Uncertainty-Aware Road Obstacle Identification

Project developed by:

Simona Pia Vestita
vestita.2196397@studenti.uniroma1.it

Mercurio Veronica
mercurio.2213847@studenti.uniroma1.it

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Problem Statement

Reliable identification of road obstacles is crucial for the safety of autonomous vehicles. However, traditional methods of object detection often recognize only predefined categories and struggle to detect unknown or unexpected obstacles. The challenge is to make the model capable of detecting unknown obstacles.

State of the Art

- Neural networks for object detection and semantic segmentation:

  -> Limited to predefined classes, difficulty in recognising unknown obstacles

- Anomaly detection and open set recognition

  ->Techniques for identifying objects not belonging to known classes

- Quantification of uncertainty

  ->Bayesian and Conformal Prediction methods to provide confidence in predictions

- Quantification of uncertainty

  ->Flexible and modular systems usable with different segmentation networks

Proposed Method

1 SETUP AND CONFIGURATION:

Initialization of the DeepLabV3+ model.

2 AUTOMATIC CALCULATION OF CLASS WEIGHTS:

Calculating normalized inverse weights to balance the boundary aware Loss.

3 TRAIN:

SGD optimizer, scheduler to adapt the learning rate (polynomial or step policy).

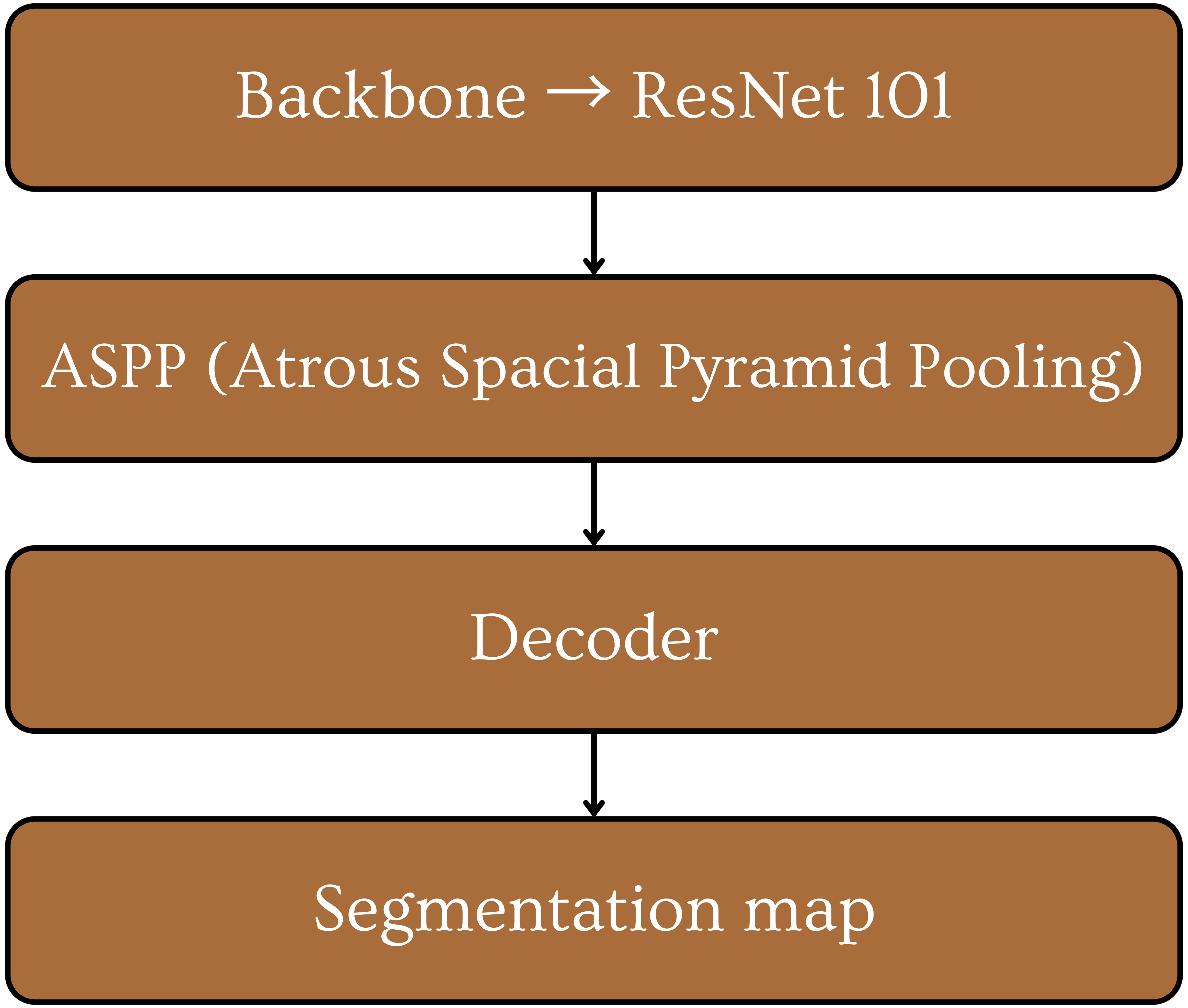
4 VALIDATION AND CHECKPOINT:

Calculation of Mean IoU, Overall Accuracy, Mean Accuracy and FreqW. Saving of the best metric.

5 ANOMALY-AWARE DETECTION USING CONFORMAL PREDICTION:

Automatic calibration of the confidence. Identification certain pixels as anomalies ("unknown").

Architecture



Dataset

The dataset used for training is LostAndFound. It is a dataset designed for anomaly detection in autonomous driving, specifically focused on detecting small, unexpected obstacles on the road. Its images were preprocessed, so the resulting masks are made of 2 classes: normal and anomaly.

lostandfound:

- train
  - images
  - masks
- test
  - images
  - masks

Experimental Setup

Consulting the papers, we chose to use DeepLabv3plus and tune it on the LostAndFound dataset. Before implementing the tuning, there was the preprocessing phase on the dataset in order to create binary masks.
During the tuning phase, we realized that the suitable loss was boundary-aware (related to semantic segmantation) weighted because the classes were unbalanced. As a next step we implemented anomaly detection by verifying that the masks contained labels equal to 1 (anomalous class), verifying also the safety of the model by conformal prediction. As a final step there is evaluation with the following merics.

Model Evaluation

During the tuning phase we calculated, on validation, the Overall accuracy, Mean accuracy, freqW and mean IoU, noting the difference between the mean IoU of the pre-trained and the mean IoU resulting from tuning (with a 40% difference) due to the fact that the model head train was done only on half the dataset due to computational power issues!
During the testing phase, we dynamically estimated the CP threshold of 0.62 and typical anomaly detection metrics.

Metrics	Train	Test
Overall accuracy	95%	87%
Mean accuracy	97%	87%
FreqW	94%	87%
Mean IoU	35%	43%
ROC-AUC		60%
PR-AUC		0.02
Max F1		0.06

Conclusion

The metrics derived are not optimal, an indication that the challenge of anomaly-aware detection is daunting; however, work can be done on it.
In fact, as a future development, there is to complete the training on the whole dataset and run it on multiple epochs so as to improve the Mean IoU and specific metrics of anomaly detection, also thinking of implementing dataset augmentation and more effective balancing.

References

Noguchi, C., Ohgushi, T., & Yamanaka, M. (2024). Road Obstacle Detection based on Unknown Objectness Scores. arXiv [Cs.CV].