies to fill the gaps, resolve biases, and increase diversity in research in as many ways as possible.

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CONFLICT OF INTEREST

The authors reported no conflict of interest

DATA AVAILABILITY

Unprocessed data is included as a Supplementary File 2. Data and processing code are available on GutHub at https://github.com/mlagisz/SM_machine_learning_animals.

AUTHOR CONTRIBUTIONS

All authors contributed to the conceptualization of the project and discussed the ideas and study design. ML, RF, JT and XL conducted the survey with inputs from the others. SN and ML wrote the first draft and all authors contributed to editing versions of the manuscript.

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Supplementary File 1

May 2022

Supplementary File 1 for “Rapid literature mapping on the recent use of machine learning for wildlife imagery”

Supplementary methods

Benchmarking set of papers

We used a set of 10 manually-located relevant papers from our scoping searches as a benchmark set during search string development. This benchmarking set was used for benchmarking precision of search strings for Scopus database to ensure that most of the relevant can be captured while minimising the number of irrelevant hits.

References of articles in the benchmarking set:

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2. Norouzzadeh, M.S., Morris, D., Beery, S., Joshi, N., Jojic, N., Clune, J. A deep active learning system for species identification and counting in camera trap images (2021) Methods in Ecology and Evolution, 12 (1), pp. 150-161. DOI: 10.1111/2041-210X.13504

3. Villon, S., Mouillot, D., Chaumont, M., Subsol, G., Claverie, T., Villeger, S. A new method to control error rates in automated species identification with deep learning algorithms (2020) Scientific Reports, 10 (1), art. no. 10972. DOI: 10.1038/s41598-020-67573-7

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5. Patel, A., Cheung, L., Khatod, N., Matijosaitiene, I., Arteaga, A., Gilkey, J.W., Jr. Revealing the unknown: Real-time recognition of galápagos snake species using deep learning (2020) Animals, 10 (5), art. no. 806. DOI: 10.3390/ani10050806

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8. Willi, M., Pitman, R.T., Cardoso, A.W., Locke, C., Swanson, A., Boyer, A., Veldthuis, M., Fortson, L. Identifying animal species in camera trap images using deep learning and citizen science (2019) Methods in Ecology and Evolution, 10 (1), pp. 80-91. DOI: 10.1111/2041-210X.13099

9. Norouzzadeh, M.S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M.S., Packer, C., Clune, J. Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning (2018) Proceedings of the National Academy of Sciences of the United States of America, 115 (25), pp. E5716-E5725. DOI: 10.1073/pnas.1719367115

10. Gomez Villa, A., Salazar, A., Vargas, F. Towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neural networks (2017) Ecological Informatics, 41, pp. 24-32. DOI: 10.1016/j.ecoinf.2017.07.004

DOI-based Scopus search string for retrieving articles in the benchmarking set:
((DOI (10.3390/ani10050806) OR DOI (10.1038/s41598-020-67573-7) OR DOI (10.1111/2041-210x.13576) OR DOI (10.1111/2041-210x.13099) OR DOI (10.1111/2041-210x.13504) OR DOI (10.1111/2041-210x.13120) OR DOI (10.1111/2041-210x.13436) OR DOI (10.1073/pnas.1719367115) OR DOI (10.1016/j.ecoinf.2017.07.004) OR DOI (10.1371/journal.pone.0219570)))

Search string development for Scopus database:

1. Returning 27,730 hits, 9/10 sensitivity:
   (TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm*” OR “Support Vector*”) AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR environment* OR biodiversity OR ecolog*))) AND PUBYEAR > 2016

2. Returning 7,074 hits, 9/10 sensitivity:
   (TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm*” OR “Support Vector*”) AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR “species identif*” OR (behav* AND within/ 5 classif*))) AND PUBYEAR > 2016

3. Returning 3,331 hits, 9/10 sensitivity:
   (TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm*” OR “Support Vector*”) AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR “species identif*” OR (behav* AND within/ 5 classif*)) AND NOT (“natural language” OR acoust* OR vocal* OR clinical* OR industr* OR agricult* OR farm* OR leaf OR husbandry OR food* OR tissue* OR cell* OR cultur* OR forest* OR hydrolog* OR engineer* OR “oxygen species” OR molec* OR bacteria* OR microb* OR chemi* OR spectrom* OR brain* OR drug*))) AND PUBYEAR > 2016

4. Returning 2,451 hits, 9/10 sensitivity:
   (TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm*” OR “Support Vector*”) AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR “species identif*” OR (behavio* AND within/ 5 classif*) OR (behavio* AND within/ 5 recogn*)) AND NOT (“natural language” OR acoust* OR vocal* OR clinical* OR industr* OR agricult* OR farm* OR leaf OR husbandry OR food* OR tissue* OR cell* OR cultur* OR forest* OR hydrolog* OR engineer* OR “oxygen species” OR molec* OR bacteria* OR microb* OR chemi* OR spectrom* OR brain* OR drug* OR patient* OR cancer* OR smoking OR disease OR diabet* OR scan* OR “X-ray” OR “health care” OR participant* OR emotion* OR speech OR proceedings))) AND PUBYEAR > 2016

5. Returning 2,853 hits, 10/10 sensitivity:
   (TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm*” OR “Support Vector*”) AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR “species identif*” OR “species label*” OR “species richness” OR (behavio* AND within/ 10 classif*) OR (behavio* AND within/ 10 recogn*)) AND

NOT (“natural language” OR accelomet* OR clinical* OR industr* OR agricult* OR farm* OR leaf OR husbandry OR food* OR tissue* OR cell* OR cultur* OR “tree growth” OR hydrolog* OR engineer* OR “oxygen species” OR molec* OR bacteria* OR microb* OR chemi* OR spectrom* OR brain* OR drug* OR patient* OR cancer* OR smoking OR disease OR diabet* OR scan* OR “X-ray” OR “health care” OR participant* OR emotion* OR employee* OR speech OR proceedings))) AND PUBYEAR > 2016

6. Returning 2,051 hits, 9/10 sensitivity:
   (TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm” OR ”Support Vector”) AND (image* OR camera* OR video* OR vision) AND (animal* OR population* OR “species identif*” OR “species label*” OR “species richness” OR (behavio* AND within/ 10 classif*) OR (behavio* AND within/ 10 recogn*)) AND NOT (“natural language” OR “sign language” OR accelomet* OR clinical* OR industr* OR agricult* OR farm* OR leaf OR husbandry OR food* OR tissue* OR cell* OR cultur* OR wildfire* OR “tree growth” OR forestry OR hydrolog* OR engineer* OR “oxygen species” OR molec* OR bacteria* OR microb* OR chemi* OR spectrom* OR brain* OR drug* OR patient* OR cancer* OR smoking OR disease OR diabet* OR landsat* OR sentinel OR satellite* OR “land cover” OR “land use” OR “vegetation map*” OR galax* OR “Google Earth” OR scan* OR “X-ray” OR “health care” OR participant* OR emotion* OR employee* OR speech OR proceedings))) AND PUBYEAR > 2016

Literature search

We run a search in Scopus on 2021/10/10 using a pre-piloted search string (for details on the development including validation set refer a dedicated Notion notebook):

(TITLE-ABS-KEY ((*automatic* OR “machine learning” OR “computer learning” OR “deep learning” OR “neural network*” OR “random forest*” OR “convolutional neural” OR “convolutional network*” OR “learning algorithm*” OR “Support Vector*”) AND (image* OR camera* OR video* OR vision) AND (*wild* OR population* OR “species identif*” OR “species label*” OR “species richness” OR (behavio* AND within/ 10 classif*) OR (behavio* AND within/ 10 recogn*)) AND NOT (“natural language” OR “sign language” OR accelomet* OR clinical* OR industr* OR agricult* OR farm* OR leaf OR husbandry OR food* OR tissue* OR cell* OR cultur* OR wildfire* OR “tree growth” OR forestry OR hydrolog* OR engineer* OR “oxygen species” OR molec* OR bacteria* OR microb* OR chemi* OR spectrom* OR brain* OR drug* OR patient* OR cancer* OR smoking OR disease OR diabet* OR landsat* OR sentinel OR satellite* OR “land cover” OR “land use” OR “vegetation map*” OR galax* OR “Google Earth” OR scan* OR “X-ray” OR “health care” OR participant* OR emotion* OR employee* OR speech OR proceedings))) AND PUBYEAR > 2016

Retrieved bibliographic records were then downloaded and screened for inclusion.

Inclusion criteria at the title and abstract screening phase

Following PICO framework, we included articles if all criteria below were fulfilled:

- **Population:** wild or semi-wild vertebrate species (exclude domestic or farmed animals, invertebrates, museum specimens).

- **Intervention / Innovation:** use of computer vision machine learning algorithms (include neural-network type methods, such as deep learning, CNN), support vector, random forest) for automated or semi-automated processing of image data (e.g. from camera traps, video tracking, thermal imaging) at a scale where individual animals are visible (include aerial and drone images (exclude images gathered from satellites, biologing, X-ray, MRI images or equivalent *).

- **Comparator / Context**: images taken in the wild or semi-wild (includes zoo enclosures, excludes lab-based or agricultural/aquaculture/pet studies).
- **Outcomes**: analyses focus on animal / species individual recognition/classification or animal behaviour recognition/classification.
- Additional criteria: studies published in last 5 years (2017-2021), peer-reviewed (including full-text conference proceedings).

*Note: Aerial and drone images are used to capture images of medium to large vertebrates, such as birds and ungulates; however, satellite images are only useful for huge mammals such as elephants and whales and require different processing pipelines. Biologging image-based studies attach small cameras to animals to record their movements and activities only and usually require capturing the animals before releasing them back in the wild. X-ray and MRI images are typically used in a laboratory setting or at sub-individual scale and were excluded.

Abstract screening procedure and results

We used Rayyan QCRI software to screen unique bibliographic records downloaded from Scopus. Thre researchers (ML, JT, RF) independently performed the screening assessing titles abstracts and keywords of each article. This screening resulted in 225 articles included for full-text assessment and data extraction.

Inclusion criteria at full-text screening

- Full text available
- Full-text studies should fulfill the same criteria as defined for the title and abstract screening phase

Full text screening and data extraction

Out of the 225 papers included, we obtained full-text for 215 papers.
For data extraction we used a two-part custom questionnaire implemented as a Google Form (Table S1). To pilot the form, we randomly selected 14 papers for independent screening aand extraction by three researchers (ML, JT, RF). We resolved disagreements by discussion until consensus was reached, and we refined the questionnaire form before the main round of full-text screening and data extraction.
One researcher (ML) performed full-text screening and data extraction for the remaining 195 papers. Second researcher (RF) cross-checked 58 of these papers for accuracy and to potentially resolve cases where information provided in the papers was unclear. We used GoogleSheet to record data checks and any additional comments. There, we also recoded whether a given paper was used in the pilot rounds, and if it was included or excluded from the final dataset, with a note on the main reson for exclusion.

Table S1 - full-text assessment and data extraction form

Question	Answer options
Paper's title:	[text]
First author's family name:	[text]
Publication year:	[number]
Journal name:	[text]
Article doi:	[text]
C1. Peer-reviewed empirical study	[yes; no; unsure/other]
C2. Is full text available in English?	[yes; no; unsure/other]

Question	Answer options
C3. Population: wild or semi-wild vertebrate species?	[yes; no; unsure/other]
C4. Intervention / Innovation: use of computer vision machine learning algorithms (for automated or semi-automated processing of image data at a scale where individual animals are visible)?:	[yes; no; unsure/other]
C5. Comparator / Context: are the studied animals in the wild or semi-wild?	[yes; no; unsure/other]
C6. Outcomes: focus on animal / species individual recognition / classification or animal behaviour recognition / classification?:	[yes; no; unsure/other]
Q1. Number of studied species	[number]
Q2. Study species (Latin name)	[text]
Q3. Studied species group:	[mammals; birds; reptiles; amphibians; fishes; other/unclear]*
Q4. Used image type source:	[camera trap or surveillance camera (fixed); aerial (including drone); hand camera (or mobile phone camera); other/unclear]*
Q5. Study context or setting:	[wild; semi-wild; unclear/other]*
Q6. Location country/region:	[text]
Q7. Location details:	[text]
Q8. Algorithm type:	[Neural Network; Random forest; Gradient boosting model; Support Vector Machines; Rule-based learners; Decision trees; K-Nearest Neighbour; unclear/other]*
Q9. Outcome type:	[counting individuals (at given time); individual recognition (re-identification); species recognition/classification (class/object detection); behaviour detection (at given time); tracking (following through space); behaviour classification (changes over time); unclear/other]*
Q10. Analysis code	[yes; no; unclear/other]

Note: * indicates plural variables (i.e. more than one answer option can be chosen).

Each question in the data extraction form (**Table S1**) was followed by a dedicated comment field used to record any additional details, including relevant quotes from the paper. We excluded any papers that were coded as "no" at questions C1 to C6 (full-text screening questions - whether the paper fulfills our inclusion criteria), i.e. these papers were not subject to any further data extraction and analyses.

After data extraction additional data were added to the GoogleSheet, as follows:
- Q7_coordinates: latitude and longitude of the study location, as in the paper or from Google Maps, if not reported
- Q7_location_unclear: 0 = "clear" (location at least at the level of national park, state, province, city, or equivalent - reported in the article or inferred from the data set name); 1 = "unclear", location either not reported or cannot be assigned to a specific location (e.g., global data, broad regions such as Arctic, Northern Atlantic, Africa, America)
- Pilot: whether study was used in the piloting phase
- Checked: whether record was cross-checked by an indpendent researcher

- Checking_comments: any comments from data extraction checking
- Changed: whether record was changed after cross-checking
- Changed_comment: how record was changed after cross-checking
- Included: whether study was included in the final data set for extraction
- Exclusion reason: main reason for excluding study from the final data set for extraction, if excluded
- Journal category: based on the journal title and Scimago Journal & Country Rank (https://www.scimagojr.com/). The following journals were categorised as multidisciplinary: "Scientific Reports", "Science Advances", "Proceedings of the National Academy of Sciences of the United States of America". The following journals had "ecology" in SUBJECT AREA AND CATEGORY information, or in their title and were thus classified as "ecology": "Behavioral Ecology and Sociobiology", "Ethology", "Global Ecology and Conservation", "Integrative Zoology", "Mammal Study", "Wildlife Society Bulletin", "Journal of Coastal Research", "Condor", "Methods in Ecology and Evolution", "Environmental Monitoring and Assessment", "Remote Sensing in Ecology and Conservation", "Ornis Fennica", "Ecology and Evolution", "European Journal of Wildlife Research", "Frontiers in Marine Science", "Conservation Biology", "Animals", "Ecological Informatics". The remaining journals were classfied as computer science / technology".

Supplementary Results

This section contains additional tables and plots complementing results presented in the main text of the manuscript.

```
rawdata <- read_excel(here("data", "mapping_dataset_reconciled.xlsx"), sheet = 1)
# dim(rawdata) #225 rows 47 columns
```

Table S2 List of articles excluded at full-text screening, with main reasons for exclusion.

```
#table(rawdata$"exclusion_reason") #table of exclusion reasons for the excluded studies

#remove included studies and select a few relevant columns
rawdata_excl <- rawdata %>% filter(Included == "0") %>%
  select(c("First author's family name:", "Paper's title:",
           "Journal name:" , "Publication year:", "Exclusion reason"))
#dim(rawdata_excl) #16 articles, 6 columns
#names(rawdata_excl)
names(rawdata_excl) <- c("First_author", "Title", "Journal", "Year", "Exclusion_reason")
#shorten one of the exclusion resons type
rawdata_excl$Exclusion_reason <-
  recode(rawdata_excl$Exclusion_reason,
         "not focusing on animal / species individual recognition /
         classification or animal behaviour recognition / classification" = "wrong outcome type")

#make a table of excluded  studies
kbl(rawdata_excl,
    format = "latex",
    align = "l",
    booktabs = TRUE,
    longtable = TRUE,
    linesep = "") %>%
  column_spec(1, width = "1.5cm") %>%
  column_spec(2, width = "5cm") %>%
  column_spec(3, width = "3cm") %>%
  kable_styling(latex_options = c("hold_position", "repeat_header"), font_size = 6)
```

First_author	Title	Journal	Year	Exclusion_reason
Adam	The Role of Citizen Science and Deep Learning in Camera Trapping	Sustainability	2021	not empirical
Baralle	Individual identification of cheetah (Acinonyx jubatus) based on close-range remote sensing: First steps of a new monitoring technique	Remote Sensing	2021	analysing footprints, not animals
Beaver	Evaluating the Use of Drones Equipped with Thermal Sensors as an Effective Method for Estimating Wildlife	Wildlife Society Bulletin	2020	not using machine learning
Borchers	A latent capture history model for digital aerial surveys	Biometrics	2020	not wild or semi-wild vertebrate species
Brack	Detection errors in wildlife abundance estimates from Unmanned Aerial Systems (UAS) surveys: Synthesis, solutions, and challenges	Methods in Ecology and Evolution	2018	not empirical
Bruijning	trackdem: Automated particle tracking to obtain population counts and size distributions from videos in r	Methods in Ecology and Evolution	2018	not wild or semi-wild vertebrate species
Colefax	Reliability of marine faunal detections in drone-based monitoring	Ocean and Coastal Management	2019	not using machine learning
Cunha	Filtering empty camera trap images in embedded systems	IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recogn. Workshops	2021	not focusing on animal / species individual recognition / classi
Florko	Narwhal (Monodon monoceros) detection by infrared flukeprints from aerial survey imagery	Ecosphere	2021	not using machine learning
Ilich	Integrating towed underwater video and multibeam acoustics for marine benthic habitat mapping and fish population estimation	Geosciences (Switzerland)	2021	not focusing on animal / species individual recognition / classi
Jia	Neural Architecture Search Based on Model Statistics for Wildlife Identification	Journal of the Franklin Institute	2020	no full-text
Kalafi	Comparison of fully automated and semi-automated methods for species identification	Folia Biologica (Czech Republic)	2018	not wild or semi-wild vertebrate species
Kellenberger	AIDE: Accelerating image-based ecological surveys with interactive machine learning	Methods in Ecology and Evolution	2020	not wild or semi-wild vertebrate species
Kim	Intelligent intrusion detection system featuring a virtual fence, active intruder detection, classification, tracking, and action recognition	Annals of Nuclear Energy	2018	not focusing on animal / species individual recognition / classi
Lee	Backbone alignment and cascade tiny object detecting techniques for dolphin detection and classification	IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences	2021	no full-text
Lopez-Marcano	The slow rise of technology: Computer vision techniques in fish population connectivity	Aquatic Conservation: Marine and Freshwater Ecosystems	2021	not empirical
Łopucki	The city changes the daily activity of urban adapters: Camera-traps study of Apodemus agrarius behaviour and new approaches to data analysis	Ecological Indicators	2020	not using machine learning
Maheswari	Identification and classification of multiple species of wild animals using convolutional neural networks	Journal of Green Engineering	2020	no full-text
McInnes	A new model study species: high accuracy of discrimination between individual freckled hawkfish (Paracirrhites forsteri) using natural markings	Journal of Fish Biology	2020	not using machine learning
Nayab	Wildlife monitoring in zoological parks using RASPBERRYPI and machine learning	International Journal of Recent Technology and Engineering	2019	not empirical
Nilssen	Active Learning for the Classification of Species in Underwater Images from a Fixed Observatory	IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)	2017	not wild or semi-wild vertebrate species
Pardo	Snapshot Safari: A large-scale collaborative to monitor Africa,Äôs remarkable biodiversity	South African Journal of Science	2021	not empirical
Peng	Implementation of Smart Animal Tracking System Based on Artificial Intelligence Technique	IEEE International Conference on Consumer Electronics - Taiwan (ICCE-TW)	2020	not empirical
Pulido	Methodology for mammal classification in camera trap images	Proceedings of SPIE - The International Society for Optical Engineering	2017	no full-text

(continued)

First_author	Title	Journal	Year	Exclusion_reason
Ravoor	Deep Learning Methods for Multi-Species Animal Re-identification and Tracking a Survey	Computer Science Review	2020	not empirical
Sullivan	Automated detection, tracking, and counting of gray whales	Proceedings of SPIE - The International Society for Optical Engineering (Proceedings of SPIE)	2020	no full-text
Tariq	Snow leopard recognition using deep convolution neural network	ACM's International Conference Proceedings Series (ICPS)	2018	no full-text
Teto	Automatically identifying of animals in the wilderness: Comparative studies between CNN and C-Capsule Network	ACM's International Conference Proceedings Series (ICPS)	2019	no full-text
Uwanuakwa	Traffic Warning System for Wildlife Road Crossing Accidents Using Artificial Intelligence	International Conference on Transportation and Development	2020	no full-text
Vishnuvardhan	Automatic detection of flying bird species using computer vision techniques	Journal of Physics: Conference Series (JPCS)	2019	not empirical
Wang	Classification of Wildlife Based on Transfer Learning	ACM International Conference Proceeding Series (ICPS)	2020	no full-text
Yu	AniWatch: Camera trap data processor for deep learning-based automatic identification of wildlife species	Asian Conference on Remote Sensing (ACRS)	2018	no full-text
Zhuang	Wildfish: A large benchmark for fish recognition in the wild	Proceedings of the ACM Multimedia Conference (MM)	2018	no full-text

```
#kable_styling(full_width = T)
```

Table S3 List of included articles with key bibliographic information.

```
#remove 4 excluded studies and remove all columns with "Comment", "checked" and  first 2 columns
rawdata_incl <- rawdata %>% filter(Included == "1") %>%
  select(c("First author's family name:", "Paper's title:", "Journal name:", "Publication year:"))

#make a table of included studies
names(rawdata_incl) <- c("First_author", "Title", "Journal", "Year")

#make a table of included  studies
kbl(rawdata_incl,
    format = "latex",
    align = "l",
    booktabs = TRUE,
    longtable = TRUE,
    linesep = "") %>%
  column_spec(1, width = "1.5cm") %>%
  column_spec(2, width = "8cm") %>%
  column_spec(3, width = "5cm") %>%
  kable_styling(latex_options = c("hold_position", "repeat_header"), font_size = 6)
```

First_author	Title	Journal	Year
Afan	Drone Monitoring of Breeding Waterbird Populations: The Case of the Glossy Ibis	Drones	2018
Akcay	Automated bird counting with deep learning for regional bird distribution mapping	Animals	2020
Allken	A real-world dataset and data simulation algorithm for automated fish species identification	Geoscience Data Journal	2021
Alqaralleh	Reliable Multi-Object Tracking Model Using Deep Learning and Energy Efficient Wireless Multimedia Sensor Networks	IEEE Access	2020

(continued)

First_author	Title	Journal	Year
Amir	Image classification for snake species using machine learning techniques	Advances in Intelligent Systems and Computing	2017
Arshad	Where is my Deer?-Wildlife Tracking and Counting via Edge Computing and Deep Learning	Proceedings of IEEE Sensors	2020
Atanbori	Classification of bird species from video using appearance and motion features	Ecological Informatics	2018
Bain	Count, crop and recognise: Fine-grained recognition in the wild	Proceedings - 2019 International Conference on Computer Vision Workshop, ICCVW 2019	2019
Banupriya	Animal detection using deep learning algorithm	Journal of Critical Reviews	2020
Beery	Recognition in Terra Incognita	Lecture Notes in Computer Science	2018
Ben Tamou	Transfer Learning with deep Convolutional Neural Network for Underwater Live Fish Recognition	2018 IEEE International Conference on Image Processing, Applications and Systems (IPAS)	2018
Bogucki	Applying deep learning to right whale photo identification	Conservation Biology	2019
Borowicz	Social Sensors for Wildlife: Ecological Opportunities in the Era of Camera Ubiquity	Frontiers in Marine Science	2021
Bouma	Individual Common Dolphin Identification Via Metric Embedding Learning	International Conference on Image and Vision Computing New Zealand	2019
Bowley	Detecting wildlife in uncontrolled outdoor video using convolutional neural networks	Proceedings of the IEEE International Conference on e-Science	2017
Bowley	Toward using citizen scientists to drive automated ecological object detection in aerial imagery	Proceedings of the IEEE International Conference on e-Science	2017
Bowley	Detecting wildlife in unmanned aerial systems imagery using convolutional neural networks trained with an automated feedback loop	Lecture Notes in Computer Science	2018
Brust	Towards automated visual monitoring of individual gorillas in the wild	Proceedings of the EEE/CVF International Conference on Computer Vision Workshop (ICCVW)	2017
Butgereit	On Safari with TensorFlow: Assisting Tourism in Rural Southern Africa Using Machine Learning	International Conference on Advances in Big Data, Computing and Data Communication Systems, icABCD	2018
Carl	Automated detection of European wild mammal species in camera trap images with an existing and pre-trained computer vision model	European Journal of Wildlife Research	2020
Castro	Humpback Whale's Flukes Segmentation Algorithms	Communications in Computer and Information Science	2021
Chamidullin	A deep learning method for visual recognition of snake species	CEUR Workshop Proceedings	2021
Cheema	Automatic Detection and Recognition of Individuals in Patterned Species	Lecture Notes in Computer Science	2017
Chehrsimin	Automatic individual identification of Saimaa ringed seals	IET Computer Vision	2018
Cheng	Detection Features as Attention (Defat): A Keypoint-Free Approach to Amur Tiger Re-Identification	Proceedings - International Conference on Image Processing, ICIP	2020
Choudhury	Detection of one-horned rhino from green environment background using deep learning	Journal of Green Engineering	2020
Clapham	Automated facial recognition for wildlife that lack unique markings: A deep learning approach for brown bears	Ecology and Evolution	2020
Corcoran	Evaluating new technology for biodiversity monitoring: Are drone surveys biased?	Ecology and Evolution	2021
Corcoran	New technologies in the mix: Assessing N-mixture models for abundance estimation using automated detection data from drone surveys	Ecology and Evolution	2020
Corcoran	Automated detection of koalas using low-level aerial surveillance and machine learning	Scientific Reports	2019
Concoran	Modelling wildlife species abundance using automated detections from drone surveillance	International Congress on Modelling and Simulation - Supporting evidence-based decision making: the role of modelling and simulation MODSIM 2019	2019
Coro	An intelligent and cost-effective remote underwater video device for fish size monitoring	Ecological Informatics	2021
Corregidor-Castro	Counting breeding gulls with unmanned aerial vehicles: Camera quality and flying height affects precision of a semi-automatic counting method	Ornis Fennica	2021
Curtin	Deep Learning for Inexpensive Image Classification of Wildlife on the Raspberry Pi	IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)	2019
Datar	Detection of Birds in the Wild using Deep Learning Methods	IEEE International Conference for Convergence in Technology (I2CT),	2018
Dawkins	An open-source platform for underwater image & video analytics	IEEE Winter Conference on Applications of Computer Vision (WACV)	2017
De Arruda	Recognition of Endangered Pantanal Animal Species using Deep Learning Methods	Proceedings of the International Joint Conference on Neural Networks	2018
Deep	Underwater Fish Species Recognition Using Deep Learning Techniques	International Conference on Signal Processing and Integrated Networks (SPIN)	2019
Delplanque	Multispecies detection and identification of African mammals in aerial imagery using convolutional neural networks	Remote Sensing in Ecology and Conservation	2021
Ditria	Deep learning for automated analysis of fish abundance: the benefits of training across multiple habitats	Environmental Monitoring and Assessment	2020

(continued)

First_author	Title	Journal	Year
Dlamini	Automated Identification of Individuals in Wildlife Population Using Siamese Neural Networks	International Conference on Soft Computing & Machine Intelligence (ISCMI)	2020
Dlamini	Comparing class-aware and pairwise loss functions for deep metric learning in wildlife re-identification	Sensors	2021
Duggan	An approach to rapid processing of camera trap images with minimal human input	Ecology and Evolution	2021
Eikelboom	Improving the precision and accuracy of animal population estimates with aerial image object detection	Methods in Ecology and Evolution	2019
Elias	Where's the bear?- Automating wildlife image processing using IoT and edge cloud systems	IEEE/ACM Fifth International Conference on Internet-of-Things Design and Implementation (IoTDI)	2017
Falzon	ClassifyMe: A field-scouting software for the identification of wildlife in camera trap images	Animals	2020
Fan	Multi-Background Island Bird Detection Based on Faster R-CNN	Cybernetics and Systems	2020
Fang	A Detection Algorithm of Giant Panda in Wild Video Image Based on Wavelet-SSD Network	IEEE Transactions on Systems, Man, and Cybernetics: Systems	2020
Favorskaya	Selecting informative samples for animal recognition in the wildlife	Smart Innovation, Systems and Technologies	2019
Favorskaya	Animal species recognition in the wildlife based on muzzle and shape features using joint CNN	Procedia Computer Science	2019
Feng	Action recognition using a spatial-temporal network for wild felines	Animals	2021
Feng	A novel hierarchical coding progressive transmission method for WMSN wildlife images	Sensors (Switzerland)	2019
Feng	High-Efficiency Progressive Transmission and Automatic Recognition of Wildlife Monitoring Images with WISNs	IEEE Access	2019
Ferreira	Deep learning-based methods for individual recognition in small birds	Methods in Ecology and Evolution	2020
Ferreira	Dashcam based wildlife detection and classification using fused data sets of digital photographic and simulated imagery	Proceedings of the International Conference on Information Fusion	2020
Francis	Counting mixed breeding aggregations of animal species using drones: Lessons from waterbirds on semi-automation	Remote Sensing	2020
Gabriel	Wildlife detection and recognition in digital images using YOLOv3: Extended abstract	Proceedings of the IEEE Cloud Summit Conference	2020
Gao	CycleGAN-Based Image Translation for Near-Infrared Camera-Trap Image Recognition	Lecture Notes in Computer Science	2020
Gavali	Bird Species Identification using Deep Learning on GPU platform	International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)	2020
Ghosh	Amur Tiger Detection for Wildlife Monitoring and Security	Communications in Computer and Information Science	2021
Gomez	Towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neural networks	Ecological Informatics	2017
Gorkin	Sharkeye: Real-time autonomous personal shark alerting via aerial surveillance	Drones	2020
Granados	Classifying False Alarms in Camera Trap Images using Convolutional Neural Networks	International Conference on Computer Science and Computational Intelligence (ICCSCI)	2020
Gray	Drones and convolutional neural networks facilitate automated and accurate cetacean species identification and photogrammetry	Methods in Ecology and Evolution	2019
Gray	A convolutional neural network for detecting sea turtles in drone imagery	Methods in Ecology and Evolution	2019
Guo	Varied channels region proposal and classification network for wildlife image classification under complex environment	IET Image Processing	2020
Hahn-Klimroth	Deep learning-based pose estimation for African ungulates in zoos	Ecology and Evolution	2021
Hans	On-road deer detection for advanced driver assistance using convolutional neural network	International Journal of Advanced Computer Science and Applications	2020
Harjoseputro	MobileNets: Efficient Convolutional Neural Network for Identification of Protected Birds	International Journal on Advanced Science, Engineering and Information Technology	2020
Hayes	Drones and deep learning produce accurate and efficient monitoring of large-scale seabird colonies	Condor	2021
Hj	Photo identification of sea turtles using alexnet and multi-class SVM	Frontiers in Artificial Intelligence	2020
Hsu	Dolphin Recognition with Adaptive Hybrid Saliency Detection for Deep Learning Based on DenseNet Recognition	IEEE Asia Pacific Conference on Circuits and Systems (APCCAS)	2019
Ibraheam	Animal Species Recognition Using Deep Learning	Advances in Intelligent Systems and Computing	2020
Islam	Bird species classification from an image using VGG-16 network	ACM's International Conference Proceedings Series (ICPS)	2019
Islam	Identification of Wild Species in Texas from Camera-trap Images using Deep Neural Network for Conservation Monitoring	Annual Computing and Communication Workshop and Conference (CCWC)	2020
Islam	Herpetofauna Species Classification from Images with Deep Neural Network	Intermountain Engineering, Technology and Computing (IETC)	2020
Jalal	Fish detection and species classification in underwater environments using deep learning with temporal information	Ecological Informatics	2020
Jamil	Deep Learning and Computer Vision-based a Novel Framework for Himalayan Bear, Marco Polo Sheep and Snow Leopard Detection	International Conference on Information Science and Communication Technology (ICISCT)	2020

(continued)

First_author	Title	Journal	Year
Jasko	Animal detection from traffic scenarios based on monocular color vision	International Conference on Intelligent Computer Communication and Processing (ICCP)	2017
Jawad	Deep Learning Technologies to Mitigate Deer-Vehicle Collisions	Studies in Computational Intelligence	2021
Jones	Processing citizen science- and machine-annotated time-lapse imagery for biologically meaningful metrics	Scientific Data	2020
Jose	Genus and Species-Level Classification of Wrasse Fishes Using Multidomain Features and Extreme Learning Machine Classifier	International Journal of Pattern Recognition and Artificial Intelligence	2020
Kabani	Improving Right Whale recognition by fine-tuning alignment and using wide localization network	Conference on Electrical and Computer Engineering (CCECE)	2017
Kellenberger	Half a percent of labels is enough: Efficient animal detection in UAV imagery using deep CNNs and active learning	IEEE Transactions on Geoscience and Remote Sensing	2019
Kellenberger	Fast animal detection in UAV images using convolutional neural networks	Dig Int Geosci Remote Sens Symp (IGARSS)	2017
Kierdorf	What Identifies A Whale by Its Fluke? On the Benefit of Interpretable Machine Learning for Whale Identification	The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS Archives)	2020
Kishore	Deep CNN Based Automatic Detection and Identification of Bengal Tigers	Communications in Computer and Information Science (CCIS)	2021
Kong	Feature cascade underwater object detection based on stereo segmentation	Journal of Coastal Research	2020
Kupyn	Fast and efficient model for real-time tiger detection in the wild	International Conference on Computer Vision Workshop (ICCVW)	2019
Labao	Cascaded deep network systems with linked ensemble components for underwater fish detection in the wild	Ecological Informatics	2019
Latupapua	Performance evaluation of convolutional neural networks and optimizers on wildlife animal classification	International Journal of Advanced Trends in Computer Science and Engineering	2020
Lee	Beluga whale detection in the Cumberland Sound Bay using convolutional neural networks	Canadian Journal of Remote Sensing	2021
Lee	Feasibility analyses of real-time detection of wildlife using uav-derived thermal and rgb images	Remote Sensing	2021
Li	Enhanced Bird Detection from Low-Resolution Aerial Image Using Deep Neural Networks	Neural Processing Letters	2019
Li	ATRW: A Benchmark for Amur Tiger Re-identification in the Wild	ACM International Conference on Multimedia (ACM Multimedia)	2020
Lili	Gait Recognition of Amur Tiger Based on Deep Learning	Journal of Physics: Conference Series (JPCS)	2021
Lin	Learning niche features to improve image-based species identification	Ecological Informatics	2021
Liu	Towards Efficient Machine Learning Methods for Penguin Counting in Unmanned Aerial System Imagery	IEEE OES Autonomous Underwater Vehicle Symposium (AUV)	2020
Loos	Towards automatic detection of animals in camera-trap images	European Signal Processing Conference (EUSIPCO)	2018
Lu	Turtle species identification design based on CNN	Journal of Physics: Conference Series (JPCS)	2019
Manasa	Wildlife surveillance using deep learning with YOLOv3 model	International Conference on Communication and Electronics Systems (ICCES)	2021
Mannocci	Leveraging social media and deep learning to detect rare megafauna in video surveys	Conservation Biology	2021
Mathur	Crosspooled FishNet: transfer learning based fish species classification model	Multimedia Tools and Applications	2020
McCarthy	Drone-based thermal remote sensing provides an effective new tool for monitoring the abundance of roosting fruit bats	Remote Sensing in Ecology and Conservation	2021
Mo	Large-scale automatic species identification	Lecture Notes in Computer Science	2017
Moallem	An explainable deep vision system for animal classification and detection in trail-camera images with automatic post-deployment retraining	Knowledge-Based Systems	2021
Moskvyak	Learning Landmark Guided Embeddings for Animal Re-identification	IEEE Winter Conference on Applications of Computer Vision Workshops (WACVW)	2020
Munian	Intelligent System for Detection of Wild Animals Using HOG and CNN in Automobile Applications	International Conference on Information, Intelligence, Systems and Applications (IISA)	2020
Munian	Design and Implementation of a Nocturnal Animal Detection Intelligent System in Transportation Applications	International Conference on Transportation and Development	2021
Murugaiyan	Fish species recognition using transfer learning techniques	International Journal of Advances in Intelligent Informatics	2021
Naddaf-Sh	Design and Implementation of an Assistive Real-Time Red Lionfish Detection System for AUV/ROVs	Complexity	2018
Nakhatovich	Applications of classical and deep learning techniques for polar bear detection and recognition from aero photography	Communications in Computer and Information Science	2020
Nepovinnykh	Identification of Saimaa Ringed Seal Individuals Using Transfer Learning	Lecture Notes in Computer Science	2018
Nguyen	Animal recognition and identification with deep convolutional neural networks for automated wildlife monitoring	IEEE International Conference on Data Science and Advanced Analytics (DSAA)	2017
Nipko	Identifying Individual Jaguars and Ocelots via Pattern-Recognition Software: Comparing HotSpotter and Wild-ID	Wildlife Society Bulletin	2020
Norouzzadeh	A deep active learning system for species identification and counting in camera trap images	Methods in Ecology and Evolution	2021

(continued)

First_author	Title	Journal	Year
Norouzzadeh	Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning	Proceedings of the National Academy of Sciences of the United States of America	2018
Okafor	Comparative study between deep learning and bag of visual words for wild-animal recognition	IEEE Symposium Series on Computational Intelligence (IEEE SSCI)	2017
Otani	Potency of Individual Identification of Japanese Macaques (Macaca fuscata) Using a Face Recognition System and a Limited Number of Learning Images	Mammal Study	2021
Padubidri	Counting sea lions and elephants from aerial photography using deep learning with density maps	Animal Biotelemetry	2021
Palencia	Innovations in movement and behavioural ecology from camera traps: Day range as model parameter	Methods in Ecology and Evolution	2021
Parham	Animal population censusing at scale with citizen science and photographic identification	AAAI Spring Symposium Series Technical Reports	2017
Park	Marine Vertebrate Predator Detection and Recognition in Underwater Videos by Region Convolutional Neural Network	Lecture Notes in Computer Science	2019
Patel	Revealing the unknown: Real-time recognition of Galapagos snake species using deep learning	Animals	2020
Pena	Hammerhead Shark Species Monitoring with Deep Learning	Communications in Computer and Information Science	2021
Pena	Tracking Hammerhead Sharks with Deep Learning	IEEE Colombian Conference on Applications in Computational Intelligence	2020
Picek	Overview of SnakeCLEF 2021: Automatic snake species identification with country-level focus	CEUR Workshop Proceedings	2021
Pramunendar	New workflow for marine fish classification based on combination features and CLAHE enhancement technique	International Journal of Intelligent Engineering and Systems	2020
Pramunendar	Fish classification based on underwater image interpolation and back-propagation neural network	International Conference on Science and Technology (ICST)	2019
Pramunendar	A robust image enhancement techniques for underwater fish classification in marine environment	International Journal of Intelligent Engineering and Systems	2019
Ragib	PakhiChini: Automatic bird species identification using deep learning	World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4)	2020
Reno	Exploiting species-distinctive visual cues towards the automated photo-identification of the Risso’s dolphin Grampus griseus	IEEE International Workshop on Metrology for the Sea; Learning to Measure Sea Health Parameters (MetroSea)	2019
Rey	Detecting animals in African Savanna with UAVs and the crowds	Remote Sensing of Environment	2017
Rohilla	GPU based Re-trainable Pruned CNN design for Camera Trapping at the Edge	International Conference on Electronics and Sustainable Communication Systems (ICESC)	2020
Rum	FishDeTec: A Fish Identification Application using Image Recognition Approach	International Journal of Advanced Computer Science and Applications	2021
Saqib	Real-Time Drone Surveillance and Population Estimation of Marine Animals from Aerial Imagery	International Conference Image and Vision Computing New Zealand	2019
Saxena	An Animal Detection and Collision Avoidance System Using Deep Learning	Lecture Notes in Electrical Engineering	2021
Sayed	An Automated Fish Species Identification System Based on Crow Search Algorithm	Advances in Intelligent Systems and Computing	2018
Schindler	Saving costs for video data annotation in wildlife monitoring	Ecological Informatics	2021
Schneider	Three critical factors affecting automated image species recognition performance for camera traps	Ecology and Evolution	2020
Schneider	Deep learning object detection methods for ecological camera trap data	Conference on Computer and Robot Vision (CRV)	2018
Schneider	Similarity Learning Networks for Animal Individual Re-Identification-Beyond the Capabilities of a Human Observer	IEEE Winter Conference on Applications of Computer Vision Workshops (WACVW)	2020
Schofield	Chimpanzee face recognition from videos in the wild using deep learning	Science Advances	2019
Shahinfar	How many images do I need? Understanding how sample size per class affects deep learning model performance metrics for balanced designs in autonomous wildlife monitoring	Ecological Informatics	2020
Shepley	U-infuse: Democratization of customizable deep learning for object detection	Sensors	2021
Shepley	Automated location invariant animal detection in camera trap images using publicly available data sources	Ecology and Evolution	2021
Shi	Amur tiger stripes: individual identification based on deep convolutional neural network	Integrative Zoology	2020
Shukla	A hybrid approach to tiger re-identification	IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)	2019
Shukla	Primate Face Identification in the Wild	Lecture Notes in Computer Science	2019
Singh	Animal Localization in Camera-Trap Images with Complex Backgrounds	Proc IEEE Southwest Symp Image Anal Interpret	2020
Sinha	Exploring bias in primate face detection and recognition	Lecture Notes in Computer Science	2019
Song	CNN Based Wildlife Recognition with Super-Pixel Segmentation for Ecological Surveillance	Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems, CYBER	2019
Stavelin	Applying object detection to marine data and exploring explainability of a fully convolutional neural network using principal component analysis	Ecological Informatics	2021

(continued)

First_author	Title	Journal	Year
Suhas	Performance analysis of SVM with quadratic kernel and logistic regression in classification of wild animals	Compusoft	2018
Surender	Automatic Identification of Bird Species from the Image Through the Approaches of Segmentation	Lecture Notes in Networks and Systems	2019
Swarup	Giant panda behaviour recognition using images	Global Ecology and Conservation	2021
Tabak	Improving the accessibility and transferability of machine learning algorithms for identification of animals in camera trap images: MLWIC2	Ecology and Evolution	2020
Tabak	Machine learning to classify animal species in camera trap images: Applications in ecology	Methods in Ecology and Evolution	2019
Tamou	Underwater live fish recognition by deep learning	Lecture Notes in Computer Science	2018
Tekeli	Elimination of useless images from raw camera-trap data	Turkish Journal of Electrical Engineering and Computer Sciences	2019
Thangarasu	Recognition of animal species on camera trap images using machine learning and deep learning models	International Journal of Scientific and Technology Research	2019
Timm	Large-scale ecological analyses of animals in the wild using computer vision	IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops	2018
Torney	A comparison of deep learning and citizen science techniques for counting wildlife in aerial survey images	Methods in Ecology and Evolution	2019
Trnovszky	Animal recognition system based on convolutional neural network	Advances in Electrical and Electronic Engineering	2017
Ueano	Automatically detecting and tracking free-ranging Japanese macaques in video recordings with deep learning and particle filters	Ethology	2019
Ulhaq	Automated detection of animals in low-resolution airborne thermal imagery	Remote Sensing	2021
Ulloa	Hammerhead shark detection using regions with convolutional neural networks	IEEE ANDESCON, ANDESCON	2020
Vaca-Castano	Multispectral camera design and algorithms for python snake detection in the Florida Everglades	Proceedings of SPIE - The International Society for Optical Engineering (Proceedings of SPIE)	2019
Vasmatkar	Snake species identification and recognition	IEEE Bombay Section Signature Conference (IBSSC)	2020
Verma	Wild Animal Detection from Highly Cluttered Images Using Deep Convolutional Neural Network	International Journal of Computational Intelligence and Applications	2018
Villon	A Deep learning method for accurate and fast identification of coral reef fishes in underwater images	Ecological Informatics	2018
Villon	A new method to control error rates in automated species identification with deep learning algorithms	Scientific Reports	2020
Wang	New approach for detection of giant panda head in wild environment	Acta Technica CSAV (Ceskoslovensk Akademie Ved)	2017
Wang	Study on Freshwater Fish Image Recognition Integrating SPP and DenseNet Network	IEEE Int. Conf. Mechatronics Autom., ICMA	2020
Wang	Learning deep features for giant panda gender classification using face images	IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)	2019
Wang	Grouping Feature Learning for Giant Panda Face Recognition	IEEE Transactions on Systems, Man, and Cybernetics: Systems	2020
Wang	Giant Panda Identification	IEEE Transactions on Image Processing	2021
Wei	Zilong: A tool to identify empty images in camera-trap data	Ecological Informatics	2020
Whytock	Robust ecological analysis of camera trap data labelled by a machine learning model	Methods in Ecology and Evolution	2021
Willi	Identifying animal species in camera trap images using deep learning and citizen science	Methods in Ecology and Evolution	2019
Williams	Deep learning analysis of nest camera video recordings reveals temperature-sensitive incubation behavior in the purple martin (Progne subis)	Behavioral Ecology and Sociobiology	2020
Xie	An integrated wildlife recognition model based on multi-branch aggregation and squeeze-and-excitation network	Applied Sciences (Switzerland)	2019
Xu	Underwater fish detection using deep learning for water power applications	International Conference on Computer Science and Computational Intelligence (ICCSCI)	2018
Yang	An Adaptive Automatic Approach to Filtering Empty Images from Camera Traps Using a Deep Learning Model	Wildlife Society Bulletin	2021
Yu	A strong baseline for tiger Re-ID and its bag of tricks	IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)	2019
Yu	Animal detection in highly cluttered natural scenes by using faster R-CNN	International Journal of Recent Technology and Engineering	2019
Zhang	Omni-supervised joint detection and pose estimation for wild animals	Pattern Recognition Letters	2020
Zhao	Image-Based Recognition of Individual Trouts in the Wild	European Workshop on Visual Information Processing (EUVIP)	2019
Zhu	Towards Automatic Wild Animal Detection in Low Quality Camera-Trap Images Using Two-Channeled Perceiving Residual Pyramid Networks	IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)	2017
Zotin	Animal detection using a series of images under complex shooting conditions	The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS Archives)	2019

(continued)

First_author	Title	Journal	Year
Zualkernan	Towards an IoT-based Deep Learning Architecture for Camera Trap Image Classification	IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT)	2020
Zuffi	Three-D safari: Learning to estimate zebra pose, shape, and texture from images 'in the wild'	Proceedings of IEEE International Conference on Computer Vision	2019

```
  #kable_styling(full_width = T)
```

Preprocessing extracted data

Data cleaning before generating summaries and plotting.

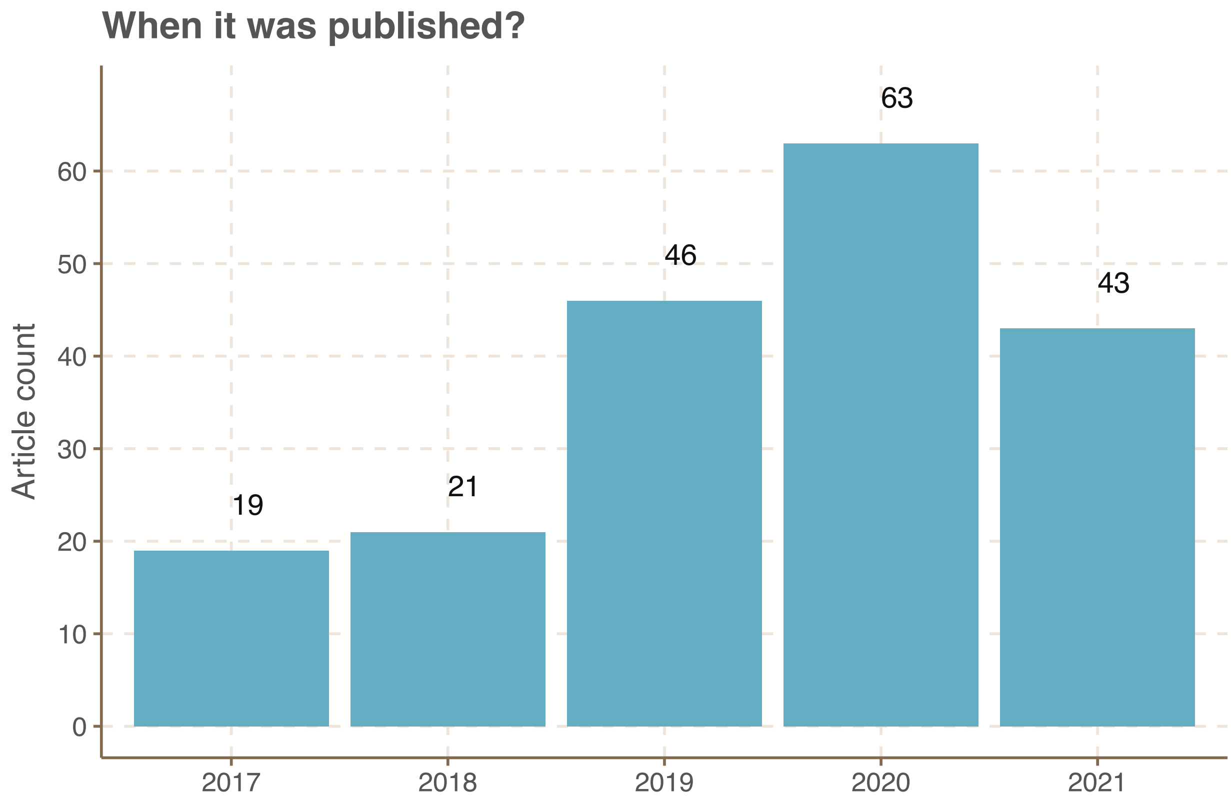
```
#remove unnecessary columns
rawdata_incl <- rawdata %>%
  filter(Included == "1") %>%
  select(-starts_with("C")) %>%
  select(-c("Timestamp", "Respondent's initials:", "Pilot", "Included", "Exclusion reason"))

#replace column names with shorter variable names for rawdata_incl analyses
names(rawdata_incl) <- c("Title",
                 "Author",
                 "Year",
                 "Journal",
                 "DOI",
                 "Species_number",
                 "Study_species",
                 "Studied_species_type",
                 "Image_source_type",
                 "Study_setting",
                 "Location_country",
                 "Location_details",
                 "Location_coordinates",
                 "Location_unclear",
                 "Algorithm_type",
                 "Outcome_type",
                 "Analysis_code")

#unique(rawdata_incl$Journal)

# classify journals into comp.sci vs. ecology journals
rawdata_incl$Journal_discipline <-
  recode(rawdata_incl$Journal,
         "Behavioral Ecology and Sociobiology" = "ecology",
         "Ethology" = "ecology",
         "Global Ecology and Conservation" = "ecology",
         "Integrative Zoology" = "ecology",
         "Mammal Study" = "ecology",
         "Wildlife Society Bulletin" = "ecology",
         "Journal of Coastal Research" = "ecology",
         "Condor" = "ecology",
         "Methods in Ecology and Evolution" = "ecology",
         "Environmental Monitoring and Assessment" = "ecology",
```

```
        "Remote Sensing in Ecology and Conservation" = "ecology",
        "Ornis Fennica" = "ecology",
        "Ecology and Evolution" = "ecology",
        "European Journal of Wildlife Research" = "ecology",
        "Frontiers in Marine Science" = "ecology",
        "Conservation Biology" = "ecology",
        "Animals" = "ecology",
        "Ecological Informatics" = "ecology",
        "Scientific Reports" = "multidisciplinary",
        "Science Advances" = "multidisciplinary",
        "Proceedings of the National Academy of Sciences of the United States of America" =
          "multidisciplinary",
        .default = "computer science / technology")

#table(rawdata_incl$Journal_discipline)
```

Supplementary data summaries and plots

Figure S1 Displaying annual counts of included articles.

```
count(rawdata_incl, Year) %>%
  mutate(class = factor(Year, levels = Year)) %>%
  ggplot(aes(x = class, y = n)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_text(aes(label = as.integer(scales::comma(n))), hjust = 0, nudge_y = 5) +
  scale_y_continuous(breaks = seq(0, 60, 10)) +
  labs(x = "", y = "Article count", title = "When it was published?")
```



Number of species / animal classes used Most data sets have prespecified number of animal species / classes present. Class can represent a species or a higher taxonomic group, such as genus, family, order, super-order, etc. (even "animals" can ba a class). Classes of non-animal objects (e.g. humans, vehicles) were not counted. When more than one dataset was used, the number was extracted for the biggest dataset.

A brief summary statistics on the number of animal species/classes per study.

```
#table(rawdata_incl$Species_number == "NA") #13 values of NA = no information in the paper
#table(as.integer(rawdata_incl$Species_number), useNA = "always")

# summarise Species_number column
rawdata_incl %>%
  filter(Species_number != "NA") %>%
    mutate(Species_number_NUM = as.numeric(Species_number)) %>%
    summarise(min = min(as.numeric(Species_number_NUM)),
              max = max(as.numeric(Species_number_NUM)),
              mean = mean(Species_number_NUM),
              sd = sd(Species_number_NUM),
              median = median(Species_number_NUM),
              n = n()
            )
```

```
## # A tibble: 1 x 6
##     min   max  mean    sd median     n
##   <dbl> <dbl> <dbl> <dbl>  <dbl> <int>
## 1     1 16583  118. 1241.      3   179
```

Table S4 List of papers with > 100 species/animal classes.

```r
#Filter studies and select a few relevant columns
rawdata_incl %>%
  filter(Species_number != "NA") %>%
  mutate(Species_number_NUM = as.integer(Species_number)) %>%
  filter(Species_number_NUM > 100) %>%
  select(c("Author", "Title", "Journal", "Year", "Studied_species_type", "Species_number")) ->
  rawdata_topspeciesnumbers

#make a table of included  studies
kbl(rawdata_topspeciesnumbers,
    format = "latex",
    align = "l",
    booktabs = TRUE,
    longtable = TRUE,
    linesep = "") %>%
  column_spec(1, width = "1.5cm") %>%
  column_spec(2, width = "6cm") %>%
  column_spec(3, width = "3cm") %>%
  column_spec(4, width = "1cm") %>%
  column_spec(5, width = "2cm") %>%
  kable_styling(latex_options = c("hold_position", "repeat_header"), font_size = 6)
```

Author	Title	Journal	Year	Studied_species_type	Species_number
Chamidullin	A deep learning method for visual recognition of snake species	CEUR Workshop Proceedings	2021	reptiles	772
Gavali	Bird Species Identification using Deep Learning on GPU platform	International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)	2020	birds	200
Li	Enhanced Bird Detection from Low-Resolution Aerial Image Using Deep Neural Networks	Neural Processing Letters	2019	birds	200
Mo	Large-scale automatic species identification	Lecture Notes in Computer Science	2017	mammals, birds, reptiles, amphibians, fishes, other	16583
Norouzzadeh	A deep active learning system for species identification and counting in camera trap images	Methods in Ecology and Evolution	2021	mammals, birds	270
Picek	Overview of SnakeCLEF 2021: Automatic snake species identification with country-level focus	CEUR Workshop Proceedings	2021	reptiles	772
Ragib	PakhiChini: Automatic bird species identification using deep learning	World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4)	2020	birds	200
Sayed	An Automated Fish Species Identification System Based on Crow Search Algorithm	Advances in Intelligent Systems and Computing	2018	fishes	260
Shahinfar	How many images do I need? Understanding how sample size per class affects deep learning model performance metrics for balanced designs in autonomous wildlife monitoring	Ecological Informatics	2020	mammals, birds	126
Surender	Automatic Identification of Bird Species from the Image Through the Approaches of Segmentation	Lecture Notes in Networks and Systems	2019	birds	200
Willi	Identifying animal species in camera trap images using deep learning and citizen science	Methods in Ecology and Evolution	2019	mammals, birds	139

Figure S2 Displaying total counts of papers by the settings in which animal images were taken.
Note: a single study could be coded as using one or more categories of settings, e.g. mix of images from the wild and captive (semi-wild) animals.

```r
#table(rawdata_incl$Study_setting, useNA = "always") #0 NA, need to split at comma
rawdata_incl$Study_setting <- recode(rawdata_incl$Study_setting,
                                      "unclear/other" = "other / unclear") #standarise wording

Study_setting_sep <- separate_rows(rawdata_incl,
                                    Study_setting, sep = ", ") #split rows with multiple values
Study_setting_sep$Study_setting <- as.factor(Study_setting_sep$Study_setting)
#table(Study_setting_sep$Study_setting, useNA = "always")

Study_setting_sep %>%
  filter(!is.na(Study_setting)) %>%
  count(Study_setting) %>%
  arrange(n) %>%
  mutate(class = factor(Study_setting, levels = Study_setting)) %>%
  ggplot(aes(x = class, y = n)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_text(aes(label = as.integer(scales::comma(n))), hjust = 0, nudge_y = 1) +
  coord_flip() +
  scale_y_continuous(breaks = seq(0, 150, 10)) +
  labs(x = "", y = "Article count", title = "What types of settings were studied?",
       caption = "Note: some studies used more than one")
```

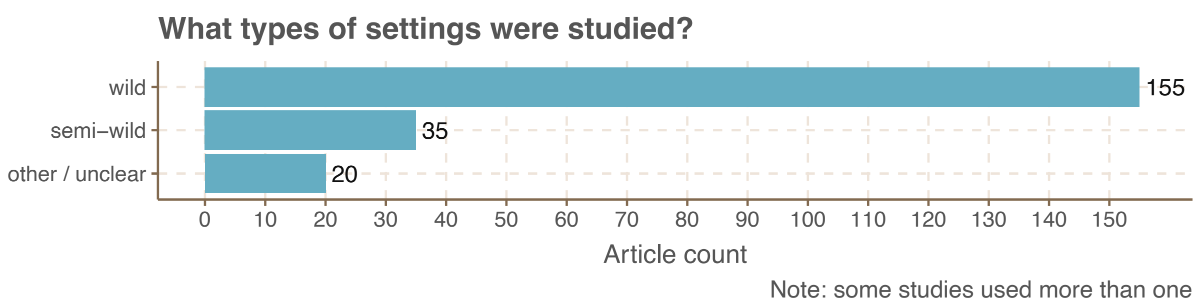


Figure S3
Barplot of counts of a country or a larger region where animal images were collected. A single study could be coded as using images from one or more countries/regions. Some studies using images of captive animals kept in zoos likely across mutiple countries were coded as "global" (often images sourced from the Internet/social platforms).

```r
#table(rawdata_incl$Location_country, useNA = "always") #0 NA, need to fix some names
rawdata_incl$Location_country <- gsub("Botswanam Australia", "Botswana, Australia",
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("Falkland \\(Malvinas\\) Islands", "Falkland Islands",
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("Asutralia", "Australia",
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("Soith Africa", "South Africa",
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("The Netherlands" , "Netherlands" ,
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("NZ", "New Zealand",
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("Korea", "South Korea",
                                      rawdata_incl$Location_country)
```

```r
rawdata_incl$Location_country <- gsub("Congo", "Republic of Congo",
                                      rawdata_incl$Location_country)
rawdata_incl$Location_country <- gsub("UAE", "United Arab Emirates",
                                      rawdata_incl$Location_country)
Location_country_sep <- separate_rows(rawdata_incl, Location_country, sep = ", ")
Location_country_sep$Location_country <- as.factor(Location_country_sep$Location_country)
```

Figure S4
A barplot of the counts of articles originating form a given country / larger region. "Global" are usually datasets based on images collected from the Internet or social media.

```r
Location_country_sep %>%
  filter(Location_country!="unclear") %>%
  count(Location_country) %>%
  arrange(n) %>%
  mutate(class=factor(Location_country, levels = Location_country)) %>%
  ggplot(aes(x = class, y = n)) +
  geom_bar(stat = "identity", position = "dodge") +
 # geom_text(aes(label = scales::comma(n)), hjust = 0, nudge_y = 1) +
  coord_flip() +
  scale_y_continuous(breaks = seq(0,30,5)) +
  labs(x = "", y = "Article count", title = "Most popular location country/region?",
       caption = "Note: some studies used more than one")
```

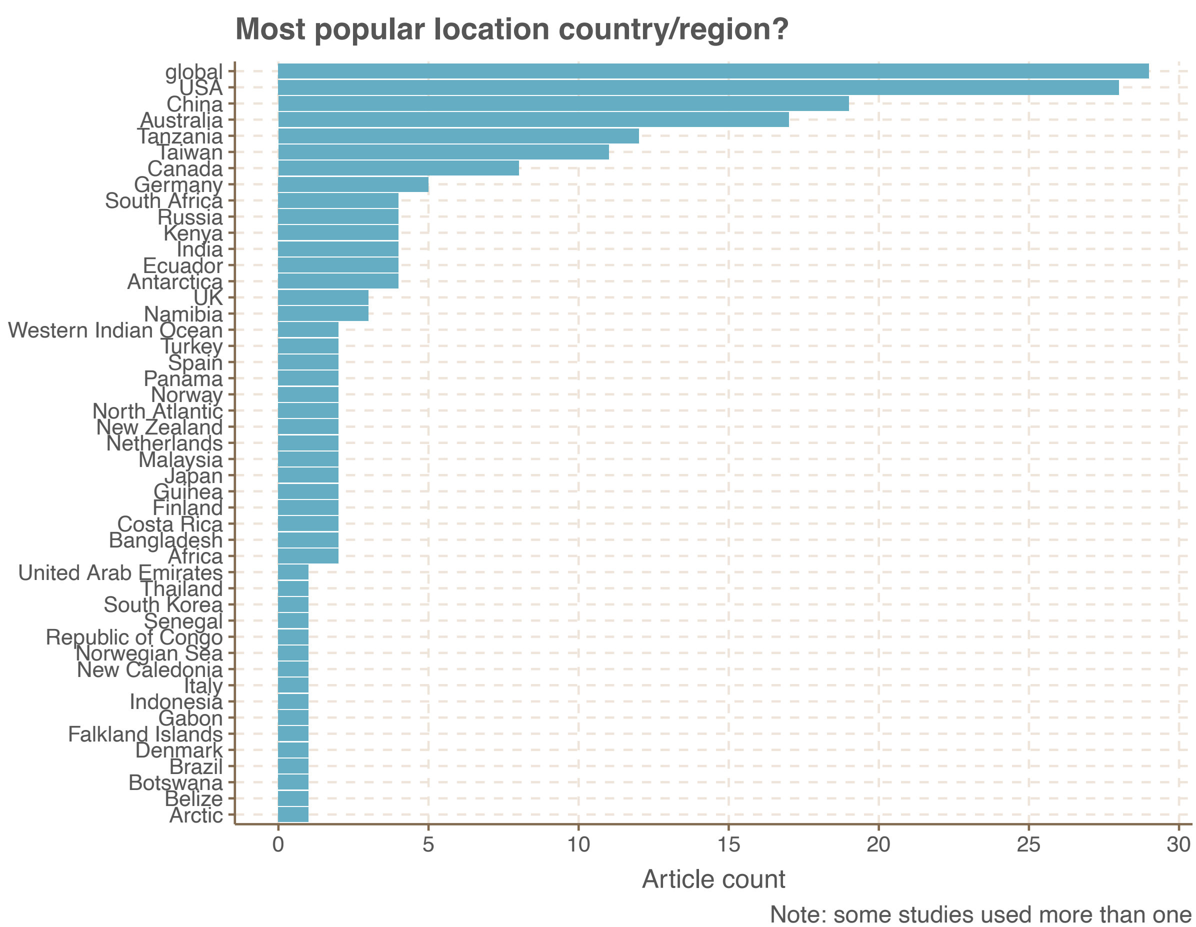


Figure S5

Location coordinates representing either a specific location (green circles) or centroids of a broader region (orange circles) where animal images originated from. Darker circles indicate a larger number of studies for a given location. "Global" image datasets (e.g. gathered from the Internet or social media) are not shown.

```
#table(rawdata_incl$Location_unclear, useNA = "always")
# 1 = yes for 78 studies, 3 is NA (global or multi-location studies)
#table(is.na(rawdata_incl$Location_coordinates), useNA = "always")
# 133 have coordinates, 59 have no

#table(rawdata_incl$Study_setting, rawdata_incl$Location_unclear, useNA = "always")
# 97+7 wild/semi-wild have clear location
#table(is.na(rawdata_incl$Location_coordinates), rawdata_incl$Location_unclear, useNA = "always")
# 110 have coordinates and clear location, 56 of 78 with unclear location have no coordinates
#table(is.na(rawdata_incl$Location_coordinates), rawdata_incl$Study_setting, useNA = "always")
# 116 of the wild-based studies has coordinates

# to plot dots at coordinates for wild-based studies only -
# first filter data and split coordinates column into longitude and latitude:
rawdata_incl %>% filter(Study_setting == "wild" | Study_setting == "wild, semi-wild") %>%
  filter(is.na(Location_coordinates) == FALSE) %>%
  separate(col = Location_coordinates, into = c("Latitude", "Longitude") , sep = ", ") ->
  coordinates_sep
coordinates_sep$Longitude <- as.numeric(coordinates_sep$Longitude)
coordinates_sep$Latitude <- as.numeric(coordinates_sep$Latitude)
coordinates_sep$Approximate_location <- recode(coordinates_sep$Location_unclear,
                                               "0" = "no", "1" = "yes")

map.world <- map_data("world")

#make a plot
ggplot() +
  geom_map(
    data = map.world, map = map.world,
    aes(long, lat, map_id = region),
    color = "white", fill = "lightgray", size = 0.1
  ) +
  geom_point(
    data = coordinates_sep,
    aes(Longitude, Latitude, color = Approximate_location), size = 4,
    alpha = 0.4, position = position_jitter(width = 2, height = 2)
  )  +
  scale_colour_manual(values = c("darkgreen", "orange")) +
  theme(legend.position = "top")
```

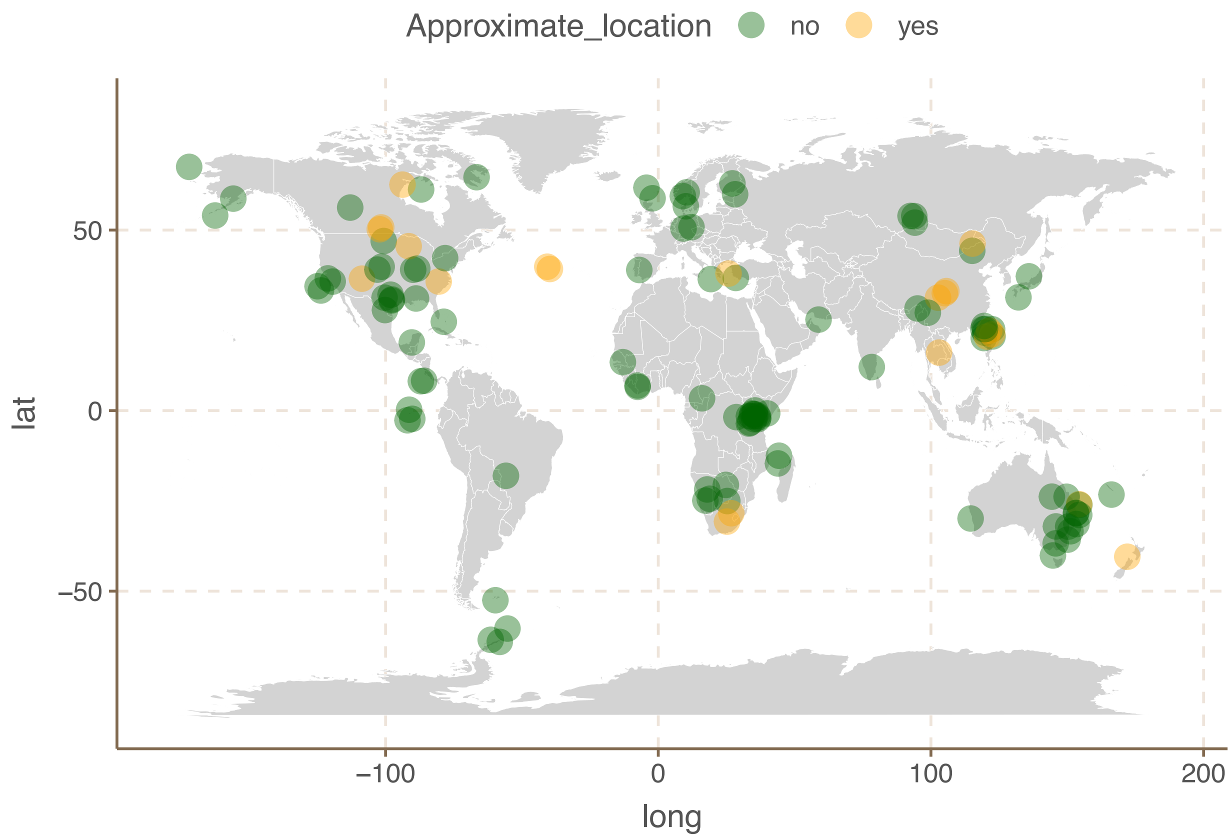


Figure S6
Barplot of the main types of machine learning algorithms used in the included studies. A single study could be coded as using one or more types.

```
#table(rawdata_incl$Algorithm_type, useNA = "always") #0 NA, need to split at comma
Algorithm_type_sep <- separate_rows(rawdata_incl, Algorithm_type, sep = ", ")
Algorithm_type_sep$Algorithm_type <- recode(Algorithm_type_sep$Algorithm_type,
                                            "unclear/other" = "other / unclear")
Algorithm_type_sep$Algorithm_type <- as.factor(Algorithm_type_sep$Algorithm_type)

Algorithm_type_sep %>%
  filter(!is.na(Algorithm_type)) %>%
  count(Algorithm_type) %>%
  arrange(n) %>%
  mutate(class = factor(Algorithm_type, levels = Algorithm_type)) %>%
  ggplot(aes(x = class, y = n)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_text(aes(label = as.integer(scales::comma(n))), hjust = 0, nudge_y = 1) +
  coord_flip() +
  scale_y_continuous(breaks = seq(0, 200, 50)) +
  labs(x = "", y = "Article count", title = "What types of algorithms were used?",
       caption = "Note: some studies used more than one")
```

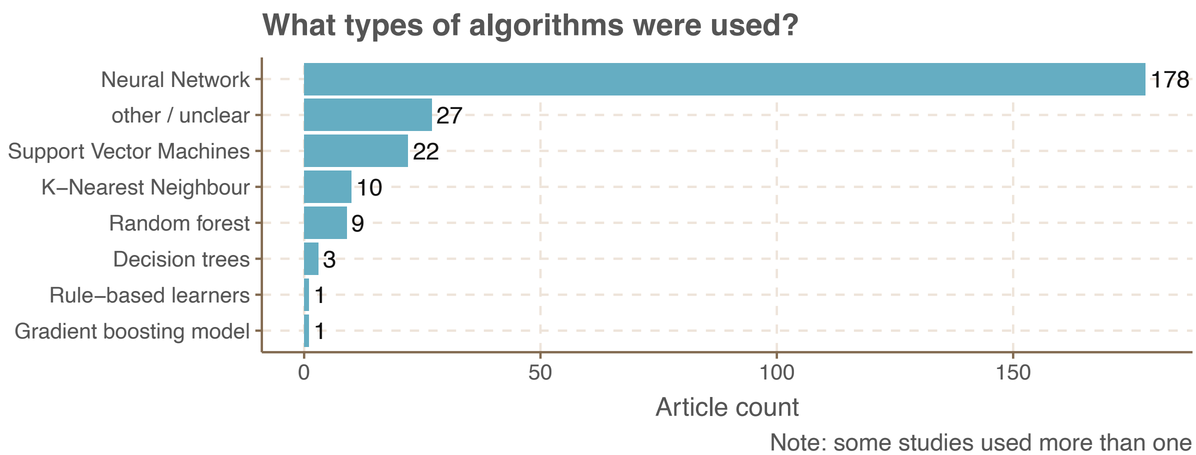


Figure S7
Barplot of the main types of outcomes / purposes of analyses in the included studies. A single study could be coded as using one or more types.

```
#table(rawdata_incl$Outcome_type, useNA = "always") #1 NA, need to split at comma
Outcome_type_sep <- separate_rows(rawdata_incl, Outcome_type, sep = ", ")
Outcome_type_sep$Outcome_type <- recode(Outcome_type_sep$Outcome_type,
                                        "unclear/other (add comment)" = "other / unclear")
Outcome_type_sep$Outcome_type <- as.factor(Outcome_type_sep$Outcome_type)

# berplot of article counts for different outcomes (separated)
Outcome_type_sep %>%
  filter(!is.na(Outcome_type)) %>%
  count(Outcome_type,) %>%
  arrange(n) %>%
  mutate(class=factor(Outcome_type, levels = Outcome_type)) %>%
  ggplot(aes(x = class, y = n)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_text(aes(label = as.integer(scales::comma(n))), hjust = 0, nudge_y = 1) +
  coord_flip() +
  scale_y_continuous(breaks = seq(0, 200, 50)) +
  labs(x = "", y = "Article count", title = "What types of outcomes were analysed?",
       caption = "Note: some studies used more than one")
```

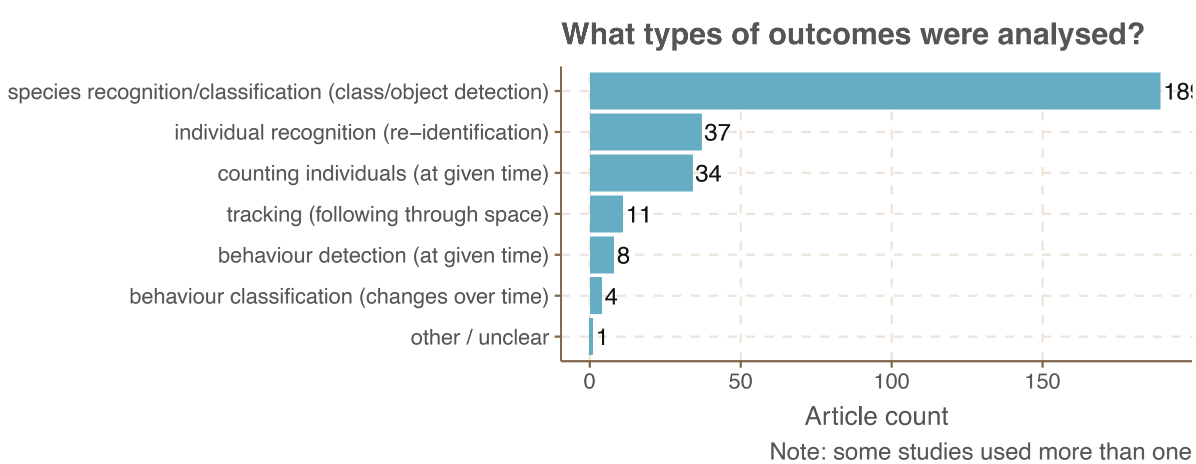
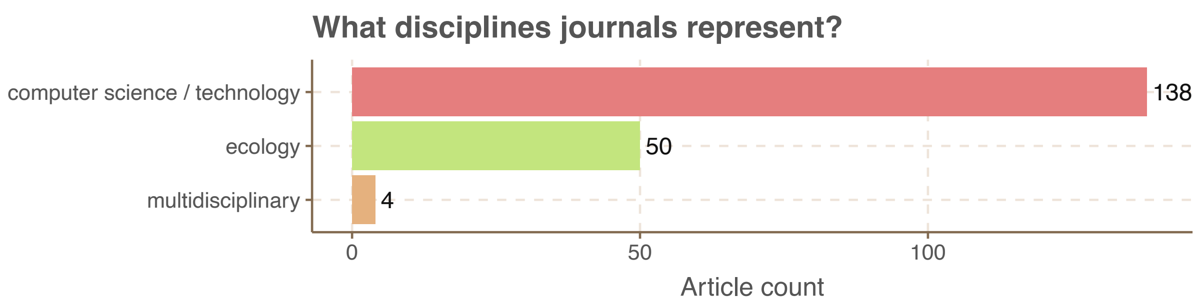


Figure S8
Barplot of total counts of journals by discipline.

```
rawdata_incl %>%
  filter(!is.na(Journal_discipline)) %>%
  count(Journal_discipline) %>%
  arrange(n) %>%
  mutate(class = factor(Journal_discipline, levels = Journal_discipline)) %>%
  ggplot(aes(x = class, y = n, fill = Journal_discipline)) +
  geom_bar(stat = "identity", position = "dodge") +
  geom_text(aes(label = as.integer(scales::comma(n))), hjust = 0, nudge_y = 1) +
  coord_flip() +
  scale_y_continuous(breaks = seq(0, 200, 50)) +
  scale_fill_manual(values = c("#E57E7E", "#C3E57E", "#E5B17E")) +
  theme(legend.position = "none") +
  labs(x = "", y = "Article count", title = "What disciplines journals represent?")
```



Bibliometric analyses

These analyses are based on the information extracted from bibliographic records downloaded from Scopus. Initial preprocessing and summaries using bibliometrix R package. Subsequently this data was combined with manually coded data from the full texts.
Load and export author affiliation country from bibliographic records (*scopus_AI_1and2.bib*).

```
bib <- convert2df(here("data", "scopus_AI_1and2.bib"), dbsource = "wos", format = "bibtex")
```

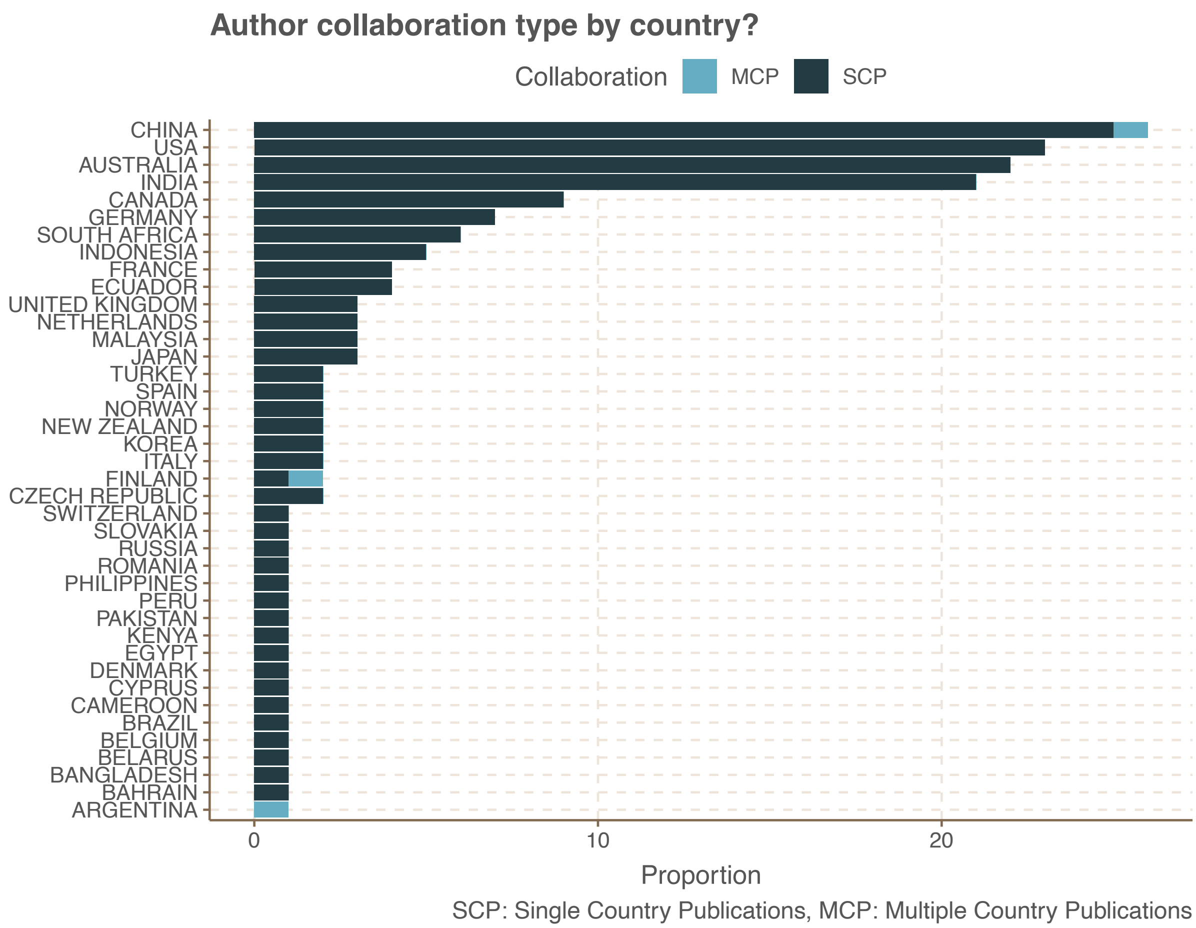
```
##
## Converting your wos collection into a bibliographic dataframe
##
##
## Warning:
## In your file, some mandatory metadata are missing. Bibliometrix functions may not work properly!
##
## Please, take a look at the vignettes:
## - 'Data Importing and Converting' (https://www.bibliometrix.org/vignettes/Data-Importing-and-Converti
## - 'A brief introduction to bibliometrix' (https://www.bibliometrix.org/vignettes/Introduction_to_bibl
##
##
## Missing fields:  ID CR
## Done!
##
```

```
##
## Generating affiliation field tag AU_UN from C1:  Done!
```

```
# Initial data cleaning and merging with manually coded data frame.

# Remove all non-alphanumeric, punctuation and extra white spaces in bib object
bib$TI2 <- gsub("[^[:alnum:] ]", "", bib$TI) %>% str_replace_all(.,"[ ]+", " ")

# Remove all non-alphanumeric, punctuation and extra white spaces in rawdata_incl object
rawdata_incl$TI2 <- str_to_upper(gsub("[^[:alnum:] ]", "", rawdata_incl$Title)) %>%
  str_replace_all(.,"[ ]+", " ")

# Clean-up of 6 non-matching titles before merging -
# replace title TI2 in bib (not-matching) with TI2 from rawdata_incl
bib[bib$TI2 %like% "MODELLING WILDLIFE SPECIES ABUNDANCE USING", "TI2"] <-
  rawdata_incl[rawdata_incl$TI2 %like% "MODELLING WILDLIFE SPECIES ABUNDANCE USING", "TI2"]
bib[bib$TI2 %like% "COUNTING BREEDING GULLS", "TI2"] <-
  rawdata_incl[rawdata_incl$TI2 %like% "COUNTING BREEDING GULLS", "TI2"]
bib[bib$TI2 %like% "COMPARING CLASSAWARE AND PAIRWISE LOSS FUNCTIONS", "TI2"] <-
  rawdata_incl[rawdata_incl$TI2 %like% "COMPARING CLASSAWARE AND PAIRWISE LOSS FUNCTIONS", "TI2"]
bib[bib$TI2 %like% "BELUGA WHALE DETECTION IN THE CUMBERLAND", "TI2"] <-
  rawdata_incl[rawdata_incl$TI2 %like% "BELUGA WHALE DETECTION IN THE CUMBERLAND", "TI2"]
bib[bib$TI2 %like% "REVEALING THE UNKNOWN REALTIME RECOGNITION OF", "TI2"] <-
  rawdata_incl[rawdata_incl$TI2 %like% "REVEALING THE UNKNOWN REALTIME RECOGNITION OF", "TI2"]

#Join the data frames
bib_title <- left_join(rawdata_incl, bib, by = "TI2")
results <- biblioAnalysis(bib_title, sep = ";") #this calculates the main bibliometric measures,
#sum(results$CountryCollaboration$SCP) #4only 3 multi-country papers out of 173 with data
```

Figure S9
A barplot of country assigned to each publication based on the affiliation country of the first author. Co-authorship type is based on country of all authors of a given publication. SCP indicates all authors were affiliated with the same country. MCP indicates international co-authorship.

```
#reshape dataframe into long format:
CountryCollaboration_ord <- results$CountryCollaboration
CountryCollaboration_ord$Country <- factor(CountryCollaboration_ord$Country)
CountryCollaboration_long <- gather(CountryCollaboration_ord, Collaboration,
                                    value, MCP:SCP, factor_key=TRUE)
#reorder by total frequency
CountryCollaboration_long$Country <- factor(CountryCollaboration_ord$Country, levels = levels(reorder(Co

CountryCollaboration_long %>%
  arrange(value) %>%
  ggplot(aes(fill = Collaboration, y = value, x = Country)) +
  geom_bar(stat = "identity") +
  coord_flip() +
  theme(legend.position = "top") +
  labs(x = "", y = "Proportion", title = "Author collaboration type by country?",
       caption = "SCP: Single Country Publications, MCP: Multiple Country Publications")
```



Author collaboration type by country?
Collaboration
MCP
SCP
CHINA
USA
AUSTRALIA
INDIA
CANADA
GERMANY
SOUTH AFRICA
INDONESIA
FRANCE
ECUADOR
UNITED KINGDOM
NETHERLANDS
MALAYSIA
JAPAN
TURKEY
SPAIN
NORWAY
NEW ZEALAND
KOREA
ITALY
FINLAND
CZECH REPUBLIC
SWITZERLAND
SLOVAKIA
RUSSIA
ROMANIA
PHILIPPINES
PERU
PAKISTAN
KENYA
EGYPT
DENMARK
CYPRUS
CAMEROON
BRAZIL
BELGIUM
BELARUS
BANGLADESH
BAHRAIN
ARGENTINA
0
10
20
Proportion
SCP: Single Country Publications, MCP: Multiple Country Publications