INTELLIGENT SMART SURVEILLANCE FOR WILDLIFE: INTEGRATING ARTIFICIAL INTELLIGENCE FOR ANIMAL MONITORING AND ROAD SAFETY

Vaibhav D. Kalambe Research Scholar, Vidya Vikas Arts, Commerce and Science College, Samudrapur Dist. Wardha - 442305, Email:- *vaibhavkalambe80@gmail.com*	**Dr. Archana M. Bhende** Associate Professor, Department of Zoology, Vidya Vikas Arts, Commerce and Science College, Samudrapur Dist. Wardha - 442305
Tejaswita Sahastrabuddhe Research Scholar, Vidya Vikas Arts, Commerce and Science College, Samudrapur Dist. Wardha – 442305	**Pranjali Kubade** Research Scholar, Vidya Vikas Arts, Commerce and Science College, Samudrapur Dist. Wardha – 442305

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Abstract :

Due to the rapid growth in traffic management and the growth of human settlements, there has been an increased fragmentation of habitats, and this has given rise to a huge increase in the number of animal-vehicle accidents. This is very dangerous to the conservation of wildlife as well as human life. The first techniques of wildlife monitoring are mainly manual surveys and tracking by telemetry but these are found to be an intensive exercise, invasive to the wildlife and hard to perform in large geographical and temporal areas. The growing popularity of camera traps and sensor-based surveillance has allowed gathering plenty of information about the behavior of animals in a non-invasive way however, the process of analyzing this large volume of data as fast and precise has become a significant issue. Against this backdrop, artificial intelligence technologies such as deep learning and computer vision have enabled measurable and comprehensive solutions for automated animal detection, species classification, individual re-identification, animal tracking, and behavior analysis. In this article, the authors have presented the concept of wildlife and environmental monitoring based on artificial intelligence, with particular emphasis on animal safety and accident prevention.

Keywords : Artificial Intelligence, Wildlife Monitoring, Camera Traps, Animal Safety, Animal-Vehicle Collision Prevention, Edge AI, Computer Vision, Conservation Technology

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Introduction :

The Environmental sustainability and ecosystem stability depend to the conservation of biodiversity and the protection of animals. The animals that are important to environmental processes and stability of the nature like the control of the population, restoration of the nutrient cycles, and preservation of the habitat. Nevertheless, human actions such as urbanization, transport facilities, and land use are swiftly transforming habitats resulting in an augmented fragmentation of habitats and elevated death of animals. This has consequently led to a high rate of human - animal conflict (Xu et al., 2024). Animal surveillance is thus very important in the conservation of wildlife, welfare of domestic animals and provision of sustainable ecosystems. Animal monitoring is conducted through traditional tools like manual observation, GPS tracking, and invasive tagging and these offer good information about the environment, but they have a number of limitations. These are intensive, costly and stressful to animals, and this brings into question the morality of the methods. Moreover, endangered or rare species cannot be studied in large scale or over several years, which is constrained by these techniques (Price Tack et al., 2016; Herraiz et al., 2024). In contrast, camera traps and automated visual surveillance systems are relatively more non-invasive methods and help in studying various species over long periods and across extensive geographic areas (Blount et al., 2021; Wong and Kachel, 2024).

This is why camera traps have become essential tools for wildlife conservation, biodiversity measurement, and environmental studies. Despite their numerous advantages, camera traps and video surveillance systems present huge amounts of visual information, a lot of which is blank frames or background activity. Such data cannot be easily analysed manually, requiring a significant amount of time, money, and human resources and poses a big challenge to the process of timely performing environmental research and making decisions related to conservation (Wei et al., 2020; Schindler and Steinhage, 2021). The same problem can be noticed in the field of agricultural and livestock monitoring when manual processing of the constantly streamline visual data flows is actually beyond human limits and real-time interventions are still limited (Mahmud et al., 2021). Recent developments in artificial intelligence (AI) especially machine learning and deep learning generated a radical change in the concept of animal monitoring. Nowadays, it becomes possible automatically identify animals in large-scale images and video, identify their location, identify, and analyze their behavior. Computer vision models based on deep learning can analyze images of natural and intricate scenes with high precision and speed, saving much effort on human workers and improving analytical capacity and consistency (Beery et al., 2020; Jiang et al., 2022). The prior experiments demonstrated that deep convolutional neural networks are capable of classifying even difficult camera trap images and classify species in camera traps (Gomez-Villa et al., 2017). Going further, recent models can perform large-scale wildlife detection, localization, and behavior estimation across an entire AI system (Simoes et al., 2023).

With AI-based monitoring systems, it has become possible to monitor animal presence, movement, posture, and behavior in all ways non-invasively and nearly in real-time across different environments (natural habitats, agriculture, and aquatic ecosystems) (Achour et al., 2020; Okuley et al., 2025). The features allow identifying abnormal animal behaviour or any threat in time to improve the welfare of animals, manage wildlife conservation, and eliminate accidents in areas of human-wildlife contact (Bao and Xie, 2022; Johanns et al., 2022). The on-device intelligence will also improve in future, where the camera traps will be capable of inference on-site. It will decrease the necessity of transmitting data and enable a response to it on the spot in such regions (Nazir and Kaleem, 2024; Velasco-Montero et al., 2024). All in all, the camera traps plus the AI-driven computer vision offer an impressive and very expandable system of wildlife surveillance.

The solutions based on AI are valuable in coping with the shortcomings of the traditional surveillance system and the inconveniences of handling large amounts of visual data. Consequently, this technology is extensively used for biodiversity conservation, wildlife protection, livestock management, as well as reducing human–animal conflicts. Such intelligent wildlife monitoring systems are becoming a crucial component of sustainable environmental management in areas where human-made dominance is increasing.

Artificial Intelligence in Animal and Environmental Monitoring :

Artificial Intelligence (AI) has emerged as an important key enabler technology in animal and environmental monitoring because it can effectively analyze extensive and complex environmental data. Modern AI systems are primarily based on non-invasive methods, such as computer vision and smart image analysis, enabling continuous monitoring of animals' natural behaviors or habitat structures without causing any disruption (Xu et al., 2024; Ben Gamra and Akhloufi, 2021).

The prevailing models in this domain are deep learning models, and one of them is convolutional neural networks (CNNs). Their ability to learn attributes of raw images and videos makes them unnecessary because they do not require handwritten rules (Ravoor and Sudarshan, 2020). The camera trap-based monitoring is one of the most commonly employed AI-based applications in conserving wildlife.

Even though camera traps have allowed the sampling of data during extended periods of time and in a non-invasive format, they produce huge quantities of heterogeneous data, such as empty frames and non-target shots of a human or domestic animal. This kind of data cannot be processed manually, and this slows down the environmental analysis. AI filtering and classification techniques are automated and filter out empty pictures as well as differentiate between wildlife and irrelevant data. This allows greatly minimizing the required annotation and growing the system in the scale (Price Tack et al., 2016; Wei et al., 2020; Meng et al., 2023). Object detecting networks are beneficial in finding the animals in a noisy natural habitat, and further information applied in behaviour analysis or population estimation (Beery et al., 2020; Blount et al., 2021).

Besides wildlife surveillance, AI is also finding application in precision livestock farming and environmental surveillance. On the farm, deep learning models are trained to examine the body language, movement, and activities of the animals to identify stress, disease, or abnormal behaviour in animals early enough to maintain constant monitoring of the animals even in areas where humans are not able to observe (Bao and Xie, 2022; Rohan et al., 2024). The most prevalent type of vision-based systems is one based on RGB cameras and infrared cameras because they are cheap and do not require any intrusion into the animal; together with sensor data, such systems are used to make more comprehensive decisions regarding animal welfare (Mahmud et al., 2021; Iwasaki et al., 2019). In recent times, there has been a focus on the practical application of AI systems by designing the systems at the system level. The hybrid IoT, edge computing solutions minimize the latency, bandwidth expenses, and the total cost of operations by processing them near the data source. This is especially important in applications that are related to safety and close to real-time (Raju et al., 2020; Delgado-Rajo and Travieso-Gonzalez, 2025). Intelligent cameras installed on the device can aid in the early awareness of dangerous wildlife that is approaching human settlement (Nazir and Kaleem, 2024).

Hardware and software co-design and continual learning methods enhance the resilience and flexibility of systems in various environmental conditions (Velasco-Montero et al., 2024). Overall, AI automates processes such as species identification, filtering empty images, localization, and behavior analysis by generating meaningful environmental information from raw visual data and sensor data. These innovations play a crucial role in improving the efficiency, scalability, and practicality of animal and environmental monitoring systems, thereby creating a robust technical foundation for wildlife conservation, livestock welfare, and reducing human–wildlife conflict.

AI-Based Techniques for Animal Detection, Tracking, and Behavior Analysis :

The foundation of AI-based monitoring systems is accurate animal detection, because without precisely locating animals in images and video streams, subsequent steps-such as species recognition, tracking, or behavior analysis-cannot be performed. The latest models in deep learning models employed in object detection (in particular, Convolutional Neural Networks - CNNs) automatically extract discriminative features of the raw data, and they exhibit high performance even when operating under adverse conditions, including occlusion, changing lighting, low contrast, and complex natural backgrounds (Xu et al., 2024; Wang et al., 2022; Liu et al., 2024). In real-time or close to the real-time, animals in camera traps and surveillance images are detected with advanced animal detection systems-including YOLO and Detectron-based systems (Ansari et al., 2024). Individual re-identification and tracking add a temporal dimension to the research process, enabling the study of movement patterns of animals, habitat use, home-range dynamics, and population connectivity. Deep learning-based re-identification methods show high accuracy for species with characteristic visual patterns, providing useful information for long-term monitoring and in-depth population studies (Ma et al., 2025; Ravoor and Sudarshan, 2020). Distance estimation technology allows non-invasive estimates of animal density and numbers without human interference (Johanns et al., 2022). Using probabilistic tracking algorithms along with optical flow in mobile sensing platforms can reduce the effects caused by camera movements and obstacles (Oiwa et al., 2017). Behavior analysis helps in better understanding of animal health, welfare, and environmental interactions. By using deep learning neural networks, feeding, walking, resting, aggression, as well as abnormal behavior can be identified in livestock management, allowing early detection of disease and welfare-related issues without using any aggressive tools or tagging (Alameer et al., 2020; Rohan et al., 2024; Achour et al., 2020). Pose estimation techniques allow in-depth study of body language and movements; however, differences across species and the lack of sufficiently annotated datasets pose certain challenges (Jiang et al., 2022). By processing camera trap data in real-time, it is possible to analyze how species respond to external or human-made disturbances, interactions among species, and the presence of species over specific time periods (Wong and Kachel, 2024). The detection, tracking, and behavior analysis of the AI tools such as DeepWILD rely on pipelines, which allows automated analysis of large datasets of wildlife (Simoes et al., 2023). Prior to deep learning, hybrid pipelines that filtered empty images boosted computational efficiency and lowered the annotation expenses (Wei et al., 2020). Smart camera trap inference over the device can also capture almost real-time tracking and alerts, thus facilitating prompt actions during an emergency of conservation and safety (Nazir and Kaleem, 2024; Velasco-Montero et al., 2024).

Stakeholder	Key Role	Action Using AI-Based Monitoring	Expected Impact
Government & Policy Makers	Policy design and implementation	Integrate AI-based wildlife monitoring with road safety and biodiversity programs; deploy smart camera traps in wildlife corridors and accident-prone zones.	Reduced animal-vehicle collisions; data-driven conservation planning.
Research & Academic Institutions	Technology development and validation	Develop environment-adaptive AI models; create open datasets and standardized benchmarks for wildlife monitoring systems.	Improved model robustness and real-world deployability of AI tools.
Agricultural Sector & Farmers	Human-wildlife coexistence in farmlands	Deploy AI-enabled camera traps at farm boundaries to detect wildlife intrusion and provide early warnings to prevent crop damage.	Reduced crop loss; minimized human-wildlife conflict.
Local Communities & NGOs	Ground-level conservation support	Use AI-based alerts to inform communities about animal movement near villages; support community-driven monitoring initiatives.	Enhanced public awareness; safer coexistence with wildlife.
Transport & Infrastructure Authorities	Road and rail safety planning	Apply AI-driven risk mapping to identify collision hotspots and install dynamic warning systems, fencing, and wildlife crossings.	Improved road safety; long-term reduction in wildlife mortality.

Table 1. presents a stakeholder-action framework illustrating how AI-based wildlife monitoring can be operationalized across policy, research, agriculture, community engagement, and infrastructure planning to achieve tangible conservation and safety outcomes.

Role of AI in Animal Safety and Accident Prevention :

It is used AI-based monitoring system, which gains significant importance in minimizing animal safety and decreasing the number of accidents in the regions of the animal-infrastructure conflict - roads, railway routes, farmland, and human settlements. Detection and real-time analysis make it possible to identify the presence of animals in the dangerous zone in time to take the necessary measures and avoid accidents or injuries (Xu et al., 2024; Jiang et al., 2022). With the continuous analysis of the data, collected by camera traps, surveillance systems, and so on, AI systems are used to define the conflict-prone regions and the most dangerous times, and, on these grounds, certain preventive actions can be developed. Efficient filtering and classification of the large volumes of wildlife data collected also help prevent accidents. Automated processing of images and empty frames saves human time and effort and enables conservation authorities to quickly identify patterns related to emerging threats and respond rapidly (Meng et al., 2023; Li et al., 2025; Wei et al., 2020). AI-processed continuous camera trap data reveals local 'hotspots' of wildlife movements and human activities, as well as their changing spatio-temporal overlap over time. It can be used to locate wildlife crossings, fences, or warning apparatus in an appropriate way (Blount et al., 2021). Personal re-identification and monitoring contribute to the realization of long-term animal movements, habitat utilization, and exposure to dangerous infrastructure, which will improve safety. Re-identification systems based on deep learning allow the more effective analysis of populations and the targeted preservation of an endangered species, particularly in relation to vulnerable populations such as large carnivores and primates (Ma et al., 2025; Ravoor and Sudarshan, 2020; Ansari et al., 2024). Automation of distance estimation and local analysis allows for accurate assessment of animal proximity to hazardous infrastructure and potential human and animal interactions. This provides a more scientific basis for safety-focused decision-making processes (Johanns et al., 2022).

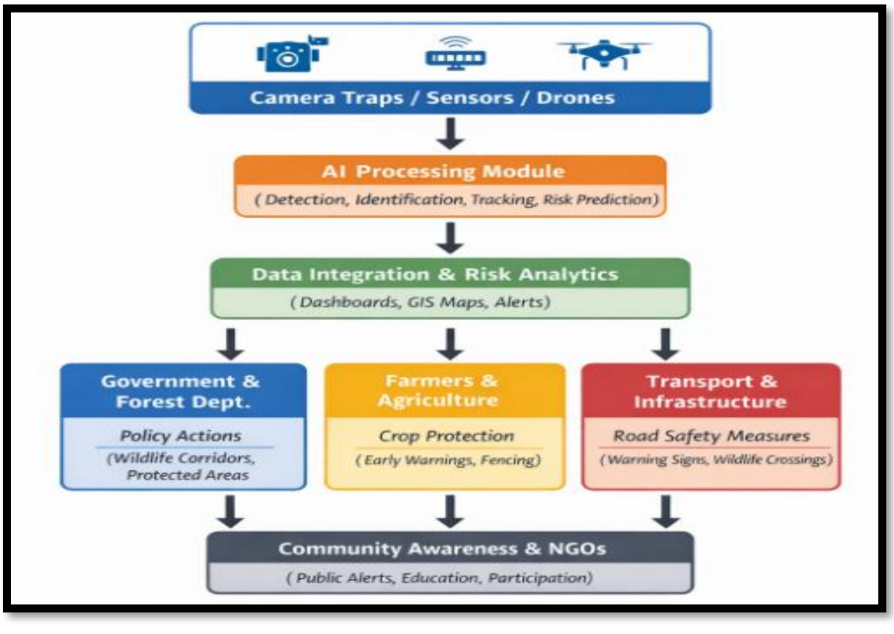

Fig. 1. Conceptual Framework of AI-Driven Wildlife Monitoring and Safety Interventions

Recently, there has been significant progress in edge AI and hybrid edge–cloud models, and this technology can be used to make security-related applications more effective, to process data on-device with low latency, and to provide near real-time alerts. Smart camera traps are capable of applying AI to issue warnings in real time or propose preventive actions in case dangerous species are caught around roads or human communities. These systems can be successfully used even in locations where the network is not more than partial (Nazir and Kaleem, 2024; Velasco-Montero et al., 2024; Delgado-Rajo and Travieso-Gonzalez, 2025). Lastly, virtual behavior modeling, which is carried out in a simulated setting, will give additional data regarding the response of animals to disturbances created by humans. The data can be useful in creating less hazardous living and infrastructure design, which is advantageous in eliminating accidents in the future (Turan and Cetin, 2019).

Challenges, Future Scope, and Conclusion :

In spite of the major breakthroughs, animal monitoring systems with the help of AI continue to meet many obstacles. The largest limitations are data imbalance and the lack of data since data obtained with the camera traps is often biased towards the most common species. This limits the effectiveness of the models in addressing rare or endangered species (Li et al., 2025; Gomez-Villa et al., 2017). This bias contributes to the unfairness of the model and its generalization in other species and ecosystems. Environmental variability (alteration in the factors of the environment) also harms the stability of the model. The performance of models, which have been trained in particular settings, cannot be adequate in novel or dramatically different settings without retraining (Xu et al., 2024; Okuley et al., 2025). It is specifically difficult to generalize the tasks, including pose estimation, multi-species re-identification, and behaviour recognition because the body structure and visual features of various species vary significantly, and there are no annotated datasets that are adequate (Jiang et al., 2022; Ravoor and Sudarshan, 2020). When we track the dynamic scenes, there is the issue of occlusion, background movement, and also switching of identities. Movement of the camera and human interaction make the computations more complex and prone to error (Oiwa et al., 2017; Liu et al., 2024). Also, practically speaking, edge devices have limited power, memory, and computational vulnerabilities, which require model optimization to ensure accuracy on resource limits (Nazir and Kaleem, 2024; Youseif and Al-Milaji, 2026).

Annotation of data is also a major issue, particularly in rare species and complicated behaviors, in which a large amount of human effort needs to be put into labeling the data with the correct labels (Wang et al., 2022).

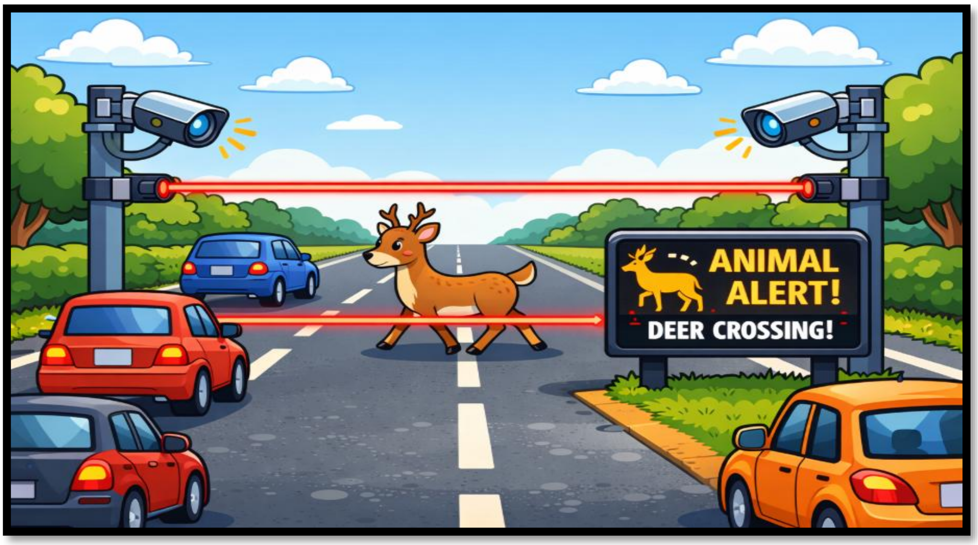

Fig. 2. AI-Enabled Smart Roadside Wildlife Alert System (Conceptual Illustration)

Future Directions :

Future studies should consider integrated scalable pipelines and end-to-end AI models that include detection, recognition, tracking, and behavior analysis. Using an edge–cloud architecture enables low-latency signaling in security-related applications while maintaining the scalability needed for long-term environmental analysis. To ensure system performance amid changing environmental conditions, species distribution, and seasonal dynamics, continual learning and domain adaptation are necessary. The growth of diverse and rich annotated datasets, along with environment-directed training, can increase the robustness of models and reduce bias. There are various sensing methods like we already knew such as the camera traps, IOT devices which have the computer visions which can enhance the coverage and the reliability of the monitoring system, various sensors alarm which is used. The use of explainable AI can be increasing the transparency and the trust for the environmental decisions making to the process. For long-term implementation-especially in remote areas or regions with limited infrastructure-hardware and software co-design will be necessary. This co-design is also important for energy-aware model optimization, enabling AI systems to operate effectively in long-running, resource-constrained environments.

Conclusion :

Reviewed research articles indicate that AI-based camera traps are scalable, non-invasive, and increasingly real-time systems that can be effectively used for monitoring wildlife and the environment. By incorporating deep learning, edge computing, and continual learning, current monitoring systems are helping to improve wildlife conservation outcomes, enhance animal safety, and actively prevent accidents in human-wildlife shared ecosystems. However, some limitations still remain-for example, bias in datasets, environmental variability, and challenges in achieving broad generalization of detection models across different habitats. Models trained in a specific environment do not perform as expected in a new environment without domain adaptation. Even though pre-processing tools like Zilong can filter out empty images, their performance decreases in conditions such as dense vegetation movement or fog. Therefore, there is a need for more capable hybrid pipelines that combine traditional image processing techniques with deep learning. In the future, it will be necessary to develop a more adaptive monitoring system by integrating AI, multi-modal sensing (e.g., visual and audio sensors), and continuous learning. Additionally, the use of a virtual environment can be useful for testing under controlled conditions and for proposing new behavioural hypotheses about animals.

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