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Animal Recognition and Identification Using AI

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Abstract- ***This paper introduces Animal Vision, a system based on AI for the automatic detection and recognition of animals using state-of-the-art deep learning techniques. It focuses its study only on approaches and techniques concerning the identification of wildlife without including results related to system performance. This system integrates object detection architectures like YOLOv5, FCOS, and Cascade R-CNN, together with CNN-based frameworks for species classification. These techniques make it possible to analyze camera-trap images automatically, thereby supporting applications on wildlife conservation, ecological monitoring, and surveillance.***

Index Terms- ***Artificial Intelligence, Deep Learning, YOLOv5, FCOS, Cascade R-CNN, CNN, Animal Identification***

I. INTRODUCTION

Identifying animals matters a lot in tracking wildlife, studying biodiversity, and doing ecological work. Old ways of spotting them by hand take too much time and effort. Now that deep learning has come along, automated tools can handle huge sets of pictures from camera traps pretty easily.New studies show how deep neural networks work well for finding and sorting species. These setups pull out details from tough settings, deal with different animal forms and positions, and help set up automatic processes for wildlife projects. Earlier methods like pulling deep features, using anchors or going without them for object spotting, and classifying by species all build the base for the Animal Vision setup.

II. METHODOLOGY

Animal Vision is founded on the basis of deep learning methodologies that have already been employed in studies related to wildlife identification. First of all, there is the preparation of camera-trap images by resizing, normalization, and structured annotation. Standard data augmentation techniques include flipping, rotation, cropping, and brightness adjustments to increase variability and help the model generalize across a wide range of environmental conditions. This preprocessing allows the system to handle diverse wildlife imagery, including variations in angle, lighting, and partial occlusion.

The system integrates several modern architectures that allow for both detection and recognition. YOLOv5 serves as a one-stage detector, realizing fast, anchor-based object detection. FCOS is an anchor-free detector that predicts object positions directly, while Cascade R-CNN is a two-stage detector that refines bounding boxes across multiple stages for higher-quality localization. Following detection, the classification of species is done through CNNs, which extract deep visual features by convolution and pooling and classify animal species by fully connected layers. Thus, putting together all of these models of detection and classification yields a complete pipeline able to automatically recognize animals in natural scenes.

III. RESULTS AND DISCUSSION

The use of YOLOv5, FCOS, and Cascade R-CNN brings a reliable framework for detecting animals under both favorable and adverse environmental conditions, while the CNN-based classifier identifies the species effectively by learning the key features, including shape and texture. Together, these techniques create a cohesive system that can automatically identify animals in camera-trap images and demonstrate the practicality of deep learning methods for streamlined and consistent wildlife monitoring.

IV. CONCLUSION

The Animal Vision system exemplifies how contemporary deep learning methods can be synthesized to develop a successful system for

automated animal identification. By merging advanced detection models, such as YOLOv5, FCOS, and Cascade R-CNN, into CNN-based species classification, the system is able to process camera-trap images in a systematic and consistent manner. These methods facilitate effective wildlife monitoring, reducing manual effort and achieving continuous identification across varying conditions. Future improvements could involve moving to a broader set of species, integrating more sensor modalities, and deploying the system on edge devices for use in real-time field applications.

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