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Hybrid Human-AI in Wildlife Image Recognition

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Abstract: The project, Hybrid Human-AI in Wildlife Image Recognition, addresses the challenge of efficiently processing large-scale camera trap image datasets for wildlife monitoring. Its primary objectives are to enhance species identification accuracy, minimize manual annotation efforts, and enable adaptability to evolving species compositions in dynamic ecosystems.

To accomplish this, the system employs an iterative deep learning framework that integrates human expertise with automated recognition. The methodology includes pre-training models on diverse datasets, fine-tuning through iterative learning cycles, and leveraging human intervention for low-confidence predictions. Advanced techniques such as Open Long-Tailed Recognition (OLTR), robust image preprocessing, and energy-based loss functions are applied to boost performance across imbalanced and complex datasets.

Experimental results reveal substantial improvements in classification accuracy, particularly for rare and previously unseen species, while significantly decreasing the need for manual annotation. A case study conducted in Gorongosa National Park demonstrates the system's adaptability to ecological changes over time, establishing a benchmark for long-term wildlife monitoring using camera traps.

I. INTRODUCTION

Wildlife monitoring plays a crucial role in biodiversity conservation, ecological research, and environmental policy-making. In recent years, camera traps have emerged as a powerful non-invasive tool for collecting vast amounts of wildlife imagery. However, the sheer volume of image data generated by these devices presents significant challenges in terms of processing efficiency, species identification, and annotation effort..

To address these challenges, this project proposes a Hybrid Human-AI approach to Wildlife Image Recognition, designed to streamline the analysis of camera trap images. The goal is to develop a system that not only enhances species identification accuracy but also reduces the burden of manual annotation and adapts to dynamic ecosystems where species composition may change over time The utilization of Densenet201 not only accelerates the recognition process but also significantly improves accuracy, marking a substantial advancement in attendance management. This state-of-the-art algorithm contributes to a seamless and reliable system, reducing the likelihood of errors and streamlining administrative tasks associated with attendance tracking.

The core of the system is an **i**terative deep learning framework that combines the strengths of automated image recognition with human expertise. Models are pre-trained on diverse wildlife datasets and further refined through iterative learning cycles. Low-confidence predictions are flagged for human validation, enabling a continuous feedback loop that improves performance with each iteration.. Moreover, the integration of Den To improve recognition under the long-tailed distribution of species typically found in ecological data, techniques such as Open Long-Tailed Recognition (OLTR),

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image preprocessing, and energy-based loss functions are integrated into the training pipeline. These methods help the system maintain high accuracy, especially when identifying rare or novel species that are often underrepresented in training datasenet201 adds an extra layer of security to the attendance system, enhancing overall efficiency and reliability.

II RELATED WORK

Sead Mustafić et al. [1] explored advanced computer vision techniques to enhance wildlife management through automatic detection and classification of animal species from camera trap images, addressing challenges like dataset imbalance and environmental variability.

Vigneshwaran Palanisamy and Nagulan Ratnarajah [2] provided a comprehensive review of deep learning techniques applied to wildlife monitoring, emphasizing challenges in species identification within imbalanced datasets and highlighting opportunities for AI integration in conservation efforts.

Chao Mou et al. [3] introduced a foundational deep learning model integrating human knowledge for incremental recognition with limited data, aiming to monitor endangered and rare wildlife species effectively in the field

Paul Fergus et al. [4] examined the Conservation AI platform, which utilizes machine learning and computer vision to identify species, monitor biodiversity, and prevent poaching, demonstrating its scalability and effectiveness in real-world conservation scenarios.

Clément Duhart et al. [5] focused on combining bio-acoustic and video data for wildlife monitoring using advanced deep learning models, discussing challenges in automating species detection and providing insights into building robust, localized databases for improved classifier accuracy.

Zhibin Ma et al.[6] developed a real-time wildlife detection system based on the YOLOv5s deep learning network, enhancing detection speed and accuracy, particularly for small and occluded targets in complex forest environments.

Andres Hernandez et al. [7] introduced Pytorch-Wildlife, an open-source deep learning framework tailored for wildlife conservation, featuring a model zoo optimized for diverse ecological environments and supporting applications like automated image filtering for camera trap.

Hung Nguyen, S. Maclagan, Dinh Q. Phung, and Svetha Venkatesh [8] developed a deep convolutional neural network framework for automated wildlife monitoring. Their system achieved over 93.8% accuracy in animal identification from camera trap images, significantly reducing the need for manual annotation.

Feng Yang, Chunying Hu, Aokang Liang, Sheng Wang, Yun Su, and Fu Xu [9] proposed CECS-CLIP, a multimodal detection model that integrates image data with textual animal descriptions. This approach enhances the detection of rare and hidden wildlife species, achieving a 25% improvement in average precision over existing methods.

Rashi Shukla, Kumar Utkarsh, Harshit Banwal, Anshul Chaudhary, Harsh Sahu, and Anup Lal Yadav [10] introduced Wildwatch, an AI-powered wildlife guardianship system utilizing YOLOv8 for real-time species detection and poaching prevention. Their system demonstrates the practical application of advanced object detection models in conservation efforts

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III METHODOLOGY

The methodology of this project centers on developing a hybrid system that combines deep learning with human expertise to enhance wildlife species classification from camera trap images. Initially, raw images undergo preprocessing techniques such as resizing, normalization, and augmentation to improve model robustness. A convolutional neural network (CNN) is trained on this dataset to perform species classification, and each prediction is accompanied by a confidence score. To address uncertain predictions, a human-in-the-loop (HITL) mechanism is integrated: when the model's confidence falls below a defined threshold, the image is flagged for human review. Model performance is evaluated using metrics like accuracy and F1-score, and comparative analysis is conducted between fully automated and hybrid approaches to quantify the benefits of human intervention in reducing misclassification, especially for rare or ambiguous species.

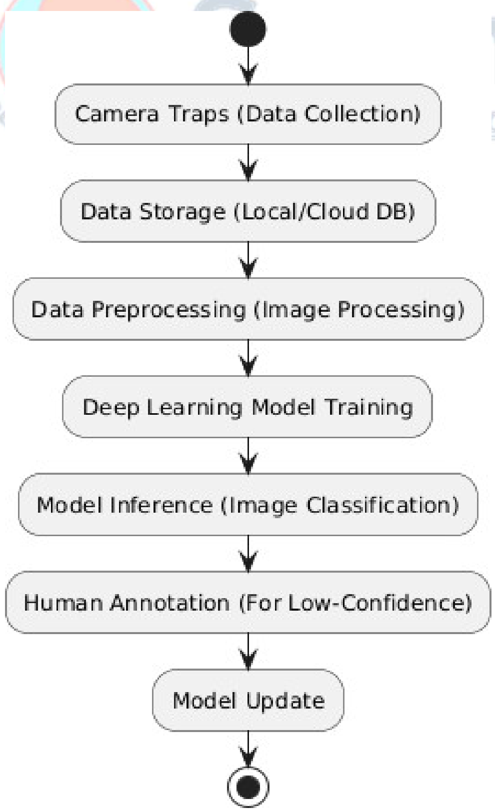

Fig1 : System Architecture

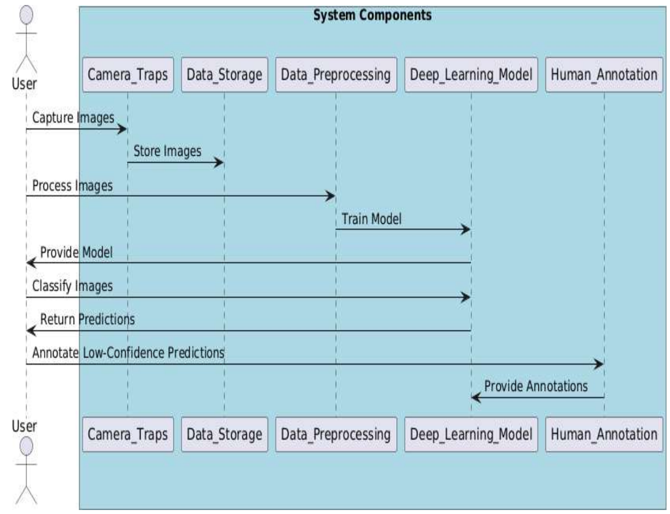

Fig.2 : Sequence Diagram

A. Dataset Description

The dataset used in this project consists of camera trap images capturing various wildlife species in natural habitats, with each image labeled according to the observed species. These images reflect real-world conditions, including variations in lighting, background, and occlusion. The dataset is inherently imbalanced, with common species appearing more frequently than rare ones, which poses challenges for accurate classification. Preprocessing steps such as resizing, normalization, and augmentation are applied to enhance the model's ability to generalize across diverse conditions.

B. Preprocessing

In this project, preprocessing plays a crucial role in preparing camera trap images for effective training of the deep learning model. The steps include resizing all images to a uniform resolution to ensure consistency in input dimensions, and normalization to scale pixel values for faster convergence during training.

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C Feature Extraction

In this project, feature extraction is performed using a deep convolutional neural network (CNN), which automatically learns hierarchical features from the camera trap images. The CNN captures low-level details like edges and textures in the initial layers and gradually identifies more complex patterns such as shapes, animal markings, and species-specific features in deeper layers. These extracted features serve as the foundation for classifying the images into different wildlife species. By leveraging the CNN's ability to learn from data, the system avoids manual feature engineering and achieves more accurate and scalable recognition across diverse and challenging image conditions.

D. Algorithm used

1. Iterative Learning Framework

The iterative learning framework used in this project begins with a pre-trained model, a labeled dataset, and additional unlabeled data. Initially, all input data undergo preprocessing, including resizing, augmentation, and denoising, to ensure quality and consistency. The pre-trained model is then used to classify the images and generate confidence scores for each prediction. Predictions are divided into high-confidence and low-confidence groups; low-confidence outputs are flagged for human annotation. These human-labeled instances are added to the training dataset, while high-confidence predictions are treated as pseudo-labels. The model is then fine-tuned using this combined data to improve its classification accuracy. This process is repeated iteratively with new data batches, resulting in a continuously improving model that becomes increasingly accurate and adaptable to diverse wildlife image datasets.

2. Open Long-Tailed Recognition Algorithm

The Open Long-Tailed Recognition (OLTR) algorithm is designed to address the challenges of imbalanced datasets, particularly in wildlife monitoring where rare species are underrepresented. Starting with a dataset that exhibits class imbalance, the algorithm first applies class-balanced sampling to ensure that both rare and common species are fairly represented during training. It incorporates an embedding memory module that retains feature representations of rare species, enhancing the model's ability to generalize from limited data.

3. Feature Augmentation with Image Preprocessing

The feature extraction process in this project begins with raw camera trap images as input. Initially, basic preprocessing steps such as contrast enhancement, noise reduction, and background removal are applied to improve image clarity and consistency. To increase the model's robustness, data augmentation techniques like rotation, scaling, and flipping are used, simulating diverse environmental conditions. Key visual features are then extracted using convolutional layers specifically optimized for wildlife imagery, capturing essential patterns and species-specific traits. During training, both original and augmented features are combined to enrich the learning process and improve detection accuracy. This results in a more informative and reliable feature representation, supporting accurate wildlife classification.

4. Dynamic Background and Occlusion Handling

To improve accuracy in complex wildlife images, this approach focuses on handling challenges such as cluttered backgrounds and occlusions. The process begins with preprocessed images captured under challenging environmental conditions. Advanced segmentation methods like U-Net or K-means clustering are employed to isolate foreground objects, separating animals from distracting backgrounds. Feature Pyramid Networks (FPN) are then used to detect occluded or partially visible objects by extracting multi-scale features. An attention mechanism is applied to

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enhance and prioritize critical visual details related to the target species. Finally, the model is trained using augmented data that includes simulated occlusions, boosting its ability to recognize species even when visibility is limited. The result is a robust model capable of accurate identification in visually complex or obstructed scenarios.

5. *Active Learning for Annotation Optimization*

To reduce manual annotation efforts while maintaining high model performance, an uncertainty-based active learning approach is employed. The process begins with an unlabeled dataset and model-generated predictions. The model assigns confidence scores to each prediction, and images are ranked based on uncertainty, with those having the lowest confidence prioritized for human review. These uncertain samples are then presented to human annotators for accurate labeling. Once labeled, the new data is integrated into the training set, and the model is retrained, allowing it to iteratively improve its predictions. This targeted annotation strategy results in a more efficient training process, yielding an enhanced dataset and a more accurate model with significantly reduced human workload.

6. *Multi-Species Adaptation Strategy*

To ensure adaptability in dynamic ecosystems, this approach focuses on enabling the model to recognize newly emerging species over time. Starting with a pre-trained model, novel species data, and the existing dataset, clustering methods such as DBSCAN are applied within the feature space to detect previously unseen species. A novelty detection module is used to automatically flag these unfamiliar samples for further review. Once identified, annotated examples of the novel species are added to the training dataset. The model is then retrained using weighted sampling to ensure a balanced representation between new and existing species. This results in an updated model capable of efficiently adapting to ecological changes while maintaining high accuracy across both known and novel classes.

7. *Tiny Object Detection Algorithm*

To improve the detection of small animals in camera trap images, this method leverages advanced image enhancement and focused detection strategies. High-resolution images are first processed using super-resolution techniques to amplify the visibility of tiny objects that might otherwise go unnoticed. Region proposal networks are then applied to concentrate on specific areas likely to contain small animals. Multi-scale convolutional layers are used to extract fine-grained features from these focused regions, capturing subtle details crucial for accurate identification. The model is validated using datasets enriched with examples of small species, ensuring it generalizes well to real-world scenarios. As a result, detection rates for tiny and often overlooked wildlife species are significantly improved.

E. Image Classification upon the completion of feature extraction. To determine how similar or unlike the feature vectors are based on the extracted characteristics, they are then compared using a distance calculation. Based on this calculated distance, it is determined whether or not two photos are of the same person. A little distance indicates resemblance, while a high distance indicates dissimilarity. With backpropagation, the system may learn from its errors and is trained on many pairs of images to increase accuracy. It is also possible to fine-tune on a smaller, task-specific dataset for adaptation following training on a larger dataset.

IV. RESULT

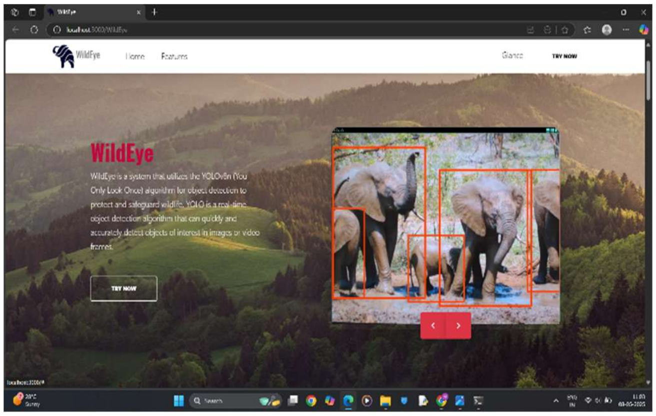

Fig 3: Home page

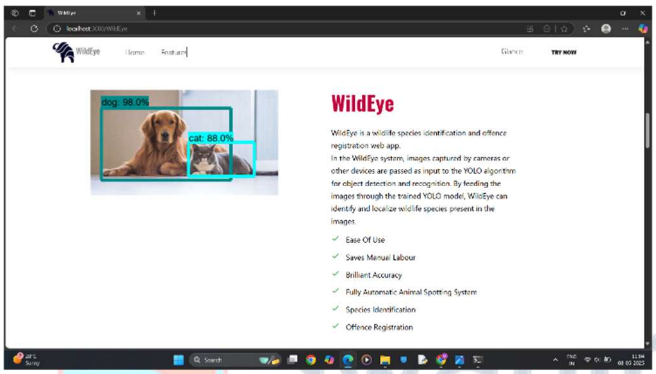

Fig 4:Home page of wildeye

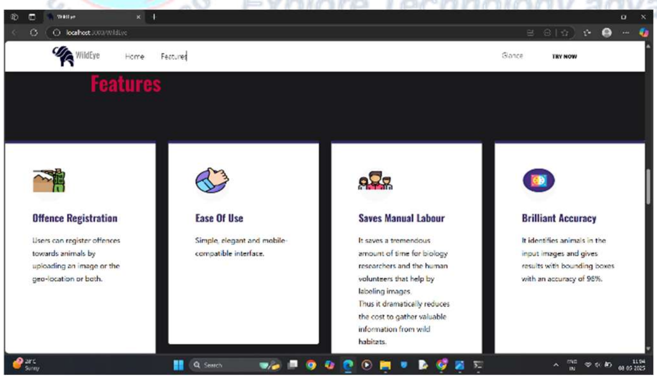

Fig 5: Home with features

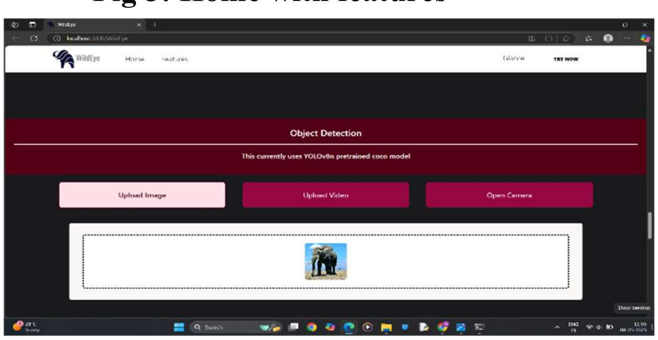

Fig 6: Loading of images

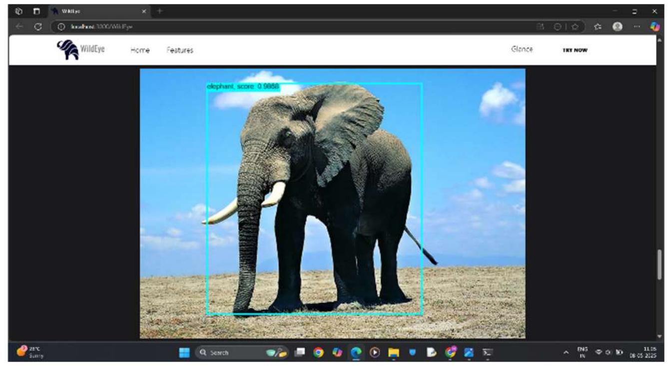

Fig 7:Capturing Student Face Through

V. CONCLUSION

The Hybrid Human-AI in Wildlife Image Recognition system presents an effective solution for automating wildlife monitoring while maintaining high accuracy through human-in-the-loop feedback. By combining deep learning with expert validation, the system addresses key challenges such as class imbalance, rare species detection, and complex environmental conditions. The iterative learning approach not only improves model performance over time but also significantly reduces the need for manual annotation. Real-world testing, such as the case study in Gorongosa National Park, demonstrates the system's adaptability and potential for large-scale deployment. This project highlights the transformative role of AI in conservation and sets a foundation for future advancements in ecological research and biodiversity protection.

VI. FUTURE ENHANCEMENT

Future enhancements of the system include integrating real-time monitoring through live feeds and edge devices, enabling on-site detection in remote areas. Incorporating multimodal data like Future enhancements of the system include integrating real-time monitoring through live feeds and edge devices, enabling on-site detection in remote areas. Incorporating multimodal data like audio and GPS can improve species identification. Adding zero-shot or few-shot learning will help

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recognize new species with minimal data. A user-friendly dashboard and citizen science integration can boost accessibility and data diversity. Predictive analytics can support proactive conservation efforts by forecasting population trends. Additionally, expanding the model to support multi-animal detection in single frames and improving performance under low-light conditions will further enhance real-world applicability.

REFERENCES

[1] S. Mustafić, A. Stojanović, and M. Subašić, "Improving Wildlife Management with AI: Species Detection and Classification from Camera Trap Data," CEUR Workshop Proceedings, vol. 3786, 2023.

[2] V. Palanisamy and N. Ratnarajah, "Detection of Wildlife Animals using Deep Learning Approaches: A Systematic Review," arXiv preprint arXiv:2205.06393, 2022.

[3] C. Mou, J. Zhao, Y. Liu, and Q. Yu, "Monitoring Endangered and Rare Wildlife in the Field: A Foundation Deep Learning Model," Animals, vol. 13, no. 20, p. 3168, 2023.

[4] P. Fergus, A. Hussain, and D. Hignett, "Harnessing Artificial Intelligence for Wildlife Conservation," Machines, vol. 9, no. 4, p. 41, 2021.

[5] C. Duhart, A. Costea, and R. Prudêncio, "Deep Learning for Wildlife Conservation and Restoration Efforts," Climate Change AI ICML Workshop, 2019.

[6] Z. Ma, Y. Liu, and J. Chen, "Wildlife Real-Time Detection in Complex Forest Scenes Based on YOLOv5s Deep Learning Network," Remote Sensing, vol. 16, no. 8, p. 1350, 2024.

[7] A. Hernandez et al., "Pytorch-Wildlife: A Collaborative Deep Learning Framework for Conservation," arXiv preprint arXiv:2405.12930, 2024.

[8] H. Nguyen, S. Maclagan, D. Q. Phung, and S. Venkatesh, "Animal Recognition and Identification with Deep Convolutional Neural Networks for Automated Wildlife Monitoring," ICPR Workshops, 2017.

[9] F. Yang et al., "CECS-CLIP: Fusing Domain Knowledge for Rare Wildlife Detection Model," Animals, vol. 14, no. 19, p. 2909, 2024.

[10] R. Shukla et al., "Wildwatch: AI-Powered Wildlife Guardianship System Using Machine Learning," ResearchGate Preprint, 2024.

[11] T. Beery et al., "Efficient Pipeline for Camera Trap Image Processing Using Deep Learning," Methods in Ecology and Evolution, vol. 12, no. 8, pp. 1484–1497, 2021.

[12] C. Norouzzadeh et al., "Automatically Identifying, Counting, and Describing Wild Animals in Camera-Trap Images with Deep Learning," PNAS, vol. 115, no. 25, pp. E5716–E5725, 2018.

[13] B. Willi et al., "Identifying Animal Species in Camera Trap Images Using Deep Learning and Citizen Science," Methods in Ecology and Evolution, vol. 10, no. 1, pp. 80–91, 2019.

[14] Y. Zhang et al., "Few-Shot Object Detection in Remote Sensing Images Based on Meta-Learning and Attention," Remote Sensing, vol. 13, no. 9, p. 1718, 2021.

[15] M. Tabak et al., "Machine Learning to Classify Animal Species in Camera Trap Images: Applications in Ecology," Methods in Ecology and Evolution, vol. 10, no. 4, pp. 585–590, 2019.

[16] J. B. M. Aide et al., "Real-Time Bioacoustics Monitoring and Automated Species Identification," PeerJ, vol. 1, p. e103, 2013.

[17] J. Norouzzadeh et al., "A Deep Active Learning System for Species Identification and Counting in Camera Trap Images," Ecological Informatics, vol. 61, p. 101249, 2021.

[18] A. Gomez Villa, A. Salazar, and F. Vargas, "Towards Automatic Wild Animal Monitoring: Identification of Animal Species in Camera-Trap Images Using Very Deep Convolutional Neural Networks," Ecological Informatics, vol. 41, pp. 24–32, 2017.

[19] J. A. Kays et al., "Camera Traps as Sensor Networks for Monitoring Animal Communities," International Journal of Research and Reviews in Wireless Sensor Networks, vol. 1, no. 2, pp. 19–29, 2011.