UNCERTAINTY AWARE ROAD OBSTACLE IDENTIFICATION (UAROI)

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INTRODUCTION & MOTIVATION

Safe autonomous driving **depends on recognizing not only the familiar set of labeled objects** (cars, people, traffic signs, etc.) **but also any unexpected obstacles** that might suddenly appear on the road. Typical **semantic-segmentation networks** excel at tagging known categories, yet they **provide no guarantee about the objects they overlook**, posing a growing safety concern. We bridge this gap with a two-step approach:

1. **Unknown Object Scores:** for every pixel, gives an object anomaly measure.
2. **Conformal Risk Control:** Provides a threshold to binarize UOS map assuring a maximun false negative rate.

Fig 1. Unknown obstacle example

TRAINING PIPELINE

It was implemented a training pipeline for Unknown-Aware Road-Obstacle Identification using a **DeepLabV3**-style **segmentation network** extended with an **objectness prediction class**. The code fine-tunes this model using the **Cityscapes dataset** with the following key components:

Architecture:

- **DeepLabV3 with a ResNet-50 backbone**.
- A **sigmoid head** implemented to produce independent multi-class segmentation maps for each original class and an additional **objectness class**, learned by colapsing all the objects lables in the dataset, indicating whether a pixel belongs to any object (known or unknown).

Loss Function:

- Boundary Aware binary cross -entropy loss function.

$$\mathcal{L}_n = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k\in C} f(y_{ik}, p_{ik}) - \frac{\lambda}{\sum_i \delta_i}\sum_{i=1}^{N}\delta_i \sum_{k\in C} f(y_{ik}, p_{ik})$$

Training Loop:

- SGD with momentum 0.9 and weight decay 0.0001.
- Boundary region weight λ=3.

Output:

- The final model outputs an 8-channel tensor per image: 7 for known classes, and 1 for the objectness score, which are later used to compute unknown object score.

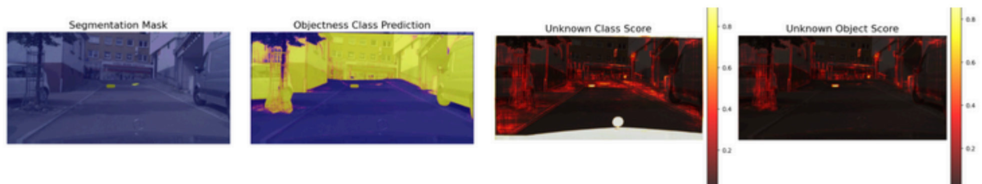

Fig 4. Output of training pipeline example

UNKNOWN OBJECT SCORES

The Unknown Objectness Score (UOS) is a pixel-wise anomaly metric that fuses two cues from the network: (i) p_{obj} the probability that the pixel belongs to any object rather than background, and (ii) p_k the set of class probabilities for the K known categories.

$$UOS_i = p_i^{\text{obj}} \prod_{k=1}^{K}(1 - p_{ik})$$

So it peaks only when the model is confident the pixel is part of an object and none of the known classes fit. High UOS regions therefore flag novel or out-of-distribution obstacles while suppressing background noise.

Fig 2. Unknown object score example

UAROI GENERAL PIPELINE

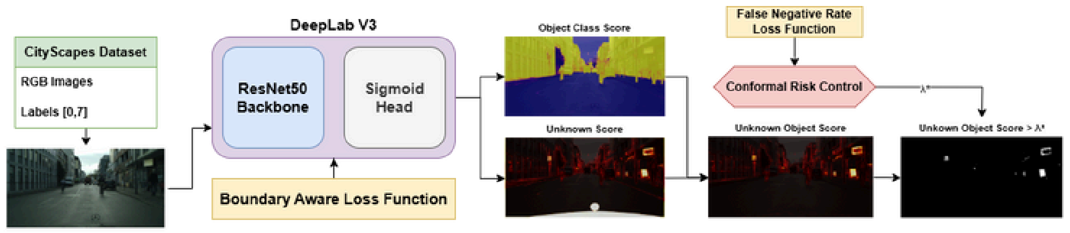

Fig 5. General pipeline of the UAROI framework

CONFORMAL RISK CONTROL

Conformal Risk Control (CRC) for False Negative Rate (FNR) is a **post-hoc calibration method** that computes a **certified threshold with a provable upper bound on risk**, transforming continuous model predictions (C_λ) into binary decisions. It uses a loss function defined as:

$$\ell_{\text{FNR}}(C_\lambda(X), Y) = 1 - \frac{|C_\lambda(X) \cap Y|}{|Y|}$$

CRC operates by evaluating this loss on a calibration set to compute the empirical risk R(λ). It then selects the smallest threshold λ* such that R(λ*) is less than a used defined risk level α. The result is a statistically guaranteed bound:

$$\mathbb{E}\left[\ell_{\text{FNR}}\left(C_{\hat{\lambda}}(X_{\text{test}}), Y_{\text{test}}\right)\right] \leq \alpha$$

Calibration set: 100 Lost & Found frames – used only to tune the conformal threshold $\hat{\lambda}$

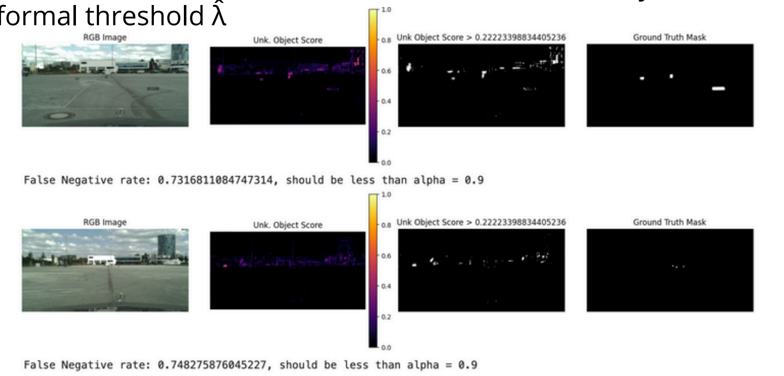

Fig 3.. Conformal Risk Control with *α = 0.9* applied to LostAndFound

EVALUATION

Setup

- **Models compared:** our three best checkpoints E-8, E-11, E-12 plus the reference results reported in *Road-Obstacle Detection Based on Unknown Objectness Scores.*
- **Test sets:** Lost & Found (≈200 frames, many tiny obstacles) and Road-Anomaly (60 images, diverse scene-level anomalies)

Discussion

- Lost & Found Model E-11 achieved the highest AUROC/AP, with E-8 only slightly behind.
- Road-Anomaly Model E-12 performed best across all metrics.

The low AP on Lost & Found can be explained from extreme class imbalance: obstacle pixels are very few compared with background, so even modest errors translate into many false positives, flattening the precision–recall curve.
While our scores are not yet state-of-the-art, the framework is modular and extensible. A targeted fine-tuning phase on Lost & Found or other imbalance-aware strategies should further improve performance.

Metrics used

- **AUROC:** Ranking quality of the UOS considering all thresholds. Higher is better.
- **Average Precision:** Area under the Precision–Recall curve. Higher is better.
- **FPR @ 95 % TPR:** percentage of background pixels that are mistakenly flagged when the detector recovers 95 % of the real obstacles. Lower is better.

Methods	OoD Data	LostAndFound Test			Road Anomaly		
		FPR95↓	AP↑	AUROC↑	FPR95↓	AP↑	AUROC↑
Softmax Entropy [33]		19.45	39.58	95.4	70.93	17.06	69.35
Max Logit [34]		16.44	53.06	96.91	68.03	18.64	72.82
Ohgushi et al. (2020) [5]		14.06	50.68	97.16	67.64	20.25	71.92
SML [4]		35.51	39.65	92.87	50.91	25.32	81.37
ROD (w/o OoD data)		3.92	81.5	98.94	44.15	48.41	89.21
Outlier Exposure [39]	✓	15.76	70.21	97.8	67.83	19.71	70.61
Outlier Head [40]	✓	13.92	73.24	97.61	71.41	24.3	73.45
SynBoost [6]	✓	22.04	78.64	96.63	66.15	35.52	81.16
ROD (w/ OoD data)	✓	1.17	87.74	99.52	45.37	49.07	88.78
UAROI (Best epoch)	✓	59.74	1.25	84.92	54.7	32.88	82.02

Fig 6. Evaluation Results