Deep Learning
Project

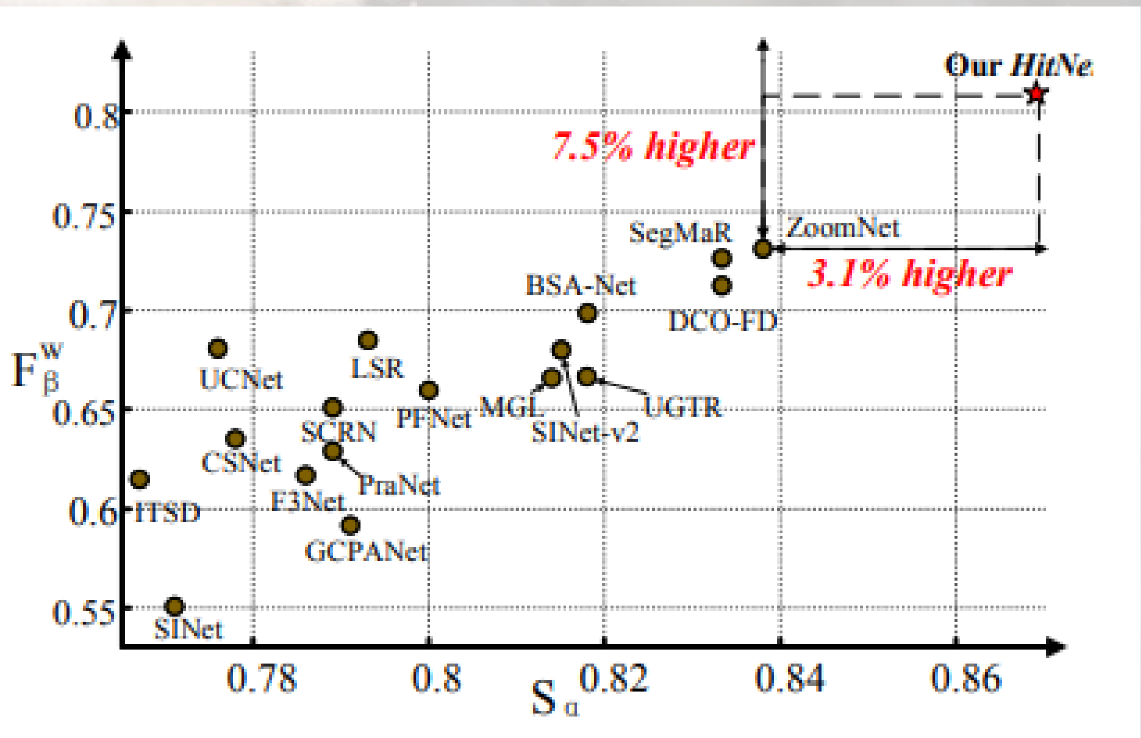
M. Tayyab Haider 26100275
M. Hammad Yousaf 26100387

High-Resolution Iterative Feedback Network for Camouflaged Object Detection

Xiaobin Hu1 , Shuo Wang2 , Xuebin Qin3 , Hang Dai4*,
Wenqi Ren5 , Donghao Luo1 ,
Ying Tai1 , Ling Shao6

June 2023

- <u>Iterative Feedback</u>: Fixes blurry edges in hidden animals (e.g., snow leopards) by refining low-res features with high-res details.
- <u>PVT Backbone</u>: Efficiently analyzes images at multiple scales (¼, ⅛, 1/16, 1/32)
- <u>Multi-Resolution Feedback Refinement (RIR)</u>: Iteratively merges HR/LR features via <u>Feedback Blocks (FB)</u> to preserve edges (e.g., fur, whiskers).
- <u>Adaptive Feature Fusion (AFF)</u>: Dynamically combines features across iterations for robustness to occlusions
- <u>Cross-Domain Learning (CDL):</u> Produces synthetic camouflaged data from salient objects to complement limited datasets.
- <u>Edge Preservation</u>: Precisely segments fine boundaries (whiskers, paw outlines) in snowy/rocky landscapes.
- *Occlusion Handling*: Robust to partial visibility (e.g., leopards behind rocks).
- <u>COD10K</u>: Obtains F-measure = 0.804 (7.5% better than ZoomNet) and MAE = 0.023 (16.9% less error).
- <u>Sparse Datasets</u>: Exceeds SOTA on CAMO (F-measure = 0.806) and CHAMELEON (edge preservation of small animals).
- Minimizes human-wildlife conflict by enhancing detection reliability in adverse environments



Weighted F-measure vs. Structure-measure of top 17 models from 35 SOTA methods

Predictive Uncertainty Estimation for Camouflaged Object Detection

Yi Zhang, Jing Zhang, Wassim Hamidouche, Olivier Deforges

Dataset Images are generally exactly centered,
Not fit for uncentered wildlife imagery
Zero Bias (Epistemic Uncertainty)

↓

Models overfit to center regions, failing to detect off-center objects in real-world scenarios.

Camouflaged objects blend into their surroundings, making it hard for annotators to precisely label boundaries.
This leads to inconsistent or noisy ground-truth masks
Data Bias (Aleatoric Uncertainty)

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Models trained on noisy labels learn incorrect object boundaries, reducing segmentation accuracy.

<u>Bayesian Conditional Variational Autoencoder (BCVAE):</u>
Epistemic Uncertainty: Models parameter uncertainty via Bayesian inference, reducing reliance on biased training patterns (e.g., center bias).
Aleatoric Uncertainty: Uses latent variables to capture inherent noise in the data (e.g., label ambiguity).

<u>Predictive Uncertainty Approximation (PUA):</u>
Combines epistemic and aleatoric uncertainties into a single predictive uncertainty map., improves efficiency

PUENet reduces overfitting to biased data (e.g., center bias) and noisy labels.
Outperforms SOTA models like SINet-V2 on benchmarks (CAMO, COD10K) with higher F1 scores and better uncertainty calibration.

<u>Limitations and Future Work</u>
Out-of-Distribution (OOD) Data: While uncertainty maps flag unreliable predictions, PUENet does not fully resolve performance drops on unseen environments.
Calibration:Predictive uncertainty may still be miscalibrated for extreme cases (e.g., novel camouflage patterns).
Scalability:Training on larger, more diverse datasets could further mitigate biases.

To crop or not to crop: Comparing whole-image and cropped classification on a large dataset of camera trap images

Tomer Gadot, Ștefan Istrate, Hyungwon Kim, Dan Morris, Sara Beery, Tanya Birch, Jorge Ahumada

First published: 24 November 2024

Datasets:
Wildlife Insights (WI): 51M images (private, long-tailed).
LILA: 14.8M public images.
iWildCam: 180k benchmark images (ID/OOD splits).

Models:
Detector:
MegaDetector v5a (YOLOv5x6) to crop animals.
Classifier:
EfficientNetV2-M trained on crops vs. whole images.
Ensembles:
Combined detector + classifier predictions.

Data Filtering:
Removed noisy labels using high-confidence MegaDetector predictions.

Key Results
Cropping Boosts Accuracy:
+25% macro F1 on long-tailed datasets (WI, LILA).
Outperformed whole-image models on all metrics (Table 6).
State-of-the-Art Performance:
61.9% macro F1 on iWildCam OOD test, rivaling top leaderboard models.
Filtering Reduces Noise:
Training on filtered data improved OOD macro F1 from 0.38 → 0.49.

Findings And Future work

- Proposed Solution:
- Leverage SOTA COD Models:
- PUENet: Addresses model/data bias via uncertainty estimation (BCVAE + PUA).
- HiNet: Uses iterative feedback (PVT backbone) to refine edges in high-resolution images.
- Data Augmentation:
- Use CycleGAN to synthesize snow leopard images from existing COD datasets (COD10K, CAMO).
- Apply MegaDetector v5a to crop wildlife images (WI, LILA) for focused training.
- Key Innovations:
- Cross-Domain Learning: Pre-train on general COD datasets, fine-tune with synthetic snow leopard data.
- Uncertainty Maps: PUENet flags unreliable predictions for human review.
- Edge Refinement: HiNet's feedback loops preserve whiskers/paw edges in snowy backgrounds.
- Next Steps:
- Generate synthetic snow leopard datasets.
- Fine-tune HiNet/PUENet on cropped wildlife images.
- Carry out further research and testing to improve and build on the already existing methodologies.