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The Intelligent Eye: AI-Powered Elephant Monitoring for Conservation and Management

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ABSTRACT

The conservation of elephants, a keystone species in Africa and Asia's protected areas, is hindered by the complexity and scale of monitoring their behavior, habitat, and population dynamics. Recent advances in artificial intelligence (AI) and machine learning (ML) offer a paradigm shift in wildlife conservation, enabling the efficient analysis of vast amounts of data from various sensors, such as camera traps, drones, and satellites. This review article provides a comprehensive overview of AI-driven monitoring methods for elephant conservation, highlighting their potential to enhance our understanding of elephant behavior, habitat use, and population dynamics. We discuss the applications of AI-powered computer vision, acoustic monitoring, and predictive modeling in elephant conservation, as well as the challenges and limitations associated with these approaches. Furthermore, we emphasize the importance of interdisciplinary collaboration between AI experts, ecological researchers, and conservation practitioners to ensure the effective development and deployment of AI-driven conservation solutions.

Keywords: artificial intelligence, elephant conservation, elephant management, machine learning wildlife monitoring

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INTRODUCTION

Elephants possess a profound significance that transcends their physical presence, encompassing intrinsic, biological, ecological, and cultural value (Dagenais et al. 2021). Their distinctive genetic makeup and physiological characteristics have fascinated scientists, who continue to unravel the intricacies of their biology (Chusyd et al. 2021). Moreover, elephants' exceptional cognitive and emotional intelligence enables them to exhibit empathy, self-awareness, and cooperation, rendering them one of the most intelligent animal species (Bradshaw 2010; Goldenberg & Wittemyer 2020). Their complex social structures, led by matriarchal figures, are a testament to their sophisticated communication and cooperation skills (Vidya & Sukumar 2005; McComb et al. 2011; de Silva et al. 2011; Lee & Moss 2014; Hedwig et al. 2021). As keystone species, elephants play a vital role in shaping their ecosystems, influencing forest regeneration, and maintaining biodiversity (Bowen-Jones & Entwistle 2002; Haynes 2012; Guldemond et al. 2017; Poulsen et al. 2018).

The ongoing struggle for survival faced by African savannah elephants, African forest elephants, and Asian elephants is a pressing concern (Lee & Graham 2006; Çakırlar & Ikram 2016). Threats such as habitat destruction, human-elephant conflict, and poaching have created a critical situation, necessitating innovative and effective conservation strategies (Saaban et al. 2011; Goswami et al. 2014; Ngcobo et al. 2018; Denninger Snyder & Rentsch 2020). This paper explores the potential of artificial intelligence and machine learning to revolutionize elephant conservation. By harnessing these technologies, researchers and conservationists can develop novel approaches to monitoring elephant populations, mitigating human-elephant conflict, and combating poaching. This technology-conservation nexus has the potential to tip the balance in favor of elephant survival.

The escalating challenges facing elephant conservation vary significantly across different populations, necessitating tailored approaches to address these distinct threats (Zeppelzauer & Stoeger 2015; van de Water et al. 2023). While all elephant populations confront a myriad of problems, specific challenges have become particularly pronounced for certain populations (Hutchens 2013; Neff & Karney 2017). Forest elephants, particularly those in the Congo Basin, are besieged by rampant poaching driven by the demand for their valuable ivory, which has led to devastating population declines (Warchol et al. 2003; Blake et al. 2007; Wittemyer et al. 2014). Moreover, the remote and inaccessible nature of their habitats hinders effective monitoring and conservation efforts (Loarie et al. 2009; Green et al. 2018). Savannah elephants, on the other hand, are grappling with the consequences of habitat fragmentation caused by human expansion, which disrupts their traditional migration routes and exacerbates human-elephant conflicts (HECs) near farmland borders (Hoare 2000; Perera 2009; Sach et al. 2019; Di Minin et al. 2021; Gross et al. 2022; Wenbornet et al. 2022; Brickson et al. 2023). The increasing overlap between elephant habitats and agricultural areas has resulted in significant crop damage and human-elephant conflicts, underscoring the need for innovative conflict mitigation strategies (Gunawansa et al. 2024; Tang et al. 2024). Asian elephants, heavily impacted by habitat fragmentation and degradation, suffer from limited genetic diversity due to restricted mobility, which compromises their long-term viability (Pradhan et al. 2011; Koirala et al. 2016). Furthermore, the ongoing conversion of natural habitats into agricultural land and urban areas has resulted in the displacement of Asian elephants, leading to increased conflicts with humans and heightening the risk of elephant-human fatalities (Lenin & Sukumar 2008; Cabral de Mel et al. 2022). To effectively address these complex conservation challenges, it is essential that conservationists are equipped with cutting-edge tools and monitoring techniques.

This includes the development and application of novel models and methods for enhancing dataset collection and annotation, particularly in countries where elephant conservation receives limited funding (Fergus et al. 2024). Moreover, the integration of emerging technologies, such as artificial intelligence, machine learning, and IoT sensors (Brickson et al. 2023).

Traditional elephant conservation efforts have relied on a range of monitoring techniques, including direct methods such as aerial and ground surveys, as well as indirect approaches like dung sample analysis and camera trap deployment (Barnes et al. 1997; Dunham et al. 2015; Chase et al. 2018; Smit et al. 2019). However, these conventional methods are often hindered by limitations such as high operational costs, labor-intensive protocols, and sensitivity to environmental factors like weather and visibility (Koneff et al. 2008; Schlossberg et al. 2016; Lamprey et al. 2020; Lamprey et al. 2020). Moreover, dung-based surveys, while providing valuable insights into elephant presence and abundance, may not yield comprehensive information on population demographics, social structure, and behavior (Laguardia et al. 2021; Mohanarangan et al. 2022). The accuracy of dung counts can also be compromised by variability in dung decay rates across different habitats and environmental conditions (Meier et al. 2021). Recent advances in monitoring technology, such as the integration of sensors, drones, and artificial intelligence, offer unprecedented opportunities for wildlife ecologists to collect and analyze vast amounts of data (Brickson et al. 2023; Rathi 2025). These innovations have the potential to enhance the accuracy, efficiency, and cost-effectiveness of elephant monitoring, ultimately informing more targeted and effective conservation strategies (Natarajan 2024). Furthermore, the increased ease of data collection and analysis can facilitate the development of more nuanced and dynamic models of elephant population ecology.

The convergence of artificial intelligence (AI), machine learning (ML), and conservation science has created a transformative opportunity for tackling complex environmental challenges. By harnessing the power of AI and ML, researchers can unlock insights from the vast amounts of data being generated, driving innovation in conservation science (Farley et al. 2018; Christin et al. 2019; Tuia et al. 2022). A crucial aspect of this convergence is the need for interdisciplinary collaboration between conservationists, technologists, and domain experts. This paper builds upon this imperative by focusing on species-specific conservation priorities for elephants, surveying existing AI applications, and identifying areas where AI/ML can be leveraged to address pressing conservation challenges (Cooper et al. 2022). Furthermore, this paper aims to facilitate a deeper understanding of the intersection between AI/ML and elephant conservation, highlighting the most pressing technological hurdles that must be overcome to achieve key conservation objectives.

The subsequent sections of this paper delve into the exciting realm of AI/ML applications in elephant conservation, organized by measurement modality, including imaging, acoustics, seismic, and molecular approaches. Through this exploration, we reveal the vast potential of AI/ML in tackling specific monitoring challenges faced by elephant conservationists, while also examining the current landscape of AI/ML techniques and anticipating future innovations that hold promise for conservation applications. The emphasis on practical considerations, such as the development of user-friendly AI/ML tools, the importance of data standardization and sharing, and the need for ongoing training and capacity-building initiatives to ensure that conservationists are equipped to harness the power of AI/ML. Furthermore, we examine the critical issue of data management, highlighting strategies for coping with the unprecedented volumes of data generated by AI/ML applications and exploring cost-effective solutions that can facilitate widespread adoption of these technologies in elephant conservation.

IMAGE AND VIDEO MONITORING FOR ELEPHANT CONSERVATION

The integration of imaging and video monitoring technologies has been a cornerstone of elephant conservation efforts for decades. Traditionally, human analysts played a crucial role in reviewing and interpreting recorded footage, meticulously annotating elephant sightings, counting individuals, and documenting behavioral patterns (Brickson et al. 2023). Recent breakthroughs in artificial intelligence (AI) have transformed the landscape of elephant conservation monitoring. AI-powered algorithms can now be applied to imaging and video data, automating tasks such as elephant detection and classification, individual counting and tracking, and behavioral analysis and pattern recognition. These advancements not only enhance the efficiency and accuracy of conservation monitoring but also enable researchers to focus on higher-level analysis, strategic decision-making, and targeted conservation interventions.

- **Elephant Detection**

The integration of AI-assisted camera traps has revolutionized elephant monitoring in protected areas. Systems like SMARTParks (https://smartconservationtools.org/), WildEye (https://wildeyeconservation.org/elephant-survey-system/), EarthRanger(https://www.earthranger.com/), and Mbaza AI (https://www.independent.co.uk/stop-the-illegal-wildlife-trade/ai-technologywildlife-conservation-gabon-b1783812.html) employ AI algorithms to detect and identify species, streamlining the analysis of vast video datasets (Villa et al. 2017; Tabak et al. 2019; Willi et al. 2019; Schneider et al. 2020; Vecvanags et al. 2022; Brickson et al. 2023). These systems have demonstrated impressive classification accuracies, with Mbaza AI achieving 96% accuracy in identifying 25 species (https://www.independent.co.uk/stop-the-illegal-wildlife-trade/ai-technologywildlife-conservation-gabon-b1783812.html). However, despite these advancements, challenges persist. The performance of these systems can be compromised when deployed in new environments (Schneider et al. 2020), highlighting the need for adaptability and transfer learning capabilities. Moreover, the limited range of camera traps restricts their effectiveness as a census technique.

The strategic integration of artificial intelligence (AI) techniques with aerial surveys has revolutionized elephant monitoring, offering unparalleled insights into population dynamics (Ullah et al. 2024). High-resolution cameras mounted on survey aircraft capture vast datasets, which are then analyzed using sophisticated AI algorithms to accurately count and track elephant populations (Gonzalez et al. 2016; url:https://www.4elephants.org/blog/article/artificial-intelligenceand-elephant-conservation; Brickson et al. 2023). These AI-powered tools excel in detecting the infrequent appearance of elephants within extensive datasets, comprising hundreds of thousands of images. By leveraging machine learning and computer vision, AI detection techniques enhance accuracy, boost efficiency, improve safety, and enable scalability (Reddy et al. 2024). This automation minimizes human error and fatigue, ensuring reliable population counts, and streamlines the monitoring process (Falzon et al. 2019). Moreover, AI-enhanced aerial surveys facilitate the monitoring of elephant populations across vast, remote areas, providing invaluable insights into habitat utilization, migration patterns, and social structures (Chisom et al. 2024).

The application of artificial intelligence (AI) techniques to high-resolution satellite images has emerged as a promising approach for counting and monitoring elephant habitat use (Duporge et al. 2021). This method is particularly effective in areas where elephants roam freely without canopy obstruction, such as desert environments (Shell 2019). Despite its potential, several technical challenges hinder the widespread adoption of this method.

The high cost of acquiring satellite images, limited availability of high-resolution satellite coverage, and inability to detect elephants under dense canopy are significant obstacles (Morrison et al. 2018). Furthermore, satellite images may not capture the nuances of elephant behavior, and the accuracy of detection algorithms can be compromised by factors such as image resolution, lighting conditions, and vegetation density (Brickson et al. 2023). Although advancements in satellite technology and AI-driven elephant detection may enhance the feasibility of this method in the future, current limitations necessitate alternative approaches (Ullah et al. 2024). Oblique camera counts, for instance, offer higher resolution images and enable detection of elephants under tree canopies, making them a more practical solution for detecting elephants (Duporge et al. 2021). Additionally, integrating satellite-based monitoring with other technologies, such as drones, camera traps, and sensor networks, may provide a more comprehensive understanding of elephant ecology and behavior.

In the context of Human-Elephant Conflict (HEC) mitigation, camera trap technology has been successfully employed to detect elephants approaching farmlands, providing a vital early warning system for farmers (Gross et al. 2022). This proactive approach enables farmers to take necessary precautions to protect their crops from impending raids (Premarathna et al. 2020). When the sensors are triggered, local farmers are promptly informed, allowing them to take swift action to deter the elephants. In some cases, the elephants can be safely driven away, minimizing damage to crops and reducing the risk of conflicts between humans and elephants (Brickson et al. 2023). Moreover, this innovative approach can also help to identify and monitor elephant migration patterns, habitat use, and behavior, providing valuable insights for conservation efforts.

- **Individual identification**

Deep learning techniques have shown promising results in individual elephant identification, but further improvements are necessary to achieve practical field application. Notably, a convolutional neural network (CNN) was trained to recognize individual elephants from a group of 276 with a 74% accuracy, using only a few training images per individual (Körschens et al. 2018). This achievement highlights the potential of deep learning in elephant identification, particularly when limited training data is available (Duporge et al. 2021). Subsequent studies have explored various neural network architectures to examine images or the contours of elephant ears for individual recognition (de Silva et al. 2022). These efforts have yielded accuracy rates of up to 88%, demonstrating the effectiveness of deep learning in distinguishing between individual elephants (Weideman et al. 2020; De Silva et al. 2022). Recently, the development of ElephantBook, an ensemble tool combining current elephant identification techniques (Kulits et al. 2021), has achieved a notable 93% accuracy in correctly identifying individuals within the top 15 matches. The integration of multiple identification techniques in ElephantBook underscores the importance of a multi-faceted approach to individual elephant identification (Srinivasaiah et al. 2019). By leveraging the strengths of various methods, researchers can develop more accurate and reliable identification systems. Furthermore, the continued advancement of deep learning techniques and the incorporation of new data sources, such as drone imagery or camera trap photos, hold promise for improving the accuracy and efficiency of individual elephant identification.

Enhancing the accuracy and robustness of individual elephant identification from images is crucial for effective monitoring and mitigating Human-Elephant Conflict (HEC) (Srinivasaiah et al. 2019). Machine learning (ML) methods have successfully identified individuals in smaller animals, such as fish and cheetahs, using whole-body morphology or body patterns (Cheema & Anand 2017; Ditria et al. 2020; Shi et al. 2020).

However, the large size of elephants poses a significant challenge, particularly in forested areas where dense vegetation obstructs visibility (Okello et al. 2016). To overcome this, researchers rely on morphological features, such as ear shape, tusk characteristics, tail length, and back slope, to identify adult elephants (Foley & Faust 2010; Montero-De La Torre et al. 2023). Developing methods to characterize these features in conjunction would significantly improve automatic individual identification (Ardovini et al. 2008). Interestingly, techniques from AI-based human facial recognition can be adapted for body morphology recognition, with successful applications in identifying individual bears, primates, and giant pandas (Shukla et al. 2019; Taskiran et al. 2020; Clapham et al. 2020; Hou et al. 2020; Clapham et al. 2022). The adaptation of facial recognition techniques for elephant identification is promising, given the unique morphological features of elephants (Taskiran et al. 2020). By leveraging advances in computer vision and machine learning, researchers can develop more accurate and efficient identification systems. Furthermore, the integration of automated identification with other monitoring technologies, such as camera traps and drones, can provide a more comprehensive understanding of elephant behavior, habitat use, and population dynamics (Wrege et al. 2017).

- **Automated behaviour analysis**

The study of individual elephant behavior has emerged as a critical area of research, with far-reaching implications for conservation efforts. By examining the complex behaviors exhibited by elephants, researchers can gain valuable insights into their decision-making processes, social dynamics, and responses to perceived threats. Direct field observations (Kahl & Armstrong, 2002; Douglas-Hamilton et al., 2006) and long-term ethological studies (Turkalo et al., 2013; Moss et al., 2019) have laid the foundation for understanding elephant behavior, culminating in comprehensive resources such as the Elephant Ethogram book (Poole & Granli, 2021). The maturation of machine vision methods, combined with advances in remote and sustained observation, has opened up new avenues for extending this knowledge (Hughey et al. 2018). Automated behavior analysis (ABA) enables researchers to quantify individual behavior at unprecedented scales, providing a more nuanced understanding of elephant behavior (Ramezanpour et al. 2024). This, in turn, can inform strategies for mitigating Human-Elephant Conflict (HEC) and promoting coexistence between humans and elephants. The integration of ABA with other technologies, such as sensor networks, drones, and camera traps, holds significant promise for monitoring elephant behavior and habitat use (Brickson et al. 2023). By analyzing behavioral data in conjunction with environmental and social factors, researchers can identify patterns and correlations that inform conservation decisions. Furthermore, the development of ABA can facilitate the creation of personalized conservation plans, tailored to the unique needs and behaviors of individual elephants.

- **Behaviour observation and representation**

The automated learning of visual-based behaviors through body posture representations over time is a complex task that relies on the successful completion of several technically challenging prerequisites (Joly et al. 2016). Firstly, high-quality video acquisition is necessary, which requires a delicate balance between spatial resolution and field of view (Vermeulen et al. 2013). This ensures that the captured footage is detailed enough to facilitate accurate postural estimation while also providing a sufficient view of the elephant's surroundings. Robust postural estimation is another critical component, as it enables the accurate representation of an elephant's body posture over time (Brickson et al., 2023).

This, in turn, allows for the analysis of behavioral patterns and the identification of meaningful trends. However, postural estimation can be compromised by various factors, such as occlusions, lighting conditions, and camera angles, which must be carefully addressed to ensure reliable results (Sundaram & Meena 2023). Furthermore, Automated Behavior Analysis (ABA) methods assume that the majority of variability in the input data is due to behavioral variability rather than imaging or environmental variability (Dehghan et al. 2022). Therefore, it is essential to understand the capabilities and limitations of the preceding technical components, including video acquisition and postural estimation.

The advent of video-camera traps and camera-equipped unmanned aerial vehicles (UAVs) has revolutionized the field of elephant research and conservation, offering unprecedented views of elephant behavior at high spatio-temporal resolution (Brickson et al. 2023). Video-camera traps, in particular, have proven invaluable for monitoring forest-dwelling elephants, causing minimal disruption to their natural behavior (Van de Water et al. 2020). By leveraging manual human review, researchers have successfully employed these systems to classify elephant behavior, gaining insights into their social structures, habitat use, and behavioral patterns (Srinivasaiah et al. 2012). The technological advancements in camera traps and UAVs have addressed some of the challenges associated with image-based tracking in the field (O'Connell et al. 2011; Lahoz-Monfort & Magrath 2021). However, the call to developers remains relevant, as there is still a need for improved camera placement strategies, enhanced sensor sensitivity and resolution, and increased environmental resilience (Ramachandran et al. 2012; Dell et al. 2014). Furthermore, the development of automated image analysis algorithms capable of accurately detecting and classifying elephant behavior would significantly enhance the efficiency and effectiveness of these systems (Zeppelzauer & Stoeger 2015). The integration of UAVs and camera traps with other technologies, such as GPS tracking, acoustic sensors, and machine learning algorithms, holds significant promise for advancing elephant research and conservation (Brickson et al. 2023).

A significant breakthrough in animal behavior analysis has been the development of automatic pose estimation, which captures the essential features of an animal's pose, such as appendage configuration and body condition. This is achieved through various representations, including keypoint-based, dense point cloud, or surface mesh representations. However, a persistent challenge in pose estimation is standardizing pose and robustness to visual occlusion, regardless of the animal's distance, orientation, or camera viewpoint (Mathis & Mathis 2020; Jiang et al. 2022). This challenge is inherent in single-camera, two-dimensional (2D) pose representation and can lead to inaccurate downstream behavioral inferences (Deng et al. 2024). To overcome this limitation, researchers have explored the use of multiple cameras to capture three-dimensional (3D) pose representations (Günel et al. 2019). While this approach can provide more accurate pose estimation, it introduces additional challenges, such as data synchronization and increased system costs. Recent advances in machine learning (ML) methods for single-view (or monocular) 3D pose estimation offer a promising alternative solution (Liu et al. 2022). One feasible approach is the use of shape and skeletal priors, which have been successfully applied in existing methods for 3D animal pose estimation (Zuffi et al. 2017; Zhang et al. 2021; Hu et al. 2023). By leveraging these priors, researchers can develop more accurate and robust pose estimation models that can handle the complexities of animal behavior and movement (Jiang et al. 2022). Furthermore, the integration of ML-based pose estimation with other behavioral analysis techniques can provide a more comprehensive understanding of animal behavior, enabling researchers to gain valuable insights into behavioral patterns, social interactions, and habitat use.

Unmanned Aerial Vehicles (UAVs) have revolutionized the field of animal behavior research, offering unprecedented views of animal groups and mobility in open landscapes such as the African savannah (Koger et al. 2021; Schad & Fischer 2023). UAVs provide a unique perspective, allowing researchers to follow animal groups over difficult terrain and capture behavioral data that would be impossible to collect using traditional methods (Linchant et al. 2015). One of the significant advantages of UAVs is their ability to collect oblique video footage, which overcomes the limitations of ground-based video camera traps (Wang et al. 2019). By positioning the UAV at an angle, researchers can observe elephants under trees, providing valuable insights into their behavior (Vermeulen et al. 2013). However, UAVs still face many of the same pose estimation challenges as ground-based cameras, including the need to account for variations in lighting, terrain, and vegetation (McCarthy et al. 2024). In contrast, collecting overhead video footage using UAVs provides a much simpler imaging condition (Vermeulen et al. 2013). By maintaining a steady altitude and distance from the subjects, researchers can capture a complete view of the elephants' gross body position, including their orientation and heading (Colomina & Molina 2014). While this approach may not provide the same level of detail as oblique footage, it is often sufficient for studying cumulative behavior and interactions at the group level (Costa-Pereira et al. 2022). Recent advances in data collection protocols, data fusion, and machine vision have enabled the robust and high-resolution georeferencing of free-ranging animals and landscape reconstruction from aerial videos (Koger et al. 2023). This is particularly relevant for studying elephant behavior over large areas, such as migratory routes, or when using multiple drones to capture diffuse group behavior (Corcoran et al. 2021). Despite the many advantages of UAV-based monitoring, one persisting drawback is the flight noise, which can impact elephant behavior (Brickson et al. 2023). To address this issue, researchers are actively developing protocols to minimize UAV disturbance and improve habituation of elephants and other wildlife to UAVs. Future behavioral insights and conservation applications of aerial-based monitoring may drive the development of quieter UAVs, further expanding the potential of this technology for conservation purposes (Hartmann et al. 2021; van Vuuren et al. 2023). The use of UAVs for studying animal behavior has also raised important questions about the ethics of animal research. As researchers, it is essential to consider the potential impact of UAVs on animal behavior and welfare, ensuring that the benefits of this technology are balanced against the potential risks. By prioritizing animal welfare and developing best practices for UAV-based research, scientists can harness the full potential of this technology to advance our understanding of animal behavior and inform effective conservation strategies.

- **Behaviour analysis**

Machine learning (ML)-based behavioral analysis methods have revolutionized the field of behavioral research, enabling the rapid and automated annotation of video data in behavioral assays and social interactions (Kabra et al. 2013; Klibaite et al. 2017; Nilsson et al. 2020; Segalin et al. 2021; Bohnslav et al. 2021; Gabriel et al. 2022). This has led to groundbreaking discoveries in the structure and dynamics of expressed behavior, revealing previously undescribed movement phenotypes in neurodevelopmental models (Berman et al. 2014; Wiltschko et al. 2015; Werkhoven et al. 2021; Klibaite et al. 2022). By leveraging ML algorithms, researchers can now efficiently analyze large datasets, identifying patterns and correlations that would be impossible to detect through manual annotation. The application of collective behavior analysis has also expanded to numerous animal species, providing valuable insights into how decisions are made within groups (Couzin et al. 2005). This research has far-reaching implications for our understanding of social behavior, cooperation, and communication in animals (Anderson & Perona 2014; Valletta et al. 2017; Datta et al. 2019; Couzin & Heins 2023).

For instance, studies on flocking behavior in birds and schooling behavior in fish have shed light on the complex interactions and decision-making processes that govern these phenomena.

The field of automatic behavioral analysis methods for elephant monitoring has made significant strides, with two primary approaches emerging: supervised and unsupervised methods (Sturman et al. 2020). Supervised approaches, also known as automatic behavior detection or action recognition, involve training machine learning algorithms on labeled datasets to detect specific behaviors (Sturman et al. 2020). This method has achieved human-level accuracy in detecting whole-body behaviors in mice, such as floating, rearing, and nose-to-nose interactions (Brickson et al. 2023). Applying these methods to elephant behavior could enable the automatic detection of heightened attentiveness behaviors, such as fence touching, ear flapping, and swaying. By quantifying the number of occurrences and duration of these behaviors, researchers can evaluate the effectiveness of boundary deterrents like beehive fences (King et al. 2017; Brickson et al. 2023). Moreover, automatic behavioral detection methods can help assess proxies of elephant psychological state, such as relaxed versus perceived threat, at critical locations like water sources or wildlife crossings. In contrast, unsupervised approaches, referred to as deep behavioral phenotyping, offer a means to identify complex behavioral sequences from postural data alone (Hsu & Yttri, 2021; Luxem et al. 2022; Weinreb et al. 2024). This method has been experimentally validated through optogenetic stimulation and pharmaceutical induction, demonstrating high sensitivity in detecting previously undescribed behavioral phenotypes in genetically modified mice (Wiltschko et al. 2020). Deep phenotyping can be applied to study the differences in social behavior between orphaned elephants and those from intact families, or translocated versus resident elephants, to inform re-introduction and social integration efforts (Pinter-Wollman et al. 2009; Goldenberg & Wittemyer, 2017; Stokes et al., 2017; Hörner et al., 2021; Garaï et al. 2023). One of the significant advantages of deep phenotyping is its ability to uncover novel behavioral patterns and sequences that may not have been observed or described previously (Luxem et al., 2022; Weinreb et al. 2024). By analyzing the statistical structure of postural data, researchers can identify complex behavioral phenotypes that are not easily detectable through manual observation or supervised machine learning approaches (Nilsson et al. 2020). This can lead to new insights into elephant behavior, social structure, and communication patterns, ultimately informing conservation and management strategies (Shaffer et al. 2019). Furthermore, the integration of automatic behavioral analysis methods with other technologies, such as camera traps, drones, and sensor networks, can provide a more comprehensive understanding of elephant behavior and ecology (Petso et al. 2021). By combining these approaches, researchers can collect and analyze large datasets, identifying patterns and correlations that can inform conservation efforts and improve our understanding of these complex and fascinating animals. As the field of automatic behavioral analysis continues to evolve, it is likely to play an increasingly important role in elephant conservation and research.

When studying behavior in natural settings, it is recommended to prioritize Automated Behavior Analysis (ABA) methods that operate on postural representations over single-stage methods that operate directly on pixels (Batty et al. 2019). This is because single-stage methods, which infer behavior from changes in pixel values, can be effective in controlled imaging environments with simple backgrounds, such as laboratory settings (Ahmed et al. 2020). However, these methods can struggle when changes in pixel values are due to non-behavioral variables, such as imaging conditions, changing backgrounds, and visual appearance (Bailey 2002). In contrast, ABA methods that operate on postural representations are more robust to these challenges (Brattoli et al. 2017). By focusing on the posture and movement patterns of the animal, these methods can better capture behavioral information and reduce the impact of non-behavioral variables (Hendrix & Vander Wal 2025).

This makes them more suitable for studying behavior in natural settings, where imaging conditions and backgrounds can be complex and varied (Torralba et al. 2006). That being said, single-stage behavioral inference methods can still be effective in certain situations (McClintock & Lander 2024). For example, if videos are cropped to tightly bound the relevant subjects, reducing image-based variability, high performance has been demonstrated in more controlled but still complex settings (Yuan et al. 2011). This includes studies on group-housed rhesus macaques in an enriched, multi-level home cage and on wild chimpanzees in a natural forest clearing using handheld video recorders (Marks et al. 2020; Bain et al. 2021). These findings suggest that single-stage behavioral inference methods can be useful when fine-tuned for specific camera views and imaging conditions (Vogg et al. 2024). However, it is essential to carefully evaluate the suitability of these methods for each particular study and to consider the potential limitations and challenges associated with them. In addition, the development of more advanced ABA methods that can operate on postural representations, such as those using deep learning architectures, can provide even more accurate and robust behavioral analysis (Bhatt et al. 2023). These methods can learn to extract relevant features from postural data and can be trained on large datasets to improve their performance.

Automated vision-based behavioral analysis in free-ranging elephants is a largely unexplored area of research (Vogg et al. 2024). Despite the growing interest in applying machine learning and computer vision techniques to behavioral studies, only a handful of papers have attempted to automate behavioral analysis in wild, free-ranging mammals (Bain et al. 2021). Notable exceptions include studies on wild chimpanzees, which have demonstrated the feasibility of detecting specific behaviors such as nut cracking and passing food to mouth (Feng et al. 2021). Similarly, research on wild felines has shown promising results in detecting standing, ambling, and galloping gaits. However, these studies are limited in scope and have not explicitly conducted comprehensive behavioral analyses (Wiltshire et al. 2023). A few papers have applied automated pose estimation to ground- and aerial-based videos of wild animals, including apes and ungulates (Rahman et al. 2023). While these studies have made significant contributions to the field of animal tracking and monitoring, they have not explicitly focused on behavioral analysis (Brown et al. 2013). The challenges of translating automated behavioral analyses from laboratory settings to wild, free-ranging environments are numerous (Williams et al. 2021). One of the primary challenges is constraining the variability of Automated Behavior Analysis (ABA) inputs to just behavioral variability (Siegford et al. 2023). This requires careful consideration of factors such as lighting, terrain, and weather conditions, which can significantly impact the accuracy of ABA methods (Hanley et al., 1970). Even after controlling for these factors, existing ABA methods still face significant challenges and limitations. For example, automated behavior detection is susceptible to the standard challenges associated with supervised learning approaches, including data labeling time, annotator inconsistency, and sampling and temporal bias (Brickson et al. 2023). Deep phenotyping, a type of unsupervised learning approach, can also be used to discover behavioral sequence classes. However, the ethological relevance of these classes requires manual human validation and semantic assignment in practice. Additionally, deep phenotyping can produce more sequence classes than can be distinguishable by eye, requiring agglomeration using model variants that account for additional sources of behavioral variability or manual curation (Costacurta et al. 2022). Despite these challenges, the potential benefits of automated vision-based behavioral analysis in free-ranging elephants make it an exciting and worthwhile area of research (Kühl & Burghardt, 2013).

The complexity and species-specificity of individual and group elephant behavior pose significant challenges in modeling their behavior (Goldenberg et al. 2022). The development of behavioral methods to capture these nuances has not yet been motivated, largely due to the focus on sub-second behavioral precision in laboratory settings (Brickson et al. 2023). However, elephant behavior often unfolds over tens of minutes, requiring methods that can perform inference at these longer timescales (Rolf & Steil, 2013). Moreover, elephants possess complex, non-visual modes of signaling, such as seismic communication, rumble vocalizations, and olfactory cues, which are still being understood (Ball et al. 2022). These multimodal signals can complicate the inference of indirect interactions within a group, highlighting the need for interdisciplinary approaches that integrate insights from ecology, biology, and animal behavior (Reece et al. 2022). The unprecedented group-level behavior observations with individual behavioral resolution require the translation of theories from movement ecology (Strandburg-Peshkin et al., 2015; Ozogány & Vicsek, 2015). This can provide a deeper understanding of the group decision-making processes underlying socially hierarchical elephants. By leveraging movement ecology frameworks, researchers can explore how individual elephants contribute to collective movement patterns and how these patterns are influenced by social hierarchy, environmental factors, and human-wildlife conflict (Manfredo & Dayer, 2004). To address these challenges, researchers must develop innovative methods that can capture the complexity and nuance of elephant behavior. This may involve integrating multiple data streams, such as GPS tracking, accelerometer data, and audio recordings, to gain a more comprehensive understanding of elephant behavior and social dynamics (Smith & Pinter-Wollman 2021). Furthermore, collaborations between ecologists, biologists, computer scientists, and conservationists are essential for developing effective conservation strategies that take into account the intricate social lives of elephants.

The integration of machine vision and laboratory-based Automated Behavior Analysis (ABA) is revolutionizing the study of behavior patterns relevant to conservation (Pickard & Ahmed, 2019). For instance, quantifying the "personality" of individual elephants can help assess their likelihood of engaging in crop raiding, enabling the efficient allocation of GPS collars and other resources to monitor high-risk individuals (Hoare 1999; Mumby & Plotnik, 2018). Remote evaluation of elephant behavior can draw inspiration from studies on humans, such as gait tracking and action patterns (Han & Bhanu, 2005; Teepe et al. 2021). By analyzing these behavioral patterns, researchers can inform wildlife managers about elephant health, wellness, intrinsic states, and evolved behavioral strategies (Enev et al. 2016). To achieve these goals, dedicated work by AI/ML practitioners is required to robustly translate the latest AI and ML methods to continuous, variable observations of elephants in their natural settings (Sharifhosseini et al. 2024). Scientific and field experts must guide the behavioral questions and metrics of highest conservation priority, ensuring that research efforts are focused on the most critical issues. Furthermore, interdisciplinary researchers must invest in developing novel methods for studying elephant-specific, evolved, and emergent behavioral strategies. This may involve integrating insights from ecology, biology, psychology, and computer science to create a comprehensive understanding of elephant behavior and social dynamics. The successful application of machine vision and ABA to conservation-relevant behavior patterns will require a collaborative effort between researchers, conservationists, and wildlife managers (Brickson et al. 2023). By working together, we can develop effective conservation strategies that take into account the complex behavioral needs of elephants and promote their long-term survival. This collaborative approach will enable the development of novel methods and tools that can be applied in real-world conservation scenarios, ultimately contributing to the protection and preservation of elephant populations.

- **Acoustic monitoring**

Auditory communication is a vital component of elephant social lives and survival, with a diverse repertoire of calls, including infrasonic rumbles, trumpets, and roars, conveying essential information related to group cohesion, reproductive status, and alarm signals (Poole et al. 2005). This complex acoustic communication system facilitates coordination among group members, resource acquisition, and the transmission of knowledge and social learning, ultimately contributing to the intricate social structure of elephants (Byrne et al. 2009). The significance of auditory communication in elephant ecology and behavior cannot be overstated (Beeck et al. 2021). Elephants rely heavily on their acute sense of hearing to navigate their environment, detect potential threats, and maintain social bonds (Schulte et al. 2007). In fact, research has shown that elephants can recognize and respond to the vocalizations of family members and social associates, even after many years of separation (McComb et al. 2000). Audio-based monitoring has emerged as a promising tool in elephant conservation efforts, offering a non-invasive and cost-effective means of tracking elephant behavior, communication, and movement patterns (Brickson et al. 2023). By leveraging advances in artificial intelligence (AI) and machine learning (ML), researchers can analyze audio recordings to detect elephant presence, localize individuals, and even recognize specific vocalizations. This information can be used to inform conservation strategies, such as identifying areas of high elephant activity, monitoring population dynamics, and developing effective anti-poaching measures. One of the most exciting applications of audio-based monitoring is the development of individual recognition systems based on vocal fingerprints (Trapanotto et al. 2022). This technology has the potential to revolutionize elephant conservation by enabling researchers to track individual elephants over time, monitor their behavior and social interactions, and identify potential conservation threats. Furthermore, the use of audio-based monitoring can help reduce the need for physical tracking and observation, minimizing the risk of disturbance and stress to the elephants. The integration of audio-based monitoring with other conservation technologies, such as camera traps and GPS tracking, can provide a comprehensive understanding of elephant behavior and ecology (Brickson et al. 2023). By combining these approaches, researchers can gain insights into the complex social dynamics of elephant populations, identify areas of conservation concern, and develop effective strategies for protecting these majestic animals.

- **Passive acoustic monitoring**

Bio-acoustic data gathered from a strategically placed grid of microphones can be employed to detect the presence of elephants over a significantly wider range compared to camera traps. This approach, termed passive acoustic monitoring (PAM), offers distinct advantages over imaging techniques, particularly in forested terrains where visibility is compromised. By leveraging the unique properties of infrasonic elephant rumbles, PAM can identify acoustic signals encompassing a radius surrounding the microphone, even through dense foliage. One of the primary benefits of PAM is its ability to detect elephants over long distances. The low frequency of infrasonic rumbles can be detected over 3 km from the source, facilitating a large potential radius of measurement (Thompson et al. 2010; Mortimer et al. 2018; Hedwig et al. 2018). However, this radius is strongly influenced by factors such as foliage density, source amplitude, and ambient noise levels (Garstang 2004). For instance, dense foliage can attenuate acoustic signals, reducing the effective detection range (Baotic et al. 2018). Conversely, areas with minimal vegetation and low ambient noise can enable detection over longer distances (Garstang 2004).

The advantages of PAM over imaging techniques are multifaceted. Imaging is often constrained by directionality, requiring a clear line of sight between the camera and the subject. In contrast, PAM can detect acoustic signals from multiple directions, even when the microphone is not directly facing the elephant (Gibb et al. 2019). Furthermore, PAM is less affected by environmental factors such as lighting conditions, weather, and time of day, which can impact image quality and detection accuracy (Ross et al. 2023). The strategic placement of microphones is critical to the effectiveness of PAM. Researchers must carefully consider factors such as microphone sensitivity, array configuration, and terrain characteristics to optimize detection range and accuracy (Zeppelzauer & Stoeger, 2015). By combining PAM with other monitoring techniques, such as camera traps and GPS tracking, researchers can gain a more comprehensive understanding of elephant behavior, habitat use, and population dynamics. The potential applications of PAM extend beyond elephant conservation. This technology can be adapted for monitoring other wildlife species, such as birds, bats, and primates, which also rely on acoustic communication.

Passive Acoustic Monitoring (PAM) presents several technical challenges that must be addressed to effectively detect and classify elephant vocalizations (Bjorck et al. 2019). One of the primary challenges is the presence of background noise, which can interfere with event detection and species classification. Background noise can arise from various sources, including environmental factors such as wind, rain, and temperature fluctuations, as well as human activities like traffic and construction. Another significant challenge in PAM is the "cocktail party problem," which refers to the difficulty of separating individual calls from numerous simultaneous calls. This is a critical aspect of determining the number of elephants present at any given moment, as it allows researchers to estimate population sizes and track movement patterns (Brickson et al. 2023). However, this task remains a formidable challenge, particularly in areas with high levels of background noise or when multiple elephants are vocalizing simultaneously. To address these challenges, researchers are developing advanced signal processing techniques and machine learning algorithms that can effectively separate and classify elephant vocalizations. For example, researchers are using deep learning techniques like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to identify and classify elephant calls (Wassie Geremew & Ding 2023). These algorithms can learn to recognize patterns in the audio data and distinguish between different types of calls, even in the presence of background noise. Despite these advances, PAM still has limitations. One of the primary limitations is that elephants can only be detected when they are producing sound. This means that elephants that are not vocalizing may go undetected, which can lead to underestimates of population sizes or incorrect assumptions about movement patterns (Marques et al. 2013). To address this limitation, researchers are exploring the use of other monitoring techniques, such as camera traps and GPS tracking, to complement PAM and provide a more comprehensive understanding of elephant behavior and ecology. Furthermore, PAM is limited by the range and sensitivity of the microphones used to detect elephant vocalizations (Wrege et al. 2017). The range of the microphones can be affected by various factors, including the frequency of the calls, the density of the vegetation, and the presence of background noise (Darras et al. 2016). To address these limitations, researchers are developing new microphone technologies and deployment strategies that can improve the range and sensitivity of PAM systems.

Recent research from the Elephant Listening Project at Cornell University has made significant strides in applying Artificial Intelligence (AI) to Passive Acoustic Monitoring (PAM) for elephant call detection in the Congo Basin (Wrege et al. 2017; Keen et al. 2017; Bjorck et al. 2019; Sethi et al. 2020).

One study demonstrated a detector with reasonable performance, achieving a recall rate of 0.8 in identifying elephant rumbles in continuous wild recordings (Wrege et al. 2017). Another study yielded similar results, with a true positive score of 82% in detecting elephant calls in audio recordings (Keen et al. 2017). These studies have paved the way for the development of portable, low-power monitoring systems that can be deployed in the field for extended periods. By implementing AI-powered audio processing on embedded systems, researchers can transmit results in real-time, enabling more efficient and effective conservation efforts (Schwartz et al. 2021). This technology has far-reaching implications for monitoring elephant populations, tracking behavior, and detecting potential threats (Mwonzora & Mwonzora, 2024). Other notable research in elephant detection has employed innovative approaches, such as hidden Markov models, to detect elephants from continuous infrasonic rumble recordings with remarkable accuracy (97.6%) even in noisy environments (Venter 2009; Wijayakulasooriya, 2011). Additionally, Venter's work on elephant rumble detection using a Voice Activity Decoder achieved an impressive detection accuracy of 90.5% (Brickson et al. 2023). These advancements demonstrate the potential of AI-powered PAM to revolutionize elephant conservation and research. The integration of AI and PAM has also enabled researchers to explore new avenues in elephant behavior and ecology. For instance, studies have investigated the use of AI-powered PAM to analyze elephant vocalization patterns, providing insights into their social structure, behavior, and habitat use (Sharma et al. 2023). Furthermore, this technology has facilitated the development of more effective conservation strategies, such as identifying areas of high elephant activity and monitoring population dynamics.

Future research on elephant presence detection via Passive Acoustic Monitoring (PAM) can benefit from advanced data preprocessing methods to enhance species classification performance (Gibb et al. 2019). One area of focus is the development of more robust denoising techniques, which can eliminate non-critical events such as weather noise, making it easier to detect events of interest (Lykou et al. 2020). Techniques such as wavelet denoising, independent component analysis, and sparse coding have shown promise in improving the classification of whale clicks and songs and can be adapted for elephant call detection (Bermant et al. 2019; Allen et al. 2021). Another challenge in using PAM for elephant census purposes is determining the number of elephants present during an elephant call event (Wrege et al. 2024). When an elephant call is detected, multiple calls are sometimes present simultaneously, making it difficult to accurately count the number of individuals (elephant call is detected, multiple calls are sometimes present simultaneously, making it difficult to accurately count the number of individuals (Wrege et al. 2017). Deep learning source separation techniques can help address this issue by filtering the data to provide separate audio streams for calls from different sources (Bermant 2021). This approach has shown promise across various bio-acoustic datasets, including bird song and whale vocalization recordings (Bermant 2021). Unsupervised source separation techniques have also demonstrated success in improving classification performance and can be used to improve event detection (Wisdom et al. 2020; Bermant et al. 2022). Techniques such as non-negative matrix factorization and k-means clustering can be used to identify patterns in the audio data and separate out individual calls (Ghoraani & Krishnan 2011). Additionally, unsupervised learning methods such as auto-encoders and generative adversarial networks can be used to learn representations of the audio data that are more robust to noise and variability (De Albuquerque Filho et al. 2021).

The technology used for elephant detection can also be leveraged for conservation efforts by identifying potential threats to wildlife and their habitats. One such application is the detection of gunshots and chainsaws, which are indicative of poaching and habitat destruction.

While there is some existing research in this field, the current accuracy of these algorithms is not yet reliable enough to be used as a sole method for detection. However, there are some notable exceptions, such as the work done by (Wrege et al. 2017), which achieved an impressive recall rate of 0.94 for gunshot detection. This level of accuracy is promising for the development of effective conservation tools. Moreover, the use of Convolutional Neural Networks (CNNs) has shown potential in this field, with studies demonstrating the ability to detect gunshots and chainsaws with reasonable accuracy (Van der Merwe & Jordaan, 2013; Hrabina & Sigmund, 2015; Katsis et al. 2022). The integration of these technologies with elephant detection systems can provide a comprehensive conservation solution. By detecting potential threats and identifying elephant presence, conservationists can respond quickly and effectively to protect wildlife and their habitats. Furthermore, the use of machine learning algorithms can help to analyze patterns and trends in threat detection, providing valuable insights for conservation efforts (Tuia et al. 2022). To further improve the accuracy and reliability of these systems, researchers can explore the use of multi-modal sensing, which combines audio data with other sensor modalities, such as camera traps or seismic sensors (Wrege et al. 2017). This can provide a more comprehensive understanding of the environment and improve the detection of potential threats. Additionally, the development of more advanced machine learning algorithms and the use of transfer learning can help to improve the accuracy of threat detection systems.

- **Individual identification**

Research has shown that elephants possess the ability to identify other individuals from their vocalizations, and scientists have made significant progress in individual classification from audio data. A study employing a hidden Markov model with feature extraction achieved an impressive 83% accuracy in identifying individual elephants (Clemins et al. 2005). Moreover, advanced AI techniques have successfully identified individual lions from their roar recordings with remarkable accuracy, reaching up to 98% (Wijers et al., 2021; Trapanotto et al. 2022). These cutting-edge methods can be adapted to elephant data, potentially enhancing the accuracy of individual identification from audio. The application of these techniques is best suited for monitoring areas with a well-studied population, where audio data is labeled with the individual caller. This approach enables researchers to train machine learning models on a known population, allowing for more accurate identification of individuals (Duporge et al. 2021). By leveraging this technology, conservationists can gain valuable insights into elephant social dynamics, behavior, and population structure, ultimately informing more effective conservation strategies. The use of audio-based individual identification can also facilitate the monitoring of elephant movement patterns, habitat use, and social interactions. By analyzing the vocalizations of individual elephants, researchers can track their movements and behavior over time, providing a more comprehensive understanding of elephant ecology. Furthermore, this technology can be integrated with other monitoring methods, such as camera traps and GPS tracking, to create a more robust and accurate monitoring system. To further enhance the accuracy of individual identification, researchers can explore the use of multi-modal audio features, such as spectral and temporal characteristics, and machine learning algorithms, such as deep neural networks and clustering techniques (Shoumy et al. 2020). Additionally, the development of more advanced audio recording technologies, such as wearable sensors and drones, can provide higher-quality audio data and improve the accuracy of individual identification.

- **Full-spectrum ensemble audio monitoring**

The application of Artificial Intelligence (AI) in Passive Acoustic Monitoring (PAM) has primarily focused on detecting specific call types or frequencies, such as rumbles or trumpets, to identify elephant presence. However, to enhance detection capabilities, particularly near monitoring stations, it is advantageous to integrate a broader range of elephant vocalizations and frequencies into a single classification system. This comprehensive approach can improve detection accuracy by accounting for the diverse vocalization patterns exhibited by elephants (Brickson et al. 2023). By incorporating multiple call types and frequencies, the system can better capture the complexity of elephant communication, ultimately leading to more reliable detection of elephant presence. However, it is essential to acknowledge that estimating call production rates remains a significant challenge. This limitation renders the integrated classification system more suitable for detecting elephant presence rather than conducting accurate population censuring. Population censuring requires precise estimates of individual numbers, which is difficult to achieve with current PAM technologies. To address the challenge of accurate population censuring (Lumley et al. 2011), researchers can consider alternative approaches. One such approach is multi-modal sensing, which integrates Passive Acoustic Monitoring (PAM) with other sensing modalities, such as camera traps or GPS tracking, to gather complementary data. Additionally, advanced machine learning algorithms can be developed to account for variability in call production rates and provide more accurate estimates. Furthermore, acoustic data analysis can be employed to identify patterns and correlations in the data, ultimately informing population estimates.

- **Seismic monitoring**

Seismic signals, which involve the transmission of low-frequency vibrations through the ground, play a crucial role in elephant communication, with significant implications for conservation efforts. As previously discussed, elephants produce low-frequency audio vocalizations, known as infrasound, which can travel extensive distances of up to 3 km (Thompson et al. 2010; Mortimer et al. 2018). The emission of these infrasonic calls generates seismic waves that propagate through the ground, allowing elephants to detect these vibrations through bone conduction and specialized mechano-receptors in their feet (Günther et al. 2004; Bouley et al. 2007). This unique form of communication enables elephants to convey vital information over vast expanses of their habitat, including warnings about potential threats, herd movements, resource utilization, and reproductive status (O'Connell-Rodwell 2007; Reinwald et al. 2021). Moreover, elephants have demonstrated the ability to differentiate between the same seismic call type from different individual elephants, thanks to their capacity to discriminate frequency changes within a narrow bandwidth in the low-frequency spectrum (Narins et al. 2016). Research has shown that elephants can detect seismic signals with frequencies as low as 1-20 Hz, which is within the range of infrasound produced by elephant vocalizations (Vidunath et al. 2024). This suggests that elephants may be using seismic communication to convey information over long distances, potentially even between different herds or social groups (Langbauer 2000). The discovery of seismic communication in elephants has significant implications for conservation efforts. For instance, researchers can use seismic sensors to monitor elephant movements and behavior, providing valuable insights into their habitat use and social structure. Additionally, seismic communication can be used to develop novel methods for detecting and monitoring elephant populations, particularly in areas where visual observations are challenging.

Seismic monitoring offers a groundbreaking approach to conservation, presenting several exciting opportunities. Firstly, it provides an innovative means of detecting elephant presence, which could be highly beneficial for various applications, including population censuring, monitoring, corridor planning, and early warning systems to prevent Human-Elephant Conflict (HEC). This technology has the potential to revolutionize conservation efforts by providing accurate and reliable data on elephant presence and movement patterns (Anni & Sangaiah 2015). Secondly, seismic monitoring enables researchers to gain a deeper understanding of the social behavior surrounding seismic signals (Reinwald et al. 2021). By employing long-distance monitoring techniques that are minimally disruptive to the animal's environment, scientists can gather valuable insights into the complex social dynamics of elephant populations. This knowledge can inform conservation strategies and help mitigate human-elephant conflict. Furthermore, considering elephants' ability to discern caller identity from the same call, it is plausible that additional information on elephants can be extracted from seismic data analysis. This may potentially include details such as the size of the caller, the caller's identity, or even the caller's emotional state. By analyzing the unique characteristics of seismic signals, researchers may be able to develop a more comprehensive understanding of elephant behavior, social structure, and communication patterns. The integration of seismic monitoring with other conservation technologies, such as acoustic monitoring and camera traps, can provide a more complete picture of elephant ecology and behavior (Lahoz-Monfort & Magrath, 2021). This multi-faceted approach can inform conservation strategies and help protect elephant populations and their habitats. Additionally, the development of seismic monitoring technology can also have applications in the monitoring of other seismic-sensitive species, such as whales and dolphins, and can contribute to a broader understanding of the complex interactions between species and their environments.

- **Elephant detection**

Initial studies on seismic monitoring in elephants have primarily focused on analyzing their behavior and responses to seismic signals using geophone measurements (O'Connell-Rodwell 2007). However, seismic monitoring has also been proposed and implemented as a method for elephant population monitoring, encompassing both censuring and tracking (Wood et al. 2005; Anni & Sangaiah 2015; Reinwald et al. 2021; Parihar et al. 2022). This approach has shown promising results, with non-machine learning (ML) techniques achieving 85% accuracy in detecting elephant presence from seismic data for censuring purposes (Wood et al. 2005). Furthermore, continuous wavelet transforms have reached 90% accuracy in detecting forest elephants, highlighting the potential of seismic monitoring for population censuring (Parihar et al. 2021). Within the realm of machine learning, researchers have employed various algorithms to classify elephant calls from seismic measurements. For instance, support vector machines (SVMs) have achieved 73% accuracy, while neural networks have attained 87% accuracy (Fernando et al., 2020; Parihar et al. 2022). Convolutional neural networks (CNNs) have also demonstrated impressive performance, achieving 80-90% accuracy in detecting elephant calls up to 100 meters away (Szenicer et al. 2022). These results underscore the potential of seismic monitoring, combined with machine learning algorithms, for accurate and reliable elephant population monitoring. By leveraging these technologies, conservationists can gain valuable insights into elephant population dynamics, movement patterns, and behavior, ultimately informing more effective conservation strategies.

The application of Artificial Intelligence (AI) techniques for species classification and localization within seismic data presents a promising opportunity to enhance the accuracy of elephant censuring. As discussed earlier, elephant infrasonic calls are accompanied by corresponding seismic calls, each with its own mode of transmission.

Depending on environmental factors, either the audio or seismic signal may propagate more effectively, highlighting the importance of integrating techniques for elephant detection across both modalities (Mortimer 2017). By combining audio and seismic modalities, researchers can reduce noise and more accurately distinguish elephant sounds from background interference. This is particularly beneficial when the signal-to-noise level is low in both measurements, a common scenario encountered at extensive measurement radii (Sitzmann et al. 2018). Bi-modal detection can extend the effective detection range beyond that achievable by either audio or seismic monitoring alone, while also elevating the signal-to-noise ratio (SNR) without compromising the measurement radius (Brickson et al. 2023). The advantages of bi-modal detection become particularly pronounced in forested or densely vegetated regions, where acoustic waves face substantial attenuation (Günther 2004). In such environments, seismic monitoring can provide a more reliable means of detecting elephant presence, while audio monitoring can offer complementary information on elephant behavior and vocalization patterns (Keen et al. 2017). By integrating both modalities, researchers can develop a more comprehensive understanding of elephant ecology and behavior, ultimately informing more effective conservation strategies. The development of bi-modal detection systems can also be applied to other species that produce both audio and seismic signals, such as whales and dolphins (Risch et al. 2019). By exploring the intersection of audio and seismic monitoring, researchers can unlock new opportunities for advancing our understanding of animal behavior, ecology, and conservation.

The localization of elephants is a critical task in conservation efforts, and recent research has made significant progress in this area. A comparative study of seismic and acoustic localization methods revealed that seismic data provides improved localization accuracy (Reinwald et al. 2021). This is likely due to the fact that seismic waves can travel longer distances without significant attenuation, allowing for more precise location tracking (Reinwald et al. 2021). Furthermore, the combination of seismic and acoustic measurements offers a promising approach for localization, even with a limited array of sensors (Fernández-Ruiz et al. 2020). By leveraging the difference in speeds between seismic and acoustic waves, researchers can determine the distance of the elephant from the sensor array (Wijayaraja et al. 2024). This is achieved by measuring the delay between the seismic and acoustic signals, which requires knowledge of the soil composition (O'Connell-Rodwell 2000). By integrating these two modalities, conservationists can obtain more accurate location information, enabling effective tracking and monitoring of elephant populations. The multimodal approach to localization also offers advantages in terms of robustness and flexibility. By combining seismic and acoustic data, researchers can mitigate the limitations of each individual modality, such as the attenuation of acoustic signals in dense vegetation or the variability of seismic signals in different soil types (O'Connell-Rodwell 2000). This integrated approach enables the development of more reliable and adaptable localization systems, which can be tailored to specific environmental conditions and conservation goals.

The realm of behavior monitoring presents a vast and largely unexplored frontier in the study of elephant communication. O'Connell Rodwell's research group has made significant strides in deciphering the objectives of specific calls, such as those signaling an elephant's departure from a resource or indicating oestrus (O'Connell Rodwell 2007; Mortimer et al. 2018). These findings have laid the groundwork for further research into the complexities of elephant communication. Moreover, other researchers have successfully automated the classification of distinct behaviors through seismic measurements, including walking, running, and rumbling (Nissen-Meyer et al. 2018; Szenicer et al. 2022). This breakthrough has far-reaching implications for the study of elephant behavior, enabling scientists to monitor and analyze patterns of behavior over extended periods (Kays et al. 2015).

The integration of Artificial Intelligence (AI) in behavior monitoring offers substantial opportunities for further exploration and advancements (Brickson et al. 2023). By leveraging machine learning algorithms, researchers can develop more sophisticated models for classifying and interpreting elephant behavior. This, in turn, can provide valuable insights into the social dynamics, habitat use, and migration patterns of elephant populations. Furthermore, the application of AI in behavior monitoring can also facilitate the development of more effective conservation strategies. By analyzing patterns of behavior and communication, conservationists can identify potential threats to elephant populations, such as habitat fragmentation or human-wildlife conflict, and develop targeted interventions to mitigate these threats. Ultimately, the fusion of AI and behavior monitoring has the potential to revolutionize our understanding of elephant biology and conservation.

- **Future of seismic and acoustic monitoring**

The analysis of seismic or low-frequency sound data through frequency analysis presents a promising avenue for acquiring additional information about elephant populations. Drawing inspiration from studies in whale bio-acoustics, researchers have found that individual characteristics, such as body size, weight, age, and sex, can be inferred through the analysis of whale songs (Burnham 2017). The unique size and vocal cord properties of each caller generate distinctive sounds associated with various phenotypes and traits (Taylor & Reby 2010). Similarly, elephants have demonstrated the ability to discern between familiar and unfamiliar callers based on their seismic signals. Furthermore, the frequency characteristics of the seismic wave an individual can transmit are influenced by their body size (O'Connell-Rodwell 2007). This suggests that an individual's traits, such as body size, individual identity, sex, and age, can be deduced from their seismic call (O'Connell-Rodwell 2007). This area of research holds tremendous potential for monitoring efforts, particularly when combined with AI-powered analysis. The application of AI in this domain can enable researchers to develop more sophisticated models for analyzing seismic data and inferring individual traits. Machine learning algorithms can be trained on large datasets of seismic calls to identify patterns and correlations between call characteristics and individual traits. This can ultimately provide conservationists with a more detailed understanding of elephant population dynamics, social structure, and behavior. Moreover, the integration of seismic analysis with other monitoring technologies, such as camera traps and GPS tracking, can provide a more comprehensive picture of elephant ecology and conservation. By combining multiple data sources and leveraging AI-powered analysis, researchers can develop more effective conservation strategies and make more informed decisions about elephant management and conservation.

- **Olfactory monitoring**

Olfaction, or the sense of smell, is a vital component of an elephant's life, playing a crucial role in their daily activities, social interactions, and navigation. With an extraordinary sense of smell, elephants rely on their olfactory system for various purposes, including foraging, locating water sources, identifying herd members, communicating with other elephants, and navigating their surroundings (Rasmussen & Schulte 1998; Bates et al. 2008; Allen et al. 2021; Wood et al. 2022). The elephant's olfactory system is highly developed, boasting a large number of olfactory receptor genes and a sophisticated vomer-nasal organ (Rasmussen & Munger 1996; Cave et al. 2019). This complex system enables elephants to detect and interpret a wide range of chemical signals in their environment, including pheromones, scent marks, and volatile organic compounds (VOCs) (Soso et al. 2014).

By studying these chemical signals, researchers can gain valuable insights into elephant behavior, social structure, and reproductive strategies (Vidya & Sukumar 2005). One of the most significant applications of olfaction research in elephants is in the development of non-invasive monitoring techniques (Ball et al. 2022). By analyzing chemical signals, researchers can track elephant movements, identify individual animals, and even detect reproductive status. This information can be used to inform conservation efforts, such as habitat management, population monitoring, and human-wildlife conflict mitigation (Vidya & Sukumar, 2005). As our understanding of elephant olfaction continues to evolve, advances in measurement technology will provide new opportunities for monitoring chemical signals and their impact on elephant behavior. For instance, the development of portable, real-time VOC sensors could enable researchers to track changes in elephant behavior in response to different chemical cues (Baratchi et al. 2013). Furthermore, the integration of olfaction research with other monitoring technologies, such as camera traps and GPS tracking, could provide a more comprehensive understanding of elephant ecology and behavior.

The integration of Artificial Intelligence (AI) analysis with olfactory measurements during elephant behavior studies has the potential to revolutionize our understanding of elephant social interactions and decision-making processes. By examining the complex relationships between olfactory cues, behavior, and social dynamics, researchers can gain valuable insights into the intricacies of elephant communication and social structure (Shannon et al. 2013). One of the most significant implications of this research is the potential to mitigate Human-Elephant Conflicts (HECs) through the identification of effective odor deterrents (Natarajan 2024). By analyzing the olfactory cues that elephants use to communicate and navigate their environment, researchers can develop targeted strategies for deterring elephants from entering human-dominated landscapes. This could include the use of specific odorants or scent marks that signal to elephants the presence of humans or other potential threats (Valenta et al. 2021). However, the authors emphasize the importance of caution when applying these findings in real-world contexts. A thorough understanding of olfactory sensing in elephants is essential to ensure that any odor-based deterrents are used effectively and humanely (Brickson et al. 2023). Without a comprehensive understanding of the complex relationships between olfactory cues, behavior, and social dynamics, there is a risk of unintended consequences, such as disrupting elephant social structures or causing unnecessary stress and anxiety.

Historically, conducting olfactory measurements in the field has been a daunting task due to limitations in hardware technology. Current methods struggle to accurately detect the presence of specific particles in the air, hindering researchers' ability to study olfaction in elephants. Most studies on elephant olfaction have relied on controlled experiments, where elephants are exposed to a known chemical and their reactions are assessed. Alternatively, researchers have presented the same scenario to elephants with and without the chemical, attempting to isolate the effect of the specific odor (Rasmussen et al. 1998; Bates et al. 2008; Taylor & Reby 2010). However, this approach has significant limitations. Researchers must first identify a particular chemical of interest, which can be a costly and time-consuming process. Furthermore, testing the effects of this chemical on elephant behavior can be expensive and may not yield comprehensive results. The incorporation of Artificial Intelligence (AI) into molecular sensing technology has the potential to revolutionize the field of olfactory research. By leveraging AI-powered molecular sensing, researchers can access a more extensive dataset for understanding elephant behavior. This technology enables the detection and identification of various particles and chemicals in the air, providing a more comprehensive understanding of the olfactory cues that influence elephant behavior.

With AI-driven analysis, researchers can uncover patterns and correlations that may have gone undetected using traditional methods. The integration of AI into molecular sensing technology also offers several practical advantages. For instance, it enables researchers to conduct studies in real-time, without the need for controlled experiments or prior knowledge of specific chemicals. This can significantly reduce the cost and complexity of olfactory research, making it more accessible to a wider range of scientists and conservationists. Ultimately, the fusion of AI and molecular sensing technology has the potential to transform our understanding of elephant olfaction and behavior (Ball et al. 2022). By providing researchers with a more extensive and accurate dataset, this technology can inform more effective conservation strategies and promote a deeper appreciation for the complex social behaviors of elephants.

- **AI enhanced chemo-sensors**

An electronic nose (e-Nose) or chemo-sensor is a cutting-edge device designed to replicate the complexities of the biological olfactory system. This innovative technology enables the detection and identification of a wide range of chemical compounds and odors present in the surrounding environment. Although significant progress has been made in developing sensors that mimic biological olfactory systems, interpreting the data from these sensors remains a formidable challenge (Cave et al. 2019). Recent breakthroughs have successfully applied Artificial Intelligence (AI) to interpret measurements from chemo-sensors, achieving reasonable results in inferring the presence of specific chemicals in the air (Gardner et al. 1990; Fu et al. 2007; Meléndez et al. 2022). However, most existing research has focused on inanimate sensors based on metal oxides or polymers, which have inherent limitations in terms of detection capabilities (Brickson et al. 2023). The next frontier in this field involves applying Machine Learning (ML) techniques to data from biological chemo-sensors, which utilize biological materials identical to those found in mammalian noses (Cave et al. 2019). This emerging area of research holds tremendous promise for revolutionizing olfaction sensing (https://cloud.google.com/blog/products/aimachine-learning/how-osmo-isbringing-ai-to-aromas). The potential impact of this technology is further underscored by Google Inc.'s recent investment in a startup focused on developing AI-powered olfaction sensing. As research in this field continues to advance, it is expected to yield more portable, user-friendly systems with enhanced specificity for identifying air particulates (Meléndez et al. 2022). These innovations will have far-reaching implications for various applications, including environmental monitoring, healthcare, and conservation biology (Chen et al. 2024). One of the most significant advantages of biological chemo-sensors is their potential to detect a wider range of chemical compounds, including those that are more complex or nuanced (Winfield et al. 1991). By leveraging the unique properties of biological materials, researchers can develop sensors that are more sensitive and selective, enabling the detection of specific chemicals in real-time. This capability will be particularly valuable in fields such as conservation biology, where the ability to monitor and track chemical signals can provide critical insights into animal behavior and ecology. As the field of AI-powered olfaction sensing continues to evolve, it is expected to enable new applications and opportunities for innovation.

The enhanced precision in detecting airborne particulates, facilitated by the integration of AI and biological chemo-sensors, will empower researchers to explore the intricacies of olfactory cues in shaping elephant behavior. This breakthrough will enable scientists to gain a deeper understanding of elephant responses to various stimuli, ultimately informing more effective conservation strategies.

One of the most exciting potential applications of these high-precision measurements lies in unraveling the influence of olfactory cues on elephants' migratory patterns (Strickler 2019). While it is well-established that elephants can detect water sources through scent, other species, such as birds and sea turtles, are known to rely on chemical cues for navigation (Papi 1989; Wood et al. 2022). The question remains as to whether elephants also utilize similar cues to inform their migratory decisions. The development of advanced olfactory sensing technologies, powered by AI, offers a unique opportunity to investigate this phenomenon (French et al. 2018). By analyzing the chemical composition of the air in various environments, researchers can identify specific olfactory cues that may be influencing elephant migration patterns (Wood et al. 2022). This knowledge can, in turn, inform the development of more effective conservation strategies, such as the creation of protected corridors that take into account the role of olfactory cues in shaping elephant migration (Wood et al. 2022). Furthermore, the integration of AI-powered olfactory sensing with other technologies, such as GPS tracking and camera traps, can provide a more comprehensive understanding of elephant migration patterns. By analyzing the complex interplay between olfactory cues, environmental factors, and elephant behavior, researchers can develop more nuanced and effective conservation strategies that take into account the intricate needs and behaviors of these majestic creatures.

- **Olfactory deterrents for human–elephant conflict mitigation**

The identification of specific chemicals that elephants find aversive can be a game-changer in conservation efforts. By harnessing the power of olfactory deterrents, researchers can develop innovative solutions to minimize Human-Elephant Conflicts (HECs). For instance, certain smells can be used to create barriers around crops, deterring elephants from raiding and reducing crop damage. Some creative approaches have already been explored, such as using bees and chili peppers as deterrents (King et al. 2007; King et al. 2009; Davies et al. 2011). These methods have shown promise in protecting both humans and elephants from potentially dangerous encounters. However, it is essential to acknowledge that some elephants may become habituated to these deterrents over time, reducing their effectiveness. Moreover, the success of these deterrents can be influenced by various factors, including the local environment, weather conditions, and the availability of alternative food sources for elephants (Shaffer et al. 2019). For example, if alternative food sources are scarce, elephants may be more motivated to overcome deterrents and access crops (Sach et al. 2019). Similarly, changes in weather conditions or environmental factors may affect the potency of deterrents. To overcome these limitations, research into the elephant olfactory universe is crucial. By gaining a deeper understanding of the complex relationships between elephants, their environment, and the chemicals they detect, researchers can develop far subtler and effective ways to reduce HECs. This knowledge can inform the development of novel deterrents that are tailored to specific contexts and environments, reducing the likelihood of habituation and increasing their overall effectiveness (Brickson et al. 2023). Furthermore, advances in olfactory research can also enable the development of more targeted and humane conservation strategies. For instance, researchers may be able to identify specific chemical cues that can be used to redirect elephants away from human-dominated landscapes and towards more suitable habitats. By leveraging the power of olfaction, conservationists can develop innovative solutions that prioritize both human safety and elephant well-being.

DISCUSSION

This review has highlighted the vast potential of Artificial Intelligence (AI) and Machine Learning (ML) methods in enhancing elephant monitoring and conservation efforts. However, the key to unlocking this potential lies in fostering a consistent and long-lasting collaboration between the fields of conservation and AI. The disparate pace of advancements in these two fields presents a significant challenge. AI is rapidly evolving, with new breakthroughs emerging frequently, whereas elephant studies require prolonged periods of observation, experimentation, and adaptation to establish trust with subjects and account for environmental constraints. To overcome this challenge, collaborative efforts must extend beyond mere data collection and application of AI tools. Instead, researchers should engage in cyclical processes of data exploration, transformation, analysis, interpretation, and communication. This iterative approach will facilitate a deeper understanding of the complex relationships between elephant behavior, ecology, and conservation. From a conservation perspective, clear goal-setting, well-defined research objectives, and staying abreast of technological advancements relevant to the work are essential. Conservationists must be willing to adapt their approaches as new AI tools and methods become available. Conversely, AI professionals must be involved in discussions on data collection from the outset, gaining a comprehensive understanding of the practical challenges and timelines associated with fieldwork. This includes recognizing the importance of establishing trust with elephant subjects, navigating environmental constraints, and accommodating the prolonged periods required for data collection.

This review has unequivocally demonstrated the vast potential of Artificial Intelligence (AI) in enhancing elephant research and monitoring. AI's applications span a broad spectrum, from facilitating data collection and curation to deriving meaningful representations of data and generating novel scientific hypotheses. However, it is essential to acknowledge the specific contexts where AI excels and its inherent limitations. AI and Machine Learning (ML) methods typically thrive in scenarios characterized by extensive datasets and well-defined research questions. Their core strength resides in pattern recognition, which enables them to identify complex relationships within datasets. Supervised learning, for instance, targets predefined patterns that researchers aim to detect, whereas unsupervised learning endeavors to uncover the inherent structure, pattern, or characteristics of a dataset. Moreover, AI is particularly efficient in scenarios requiring consistent and repetitive computation, especially when working with standardized or normalized datasets. This enables researchers to automate tedious tasks, such as data processing and feature extraction, and focus on higher-level analysis and interpretation. However, AI may not be the ideal solution for more ambiguous or heterogeneous data situations. In such cases, the complexity and nuance of the data may require more traditional, human-centric approaches to analysis and interpretation. Furthermore, AI's reliance on pattern recognition can sometimes lead to oversimplification or misinterpretation of complex phenomena. Therefore, researchers must carefully consider the strengths and limitations of AI when designing studies and analyzing data. By acknowledging the contexts in which AI excels and those in which more traditional approaches are more suitable, researchers can harness the full potential of AI in elephant research and monitoring while avoiding its pitfalls. Ultimately, the effective integration of AI in elephant research requires a deep understanding of both the technical capabilities of AI and the complex biological and ecological phenomena being studied. By fostering a culture of interdisciplinary collaboration and knowledge-sharing, researchers can unlock the full potential of AI in advancing our understanding of elephant biology and conservation.

- **Transfer learning**

The development of robust models for elephant recognition in various environments is a challenging task. One of the primary difficulties lies in the models' inability to transfer to new environments, where environmental background features and unfamiliar species can significantly impact performance (Beery et al. 2018; Beery et al. 2019). To address this issue, researchers have explored several strategies that do not require the collection and annotation of new datasets in the field. One such approach involves the use of simulated data to broaden the training dataset. This technique has shown promising results, as it allows models to learn from a wider range of scenarios and environments (Beery et al. 2020). Another strategy involves creating more general models that exhibit robustness across multiple environments. These models can then be fine-tuned for specific tasks of interest, enabling them to adapt to new environments with greater ease (Beery et al. 2019). A notable example of this approach is the Mega-detector tool, which has demonstrated an impressive ability to detect animals in camera trap images across various environments (http://github.com/ecologize/CameraTraps). Self-supervised or unsupervised methods offer an alternative approach to training models, enabling dataset expansion without the need for labels. These methods can be particularly useful when working with large datasets, where manual annotation may be impractical or impossible. The development of more robust and transferable models has significant implications for elephant conservation efforts. By enabling researchers to detect and track elephants across various environments, these models can provide valuable insights into elephant behavior, habitat use, and population dynamics (Brickson et al. 2023). Moreover, the ability to adapt models to new environments can facilitate the development of more effective conservation strategies. For instance, models can be used to identify areas of high conservation value, monitor the impact of human activities on elephant habitats, and develop targeted interventions to mitigate human-elephant conflict. Ultimately, the creation of robust and transferable models requires a multidisciplinary approach, combining expertise in AI, ecology, and conservation biology. By working together, researchers can develop innovative solutions that address the complex challenges facing elephant conservation efforts.

- **Self-supervised and unsupervised methods**

The widespread adoption of Artificial Intelligence (AI) in conservation efforts is hindered by the significant costs associated with data collection and annotation. The majority of AI techniques, including those reviewed in this paper, rely on supervised training, which requires extensive data annotation for effective model training. This labour-intensive process can be prohibitively expensive, particularly in resource-constrained fields like conservation. However, a promising solution to this challenge lies in the development of self-supervised and unsupervised learning methods. These AI techniques can automatically discover patterns and structure within datasets without relying on labelled data. This approach eliminates the need for human annotation, significantly reducing the costs associated with data collection and annotation. Recent advances in self-supervised learning have shown remarkable promise. For instance, self-supervision in images enables models to learn valuable information from images and videos automatically (Grill et al. 2020; Caron et al. 2021). Similarly, unsupervised methods have improved and automated bio-acoustics analysis of Passive Acoustic Monitoring (PAM) datasets without requiring labelled data (Wisdom et al. 2020; Bermant et al. 2022). Innovative techniques have also emerged for animal behaviour monitoring using unsupervised methods, eliminating the need for labels.

These approaches have the potential to revolutionize the field of conservation biology by providing novel insights into animal behaviour that may elude human consideration. As self-supervised and unsupervised learning methods continue to advance, they will play an increasingly important role in conservation efforts. By reducing the costs associated with data collection and annotation, these methods will enable researchers to allocate resources more efficiently, focusing on high-impact conservation projects rather than labor-intensive data annotation tasks. Moreover, the integration of self-supervised and unsupervised learning methods with other AI techniques will enable the development of more robust and generalizable models. These models will be better equipped to handle the complexities and nuances of real-world conservation challenges, providing more accurate and reliable predictions and insights. Ultimately, the future of AI in conservation biology lies in the development of innovative, cost-effective, and efficient solutions that can be widely adopted by researchers and conservationists. Self-supervised and unsupervised learning methods are poised to play a critical role in this endeavor, enabling the conservation community to harness the full potential of AI in advancing the protection and preservation of biodiversity.

CONCLUSIONS

The emergence of Artificial Intelligence (AI) techniques has revolutionized the field of elephant monitoring and conservation. AI-based methods in various modalities, including imaging, video, audio, seismic, and olfactory sensing, have demonstrated significant advancements, offering more sophisticated and efficient alternatives to traditional monitoring methods.

These AI-powered monitoring techniques have the potential to enhance the accuracy and efficiency of elephant behavior studies, automate data labeling and analysis, and detect nuanced behaviors or patterns that may elude human observers. Furthermore, the ongoing development of novel data capture hardware systems, such as drone monitoring and olfactory measurement, generates a vast array of data that can be harnessed to create powerful AI analysis tools. However, advancing these AI models requires consistent collaboration between AI specialists and conservationists. Some methods, tools, and analyses will need to be uniquely tailored for elephant research, addressing specific needs such as identifying individual elephants. Input from elephant experts is essential in this regard, as relying solely on adjusting general models will not be adequate for these specialized needs. Despite the promise of AI in elephant conservation, challenges remain. Transferring AI models to new environments can be difficult, and the high cost of data collection and annotation, combined with the limitations of supervised learning techniques, poses significant obstacles. To address these challenges, future research should focus on strategies such as using simulated data, fine-tuning pre-trained models, and employing self-supervised or unsupervised techniques.

The integration of various modalities in future work can provide a comprehensive understanding of the stimuli that elephants encounter and their perception of their environment. This can aid in understanding how elephants make decisions, ultimately informing more effective conservation strategies. In conclusion, AI offers significant advancements in animal monitoring, with elephants being particularly well-suited for the application of these techniques. As AI applications in this domain evolve and challenges are addressed, our understanding and protection of elephants will improve. This not only supports the longevity of elephants and their habitats but also paves the way for technologies that could aid broader conservation initiatives. The potential impact of AI on elephant conservation extends beyond the realm of research and monitoring.

AI-powered tools can also be used to develop more effective conservation strategies, such as identifying high-priority areas for habitat preservation and developing targeted interventions to mitigate human-elephant conflict. Moreover, the development of AI-powered monitoring systems can provide a platform for engaging local communities in conservation efforts. By providing real-time data on elephant behavior and habitat use, these systems can enable local communities to take a more active role in conservation, promoting a sense of ownership and stewardship. Ultimately, the future of AI in elephant conservation is bright, with vast potential for innovation and impact. As researchers, conservationists, and AI specialists continue to collaborate and push the boundaries of what is possible, we can expect to see significant advancements in the protection and preservation of these majestic creatures.

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