Automatic Detection and Multi-Class Segmentation of Underwater Pipelines: A Comparative Study on Different Approaches using Computational Models

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Introduction

- Underwater pipeline detection and segmentation are important for infrastructure safety and environmental protection, but traditional detection methods struggle in noisy and low-visibility conditions.

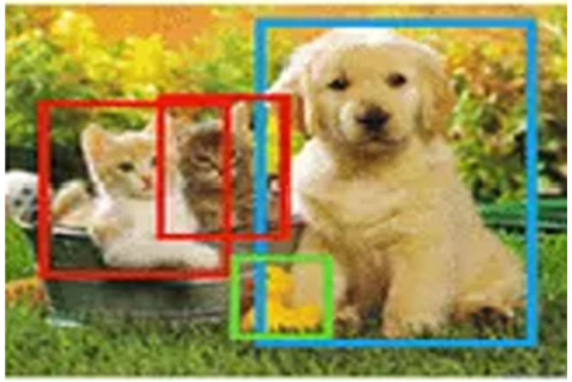

Figure: Detection vs Segmentation

Objectives

- The primary objective of this study is to detect and segment underwater pipelines and features with YOLOv8 and Mask R-CNN models and analyse their applicability qualitatively and quantitatively for underwater environments.
- This study evaluates the influence of data augmentation methods on model performance for enhanced accuracy to mitigate class imbalance as a sub-objective.

Dataset Description

- Data Set consists of 5 different classes

1. Pipe
2. Concrete Mat
3. Concrete Weight
4. Pipe Coupling
5. Leakage

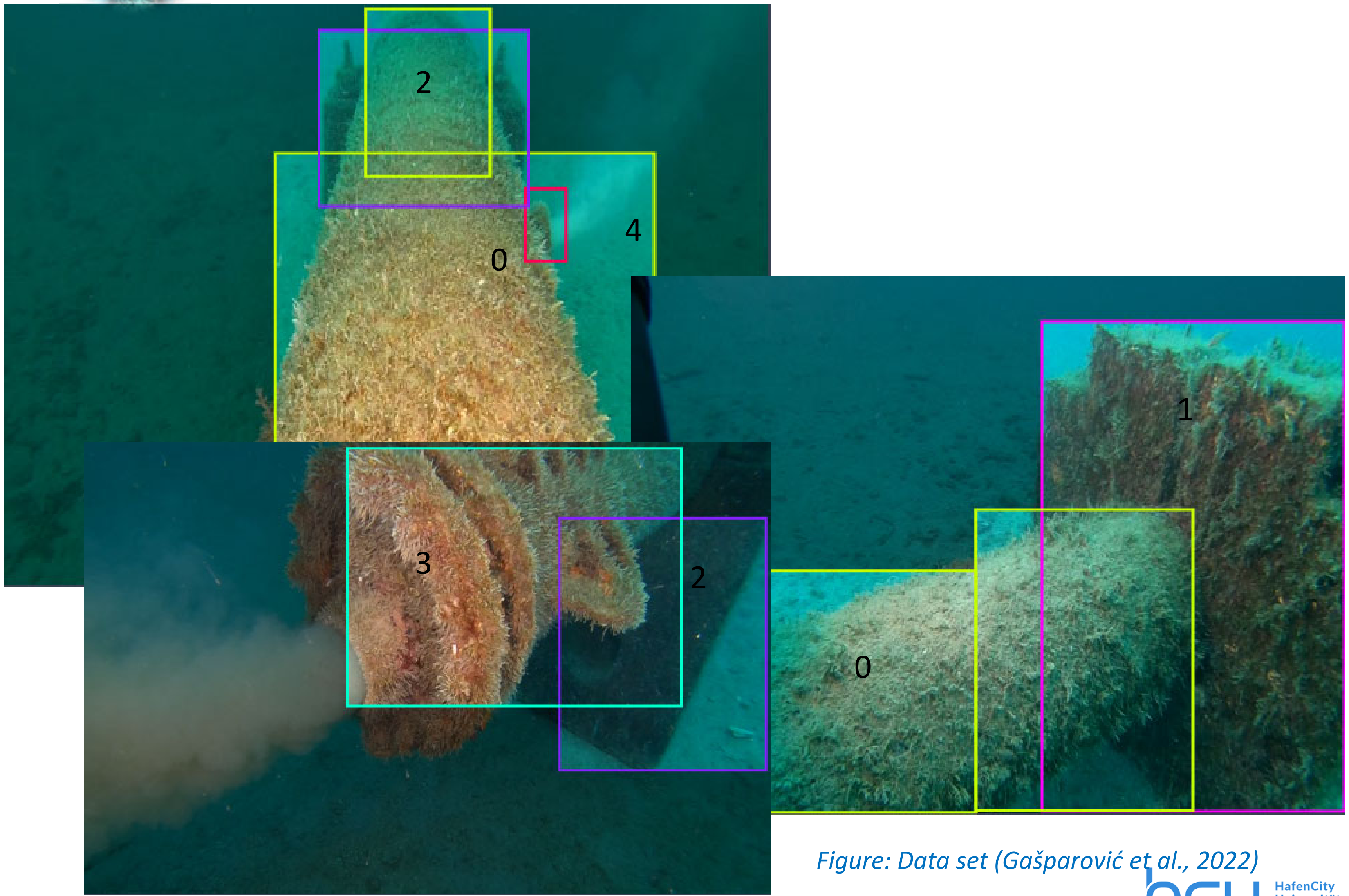

Figure: Data set (Gašparović et al., 2022)

Dataset Description and Data Augmentation

- The dataset is divided into subsets. 70% of the data is used for training, 20% is used for validation, and 10% is used for testing.

Table: Data Set Description

Version	Training	Validation	Testing
V4	739	212	105
V5	791	227	113

Table: Class – Wise Instances Description

Class Name	Instances(V4)	Instances(V5)
Concrete Mat	364	379
Concrete Weight	763	803
Leakage	**117**	**148**
Pipe	1085	1281
Pipe Coupling	**88**	**124**

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Design and Implementation

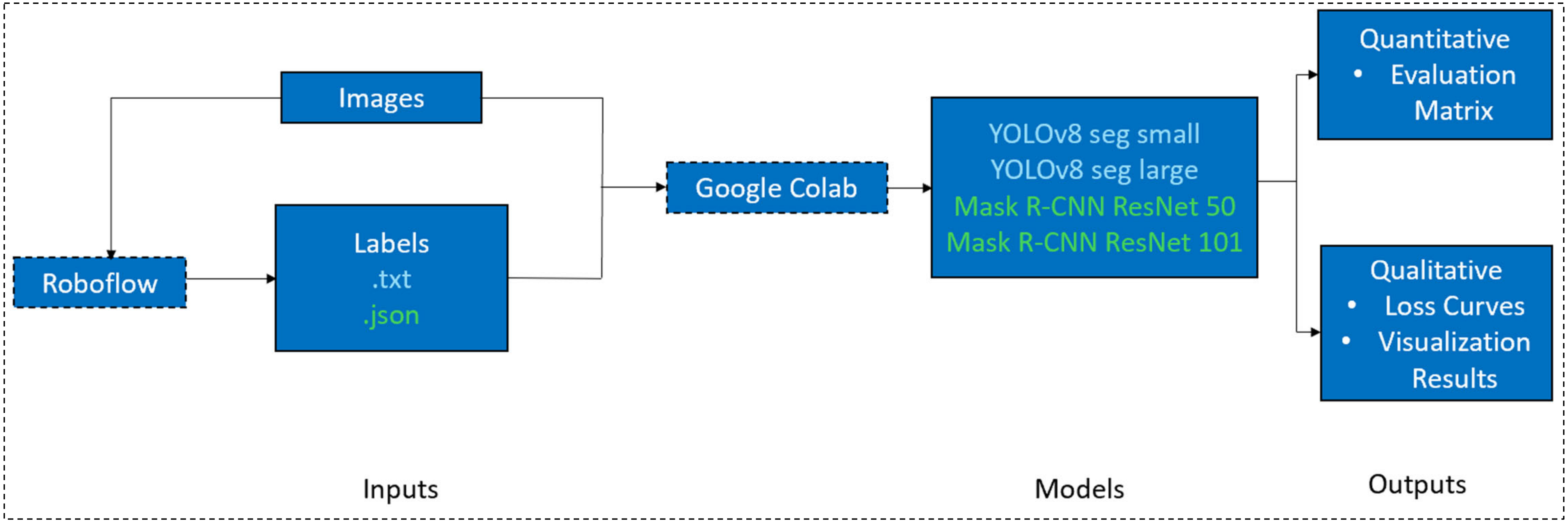


Figure: Workflow

Training Parameters

- Batch size, learning rate and number of epochs are defined for all models with the same values to provide an equivalent environment for the training.

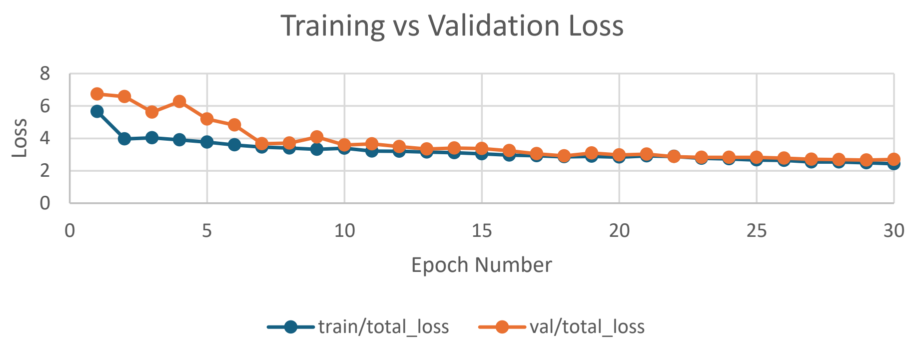
Table: Training Parameters

Parameter	Value
Batch size	8
Learning Rate	0.001
Number of Epochs	30

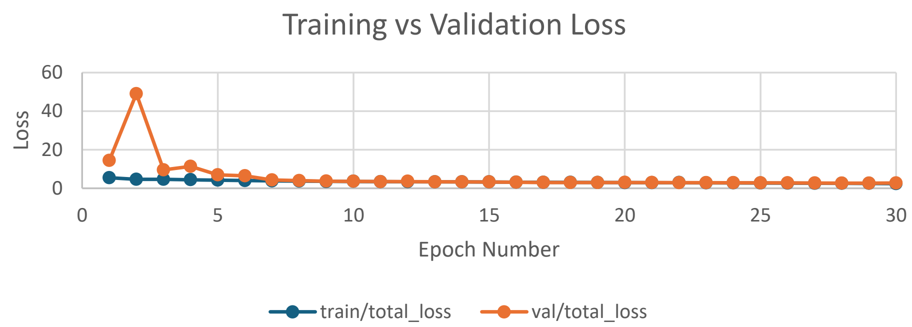
Results and Analysis

- The **training and validation loss curves** represent how well a model learns over time in the training and validation datasets.
- It is crucial for detecting overfitting and underfitting and to ensure the model fits well in real-world scenarios.

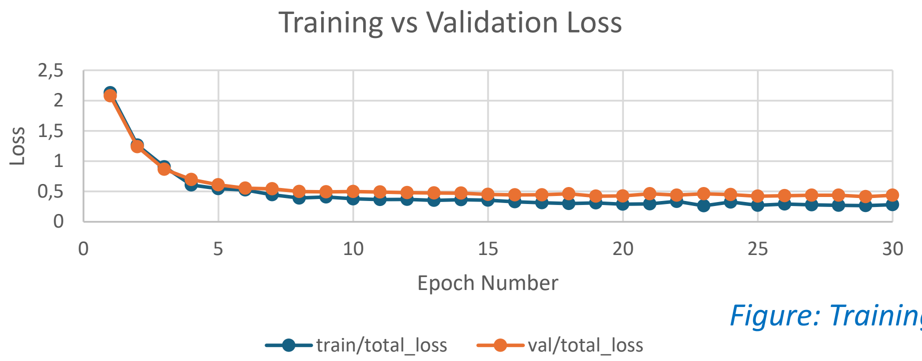
YOLOv8- Seg Small Model



YOLOv8- Seg Large Model



Mask R-CNN ResNet 50 Model



Mask R-CNN ResNet 101 Model

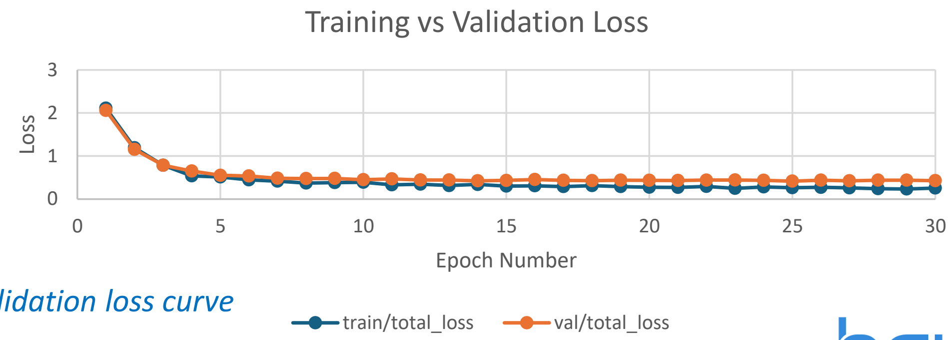


Figure: Training and validation loss curve

Evaluation Matrix

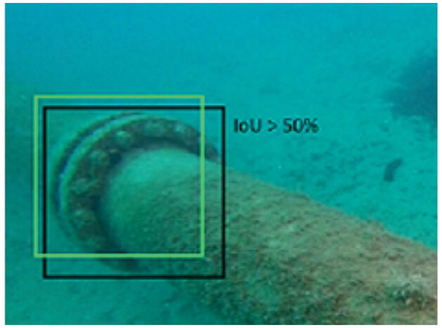


Figure: IoU >= 50

$$Precision = \frac{TP}{FP + TP}$$

$$Recall = \frac{TP}{TP + FN}$$

Equation: Precision and Recall

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Figure: Confusion Matrix

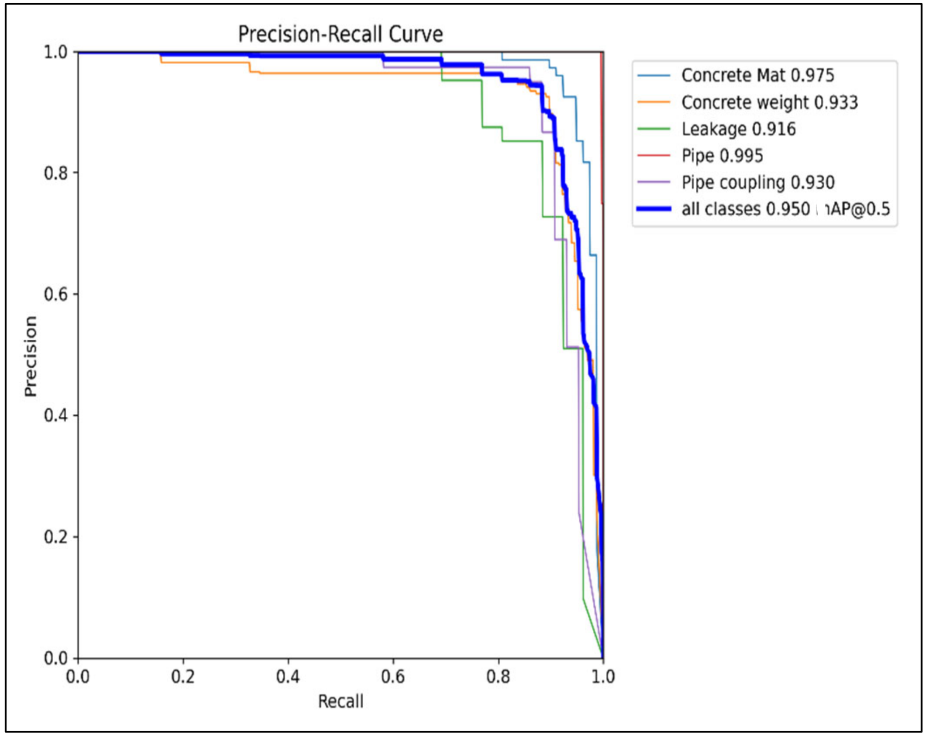


Figure: P-R curve of YOLOv8-seg small model @ 50

$$AP\ @\ 50 = \int_0^1 P(R)dR$$

Equation: Average Precision

$$mAP_{50-95} = \frac{1}{10}\sum_{t=0.50}^{0.95} AP(t)$$

Equation: Mean Average Precision

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Comparison

- YOLO models outperform Mask R-CNN.
- The pre-trained models show improved precision compared to the base models.

Table: Model precision comparison

Model	mAP(50-95) Base Model		mAP(50-95)		AP(50)	
	bbox	segm	bbox	segm	bbox	segm
YOLO V8 seg -small	0.446	0.368	0.777	0.747	**0.962**	**0.965**
YOLO V8 seg -large	0.523	0.426	0.774	0.724	**0.961**	**0.959**
Mask RCNN Resnet 50	0.340	0.336	0.677	0.668	**0.904**	**0.922**
Mask RCNN Resnet 101	0.382	0.354	0.691	0.665	**0.937**	**0.934**

- Pipe class achieves the highest mAP score
- Underrepresented classes achieve lower mAPs.

Table: Class-wise model precision comparison

Model	mAP(50-95) Concrete Mat		Concrete Weight		Leakage		Pipe		Pipe Coupling	
	bbox	segm	bbox	segm	bbox	segm	bbox	segm	bbox	segm
YOLO V8 seg -small	0.806	0.797	0.698	0.627	0.677	0.627	0.966	0.969	0.736	0.715
YOLO V8 seg -large	0.810	0.792	0.686	0.609	0.632	0.544	0.976	0.973	0.737	0.747
Mask RCNN Resnet 50	0.758	0.741	0.619	0.615	0.509	0.489	0.899	0.909	0.602	0.587
Mask RCNN Resnet 101	0.728	0.736	0.602	0.612	0.575	0.507	0.925	0.918	0.623	0.552

Influence of Data Augmentation

Table: Comparison of impact of the data augmentation

Model	Version	mAP(50-95)	
		bbox	segm
YOLO V8 seg -small	V4	0.777	0.747
	V5	0.767	0.742
YOLO V8 seg -large	V4	0.774	0.724
	V5	0.772	0.736
Mask RCNN Resnet 50	V4	0.677	0.668
	V5	0.690	**0.692**
Mask RCNN Resnet 101	V4	0.691	0.665
	V5	0.689	**0.693**

- Data augmentation did not significantly enhance the model's performance on this dataset.
- However, segmentation mAP @ 50-95 has increased in underrepresented classes significantly.

Table: Comparison of impact of the data augmentation class-wise

Model	Version	mAP(50-95)									
		Concrete Mat		Concrete Weight		Leakage		Pipe		Pipe Coupling	
		bbox	segm	bbox	segm	bbox	segm	bbox	segm	bbox	segm
YOLO V8 seg -small	V4	0.806	0.797	0.698	0.627	0.677	0.627	0.966	0.969	0.736	0.715
	V5	0.806	0.793	0.696	0.609	0.646	0.605	0.951	0.958	0.737	0.747
YOLO V8 seg -large	V4	0.810	0.792	0.686	0.609	0.632	0.544	0.976	0.973	0.737	0.747
	V5	0.815	0.798	0.688	0.613	0.609	0.590	0.965	0.957	0.783	0.723
Mask RCNN Resnet 50	V4	0.758	0.741	0.619	0.615	0.509	0.489	0.899	0.909	0.602	0.587
	V5	0.738	0.741	0.621	0.589	0.542	**0.563**	0.896	0.884	0.654	**0.683**
Mask RCNN Resnet 101	V4	0.728	0.736	0.602	0.612	0.575	0.507	0.925	0.918	0.623	0.552
	V5	0.705	0.704	0.619	0.600	0.555	**0.577**	0.907	0.902	0.653	**0.681**

Visualisation Results

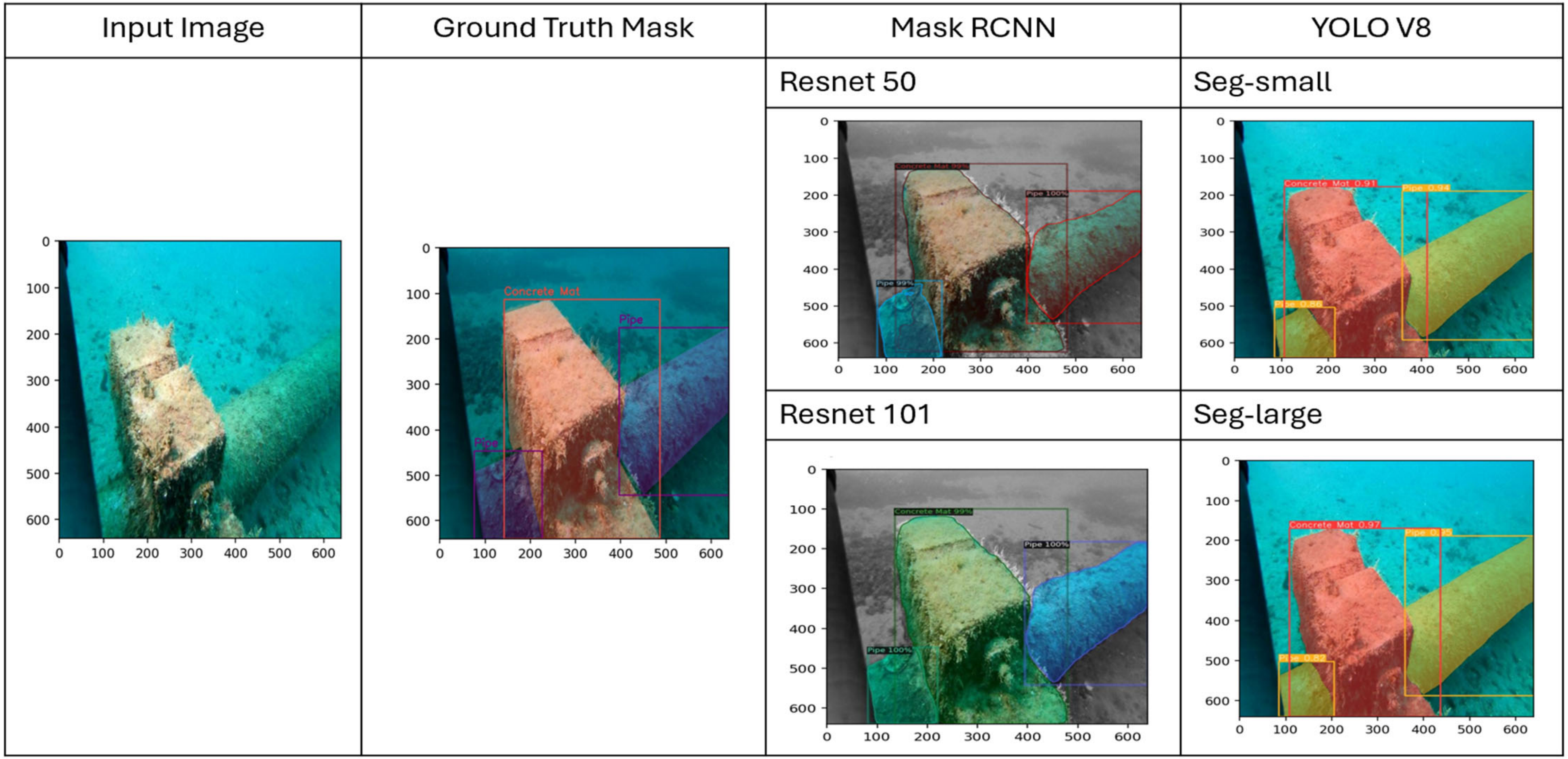

Figure: Concrete Mat detection and segmentation

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Visualisation Results

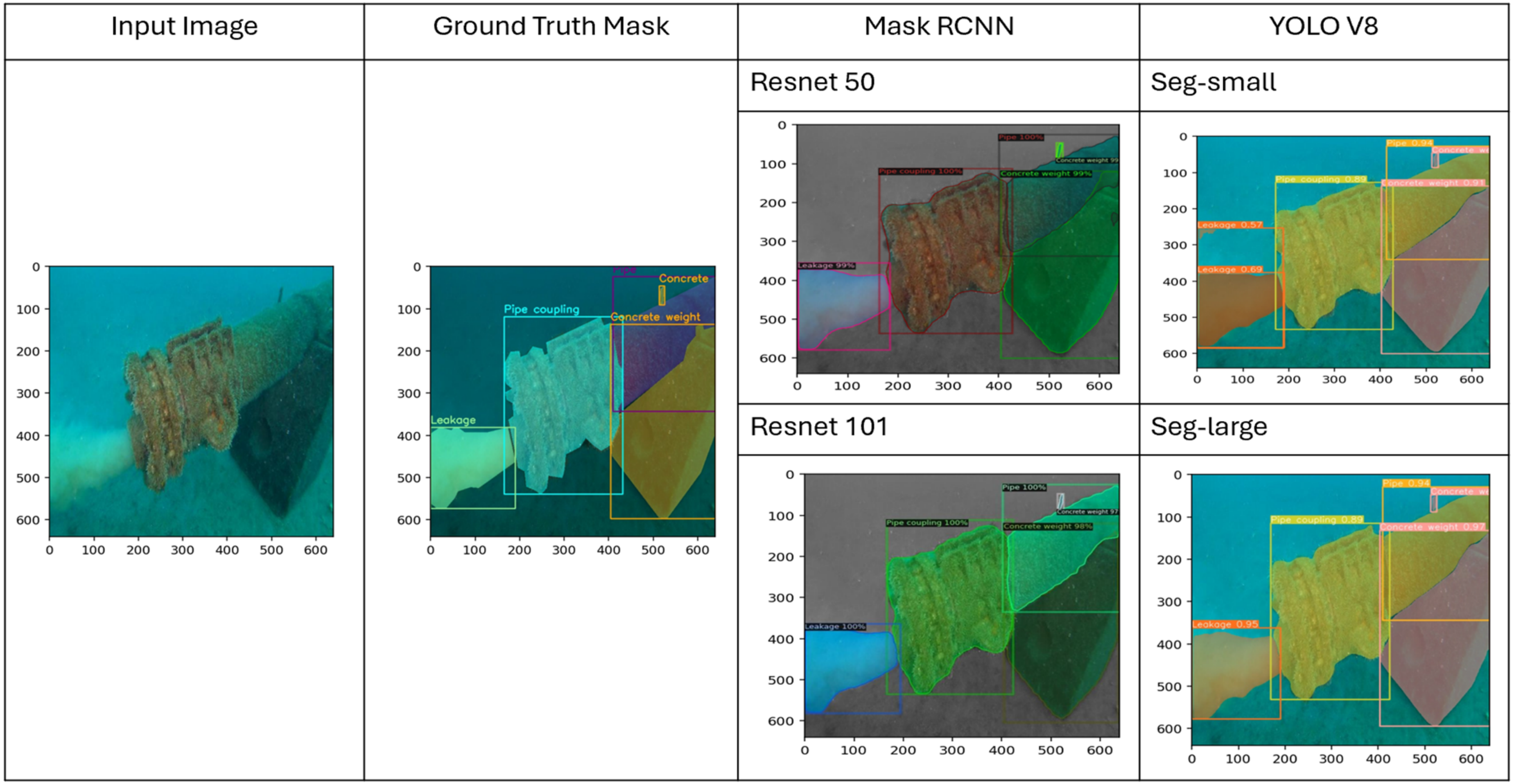

Figure: Leakage detection and segmentation

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Practical Deployment

- **Inference speed** defines the speed of predicting the results on unseen data.

Table: Inference time and number of parameters

Model	Inference Time on GPU A100 (ms)
YOLO V8 seg small	**1.2**
YOLO V8 seg large	**3.1**
Mask RCNN Resnet 50	43
Mask RCNN Resnet 101	65.5

Conclusion and Outlook

- YOLOv8, both small and large models, achieved higher precision values compared to Mask R-CNN.
- The study demonstrates that YOLOv8-Seg Small is a highly efficient and practical model for real-time detection and segmentation.
- Mask R-CNN models need to be fine-tuned to improve the precision for underrepresented classes.

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Thank You!

Loss Function

- Mask R-CNN and YOLOv8 use different loss functions to help the model learn how to detect and segment objects accurately.

Table: Losses of YOLOv8 and Mask R-CNN

Aspect	YOLOv8 Seg	Mask R-CNN
Segmentation Loss	BCE + Dice Loss	BCE Loss
Bounding Box Loss	CIoU + SIoU	Smooth L1_Loss
Classification Loss	Cross Entropy + Focal Loss	Cross Entropy Loss
Distribution Focal Loss	Cross Entropy Loss	-