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The Role of AI in Zoology: Emerging Applications, Challenges and Future Perspectives

Dr. G. Suhasini

Associate Professor and HOD, Department of Zoology,

Pingle Govt. College for Womens (Autonomous), Hanumakonda, Telangana, India

Corresponding Author - Dr. G. Suhasini

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Abstract:

Artificial Intelligence (AI) is rapidly transforming zoological research by enabling researchers to analyse large, complex and heterogeneous biological datasets with greater speed, consistency and scalability. Zoology traditionally depends on field observations, laboratory experiments, taxonomic identification and long-term monitoring, but these approaches can be labour-intensive and difficult to apply at large spatial and temporal scales. AI, particularly machine learning, deep learning, computer vision, bioacoustics and predictive modelling, provides new opportunities for species identification, animal behaviour analysis, wildlife monitoring, biodiversity assessment, conservation planning, aquaculture and animal health. AI also supports species-distribution modelling, threat assessment and conservation decision-making. Despite these benefits, challenges related to data quality, model bias, interpretability, computational requirements, privacy, ethical considerations and limited biological validation remain. Integration of zoological expertise with AI development will therefore be essential for responsible and scientifically reliable applications.

Keywords: Artificial Intelligence, Zoology, Animal, Species, Research.

Introduction:

Within just 2.4% of its land area, India is home to about 8% of all known species on Earth, making it one of the 17 megadiverse nations. Over 45,000 plant species, 91,000 animal species, and many microorganisms of which are peculiar to the area and make up this enormous biodiversity (Chitale *et al*., 2014). From mangroves and coral reefs to the Himalayan mountains and Western Ghats, the nation's varied ecosystems are essential to preserving natural balance and sustaining livelihoods. Furthermore, because India is a reservoir for genetic resources necessary for agriculture, health, and climate resistance, its high biodiversity makes a substantial contribution to international conservation efforts. India's biodiversity is critical for sustaining livelihoods, providing ecosystem services, and supporting global conservation goals, such as the United Nations Sustainable Development Goals (SDGs) and the Convention on Biological Diversity targets. Despite this abundance of biological diversity, conventional taxonomic techniques have found it difficult to keep up with the swift extinction of species brought on by invading species, habitat damage, and climate change. Historically, taxonomy the science of recognizing, categorizing, and naming organisms has relied on labor-intensive, time-consuming manual procedures that are frequently unavailable to researchers outside of specialized institutions. At the vanguard of contemporary scientific advancement is artificial intelligence (AI). The field of AI research is constantly growing, with applications ranging from climate tracking to medical diagnostics. Notably, AI is advancing zoological research in a particularly noteworthy way. Managing and interpreting large and complicated datasets is a challenge in zoological research, a field that focuses on animal classification, behavior, physiology, development, genetics and evolution, disease modeling, and paleozoology. An era of intelligent data-centric zoological research has begun with the quick development of powerful AI techniques like machine learning (Jordan & Mitchell, 2015), particularly deep learning, and big data. AI is valuable in zoology not just for replacing human observation but also for increasing zoologists' ability to gather, analyze, and interpret biological data. For instance, automated image-based tracking can measure animal interactions and movements at scales that would be challenging to accomplish with just direct observation. The potential of automated tracking to link individual animal behavior with ecological processes at the population and ecosystem levels was emphasized by Dell *et al*. (2014).

Role of AI in Animal Identification and Taxonomy:

Species identification is one of the fundamental activities in zoology. Traditional identification generally depends on morphological characteristics, taxonomic keys and expert knowledge. Although these methods remain essential, identification can become challenging when species are morphologically similar, specimens are damaged, or large numbers of observations must be processed. Computer vision and deep learning can assist in automated animal identification from photographs and videos. Convolutional neural networks (CNNs), for example, can learn visual characteristics such as body shape, colour patterns, texture and anatomical features. Camera traps have become particularly important because they generate enormous quantities of wildlife images that would otherwise require extensive manual examination. Tabak *et al*. (2019) demonstrated the potential of machine learning for classifying species from camera-trap images using millions of wildlife photographs. Their study demonstrated that automated classification can greatly accelerate the processing of ecological image datasets while maintaining high classification performance. By screening specimens, identifying diagnostic morphological traits, and ranking challenging specimens for expert review, AI can also help taxonomists. For biodiversity surveys involving insects, birds, amphibians, reptiles, and mammals, this is quite helpful. However, because superficially identical species and geographically underrepresented taxa may generate inaccurate predictions, AI-based identification should often be viewed as a decision-support technology rather than a complete replacement for taxonomic competence.

Table 1: Statistical Evidence for The Role of Artificial Intelligence in Zoology

Zoological Application	AI method	Study Scale	Result	References
Wildlife Species Identification	Deep learning/ CNN	3.2 million camera-trap images; 48 species	>93.8% identification accuracy; 99.3% of images could be automated at 96.6% accuracy; saved >8.4 years (>17,000 h) of human labelling	Norouzzadeh et al. (2018)
Camera-trapSspecies Classification	CNN/ResNet-18	3,367,383 images from 5 U.S. states	98% accuracy in U.S. test data; 82% accuracy on Canadian out of sample data; ~2,000 images/minute on a laptop	Tabak *et al.* (2019)
Animal Behaviour Analysis	Deep learning	Multiple animal species and behaviour	With only approximately 200 labelled frames, markerless pose estimation achieved performance comparable to human accuracy	Mathis *et al.* (2018)
Aquaculture Research	Machine learning / deep learning	Review of 73 studies published from 2016–2020	Shows rapid growth of AI applications in fish biomass, identification, behaviour and water-quality prediction	Zhao *et al.* (2021)

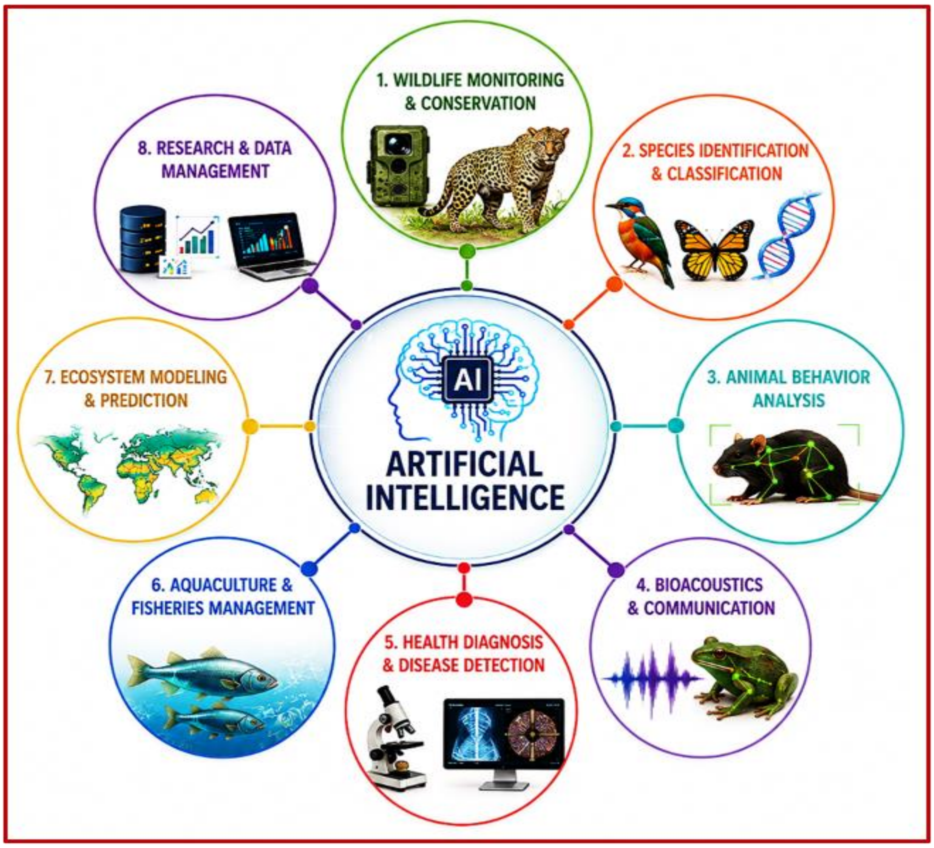
Zoological Application	AI method	Study Scale	Result	References
Wildlife Conservation	Computer vision	Multidisciplinary conservation applications	Demonstrates expansion of AI from individual species identification toward ecosystem-level conservation	Tuia *et al.* (2022)

Significance of AI in Animal Behaviour Studies:

Animal behaviour is a central component of zoology because behaviour influences survival, reproduction, social organization and ecological interactions. Traditional behavioural studies commonly rely on direct observation or manually scoring recorded video. Such approaches can be time-consuming and may introduce observer bias. Machine learning provides methods for extracting behavioural information from large datasets. Algorithms can identify movement patterns, feeding events, aggression, mating behaviour, locomotion, social interactions and abnormal behaviour. Dell *et al*. (2014) emphasized that automated image-based tracking enables quantitative analysis of animal behaviour and provides opportunities for studying ecological processes across multiple scales. Deep learning has further advanced behavioural research through markerless tracking. Mathis *et al.* (2018) developed DeepLabCut, a deep-learning framework capable of estimating user-defined animal body parts without requiring physical markers. The approach demonstrated that detailed animal poses could be estimated using relatively small labelled datasets, opening opportunities for automated analysis of movement and posture across species. Such approaches have applications in ethology, neuroscience, animal welfare and wildlife research. For example, AI could automatically quantify locomotion in laboratory animals, identify social interactions in group-housed animals or detect changes in movement associated with stress or disease.

AI for Wildlife Monitoring and Population Estimation:

Wildlife monitoring is one of the most promising applications of AI in zoology. Conventional population surveys may require large teams of researchers, extensive fieldwork and considerable financial resources. Camera traps, drones, acoustic sensors and satellite platforms can generate large datasets without requiring continuous human presence. Machine learning can automatically detect animals, classify species, count individuals and identify empty images. Tabak *et al.* (2020) developed MLWIC2 using approximately three million camera-trap images from multiple studies and demonstrated the potential of deep neural networks for automatically identifying wildlife species and separating images containing animals from empty images. Norouzzadeh *et al.* (2021) further demonstrated the use of active learning and computer vision for species identification and counting in camera-trap datasets. Such approaches are particularly valuable because wildlife surveys can generate millions of photographs, making complete manual analysis impractical. AI-based monitoring can also support population estimation, movement analysis and individual identification. Deep-learning systems can process video rather than individual photographs, allowing researchers to study movement trajectories and group behaviour. Recent wildlife applications have also combined AI with drones and remote sensing, providing opportunities for monitoring animals in landscapes that are difficult or dangerous for researchers to access.



AI and Biodiversity Conservation:

Biodiversity conservation requires reliable information about species distribution, population trends, habitat conditions and threats. AI can integrate information from environmental variables, species observations, remote sensing, camera traps and ecological surveys. Tuia *et al.* (2022) argued that the rapid growth of inexpensive sensors is producing ecological datasets at unprecedented scales and that machine learning can help transform these datasets into useful ecological information. They emphasized that effective applications require collaboration between ecological specialists and data scientists rather than treating AI as an independent replacement for ecological knowledge. Machine learning is also increasingly used for species-threat assessment and conservation planning. Branco *et al.* (2023) reviewed applications of machine learning in conservation and reported widespread use in niche modelling, monitoring and decision support. Their review also highlighted the importance of model selection and interpretability, particularly when AI predictions are used for conservation decisions. AI can therefore contribute to identifying potential habitats, predicting distribution changes, assessing extinction risk and prioritizing conservation interventions. When combined with geographic information systems and satellite data, AI can also help identify habitat fragmentation, land-use change and environmental degradation.

AI in Bioacoustics and Animal Communication:

Many animals communicate using sound. Birds, frogs, insects, bats, marine mammals and other taxa produce acoustic signals that provide information about species identity, reproductive activity, social interactions and environmental conditions. However, long-term acoustic recordings can contain thousands of hours of data and are difficult to analyse manually. AI and deep learning have created new possibilities for automated bioacoustic analysis. Stowell (2022) reviewed deep-learning approaches in computational bioacoustics and emphasized the value of animal vocalizations and natural soundscapes as evidence for studying behaviour, populations and ecosystems. AI algorithms can classify animal calls, detect target species and identify changes in acoustic activity. In bird research, machine-learning models can classify vocalizations according to species or call type. Such approaches can support biodiversity surveys in forests, wetlands and agricultural landscapes. Bioacoustic monitoring is particularly useful when animals are difficult to observe visually. Nocturnal species, dense-forest animals and marine organisms may be monitored acoustically without direct observation. AI therefore provides an important non-invasive approach to studying animal communication and biodiversity.

AI in Aquaculture and Fisheries:

Aquaculture represents another important area where zoological science intersects with AI. Fish farmers and fisheries researchers need accurate information about fish biomass, growth, behaviour, feeding and environmental conditions. Conventional assessment can require manual sampling and may disturb animals. Machine learning can analyse underwater images and sensor data to estimate fish size, biomass and population characteristics. Zhao *et al.* (2021) reviewed machine-learning applications in intelligent aquaculture, including fish biomass estimation, species identification, behavioural analysis and prediction of water-quality parameters. Deep learning can also support smart feeding systems. Yang *et al.* (2021) reviewed applications of deep learning in fish farming, including fish identification, behaviour analysis, feeding decisions, biomass estimation and water-quality prediction. However, they also identified the requirement for substantial labelled datasets as an important limitation. AI-based aquaculture can therefore contribute to precision feeding, disease-risk detection, environmental management and production efficiency. Integration with Internet of Things (IoT) sensors could allow real-time monitoring of temperature, dissolved oxygen, pH and other parameters, enabling rapid management responses.

AI in Animal Health and Welfare:

Animal health is another emerging application of AI in zoology. Behavioural changes can sometimes indicate disease, stress or injury before obvious clinical signs appear. Computer vision can potentially detect changes in locomotion, feeding, posture or social interactions. AI can also support veterinary diagnostics by analysing images, physiological measurements and other biological data. In research animals, automated behavioural monitoring can reduce the need for continuous human observation. In wildlife, abnormal movement or changes in acoustic activity may provide early warning of disease or environmental stress. The combination of behavioural monitoring and predictive analytics may eventually allow researchers to identify subtle deviations from normal behaviour. However, biological validation remains essential. An AI model detecting an unusual movement pattern does not necessarily establish a specific disease diagnosis. Zoologists and veterinarians must therefore interpret AI outputs within the broader biological context.

AI in Genetics, Evolution and Ecological Modelling:

The application of AI is also expanding into molecular zoology, evolutionary biology and ecological modelling. Biological datasets increasingly include genomic sequences, transcriptomic information, environmental variables and phylogenetic data. Machine-learning approaches can identify complex relationships within these datasets. In ecological modelling, AI can assist with predicting species distributions and environmental suitability. Models can incorporate temperature, precipitation, vegetation, elevation, land-use and species-occurrence information. Such predictive systems are particularly valuable for studying how animal distributions may change under environmental disturbance and climate change. Branco *et al*. (2023) noted that machine-learning methods are increasingly relevant to conservation problems involving complex interactions among environmental variables, species characteristics and human pressures. Future integration of genomic information with ecological and behavioural datasets could provide a more comprehensive understanding of adaptation, population structure and evolutionary responses.

Advantages of AI in Zoology:

- **Rapid data processing:** AI can process millions of images, videos or acoustic recordings much faster than manual analysis.
- **Automation:** Repetitive tasks such as species detection and image classification can be automated.
- **High-throughput behavioural analysis:** Continuous video data can be converted into quantitative behavioural measurements.
- **Non-invasive monitoring:** Camera traps, drones and acoustic sensors reduce the need to capture or disturb animals.
- **Predictive capability:** AI can identify patterns and generate predictions concerning population trends, habitat suitability and environmental conditions.
- **Large-scale monitoring:** AI facilitates monitoring across broad geographic and temporal scales.

Future Perspectives:

The future of AI in zoology is likely to involve increasing integration of computer vision, bioacoustics, remote sensing, robotics, IoT sensors and ecological modelling. Multimodal AI systems may combine images, sounds, movement trajectories, environmental information and genetic data to generate more comprehensive assessments of animal populations. The development of automated wildlife-monitoring networks could allow near-real-time detection of changes in species abundance or behaviour. In protected areas, AI-enabled cameras and acoustic sensors could provide continuous biodiversity surveillance. In aquaculture, AI may enable increasingly autonomous feeding, environmental control and health monitoring. Another important direction is explainable AI. Zoologists need models that not only produce accurate predictions but also provide biologically interpretable explanations. Interdisciplinary education will therefore become increasingly important. Future zoologists may require basic knowledge of machine learning, data management and computational biology, while computer scientists working in zoology will need a strong understanding of biological principles. Importantly, future development should focus on human–AI collaboration. AI is highly effective at identifying patterns in large datasets, whereas zoologists provide biological interpretation, experimental design and ecological context. Combining these strengths is likely to produce more reliable and scientifically meaningful results.

Conclusion:

Artificial Intelligence is emerging as a powerful technology for modern zoology. Its applications extend from species identification and taxonomy to animal behaviour, wildlife monitoring, biodiversity conservation, bioacoustics, aquaculture, animal health and ecological modelling. Machine learning and deep learning have particularly transformed the analysis of images, videos and acoustic recordings, allowing researchers to process datasets that would be impractical to analyse manually. The development of automated camera-trap classification, markerless behavioural tracking and computational bioacoustics demonstrates the growing capacity of AI to transform conventional zoological research. AI can improve the speed, scale and consistency of data analysis while enabling non-invasive monitoring of animals. Nevertheless, successful application depends on high-quality datasets, appropriate model selection, biological validation, transparency and interdisciplinary collaboration. AI should therefore be viewed not as a replacement for zoologists but as an advanced analytical partner. With responsible implementation, AI has the potential to strengthen zoological research, improve biodiversity conservation and contribute to a more data-driven understanding of the animal kingdom.

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