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Application of AI in wildlife monitoring & Conservation - A comprehensive review

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Abstract

Artificial Intelligence (AI) has emerged as a transformative tool in the field of wildlife monitoring and conservation, revolutionizing the way we understand, protect, and manage biodiversity. AI technologies, such as machine learning algorithms and computer vision, are being increasingly utilized to monitor wildlife populations. These systems can analyze vast amounts of data from camera traps, acoustic recordings, and satellite imagery with remarkable accuracy and speed. By automating the identification and classification of species, AI helps researchers track population trends, detect illegal activities like poaching, and assess the health of ecosystems in real-time. Moreover, AI-driven predictive models play a crucial role in habitat monitoring and conservation planning. By analyzing environmental data and species behaviour patterns, AI can predict habitat changes, identify conservation hotspots, and optimize resource allocation for conservation efforts. This proactive approach enables conservationists to prioritize interventions effectively and mitigate threats before they escalate. In addition to monitoring and management, AI is advancing our understanding of complex ecological processes. By integrating data from diverse sources and generating insights at scales previously unimaginable, AI facilitates interdisciplinary research and fosters collaboration among scientists, conservationists, and policymakers worldwide. In conclusion, AI may not be a panacea for all conservation challenges, still its integration into wildlife monitoring and conservation practices represents a paradigm shift in how we approach conservation science. By leveraging AI's capabilities, we can make informed decisions, implement targeted interventions, and secure a sustainable future for biodiversity on our planet. In this paper we would like to present various types of traditional methods of wildlife monitoring and conservation, their limitations and the application of AI in resolving these challenges.

Keywords: Artificial Intelligence, wildlife monitoring and conservation, camera traps, acoustic recordings, satellite imagery & sustainable future.

Introduction

Wildlife monitoring

Monitoring wildlife is an essential component of conservation. Wildlife monitoring involves keeping track of the natural environment and its various elements through systematic observation and data collection over an extended period. This ongoing process helps identify trends by focusing on specific species, their populations, ecosystems, and the influence of human activities, as well as understanding the interactions and impacts among these factors.

Why Wildlife monitoring?

Assessing and monitoring wildlife populations enables comparisons of baseline data over time, enhancing our understanding of key ecological, epidemiological, and socioeconomic processes. Analyzing this data provides crucial insights into ecological relationships and informs conservation strategies, supporting more informed decision-making based on scientific evidence. Additionally, wildlife monitoring helps to calibrate and better understand the link between population abundance and potential damages, such as overabundance. This early detection of threats is vital for protecting biodiversity, agriculture, animal health, and human well-being [1].

Wildlife conservation

Wildlife conservation refers to the efforts and practices aimed at protecting, preserving, and managing wildlife and their habitats to ensure their survival and health. wildlife conservation aims to maintain biodiversity, ensure the resilience of ecosystems, and promote coexistence between humans and wildlife. This field encompasses a range of activities, including:

1. **Habitat Protection**: Safeguarding natural environments where wildlife lives to prevent habitat loss due to human activities like deforestation, urbanization, or pollution.
2. **Species Preservation**: Implementing measures to protect endangered or threatened species from extinction, including legal protections, breeding programs, and habitat restoration.
3. **Human-Wildlife Conflict Management**: Addressing and mitigating conflicts between humans and wildlife, such as crop damage or livestock predation, through sustainable solutions and community engagement.
4. **Research and Monitoring**: Conducting scientific studies to understand wildlife behavior, population dynamics, and ecosystem health, and using this information to inform conservation strategies.
5. **Education and Advocacy**: Raising awareness about the importance of wildlife and conservation issues, and advocating for policies and practices that support environmental protection.

Traditional Methods of wildlife monitoring and conservation

Traditional methods of wildlife monitoring have been used for decades to study and manage wildlife populations. These techniques often involve direct observation and physical data collection. some of the key traditional methods include

1. **Direct Observation**: Watching and recording the behavior, movement, and interactions of wildlife in their natural habitats. This method can be done from a distance using binoculars, spotting scopes, or cameras. Observations by humans of wildlife or their signs have traditionally been the most commonly used method (Heyer et al., 2014; Plumptre, 2000; Sutherland, 2008; Wilson et al., 1996)
2. **Trapping and Marking**: Capturing animals to place physical markers (like bands, tags, or collars) on them. This allows researchers to track individual animals and gather data on their movements, behavior, and population dynamics.

3. **Camera Traps**: Camera traps are now a well-established monitoring tool (Beaudrot et al., 2016; Rovero & Zimmermann, 2016) that involves setting up motion-activated cameras in the field to capture images or videos of wildlife. This non-invasive method helps monitor species presence, abundance, and activity patterns without disturbing the animals. Camera traps record continuously and automatically, eliminating biases related to the timing of the target species' activity or the skill and fatigue of human observers. This results in a more standardized and transparent data collection process compared to manual observations. Additionally, each recorded event is accompanied by a photograph, which provides a reliable means for verification and validation (Zwerts et al 2021).
6. **Track and Sign Surveys**: Collecting and analyzing physical evidence such as footprints, scat, and fur to identify species and estimate population size. This method is useful for studying elusive or nocturnal animals.
7. **Aerial Surveys**: Using aircraft or drones to observe and count wildlife from the air. This method is often employed for large-scale surveys in areas like forests, savannas, or oceans.
8. **Bioacoustics**: It is the process of recording and analyzing animal sounds to monitor species presence and behavior. This method is particularly useful for studying birds, amphibians, and insects. The use of acoustic sensors for passive acoustic monitoring (PAM) is growing fast (Alvarez-Berríos et al., 2016; Blumstein et al., 2011; Deichmann et al., 2018; Sugai et al., 2019). Acoustic recordings capture the soundscape of an area continuously and over extended periods, documenting all sounds as they vary in frequency and intensity over time. This soundscape includes biotic sounds (e.g., animal calls), abiotic sounds (e.g., rain, wind), and anthropogenic sounds (e.g., vehicle traffic) (Pijanowski et al., 2011). Species that produce distinct calls or sounds, such as elephants trumpeting or rumbling (Wrege et al., 2017) and chimpanzees buttress drumming or gorilla's chest beating (Heinicke et al., 2015), can be effectively monitored using acoustic methods.
9. **Nesting and Breeding Site Monitoring**: Inspecting and documenting nesting sites or breeding grounds to study reproductive success and population trends.

These traditional methods provide foundational data and have been instrumental in understanding wildlife populations and their needs. Despite their value, traditional monitoring methods have many limitations. However, these methods are increasingly being enhanced by modern technologies and approaches.

Limitations of Traditional Methods

Traditional methods face numerous limitations due to the vast streches of protected areas, challenging terrains, harsh environments, and limited economic resources and manpower. Additionally, manual monitoring can be time-consuming, inefficient, and physically demanding. The highest costs of human observations are related to salaries and fuel, due to an extensive training phase and continued time investment of field personnel. Direct observations tend to favor mammals and birds that are easily detected due to their vocalizations, size, and daytime activity. In contrast, rare, small, burrowing, nocturnal, and cryptic species are less likely to be observed. Direct observation also demands highly skilled observers, and observer bias can occur due to differences in expertise and fatigue. While these issues can be mitigated through thorough training, shorter monitoring sessions, and restricting the number of tasks assigned to each observer (Emlen & DeJong, 1992; Kühl et al., 2008), such biases make direct field observations more suitable for easily detectable species. Consequently, this method is less ideal for comprehensive community assessments that require broad taxonomic coverage (Roberts, 2011). Teams may spend weeks in the forest to gather repeated observations for occupancy estimates or to cover extensive areas (Cappelle et al., 2019; Diggins et al., 2016). Monitoring large regions can therefore be quite costly, as it requires significant investment in labor, provisions, and field equipment. Camera trapping is generally most effective for medium to large terrestrial animals but a camera trap can cover a small surface area of 10-20m^2 (Zwerts et al 2021). The initial cost of camera traps is relatively high, ranging from $150 to $800 per unit for midrange to high-end models. In addition to the camera traps themselves, expenses include SD cards, batteries, locks, hard drives, and sometimes security boxes. In tropical forests, the high humidity and termite activity can cause some camera traps to fail. The challenges and risks associated with placing camera traps in the canopy may make this approach impractical for many monitoring projects. Acoustic monitoring is also a costly affair that requires an initial investment in the range of 250–600 USD (Darras et al., 2019), although low cost (<200 USD) alternatives exist (Hill et al., 2018). Costs of batteries and SD cards and the size of field teams (2–5 persons) are comparable to those of camera traps.

Effective management of threatened and invasive species hinges on precise population estimates (Cristescu et al., 2015). However, current monitoring methods—such as remote photography, camera traps, tagging, GPS collaring, scat detection dogs, and DNA sampling—often demand significant time and financial investment (Burton et al., 2015; Witmer, 2015). Additionally, these techniques frequently fall short in delivering accurate and precise population estimates (Christiansen et al., 2014). Wildlife monitoring faces several challenges, including the vast geographic ranges of species (Gaston et al., 2009), low population densities (Witmer, 2015), inaccessible habitats (Murray et al., 2008; Schaub et al., 2007), elusive behavior (Ditmer et al., 2015), and sensitivity to disturbances (Chabot et al., 2015).

Artificial Intelligence Revolutionizing Wildlife Monitoring and Conservation

Artificial Intelligence (AI) has become a transformative tool in wildlife monitoring and conservation, fundamentally changing how we understand, protect, and manage biodiversity. Surveying threatened and invasive species to obtain accurate population estimates is a crucial but challenging endeavor that demands significant time and resources. Current ground-based monitoring methods, such as camera traps and on-foot surveys, are often resource-intensive, potentially inaccurate, and difficult to validate. Technology has the potential to overcome the limitations of traditional data gathering and analysis methods, playing a crucial role in improving forest management and conservation. The development and implementation of AI in these fields rely on access to large, high-quality datasets, Internet-of-Things (IoT) network infrastructure, and advanced technologies such as high-resolution cameras, satellite technology, sensors, drones, and unmanned aerial vehicles (UAVs), as well as sufficient computational space and storage.

The necessity of combining these resources has driven research into AI applications across various areas of biodiversity protection and forestry. These areas include forest inventory, detection of illegal wildlife activities, timber trafficking, and unauthorized logging. Furthermore, this research has significantly accelerated the adoption of AI technology in biodiversity conservation and forestry, as demonstrated by the increasing number of start-ups leveraging AI in these sectors. By automating species identification and classification, AI allows researchers to track population trends, detect illegal activities like poaching, and assess ecosystem health in real-time.

Application of remote sensors to track animal movements

The use of remote sensors to track animal movements has significantly advanced, evolving from very high frequency (VHF) radio beacons to Global Navigation Satellite Systems like the Global Positioning System (GPS) (wall J. et al.,2014). These systems allow for precise pinpointing of an animal's location at any given time. Technological advancements—particularly in the miniaturization of electronics, reduction of energy consumption, and extension of battery life—have greatly expanded the range of species that can be tracked and the quantity and quality of data that can be collected (Ropert-Coudert and Wilson 2005, Wilson et al. 2008).

Current analytical methods applied to this high-resolution data offer new insights into animal life history and behaviour, including the mapping of travel routes (Berger et al. 2006, Wall et al. 2013), the spatial differentiation of behaviors (Patterson et al. 2008), and novel information on energy budgets (Fryxell et al. 2004). Additionally, sensor units can now be configured to record various environmental factors (e.g., ambient temperature, relative humidity, light levels) and physiological data (e.g., skin temperature, heart rate), collectively referred to as "biospatial" data.

Satellite-based technology

Moreover, advancements in communication technology, such as satellite-based systems (e.g., "Argos," "Iridium," or "Inmarsat" constellations) or ground-based global system for mobile communications (GSM) technologies, can now be integrated into tracking units. This integration enables the tracking of animals and processing of data in near real-time (Dettki et al. 2004, Urbano et al. 2010). In this context, we define "real-time" as any data that are transmitted immediately upon acquisition and made available for analysis within five minutes. Real-time monitoring (RTM) holds significant potential in wildlife ecology and conservation, particularly for at-risk species, such as those vulnerable to poaching (Wittemyer et al. 2011) or animals prone to frequent interactions with humans (e.g., mountain lions entering residential areas; Kertson et al. 2011). It is also valuable for studies requiring immediate data retrieval, such as research on prey-predator interactions (Knopff et al. 2009).

Wildlife monitoring through soundscape recording

AI-driven predictive models are also crucial in habitat monitoring and conservation planning. Researchers from The Nature Conservancy and its partner organizations have developed an innovative method for automated soundscape monitoring. They designed miniature sound recording devices and strategically placed them throughout various forest areas. These devices captured the forest's soundscape, allowing researchers to analyze the vocalizations of different species and observe their activity patterns across different times of day and seasons. A global platform is being developed to store data collected from various conservation projects worldwide. This platform will also provide analytical tools to help researchers gain insights into the benefits of conservation efforts. This technology has wide-ranging implications for understanding how organisms respond to environmental disruptions and how they benefit from conservation interventions. By analyzing environmental data and species behaviour patterns, AI can forecast habitat changes, identify key conservation areas, and optimize resource allocation. This proactive approach helps conservationists prioritize interventions and mitigate threats before they escalate.

Unmanned Aerial Vehicles (UAVs)

Moreover, AI enhances the efficiency of wildlife management strategies. AI-powered drones and unmanned aerial vehicles (UAVs), for example, enable rapid and non-invasive monitoring of wildlife in remote or difficult-to-access areas. These technologies reduce costs, simplify logistics, and minimize human disturbance in sensitive habitats. The growing availability of affordable Unmanned Aerial Vehicles (UAVs) also offers wildlife experts a valuable tool for monitoring wildlife and addressing challenges in accurately estimating species abundance (Anderson et al., 2013). In recent years, the use of UAVs capable of autonomous flight paths and acquiring geo-referenced sensor data has seen a significant rise, particularly in agricultural, environmental, and wildlife monitoring applications (Soriano et al., 2009). UAVs can be applied to reforest newly deforested areas, facilitating the planting of an additional 1.2 trillion trees worldwide (Bastin et al., 2019). This has the capacity to sequester hundreds of gigatons of CO_2 from the atmosphere. UAVs such as drones are used to scan the designated study area to detect favorable planting conditions, such as adequate moisture. Once suitable conditions are identified, the drones deploy seed containers. This technique offers several advantages over traditional manual forestry methods. It enables faster seed dissemination and can cover a much larger area than hand planting. Additionally, drones allow for efficient monitoring and measurement of regeneration progress. By providing a comprehensive overview, this approach also helps identify specific problematic areas where targeted interventions can be applied for better results.

Artificial Intelligence (AI) and Machine Learning (ML)

Technologies like machine learning algorithms and computer vision are increasingly used to monitor wildlife populations, processing vast amounts of data from sources such as camera traps, acoustic recordings, and satellite imagery with impressive accuracy and speed. Artificial Intelligence (AI) and Machine Learning (ML) techniques, combined with spatial analysis, have been used to predict and monitor deforestation rates globally (Larrea et al., 2022, Mayfield et al. 2020, Dominguez et al, 2022). One organization addressing deforestation is "Rainforest Connection." This startup repurposes old mobile devices, powers them with solar energy, and attaches them to the highest branches of trees to detect the sounds of chainsaws in the forest. The captured audio is transmitted to cellular towers and then to a base station, where Google's TensorFlow, an AI and ML framework, is used to distinguish the sound of chainsaws from other noises. Once detected, the information, along with the sensor location data, is shared with forest managers. This allows them to investigate further and take necessary actions to identify and prevent illegal logging as well as poaching.

Beyond monitoring and management, AI is advancing our understanding of complex ecological processes. By integrating data from various sources and generating insights at unprecedented scales, AI supports interdisciplinary research and fosters collaboration among scientists, conservationists, and policymakers globally.

AI in species identification

Species identification has traditionally been a labor-intensive task, relying on experts to manually identify animals in images or videos. However, the introduction of AI has transformed this process, making it more efficient and accurate. A prime example of AI's impact in this field is the Wildbook project, which employs AI algorithms to identify individual animals based on their unique physical characteristics, such as the pattern of spots on a giraffe or the shape of a whale's tail. This automation greatly reduces the time and effort needed for species identification, enabling scientists to process much larger volumes of data.

Virtual wildlife observatories

Desktop or mobile software programs, like Environmental Systems Research Institute (ESRI) software or Google Earth, can serve as virtual wildlife observatories when continuous field observation is not possible. These tools allow for the visualization of the topographic and ecological context in which animal movements occur, with the added capability of incorporating multiple layers of geographic information.

AI in Monitoring Wildlife Health

AI is revolutionizing wildlife health monitoring by providing tools that can analyze and track animal health in unprecedented ways. One example is the WILD-AI project, which utilizes AI to monitor wildlife populations. By applying machine learning algorithms to data from sources like camera traps, drones, and satellite imagery, WILD-AI can detect patterns that may indicate health issues, such as changes in movement or physical appearance signaling disease outbreaks. Beyond identifying problems, AI also plays a role in predicting and preventing them. Machine learning models, trained on historical data and current observations, can forecast potential health issues, enabling conservationists to take proactive measures. Additionally, AI can assist in diagnosing and treating individual animals, especially in remote areas with limited access to veterinary care, by analyzing images or videos to identify injuries or illnesses.

AI in mitigating human-wildlife conflict

Human-wildlife conflict is a significant issue in many regions, causing harm to both people and animals. The use of AI to prevent these conflicts is a promising advancement that offers a solution beneficial to both sides. A notable example of this innovation is the Maharashtra-based platform 'Wildlife Eye,' developed by the Indian company Valiance as part of the AI for Bharat initiative. This groundbreaking solution combines computer vision and artificial intelligence to detect potential animal encroachments and sends early alerts to first responders and villagers. Smart cameras installed on the outskirts of villages detect approaching animals and trigger alerts. The system's AI-powered cameras, along with hooters, red lights, LED lights, edge analytics, and power and communication panels, enable precise tracking and monitoring of individual tigers, even detecting specific behavioral changes.

Artificial intelligence in wildlife conservation can also be employed in Habitat Suitability Modeling and Corridor Identification by analyzing environmental factors such as climate, vegetation, and topography. These algorithms can model suitable habitats for various species, providing valuable insights for identifying and protecting critical habitats. Additionally, this information can be used to establish wildlife corridors that promote species movement and maintain gene flow.

Challenges to AI based wildlife monitoring and conservation

However, deploying AI in wildlife conservation is not without challenges. Concerns like data privacy, algorithm bias, and the ethical implications of AI-driven decision-making must be carefully addressed. Additionally, the accessibility of AI technologies in developing regions and the need for capacity building among conservation practitioners are significant barriers to widespread adoption. Stakeholders, such as forest managers, policymakers, and civil society, often lack a clear understanding of the availability and suitability of various technologies. The use of terms like AI can sometimes create unrealistic expectations for what these solutions can achieve. Therefore, improving stakeholders' proficiency in effectively utilizing these technologies is a critical step toward successfully implementing them in practical situations. Challenges such as climatic and weather conditions, animal interference, and vandalism also present significant obstacles for these systems (Khatun et al., 2022). The predictions made by Artificial Intelligence (AI) and Machine Learning (ML) models can sometimes be unreliable due to uncertainties in both the data and the expertise involved. Without an adequate number of labeled images of natural forests, plantations, and reforestation areas, AI and ML algorithms may struggle to differentiate between these distinct types of landscapes, especially in species-rich tropical forests (Zhang et al., 2022, Nicora et al., 2022, Elenchezhian et al., 2021).

Conclusion

Looking ahead, AI's role in wildlife monitoring and conservation is full of promise if the above challenges are resolved. As AI algorithms continue to advance, along with innovations in sensor technology and data analytics, our ability to protect biodiversity and tackle global environmental challenges will only grow. Collaboration between academia, industry, and conservation organizations is crucial to fully harness AI's potential for the benefit of wildlife and ecosystems worldwide. In conclusion, while AI is not a cure-all for conservation challenges, its integration into wildlife monitoring and conservation practices marks a significant shift in conservation science. By leveraging AI's capabilities, we can make more informed decisions, implement targeted interventions, and secure a sustainable future for biodiversity on our planet.

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