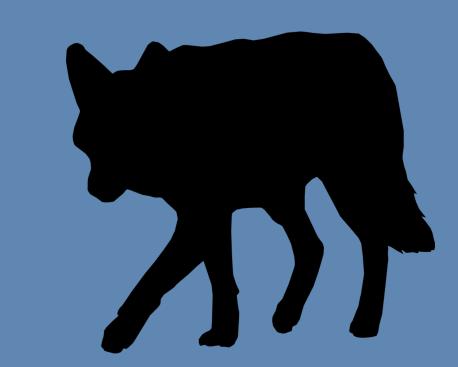


## Wildlife Camera-Trap Classification

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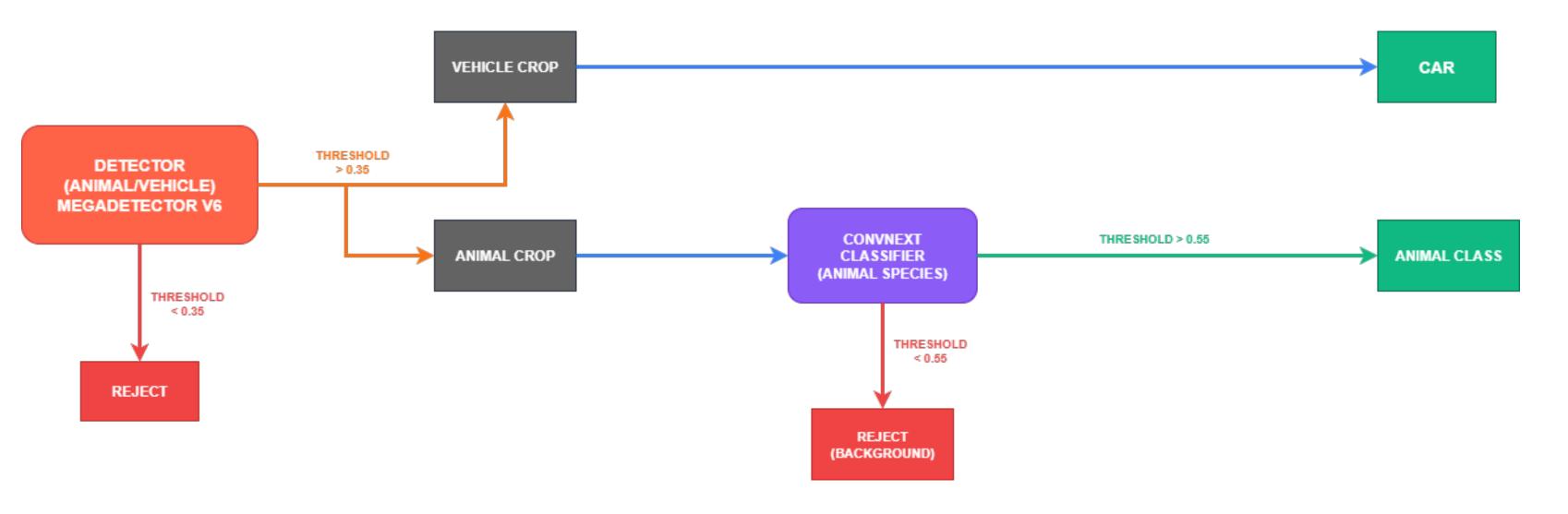


## **Abstract**

Camera-trap imagery enables large-scale wildlife monitoring but suffers from domain shift, where models fail on unseen locations. We propose a two-stage pipeline (MegaDetector v6 + ConvNeXt-Small) for detection and classification, achieving F1 scores of 0.84 (seen) and 0.71 (unseen) on CCT20. Our modular design cuts cross-domain error by 24.2% while maintaining high recall for rare species, enabling robust and scalable conservation monitoring.

## **Problem Definition and Contribution**

**Problem:** Camera trap images present unique difficulties, night-time infrared capture, motion blur, partial occlusion, weather conditions, and class imbalance. Models struggle to generalize across different camera locations due to site-specific environmental variations.



Two-Stage Pipeline: MegaDetector v6 → ConvNeXt Classifier

**Key Innovation:** Modular design with threshold-based decision points (0.35 detection, 0.55 classification) enables independent optimization and robust cross-domain deployment.

## Dataset & Challenges

**CCT20 Dataset:** 51,000+ images, 20 locations, 13 species + vehicle

### **Main Challenges:**

- Domain shift: performance drops on new locations
- Class imbalance: some species are very rare
- Poor conditions: night vision, motion blur, occlusion
- Environmental noise: rain, fog, camera malfunctions







Unseen (test) — Coyote, night IR, motion blur.

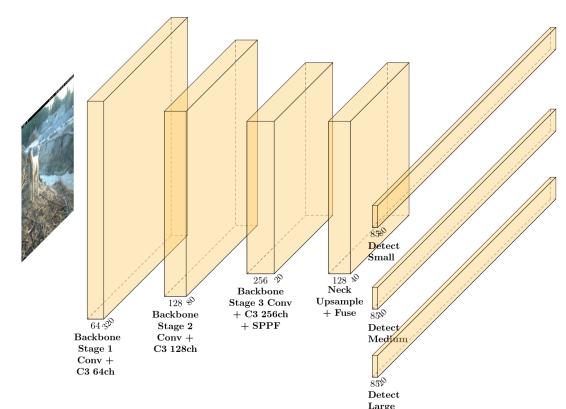
## Method

## $\begin{array}{c} \textbf{ConvNeXt-Small} \\ \hline \\ \textbf{GAP} \\ \textbf{Stage 0} \\ \textbf{Stage 0} \\ \textbf{Down} \\ \textbf{Stage 1} \\ \textbf{Stage 2} \\ \textbf{Stage 2} \\ \textbf{384ch} \\ \textbf{Stage 2} \\ \textbf{384ch} \\ \textbf{Stage 3} \\ \textbf{768ch} \\ \textbf{Stage 3} \\ \textbf{768ch} \\ \textbf{Stage 1} \\ \textbf{192ch} \\ \textbf{Stage 2} \\ \textbf{384ch} \\ \textbf$

- Efficient CNN with depthwise  $7 \times 7$  convolutions and MLP blocks.
- Large receptive field for robustness to domain shift.

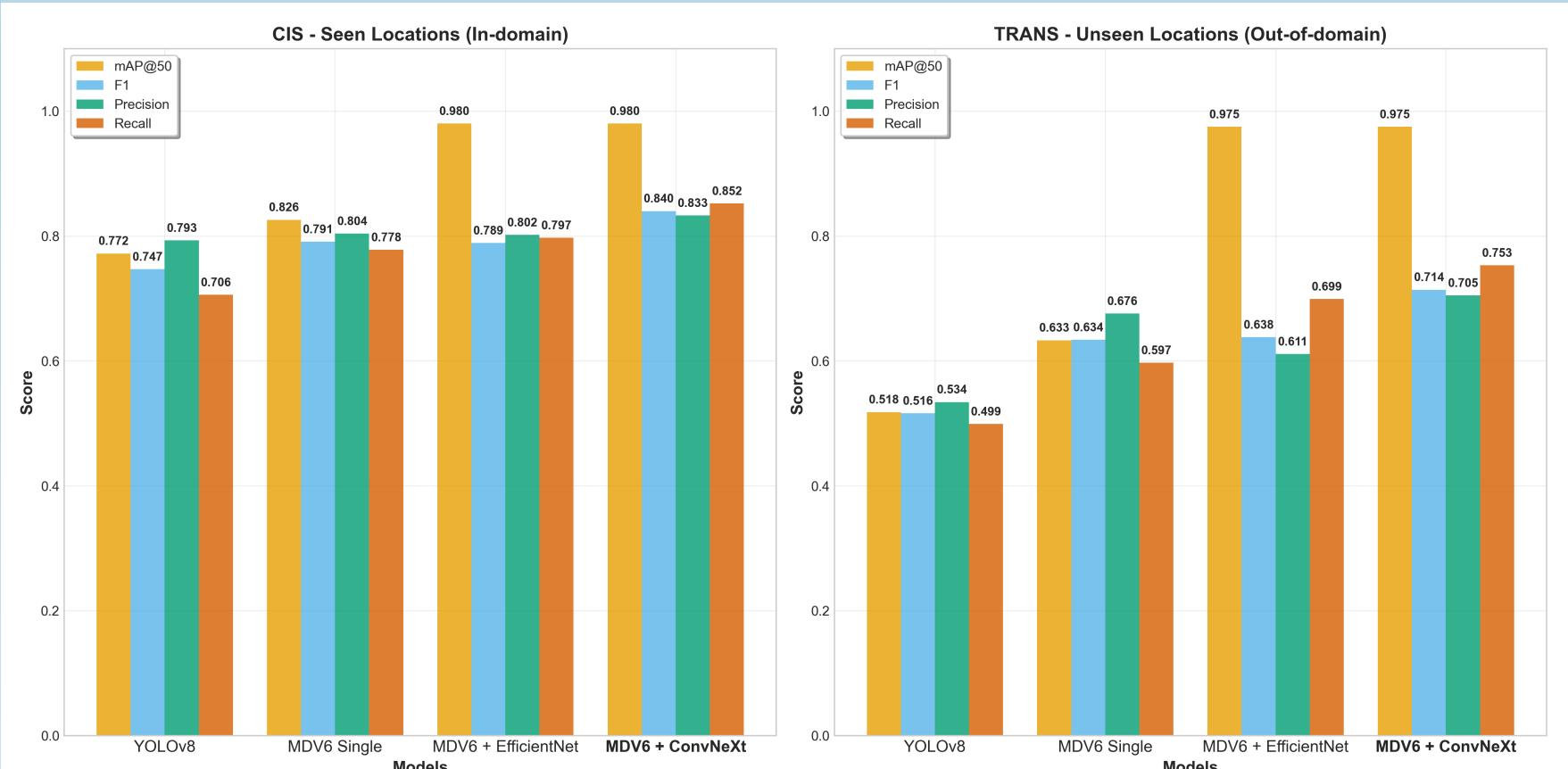
**CIS** (seen) — row-normalized

## MegaDetector v6 (YOLOv9-c)

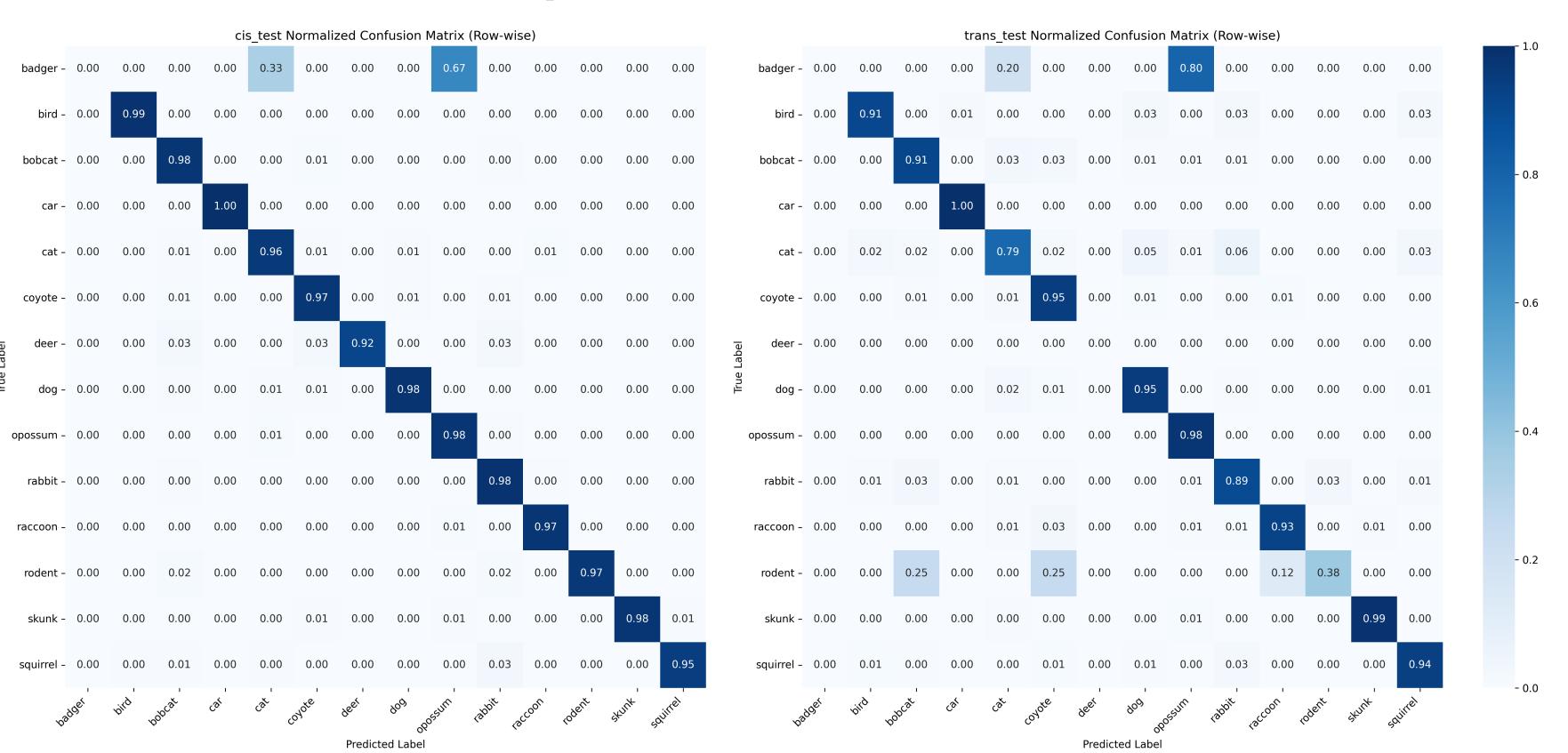


- YOLO-style detector with FPN, SPPF, and 3-scale heads.
- Trained for binary animal vs. vehicle detection with high recall.

## **Experiments & Results**



Detector (MDV6) achieves high accuracy in separating animals from vehicles: CIS - 97.9% precision, 97.3% recall (F1 = 97.6%); TRANS - 96.4% precision, 95.6% recall (F1 = 96.0%).



TRANS (unseen) — row-normalized

# MDV6 + EfficientNetV2-S MDV6 + ConvNeXt-S MDV6 + ConvNeXt-S

## **Future Work & Conclusion**

- Two-stage MDv6 + ConvNeXt-Small reduces domain shift and maintains high precision/recall on unseen locations.
- Enhance rare-class detection via active learning on hard negatives & tail species.
- Leverage photo metadata (e.g., time of day, location) for context-aware classification.
- Experiment on the full CCT dataset for broader generalization.



Web App

References

GitHub Repository

- 1. Beery, S., et al. (2018). Recognition in Terra Incognita. *ECCV*.
- Norouzzadeh, M. S., et al. (2018). Auto ID of wild animals. *PNAS*.
   Microsoft AI for Earth (2023). MegaDetector v6. GitHub.
- 4. Liu, Z., et al. (2022). ConvNeXt. *CVPR*.