

AI Based Wildlife Recognition System

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Abstract: *Wildlife recognition plays a crucial role in biodiversity conservation, ecological research, and wildlife monitoring. Traditional methods are time-consuming and error-prone, necessitating automated solutions. This research explores the implementation of an AI-based wildlife recognition system using the Residual Network (ResNet) model. The system classifies various wildlife species based on image inputs, improving accuracy and efficiency in wildlife monitoring. By leveraging deep learning techniques, the system enhances real-time species identification and minimizes human intervention, ensuring more reliable data collection for conservationists and researchers. Additionally, this study aims to improve scalability and deployment across various platforms, allowing integration with mobile applications, cloud services, and IoT-enabled wildlife monitoring systems. The proposed model is trained on a diverse dataset to ensure robustness in real-world applications.*

Keywords: Wildlife Recognition, AI, Deep Learning, ResNet, Image Classification, Conservation

I. INTRODUCTION

Wildlife recognition is an essential component of conservation efforts, allowing researchers, environmentalists, and park authorities to monitor and protect biodiversity. Traditional wildlife monitoring methods rely on manual identification through camera traps, direct observation, and expert classification, which can be time-consuming and prone to human errors. The advancement of Artificial Intelligence (AI) and deep learning has revolutionized species identification by enabling automated, accurate, and real-time classification of animals based on image data.

One of the most effective AI models for image classification is the Residual Network (ResNet), a deep learning architecture that overcomes the limitations of traditional Convolutional Neural Networks (CNNs). Introduced by He et al. in 2015, ResNet was designed to address the problem of vanishing gradients in deep neural networks. This issue often arises when networks become too deep, making it difficult for earlier layers to propagate meaningful gradients during backpropagation. ResNet introduces residual learning, which allows networks to train deeper architectures without suffering from degradation in accuracy.

ResNet Model and How It Works

ResNet is built on the concept of residual learning, where instead of learning the direct mapping between input and output, the model learns residual functions with reference to the input. This is achieved through the introduction of residual blocks. Each residual block contains shortcut connections (or skip connections) that bypass one or more layers. These shortcut connections help gradients flow directly through the network, mitigating the vanishing gradient problem and enabling training of very deep networks, such as ResNet-50 and ResNet-101.

Key components of ResNet include:

- **Residual Blocks:** These allow the model to learn identity mappings, ensuring that deeper networks do not suffer from accuracy degradation.
- **Batch Normalization:** Applied to each layer to normalize activations and accelerate training.
- **ReLU Activation Function:** Introduced after each convolutional layer to add non-linearity and enhance learning capacity.
- **Global Average Pooling Layer:** Reduces the dimensions of the feature maps before passing them to the fully connected layers for final classification.

ResNet's ability to effectively train deep networks makes it an ideal choice for wildlife recognition. By leveraging large-scale datasets, the model can accurately classify various species based on their unique features, such as fur

patterns, body shape, and coloration. This ensures that conservationists and researchers have access to reliable automated identification tools, improving monitoring efficiency and aiding in the protection of endangered species. By integrating ResNet into a wildlife recognition system, this study aims to enhance species identification with high precision, ultimately contributing to conservation efforts and ecological research.

II. PROBLEM STATEMENT

Wildlife conservation efforts require accurate and efficient species identification for monitoring biodiversity and protecting endangered species. Traditional methods of wildlife recognition involve manual classification using camera traps and direct observation, which are time-consuming, prone to human error, and often inefficient when dealing with large-scale datasets. These limitations hinder real-time monitoring and decision-making in conservation efforts.

With the advancement of Artificial Intelligence (AI) and deep learning techniques, automated wildlife recognition has become a viable solution. However, many existing AI-based models struggle with accuracy, particularly in distinguishing similar species and recognizing animals in complex backgrounds. The challenge lies in developing a robust, scalable, and high-accuracy model that can effectively classify multiple wildlife species in diverse environmental conditions.

This research aims to address these challenges by implementing a deep learning-based wildlife recognition system using the Residual Network (ResNet) model. The system will leverage ResNet's residual learning capabilities to enhance feature extraction, improve classification accuracy, and enable real-time species identification. By integrating this technology into wildlife conservation, the proposed system seeks to minimize manual intervention, enhance efficiency, and contribute to global biodiversity protection efforts.

III. OBJECTIVE AND SCOPE

The primary objectives of this research include:

- Developing an AI-driven system for wildlife species identification using deep learning.
- Enhancing classification accuracy by utilizing ResNet's residual learning framework.
- Reducing human intervention and improving real-time recognition capabilities.
- Assisting conservationists and researchers in monitoring and protecting wildlife.
- Creating a scalable and adaptable model that can be integrated into mobile and web applications.
- Exploring the possibility of real-time tracking and behavioral analysis of species.
- Improving dataset diversity to ensure the system performs well in different ecological conditions.

The scope of this research includes:

- Utilizing publicly available wildlife image datasets for training and testing.
- Implementing ResNet-50 due to its efficiency in deep learning-based image classification.
- Evaluating model performance based on accuracy, precision, recall, and F1-score.
- Testing the system on a variety of species across different ecological regions.
- Potential future integration with drone-based and real-time wildlife monitoring systems.
- Expanding the system to include real-time detection and identification of endangered species.
- Investigating the feasibility of integrating AI-powered tracking with IoT devices for continuous monitoring.

IV. PROPOSED METHODOLOGY

Data Collection:

- Gather a dataset of wildlife images from publicly available repositories, camera traps, and conservation organizations.
- Ensure the dataset includes multiple species, different lighting conditions, and varying backgrounds for robustness.
- Label the dataset with accurate species names for supervised learning.

Data Pre-processing:

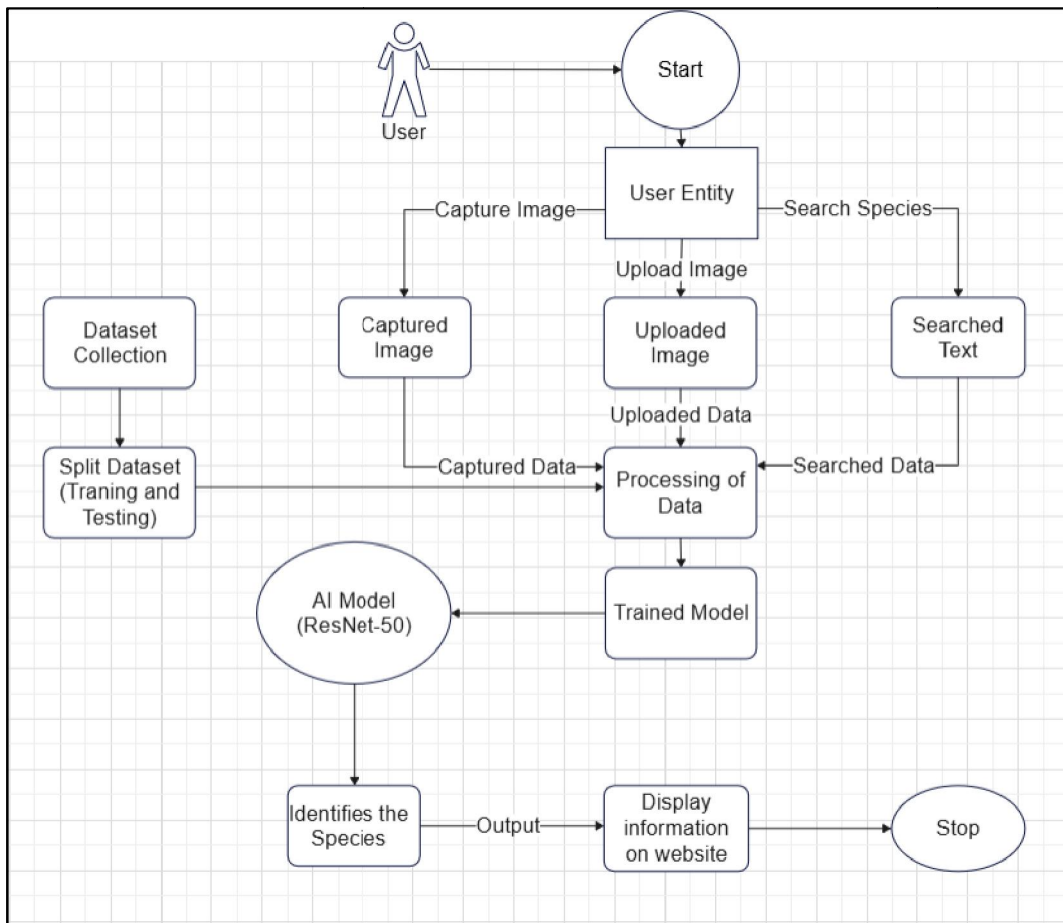
- Resize images to a uniform dimension suitable for ResNet processing (e.g., 224x224 pixels).
- Normalize pixel values to a specific range to enhance model training.
- Apply data augmentation techniques such as rotation, flipping, and contrast adjustments to improve generalization.

Model Selection and Training:

- Use a pre-trained ResNet model (ResNet-50 or ResNet-101) and fine-tune it for wildlife classification.
- Implement transfer learning by replacing the final classification layer with species-specific categories.
- Train the model using a split dataset (training, validation, and testing) to ensure high accuracy and prevent overfitting.

Model Evaluation:

- Evaluate the model using metrics such as accuracy, precision, recall, and F1-score.
- Use confusion matrices to analyze misclassifications and optimize the model.
- Conduct validation using unseen wildlife images to assess real-world performance.



Deployment and Integration:

- Develop an interactive web-based or mobile application for real-time wildlife recognition.
- Integrate the trained ResNet model into the application for instant species identification.
- Implement a database to store recognized species and provide insights for conservation efforts.

Testing and Optimization:

- Perform user testing to assess the functionality and accuracy of the system.
- Optimize model parameters and retrain with additional data if necessary.
- Enhance system performance by reducing latency and improving real-time classification speed.

Final Implementation and Monitoring:

- Deploy the system in real-world environments such as national parks and conservation centers.
- Continuously monitor and update the model with new wildlife data to improve accuracy over time.
- Collect feedback from conservationists and researchers for further improvements.

V. LITERATURE REVIEW

Sr. No.	Name of the document	Inference
1	Hao, X., Yang, G., Ye, Q., & Lin, D. (2019). <i>Rare Animal Image Recognition Based on Convolutional Neural Networks</i> . 12th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI). IEEE.	This paper proposes a convolutional neural network (CNN)-based approach to recognize rare animal species, specifically focusing on the Asian Slow Loris. The method eliminates the need for manual preprocessing and allows direct image input for identification. Experimental results show that increasing training sample size improves recognition accuracy. The study demonstrates CNN's efficiency in image classification and suggests future improvements in network structure for better accuracy.
2	Perera, T. A. S. A., & Collins, J. (2015). <i>Imaged Based Species Recognition System</i> . Ninth International Conference on Sensing Technology. IEEE.	This paper presents an animal species recognition system using the eigenface technique, originally developed for human face recognition. The study focuses on pest control in New Zealand, aiming to identify possums, cats, and weasels. Initial experiments showed low detection rates due to background variations, but accuracy improved when background was removed. The study concludes that eigenface-based recognition is computationally efficient but requires preprocessing for better accuracy.
3	Reddy, B. K., Kommineni, R., Bano, S., Reddy, G. G., & Reddy, P. Y. (2021). <i>Convolutional Network based Animal Recognition using YOLO and Darknet</i> . Sixth International Conference on Inventive Computation Technologies (ICICT). IEEE.	This paper explores the use of YOLOv3 and Darknet for real-time animal recognition. The proposed system processes input images and identifies animals using a pre-trained COCO dataset. The model performs well with high accuracy and fast processing times. However, misclassifications occur in some cases, indicating areas for improvement. The study highlights the effectiveness of YOLOv3 for automated animal detection and suggests further optimizations for better performance.

4	<p>Manohar N, Subrahmanya S, Bharathi R K, Sharath Kumar Y H, Hemantha Kumar G. (2016). "Recognition and Classification of Animals based on Texture Features through Parallel Computing." 2016 <i>Second International Conference on Cognitive Computing and Information Processing (CCIP)</i>, IEEE.</p>	<p>The paper presents a method for animal recognition and classification using texture-based features extracted with Gabor filters, employing k-Nearest Neighbors (k-NN) and Support Vector Machines (SVM) for classification. Parallel computing is used to improve processing efficiency, especially for large datasets of over 3000 images across 30 animal classes. Experimental results show that k-NN outperforms SVM in accuracy, and parallelization significantly reduces computational time. The study highlights the importance of texture features in distinguishing animals and suggests that future work could integrate deep learning for further improvements.</p>
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VI. CONCLUSION

In this study, we proposed an AI-based wildlife recognition system using the ResNet model to enhance species identification and conservation efforts. The implementation of deep learning techniques enables accurate, real-time classification of animals, reducing dependency on manual observation and minimizing errors. Through data collection, preprocessing, model training, evaluation, and deployment, we developed a scalable and efficient solution for automated wildlife monitoring.

The use of ResNet, with its residual learning capabilities, significantly improves classification accuracy, even in complex environments with diverse species and challenging backgrounds. By integrating this system into conservation programs, researchers and environmentalists can make data-driven decisions for wildlife protection and biodiversity management.

Future enhancements may include expanding the dataset with more diverse species, improving real-time processing capabilities, and integrating additional AI techniques for better species differentiation. This system represents a step forward in leveraging AI for ecological preservation, contributing to global efforts in wildlife conservation and environmental sustainability.

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