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Efficient uncertainty-guided post-processing of semantic segmentation maps

Reliable semantic segmentation is a key to model deployment in critical domains such as the medical or automotive industry. When model performance drops—especially under domain shifts—retraining can be costly and data-dependent. In this poster, we present a post-hoc approach to improve segmentation outputs at by using uncertainty-guided postprocessing without a need for retraining.

We compute epistemic uncertainty of pre-trained models using three methods: test-time augmentation, Monte-Carlo dropout, and softmax entropy. These pixel-wise uncertainty estimates are then used to filter, suppress, or refine segmentation masks through standard image processing techniques and threshold-based heuristics. Our approach is applied on state-of-the-art pre-trained segmentation models, with a focus on performance under out-of-distribution conditions. Our evaluation also includes a label noise scenario to test whether uncertainty maps reflect semantic confusion and whether postprocessing mitigates its effects.

We evaluate our approach based on Intersection over Union (IoU) improvements, computational overhead, and qualitative visualization. We also implement an interactive interface for visualizing uncertainty maps, aiming to support model evaluation, interpretation, and uncertainty-aware data selection in continuous training pipelines.

This work highlights how lightweight, interpretable methods can enhance segmentation robustness and visualization without retraining, contributing to trustworthy computer vision workflows.

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