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RESEARCH ARTICLE

LEVERAGING MACHINE LEARNING AND REMOTE SENSING FOR WILDLIFE CONSERVATION: A COMPREHENSIVE REVIEW

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Abstract

In recent years, the application of machine learning and remote sensing technologies in wildlife conservation has demonstrated tremendous promise. This article provides a comprehensive overview of the advancements in these fields and the impact they have had on various aspects of wildlife conservation. These technologies contribute to more efficient and effective conservation strategies by automating species identification, mapping and monitoring habitats, tracking population dynamics, detecting wildlife crime, and analysing animal vocalisations. This article talks about the development of machine learning algorithms capable of classifying bird and amphibian calls, differentiating fish species, and identifying plant species such as orchids and cacti has made automated species identification possible. Incorporating machine learning algorithms with remote sensing techniquesprovides significant advantages for mapping and monitoring habitats. This article discusses that images captured by camera trapswhen combined with acoustic analysis, can help in monitoring population by enabling automated detection and tracking. These technologies provide efficient and non-invasive approaches to monitor and manage animal populations, from estimating animal density using passive acoustics to identifying and tracking endangered species such as tigers, cheetahs, and sea turtles using camera trap images. The analysis of animal vocalisations using machine learning techniques has revealed information about species behaviour, population dynamics, and habitat quality. Examining the acoustic communication of species such as black rhinoceros and Yangtze finless porpoise has been the focus of research. Acoustic analysis provides a non-invasive method for comprehending the communication patterns of animals and their implications for conservation efforts. By utilising artificial intelligence and remote sensing data, conservationists can make informed decisions and take targeted actions to protect and preserve endangered species and their habitats. These technologies' continued development and application hold great promise for the future of wildlife conservation.

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Introduction:-

Understanding AI and its Applications:

Artificial Intelligence (AI) refers to the creation of computer systems that are capable of performing tasks that normally require human intelligence. It involves the development of intelligent machines that can learn, reason, solve problems, and make decisions. AI encompasses a vast array of techniques and methodologies, including machine learning, natural language processing, computer vision, robotics, and expert systems. Among the most notable AI applications are:

1. Large datasets are used to train AI algorithms to recognise patterns, make predictions, and classify information. Applications include image and speech recognition, recommendation systems, and fraud detection.
2. Natural Language Processing (NLP): Natural Language Processing enables computers to comprehend, interpret, and generate human language. It is the driving force behind applications such as chatbots, virtual assistants, language translation, sentiment analysis, and voice-controlled systems.
3. Computer Vision: Computer vision systems based on artificial intelligence can analyse and interpret visual data, including images and videos. Object detection, facial recognition, autonomous vehicles, medical imaging, and surveillance systems are examples of applications.
4. AI plays an essential role in robotics, allowing machines to perceive and interact with their surroundings. Robots can perform a variety of tasks, including industrial automation, surgical procedures, exploration of hazardous environments, and daily assistance.
5. Expert Systems: These artificial intelligence systems replicate human expertise in particular domains and provide intelligent decision support. They are utilised in fields such as medicine, finance, engineering, and complex system troubleshooting.
6. AI is crucial to the development of autonomous systems that can operate independently and make decisions based on real-time information. Examples include autonomous vehicles, drones, and intelligent home automation.
7. Recommendation Systems: Artificial intelligence (AI) algorithms analyse user preferences and behaviour in order to provide personalised recommendations in e-commerce, streaming services, and content platforms.
8. AI is applied to the analysis of financial data, the detection of patterns, the prediction of market trends, and the automation of trading strategies. It enhances risk assessment, fraud detection, and portfolio management.
9. Disease diagnosis, medical imaging analysis, drug discovery, personalised treatment recommendations, and health monitoring systems are examples of AI applications in healthcare.
10. AI aids in the analysis and interpretation of environmental data for monitoring and managing ecosystems, climate modelling, wildlife conservation, and pollution detection.
11. AI techniques are utilised to create intelligent game opponents, generate realistic virtual environments, and improve immersion in virtual reality (VR) and augmented reality (AR) applications.
12. Cybersecurity: AI algorithms aid in the detection and prevention of cyber threats, the identification of network traffic anomalies, and the improvement of data security via advanced encryption and authentication techniques.

Historical Developments in Using AI for Biodiversity Conservation

Early Applications (1990s-2000s):

It was in the 1990s and early 2000s that AI was first put to use in the field of biodiversity conservation. Machine learning algorithms have recently been the focus of research into their potential use in species identification and classification. Expert systems and decision support tools based on rules were developed early on to aid in species identification and conservation planning (Moritz et al., 1991).

1. Species Identification and Classification: For species identification and classification, AI techniques such as rule-based expert systems were used. These systems identified species based on morphological or ecological characteristics using a set of predefined rules and knowledge bases. Moritz et al. (1991), for example, used molecular differentiation techniques and expert systems to classify Pacific jumping mouse (Zapus trinotatus) populations in the Sierra Nevada.
2. Habitat Mapping and Land Cover Classification: For habitat mapping and land cover classification, AI algorithms such as neural networks and support vector machines were used. The researchers used remote sensing data, such as satellite imagery and aerial photographs, to train AI models to recognise various habitat types and land cover classes. Using AVHRR (Advanced Very High-Resolution Radiometer) pathfinder data, DeFries et al. (2000) used neural networks to classify land cover types.

3. Expert Systems for Decision Support: Expert systems, a subset of AI, were created to aid in species conservation decision making. These systems included expert knowledge and rules to help conservationists make informed decisions. They helped prioritise conservation actions, design protected areas, and optimise resource allocation. Despite being unrelated to species conservation, AI-based decision support systems have been used in conservation planning and management. These early applications laid the groundwork for more advanced AI techniques in the years to come.

It is worth noting that AI applications in species conservation were still limited during this time period due to a lack of comprehensive datasets, limited computational capabilities, and the nascent stage of AI technology. Nonetheless, these early applications paved the way for future AI advancements and their incorporation into conservation practises.

Remote Sensing and Habitat Mapping (2000s-2010s):

With the advent of high-resolution satellite imagery and remote sensing technologies, AI applications in habitat mapping gained a valuable data source. Researchers began analysing remote sensing data and classifying different habitat types using AI techniques such as neural networks and support vector machines. These methods enabled more accurate and efficient mapping of biodiversity-rich areas, which aided in landscape-level conservation planning (DeFries et al., 2000).

1. Monitoring of Species and Acoustic Analysis (2000s-2010s):During this time, scientists investigated the use of AI for species monitoring and acoustic analysis. Large datasets of species vocalisations were used to train machine learning algorithms, allowing for automated species identification based on acoustic patterns. This method made it easier to monitor elusive and nocturnal species, as well as identify vocalisation changes in response to environmental disturbances (Acevedo et al., 2009).
2. Using artificial intelligence (AI) in remote sensing and habitat mapping significantly aided biodiversity conservation efforts from the 2000s to the 2010s. Artificial intelligence (AI) techniques like machine learning and neural networks were used to analyse remote sensing data and classify habitat types, resulting in more accurate and efficient mapping of biodiversity-rich areas. Here is a discussion of how artificial intelligence was used in remote sensing and habitat mapping during this time period:
3. Automated Habitat Type Classification:Based on remote sensing data, AI algorithms, specifically machine learning techniques, were used to classify habitat types. These algorithms were developed using labelled training datasets containing remote sensing imagery associated with known habitat classes. AI models could automatically classify and map habitat types over large areas by learning the spectral patterns and spatial characteristics of different habitats (Wang et al., 2016). The classification outputs were useful for conservation planning and management.
4. Feature Extraction and Selection: For habitat mapping, AI techniques were used to extract relevant features from remote sensing data. Advanced neural network architectures, such as convolutional neural networks (CNNs), have been used, for example, to automatically learn discriminative features from satellite imagery (Zhu et al., 2017). AI models were capable of detecting informative spectral, textural, and contextual features that were critical for differentiating between habitat types. Techniques for feature selection were also used to identify the most relevant and informative features for accurate habitat mapping (Cao et al., 2010).
5. Change Detection and Monitoring: AI algorithms were used to detect and monitor changes in habitat areas over time. AI models could identify and quantify changes in land cover and habitat characteristics by analysing multi-temporal satellite imagery. AI-based change detection algorithms assisted in assessing habitat loss, fragmentation, and other land cover changes, providing critical data for conservation planning and monitoring programmes (Carranza-Rojas et al., 2016).
6. Fusion of Multiple Data Sources: Artificial intelligence was used to integrate and fuse data from various sources, including satellite imagery, aerial photographs, and ground-based observations. AI models improved the accuracy of habitat mapping and characterization by combining different data types. LiDAR data, for example, which provides detailed information on vegetation structure, was combined with satellite imagery using AI algorithms to improve habitat mapping and assess habitat quality (Schroeder et al., 2018).

During the 2000s and 2010s, AI applications in remote sensing and habitat mapping were critical in advancing our understanding of biodiversity patterns and dynamics. They were extremely useful for conservation planning, protected area design, and landscape-scale assessments.

Camera Traps and Image Analysis (2010s-present):
AI-based image analysis has gained prominence in the conservation field as camera trap technology has advanced. Convolutional neural networks (CNNs) and other deep learning algorithms were used to analyse camera trap images and identify individual animals and species. These methods use machine learning algorithms to automate species identification based on acoustic patterns, allowing researchers to track nocturnal and elusive species as well as detect changes in species vocalisations in response to environmental disturbances.

1. Automated Species Identification: AI algorithms, particularly those based on machine learning, were used to automate acoustic signal-based species identification. Researchers amassed massive datasets of species vocalisations and trained AI models to recognise patterns and classify various species. Support vector machines and random forests were used to develop classification models that could accurately identify species based on their acoustic characteristics (Acevedo et al., 2009).
2. Vocalization Analysis: Artificial intelligence techniques enabled the analysis of complex vocalisations emitted by species. AI models could detect variations in vocalisations and classify different vocalisation types by extracting acoustic features from recordings, such as frequency, duration, and spectral characteristics. This analysis aided in the identification of individual species, the tracking of population trends, and the evaluation of the impact of environmental changes on species vocalisations (Acevedo et al., 2016).
3. Habitat Assessment and Biodiversity Surveys: The use of artificial intelligence in acoustic analysis aided in habitat assessment and biodiversity surveys. The identification of species-specific vocalisations within recorded soundscapes was made possible by AI algorithms, providing valuable information on species composition and biodiversity. This method enabled the rapid evaluation of habitat quality, biodiversity hotspots, and the presence of endangered or rare species (Marques et al., 2013).
4. Passive Acoustic Monitoring: Artificial intelligence-based techniques aided in the deployment of passive acoustic monitoring systems. These systems used AI-enabled autonomous recorders to continuously monitor and analyse acoustic data in remote or difficult-to-reach locations. These systems provided a cost-effective and efficient means of monitoring species presence and behaviour over long periods of time by automatically detecting and classifying species vocalisations (Pieretti et al., 2011).
5. Species Conservation and Management: By combining AI with species monitoring and acoustic analysis, conservation and management efforts were aided. AI models provided valuable information on species distribution, abundance, and behaviour, allowing conservationists to make informed decisions about habitat protection, population monitoring, and management strategies. AI also aided in the evaluation of the efficacy of conservation interventions and the identification of potential threats to species (Kalan et al., 2018).

During the 2000s and 2010s, the use of AI in species monitoring and acoustic analysis revolutionised the field, allowing for more efficient and accurate species identification and monitoring. These advances aided in gaining a better understanding of species dynamics, habitat quality, and ecosystem health, thereby assisting in biodiversity conservation and management efforts.

Big Data and Citizen Science (2010s-present):
The proliferation of big data and the involvement of citizen science initiatives have contributed to the growth of AI applications in biodiversity conservation. AI techniques such as machine learning and data mining have been used to analyse large-scale biodiversity datasets collected through citizen science projects. These methods have aided in the identification of species distributions, the tracking of population trends, and the generation of valuable insights into biodiversity dynamics (Silvertown, 2009).

1. Big Data in Biodiversity Conservation: The introduction of big data in biodiversity conservation has transformed the way researchers approach data analysis and decision-making. Large-scale datasets, such as species occurrence records, environmental variables, and remote sensing data, provide a comprehensive understanding of ecological patterns and processes. AI techniques such as machine learning and data mining have been used to process and extract meaningful information from these massive datasets.
2. Citizen Science and Data Collection: Citizen science initiatives have enabled widespread data collection on a scale previously unattainable by traditional research methods alone. These projects involve volunteers from a variety of backgrounds, allowing them to contribute to biodiversity monitoring, species identification, and data collection efforts. Citizen scientists collect observations, photographs, and audio samples using smartphone apps, online platforms, and collaborative projects, resulting in a wealth of data for analysis.
3. AI for Data Analysis: AI techniques, particularly machine learning, have been critical in analysing and interpreting large volumes of data collected through citizen science initiatives. Machine learning algorithms can detect patterns, relationships, and trends in data, allowing for species identification, distribution modelling, and

the detection of ecological changes. These algorithms learn from labelled or unlabeled datasets and can make predictions or classifications based on learned patterns.

4. Species Distributions and Population Trends: Using big data and AI, researchers have been able to model species distributions at regional and global scales. Machine learning algorithms analyse species occurrence records in conjunction with environmental variables to predict suitable habitats and identify areas of high biodiversity significance. This data helps with conservation planning, protected area design, and conservation effort prioritisation. AI techniques also make it easier to track population trends and detect species declines or expansions over time.
5. Insights and Conservation Actions: The integration of big data, citizen science, and AI provides valuable insights into biodiversity dynamics and ecosystem functioning. Researchers gain a comprehensive understanding of species interactions, ecological processes, and the impacts of environmental changes on biodiversity by analysing large and diverse datasets. These findings inform evidence-based conservation actions such as habitat restoration, invasive species management, and the development of targeted conservation strategies.

AI in Wildlife Crime Prevention (2010s-present):

The use of artificial intelligence (AI) to combat illegal wildlife trade and poaching has gained traction in recent years. To assist law enforcement agencies in detecting and preventing wildlife crimes, computer vision algorithms have been used to analyse online platforms and identify illegal wildlife products. Natural language processing techniques have also been employed in the monitoring and analysis of social media platforms for illegal wildlife trade-related activities (Wan et al., 2019).

AI algorithms have been developed to automatically detect and recognise wildlife species, animal parts, and illegal wildlife products in images and videos. These algorithms analyse visual data using machine learning and computer vision techniques, allowing for the rapid identification of wildlife species and illegal items. AI-based systems, for example, can identify ivory, rhino horns, or tiger skins in images, assisting in the detection of wildlife trafficking (Yu et al., 2019).

1. Wildlife Trafficking Network Analysis: Artificial intelligence-powered algorithms can analyse large-scale datasets related to wildlife trafficking, such as seizure records, shipping data, and social media posts, to identify key actors and networks involved in the illegal trade. AI systems can uncover hidden relationships, routes, and patterns in trafficking activities by using network analysis techniques, assisting law enforcement agencies in targeting the major players in these criminal networks (Zhang et al., 2020).
2. Real-time Monitoring and Alert Systems: AI-based systems allow for real-time monitoring of wildlife habitats, protected areas, and border regions in order to detect and respond to illegal activities as soon as possible. AI algorithms can analyse data streams in real-time and generate alerts for potential wildlife crime events by integrating technologies such as remote sensing, camera traps, and acoustic sensors. These systems help law enforcement prevent and apprehend poachers and traffickers (Wasser et al., 2019).
3. Data Analysis for Risk Assessment: AI techniques make data analysis for risk assessment and predictive modelling easier, allowing for the identification of high-risk areas or times for wildlife crime. AI models can identify spatial and temporal patterns of wildlife crime occurrence by analysing various data sources such as environmental data, historical crime records, and socioeconomic factors. This data assists in prioritising resources and implementing targeted interventions in high-risk areas (Wang et al., 2020).
4. Collaboration and Information Sharing: AI-powered platforms and data-sharing systems foster collaboration and information sharing among law enforcement, conservation organisations, and researchers. These platforms make it easier to integrate multiple data sources, share real-time information, and support coordinated efforts to combat wildlife crime. AI systems contribute to the global fight against illegal wildlife trade by improving communication and collaboration (Shanafelt et al., 2020).

Integration with Other Technologies (2010s-present):

1. In recent years, there has been a growing trend toward combining AI with other emerging technologies to improve biodiversity conservation efforts. For example, to monitor habitats and collect real-time data, AI algorithms are being combined with remote sensing, drones, and IoT devices. This integration allows for more accurate and timely conservation management decision-making (Hoffmann et al., 2020).
2. Finally, there has been significant historical progress in the use of AI in biodiversity conservation. AI has transformed the way we approach conservation challenges, from early applications in species identification and expert systems to the current use of deep learning for camera trap analysis and combating wildlife crime. The

combination of AI and remote sensing, big data, and citizen science has increased the potential impact of AI on biodiversity conservation. AI is expected to play an increasingly important role in shaping effective and data-driven conservation strategies as technology advances.

Species Identification using AI

AI applications have greatly advanced species identification in recent years. Machine learning algorithms can now analyze various forms of data, such as images, sounds, and genetic information, to accurately classify and identify different species. This technology has been successfully applied to identify birds and amphibians based on their vocalizations, differentiate fish species from underwater images, and even identify plant species through leaf analysis. Automated species identification enhances monitoring efforts, facilitates large-scale data collection, and provides valuable insights for conservationists. The continued development of AI in this field holds significant potential for improving our understanding and protection of biodiversity.

Different species identified using AI:

Category	Species	AI Technique
Birds	American crow (Corvus brachyrhynchos)	Automated Acoustic Identification
	Golden-winged warbler (Vermivora chrysoptera)	Machine Learning and Computer Vision
	Black-capped chickadee (Poecile atricapillus)	Deep Learning and Image Analysis
Mammals	African elephants (Loxodonta africana)	Camera Trap Image Analysis
	Cheetahs (Acinonyx jubatus)	Deep Learning and Object Detection
	Tigers (Panthera tigris);	Computer Vision and Image Analysis
Fishes	African cichlids (Pseudotropheus spp.)	Image-based Pattern Recognition
	Whale sharks (Rhincodon typus)	Computer Vision and Image Analysis
	Atlantic cod (Gadus morhua)	Machine Learning and Image Analysis
Insects	Monarch butterfly (Danaus plexippus)	Image-based Morphological Analysis
	Honey bees (Apis mellifera)	Deep Learning and Image Analysis
	Dragonflies (Odonata)	Machine Learning and Image Analysis
Plants	Sunflowers (Helianthus spp.)	Image-based Leaf and Flower Analysis
	Orchids (Orchidaceae)	Machine Learning and Image Analysis
	Roses (Rosa spp.)	Computer Vision and Image Analysis

Birds:

1. American crow (Corvus brachyrhynchos); AI technique: Automated Acoustic Identification. The algorithms learn from audio recordings that have been labelled and pull out patterns and traits that are unique to each species (Wilber et al., 2019).
2. Golden-winged warbler (Vermivora chrysoptera); AI technique: machine learning and computer vision. Labeled data is used to teach machine learning algorithms how to classify different bird species based on these visual clues (Farrell et al., 2019).
3. Black-capped chickadee (Poecile atricapillus); AI technique: deep learning and image analysis. Based on the patterns they find in the images, these algorithms learn to recognise and sort the different kinds of birds (Berg et al., 2020).

Mammals:

1. African elephants (Loxodonta africana); AI technique: camera trap image analysis. To identify and classify mammal species, AI algorithms are used to process images taken by camera traps. Pattern recognition and machine learning are used to look at important visual features, like body size, shape, and tusks, to tell different species apart (Rovero et al., 2014).
2. Cheetahs (Acinonyx jubatus); Deep Learning and Object Detection are two types of AI techniques. Deep learning algorithms, like object detection models, look at pictures or videos of cheetahs to find and identify their unique visual features, like their coat patterns and body structure. Convolutional neural networks (CNNs) are used by these algorithms to find and classify cheetahs in images (Swanson et al., 2015).
3. Tigers (Panthera tigris); AI technique: computer vision and image analysis. Deep learning and image recognition are used by these algorithms to tell the different kinds of tigers apart (Jhala et al., 2011).

Fish:

1. African cichlids (Pseudotropheus spp.); AI technique: image-based pattern recognition. Explanation: AI algorithms look at images of fish species to identify and classify them based on their distinct visual patterns, such as body coloration, fin shape, and markings. These algorithms use pattern recognition to tell the difference between different kinds of cichlids (Ruban et al., 2020).
2. Whale sharks (Rhincodon typus); AI technique: computer vision and image analysis; whale sharks are identified and put into groups based on their unique physical features, such as their size, markings, and body shape. These algorithms use deep learning and image recognition to tell the difference between different shark species (Cahill et al., 2018).
3. Atlantic cod (Gadus morhua); AI technique: machine learning and image analysis. Explanation: Machine learning algorithms analyse images of fish species to identify and classify them based on their specific visual traits, such as body shape, colour patterns, and fin structures. These algorithms use labelled data to classify different fish species (Christensen et al., 2017).

Insects:

1. Monarch butterfly (Danaus plexippus); AI technique: image-based morphological analysis. The algorithms use things like wing shape, colour, body structure, and other unique features to tell different insect species apart (Ball et al., 2017).
2. Apis mellifera, or honey bees; Deep Learning and Image Analysis, two AI techniques. Deep learning algorithms look at pictures of honey bees to figure out how to identify and group them based on their unique shapes, colours, and wing structures, among other things. Based on the patterns they find in the pictures, these algorithms learn to recognise and sort honey bee species (Wario et al., 2019).
3. Dragonflies (Odonata); AI technique: machine learning and image analysis. Explanation: Machine learning algorithms analyse images of dragonflies to identify and classify different species based on their specific visual characteristics, like body shape, wing patterns, and coloration. These algorithms learn how to classify different dragonfly species from data that has been labelled (Joshi et al., 2017).

Plants:

1. Sunflowers (Helianthus spp.); AI technique: image-based leaf and flower analysis. To identify and classify different plant species, AI algorithms look at images of sunflower leaves or flowers. The algorithms use things like leaf shape, vein patterns, flower structure, and flower colour to tell different types of sunflowers apart (Barfuss et al., 2018).
2. Orchids (Orchidaceae); Machine Learning and Image Analysis, which are AI techniques. Machine learning algorithms look at pictures of orchids to identify and group them into different species based on their shape, colour patterns, and petal structures, among other things. These algorithms learn how to sort different orchid species from data that has been labelled (Arya et al., 2019).
3. Roses (Rosa spp.); AI technique: computer vision and image analysis. Deep learning and image recognition are used by these algorithms to tell the difference between different types of roses (Zhao et al., 2019).

Species being Conserved using AI

1. To study the Amur leopard (Panthera pardus orientalis), researchers use camera traps equipped with artificial intelligence (AI) to capture stills and videos of the cats in their natural environment. Artificial intelligence algorithms are then applied to these images in order to track leopard populations, determine where they are located, and study their habits. Using this information, conservationists can better ensure the species' safety (Goodrich et al., 2018).
2. Audio recordings of black rhinoceros (Diceros bicornis) calls are analysed using artificial intelligence methods for research purposes. To better understand the whereabouts and activities of these rhinos, machine learning algorithms are used to decipher between vocalisations like mating calls and distress signals. This data is useful for keeping tabs on their numbers and identifying potential dangers (Kaburu et al., 2021).
3. Machine learning algorithms analyse satellite imagery to identify and monitor suitable orangutan habitats, such as forest cover, canopy density, and landscape connectivity, for the Sumatran orangutan (Pongo abelii). Important conservation targets can be pinpointed, and preservation strategies can be better developed, with the help of this data (Miettinen et al., 2017).
4. The nests of the endangered Hawksbill sea turtle, Eretmochelys imbricata, are monitored and tracked using AI-powered systems. The number of nests, signs of disturbance, and hatchling survival rates can all be tracked by

these systems thanks to image analysis and thermal sensors. This data is useful for determining the health of nesting populations and planning conservation strategies (Luque et al., 2019).
5. Artificial intelligence algorithms are used to examine Ailuropoda melanoleuca (giant panda) photos taken with camera traps. These algorithms use pattern recognition methods to determine the identity of specific pandas by analysing their fur. This is useful for determining panda population size, keeping tabs on how the habitat is being utilised, and learning more about panda (Zhu et al., 2020).
6. Sumatran Orangutan (Pongo abelii):AI is used for habitat monitoring, species identification through image analysis, and population estimation (Miettinen et al., 2017).
7. Black Rhinoceros (Diceros bicornis):AI helps in acoustic monitoring and analyzing rhinoceros vocalizations for population assessment and anti-poaching efforts (Kaburu et al., 2021).
8. Amur Leopard (Panthera pardus orientalis):AI-powered camera traps and image analysis assist in monitoring leopard populations, identifying individuals, and understanding their behavior (Goodrich et al., 2018).
9. Hawksbill Sea Turtle (Eretmochelys imbricata):AI-based nest monitoring systems help in tracking nesting activities, monitoring nest success rates, and implementing conservation measures (Luque et al., 2019).
10. Javan Rhino (Rhinoceros sondaicus):AI technologies, including camera traps and acoustic monitoring, are utilized to monitor and protect Javan Rhino populations (Kurniawan et al., 2020).
11. Sumatran Tiger (Panthera tigris sumatrae):AI techniques aid in population monitoring, habitat analysis, and detecting illegal activities through camera traps and data analysis (Anwar et al., 2021).
12. Northern White Rhinoceros (Ceratotherium simum cottoni):AI is employed for assisted reproduction techniques, including embryo transfer and in vitro fertilization, to save the critically endangered northern white rhino (Gomez et al., 2020).
13. Yangtze River Dolphin (Lipotes vexillifer):AI-based acoustic monitoring systems are used to track the presence and behavior of the critically endangered Yangtze River dolphin (Turpin et al., 2021).
14. Vaquita (Phocoena sinus):AI techniques are employed to monitor and identify vaquita individuals using acoustic monitoring, helping in conservation efforts for the world's most endangered marine mammal (Barlow et al., 2021).

Plants:
1. Sequoia sempervirens): Method: LiDAR and Machine Learning Explanation: High-resolution 3D models of redwood forests are created using LiDAR technology in conjunction with machine learning algorithms. These models aid in the estimation of forest structure, the measurement of tree heights, and the assessment of biomass, all of which are important in the preservation and management of these venerable trees (Duncanson et al., 2015).
2. Computer Vision and Image Analysis Object: Cacti (Cactaceae) Images of cacti are analysed by computer vision algorithms, which look for telltale visual differences between species, such as spines, size, and overall form. This is useful for keeping tabs on cactus populations, doing ecological assessments, and developing conservation plans for endangered plant species (Meyer et al., 2017).
3. In order to automatically recognise and categorise different orchid species based on visual features like flower shape, colour pattern, and petal structure, deep learning algorithms are used to analyse images of orchids. This provides precise and time-saving species identification, which is useful for conservation (Arya et al., 2019).

Limitations of AI in Conserving Biodiversity

While artificial intelligence (AI) has shown a lot of potential in protecting biodiversity, it is important to keep in mind that it also has some significant drawbacks. The precision, dependability, and morality of AI in this area may suffer as a result of these constraints. For AI to be used effectively in protecting biodiversity, these limitations must be recognised and worked around.
1. Quality and bias in the data are major concerns for AI models. Predictions can be inaccurate or biased if the training data is unreliable. Data bias can occur in biodiversity conservation if the training data disproportionately represents some species or habitats, leading to subpar performance when trying to identify species or environments that are underrepresented in the data. The accuracy of AI-based species identification systems can also be compromised by poor data quality, such as missing or incorrectly labelled information.
2. Insufficient Training Data: Large and varied datasets are required for training AI models. However, it can be difficult to acquire complete and well-curated datasets for biodiversity studies. It may be challenging to train accurate AI models for the identification of some species due to a lack of data. Furthermore, for less-studied or rare species, it can be time-consuming and resource-intensive to acquire high-quality labelled data.

3. It's possible that AI models trained on limited datasets will have trouble extrapolating their acquired knowledge to novel species or unexplored environments. This constraint may make it harder for AI applications in biodiversity conservation to scale and adapt. It is essential that AI models are flexible enough to account for differences in species' outward appearance, behaviour, and environmental setting.
4. Oftentimes, AI models function as black boxes, making it difficult to understand how they arrived at their conclusions. In biodiversity conservation, where decisions need to be justified and understood, this lack of transparency can be problematic. In order for scientists and conservationists to have faith in and validate the results, it is essential to create AI models that can explain their predictions.
5. Ethical Considerations: There are concerns about privacy, data ownership, and the possible displacement of human expertise brought up by the use of artificial intelligence in biodiversity conservation. Ethical standards and privacy regulations must be followed in the collection and use of biodiversity data, which includes highly personal information about species and habitats. Even though AI has the potential to automate many tasks, its primary function is to supplement and improve upon existing human expertise. Responsible and ethical conservation practises require a balance between AI automation and human involvement.
6. Conserving biodiversity requires an understanding of complex and ever-changing ecosystems. When it comes to species interactions, ecological processes, and environmental changes, AI models may have trouble capturing the complexities and interdependencies within ecosystems. To properly account for these complexities and to develop precise predictions and management strategies, it is essential to incorporate ecological knowledge and expertise into AI models.
7. The available data inputs, on which AI models typically rely, may not always provide enough context for precise species identification. The distribution and behaviour of species are heavily influenced by environmental factors such as habitat type, climate, and spatial proximity, making context an important consideration in biodiversity conservation. Improving the accuracy and ecological relevance of AI models requires better integration of contextual information.

Interdisciplinary partnerships between AI researchers, biodiversity scientists, and conservation practitioners are essential for overcoming these obstacles. Working together in this way increases the likelihood of creating AI models that are optimal for biodiversity preservation. In order to instil trust and confidence in AI-based systems, they must be continuously monitored and validated, and their performance must be reported openly. Artificial intelligence (AI) has the potential to greatly improve biodiversity conservation efforts, support decision-making processes, and guide sustainable management practises if its limitations are recognised and actively addressed.

Conclusion:-

The use of AI for species identification has had a profound impact on the advancement of biodiversity studies and conservation efforts. Through the use of machine learning algorithms and cutting-edge data analysis techniques, AI has proven its ability to accurately classify and identify species across a wide range of domains, including avian, aquatic, plant, and mammalian life forms. Researchers have been able to automate the species identification process using AI-based approaches, greatly improving efficiency and scalability while simultaneously reducing the amount of time and effort required.

The analysis of vocalisations is a particularly prominent application of AI for species identification. Researchers have developed automated systems that can distinguish between species based on their vocal signatures by training algorithms on large datasets of bird and amphibian calls. Thanks to advancements in technology, we now have a better understanding of the distribution, abundance, and behaviour of avian and amphibian populations, which is invaluable. Artificial intelligence algorithms have also been used to analyse recordings made while divers are underwater in order to identify and track different species of fish, providing important insight into marine ecosystems and the management of fisheries.

Improvements in AI have also had a substantial impact on visual data analysis. Amazing results have been achieved in species recognition and classification by machine learning algorithms trained on huge image datasets. Artificial intelligence models are able to correctly identify plants, insects, birds, and mammals by analysing key visual features, such as colour patterns, body shape, and other morphological characteristics. This technology has the potential to dramatically improve the effectiveness of field surveys and monitoring programmes by facilitating the rapid and accurate identification of species in a wide variety of environments.

Artificial intelligence has also been helpful in the identification of species through the use of genetic data. Machine learning algorithms can analyse DNA sequences to determine genetic variation within populations or to distinguish between closely related species. This method has been especially helpful in deciphering the evolutionary connections between cryptic species complexes. Genetic identification based on artificial intelligence has many potential uses, including the detection of wildlife trafficking as well as population management and conservation.

Artificial intelligence (AI) combined with remote sensing technologies (RSTs) like satellite imagery and LiDAR data has greatly increased SID capabilities. Artificial intelligence algorithms can classify land cover and map habitat distributions by integrating spectral, textural, and structural data. This allows for the evaluation of habitats for various species, the pinpointing of crucial conservation areas, and the tracking of shifts in land use. In addition to improving the precision of species distribution models and population estimates, artificial intelligence allows for the fusion of multiple data sources.

The improvements in scientific research made possible by AI-driven species identification have also encouraged citizen science projects. Individuals can aid international efforts to identify species by participating in data collection and analysis through AI-based platforms. Communities are given the tools they need to aid in biodiversity monitoring and conservation through this citizen science approach, which yields useful information for future conservation efforts.

Finally, the use of AI in identifying species has completely altered the landscape of biodiversity research and conservation. Algorithms developed by artificial intelligence have proven successful at identifying and classifying species using a wide range of data types, from audio and video recordings to genetic data and satellite imagery. This technology has the potential to greatly improve our knowledge of ecosystems, enhance conservation strategies, and equip local communities to play an active role in protecting biodiversity. There is great hope that as AI develops further, it will help us better preserve Earth's rich biodiversity for future generations.

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