SAPIENZA
UNIVERSITÀ DI ROMA

Uncertainty-Aware Road Obstacle Identification

Master's Degree in Artificial Intelligence and Robotics 24/25

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Outline

Problem Statement

Model-agnostic framework for road **obstacle identification**, starting from the outputs of any semantic segmentation network

The system will focus on **anomaly-aware** semantic segmentation to detect obstacles **outside the predefined classes**

Integrated **uncertainty quantification** through **Conformal Prediction** methods, to ensure a reliable measure of **confidence**

- Anomaly-Aware Obstacle Segmentation

- Statistical Uncertainty Quantification

- Comprehensive Evaluation

State of the Art

Anomaly-detection techniques, such as **uncertainty estimation** and **perceptual difference** from reconstructed images, make it possible to identify pixels of unknown objects as OoD samples

When applied to images with many unknowns and complex components, such as driving scenes, these methods often exhibit **unstable performance**

Autoencoder-based Approaches

Encoder maps images into a feature space and decoder attempts to reconstruct the original image

Uncertainty-based Approaches

Bayesian neural networks methods, Softmax entropy methods

Proposed Method

Multi-label One-Hot Encoding and Classes

redefinition of CityScapes macro-classes and computation of **multi-label masks**

DeepLabV3+ ResNet50 with sigmoid head

implementation of the ResNet50 network with a final **sigmoid head** instead of softmax

Boundary Aware BCE and Boundary Identification

adaptive-behavior loss function with respect to boundary regions

Unknown Objectness Score and Conformal Prediction

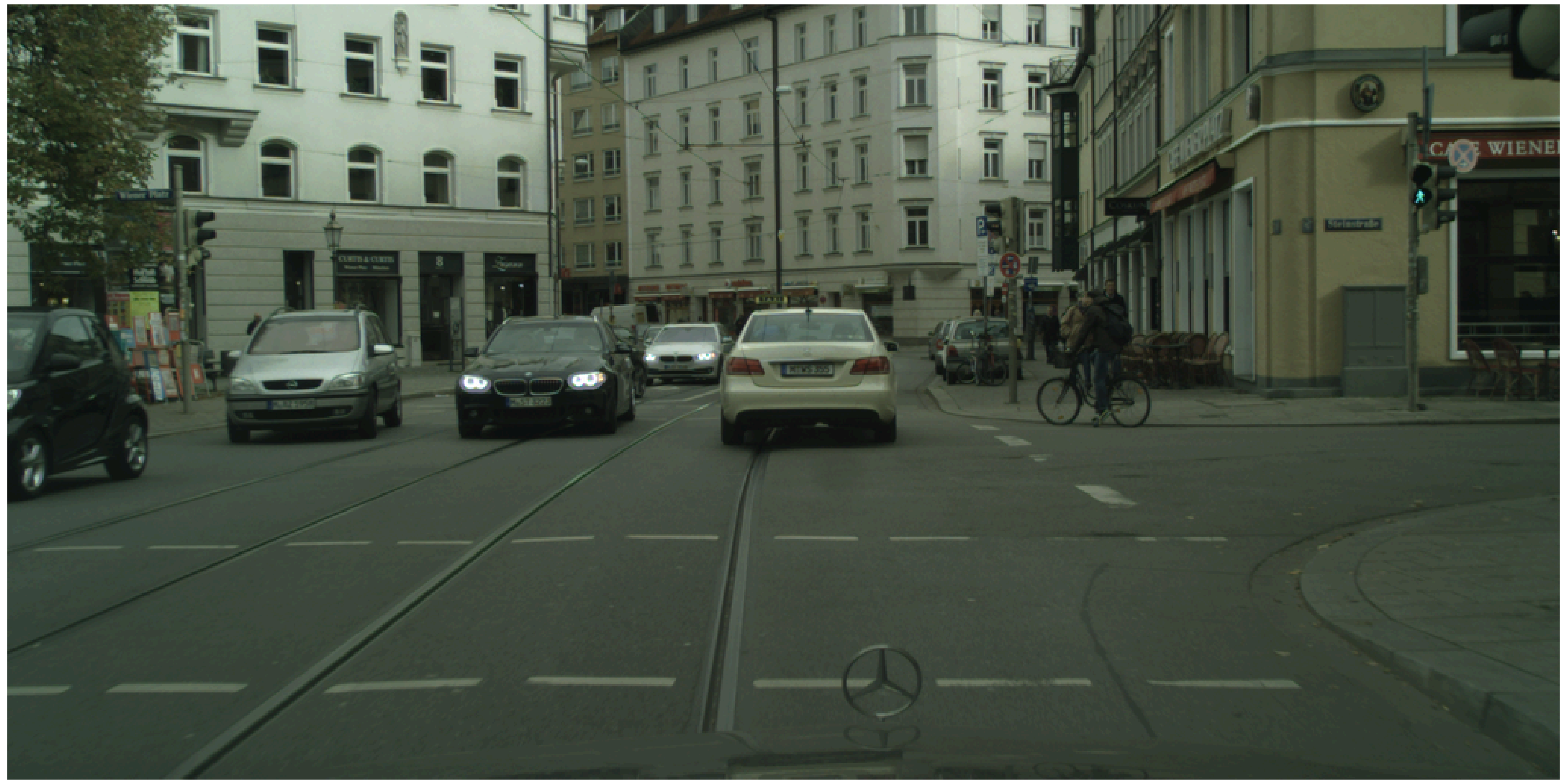
unknown object detection and **uncertainty quantification** to guarantee its reliability

Final step: experiments to find the **best configuration** for Training and Fine-Tuning parameters

Datasets for Training

CityScapes

- Train Set: Training 80%, Calibration 10%, Validation 10%
- Validation Set: Benchmark Evaluation Set



LostAndFound

Train Set: Training 80%, Validation 20%

Datasets for UOS Evaluation

LostAndFound

Test Set used as a Benchmark Evaluation Set

Road Anomaly

Whole Dataset used as a Benchmark Evaluation Set

Experimental Setup

HyperParam Tuning → Training on Cityscapes → Fine-Tuning on LostAndFound → UOS and Conformal Prediction Map

Hardware & Software

NVIDIA RTX 4070 Ti Super, 32GB RAM, 16GB VRAM, Python 3.12.4, PyTorch 2.7, CUDA 12.7

Hyper-Parameters

- Num Epochs
- Boundary Mask
- Lambda Value

Preprocessing Pipeline

Image Transformations:
- resize
- normalization

Additional Strategies

- Early Stopping
- Different Loss for Training and Fine-Tuning

Additional Other parameters taken from papers

Experiments

Improvement of Class Mapping

False positives were reduced by adding an **eighth macro-class** and requiring every in-distribution pixel to belong to at least one class other than "object"

Fine-Tuning and related Loss Function

To improve true road obstacle detection, we fine-tuned on a dedicated dataset using a loss function that focuses on **relevant pixels**

Use of OoD Data

We trained with OoD data to **boost unknown scores**, then excluded them during fine-tuning to focus on meaningful areas

Smart Boundary Masks Use

Thanks to our implementation of boundary masks, we were able to control the **boundary thickness** for different phases of the process

Model Evaluation

Uncertainty Metrics

1

AUROC

Measures the model's ability to **distinguish between classes**; useful for evaluating separability on OOD data

2

AP

Aggregates **precision–recall trade-off** across thresholds; relevant for ranking uncertainty outputs

3

FPR@95TPR

False Positive Rate when 95% of true positives are detected; lower values indicate better OOD rejection

Detection Performance Metrics

4

Pixel Accuracy

Proportion of **correctly classified pixels**; a basic metric for assessing segmentation performance

5

mIoU

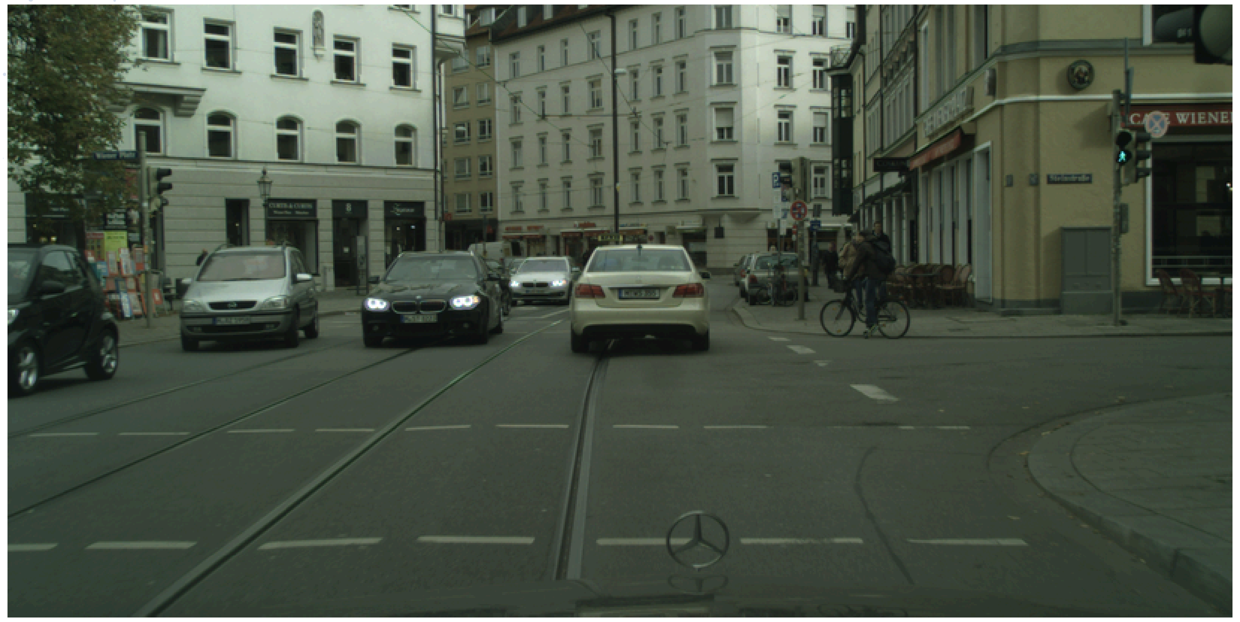
Average overlap between predicted and ground truth masks; core metric for segmentation quality

6

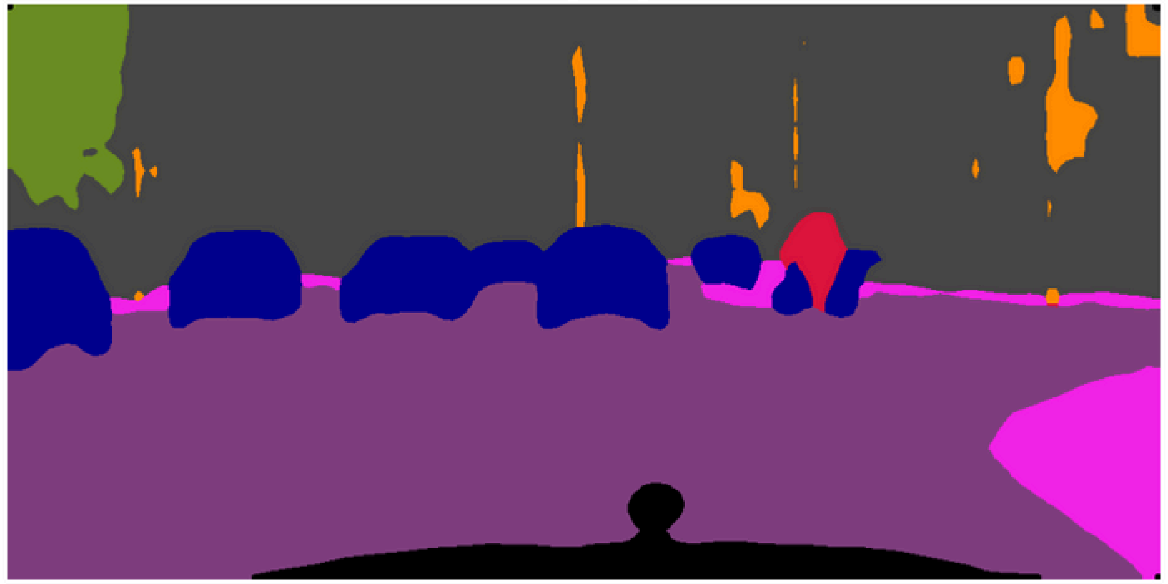
F1-Score

Harmonic mean of **precision** and **recall**; summarizes classification balance at pixel level

Predictions on Image Segmentation



Prediction Image Segmentation



Prediction Image Segmentation

CityScapes
Training
Dataset

Predictions on UOS and CP

LostAndFound Test Dataset

RoadAnomaly Dataset

Results

Here are reported our results with respect to all benchmark and evaluation metrics

Methods	OoD Data	LostAndFound Test			Road Anomaly		
		FPR95↓	AP↑	AUROC↑	FPR95↓	AP↑	AUROC↑
Outlier Exposure	✓	15.76	70.21	97.80	67.83	19.71	70.61
Outlier Head	✓	13.92	73.24	97.61	71.41	24.30	73.45
SynBoost	✓	22.04	78.64	96.63	66.15	35.52	81.16
Reference Paper*	✓	**1.17**	**87.74**	**99.52**	**45.37**	**49.07**	**88.78**
Ours	✓	**9.80**	**34.57**	**97.94**	**21.17**	**65.45**	**94.24**

Table 1: Performance comparison between proposed and existing methods.

Methods	OoD Data	CityScapes mIoU
Softmax Entropy		77.74
Outlier Exposure	✓	68.83
Outlier Head	✓	77.27
Reference Paper*	✓	**76.85**
Ours	✓	**63.65**

Table 2: Comparison of Cityscapes mIoU values.

Mean mIoU	Pixel Accuracy	F1-Score
63.65	83.90	76.04

Table 3: Detection Performance Metrics

Conclusions

Satisfying Results

Our method achieved **outstanding AUROC and FPR95** across all benchmarks, with strong mIoU performance on Cityscapes

Limits

Performance drops in highly cluttered scenes. **AP** is **sensitive** to threshold selection

Interpretation

This confirms the benefit of **incorporating OoD data and uncertainty estimation** in segmentation models

Future Work

Extend the model with **adaptive confidence calibration** and evaluate on real-world anomalies

References

Reference Paper*

Chihiro Noguchi, Toshiaki Ohgushi, Masao Yamanaka. **Road Obstacle Detection based on Unknown Objectness Scores**

Luca Mossina, Joseba Dalmau, Léo Andéol. **Conformal Semantic Image Segmentation: Post-hoc Quantification of Predictive Uncertainty**

Liang-Chieh Chen, George Papandreou, Florian Schroff, Hartwig Adam. **Rethinking Atrous Convolution for Semantic Image Segmentation**

Anastasios N. Angelopoulos and Stephen Bates. **A Gentle Introduction to Conformal Prediction and Distribution-Free Uncertainty Quantification**

Richard Szeliski. **Computer Vision - Algorithms and Applications**

Thank you for the attention!

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