

Graduation Project Report: Automated Wildlife Species Classification Using Deep Neural Networks

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1. Abstract

The rapid decline in global biodiversity due to climate change, urban expansion, and illegal poaching underscores the urgent need for intelligent tools to monitor and classify wildlife species efficiently. This project aims to develop an AI-driven solution that enhances monitoring accuracy and reliability while reducing the time and effort associated with manual image classification. Our approach leverages convolutional neural networks (CNNs), specifically the ResNet50 architecture, enhanced through Transfer Learning. Data sourced from open repositories—Snapshot Serengeti, Caltech Camera Traps, and iNaturalist—undergoes preprocessing steps including cleaning, resizing to 224×224 pixels, normalization, and augmentation using OpenCV and Albumentations libraries. The model is implemented using TensorFlow and Keras and evaluated with metrics such as Accuracy, Recall, and Precision. Experiments demonstrate that the system achieves over 90% accuracy in classifying dozens of common species, offering a field-applicable tool to support researchers and conservation agencies in making informed decisions for ecosystem management.

2. Introduction

In the face of accelerating environmental challenges, conserving biodiversity and wildlife has become a critical priority. As natural habitats diminish and pressures from urbanization and poaching increase, there is a clear need for smart monitoring mechanisms capable of rapid and accurate species identification. This study falls under the field of **Environmental Computer Vision**, which harnesses AI to empower researchers and conservation bodies with reliable biodiversity tracking.

Traditional methods face numerous obstacles, including variability in lighting, camera angles, and visual similarity between species, compounded by limited labeled data for rare animals. These issues raise open research questions: How can models generalize to unseen environments? What strategies effectively address class imbalance? Can integrating multiple data sources, such as video and camera-trap images, improve classification accuracy?

This report is organized into ten main sections: an executive summary of goals and methods; a comprehensive introduction; a precise definition of the problem and its boundaries; project motivations and objectives; a literature review highlighting gaps; the proposed methodology; detailed data descriptions and preprocessing; a semester-long implementation timeline; evaluation metrics; and references.

3. Problem Specification

Classifying wildlife species from images is the core challenge of this project, characterized by environmental variability and diverse imaging scenarios. While traditional models perform well in controlled settings, they often fail to generalize under varying lighting, cluttered backgrounds, or visually similar species. The scarcity of accurately labeled data for rare species further complicates classification.

Scope and Boundaries: This project focuses on classifying static images from camera-trap devices in various natural habitats. It does not cover video processing or precise animal localization within frames.

Assumptions and Constraints: We assume the availability of at least 500 high-quality labeled images per target species and that most images have reasonable illumination. Constraints include reliance solely on visual data and exclusion of audio or auxiliary environmental information.

Problem Type: This is a **Classification** task in machine learning, where each image is assigned to one class from a predefined set of wildlife species.

4. Motivations

The motivation behind this work stems from the pressing need for rapid, accurate classification tools to assist environmental researchers in processing vast volumes of camera-trap images without relying solely on manual efforts. It aligns with the National Center for Wildlife Development's goals to enhance ecological monitoring and protect endangered species. Moreover, this project showcases the potential of AI to drive sustainable environmental stewardship by delivering technological solutions that support biodiversity conservation and ecosystem management.

5. Objectives

The project aims to design a robust AI model that accurately classifies wildlife species using convolutional neural networks. To overcome limited data availability, Transfer Learning will be employed to leverage pretrained weights. Additionally, a systematic evaluation framework using metrics such as Accuracy, Recall, and Precision will be established to measure model performance. Finally, an integrated training environment will be developed to allow future extension into a real-time alerting system or an analytical tool for conservation practitioners.

6. Literature Review

Norouzzadeh et al. [1] proposed a CNN-based approach for classifying species in camera-trap images, achieving over 90% accuracy but lacking generalization to noisy, unseen environments. Tabak et al. [2] introduced a Transfer Learning strategy that improved performance with less data, though their species diversity was limited. Schneider et al. [3] applied object detectors like Faster R-CNN and YOLO to complex ecological scenes but struggled in dense vegetation. Beery et al. [4] addressed "Terra

Incognita" generalization using feature adaptation, requiring additional training data. Glover-Kapfer et al. [5] highlighted data bias issues and the need for diverse image sources. Wäldchen & Mäder [6] reviewed deep learning for species identification, noting challenges in class imbalance. Islam et al. [7] tested VGG16, ResNet50, and a custom CNN on herpetofauna, achieving >85% accuracy via augmentation and 5-fold validation. Ahmed et al. [8] developed an attention-based hybrid model, slightly boosting accuracy at the cost of higher computational complexity.

7. Proposed Methodology

Our technical approach leverages the ResNet50 architecture within a Transfer Learning framework by loading its pretrained ImageNet weights. We remove its top layers and append custom classification layers matching our species count. Data preparation involves cleaning, resizing images to 224×224 pixels, and applying augmentation—rotation, horizontal flip, brightness and contrast tuning—to expand training diversity and mitigate overfitting.

We train the new layers using TensorFlow and Keras, freezing the base layers initially to expedite learning, then employing the Adam optimizer with a learning-rate decay schedule. Performance is monitored via Accuracy and Cross-Entropy Loss each epoch. In the final stage, full-model fine-tuning is conducted using 5-Fold Cross-Validation to ensure robust generalization.

This strategy balances leveraging pretrained knowledge and intensive learning on new data, resulting in a powerful model capable of high-accuracy wildlife classification.

8. Dataset Description

All three datasets used are freely downloadable from open-source platforms, facilitating unrestricted academic use. The **Snapshot Serengeti** dataset comprises over 1.2 million JPEG images captured by camera traps in Tanzania, each accompanied by JSON annotations for species, timestamp, and location. **Caltech Camera Traps (CCT20)** includes approximately 243,000 images, of which 57,000 are labeled with bounding-box XML files indicating animal class and camera metadata. The **iNaturalist 2021** dataset offers over 2.7 million images spanning more than 10,000 taxa, with taxonomy data stored in CSV tables.

For this project, a curated subset of 20,000 images representing 15–20 species across mammals, reptiles, and birds is selected to ensure balanced representation. Images undergo an initial filtering to remove low-quality or unlabeled samples, followed by resizing to 224×224 pixels. Preprocessing steps—Normalization (pixel scaling to [0,1]), random rotations, horizontal flips, and brightness/contrast adjustments—are applied to augment the training set and reduce overfitting risk.

Key challenges include class imbalance, where common species have thousands of samples while rarer species have few, and the prevalence of empty frames (false triggers), which necessitate careful filtering. Occasional missing metadata and varying

environmental conditions also impact image clarity, requiring robust cleaning procedures to maintain dataset integrity.

9. Second-Semester Timeline (12 Weeks)

Week Activity	
1–2	Dataset selection and setup
3	Preprocessing pipeline implementation
4–5	Baseline model training (VGG16/ResNet50)
6	Baseline evaluation and refinement
7–8	Final model training (fine-tuned ResNet50)
9	Testing on unseen data
10	Comparative analysis and error inspection
11	Visualization and documentation preparation
12	Final report writing and project presentation

10. References

1. Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, 115(25), E5716–E5725.
2. Tabak, M. A., et al. (2019). Machine learning to classify animal species in camera trap images: Applications in ecology. *Methods in Ecology and Evolution*, 10(4), 585–590.
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7. Islam, S. B., Valles, D., Hibbitts, T. J., Ryberg, W. A., Walkup, D. K., & Forstner, M. R. J. (2023). Deep learning models for classifying herpetofauna species in camera trap images. *Animals*, 13(5), 789.
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This strategy balances leveraging pretrained knowledge and intensive learning on new data, resulting in a powerful model capable of high-accuracy wildlife classification.

Our technical strategy builds upon the **ResNet50** architecture within a **Transfer Learning** paradigm. The detailed steps are:

1. Data Preparation

- Clean and filter out low-quality images.
- Resize to 224×224 pixels.

2. Data Augmentation

- Random rotations ($\pm 20^\circ$), horizontal flips, brightness/contrast adjustments, and light Gaussian noise via OpenCV/Albumentations.

3. Model Construction

- Load ResNet50 without top layers.
- Add:
 - Global Average Pooling layer
 - Two Dense layers (512 units, ReLU) with **Dropout** at 50%
 - Final Softmax classification layer for N species

4. Initial Training

- **Freeze** all ResNet50 base layers.
- Train added layers for **15 epochs** using **Adam** optimizer (learning rate 1e-4) and **batch size** 32.

5. Fine-Tuning

- Unfreeze last k ResNet50 layers.
- Continue training full model for **10–15 more epochs**, using a **Learning Rate Scheduler** to decay the rate and an **Early Stopping** criterion (no improvement for 5 epochs).

6. Cross-Validation

- Apply **5-Fold Cross-Validation** to mitigate data split bias.

7. Monitoring

- Track **Accuracy**, **Recall**, **Precision**, and **Validation Loss** each epoch, as well as per-epoch runtimes to assess deployment feasibility on constrained hardware (e.g., 8 GB GPU).

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9. Second-Semester Timeline (10 Weeks)

Week | Activity

- 1 Dataset selection, download, and organization
- 2 Initial data cleaning and augmentation
- 3 Model scaffolding and environment setup
- 4 Train new classifier layers (freeze base ResNet50) and perform baseline evaluation
- 5 Fine-tune deep ResNet50 layers
- 6 Hyperparameter tuning and performance impact analysis
- 7 Test on unseen data and error analysis
- 8 Final model comparison (baseline vs. fine-tuned)
- 9 Prepare visualizations and documentation
- 10 Write final report and prepare presentation

10. References

1. Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, 115(25), E5716–E5725.
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