Multi-sensor rail track detection in automatic train operations

Master's thesis in Data Science

Student: Attila Kovacs

1st Advisor: Lukas Rohatsch (FH Technikum)

2nd Advisor: Daniele Capriotti (M2C Expert Control GmbH)

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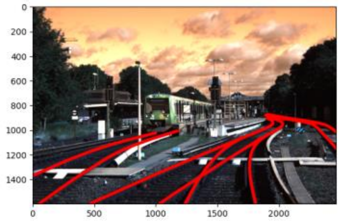
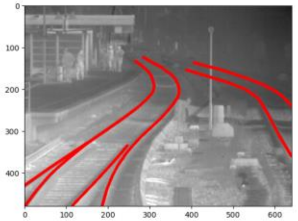
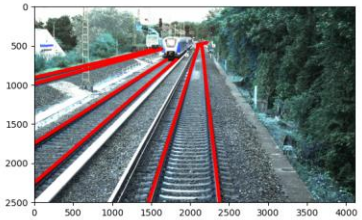
Problem setting

What is Automatic train operations (ATO)
Technology is used to automate
tasks that were previously performed
by rail personnel (e.g., conductor)







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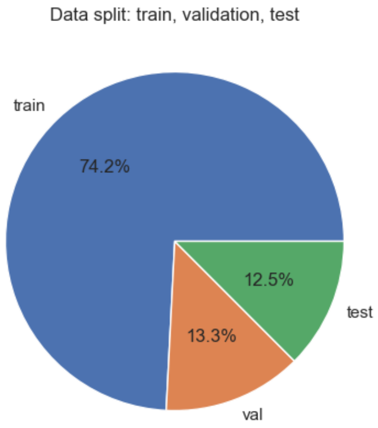
Dataset

- Deutschbahn:
  - Multisensor dataset
    - Infrared
    - RGB 5MP
    - RGB 12MP
    - Left, right, and center, respectively
  - Large similarity between frames of video → split on videos



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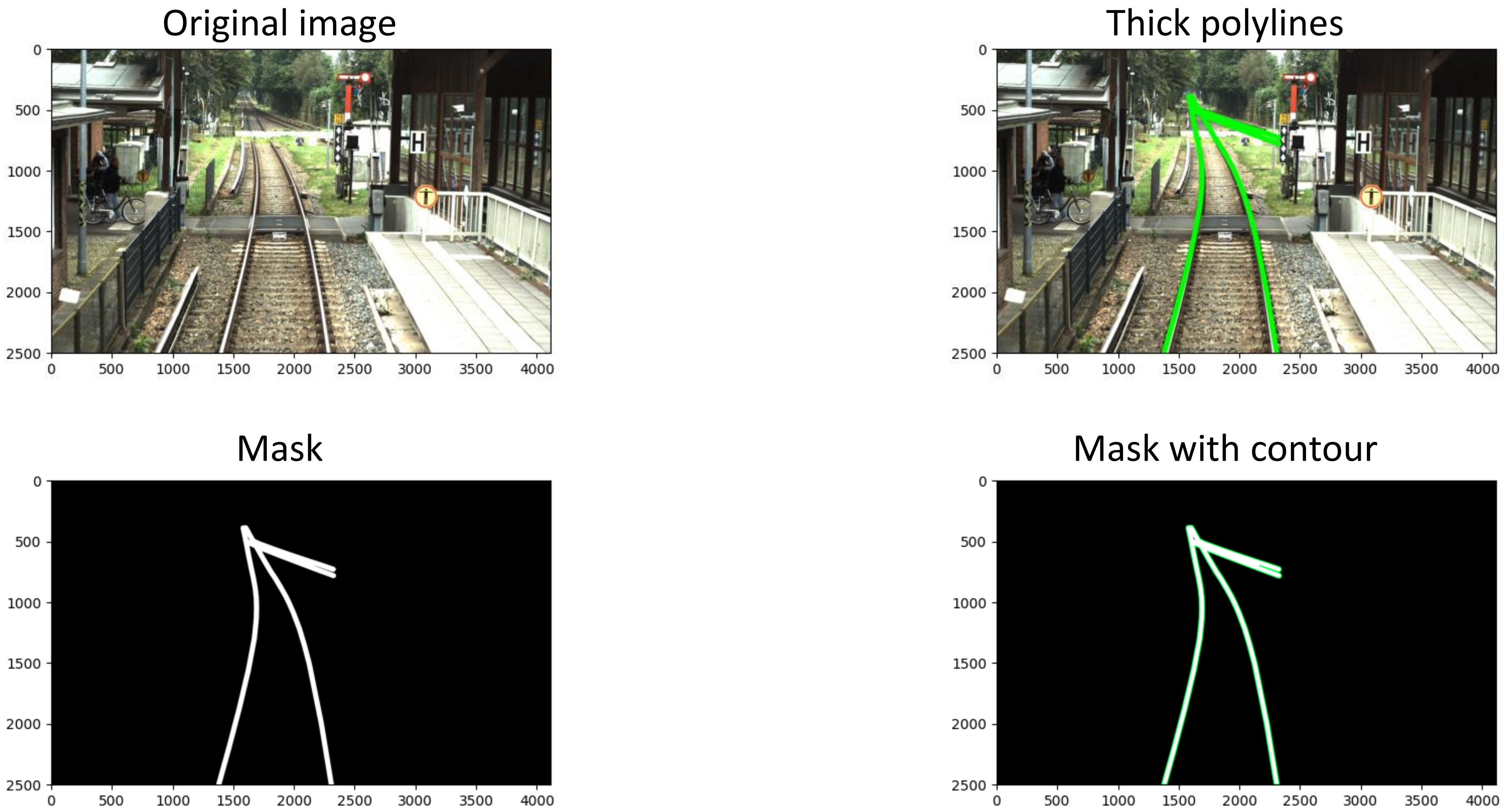
Modelling rail detection as segmentation

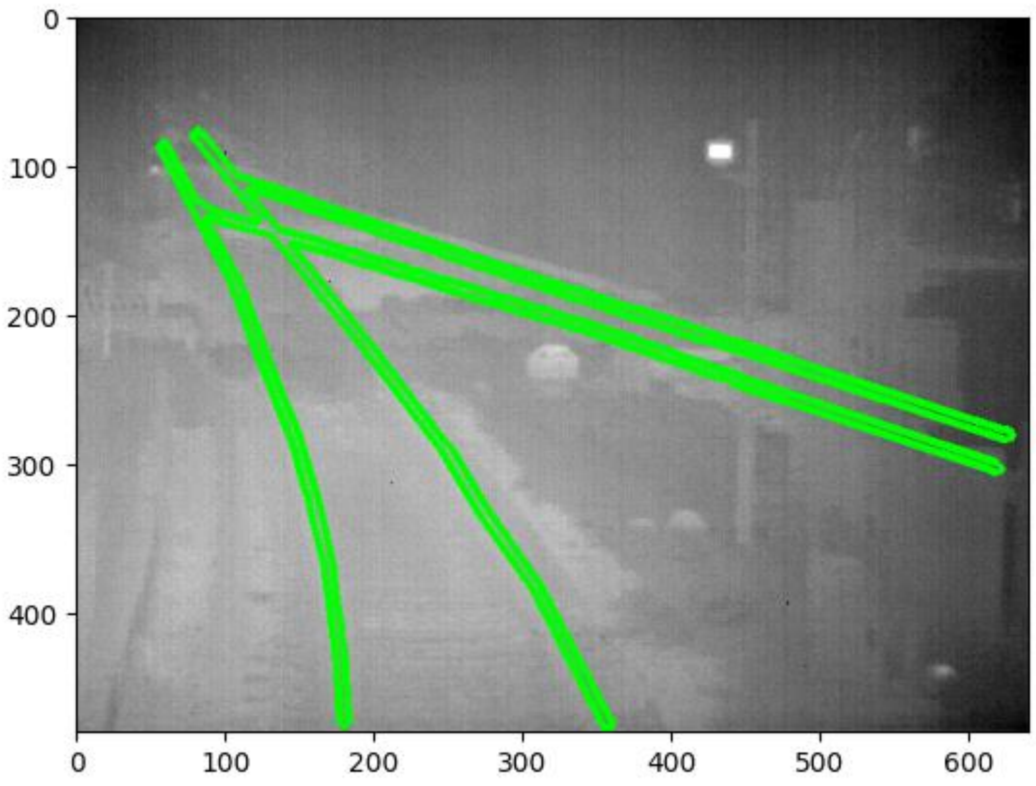
- Semantic segmentation → deep learning algorithm that associates a label or category with every pixel in an image
- Distinguish background pixels and track pixels
- In the data tracks are annotated by lines rather than pixel masks

Modelling rail detection as segmentation

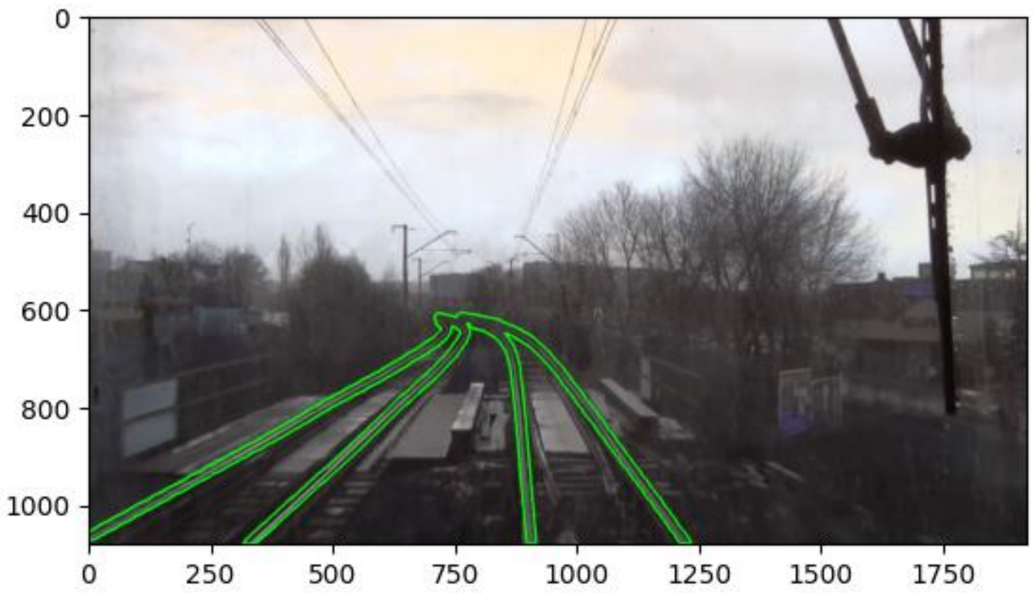


Modelling rail detection as segmentation

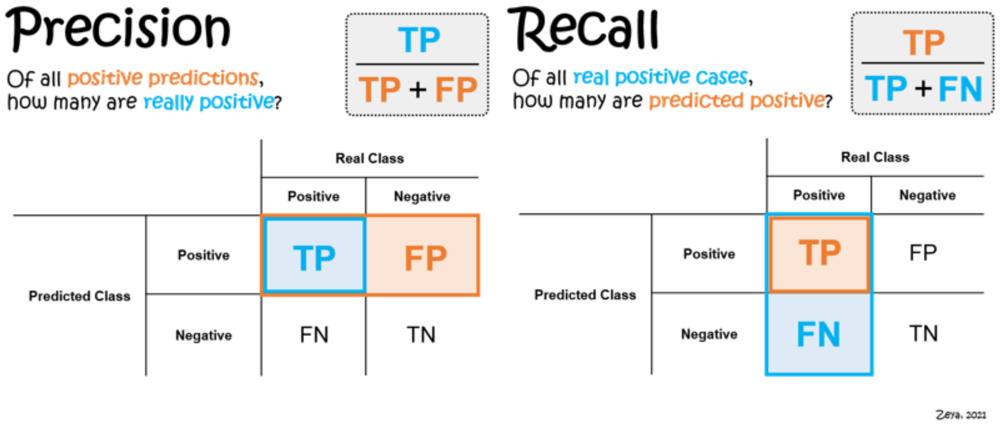
Example IR



Example RailSem



Performance metrics



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

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

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP}$$

$$Dice = \frac{2TP}{2TP + FP + FN}$$

$$IoU = \frac{TP}{TP + FP + FN}$$

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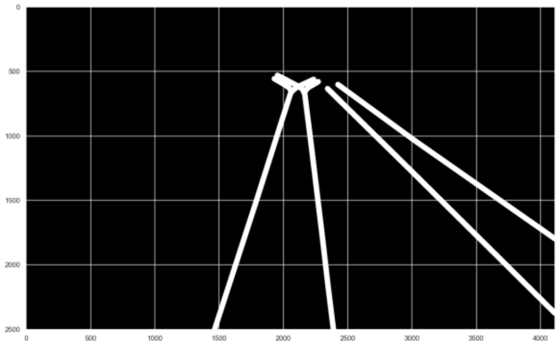
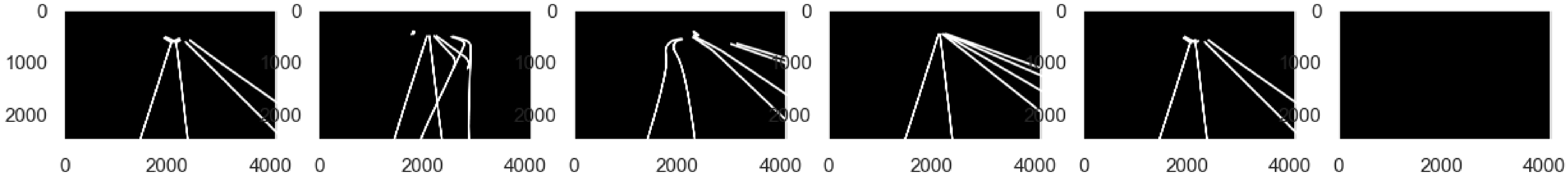
Performance metrics





pixel_acc: 0.9983
dice: 0.9775
precision: 0.9812
recall: 0.9738
iou: 0.9559

pixel_acc: 0.9499
dice: 0.3762
precision: 0.3557
recall: 0.3992
iou: 0.2317

pixel_acc: 0.9205
dice: 0.0567
precision: 0.0514
recall: 0.0633
iou: 0.0292

pixel_acc: 0.9435
dice: 0.3703
precision: 0.3201
recall: 0.4392
iou: 0.2272

pixel_acc: 0.9979
dice: 0.9714
precision: 0.9787
recall: 0.9643
iou: 0.9444

pixel_acc: 0.9622
dice: 0.0000
precision: 1.0000
recall: 0.0000
iou: 0.0000

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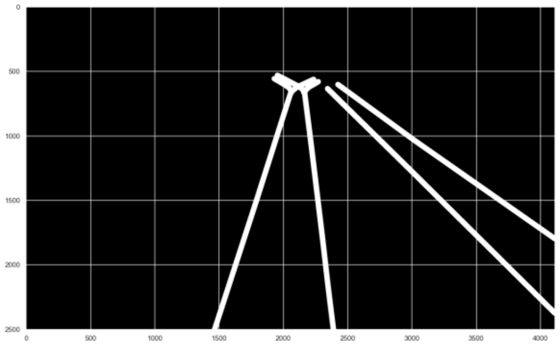
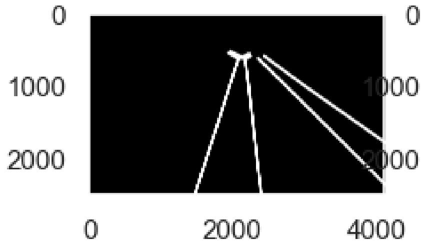
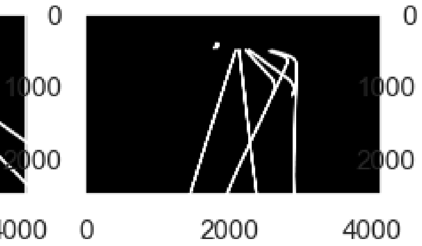
Performance metrics

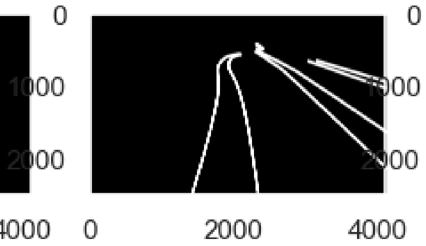




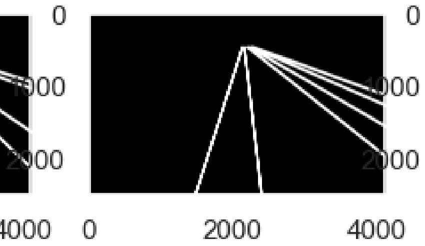
pixel_acc: 0.9983
dice: 0.9775
precision: 0.9812
recall: 0.9738
iou: 0.9559



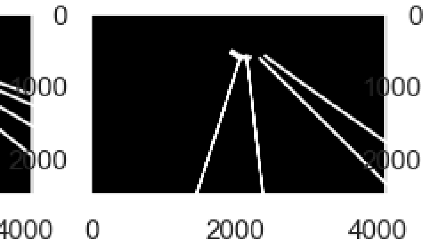
pixel_acc: 0.9499
dice: 0.3762
precision: 0.3557
recall: 0.3992
iou: 0.2317



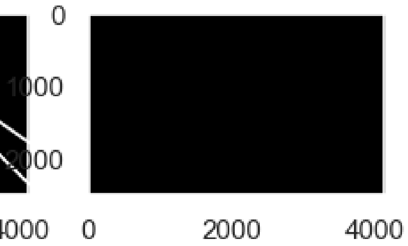
pixel_acc: 0.9205
dice: 0.0567
precision: 0.0514
recall: 0.0633
iou: 0.0292



pixel_acc: 0.9435
dice: 0.3703
precision: 0.3201
recall: 0.4392
iou: 0.2272



pixel_acc: 0.9979
dice: 0.9714
precision: 0.9787
recall: 0.9643
iou: 0.9444



pixel_acc: 0.9622
dice: 0.0000
precision: 1.0000
recall: 0.0000
iou: 0.0000

```
precision = (tp + self.eps) / (tp + fp + self.eps)
```

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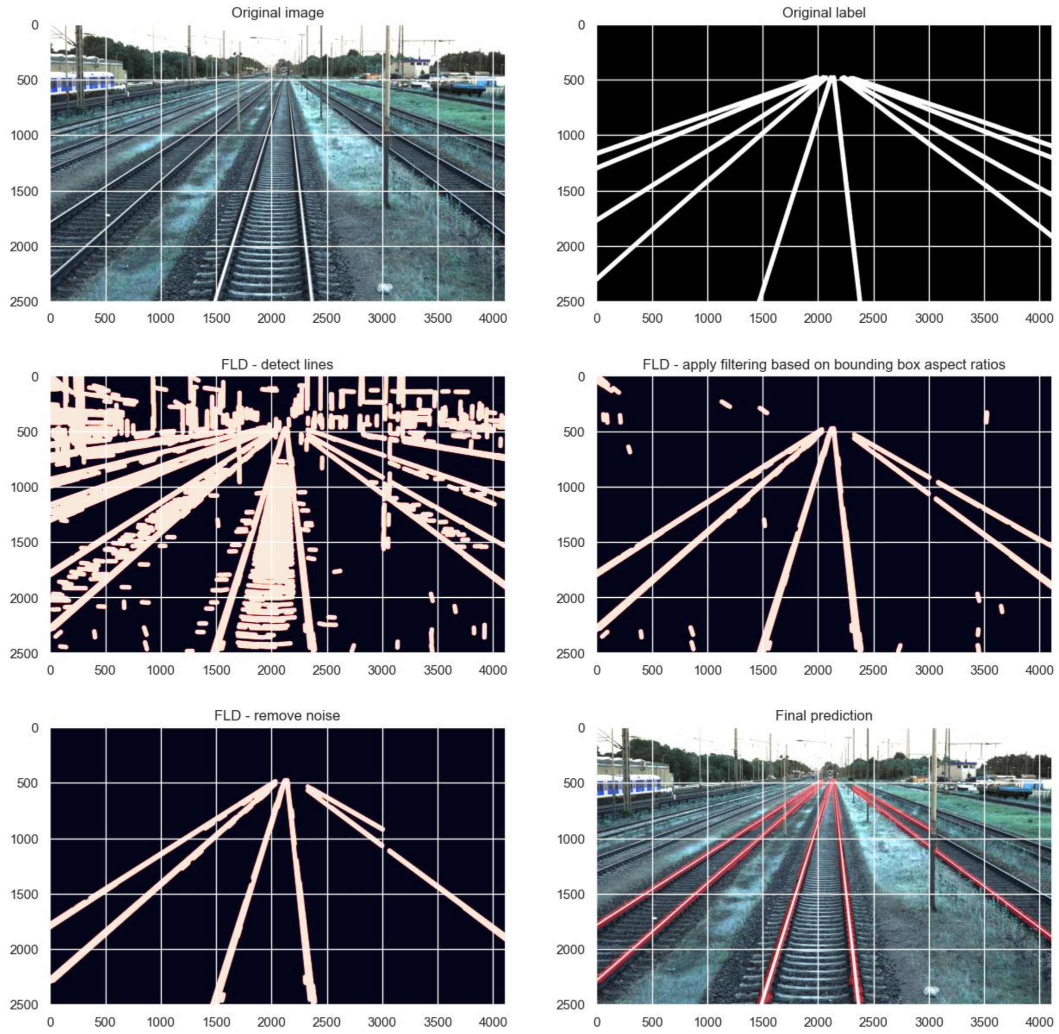
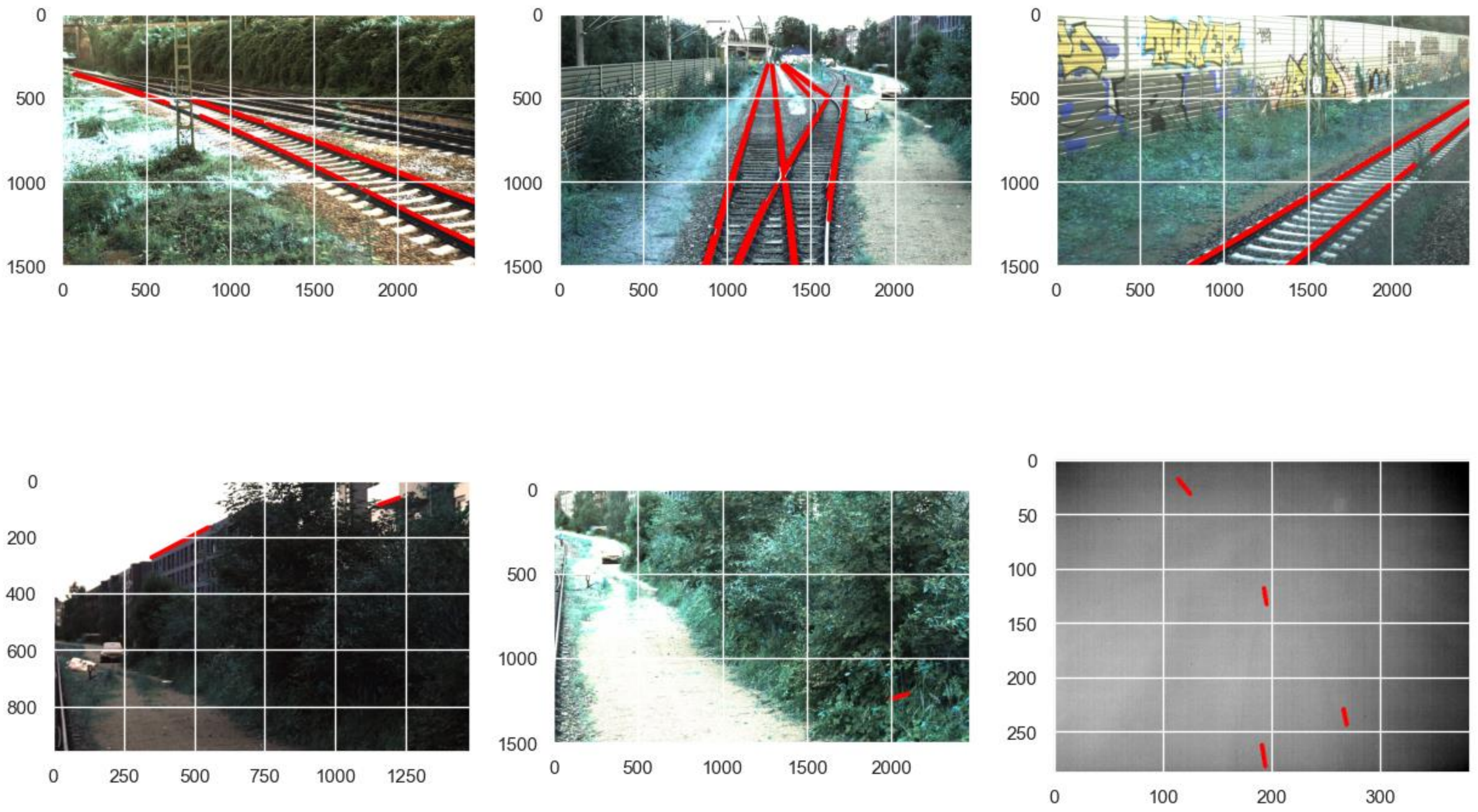
Baselining with fast line detection



Baselining with fast line detection
Good examples and bad examples



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Deep learning approach

- YOLOv8 as framework
- Can be used for segmentation and object detection
- State-of-the-art computer vision model built by Ultralytics
- Easy to use
- Open source

YOLO experiments

- Model backbone: yolov8n-seg
- Combined loss function consisting of
  - bounding box loss (error between the predicted and the ground truth boxes' geometry)
  - objectness loss (how confident the model is about the presence of an object in the bounding box)
  - segmentation loss (how close the predicted segmentation map is to the ground truth map)
- Paramters
  - epochs: 300
  - image size: 640, 1280 (where applicable)
  - batch size: auto selection based on image size and available memory
  - Yolo defaults
- Logging: Comet ML

YOLOv8
First experiments - RGB

Without RailSem data

With RailSem data

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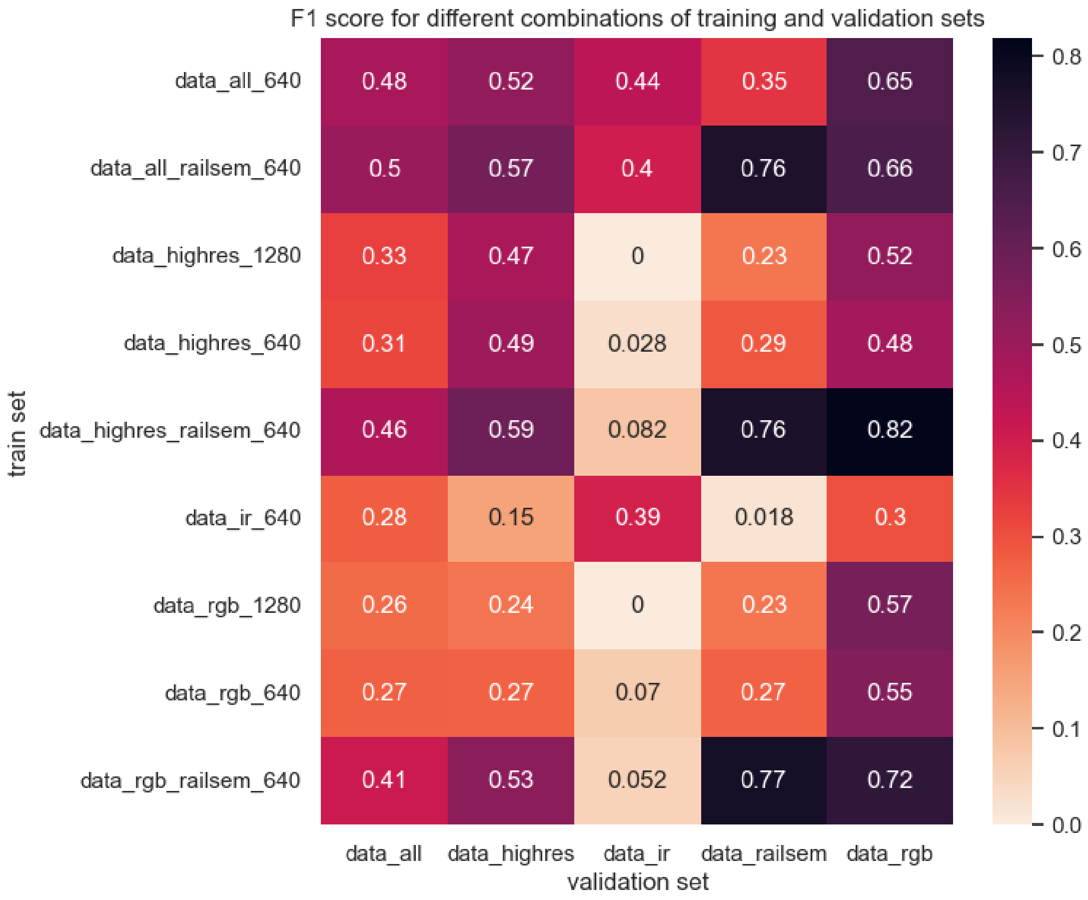
9 models have been trained and validated



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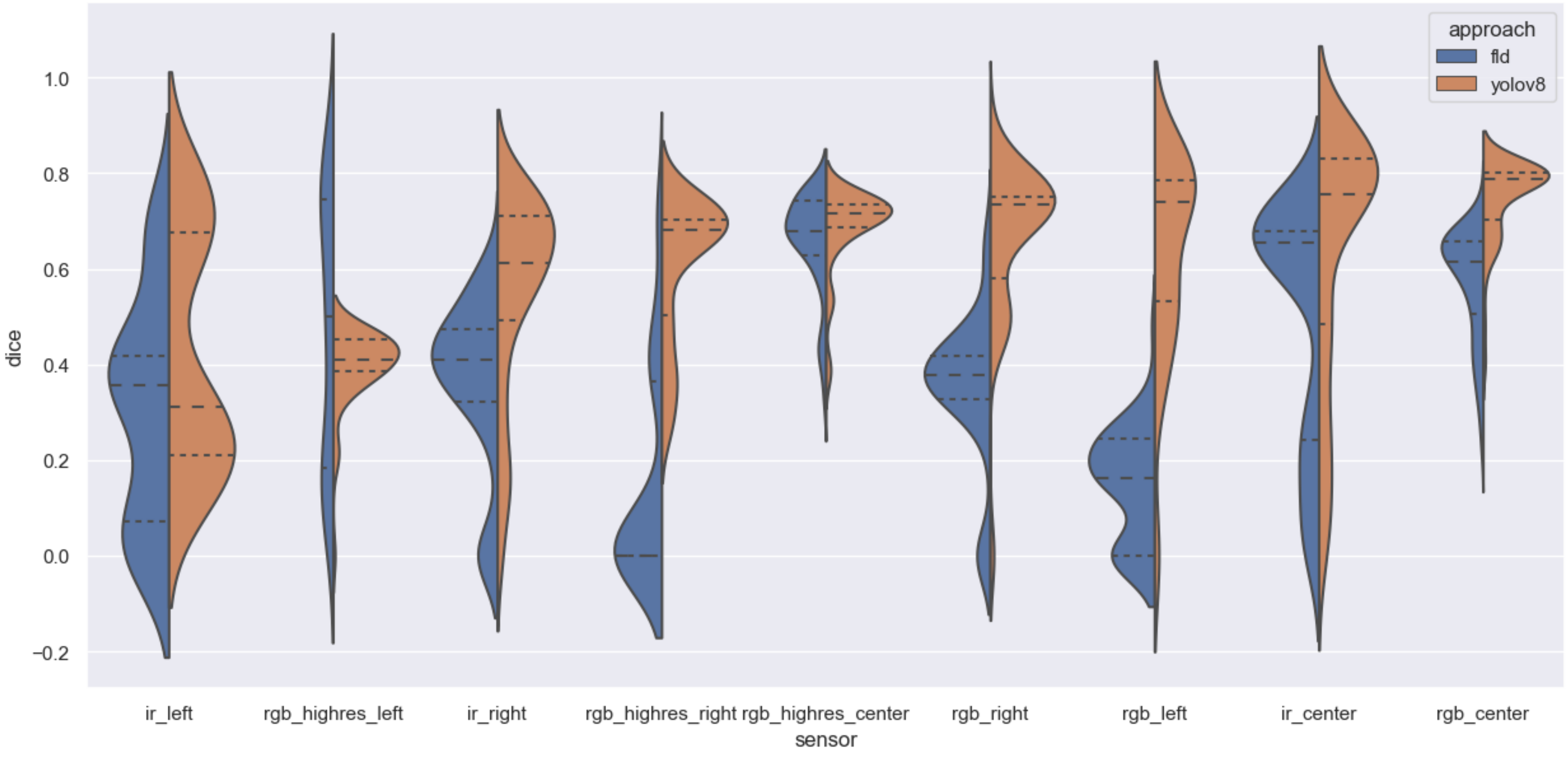
YOLOv8 vs FDL
Performance on **validation** data



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Conclusion

- Image segmentation seems to be a proper approach for modelling and solving the rail track detection problem
- Dice or f1 are well suited to assess the performance of different segmentation approaches
- Fast line detection provides a solid baseline, however YOLO outperforms FDL in most scenarios
- It seems that the performance across different sensors is similar – the orientation of the sensors has a larger impact on the results
- YOLO is well suited to be applied in real life due to fast inference

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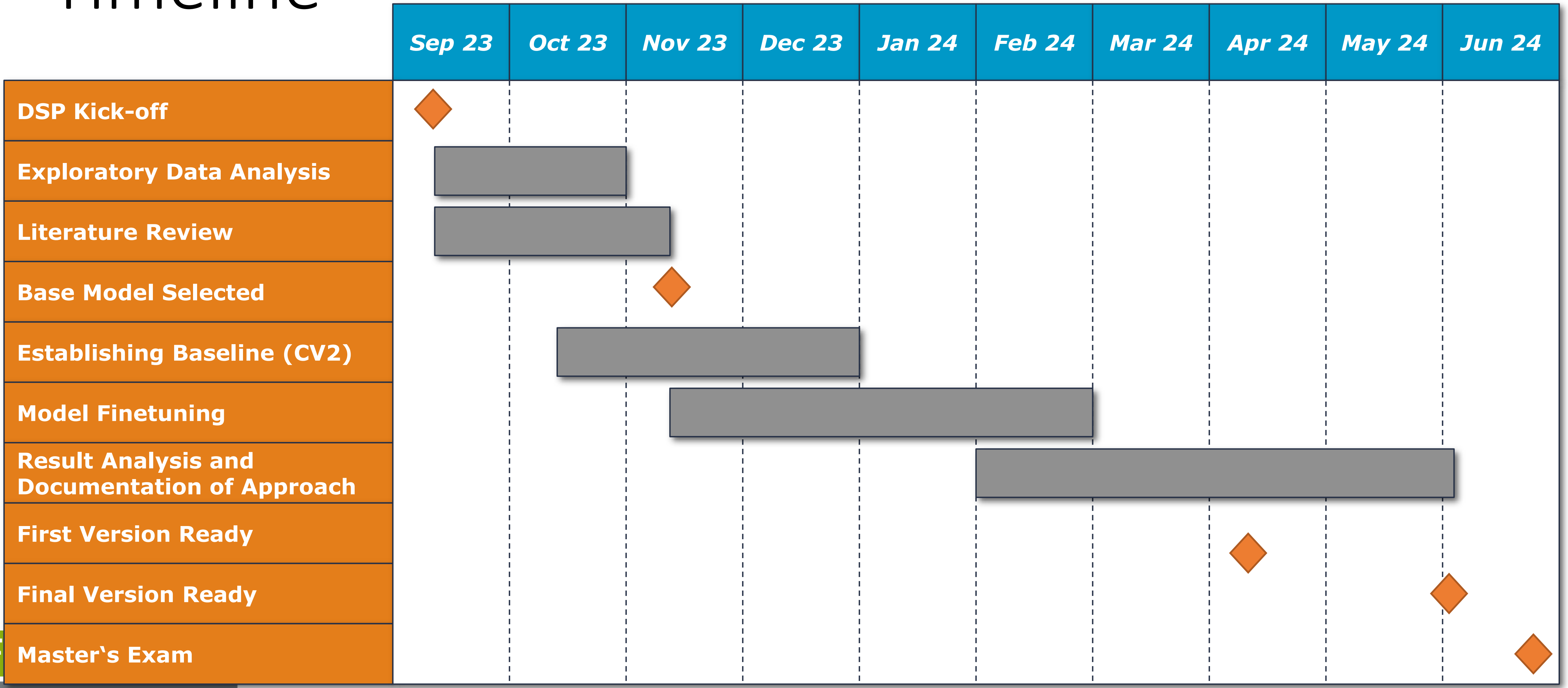
Timeline



Sep 23
Oct 23
Nov 23
Dec 23
Jan 24
Feb 24
Mar 24
Apr 24
May 24
Jun 24
DSP Kick-off
Exploratory Data Analysis
Literature Review
Base Model Selected
Establishing Baseline (CV2)
Model Finetuning
Result Analysis and Documentation of Approach
First Version Ready
Final Version Ready
Master`s Exam

Thank you!