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ORIGINAL RESEARCH

Socially responsible facial recognition of animals

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Abstract

Automated identification of people using facial recognition algorithms, while of widespread potential use, has been criticized for being biased, unfair, discriminatory, or potentially harmful. Facial recognition algorithms to identify individual domesticated and wild non-human animals are increasingly used but there has been much less discussion of their potential dangers. This paper explores the ways in which such algorithms are used in farming and conservation, and discusses potential issues in such uses.

Keywords Facial recognition · Socially responsible algorithms · Precision livestock farming · Factory farming · Animal ethics · Wildlife populations · Camera traps

Abbreviations

ASF	African swine fever
BSE	Bovine spongiform encephalopathy
FACS	Facial action coding systems
FAUs	Facial action units
LINC	Lion identification network of collaborators
NIST	U.S. National Institute of Standards and Technology
NOAA	U.S. National Oceanic and Atmospheric Administration
PLF	Precision livestock farming

1 Introduction

Facial recognition algorithms show tremendous promise in applications, such as policing, medicine, and commerce [1]. However, automated identification of people using such algorithms has been shown to be biased, unfair, discriminatory, or potentially harmful [1], and these considerations have led to an emphasis on social responsibility of algorithms involving facial recognition of people (see, for example, [2]). Facial recognition algorithms are increasingly used with both domesticated and wild non-human animals (hereafter just referred to as animals), to aid in more efficient farming and in conservation of wild populations. However, there has been much less discussion of the potential dangers of using facial recognition algorithms for animals. This paper explores the applications of such algorithms and the social responsibility issues that arise.

Issues with facial recognition of humans have been well-documented. For instance, U.S. government tests find even top-performing facial recognition systems misidentify blacks at rates five to 10 times higher than they do whites [3]. The French company Idemia's algorithms scan millions of faces in uses by police in the US, Australia, and France, but a U.S. National Institute of Standards and Technology study showed that two of Idemia's algorithms were significantly more likely to mix up black women's faces than those of white women, or black or white men [3]. Buolamwini and Gebru [4] showed that in three commercial gender classification systems, darker-skinned females were misclassified with error rates up to 34.7%, where lighter-skinned males had a maximum error rate of 0.8%.

Amazon's "Rekognition" mistakenly identified 28 members of the U.S. Congress (disproportionately people of color) as criminals [5, 6]. Leslie [7] describes a variety of examples, where use of facial recognition algorithms has led to problems, e.g., in faulty face recognition algorithms leading to arrests or denial of passport photos for dark-skinned people. As Cavazos, et al. [8] observe, "Nearly all of the face recognition algorithms studied over the past 30 years show some performance differences as a function of the race of the face." A U.S. National Institute of Standards and Technology (NIST) study [9] tested 189 face recognition algorithms and found a wide range of accuracy. It found that for "one-to-one

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matching" as in identifying a smartphone owner, there were 10 to 100 times as many false positives for Asian and African American faces relative to images of Caucasians. For "one-to-many matching" as in matching a person to a police mugbook, there were higher rates of false positives for African American females. These results hold at the same time that, overall, the accuracy of facial recognition has improved drastically [10].

Problems with applying facial recognition algorithms arise because the algorithms use data that may be biased, depending on racial and gender biases, or because there is a problem in applying the algorithm, for example because of flaws in or misuse of technology, such as cameras, or in the ways data from algorithms are used to make decisions. These problems raise a variety of ethical and moral dilemmas: privacy, fairness, transparency, etc., and have given rise to major directions of research on social responsibility of algorithms. The ethical and moral dilemmas go beyond inaccuracies. They involve concerns about misuse such as whether it is ethical to do widespread surveillance of innocent people and whether there need to be criteria for placing an individual on a watch list [10]. They involve the trade-off between safety and security as against privacy, individual consent, and other individual and civil liberties [7]. There is concern that the ubiquitous use of cameras and associated facial recognition algorithms will infringe upon anonymity, self-expression and freedom of movement and affect political protest, free assembly, etc. [7]. A recent incident of facial recognition screening leading to a lawyer being banned from entering New York City's Madision Square Garden for a performance, because her firm was in litigation against the venue, illustrates the civil liberties concerns [11]. Furthermore, there is an exploding industry that purports to be able to detect emotion from facial expressions, with potential applications in vetting job applicants, workplace monitoring, attention-level assessment in classrooms, and deception analysis in law enforcement, all with the potential for misuse [7].

Because of ethical concerns, e.g., about racism and "structural discrimination," there has been a backlash against use of facial recognition. Microsoft and Amazon placed a moratorium on production of facial recognition software and services, IBM stopped these activities entirely, and there have been a variety of communities that have banned the use of face recognition by law enforcement [7].

Increasingly we are using facial recognition and video analysis to identify animals. They are used to identify diseases, protect against theft of animals, understand animal behavior, and to measure the biodiversity of ecosystems, even to address world hunger. They have potentially major economic impact. But are there problems that might arise that require a socially responsible perspective? Could animals be injured as a result of applications of facial recognition? Could misuse of facial recognition algorithms applied to animals have an effect on people who interact with them as owners or in other ways, or have an effect on environments that both the people and the animals share or on our understanding of trends in animal populations or their natural environments? Coghlan and Parker [12] point out that questions like these are often neglected in AI ethics. Just as with humans, the issues we discuss stem from numerous causes: the way in which data used in facial recognition are obtained, the quality of that data, the quality of the facial recognition algorithms, the technology that is used to obtain the data and reach decisions, and the procedures for making decisions using the data. We explore various applications of facial recognition of animals, the data and application challenges involved, and related issues of social responsibility. We distinguish in this paper between the impacts of facial recognition on animals and those on humans that result from the impacts of facial recognition on animals they may relate to, for example, as owner.

There is a considerable AI and ethics literature on animals and also on the impact of AI on animals. Singer and Tse [13], Hagendorff, et al. [14], and Owe and Baum [15], for example, make the case for including animals in moral considerations of the impacts of AI. Hagendorff [16] and Scheessele [17] discuss anthropocentric tendencies toward animals in discussions of AI and ethics. However, little of this literature deals with facial recognition.

In Sect. 2, we describe the use of facial recognition algorithms for domesticated animals, such as cows, sheep, and pigs, which are increasingly raised on large factory farms, as well as dogs and cats, fish, etc. There is discussion of recognition of pain and injury. Section 3 does the same for wild animals, including elephants, whales, seals, lemurs, and lions. There is discussion of biometrics in studying biodiversity, the use of camera traps in the wild, and the advantages of automated facial recognition over citizen science. Sections 4 and 5 turn to discussion of social responsibility of animal identification algorithms, the former for domesticated and the latter for wild animals. Both sections discuss potential physical and emotional injury to animals, and animal welfare in general. Section 4 also raises issues about economic injury to their owners. Section 5 explores potentially biased and misleading conclusions about animal populations, health of ecosystems, etc., and the potential danger to animals of revealing information about their whereabouts. Section 6 makes some closing comments about future work.

2 Applications of facial recognition for domesticated animals

Today's farms have gotten massive, and that makes it increasingly difficult to identify and care for individual animals without modern technology. Today's "precision livestock farming" (PLF) uses technology, in particular facial recognition, to monitor individual animals with the goal of optimizing production, improving animal health, speedier adjustment of animal food and medical treatment, etc. Take the case of PLF for pigs. "As the pig herds grow larger and at the same time the number of farmers decreases worldwide, it is almost impossible for the farmers to assess every individual animal and assure its well-being. Precision Livestock Farming (PLF) could provide solutions to these problems" [18]. PLF is intending to achieve fully automated continuous monitoring of pigs or other farm animals when a farmer is unable to monitor individual animals closely due to the large number of such animals on a huge factory farm [19]. In addition to its value at the individual farm level, such monitoring can also have benefits at national and international levels to safeguard against the spread of disease [20]. Moreover, precision livestock farming can aid in monitoring the environmental impact of agriculture. (See [21] for a recent comprehensive book on PLF.) There are, however, problems and concerns about PLF and in particular the implications of use of facial recognition algorithms (see [22] for a review). In addition, there are many issues relating to environmental impact of applications of AI, such as facial recognition methods, both negative and positive, that would be important to explore further.

2.1 Biometrics

Facial recognition is only one tool for identification of individual animals. Biometrics, the study of biological systems using metrics derived from biological features, involves much more than facial features. Biometrics in use include not only face, but also body, fur, feather, or skin patterns; footprint identification; and acoustic profiling. Biometric data can be collected without invasive intervention [23] and data can increasingly be collected by machine rather than by a human, allowing for scaling up the application and applying it to larger and larger farms.

2.2 Cattle

As the number of farms decreases but the number of cattle on each farm grows, it becomes increasingly important to identify individual animals in an efficient way for health monitoring, adjusting feeding to enhance milk production, tracking food and water consumption, and tracking and registering of cattle. Existing methods such as microchip embedding or ear tagging can be expensive and are subject to forgeries or damage and can cause pain and injury to animals. Identification of individual livestock is also important to contain spread of disease and has become recognized as important by international organizations, e.g., in preventing spread of diseases, such as Bovine Spongiform Encephalopathy (BSE) [24]. Recent work shows that individual cattle can be identified through a deep learning approach based on "primary muzzle point (nose pattern)" characteristics. This addresses the problem of missing or swapped animals (especially during large movements of cattle) and false insurance claims. (See, [25, 26].) Cainthus, an artificial-intelligence startup based on Dublin (and acquired by Ever.ag in 2022), specializes in facial recognition for cows. It uses surveillance cameras, computer vision, and predictive imaging to track animals and analyze their behavior. However, there is a limited database of cattle faces (hundreds of thousands vs. millions for humans); due to the difficulty in obtaining only face-on views, facial recognition software for animals requires high definition photos and a variety of views overcoming occlusion, illumination issues, blur and background clutters; and animal faces require hundreds of reference points, many more than for humans [27–29]. A major challenge to biometric algorithms is the size and diversity of herds, which, therefore, call for extremely high standards of accuracy [30]. Nevertheless, some algorithms have shown up to 95.87% accuracy [31]. Recent work by Chen, et al. [27] using a deep learning network re-identification model has shown continued improvement. Xu, et al. [32] evaluated a number of different deep learning models for cattle face recognition and identified a RetinaNet method called ResNet 50 that has an average precision score of 99.8% and also improves on speed of recognition, with an average processing time of 0.0438 s per image. Shojaeipour, et al. [30] developed a two-stage YOLOv3–ResNet50 algorithm that achieves 99.13% accuracy. Getting technology like this to work in practice with moving cattle, dirt, and other issues remains a challenge [33]. Moreover, being able to observe animals in today's massive farms may not work with simple stationary camera setups; the use of drones may be required [34].

2.3 Pigs

In the pig breeding industry, typically either ear tags or RFID chips are used to identify individual pigs. However, inserting an ear tag requires cutting and causes pain, while RFID does not always work well when multiple pigs are involved or over larger areas. These observations led Wang and Liu [35] to develop a pig recognition method using a deep convolutional neural network algorithm that even does well when mud on pig faces is an issue. They observe that when individual pigs can be identified, tested, and isolated if infected, then diseases such as African Swine Fever (ASF) Virus that dramatically impacted the Chinese pork production market in the years following 2019 could be controlled. JD.com is China's equivalent to Amazon.com. It has developed facial recognition methods to monitor large groups of pigs to quickly detect metrics like age, weight, health and diet that are significant in improving pig breeding outcomes and offer promise to make China's pork production 30–50% more efficient as well as to offer defenses against diseases, such as ASF [5, 36]. In the United States and the European Union, as well as China, the huge factory farm is becoming the norm for raising pigs. In such a huge farm, the workers cannot get to know individual animals, and so any methods that will help them identify when an animal is in distress could be helpful. Convolutional neural networks are beginning to be used to identify individual pigs through facial recognition, but also to recognize the difference between stressed and unstressed animals—a conclusion that is informed by checking cortisol levels in saliva and blood—and has achieved an accuracy of over 90%; this leads to the possibility of intervening when an animal might be suffering [37, 38].

2.4 Fish farms

Traditionally fish farms such as salmon farms treat fish as a group, and if a few fish are found to have a disease or parasite, the entire farm is treated. The Norwegian Company Cermaq Group AS has developed a 3D scanner that can tell salmon apart based on the distinct pattern of spots around their eyes, mouth and gills. The goal is to prevent the spread of epidemics like sea lice that infect hundreds of millions of farmed fish and cost the industry almost $1 billion each year. The ultimate plan is to build a medical record of each individual fish and develop "individual aquaculture." If you see abnormality like lice or skin ulcer, you identify the individual fish through facial recognition using a pattern of spots on their mouth or gills, and quarantine the affected fish for medical treatment. The first phase of this development has been completed, with the need for "de-licing" reduced by 50%. The economic and food-supply implications of new "radical marine-farming methods" are great. For instance, the aquaculture industry is already a $232 billion industry. In addition, if it can become more efficient and could ward off fish diseases, it could help "feed the world." (See [39–41].)

2.5 Dogs and cats

Recognizing dogs and cats through facial recognition is complex for a variety of reasons, for example, because of changing position of mouth, ears, and nose. Makai, et al. [42] built classifiers for dog and cat faces and compared the use of the whole face vs. part of the face, such as nose or eyes. Facial recognition is already being used to find missing pets. In the U.S. alone, over 4 million pets go missing each year, and only a small percentage are found, e.g., 2% of cats. Tags, tattoos, and microchips are all used for pet identification. However, tags fall off, tattoos get rubbed off, and microchips move around an animal's body, making detection difficult. Facial recognition is more difficult for dogs and cats than for humans for reasons noted. However, there are now facial recognition apps that help in finding lost pets. For example, with the app called PiP, you pay a monthly fee and supply a photo of your pet. If it goes missing, you send the photo to vet clinics, animal shelters, municipal control officers, and other PiP clients. The app does a facial match. The developers claim a 98% accuracy rate. (See [43].) Other apps include PetcoLoveLost (formerly FindingRover) [44]. Rabies is a major problem in parts of the world, in particular in Africa and Asia. The PiP facial recognition technology is being rolled out to identify whether or not a dog has been vaccinated against rabies without the cost of embedding a microchip [45].

2.6 Recognizing pain in domestic animals

Assessing the level of pain in animals is an important factor in assuring their welfare. This can enable a farmer to detect diseases, study behavioral changes, and make adjustments in care for animals. For instance, in sheep, pain indicates potential diseases, such as footrot and mastitis [5, 46]. What we learn about pain in domesticated animals can also potentially teach us about wild animals and aid in conservation measures. Pain is only one of many emotions and the study of emotions in animals is complex. See Neethirajan, Reimert, and Kemp [34] for a recent survey. While humans can express emotions with language, with animals we have to depend upon other cues, including visual ones, such as monitoring of facial expressions and body posture, and also vocalizations. In studying human emotion, Facial Action Coding Systems (FACS) are based on individual "facial action units" (FAUs) that measure muscle movements in the face. FACS have been developed for primates, dogs, and cats, but they require extensive training of human observers and are subject to human error or bias [38]. Simpler "grimace scales" aimed at pain, not other emotions, have been developed for rodents, rabbits, cats, horses, and sheep [47, 48]. Piglet grimace scales, for example, are studied in Di Giminiani, et al. [47] and Vullo, et al. [49]. FAUs are related to the eyes, nose, cheeks, and mouth. For instance, widening of the eyes increases in cows, horses, and pigs when they are in stressful situations [34]. Pain recognition for horses using facial activity is in its infancy, but promising tools using computer vision and machine learning are under development [50]. The Sheep Pain Facial Expression Scale is a standardized measure to assess pain level based on facial expressions. It has been shown to recognize pain in sheep faces with relatively high accuracy (67%). However, training of scorers and the scoring process can be time-consuming and individual bias may lead to inconsistent scores (see [5, 46]). Because it is becoming harder and harder for farmers to adequately monitor individual animals on larger and larger farms, there is need for an automated system that would identify individual sheep (or other animals), and detect changes in their facial expression and alert farmers that individual sheep need further assessment. Automated pain recognition through facial features has been studied for rodents, horses, sheep, and cats, but challenges in this field include lack of data (compared to human pain measurement) and lack of ground truth (animals cannot describe pain the way humans can) [48]. McLennan and Mahmoud [20] present an automated pain facial expression detection system for sheep. Noor, et al. [51] have used transfer learning for automating classification of sheep pain into pain/no pain that improves accuracy and speed over manual classification. Earlier and continued work addresses similar issues for cattle, pigs, chickens, etc. See Berckmans [21] for extensive discussion of technological systems of precision livestock farming for details. Once automated pain recognition has occurred, machine learning could then be used to detect coughing, appetite loss, or lethargy, and allow for automated dispensing of medicine or revised feeding programs—without human involvement [12]. Bos, et al. [52] suggest, however, that precision farming in this or other ways interrupts important human–animal relationships, including those that aid in early identification of animal health issues by non-automated methods. In addition, Tuyttens, et al. [22] argue that PLF could "directly harm the animals because of (1) technical failures, (2) harmful effects of exposure, adaptation or wearing of hardware components, (3) inaccurate predictions and decisions due to poor external validation, and (4) lack of uptake of the most meaningful indicators for animal welfare. PLF may create indirect effects on animal welfare if the farmer or stockperson (5) becomes under- or over-reliant on PLF technology, (6) spends less (quality) time with the animals, and (7) loses animal-oriented husbandry skills."

3 Applications of facial recognition for wild animals

Identifying species from observation is important in gaining insight into the changing biodiversity on our planet, population trends, and factors affecting those population trends. Identification of individual wild animals is important in measuring biodiversity, e.g., in counting numbers of individuals, Thus, if we see a leopard, we want to know if we have counted it before. Invasive methods such as capture, instrumentation, and tagging can be expensive, may interfere with animal behavior once released, and can interfere with oxygen consumption and metabolic rate, among other things [53]. Modern methods of artificial intelligence and machine learning to identify species and individuals from biometric data such as facial features show promise in overcoming some of the difficulties in identification with earlier noninvasive methods, and allow for the possibility of utilizing larger amounts of data from a wider variety of sources. International agencies and agreements such as the Intergovernmental Science–Policy Platform on Biodiversity and Ecosystem Services and the Convention on Biological Diversity include the importance of performing regular assessments of knowledge on biodiversity [54]. Our current knowledge of both numbers and distribution of species is inadequate to support this task. Estimates of the total number of species on Earth range widely from around 2 million to 1 trillion [55, 56].

3.1 Biometrics revisited

As discussed in Sect. 2.1, facial recognition is only one aspect of biometrics. In the wild, biometrics is increasingly used to identify species and even individuals, and has become a very useful tool in the study of biodiversity. In the wild, biometrics has several advantages over other monitoring tools: (a) biometric data can be collected without invasive intervention, instrumentation or tagging [23], (b) data collection can often be made by remote sensors, thus reducing field labor and cost [57], and (c) biometric identifiers are often able to classify not only at the species level, but also at the individual, sex and age-class level [58].

3.2 Camera traps and citizen science

For wild animals, as for domesticated ones, facial recognition algorithms are starting to play a role. They have mostly emphasized "iconic species", such as lions, tigers, elephants, etc. Methods widely in use depend to a great extent on motion-sensor cameras ("camera traps"). All these methods rely to some extent on crowdsourcing/citizen science, and require human interpretation of data. Some examples dealing with species identification (as opposed to identification of individuals) are: (a) the site iNaturalist.org/ [59–62], where users post pictures of plants or animals from all over the world and a volunteer expert identifies them, (b) "Snapshot Serengeti," the original initiative of what is now called "Snapshot Safari," which uses "camera traps" in Tanzania and other parts of Africa that have collected millions of images of animals, such as lions, leopards, cheetahs, and elephants, which are then manually labeled by volunteers ("citizen scientists", [63–65], (c) Wildlife Spotter, which has collected millions of images of wildlife in Australia and used citizen scientists to help analyze images [66]. iNaturalist alone has over 25 million records, representing over 230,000 species, collected by over 700,000 people, with over 90,000 volunteers doing identifications [60].

Using citizen science is slow and there are challenges in interpretation of the data. There is bias in the data, because images tend to be collected in accessible areas and observers favor large, visible animals. Inexperienced observers make errors in labeling images. (For studies of accuracy of citizen iNaturalist data, see [67, 68].) Moreover, the data available have rapidly outpaced the number of human experts available to label it. Totally automated methods are needed. AI methods are starting to be used by iNaturalist, Snapshot Serengeti/Safari, Wildlife Spotter, and other formerly just citizen science projects. Norouzzadeh et al. [63] describe the use of "deep convolutional neural networks" to identify and count species in the Snapshot Serengeti data set. Identification is accurate 97% of the time. They estimate that this has saved some 17,000 hours of human effort for this data set. Thel, et al. [69] is a recent study of how citizen scientists performed on some Snapshot Serengeti data. Palmer, et al. [65] describe how Snapshot Safari has successfully integrated human and machine classifications into what they call "Crowd AI" and also outline current challenges such as how to get population counts for species traveling in enormous herds; how to handle bimodal data arising from some observers only counting animals close by the camera and others counting animals in the distance; and the fact that current algorithms limit identification to one species even if there are multiple species in an image. See also Green, et al. [70].

We now turn to some examples that are specifically using face recognition algorithms.

3.3 Elephants

The London Zoo and Google are teaming up to use facial recognition to identify elephants in the wild and learn when they are in trouble. Google's Photos app looks at human eyes, nose, and chin when studying people, and by contrast with elephants it looks at tusks, trunk, and tail. Google's machine learning software Cloud AutoML Vision gets to "know" an elephant. In a different kind of application, if a human appears in a frame with the elephant and the human cannot be identified as a known person, such as a wildlife ranger, then the person could be a poacher, and a warning is sent out. The zoo's 1.5 M animal images were scanned into Google servers and aim to aid elephants, giraffes in Kenya, orangutans, stink badgers, pangolins in Borneo, etc. (See [71, 72].)

3.4 Whales

"Right whales" can be individually identified through distinctive spots on their heads known as callosities, or "whale lice." Information about individual right whales can be helpful in making plans for conservation and management, such as setting aside seasonal management areas or marine protected areas. Another use is to help whales tangled in nets. If crews could find out in real time what whale they are untangling, they would know more about the individual's health, and whether or not they should intervene and cut the rope. The tool might even be able to better pinpoint problem areas in the ocean, where multiple whales are getting tangled up with nets. (See [73, 74].) These observations led the U.S. National Oceanic and Atmospheric Administration (NOAA) to run a competition in 2015 on identification of individual North Atlantic right whales, which are endangered. Deepsense.io developed the winning software that identifies individual right whales. The software was 87% accurate, even based on a small data set of 4,500 images. NOAA followed this up by adapting the Pose Invariant Embeddings (PIE) Algorithm [75] originally developed for identification of individual manta rays and humpback whales from belly patterns and flukes, respectively. The adaptation was applied to lateral photos of right whale heads, and this method has turned out to be promising for identification of gray whales, killer whales, and sperm whales [74, 76]. In related work, Genov, et al. [77] discuss facial identification of individual cetaceans such as humpback whales and in particular common bottlenose dolphins (though not automated facial recognition). They argue that facial features are long-term and consistent as opposed to dorsal fins, which are more commonly used for identification but which do not have useful markings in calves. However, they point out the possibility of bias in sampling a population, since not all individuals regularly lift their heads out of the water upon surfacing.

3.5 Seals

A recent application of facial recognition for marine animals is SealNet, developed to identify individual harbor seals using features such as eyes and nose shape. SealNet has been shown to be almost 100% accurate. Being able to identify individual seals when they move around a great deal is a challenge but this new methodology shows promise for conservation efforts, and could be applied to the much rarer Mediterranean Monk Seal, of which only several hundred remain [53, 78]. Whisker pattern identification has been used for identification of individual large carnivores, e.g., Australian sea lions [79] and polar bears [80]. Accuracy of identification depends on getting detailed images from suitable angles. This is a much more stringent requirement than demanded of regular camera trap images.

3.6 Lemurs

Lemurs are among the world's most endangered mammal species. A team at George Washington University developed a modified version of human facial recognition software to identify individual lemurs which is 97% accurate. It aims at enhancing tracking and understanding of this endangered species. Previous efforts to track wild lemurs usually required researchers to trap and individually tag the animals, though in the case of larger mammals, including some primates, air guns have been used. All such methods have been shown to potentially cause pain or injury to the animals. An alternative method that depends on individual researchers getting to "know" and identify individual animals has been used successfully before in studies of elephants, great apes, and baboons, but suffers from intra- and inter-observer error. (See [81, 82].)

3.7 Lions

Unlike tigers or jaguars, whose stripes act like fingerprints, lions are very difficult to identify via their skin. But that is where face recognition comes in [83, 84]. The Kenya-based Lion Guardians has launched the Lion Identification Network of Collaborators (LINC) [64]. Its original database of some 1,000 lion profiles was built with facial-recognition software. The tool they use consists of a combination of computer vision and pattern recognition algorithms that use a combination of face and whisker identification. The goal is to help conservationists better understand where lions find mates, water and prey; and changes to population dynamics caused by human expansion. Previously, tracking efforts have used GPS transmitters which are expensive, run out of batteries every 1–3 years, and can be fitted only when an animal is sedated. (See [85, 86].) Face recognition is of considerable interest for mountain lions as well. Camera traps are placed along paths frequented by mountain lions and the sound of a mountain lion kitten is played when motion is detected, resulting in individuals raising their heads to make for good facial images [83, 84]. A challenge for lion facial identification, and indeed identification of any animals, is that certain characteristics of faces change over time. For example, whisker spot patterns remain unchanged over the lifetime of a lion, but manes (in males) and nose pigmentation change [87].

4 Social responsibility of animal identification algorithms: domesticated animals

While human facial recognition algorithms have promising applications, there are problems as discussed in Sect. 1, and these have given rise to a rapidly expanding literature on social responsibility of algorithms. There has been much less discussion of the potential dangers of using facial recognition and other biometric-based algorithms with animals, and we believe that there is an important need to extend the concepts of socially responsible algorithms to this domain. In this section and the following one, we speculate about possible problems arising from applying facial recognition algorithms to identification of animals.

Potential dangers of use of facial recognition algorithms for animals include physical injury to animals, emotional injury, disease spread arising from inaccurate identification, miscalculation of animal population sizes, economic loss to animal owners from dependence on animal identification algorithms, etc.

As we have observed, automated biometric identification such as from facial recognition algorithms avoids some of the issues with more invasive methods of animal identification, e.g., risks from applying tags or microchips. However, are there still some risks (both physical and emotional) to animals or their owners from automated biometric identification?

4.1 Physical injury to animals and economic injury to owners

Could there be physical injury to an animal from use of facial recognition technology? Errors can arise from poor lighting conditions, leaves or trees blocking an image, rapid movement of an animal blurring an image, etc. The impact of errors could be significantly worse if the facial recognition algorithms are combined with automated dispensing of medicines or changes in feeding patterns, which is one of the goals of precision livestock farming. What if a facial recognition system mis-identifies a cow or pig as sick and the cow or pig is sacrificed, because it is in a large farm and the farmer does not have the time to study each animal carefully? Of course this is the ultimate injury to the animal. (In today's huge factory farms for pigs, as many as a third of the animals die before ever reaching market, causing huge economic losses to farmers [37]. Apparently, owners of huge factory farms are willing to accept this outcome in exchange for the huge economies of scale involved in precision livestock farming using AI-based methods [88].) Alternatively, what if an algorithm fails to identify a sheep or cow or pig with an infectious disease and the disease spreads rapidly? This could cause injury to many animals. The same question applies to a salmon farm. If a sheep is identified as not being in pain when in fact it is, that could cause injury to the animal. If it is identified as being in pain when in fact it is not, this too could cause injury. These issues raise the question of whether to use facial recognition algorithms at all, and if so, when. The issues may call for development of cost–benefit analysis, if we just take the economics of farming into account, and we consider the potential economic gains and losses of using/mis-using facial recognition technology. However, the issues are much more subtle if the ethics of overall animal welfare are considered. In human medicine, detection of diseases, such as different kinds of cancers, is aided by AI-based algorithms, but these algorithms are serving to provide second opinions [89, 90]. However, in the case of animals, especially those on huge farms, some argue that the AI-based algorithms should be used to trigger automated dispensing of medicine or new diets, using dynamic mathematical models, and without human intervention [12]; the argument is that there are too many animals to use AI for second opinions, making the situation very different from human medicine. An alternative view is presented by Hartung et al. [91], who report interviewed farmers' views that the final decisions in precision livestock farming should be made by a human being, with the input from digital monitoring only there as useful guidance.

Presumably cameras used in face recognition could scare an animal, leading it to panic and perhaps hurt itself through a fall or other accident. As Rovero, et al. [92] point out, no cameras go completely unnoticed by animals, as the camera's flash is seen and the camera's ultrasound is heard. According to Clark and Dunn [93], research shows that noise can cause confined animals fear, and conceivably this could be the result of a camera clicking (animals hear many sounds that humans do not) See also [94]. If drones with cameras are used, as suggested in Sect. 2.1, they could also lead to panic. This is an issue for wild animals as well as for domesticated animals. A study of black bears showed that their heart rates rose as much as 123 beats per minute above baseline when drones were present [95]. Whether it is cameras utilized by people or cameras utilized by drones, we are not talking about a possible issue with facial recognition technology itself, but a possible issue with the way in which cameras are used in conjunction with the technology. There are many possibilities that need to be considered, and so that is why there needs to be an analysis of the tradeoff between potential benefits of early identification of diseased animals or animals in pain as opposed to potential costs/harm of applying algorithms to make such early identification.

The question of cost–benefit analysis arises in part, because one of the main reasons for use of facial recognition on today's large farms is its importance in the economics of farming. For the high attrition rate for animals in today's huge factory farms, methods for identifying disease, pain, or stress in animals can hopefully make a difference. However, things are not straightforward. Are mis-identifications more likely to happen with certain kinds of farms than others? Is there need for a backup disease-ID system to supplement automated systems for identifying sheep, cows, pigs, or salmon with an infectious disease? How can we measure the expected cost of disease spread vs. cost of a backup system? Further to economic consequences, what if an algorithm identifies a cow, pig or sheep that is not growing fast enough or eating enough? Could this cause the farmer to change to a more expensive diet—in error? Purchase medicine for the animal—in error? Select the animal for slaughter too early—in error?

Facial recognition is increasingly being used in identifying the owner of an animal, or for insurance purposes. What if a facial recognition system mis-identifies a cow as yours when it is mine and I am subject to a lawsuit as a result, leading to economic loss? What recourse do I have? Is this more likely to happen with certain kinds of farms than with others?

Economic and other losses to animal owners can also arise for owners of pets. If you lose your dog or cat, what are the chances that a facial recognition algorithm you have paid for will lead to the conclusion that your pet is not in a clinic when in fact it is? In this case, you have paid for protection for your pet and do not get it. More importantly, of course, you have lost your valued companion. The other side of the coin is: what if a facial recognition algorithm leads you incorrectly to one or more clinics, animal shelters, or other places?

4.2 Emotional injury

The case of emotional injury is complex but there is a great deal of relevant literature. (See, for example, [96].) The literature on farm animals suggests that animals have complex emotions. For example, "Basic emotional valence (positive/negative) studies indicate that sheep express their internal subjective states through multiple behavioral and physiological changes." Thus, "fearfulness has been tested and reliably measured in sheep for decades. Although there is wide individual variation in fear reactions in sheep based on personality, as a prey species, fear in sheep is typically expressed by behaviors such as highly focused visual and auditory vigilance, immobilization (a 'frozen' posture), fleeing/attempts to escape, and defecation" [97]. There is even evidence that chronic stress leads to long-term fearful reactions in sheep [97]. Similarly, cows show a wide range of complex emotions, including distress and fear, as measured by nasal temperature, eye white visibility, ear posture heart rate, and also defecation and vocalization [98]. Many studies demonstrate that chickens also experience a wide range of complex emotions, including fear, with accompanying physiological reactions, such as tachycardia and "body fever" [99]. In addition, as already mentioned in Sect. 2.3, levels of stress in animals such as pigs vary and are reflected in differing cortisol levels in saliva and blood. These can be correlated with environments that are relatively stress-free (e.g., with abundant "all you can eat buffets") and those that are relatively stressful (e.g., where there are multiple generations bunched together) [37, 38]. More generally, the issue of animal emotions, and in particular emotional injury, is part of the broad topic of "animal sentience." See, for example, Browning and Birch [100] and Marino and Merskin [97]. We can identify different kinds of animal emotions, such as fear, pain, distress—and have already discussed pain measurement in detail in Sect. 2.6—but most of the methods available for analyzing emotion are time-consuming, interrupt the processes of farming, and are somewhat subjective [101]. They involve observations of behavior involving vocalizations, body movements, facial expression, and body posture; monitoring of physiological parameters, such as heart rate, respiratory rate, and temperature; and study of biochemical signals such as levels of cortisol, lactate, and oxytocin in blood and saliva [101]. There is a growing interest in using such observations in an automated way, and not just for identifying animal problems but for improving animal welfare.

There is evidence that large factory farms can cause animals distress or be otherwise harmful to animals [88]. For instance, pregnant pigs kept in gestation crates that are not much bigger than their bodies show signs of depression. Confining pigs to crowded pens on concrete flooring can lead to abnormal biting behavior [37]. In large, crowded factory farms, facial recognition algorithms are touted as key ways to keep animals healthy. As noted earlier, in these farms, the workers cannot get to know individual animals, and so any methods that will help them identify when an animal is in distress could be helpful; facial recognition methods can help to recognize the difference between stressed and unstressed animals and thus contribute to early intervention in case of disease or pain [5, 36–38]. However, the argument that facial recognition algorithms make it easier to keep animals healthy might deflect from other issues involving factory farms, and in particular efforts to make them overall safer environments for animals. Here is a case where the technology is not necessarily causing a problem, but the argument that the technology is a solution is what could be contributing to the problem. There is an effort to measure "happiness" of animals—something that is even more complex and difficult for animals than it is for humans [37]. There are some who feel that large factory farms can never be a place, where animals are "happy." There are those who feel that factory farming is perhaps the most critical current issue in animal ethics. (Neethirajan [102] provides an interesting survey of issues in the ethics of "digital" animal farming.) This is an issue that requires the attention of an entire article or articles, rather than an occasional section or paragraph in a paper like this. Basically, the question is whether or not use of facial recognition and other AI-based technologies can ever overcome the many really serious concerns about the impact of factory farms on the welfare of animals raised there. This issue is complex and beyond the scope of this paper, but it does enter into the debate about whether the efforts at using facial recognition in factory farms to increase health of animals is enough to compensate for the overall damage to animal health of crowded environments and "unnatural" conditions.

Emotional contagion arises when emotional arousal (e.g., stress) in one animal arises from observing emotional arousal in another. Could increased emotional contagion result from extensive facial recognition use in the farmyard? Emotional contagion has been demonstrated in socially complex animals, such as dogs, wolves, and great apes, but also in farmyard animals, such as pigs [103]. For more information and other references, see Marino [104], and for a recent survey of the topic, see Perez-Manrique and Gomila [105]. The latter paper explores experimental and anecdotal evidence for emotional contagion among rodents, pigs, horses, dogs, elephants, domestic and wild birds, and even fish. It seems plausible that presence of restraints needed to capture suitable images, or just the presence of camera light or noise, and people taking pictures, could cause distress, fear, emotional contagion, or other reactions in animals. As noted in Sect. 4.1, Clark and Dunn [91] observe that research shows that noise can cause confined animals fear. Then, emotional contagion could lead to the spread of emotional arousal. While emotional contagion such as spread of fear among animals in a group can aid in allowing most individuals to escape from danger in natural settings [105], it can also lead to spread of fear and added stress even when initially only one individual becomes fearful; it only takes one animal to be stressed or fearful as a result of, say, a camera noise, for other animals to become stressed or fearful through emotional contagion. Indeed, in some experiments described by Perez-Manrique and Gomila, emotional contagion is studied by first stressing an individual. While emotional contagion resulting from, say, camera noise, is not specifically the result of a facial recognition algorithm, it could be described as the result of seeking data to be able to use such an algorithm.

5 Social responsibility of animal identification algorithms: wild animals

5.1 Physical and emotional injury to animals resulting from camera traps

As with the case of domestic animals, there could be physical or emotional injury to animals in the wild, e.g., from widespread use of motion-sensor cameras in the wild or entry into wildlife habitat where a sensitive species lives, to take photos. The use of camera traps is spurred through the improvement in facial recognition technology, but the use of camera traps can lead to modification in animal behavior. Human presence to set camera traps, or simply walking along trails in undisturbed habitat, can change the behavior and distribution of sensitive species [106]. As noted in Sect. 4.1, no cameras go completely unnoticed by animals, as the camera's flash is seen and the camera's ultrasound is heard. As Caravaggi, et al. [107] observe, camera traps emit light and sound, carry human scent; their flashes to illuminate wildlife could disrupt natural behavior and their sound might not be detectable by humans but can emit a reaction by animals. Gibeau and McTavish [108] have observed that camera traps sometimes lead to a "startle" response in gray wolves: they "will stop abruptly when they see a camera flash at night. Individuals will flee, and packs will rapidly disperse, resulting in displacement to the site and significant travel-route changes."

But is there the possibility of physical injury of some sort as a result? Jewell [23] observes that when monitoring techniques are invasive (as in tagging or even long physical human presence), they "can result in animal welfare problems, through the wide-ranging physiological effects of acute and chronic stress and through direct or indirect injuries or compromised movement." However, she does not count camera traps as invasive. As noted in the discussion of mountain lions in Sect. 3.7, sometimes camera traps add sound to attract the attention of animals when motion is detected, and if these are mountain lion kitten sounds, could the sounds be leading to animal stress? Could the fear-and-avoidance behavior observed in gray wolves by Gibeau and McTavish [108] lead to injury in fleeing individuals not even photographed? While many camera traps are placed randomly or at water holes or wildlife trails, some are placed at baited stations. Could the baited stations affect the health or the movements of animals in the wild? Just the presence of camera-traps has been shown to both attract and repel different species [109] and surely presence of bait could also have that effect. Gibeau and McTavish [108] speculate that it is possible that camera trap photos could affect the night vision of animals, thus affecting both predator and prey in a negative way. They also ask whether the use of camera traps near den sites could cause females to abandon or move litters, leading to increased mortality of the young. In addition, they point out that this may be the case with rare or sensitive species, such as snow leopards. Placing cameras near mineral licks or other feeding grounds could lead animals to avoid those places, thus affecting their acquisition of essential nutrients. In general, as Gibeau and McTavish observe, there is desire to place cameras parallel to direction of travel, as this gets the best head shot (and, therefore, the highest probability of correct face recognition of an individual), but this is most likely to startle the animal if there is a flash. The issues described here are not issues with the accuracy or effectiveness of facial recognition algorithms, but with how the algorithms are applied.

5.2 Biased and misleading conclusions about animal populations and ecosystems

Some of the problems arising from facial recognition of animals are related to how data feeding into the algorithms are obtained (e.g., through the very act of taking photos), while others are related to the quality of the data used by the algorithms (which may be of low quality because of problems arising from the technology of obtaining it or because of a faulty experimental design or the bias of citizen scientists, etc.) or by the ways in which the data obtained from algorithms are used to draw conclusions or make decisions. The quality of data obtained from camera traps in the wild varies. However, the issues are similar to those on farms: faces can be distorted by blood (e.g., when a big cat has just eaten); leaves and trees can partially block an image; the images can be blurry, because an animal was moving rapidly; or images can be dim because of lighting conditions. These can all lead to misleading identifications. Jewell [23] asks: "If the techniques used in monitoring interfere with the natural behavior of the individual or population, either in terms of physical harm or significant disturbance, how does this affect the quality of the data collected, and how in turn does it affect the conclusions drawn and decisions made?" The quality of data is a particular issue if crowdsourcing/citizen science is used, as discussed in Sect. 3.2. The quality of the data received from non-experts may be lower than that obtained from experts, and moreover, if those data are labeled by non-experts, there tend to be more errors. Since crowdsourcing systems employ various data types and sources, it is important to apply metrics and tools about data quality before further data processing. Errors in the data could lead to misleading understanding of trends in populations sizes and movements, assessment of biodiversity, and resulting faulty conservation strategies and policies.

Using camera traps to identify species or individuals from facial recognition can lead to misleading and biased conclusions. Many factors influence the ability of camera traps to detect animals. Larger animals are easier to detect, but faster animals might not be. Denseness of vegetation is of course another source of potential bias [110]. It is likely that the very presence of camera traps can lead to biased descriptions of behavior, since animals respond to cameras and human presence at camera trap sites [107, 108]. Specifically, you could miscount populations if camera traps scare off following animals, as in the case of gray wolves. Baited traps can attract certain kinds of species, such as carnivores, but repel prey species, thus again leading to misleading population counts [107]. If you miscount the population of leopards or lemurs in a given region because of human emphasis on certain areas or because of baited sites for camera traps or because of faulty algorithms, what are the implications? Is there an impact due to the use of population estimates to draw research conclusions or to make conservation policy [107, 108]? An impact on an endangered species? Is there damage from an inaccurate assessment of biodiversity? These same issues arise whether a population estimate results from the use of camera traps or some other method. Multiple surveys using different tools and technologies can aid in the development of more accurate estimates. As Jewell [23] points out, "Ethical monitoring of wildlife is not only a laudable aim, uniting ethicists and conservationists and the public and scientists, but also is fundamental in acquiring reliable data required for good science." She asks, is it possible to behave ethically when interfering with the lives of the animals being studied? This is a question that needs serious study and debate. It is related to a large body of literature on the ethics of wildlife photography (which is aimed more at the photographer than in applications of facial recognition). Some papers in this literature are Bodine [111], Groo [95], Mills [112].

Other issues arise from various applications that use potentially incorrect results from facial recognition algorithms, or with problems arising from the way in which data are used. If you are looking for elephant poachers and misidentify the elephant, could this cause a delay in reaching the elephant, leaving an opening for a poacher? Similarly, if you identify the elephant correctly but miss the poacher. If a whale gets tangled in a net and you mistakenly identify it as a very healthy whale that should be able to untangle itself, could the whale hurt itself? Are backup systems needed in cases like those for the elephants or the whales? How do we measure the negative impact of mistakes from an algorithm vs. the cost of such a backup system? Using multiple features can aid in animal identification in the wild. Geolocation through a mobile device can help identify the species in an image because of knowledge of species known to reside in a given region. However, posting geolocation data along with facial image data through social media could assist poachers in finding animals [113]. How do we design algorithms to minimize the probability of inadvertently hurting animals in this and other ways?

5.3 Welfare of an individual vs. welfare of a species

In discussing the impact on animals of many observational studies, Jewell [23] asks how to reconcile the welfare of an individual with the welfare of a species. This question is at the heart of the debate as to whether "compassionate conservation" that includes an emphasis on protecting individual animals [114] serves the goals of "conservation biology," including such goals as preserving biological diversity and preventing extinctions. These issues are not exactly the issues of potential dangers of applying facial recognition algorithms to wild animals, but they are clearly related. Wallach, et al. [114] argue that "With growing recognition of the widespread sentience and sapience of many nonhuman animals, standard conservation practices that categorically prioritize collectives without due consideration for the well-being of individuals are ethically untenable." They give the example of the moral dilemma of killing numerous individuals of an invasive species. As another example, some ecologists are developing AI systems using facial recognition that lead to capturing of "feral" animals or spraying them with poison. This is touted as a useful result of the use of facial recognition. However, as a result, even non-targeted animals could be injured through mis-identification [107, 115, 116]. Thus, as Griffin, et al. [117] argue, "compassionate conservation can seriously lead to more net harm to individuals than it aims to stop." The tradeoff between positive and negative impacts of use of facial recognition algorithms is an intriguing issue. As another side of this argument, Callen, et al. [118] argue that "Extinction is permanent, while the pain of a microchip or stress of translocation is only temporary." The issue here is whether adding facial recognition because microchips cause pain will help or hurt the species as a whole, as opposed to relieving stress of individual animals. The issues involving "compassionate conservation," which have a variety of connections with the costs and benefits of use of facial recognition algorithms for wildlife identification, deserve much more analysis than we have space for here. The issues involve many more factors and approaches to wildlife identification than just facial recognition, and future analysis needs to seek general principles applicable to numerous approaches.

6 Closing comments

We have speculated about potential problems from using facial recognition algorithms with animals, domesticated or wild. The issues we have raised suggest that in animal facial recognition, there are serious questions of social responsibility of algorithms. These issues relate to possible injuries (physical or emotional) to animals; to fair treatment of the people interacting with the animals as owners or in other roles; to economic implications; and to ecological policy making based on application of facial recognition algorithms.

This paper has touched upon a wide variety of issues and posed many questions. The goal was to raise issues involved with socially responsible use of facial recognition in particular and AI-based technology in general for both domestic and wild animals. A few of the areas that need more research are the following. Most of these would require substantial studies of their own, either experiments with observations in long longitudinal studies, the development of new cost–benefit tools in the field of animal welfare, interviews with farmers and users of precision livestock farming methods, and dialogues concerning the ethics of increasingly digitized farming and digitized health and welfare assessments of wild animals.

a. What is the likelihood that mis-identification of a sick domesticated animal will lead to a disease outbreak in a farm or a region? And what is the likelihood of missing a sick animal if available facial recognition is not used?

Perhaps analysis of real data about disease outbreaks in large factory farms could be helpful here as well as analysis of false negatives from other disease surveillance systems.

b. How serious is the risk of cameras in the farmyward or the wild scaring an animal into panic and injury? Could use of drones to take photos have a similar risk? What can be done to minimize such risks? As mentioned in Sect. 4.1, drones are known to increase heart rate of animals. Groo [95] mentions the beginning of uses of "microcopters" that may not disturb animals. Perhaps we need more research to develop cameras or drones that do not make sounds that animals can hear and humans cannot.

c. What are the costs and benefits, pros and cons, of using facial recognition algorithms combined with automated medicine or food dispensing algorithms in precision livestock farming? A key issue here is to analyze the importance of human–animal relationships, and the extent to which PLF makes a farmer less an observer of animals and more an observer of data [19]. Another issue is to develop guidance for how a farmer might use data obtained from PLF to make better decisions, and in particular guidance about when and how to be skeptical of the data.

d. How serious is the risk that emotional contagion resulting from use of cameras will lead to injuries of domesticated animals in large farms? The answer to this question requires both study of animals in farms and experiments with animals in controlled settings. A review of such experiments in Perez-Manrique and Gomila [105] was mentioned in Sect. 4.2. There is need, for example, to understand which emotions to study in different species, to understand why emotional response may differ depending on environmental and other conditions, and why the power of the emotional response may differ from individual to individual.

e. How accurate are facial recognition algorithm-based identifications of pain in domesticated animals? What about the possibility of identifying other emotions, including "happiness"? A major issue here is to study the relationship between pain, stress, and fear and "unhappiness." Going beyond just facial recognition systems, we might study in turn the relationship between pain, stress, and fear and the lack of access to "normal" feeding, exercising, and fresh air environments that animals in large factory farms face, and to study what changes farms could make to eliminate crowded conditions that prevent normal exercise or pecking and dust bathing behavior, lack of outdoor access and normal grazing behavior, or even the emphasis on feeding protocols that stress rapid growth (see, for example, [37, 88]). The European Union already disallows certain factory farm practices such as overcrowding that does not allow hens to turn around or spread their wings [88]. Perhaps similar restrictions could be developed for facial recognition algorithms and other uses of AI as well.

f. How much will the impact of improved medical care and better ability to monitor and modify animal diets, resulting from facial recognition in large factory farms, compensate for decreased animal health from overcrowding and unnatural environmental conditions in such farms? Today's factory farms accept a high attrition rate for animals, since it is outweighed by a massive "production" rate [88]. Could regulations limit allowable attrition rate? Such regulations would be useful for other AI tools used in farming, not just facial recognition. Precision livestock farming produces massive amounts of data about animal health, behavior, growth rates, etc., data that are not dependent on periodic human observation. Could these data be analyzed to understand the ways in which animal health might be improved either in large factory farms or the remaining small farmyards?

g. What are the potential impacts on wild animal behavior and health from use of camera traps? How can one modify the potential impacts from using camera traps on animal pathways? At mineral licks? From using bait? From adding sounds to make animals look up? As Caravaggi, et al. [107] observe, there is considerable variation in amount of noise from camera to camera. Research is needed to identify which cameras in the wild might minimize impact on animals, or even make noise that is not detectable by most animals. While there is little difference between wavelengths of infrared illumination between different cameras used in camera traps, the length of time that illumination is used if video rather than still images are sought could be minimized [107]. This is an area, where more research is needed.

h. How can we minimize mis-identifications of wild animals leading to errors in estimates of population sizes and biodiversity? Are there improvements in camera trap technologies and their locations that will achieve such a goal? One approach here is to vary the seasons one uses camera traps, as animal populations and movements vary from season to season [119]. Similarly, observing populations in a variety of habitats can compensate for bias in observations. Development of new statistical tools to compensate from bias in counts resulting from size, speed, environmental factors, and other factors would help.

i. To what extent is "ethical" monitoring of wildlife through facial recognition central to devising good conservation policy? Some basic ethical principles developed for wildlife photographers interested in taking photos of animals include "do no harm" to wildlife or their habitat, "leave no trace" of your presence, "keep it wild" (in particular do not feed the animals), etc. [95, 112]. Similar basic ethical principles should be developed for camera traps.

j. Can we minimize the potential danger to wild animals from poachers or from injuries through improved applications of face recognition? Using facial recognition to identify unknown persons coming into a wildlife reserve is one approach. Some of the improvements are likely to come from physical improvements in the way that images are obtained. Improving miniaturization is one way in which cameras can be hidden from poachers; longer battery life would also make the use of such cameras more effective [120]. Both are areas for more research.
k. A common approach to minimizing errors in decision making involves gathering a variety of data from different sources. This is certainly the case with use of tools of AI in the farmyard or the wild. What kinds of alternative tools would backup facial recognition systems to minimize errors from facial recognition of animals in the farmyard or in the wild, and what might those backed-up systems be? Surely increased use of monitoring vocalizations, using DNA analysis of feces, and other tools could be helpful,

We have concentrated here in giving a wide variety of examples and presenting a wide variety of issues, rather than going into depth on several of the major ones, some of which we have not had time to say much if anything about. Much more needs to be said or discovered about major issues, such as:

a. How can facial recognition minimize injury from factory farming? Is minimizing injury sufficient to overcome the many serious concerns about the ethics of factory farming?
b. What are the ethical issues involved in "compassionate conservation"; what is the tradeoff between welfare of a species and welfare of an individual, welfare of an ecosystem and welfare of its components?
c. What issues about quality of life of animals need to be added to cost–benefit analyses of introduction of AI-based methods, such as facial recognition?
d. What are the key environmental impacts (positive or negative) of the use of facial recognition or other AI methods related to animals, for example, the environmental impacts of precision farming?
e. How can we minimize the probability of biased or misleading conclusions about the health of ecosystems that result from the use of facial recognition algorithms to count animal populations and identify trends in biodiversity?

Research on social responsibility of algorithms is taking off. The topic is of great interest in academia, government, and industry. However, discussion of issues of social responsibility of algorithms related to animals, both domesticated and wild, is only in its most primitive state. Much more thought needs to be given to the issues we have raised.

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