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Implication of Computer-Based Strategies in Biodiversity Conservation: A Review

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Abstract
Climate change is the long-term alteration in original construction of the nature. The growing human population day by day alarm greatest threat to biodiversity. The population of wild animals on earth declines as a result of disruptions to biodiversity. This ongoing process will cause the ecosystem as a whole to become unstable and eventually collapse. Therefore, preserving the earth's biodiversity is essential to preserving the balance of all of its ecosystems. However, the resolutions of the current monitoring systems are insufficient to extend internationally. Conventional methods and researchers' boring manual labour are ineffective for conserving biodiversity. Because they work more effectively and produce better outcomes, modern technologies like artificial intelligence (AI) and machine learning (ML) are in demand today for conservation. The preservation of the earth's biodiversity can be aided by the application of AI and ML-based solutions to wildlife conservation.

Keywords: *Climate change, biodiversity, ecosystem, conservation, monitoring system*

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I. INTRODUCTION

To keep biodiversity alive generation to generation it's very essential that it should be protected through modern techniques. Artificial intelligence (AL)and machine learning (ML) simulate human behavior towards conservation of biodiversity. The goal of AI is to solve present conservation of biodiversity. Day to day invention in artificial intelligence and machine learning; prove to be a great boon for the conservation of biodiversity.

The scope and character of illegal wildlife trafficking have changed dramatically in recent years, (Lavorgna, 2014). Number of animals, plant's related goods are traded globally to meet essential necessity of mankind. Wildlife trafficking is a multibillion-dollar industry. Growing amount of wildlife commerce is illegal and unsustainable and becomes a crisis to threaten the survival of numerous species of wildlife (Ripple et al., 2016). Illegal trade threatens wild animal of species of great importance as well as a species of less importance ((Wittemyer et al. 2014; Di Minin et al. 2015), Rosen & Smith 2010; Phelps and Webb 2015). The unlawful wildlife traffic is one of the most lucrative illegal enterprises and low monitoring borders, poverty, corruption, and poor legal laws and enforcement are all factors that continue to rise and provide a great threat to fauna and flora around the world. (Dalberg Global Development Advisors, 2012).

In the past, researchers laboriously execute tasks such as identifying unique animals from photo shoots for population studies. Camera photographs are afterwards manually categorized with greater effort and time. Man-made technology has the potential to benefit nature and keep an eye on deforestation, pollution, and global warming in particular. Animals are notoriously difficult to identify and monitor and rely on technology to learn where they are and how their numbers are decreasing. Such jobs can be conducted more efficiently and with better results using Artificial Intelligence (AI) and Machine Learning (ML). The amalgamation of AI and machine learning-based solutions in wildlife conservation can aid in the preservation of the planet's biodiversity. Certainly the potential of AI proves to change the conservation environment. This review chapter will help the readers and researchers to acquaint with various methods of Al and ML to cope up various problems of wildlife trafficking, location, and monitoring of healthof animals and plants in their natural environment as well as their conservation.

II. SEARCHING METHODS

A thorough assessment of the literature was done using Google Scholar, PubMed, Elsevier, the Scientific Information Database, Biodiversity and Conservation review articles, Scientific reports, Science Direct and various research Articles,

III. CONSERVATION OF FAUNA THROUGH AI AND ML

A major challenge in the fight to preserve the biodiversity of the globe is the identification, recognition, and tracking of wild animals in their natural habitats or in wildlife sanctuaries. AI has the potential to play a significant role in this effort. Most importantly, AI has the potential to contribute to the extinction of rare species of plants and animals. Such animals can be safeguarded against nefarious activities like poaching as well as natural disasters like forest fires and floods if they are kept under observation or tracked by forest rangers. Conservation initiatives are being transformed by machine learning (ML). For thousands of species, the likelihood of extinction is being predicted using ML algorithms.

3.1. Motion-sensor cameras

The field of wildlife conservation is being revolutionized by machine learning (ML). Artificial intelligence security cameras collect wildlife, and ML algorithms are being used to predict the risk of extinction for thousands of species, evaluate the global footprint of animals and humans, and record data in the field for subsequent interpretation and action(Darrah et al., 2017;Wearn et al., 2019).Research and conservation of ecosystemscan be up-to-dateif knowledge regarding the location and behavior of wild animals are known. Deep neural networks can automatically characterize photographs taken by motion-sensor cameras, resulting in automate animal identification. (Norouzzadeh*et al*., 2018).Placing motion-sensor cameras termed "camera traps" in natural environments has revolutionized wildlife ecology and conservation over the last decades (O'Connell et al., 2010). Ecologists relied on video traps to analyses population levels and dispersion as well as evaluate habitat utilization (Silveira et al.2003; Bowkett et al., 2008).

Humans have typically extracted insight from camera-trap photographs, despite the fact that they can take millions of images (Fegraus et al., 2011; Krishnappa YS, Turner WC 2014;Swinnen et al., 2014). The Earth is currently in the Anthropocene geological epoch, during which human activity is the primary driver of change. As we enter the sixth mass extinction, many wildlife species are under jeopardy across their geographic ranges (Barnosky et al., 2014; Cardinale, 2012; Skogen et al., 2018).Numerous factors, including as fires, floods, poisoning, and poaching, result in the deaths of hundreds of animals each year. The loss of Keystone species might disrupt entire food chains and ecosystems. We have failed in our efforts to monitor animal conservation using conventional and laborious approaches. Poaching poses a serious threat to the world's wildlife. Artificial Intelligence security cameras with night vision and object identification in the dark can make forests safer for animals. Cameras can detect people carrying weapons and installed at places where poachers invade and alert authorities to save animals (Saripalli et al., 2002; Lange et al., 2008).

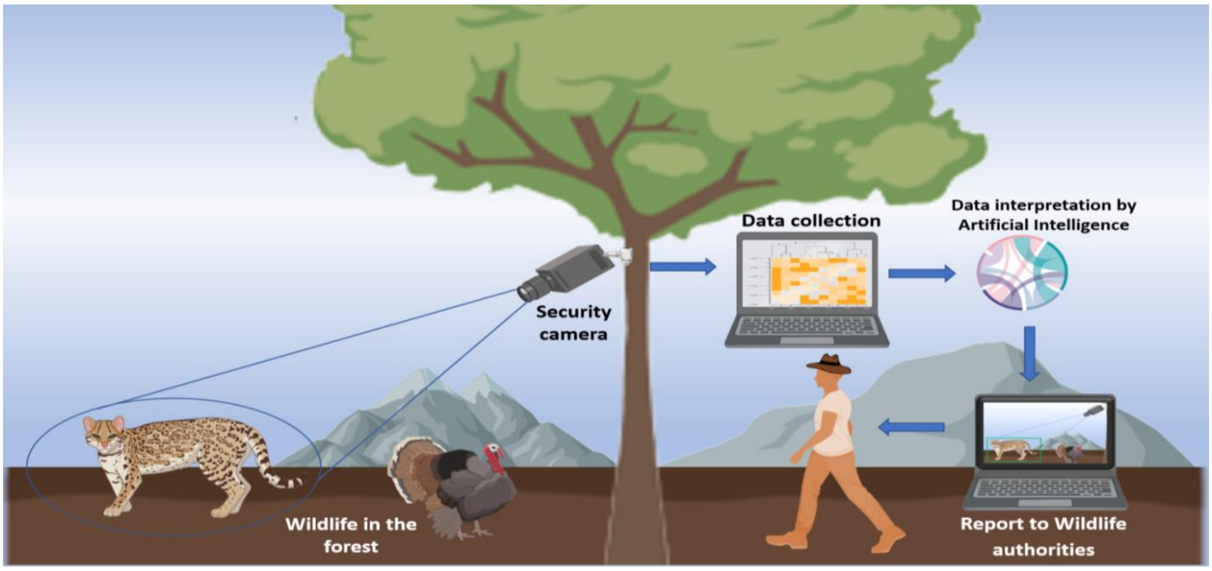

Fig.1: Footprint of animals and humans in forest captured by artificial intelligence security cameras

3.2. PICTUREELUCIDATION BY ARTIFICIAL INTELLIGENCE (AI) IN ANIMAL ONSERVATION

3.2.1. Animal Counting

In order to create effective environmental restrictions, monitor population trends in relation to biodiversity, and preserve species balance, it is essential to have the ability to count animals automatically. 60% of all mammals that are alive today on Earth are livestock, 36% are humans, and 4% are wild creatures. Image Bounding Box Annotation to make such animals recognisable to technologies like drones, the rise of human civilisation led to the extinction of 83% of wildlife and 50% of plants in a relatively short period of time. Here, all types of animals are accurately marked with the highest level of visibility for proper detection (Baron et al., 2018; Carrington, 2020; Padubidri et al., 2021).

3.2.2. Annotation for Animal Detection

Animal conservation includes not just counting but also detecting distinct sorts or species of animals. Individual animal identification from photos allows for population surveys using sight-resight statistics and forms the basis for demographic studies (Berger-Wolf et al., 2016). The spatial and temporal resolution of animal identification and conservation can be improved by AI (Sullivan et al., 2009; Chase et al., 2016).

3.2.3. Annotation for Animal Recognition

An important computer vision challenge is object recognition in images. Better object recognition would result in a smaller semantic gap, making content-based image retrieval more successful (CBIR). The semantic segmentation annotation technique aids in the identification of animals belonging to a particular class. AI Drones can recognize species caught in a single frame, making biodiversity conservation easy (Smeulders et al., 2000). Manual segmentations can be used to test image segmentation and object recognition systems, as well as their interdependencies. The boundaries of the animals should be established as soon as possible by segmentation algorithms beneficial for animal recognition. The characteristics within the regions manually indicated as animals can be used as noise-free training and testing data, according to a boundary assessment technique by Martin et al., 2004.

3.2.4. Annotation for Species Identification

The various species that exist in the ocean or on land can be easily detected by AI. The AI can recognize a variety of animal species. It is necessary to identify the creatures in a particular class more precisely. The best strategy for precisely identifying such animals in remote locations is semantic segmentation image annotation.

3.2.5. Annotation for Poachers Detection

Illicit killing of animals can be detected by wildlife conservation employing the AI-enabled security surveillance established at suspect places; animals that are close to extinction can be protected. With AI security cameras, poachers can be found even at night or in complete darkness. The preservation of animals and the preservation of the earth's biodiversity are both aided by image annotation for AI cameras, night vision views, and object identification in the dark and at night.

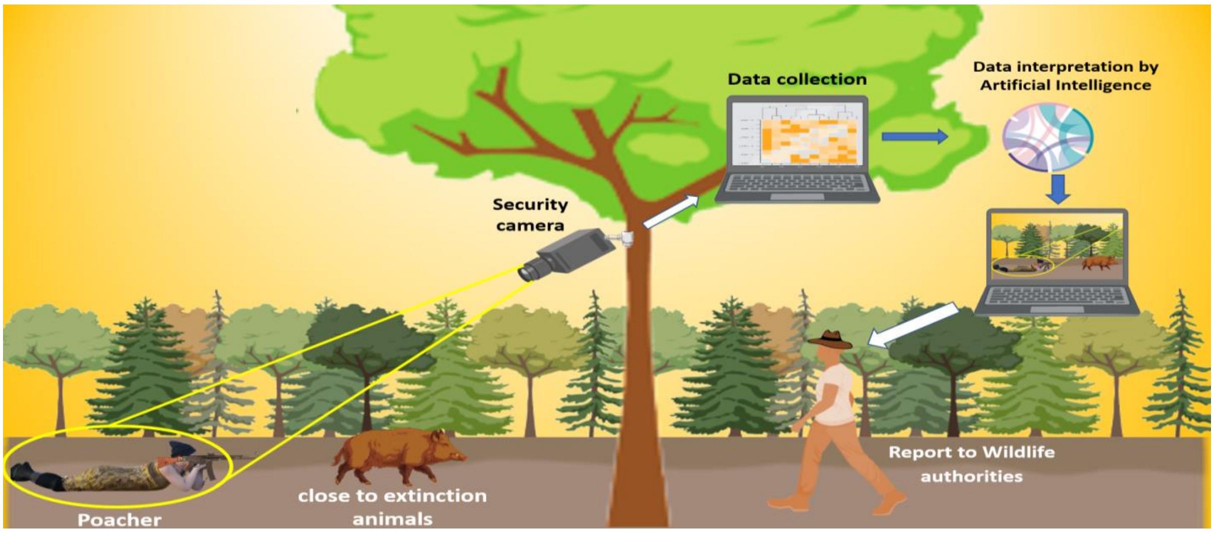

Fig. 2: Footprints of poacher through artificial intelligence security cameras

3.3. Internet Monitoring System

The spread of potentially invasive species can be stopped and the possibility of an introduction decreased by monitoring internet-related sales or trade operations. The practice of looking for websites on the internet that might be contributing to the spread of invasive species is automated by the Invasive Species Internet Monitoring System (e.g., internet commerce, chat rooms, and so on) (Suiter et. al., 2007).

3.4. Robotics and Drone Monitoring

Artificial intelligence systems assist in animal detection through typically mounted cameras. The Folio3 animal detection and counting technology helps in the livestock management operations. Drones assist the farmers with reliable animal tracking across vast farmlands and pastures, counting animals in picture or video data, delivering alerts and reports, predator detection, cow gender identification, and pose detection, among other things (Gomez et al., 2016). To keep track of the animal population, wildlife conservation authorities deploy AI-enabled robots or drones with image databases and processing. AI Drones recognize critters captured in a single shot, making animal identification faster for the forest wildlife protection organization (Norouzzadeh et al., 2018).

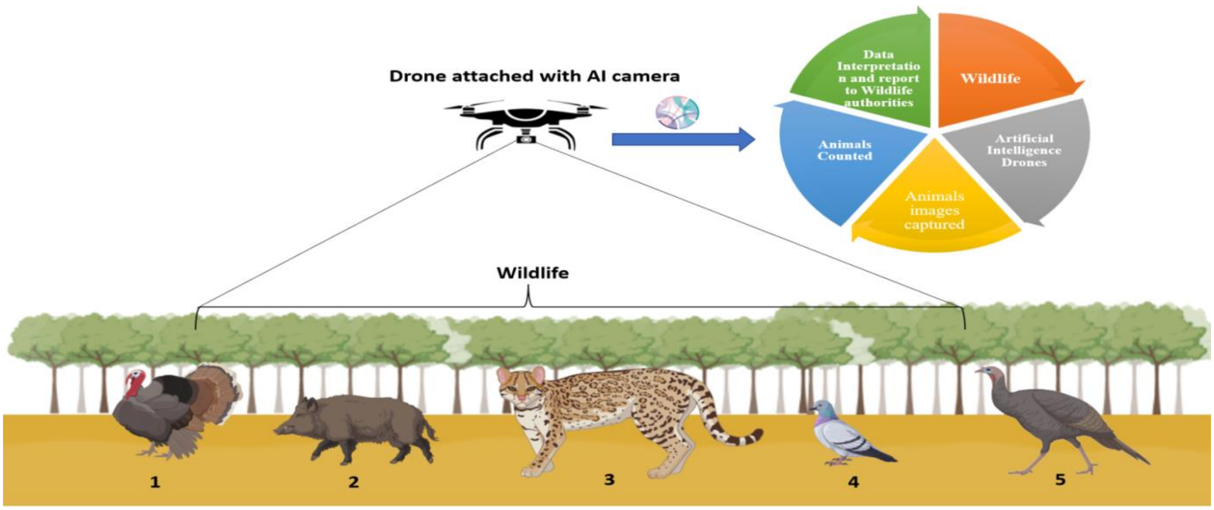

Fig. 3: Counting of animals through artificial intelligence drones

Drones provide a bird's eye perspective of the animals. To remotely monitor cattle, drones equipped with thermal imaging cameras take high-definition photos (Chattopadhyay et al., 2016). Computer vision technology in AI-enabled drones can determine the types and kinds of animals (Weinstein, 2017). The identification and prediction of waste in the water are two deep learning-based uses of Al (Honggui et al., 2014). Plastic is poisonous to living things and serves as a breeding ground for invasive species, jeopardizing biodiversity and ecosystems. The dispersed plastic waste in the water is difficult to recognize and explain. Using AI algorithms and models, plastics can be quickly discovered and removed from natural ecosystems before they harm species and their extinctions. Data on marine waste is collected using AI-enabled cameras and drones to discriminate between the various types of waste goods thrown into the ocean (Ahmed et al., 2019; Panwar et al.,2020).

3.5. Acoustic sensors

For evaluating the effects of human activity on biodiversity, passive acoustic detection has emerged as a potential technique, particularly for echo-locating bat species. Since acoustic monitoring is a passive, non-intrusive method of gathering information regarding echo locating bat population dynamics and species occurrence, it is increasingly being used to survey and monitor bat populations (Jones et al., 2013; Newson et al., 2015; Barlow et al., 2015). Forest authorities are alerted when irregularities like as chainsaws, gunshots, or motor vehicles are detected in a forest region, and they can act to suppress poaching and logging (Olivares-Mendez et al., 2015).

3.6. High-resolution satellite imaging

A number of wildlife species have been successfully detected and counted using very high-resolution satellite imaging (Duporge et al., 2021). Since human intervention is absent from satellite remote sensing, there is no possibility of upsetting the reported species (Mulero-Pazmany et al., 2017). With automated image acquisition and less logistical difficulty than traditional aircraft surveys, the use of high resolution satellite photography for wildlife surveying will undoubtedly increase in the future (Stapleton et al., 2014). As satellite image surveying capabilities advance, automatic detection techniques are created to enable the application of wildlife monitoring on a greater scale (Cao et al., 2019; Pang et al., 2019; LaRue et al., 2017).

IV. CONSERVATION OF FLORA THROUGH ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML)

Human activities are responsible in ecological imbalance and biodiversity loss. Plants must be maintained because they provide the basic habitat that all other species rely on. Plants assist us in meeting essential human needs such as food, medicine, and shelter. Trees and forest cover minimize greenhouse gas emissions while also producing oxygen. More than 20% of plants, according to scientists, are threatened with extinction. Artificial intelligence can help to save endangered species from extinction and plant species, allowing for a healthy ecosystem (Huntingford et al., 2019). Artificial intelligence has the ability to help save trees and plant species. Artificial intelligence offers the following options for forest and plant preservation:

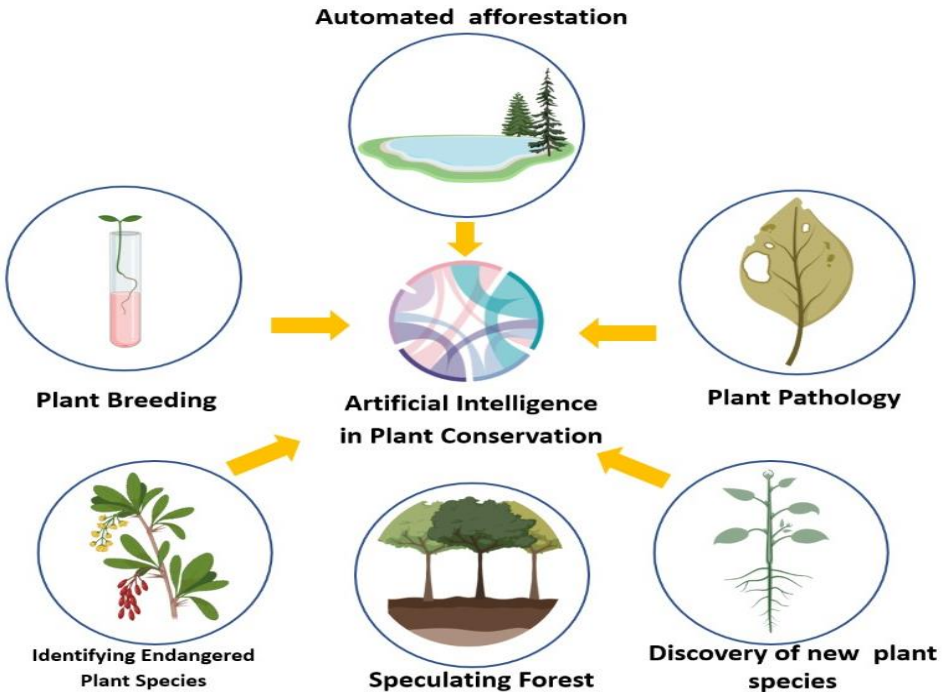

Fig. 4: Various ways of artificial intelligence in forest and plant conservation

4.1. Artificial Neural networks

An algorithm is used to track the conservation status of 150,000 plant species based on their geographical patterns, forms and structures, ecosystem traits, and climatic trends. The exercise of AI aided in data analysis and identification of plants on the verge of extinction (Azzari and Lobell, 2017). Artificial intelligence may be used to track changes in plant genotypes and phenotypes, as well as to find the ideal genome combination for enhanced plants that can adapt to their environment (Dijk et al., 2021). Artificial intelligence (AI) could be used to solve the tough taxonomic problem of detecting species and discovering new plant species all over the world. AI-based autonomous systems are used to collect data on a large scale in a short amount of time (Carranza-Rojas and colleagues, 2017).On the basis of climate variables as predictors, artificial neural networks predict the geographic distribution of groups of polyphagous plant pests. For predicting insect dispersion, artificial neural network models were compared to binary logistic models (Peacock et al., 2007).Wildfires cause the loss of many plant and animal species, posing a serious danger to biodiversity. Artificial intelligence is being utilized to manage wildfires, with neural networks and machine learning (ML) being used to detect wildfires and maintain the environment's health. (Castelli et al., 2015; Jain et al., 2020). Artificial neural networks (ANN) have been used to forecast the occurrence of catastrophic fires and estimate their frequency (Watts & Hall, 2016). The Multi-layer Perceptron (MLP) and the Radial Basis Function (RBF) were utilized to identify areas that are more prone to fire (Surya, 2017). Garzón et al. (2008) and Schmitt et al. (2009) employed AI to map out where a forest should be planted.

4.2. Remote Sensing Assisted Control System (RSCS)

Climate change has posed a danger to agricultural productivity; temperature and humidity extremes, as well as other abiotic stresses, all have a role in the genesis of disease and pest on crops (Corrales, 2015). Green infrastructure, as well as an intelligent system and Remote Sensing Assisted Control System (RSCS) have to meet the needs of greenhouse agriculture (Zhou et al., 2021).

4.3. Vector Machines Support

The expansion of invasive and growing species is one of the biggest threats to biodiversity and ecological health (Mooney and Cleland, 2001). Support vector machines (SVMs) techniques were used at the Selkeh Wildlife Refuge in the Anzali wetland (southern Caspian Sea, northern Iran) to forecast the distribution pattern of the invasive aquatic fern *Azolla filiculoides* (Lam. (Sadeghi et al., 2012). Machine learning approaches applied in agriculture for pest management include Decision Trees, Regression Analysis, and Bayesian belief networks (Mishra et al., 2016; Kim et al., 2013). Soft computing methods are used to forecast next year's seasonal temperatures (Hill et al., 2014).

4.4. Semantic Data Masters (SDMs)

SDMs display and forecast species distributions and preferences in various habitats, as well as to identify priority conservation sites. SDMs based on ML techniques integrate remote sensing to replicate each species' dispersal capacity and designate conservation priority regions (Loyola et al. 2012; Garzón et al. 2008; Chapman and Purse 2011; Vaca et al. 2011; Pouteau et al. 2012; Faleiro et al. 2013). The advance of ML and AI is critical to the conservation of forest ecosystems (Ghahramani, 2015).

V. CONCLUSION

Animal conservation can be plausible when AI models are trained with the appropriate machine learning datasets and used to animal detection. Machine learning algorithms can protect a variety of plant types from pests and illnesses. Artificial intelligence can help to prevent the extinction of endangered plant species, resulting in a healthy environment. Artificial intelligence (AI) has the prospective to be a valuable device for ecological protection. Its misuse might have serious real-world ramifications for humans and species. Accountable use of AI in management will need to be established in the application domain of AI and machine learning in conservation of fauna and flora which provides maximum benefit with minimal harm.

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