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Project: Wildlife Monitoring

Project Overview:

This project aims to improve the classification accuracy of snow leopards using deep learning techniques applied to camera trap images. Current wildlife monitoring systems face challenges in accurately detecting and distinguishing snow leopards from other animals, particularly in the night or bad weather. Our approach involves developing an optimized deep learning pipeline that integrates advanced convolutional neural networks (CNNs) models to enhance feature extraction and classification. We will experiment with data augmentation techniques, domain adaptation strategies, and self-supervised learning to improve robustness across varying environmental conditions. The final system will be evaluated against existing baselines using standard metrics such as precision, recall, and F1-score, with the goal of deploying an efficient and scalable snow leopard classification model to support wildlife conservation efforts.

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Literature Review:

Recent advancements in deep learning have significantly enhanced wildlife monitoring, particularly in challenging environments. Several studies focus on optimizing object detection under low-light conditions, which is crucial for nocturnal species like snow leopards. For instance, Alam et al. introduced **YOLOv8-night**, integrating a novel channel attention mechanism to improve nighttime detection accuracy in infrared imagery [1]. This architecture dynamically selects between orthogonal and average pooling channel compression, enhancing feature focus while suppressing noise. Such innovations address key challenges in our project, such as detecting snow leopards in nocturnal or obscured environments. Similarly, Redmon et al. demonstrated the efficacy of **YOLO** frameworks for real-time detection, emphasizing global image context to reduce background errors—a critical advantage for minimizing false positives in complex terrains [5]. These works collectively highlight the potential of combining attention mechanisms with real-time detection pipelines to improve robustness in varying environmental conditions.

Species-specific classification, another core aspect of our project, has been advanced through convolutional neural networks (CNNs). Chen et al. achieved 98.05% binary classification accuracy using CNNs for badger identification, underscoring their utility in differentiating species in camera-trap data [2]. Further, Smith et al. employed cascading CNNs for hierarchical detection, achieving 99.8% object detection accuracy and 97.6% species recognition, while addressing challenges like pose variation through data augmentation [3]. These approaches align with our goal of refining snow leopard identification and reducing human-leopard conflicts via real-time alerts. Additionally, Patel et al. emphasized feature extraction and dataset balancing using dense SIFT and LBP features, achieving 82% accuracy on an 18-species dataset [4]. Their insights into handling imbalanced data and poor illumination directly inform our strategies for optimizing camera-trap images.

The datasets used for wildlife classification in these studies vary in size, structure, and complexity, depending on the specific application and species diversity. Many studies utilize publicly available datasets such as iNaturalist, Snapshot Serengeti, and Caltech-UCSD Birds (CUB-200), which contain labeled images of various animal species captured in diverse environmental conditions **(Smith et al., 2020)**. These datasets often feature high intra-class variability due to differences in lighting, pose, background clutter, and occlusion. One study leveraged a large-scale dataset with over 3.4 million labeled images across 814 species, significantly enhancing model generalization and robustness **(Chen et al., 2023)**. Additionally, some research incorporates custom-curated datasets collected from camera traps, drones, or satellite imagery to address real-world challenges such as imbalanced class distributions and low-resolution images. Data preprocessing techniques such as image augmentation, normalization, and filtering are commonly employed to improve model generalization. Annotation methods vary from expert manual labeling to semi-automated approaches using weak supervision or active learning. The choice of dataset and its characteristics significantly impact the performance of classification models, and thus careful selection and preprocessing is required to achieve optimal results.

Together, these studies provide a foundation for integrating real-time detection, attention mechanisms, and hierarchical CNNs into our system. However, gaps remain in adapting these methods to snow leopard-specific challenges, such as sparse training data and camouflage in rocky habitats. Unlike traditional wildlife classification problems where species are more visually distinct, snow leopards often blend into their surroundings, making feature extraction more difficult. Our work builds on these existing frameworks by tailoring channel attention mechanisms and cascading CNNs to enhance both detection and classification accuracy in this unique context.

GitHub Resources and Datasets:
Github:

1. Pytorch-Wildlife: a working space to use datasets and deep learning architectures for wildlife conservation. https://github.com/microsoft/CameraTraps
2. Leopard Detection: This project implements custom object detection for leopards using the YOLO framework. It includes scripts for training models and processing live camera feeds. https://github.com/arnav-deep/leopard-detection
3. WildTrack AI: Footprint Identification for Wildlife Monitoring. https://github.com/jtdsouza/w251-WildTrackAI

Datasets:

1. 1.3K Snow leopard labeled image dataset https://images.cv/download/snow_leopard/1286
2. Wildlife Animals (SnowLeopard-BrwonBear-Markhor) https://www.kaggle.com/datasets/hunzaikashif49/wildlife-animals-snowleopard-brwonbear-markhor
3. Animal_classification https://universe.roboflow.com/animal-classification-1sqi5/animal_classification-xbfiq/dataset/2

References:

[1] Wang, et al. *"Night Time Wildlife Object Detection Based on YOLOv8-Night."* 2023. https://ietresearch.onlinelibrary.wiley.com/doi/full/10.1049/ell2.13305

[2] Chen, Ruilong, et al. *"Wildlife Surveillance Using Deep Learning Methods." Ecology and Evolution*, vol. 9, 2019. https://onlinelibrary.wiley.com/doi/epdf/10.1002/ece3.5410 .

[3] Smith, et al. *"Animal Species Recognition Using Deep Learning."* 2021. https://www.researchgate.net/publication/340244662_Animal_Species_Recognition_Using_Deep_Learning .

[4] Patel et al., "Automated Identification of Animal species in Camera Trap Images," 2020. https://jivp-eurasipjournals.springeropen.com/articles/10.1186/1687-5281-2013-52

[5] Redmon et al., "YOLO-Unified Real time object detection," 2016. https://arxiv.org/abs/1506.02640

[6] Sydel, Rachel, et al. "Human expertise combined with artificial intelligence improves performance of snow leopard camera trap studies." *Global Ecology and Conservation*, vol. 39, 2022, e02210. ScienceDirect, https://www.sciencedirect.com/science/article/pii/S2351989422003523?ref=pdf_download&fr=RR-2&rr=9270fe1438c8a75a