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REVIEW

Review on methods used for wildlife species and individual identification

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Abstract

This work presented a literature review on animal species and individual identification tools, as well as animal monitoring capabilities. We gathered the literature to cover different aspects of technologies that are widely in use for animal identification, from the traditional up to the latest methods. This study includes species and individual animal identification attributes namely body patterns, footprints, facial features, and sound for identification purposes. The large volume of data collected could be automatically processed using machine learning and deep learning techniques to achieve both species and individual animal identification more efficiently as compared to the human workforce. It is a much faster and accurate approach considering the large volume of data, than manual processing, which is extremely expensive, time-consuming, tedious, and monotonous. We established that machine learning and advancements in deep learning hold significant promise to high-accuracy identification of both species and individual animal. Methods used for individual identification are mainly implemented in endangered species by the conservation management. The traditional methods such as the use of footprints, drawings of animal biometrics are integrated into the recent growth of technology to eliminate the human skill needed to achieve species and individual identification through the use of machine learning and deep learning algorithms for automatic identification purposes.

Keywords Animal monitoring · Deep learning · Individual identification · Machine learning · Machine vision · Species identification

Introduction

Animal species and individual identification are both critical for monitoring wildlife more efficiently (Goldsworthyand Matam 2021). It is primarily done for population counts, movement tracking, health and disease control, tourism, and anti-poaching (Banga et al. 2010). Species identification relies on the general characteristics such as animal body pattern, footprint, and sound. Individual identification is normally based on uniqueness an animal biometrics such as facial, visual patterns, footprint, nose prints (Bugge et al. 2011; Kühl and Burghardt 2013). It allows direct monitoring for detailed animal life history, future follow-up, and survivorship (Pollard et al. 2010). It is mostly implemented to endangered species for specific conservation and management practices (Gibbon et al. 2015; Vidya et al. 2014). Over the years, different technologies have been investigated to improve their capability to carry out automatic species and individual identification to yield more reliable results. It aids in activities that have to be repeated several times. Its application does not remove the requirement of a human involvement (Gaston and O'Neill 2004), and thus it complements their traditional methods of monitoring wildlife. The developments of automatic species and individual animal identification are based on statistical and computer vision machine learning techniques. These techniques offer tremendous opportunities by extracting features needed for automatic species and individual identification (Mmereki et al. 2021).

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Figure 1 shows an automatic aerial zebra (*Equus quaggas*) species identification with a custom computer vision algorithm from a drone footage with the capability to enhance wildlife monitoring techniques.

Accurate individual identification is important in conservation projects for critically endangered species. Some countries in South Asia with one-horned rhinoceros (*Rhinoceros unicornis*) have extreme individual identification monitoring programmes to ensure their survivability as well as to understand the relationship between rhinoceros (Subedi et al. 2013; Talukdar 2009). Other programmes such as assisted reproductive techniques are implemented to ensure optimum animal growth rate. Accurate individual identification is also used to prevent an imbalance of sexes which can create fights among males that can cause male species death (Dunham 2001). Around the 1900's most African countries relocated their black rhinoceros (*Diceros bicornis*) from the wild to sanctuaries to protect them from extinction (Patton et al. 2007) due to the increased poaching. In 2016, it was approximated that for every eight hours, one rhinoceros is killed in South Africa hence the need to implement better monitoring methods for them (Kamminga et al. 2018).

When populations are not monitored, we cannot track changes in abundance over time. In the case of overpopulation, animals are most likely to intrude into human territory leading to human–animal conflict. Due to its increased incidents, wildlife conservation authorities have great interest in improving monitoring methods (Cheteni 2014). An effective monitoring system of wildlife populations can assist in managing their numbers. In the case of extinction, wildlife conservation efforts are increasing. From DeMotts and Hoon (2012), the increase of elephant population by 133% within a period of two decades resulted in a conflict over water, fodder, and space with residents in the northern countryside of Botswana. Additionally, the human–animal conflict was found to exists when Asian elephants destroy crops in agricultural fields and sometimes kill people when they leave their sanctuaries in southern India (Münster and Münster 2012).

Invasive species management ensures monitoring and balance of species in the ecosystem. The study conducted by (Connally et al. 2021) recommended the wildlife authorities to establish management plans to monitor the wild pig population in Texas. Another study recommended Asian carps for human consumption to address their intrusion to fishermen as well as other fish species in Midwest and the southern USA (Varble and Secchi 2013).

This paper mainly focuses on the methods used to collect data for species and individual identification purposes. It also covers the method techniques based on the unique body shape, footprint characteristics, facial attributes, sound and pattern for both species and individual identification. Other noninvasive techniques such as the use of genetics sampling for species and individual identification from animal waste remains and hair are not covered in this review study.

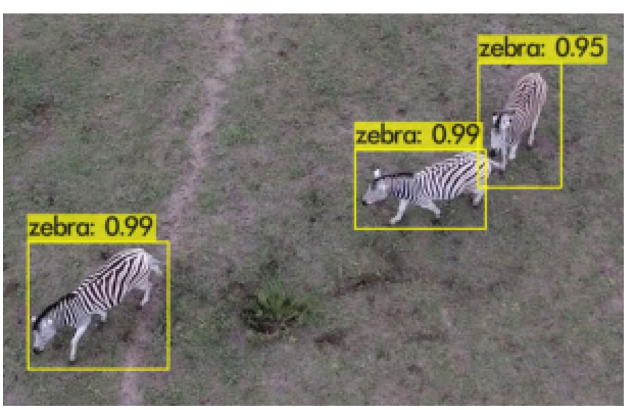


Fig. 1 Automatic aerial wildlife species identification from a drone footage

Methods used of gathering data for species and individual identification

Manual data gathering

The globally practiced method of manual data gathering is primarily dependent on the detailed drawings or memory knowledge of an individual on an animal distinguishing biometrics features such as the ear, face, footprints, and nose prints. Individual endangered species such as one-horned rhino in Nepal with distinguishing features are manual recorded in a sight booklet to enhance the monitoring techniques (AsRSG 2009). The memory knowledge is dominated by local experts who are most likely to be illiterate. Most of this personnel typically lack scientific knowledge, thus a challenge to attain proper detailed data gathering for an orthodox scientific basis (Elbroch et al. 2011). Questionnaires are normally conducted to acquire the information for species and individual identification for wildlife monitoring purposes. A method of identifying animals by their footprints has been one of the oldest method used by traditional expert trackers in Africa (Blake 2002). The ability to identify species based on their tracks, is usually an integral part of hunting (Hewes 1994; Stander et al. 1997). It had been used by the hunter-gatherers for over a hundred thousand years (Liebenberg et al. 1998). Hunting guides, ecologists, military, and search and rescue personnel still use it (Liebenberg et al. 2010). It is based primarily on visual inspection which involves the skills of an expert tracker (Bothma and Le Riche 1993), to look at the footprint, associate it with a particular species and get information about their direction of movement and number.

Hence, trackers aid researchers to collect data to study animal behavior (Liebenberg et al. 1998, 1999). Local people were used to assist on Armur tiger footprints data collection in China for the development footprint identification technology (FIT) (Gu et al. 2014).

The use of ear patterns for individual African elephant identification in South Africa had been established to be a reliable approach based on human memory as wells the manual matching drawings (Bedetti et al. 2020). Rhinoceros kept in national parks in Africa are ear-notched for individual identification purposes in Zimbabwe (Hall-Martin 1986; Matipano 2004). The use of eye and profile wrinkles is another feature tool that had been established to aid in individual identification of rhinoceros either alive or recently deceased. The acquisition of the eye wrinkles patterns data is through the manual approach during anesthetized for translocation, notching, or treatment in UK (Patton and Campbell 2011). Though this approach can accurately identify individual rhinoceros, it was recommended not to be used alone (Patton and Jones 2010). Figure 2 shows eye wrinkle patterns used for individual rhinoceros identification.

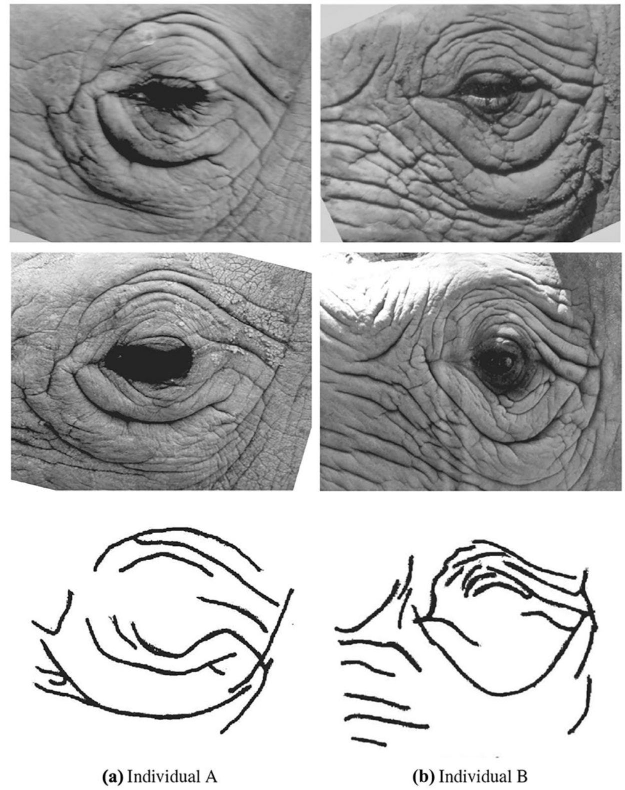


Fig. 2 Two black rhinoceros left eye wrinkles used for individual identification, top set of images shows left eye wrinkles with the eye nearly closed, middle set of images shows the eye open, and the last set of images are the drawings of the key wrinkles cited with permission from Patton and Jones (2010)

Data gathering by technology with human aid

Different techniques of acquiring data by technology for animal identification with human aid have been used over the years. Some of them include cameras to gather animal footprints and animal images, as well as acoustic recorder to gather animal sounds (Anderson and Hitchins 1971; Dos Santos et al. 2014; Shrader and Beauchamp 2001), to name a few. More advanced technologies are used to assist wildlife monitoring effectively through the use of artificial marks and proximity loggers.

Camera trapping is a method of automatically recording videos and images remotely, by activating a motion sensor without human assistance. Camera trapping for animals with unique markings can be used as a possible method to monitor their populations, as done for black rhinoceros (Stein et al. 2010). Other methods of automatically collecting information about wild animals are the use of satellites and manned or unmanned aircraft. Through these methods, a wealth of information through videos and images of animals are obtained. However, effectively analyzing and identifying animals within this wealth of data are demanding tasks.

The affordability of unmanned aircraft vehicles (UAVs) also commonly known as drones in the market had made them readily available for many applications such as agricultural fields, emergency and rescue, military, wildlife conservation, and different research areas, to name a few (Makgantai et al. 2021; Ramalepa and Jamisola 2021). The current increase of usage of UAVs is vital in further exploring its capabilities for animal monitoring. The use of UAVs is an effective means to monitor wildlife species (Linchant et al. 2015). A UAV was used to conduct a population census for large herbivorous, namely kiangs, Tibetan gazelles, blue sheep, domestic yaks, and domestic sheep and was established to be fast, economical, and reliable compared to the manual method (Guo et al. 2018). In Nepal, government patrolling officers concurrently used UAVs to effectively protect wild animals (Goodyer 2013).

Animals can also be identified by the sound they make. One method is by vocal sound, and another is by seismic vibrations. Vocal sound is a form of communication by animals within the same species and between species. The elephants were fitted with microphones and radio transmitters to allow for individual identification (Soltis et al. 2005). It was established that females did not produce rumbles at random.

The use of artificial marks includes the use of dyes and ear tags can be used to gather individual data in operations such as capture–recapture studies for species population count (Alonso et al. 2015). The use of proximity loggers such as global positioning system (GPS) collars and radio frequency identification (RFID) technology on animals is another method used to gather data about their location and that can be used to identify each individual for behavioral studies (Cagnacci et al. 2010; Ungar et al. 2005). The individual animal is known as the animal was captured when the logger was placed. Thus, this method can be considered as invasive. A study conducted by Grünewälder et al. (2012) affixed six cheetahs with GPS collars for a period of around one year, to monitor their feeding, mobile and stationary behaviors. Radio frequency transmitters were implanted into the horns of rhinoceros mainly for future individual animal identification (Koschan et al. 2006; Van Nguyen et al. 2018) An application of using a small fixed-wing UAV with radio frequency receiver on-board for individual identification was used to improve the traditional approach of "on foot" (Dos Santos et al. 2014; Van Nguyen et al. 2018; Webber et al. 2017).

Use of camera for data gathering for species and individual identification

On ground

Camera traps in the wild had been used as early as the 1950s in Australia (Meek et al. 2015). Researchers and natural resource managers primarily use them to assist in the acquisition of the ecological data (Meek et al. 2014). These ecological data are used for research studies such as animal behavior, population monitoring and fauna–flora interaction (Mohd-Azlan 2009). The millions of pictures and videos acquired can be a challenging task to efficiently identify the species. Hence the application of machine learning and computer vision had been employed to efficiently analyse the data collected (Carl et al. 2020; Tabak et al. 2019). As the camera motion sensors in the wild are vital tools to acquire images of animals, they can also 'capture' humans who might be poachers. The study conducted by Yousif et al. (2017), classified regions with human, animals, and background patches based on data collected from camera traps, while Willi et al. (2019) were interested in developing convolutional neural network (CNN) to differentiate different animal species, images of human, vehicle, and empty images. Attaining accurate and detailed information from the images is essential to study animal behavior also tackle automatic animal identification. Hence, the application of animal identification by computer tools can also be accompanied with human visual animal identification to assist the users to reach an identification agreement, and this approach was attempted Mendoza et al. (2011) on the bobcat identification.

Individual identification is a crucial step for animals subject to close monitoring programmes. The study conducted by Ferreira et al. (2020) yielded positive outcomes for the feasibility of automatic individual bird identification through the application of deep learning algorithms in laboratory and wild environmental fields through the use of a camera for data collection. Another study used the unique individual biometric natural marking in the chest of the African penguins with a high success rate that yielded false detection occurring at 1 in 10,000 comparisons (Sherley et al. 2010). It was established to be an ideal approach with minimum stress toward the animal.

Despite the significant developments of both species and individual identification from camera traps images, some challenges still exist from environmental conditions. Environmental conditions such as poor illumination, overexposure, occlusion, and rain to name a few, affect the resolution quality in the image for both species and individual capabilities. The distinguishing features or natural marks such as scars, unique spots, or stripe patterns for individual identification, and sometimes, they are not captured in the images and thus remain as a challenge to achieve individual identification (Dorning and Harris 2019). This makes the task to achieve individual identification to have several images taken at different positions and angles, with varying seasonal and environmental conditions to have a detailed profile of the unique characteristics. The study conducted by Johansson et al. (2020) concluded that unique individual identification based from camera trap images attained an overestimation in their population count. The application of a capture–recapture method for animal population estimate requires each animal to be individually recognized, and thus without the unique individual distinguishing feature from the camera trap images, the viability of population estimate by this method is unreliable (Stevenson et al. 2019).

Aerial view

Aerial view refers to the videos and images collected from an aerial camera where the data are collected and then analyzed offline. An increase in UAVs in the research field had opened doors to a complementary approach to animal identification from an aerial view. Computer vision is a method that is proposed to assist in improving precision and accuracy in the aerial surveying approach to wildlife management (Naude and Joubert 2019). Conducting animal population census is an essential aspect for animal monitoring for conservation management (Greene et al. 2017; Sirmacek et al. 2012). A case study of using aerial images to train a classifier that detects the presence of wildebeests for population census is shown in Valletta et al. (2017). The study identified four other classes namely grass, rocks, trees, and zebra. Its predictive performance evaluated on the testing data sets indicated an accuracy ranging from 80% to 100% based on random forest algorithm (RFA). Another study on wildebeest population census at Serengeti National Park used Fourier histogram oriented gradient (HOG) feature for classification that is confirmed to be more accurate than manual count

(Torney et al. 2016). It is a technique that uses the Fourier series for a continuous function to extract constant features even when the object of interest in an image rotates. Population estimates using aerial data for five large herbivores were established from animal density, that is confirmed to be better than ground estimates (Guo et al. 2018). Another study by Ezat et al. (2018) performed crocodile populations census from aerial view with high resolution cameras which, yielded 26% more accurate than ground survey. Wild birds are monitored using UAV aerial images for population estimation as well as habitat identification (Hong et al. 2019).

An approach to tackle an increase in illegal wildlife poaching led to the development of an object detection method to detect large animals from UAV images (Kellenberger et al. 2017), operating in near-real-time. Aerial approach to automatic species identification improved wildlife population census, and in some cases helped to fight poaching. Figure 3 shows automatic animal identification of giraffe and zebra indicated in red and blue boundary boxes, respectively.

The use of very high-resolution satellite imagery had been established to yield positive results for species identification such as whales, polar bears, grey seals, cetaceans, Macaroni penguin and African elephant (Borowicz et al. 2019; Cubaynes 2020; Duporge et al. 2020; Guirado et al. 2018, 2019; LaRue et al. 2017). This approach is cost-effective, less time-consuming logistically as compared to use an aircraft for wildlife researches (Cubaynes et al. 2019, Höschle et al. 2021). The study conducted by Borowicz et al.

Fig. 3 Aerial image containing giraffe and zebra cited with permission from Eikelboom et al. (2019)

(2019) highlighted the efficiency of using convolutional neural networks (CNN) to detect cetaceans from satellite tiled imagery with model accuracy of 100% and 94% for whales and water only, respectively. A combination of whale detection and counting through the application of deep learning algorithms increment the accuracy by 36% against the detection model alone (Guirado et al. 2019).

Some of the challenges associated with aerial species identification includes: animal camouflage with the surrounding environment, animal occlusion due to the vegetation cover in the wild, low detection accuracy due to the low species pixel quality at high altitude and presence of wildlife species that is active at night and rest during the day. High-resolution imagery was established to achieve positive aerial species identification through the use of convolutional neural networks in an open area with the capability to save human time (Delplanque et al. 2021).

Moving camera

Moving camera refers to the collection of images and videos from an aerial camera where the data are analyzed in real or near-real-time. The ability to detect and track a moving object of interest from a moving camera has been a challenging field for researchers (Burt et al. 1989). The use of UAVs in wildlife research field has led to an interest in investigating their capability for both species and individual identification. An approach to detect moving zebra and antelope was investigated by Fang et al. (2016). The optical flow method used proved to be an effective way for species identification and tracking. To protect wild animals from extinction, traditional approaches that had been used over the years needed improvement. Hence Olivares-Mendez et al. (2015) investigated the use of vision sensors on UAVs for detecting and tracking of animals and poachers.

Computer assistance techniques used for both automatic species and individual identification

There are three main categorical domains from computer-based techniques used to aid species and individual animal identification which are artificial intelligence (AI), machine learning (ML), and deep learning (DL). Definitions for the commonly used techniques for automatic species and individual identification are highlighted in Table 1. Some of the machine learning algorithms that are commonly applied for automatic species and individual identification are *k*NN, SVM, random forest, and decision tree, to name a few. DL consists of different types such as artificial neural network (ANN), convolutional neural network (CNN), and recurrent neural network (RNN), to name a few. CNN is mainly

Table 1 Definitions for the commonly used techniques for automatic species and individual identification

AI Domain	Technique or Algorithm	Definition
ML	Support Vector Machine (SVM)	Discriminative classifier with hyperplanes as margins (Chauhan and Singh 2018).
ML	Scale-Invariant Feature Transform (SIFT)	Feature detection algorithm (Hu et al. 2008)
ML	Ensemble of Exemplanar Support Vector Machine (EESVM)	Has much more defined discriminative classifier by incorporating inputs from the negative samples (Malisiewicz et al. 2012)
ML	Random Forest Algorithm	Classifier algorithm based on the decision tree model (Chen et al. 2016)
ML	Optical Flow	Apparent distribution of velocities (Shafie et al. 2009)
ML	*k*-nearest neighbor classifier (*k*NN)	A distance function that takes into account the difference or similarity between two instances (Xin et al. 2018)
DL	Convolutional Neural Network (CNN)	Main architecture successive layers (Huang et al. 2018)
DL	Recurrent Convolutional Network	ANNs with recurrent connections
DL	VGG-Face Convolutional Neural Network	Facial CNN models developed by Visual Geometry Group (VGG)
DL	Deep segmentation convolutional neural network	Identifying portions of an input image and classifies based on CNN
DL	You Only Look Once (YOLO)	One step approach that detects and classifies (Huang et al. 2018).

implemented for computer vision for species and individual identification. The name originates from convolutional layers. CNN comprises of three layers which are convolution, pooling and fully connected. The illustration of architecture is shown in Fig. 4. It is mainly inverted to process pixel information. Convolution layer extracts and learns feature elements of the input image (Gu et al. 2018). The pooling layer used to reduce the feature map resolution to reduce computation (Zhang et al. 2019). Fully connected layer high-level feature elements are attained that maps features to the classes (Zhang et al. 2019). Application of convolutional neural network includes image classification, object detection, object tracking, post-estimation, text detection and recognition, action recognition, scene labeling, speech and natural language processing. Wild-ID and interactive individual identification system (I3SPattern) are feature detection and matching algorithms that apply scale-invariant feature transform (SIFT) and speeded up robust features (SUFT) algorithms. They are both used for individual identification. APHIS and Amphldent are both pixel-based matching algorithm approach.

Identification attributes

Animal body patterns

The large volume of data collected from camera traps and remote sensing systems from UAVs usually apply computer vision techniques to aid animal species or individual identification based on its unique body shape and pattern (Loos et al.

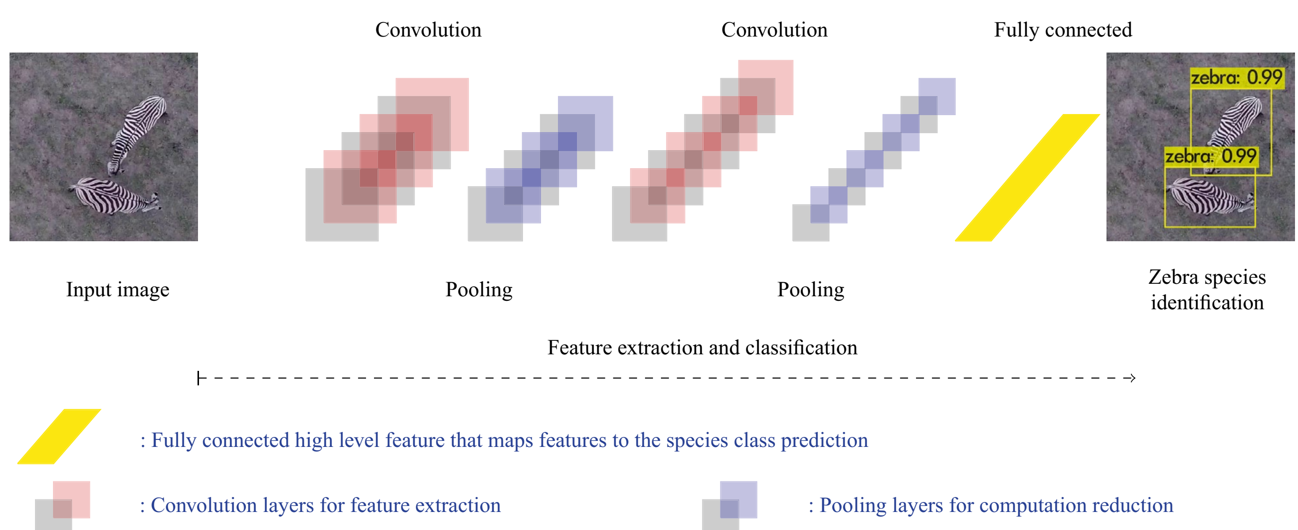


Fig. 4 The architecture of the original convolutional neural network

2018; Norouzzadeh et al. 2018; Stein et al. 2010). The ability to efficiently identify the species captured by these systems is necessary in animal research for near-real-time monitoring (Kellenberger et al. 2017; Rey et al. 2017; Villa et al. 2017; Yu et al. 2013). Studies conducted in (Kellenberger et al. 2017; Rey et al. 2017) performed automatic animal detection for near-real-time application to aid conservation effort in the war against poaching.

Species identification

Deep neural networks (DNNs) were applied by Norouzzadeh et al. (2018) to automatically extract information for animal identification thereby saving a tremendous amount of time by 99.3% compared to manual labor. Another study by Zeppelzauer (2013) used color model with different backgrounds and lighting conditions to automatically detect and track elephants in wildlife videos. It enabled biologists to effectively conduct behavioral and ecological studies. Object recognition and ensemble of exemplar support vector machine (EESVM) models were used to detect large mammals in semi-arid savanna for wildlife management conservation (Rey et al. 2017). A study by Kellenberger et al. (2017) conducted animal recognition based on pre-trained AlexNet from CNN architecture which was optimized for fast detection based on large animals. An investigation by Yu et al. (2013) used linear support vector machine algorithm to identify wild mammals on sequences of photographs. The technique was used for animal recognition in real, complex scenarios. Deep semantic segmentation CNN was used to recognize and detect kangaroos in a dynamic environment to minimize the number of kangaroo-vehicle collisions (Saleh et al. 2016).

Individual identification

The study conducted by Lahiri et al. (2011) extract simple image features and compare them based on animal coat markings, e.g., stripecoats, and dynamic programming algorithms for individual identification of zebra. A study by Dixon (2003) attained 95% for correct individual badger *Meles meles* based on their tail patterns. Its implementation provided tolerance to scale, exposure, occlusion, and mild perspective skews. It was established by Stein et al. (2010) that both black and white rhinoceros have unique horn sizes, shapes, and scarring, and hence, it was applied to monitor their population. When a rhinoceros possess a unique ear or notch pattern, possibly obtained from being torn by bushes or fighting with predators, it can be used as an individual identification attribute (Patton 2017). This approach was determined to have limitations as no correct identification was obtained at 30 m in the bush and 65 m in the open area without the use of binoculars (Hussek et al. 2020). Figure 5 shows a female rhinoceros born July 2011 where ear tufts were used to assist for individual identification. The first photograph was from October 2012 to July 2016. Inception V3-based biometric long term recurrent convolutional network was used for individual Holstein Friesian cattle identification based on unique coat pattern (Andrew et al. 2019). An error-free identification was achieved for an online experiment which opens future application in uniquely patterned species in the wild such as zebras and giraffes. The study conducted by Suriyamongkol and Mali (2018) addressed the use of four computer-assisted softwares (wild-ID, APHIS (ITM), APHIS (SPM), and I3S Pattern) for the individual recognition of Rio Grande Cooter. It was established that wild-ID performed better with an accuracy of 83.87% and can be implemented for population count. Hotspotter and wild-ID were investigated for the individual identification of jaguar and ocelots (Nipko et al. 2020). Hotspotter attained an accuracy of 71% to 82% whereas wild-ID 58% to 73% hence these computer-assisted softwares are ideal for wildlife management. Despite these great efforts both the software platforms were applied for individual identification of Wyoming toad but failed to match by 48% and 64% for wild-ID and hotspotter respectively (Morrison et al. 2016).

Footprint identification technology

Footprint identification technology (FIT) was initially developed by WildTrack to improve wildlife monitoring techniques, currently been used several continents in Africa, Asia, and America (Suwal 2015). FIT is a complementary tool that was originally developed to aid in monitoring

Fig. 5 Ear tufts used as an identification feature cited with permission from Patton (2017)

endangered animal species such as Amur tiger, Bengal tiger, polar bear, cougar, Baird's tapir, and lowland tapir (Jewell and Alibhai 2013; Jewell et al. 2016; Raj et al. 2015). It is a radical improvement from the ancient traditional animal identification and tracking techniques to a modern technology that is non-invasive, fast, consistent, and without the need for tracking skills training. Figure 6 shows landmark points and derived measurements that FIT generates automatically. It applies statistical models and needs points with clear outlines.

Species identification

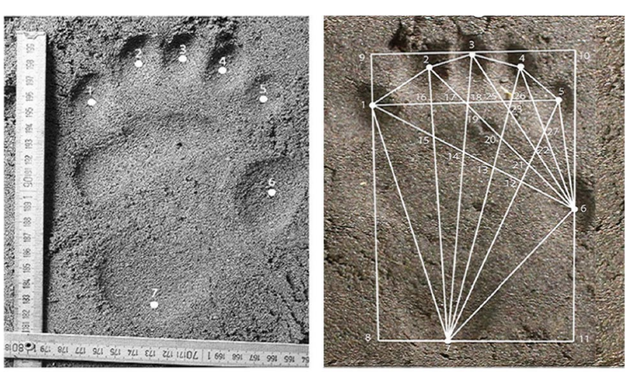
FIT was implemented for species identification between white rhino and black rhino. It was established that FIT was highly accurate for discriminating white rhino from black rhino (Alibhai et al. 2008). Other studies applied FIT for population monitoring of animal species, (Alibhai et al. 2017, 2008; Alli and Viriri 2013; Jewell et al. 2001; Sharma et al. 2005).

Individual identification

The study conducted by Li et al. (2018), successfully identified individual pandas according to sex, as well as classified them according to age. Another study by Laity (2015) implemented individual identification of free-roaming cheetahs based on FIT. It was established that lower quality footprints had lower accuracy as more individuals were predicted.

Facial recognition

Facial recognition is a noninvasive imaging system of recognizing the face of a subject of interest, through technology. Some of its application include animal disease control,



(a) Manual seven landmarks **(b)** Derived measurements

Fig. 6 FIT generates automatic identification cited with permission from Li et al. (2018)

behavior, population, and growth monitoring (Brust et al. 2017; Corkery et al. 2007; Freytag et al. 2016; Hansen et al. 2018; Loos and Ernst 2013; Matkowski et al. 2019). It is highly used on threatened animal species.

Individual identification

Automatic individual facial identification to wild animals is encouraged as it does not rely on analysis by expects which is a tedious, intensive, and term consuming process (Shukla et al. 2019). Log-Euclidean CNN was applied to facial texture information of chimpanzees by predicting attributes such as identity, age, age group, and gender (Freytag et al. 2016). Another study by Crouse et al. (2017) was capable of attaining an accuracy of 98.7% ± 1.81% by the application of computer-assisted facial recognition system of lemurs which could aid in the future for long-term monitoring of known individuals. A deep learning approach was used for automatic individual identification from videos and still images with correct identification accuracy of 94.1% with speed of 50 images per second (Guo et al. 2020). As primate species are endangered, an application of a face recognition using CNN architecture was implemented for individual recognition of lemurs, golden monkeys, and chimpanzees. A study by Schofield et al. (2019) applied CNN for chimpanzee face identification and sex recognition mainly for behavior studies. A similar approach was implemented for individual identification of giant pandas with an accuracy of 95% (Hou et al. 2020). It was established that the application of DNN for facial recognition of pandas is an economical approach of monitoring them as compared to the traditional approach (Chen et al. 2020). A study by Brust et al. (2017) achieved an accuracy of 90.8% for individual facial identification of gorillas which was established to be a complementary tool for human manual identification. Haar-like features and AdaBoost classifiers were utilized for lion face detection and Kanade–Lucas–Tomasi tracker was implemented for tracking behavioral patterns (Burghardt and Ćalić 2006).

Sound

Animals can communicate by sound that can be used to assist in identifying and monitoring them (Cakir et al. 2017; Clemins et al. 2005; Ovaskainen et al. 2018; Pabico et al. 2015; Yen and Fu 2001). Automatic identification of animal species from their sound is an important aspect for animal monitoring, research and behavior studying (Frommolt et al. 2008; Lopes et al. 2011; Stowell et al. 2017, 2019).

Species identification

Animal sound identifier (ASI) provided an essential tool for classifying species from field recordings as shown in Fig. 7 (Ovaskainen et al. 2018). It was applied to classify 14 species of Amazonian birds based on their vocalizations. The ability of acoustic monitoring and simultaneous video recordings aided in behavior monitoring for elephants (Payne et al. 2003). As wolves are established to be difficult to be monitored, their capabilities to communicate acoustically to attain clear identification up to a distance of 3 km (Suter et al. 2017). Hidden Markov models (HMMs) were implemented for species identification (birds, frogs, insects, and mammals) based on the sound they produce. The highest and lowest accuracy attained was 99% and 79% respectively highlighting a positive element for ecological monitoring (Aide et al. 2013). Another study by Rai et al. (2016) used feature extraction and SVM classification for automatic identification of four bird species with a maximum accuracy of 89.4%. A comparison between humans and artificial neural networks (ANNs) was implemented for birds automatic species identification, it was established that ANNs performed better about 75% to humans (Jennings et al. 2008). The ability of an African elephant to communicate by sound within the same bond group members was determined to a distance about 2.5 km (McComb et al. 2003; Soltis 2010; Soltis et al. 2005). This skill is also used as an early warning and monitoring system within the elephant family without seeing the potential threat (Mortimer et al. 2018; O'Connell-Rodwell 2007; Zeppelzauer and Stoeger 2015).

Fig. 7 Autonomous audio recorders in 224 sites cited with permission from Ovaskainen et al. (2018)

Use of thermal imaging

Species identification

Thermal images taken by UAVs for species identification improved wildlife management (Oishi et al. 2018; Seymour et al. 2017). A study by Christiansen et al. (2014) used thermal images and discriminated animals from non animals through automatic detection and recognition using *k*-nearest-neighbor (*k*-NN) classifier. In a combination of UAV, thermal imagery, and automated detection was used to carry out population census for two grey seal breeding colonies . To reduce manpower hours required to survey wild animals from a large piece of land, (Oishi et al. 2018) automatically identified animals from thermal remote sensing images using moving wild animals algorithm. Thermal camera attached to UAV detected wildlife from heat signatures to obtain animal GPS location (Ward et al. 2016). HOG and SVM were applied for near-real-time deer identification to warn drivers against deer-vehicle collisions (Zhou and Wang 2011; Zhou et al. 2012). As poaching is likely to occur at dawn, thermal camera-enhanced RGB images helped anti-poaching operations to detect animals and poachers near-real-time (Bondi et al. 2018; Karlsson Schmidt 2015; Mulero-Pázmány et al. 2014). A workload reduction of 97% was obtained in Marais (2018) by using infrared images for automatic elephant detection.

Real-time implementation of automatic species and individual identification

The ability for real-time automatic species and individual identification is highly ideal for wildlife protection from poaching (Bondi et al. 2018; Karlsson Schmidt 2015; Wich 2015) as well as animal-vehicle collision (Huijser and McGowen 2003; Schwartz et al. 2020; Zahrani et al. 2011; Zhou and Wang 2011). The capabilities of animal detection and animal warning systems were reviewed by Huijser and McGowen (2003) and the authors concluded that all in all the reviewed systems were found to be effective mitigation tools in animal-vehicle collisions. A combination of YOLO for object detection and joint probabilistic data association (JPDA) for tracking was applied on aerial videos, where the JPDA tracking algorithm affected the YOLO detection capabilities (Xu et al. 2018). Detection of large animals at 72 images per second using CNN was obtained by Kellenberger et al. (2017) allowing near-real-time application. Another study automatically detected poachers and animals in thermal infrared aerial videos in near-real-time (Bondi et al. 2018). It provided aid for new anti-poaching strategies using UAVs. Figure 8 shows a screenshot of automatic detection of poachers in an infrared image.

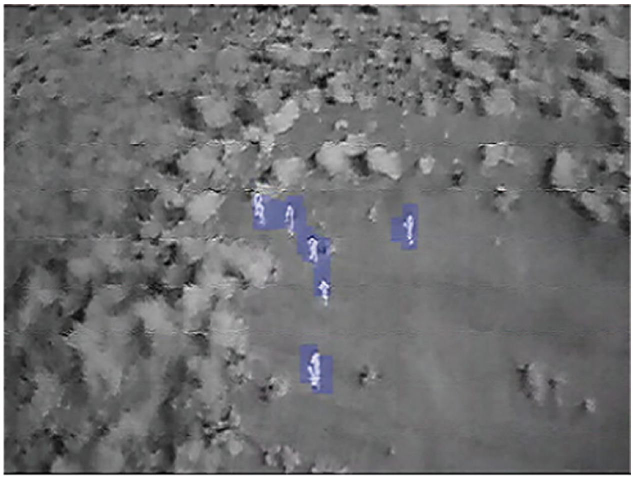


Fig. 8 Screenshot for near-real-time application cited with permission from Bondi et al. (2018)

Discussion

Different techniques for automatic species and individual identification have been employed over the years, for various reasons such as wildlife research and monitoring. Specifically animal protection, population monitoring, behavior monitoring, and movement tracking to name a few. Table 3 provides an overview of the species and individual identification with different algorithms used by the reviewed studies. The advantages and disadvantages of using different body features for species and individual animal identifications are highlighted in Table 2.

Species identification accommodates animal identification based on general characteristics such as body pattern, footprint, and sound, whereas individual is narrowed to the uniqueness of an animal body pattern, footprint, and facial attributes.

Species identification

From the reviewed studies, the highest accuracy attained was 99.3% using the DNN algorithm in species identification considering animal body patterns. There could be several reasons why the DNN algorithm performs the highest. One possible reason could be the training architecture that goes into iterations of feature extraction and classification. This is one of the strong characteristics of algorithms based on deep learning, where the majority of the algorithms are used for automatic animal identification. Most of the algorithms used in this review study based on deep learning have an accuracy higher than 80%. The other reason for deep learning to perform better is the amount of data that is fed into the algorithm, that is, the bigger the data size, the better the performance. Where in the case of automatic animal identification, a huge amount of data is fed into the algorithm.

One possible reason why the body patterns feature has the highest accuracy is how data are collected, in this case, the image data. For one, camera technology has become very advanced to capture images at a very high resolution and thus is less susceptible to image noise. In the case of sound, it is highly susceptible to environmental noise, and for footprints, it is susceptible to environmental forces like wind that could distort footprint characteristics. This is supported by Priyadarshani et al. (2018) stating the capability of attaining high accuracy is hampered by the unavoidable environmental noise overlapping with the recordings.

Species identification has higher accuracy than individual because of the bigger discrepancy of features among different species compared to the difference in features among individual animals. The other possible reason could be that there is a higher demand in collectively identifying species to study their population, migration, etc., compared to studying individual animal.

Table 2 Advantages and disadvantages of using computer-based species and individual animal identification

Body feature	Application	Advantages	Disadvantages
Body pattern	Species and individual	Non-invasive approach	Needs quality images
		Saves time as compared to human identification	High computational power required for analysis
Footprints	Endangered: species and individual	Non-invasive approach	Needs quality footprints
		No tracking skilled personnel required	
		Cost effective with respect to digital camera needed	
Facial attributes	Mainly individual	Non-invasive approach	Needs quality images
		No skilled personnel required	High computational power required for analysis
Sound	Mainly species	Non-invasive approach	Needs quality sound
		No skilled personnel required	High computational power required for analysis

Table 3 Techniques Used for Species and Individual Identification

Body Feature	Species/Individual	Technique	Accuracy	Study
Body patterns	Wildlife species	CNN	Specific species: 88.7% to 92.7%	Willi et al. (2019)
Body patterns	Wildlife species	DCNN	Average: 94.5%	Yousif et al. (2017)
Body patterns	Wildlife species	CNN	**Images from–**	Tabak et al. (2019)
			USA: 98%	
			Canada: 82%	
			Tanzania: 94%	
Body patterns	Wildlife species	Linear SVM	Average: 82%	Yu et al. (2013)
Body patterns	Wildlife species	DNN	Deep learning: 99.3%	Norouzzadeh et al. (2018)
			Human count: 96.6%	
Body patterns	Wildlife species	DCNN	Detecting animal: 96.6%	Nguyen et al. (2017)
			Three (3) common species: 90.4%	
Body patterns	Wildlife species	DCNN	**Balanced dataset–**	Villa et al. (2017)
			Top 1: 88.9%	
			Top 5: 98.1%	
Body patterns	Kangaroo species	Deep semantic segmentation CNN	Overall: 93.0%	Saleh et al. (2016)
Body patterns	Deer species	SVM and HOG	95%	Zhou et al. (2012)
Body patterns	Deer species	SVM and HOG	Overall: 85%	Zhou and Wang (2011)
Body patterns	Wildlife species	Mean shift segmentation	True detection: 90%	Sirmacek et al. (2012)
			False alarm: 38.52%	
Body patterns	Wild birds	RCNN, RFCN, YOLO v2, SSD and RetinaNet	Range: 85.01% to 95.44%	Hong et al. (2019)
Body patterns	Wildlife species (Elephant, giraffe and zebra)	CNN	Elephant: 95%	Eikelboom et al. (2019)
			Giraffe: 91%	
			Zebra: 90%	
Body patterns	Wildlife species	Faster R-CNN YOLO v2.0	Faster R-CNN: 93.0%	Schneider et al. (2018)
			YOLO v2.0: 76.7%	
Body patterns	Elephant species	CNN	98%	Marais (2018)
Body patterns	Wildlife species	CNN	72 images per second	Kellenberger et al. (2017)
Body patterns	Individual rio grande cooter	I3S Pattern, wild.ID and APHIS	I3S Pattern: 61.29%	Suriyamongkol and Mali (2018)
			wild.ID: 83.87%	
			APHIS: 68.55%	
Body patterns	Individual jaguars and ocelots	HotSpotter and wild.ID	HotSpotter: 71 - 82%	Nipko et al. (2020)
			wild.ID: 58 - 73%	
Body patterns	Individual wyoming toad	HotSpotter and wild.ID	HotSpotter: 64%	Morrison et al. (2016)
			wild.ID: 47%	
Footprints	Endangered species	DA	> 90%	Jewell and Alibhai (2013)
Footprints	Individual cheetah	PDA and WCA	> 90%	Jewell et al. (2016)
Footprints	Wildlife species	CERT and CPCT	Population: 91% and 95%	Raj et al. (2015)
	Individual rhinoceros		Monitoring: 97% and 99%	
Footprints	Tiger species	Feature extraction	94.3%	Raj et al. (2015)
Footprints	Individual rhinoceros	CPT and DA	Population: > 94%	Jewell et al. (2001)
			Monitoring : > 87% - 88%	
Footprints	Individual tiger	DFA	-	Sharma et al. (2005)
Footprints	Wildlife species	DA and WCA	Individual: > 90%	Alibhai et al. (2017)
	Individual puma		Sex: > 99%	
Footprints	Individual pandas	DA and WCA	Individual: > 90%	Li et al. (2018)

Table 3 (continued)

Body Feature	Species/Individual	Technique	Accuracy	Study
Facial	Chimpanzee species	Log-Euclidean CNN	Recognition Rate: 92%	Freytag et al. (2016)
			Gender estimation: 98%	
Facial	Individual lemurs	Feature extraction	98.7% ± 1.81%	Crouse et al. (2017)
Facial	Individual primates	Deep learning	94.1%	Guo et al. (2020)
Facial	Individual chimpanzee	CNN	Individual: > 92.5%	Schofield et al. (2019)
			Sex: > 96.2%	
Facial	Individual giant panda	Deep learning	95%	Hou et al. (2020)
Facial	Individual gorillas	DCNN	90.8%	Brust et al. (2017)
Sound	Bird species	CRNN	88.5%	Cakir et al. (2017)
Sound	Bird species	Feature extraction and SVM	89.4%	Rai et al. (2016)
Sound	Elephant species	HMM	Classification: 94.3%	Clemins et al. (2005)
			Identification : 82.5%	
Sound	Wildlife species (Birds, insects and amphibians)	GMMs and HMMs	91.25%	Potamitis (2014)
Sound	Wildlife species (Birds, dogs and frogs)	ANN	Birds: 71.43%	Pabico et al. (2015)
			Dogs: 94.44%	
			Frogs: 90.91%	
Sound	Bat species	ANN	62%	Jennings et al. (2008)

ANN Artificial Neural Network, *CERT* Canonical Ellipse Reduction, *CNN* Convolutional Neural Network, *CPCT* Canonical Pairwise Comparison Techniques, *CPT* Centroid Plot Technique, *CRNN* Convolutional Recurrent Neural Network, *DA* Discriminant Analysis, *DCNN* Deep Convolutional Neural Network, *DFA* Discriminant Function Analysis, *DNN* Deep Neural Network, *GMM* Gaussian Mixture Models, *HMMs* Hidden Markov Models, *HOG* Histogram of Oriented Gradients, *I3S* Interactive Individual Identification System, *SSD* Single Shot Detector, *SVM* Support Vector Machine, *RCNN* Region Convolutional Neural Network, *YOLO v2.0* You Only Look Once version 2, *RFCN* Region-based Fully Convolutional Network, *PCA* Principal Component Analysis, *PDA* Pairwise Discriminant Analysis, *WCA* Ward's Clustering Analysis

The future direction in species identification could be to improve identification on other forms of data, e.g, footprints, sound, etc. that can help confirm identification process by data fusion from different inputs. Most likely the algorithm that can be recommended will be based on deep learning. Considering the huge amount of data in this kind of study.

Individual animal identification

From reviewed studies, individual automatic animal identification was implemented in endangered wildlife animals only. Hence the application on non-endangered wildlife animals make individual animal identification to be not yet fully exploited. The reason could be that there is a huge demand for health and population monitoring of endangered wildlife species. The commonly used features for individual identification includes spot pattern, stripe pattern, facial fur pattern and coat pattern, to name a few. Individual identification is prone to be easily attained at close proximity towards the animal by attaining the rich distinguishing detailed characteristics from one another. It is a great challenge to identify a possible individual animal from a large herd as it is time-consuming. The use of fin photographs for individual identification for white sharks was deemed good though its application can be used for a short period time nearly 5 years (Gubili et al. 2009). Manually tracking them can be manpower demanding and time-consuming considering the vast area that they freely roam. The highest accuracy attained was 99% by the CPCT with the application of statistical algorithms on footprint identification of wild animals of endangered wildlife. We note that the data gathering method that is used here is by camera. Compared to the species identification that achieved the highest accuracy, the data gathering was also by camera. Thus it may be safe to say that the higher accuracy of the machine learning results is highly influenced by the method of data gathering. It is also worth noting that, FIT is highly susceptible to environmental disturbances like wind as well as other animals' movements. But despite these disturbances, FIT was still able to achieve 99%. The algorithm used is CPCT that is not based on neural network. Despite the fact that neural network-based methods, specifically deep learning, showed very high accuracy results in using very large datasets, CPCT, in this case, also showed very high accuracy. The two algorithms, e.g., CPCT and deep learning, have different computational approaches but having superior results in individual and species identification.

In the future, individual identification can be implemented for all wildlife animals, not just for endangered species, in order to track and monitor them, given that all of them are freely roaming. There could be a need to study footprints identification using deep neural network and compare results against CPCT.

Body patterns

The reviewed studies implemented animal body patterns in various species, which yielded high accuracies compared to individual automatic identification. Body patterns use cameras to gather data. However, the accuracy of results in species identification using body patterns is much more accurate than individual identification. The highest accuracy for species identification is 99.3% while for individual is 83.87%. The difference in accuracy can be attributed to the fact that body patterns between the species are much more distinct than body patterns within the same species.

In the future, body patterns can be more accurately used for individual animal identification in the same way as a person's fingerprint. However, this could be a challenge because it may be necessary to take the 3D image of the whole animal body patterns and transform them into a 2D image to make the analysis. This data gathering method can be tedious such that the current individual animal identification results can be significantly improved.

Footprints

The use of physical footprint characteristics for both endangered species and individual animal identification is a promising application with a minimum accuracy of 87%. Factors such as soil moisture, weather condition, animal gait, and soil type contribute to the footprint's quality for identification purposes. Again, the reason for high accuracy can be the fact that data gathering in footprint identification uses a camera, where such a technology has significantly advanced in the past several decades.

In the future deep neural networks can be implemented for footprint identification which can be compared to the current machine-based algorithms. This can be a good approach considering the fact that footprints are highly susceptible to environmental disturbances such as wind and rain as well from other animals. Deep neural networks are known to be able to handle distortion in the data such as these disturbances to the footprint image.

Facial

Using facial attributes from the reviewed studies is highly applied to individual endangered animals with complex social life dynamics. Applying the advancement of deep learning algorithms to these images aids the critical capabilities of monitoring and understanding the demographic and evolution of individual animals in their natural environments with high accuracies greater than 90%. The uses of camera aids in achieving these high accuracies.

In the future, facial identification can be fully utilized to individual wildlife animals and not just to the endangered ones. But the difficulty can be on data gathering because it is very tedious to track individual wildlife animal that is freely roaming. Camera traps for sure will not be enough. A flying drone may be used to gather data, but it has a minimum height limitation not to disturb the wildlife from its noise. Taking a high-resolution image from a long distance can be difficult.

Sound

Sound identification is limited to animals that produce sound, mainly bird species. Both deep and machine learning techniques are implemented to extract acoustic features for automatic identification. The highest accuracy attained was 94.44% using ANN. It is most likely that ANN is a more appropriate tool in processing and classifying sound features. The challenge of the presence of noise in the wild can be a challenge in attaining high automatic species identification.

In the future, data collection can be improved by better sensors and data processing that can significantly reduce the unwanted noise from the data. Current approaches can still be used but results can be significantly improved if the unwanted noise can be considerably removed.

Conclusion

In this review, manual animal identification had been established to be time-consuming, monotonous, tedious, and require human skills acquired through experience. Thus the development of automatic identification based on machine learning and deep learning techniques are beneficial for analysing large amount of data for faster and more efficient processing. The capabilities of automatic species and individual identification with very high accuracy as highlighted in Table 3 requires more than one computational method. Despite automatic identification capabilities, quality images, footprints, and sound quality are essential. Real-time animal identification is highly valuable to combat operations like poaching to save wildlife species.

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Declarations

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