AI APPLICATIONS IN BIODIVERSITY MONITORING: TRANSFORMING ZOOLOGICAL RESEARCH

Dr. Ved Ramesh Patki
Head, Department of Zoology, Indira Mahavidyalaya, Kalamb, Dist. Yavatmal
vedpatki@gmail.com

Abstract
Biodiversity monitoring is an essential part of zoological research, as it provides insights into how species live, move, and interact with their environment. For a long time, researchers relied mainly on fieldwork and manual identification, which though reliable, had serious limitations in terms of scale and efficiency. With recent advances in artificial intelligence (AI), biodiversity studies have entered a new phase. AI now plays a role in automated species identification, bioacoustics monitoring, large-scale habitat mapping, and predictive modeling of ecological changes. This paper reviews some of the key ways AI is being applied in zoological research, highlights recent findings, and discusses how these tools are shaping the future of biodiversity conservation.
Keywords *- Artificial Intelligence, Biodiversity Monitoring, Zoological Research, Conservation, Machine Learning, Remote Sensing, Acoustic Monitoring*

Introduction

Biodiversity, which includes the variety of plants, animals, and microorganisms and their roles in ecosystems, is crucial for maintaining balance in nature and supporting human well-being. Monitoring biodiversity helps researchers understand species distribution, ecosystem health, and population changes, which in turn guides conservation decisions (Butchart et al., 2010; Pereira et al., 2013). Despite its importance, biodiversity is declining at a worrying pace, mainly because of human-driven activities such as habitat destruction, climate change, and overexploitation of resources (Pimm et al., 2014; Díaz et al., 2019).

Conventional monitoring methods like surveys, manual identification, or using camera traps have contributed a lot to ecological knowledge. However, they are also known to be slow, expensive, and difficult to apply on a large scale (Yoccoz et al., 2001; Steenweg et al., 2017). For instance, camera traps can capture thousands of images, but classifying them manually can take months. Similarly, acoustic recordings provide rich data but require expert ears to identify species. These challenges often delay conservation actions and make it hard to study remote or less accessible habitats.

AI offers a fresh solution to these long-standing issues. With the help of computer vision, deep learning, and other machine learning approaches, scientists are now able to process vast ecological datasets with great speed and accuracy (Wäldchen & Mäder, 2018; Christin et al., 2019). AI systems are capable of identifying species from photos, recognizing animal calls from sound recordings, and even analyzing drone and satellite imagery to track habitat change (Corbane et al., 2015; Xie et al., 2019). In this way, AI reduces the time between data collection and interpretation, allowing quicker responses to biodiversity threats.

Several global initiatives are now putting AI into practical use for conservation. Platforms like Wildlife Insights use AI to automatically classify animals from camera-trap photos, while eBird combines citizen science with AI to track bird populations worldwide (Sullivan et al., 2014; Ahumada et al., 2020). The Global Biodiversity Information Facility (GBIF) also integrates AI-based data handling to make biodiversity information accessible globally. These projects show how AI is no longer a future concept, but already an active part of zoological research and conservation efforts.

Materials and Methods

This paper is a review based on research articles, reports, and case studies published between 2010 and 2024. The material was collected through databases such as Web of Science, Scopus, and Google Scholar. Keywords including "AI in biodiversity monitoring," "machine learning zoology," "deep learning in ecology," and "remote sensing conservation" were used for the search. Only studies that demonstrated practical applications of AI in monitoring species, habitats, or ecosystems were included. Peer-reviewed journal papers and reports from established organizations were given preference to maintain credibility.

Results

The review shows that AI has made important contributions to biodiversity monitoring in four key areas:

1. Automated Species Identification Deep learning and computer vision models are now used to automatically classify species from images and

videos. Studies show that such systems can identify mammals, birds, and even insects with high accuracy (Norouzzadeh et al., 2018). Wildlife Insights, for example, has reduced the time required to analyze camera trap images from months to just hours.

2. Acoustic Monitoring AI has proven highly effective in processing large bioacoustic datasets. Algorithms can detect bird calls, frog croaks, and marine mammal sounds in noisy environments where human identification would be too slow (Stowell et al., 2019). This method is particularly useful in dense forests and oceans, where visual observation is limited.

3. Remote Sensing and Habitat Mapping AI applied to drone footage and satellite imagery provides valuable insights into habitat change, vegetation cover, and landscape fragmentation (Corbane et al., 2015; Zimmermann et al., 2010). These tools help researchers assess how habitats are shifting and which areas need urgent protection.

4. Predictive Modeling for Conservation Machine learning is increasingly being used to predict species distribution, extinction risks, and impacts of climate change (Willcock et al., 2018). By analyzing historical data along with environmental variables, these models help conservationists plan more effectively.

Conclusion

AI is steadily changing the way biodiversity is monitored and studied. From identifying animals in photos to analyzing complex environmental data, it brings speed, accuracy, and scale that traditional methods cannot match. Of course, there are challenges such as data biases, the need for high-quality training datasets, and ethical concerns around data sharing. Yet the potential of AI to support conservation and zoological research is undeniable. Moving forward, collaborations between computer scientists, ecologists, and policymakers will be essential to make full use of AI. Equally important is building local capacity in biodiversity-rich regions, so that AI-driven conservation benefits are not limited to only a few countries.

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