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A narrative review on the use of camera traps and machine learning in wildlife research

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Abstract: Camera trapping has become an important tool in wildlife research in the past few decades. However, one of its main limiting factors is the processing of data, which is labour-intensive and time-consuming. Consequently, to aid this process, the use of machine learning has increased. A summary is provided on the use of both camera traps and machine learning and the main challenges that come with it by performing a general literature review. Remote cameras can be used in a variety of field applications, including investigating species distribution, disease transmission and vaccination, population estimation, nest predation, animal activity patterns, wildlife crossings, and diet analysis. Camera trapping has many benefits, including being less invasive, allowing for consistent monitoring and simultaneous observation (especially of secretive or aggressive animals even in dangerous or remote areas), providing photo/video evidence, reducing observer bias, and being cost effective. The main issues are that they are subject to their environment, dependent on human placements, can disrupt animal behaviour, need maintenance and repair, have limitations on photographic data, and are sensitive to theft and vandalism. When it comes to machine learning, the main aim is to identify species in camera (trap) images, although emerging technologies can provide individual recognition as well. The downsides include the large amount of annotated data, computer power, and programming and machine learning expertise needed. Nonetheless, camera trapping and machine learning can greatly assist ecologists and conservationists in wildlife research, even more so as technology further develops.

Keywords: camera trapping, wildlife research, conservation, machine learning, artificial intelligence

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Introduction

Camera trapping has become a new scientific tool in wildlife conservation since the early 1990s and are increasingly being used to study and monitor animal behaviour and ecology (O'Connell et al., 2011; Rovero et al., 2013; Rovero & Zimmermann, 2016). Consequently, the demand for trail cameras in wildlife research and management continues to increase as this method meets the accrescent needs and specialisations in this field (Parker et al., 2020). Moreover, the number of scientific publications that used camera trapping has exponentially increased since the early 1990s; from less than 50 studies per year between 1991-2004 to more than 200 studies per year since 2012 (Rovero & Zimmermann, 2016). According to Delisle et al. (2021), annual publications on camera trapping increased 81-fold since 1994 but are decelerating since 2017. However, to use camera traps, whether for research or recreational purposes, all images and videos need to be classified and analysed manually when no software assistance is available. This traditional method of data analysis poses a large limitation which can result in the reduction of sampling intensity (e.g., the number of camera traps that are used), limiting the geographical extent and the duration of studies (Tabak et al., 2019). Consequently, machine learning, which is the ability of a computer to perform prediction tasks by learning from data based on an algorithm, is becoming an increasingly popular tool in wildlife conservation (Tuia et al., 2022). Therefore, machine learning can be a potential solution as it greatly reduces the time and effort needed to analyse all data, because it automatically discerns images from camera traps. Moreover, the synthesis and evaluation of international experiences are particularly important in domestic research in wildlife biology and conservation biology. The reason for this is that although camera traps are used for individual observations, collecting information, proving the presence of certain species or detecting certain behaviours, we are not aware of any large-scale projects with a large number of elements and a uniform methodology. Therefore, in this study, we undertook a literature review on camera trapping studies and the use of machine learning as a solution to analyse images or video data without time-consuming manual work and thus, providing a summary of international camera trapping application methods and current data evaluation practices.

Materials and Methods

A general literature review was conducted on the use of camera traps and the use of machine learning in camera trapping by using Web of Science as the main search engine. The review is made up of two sections: camera trapping in different field applications and the use of machine learning for processing data from camera traps. For each part, separate data collection was carried out. For the first section, the uses of trail cameras are based on Parker et al. (2020). Then, to specify the findings, further data collection was done by using the search engine with the keywords "*camera trap*" followed by the field application in question, namely *"species occupancy and distribution", "disease transmission", "population estimation", "nest predation", "activity patters", "crossing", "diet analysis"; e.g.*, camera trap activity patterns. For the second part, the keywords were "*machine learning*" AND "*camera trapping*". As there were limited results for this data collection, no further specification was needed. Keywords were looked for in the title and abstract, and publications from all years were used and from all continents. Due to the high number of results in the data collection for the first section, papers were selected based on novelty and relevance to the scope of this study. For the second section, publications within the found papers were used as well. This resulted in 1,890 papers found and 52 processed for the first section and 60 papers found and 24 processed for the second section. Overall, the list of scientific documents is not exhaustive and does not include all studies related to camera trapping and machine learning. However, we believe that the list of publications is sufficient to give a clear and concise overview of current practices of camera trapping and machine learning and the main issues with data analysis and processing.

Results

Field applications

Camera traps are an effective and common tool to collect data on different aspects of wildlife research but can be also used in hunting. In fact, manufacturers of trail cameras mainly serve the needs of North American hunters (Meek & Pittet, 2012). However, camera trapping (mainly in research) can help determine the occu pancy of certain species, analyse behaviour, investigate conservation threats, and even aid communication with policymakers and the public (McCallum, 2013). Based on Parker et al.

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Table 1: Summary of the results of 10 papers on the use of camera traps in species occupancy and distribution

Main objective	Target species	Number of cameras	Main results	Source
Biodiversity monitoring to compare species richness and occupancy	Medium to large-sized mammals and pheasants	94 stations	23 mammal and 7 pheasant species; alpine/subalpine zone and dry-hot valleys have the highest richness	Li et al. (2018)
Examining distribution patterns and occupancy trends	Ground-dwelling rainforest birds	18-30 stations with two cameras per station	4083 detections of 28 bird species; occupancy in protected area complex and annual trends in occupancy at three surveyed sites for five commonly observed species	Murphy et al. (2018)
Determining the factors that affect occupancy patters	African forest elephant (*Loxodonta cyclotis*)	87 cameras	Key factors were the distance to the nearest research or ecotourism areas, the distance to the periphery and the rate of poaching index of the installation site	Kely et al. (2021)
Establishing the first range-wide baseline of occurrence	Crested black macaque (*Macaca nigra*)	111 cameras	Species occupancy of 0.66 and highest inside protected areas and closed canopy forests	Johnson et al. (2020)
Comparing two occupancy-based sampling methods	Sun bear (*Helarctos malayanus*)	60 cameras	Camera traps are a more appropriate tool to study sun bears in tropical forests	Bisi et al. (2019)
Better understanding the distribution and habitat relationship	Mohave ground squirrel (*Xerospermophilus mohavensis*)	24 cameras	Site occupancy was positively related to the length of ephemeral stream channels within a site	Kotschwar Logan (2016)
Gathering information on the ecology and distribution of muntjacs	Large-antlered muntjac (*Muntiacus vuquangensis*), northern red muntjac (*Muntiacus vaginalis*), dark muntjac species complex (*Muntiacus rooseveltorum/ truongsonensis*)	134 stations with two cameras per station	Large-antlered muntjac and northern red muntjac were widespread; dark muntjac was restricted to a single high elevation area	Alexiou et al. (2022)
Obtaining baseline data on the current distribution and abundance	Florida Key deer (*Odocoileus virginianus clavium*)	30 stations (two stations per island complex)	Abundance was well below estimated carrying capacities on all outer islands, with larger natural populations occurring closest to Big Pine Key	Watts et al. (2008)
Information on abundance and distribution	Brown hyaena (*Hyaena brunnea*)	6 cameras	Population density of 2.8/100 km2, occupancy at 1.0 and model-averaged detection probability at 0.1	Thorn et al. (2009)
Comparing scat detection dogs, cameras, and hair snares for detecting carnivores	Black bear (*Ursus americanus*), fisher (*Martes pennanti*), and bobcat (*Lynx rufus*)	74 cameras	Scat detection dogs yielded the highest raw detection rate and probability of detection for each of the target species, as well as the greatest number of unique detections	Long et al. (2007)

Table 2: Summary of the results of 6 papers on the use of camera traps in disease transmission and vaccination

Main objective	Target species	Number of cameras	Main results	Source
Estimating rates of interaction between wild and farmed deer	White-tailed deer (*Odocoileus virginianus*)	18 cameras	Little direct contact between wild and captive deer through fences	VerCauteren et al. (2007)
Monitoring carcasses of fallow deer to study the role of ungulates as disease reservoirs	Wild boar (*Sus scrofa*), red deer (*Cervus elaphus*), fallow deer (*Dama dama*)	Not specified	All carcasses were consumed by wild boar	Gortázar et al. (2008)
Identify mammalian and avian scavengers that are potentially exposed to CWD from consumption of deer carcasses	Scavengers	Not specified	Infected deer carcasses or gut piles can serve as potential sources of CWD prions to a variety of scavengers	Jennelle et al. (2009)
Determining vaccine bait contact	Raccoon (*Procyon lotor*)	7 cameras	Detected raccoon movement in all culverts; half of the bait contacts in the culverts were by raccoons	Wolf et al. (2003)
Comparing species-specific visitation and removal rates of baits with and without raccoon repellent	No specific target species	40 cameras	Cumulative bait removal rates after four nights ranged from 93% to 98%	Campbell and Long (2007)
Conducting a synthesis on banded civet habitat preferences with a focus on factors relevant to the species conservation and the risk of zoonotic disease transmission to humans	Banded civet (*Hemigalus derbyanus*)	5 cameras within a sampling area (49 areas in total)	Low likelihood of overlap with humans in degraded habitats, and therefore, a low risk of zoonotic disease transmission from the banded civet in the wild	Dunn et al. (2022)

(2020), the following field applications are explained in more detail.

Species occupancy and distribution

Camera trapping is an efficient way to monitor animal populations remotely and provide real-time observations (Parker et al., 2020). One of the most used applications is the occupancy and distribution of species, in particular rare, endangered, or elusive species (Alexiou et al., 2022; Bisi et al., 2019; Johnson et al., 2020; Kely et al., 2021; Li et al., 2018; Kotschwar Logan, 2016; Murphy et al., 2018; Parker et al., 2020) (Table 1). Traditionally, these were done by visual or auditory surveys, track counts, scat analysis, detection dogs, driven counts, and trapping (Parker et al., 2020). Moreover, camera traps can be used for remote areas as well, like the monitoring of Florida key deer on outer islands that were difficult to visit (Watts et al., 2018). Moreover, camera trapping with the help of baits can increase encounter rates and detection probability (Thorn et al., 2009). Therefore, when properly used, camera traps can be an effective tool, however, in some cases, other methods like the use of detection dogs can be more effective depending on the

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Table 3: Summary of the results of 12 papers on the use of camera traps in population estimation

Main objective	Target species	Number of cameras	Main results	Source
Determining if infrared-triggered cameras could be used for population estimation of freeranging antlered white-tailed deer	White-tailed deer (*Odocoileus virginianus*)	49 stations	Population and sex-ratio estimates differed among camera-station densities, but infrared-triggered cameras are useful tools to census deer in forested environments	Jacobson et al. (1997)
Comparing data from infrared-triggered cameras and replicated helicopter counts to estimate pre-hunt population size and sex and age ratio	White-tailed deer (*Odocoileus virginianus*)	31 stations	Both techniques resulted in a reasonable population estimate for the area indicating the camera technique may be a viable option for counting deer	Koerth et al. (1997)
Investigating the utility of time-lapse photography to provide population estimates and lamb:ewe ratios	Bighorn sheep (*Ovis canadensis*)	Not specified	Failed to reject the null hypothesis that population estimates and lamb:ewe ratios from time-lapse and direct observation sampling were the same	Jaeger et al. (1991)
Developing cost-effective and quantitative methods for estimating population parameters based on mark-sight techniques using automatic camera systems	Feral hogs (*Sus scrofa*)	54 stations	Obtained sufficient sightings for reliable estimates	Sweitzer et al. (2000)
Estimating population size using camera sightings	Grizzly bear (*Ursus arctos horribilis*)	5-8 cameras per 100 km^2	Sighting rates varied considerably (18-178 camera-nights/sighting), but were generally highest during spring when attractants were more effective	Mace et al. (1994)
Estimating density	American black bear (*Ursus americanus*)	8 stations	Bear densities of 0.18 (0.09-0.32) and 1.33 (0.54-3.29) bears/km^2 on the two sites	Matthews et al. (2008)
Estimating density	Red fox (*Vulpes vulpes*)	22-30 stations	Estimated density ranged from 0.91 $\pm$ 0.12 foxes/km^2 to 0.74 $\pm$ 0.02 foxes/km^2	Sarmento et al. (2009)
Estimating density	Tiger (*Panthera tigris*)	20 cameras	Estimated population size and standard error of 29 (9.65) and a density of 6.94 (3.23) tigers/100 km^2	Karanth and Nichols (1998)
Estimating density	Bobcat (*Lynx rufus*)	10 units	Abundance estimation of 15 individuals from 56 bobcat photographs	Heilbrun et al. (2006)
Estimating density	Ocelot (*Leopardus pardalis*)	7-19 stations with two cameras per station	Densities of 25.82–25.88 per 100 km^2 in the broadleaf versus 2.31–3.80 per 100 km^2 in the pineforest	Dillon and Kelly (2007)

Table 3: continued. Summary of the results of 12 papers on the use of camera traps in population estimation

Main objective	Target species	Number of cameras	Main results	Source
Estimating density	Bobcat (*Lynx rufus*)	0.5-8 cameras/ km^2	Estimated density of 0.27 bobcats per km^2 overall in an area in the northern Sacramento River Valley and 0.35/km^2 in a steep and rocky canyon within the area; at a third site in the Coast Range, the estimate was 0.39/km^2	Larrucea et al. (2007)
Estimating relative abundance	Not specified	60 cameras	19 large and medium-sized mammal species were recorded; spotted deer was the most frequently captured species which represented high relative abundance and the rusty spotted cats were represented by a relatively low abundance	N. C. Palei et al. (2021)

specific case (Long et al., 2007).

Disease transmission and vaccination

Camera traps can aid in vaccine intake by monitoring visitation rates to the baits or individual bait consumption (Parker et al., 2020). Additionally, intra- or interspecies disease transmission can be studied by gaining knowledge on direct or indirect individual contact, such as nuzzling, faecal-oral contact, and site visitation (Parker et al., 2020). This way, camera trapping can cover knowledge gaps and therefore, aid in disease mitigation strategies and vaccine delivery methods, with lower costs and higher effectiveness (Parker et al., 2020). Several studies observed disease transmission and the intake of vaccines (Table 2). For example, VerCauteren et al. (2007) looked at possible transmission routes for bovine tuberculosis and chronic wasting disease by providing moment-of-contact pictures between wild and farmed cervids. Gortázar et al. (2008) and Jennelle et al. (2009) monitored cervid carcasses for possible ways of bovine tuberculosis and chronic wasting disease (CWD) transmission from carrion consumed by scavengers. Dunn et al. (2022) gained information on intermediator species for the SARS-CoV-1 outbreak through camera trapping. Moreover, Wolf et al. (2003) and Campbell and Long (2007) monitored baits containing vaccines for rabies by using trail cameras. Overall, using camera traps to monitor the access and behaviour of wildlife towards vaccines is not a sole data collection effort, but is rather part of a larger disease monitoring programme (Parker et al., 2020).

Population estimation

One of the most common ways to use camera trapping is in estimating population abundances. There are many (traditional) methods to estimate population size, including driven counts, strip counts, line transects, removal methods, and capture-mark-recapture strategy (Parker et al., 2020). The use of camera traps is based on the mark-recapture tech-

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Table 4: Summary of the results of 10 papers on the use of camera traps in nest predation

Main objective	Target species	Number of cameras	Main results	Source
Assessing whether restricted-area culling of foxes was associated with local reduction in an index of predation risk	Red fox (*Vulpes vulpes*)	Not specified	Restricted area culling of red foxes was not associated with local reductions in predation risk, nor lower probability of a fox sighting, even for the plots with the largest hunting bags	Kämmerle et al. (2019)
Assessing conditioned food aversion (CFA) as a method to reduce nest predation	Red-legged partridge (*Alectoris rufa*)	1 camera per nest (3-4 nests in each territory)	CFA reduced ground nest predation by foxes and had a positive effect on the partridge population despite the compensatory predation	Tobajas et al. (2020)
Describe black grouse nest predators and potential predation risk	Black grouse (*Lyrurus tetrix*)	1 camera per nest (50 nests in total)	56% of nests were predated; stone marten was the main potential nest predator in both study areas, followed by common raven and red fox	Cukor et al. (2021)
Identifying duck nest predators on real and artificial nests	Boreal ducks	15 cameras	8 species of duck nest predators that ate or removed eggs from nests: American black bear, short-tailed or least weasel, Canada lynx, coyote, American marten, red squirrel, common raven, and red-tailed hawk	Dyson et al. (2020)
Highlighting the impact of a semi-feral cat on a threatened seabird	Australian Fairy Terns (*Sternula nereis nereis*) and feral cat (*Felis catus*)	2 cameras (+ human obser-vations)	Significant predator-induced mortality, alteration of natural behaviour of nesting birds, and complete reproductive failure of 111 nests due to predation by a single, desexed, semi-feral cat	Greenwell et al. (2019)
Monitoring interspecies interactions	Harpy eagle (*Harpia harpyja*)	9 cameras	Mammals at high risk of predation that visited the nest did not avoid daylight hours	Aguiar-Silva et al. (2017)
Investigating nest visitation rates to examine their effect on breeding success	Hooded vulture (*Necrosyrtes monachus*)	Not specified	Observations of 33 species recorded at 12 nests	Thompson et al. (2017)
Assessing predation on nests	Loggerhead sea turtle (*Caretta caretta*)	12-30 traps	Yellow-spotted goannas appeared at nests more frequently than lace monitors did	Lei and Booth (2017)

Table 4: continued. Summary of the results of 10 papers on the use of camera traps in nest predation

Main objective	Target species	Number of cameras	Main results	Source
Investigating nesting biology	Nile crocodile (*Crocodylus niloticus*)	2-3 cameras per nest (in total 26 cameras)	Of 19 monitored nests, 37% were raided by predators; all females returned to their nests following first predation, and on average returned three times between predator raids before nest abandonment; water monitors and marsh mongoose were the main egg predators	Combrink et al. (2016)
Quantifying the impact of mongoose predation on iguana nests, and to assess the utility of a trap-removal program designed to mitigate mongoose impacts	Jamaican rock iguana (*Cyclura collei*) and small Asian mongoose (*Herpestes auropunctatus*)	8 cameras	Catastrophic levels of nest loss (at or near 100%) can be ameliorated or even eliminated by removal trapping of the mongoose	van Veen and Wilson (2017)

nique by using Petersen estimators (Sweitzer et al., 2000). During the "capture", the animals in the pictures are "marked" based on their physical characteristics (e.g., unique antlers, pelage, or other visible features) and then "recaptured" whenever they appear in new pictures. Camera trapping for estimating abundance has been used for a long time, for example, for white-tailed deer (Jacobson et al., 1997; Koerth et al., 1997), bighorn sheep (Jaeger et al., 1991), feral hogs (Sweitzer et al., 2000), bears (Mace et al., 1994; Matthews et al., 2008), red fox (Sarmento et al., 2009), various feline species (Dillon & Kelly, 2007; Heilbrun et al., 2006; Karanth & Nichols, 1998; Larrucea et al., 2007), and even for censusing complete areas (N. C. Palei et al., 2021) (Table 3). Even though the use of remote cameras for population estimates are encouraging, several factors need to be considered. Such as the use of baited stations to maximise captures, which violates the assumption of equal catchability, and therefore, affects the accuracy and precision of the estimate (White et al., 1982). Other factors include camera placement, sample size, survey duration and timing, which are to overcome demographic and geographic closure of highly mobile and wide-ranging species (Parker et al., 2020).

Nest predation

The identification of nest predators is usually done by using physical evidence, such as eggshell fragments or animal signs like hair, scat, or tracks (Lariviére, 1999). However, these can be subjective and time-consuming and fail to report predation by multiple predators (Leimgruber et al., 1994). Moreover, human presence in order to collect these evidences can disrupt nesting patterns or deter certain predators (Parker et al., 2020), conflicting with the very aim of the investigation. Therefore, camera traps are a preferred method by many researchers to provide information on predation events, predator identification, and timing of preda-

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tion (Cutler & Swann, 1999). This method is not only used for monitoring birds' nests, such as ground nesting birds (Cukor et al., 2021; Kämmerle et al., 2019; Tobajas et al., 2020), ducks (Dyson et al., 2020), seabirds (Greenwell et al., 2019), birds of prey (Aguiar-Silva et al., 2017; Thompson et al., 2017) but also for reptiles' nests, such as turtles (Lei & Booth, 2017), crocodiles (Combrink et al., 2016), and iguanas (van Veen & Wilson, 2017) (Table 4).

Animal activity patterns

Investigating diel or seasonal activity patterns of wildlife species is essential to better understand their ecology. Additionally, activity data allows us to understand interspecific and intraspecific interactions as well as predator-prey relationships (Hernández et al., 2015; N. C. Palei et al., 2021; Foster et al., 2013; Tang et al., 2019) (Table 5). Often radiotags are used as they provide relatively large datasets that can be used remotely and in real time (Millspaugh & Marzluff, 2001). However, this method is occasionally invasive, expensive, labour intensive and often not feasible when it comes to elusive species (Lashley et al., 2018). On the other hand, camera trapping is a non-invasive method that can be used to study activity patterns due to time stamps on the images. For instance, assessing the activity patterns of deer species can result in more efficient culling programs (Ikeda et al., 2015; Soria-Díaz & Monroy-Vilchis, 2015). Another strategy which has the same idea as radiotags, is attaching a camera to the animal itself. For example, Brockman et al. (2017) used neck-mounted cameras on brown bears to determine kill rates of moose and caribou in south-central Alaska. The results showed higher kill rates than previous estimates via other methods and gives insight to the diet of the species as well. Moreover, monitoring activity patterns can also aid in reducing damage to wildlife; e.g., Christiansen et al. (2014) combined thermal monitoring with unmanned aerial vehicles, to inform landowners and managers about wildlife in their area and therefore, reduce wildlife injury and mortality during agricultural activities. Furthermore, camera traps are not only used on land; there is a novel type of remote camera that can be used under water by using stereo cameras, which greatly increases the information that can be extracted from underwater systems and marine animals (Williams et al., 2014).

Wildlife crossings

Roadways can have a negative effect on wildlife movement patterns, like its dispersal, migration, and corridor connectivity (Jackson, 2000), sometimes resulting in wildlife-vehicle collisions. Therefore, to provide safe alternative movement corridors, wildlife-crossing structures can be constructed (Ng et al., 2004). To ensure proper function, these structures must be strictly monitored on how the crossings are accepted and used by wildlife (Braden et al., 2008). In this case, camera traps are often the preferred method for data collection. Examples of this can be seen in Mexico (González-Gallina et al., 2018), India (Chakraborty et al., 2021), China (Wang et al., 2017), and Canada (Pomezanski & Bennett, 2018) (Table 6).

Diet analysis

There are direct (observation) and indirect (scat or stomach analysis, prey remains) methods for analysing wildlife diets (Lanszki, 2012). Trail cameras offer an alternative to direct observation by monitoring multiple areas simultaneously (Parker et al., 2020). This is especially the case with nesting raptors, where they found that the trail-camera system provided the largest number of prey items and is probably the least biased method (García-Salgado et al., 2015) (Table 7). However, the downside is that a lot of prey items remain unidentified to species level and it underestimates small prey, more-

Table 5: Summary of the results of 8 papers on the use of camera traps in animal activity patterns

Main objective	Target species	Number of cameras	Main results	Source
Comparing daily activity patterns and the relationship with prey	Jaguar (*Panthera onca*) and puma (*Puma concolor*)	34-119 stations with two cameras per station	Both cats showed intensive nocturnal and crepuscular activity; only in one region a pattern of concentrated diurnal activity for both species was observed; little temporal segregation; significant overlap between the activity patterns of the predators and their main prey species	Foster et al. (2013)
Exhibiting activity patterns by spotted and melanistic colour morphs	Guiña (*Leopardus guigna*)	127 stations	Guiñas are mainly active at night; melanistic guiñas were more nocturnal than the more common spotted cats; spotted guiñas were more active on cloudy and moonless nights	Hernández et al. (2015)
Detecting population size and activity patterns	Eurasian lynx (*Lynx lynx*)	50 cameras	20 lynx identified; daily activity rhythms overlapped with those of different prey in different seasons; yearly activity pattern was influenced by its main prey's biology	Tang et al. (2019)
Investigating activity pattern in relation to prey	Leopard (*Panthera pardus*)	211 cameras	Cathemeral activity pattern and positive co-occurrence pattern and significant spatial and temporal overlap with its main prey, the wild pig	H. S. Palei et al. (2021)
Investigating activity patterns in central Mexico	White-tailed deer (*Odocoileus virginianus*)	10 cameras	Mostly diurnal with activity peaking between 16:00-18:00h and 10:00-12:00h; the peak activity at night was between 0:00-2:00h with low or no crepuscular activity	Soria-Díaz and Monroy-Vilchis (2015)
Investigating seasonal variation of activity patterns	Sika deer (*Cervus nippon*)	12 cameras	Deer activity at dawn, dusk and night showed clear seasonal patterns, with peaks in September, while the activity pattern during the day was constant in all seasons; activity at dawn and dusk tended to be higher than that at day during Jul–Oct and Jul–Nov	Ikeda et al. (2015)
Estimating kill rates by individual bears	Brown bear (*Ursus arctos*)	17 cameras	Kill rates considerably greater than previous estimates; median handling times were 40 min for caribou calves and 60 min for moose calves	Brockman et al. (2017)

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Table 5: continued. Summary of the results of 8 papers on the use of camera traps in animal activity patterns

Main objective	Target species	Number of cameras	Main results	Source
Assessing the suitability of thermal imaging in combination with digital image processing to automatically detect a chicken and a rabbit in a grassland habitat	Domestic rabbit (*Oryctolagus cuniculus domesticus*) and a domestic chicken (*Gallus domesticus*)	1 camera	The study animals were detected with a high precision, although the most dense grass cover reduced the detection rate; thermal imaging and digital imaging processing may be an important tool for the improvement of wildlife-friendly farming practices in the future	Christiansen et al. (2014)

over, cameras can alter the birds' behaviour which is an aspect that must be controlled (García-Salgado et al., 2015). Although using cameras for diet analysis has mainly been done for raptor species, it has also been used for bats (Pereira et al., 2017), although these studies are usually in combination with other diet analysis methods.

Data management and machine learning

Difficulties of manual data processing

Camera trapping can be used in a variety of applications and provides many benefits. However, one of its main limiting factors is the processing of data. Sometimes millions of images need to be visually reviewed one by one in order to extract information (Tabak et al., 2019). Newey et al. (2015) showed that one camera typically captures around 2,000–10,000 images per month of deployment, which only increases the more cameras are used. Although this greatly varies per habitat and species activity, it displays the amount of effort it would take to process these images. Consequently, one of the problems they experienced was falling behind in cataloguing images due to a lack of in-built tools to facilitate image and data management (Newey et al., 2015). An additional problem might be the asynchrony between camera trap units, which makes it difficult to compare images from different cameras but mainly hinders the linking of imagery to corresponding (time-stamped) meteorological data (Newey et al., 2015), if this is one of the objectives of the study. This results in manually extracting weather variables from the meteorological data and linking them with the appropriate images and then augmenting by visual assessment of weather from images, which is a long process that took around 14 hours for every 1,000 images (Newey et al., 2015). Therefore, processing imagery manually can cause latency and is time-consuming and costly, moreover, these limitations will only increase as camera trapping becomes more complex (Duggan et al., 2021).

Machine learning models

Although models can be individually made, this requires a lot of annotated data, computer power, and programming and machine learning expertise (Carl et al., 2020). Therefore, there are several pre-trained, open-source example models available for object detection and classification of camera (trap) images for certain datasets. The most common object detectors include Faster R-CNN (region convolutional neural network (Ren et

Table 6: Summary of the results of 4 papers on the use of camera traps in wildlife crossings

Main objective	Target species	Number of cameras	Main results	Source
Describing differential use of available crossing structures	Mammals	28 cameras	24 jaguar crossings; at least 18 other mammal species including five of the target priority species (protected by Mexican law) were documented; wildlife underpasses show higher diversity values compared to culverts because they allow bigger species to cross	González-Gallina et al. (2018)
Assessing corridor's functionality	Not specified	5 cameras	39 mammal and avian species were identified; elephants used the corridor patch most frequently, followed by hog deer, while hog badgers were most rarely recorded	Chakraborty et al. (2021)
Determining what species uses wildlife crossing structures to cross the highway, the frequency, and time of crossings	Not specified	8 cameras	A total of 13 medium and large-sized wildlife species crossed the highway; one third of species were Chinese national protective species, and almost all species that were present within 500 m from the highway used bridges and culverts to cross this highway	Wang et al. (2017)
Characterising the seasonal and daily usage patterns of species using crossing structures	Not specified	2 cameras	Of the 1178 mammal crossing events, 74% were by small mammals and 26% were by larger mammals; large mammal crossings took place consistently, while small mammal crossings were particularly frequent during September and October	Pomezanski and Bennett (2018)

al., 2017)), R-FCN (region-based fully convolutional network (Dai et al., 2016)), SSD (single shot multibox detector (Liu et al., 2016)), FPN (future pyramid network (Lin, Dollár, et al., 2017)), RetinaNet (Lin, Goyal, et al., 2017), and YOLO9000 (you only look once (Redmon & Farhadi, 2017)). According to a summary of object detectors by Hui (n.d.), one of the best models is the combination of Faster R-CNN and Inception-ResNet V2, which results in a high average precision. Moreover, by using bounding boxes, it is easier to identify the region of interest which surrounds the animal (Carl et al., 2020), because models without these are problematic (Miao et al., 2019). This means that when using images of the same camera trap, the background stays the same and when a specific animal frequently visits this area, false results are given when a new animal appears (Carl et al., 2020). Hence, bounding boxes can aid in detecting the animal and classifying the animal(s) within the boxes (Carl et al., 2020). See Figure 1 for examples of the use of Faster-RCNN+InceptionResNet V2.

Species identification accuracy

The main aim of object detectors in machine learning in wildlife research is to detect and

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Table 7: Summary of the results of 2 papers on the use of camera traps in diet analysis

Main objective	Target species	Number of cameras	Main results	Source
Evaluating the usefulness of commercially available trail-cameras for analysing diet	Northern goshawks (*Accipiter gentilis*)	1 camera per nest (80 nests)	Cameras registered the greatest number of prey items and were probably the least biased method for estimating diet composition	García-Salgado et al. (2015)
Providing evidence on the consumption of leaves	Seba's short-tailed bat (*Carollia perspicillata*)	1 camera	Consumption of the whole leaf (juices and fibers), which was never recorded in Neotropical bats	Pereira et al. (2017)

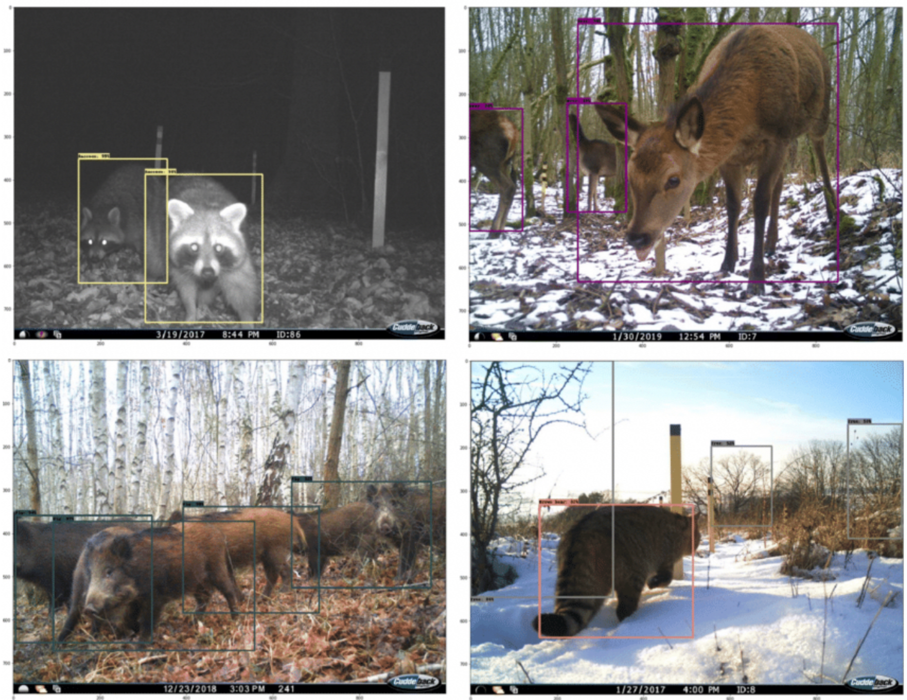

Figure 1: Detection and classification of wildlife species using Faster-RCNN+InceptionResNet V2 network - examples of correct classification (upper images) and none detection (two hidden wild boars) and incorrect classification ("brown bear" instead of "cat") (lower images) (Carl et al., 2020).

classify animal species in camera trap images. Depending on the model(s) used and the training process beforehand, there are different rates of accuracy. Norouzzadeh et al. (2018) used deep learning models to automatically identify the species, their numbers, the presence of young animals, and even the behaviour of the animals in the Serengeti in Africa with an accuracy of 93.8%. Miao et al. (2019) utilised the same dataset to analyse the usability to classify and cluster 20 wildlife species with 87.5% accuracy. Banupriya et al. (2020) used machine learning to test the applicability to classify elephants and cheetahs with an accuracy of 79%. Carl et al. (2020) looked at ten different European wildlife species and found a classification accuracy of 71% for the correct name of the species as mammals and 93% for the correct species or higher taxonomic ranks. The highest accuracy rate was achieved by Tabak et al. (2019) with 98% by using CNNs with the ResNet-18 architecture and 3.37 million images. Kutugata et al. (2021) came close with an overall accuracy of 97% with 120,000 images. Moreover, Bilodeau et al. (2022) represent the first successful method for underwater camera trap deployment and machine learning classification of fish; they achieved 92.5% accuracy with over 100,000 images.

Furthermore, machine learning can be used not only for identifying objects in images, but also for identifying empty images (false positives) and deleting these, which is one of the most acknowledged problems in camera trapping, along with false negatives (Newey et al., 2015). False triggers like wind or lose shrubs as well as camera settings and animal behaviour specific to a camera site will add noise to the dataset (Newey et al., 2015). Wei et al. (2020) compared a freely available software Zilong with a CNN-based R package MLWIC (Machine Learning for Wildlife Image Classification) and found that Zilong performed better than MLWIC in identifying empty images; Zilong identified 87% of animal images and 85% of empty images correctly, whereas MLWIC identified correctly 65% and 69%, respectively. However, Tabak et al. (2020) found that MLWIC2 performed with 97.3% accuracy in their empty-animal model. In this case, the high accuracy rate can be attributed to the high number of training images (three million).

Taking it a step further, there are emerging technologies to identify not only the species but also individuals for species that lack consistent or unique body markings. Clapham et al. (2020) used object detection, landmark detection, a similarity comparison network, and a support vector machine-based classifier to identify brown bear individuals. They achieved facial detection with an average precision of 0.98 and an individual classification accuracy of 83.9% based on 4674 images with an 80-20% split for training and testing, respectively (Clapham et al., 2020). de Silva et al. (2022) similarly looked at individual identification, but in wild Asian elephants by using five different types of CNN models. The highest level of accuracy was achieved by using an Xception model which was specifically trained on the ears of the elephants and reached an accuracy of 89.02% for matching the top candidate and 99.27% for including the right individual in the top five (de Silva et al., 2022). Sforzi and Lapini (2022) propose new criteria to evaluate European wildcats from domestic cats from camera trap observations; however, be it either human or computer, specific expertise on the identification of the species in question is needed. To further increase accuracy, another method is combining both artificial intelligence and humans as a way to increase data processing efficiency, for example, where machine learning is used as an additional vote to citizen science (Adam et al., 2021; Green et al., 2020; Willi et al., 2019).

Discussion

Since the invention of the camera traps in the late 1860s by George Shiras III and the rediscovery by Seydack in 1984, the use of remote cameras has significantly increased since then (Rovero & Zimmermann, 2016). Camera trapping has many benefits, including being less invasive, allowing for consistent monitoring and simultaneous observation (especially of secretive or aggressive animals even in dangerous or remote areas), providing photo/video evidence, reduc-

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ing observer bias, and declining costs (Parker et al., 2020). Additionally, the effectiveness of camera systems is dependent on their technology, i.e., battery life, data storage capacity, and picture/video quality (Parker et al., 2020). Consequently, the better the technology, the more opportunities this tool can provide, whereas the worse the technology, the harder it is to apply. Moreover, the usefulness largely depends on the quality of the study design and the capabilities of the operator (Parker et al., 2020). The opportunities for camera traps are in areas or situations where humans would cause disturbance to wildlife, extended observational periods are required, monitoring takes place in dangerous and/or remote areas, permanent and provable data is needed, or just different capabilities from the human eye are needed (Parker et al., 2020). Also, Dubois and Harshaw (2013) found that the general public is more supportive of less invasive data collection techniques, including camera trapping, than other techniques where animal handling or killing is needed. On the other hand, the negatives of camera traps are that they are subject to their environment, dependent on human placements, can disrupt animal behaviour, need maintenance and repair, limitations of photographic data, and the sensitivity to theft and vandalism (Parker et al., 2020). For example, Meek et al. (2019) found that the theft of camera traps is a global issue with a maximum financial loss of USD 1.48 million between 2000 and 2015. Also, according to Newey et al. (2015), one of the main issues with camera trapping is data management; e.g., large number of images, highly variable proportion of false positives/negatives, even between locations, time periods of cameras, and the lack of tools to simultaneously log or match external data sources to the images. Therefore, machine learning could partially solve these issues and reduce the burden of manual classification (Table 8).

However, to use machine learning models, advanced computational skills are needed, which quickly make them inaccessible to biologists (Tabak et al., 2020). Machine learning also never has a 100% accuracy level and largely depends on the information that is provided during the training process. van Horn et al. (2015) support this by mentioning that learning algorithms are robust to annotation errors and training data corruption. However, Gomez Villa et al. (2017) emphasise that if a training set has sufficient samples, then the results show robustness to data corruption, which can be achieved with the help of citizens. Consequently, object recognition problems can be reduced. This is further supported by Norouzzadeh et al. (2018), who show that deep learning technology can save 98.2% of manual labour with an accuracy level of 96.6%, and that this time (over 17,000 hours) could be redirected to other scientific purposes. Lastly, Tuia et al. (2022) highlight the importance of interdisciplinary thinking, as processing big ecological data requires complex analytical techniques that no single conservationists or biologist can carry out on their own. Overall, camera trapping along with the use of machine learning can greatly assist ecologists and conservationist in wildlife research, even more so as technology further develops.

We encourage wildlife biologists to utilise (open-source) software and machine learning algorithms and cooperate with computer programmers to optimise the use of available modern technology in wildlife research, especially when analysing camera trap data. Moreover, the use of such data management solutions should be user-friendly, accessible, and preferably open-source (Steenweg et al., 2017). This could also aid in increasing the transparency and repeatability of projects (Young et al., 2018), and provide a standardised solution (Scotson et al., 2017). Whether the project is big or small, the understanding of ecological systems and closing knowledge gaps should be at the forefront and consume

Table 8: SWOT analysis of the use of machine learning algorithms for trail camera data analysis

Strengths	Opportunities
• Decreases human labour • Decreases the amount of human error • Saves money as no human employment is needed	• Robustness to data corruption • Can be paired with citizen science • Can process big data
Weaknesses	**Threats**
• High number of training images are needed for high accuracy • Advanced computational skills are needed • Individual models need to be made first according to the given datase • Data annotation during training is time-consuming	• Unbalanced dataset with uncommon species can cause issues • Errors in image objectification (false positives/negatives) • Very few open-source algorithms

most of the time instead of generating big data (Nichols et al., 2011; Steenweg et al., 2017; Young et al., 2018)).

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