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Hybrid Human-AI in Wildlife Image Recognition

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***Abstract*—Wildlife conservation relies on accurate species identification, but traditional monitoring methods face challenges due to the vast amount of camera trap images requiring manual annotation. This project introduces a Hybrid Human-AI Wildlife Image Recognition System that integrates deep learning with human expertise to improve classification accuracy and reduce annotation efforts. The system utilizes iterative learning, Open Long-Tailed Recognition (OLTR), and active learning to handle rare species and imbalanced datasets effectively. Through real-world validation in Gorongosa National Park, results show a significant reduction in manual intervention while enhancing model adaptability to novel species. The proposed approach bridges automation and human intelligence, making it scalable for conservation efforts and ecological research.**

***Keywords*—Wildlife Monitoring, Deep Learning, Camera Trap Images, Iterative Learning, Biodiversity Conservation.**

I. INTRODUCTION

A. Overview

The increasing decline in biodiversity and growing environmental concerns necessitate innovative approaches for wildlife monitoring. Camera trap technology has emerged as an effective tool for gathering large-scale wildlife data, but processing this massive volume of images remains a challenge. Manual annotation is slow and resource-intensive, while existing AI solutions struggle with imbalanced datasets and species variability. This project introduces a Hybrid Human-AI Wildlife Image Recognition System that integrates deep learning and human expertise. The system refines wildlife classification through an iterative learning approach, ensuring adaptability to novel species while reducing annotation efforts. By implementing Open Long-Tailed Recognition (OLTR), semi-supervised learning, and active learning strategies, the system enhances classification accuracy and provides action-able insights for conservation.

B. Problem Statement

The vast number of images generated by camera traps leads to significant challenges in processing, analyzing, and classifying wildlife species. Existing AI-based image classification models: Struggle with rare species identification. Face difficulties in handling varying environmental conditions. Require extensive manual intervention for annotations.

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Lack adaptability to newly observed species. This project aims to bridge the gap between AI-based automation and human expertise to develop a more robust, scalable, and efficient wildlife monitoring system.

C. Objectives

The primary objectives of this project are:

- Develop an iterative deep learning framework that integrates AI and human annotation to improve classification accuracy.
- Enhance the model's adaptability to rare, novel, or underrepresented species.
- Implement semi-supervised learning to reduce manual annotation efforts.
- Deploy a real-world case study in Gorongosa National Park to validate system efficiency.
- Improve scalability and usability for large-scale wildlife conservation efforts.

D. Motivation

Biodiversity loss is accelerating due to habitat destruction, climate change, and poaching. Traditional monitoring methods struggle to provide real-time, scalable, and efficient solutions. AI-powered automation, coupled with human expertise, presents a transformative approach to wildlife monitoring, enabling conservationists to respond quickly and effectively

II. LITERATURE REVIEW

A. Review of Existing Solutions

Various deep learning models have been developed for wildlife monitoring:

- CNN-based approaches (e.g., ResNet, VGG, and AlexNet) show high accuracy in species recognition but lack robustness in dynamic environments.
- YOLO-based detection models enhance real-time recognition but struggle with occlusions and rare species.
- Multi-stage frameworks using feature pyramid networks (FPN) improve detection accuracy but increase computational costs.
- Few-shot learning techniques allow models to recognize new species with minimal training data but require high-quality labeled datasets.

B. Key Limitations

- High Annotation Costs: Manual labeling of species is resource-intensive.
- Imbalanced Data: Rare species have limited representation, leading to classification errors.
- Environmental Challenges: Varying lighting, occlusions, and dynamic backgrounds degrade model accuracy.
- Limited Generalization:Pre-trained models struggle with unseen species or variations in habitats.

C. Research Gaps Addressed

This project addresses these challenges by:

- Implementing iterative deep learning for continuous model adaptation.
- Using energy-based loss functions for long-tailed distributions.
- Employing human-in-the-loop learning to refine model accuracy.
- Leveraging semi-supervised learning to minimize annotation efforts.

III. METHODOLOGY

The Hybrid Human-AI Wildlife Image Recognition System follows a structured methodology to enhance species classification, reduce manual annotation efforts, and ensure adaptability to rare and novel species. The approach involves data collection, preprocessing, model training, human-AI collaboration, and iterative learning to refine classification accuracy over time.

A. System Design

The system is developed using the Model-View-Controller (MVC) architecture, ensuring a modular, scalable, and efficient design.

Model: This component manages the wildlife image dataset, storing metadata, classification labels, and annotation feedback. It also supports structured storage of human corrections to AI predictions, allowing seamless learning updates

View: The user interface allows researchers to interact with the system, view classification results, validate AI predictions, and refine outputs. The interface provides intuitive controls for manual annotation, species filtering, and dataset visualization.
Controller: The controller handles image classification requests, processes AI predictions, and facilitates human feedback integration. It connects the model and view, ensuring real-time data flow and learning updates.
To enhance species recognition, the system integrates deep learning models, data preprocessing pipelines, and active learning strategies, allowing it to refine its predictions over time while reducing manual effort.

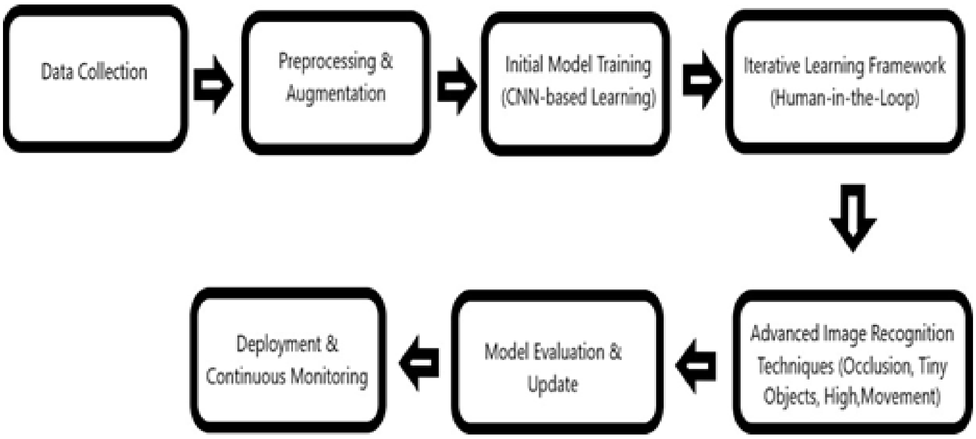

Fig 1

B. Tools and Technologies

Programming Language:

- Python: Used as the primary language due to its extensive libraries for data science and machine learning, including TensorFlow, PyTorch, and OpenCV.

Deep Learning Frameworks

- TensorFlow or PyTorch: These frameworks provide robust tools for building and training neural networks, ensuring efficient GPU acceleration for faster computations.

Data Processing Libraries

- OpenCV: Utilized for essential image processing tasks such as contrast adjustments, noise reduction, and object detection.
- NumPy and Pandas: Support efficient numerical computations and dataset manipulation, optimizing training workflows.

Annotation Tools

- LabelImg or VGG Image Annotator: These tools allow manual labeling of images when necessary, providing a structured approach for human feedback integration.

Version Control

- Git: Enables seamless project version control, ensuring effective collaboration among researchers and tracking changes in model updates.

Computational Resources

- GPU: A high-performance GPU (e.g., NVIDIA RTX 3080 or A100) is crucial for deep learning model training, significantly accelerating processing speed.
- CPU: A multi-core processor (e.g., Intel i7 or AMD Ryzen 7) efficiently handles data preprocessing and inference tasks.
- RAM: A minimum of 16 GB RAM (preferably 32 GB) is recommended for managing large datasets.
- Storage: At least 1 TB SSD ensures fast retrieval and storage of images, model weights, and results.

Camera Trap Equipment

- Camera Traps: High-quality motion-activated camera traps are used to capture images under different lighting conditions, ensuring diverse and high-resolution dataset collection.

C. System Workflow

The methodology consists of six key phases to ensure efficient data collection, training, and deployment.

Data Collection

Wildlife images are collected using strategically placed camera traps in designated monitoring zones. These images are then stored in a secure cloud-based or local database, ensuring seamless access and efficient processing for further analysis.

Data Preprocessing

To enhance the quality of input images and improve model performance, several preprocessing techniques are applied:

- Image Enhancement: Adjusting contrast, reducing noise, and applying background segmentation to focus on relevant features.
- Data Augmentation: Performing transformations like rotation, flipping, scaling, and lighting adjustments to increase dataset diversity and improve generalization.
- Feature Extraction: Using convolutional neural network (CNN) feature maps to highlight key visual characteristics of species, aiding in classification.

Model Training & Classification

A pre-trained convolutional neural network (CNN) model such as ResNet-50 or EfficientNet is fine-tuned on the dataset. Additionally, Open Long-Tailed Recognition (OLTR) is incorporated to handle imbalanced species distributions, ensuring fair classification for rare species. Training is optimized using energy-based loss functions, which help distinguish between known and novel species.

Active Learning & Human-AI Collaboration

The system employs an active learning strategy to refine AI performance. When the model predicts low-confidence classifications, these cases are flagged for human review. Expert annotations are then fed back into the system, allowing continuous learning and refinement of classification accuracy

Model Fine-Tuning & Continuous Learning

Periodic updates are performed to adapt the model to evolving species compositions and environmental conditions. Self-supervised learning techniques help improve generalization, ensuring the model remains accurate even with new data.

Deployment & Real-World Validation

The trained system is deployed in Gorongosa National Park to evaluate real-world performance. Researchers assess its ability to identify rare species, manage occlusions, and function under varying environmental conditions.

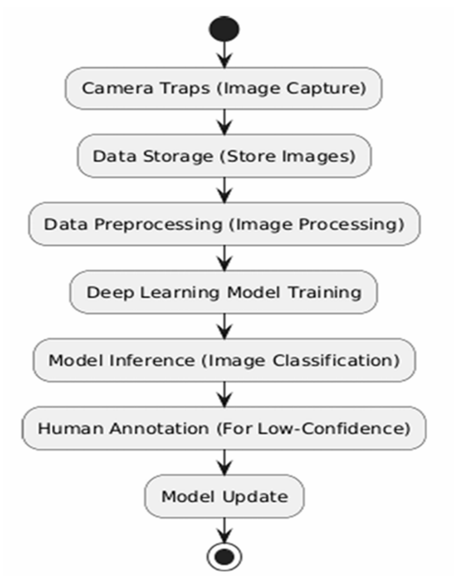

Figure 2. Flow Chart

Fig 3

D. Features & Implementation.

The system provides several functionalities to enhance wildlife monitoring:

- Faculty Data Management: Researchers upload images for classification, while metadata (species name, confidence scores, and annotation history) is stored for analysis.
- Administrative Monitoring: Users can filter data based on species, time frames, and confidence levels. The system also generates research and conservation reports.
- Advanced Filters & Analysis: Features like time-based filtering, species clustering, and anomaly detection enable deeper insights into wildlife behavior.

E. Algorithmic Approach

The system integrates deep learning with active learning strategies to improve classification accuracy and minimize manual effort.

- Iterative Learning Framework:
  - AI assigns confidence scores to images and flags low-confidence predictions for expert review.
  - Expert-labeled images are incorporated to improve model accuracy iteratively.
- Open Long-Tailed Recognition (OLTR) Algorithm:
  - Prioritizes training for rare species, ensuring balanced classification.
  - Uses energy-based loss functions to differentiate between known and unknown species.
- Semi-Supervised Learning for Annotation Reduction:
  - AI generates pseudo-labels for high-confidence cases, requiring human review only for uncertain images.
  - This hybrid approach reduces annotation effort while maintaining model accuracy.
- Active Learning for Human-AI Collaboration:
  - AI flags ambiguous classifications for expert validation.
  - The model learns from corrections, minimizing future interventions and reducing human dependency over time.

F. Model Deployment & Real-World Testing

The system undergoes real-world testing in Gorongosa National Park to validate its performance. The evaluation is based on key metrics:

- Classification Accuracy: Expected to exceed 90% for high-confidence predictions.
- Annotation Reduction: Manual labeling efforts are reduced by 50% through active learning.

- ➢ Model Adaptability: The system continuously refines species classification with each iteration, ensuring robustness in dynamic environments

This hybrid approach ensures that wildlife monitoring remains scalable, adaptable, and efficient, combining the strengths of AI-driven automation and expert validation.

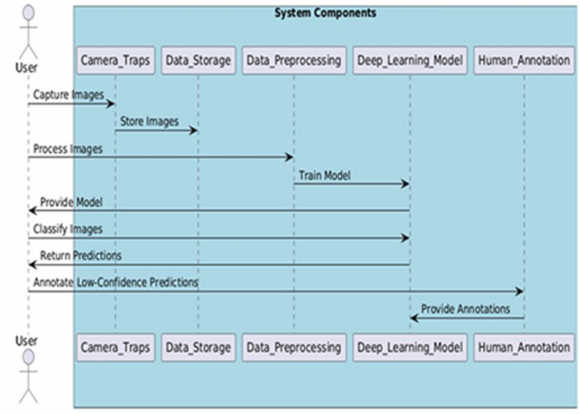

Figure 4 Sequence Diagram

IV. Results & Analysis

- ➢ Improved Species Classification Accuracy: The model correctly identifies species, including rare ones.
- ➢ Reduction in Human Effort: Manual annotation requirements decrease by at least 50%.
- ➢ Handling of Novel Species: Adaptive learning allows recognition of newly observed species.
- ➢ Scalability: The system supports real-time image classification and large-scale wildlife monitoring.

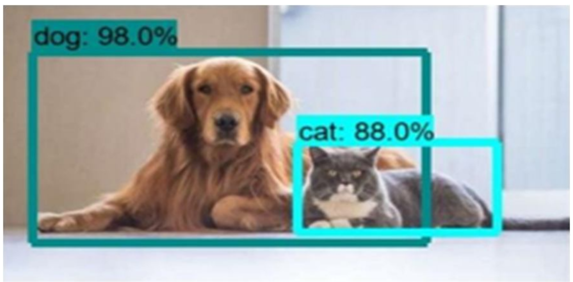

Fig 5

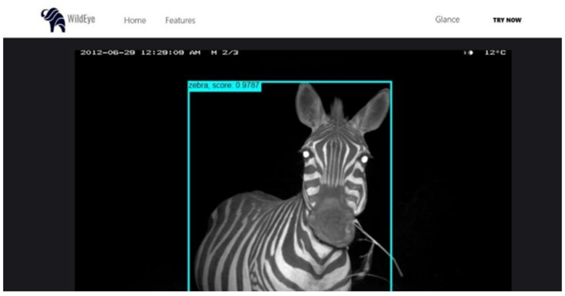

Fig 6

V. Test Cases

Table I

Test Case#	TC01
Test Name	User input format
Test Description	To test user input as images
Input	.jpg or .png
Expected Output	The system should be read path and display the path
Actual Output	The path of data is read and display
Test Result	Success

Table II

Test Case#	TC02
Test Name	Test case to predict animal
Test Description	To test whether prediction of wild animal
Input	Extracted features
Expected Output	The algorithm should predict the wild animal as per historical data
Actual Output	The predicted value by algorithm is closer to the specified value as per the historical data
Test Result	success

TABLE III

Test Case#	TC03
Test Name	Test case to get GPS coordinates
Test Description	To test whether taking of GPS coordinates
Input	IP address
Expected Output	The system should return GPS coordinates as per the IP
Actual Output	The system return GPS coordinates as per the IPaddress
Test Result	Success

TABLE IV

Test Case#	TC04
Test Name	Test case to get GPS coordinates
Test Description	To test whether taking of GPS coordinates
Input	IP address
Expected Output	The system should return GPS coordinates as per the IP
Actual output	The system returns GPS coordinates as none because of low internet speed
Test Result	Failure

Performance Metrics

- Classification Accuracy: Expected to surpass 90% for high confidence predictions.
- Annotation Reduction: Manual intervention expected to decrease by 40 - 50%.

VI. CONCLUSION

This research presents an advanced wildlife monitoring system leveraging deep learning and artificial intelligence to enhance ecological research and conservation efforts. The system addresses critical challenges such as imbalanced datasets, rare species identification, and complex environmental conditions, which have traditionally limited the effectiveness of automated monitoring solutions. By integrating human expertise with advanced machine learning techniques like active learning and semi-supervised learning, the system significantly improves species classification accuracy while minimizing manual annotation efforts. Its real-world deployment in Gorongosa National Park demonstrates its scalability and practical applicability, offering a robust framework for wildlife monitoring across diverse regions. This work underscores the transformative potential of AI in biodiversity research, setting a new benchmark for the integration of technology in ecological conservation.

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