RESEARCH ARTICLE

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

Shinichi Nakagawa[1]*, Malgorzata Lagisz[1]*, Roxane Francis[2], Jessica Tam[2], Xun Li[3], Andrew Elphinstone[4], Neil R. Jordan[2,4], Justine K. O'Brien[4], Benjamin J. Pitcher[4,5], Monique Van Sluys[4], Arcot Sowmya[3], and Richard T. Kingsford[2]

[1] UNSW Data Science Hub, Evolution & Ecology Research Centre and School of Biological, Earth and Environmental Sciences, UNSW, Sydney, NSW 2052, Australia

[2] Centre for Ecosystem Science and School of Biological, Earth and Environmental Sciences, UNSW, Sydney, NSW 2052, Australia

[3] School of Computer Science and Engineering, UNSW Sydney, NSW 2052, Australia

[4] Taronga Institute of Science and Learning, Taronga Conservation Society Australia, Mosman, NSW 2088, Australia

[5] School of Natural Sciences, Macquarie University, Sydney, NSW 2109, Australia

* These authors contributed equally

* Correspondence: S. Nakagawa, e-mail: s.nakagawa@unsw.edu.au; M. Lagisz, e-mail: m.lagisz@unsw.edu.au

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.

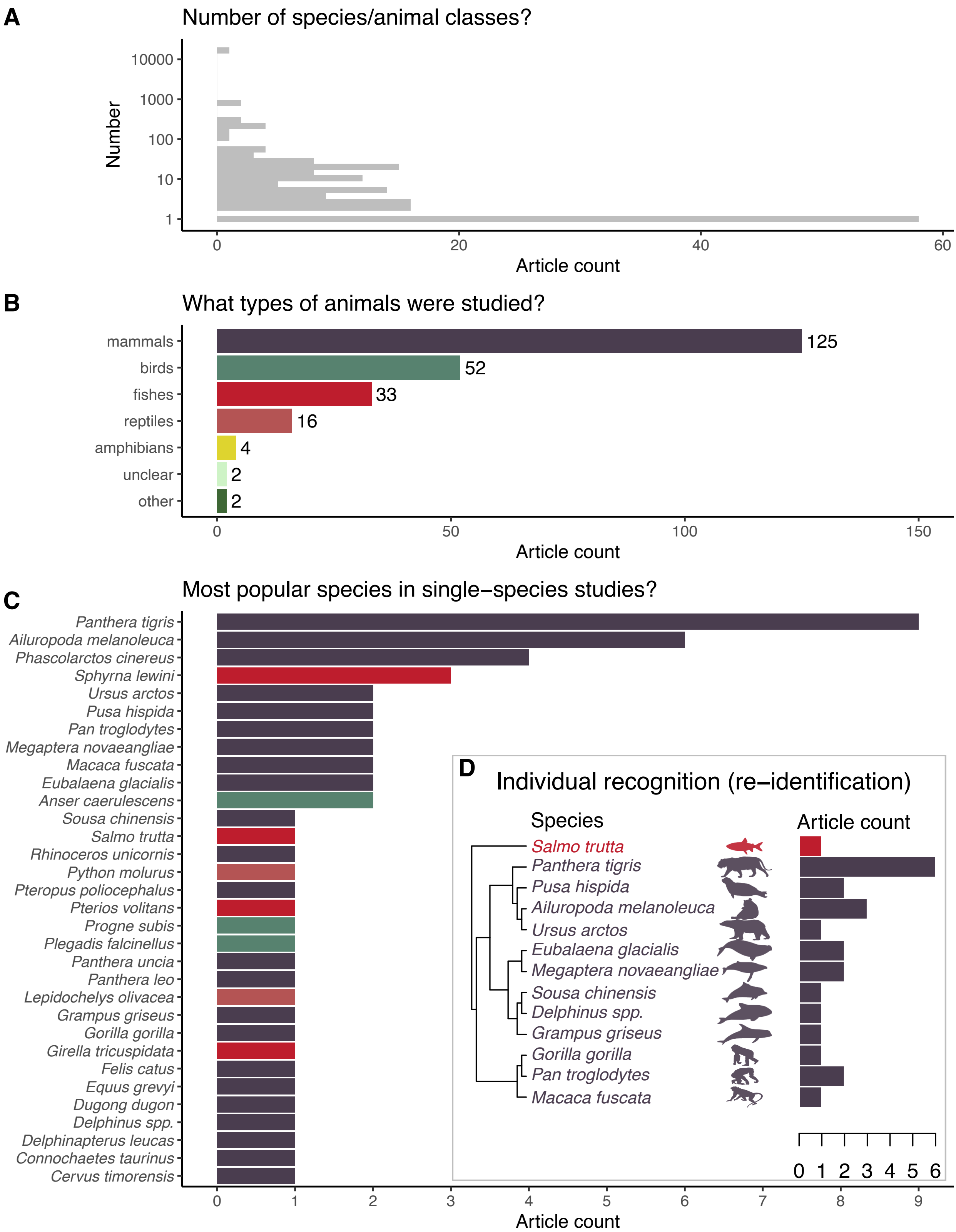

FIGURE 1. Diversity of the vertebrate species studied in the included machine learning studies. A – numbers of species / animal classes per study. B – counts of articles that studied each vertebrate class, C – counts of articles focused on a given species from one-species studies only (bar colours

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.

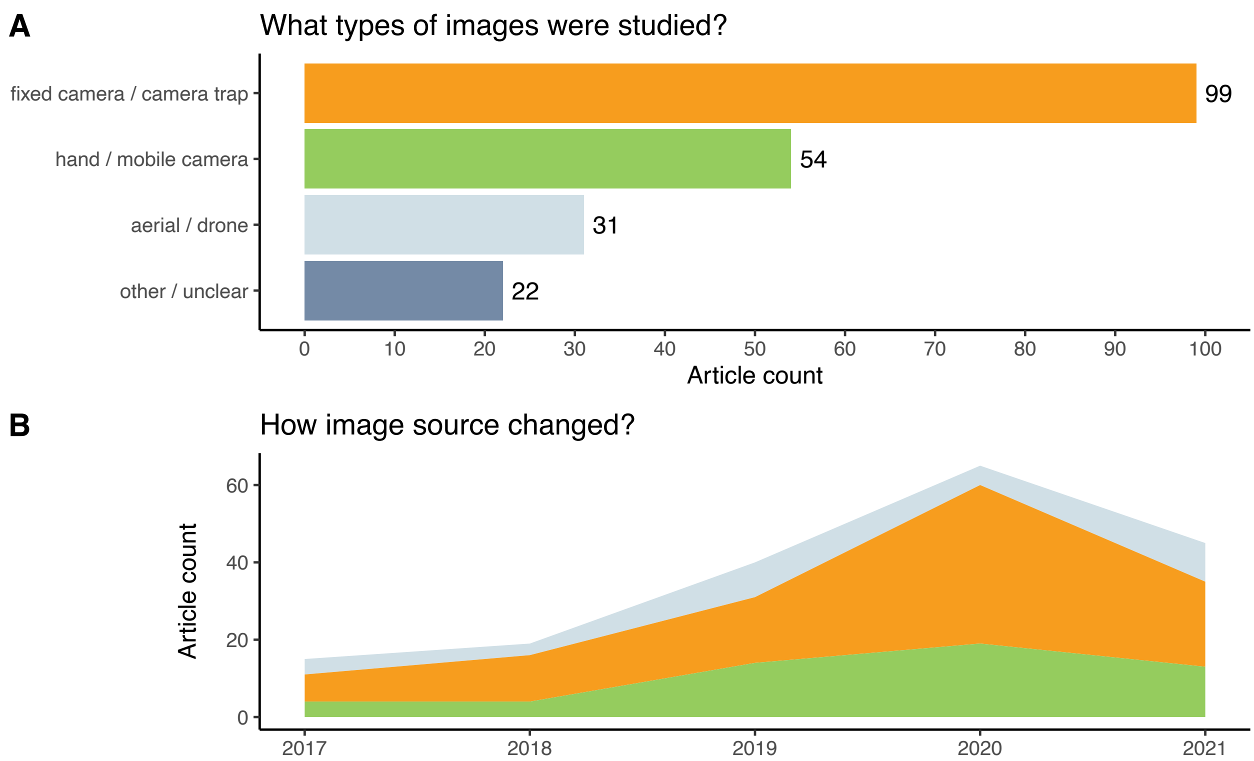

FIGURE 2. Diversity of the wildlife imagery analysed in machine learning studies. A - article counts by image source hardware type (one study could use more than one image type), B - temporal trends (annual counts) across the last five years. Year 2021 is included only up to October; colours are corresponding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

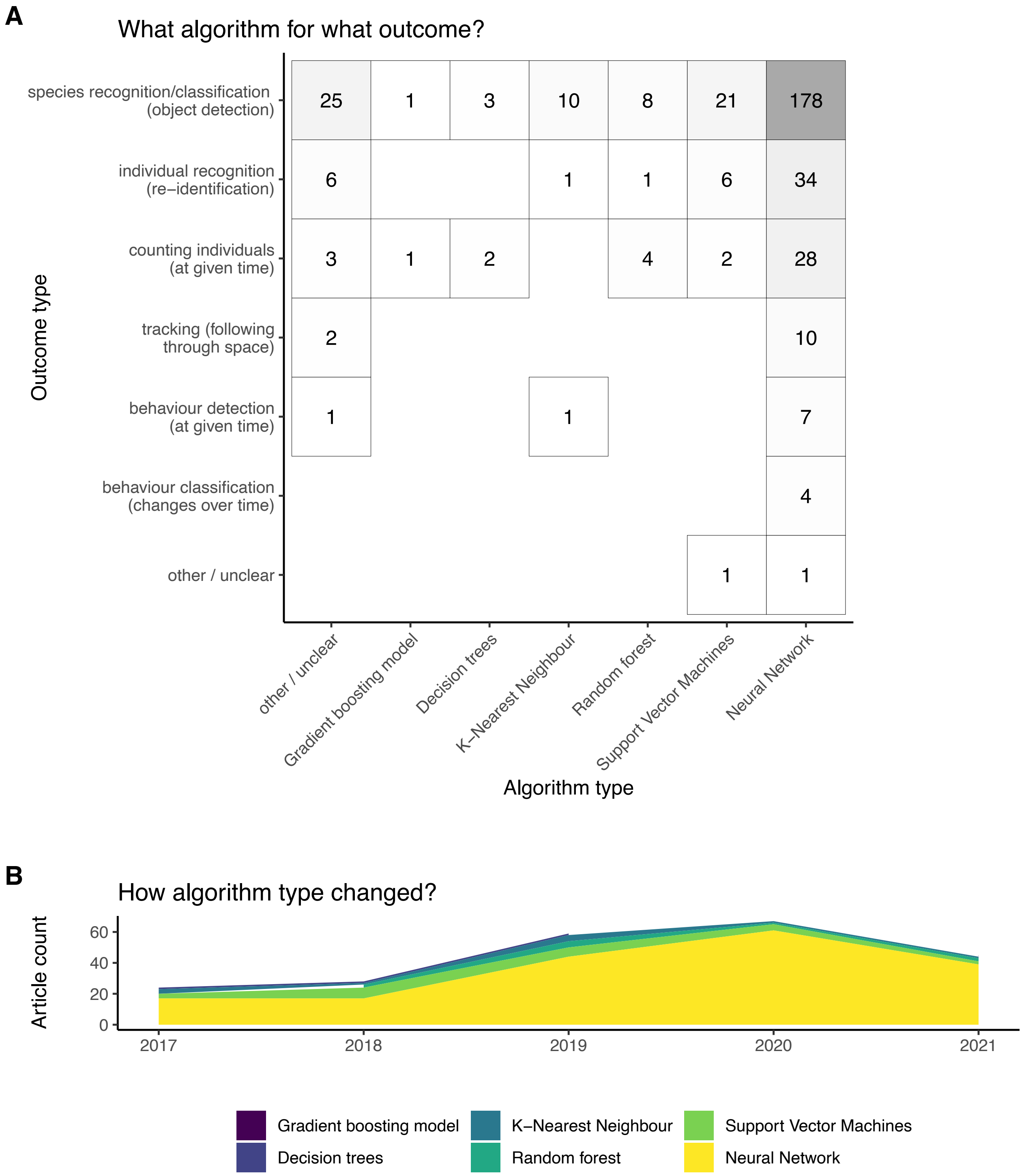

FIGURE 3. Machine learning algorithm types and wildlife outcome types analysed in the included studies. A – article counts by algorithm type and outcome type (one study could use more than one type of each), B – temporal trends (annual counts) in types of algorithms used across the last five years; "other/unclear" 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).

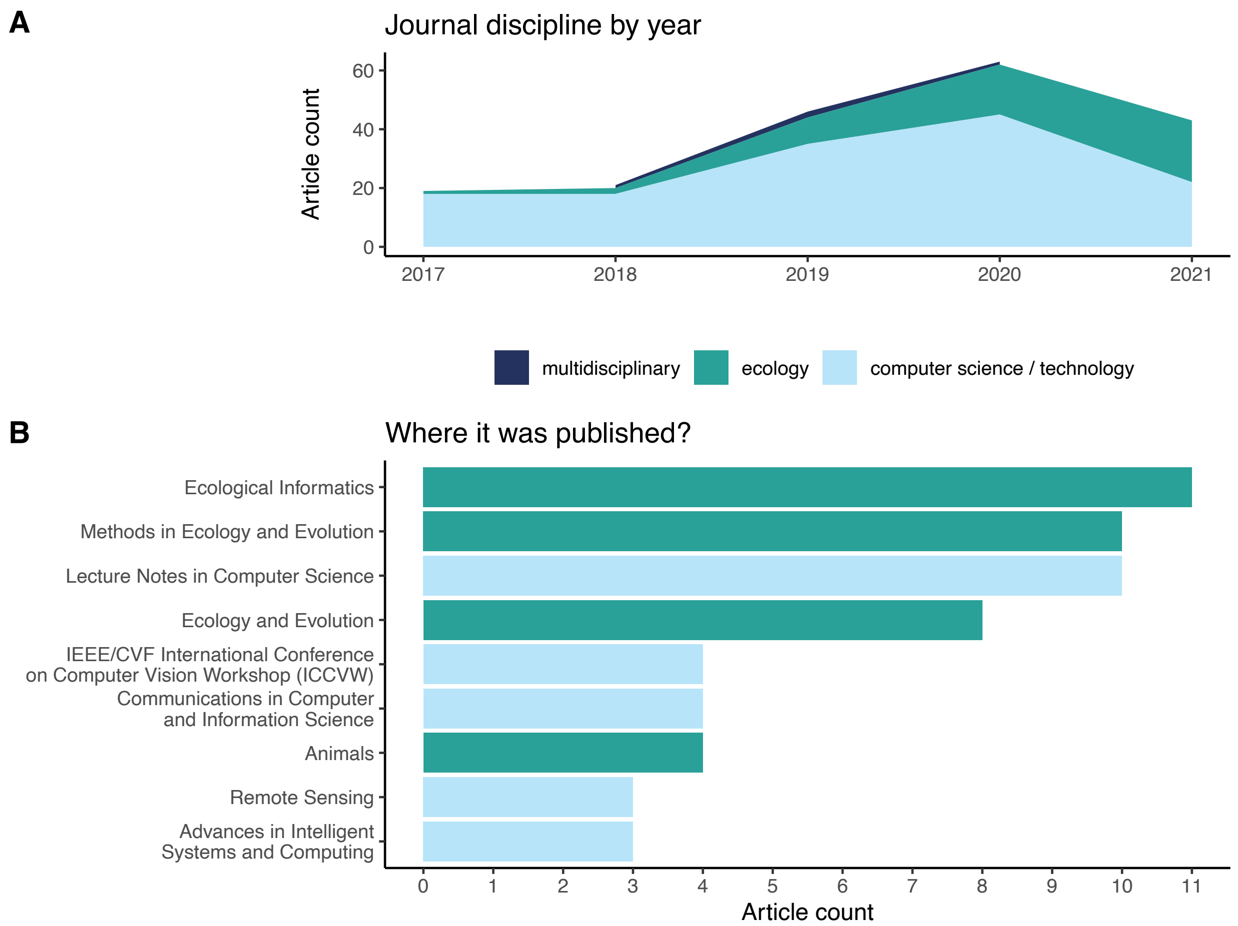

FIGURE 5. Diversity of the journals publishing machine learning studies on wildlife imagery. A – temporal trends (annual counts) in three main journal subject disciplines across the last five years. Year 2021 is included only up to October . B – article counts for journals with at least three articles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

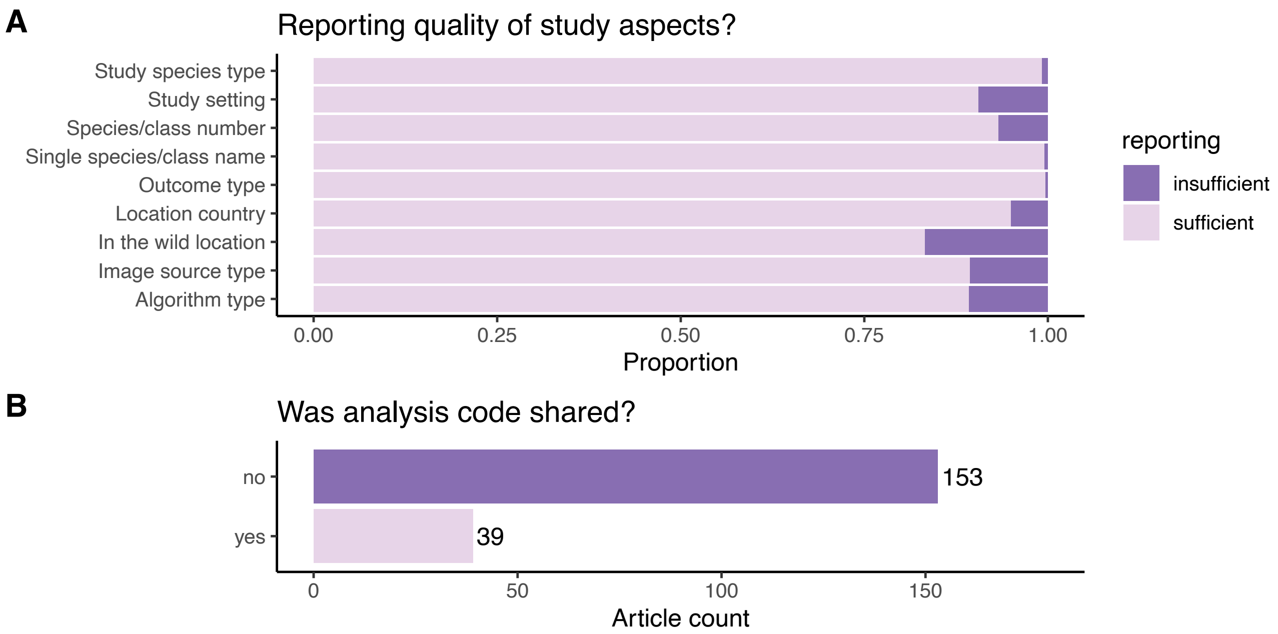

FIGURE 6. Aspects of reporting quality and openness of the included machine learning studies. A – percentages of relevant articles providing sufficient or insufficient information to code a given variable. B – article counts for studies that shared or did not share their analysis programming code.

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.

ORCID

Shinichi Nakagawa: 0000-0002-7765-5182

Malgorzata Lagisz: 0000-0002-3993-6127

Roxane Francis: 0000-0003-3172-5445

Jessica Tam: 0000-0003-3655-1974

Xun Li: 0000-0002-1717-0669

Benjamin J. Pitcher: 0000-0002-8580-0343

Justine O'Brien 0000-0003-2011-9626

Neil R. Jordan: 0000-0002-0712-8301

Arcot Sowmya 0000-0001-9236-5063 .

Richard Kingsford**:** 0000-0001-6565-4134

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