



Machine Learning for Wildlife Monitoring and Conservation: A Review of Methods, Outcomes, and Ethical Challenges

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ARTICLE INFORMATION	ABSTRACT
<p>Submitted: July 15, 2026 Accepted: September 29, 2026 Published: October 14, 2026 Volume: 2 Issue: 1</p> <hr/> <p>KEYWORDS</p> <p>Machine learning; wildlife monitoring; biodiversity conservation; deep learning; species identification; ethical challenges.</p>	<p>Machine learning (ML) has emerged as a transformative technology in wildlife monitoring and conservation, offering new opportunities to improve species identification, population estimation, habitat assessment, and biodiversity protection. This review examines the principal machine learning methods applied in wildlife conservation, their reported outcomes, and the ethical and practical challenges associated with their implementation. It synthesizes research on supervised and unsupervised learning, deep learning, computer vision, acoustic classification, and remote sensing, with particular attention to their applications in camera-trap image analysis, automated species recognition, wildlife population monitoring, movement tracking, poaching detection, and habitat change assessment. The review highlights how these approaches can accelerate the processing of large ecological datasets, reduce the workload associated with manual identification, support near-real-time monitoring, and improve evidence-based conservation planning. However, their effectiveness depends on the availability of representative training data, model accuracy, technological infrastructure, and the ecological contexts in which they are deployed. Key challenges include biased or incomplete datasets, limited generalizability across species and geographical regions, high computational costs, inadequate technical capacity, and difficulties in interpreting model predictions. Ethical concerns also arise from the collection and governance of wildlife data, the potential misuse of precise species-location information by poachers, surveillance-related risks affecting Indigenous and local communities, and unequal access to conservation technologies. The review emphasizes the importance of transparent model development, data protection, community participation, interdisciplinary collaboration, and human oversight. It concludes that machine learning can strengthen wildlife conservation when integrated with ecological expertise, locally informed conservation strategies, and robust ethical safeguards. Future research should prioritize explainable and resource-efficient models, geographically diverse datasets, standardized evaluation frameworks, and equitable technological approaches that support long-term biodiversity conservation.</p>

1. Introduction

Wildlife conservation has become an increasingly urgent global priority as biodiversity loss, habitat destruction, climate change, illegal wildlife trade, and human–wildlife conflicts continue to threaten ecosystems and species survival. Effective conservation depends on reliable information about wildlife populations, species distribution, migration patterns, reproductive behavior, habitat conditions, and responses to environmental changes. However, collecting such information across large, remote, and ecologically diverse landscapes remains challenging. Traditional wildlife monitoring approaches, including direct field observations, camera trapping, radio telemetry, and aerial surveys, often require substantial financial resources, specialized personnel, and considerable time (Lakavath, 2025). Although these approaches have contributed significantly to ecological research and conservation management, their scalability and effectiveness may be limited by inaccessible habitats, inconsistent

observation conditions, incomplete datasets, and difficulties in processing large volumes of monitoring information. These challenges have encouraged the adoption of advanced computational technologies, particularly machine learning (ML), to improve the efficiency, accuracy, and scalability of wildlife monitoring and conservation initiatives.

Machine learning, a branch of artificial intelligence that enables computational systems to identify patterns in data and generate predictions or classifications, offers considerable opportunities for addressing longstanding challenges in wildlife ecology. By analyzing large and complex datasets collected through camera traps, acoustic sensors, satellite imagery, drones, GPS tracking devices, and environmental monitoring systems, ML algorithms can support species identification, population estimation, behavioral classification, habitat suitability assessment, and the detection of ecological changes (Espindola, 2025). Computer vision techniques, for example, can automatically identify animals in camera-trap images, distinguish species, and facilitate individual recognition, while acoustic classification models can detect species from their vocalizations and identify changes in biodiversity through environmental sound recordings. Similarly, remote-sensing applications can combine satellite imagery and ML algorithms to assess habitat degradation, monitor deforestation, and identify areas requiring urgent conservation intervention. These capabilities can reduce the time required for manual data analysis and enable researchers and conservation practitioners to generate more timely and comprehensive ecological information.

The development of machine learning applications for wildlife conservation reflects broader advances in ecological informatics, automated sensing, and data-driven environmental management. Supervised learning methods, including support vector machines, random forests, decision trees, and gradient boosting algorithms, have been applied to species classification, habitat modeling, and wildlife occurrence prediction. Deep learning approaches, particularly convolutional neural networks and transformer-based architectures, have expanded the possibilities for processing complex visual and acoustic data. Unsupervised learning techniques can also assist in identifying patterns in ecological datasets where labeled observations are limited, while reinforcement learning and other optimization approaches may support selected resource-allocation and monitoring decisions (Ogayemi, 2026). Furthermore, integrating ML with geographic information systems, satellite-based observations, and Internet of Things sensor networks creates opportunities for near-real-time wildlife monitoring and more coordinated conservation planning. For example, automated camera-trap systems can help identify the presence of threatened species, acoustic monitoring platforms can detect the activity of elusive or nocturnal animals, and predictive models can identify potential wildlife movement corridors or areas at elevated risk of human–wildlife encounters. Nevertheless, the practical value of these technologies depends on the availability of representative data, the suitability of algorithms for particular ecological settings, and the capacity of conservation organizations to interpret and apply model outputs.

Despite these opportunities, the adoption of machine learning in wildlife monitoring is associated with important methodological and operational limitations. Ecological datasets are frequently imbalanced, geographically uneven, and insufficiently representative of different species, habitats, seasons, and environmental conditions. Rare and endangered species may generate relatively few observations, making reliable model training and evaluation particularly difficult. Variations in lighting, vegetation, weather, sensor placement, animal behavior, and recording quality can further reduce model performance when algorithms are deployed beyond the environments in which they were developed. Models trained using data from one geographical region may not generalize effectively to another, while false detections and missed observations can distort population estimates or lead to inappropriate management decisions (Ahmed, 2024). In addition, the increasing use of automated monitoring technologies raises questions about infrastructure costs, energy consumption, technical maintenance, data interoperability, and the availability of trained personnel. These constraints are especially relevant to conservation organizations operating in resource-limited settings, where access to reliable connectivity, computing infrastructure, and specialist expertise may be restricted. Consequently, evaluating machine learning systems requires more than assessing predictive accuracy; it also involves determining their ecological validity, operational feasibility, reproducibility, and usefulness for conservation decision-making.

Ethical considerations constitute another essential dimension of machine learning-based wildlife conservation. Although advanced monitoring technologies can strengthen biodiversity protection, the collection, storage, and sharing of wildlife location data may expose vulnerable species to poaching, illegal trafficking, or other forms of exploitation when sensitive information is inadequately protected. The deployment of drones, acoustic devices, tracking collars, and other monitoring equipment may also disturb wildlife, alter natural behavior, or introduce risks when systems are poorly designed or improperly managed. Furthermore, algorithmic biases arising from uneven species representation or geographically concentrated datasets may result in conservation priorities that favor well-studied species and accessible ecosystems over less visible or underrepresented populations (Obisa, 2025). Questions of data ownership, Indigenous and local community rights, informed participation, transparency, and accountability are equally important, particularly when monitoring activities affect customary lands, livelihoods, and relationships between communities and wildlife. There is also a risk that excessive reliance on automated predictions could marginalize local ecological knowledge or create unwarranted confidence in models that remain uncertain.

Responsible implementation therefore requires appropriate data governance, protection of sensitive ecological information, meaningful stakeholder participation, transparent reporting of uncertainty, and human oversight of consequential conservation decisions.

Although research on artificial intelligence and ecological monitoring has expanded, the field encompasses diverse technologies, conservation objectives, study designs, and evaluation criteria. Findings from individual applications may be difficult to compare because studies differ in data sources, taxonomic groups, geographical settings, model architectures, validation procedures, and definitions of conservation success. Moreover, strong technical performance does not necessarily translate into measurable improvements in biodiversity outcomes. A model may classify species accurately without demonstrating that its use improves population recovery, reduces poaching, protects habitats, or strengthens conservation policy (Lakavath, 2025). Distinguishing between technical outputs, operational benefits, and long-term ecological outcomes is therefore essential for understanding the actual contribution of machine learning to wildlife protection. A comprehensive review is needed to synthesize the principal methodological developments, assess reported outcomes across different monitoring applications, identify recurring barriers to implementation, and examine the ethical and governance implications of increasingly automated conservation practices. Such synthesis can also clarify where evidence remains limited and which research priorities are most likely to improve the practical effectiveness of ML-based interventions.

Against this background, this review examines machine learning for wildlife monitoring and conservation, focusing on methods, outcomes, and ethical challenges. Specifically, it explores the principal ML techniques used in wildlife monitoring; examines their applications in species identification, population assessment, behavioral analysis, habitat monitoring, and conservation risk prediction; evaluates reported benefits and limitations in terms of accuracy, efficiency, scalability, and practical conservation value; and analyzes methodological, institutional, and ethical challenges associated with their implementation. The review further considers responsible data management, algorithmic transparency, ecological validity, community participation, and the integration of automated analysis with field-based expertise and established conservation practices (Nandutu, 2023). By bringing these dimensions together, the study aims to provide an integrated understanding of how machine learning can support evidence-based wildlife management while recognizing the limitations and risks that accompany its adoption. Ultimately, the review seeks to inform researchers, conservation practitioners, policymakers, and technology developers about the opportunities, conditions, and safeguards necessary to ensure that machine learning contributes meaningfully, equitably, and responsibly to biodiversity conservation.

2. Methodology

2.1. Research Design

This study adopted a systematic literature review approach to examine the applications of machine learning in wildlife monitoring and conservation, focusing on methodological developments, conservation outcomes, and associated ethical challenges. A systematic review was considered appropriate because research on machine learning in wildlife conservation spans multiple disciplines, including ecology, environmental science, computer vision, bioacoustics, remote sensing, and computational biology. The review sought to synthesize existing evidence on how machine learning techniques are applied to wildlife detection, species identification, population estimation, behavioral analysis, habitat monitoring, and biodiversity conservation. It also examined the effectiveness and limitations of these techniques across different ecological settings. Particular attention was given to the relationship between technological performance and practical conservation outcomes, recognizing that high model accuracy does not necessarily translate into improved species protection or ecosystem management.

2.2. Literature Search Strategy

The literature search was designed to identify relevant peer-reviewed studies and scholarly publications addressing machine learning applications in wildlife monitoring and conservation. Academic databases and scholarly search platforms, including Scopus, Web of Science, PubMed, IEEE Xplore, and Google Scholar, were identified as appropriate sources for retrieving literature across ecological and technological disciplines. The search strategy combined keywords relating to machine learning techniques, wildlife monitoring, biodiversity conservation, and ethical considerations. Search terms included "machine learning and wildlife conservation," "deep learning for animal detection," "artificial intelligence in biodiversity monitoring," "computer vision for species identification," "bioacoustic monitoring and machine learning," "remote sensing for wildlife conservation," and "ethical challenges of AI in conservation." Boolean operators, including AND and OR, were used to combine related terms and improve the relevance of retrieved publications. The search strategy also considered variations in terminology, including automated wildlife monitoring, animal recognition, ecological informatics, and intelligent conservation systems, to capture research published across different disciplinary traditions.

2.3. Inclusion and Exclusion Criteria

The selection of studies was guided by predefined inclusion and exclusion criteria to maintain relevance and consistency throughout the review process. Studies were considered eligible when they examined machine learning or deep learning applications directly related to wildlife monitoring, species identification, animal population assessment, movement tracking, habitat analysis, ecological forecasting, or conservation decision-making. Research investigating computer vision, camera traps, satellite imagery, unmanned aerial vehicles, acoustic sensors, environmental DNA classification, and other technology-assisted monitoring approaches was considered where machine learning formed a substantive part of the analytical process. Studies discussing ethical, social, environmental, or governance concerns associated with deploying these technologies in conservation were also included. Priority was given to peer-reviewed journal articles and relevant conference proceedings that presented empirical findings, methodological contributions, systematic reviews, or theoretically grounded analyses. Publications were excluded when they focused exclusively on machine learning applications unrelated to wildlife or biodiversity, described technologies without a meaningful conservation application, or lacked sufficient methodological or conceptual information to support the review objectives. Duplicate publications and inaccessible records without sufficient information for assessment were also excluded where appropriate.

2.4. Study Selection Process

The study selection process followed the principal stages of systematic literature reviewing: identification, screening, eligibility assessment, and final inclusion. Initially, records retrieved from the selected databases were considered for relevance based on their titles, abstracts, keywords, and publication information. Duplicate records were identified and removed before the screening process proceeded. The remaining publications were assessed against the predefined inclusion and exclusion criteria, with particular emphasis on their relevance to machine learning methods, wildlife monitoring applications, conservation outcomes, and ethical challenges. Publications that appeared relevant at the title and abstract screening stage were subjected to full-text assessment to establish whether they provided sufficient evidence to address the research objectives. The selection process was intended to ensure that the final body of literature represented both technological advances and their ecological and conservation implications. To strengthen transparency and reproducibility, the review should document the database-specific search dates, the number of records retrieved, the number of duplicates removed, the reasons for excluding full-text studies, and the final number of included publications. Where applicable, these details can be reported using a PRISMA flow diagram. As the review's actual screening counts were not provided, no numerical selection totals are assumed in this methodology.

2.5. Data Extraction and Classification

A structured data extraction framework was used to organize the information relevant to the study's objectives. The principal information categories included publication year, geographical setting, ecosystem type, target species or taxonomic group, data source, machine learning technique, monitoring application, evaluation metrics, reported conservation outcomes, and identified limitations. The review also considered whether studies used traditional machine learning algorithms, deep learning architectures, or hybrid analytical approaches. Traditional methods included algorithms such as random forests, support vector machines, decision trees, and other supervised or unsupervised learning techniques. Deep learning approaches included convolutional neural networks for image classification, object detection models for identifying wildlife in camera-trap images, and neural network architectures for processing acoustic recordings and remote-sensing data. Where relevant, information was extracted on dataset size, class imbalance, model validation procedures, geographic transferability, computational requirements, and the availability of code or training data. Ethical information was recorded separately, including potential risks to endangered species, sensitive location data, surveillance of local communities, algorithmic bias, unequal access to monitoring technologies, and the environmental costs of computational infrastructure.

2.6. Analytical Framework and Synthesis of Evidence

The extracted evidence was analyzed through a thematic synthesis approach to identify recurring patterns, methodological developments, reported benefits, and persistent limitations in the literature. The analysis was organized around three principal dimensions: machine learning methods, wildlife conservation outcomes, and ethical challenges. The first dimension examined how different algorithms and data acquisition technologies were used to detect, classify, count, track, and predict wildlife populations or ecological changes. The second assessed reported contributions to conservation, including improvements in monitoring efficiency, early detection of threats, identification of endangered species, habitat assessment, and support for evidence-based conservation planning. The third examined ethical and governance concerns associated with data collection, model development, technology deployment, and the interpretation of machine-generated outputs.

Comparative analysis was used to identify differences between monitoring approaches and the ecological contexts in which they were applied. For example, image-based deep learning systems were considered in relation to their ability to process large volumes of camera-trap photographs, while bioacoustic models were examined for their contribution to identifying species from

vocalizations and monitoring changes in ecological soundscapes. Remote-sensing approaches were assessed in terms of their usefulness for habitat characterization and landscape-level monitoring. The synthesis also considered recurring technical challenges, such as limited training data, false detections, variation in environmental conditions, poor generalization across geographical regions, and difficulties in identifying rare species. Rather than assuming that all studies were directly comparable, the review interpreted reported findings in relation to their data sources, study designs, validation procedures, and ecological settings.

2.7. Assessment of Methodological Quality and Reliability

The methodological quality of the included studies was considered in relation to the robustness of their research designs, the suitability of their machine learning techniques, the quality and representativeness of their datasets, and the reliability of their reported findings. Particular attention was given to whether studies used independent test datasets, appropriate validation strategies, clearly defined performance metrics, and transparent descriptions of model development. Relevant performance indicators included precision, recall, F1-score, classification accuracy, and area under the receiver operating characteristic curve, where appropriate to the research task. For wildlife detection and counting applications, additional consideration was given to detection error, false-positive and false-negative rates, and the agreement between automated estimates and expert-verified observations.

The assessment also considered ecological validity, particularly whether models were evaluated across different habitats, seasons, species, or geographical regions. Studies relying on narrow datasets or limited validation were interpreted cautiously, especially when their conclusions implied broader applicability to conservation practice. In addition, the review distinguished between technical performance and demonstrated conservation effectiveness. A model that accurately identifies an animal in an image, for instance, does not independently establish that its deployment improves population recovery, reduces poaching, or strengthens habitat protection. This distinction supported a more balanced assessment of the evidence and helped identify areas where further longitudinal or field-based evaluation is required.

2.8. Ethical Considerations

Ethical considerations were incorporated into the review framework because machine learning applications in wildlife conservation can produce both environmental benefits and unintended harms. The analysis examined concerns relating to privacy, data ownership, informed participation, species protection, algorithmic fairness, and the governance of conservation technologies. Particular attention was given to the potential misuse of precise wildlife location data, which may expose endangered animals to poaching, illegal trade, or disturbance when sensitive information is inadequately protected. The review also considered the implications of deploying camera traps, acoustic sensors, drones, and other monitoring technologies in areas inhabited or used by Indigenous Peoples and local communities, especially where data collection may occur without meaningful consultation or clear data-governance arrangements.

Furthermore, the review examined potential biases arising from underrepresentation of particular species, habitats, geographical regions, or ecological conditions in training datasets. Such biases may reduce the reliability of automated monitoring systems and lead to unequal conservation attention across species or landscapes. Other considerations included the energy consumption associated with computationally intensive models, the accessibility of advanced technologies to conservation organizations with limited resources, and the risk of excessive dependence on automated predictions without expert ecological interpretation. Ethical assessment therefore extended beyond technical accuracy to consider accountability, transparency, proportionality, community participation, and the long-term implications of machine learning for biodiversity protection.

2.9. Limitations of the Review Methodology

Several limitations may influence the comprehensiveness and interpretation of the review. First, the interdisciplinary nature of machine learning and wildlife conservation means that relevant research may be distributed across databases and publication outlets with different indexing practices. Consequently, even a structured search may not identify every relevant study, particularly research published in regional journals, technical reports, conservation agency publications, or other forms of grey literature. Second, the rapid development of machine learning techniques means that findings may become outdated as new algorithms, datasets, and monitoring technologies emerge. Third, differences in study designs, target species, ecological conditions, datasets, and evaluation metrics may limit direct comparisons across publications. Finally, many studies emphasize model performance rather than long-term ecological or conservation outcomes, making it difficult to determine whether reported technological improvements produce sustained benefits for biodiversity. These limitations support the need for cautious interpretation and highlight opportunities for future research involving standardized evaluation frameworks, geographically diverse datasets, longitudinal conservation assessments, and stronger integration of ecological expertise with machine learning development.

3. Findings and Discussion

The reviewed literature indicates that machine learning (ML) is increasingly important in wildlife monitoring and conservation because it enables researchers to process large volumes of ecological data, identify species, estimate population trends, predict habitat suitability, and detect environmental threats. Its applications span computer vision, deep learning, acoustic classification, remote sensing, and predictive modelling. These technologies have expanded the scale and frequency of wildlife observations while reducing the amount of manual work required to analyse camera-trap images, animal vocalisations, aerial photographs, and satellite data (Kumar, 2025). However, the evidence also indicates that the effectiveness of ML depends on data quality, ecological context, model generalisability, and the availability of appropriate technical infrastructure. Furthermore, improved detection and prediction do not automatically translate into successful conservation outcomes; their practical value depends on whether the information informs timely, scientifically justified, and locally appropriate management decisions.

As a synthesis of the literature, the findings are organised around five themes: ML methods, population monitoring applications, conservation outcomes, ethical and operational challenges, and future research directions. The discussion draws on established studies and representative applications to identify both the demonstrated benefits and the limitations of ML-based conservation approaches (Lakavath, 2024). Because this is a review-based discussion rather than a report of newly collected field data, the findings are presented as patterns and conclusions emerging from previous research, rather than as original experimental results or newly calculated effect sizes.

3.1. Machine Learning Methods for Wildlife Monitoring and Conservation

The reviewed literature identifies computer vision, deep learning, acoustic classification, and remote-sensing analytics as major methodological approaches used in wildlife monitoring. These methods address different ecological observation challenges, ranging from identifying individual animals in photographs to detecting species through their vocalisations and predicting landscape-level changes (Goyal, 2025). Their complementary capabilities have encouraged the development of integrated monitoring systems in which data from multiple sources are analysed to provide a more comprehensive understanding of wildlife populations and their habitats. Nevertheless, the suitability of each method varies according to the target species, observation environment, available data, and conservation objective.

3.1.1. Computer Vision and Deep Learning for Wildlife Detection and Species Identification

Computer vision and deep learning have become prominent methods for automating wildlife detection and species identification. Convolutional neural networks (CNNs), object-detection architectures, and vision-transformer-based approaches can learn visual characteristics that distinguish species, identify animals within complex backgrounds, and classify images according to species or behavioural categories. These capabilities are particularly valuable in conservation projects that generate thousands or millions of images through camera traps, aerial surveys, and other automated observation systems (Shekhawat, 2025). Rather than requiring researchers to examine every image manually, trained models can prioritise images containing animals, assign probable species labels, and direct uncertain cases to human experts.

A representative example is the use of deep learning to classify animals recorded by camera traps in African savannahs, tropical forests, and protected landscapes. A model trained on images of elephants, lions, zebras, antelopes, and other mammals can assist researchers in identifying species and analysing their temporal patterns of activity. Similarly, computer vision can support the identification of marine mammals from aerial photographs or the detection of birds in wetland habitats. Lakavath (2024) demonstrated the potential of computer vision for automated animal identification using camera-trap images, illustrating how ML can support wildlife research at scales that would be difficult to manage through manual classification alone. Goel (2025) also showed that deep learning could classify camera-trap images across a wide range of animal species and behaviours, highlighting its potential to accelerate ecological data processing.

The findings suggest that the principal contribution of deep learning lies not simply in classifying individual images but also in transforming large image collections into analysable ecological datasets. Automated classification can help establish species-activity patterns, identify changes in animal presence, and support comparisons across locations and seasons. However, classification performance is not uniform across species or environmental conditions. Rare species may be poorly represented in training data, while poor lighting, partial visibility, overlapping animals, unusual poses, and vegetation can reduce detection accuracy (Lakavath, 2024). Models trained in one geographic region may also perform less effectively in another because species composition, camera placement, and environmental conditions differ.

Consequently, high overall classification accuracy should not be interpreted as evidence that a model performs equally well for every species. Errors involving rare or endangered species may be particularly consequential because these species can be underrepresented in datasets and may be the primary focus of conservation interventions (Ojija, 2025). The reviewed evidence therefore supports a human-in-the-loop approach in which automated predictions are checked through expert validation,

especially when the results inform population assessments or management decisions. Deep learning is most valuable when it complements ecological expertise rather than replacing it.

3.1.2. Machine Learning Applications in Camera Traps, Drones, and Satellite Imagery

Machine learning has broadened the use of camera traps, drones, and satellite imagery by enabling automated extraction of ecological information from different observation platforms. Camera traps provide repeated observations of terrestrial wildlife, drones capture high-resolution images of habitats and animals, and satellites provide broad spatial coverage for monitoring vegetation, land-use change, and environmental disturbance. ML algorithms can analyse these data to identify animals, classify land cover, detect changes in habitat structure, and relate environmental conditions to wildlife occurrence (Raghav, 2025). Camera traps are particularly useful for observing elusive, nocturnal, and disturbance-sensitive species. However, conventional camera-trap studies can generate large volumes of empty images, requiring substantial human effort to separate wildlife observations from irrelevant records. Automated image filtering and species classification reduce this burden and allow researchers to concentrate on ecological interpretation. Lakavath (2024) illustrated the feasibility of deep-learning systems for processing large-scale camera-trap datasets, while Watara (2025) further demonstrated the potential of automated classification for wildlife research and monitoring. These findings support the use of ML as a means of increasing the analytical capacity of long-term camera-trap programmes.

Drone-based monitoring offers complementary advantages, particularly in wetlands, coastal ecosystems, open grasslands, and habitats that are difficult to survey on foot. ML models can identify animals in aerial imagery, count visible individuals, and classify vegetation or other habitat characteristics. For example, aerial surveys combined with object-detection algorithms can assist in estimating populations of large mammals in open landscapes or monitoring bird colonies in coastal environments (Tuia, 2022). Nevertheless, the accuracy of aerial detection depends on flight altitude, image resolution, shadows, weather conditions, vegetation cover, and the degree to which animals are concealed. Drone surveys may also disturb sensitive wildlife if flight operations are not carefully designed.

Satellite imagery is especially relevant to landscape-level conservation because it supports repeated assessment of forest loss, fragmentation, vegetation condition, fires, and changes in land use. ML algorithms can classify satellite pixels or image segments into ecological categories and identify patterns associated with habitat degradation. For example, satellite-based classification can reveal forest clearing near protected areas, while vegetation indices combined with predictive models can help identify habitat changes that may affect wildlife distribution. However, satellite imagery usually provides less direct information about the presence of individual animals than camera traps or high-resolution drone imagery (Jain, 2024). Its contribution is therefore often indirect, through the measurement of environmental conditions associated with species occurrence and persistence.

The reviewed studies indicate that these monitoring platforms should be understood as complementary rather than interchangeable. Camera traps provide detailed observations at specific locations, drones offer flexible and relatively high-resolution aerial coverage, and satellites enable broad spatial and temporal assessment. Combining them can improve ecological interpretation, but integration requires consistent spatial references, compatible temporal sampling, and methods for handling differences in resolution and measurement error (Watara, 2026). Accordingly, effective ML-based monitoring depends on selecting the observation platform that best matches the ecological question rather than adopting the most technologically advanced tool available.

3.1.3. Acoustic Monitoring and Bioacoustic Classification of Wildlife Species

Bioacoustic monitoring is another important application of ML in wildlife conservation. Many species produce vocalisations that provide information about their presence, activity, breeding behaviour, and responses to environmental disturbance. Passive acoustic monitoring uses recording devices to collect these sounds over extended periods, while ML algorithms classify recordings and identify vocal patterns associated with target species. This approach is particularly useful for birds, bats, amphibians, insects, and marine mammals, many of which are difficult to observe consistently through visual surveys. Deep-learning models can distinguish species-specific calls from background sounds and identify vocal activity across extensive audio datasets. For instance, acoustic classifiers can detect bird calls in forest habitats, identify frog vocalisations in wetlands, or analyse whale sounds recorded by underwater hydrophones. Sharma (2023) reviewed the expanding role of computational bioacoustics in ecological research, demonstrating the importance of automated sound analysis for studying animal communication and biodiversity. The development of platforms such as BirdNET has further illustrated how ML can support large-scale bird-sound identification and make acoustic analysis more accessible to researchers and citizen scientists.

The findings suggest that acoustic classification is particularly valuable where repeated visual observation is impractical. Recorders can operate during the night, in dense vegetation, or in remote environments, producing observations across periods when human surveys would be difficult or costly. Acoustic monitoring can also provide information about seasonal changes in

calling activity and the occurrence of species across different habitat conditions. When combined with environmental variables, these records may help researchers investigate how temperature, rainfall, vegetation, or anthropogenic noise influence wildlife activity. However, acoustic detection does not necessarily establish the number of animals present. A single individual may call repeatedly, several individuals may vocalise simultaneously, and calling rates can change according to season, weather, or reproductive behavior (Nandutu, 2022). Background noise from roads, aircraft, wind, and other animals may also affect classification performance. Moreover, a species may be present without vocalising during the recording period. Therefore, acoustic detections should be interpreted as evidence of vocal activity rather than definitive population counts unless the monitoring design includes appropriate methods for estimating detectability and individual abundance.

These limitations reinforce the importance of combining acoustic evidence with other ecological observations. Integrating sound recordings with camera-trap images, field surveys, and environmental measurements can improve species identification and provide a more complete account of ecological conditions (Watara, 2026). Such integration is particularly important when acoustic data are used to assess threatened species or determine whether conservation interventions have improved habitat quality.

3.2. Applications of Machine Learning in Wildlife Population Monitoring

The literature demonstrates that ML contributes to wildlife population monitoring by improving the analysis of species occurrence, habitat suitability, population distribution, movement patterns, and biodiversity change. Traditional monitoring methods, including field surveys, transects, and direct counts, remain important but can be constrained by limited geographical coverage, high costs, and difficulties observing elusive species. ML can complement these approaches by integrating ecological observations with climatic, geographical, and remote-sensing data (Hammouch, 2025). The resulting models can help researchers identify suitable habitats, examine population changes, and detect species that require targeted conservation attention. However, the reliability of these applications depends on sampling design, data representativeness, and the ability to distinguish genuine ecological changes from variations in observation effort.

3.2.1. Species Distribution Modelling and Habitat Suitability Prediction

Species distribution modelling is a major application of ML in conservation because it helps predict where species are likely to occur under particular environmental conditions. These models typically combine species-occurrence records with variables such as temperature, rainfall, elevation, vegetation cover, land use, and distance from water sources. Algorithms such as random forests, support vector machines, gradient-boosting methods, and neural networks can identify complex relationships between environmental conditions and species occurrence (Lotfian, 2021). The resulting predictions can support habitat assessment, conservation prioritisation, and evaluation of potential responses to environmental change.

A representative application involves modelling the distribution of large mammals in African savannah ecosystems using vegetation condition, rainfall, temperature, and human land-use patterns. Such models can help identify areas that are likely to support elephants, antelopes, or large carnivores and reveal locations where habitat fragmentation may constrain their distribution. In tropical forests, similar approaches can identify suitable habitats for endangered primates or other species with limited occurrence records. Sher (2025) provided an influential comparison of species distribution modelling methods, demonstrating the importance of algorithm selection and evaluation when predicting species–environment relationships. Branco (2023) also established the value of maximum-entropy modelling for predicting species distributions from presence-only data, a common situation in biodiversity research.

The reviewed evidence indicates that ML-based distribution models can support conservation planning by identifying potential habitats that have not been adequately surveyed. This is especially useful when field observations are geographically uneven or when conservation organisations must prioritise limited survey resources. Habitat suitability maps can guide field investigations, identify potential corridors between fragmented habitats, and support decisions about protected-area expansion or restoration. By combining species observations with environmental predictors, researchers can also examine how changing climatic conditions may alter the geographical suitability of habitats (Isabelle, 2022). Nevertheless, predicted habitat suitability should not be confused with confirmed species presence or population viability. A model may identify an area as environmentally suitable even though the species cannot reach it because of barriers, human disturbance, or historical range restrictions. Similarly, the presence of suitable habitat does not guarantee adequate food resources, breeding opportunities, or long-term survival. Models may also produce misleading predictions when trained on biased occurrence records or extrapolated beyond the environmental conditions represented in their training data.

These findings highlight the need to combine model outputs with field verification, ecological knowledge, and information about habitat connectivity. Model evaluation should consider spatially independent validation where possible, since random division of nearby observations between training and testing datasets may overestimate predictive performance (Fergus, 2024). The

practical value of distribution modelling is therefore greatest when predictions are treated as evidence to guide further investigation and conservation action rather than as definitive maps of species occupancy.

3.2.2. Wildlife Population Estimation, Tracking, and Migration Pattern Analysis

ML supports wildlife population estimation and movement analysis through the processing of images, acoustic recordings, GPS telemetry, and other tracking data. Computer vision can help count animals in photographs or aerial imagery, while predictive models can identify movement patterns and relate animal behaviour to environmental conditions. GPS collars and tracking devices generate spatial and temporal records that can be analysed to investigate migration routes, seasonal habitat use, dispersal, and responses to human activity. These methods are particularly relevant for migratory birds, elephants, large carnivores, and marine mammals whose movements frequently cross administrative or protected-area boundaries (McClure, 2020). For example, tracking data from elephants can be combined with land-use maps, water availability, and human settlement patterns to identify seasonal movement corridors and areas where animals are likely to encounter roads, agricultural land, or settlements. Similarly, ML analysis of migratory bird observations can help identify stopover sites and investigate how changing climatic conditions influence migration timing. In marine conservation, movement records can reveal frequently used feeding grounds or areas where wildlife may encounter fishing activity and vessel traffic. Such applications can inform the placement of wildlife crossings, corridor protection, seasonal restrictions, and targeted monitoring programmes.

Ogayemi (2026) highlighted the importance of camera-trap networks and large-scale ecological data for understanding mammalian communities and changes in wildlife populations. More broadly, the growth of computational movement ecology has demonstrated how large tracking datasets can be analysed to identify recurring behavioural patterns and relationships between animal movements and environmental conditions. ML can extend these approaches by detecting patterns that may be difficult to identify through visual inspection alone. However, population estimation presents challenges beyond the accurate detection of individual animals. Repeated observations may involve the same individual, animals may be missed because of vegetation or limited detector coverage, and some species cannot be reliably distinguished by appearance. Consequently, counts derived from images or recordings do not automatically provide unbiased estimates of population size. Statistical methods that account for detectability, sampling effort, repeated observations, and individual identification remain essential.

Migration analysis also requires attention to temporal coverage and spatial resolution. Tracking devices may be concentrated on particular individuals or demographic groups, making it difficult to generalise their movements to an entire population. In addition, missing telemetry records and differences in device performance can introduce uncertainty (Lakavath, 2025). The findings therefore suggest that ML is most effective when integrated with established ecological sampling methods, population-estimation frameworks, and field-based validation. This combination enables researchers to distinguish changes in animal movement or detection from genuine changes in population status.

3.2.3. Biodiversity Assessment and Detection of Rare, Endangered, and Invasive Species

ML can contribute to biodiversity assessment by processing large and diverse datasets to identify species, characterise ecological communities, and detect changes in species occurrence. Automated analysis of camera-trap images, acoustic recordings, environmental DNA results, and remote-sensing data can support more frequent assessments of biodiversity across different habitats. These capabilities are important for conservation because conventional surveys may overlook rare, cryptic, nocturnal, or geographically restricted species. ML can help identify potential locations for targeted surveys and improve the efficiency of biodiversity inventories. The detection of endangered species is a particularly important application (Espíndola, 2025). For instance, acoustic classifiers may identify the calls of threatened birds or amphibians, while image-recognition systems can flag possible records of rare mammals for expert verification. Automated identification can also help researchers analyse historical photographs and long-term monitoring records to determine whether a species continues to occur at a particular site. In biodiversity-rich tropical forests, these tools may improve the identification of species that are difficult to observe directly, although the benefits depend on the availability of representative training examples.

ML can also support invasive-species surveillance. Image classification, environmental modelling, and remote-sensing analysis can help identify the spread of invasive plants or animals and locate habitats vulnerable to colonisation. For example, satellite imagery combined with classification algorithms can identify changes in vegetation associated with invasive plant expansion, while image-based models can flag potentially invasive organisms in field observations. Early identification can provide conservation managers with more time to investigate, verify, and respond to a developing invasion. The findings indicate that the conservation value of automated biodiversity assessment lies in its capacity to expand surveillance coverage and identify potential ecological changes more quickly (Ahmed, 2024). Nevertheless, rare species present a fundamental data challenge because their observations are often too limited to support conventional supervised learning. Models may also misclassify similar-looking species, perform poorly on juveniles or unusual colour variants, or produce false positives when trained on

geographically narrow datasets. Invasive species may be particularly difficult to detect at low densities, when observations are sparse and environmental signals are weak.

Moreover, detecting a species is not equivalent to demonstrating that its population is increasing, declining, or ecologically harmful. Conservation assessments must consider observation effort, detection probability, species interactions, and relevant ecological conditions. Accordingly, the literature supports using ML-generated records as part of a broader biodiversity assessment framework that includes taxonomic expertise, repeated surveys, and transparent verification procedures (Obisa, 2025). This is especially important when detection results trigger costly interventions or decisions affecting endangered species and sensitive habitats.

3.3. Outcomes and Effectiveness of Machine Learning in Wildlife Conservation

The reviewed literature suggests that ML can improve the operational capacity of wildlife conservation by increasing the speed of data processing, expanding monitoring coverage, and supporting the early identification of ecological threats. These benefits are particularly evident in projects that generate large volumes of images, sound recordings, tracking records, or satellite observations. ML can make it feasible to analyse data that would otherwise require substantial manual effort, allowing conservation teams to direct more attention towards field verification, ecological interpretation, and management planning (Lakavath, 2025). Nevertheless, effectiveness should be evaluated across several dimensions, including predictive accuracy, reliability across species and locations, cost, timeliness, and demonstrable conservation impact.

3.3.1. Improvements in Monitoring Accuracy, Efficiency, and Scalability

One of the principal outcomes of ML adoption is the ability to process ecological observations more efficiently than fully manual workflows. Automated image and audio classification can reduce repetitive data-labelling tasks, accelerate the identification of potential species records, and enable the analysis of larger datasets. This is particularly valuable for long-term monitoring programmes in which the volume of observations increases continuously as additional camera traps, acoustic recorders, or remote-sensing systems are deployed. Nandutu (2023) demonstrated the potential of deep learning to automate the classification of camera-trap images across numerous species and behaviours. Kumar (2025) similarly examined automated wildlife identification and highlighted the role of computer vision in improving the management of ecological image data. These studies illustrate how ML can extend the practical scale of wildlife monitoring by reducing the human effort needed to convert raw observations into usable datasets. In acoustic monitoring, automated classification offers comparable benefits by identifying likely species vocalisations across lengthy recordings.

The findings suggest that improved efficiency can also enhance monitoring consistency. Automated systems apply the same classification procedure across large datasets, reducing some forms of variation associated with individual observers. They can also help standardise data processing across sites and survey periods, making comparisons more manageable. However, consistency does not necessarily mean correctness: a model may systematically misclassify the same species across thousands of images. Human observers can also disagree, particularly when species are visually similar or recordings are unclear. Accordingly, efficiency gains should be assessed alongside classification errors, expert-review requirements, and the time needed to maintain the system (Lakavath, 2024). A model that processes millions of images rapidly may still have limited practical value if its false-positive rate creates an unmanageable verification workload. Similarly, accuracy measured on a familiar test dataset may not reflect performance in a different ecosystem or season. Appropriate evaluation should therefore include class-specific precision and recall, uncertainty assessment, external validation, and estimates of the total cost of producing reliable ecological information.

A further distinction concerns monitoring performance versus conservation effectiveness. Faster identification and broader survey coverage are important operational achievements, but they do not independently demonstrate improved species survival or habitat recovery. Evidence of conservation effectiveness requires linking ML-supported monitoring to subsequent management actions and measurable ecological outcomes (Goyal, 2025). The findings therefore support evaluating ML systems not only by their technical performance but also by whether they improve the quality, timeliness, and practical usefulness of conservation decisions.

3.3.2. Early Detection of Threats, Poaching Activities, and Habitat Degradation

ML can strengthen early-warning systems by identifying unusual patterns in wildlife observations, environmental conditions, and human activity. Image-recognition systems may flag suspected human presence in restricted areas, acoustic models can detect certain forms of mechanical activity, and satellite-based classifiers can identify forest clearing or other landscape disturbances. When combined with spatial analysis, these methods can help conservation managers prioritise areas for investigation and allocate patrols or restoration resources more strategically. For example, protected-area managers may combine camera-trap detections, patrol records, road networks, and historical incident locations to identify areas where illegal human activity is more

likely to occur (Shekhawat, 2025). Satellite-based change detection can similarly highlight forest loss or expanding agricultural activity near protected habitats. ML may help distinguish recurring patterns from unusual changes, enabling managers to direct attention towards locations that warrant rapid assessment. In landscapes affected by illegal logging, mining, or habitat conversion, automated analysis can support surveillance across areas too extensive to inspect regularly through ground patrols alone.

However, the use of ML for poaching prevention requires careful interpretation. A system detecting human movement or unusual activity does not necessarily establish that a crime has occurred. Local residents, researchers, tourists, and authorised resource users may produce signals that resemble suspicious behaviour. If models are poorly calibrated, false alarms can divert limited patrol resources, undermine trust, or expose legitimate activities to inappropriate scrutiny. Consequently, algorithmic alerts should be treated as leads for verification rather than conclusive evidence of illegal activity (Lakavath, 2024). Habitat degradation monitoring presents related opportunities and limitations. Satellite imagery and environmental predictors can help detect changes in vegetation cover, fragmentation, and landscape condition. Nevertheless, changes in vegetation indices may reflect seasonal cycles, drought, fire, or natural ecological variation rather than permanent habitat loss. Effective monitoring therefore requires appropriate temporal baselines, ecological interpretation, and validation against independent observations.

3.3.3. Contributions to Conservation Planning, Protected-Area Management, and Policy Decisions

ML-generated information can support conservation planning by helping managers identify priority habitats, assess threats, evaluate restoration opportunities, and compare alternative management strategies. Species distribution models can identify potentially suitable conservation areas, remote-sensing models can track changes in habitat condition, and movement analyses can reveal ecological corridors requiring protection. When integrated with information on land ownership, human activities, protected-area boundaries, and conservation costs, these outputs can help decision-makers assess competing priorities. For example, a conservation authority may combine predicted habitat suitability, observed species occurrence, forest-loss data, and connectivity measures to identify areas where restoration could reconnect fragmented habitats (Goel, 2025). In marine environments, ML-supported analysis of species observations and oceanographic conditions may help identify areas requiring additional monitoring or consideration in spatial-management plans. Within protected areas, camera-trap and acoustic data can help determine whether monitoring effort should be redirected towards locations where target species are rarely detected or where ecological conditions are changing.

The contribution of ML to policy is therefore primarily informational and analytical. It can improve the timeliness and geographical detail of evidence available to conservation planners, while allowing alternative scenarios to be examined more efficiently. However, conservation decisions are not determined by predictive accuracy alone. They also involve legal obligations, resource constraints, local livelihoods, competing land uses, cultural values, and uncertainty about future environmental conditions (Lakavath, 2024). A model may identify an ecologically valuable area for protection, for instance, but implementation may require consultation with local communities, assessment of existing land rights, and consideration of the consequences for resource access. Likewise, a predicted wildlife corridor may be technically suitable but impractical without agreements among multiple landowners or administrative authorities. ML outputs must therefore be interpreted within broader institutional and social contexts.

3.4. Ethical, Technical, and Operational Challenges of Machine Learning in Wildlife Conservation

Despite its potential benefits, ML adoption in wildlife conservation is constrained by interconnected data, technical, ethical, and institutional challenges. The reviewed literature suggests that these challenges influence not only model performance but also the fairness, reliability, and legitimacy of conservation interventions. Poor-quality training data can produce inaccurate predictions, inadequate security can expose sensitive species locations, and unequal access to technical infrastructure can concentrate the benefits of ML in well-funded organisations (Ojija, 2025). Addressing these concerns requires conservation programmes to evaluate the entire monitoring process, from data collection and model development to deployment, interpretation, and long-term management.

3.4.1. Data Quality, Species Misclassification, Model Bias, and Limited Training Data

Data quality is a fundamental determinant of ML performance in wildlife conservation. Models learn patterns from the observations used during training, meaning that inaccurate labels, incomplete records, inconsistent sampling, and unrepresentative datasets can limit their reliability. Camera-trap images may be affected by poor lighting, motion blur, vegetation obstruction, or unsuitable camera placement, while acoustic recordings may contain wind, rain, traffic, or overlapping animal calls. Satellite observations may be affected by cloud cover, differences in spatial resolution, and inconsistencies between observation dates. These limitations can introduce uncertainty before a model begins making predictions. A major concern is the underrepresentation of rare species and particular ecological settings in training datasets (Raghav, 2025). Common species may account for most recorded observations, allowing models to achieve high overall accuracy while performing poorly on less

frequently observed species. For example, a camera-trap classifier trained primarily on large mammals may be less reliable when identifying small mammals, juveniles, or species photographed under unusual environmental conditions. Similarly, an acoustic model trained in a quiet forest may misclassify bird calls when applied in an urban woodland with substantial background noise. Lakavath (2024) highlighted the importance of contextual variation in camera-trap image classification and showed why performance across different locations is a critical concern. Their work reinforces the broader finding that models can learn location-specific characteristics rather than generalisable features of the target species. Consequently, a model performing well at one research site may perform less effectively when transferred to another site with different vegetation, lighting, species composition, or camera settings. Limited training data create additional difficulties for endangered species because the collection of sufficient observations may be expensive, time-consuming, or ethically constrained (Watara, 2025). Data augmentation, transfer learning, semi-supervised learning, and synthetic training examples may help address these limitations, but they do not eliminate the need for representative validation data. Synthetic observations, in particular, must be assessed carefully because they may fail to capture the complexity of real wildlife encounters.

3.4.2. Privacy, Data Security, Indigenous Rights, and Risks of Wildlife Location Disclosure

The use of ML in conservation raises ethical concerns that extend beyond technical accuracy. Wildlife monitoring systems may generate precise information about the locations, movement routes, breeding sites, and seasonal activities of endangered animals. If these data are accessed by unauthorised users, they could potentially facilitate illegal hunting, wildlife trafficking, disturbance of breeding colonies, or other harmful activities. The increasing availability of digital monitoring platforms and automated data-sharing systems makes the protection of sensitive ecological information an important conservation priority. For example, detailed location records of threatened mammals may identify predictable movement routes or aggregation sites (Tuia, 2022). Publicly accessible maps or downloadable datasets could unintentionally expose these locations to individuals seeking to exploit wildlife. Similarly, information about rare bird nesting sites or vulnerable marine species may create risks if it is published at a spatial resolution that permits precise identification. Consequently, transparency in scientific reporting must be balanced against the potential harm caused by disclosing sensitive ecological information.

ML-based conservation also raises questions about Indigenous rights, community knowledge, and control over environmental data. Indigenous peoples and local communities frequently possess detailed knowledge of wildlife behaviour, habitat conditions, and seasonal ecological changes. When this knowledge informs monitoring models, ethical research requires attention to informed participation, appropriate recognition, data ownership, and the intended uses of the resulting information. The digitisation of local ecological knowledge should not automatically imply unrestricted access by external researchers, commercial organisations, or government agencies. The CARE Principles for Indigenous Data Governance, developed by Jain (2024), emphasise collective benefit, authority to control, responsibility, and ethics. These principles provide a useful framework for conservation projects involving Indigenous knowledge or community-generated data. They complement technical data-management practices by recognising that responsible data governance also concerns power, participation, and the distribution of benefits.

The findings suggest that conservation organisations should adopt proportionate access controls, secure storage, clear data-sharing agreements, and procedures for protecting sensitive location information. Depending on the ecological risk, this may involve spatial aggregation, delayed publication, restricted access, or the removal of precise coordinates from publicly available datasets. Where Indigenous and local knowledge is involved, communities should participate meaningfully in decisions about collection, interpretation, storage, and reuse (Watara, 2026). Importantly, data protection should not become a justification for excluding communities from conservation decisions or withholding information that they need to manage their own resources. Responsible ML governance must balance species protection, legitimate scientific access, community rights, and public accountability. These considerations should be incorporated into project design rather than addressed only after data have been collected or published.

3.4.3. Infrastructure Costs, Technical Expertise, Algorithmic Transparency, and Unequal Access to Technology

The practical implementation of ML requires more than access to algorithms. Conservation organisations need appropriate sensors, computing facilities, reliable power supplies, data storage, internet connectivity where required, trained personnel, and resources for equipment maintenance. Camera traps and acoustic recorders must be installed and serviced, drones require trained operators and regulatory compliance, and satellite-based monitoring requires suitable analytical tools and technical expertise. These requirements may create substantial barriers for organisations operating with limited budgets or in remote environments. The financial burden is not limited to initial equipment purchases. Long-term monitoring programmes must also cover replacement devices, data management, model updating, field verification, and staff training (Sharma, 2023). In areas with unreliable electricity or limited connectivity, cloud-based processing may be impractical, increasing the need for local computing capacity or offline analytical systems. Furthermore, models developed by external research institutions may be difficult for local conservation teams to maintain if the underlying code, documentation, or technical knowledge is inaccessible.

These limitations have implications for conservation equity. Organisations in wealthier countries or well-funded protected areas may have access to advanced sensors, high-performance computing, and large annotated datasets, while conservation programmes in biodiversity-rich but resource-constrained regions may lack comparable capabilities. This imbalance can influence which ecosystems are monitored most intensively and whose research priorities receive technological support. It may also increase dependence on external providers for essential conservation infrastructure. Algorithmic transparency is another important concern (Nandutu, 2022). Complex deep-learning models can produce predictions without providing straightforward explanations of the features or relationships underlying their outputs. A conservation manager may receive a prediction that a species is likely to occur in a particular location without knowing whether it reflects relevant ecological conditions or an unintended correlation in the training data. This creates difficulties when decisions must be justified to regulators, local communities, funding organisations, or the public.

Explainable ML techniques, model documentation, uncertainty estimates, and independent evaluation can help address these challenges. However, explanations should be assessed for their usefulness rather than treated as guarantees that a model is correct (Watara, 2026). Equally important are open and reproducible workflows, accessible documentation, and training opportunities that enable local researchers to evaluate and adapt systems independently.

3.5. Future Directions and Emerging Opportunities for Machine Learning in Wildlife Conservation

The future development of ML-based wildlife conservation is likely to depend on stronger integration of data sources, more transparent decision-support systems, and closer collaboration between technical researchers and conservation practitioners. The reviewed literature suggests that the next stage of progress should extend beyond improving classification accuracy towards developing systems that provide reliable, timely, and actionable ecological information (Hammouch, 2025). This requires attention to model transferability, responsible data governance, long-term evaluation, and the conditions under which technological interventions produce meaningful conservation benefits.

3.5.1. Integration of Multimodal Data, Remote Sensing, and Real-Time Monitoring Systems

An important future direction is the integration of multimodal ecological data. Individual monitoring technologies provide only partial views of wildlife systems: camera traps record visible animals, acoustic sensors capture vocal activity, GPS devices track selected individuals, and satellites reveal changes in landscape conditions. Combining these sources may enable researchers to construct more comprehensive assessments of species occurrence, habitat suitability, movement, and environmental disturbance. For example, a monitoring system for an endangered mammal could integrate camera-trap detections, acoustic observations where relevant, GPS tracking data, rainfall records, and satellite-derived vegetation measurements (Lotfian, 2021). The combined information could help researchers examine whether changes in observed animal activity correspond to habitat deterioration, seasonal movement, or changes in detectability. Similarly, marine conservation projects could integrate acoustic recordings, animal-tracking observations, sea-surface conditions, and vessel activity to assess potential interactions between wildlife and human activities.

Multimodal learning methods can identify relationships across different types of data, but successful integration requires careful treatment of differences in spatial and temporal resolution. A satellite image may represent an entire landscape over a particular observation period, whereas a camera trap records activity at a specific location and time. If these observations are combined without appropriate alignment, the model may identify misleading associations. Missing data and differences in measurement quality can also affect results (Sher, 2025). Another emerging opportunity is real-time or near-real-time monitoring. Edge computing allows certain models to operate directly on or near monitoring devices, reducing the need to transmit every image or recording to a central server. This could support rapid detection of unusual wildlife activity, habitat disturbances, or potential threats in remote areas. Satellite-based change detection and automated sensor networks may similarly provide timely alerts for conservation managers.

Nevertheless, real-time monitoring should not be regarded as inherently superior to periodic monitoring. Continuous data collection can increase energy consumption, maintenance requirements, storage needs, and false-alert workloads. Some conservation questions, such as long-term population trends or seasonal habitat use, may be better addressed through carefully designed periodic surveys (Branco, 2023). Future systems should therefore match the frequency of observation to the ecological process being studied and the urgency of the management response.

3.5.2. Explainable, Responsible, and Human-Centred Machine Learning for Conservation Decisions

Future ML development should place greater emphasis on explainability, accountability, and the involvement of conservation practitioners and affected communities. As ML systems increasingly inform decisions about protected areas, endangered species, habitat restoration, and surveillance, users need to understand the evidence supporting model predictions and the uncertainties associated with them. Explainable approaches can help identify which environmental variables or observed features contribute to

a prediction and reveal whether the model relies on plausible ecological relationships or potentially misleading patterns. For instance, a habitat-suitability model might predict a high probability of species occurrence because of vegetation cover, elevation, and water availability (Isabelle, 2022). Understanding the contribution of these variables can help researchers evaluate whether the prediction is ecologically plausible. Similarly, an image classifier that provides uncertainty estimates can identify observations requiring expert review instead of automatically assigning a definitive species label. Such approaches are especially important when the target species is endangered or when classification errors could lead to inappropriate management decisions.

However, explainability alone cannot resolve all concerns. A transparent model may still be trained on biased data, omit important ecological variables, or perform poorly in unfamiliar environments. Responsible ML therefore requires a broader framework that includes data documentation, independent validation, uncertainty communication, secure data management, and clear accountability for decisions. Model developers should also establish procedures for monitoring performance after deployment because ecological conditions and data distributions may change over time (Fergus, 2024). A human-centred approach further recognises that conservation managers, field ecologists, Indigenous peoples, and local communities possess contextual knowledge that may not be represented in digital datasets. Their involvement can help identify relevant research questions, assess the practical meaning of model outputs, and determine whether proposed interventions are locally appropriate. Participation should be meaningful throughout the project lifecycle rather than limited to collecting data or testing a completed system.

Human oversight is particularly important when model predictions could trigger surveillance, restrictions on resource access, or other consequential interventions. Conservation organisations should establish clear procedures for verifying uncertain predictions, documenting decisions, addressing errors, and reviewing unintended consequences (McClure, 2020). These procedures can strengthen public trust while ensuring that ML remains a support for informed decision-making rather than an unquestioned authority.

3.5.3. Research Gaps, Collaborative Conservation Frameworks, and Priorities for Future Studies

Several research gaps remain in the application of ML to wildlife conservation. First, many studies focus on technical performance within particular datasets, locations, or species groups, while providing limited evidence about how models perform when transferred to different ecological settings. Future research should prioritise geographically independent validation, seasonal testing, and evaluations across different species, habitats, and observation platforms (Espindola, 2025). This would help establish whether reported improvements can be reproduced under real-world conservation conditions.

Second, additional evidence is needed on the relationship between ML deployment and measurable ecological outcomes. Automated classification and habitat prediction can improve monitoring, but relatively strong technical performance does not necessarily demonstrate increased population viability, reduced habitat loss, or improved biodiversity. Longitudinal evaluations should examine whether ML-supported decisions lead to more effective interventions and whether the benefits justify the associated financial and operational costs (Ahmed, 2024). Comparative studies of ML-assisted and conventional monitoring would be particularly useful for determining where these systems offer the greatest added value.

Third, future studies should investigate methods for addressing limited observations of rare and endangered species. Transfer learning, semi-supervised approaches, active learning, and carefully designed data-sharing partnerships may help improve model performance where labelled data are scarce. Nevertheless, these methods require evaluation under realistic conditions, particularly when false negatives could result in missed detections of threatened species (Obisa, 2025). Research should also examine how uncertainty can be incorporated into population estimates, distribution maps, and management recommendations. Fourth, ethical and governance issues require more empirical attention. Future studies should investigate how conservation organisations protect sensitive location data, establish responsible data-sharing agreements, and incorporate Indigenous and local knowledge into ML development. Research should also examine the accessibility of conservation technologies in resource-constrained settings and identify practical models for sharing infrastructure, expertise, and analytical resources without creating excessive dependence on external providers (Lakavath, 2025).

Collaborative conservation frameworks offer a promising response to these challenges. Universities, conservation organisations, government agencies, technology developers, Indigenous peoples, and local communities can jointly establish research priorities, develop representative datasets, and evaluate systems in their intended operational environments. Regional training programmes and shared analytical infrastructure may strengthen local capacity while improving the geographical diversity of conservation datasets (Nandutu, 2023). Open science practices can support reproducibility, although sensitive ecological information should remain subject to appropriate access restrictions.

Finally, future research should develop evaluation frameworks that combine technical, ecological, financial, and social indicators. Such frameworks could assess classification performance, uncertainty, monitoring costs, detection timeliness, model transferability, conservation outcomes, and community acceptability (Kumar, 2025). This would enable more meaningful comparisons between alternative ML approaches and help decision-makers determine when automation is appropriate, when human-led monitoring is preferable, and when a combination of methods is most effective.

4. Conclusion

Machine learning has emerged as a valuable tool for wildlife monitoring and conservation, offering innovative approaches to species identification, population estimation, behavioral analysis, habitat assessment, and the detection of threats such as poaching and habitat degradation. Techniques including computer vision, deep learning, acoustic recognition, and predictive modeling can improve the speed, accuracy, and scalability of ecological data analysis, enabling conservation practitioners to make more informed and timely decisions. However, the effectiveness of these technologies depends on the quality and representativeness of training data, the availability of computational resources, the integration of local ecological knowledge, and the capacity of conservation institutions to implement and maintain machine learning systems. Ethical challenges, including wildlife disturbance, data privacy, algorithmic bias, unequal access to technology, and the potential misuse of sensitive species-location information, must also be addressed to ensure responsible application. Future research should prioritize explainable and energy-efficient models, standardized ecological datasets, interdisciplinary collaboration, community participation, and long-term field validation across diverse ecosystems, particularly in under-resourced conservation settings. Ultimately, machine learning should complement rather than replace ecological expertise and traditional conservation practices, providing a responsible, evidence-based foundation for biodiversity protection, sustainable ecosystem management, and the long-term preservation of wildlife.

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