AI-Based Wildlife Conservation And Monitoring

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***Abstract*—AI-based wildlife Conservation Monitoring introduces a pioneering approach to wildlife preservation named Wildlife Conservation Monitoring Enhanced by Technology. The study endeavors to redefine the methodologies utilized in monitoring, comprehending, and conserving animal species and their habitats, while highlighting the imperative requirement to safeguard biodiversity and uphold ecological equilibrium.. By amalgamating advanced technology in remote sensing and innovative algorithms, this research endeavors to overhaul conventional conservation practices. The real-time analysis of wildlife behaviors, population dynamics, and habitat conditions equips conservationists with actionable insights, enabling informed decision-making.By using some effective strategies, this study helps us to ensure the welfare of a multitude of kinds of species. The collaboration of experts in ecology and data science aims to create some interdisciplinary methods. The research gives ethical considerations as first priority. Finally, this study aims to change modern wildlife conservation practices. environmental changes.**

Keywords—Artificial Intelligence, Monitoring, Convolutional Neural Networks

I. Introduction

Conservation of wildlife is a critical and complicated attempt that aims at the Earth's sustainable diversity of shops and creatures while maintaining the balance in the terrain. the utmost of the major changes done by mortal conditioning which affect the drop in the surroundings, pollution, climatic changes, and major operation of coffers, which indicates the critical need for effective and original groups that are essential in achieving an affable and balanced equilibrium.

Methods employed in recent years range from looking after the natural backyard, and executing origin-controlled regimes, to creating less illegal stalking and much greater public education campaigns have been carried out. Scientific research and technological methods, including satellite monitoring, DNA analysis, and AI are all indispensable in creeping in on the ecology feather allowing reasonably informed decisions to be made about preservation or operation.

Artificial intelligence has become a potent weapon to combat wild crime and it is rapidly gaining popularity in many quarters. Accessible, powerful tools that anyone can master with ease will expedite the value of AI education. Alerts such as GPS collars, video traps, and acoustic sensors have enabled people to accomplish jobs that could not previously have been done. Whether a policeman or stat team data collector, in both cases, UE statistics should be presented on radar plots that make sense to people who do not understand "This isn't any fun!", so he sat down to design the way he would want to consume content himself.

To gain insights, the process of dataset processing is very important. Machine learning algorithms that are under the subset of AI plays an important role in identifying patterns from datasets. It also creates a model that predicts wildlife behaviors along with the ecological trends. The capability of prediction of this model enhances the response. This predictive capability enhances the response to emerging challenges. This monitoring that is driven by AI provides us with insights. These insights are useful to protect species. Comprehensive analysis and visual representation is mostly used in order to achieve this.

II. Literature Survey

H. Nguyen et al [5], According to this paper, to inform on wildlife protection and the way in which animals are organized in their natural habitat, reliable monitoring of wild animals is critical. The study proved that a new deep-learning method could be employed to create intelligent automatic wildlife monitoring devices, using South-central Victoria's Wildlife Spotter dataset as a foundation. In various connotations of the term, the word "ripple" appears ten times. When it does something like this though, it actually ripples right across all major search engines. The models have shown robustness and versatility in several experimental settings, with recognition rates above 96% for images containing animals and near 90% for the identification of the three most common animals (bir, rat, bandicoot). [19] To continue improving system performance.

This paper (Aarju, R. Bahuguna, S. Pandey, R. Singh, H. Kaur, and G. Chhabra) [18] discusses how Industry 4.0 technologies, like drones and AI, are transforming wildlife conservation. By improving our ability to accurately monitor endangered species in their habitats, these advancements represent a significant shift from relying solely on human intelligence. While they've successfully helped reduce biodiversity loss, challenges persist, emphasizing the need for ongoing innovation in conservation technology. [20] The evolving computational technology landscape provides a strong foundation with diverse tools to reshape conservation practices and preserve biodiversity. Success depends on individual contributions and sustained commitment. Although this paper focuses on two Sustainable Development Goals (SDGs), integrating AI and drones in wildlife conservation has a broader potential for addressing other SDGs. Recognizing wildlife ecosystems as cultural heritage highlights the collective responsibility for protection. Ongoing technological advancements in conservation are not just justified but essential for safeguarding our natural heritage.

This paper (M. Mangaleswaran and M. Azhagiri,) [17] aims to create an effective animal identification algorithm, addressing various concerns. Scientific investigations focus on animal taxonomy and detection methods. Deep learning, a powerful machine learning technique, has achieved breakthroughs in diverse applications. Convolutional neural networks, a part of deep learning, use multiple processing levels to solve complex problems. The research examines and compares over 25 studies using learning algorithms for animal identification. It highlights challenges and emphasizes the urgent need for AI advancements in this field. By synthesizing insights, the paper underscores the importance of refining algorithms, addressing ethics, and fostering collaboration for successful AI implementation in wildlife conservation. This sets the stage for future research contributing to the goal of preserving biodiversity and ensuring the sustainable coexistence of all species.

This paper (S. B. Islam and D. Valles) [8] concludes the main goal of this project is to create a framework that can transport, store, and analyze the vast amount of camera trap information systematically. Although there is a potential performance decrease for camera trap images in sites not encountered during model training. Challenges include variations in object positions, lighting, and weather conditions. The primary hurdle is handling highly imbalanced data, which necessitates careful re-training to enhance prediction accuracy with new camera data. Future improvements hold the promise of achieving higher performance. This paper underscores the significance of addressing these challenges to establish a robust framework for wildlife conservation through innovative AI-based approaches in camera trap data analysis.

This paper (S. V. Viraktamath, J. R, V. A, A. S. Bhat, and S. Nayak) [10] represents that Image recognition and prediction is a vast and intricate domain, and leveraging deep learning concepts has proven instrumental in achieving efficient outcomes within this realm. The application of deep learning, particularly in image classification, is notably effective. In experiments employing various parameters, optimal performance is observed with an image size of (50x50), 30 epochs, and ReLU activation. [21] The model developed exhibits an impressive accuracy of 92% on training data and 65% on testing data. This experimental outcome underscores the system's superior accuracy compared to preceding methods. Moving forward, the prospect of transitioning to a fully automated wild animal recognition system holds promise, potentially reducing manpower requirements by approximately 70%. This paper not only sheds light on the efficacy of deep learning in image recognition but also hints at the transformative potential of automation in wildlife monitoring and conservation efforts.

This paper (S. Sisodia, S. Dhyani, S. Kathuria, S. Pandey, G. Chhabra, and R. Pandey,) [15] emphasizes the crucial role of AI in analyzing large datasets to improve decision-making for Sustainable Development Goals (SDGs). It highlights the need to support and trust AI, stressing the importance of laws and ethical regulations for transparency and safety. The United Nations actively uses AI for real-time analysis, emissions monitoring, and environmental footprint reduction. As we approach the 2030 SDG deadline, AI becomes a key accelerator. [22] The study explores the current use of AI and Industry 4.0 in wildlife conservation, proposing improvements. It urges scrutiny of potentially harmful tech impacts on SDGs, advocating for responsible AI and industry practices. The study suggests further research on the negative effects of the FishCoin blockchain on climate. In conclusion, it aims to aid researchers in tackling this century's paramount challenge. Looking forward, integrating blockchain, robotics, and IoT with AI holds promise for diverse conservation needs, emphasizing the use of robotics for precision in hazardous tasks. The findings confirm AI's positive role in achieving SDG 15, a significant step toward a sustainable future.

This paper (T.A. de Lorm1, C. Horswill 2,3,4, D. Rabaiotti 2,3, R.M. Ewers1, R. J. Groom2,5, J. Watermeyer5, R. Woodroffe2,3)[14] introduces a novel automated method for preprocessing image datasets in wildlife conservation. By automating the cropping of animals, removing hindering postures, separating flanks, and eliminating background images, this framework significantly expedites the analysis of large datasets. This efficiency enhances monitoring efforts, facilitating rapid responses in conservation action. The study also evaluates various image-matching software packages, with Hotspotter emerging as a top performer, albeit with variations in performance between populations with intra-specific coat pattern differences. The presented pre-processing method, coupled with Hotspotter, holds immediate applicability in research and monitoring endeavors for African wild dogs and other species. The potential for cost-effective, large-scale monitoring using this approach underscores its significance in supporting the implementation of effective conservation measures for endangered species.

In this study (Mohammad Sadegh Norouzzadeha, Anh Nguyen, Margaret Kosmalac, Alexandra Swanson, Meredith S. Palmer, Craig Packer, and Jeff Clune,f,1) [6] we tested advanced computer vision methods, known as DNNs, to extract information from images in the SS dataset, the largest labeled dataset of wild animals. We found that DNNs perform well on the SS dataset, though less so for rare classes. Importantly, our results highlight that using deep-learning technology can save significant time for biology researchers and their volunteers by automating image labeling. Specifically, our system can reduce manual labor by 99.3% (>17,000 hours) while maintaining an accuracy level of 96.6%, equivalent to human volunteers. [24] This automation allows redirected human efforts for other scientific purposes and facilitates knowledge extraction in camera-trap projects with limited human resources. Automated data extraction significantly lowers the cost of gathering valuable information from wild habitats, promising to enhance studies on animal behavior, ecosystem dynamics, and wildlife conservation. In summary, integrating deep-learning technology not only boosts efficiency but also paves the way for more impactful and cost-effective wildlife research and conservation efforts.

This paper (Juliana Vélez, William McShea, Hila Shamon, Paula J. Castiblanco-Camacho, Michael A. Tabak, Carl Chalmers, Paul Fergus, John Fieberg) [13] concludes that the development of AI models for species identification is an active and dynamic field of research, as highlighted in this paper. The platforms under review are continuously evolving, with ongoing model enhancements driven by the integration of new data. Notably, advancements like the updated MegaDetector (MDv5) showcase improved processing speed and expanded capabilities in detecting specific classes and taxa. Beyond model updates, AI platforms are refining features for efficient data storage, management, and seamless integration into data-processing workflows. [25] These enhancements empower users to review and correct classifications, assign species labels, and capture additional pertinent information in images. While the current focus lies predominantly on species identification, the future trajectory anticipates the integration of deep learning to discern individual characteristics and behaviors, such as an animal's sex, age class, or specific activities. This projection underscores the evolving role of AI in wildlife monitoring, poised to make significant strides as more data becomes available for training advanced models.

This paper (Sachini Kuruppu) [16] uses deep learning methods, using AI to identify poachers by detecting their weapons. In our system, we will use a one-stage object detection algorithm, YOLO-V5. Deep learning methods such as Faster R-CNN were previously used in object detection systems. However, those techniques use two-stage detection and because of the many inference steps per image, their performance is low and is found to be not ideal for real-time video surveillance. [28] These techniques have high computational overhead and fail to detect guns due to low quality and visibility issues in surveillance videos. In comparison, one-stage detectors like YOLO-V5, generally have a faster detection speed and greater structural simplicity and efficiency. However, large datasets with annotated images are needed for model training in any case, as we are using a deep learning method.

This paper [23] discusses the use of deep neural networks (DNNs) for identifying animals in camera trap images. The authors trained multiple DNN models using different architectures and ensemble methods to improve classification accuracy. They also addressed the challenges of identifying species and additional attributes in the images. The results showed high accuracy levels for detecting animals and identifying species, with the ensemble of models performing the best. The paper also highlights the potential of using DNN models to automate information extraction and save human labor.

The paper (Christensen, David R) [4] describes a multi-laboratory exercise for undergraduate courses in conservation biology, wildlife biology, or animal behavior that uses remote-camera technology. This exercise involves students deploying remote cameras in a biological corridor to estimate wildlife diversity, diel behavior, and relative abundance. [29] Tools used include Google Earth, remote cameras, and MassGIS for delineating boundaries and identifying habitat characteristics. Remote cameras are set up perpendicular across the Little River floodplain, approximately 50-100 apart and adjacent to animal trails. The time of day for each mammal observed is recorded, and the trapping effort for each camera is calculated. A relative abundance index is used to compare data with other courses and across temporal-spatial scales.

This paper (Shreya Kakhandiki) [11] has the main goal of building a low-cost device that can detect poaching activity in wilderness areas and send real-time alerts to park officials. The device consists of a Raspberry Pi computer with a power bank, camera, and antenna. An image classification algorithm was built using pre-trained AI models to detect the presence of humans, weapons, and animals in a photo. The MegaDetector17 model was used to detect humans, animals, and vehicles in images. [30] The device successfully meets all engineering goals, with a cost of about US$100, over 90% accuracy in recognizing humans, weapons, and animals, and the ability to generate notifications. Face recognition is used to identify whether the human in the photo is a ranger or a potential poacher.

This paper (D. Mahatara1*, S. Rayamajhi2 and G. Khanal3) [7] tells us about the conservation efforts in Chitwan National Park(CNP) which uses a SMART monitoring system which provides regular and rapid communication of information on illegal activities and reports of protected areas. Nepal army and park staff, based on reports from informants, are considered crucial for the decline in poaching incidents. Some methodologies like sweeping and camping operations, Joint patrolling by the Nepal army and park staff, Regular monitoring of illegal activities, and Data collection and analysis are used. All the occurrences of illegal activities, such as poaching are considered which gives the values for patrol effect and patrol frequency.

The paper (Jamali Firmat Banzi) [1] discusses the issue of poaching in Tanzania and processes a sensor-based anti-poaching system that involves using animals as mobile biological sensors(MBS) equipped with visual, infrared cameras, and GPS. The MBS transmits their location data to access points, which continuously receive and classify the data to detect sudden movements or panic in animal groups. It then processes the received image using edge detection, thresholding, and filtering to provide a clear image of what is happening by attaching sensors to animals, the system can detect abnormal behavior and alert game reserve officers. The value lies in addressing issues leading to the preservation of wildlife and the prevention of ecological balance.

The research paper (Sachini Kuruppu) [16] proposes an AI system to protect endangered animal populations and prevent poaching threats by implementing an automated weapon detection system in forest areas with high population density of endangered species. Camera traps, the YOLOv5 algorithm and LoRa technology are integrated into the system.

T. A. S. Achala Perera and J.Collins [2] proposed the way how an automated detection system is implemented in the forest region that has a considerable number of endangered species. The process of combining the YOLOv5 algorithm, camera traps and LoRa technology is involved to find out the poachers with weapons [26]. The main aim of the system is to make sure that the park rangers are safe and required time must be spent on patrols..

This paper (T. Sarma and V.Baruah) [3] introduces a system that has been developed with the purpose of identifying instances of poaching within a forested area. This system utilizes acoustic sensors in order to detect sound intensity levels that surpass a predetermined threshold. The sensor output is transmitted to a computer system using a wireless module. The system uses a high-sensitive sound sensor and an Xbee wireless receiver following the Zigbee protocol for signal transmission. The computer module with the help of MATLAB software determines the received audio frequency by comparing it with its database. Overall, the design approach aims to save wild animals from extinction, reduce human-animal conflict, and provide timely assistance to injured animals.

This research paper (Mateusz Choiński, Mateusz Rogowski, Piotr Tynecki, Dries P. J. Kuijper, Marcin Churski & Jakub W. Bubnicki) [9] focuses on developing an image-based species recognition system for feral rodents. Initially, the detection rates for possums, cats, and weasels were 55%,33%, and 45%respectively. [27] However, after removing the background from the training images, the detection rates increased significantly to 65%, 52%, and 64%. The proposed system aims to replace the need for specialized experts to identify animal species from footprint patterns or fur samples. It may also have the potential to monitor and study animal populations and behavior in the future.

TABLE 1: COMPARISON TABLE

Author	***Year***	***Approach***	***Description***
Jamali.F Banzi	2014	Sensor-based anti-poaching System	Developing a sophisticated technology system for anti-poaching and protecting endangered species.
T. A. S. Achala Perera and J. Collins	2015	Eigenface technique	Commonly used in human face recognition and applied in research papers for species recognition. Creating a set of animal images and normalizing them by subtracting the mean from the animal faces to obtain mean-shifted images.
T. Sarma and V. Baruah	2015	Digital Signal Processing	The system is designed to determine the distance between sensor position, and the sound source, aiding in the capture of poachers and providing medical aid to injured animals.

Author	Year	Approach	Description
Christensen, David R	2016	Camera-Trap Methodology	It allows increased sampling, which can capture and expose trends in wildlife abundance and behavior.
H. Nguyen et al	2017	Deep learning, convolutional neural networks, large-scale image classification, animal recognition and wildlife monitoring.	We created an automated wildlife monitoring system using a dataset from the Wildlife Spotter project, contributed by citizen scientists. Using advanced neural networks, our system filters and identifies animal species in the wild.
Mohammad Sadegh Norouzzadeha, Anh Nguyenb, Margaret Kosmalac, Alexandra Swansond, Meredith S. Palmere,Craig Packere, and Jeff Clunea,f,1	2018	Artificial intelligence and camera-trap images and deep learning neural networks.	The solution utilizes deep neural networks (DNNs) to automatically extract features from raw data, such as images taken from camera traps.
D.Mahatara1*, S. Rayamajhi2 andG. Khanal3	2018	SMART patrolling	The Findings of this study can be used to inform policy decisions and improve the effectiveness of anti-poaching efforts in other rhino conservation areas.
S. B. Islam and D. Valles	2020	CNN, image classification, species recognition, camera traps, and wildlife monitoring.	The solution aims to automate data analysis in computer vision tasks, particularly in detecting and classifying animal species. Using deep learning methods and CNNs, the solution can manage difficult images and extract important features for precise species identification.
Mateusz Choiński, Mateusz Rogowski, Piotr Tynecki, DriesP.J.Kuijper ,Marcin Churski & Jakub. Bubnicki	2021	Computer vision, Deep learning, YOLOv5, Camera trap, TRAPPER , Wildlife	The goal of this solution is to automate the object detection and species-level classification in camera trapping data to improve wildlife monitoring and conservation efforts, addressing the challenge of
			efficiently processing vast 20 amounts of multimedia data to secure mammal populations and minimize conflicts with humans.
S.V.Viraktamath, J. R, V. A, A. S. Bhat and S. Nayak	2022	Animal Detection, object detection, image processing, computer vision, convolutional neural networks.	The suggested approach for animal classification and detection relies on deep convolutional neural networks (CNN). The solution integrates crucial computer vision and image processing techniques, which attain a high accuracy rate, capable of automatically extracting, learning, and classifying features from animal images.
Shreya Kakhandiki	2022	Image classification algorithms	To address wildlife poaching through the development of a low-cost device that can detect and alert officials which is also deployed in many geographical regions, allowing for increased monitoring and protection of wildlife
S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz and D. Terzopoulos	2022	Image segmentation, Computer architecture, Semantics, Deep Learning, Computational modeling, Generative adversarial networks, Logic gates.	Image segmentation, vital in computer vision and processing, has diverse applications including scene understanding, medical analysis, robotics, surveillance, augmented reality, and compression. Various segmentation algorithms exist in the literature.
Juliana Vélez, William McShea, Hila Shamon, Paula J. Castiblanco-Camacho, Michael A. Tabak, Carl Chalmers, Paul Fergus, John Fieberg	2022	Camera Traps, Artificial Intelligence (AI), MegaDetector, MLWIC2: Machine Learning	Offering the application of artificial intelligence (AI) and deep learning algorithms for processing camera trap image data. This solution involves using AI to perform tasks such as image classification,

Author	*Year*	*Approach*	*Description*
			object detection, species identification, and data processing in ecological research.
T.A. de Lorm1, C. Horswill2,3,4, D. Rabaiotti2,3, R.M. Ewers1, R. J. Groom2,5, J. Watermeyer5, R. Woodroffe2,3	2023	automated individual recognition, Hotspotter, I3S-pattern, Lycaon pictus, photographic identification, Wild-ID	Developing a framework that automates the selection of suitable images for individual identification and comparing the performance of three identification software packages i.e Hotspotter, I3SPattern, and WildID
S. Sisodia, S. Dhyani, S. Kathuria, S. Pandey, G. Chhabra and R. Pandey	2023	Artificial Intelligence, wildlife, SDGs, Machine learning, Deep learning, sensors.	This project uses artificial intelligence to address issues such as deforestation, biodiversity loss, invasive species, and wildlife trafficking. The major goal is to assist SDG 15, which focuses on land-based life, by applying AI to inform successful wildlife conservation policies and initiatives.
Sachini Kuruppu	2023	Object Detection Algorithm, LoRa Technology	Using AI the system can monitor the presence of endangered animals and give alerts to the rangers.
M. Mangaleswaran and M. Azhagiri	2023	Deep Learning, Animal Detection, Convolutional Neural Network, Thermal Images, Classification.	The system employs image processing techniques such as feature extraction, detection, and classification to accurately identify and categorize animals. The goal of the solution is to reduce animal-vehicle accidents and conflicts, protect agriculture and human lives from animal predation, and track and detect animal activities for wildlife management and biodiversity preservation.

Author	*Year*	*Approach*	*Description*
Aarju, R. Bahuguna, S. Pandey, R. Singh, H. Kaur and G. Chhabra	2023	convolutional neural networks, deep learning, and machine learning algorithms, radio tracking, robotic aircraft, wildlife conservation	Using cloud computing, drones, and artificial intelligence has changed how we protect wildlife. These technologies help us monitor and understand species accurately.

III. Problem Formulation

The project aims to have a big impact on important aspects of protecting wildlife. First, it wants to reduce poaching and illegal activities by using advanced technologies like AI-based monitoring and surveillance, giving extra protection to endangered species. Second, by watching wildlife in real-time and using insights from data, the project wants to improve the overall health and stability of animal populations. Detecting health issues early and making informed conservation decisions are key to making sure animals are well. Also, the project focuses a lot on protecting and fixing habitats using AI-based analyses. Understanding how nature works and finding possible dangers helps guide efforts to save and restore crucial habitats. Lastly, by using all the collected data and insights, the project wants to help make better decisions about how to conserve wildlife.

The impact of this project is as follows:

- Reduces poaching and illegal activities.
- Improved wildlife health and population strategy.
- Enhanced habitat protection and reduction.
- Decision-making for a sustainable future.

IV. Solution

The objective of the proposed solution is to design a framework for animal recognition in the wild, aiming at a fully automatic wildlife spotting system. The solution utilizes deep convolutional neural network (CNN) models for image classification, taking advantage of their state-of-the-art performance in object recognition tasks. The goal is to automate the process of wildlife identification and monitoring, which is currently hindered by the overwhelming amounts of data and the need for manual pre-processing.

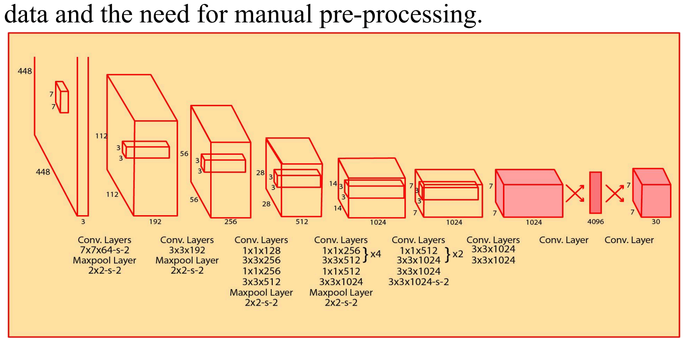


Fig. 1. Architecture of YOLO

YOLO(You Only Live Once) and CNN (Convolutional Neural Networks) are both used in animal detection. Basically, YOLO is an object detection algorithm that can detect multiple objects in an image simultaneously with a single pass through a neural network. It divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell. YOLO is popular for its speed and efficiency. The YOLO model is trained with a dataset of images containing various animals. Once trained, the YOLO model will be able to detect and localize animals in images or videos, which helps in monitoring the wildlife population, tracking animal movements and detecting potential threats such as poachers and predators.

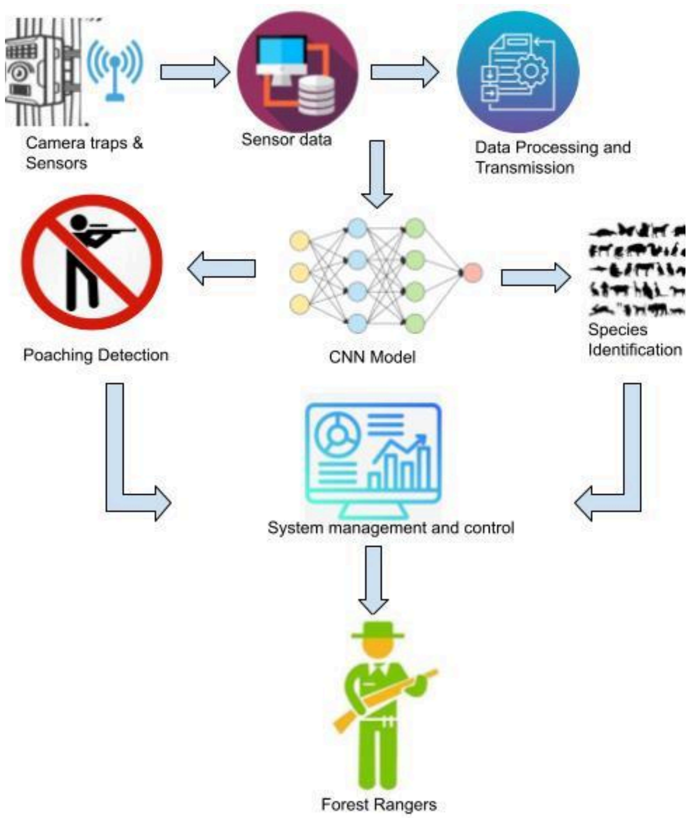


Fig. 2. Architecture of AI-based wildlife conservation and monitoring.

In animal detection, CNNs are mostly used as the backbone architecture with the YOLO. CNNs are composed of multiple layers, including convolutional layers that learn to extract meaningful features from images, and fully connected layers are then used for classifying and identifying animals. These are designed to automatically adapt spatial features from input images. CNN can be trained on large datasets of annotated images which contain various animal species. Once the model is trained, they can accurately detect and classify the animals in images or videos.

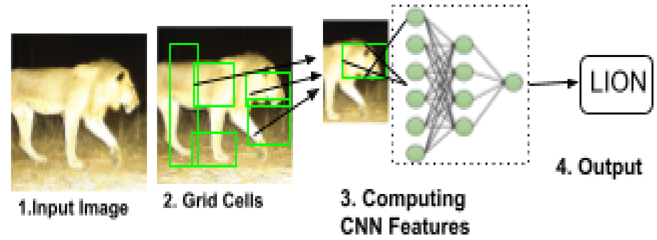
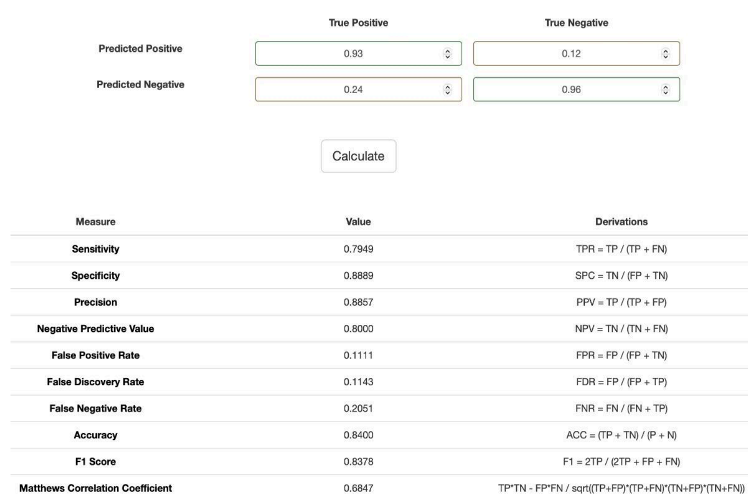


Fig. 3. Architecture of CNN Model in predicting the output.

In Summary, YOLO and CNN are both integral components of animal detection systems which are used in wildlife conservation and monitoring. These are used to achieve both fast and accurate detection and classification of animals in images and video streams. YOLO can efficiently identify the presence and location of animals, while CNNs can further classify detected animals into specific species or categories based on their visual characteristics. This combined approach enables effective monitoring and conservation efforts as well as aiding in research and wildlife management.

V. Expected Output

The expected accuracy and F1 score of the model are given by the resultant metrics where it is used to evaluate the effectiveness and impact of wildlife management. By integrating these metrics we can assess the progress, identify strengths and weaknesses, and refine strategies to achieve long-term conservation objectives effectively.



	True Positive	True Negative
Predicted Positive	0.93	0.12
Predicted Negative	0.24	0.96

Calculate

Measure	Value	Derivations
Sensitivity	0.7949	TPR = TP / (TP + FN)
Specificity	0.8889	SPC = TN / (FP + TN)
Precision	0.8857	PPV = TP / (TP + FP)
Negative Predictive Value	0.8000	NPV = TN / (TN + FN)
False Positive Rate	0.1111	FPR = FP / (FP + TN)
False Discovery Rate	0.1143	FDR = FP / (FP + TP)
False Negative Rate	0.2051	FNR = FN / (FN + TP)
Accuracy	0.8400	ACC = (TP + TN) / (P + N)
F1 Score	0.8378	F1 = 2TP / (2TP + FP + FN)
Matthews Correlation Coefficient	0.6847	TP*TN - FP*FN / sqrt((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN))

Fig. 4. Expected Resultant Metrics Model

The precision-recall curve of the model visualizes the relationship between precision and recall across different thresholds or confidence levels set by the model. A model with high precision reaches the upper-right corner of the plot, indicating excellent performance across all thresholds.

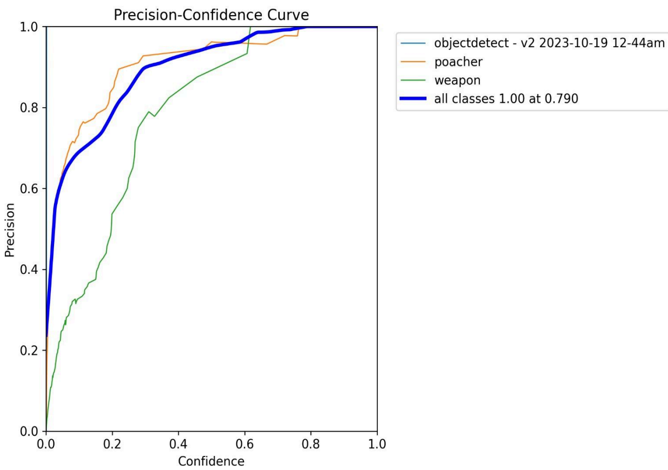


Fig. 5. Expected Precision-Recall Curve of the Model

VI. Conclusion

In Conclusion, the incorporation of advanced technological methods, particularly in the realm of wildlife conservation and monitoring, represents a crucial stride towards implementing more effective and enduring strategies. Innovative technologies, such as enhanced monitoring and surveillance techniques, exhibit immense promise in curtailing poaching activities, bolstering the well-being of wildlife, and steering initiatives aimed at safeguarding and rejuvenating habitats. The data-centric approach facilitated by these technological advancements not only aids in steering conservation decisions but also lays the groundwork for sustainable practices, fostering a harmonious coexistence between human endeavors and the preservation of our planet's diverse ecosystems. Confronting contemporary challenges, the integrating of advanced technology into wildlife conservation emerges as a potent asset, offering inventive resolution to uphold the fragile equilibrium for our ecosystem for the benefit of future generations..

References

[1] Jamali Firmat Banzi "A Sensor-Based Anti-Poaching System in Tanzania National Parks" International Journal of Scientific and Research Publications, Volume 4, Issue 4, April 2014

[2] T. A. S. Achala Perera and J. Collins, "Imaged-based species recognition system," 2015 9th International Conference on Sensing Technology (ICST), Auckland, New Zealand, 2015, pp. 195-199, doi: 10.1109/ICSensT.2015.7438391.

[3] T. Sarma and V. Baruah, "Real-time poaching detection: A design approach," 2015 International Conference on Industrial Instrumentation and Control (ICICI), Pune, India, 2015, pp. 922-924, doi: 10.1109/IIC.2015.7150875.

[4] Christensen, David R."A Simple Approach to Collecting Useful Wildlife Data Using Remote Camera-Traps in Undergraduate Biology Courses" Bioscene: Journal of College Biology Teaching, v42 n1 p25-31 May 2016, Association of College and Biology Educators. Web site: http://acube.org

[5] H. Nguyen et al., "Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring," 2017 IEEE International Conference on Data Science and Advanced Analytics (DSAA), Tokyo, Japan, 2017, pp. 40-49, doi: 10.1109/DSAA.2017.31.

[6] Mohammad Sadegh Norouzzadeha, Anh Nguyen, Margaret Kosmalac, Alexandra Swanson, Meredith S. Palmer, Craig Packer, and Jeff Clune,f,1"Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning" Edited by James A. Estes, University of California, Santa Cruz, CA, and approved April 30, 2018, http://www.pnas.org/cgi/doi/10.1073/pnas.171936711

[7] D. Mahatara1*, S. Rayamajhi2 and G. Khanal3 "Impact of anti-poaching approaches for the success of Rhino conservation in Chitwan National Park, Nepal" Banko Janakari, Vol 28 No. 2, 2018

[8] S. B. Islam and D. Valles, "Identification of Wild Species in Texas from Camera-trap Images using Deep Neural Network for Conservation Monitoring," 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 2020, pp. 0537-0542, doi: 10.1109/CCWC47524.2020.9031190

[9] Mateusz Choiński, Mateusz Rogowski, Piotr Tynecki, Dries P. J. Kuijper, Marcin Churski & Jakub W. Bubnicki"A First Step Towards Automated Species Recognition from Camera Trap Images of Mammals Using AI in a European Temperate Forest" 17 September 2021, DOI:https://doi.org/10.1007/978-3-030-84340-3_24

[10] S. V. Viraktamath, J. R, V. A, A. S. Bhat, and S. Nayak, "Wildlife Monitoring and Surveillance," 2022 International Conference for Advancement in Technology (ICONAT), Goa, India, 2022, pp. 1-4, doi: 10.1109/ICONAT53423.2022.9725874.

[11] Shreya Kakhandiki "Poacher Activity Detection Device for Wildlife Conservation" 2022 Terra Science and Education, DOI: 10.36838/v4i5.17

[12] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz and D. Terzopoulos, "Image Segmentation Using Deep Learning: A Survey," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 7, pp. 3523-3542, 1 July 2022, doi: 10.1109/TPAMI.2021.3059968.

[13] Juliana Vélez, William McShea, Hila Shamon, Paula J. Castiblanco-Camacho, Michael A. Tabak, Carl Chalmers, Paul Fergus, John Fieberg "An evaluation of platforms for processing camera-trap data using artificial intelligence"28 December 2022 https://doi.org/10.1111/2041-210X.14044.

[14] T.A. de Lorm1, C. Horswill 2,3,4, D. Rabaiotti 2,3, R.M. Ewers1, R. J. Groom2,5, J. Watermeyer5, R. Woodroffe2,3 "Optimizing the automated recognition of individual animals to support population monitoring" March 10, 2023, DOI: 10.22541/au.167845477.77416758/v1

[15] S. Sisodia, S. Dhyani, S. Kathuria, S. Pandey, G. Chhabra and R. Pandey, "AI Technologies, Innovations and Possibilities in Wildlife Conservation," 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India, 2023, pp. 1090-1095, doi: 10.1109/ICIDCA56705.2023.10099721.

[16] Sachini Kuruppu "AI System to Protect Endangered Animal Population and Prevent Poaching Threats using Weapon Detection" Volume 8, Issue 9, September 2023, International Journal of Innovative Science and Research Technology ISSN No:-2456-2165

[17] M. Mangaleswaran and M. Azhagiri, "A Comparison of Different Learning Algorithms for Wildlife Detection and Classification in Animal Conservation Applications," 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2023, pp. 920-923, doi: 10.1109/ICAIS56108.2023.10073833.

[18] Aarju, R. Bahuguna, S. Pandey, R. Singh, H. Kaur, and G. Chhabra, "Enabling Technologies for Wildlife Conservation," 2023 IEEE Devices for Integrated Circuit (DevIC), Kalyani, India, 2023, pp. 217-220, doi: 10.1109/DevIC57758.2023.10134561.

[19] S. Pandey, A. K. Dixit, R. Bahuguna, S. V. Akram, V. Pandey, and S. Kathuria, "AI and IoT Enabled Technologies for Monitoring the Right to Health of Disabled People," in 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), 2022, pp. 2227–2231.

[20] P. Madan et al., "An Optimization-Based Diabetes Prediction Model Using CNN and Bi-Directional LSTM in Real-Time Environment," Applied Sciences (Switzerland), vol. 12, no. 8, p. 3989, 2022,

[21] K. Su, J. Ren, Y. Qin, Y. Hou, and Y. Wen, Efforts of indigenous knowledge in forest and wildlife conservation: A case study on bulang people in mamba village in Yunnan province, china, vol. 11. 2020, pp. 1–16.

[22] A. K. Thakur, Rajesh Singh, Anita Gehlot, Ajay Kumar Kaviti, Ronald Aseer, S.KousikSuraparaju, S.K. Natarajan, and V. S.Sikarwar.Advancements in solar technologies for sustainable development of the agricultural sector in India: a comprehensive review on challenges and opportunities. Environmental Science and Pollution Research, vol. 29, no. 29, p. 43635, 2022.

[23] S. Kathuria, P. Rawat, R. Singh, A. Gehlot, A. Kathuria, and S. Pandey, "Technical Intercession of Mixed Reality 4.0: Upholding Senior Citizens Health," in 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), 2022, pp. 1733– 1737.

[24] D. A. Isabelle and M. Westerlund, A Review and Categorization of Artificial Intelligence-Based Opportunities in Wildlife, Ocean and Land Conservation, vol. 14. 2022. doi: 10.3390/su14041979.

[25] T. Huang, L. Zhou, and M. Zhou, "Key Technologies and Applications of Wild Animal Satellite Tracking," Journal of Physics: Conference Series, vol. 1757, no. 1, p. 12180, 2021,

[26] A. Desrochers, J. A. Tremblay, Y. Aubry, D. Chabot, P. Pace, and D. M. Bird, Estimating wildlife tag location errors from a VHF receiver mounted on a drone, vol. 2. 2018, pp. 1–9.

[27] J. J. López and M. Mulero-Pázmány, Drones for conservation in protected areas: Present and future, vol. 3. 2019, pp. 1–23.

[28] K. E. Doull, C. Chalmers, P. Fergus, S. Longmore, A. K. Piel, and S. A. Wich, An evaluation of the factors affecting 'poacher' detection with drones and the efficacy of machine-learning for detection, vol. 21. 2021, p. 4074.

[29] B. Ivošević, Y. G. Han, Y. Cho, and O. Kwon, The use of conservation drones in ecology and wildlife research, vol. 38. 2015, pp. 113–118.

[30] J. C. van Gemert, C. R. Verschoor, P. Mettes, K. Epema, L. P. Koh, and S. Wich, "Nature conservation drones for automatic localization and counting of animals," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2015, vol. 8925, pp. 255–270.