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 have a very few systematic literature surveys 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. We found that increasing number of studies used convolutional neural networks (i.e., deep learning). Typically, studies have focused on large charismatic or iconic mammalian species . Increasing number of studies is published in ecology-specific journals indicating the uptake of deep learning to transform detection, classification and tracking of wildlife. Sharing of code was limited, with only 20% of studies providing links to analysis code.

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; Besson *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 vision analysis pipelines (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 around one year by automating up to 99% of the entire (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; Besson *et al.* 2022). This is increasingly useful for both *in-situ* and *ex-situ* conservation. Unsurprisingly, 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 applications of machine (deep) learning can support ecological research and conservation (e.g., Christin, Hervet & Lecomte, 2019; Lamba *et al.*, 2019; Nazir & Kaleem, 2021; Besson *et al.* 2022).

Yet, there is no systematic survey of this emerging and important field (cf. Caravaggi *et al.*, 2017; a review by Christin, Hervet & Lecomte, 2019 is mostly narrative and includes only a brief survey in one of its sections). 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 accelerated some of the systematic-map processes by focusing on more recent articles and using one database. Such a accelerated review (mapping) is useful especially for a rapidly moving fields like the topic of this article. Notably, a fully comprehensive Systematic Review takes on average 2 years (Tricco *et al,* 2015; Morah *et al.*, 2017)and a Rapid Review can be completed in a few months (Schünemann *et al.*, 2015; Haby *et al.*, 2016), providing more timely, and usually unbiased, snapshot of the research knowledge (Ganann *et al.*, 2010; Affengruber *et al.*, 2020). In this work, we also use a 'research weaving' approach to incorporate bibliometric information in a systematic-like map of the empirical studies (Nakagawa *et al.*, 2019), to provide deeper insights on the topic. First, we manually map the content of recent studies (published between 2017 and 2021) that were utilising machine learning to process wildlife imagery. For these studies, we attempt answer 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 source code to reproduce the analysis (i.e., 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.

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 | 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 fully comprehensive systematic map, but it can be considered more as a map or literature survey on a group of representative articles revealing key trends and patterns.

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 (e.g., 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 /Convolutional 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. We recognised six main outcome types: "species recognition/classification (object detection)", "individual recognition (re-identification)", "counting individuals (at given time)", "tracking (following through space)", “behaviour detection (at given time)”, “behaviour classification (changes over time)”.

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 conducted a search update in 2022 to capture all articles published in 2021 (details in Supplementary File 1). Further, 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 and waiting for around two weeks for their responses.

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.

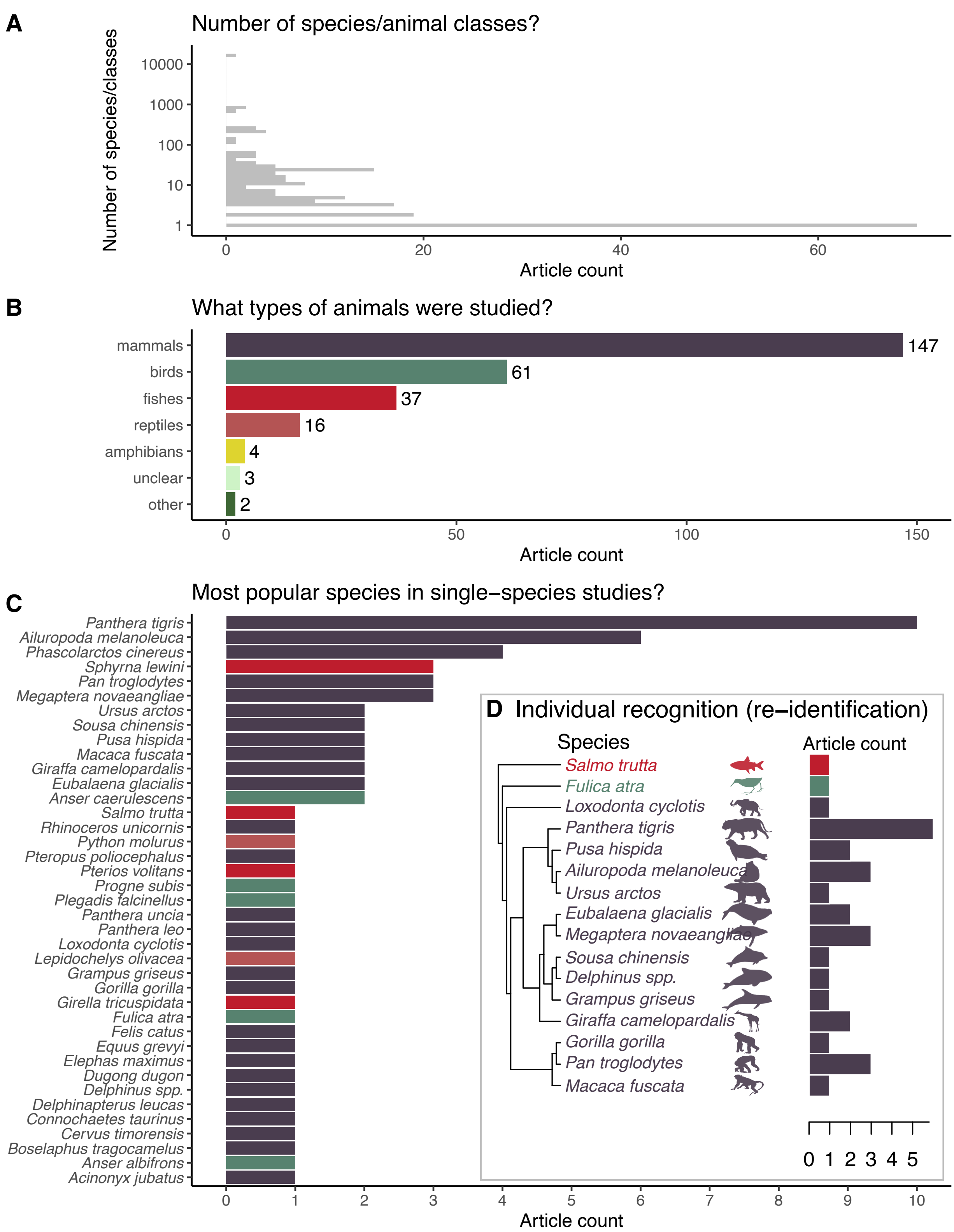
2.6 | Data synthesis and presentation

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). Search update provided additional 31 articles from 2021, bringing the total number to 223. The final dataset consists of 19 papers from 2017, 21 from 2018, 48 from 2019, 63 from 2020, and 72 from 2021.



200

201 **FIGURE 1.** Diversity of the vertebrate species studied in the included machine learning studies. A

202 – numbers of species / animal classes per study. B – counts of articles that studied each vertebrate

203 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 = 108, SD = 1,155, median = 3; Fig. 1 A). The most popular biological group among vertebrates was mammals (66% studies), followed by birds (27%), fishes (17%), reptiles (7%) and amphibians (2%) (Fig. 1 B; some articles studied more than one class so that percentages do not total 100%). Forty-six species were used in single-species studies. Here, the most popular study animals were tigers (*Panthera tigris*), pandas (*Ailuropoda melanoleuca*) and koalas (*Phascolarctos cinereus*). In single-species studies, images of 16 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).

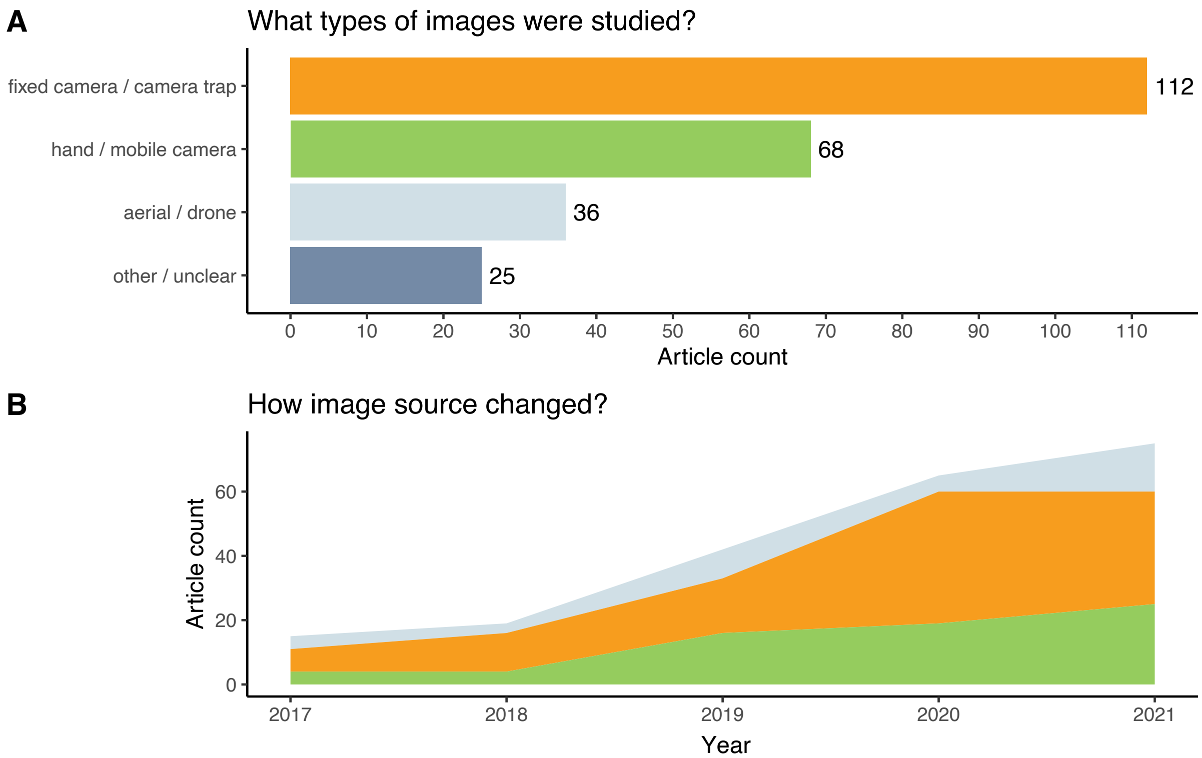


FIGURE 2. Diversity of the wildlife imagery analysed in machine learning studies. A - article counts by image source hardware type (one study could use more than one image type), B - temporal trends (annual counts) across the last five years. Colours are corresponding to image source hardware types shown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

Around half of included studies used wildlife images from fixed cameras (50%), such as camera traps and surveillance cameras, while 30% of studies used images from hand (mobile) cameras, and 16% of studies used aerial images from drones or aircraft (Fig. 2 A; some studies used more than one image type). Over the last five years, the use of images from fixed cameras and mobile cameras has markedly increased in terms of total numbers, while the use of aerial images remained stable (Fig. 2 B).

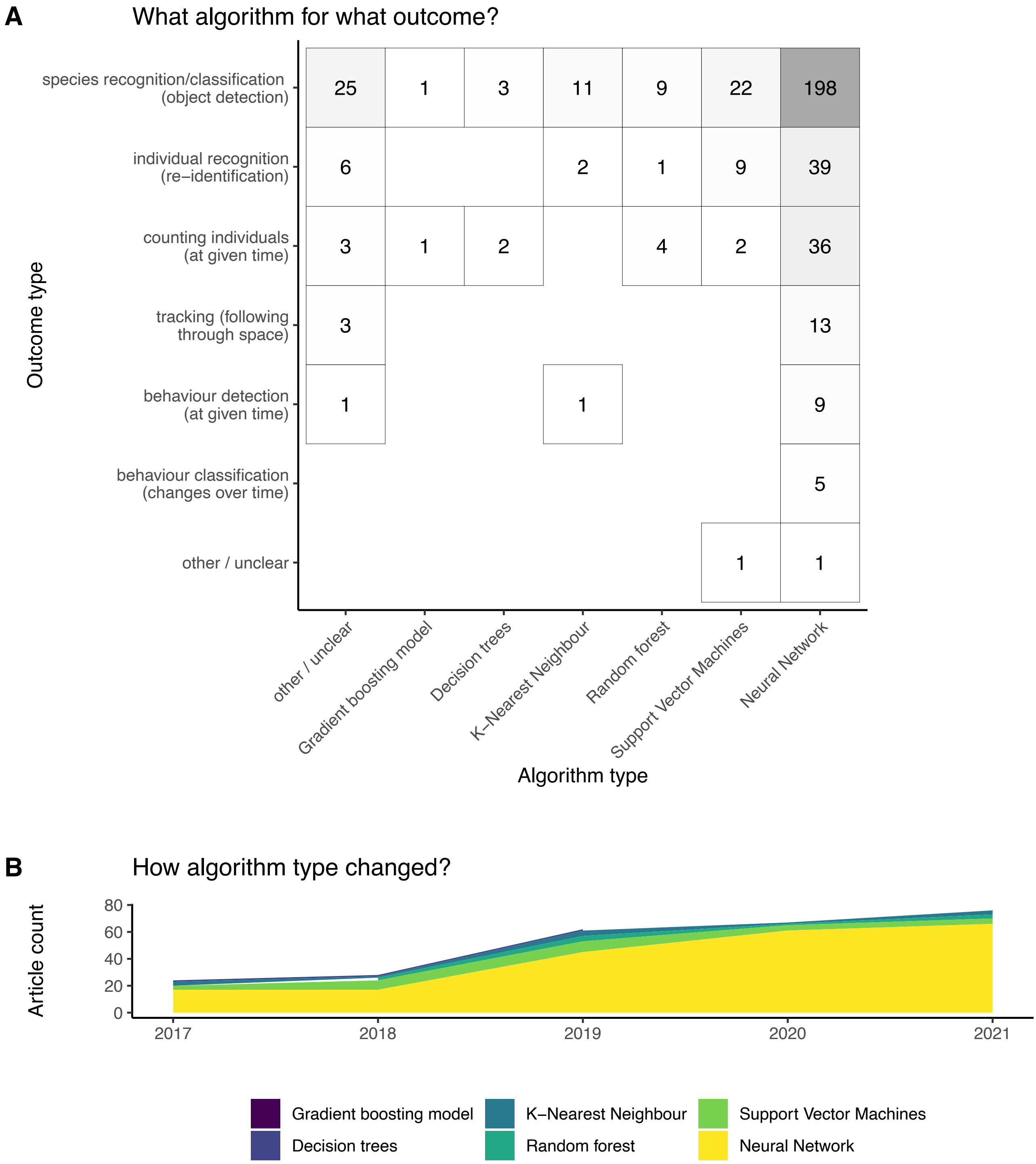


FIGURE 3. Machine learning algorithm types and wildlife outcome types analysed in the included studies. A – article counts by algorithm type and outcome type (one study could use more than one type of each), B – temporal trends (annual counts) in types of algorithms used across the last five years; “other/unclear” category not shown. Algorithm types that were outside the main six categories or were described to vaguely to be classified were coded as “other / unclear”.

3.2.2 | Algorithms and outcomes

Neural-networks were easily the most popular machine learning algorithms, appearing in 92% of included studies. This approach was often used alongside other approaches, such as Support Vector Machines (12% of studies), K-Nearest Neighbours (5%), and Random Forests (4%), or . other algorithms (13% of studies; e.g., Naïve Bayes, Bag of Visual Words, Histogram of Colors, Local Binary Patterns Histograms, Multi-class Logistic Regression, Principal Component Analysis, Linear Discriminant Analysis). Object recognition / classification, which involved object detection in the image, was the first and essential step mentioned in almost all (94%) studies. Additional steps of image processing included individual recognition (re-identification), counting individuals (at given time), tracking (following through space), behaviour detection (at given time), behaviour classification (changes over time). Individual recognition and re-identification were an objective of 20% of studies. Counting the numbers of individuals was mentioned in 19% of studies). Few studies attempted to conduct behaviour detection (4%), classification (2%), or tracking (6%). Figure 3 A shows frequencies of combinations of machine learning algorithms and outcome types mentioned in the included studies. Unsurprisingly, neural networks were used in the context of all types of image processing outcomes (Fig. 3 A). Support Vector Machines were likely to be mentioned in the context of individua re-identification studies (16%). Fig. 3 B shows that the absolute usage of Support Vector Machines is stable of across the years, but the use of Neural Network algorithms is increasing over time, dominating the field.

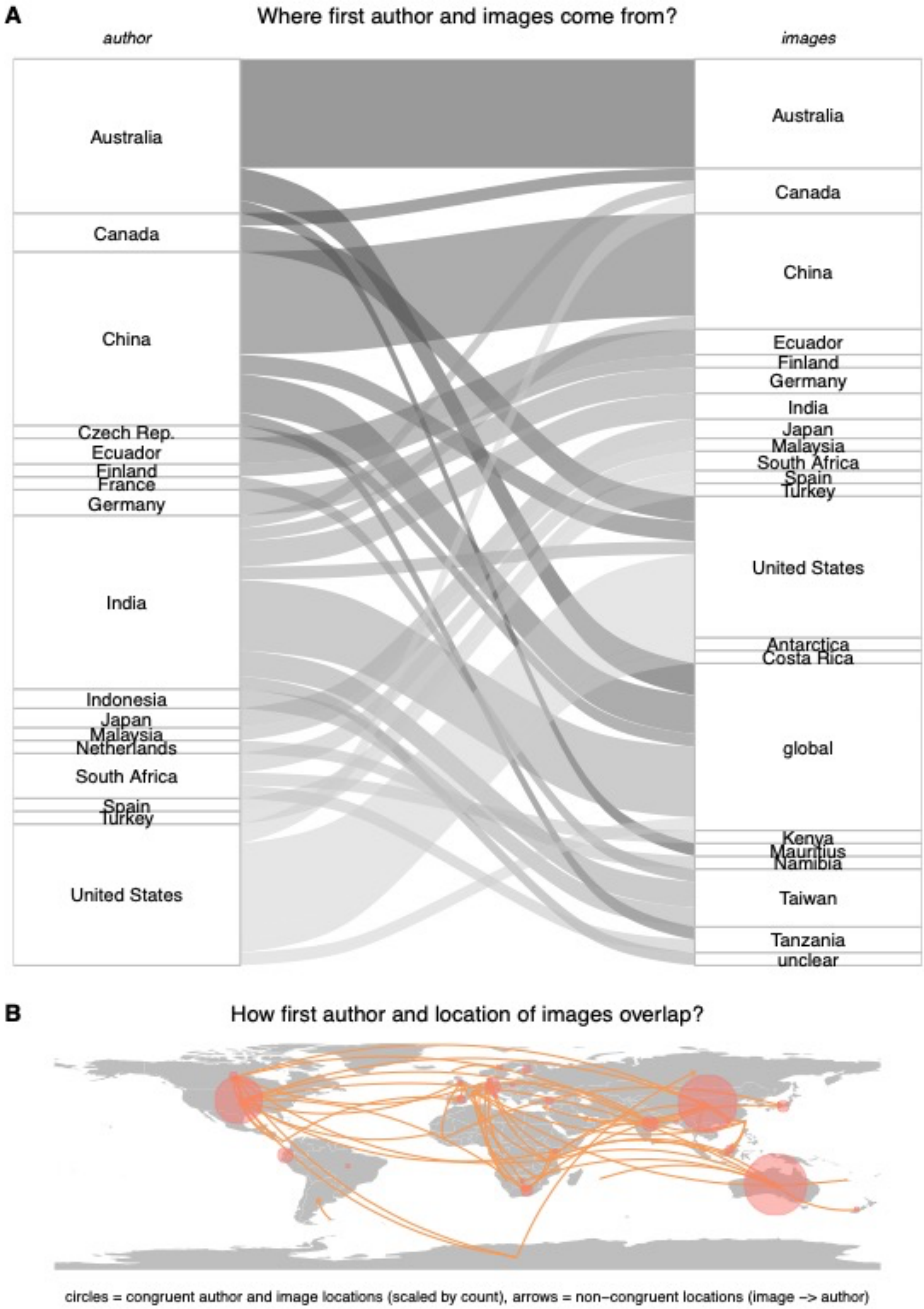


FIGURE 4. Geographic distributions and overlaps in the affiliations of first study authors and the locations of the wildlife imagery. A – connecting author's countries (in alphabetical order) and

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 44 different countries, but only 24 countries had more than one study (Fig. 4 A; left column). The analysed images came from 41 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 200 papers with complete bibliographic data on affiliations had authors from more than one country (Figure S9).

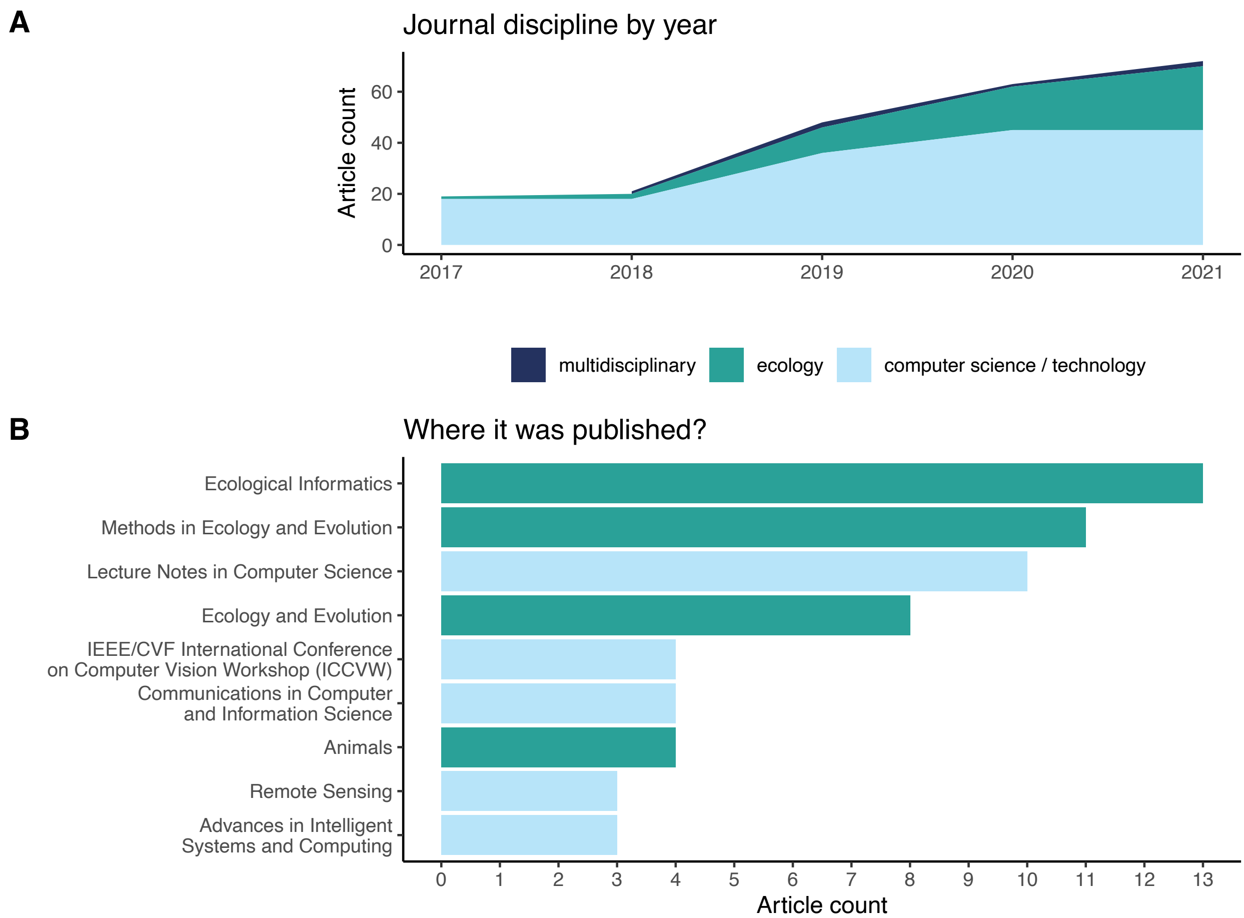


FIGURE 5. Diversity of the journals publishing machine learning studies on wildlife imagery. A – temporal trends (annual counts) in three main journal subject disciplines across the last five years.B – article counts for journals with at least three articles included in our survey data set.

Although in 2017 most publications were in 'computer science' journals (usually 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).

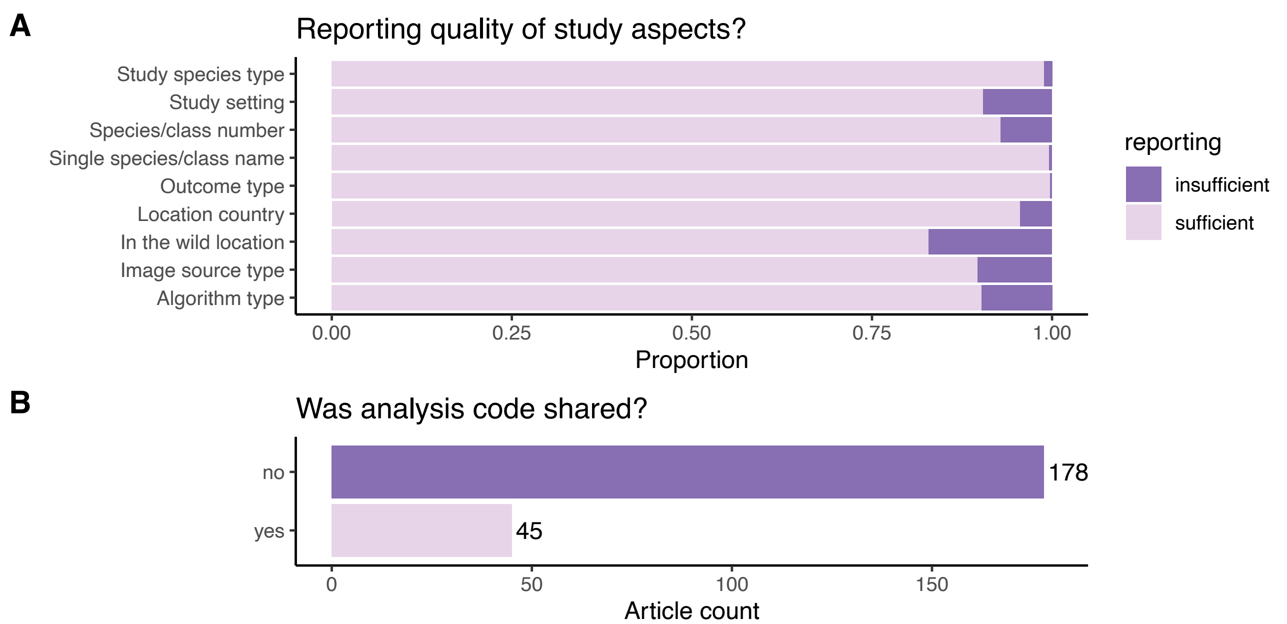


FIGURE 6. Aspects of reporting quality and openness of the included machine learning studies. A – percentages of relevant articles providing sufficient or insufficient information to code a given variable. B – article counts for studies that shared or did not share their analysis programming code.

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). The code sharing practice tended to improve over time (Figure S10), increasing from ~12% in 2017 and 2018 to ~25% in years 2019-2021. Overall, the proportion of articles with code was highest in articles from journals classified as 'ecology' (44%) and lowest in journals classified as 'computer science / technology' (12%) (Fig. S11). Among the most popular journals (shown in Fig. S12), "Methods in Ecology and Evolution" had all articles sharing links to the code (100%; 11/11). The other three popular journals classified as 'ecology' had at least some of the articles compliant with the code sharing practice: "Ecological Informatics" (15%; 2/13), "Ecology and Evolution" (63%; 5/8), "Animals" (25%; 1/4). Among the journals classified as 'computer science / technology', "IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)" stood out as a positive example (75%; 3/4), followed by "Remote Sensing" (33%; 1/3). In contrast, only one study in "Lecture Notes in Computer Science" shared link to code (10%, 1/10) and none in "Communications in Computer and Information Science" (0%; 0/4) or "Advances in Intelligent Systems and Computing" (0%; 0/3).

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 three species, Euarsian coot (*Fulica atra*), snow goose, *Anser caerulescens* (Bowley *et al.*, 2017; Bowley *et al.*, 2018) and purple martin, *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, because it tapped into

1.2 million images available on GBIF (the Global Biodiversity Information Facility; Mo, Frank & Vetrova, 2017). Other papers with over 100 species often dealt with a species recognition in a particular high-level 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 is in line with 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 16 species used for individual recognition, brown trout (*Salmo trutta*) and Eurasian coot (*Fulica atra*) did not fit in categories of iconic species or phylogenetic relatedness (all the other species were large mammals). However, the motivation behind the salmon study was related to human economic values – helping aquaculture and fishing tourism by tracing fish migration and distribution, (Zhao *et al.*, 2019). In contrast, the study on Eurasian coot was a study exporing evolution of egg recognition in birds (Gómez *et al.*, 2021).

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 (104 vs. 112 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). 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 (~94%) algorithms applied a neural network approach to recognise and / or classify animals. Neural Networks or other machine 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). the second most popular machine learning algorithm, Support Vector Machines, was only found in 26 studies. However, the observed dominance of the literature by Neural Networks is 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, e.g. Convolutional Neural Networks.

Our mapping effort elucidated future directions in the use of machine learning in wildlife imagery. The clear next step is to increase the use of 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 being 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 machine 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). Surprisingly, articles published ecological journals tended to have better reporting practices than papers published in computer science / technology-related journals. Overall, there is a slow improvement in reporting practices in the recent years, potentially driven by the journals increasingly mandating code and data sharing. 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, revealing gaps and clusters of current work and areas for improvement, especially in terms of reporting practices.

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 declare they have no conflict of interest relating to the content of this article.

DATA AND CODE AVAILABILITY

Unprocessed data and meta-data are included as a Supplementary File 2. All Supplementary Information, data, meta-data and processing code are also freely available on GutHub https://github.com/mlagisz/SM_machine_learning_animals and on Zenodo https://doi.org/10.5281/zenodo.7502948 (Lagisz & Nakagawa, 2023).

SUPPLEMENTARY INFORMATION

Supplementary File 1 – supplementary methods and results in .pdf format (also available on GitHub and Zenodo)

Supplementary File 2 – unprocessed data and meta-data in .xlsx format (also available on GitHub and Zenodo)

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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