SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I8P103

Volume 13 Issue 8, 40-51, August 2026
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Review Article

Artificial Intelligence-Driven Anti-Poaching Surveillance Systems: A Review of Advances, Challenges, and Future Directions

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Received: 07 May 2026 Revised: 11 June 2026 Accepted: 15 July 2026 Published: 31 August 2026

Abstract - *The UN Environment Programme reports an average 69% decline in wildlife population since 1970, with around 4000 species illegally poached, trafficked, and traded globally. The World Wildlife Crime Report shows a significant population revival for certain species, but overall protection remains inadequate. The 5-step approach to understanding wildlife decline can improve methods. Emerging smart technologies, such as computer vision, IoT systems, and AI, can help manage wildlife populations and prevent poaching. Drones, bio-loggers, camera traps, and GPS collars provide real-time data for wildlife monitoring and tracking. Unmanned Aerial Vehicles (UAVs) have also shown promise in wildlife welfare. This article aims to analyze the decline of wildlife populations, study smart technologies for anti-poaching efforts, and evaluate emerging technology-driven solutions to traditional wildlife welfare challenges. Human-induced factors like hunting, poaching, pollution, and habitat loss have compromised biodiversity. Poaching has led to population reduction and ecological imbalance. Traditional conservation practices have failed to revive wildlife populations. Integrating smart technologies, IoT, AI, and predictive analysis can help prevent poaching and promote ecological balance.*

Keywords - *Wildlife welfare, Internet of Things, Ecology, Artificial Intelligence, Machine Learning, Anti-Poaching, Innovation.*

1. Introduction

The Sustainable Development Goal 15: Life on Land urges the world to come together and revive, support, and safeguard the world's remaining terrestrial ecosystems. Target 15.7 especially talks about taking strict measures and quick action against the poaching and trafficking of any species of flora and fauna [1]. According to the latest report backed by the UN Environment Programme (UNEP), the ecological system has seen an average 69% decline in wildlife population since 1970 [2]. The UN's World Wildlife Crime Report data shows that although there has been a significant population revival for certain wildlife fauna, elephants, rhinos, etc, the overall protection of all flora and fauna has not improved. Across 162 countries, roughly 4000 flora and fauna have been illegally poached, trafficked, and traded across the globe [3]. However, scientific knowledge of wildlife decline has been done on incomplete data, as the data are recent. Historical data have not been taken into consideration, which can be a key to conservation. To understand and reverse the decline in wildlife species, the 5-step approach: historical, counting, evolutionary, geochemical, and correlation can improve these methods [4]. It has been set that a minimum of about 5000 adult individuals is needed for any species long-term survival and to maintain a sufficiently large population that retains genetic diversity and reduces extinction risk in a changing environment [5]. Animals play an integral part in our lives, be it a house pet or terrestrial wildlife. The responsibility of their health, safety, and welfare falls on us, as we are the reason for their declining populations, through hunting, poaching, etc. The era of emerging smart technologies can support in achieving that goal, by utilizing Computer Vision in camera traps, IoT systems in GPS collars, drones, and Artificial Intelligence (AI) and Machine Learning (ML) in analyzing this large-scale data, which has given a promising solution to build on [6, 7]. Leveraging data analytics in wildlife management through the use of an AI algorithm to detect potential threats, population, migratory patterns, etc, and release a proactive management strategy. For continuous monitoring and tracking of wildlife, and providing real-time data, Drones, Bio-loggers, camera traps, and GPS collars demonstrate significant improvements in wildlife welfare [8-10]. The United Nations and Interpol's 2014 report reported a $213 billion illegal trade of global species of flora and fauna, which also helps create armed unrest. New technologies offered new opportunities via the use of Unmanned Aerial Vehicles (UAVs), which came to the rescue. Equipping the

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UAVs with thermal imaging, which is combined with real-time video processing, a vision-based face detection algorithm, and GPS, gave promising results [11, 12]. The objective of this article is:

- To analyse the reasons and effects of the declining wildlife population.
- To study the use of smart technologies in battling against anti-poaching.
- To assess emerging technology-driven solutions against traditional challenges in wildlife welfare.

The manuscript organization of this article contains the Reasons for Wildlife Population Decline in section 2, Leveraging Smart Technologies as a Modern Approach to Problem-Solving in section 3, Combating Smart Technologies against Poaching in section 4, Legal and Ethical Governance of Smart Anti-Poaching Surveillance Systems in section 5, Recommendations are in section 6, and section 7 contains the Conclusion.

2. Reasons for Wildlife Population Decline

Decline in wildlife in and surrounding urban cities can be caused by multiple factors. Introducing foreign animal species takes a toll on the animals of their natural habitats, as the loss of their natural habitats amplifies their decline. Ignoring the long-term habitat loss triggers a direct and indirect chain of reaction that affects the survival of wild animals [13, 14]. Human behaviors and activities have caused wildlife to change their behavior and course, which could have an impact on the ecosystem and their population [15, 16]. Human-wildlife conflicts have been rising since the expansion of the urban landscape into wildlife habitats. To combat wildlife-human conflicts, compensating farmers and pastoralists to reduce the hunting of wild animals for damages caused to their livestock by wild animals can, inversely, trigger a boom in agricultural expansion, which will increase habitat conversions. Seeing wildlife as a threat to people's livelihood, they have been hunted and poached in the name of safety, causing wildlife damage [17, 18]. A new method of identifying rapid decline in wild animals shows that the human-imposed pressure points cause a decline in wildlife populations. These pressure points, such as the overexploitation of large-bodied animals, deforestation, or fragmentation causing habitat loss, disease outbreaks, genetic contamination, and pollution, are primarily driven by human-derived exploitation, which is the biggest reason for this decline [19]. Human interference with the ecological system by introducing predatory species into a new habitat results in increased mortality of medium and small-sized animals. Other human interferences, such as reduced building infrastructure, habitat productivity, overharvesting, diseases, and grazing, have caused severe mortality rates in animals [20, 21]. The common crime against wildlife is when animals are brutally poached for glamour and profit, risking their survival, in turn unbalancing the ecosystem. This illegal 9-20-billion-dollar industry may have fed some of the poorest people in the corner of the world, but it has also pushed the animals towards extinction. To stop this, proper policies to ensure the well-being of not just those poor people but also of animals, by incentivizing local communities [22, 23]. Setting up Integrated Conservation and Development Projects (ICDPs) that aim to provide support to local communities and protect wildlife cannot prove to be successful efficiently, as the park manager earns through hunting and tourism, local communities suffer from wildlife loss as they hunt for food and income [24]. The rising poverty, poaching incentives, and high wildlife prices have created organized crime rings despite investing high amounts in enforcing the anti-poaching policies and systems. A broader and long-term solution to combat the poaching problem is required [25, 26], as illustrated in Figure 1.

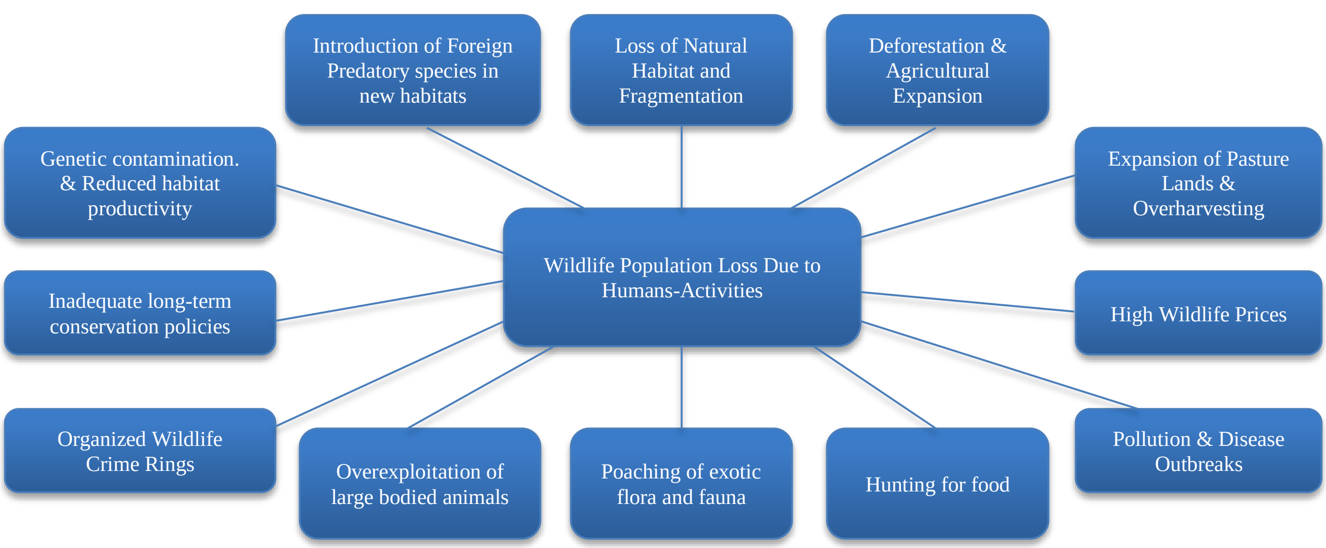

Fig. 1 Human activities that resulted in wildlife population decline

3. Smart Technologies as a Modern Approach to Problem Solving

The future of the internet is connecting physical things to a wide web of networks that exchange their information and their surroundings' information. This generates loads of data that is easily accessible and leads to innovation, increased productivity, and efficiency [27, 28].

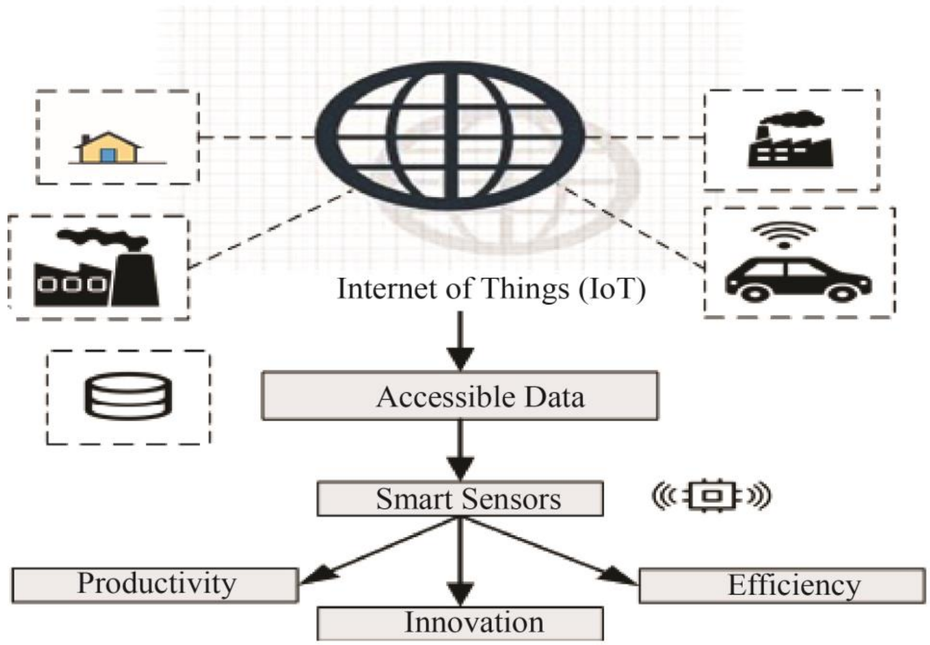

Fig. 2 Integration of IoT and smart sensors

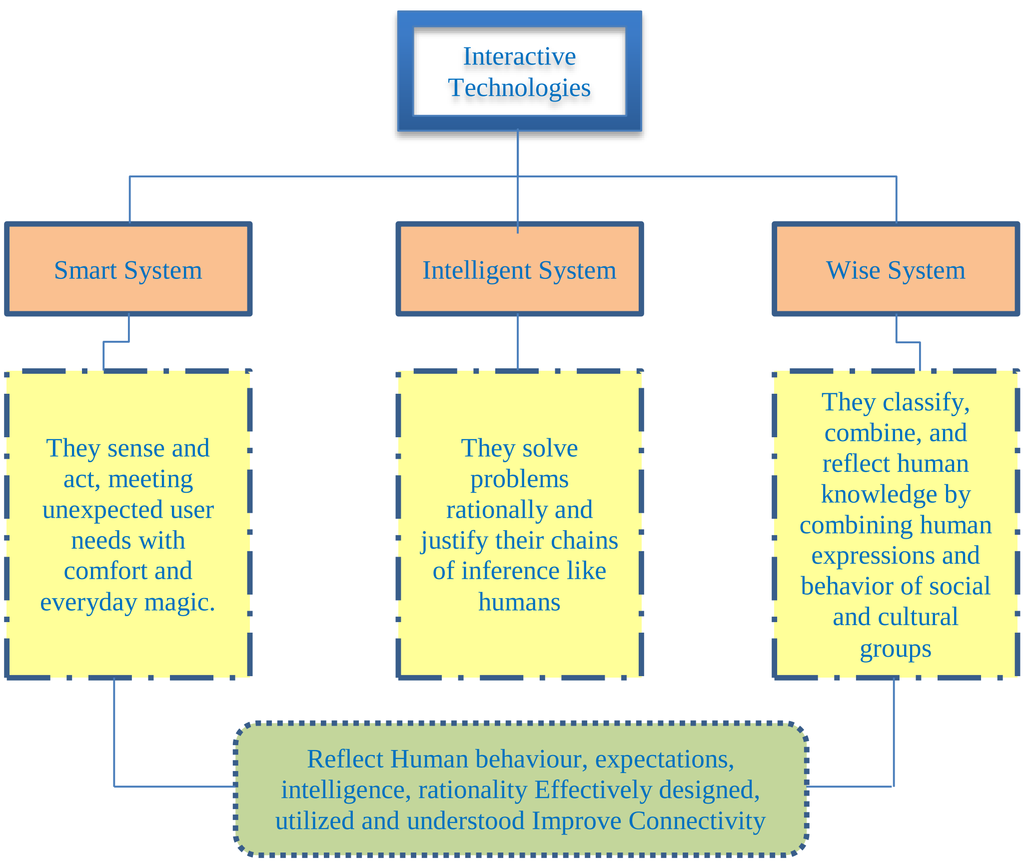

Fig. 3 Types of interactive systems and media

Industry 4.0 brought advancement and development of smart sensor technology, which enables actionable, real-time, and smart insights. With the use of machine learning and AI, the future of smart sensors is more advanced and efficient, while becoming critical for a variety of industries [29-31], as shown in Figure 2. The development of computer-based interactive learning has been called "smart", "intelligent", and "wise". When these interactive systems reflect human intelligence, behavior, expectations, and rationality, they improve connectivity, are effectively designed, understood, and utilized across various sectors [32], as detailed in Figure 3.

To create more resilient and agile governance, the smart government urges the use of innovative technologies and emerging technologies. Adopting these smarter technologies makes their cities more connected, more innovative, more efficient, more transparent, and more sustainable, making a smarter and more responsive system [33, 34]. The cities suffer a lot of challenges from the growing populations, and IoT technologies, clubbed with AI, create an efficient connectivity with various aspects [35]. To protect wildlife from human conflicts, instead of using traditionally unsustainable methods that harm biodiversity, utilize AI-driven deep learning, combined with IoT technology to enhance both biodiversity conservation and agricultural productivity [36-38].

4. Combating Smart Technologies Against Poaching

To let the wildlife roam free and yet protect them from poachers calls for taking smart solutions. To keep track of wildlife population, camera traps are used, but it takes a lot of time to filter through these videos. Hence, a deep learning automated 3-step process, i.e., using Megadetector that splits videos into images to detect, then Faster R-CNN with Inception-ResNet-v2 to enhance Megadetector for identifying species, and conclude with counting individual detected species based on bounding boxes. Such potential of AI has been found through years of investigation, which has been later applied in aiding diverse tasks [39, 40].

Classifying wild animals through videos, as compared to image-based methods, is used with the help of a Deep Residual Convolutional Neural Network (DRCNN), which is then integrated with the Tree Seed Optimization (TSO) algorithm that is pre-processed on a Fast Average Peer Group (FAPG) filter, and has shown more efficiency than the traditional methods [41]. Large animals, especially tigers, elephants, rhinos, etc, are a direct threat to poaching. Employing smart technology, such as the Comprehensive Anti-Poaching tool with Temporal and observation Uncertainty Reasoning (CAPTURE) that anticipates poachers and combats poaching. By leveraging game-theoretic algorithms, it optimizes planned patrolling and strategies [42, 43]. Traditionally, in South Africa's Kruger National Park, the methods used to combat rhino poaching were low-quality and incomplete data dispersed over a large area, resulting in limited success. Artificial intelligence tools such as Bayesian networks contribute to resource plundering and poaching by integrating limited data with expert knowledge. It is structured as a casual network that provides reasoning on scenarios, based on which helps identify key data [44], as shown in Figure 4.

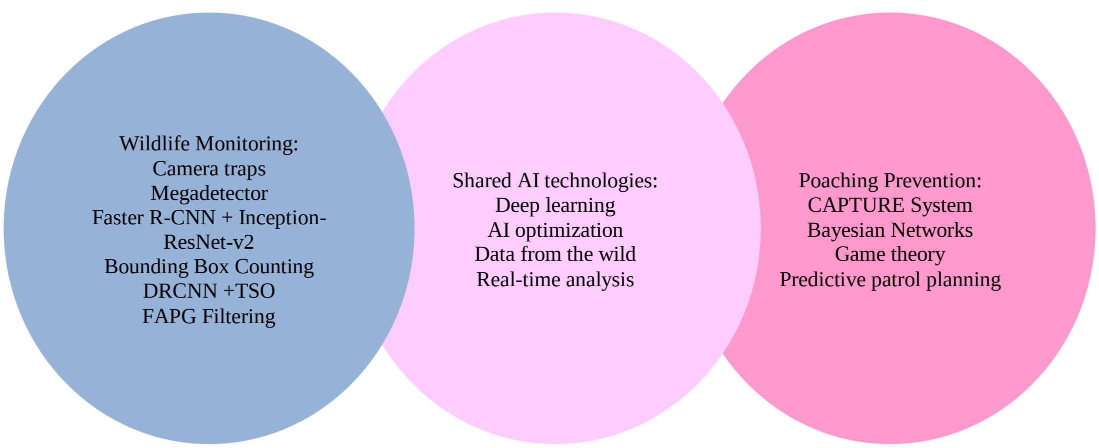

Fig. 4 Implementing AI technologies for wildlife monitoring and poaching prevention

In 2016, a rhino was poached every 8 hours. 95% of black rhinos were hunted and poached between 1960 and 1990. The different technologies used in Anti-Poaching Systems (APS) are categorized into four types: perimeter-based technology, Ground-based technology, Aerial-based technology, and Animal-tagging technology, as depicted in Figure 5.

These technologies are integrated with various types of sensors; each tailored specifically for anti-poaching strategies.

This novel type of APS, combined with sensor deployment, yields enhanced ecological safety, response time, and detection accuracy, as illustrated in Figure 6 [45, 46].

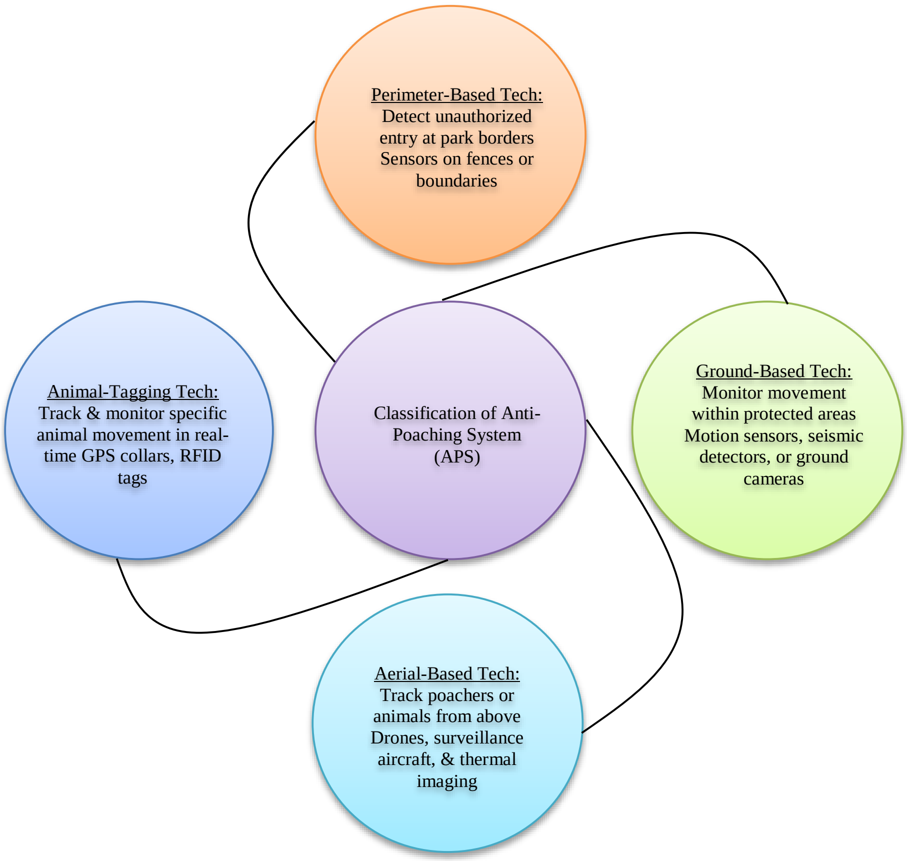

Fig. 5 Types of Anti-Poaching Technologies (APS)

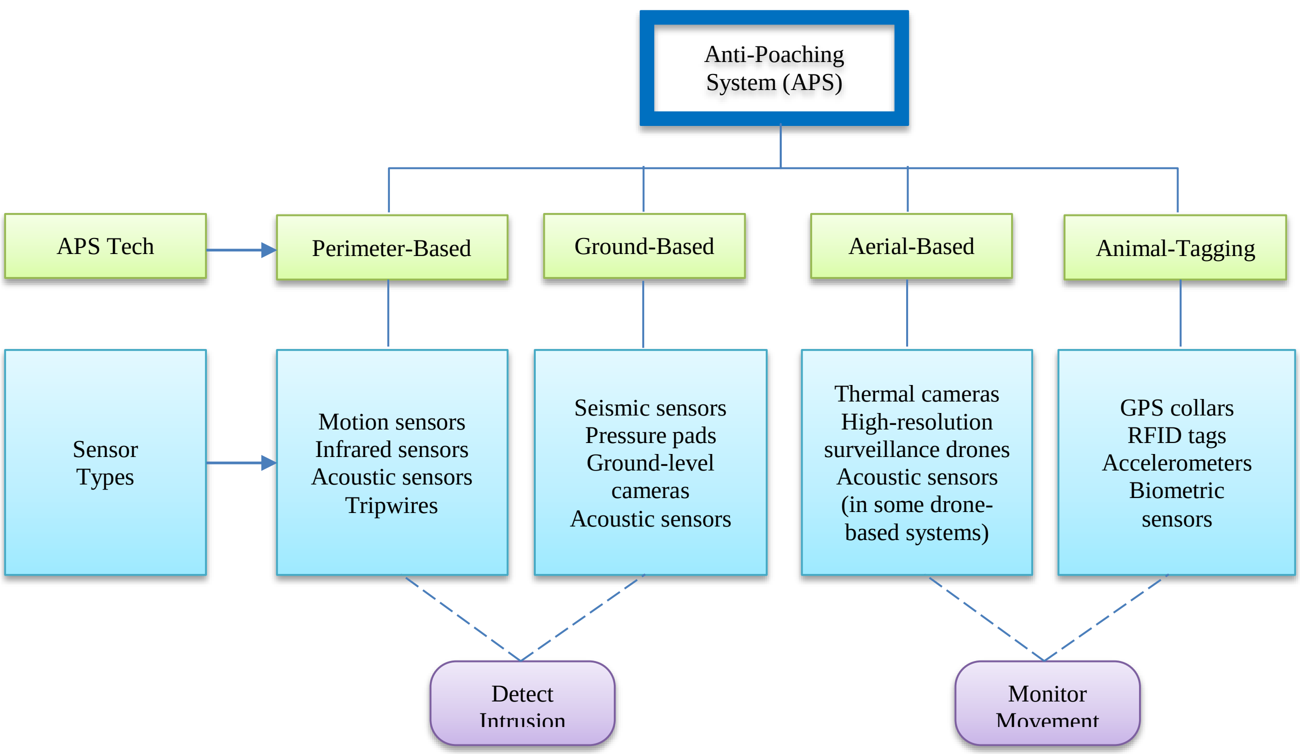

Fig. 6 Types of sensors used in APS

Adopting multimedia data mining and an advanced video surveillance system, and review the 4 techniques together that use different technologies to build a more unified and stronger model. The four techniques that were reviewed used technologies such as Region-based Convolutional Neural Network (R-CNN), Spatial Pyramid Pooling Network (SPP-Net), You Only Look Once (YOLO), and Single Shot Multibox Detector (SSD) for object detection, finding animals, and poachers. Then, to identify detected objects, Decision Tree, Support Vector Machine (SVM), and Neural Networks were used. Hidden Markov Model (HMM), Dynamic Time Warping (DTW), and Self-Organizing Maps (SOM) are used to understand how the detected object moved. Moreover, for identifying poachers entering protected areas, Negative Selection Algorithm (NSA), CNN, RNN, and Game Theory Models, such as Protection Assistant Wildlife Security (PAW) and Comprehensive Anti-Poaching Tool with Uncertainty Reasoning and Evidence (CAPTURE) technologies are used [47-50], refer to Figure 7.

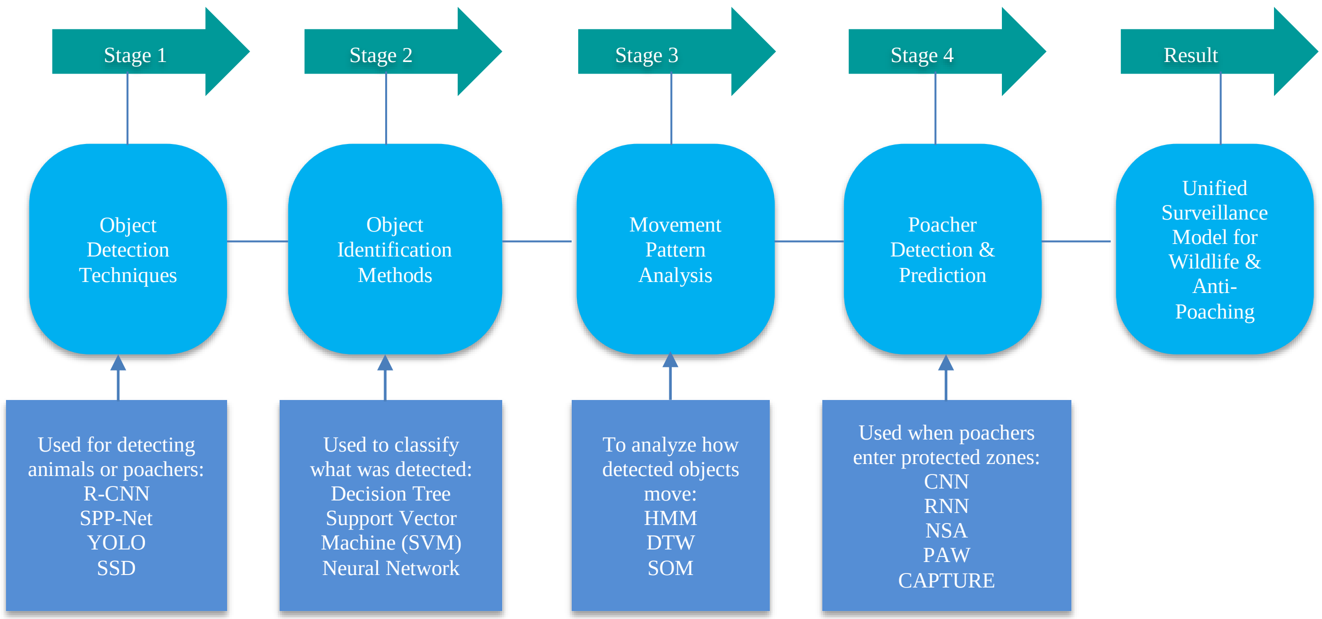

Fig. 7 Workflow of multimedia data mining techniques for Wildlife protection and poacher detection

The constant monitoring of the threatened species requires modern technology for protection from poachers. In the Zimbabwe Parks and Wildlife Management Authority (ZPWMA), they adopted the Spatial Monitoring and Reporting Tool (SMART) for monitoring species, collecting data, and developing strategic law enforcement patrols for adaptive management in protecting biodiversity [51, 52], as summarized in Table 1.

Table 1. Wildlife monitoring and Anti-Poaching technologies

Technology System	Core Method use	Purpose
Inception-ResNet-v2 Megadetector + Faster R-CNN [39, 40]	object detection with enhanced species identification and image splitting, deep learning.	Automation of wildlife identification from camera trap videos, bounding box count of individual species.
DRCNN + TSO + Filter FAPG [41]	Tree Seed Optimization (TSO) algorithm pre-processed with FAPG filter, Deep Residual Convolutional Neural Network (DRCNN)	More efficient than traditional image-based methods, as it classifies animals in video sequences.
Comprehensive Anti-Poaching tool with Temporal and observation Uncertainty Reasoning (CAPTURE) [42, 43]	Game-theoretic algorithms with observational and temporal uncertainty reasoning.	Support patrol planning, predict poacher behaviour, and combat poaching more efficiently.

Bayesian Network Model [44]	Casual reasoning is driven by experts with limited data integration.	Identifies crucial patterns in a sparse data environment and infers a poaching scenario.
Anti-Poaching Systems (APS) [45]	Sensors are based on Ground, Aerial, Animal-tagging, and Perimeter technologies.	Provides monitoring and protection across landscapes using integrated hardware tech that gives layered real-time data.
Video Surveillance System and Multimedia Data Mining [47]	Video analytics combined with R-CNN, YOLO, SSD, and SPP-Net.	A unified object detection system that finds poachers(intruders) and wildlife from multimedia sources.
Object Identification Layer [47]	Neural Networks, Decision Tree, SVM	Detected objects are classified under different species of animals and humans.
Object Movement Analysis [47]	Dynamic Time Warping (DTW), Hidden Markov Model (HMM), and Self-Organizing Maps (SOM)	Analyzing the detected objects' movement within the ecosystem.
Intrusion Detection [48, 49]	CNN, RNN, Negative Selection Algorithm.	Poachers' patterns, movement, and unauthorized entries are detected in protected wildlife areas.
Spatial Monitoring and Reporting Tool (SMART) [51, 52]	Geospatial Reporting System, data collection.	Tracking wildlife movements and threats enables patrol planning and strategic law enforcement.
Protection Assistant Wildlife Security (PAW) [47]	AI planning via uncertainty modelling and game theory.	Assists in poacher prediction and optimized patrols.

5. Legal and Ethical Governance of Smart Anti-Poaching Surveillance Systems

Wildlife crimes are often transnational and complex, making them harder to control while also facing challenges that include limited resources, poor coordination between agencies, weak laws, and low priority given to wildlife crimes; as a result, many offenders are not caught and punished, making it difficult to enforce the law against wildlife crimes [53]. 'Tragedy of the commons', where shared natural resources are overexploited due to individual gain and weak regulations, calls for stronger governance in the form of targeted enforcement, demand reduction strategies, improved monitoring, and community involvement, highlighting the fact that combining deterrence with economic and social intervention can reduce illegal wildlife activities [22, 54]. Crime against fauna, such as poaching and illegal trafficking, spans across jurisdictions and borders, which makes isolated enforcement ineffective and requires a strong interagency cooperation amongst environmental authorities, law enforcement, international organizations, and customs, which highlights joint operations, coordinated governance, and shared intelligence, as it improves prosecution and detection of wildlife crimes. Through emphasizing the need for an aligned legal framework and building institutional capacity for efficient response from agencies are more successful when paired with structured, cross-border regulatory and enforcement systems between agencies and countries. Actively involving the local communities to combat the poaching problem provides another solution while simultaneously providing alternative livelihoods, benefit-sharing, and participation in decision-making to turn potential poachers into protectors, as it strengthens anti-poaching efforts by complementing law enforcement with local cooperation and support. For long-term success and to stabilize and support the recovery of endangered fauna, continued monitoring and habitat protection along anti-poaching efforts is the way to go [55-59]. Wildlife crimes are influenced by institutional, economic, and social factors that require an interdisciplinary approach and identifying gaps and fill it with stronger data, improved research methods, and a clearer definition to form anti-poaching policies and governance strategies. The National Environmental Standards and Regulations Enforcement Agency (NESREA) Act of Nigeria makes sure that environmental rules are being followed, but it also notes that not having enough resources and weak enforcement capacity limit the agency's impact [54, 60]. Besides the traditional market place for illegal wildlife trade, the dark web facilitates anonymous trade of protected species and products, and this hidden digital space makes enforcement much harder to monitor and enforce regulation because of anonymity and encryption, creating a hindrance in law enforcement capabilities to address online wildlife trafficking routes. Even though these wildlife-related listings are linked to drug use or medical purposes rather than large-scale commercial trafficking [61, 62]. Harnessing AI tools to detect illegal activities, monitor wildlife, and support faster enforcement responses can strengthen conservation governance more efficiently by enabling surveillance and decision-making with proper data, funding, and ethical use, ensuring effective implementation. As these tools analyze large amounts of data from satellites, sensors, and cameras to detect poaching, track animals, and monitor habitats with improved speed and accuracy, unlike the traditional ways [63-65], as illustrated in Figure 8.

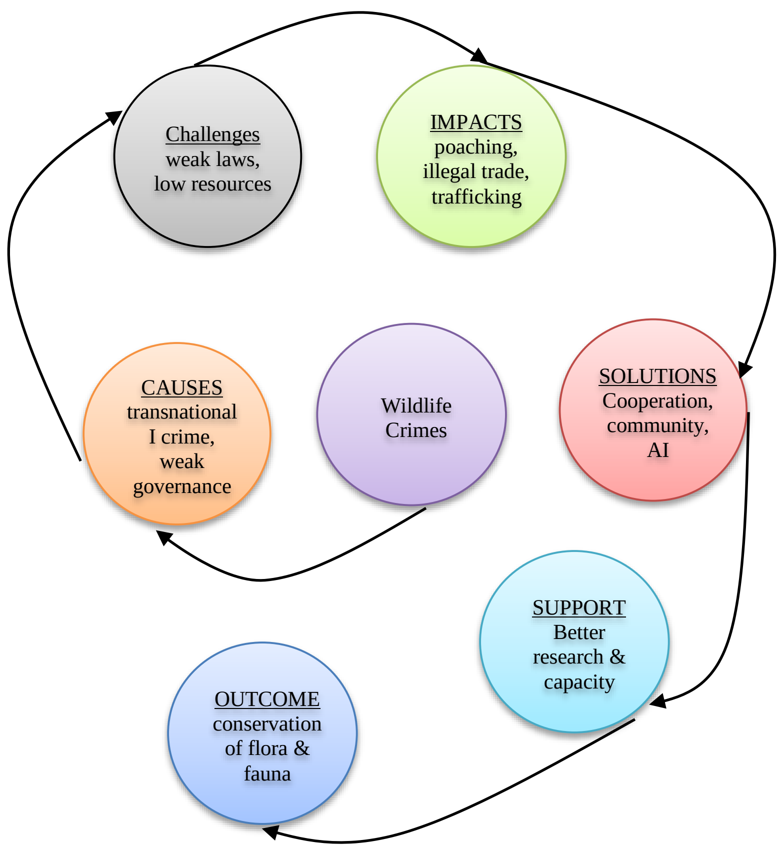

Fig. 8 Understanding the Wildlife crime flow

6. Recommendations

- Combating the decline in wildlife populations is crucial, especially when the reasons for the decline are caused by human activities. High poaching rates for large exotic wildlife have not only impacted wildlife survival but have also increased organised crime networks for quick money. Poverty, illiteracy, high wildlife incentives, etc, have been a driving factor in increased poaching. In the era of automation and intelligence, adopting innovative, AI-powered technologies backed by IoT-driven devices has created a more responsible and sustainable solution, aligning with the Sustainable Development Goals.
- Urging the government to adopt smart policies by adopting adaptive management systems like SMART, AI analytics, and digital technologies, simultaneously empowering local communities with incentives and training, and encouraging the use of smart technologies for wildlife and habitat preservation.
- Adopting the combination of multiple technologies and techniques to produce a strong infrastructure that protects wildlife against poachers, such as video analytics, YOLO, SPP-Net, satellite monitoring, etc.
- Employing Drones, GPS collars, Bio-loggers, and different types of environmental sensors that continuously monitor wildlife movement, anticipate real-time risks, and detect ecological changes when IoT-based devices are employed.
- Leveraging machine learning, AI, computer vision, and predictive models such as game-theoretic algorithms, CAPTURE, etc, for detecting species, anticipating poachers' behaviour and threats, population tracking, optimized patrol routes and resources, and improving law enforcement.

7. Conclusion

The future of Biodiversity has been compromised, which is largely driven by human-induced factors, such as hunting, poaching, pollution, habitat loss, deforestation, invasion of foreign species, etc. The biggest driving factor is poaching and hunting, either for sport or food. The illegal demands for overexploitation of large and exotic flora and fauna have rapidly reduced their population and posed a threat to their survival. Poaching problems have wiped out 95% of the black rhino population in 30 years, and the bison population went from millions to a few hundred in the 19th century in America due to hunting for sport. The constant direct and indirect human interference with biodiversity has created an ecological imbalance. While traditional conservation practices have managed to protect the remaining population of wildlife, it has failed to eliminate the poaching problems for the wildlife population to revive. Though some animal species have revived through constant efforts, protection has not been extended to the large population. The integration of smart technologies combined with IoT-based tracking sensors, AI-powered imaging, and predictive analysis has offered a promising path forward. No single method is sufficient alone against the fight to prevent poaching; a combination of technologies holds the most promise for effective poaching prevention. As civilization moves forward, embracing proactive, inclusive, and smart technologies, the same can be adopted for conservation strategies that will be the turning point in protecting, reviving, and promoting biodiversity and ecological balance that is required to sustain life on Earth.

Conflicts of Interest

There is no conflict of interest associated with this review article.

Funding Statement

No funding is received for this article.

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