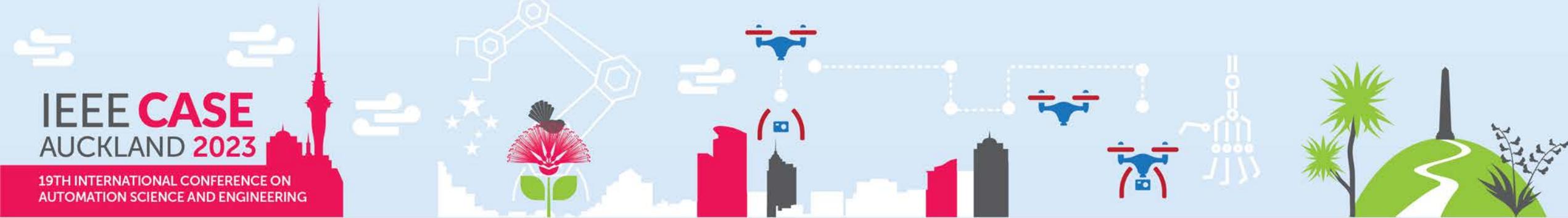


Deep Learning-Based Connector Detection for Robotized Assembly of Automotive Wire Harnesses

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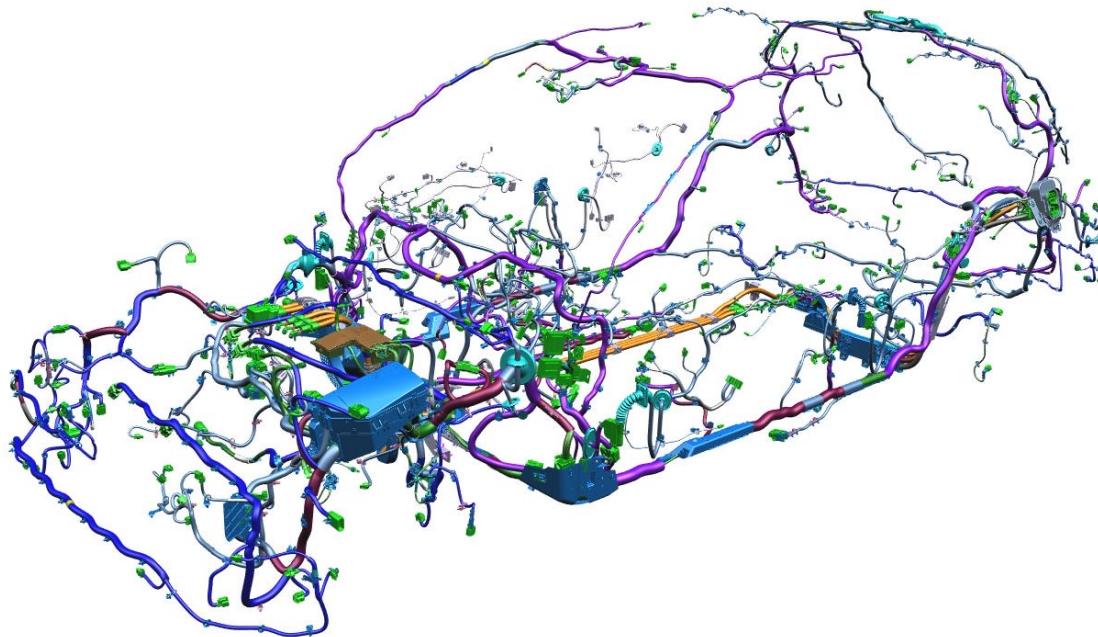
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Wire harnesses



Essential infrastructure

Critical to guarantee the assembly quality

Increasing usage



Year 2000

1000 m

Year 2003

1500 m

Year 2008

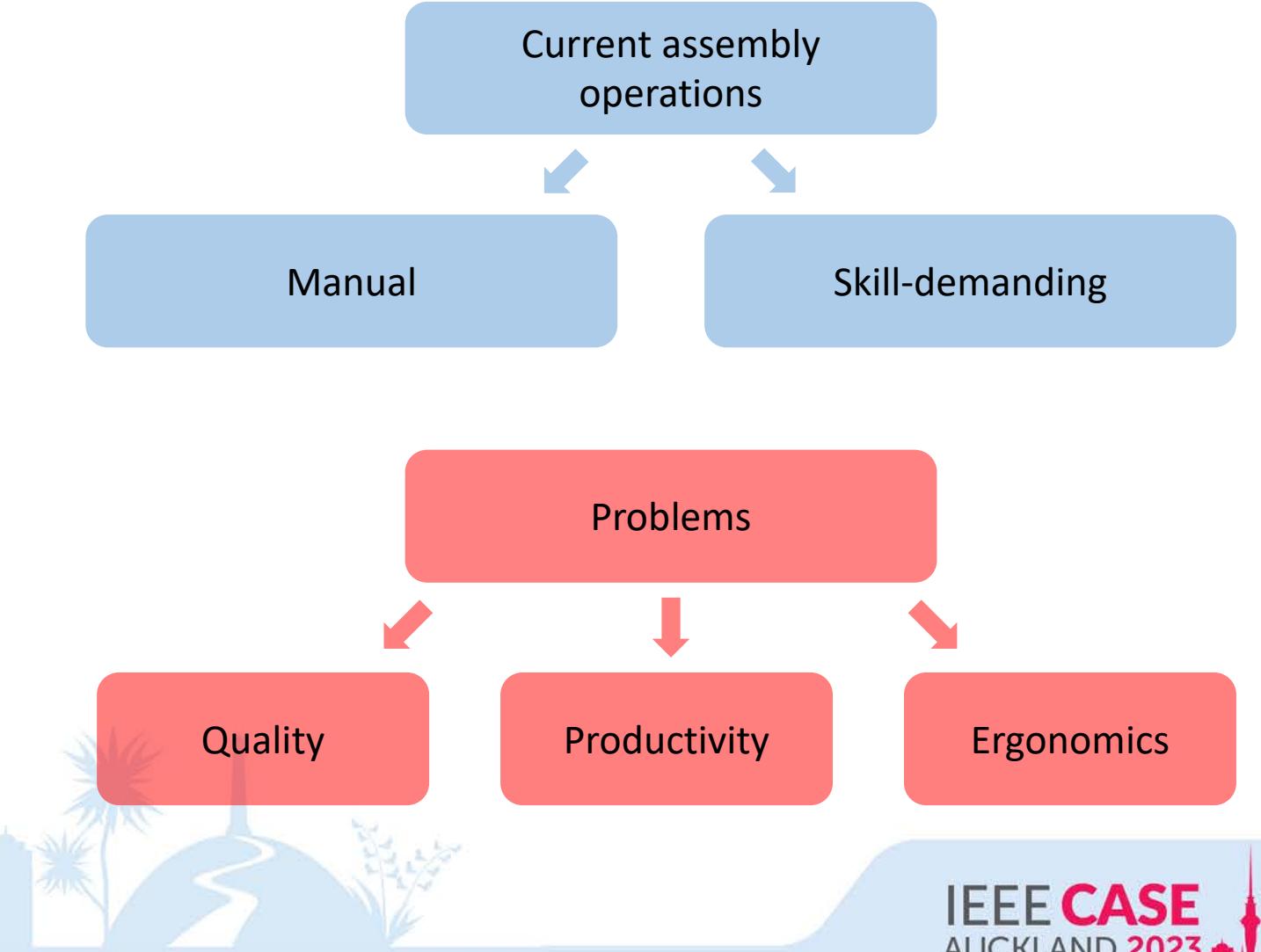
2000 m

Year 2020

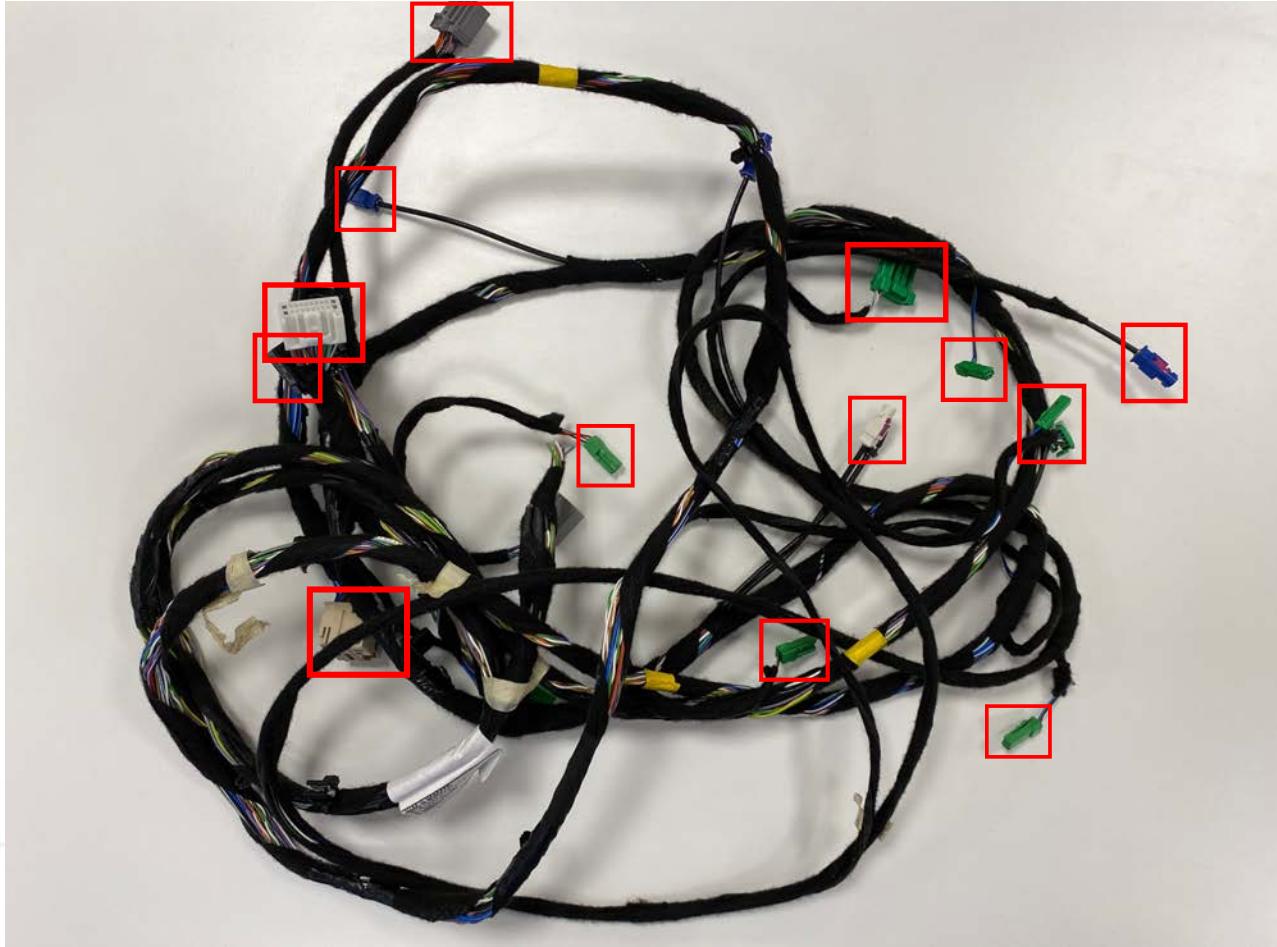
2800 m

(Images provided by Volvo Car Corporation)

Wire harness assembly



The mating of connectors



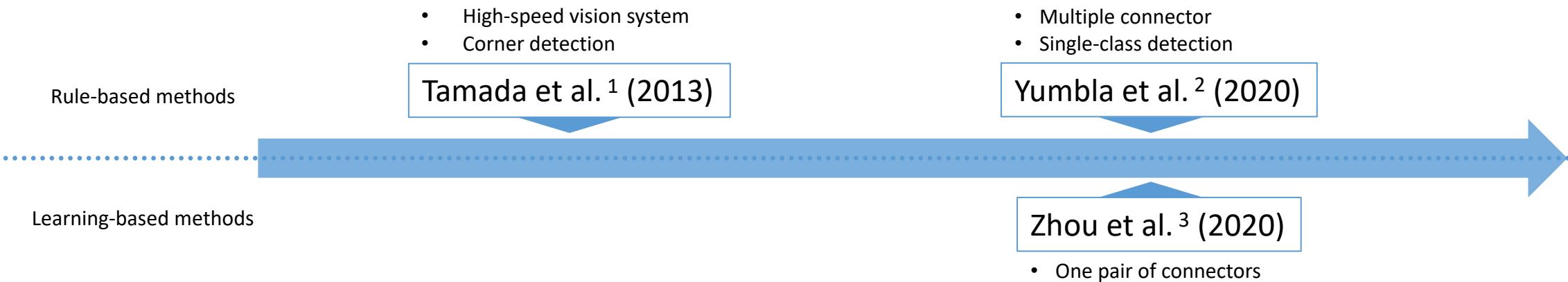
Critical for the connection and functioning of wire harnesses

Repetitive operation
(Locate, grasp, assemble)

Ergonomic issues
(High-pressure pressing)

Connector detection for robotic grasping and assembly

Previous research on connector detection

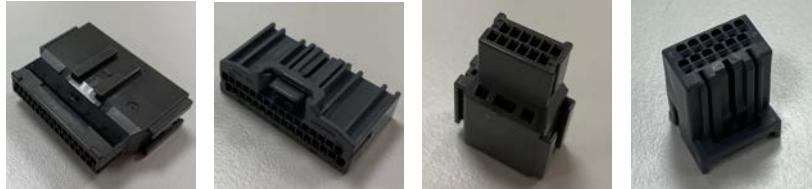


Deep learning-based multi-class connector detection

- Are deep learning-based object detectors effective on connector detection?
- What are the potential obstacles for achieving a practical learning-based connector detection?

¹T. Tamada, Y. Yamakawa, T. Senoo, and M. Ishikawa, "High-speed manipulation of cable connector using a high-speed robot hand," in 2013 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2013, pp. 1598–1604.
²F. Yumbla, M. Abeyabas, T. Luong, J.-S. Yi, and H. Moon, "Preliminary connector recognition system based on image processing for wire harness assembly tasks," in 2020 20th International Conference on Control, Automation and Systems (ICCAS), 2020, pp. 1146–1150.
³H. Zhou, S. Li, Q. Lu, and J. Qian, "A practical solution to deformable linear object manipulation: A case study on cable harness connection," in 2020 5th International Conference on Advanced Robotics and Mechatronics (ICARM), 2020, pp. 329–333.

A dataset of connectors



A0 A1 B0 B1



C D E

MX34 MX80



L M



N O P

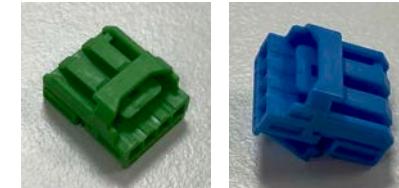
MCON 1.2 LL MX81



F G H



I J K



Q R

Image collection

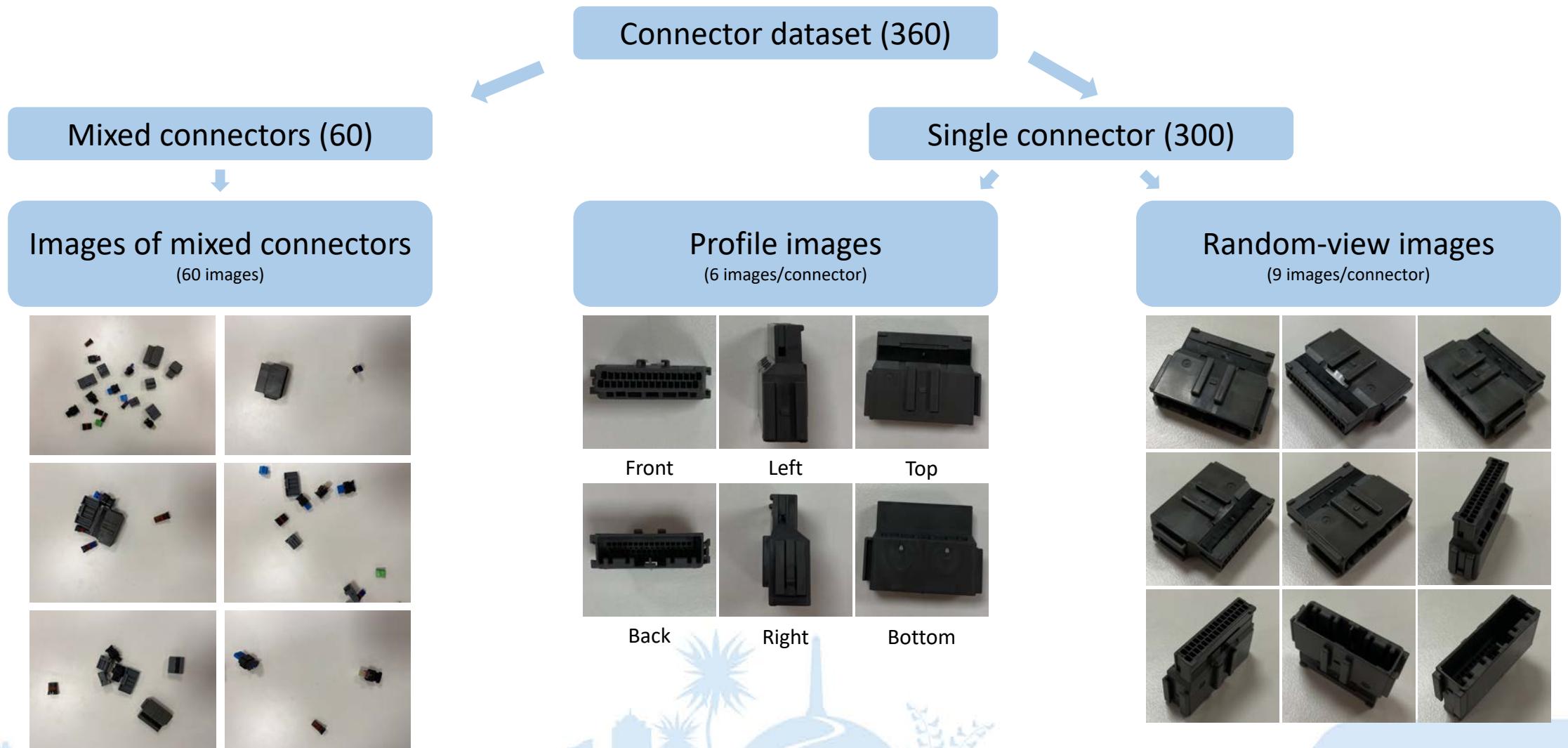
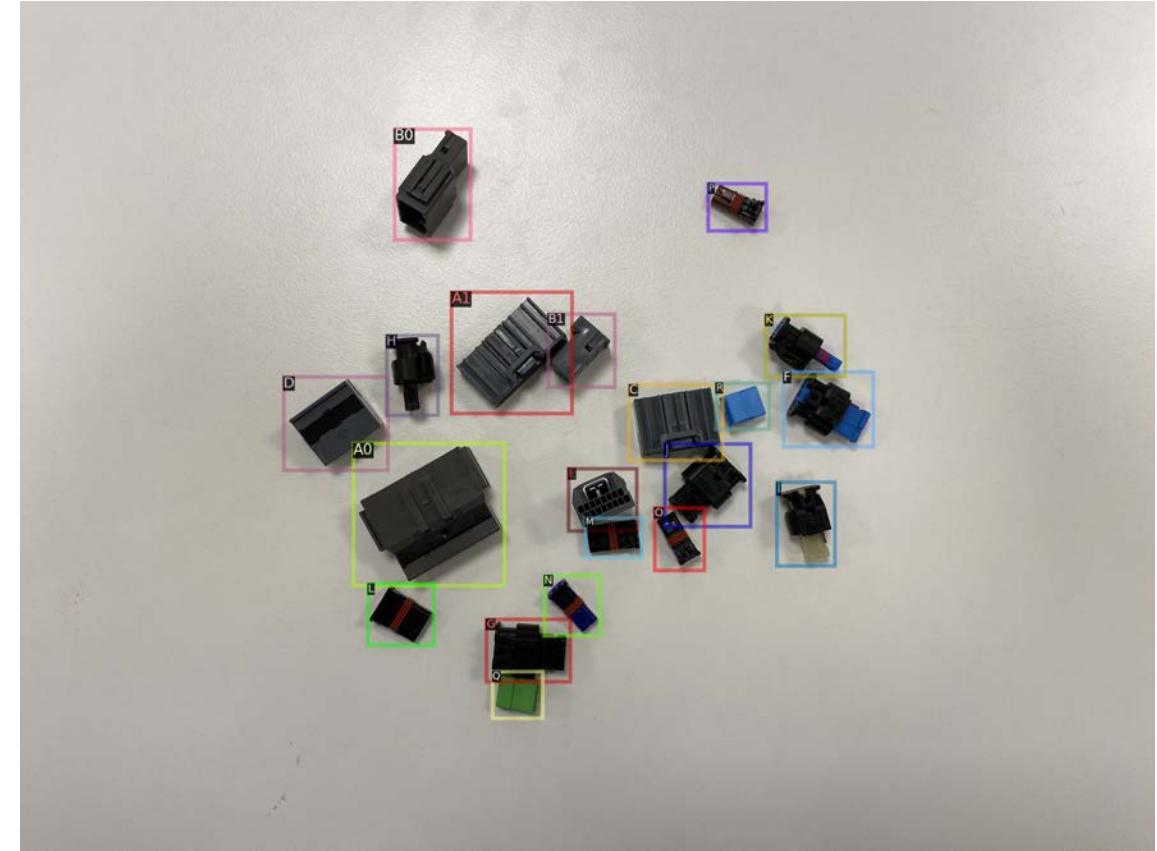
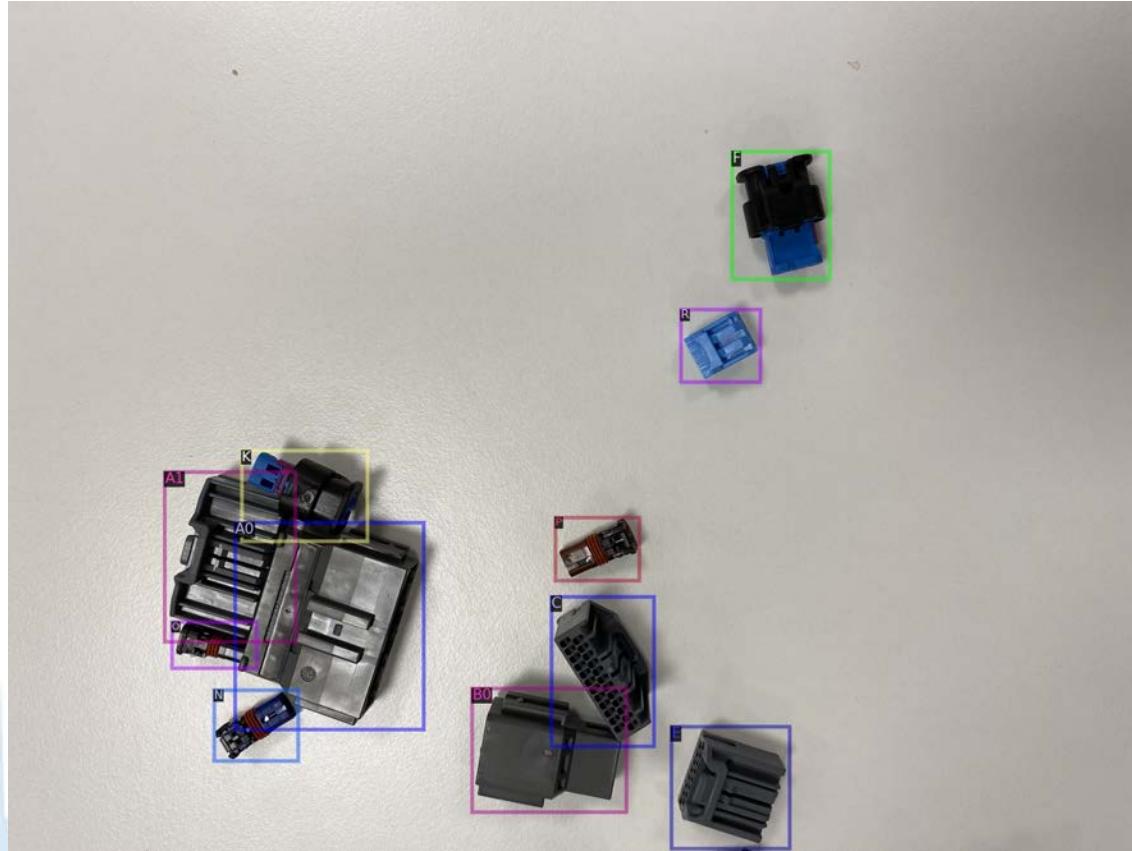


Image annotation



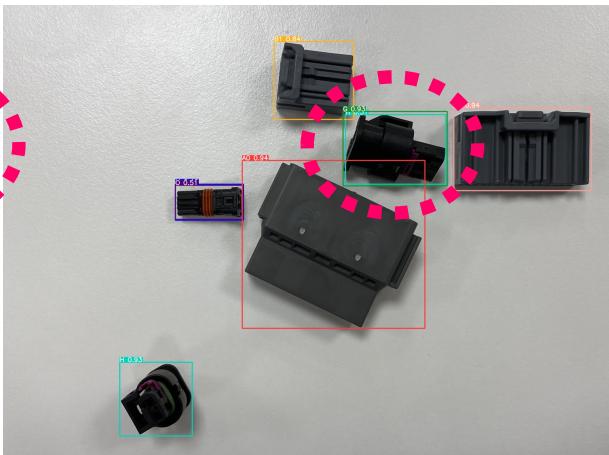
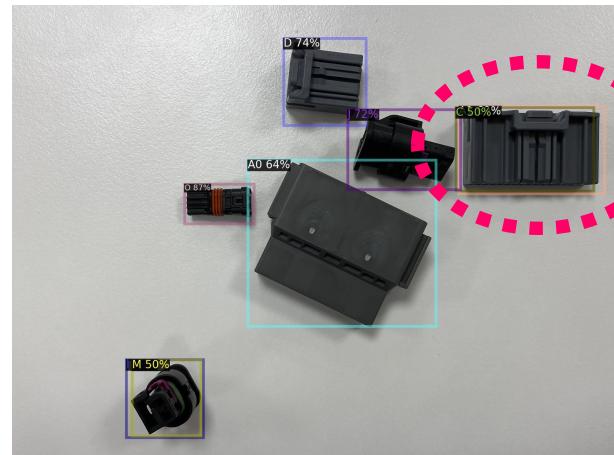
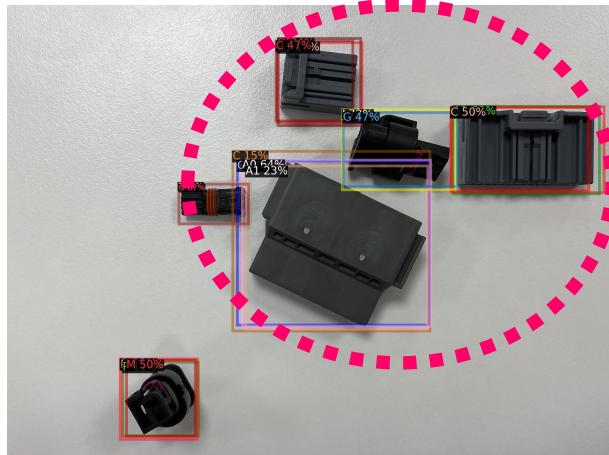
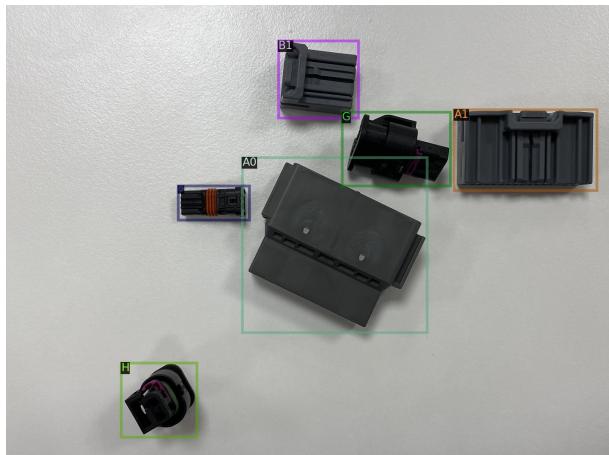
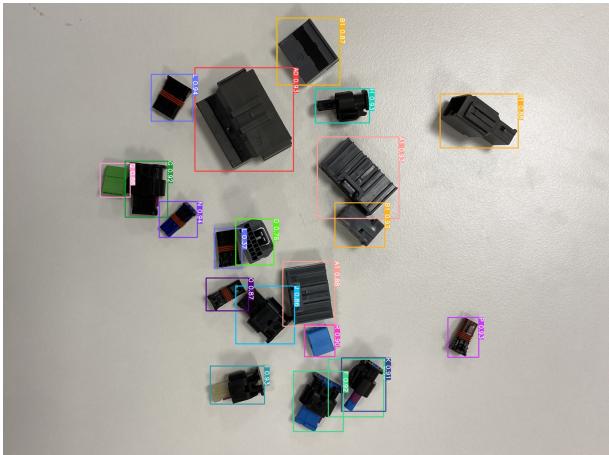
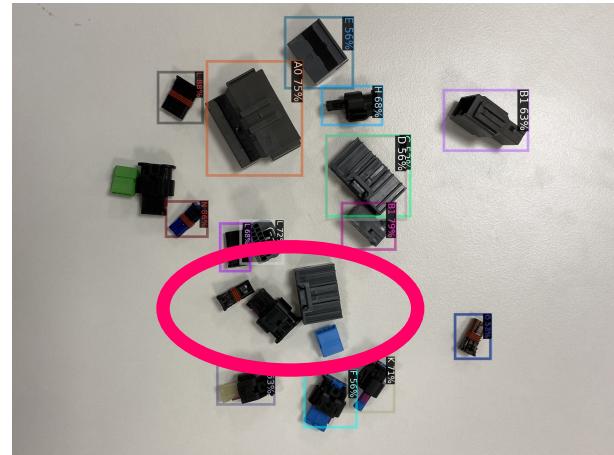
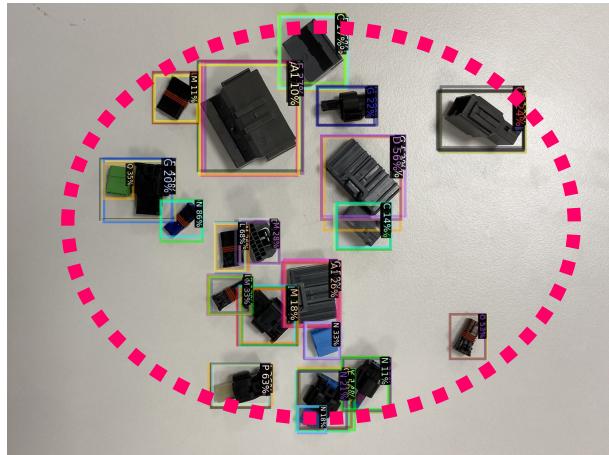
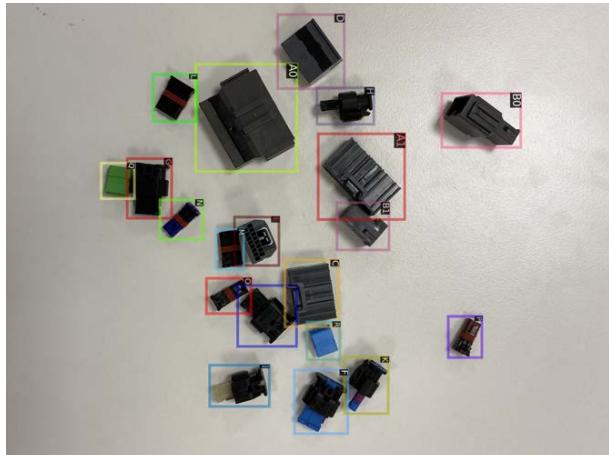
- Annotation method followed PASCAL visual object classes (VOC) challenge 2007¹
- Image annotation platform: Labelme²

¹M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman, "The pascal visual object classes (voc) challenge," International journal of computer vision, vol. 88, pp. 303–308, 2009.

²"Labelme," <https://github.com/wkentaro/labelme>, accessed: 2023-02-16.

Evaluation


 Missed


 Overlapped


Ground truth

Faster R-CNN¹ (0.1)

Faster R-CNN¹ (0.5)

YOLOv5²

¹S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards realtime object detection with region proposal networks," in Advances in Neural Information Processing Systems, C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, Eds., vol. 28. Curran Associates, Inc., 2015.

²"Yolov5," <https://github.com/ultralytics/yolov5>, accessed: 2023-02-07.

Evaluation

The Precision (%) of Faster R-CNN¹ with Threshold Values of 0.1 and 0.5 and YOLOv5² Among Classes.

Class	Precision (%)									
	A0	A1	B0	B1	C	D	E	F	G	H
Faster R-CNN ¹ (0.1)	83.2	70.3	0.0	57.3	32.8	13.2	6.7	70.1	52.4	40.4
Faster R-CNN ¹ (0.5)	83.2	48.0	0.0	48.4	0.0	0.0	0.0	70.1	30.3	40.4
YOLOv5 ²	76.4	79.2	100.0	73.8	69.7	0.0	47.2	100.0	30.9	90.7
Class	I	J	K	L	M	N	O	P	Q	R
Faster R-CNN ¹ (0.1)	45.0	48.6	80.2	80.0	60.0	93.3	63.2	72.4	35.0	78.8
Faster R-CNN ¹ (0.5)	0.0	0.0	80.2	80.0	30.3	93.3	50.4	72.4	0.0	67.2
YOLOv5 ²	88.5	53.0	63.2	85.5	100.0	91.6	96.4	94.6	93.0	96.8

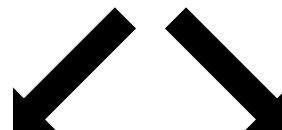
Deep learning-based detection models are effectiveness.

Missed, overlapped, unstable detection results exist.

The Mean Average Precision (%) of Faster R-CNN¹ with Threshold Values of 0.1 and 0.5 and YOLOv5².

	mAP ₅₀	mAP ₅₀₋₉₅
Faster R-CNN ¹ (0.1)	65.7	54.1
Faster R-CNN ¹ (0.5)	47.1	39.7
YOLOv5 ²	88.5	82.1

A benchmark dataset is needed!



Training

Evaluation

¹S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards realtime object detection with region proposal networks," in Advances in Neural Information Processing Systems, C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, Eds., vol. 28. Curran Associates, Inc., 2015.

²"Yolov5," <https://github.com/ultralytics/yolov5>, accessed: 2023-02-07.

Potential hindrance

Left



Top



(Almost) Identical features

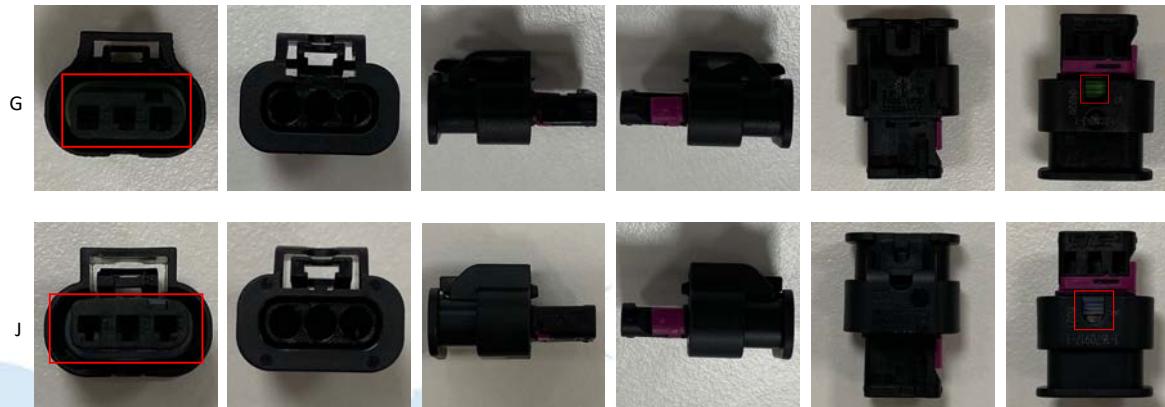
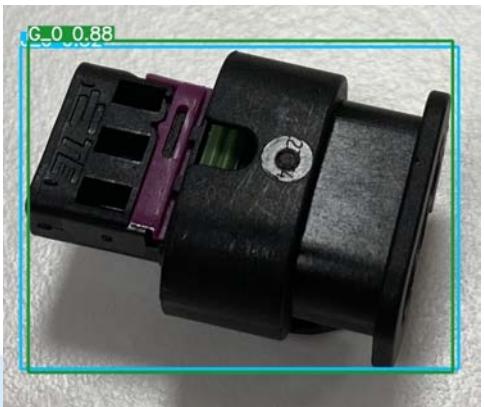
A1

B1

C

D

E



Infeasible features

Conclusion and future work

- This study verified the effectiveness of deep learning-based connector detection.
- A dataset of automotive wire harness connectors was collected for evaluation.
- This study identified the insufficient dataset and the current design of connectors as hindrances of detection.
- A benchmark dataset is desired for better training and evaluation.
- Further research will exploit the structure of wire harnesses and multi-view image-/video-based detection.



¹S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards realtime object detection with region proposal networks," in Advances in Neural Information Processing Systems, C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, Eds., vol. 28. Curran Associates, Inc., 2015.

²"Yolov5," <https://github.com/ultralytics/yolov5>, accessed: 2023-02-07.

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