*Review Article*

Advancing Biodiversity research in India through Cybertaxonomy and Artificial Intelligence - a review

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ABSTRACT

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| India is a country with diverse ecosystems, high endemism and rich biodiversity, it becomes the need of the hour to deploy large scale implementation of the most sophisticated technologies to capture and monitor the trends in biological diversity research. Traditional methods should be applied alongside these new methods especially when dealing with large data sets or when there is a problem with logistics may possibly be due to the topography of the country, with its challenging and often inaccessible terrains, makes it difficult to conduct thorough manual surveys both periodically and seasonally on various taxa. A literature review on how ‘Cybertaxonomy’ and ‘Artificial Intelligence’ can be utilized to improve the documentation of the species diversity in the biodiverse regions in India for conservation and management. The current developments in machine learning and computer vision, as being revolutionary in the assessment of species diversity, richness and possible future research directions are presented in this article. |

*Keywords: Cybertaxonomy, Artificial intelligence, Machine learning, Molecular taxonomy.*

1. INTRODUCTION

Biological diversity, or biodiversity, has been defined by E. O. Wilson as the variation in species and in the ecosystems, within genes, species, and communities. In his book, The Diversity of Life published in 1992, Wilson elaborated the important fact that not only the number of species but the interrelations of species and their surroundings are critical for the quantification of biodiversity. He defines biodiversity as ‘the entire web of organisms, the interactions between them and the processes which support them’ [1]. This definition emphasizes ecosystem maintenance, as well as the species in the ecosystem and the complex relations they create.

In India, due to the combination of diverse climate zones together with geographical features and cultural traditions, this Asian country has been ranked as one of the highest biological diversity that is important to global conservation because the region supports high level of endemism [2, 3]. India also holds the position of the 10th forested country worldwide because 24.56% of its total geographical space (81Mha) supports forests and trees [4]. The Eastern and Northeastern Himalayas together with Indo-Burma (Northeast India) and Sundaland and Western Ghats make up four hotspots among the 34 globally recognised biodiversity hotspots. India stands among the 17 megadiverse countries because it holds 7-8% of all recorded species worldwide from its 2.4% share of global landmass [5]. These hotspots hold a large number of the world’s species, many of which are unique to these regions, hence the need to implement more focused conservation efforts to these precious biorich areas [6]. Also, these areas are important for conservation at the global level due to the high level of species endemism and the functions they perform within ecosystems, and hence, are considered conservation priority areas [2, 3]. A recent study in 2024 [7] demonstrates that since 2015 India’s biodiversity has become the subject of rising interest within species distribution modelling analyses. Research on climate change impacts on biodiversity, conducted in the Himalaya stands as the leading category with the Western Ghats as the second most studied region in India.

Despite the fact that India’s biodiversity is highly diverse and comprises of various species across various habitats ranging from the Marine, Western Ghats to the Himalaya, the general assessment of the country’s biodiversity for conservation purpose is still wanting, traditional methods of survey and observations in the field are often cumbersome and are constrained by time and space [8]. Machine learning algorithms, image recognition systems and other Artificial Intelligence (AI) technologies offered the possibilities for solutions of these problems. The use of AI technologies in the assessment and documentation of species’ richness and distribution has become more relevant because of the challenges posed by conventional techniques [9]. It is much faster and more precise for AI-based tools to achieve analysis of large datasets, species identification, and population monitoring without much human interference [10]. This technological advancement not only increases the result accuracy of the biodiversity assessment but also makes it possible to monitor in real time and vital for conservation measures that need to be taken in time [11]. Additionally, AI can also address some of the issues related to the inaccessibility of some terrains thus enabling a better understanding of ecosystems [12].

Even though, Indian research institutions use AI coupled with Machine Learning (ML) to perform better analysis and monitoring of ecosystems, but not at larger scale. The publication sustainability demonstrates how AI and ML applications can serve biodiversity conservation and forest management requirements in Indian Territory [13]. Achieving effective conservation planning requires species identification and habitat mapping as well as predictive modelling and these functions can be performed through the utilization of these advanced technologies.

**2. CYBERTAXONOMY: BRIDGING CLASSICAL TAXONOMY AND DIGITAL INNOVATION FOR BIODIVERSITY DOCUMENTATION AND CONSERVATION**

The abbreviated version of cyber-enabled taxonomy (Cybertaxonomy) upholds all fundamental requirements of conventional taxonomy for species exploration and discovery alongside their characterization and naming procedures and classification approach. The approach involves examination of species relationships and distribution mapping as well as ecological study for these species [14]. The implementation of advanced cyber infrastructure together with digital technologies through cybertaxonomy improves the speed along with accuracy and efficiency of goal achievement [15]. The application of digital technologies combined with information and communication technologies (ICTs) during taxonomy work constitutes cybertaxonomy. The combination targets improve operational speed for all phases of species recognition along with their descriptions and classification procedures as well as taxonomic information [16]. Cybertaxonomy uses electronic publications along with databases and interactive identification keys which enhance the speed of documenting and comprehending biodiversity [17, 18, 57]. The digital conversion of taxonomic documents combined with online database development allows scientists from across the world to access this information [19]. The Biodiversity Heritage Library (BHL) and Global Biodiversity Information Facility (GBIF) present two major examples of biodiversity data open access programs which help researchers from different academic fields to collaborate through their shared access [20, 21].

Cybertaxonomy represents the integration of traditional taxonomy, digital and molecular tools which enhances operational efficiency and provides wider access to taxonomic resources across India. Digital illustrations combined with interactive electronic keys allow biological identification of species through their user-friendly interfaces regardless of a person's morphological expertise [54]. Automated Taxon Identification (ATI) combined with Computer Aided Taxonomy (CAT) system that use machine learning and artificial intelligence methods process morphological and genetic datasets with high precision [55]. The integration of DNA barcoding into phylogenomics brought genetic information into the molecular systematic science to better understand evolutionary relationships [56].

Taxonomists now exploit digital imaging together with software applications to transform their methods of working through morphological data collection and analysis. High-resolution X-ray microtomography imaging allows researchers to examine specimen’s external and internal details which results in better identification of cryptic species as well as evolutionary relationship discoveries [22]. Interactive identification keys and web-based biological information system become more accessible through software applications like, Fact Sheet Fusion and Lucid Phoenix Keys [23].

These modern approaches build firmly upon the foundations laid by classical taxonomy, which has catalogued Earth's biodiversity through detailed morphological studies for over two centuries. It is the rigorous work of morphological taxonomists that provides the framework for integrating novel methodologies. For example, the Barcode of Life initiative, which aims to assign DNA barcodes to all known species, heavily relies on traditional taxonomic expertise for accurate species identification [24]. The need for enhanced taxonomic research tools and infrastructure to expedite the process of species exploration and classification in India, enabling global access to its diverse flora and fauna; highlighting the importance of modern taxonomic approaches in the country. Indian field of taxonomy has seen a major transformation through cybertaxonomy for the past quarter century and large-scale implementation is urgently required to manage the increasing digital requirements for biodiversity data in present times [25].

**3. REVOLUTIONIZING BIODIVERSITY MONITORING WITH AI**

Effective use of AI means that the method of monitoring of species in the wild has shifted to a new level in the field of conservation science. The common approaches include manual surveys and field observations despite their efficiency, they are usually slow and require a lot of effort [26]. Machine learning algorithms are much more effective solution since they can process vast amounts of data or images, sounds, or other parameters in a matter of minutes [27]. For example, AI-based image recognition can eliminate the need for species identification manually from the photographs taken by the camera trap, instead can do the taxa identification on its own [28]. Also, AI-based acoustic monitoring can automatically identify bird songs or other calls produced by other species and classify them and potentially estimate species density in areas that cannot easily be surveyed [29]. The coupling of AI with satellite image and remote sensing also improves the effectiveness of the surveillance of habitats and the observation of species migration on a large scale [30]. These advancements not only help to increase the effectiveness of the monitoring of the biodiversity but also contribute to the possibility of the prevention of certain species and ecosystems degradation by using the real time data analysis and predictive models [31]. Since India is home to a vast and diverse spectrum of plants and animals, the implementation of AI in the observation of biological variety can indeed strengthen the conservation of nature and the sustainable handling of India’s environmental and biodiverse species wealth.

**3.1. AI-Powered Approaches for Comprehensive Biodiversity Surveys**

AI is fast changing the way biodiversity is documented and has brought precision and efficiency to the survey of each country’s biodiversity in ways hitherto unthinkable [32]. As manual surveys and field observation, though useful, take a lot of time to complete due to inherent human errors and restrictions on resources [33]. In the Indian context, initiatives such as the India Biodiversity Portal have leveraged AI to analyse user-contributed data, providing valuable insights into species distribution and trends. This integration of public participation with AI has enhanced the spatial and temporal coverage of biodiversity surveys.

**3.2. THE IMPACT OF AI ON BIODIVERSITY DOCUMENTATION PRACTICES**

AI technologies have played a significant role in the documentation of the existing species as well as the monitoring of the same through the improvement of the identification processes. Currently, machine learning techniques, especially Convolutional Neural Networks (CNNs), are employed to process camera trap images and quickly and accurately classify species from massive data sets [34]. Also, computer vision methods assist in the analysis of visual data, enhancing the identification of cryptic species and minimizing the use of time-consuming methods [35]. AI-based acoustic monitoring also has a great potential by analyzing the sound files to identify species by their vocalizations thus making the assessments of biodiversity more comprehensive [36]. Such improvements indicate AI’s capability in revolutionizing and enhancing the processes of documenting biodiversity in the contemporary world.

**3. 3. MACHINE LEARNING FOR SPECIES IDENTIFICATION**

Other big data tools that have been used in improving species identification from camera trap images include machine learning algorithms, including CNNs. CNNs are efficient at extracting features from images and categorizing the extracted features, which is useful when trying to distinguish multiple species from photographs or videos [10]. Such algorithms are capable of learning features from raw data hence they eliminate the need for feature extraction and enhance the accuracy in species identification [37]. The current research findings have shown that CNNs can distinguish species with greater accuracy and efficiency than conventional techniques hence making them useful in species conservation [38]. CNNs are trained on the large database of images with annotations, which allows the networks to learn the features and patterns correlated with various species. This method had been tested and found to have high accuracy and efficiency in the identification of wildlife from camera trap data minimising the amount of data that has to be processed manually [39].

**3.4. COMPUTER VISION AND IMAGE ANALYSIS**

Computer vision technologies, combined with AI, allow for the automated analysis of images and videos captured in the wild. These systems can process thousands of images quickly, identifying and classifying species based on visual characteristics. Computer vision technologies, combined with AI species identification, are revolutionizing the field of biodiversity monitoring. These advanced systems can process vast amount of visual data to accurately identify and classify species, even in challenging environment [40]. By automating the identification process, computer vision technologies significantly reduce the time and effort required for manual species identification, allowing researchers to focus on analysis and conservation efforts [41]. Additionally, the integration of AI enhances the precision of species detection and tracking, providing valuable data for ecological studies and wildlife management [42]. Recent advancements have improved the detection of elusive and cryptic species, which are often missed by traditional methods [43].

**3. 5. AI-DRIVEN ACOUSTIC MONITORING FOR BIODIVERSITY CONSERVATION**

Biodiversity conservation benefits from acoustic monitoring systems which utilizes AI technology. Recording environmental sounds through audio equipment constitutes a common approach used widely. The approach provides substantial improvement to wildlife monitoring activities together with conservation initiatives across Indian regions containing diverse fauna. AI acoustic monitoring systems evaluate large audio databases automatically thus aiding researchers to detect species while understanding natural behaviour and tracking environmental changes in a faster and more efficient way [44, 57]. The approach proves best for watching rare, nocturnal and secretive animal species such as bats, birds, sound producing insects and amphibians during wildlife monitoring. Scientists evaluate soundscapes to determine which species exist in a particular area and how many of them there are, while understanding their behaviour by deploying acoustic sensors to detect and proving how acoustic monitoring generates essential conservation data [45]. Acoustic monitoring plays a crucial role in studying marine species also, because whales and dolphins communicate using vocal sounds in ocean environment. Acoustic monitoring methods used for tracking North Atlantic marine animals and Indo-Pacific Humpback dolphins along with many other species in Arabian Sea and Bay of Bengal. Acoustic survey data helps scientists to monitor species behaviour and monitoring patterns and population distribution patterns that are important for protecting terrestrial and marine biodiversity [46]. Acoustic monitoring system used in urban areas to measure noise pollution because this type of assessment affects human residents along with wild animals living in cities and served as the tool to track and evaluate urban noise pollution in the cities [47]. Acoustic monitoring receives an enhancement through AI technology that allows for instant sound analysis and categorization. AI algorithms with pattern recognition expertise perform avian classification by analysing vocalizations and ability to detect spectrographic patterns in tropical rainforests and this method could easily be applied to India's Western Ghats or Northeast forests [48, 49].

Therefore, the integration of acoustic monitoring and AI holds immense promise for Indian biodiversity documentation, management and conservation. The use of this technology in India would significantly improve oversight of native species populations such as the Great Indian Bustard. AI provides the ability to spot irregularities in forest environment which enables it to trigger warning alerts. Professional researchers benefit from these technological solutions because they enable comprehensive understanding of wildlife activities while creating more protective measures for India's natural biodiversity. This technology would aid urban planners to develop noise reduction strategies in many cities in India which would benefit both human wellness and wildlife.

**4. BIODIVERSITY AND TAXONOMY RESEARCH IN INDIA: CHALLENGES AND FUTURE DIRECTIONS**

Premier taxonomy institutions under the Ministry of Environment Forest and Climate Change incorporated major advancements in biodiversity and taxonomy research through the development of online portals by the Zoological Survey of India (ZSI) and Botanical Survey of India (BSI) [50, 51]. Established in July, 1916 ZSI has led zoological sciences and digital data access improvement projects for taxonomic information. A key initiative of ZSI is the comprehensive digital archive that includes "Records of the Zoological Survey of India" which provides unrestricted access to a wide collection of taxonomic literature needed for species identification and classification [52]. ZSI organises the Animal Taxonomy Summit continuously for the last few years to bring together international experts who use zoological research breakthroughs for its implementation in Indian taxonomy scenario [53]. The organisation demonstrates its essential position in using digital platform to push forward taxonomy research thereby contributing towards biodiversity conservation efforts across the India.

The Botanical Survey of India (BSI) which established on February, 1890 has utilized digital platforms to rewrite plant taxonomy. The BSI operates web portal which provides researchers and taxonomists with essential access to databases, publications and research resources. Users of this platform can identify plants and benefit from widespread distribution of botanical information. The ZSI and BSI demonstrate initiatives for the implementation of latest digital technologies to fill critical taxonomical research gaps and support inter-institutional collaboration while accomplishing significant contribution towards the protection work for India's various animal and plant species and also for the curation of National Zoological, Botanical specimens for further future research activities at various levels.

Studies on biodiversity in India experience fundamental changes because of advancements in AI and Cybertaxonomy. Modern technologies have transformed the practice of species recognition and optimized evolutionary family tree analysis, strengthened protection efforts for animals. The current implementation faces ongoing obstacles that consist of maintaining data reliability as well as tackling bias issues in the algorithms. Biodiversity documentation in India using AI system may encounter major obstacles because of poor data quality problems together with biases in algorithms. India needs precise focused datasets since it contains numerous biodiverse ecosystems to prevent species identification mistakes and classification errors. Strategies to overcome these problems involve both enhancing biodiversity data collection to match Indian climate patterns and creating algorithms that work with regional habitat characteristics. The identification precision of species along with proper conservation strategy development requires complete elimination of bias. The conservation potential of open-access platforms stands evidently, that can unite classical and modern methods in biodiversity research. Such platforms can enable live interaction between Taxonomists, expert scientists including citizen scientists thereby generating better understanding about India's biodiversity. The massive biodiversity of India creates excellent opportunities for AI, molecular systematics and cybertaxonomy to identify and protect its diverse plant and animal species.

5. Conclusion

The complete assessment of biodiversity in India demands the unification of multiple data resources. AI platforms need to combine various types of information consisting of morphological data sets from curated specimens, camera trap recordings, acoustic sensor detection data, satellite enabled geo-spatial data alongside environmental data points for successful operation. Specialised AI models accepting various data types produce detailed knowledge about species movement patterns and distribution patterns together with ecological patterns throughout India's different geographical regions. Technology integration between traditional methods of taxonomy, citizen-science programs, alongside expert involvement with artificial intelligence tools, enabled researchers lead to faster workflow processes and enhanced access to vital taxonomic information to merge data gaps, while perfecting identification and conservation programs.

New technology depends on classical taxonomy's formulated system, while continuing to use the expert morphological assessment records from the last 2.6 centuries that categorised and documented Earth's biological database. Through their combined power, AI and cybertaxonomy present a transformative opportunity for Indian science and documentation of its magnificent natural biodiversity to secure its conservation for future.

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