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Article

The algorithmic guardians: AI and computer vision for global faunal welfare, conservation, and future policy trajectories in the Indian subcontinent

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Abstract: Artificial Intelligence (AI) and Computer Vision (CV) are rapidly transforming animal welfare, conservation, and ecosystem management by enabling scalable, real-time analysis of large multimodal datasets. Traditional monitoring approaches are increasingly inadequate due to the exponential growth of visual and sensor data across farms, urban ecosystems, and wildlife habitats. This paper presents a structured review of AI/CV methodologies—including convolutional neural networks, You Only Look Once (YOLO)-based detection, and pose estimation—for quantitative faunal assessment. A systematic synthesis is provided across key domains such as precision livestock farming, urban animal welfare, wildlife conservation, and marine ecosystem monitoring. The study adopts a structured literature review methodology, outlining database selection, inclusion criteria, and comparative evaluation of state-of-the-art techniques. Key findings indicate that AI-driven systems significantly enhance early disease detection, behavioral analysis, and conservation efficiency, though challenges persist in terms of data scarcity, algorithmic bias, and deployment constraints in low-resource environments. A comparative analysis highlights trade-offs between accuracy, computational efficiency, and scalability across different AI architectures. The paper also identifies critical research gaps, including the lack of standardized datasets, limited cross-species generalization, and insufficient integration with policy frameworks. Finally, the study proposes a conceptual framework integrating AI, edge computing, and ethical governance for sustainable faunal management. The findings underscore the need for interdisciplinary collaboration and responsible AI deployment to ensure equitable and scalable benefits across diverse ecological and socio-economic contexts.

Keywords: artificial intelligence (AI); computer vision (CV); animal welfare; conservation; edge computing

1. Introduction: Contextualizing AI/CV as a paradigm shift in zoo-ecosystemic management

1.1. The crisis of welfare and conservation: Data overload and monitoring gaps

Modern animal welfare and conservation systems face a fundamental challenge: data availability has increased rapidly, but analytical capacity remains limited. This is true for both controlled environments like farms, labs, and zoos, as well as large, remote natural ecosystems. High-resolution camera traps, continuous video surveillance, bioacoustic sensors, satellite imagery, and unmanned aerial vehicles (UAVs) are all examples of new sensing technologies that have led to a huge increase in multimodal ecological and behavioral datasets. Reliance on manual or semi-manual analysis creates a major bottleneck. Data collection is faster than data processing and interpretation [1]. These delays directly impact animal welfare by slowing the detection of disease, injury, and stress-related behaviors. It also has effects on conservation outcomes, where timely actions are often needed to stop poaching, habitat loss, or population decline [1]. In the context of wildlife conservation, the logistical and analytical difficulties involved in retrieving, labeling, and analyzing large amounts of remote camera trap data often lead to significant delays between data collection and management decision-making, which makes it harder to protect endangered or vulnerable species [1].

In this context, artificial intelligence (AI) and computer vision (CV) provide a scalable solution by enabling automated and real-time data analysis. The main problem is no longer a lack of data, but rather the lack of scalable, human-centered systems that can constantly pull useful information from large, fast-moving data streams. AI-driven analytical frameworks solve this problem by making it possible to automatically and in real time detect, classify, and interpret behavior in a wide range of ecological settings. AI and CV systems help move from monitoring that looks back and reacts to what has already happened to management strategies that look ahead, take action, and adapt. They do this by turning raw sensor data into structured, decision-relevant information. This change marks a major shift in how zoos and ecosystems are managed. Computational intelligence will become an important part of the infrastructure needed to protect animals and make conservation work on a large scale.

1.2. Defining the role of artificial intelligence and computer vision in faunal assessment

Artificial intelligence (AI) is generally defined as a category of computational systems intended to replicate cognitive functions typically linked to intelligent biological entities, such as perception, learning, reasoning, pattern recognition, and adaptive problem-solving [2]. In the context of faunal assessment, AI offers a methodological framework for transforming extensive, diverse datasets into comprehensible indicators of animal condition, behavior, and ecological interactions. Computer Vision (CV), a specialized subfield of AI, implements this framework by utilizing deep learning architectures—specifically convolutional and transformer-based neural networks—to derive semantic meaning from visual inputs, including images and video streams. These systems produce quantifiable and reproducible metrics that facilitate automated species identification, detailed behavioral phenotyping, posture and gait analysis, and the identification of physiological or behavioral anomalies indicative of compromised welfare or ecological stress [3].

Machine learning models used in this field are trained on carefully chosen datasets to find both discrete and continuous behavioral patterns. This makes it possible to sort complex activities and, more and more, to guess animals' emotional or affective states. CV-based systems can pick up on small changes in behavior, like changes in how someone moves, how they interact with others, or how they rest, by combining spatiotemporal features across frames. These changes could be early signs of pain, distress, or disease [3]. Conversely, these models can also find positive signs of welfare, such as play behavior, exploratory activity, and normal social bonding. This supports a more complete, multidimensional assessment of animal wellbeing that goes beyond just looking for signs of illness [3].

AI-driven faunal assessment can do a lot more than just find bad things like disease outbreaks, injuries, and illegal activities like poaching. More and more, AI systems are being used in closed-loop management and intervention frameworks that actively work to improve welfare outcomes. Intelligent feeding systems that can provide personalized nutritional plans based on real-time behavioral and physiological cues in companion and captive animals [4] are one example. Another is decision-support tools that use long-term data to help with habitat design, enrichment scheduling, and population management. AI makes it possible to find new patterns and trends in large-scale temporal datasets that would be impossible to find just by looking at them. This makes it easier to plan for welfare and conservation in a proactive and evidence-based way [3].

Even though AI and CV can transform the way we assess animals, using them on a large scale is only possible if we can solve a number of technical, ethical, and governance-related problems that are all connected. These encompass the ethical design and utilization of AI systems, the alleviation of algorithmic bias stemming from skewed or context-dependent training data, and the rectification of enduring challenges related to data ownership, privacy, security, and interoperability across institutional and geographical boundaries [3]. To make sure that AI-driven faunal assessment frameworks are not only technically sound, but also morally sound, socially acceptable, and long-lasting in a wide range of ecological and regulatory settings, these cross-cutting issues must be dealt with.

1.3. Problem statement and research objectives

Despite rapid advancements in artificial intelligence and computer vision, current faunal monitoring systems remain fragmented, reactive, and constrained by limited analytical scalability. Existing approaches either rely heavily on manual interpretation or lack integration across ecological, agricultural, and urban domains. Furthermore, there is no unified analytical framework that systematically evaluates AI-driven methodologies in terms of performance, scalability, and ethical implications.

This study aims to address the following research questions:

1. How can AI and CV techniques be systematically categorized for faunal welfare and conservation?
2. What are the comparative strengths and limitations of existing methodologies?
3. What critical research gaps exist in current AI-driven faunal monitoring systems?
4. How can a structured, ethical, and scalable framework be developed for real-world deployment?

1.4. Key contributions of the study

This paper makes the following contributions:

1. Provides a structured and systematic review of AI/CV in faunal systems.
2. Introduces a comparative analytical framework.

3. Identifies critical research gaps.
4. Proposes an integrated conceptual framework for scalable deployment.

1.5. Research methodology

This study adopts a structured literature review approach to ensure methodological rigor and reproducibility.

1.5.1. Data sources and search strategy

Relevant literature was collected from major scientific databases, including IEEE Xplore, Scopus, Web of Science, and Google Scholar. Keywords used include: "AI in animal welfare", "computer vision livestock monitoring", "wildlife conservation AI", "YOLO animal detection", and "pose estimation animals".

1.5.2. Inclusion and exclusion criteria

- Included: Peer-reviewed journal articles and conference papers (2018–2025).
- Excluded: Blogs, websites, and non-peer-reviewed sources (unless used for case examples).

1.5.3. Analysis framework

Selected studies were analyzed based on:

- Model architecture;
- Application domain;
- Accuracy/performance metrics;
- Computational requirements;
- Limitations and scalability.

1.5.4. Comparative evaluation

A structured comparison was conducted to evaluate different AI techniques across multiple domains, focusing on efficiency, generalizability, and deployment feasibility.

1.6. Integrated conceptual framework for AI-driven faunal management

To address the limitations of fragmented monitoring systems, this study proposes an integrated conceptual framework that aligns technological capabilities with ethical and operational realities. This framework, visualized in **Figure 1**, conceptualizes AI-driven faunal management as a four-layered hierarchical architecture that facilitates the transition from reactive observation to proactive, data-driven intervention.

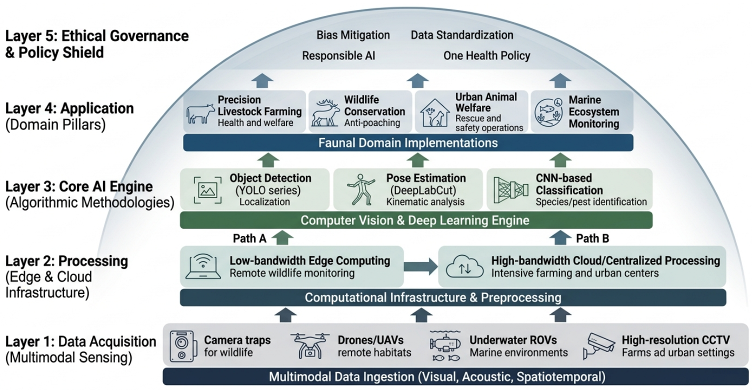

Figure 1. Integrated conceptual framework for AI-driven faunal welfare and conservation.

1.6.1. The data acquisition layer (foundation)

The foundation of the framework is built upon multimodal sensing capabilities. This layer integrates diverse data streams—including high-resolution visual feeds from closed-circuit television (CCTV), spatiotemporal data from camera traps, aerial surveillance from UAVs, and underwater imaging—to create a comprehensive digital representation of the faunal environment. The choice of sensing technology is determined by the specific ecological or agricultural context, ensuring that raw data collection is both scalable and contextually relevant.

1.6.2. The analytical intelligence layer (core)

At the core of the framework lies the AI and Computer Vision Engine, which transforms raw sensory input into structured, actionable information. This layer utilizes three primary methodological pillars:

- **Object detection and tracking (e.g., YOLO):** For real-time localization and identification of individuals or species.
- **Pose estimation and kinematics (e.g., DeepLabCut):** For granular behavioral phenotyping and objective welfare scoring.
- **Deep learning classifiers (convolutional neural networks, CNNs):** For fine-grained taxonomic classification and anomaly detection.

The intelligence layer is further bifurcated by infrastructure constraints: Edge computing is prioritized for remote wildlife conservation where bandwidth is low, while cloud-centric processing is utilized for high-throughput environments like precision livestock farms.

1.6.3. The domain-specific application layer

The analytical outputs are channeled into specialized modules tailored for diverse faunal systems. These include:

- **Precision livestock & poultry farming (PLPF):** Focused on early disease detection and automated welfare monitoring.
- **Wildlife & conservation management:** Focused on anti-poaching, habitat restoration, and population census.
- **Urban & companion animal welfare:** Focused on stray animal rescue, biometric identification, and public safety.
- **Marine & aquatic monitoring:** Focused on biodiversity assessment and marine debris detection.

1.6.4. The ethical governance & policy overlay (apex)

The apex of the framework consists of a responsible AI governance shield, which ensures that technological deployment remains ethically grounded. This layer mandates Algorithmic Bias Auditing to prevent data skew from disadvantaging marginalized species or low-resource farming communities. It also integrates One Health Policy Trajectories, aligning animal welfare with broader public health and ecological sustainability goals. By embedding ethical considerations directly into the architecture, the framework ensures that “Algorithmic Guardians” operate with transparency, accountability, and cross-species equity.

2. Foundational AI/CV methodologies for quantitative faunal analysis

This section presents key deep learning architectures and deployment strategies. These systems enable AI- and CV-based animal monitoring. These methods support diverse monitoring objectives. They enable both individual welfare assessment and large-scale environmental monitoring. The focus is on scalable and efficient models. These models operate under constraints such as poor connectivity and dynamic environmental conditions. **Figure 2** illustrates the architecture of AI-based faunal monitoring systems, highlighting the interaction between data acquisition, model processing, and deployment layers. Notably, the integration of edge computing reduces latency but introduces constraints on model complexity, indicating a trade-off between real-time processing and predictive performance.

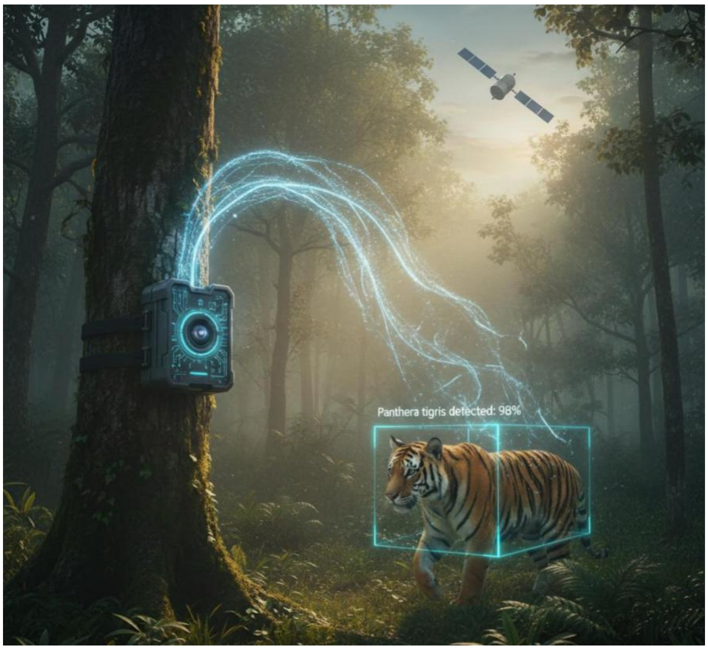

Figure 2. AI-enabled edge computing is deployed for real-time monitoring in remote wildlife habitats.

2.1. Core CV techniques: Object detection, tracking, and classification

Convolutional neural network (CNN)-based architectures that are optimized for object detection, localization, tracking, and classification are the basis for most quantitative faunal monitoring pipelines. These models make it possible to automatically find animals, body parts, or biologically important objects in pictures and videos. This is the basis for making higher-level behavioral and ecological inferences. Single-stage detectors, especially the YOLO family of architectures, have become very popular because they can find and classify objects at the same time with low inference latency and high throughput [5, 6]. Because they are so efficient, YOLO-based models are great for real-time and near-real-time applications where making decisions quickly is critical. Unlike traditional CNN-based detection approaches that prioritize accuracy and detailed feature extraction, YOLO-based frameworks emphasize scalability and real-time applicability, making them more suitable for deployment in large-scale and resource-constrained faunal monitoring systems.

Model performance in such detection frameworks is significantly influenced by hyperparameter selection, including learning rate, batch size, optimizer choice (e.g., Adam, Stochastic Gradient Descent (SGD)), number of training epochs, and anchor box configurations. In most computer vision-based faunal applications, models are trained using transfer learning with pre-trained weights (e.g., ImageNet or Common Objects in Context (COCO) datasets) to improve convergence speed, enhance generalization, and reduce the dependency on large annotated datasets.

Two-stage detectors like Region-based Convolutional Neural Networks (R-CNNs) usually have high accuracy but are harder to use. YOLO architectures, on the other hand, strike a better balance between speed and accuracy. This equilibrium has been empirically substantiated in practical livestock monitoring scenarios, such as real-time lameness detection in cattle, where swift frame-by-frame analysis is crucial for prompt intervention and welfare management [7]. The ability to keep up good performance on hardware with limited resources makes it easier to use YOLO-based systems at the edge. This means less reliance on cloud-based processing and the ability to keep an eye on things all the time.

Recent improvements in YOLO-based frameworks have helped extend CV capabilities to marine ecosystems, where visibility is limited, backgrounds are constantly changing, and light is absorbed. Advanced versions like Ultralytics YOLO11 have shown better scalability, inference speed, and detection robustness, making it possible to use them for things like automated monitoring of marine life, assessing biodiversity, and finding man-made debris that is underwater [5]. This demonstrates the adaptability of CNN-based detection across diverse ecological environments.

CNNs are also very good at fine-grained classification tasks in both conservation and agriculture settings, in addition to detection and tracking. One well-known example is the automation of Integrated Pest Management (IPM) systems, which used to depend on people checking insect traps by hand, which took significant time. Smart vision systems can use CNN-based classifiers to tell the difference between target pest species, like moths, and non-target insects caught in sticky traps. In postharvest agricultural settings, such systems have attained overall classification accuracies reaching 95.8%, markedly improving monitoring precision while decreasing labor demands and subjective error [8]. All of these applications show how important CNN-driven object detection and classification are as technologies that make it possible to do scalable, quantitative faunal analysis in many different fields [9]. Nevertheless, pose estimation approaches remain constrained by their heavy reliance on annotated datasets, which limits scalability across species and ecological contexts. While these methods provide highly granular behavioral insights, their deployment in real-world scenarios is often restricted due to annotation costs and computational complexity. This indicates a critical trade-off between analytical depth and practical deployability.

2.2. Deep learning for behavioral phenotyping and pose estimation

To do a full and unbiased assessment of animal welfare, you need to be able to turn raw video data into accurate, quantitative descriptions of movement, posture, and behavioral dynamics. Deep learning–based pose estimation has become an essential methodological framework for attaining this goal, facilitating the extraction of detailed kinematic data from conventional monocular or multi-camera video streams. These methods modify convolutional neural network (CNN) architectures—many of which were initially designed for human action recognition and biomechanics analysis—for application to non-human species, facilitating the identification and tracking of anatomically significant landmarks, such as joints, limb endpoints, and body segments, across successive image frames [10]. Pose estimation systems offer a fundamental data layer for subsequent behavioral phenotyping and welfare inference by accurately localizing keypoints with high spatial and temporal resolution.

To make accurate pose estimation models for specific species, significant data preparation and annotation are needed. This is because deep learning architectures need high-quality ground-truth labels for supervised training. For this process, key anatomical landmarks are usually marked by hand using specialized tools like DeepLabCut or the Computer Vision Annotation Tool (CVAT). These tools make it easier to label each frame and check the quality of large video datasets [7]. Even though these tools have made it much easier and more reliable to annotate, creating training datasets that are diverse and representative is still very resource-intensive. This is especially true when you think about how different animals' shapes, coat colors, lighting conditions, occlusions, and camera angles can be.

After extraction, pose keypoints undergo a mathematical transformation into higher-order kinematic descriptors, such as stride length, joint angle trajectories, step frequency, stance and swing phase durations, and symmetry indices. After that, machine learning models connect these objective, continuous parameters to established ordinal or categorical visual scoring systems that are commonly used by human experts. This integrated workflow is especially important for automated lameness detection and scoring in dairy cows, where changes in gait can be early signs of pain, injury, or musculoskeletal disease that have big effects on both animal welfare and the economy [7]. Object detection frameworks like YOLO are often used in real-time monitoring applications to quickly find animals in video frames. This makes it possible to create efficient, end-to-end pipelines that combine detection, pose estimation, and behavioral classification with very little delay [7]. **Figure 3** highlights the sequential processing stages in computer vision-based detection, where preprocessing quality directly impacts model accuracy and robustness.

Even though pose estimation-based welfare assessment has many benefits, such as being more objective, repeatable, and sensitive to small changes in behavior, it is not used as much as it could be because manual keypoint annotation is expensive and time-consuming. This limitation is especially noticeable when applying these methods to new species, rare or endangered taxa, or ecological contexts that vary greatly, where there aren't many or any already-annotated datasets. So, the fact that we rely on supervised learning paradigms right now is a big problem for scalability and cross-species generalization. This challenge highlights the necessity for ongoing methodological investigation into self-supervised, weakly supervised, and transfer learning techniques that can minimize annotation demands while maintaining model precision, thus facilitating the extensive implementation of comprehensive behavioral phenotyping and welfare assessment across various faunal systems.

Figure 3. Computer vision and pose estimation for monitoring animal behavior in farming systems.

2.3. Data preprocessing and edge computing: Strategies for remote deployment

The operational implementation of AI-driven faunal monitoring systems in remote or infrastructure-deficient settings, including national parks, wilderness reserves, or secluded marine areas, is fundamentally limited by the accessibility and dependability of network connectivity [1]. In these situations, traditional cloud-based processing pipelines that depend on constant high-bandwidth data transfer don't work, so other types of computing architectures are needed. Edge computing, which processes data locally at the point of acquisition, has become an important way to get around this problem. Unlike traditional cloud-centric AI architectures that prioritize model complexity and accuracy, edge-based systems emphasize scalability, low latency, and deployment feasibility, often at the expense of reduced computational sophistication. It allows for near-real-time inference and cuts down on the need for remote servers.

Prior to model deployment, robust data preprocessing pipelines are essential to ensure reliable performance under real-world conditions. These steps typically include image normalization, resizing to standardized input dimensions, and data augmentation techniques such as rotation, flipping, scaling, and brightness adjustments. Noise reduction and background filtering are also commonly applied to mitigate environmental variability. Such preprocessing enhances model robustness, reduces overfitting, and improves generalization across heterogeneous ecological and agricultural environments.

The Sentinel device made by Conservation X Labs is a well-known example of this method in action. This device connects a minicomputer directly to camera trap hardware, which lets deep learning models run inference on the images they capture [1]. The local AI processing pipeline does the first filtering and prioritizing of the data. This gets rid of frames that aren't needed, which can make up to 90% of the images taken by regular motion-triggered camera traps [1]. Only the most important, highly compressed information, like species presence or behavior descriptors (like "white boar detected"), is sent to centralized user dashboards over low-bandwidth satellite or cellular networks. This selective transmission greatly cuts down on data load, makes the best use of bandwidth, and makes sure that researchers and conservation managers get actionable insights in near real time, even when connectivity is very limited [1].

The difference in architecture between high-bandwidth precision livestock systems and low-bandwidth remote wildlife monitoring systems shows an important rule for using AI in real life: AI pipelines should be designed more for the limits of the communication infrastructure than for the biological needs of the target species [1]. In practice, this means that scalable, edge-based AI solutions are necessary for ecosystems that are hard to reach or far away, while cloud-based, high-throughput pipelines may still be better in controlled environments with lots of infrastructure, like farms, zoos, or research facilities. As a result, combining edge computing, data preprocessing, and smart compression techniques is a key technology that makes it possible to use AI to monitor animals in difficult-to-reach areas with limited connectivity. However, edge-based AI systems introduce constraints related to hardware limitations, model compression, and reduced computational flexibility. While they enable real-time deployment in remote environments, this often comes at the cost of reduced model complexity and potential performance degradation. This reflects a trade-off between deployment feasibility and model sophistication. **Table 1** provides a structured overview of major AI and Computer Vision techniques used in animal welfare applications, categorizing them based on functionality, use-case domains, and system capabilities. The comparison highlights the diversity of approaches and indicates how different models address specific challenges such as real-time detection, behavioral analysis, and large-scale monitoring, thereby forming the foundation for subsequent comparative analysis.

Table 1. AI and computer vision in animal welfare.

Model architecture	Primary application in animal welfare	Key advantages	Primary limitations
2D/3D Convolutional Neural Networks (CNNs)	Action Recognition, Species Classification, Automated Insect Counting [8,10]	Strong spatial and temporal feature extraction; high classification accuracy (e.g., 95.8% in moth identification) [8]	High computational cost; dependency on large, high-quality video datasets.
YOLO (You Only Look Once)	Real-Time Object Detection, Gait Analysis, Marine Tracking (YOLO11) [5,7]	High speed and efficiency; suitability for real-time edge computing (e.g., Sentinel processing) [1,7]	Lower accuracy compared to two-stage detectors in highly congested scenes; specialized training required for non-standard detection (e.g., keypoints).

Table 1. *Cont.*

Model architecture	Primary application in animal welfare	Key advantages	Primary limitations
Pose Estimation (e.g., DeepLabCut framework)	Lameness Scoring in Cattle, Detailed Behavioral Ethograms [7]	Extracts precise joint positions for objective, quantitative welfare metrics (gait analysis).	Requires extensive, labor-intensive manual annotation (labeling) for training specific keypoints [7]

While **Figure 1** provides a conceptual overview, **Table 2** offers a comparative evaluation of these techniques, enabling a more detailed analytical understanding of their performance trade-offs.

Table 2. Comparative analysis of AI techniques.

Technique	Accuracy	Speed	Scalability	Limitation
CNN	High	Medium	Medium	Data intensive
YOLO	Medium-High	High	High	Slight accuracy trade-off
Pose Estimation	Very High	Low	Low	Annotation heavy
Edge AI	Medium	High	Very High	Hardware constraints

3. Applications across the fauna spectrum (welfare and conservation)

3.1. Precision livestock and poultry farming (PLPF)

In high-density farming systems, AI and CV support data-driven management decisions. These systems improve animal welfare and operational efficiency [11]. In these situations, keeping an eye on large groups of livestock and poultry all the time provides significant behavioral and physiological data that would be too much work to process by hand at scale. CV systems convert raw data into actionable insights. They help find health and welfare problems early by noticing small changes in behavior, posture, or movement that could mean a new illness, stress, or poor environmental conditions.

The combination of AI and CV in PLPF fits well with one health frameworks. This is because proactive monitoring can stop the spread of infectious diseases, which means fewer antimicrobial interventions are needed and intensive production systems can be more sustainable overall. Some important uses of PLPF are automated animal identification, continuous monitoring of feed intake, real-time body weight estimation, and health monitoring through behavior-based indicators [11,12]. Automated lameness scoring is one of the most important uses of CV-based systems. By using pose estimation and gait analysis, these systems turn complicated biomechanical patterns into quantitative welfare metrics. This makes it possible to find and treat a condition that not only harms animal health but also costs producers significant money [7].

The use of AI-driven PLPF systems shows how computational monitoring systems can change reactive management methods into proactive, welfare-focused ones. These systems offer a scalable way to keep high standards of animal welfare while also improving production efficiency in intensive farming settings by constantly turning behavioral and physiological data streams into metrics that can be understood and acted on. However, the effectiveness of these systems is highly dependent on controlled environmental conditions and consistent data quality, limiting their applicability in heterogeneous or low-resource farming systems. This raises concerns regarding scalability and equitable deployment across diverse agricultural contexts.

3.2. Urban fauna and companion animals (pets and strays)

Artificial Intelligence (AI) has made it possible to create very personalized and responsive care systems for companion animals, such as pets in homes and stray animals in cities. In homes, smart feeding systems use deep neural networks and computer vision to accurately identify each animal, making sure that each one gets the right amount of food every time [4]. By automating portion control and taking into account the dietary needs of different species, ages, and health conditions, these systems lower the risk of overfeeding, malnutrition, or obesity. This directly improves long-term health and overall welfare [4].

AI-based identification technologies have also come up with new ways to use biometrics to take care of pets. For example, nose print recognition systems use the fact that each dog's nose has a different pattern, just like human fingerprints. Deep learning algorithms can recognize and encode these patterns even when the animal is moving, making it easier to quickly identify and register them in centralized or crowdsourced databases. These systems have shown that they can match lost pets with their owners with almost 99% accuracy, which speeds up the process of getting them back together and lowers the stress and welfare risks that come with being apart for a long time [13,14].

AI-driven surveillance is being used more and more on stray animals in cities to improve both animal welfare and public safety. Genie AI and other programs in India use cameras with computer vision to keep an eye on stray animals and automatically spot strange or dangerous behavior. The resulting data enables swift rescue operations and enhanced management of urban animal populations, thereby reducing welfare risks such as injury, starvation, or traffic-related fatalities, while concurrently alleviating dangers for humans in densely populated urban environments [15, 16]. These applications highlight dual societal benefits. AI improves animal welfare while enhancing public health and safety. Despite these advancements, such systems often rely on centralized infrastructure and high-quality imaging conditions, which may not be consistently available in all urban settings. This limits their robustness and scalability in unstructured environments. **Figure 4** demonstrates the diversity of application domains; however, the effectiveness of these systems varies significantly depending on data availability and environmental conditions.

3.3. Wildlife, national parks, and endangered species management

Artificial Intelligence (AI) has become an important technology for modern wildlife conservation. It works as both a defence against human-made threats and a tool for better understanding ecosystems. AI helps predictive modeling frameworks that can find spatial and temporal patterns linked to illegal activities like poaching by processing large amounts of different types of data from remote sensing platforms, camera traps, acoustic sensors, and unmanned aerial systems. These models help find places where poaching is most likely to happen and places where it is most dangerous, which makes it possible to use intelligence-led anti-poaching measures instead of reactive enforcement strategies [17]. These skills are especially useful in large protected areas, where limited human patrol capacity needs to be used wisely to have the biggest impact on conservation.

Figure 4. AI-based urban stray animal monitoring system illustrating automated detection, behavior analysis, and real-time intervention capabilities.

Advanced computer vision (CV) methods improve wildlife management even more by making it possible to identify not only species but also individual animals based on their coat patterns, morphological features, or unique markings. Identifying individual animals and keeping track of their movements all the time makes it possible to do detailed movement analysis, posture assessment, and social interaction mapping. This helps with more accurate population censuses, home-range estimation, and ecological modeling [18]. These detailed data streams facilitate longitudinal studies of animal behavior and habitat utilization, equipping conservation managers with substantial, evidence-based insights into population dynamics and ecosystem health.

Targeted deep learning projects have been shown to be very useful for keeping an eye on endangered species. For instance, specialized detection and tracking models have been made for animals like the Amur tiger. These models are designed to work best on platforms with limited resources, like unmanned aerial vehicles (UAVs) [19]. The possible combination of AI-enabled CV systems with aerial surveillance increases the area that can be monitored, lowers the risk to people, and makes it possible to quickly assess areas that are hard to reach or very dangerous.

AI-driven wildlife monitoring technologies have proven highly effective in managing invasive species, which pose considerable ecological and economic risks to native biodiversity, in addition to safeguarding endangered species. Platforms that were originally made to keep an eye on and protect endangered animals in real time have been successfully used to keep an eye on the populations and movement patterns of invasive species in places like New Zealand [1]. This dual-use capability demonstrates the scalability of AI-based conservation technologies. They can be used for a wide range of ecosystem management tasks, such as protecting species, controlling invasive species, and preserving biodiversity over the long term. However, wildlife monitoring systems face significant challenges related to data sparsity, environmental variability, and limited ground truth validation. These factors can reduce model reliability and hinder the large-scale deployment in complex natural ecosystems.

3.4. Aquatic, marine ecosystems, and fisheries science (ocean fauna)

The long-term viability of global fish stocks and the robustness of marine ecosystems are increasingly reliant on the incorporation of Artificial Intelligence (AI)–driven monitoring and analytical frameworks [16, 20]. Conventional fisheries assessment techniques, typically dependent on manual surveys and restricted sampling, fail to adequately represent the spatial and temporal intricacies of dynamic aquatic ecosystems. In this context, AI offers a scalable and impartial solution for the intelligent recognition, classification, and taxonomic evaluation of marine species, facilitating evidence-based fisheries management and conservation planning [20]. AI systems improve the accuracy and frequency of stock assessments by automating the identification of species and the estimation of size from visual data. This helps set sustainable harvesting quotas and ecosystem-based management strategies.

In aquatic monitoring apps, where real-time or near-real-time analysis is often needed, computer vision (CV) models that are optimized for speed and scalability are critical. Architectures like YOLO11 have been very good at finding and following marine life in video streams from underwater cameras, remotely operated vehicles (ROVs), and autonomous underwater drones [5]. These features make it possible to keep an eye on biodiversity, analyze behavior, and check the health of ecosystems over large areas, even in underwater environments that are hard to see because of changing lighting, turbidity, and background motion. **Figure 5** summarizes key ethical and technical challenges, emphasizing that bias and data limitations remain critical barriers to large-scale deployment.

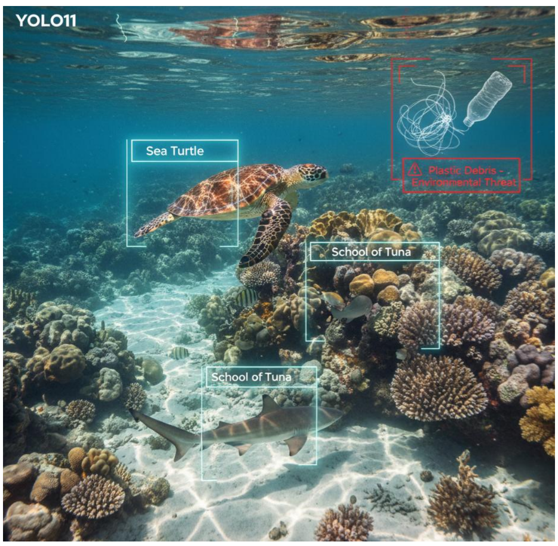

Figure 5. Underwater AI-based detection system using YOLO architectures for marine species identification and environmental monitoring under challenging visibility conditions.

AI-driven CV systems are being used more and more for environmental monitoring in marine ecosystems, in addition to biological monitoring. Models used on fixed or mobile underwater platforms can find, sort, and count human-made debris, such as plastic waste, abandoned fishing gear, and other pollutants that are already in the water [5]. These systems give useful information that helps targeted cleanup efforts and policy changes that aim to cut down on marine pollution by mapping pollution density and finding hotspots where it builds up. The use of AI in fisheries science and monitoring marine ecosystems is a major technological breakthrough that will help protect ocean biodiversity, make resources more sustainable, and reduce the damage humans do to the environment on a large scale. Nevertheless, underwater environments introduce unique challenges such as low visibility, light distortion, and dynamic backgrounds, which can significantly affect model accuracy. This highlights the need for domain-specific model adaptation.

3.5. Insect ecology and integrated pest management (all fauna)

AI and CV have completely changed how we monitor insects. In the past, this was done by hand, which was time-consuming, error-prone, and required significant work. For both agricultural productivity and ecological balance, it is important to accurately measure how insect populations change over time. This includes keeping an eye on beneficial insects like pollinators and controlling harmful pest species. In this case, AI-powered smart vision systems that use convolutional neural networks (CNNs) have been combined with sticky traps with cameras to automate the detection, counting, and fine-grained classification of insect taxa in situ [8].

These systems greatly improve classification accuracy, temporal resolution, and operational efficiency by replacing manual inspection with automated visual analysis. This makes it possible to make timely decisions about postharvest protection and integrated pest management (IPM) [8]. Automated CV pipelines reduce common human error sources like observer fatigue and subjective bias. They also let you collect data continuously and at a high frequency, which isn’t possible with traditional methods. The proposed systems have shown strong performance in real-world situations that are complicated, such as when insects overlap, when the lighting and background change, and when the traps are in different positions [8].

The proven dependability and ability to grow of CNN-based insect monitoring systems show that they could be important parts of future IPM systems. AI-driven solutions help make pest control strategies more accurate and long-lasting by allowing real-time, data-driven assessments of insect populations over large areas and periods of time. This cuts down on unnecessary chemical interventions and protects the ecosystem services that non-target and beneficial insect species provide [8]. However, overlapping objects, environmental noise, and species similarity remain significant challenges, potentially reducing classification accuracy in real-world scenarios. This indicates limitations in model generalization under complex field conditions.

4. Key challenges in AI-driven faunal monitoring

The following section discusses key limitations and challenges that constrain large-scale deployment of AI-driven faunal monitoring systems. AI and CV technologies have advanced rapidly. However, key research gaps limit scalability, generalizability, and real-world impact. One of the foremost challenges is the lack of standardized and large-scale annotated datasets across diverse species and ecological contexts. Existing datasets are fragmented and domain-specific. This limits cross-species model transferability. Closely related to this is the issue of limited generalization, where models trained in specific ecological or agricultural settings fail to perform reliably when deployed in different environmental, climatic, or socio-economic conditions.

Furthermore, current approaches remain heavily dependent on supervised learning paradigms that require extensive manual annotation, particularly for tasks such as pose estimation and fine-grained behavioral analysis. This dependency significantly increases the cost, time, and expertise required for model development, thereby hindering large-scale deployment, especially in resource-constrained regions. A lack of standardized benchmarks is a major limitation. It restricts systematic comparison of model performance.

In addition to technical constraints, ethical challenges—particularly those related to algorithmic bias and fairness—remain insufficiently addressed. Bias arising from unrepresentative training data, geographic skew, and species prioritization can lead to inequitable model performance and potentially reinforce existing disparities in conservation and agricultural systems. Collectively, these challenges highlight the need for more robust, standardized, and ethically grounded research frameworks that can support the development of scalable, transparent, and context-aware AI solutions for global faunal welfare and conservation.

5. Ethical considerations, algorithmic bias, and responsible AI deployment

AI systems are rapidly integrated into faunal management. This raises important ethical concerns related to design, deployment, and governance. AI technologies can help animals, the environment, and ecosystems in many ways, but they also come with new risks like algorithmic bias, uneven representation, and unintentionally making existing structural inequities worse. In faunal systems, these risks are evident not only through technical constraints but also through profound normative inquiries concerning whose welfare is prioritized, the representation of biological diversity within datasets, and the influence of automated decisions on intervention strategies across species and ecological contexts.

5.1. The challenge of data scarcity and ethical nuances

Ethical issues in AI for animal welfare and conservation are very different from those in AI for people. These challenges are frequently articulated through the lens of speciesism, where implicit value hierarchies among species affect data collection priorities, research funding, and algorithmic optimization goals [21]. Faunal data, in contrast to human demographic attributes, are characterized by significant heterogeneity, species specificity, and often scarcity, especially for rare, endangered, or economically undervalued taxa. This imbalance raises the likelihood that AI systems will function effectively for extensively researched species while neglecting others, thus perpetuating existing conservation and welfare inequalities through technological means [21].

Institutional and regulatory barriers limit large-scale deployment. These constraints worsen ethical challenges. Ongoing issues with data ownership, privacy, security, and limits on data sharing between the agricultural, conservation, government, and business sectors are still making it hard to create full, interoperable AI systems [3]. Fragmented data governance frameworks hinder the aggregation of longitudinal, cross-contextual datasets crucial for comprehensive model training, validation, and generalization. To deal with these limits, we need to work together on policy development, create standard data-sharing protocols, and set up ethical governance systems that strike a balance between innovation and accountability. To use AI-driven faunal welfare and conservation systems on a large scale in a responsible, fair, and effective way, these institutional problems must be fixed first.

5.2. Analysis of algorithmic bias

The ethical ramifications of algorithmic bias in AI-driven livestock and wildlife management systems necessitate immediate and thorough examination, especially considering global sustainability goals that regard animal welfare, food security, and equitable agricultural development as interconnected objectives. Algorithmic bias in this area doesn't happen on its own; instead, it shows and makes worse long-standing differences in how much money is spent on research, how much data is available, and what technologies are used in different production systems and geographic areas. If these biases are not dealt with, they could hurt the very sustainability goals that AI technologies are meant to help.

Data skew is a major source of bias. It happens when training datasets show more large-scale, industrialized farming operations than smallholder, extensive, or indigenous production systems. AI models trained on these unrepresentative datasets may work well in environments that require significant technology, but they may not work well in a wide range of real-world situations. This limitation may result in diminished accuracy in disease detection, welfare evaluation, or productivity forecasting for indigenous breeds or animals reared in low-input environments, where behavioral baselines and environmental interactions significantly diverge from those found in industrial systems. These kinds of technical problems have real social and economic effects because they can push already weak farming communities to the edge and make existing inequalities worse by giving people unreliable or hard-to-reach decision support.

Contextual gaps are similar to data skew in that they happen when AI models don't take into account local environmental, cultural, and management factors. Livestock farming practices are deeply rooted in certain weather patterns, limited resources, and traditional ways of knowing. Models that do not incorporate contextual data—such as regional climate variability, locally available feed resources, or culturally specific husbandry practices—may produce recommendations that are impractical, economically unfeasible, or potentially detrimental when implemented beyond their initial training context. For instance, AI systems designed for temperate, high-input agricultural systems may propose feed formulations or management strategies that are inappropriate or cost-prohibitive in arid or semi-arid regions, thereby intensifying existing vulnerabilities instead of mitigating them.

Many deep learning models lack transparency. This limits understanding of how inputs generate outputs. This is another ethical problem. This lack of openness makes it much harder to find, diagnose, and fix biases that are built into AI systems. In the realm of animal welfare and livestock management—where automated evaluations may affect health interventions, culling choices, or resource distribution—the incapacity to elucidate or rationalize model outputs can undermine stakeholder confidence and impede accountability. To use AI responsibly in sensitive faunal management applications, it is important to address model opacity with explainable AI techniques, clear validation protocols, and participatory system design.

5.3. Mitigation strategies and frameworks for ethical machine learning

To reduce algorithmic bias in AI-based systems for managing animals and livestock, ethical principles must be applied consistently throughout the entire AI lifecycle, from defining the problem and gathering data to deploying the model and evaluating it after the fact. In this field, technical fixes on their own aren't enough because ethical risks often come from complicated interactions between biological variability, socio-economic structures, and the way institutions make decisions. So, strategies to reduce bias must be aware of the context and the species. This is because general-purpose fairness metrics and bias detection tools made for AI applications that focus on people may not fully capture the ethical subtleties that come with animal welfare and conservation contexts [21].

To deal with these problems, it has become more important to use specialized auditing frameworks and evaluation toolkits. IBM's AI Fairness 360 (AIF360) and Microsoft's Fairlearn are two examples of platforms that offer structured ways to compare the performance of models across different subpopulations and operational conditions. This makes it easier to find systematic unfairness in prediction accuracy or decision outcomes [21]. At the same time, domain-specific projects like the Open Paws Project work to create shared datasets, benchmarks, and ethical guidelines for AI applications related to animals. This will help ensure that animals of all species, breeds, and management styles are treated fairly [21]. When used correctly, these tools help make sure that AI systems are rigorously audited and constantly monitored so that welfare assessments and management recommendations don't unfairly hurt animal categories that aren't well represented or low-resource production systems.

In addition to technical auditing, the responsible innovation framework provides a moral and practical basis for using AI in faunal systems in an ethical way. This framework stresses the need for technology to be developed in a way that is consistent with social values, such as openness, responsibility, and shared prosperity. In practice, responsible innovation in animal-focused AI means putting transparency and interpretability first by using Explainable AI (XAI) methods. This lets stakeholders understand, trust, and critically evaluate model outputs. It also needs the active involvement of a wide range of stakeholders, such as farmers, veterinarians, conservationists, policymakers, and local communities, in participatory design processes that make sure AI solutions meet real-world needs and limitations.

Lastly, research and development priorities must take into account ethical mitigation strategies. There is a growing need for AI solutions that are specifically designed for the ecological, cultural, and economic contexts in which they will be used, rather than defaulting to generic, one-size-fits-all models. Context-specific approaches are crucial for aiding smallholder farmers and marginalized communities, as poorly tailored AI recommendations may worsen their existing vulnerabilities. These mitigation strategies show that ethical machine learning in faunal management is not just a technical problem; it is also a social and technical problem that needs ongoing collaboration and governance from many different fields.

6. Future trajectories and emerging technologies (2025–2035)

AI and CV will play an expanding role in faunal management over the next decade. This will involve more integration between animal health, environmental monitoring, and public health systems. AI systems will integrate into decision-support ecosystems. These systems connect welfare monitoring, disease surveillance, and policy intervention. Advances in predictive modeling and data fusion will expand AI applications. Autonomous sensing platforms will further enhance system capabilities. At the same time, AI's operational reach will grow in both controlled and remote ecological environments as levels of autonomy rise thanks to robotics, unmanned aerial systems, and intelligent edge devices.

6.1. Integration with veterinary clinical practice and biomedical research

Artificial Intelligence is poised to fundamentally revolutionize veterinary medicine by expanding its function from routine monitoring to intricate clinical diagnostics, translational research, and biomedical innovation [2]. In clinical settings, AI-driven analytical frameworks are anticipated to advance veterinary epidemiology and disease surveillance by facilitating the earlier identification of emerging health threats, enhancing outbreak modeling, and achieving more accurate risk stratification among animal populations [2]. These capabilities are especially pertinent in One Health paradigms, where animal health data function as essential early indicators of zoonotic risk and overarching public health issues.

The combination of AI with genomics, proteomics, and other high-throughput biological data streams is expected to lead to a major change in strategy. AI-enabled analysis of genomic datasets is anticipated to expedite research into disease susceptibility, host–pathogen interactions, and selective breeding strategies, while also being instrumental in combating the escalating global issue of antimicrobial resistance (AMR) [2]. By facilitating predictive health modeling based on biological rather than solely behavioral data, veterinary AI systems may enhance drug discovery, vaccine development, and precision therapeutics, establishing animal health research as a pivotal element of global biomedical innovation [2].

Computer vision is still the most common way to monitor animals, but there is a big gap in our knowledge about how Natural Language Processing (NLP) and Large Language Models (LLMs) could help animal health and agricultural intelligence systems [11]. These technologies have significant potential for combining different types of data, such as veterinary clinical records, farm management logs, regulatory documents, and scientific literature. NLP- and LLM-based systems could make agricultural and veterinary knowledge bases much easier to access and use by allowing for advanced knowledge retrieval, decision support, and cross-domain data synthesis. This would work well with CV-driven sensing and analytics [11].

6.2. Robotics, automated platforms, and autonomous monitoring systems

The next step in AI-driven faunal management is likely to involve the widespread use of smart models on autonomous and semi-autonomous platforms. This will allow for continuous, scalable, and spatially extensive monitoring of different ecosystems. Improvements in onboard computing, energy efficiency, and edge-based inference are making it possible for ai models that can find, track, and re-identify individual species to be built right into robotic systems [22]. This means that fewer people and centralized infrastructure are needed. models created for tasks like finding and re-identifying amur tigers are being specifically designed to work with unmanned aerial vehicles (UAVs), which will allow for autonomous aerial surveillance of large, remote, and hard-to-reach protected areas [19]. These systems make people more aware of what's going on, increase how often they can monitor things, and lower both the costs of running the business and the risks to people who work there.

In agriculture, especially in precision livestock and poultry farming (PLPF), the shift toward sensor-based and data-driven management models is creating a need for more advanced robotics and automation in many areas of operation [11]. To do large-scale animal phenotyping all the time, CV, wearable sensors, and environmental monitoring are needed. This means that robotic systems that can do responsive interventions, such as automated feeding, climate control, housing adjustment, and routine animal management tasks, are also needed. As the amount of data and the complexity of systems grow, robotics will be critical for closing the gap between AI-driven perception, decision-making, and physical action. This will help make production systems that are more flexible and focused on animal welfare [11].

AI-powered autonomous platforms are being used more and more for ecological restoration and habitat management, in addition to monitoring and production. In conservation and land-use planning, AI helps improve reforestation plans, assess habitat recovery, and keep an eye on ecosystems over the long term by combining data from aerial images, remote sensing, and ground-based sensors [17]. These systems make it possible to do targeted, data-driven restoration work on a scale that would be impossible with manual intervention when used with autonomous deployment platforms like drones for seed dispersal or robotic ground units for environmental sampling. The coming together of AI, robotics, and autonomous monitoring platforms is a big step toward managing animals on a continuous, adaptable, and ecosystem-wide scale in the next ten years.

6.3. Advances in predictive modeling for ecosystem health

Artificial Intelligence is making progress all the time, which is allowing for a new generation of predictive models that can handle the complexity and nonlinearity of ecological systems. AI systems can combine and analyze huge, high-dimensional environmental datasets that include climate variables, land-use patterns, species distribution data, and anthropogenic pressures. They do this by using more powerful computers and advanced machine learning architectures. This ability makes it possible to create models of possible ecological trajectories that are much more accurate and detailed under different management and disturbance scenarios [18]. These types of models go beyond descriptive analytics by giving probabilistic forecasts that help with proactive and flexible ecosystem management.

In the fields of applied conservation and land-use planning, these advanced predictive models are anticipated to be pivotal in directing strategic land conservation efforts and enhancing investments in biodiversity preservation and natural resource management [18]. AI-driven models let decision-makers look at the long-term ecological effects of different intervention strategies. This helps them weigh the pros and cons, choose the most important conservation actions, and use limited resources more effectively. This data-driven method makes conservation policies work better by making sure that short-term actions are in line with long-term goals for ecosystem resilience.

Predictive modeling also has important benefits for dealing with serious threats to conservation, especially the illegal trade in wildlife. In conservation management, AI-enabled forecasting frameworks are increasingly employed to identify and anticipate poaching hotspots by analyzing historical incident data in conjunction with environmental, infrastructural, and socio-economic variables [18]. These predictive insights help conservation teams use patrols and surveillance resources in a proactive way instead of a reactive way. This makes deterrence more effective and cuts down on response times. Together, improvements in AI-driven predictive modeling are an important tool for protecting the health of ecosystems, making conservation more effective, and helping people make decisions based on facts in ecosystems that are becoming more complex and changing all the time.

7. Case studies in the Indian subcontinent: Policy and implementation

India provides a strong case study for AI implementation in conservation and environmental governance. The high biodiversity, large human populations, and complicated social and ecological systems in the country make it both very difficult and very interesting for AI-enabled faunal management. India’s approach is important because it includes centralized policy coordination, strong institutional leadership, and the use of digital technologies in legal conservation mechanisms. This makes it possible for AI to be used in a systematic way at many levels of wildlife management and monitoring.

7.1. AI for wildlife conservation in India

Wildlife conservation efforts in India stand out because they are very well-planned and work together with other groups. The National Tiger Conservation Authority (NTCA) and the Wildlife Institute of India (WII) are two national-level agencies that have been at the forefront of incorporating cutting-edge digital technologies into conservation efforts. They have done this through programs like the All India Tiger Estimation (AITE) program and the Monitoring System for Tigers–Intensive Protection and Ecological Status (MSTrIPES) mobile app [23]. These frameworks bring together data from camera traps, geographic information systems (GIS), and satellite-based remote sensing into a single digital platform. This makes a strong technological ecosystem that is ready for advanced AI and computer vision methods [23].

The contribution of Indian academic and research institutions in creating AI tools that are specific to conservation needs is a key part of this ecosystem. For instance, the Indraprastha Institute of Information Technology Delhi (IIIT-Delhi) created a system based on deep neural networks that makes it easy to separate, sort, and analyze large amounts of camera-trap images. This cuts down on the amount of manual annotation work that conservation researchers usually have to do [23]. These tools speed up data processing pipelines, which lets conservation teams focus on more important analytical tasks and make strategic decisions.

Simultaneously, targeted research initiatives have investigated the utilization of deep learning-based object detection and re-identification techniques for the surveillance of endangered species, including apex predators like the Amur tiger. More and more, these models are being improved so that they can be used on Unmanned Aerial Vehicles (UAVs). This increases the area that can be monitored and allows for autonomous monitoring in remote or high-risk conservation areas [19]. These initiatives collectively demonstrate how India's centralized policy frameworks, in conjunction with focused academic innovation, are enabling the successful conversion of AI research into practical conservation results.

7.2. Urban animal welfare: The success of genie AI in stray animal rescue

The management of urban stray animal populations exemplifies a unique and effective implementation of Artificial Intelligence in the Indian subcontinent, tackling both animal welfare and public safety issues associated with densely populated urban areas. The Genie AI program is a good example of this method. It uses motion sensors, surveillance cameras with computer vision, and AI-driven event detection to keep an eye on animals 24/7 and find unusual or high-risk behavior in real time [15]. The system automates the detection of incidents involving stray animals, which allows for quick situational awareness and coordinated response among municipal and animal welfare stakeholders.

Since its launch in 2020, Genie AI has helped save 248 animals in 66 documented cases. These cases include a wide range of welfare and safety situations, such as stray cattle blocking traffic, injured or distressed wildlife in cities, and animals that need immediate veterinary care [15]. A major measurable result of the program is that it has been shown to greatly shorten the time it takes to respond to a rescue, which lowers the length and severity of welfare risks and makes it less likely that secondary incidents like traffic accidents or conflicts between people and animals will happen [15].

The Genie AI project demonstrates dual benefits. It improves animal welfare and enhances urban safety: it can improve animal welfare outcomes and make cities safer and better at managing risks. The program's success is not just due to the use of technology; it also depends on active public participation and crowdsourced reporting systems [15]. Genie AI shows how important it is to include technological solutions in participatory governance frameworks by combining AI surveillance with citizen engagement. This is especially important in densely populated urban areas where decentralized reporting and quick coordination are needed for scalable and long-term animal welfare management.

7.3. AI implementation in Indian dairy and livestock farming

More and more Indian dairy and livestock farms are using computer vision (CV) systems to help with important management tasks like keeping track of animals' behavior and activities, identifying them, and spotting disease or welfare problems early [11]. These technologies have significant potential to make the sector more productive, healthier for animals, and more efficient with resources. The sector is both important to the economy and has a wide range of structures. AI-powered systems can give useful information that helps with timely interventions, lowers the burden on workers, and improves decision-making in a variety of production settings by allowing continuous, non-invasive monitoring.

But the widespread use of AI in the Indian livestock industry raises important questions about policy and governance, especially when it comes to algorithmic bias and fair access. Smallholder and traditional production systems, a wide range of indigenous breeds, and region-specific husbandry practices are all common in Indian livestock farming. As a result, AI models that were mostly trained on data from industrialized or high-input systems, which often come from different places and social and economic backgrounds, may not work well in India. This kind of misalignment could lead to less accurate models, bad management advice, or some farming communities missing out on the benefits of new technology.

AI deployment must be context-specific and inclusive. This ensures fairness in Indian livestock farming systems. This includes using training data that is representative of the area, working with farmers and extension services while the system is being built, and testing the model's performance in a variety of climates, cultures, and production settings. It is important to address these issues not only for technical robustness but also for policy legitimacy. This will make sure that AI-driven livestock management solutions help achieve sustainable development goals while also helping the livelihoods and well-being of all farming communities in India's diverse agricultural landscape.

8. Conclusion

8.1. Synthesis of AI/CV impact on global fauna welfare

AI and CV enable large-scale, continuous monitoring of animal health and conservation status. These systems transform monitoring from manual processes to proactive, data-driven approaches. AI models can pick up on small changes in behavior, physiology, and the environment almost in real time. This makes it possible to intervene earlier in a wide range of situations, from managing the health of livestock to protecting ecosystems and wildlife.

AI-driven faunal management demonstrates impact across multiple biological and operational domains. AI helps solve difficult problems like antimicrobial resistance (AMR) at the molecular and biomedical levels by working with genomics, epidemiology, and predictive health modeling in livestock systems. At larger ecological scales, CV-enabled sensing platforms help with monitoring tasks over large areas, such as finding marine debris, assessing biodiversity, analyzing habitat degradation, and intelligence-led anti-poaching operations. This multiscale applicability shows how flexible AI is as a unifying analytical framework that can connect individual-level welfare outcomes with management goals at the population and ecosystem levels.

For AI and CV to work well, the technology architecture and the operational infrastructure must be in sync. The different ways of putting these systems into action, from high-bandwidth, cloud-based pipelines in Precision Livestock and Poultry Farming (PLPF) to low-bandwidth, edge-computing–driven systems for remote conservation monitoring, show that strategic success depends more on the situation than on the species being targeted. Factors such as connectivity, energy availability, and governance structures all play a role. This insight highlights the importance of infrastructure-aware AI design as a fundamental principle for attaining fair, scalable, and enduring enhancements in global wildlife welfare and conservation results.

These findings highlight the necessity for policy-driven AI deployment, emphasizing ethical governance, data standardization, and infrastructure-aware system design. Strategic investments in edge computing and inclusive datasets will be essential to ensure equitable and scalable adoption across diverse ecological and socio-economic contexts.

8.2. Recommendations for future research investment and multi-stakeholder collaboration

In light of the demonstrated capabilities of artificial intelligence (AI) and computer vision (CV), as well as the persistent technical, ethical, and infrastructural constraints identified throughout this review, a coordinated set of policy and research investment priorities is required to ensure responsible, equitable, and scalable deployment across faunal systems. The following recommendations are proposed to guide future funding strategies, regulatory frameworks, and multi-stakeholder collaboration.

First, ethical compliance and algorithmic bias auditing must be formally mandated as integral components of the AI development and deployment lifecycle. Regulatory bodies and funding agencies should require adherence to responsible innovation frameworks and enforce systematic bias assessment using established auditing tools such as AI Fairness 360 (AIF360). These measures are essential for identifying and mitigating data skew and contextual gaps that arise from non-representative training datasets and culturally misaligned system design. Ensuring that AI systems respect region-specific husbandry practices and perform equitably across diverse production scales is particularly critical for supporting smallholder and traditional farming communities, which are most vulnerable to exclusion through poorly adapted technological solutions [21].

Second, strategic investment in edge computing architectures for conservation applications should be prioritized by both public and private stakeholders. Remote wildlife monitoring and conservation interventions are fundamentally constrained by limited connectivity and energy infrastructure. As demonstrated by the architectural success of devices such as the Sentinel platform, localized, low-power, edge-based AI processing represents the most viable pathway for achieving near–real-time situational awareness and actionable intelligence in remote environments [1]. Targeted funding for the development, field validation, and scaling of ruggedized edge-computing platforms is therefore essential for extending AI-enabled conservation capabilities into biodiversity-rich yet infrastructure-poor regions.

Third, cross-sectoral data standardization initiatives should be established as a core research priority. Collaborative efforts among academic institutions, industry partners, conservation organizations, and government agencies are needed to develop standardized protocols for data collection, annotation, and metadata representation. Such standardization is critical for enabling robust transfer learning across species, ecosystems, and geographic contexts, thereby reducing the costly and labor-intensive dependence on manual annotation that currently constrains the deployment of high-resolution behavioral phenotyping systems [3]. Improved interoperability and data sharing will accelerate model generalization and lower barriers to entry for under-resourced research and conservation programs.

Finally, policymakers should explicitly prioritize AI systems that deliver demonstrable dual societal benefits, particularly those that simultaneously advance animal welfare and public safety objectives. Urban stray animal management programs, such as AI-enabled rescue and monitoring systems, exemplify this dual-benefit paradigm by reducing animal suffering while mitigating risks to human populations in high-density urban environments [15]. Recognizing and funding such systems within municipal and national infrastructure frameworks provides a compelling justification for sustained public investment and supports the scalable integration of AI into socially impactful governance solutions.

Collectively, these recommendations emphasize that the future success of AI and CV in faunal welfare and conservation depends not only on technical innovation, but also on ethical governance, infrastructural alignment, data interoperability, and sustained collaboration across scientific, policy, and community stakeholders.

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