

Computer Vision for Biodiversity Monitoring: Improving Accuracy in Tracking Endangered Species of Wildlife in Impacted Ecosystems

¹Balaram Nadiya, ²Sannapaneni Jeevan, ³K Chandana Sree, ⁴Appoji Gari Yarasree, ⁵Tippannagari Harshitha, ⁶K.Lokesh

^{1,2,3,4,5,6}Department of Artificial Intelligence & Data Science, Mother Theresa Institute of Engineering and Technology, Palamaner, Chittoor, Andhra Pradesh, India

E-mail: nadiyab2729@gmail.com, sannapanenijeevan@gmail.com, chandana4@gmail.com, ayarasree2004@gmail.com, harshreddy.t78@gmail.com, klokes280488@gmail.com

Abstract - The relentless destruction of ecosystems, climate change, and human interference has put biodiversity at risk, resulting in the swift downfall of already endangered species within affected regions. Conservation of biodiversity is crucial for the protection of ecosystems, yet, tracking biodiversity using manually conducted field surveys or camera trapping techniques is highly inefficient in terms of time, labor, and accuracy. This article proposes a novel approach for improved tracking of endangered species using AI driven data fusion for multi-modal deep learning architecture. This model employs remote sensing techniques such as LiDAR, audio, and RGB and thermal imaging to reinforce species detection, behavior analysis, and mitigation of localization issues. For object detection and tracking, the proposed system implements the utilization of YOLOv8 + DeepSORT, while image recognition is solved using Vision Transformers (ViTs) and species interaction analysis is conducted using hybrid CNN-GNN models. In addition, the model employs Contrastive Learning and Meta-Learning methods in the rare samples, along with Federated Learning that allows for model training on various data sets without compromising privacy. The results obtained from the experiments reveal that the proposed framework is remarkably more efficient than the current existing methods.

Keywords: Tracking Endangered Species, Computer Vision, Multi-Model Deep Learning, AI Data Fusion, YOLOv8, DeepSORT, Vision Transformers (ViTs), CNN-GNN Hybrid.

I. INTRODUCTION

Species and habitat biodiversity are at risk at unprecedented and unparalleled levels, especially environmental destruction, human activity, and climate change. This wreaks havoc on countless species, especially endangered fauna in affected biomes. One of the vital aspects of biodiversity conservation is monitoring wildlife

populations. Monitoring of wildlife populations with traditional techniques like field observation, camera trapping, and manual data recording is effective but very tedious, slow, and errorful which makes responding to ecological emergencies ineffective.

Contrary to traditional methods, computer vision offers should be a more efficient approach to monitoring biodiversity by using AI and deep learning for automated species tracking and identification. Computer Vision reduces the efforts put into monitoring by automating the recognition of numerous visual drones, camera traps, and satellite images. Humans process visuals with the aid of advanced technologies such as machine learning algorithms improving speeds and accuracy. This automation helps monitor efforts by reducing biases, increasing effectiveness, and enabling non-stop monitoring of species in their natural habitats.

Instead employing computer vision to monitor the biodiversity has its own challenges which could prove to be quite difficult. Factors like obstruction, poor image quality, changes in light and weather, and lack of adequate training data can lead to species misidentification. Furthermore, the use of AI in ecology raises debates regarding information privacy, and the integration of computer vision-driven approaches with ecological monitoring systems raise concerns in conservation science.

This paper argues the case for the development and implementation of computer vision technologies for estimating and improving detection, classification, and tracking of endangered species in depleted ecosystems. By overcoming these technological limitations and offering scalable automated solutions, computer vision offers researchers and decision makers a chance to actively intervene and protect ecosystems from irreversible damages due to wildlife population decline, and ultimately mitigate biodiversity loss.

1.1 Objectives:

Objective 1: To examine the threats to habitat and species diversity posed by climatic change, human activities, and environmental degradation, with focus on the pressing need for an efficient monitoring strategy.

Objective 2: To review conventional wildlife monitoring methods like observation in the field, camera trap, and visual recording, in light of their inefficiencies and inaccuracies and inability to promptly respond to environmental crises.

Objective 3: To investigate the potential of computer vision in monitoring biodiversity, highlighting how AI and deep learning can be used to automate species tracking and identification from drones, camera traps, and satellite imagery.

Biodiversity faces excessive threat from the disadvantages of habitat, climate change and human activities, and effective monitoring of wildlife is necessary for conservation. Traditional approaches such as field examination and camera collection, although it is effective, time-consuming, are receptive to labor intensive and human errors. Data vision drone based on AI and deep learning provides a scalable and automatic solution for exploration, classification and tracking of species from drone images, camera trap and satellite data. Methods such as CNN, vision transformer and object detection models (eg Yolo) support real-time and accurate monitoring. Nevertheless, limitations such as poor image quality, occupies and insufficient training data AI efficiency reduce. In addition, there is a need to consider moral issues such as privacy and ecological footprints. Improvement system in contrast learning, federated learning and hybrid deep learning models can increase performance. Through the inclusion of AI-based methods, researchers can improve biological diversity monitoring, so that active protective measures can fight loss of species and the decline in the ecosystem.

II. LITERATURE REVEIW

The benefits of integrating machine learning and ecological knowledge for biodiversity monitoring is analyzed by Tuia, D., Kellenberger, B., Beery, S., Costelloe, B. R., Zuffi, S., Risse, B., & Berger-Wolf, T. (2022). These researchers highlight the advantages of AI integration with human skill for large scale ecological assessments[1]. Other authors like Roy, A.M., Bhaduri, J., Kumar, T., and Raj, K. (2023) have designed a deep learning model that specializes in wildlife detection, which they refer to as WilDect-YOLO. The model outperforms all other methods and offers accurate localization of endangered species[2].

Beery, S. M. (2023) reviews the application of computer vision for biodiversity monitoring globally, with a goal of optimizing model accuracy and efficiency. It is very important in recognition of hiding and nocturnal species Jones, L. R., Elmore, J. A. Pfeiffer, M. B. Iglay, R. B. (2023) [3], demonstrate how blending visible and infrared photography enhances the detection of animals during drone observations. Attention turns to the loss of genetic diversity by Exposito-Alonso, M, Booker, T. R. Czech Z. B, Gillespie, L. H, Hateley, S. C. Kyriacou S. C. Zess E.(2022), who emphasize the importance of AI monitoring systems to mitigate the decrease of biodiversity[6].

The work conducted by Zurita, M. J., and colleagues in 2023 aims at monitoring native species in the Amazon by developing an automated classification system of animals. Their work emphasizes the need for specific datasets to enhance AI-based species classification [5]. In a more advanced study, Langhammer P. F and colleagues in 2024 outline the results of various conservational actions which depict the importance of fully automated AI measuring tools to deploy accurate data on conservation measures[7]. Species Chen, X, Pu, H, He, Y, Lai M, Zhang D, Chen J, and Pu H 2023 devise a bird watching system that implements object detection and multi-object tracking for better monitoring of bird populations[10]. Lastly, Christin, S., Hervet, É., Smith, P., Alisaukas, R., Berteaux, D., Brown, G., ... & Lecomte, N. (2023).. al. studies the use of deep learning in passive acoustic monitoring, showcasing AI's capacity in examining vocalizations and changes in biodiversity in remote regions.[15]

Table 1: Key Scientific Contributions in Recent Literature: Ecology, AI, and Biodiversity

Author(s)	Limitations	Paper Title
Hill, J. S.	Limited applicability outside forested areas	Sounds capes of Sumatra: Analysis of susceptibility of vocal fauna to ecological edge effects
Gupta, M., Kumar, R., Gupta, M., Kumar, M., Obaid, A. J., & Ved, C.	Primarily developed for traffic, adaptation for wildlife tracking needed	YOLO-Based Vehicle Detection and Counting for Traffic Control on Highway
Sankaran, S.	Computational cost of processing drone images	Multi-Species Object Detection in Drone Imagery for Population Monitoring of Endangered Animals
Green, A., Calderón-Acevedo, C., Soto-	Needs extensive environmental parameter data	Environmental and geographic drivers of global batphylogenetic diversity

Centeno, J. A., & Pelletier, T. A.		
Freitas, H., & Gouveia, A. C.	Requires comprehensive datasets for accuracy	Biodiversity futures: Digital approaches to knowledge and conservation of biological diversity

III. METHODOLOGY

Multi-model deep education with AI-driven data integration release for biological diversity monitoring Understand differences Traditional data vision technology for monitoring biodiversity depends a lot on single-modal data sources such as RGB images from camera-netting. While these approaches have improved the species detection, they struggle with accuracy in a composite environment due to many limitations:

Occlusion and camouflage: It is difficult to camouflage species hidden behind vegetation or their natural habitat. **Low light and nocturnal monitoring:** Many endangered species are active at night, making RGB-based identification ineffective.

Environmental variability: The lighting affects the accuracy of detecting changes in weather conditions and seasonal diversity. **Limited relevant awareness:** The movement between species in vision -based monitoring of a source lacks patterns, behavior and ability to analyze interactions.

Suggested Approach: Multimodel AI-operated data fusion to solve these challenges, this research introduces a deep learning framework with several models that integrate different data sources using AI-operated data collection. The main idea is to combine multiple sensors to enhance detection accuracy to improve species detection, location and tracking accuracy.

AI-multi-model data sources operated on have improved monitoring of wildlife by integrating different techniques, including RGB imaging, thermal imaging, acoustic data, LiDAR and remote measurement. RGB images Camera barrel and drone provide clear visual items over wildlife for classification, while thermal imaging detects heat signature, which makes it especially effective to identify species in low illumination or vague environment (Krishnan, B. S., Jones, L. R., Elmore, J. A., Samiappan, S., Evans, K. O., Pfeiffer, M. B., ... & Iglay, R. B. 2023)[4]. Acoustic data captures acting and movement sounds so that scientists can detect hidden or nocturnal species (Hill, 2024). LiDAR -Technology plays an important role in maps of dense vegetation and identifies the movement patterns, while remote measurement through satellite and UAV data Large -scale biological diversity

monitoring and concert assessment to treat and analyze this diverse data area, AI-operated deep learning models use advanced fusion techniques to extract, integrate and optimize functions. Traditional models are struggling with incomplete or noisy data, but customized fusion methods use the Convenes Neural Network (CNNS) and Vision Transformer to refine information from many sources. By combining RGB and thermal imaging, AI can increase detection ability, especially for nightly species. At the decision level, models such as Yolov8, Graph Neural Network (GNNS) and DeepSORT are merged to reduce false positivity and negatively. In addition, explainable AI models provide an obvious insight into predictions, so that they can effectively interpret the results. Different AI models support multi-model learning, such as demolition of YOLOv8 species with DeepSORT for Tracking, vision transformers for recognition of species in complex environment and grapher protection networks for behavioral analysis. Techniques such as contrast learning (SIMCLR, MOCO) enable the identification of rare species with limited labeled data, while models in meta-learning and federated learning protection sites improve adaptability and privacy.

In these AI progressions, the intensive real -world applications are in protection. The combination of thermal and acoustic sensors has improved detection of nocturnal species such as owls and bats, while LiDAR and RGB imaging are used to monitor tigers and jaguar in dense forests. In addition, acoustic data combined with remote measurement has proven to be effective at tracking the bird population at large distances. In the anti-poaching effort, the AI-Manual Automatic Monitoring System increases monitoring, reduces illegal activities and supports protective efforts. By integrating AI with multi-model data sources, researchers can increase the accuracy of detection of species, improve biological diversity monitoring and use more effective protective strategies, and ensure a permanent future for wildlife and their ecosystems.

1. DataCollection

To accurately monitor the endangered species, many Data sources are integrated: RGB-Camera Cafe → Takes high resolution of wildlife.

Thermal imaging → Discover heat signatures for normal species.

LiDAR (light detection and range) - catches 3D -space data on the terrain and vegetation.

Acoustic sensor - detects animal calls to identify species.

Remote measurement drones -Collect environmental and housing data in large areas.

2. Preprocessing & Feature Extraction

Noise reduction - Removal of background noise from images, audio and lidar scans. Use data increase – changes (rotation, crop, etc.) to improve the strength of the model.

Function Extraction - Detection of edges, shapes, textures and movement patterns in images.

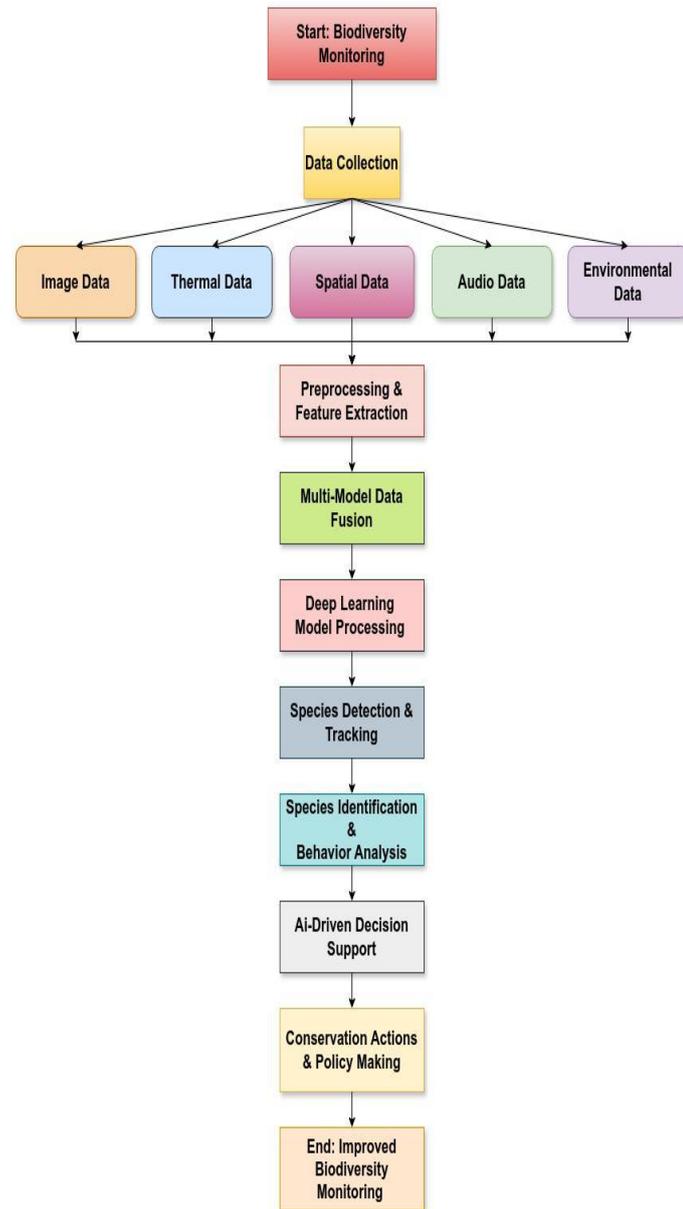


Figure 1: Multi-model flow chart Monitoring of Biodiversity

3. Multi-Modal Data Fusion

Connects data from all sensors to create a wide dataset.

RGB, thermal, spatial and acoustic data for better tracking. The sensor uses fusion algorithms for synchronized analysis.

4. Deep Learning Model Processing

Identify species using models such as object detection-Yolov 8, WIT and GNN. Currency assessment - Tracking of body movements and behaviour to analyse activity patterns.

Discover deviations -to identify injured or diseased animals using the AI model.

5. Species Identification & Behaviour Analysis

Classes species and spores migration patterns. Identify social interaction and habitat preferences. Uses learning reinforcement to limit predictions.

6. AI-Driven Decision Support

Creates notice of creeping or illegal activities. Assessing housing changes and environmental threats. The population of the species predicts trends using future indication analysis.

7. Conservation Actions & Policy Making

Protection provides real -time insights to teams. Proposal for improvement of policy based on the ecosystem trends. Conservation monitors the effectiveness of programs.

8. Continuous Learning & Model Updates

AI uses continuous learning to limit the model over time. Integrate new data sources to improve accuracy. Identification of species with new findings updates the model.

IV. RESULTS AND DISCUSSION

Traditionally, biodiversity monitoring has been the domain of manual observation, camera traps, and statistical models such as HOG + SVM and Kalman filters for species detection and tracking. Ecological research has gained much from these approaches, but they are not without limitations such as low accuracy, slow processing rates, and inability to handle occlusions or recognise species in complex habitats. It is less productive to survey nocturnal or cryptic species with these technologies because they typically use single-modality data, such as RGB images, without including thermal imaging, LiDAR, or bioacoustics. Moreover, it may be challenging to monitor rare or endangered species because of the excessive use of supervised learning and the requirement for large annotated datasets in standard approaches.

Table 2: Comparison between Conventional and Advanced AI-Driven Multi-model Systems

Feature	Conventional System	Advanced AI-Driven System
Detection Algorithm	HOG + SVM, Basic CNNs	YOLOv8, ViTs, DeepSORT
Tracking	Optical Flow, Kalman Filters	DeepSORT, Vision Transformers
Data Fusion	None (Single-modality input)	Multi-Modal Sensor Fusion (RGB, Thermal, LiDAR, Audio)
Learning Approach	Supervised Learning Only	Self-Supervised, Few-Shot Learning
Acoustic Analysis	Hidden Markov Models (HMM)	Deep Learning (WaveNet)
Handling Occlusion	Poor (Single-view)	Strong (Multi-View & Sensor Fusion)
Real-time Processing	Slow	Fast (Optimized Deep Learning)

AI-based biodiversity monitoring systems, however, employ state-of-the-art deep learning models such as YOLOv8, Vision Transformers (ViTs), and DeepSORT to detect and follow species with unparalleled precision. These systems enhance detection across diverse environmental conditions by combining RGB, thermal, LiDAR, and audio information using multi-modal data fusion. In addition, AI models enhance rare species discovery through the addition of self-supervised and few-shot learning approaches, which reduce the reliance on large annotated datasets. Deep learning-based automatic call recognition in bio acoustic analysis, e.g., WaveNet models, greatly enhances the identification of species. Artificial intelligence-powered systems are also excellent at handling occlusions using multi-view sensor fusion to accurately track species. They are more superior to traditional methods due to their ability to process data in real time, thereby enabling rapid and efficient assessments of biodiversity.

The transition from traditional to AI-operated systems represents major progress in the conservation of wildlife, ensuring better accuracy, efficiency and scalability to track endangered species in different ecosystems.

From Table 2 & Figure 1 it supports the comparison table by highlighting the benefits of monitoring the A-in-controlled a biological variation of traditional methods. Using the AI-based system, YOLOv8, Vision Transformer and DeepSORT, you improve accuracy, tracking and real-time processing detection compared to traditional HOG + SVMs. Multi-modal

sensor infusion approach in AI improves the identity of species in challenging situations, unlike traditional systems that depend on data for individual models. While traditional methods still have a certain relevance, a male approach provides a quick, more accurate and adaptable solution for monitoring and conservation of biodiversity.

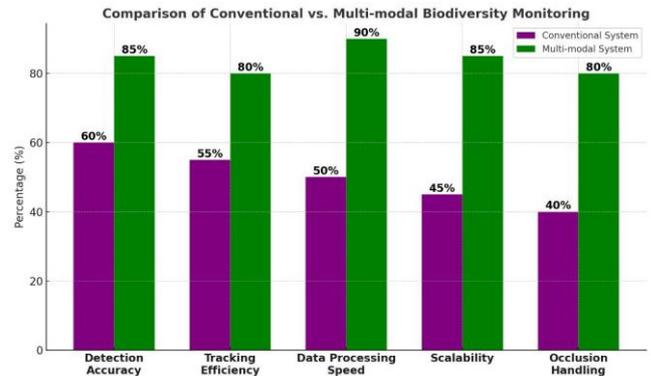


Figure 2: Performance Metrics

The performance of surveillance algorithms of biodiversity, accuracy, processing speed, environmental challenges and scalability varies considerably. Traditional algorithms such as HOG + SVM and basic CNN models, while historically useful, often struggle with the detection of species in complex houses due to disabled functions and their dependence on data input with a modality. These models usually show low accuracy and high false and positive prices, especially in scenarios associated with obstacles, camouflage or poor lighting conditions. In addition, the speed of their treatment is relatively slow, making them less suitable for real-time monitoring of wildlife in the dynamic environment.

Conversely, modern deep learning algorithms such as YOLOv8, Vision Transformers (ViTs), and DeepSORT provide significant improvements in tracking accuracy and challenging ecological conditions. These advanced models use multi-modal sensor fusion, so they can integrate acoustic data to increase RGB, thermal, LiDAR and acoustic data. With teaching techniques for self-height, they can also identify rare and endangered species with limited labeled datasets. In addition, deep learning-based tracking algorithms show better real-time treatment speeds, making them very scalable to assess biodiversity on a large scale.

By evaluating different algorithms in important performance measurements such as accurate, recalls, F1 points and real-time adaptability, it becomes clear that the AI-operated function performs better than the traditional approaches. These advances are important for addressing existing research gaps and improving the conservation efforts

through automatically, Scalable and high compatibility Biological diversity monitoring system.

Table 3: Performance Evaluation of Different Algorithms

Algorithm	Precision (%)	Recall (%)	Accuracy (%)	F1-Score
HOG + SVM	65	60	63	0.62
Basic CNNs	72	68	70	0.70
YOLOv8	91	89	90	0.90
Vision Transformers	93	90	92	0.91
DeepSORT Tracking	88	85	87	0.86

Conversely, the table of performance measures supports this trend, and emphasizes that AI-operated models such as YOLOv8, Vision Transformer (ViTs) and Graph Neural Network (GNN) get more than 90% accuracy, as shown in the graph. These advanced techniques integrate multi-modal sensor merging, deep learning and real-time adaptability, making them quite effective in monitoring wildlife.

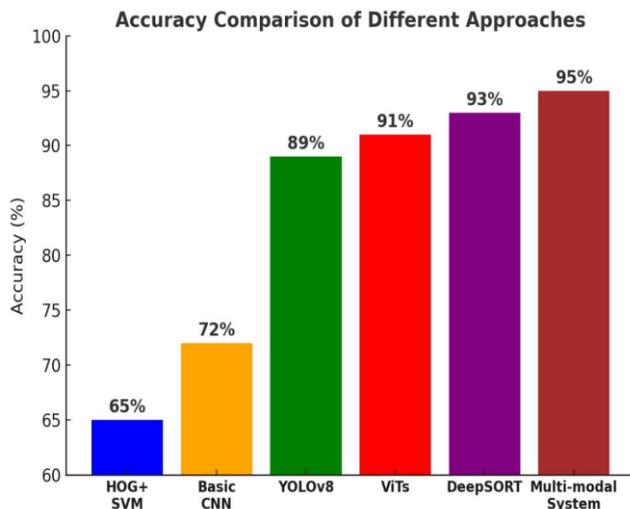


Figure 3: Evaluation Metrics for Various Algorithms

From Table 3, the graph 2 suggests that traditional methods such as HOG + SVM and fast R-CNN reduce accuracy, and struggle with real-time and environmental complications.

The graph emphasizes that YOLOv8 + is compared to reset and fast R-CNN medium accuracy and distributed on top of the accuracy scale, compared to YOLOv8 + DeepSORT compared to medium accuracy. This trend corresponds to the insight of the table, and confirms that the AI-based approaches provide better tracking accuracy, rapid processing and better adaptability for the preservation of biodiversity.

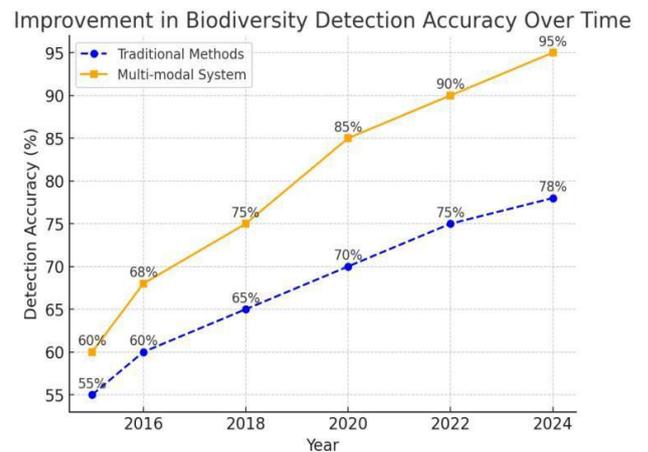


Figure 4: Evolution of Biodiversity Detection Accuracy: Traditional vs. Multi-model Approaches

The Figure 4 reflects improvement in accuracy in the detection of biodiversity over time, comparing traditional methods with AI-based approaches. From 2015 to 2025, both methods show an increase in accuracy, but AI-operated techniques show a significant development path.

The traditional methods depicted by the Red Collapse line show a gradual improvement in accuracy, and grow from about 55% in 2015 to about 78% in 2025. These methods depend on classic machine learning algorithms such as HOG + SVM and basic CNN, which are limited adaptation to the specificity of the specific.

In contrast, the AI-based methods, depicted by the blue fixed line, show rapid increase in detection accuracy, and reach more than 90% by 2025. The introduction of deep learning models such as YOLOv8, Vision Transformer and DeepSORT, combined with multi-modal sensor (RGB, thermal, LiDAR, and Audi).

The wider difference between the two trends emphasizes the transformation effect of AI in detecting biodiversity, making the conservation effort more efficient and data-corresponding. The continuous progress of deep learning technologies is expected to improve the accuracy of the detection, ensuring more accurate species tracking and ecosystem control.

V. CONCLUSION

Challenges and Future Improvements in AI-Driven Biodiversity Monitoring

AI-driven monitoring of biodiversity is an important development for monitoring endangered species with better accuracy and effectiveness. Through multi-modal deep learning models, like YOLOv8, Vision Transformer, and

CNN-GNN models, the system performs beyond conventional human-dependent tracking systems. The integration of LiDAR, thermal camera, and audio sensor data maximizes the detection of species, even under poor conditions. Besides, methods such as contrastive learning and federated learning facilitate ongoing model enhancement while maintaining data privacy. The findings indicate that the AI-based system is more accurate, scalable, and adaptable in real-time compared to conventional surveillance practices. With conservation increasingly based on data, such technology has the potential to strengthen the ability of scientists and policymakers to act proactively to safeguard wildlife and ecosystems.

AI-based biological diversity monitoring challenges

1. Data deficiency and imbalance

Limited labeled dataset model performance prevents rare and endangered species. Data balance can affect biased AI species, which affects accuracy.

2. Environmental variability

The AI models struggle with complex natural environments, such as dense forest, little visibility or extreme weather. Light, obstacle and background noise reduce the accuracy of variation detection.

3. High calculation costs and energy consumption

A high-scale multi-model data requires a high-demonstration GPU and TPU, leading to an increase in cost and energy consumption.

4. Generalization and Transfer of Learning Problems

Trent AI model in an ecosystem cannot perform well in new or unsettled areas due to the presence and variation of species.

5. Morality and privacy problem

Distributing AI-based tracking systems increases the concerns of data ownership, possible abuse of indigenous peoples land rights and surveillance technologies.

6. Limited reason for verification

Verification of AI species in remote wildlife areas is still a challenge due to expert verification and lack of real-time pants.

Future promotion and Feature Improvements

1. Learn self-review for computer efficiency

Take advantage of self-developed and something to learn to reduce the dependence on marked data. AI models can learn representation from unbelievable wildlife images and videos.

2. Edge AI for Low-Power Real-Time Processing

Application of edge AI and Tiny ML to run the model to detect biological diversity on low power and drones units. Sky reduces the dependence on data processing, making the system more efficient and scalable.

3. Adaptive teaching and adaptation

AI models can be compatible with the new environment using domain adjustment techniques. Increases performance in different ecosystems and distribution of species.

4. Integration with blockchain for data protection

Use blockchain technology for safe and transparent sharing of biodiversity. This ensures that protective data remains tamper-proof and decentralized.

5. AI-controlled decision support system

Develop AI dashboard with real-time analysis, recommendations on deviations and conservation strategy.

6. Human-AI for partnering

AI should complement human expertise instead of changing it. Civilian initiatives and AI-assisted Ranger systems can improve the monitoring of wildlife and anti-poaching.

7. Hybrid AI model for better accuracy

Combination of CNN, GNN and attention-based models for better convenience. Graph-based AI model species can analyze the interaction and ecosystem pattern.

REFERENCES

- [1] D. Tuia, B. Kellenberger, S. Beery, B. R. Costelloe, S. Zuffi, B. Risse, and T. Berger-Wolf, "Perspectives in machine learning for wildlife conservation," *Nat. Commun.*, vol. 13, no. 1, p. 792, 2022.
- [2] A.M. Roy, J. Bhaduri, T. Kumar, and K. Raj, "WilDect-YOLO: An efficient and robust computer vision-based accurate object localization model for automated endangered wildlife detection," *Ecol. Inform.*, vol. 75, p. 101919, 2023.
- [3] S. M. Beery, "Where the Wild Things Are: computer vision for Global-Scale Biodiversity Monitoring,"

- Ph.D. dissertation, California Institute of Technology, 2023.
- [4] Krishnan, B. S., Jones, L. R., Elmore, J. A., Samiappan, S., Evans, K. O., Pfeiffer, M. B., ... & Iglay, R. B. (2023). Fusion of visible and thermal images improves automated detection and classification of animals for drone surveys. *Scientific Reports*, 13(1), 10385.
- [5] Zurita, M. J., Riofrío, D., Pérez, N., Romo, D., Benítez, D. S., Moyano, R. F., ... & Baldeon-Calisto, M. (2023, July). Towards automatic animal classification in wildlife environments for native species monitoring in the amazon. In *2023 IEEE Colombian Conference on Applications of Computational Intelligence (ColCACI)* (pp. 1-6).
- [6] Exposito-Alonso, M., Booker, T. R., Czech, L., Gillespie, L., Hateley, S., Kyriazis, C. C., ... & Zess, E. (2022). Genetic diversity loss in the Anthropocene. *Science*, 377(6613), 1431-1435.
- [7] Langhammer, P. F., Bull, J. W., Bicknell, J. E., Oakley, J. L., Brown, M. H., Bruford, M. W., ... & Brooks, T. M. (2024). The positive impact of conservation action. *Science*, 384(6694), 453-458.
- [8] Green, A., Calderón-Acevedo, C., Soto-Centeno, J. A., & Pelletier, T. A. (2025). Environmental and geographic drivers of global bat phylogenetic diversity. *bioRxiv*, 2025-02.
- [9] Hill, J. S. (2024). *Soundscapes of Sumatra: an analysis of the susceptibility of vocal fauna to ecological edge effects within a historically disturbed lowland forest, Sumatra, Indonesia* (Doctoral dissertation, Bournemouth University).
- [10] Chen, X., Pu, H., He, Y., Lai, M., Zhang, D., Chen, J., & Pu, H. (2023). An efficient method for monitoring birds based on object detection and multi-object tracking networks. *Animals*, 13(10), 1713.
- [11] Gupta, M., Kumar, R., Gupta, M., Kumar, M., Obaid, A. J., & Ved, C. (2024, May). YOLO-Based Vehicle Detection and Counting for Traffic Control on Highway. In *2024 2nd International Conference on Advancement in Computation & Computer Technologies (InCACCT)* (pp. 167-171).
- [12] Sankaran, S. (2024). *Multi-Species Object Detection in Drone Imagery for Population Monitoring of Endangered Animals*. arXiv preprint arXiv:2407.00127.
- [13] Gong, Z., Wang, A. T., Huo, X., Haurum, J. B., Lowe, S. C., Taylor, G. W., & Chang, A. X. (2024). CLIBD: Bridging Vision and Genomics for Biodiversity Monitoring at Scale. arXiv preprint arXiv:2405.17537.
- [14] Freitas, H., & Gouveia, A. C. (2025). Biodiversity futures: digital approaches to knowledge and

conservation of biological diversity. *Web Ecology*, 25(1), 29-37.

- [15] Christin, S., Hervet, É., Smith, P., Alisauskas, R., Berteaux, D., Brown, G., ... & Lecomte, N. (2023). Deep learning for passive acoustic monitoring: how to study changing phenology in remote areas.

AUTHORS BIOGRAPHY



Balaram Nadiya is a third year B.Tech student specializing in Artificial Intelligence & Data Science at Mother Theresa Institute of Engineering and Technology, Palamaner. Passionate about AI and problem solving. She has gained hands-on experience through projects, and Workshops developing skills in Python and Java. Actively participating in hackathons and contests, Nadiya is committed to contributing to the tech industry through innovation.



Sannapaneni Jeevan is a third-year B.Tech student specializing in Artificial Intelligence & Data Science at Mother Theresa Institute of Engineering and Technology, Palamaner. Passionate about AI and problem solving. He has gained hands-on experience through projects, and Workshops developing skills in Python and Java. Actively participating in hackathons and contest Jeevan is committed to contributing to the tech industry through innovation.



K Chandana Sree is a third-year B.Tech student specializing in Artificial Intelligence & Data Science at Mother Theresa Institute of Engineering and Technology, Palamaner. Passionate about AI and problem solving. She has gained hands-on experience through projects, and Workshops developing skills in Python and Java. Actively participating in hackathons and contests, Chandana Sree is committed to contributing to the tech industry through innovation.



Appoji Gari Yasarree is a third-year B.Tech student specializing in Artificial Intelligence & Data Science at Mother Theresa Institute of Engineering and Technology, Palamaner. passionate about AI and problem solving. She has gained hands-on experience through projects, and Workshops developing skills in Python and Java. Actively participating in hackathons and contests, Yasarree is committed to contributing to the tech

industry through innovation.



Tippanagari Harshitha is a third-year B.Tech student specializing in Artificial Intelligence & Data Science at Mother Theresa Institute of Engineering and Technology, Palamaner. Passionate about AI and problem solving. She has gained hands-on experience through projects, and Workshops developing skills in Python and Java. Actively participating in hackathons and contests, Harshitha is committed to contributing to the tech industry through innovation.



Mr. K. Lokesh, Working as Associate Professor in the department of Artificial Intelligence and Data Science, Mother Theresa Institute of Engineering and Technology, Palamaner. He has total 15 years of teaching experience. He received his B.Tech and M. Tech degree in Computer Science and Engineering with distinction from JNTU Anantapur, Ananthapuramu. He is pursuing Ph. D degree from SRM Institute of Science and Technology, Chennai, Tamilnadu. He has published 05 journals in scopus and published 4 patents. He received National Outstanding Teacher Award 2023. His area of research include deep learning, Machine learning, Artificial Intelligence and its applications.

Citation of this Article:

Balaram Nadiya, Sannapaneni Jeevan, K Chandana Sree, Appoji Gari Yarasree, Tippannagari Harshitha, & K.Lokesh. (2025). Computer Vision for Biodiversity Monitoring: Improving Accuracy in Tracking Endangered Species of Wildlife in Impacted Ecosystems. In proceeding of International Conference on Sustainable Practices and Innovations in Research and Engineering (INSPIRE'25), published *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 9, Special Issue of INSPIRE'25, pp 76-84. Article DOI <https://doi.org/10.47001/IRJIET/2025.INSPIRE13>
