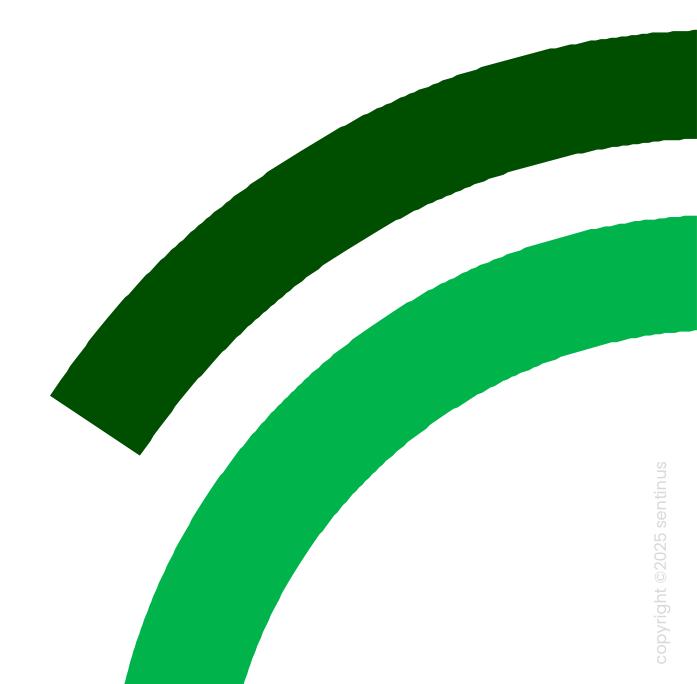


# Driving competitive advantage with computer vision

Automated quality control for manual assembly

Overview



# 01 Sense of urgency



Manual manufacturing offers high optimization potential:

- →Cost of quality
- → Skilled worker shortage & nearshoring
- → Continuous process optimization



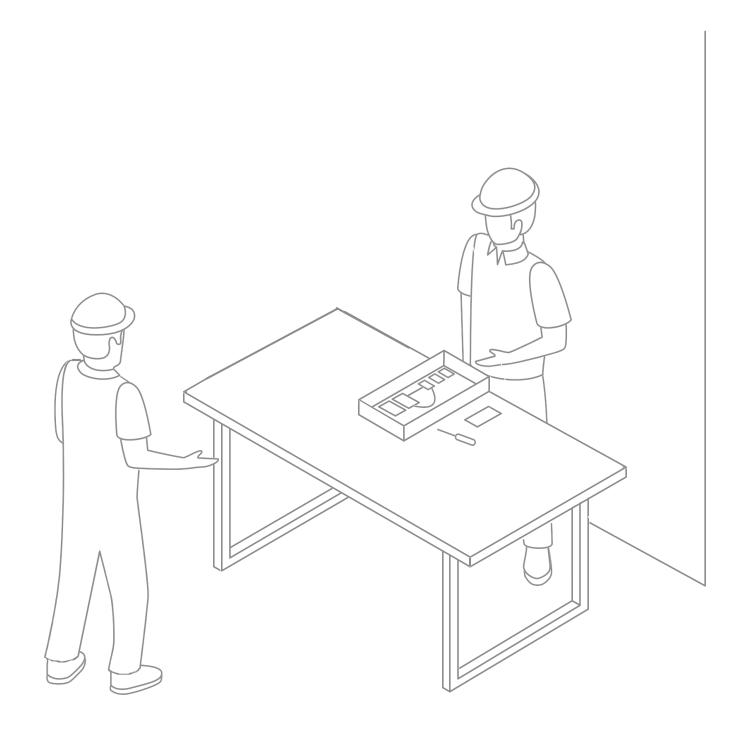


# 02 Solution

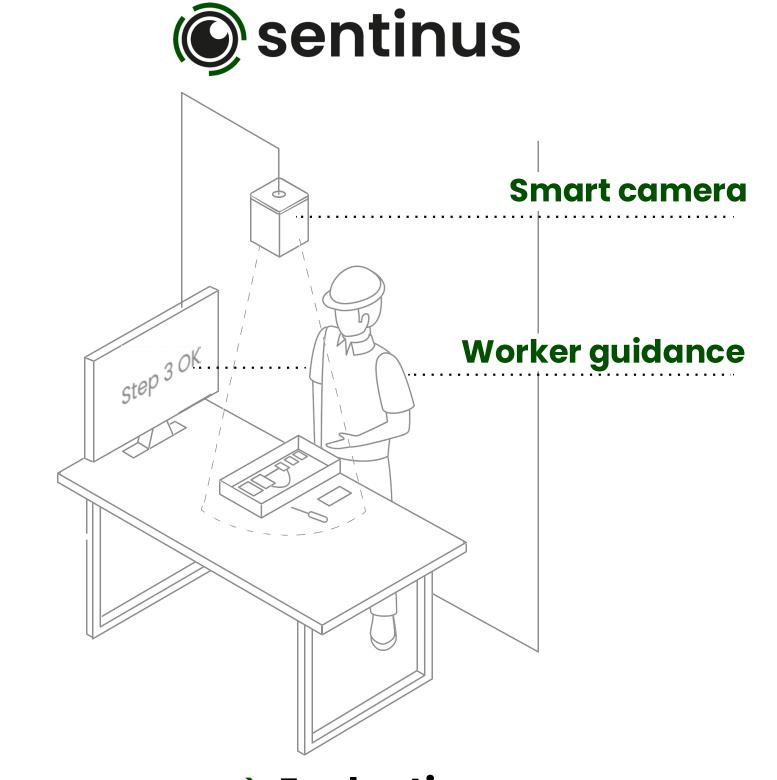


We digitize the four-eye-principle.

Four-eye-principle



Manual quality assurance



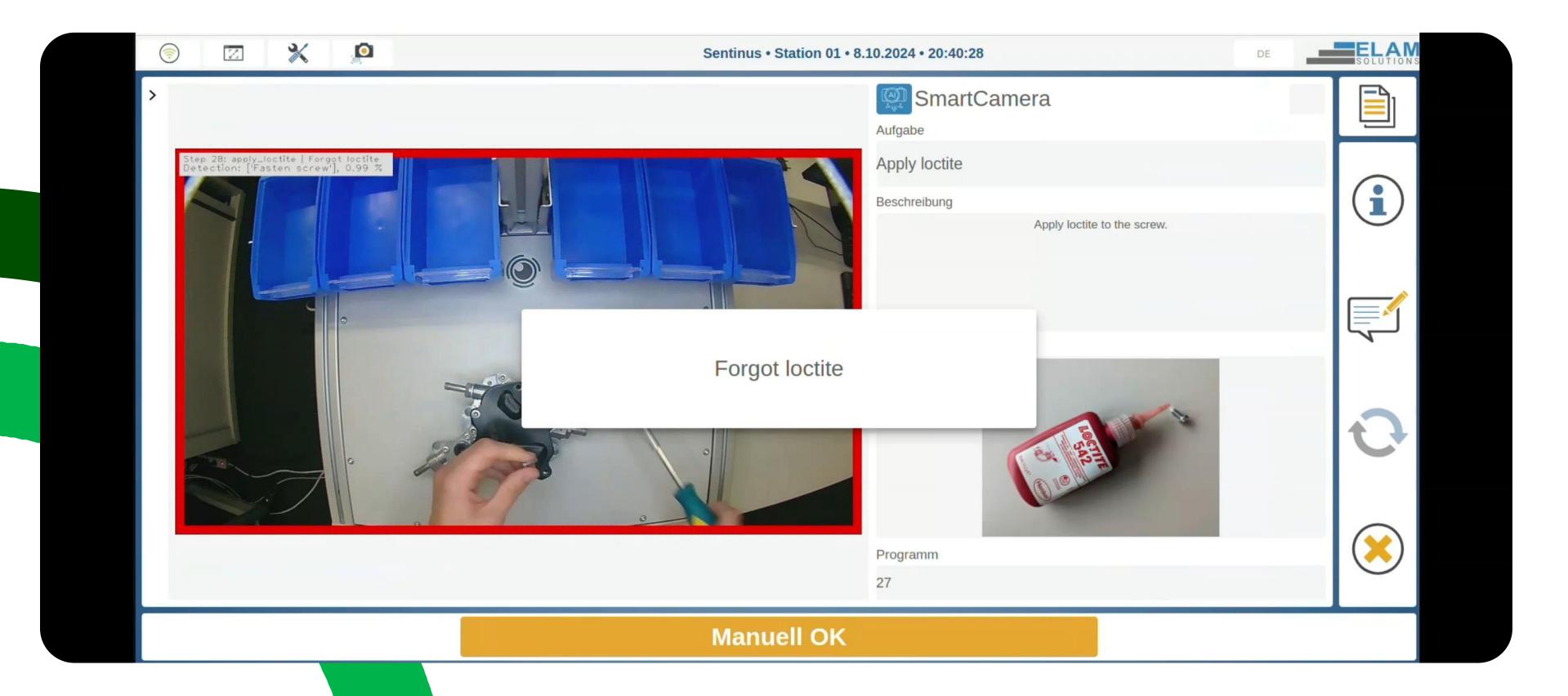
→ Evaluation
 Automated → Feedback & instructions

Documentation

# **)**'

# 04 Technology

Computer vision for assembly step recognition.



# 04 Technology



We understand the whole assembly process.

### Other solutions:

- → Automation of single end-of-line checks
- → State confirmation only
- → Focus on automated / low-mix, high-volume production: Lack of scalability
- → Fails in case of high variation, e.g., variant task execution, lighting situation, ...

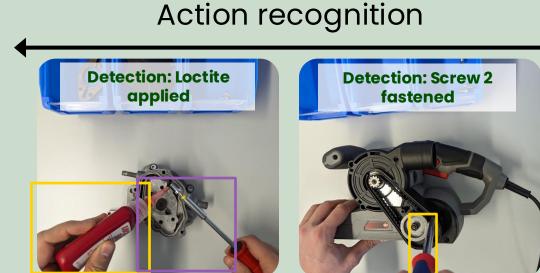
### State confirmation



### **Our solution:**

- → Applicable for the whole assembly process
- → State confirmation + action recognition
- → Simple setup / adaption manual for highmix, low-volume production
- → Robust against variation

# State confirmation Detection: Part 3 present



# 05 Roadmap



We work towards 100% in-process control starting at lot size one.

2020: Applied research

ETHzürich inspire

# 2025: Automated quality control

- → Automated assembly step recognition
- → Live feedback, instructions, documentation

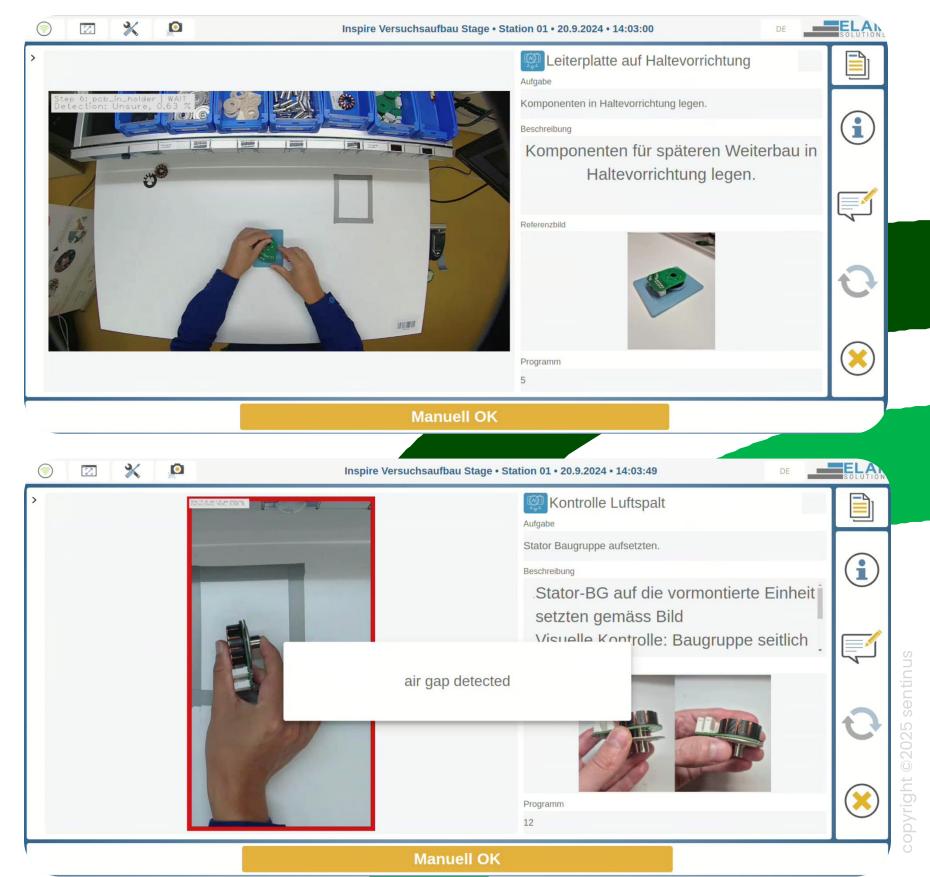
**BOSSARD** 



## 2027: Plug & play solution

- → Plug & play based on general dataset
- → Fully automated training pipeline using synthetic data

2029: 100% in-process control starting at lot size one



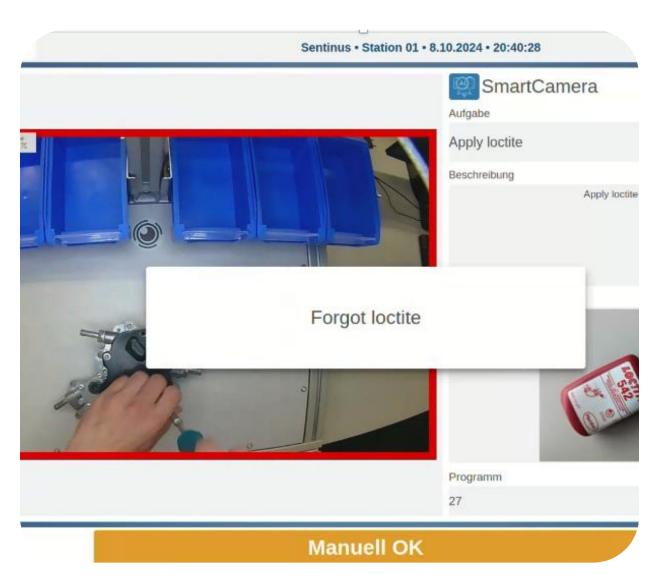
# 06 Technology vision



Tackling the hurdle of training data generation with synthetic training data.







Digital part models

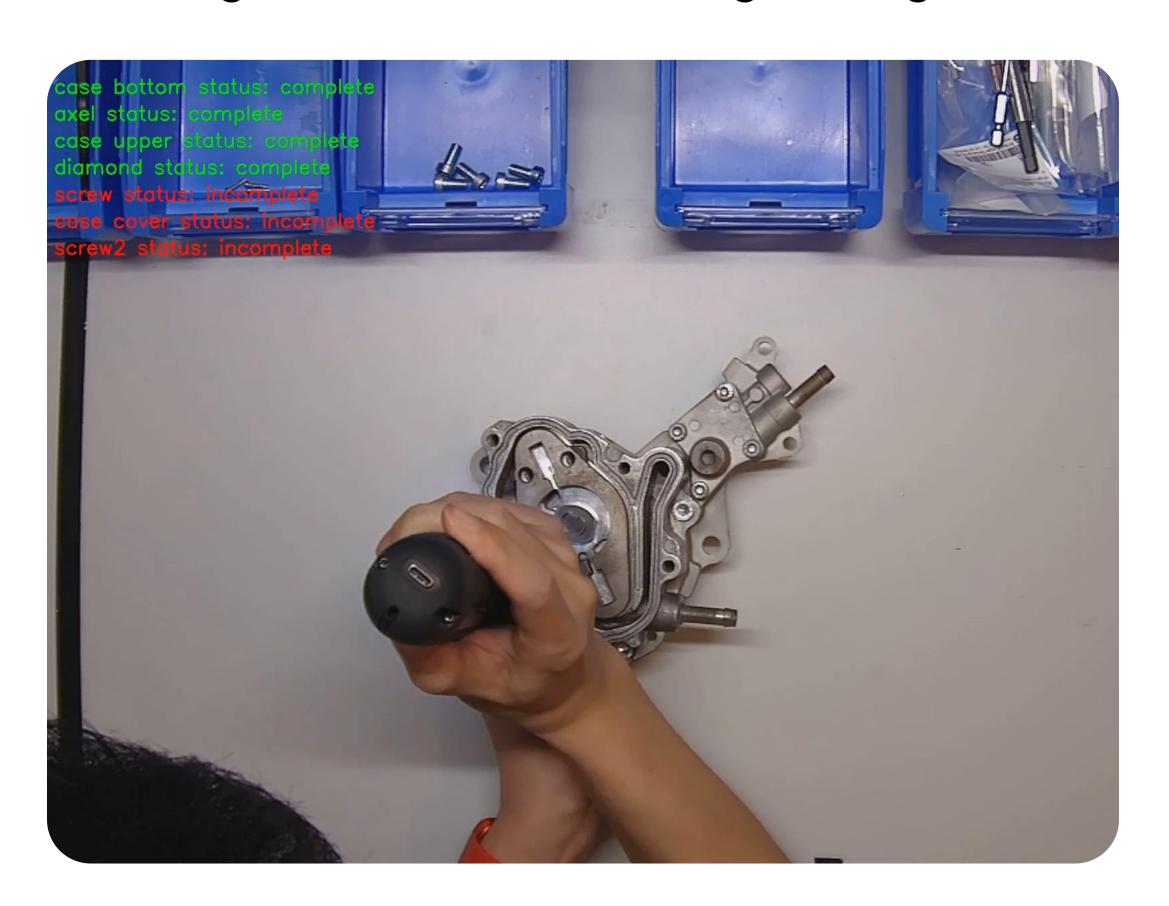
Generation of synthetic images & model training

Automated assembly step recognition

# 06 Technology vision



Tackling the hurdle of training data generation with synthetic training data.



**Applied research** 



# 06 Team



We are experts in computer vision applications and business strategy.



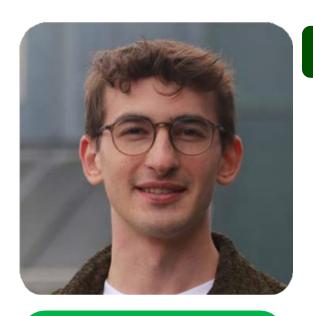
Co-founder

## Jonas Conrad

- → MSc ETH Mechanical Engineering
- → PhD Deep learning in manual assembly (WIP)

### **RESPONSIBILITIES**

→ Executive lead



**Co-founder** 

## Felix Schnarrenberger

- → MSc ETH Robotics, Systems and Control
- → Applied machine learning and computer vision

### **RESPONSIBILITIES**

→ Technical lead



**Co-founder** 

## Constantin Herbst

- → MSc ETH Mechanical Engineering
- → Data Scientist CV

### **RESPONSIBILITIES**

→ Operational lead



## Christoph Conrad

→ Former Head Marketing "Solution & Service Portfolio" at Siemens AG

### **RESPONSIBILITIES**

→ Business development



## David Filliberti

- → MSc ETH Robotics, Systems and Control
- → Applied ML & CV

### **RESPONSIBILITIES**

Embedded systems



## Wsewolod Dubinski

- → MSc EBS Management
- → Strategy & Finances

RESPONSIBILITIES

→ Strategy & Finance

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# 07 DSL Challenge



# Automated anomaly detection in manual assembly based on synthetic data

- → Challenge Giver: Constantin Herbst, Jonas Conrad, Sentinus AG
- → Academic Coach:
- → Contact Details: constantin@sentinus.ch, jonas@sentinus.ch

### **Overview:**

- → **Aim**: Perform robust anomaly detection in the manufacturing process trained on synthetic data
- → Goal: A pipeline that recognizes anomalies in single parts and wrongly assembled subassemblies based on CAD data of assembly group in real time.
- → **Tools**: python, blender, pytorch
- → Focus:

Robustness: needs to work on real data under realistic conditions
Data-Efficiency: no need to record data to prepare inspection for assembly
Semantic Scene Understanding: Correct segmentation of parts / subassemblies

→ Support:

Recording extra datasets for specific anomalies Real-time testing with sentinus smart camera hardware Guidance from Sentinus team

→ Literature: Entry points to computer vision model training based on synthetic data

https://www.mdpi.com/2076-3417/13/22/12316 https://www.sciencedirect.com/science/article/pii/S2212827124006668

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# 07 DSL Challenge



## **Dataset:**

- → Sources: MA-3 dataset
- → Content: 60 videos of manual assembly of different products; 20 operators. Focus on vacuum pump. The dataset can be enhanced by Sentinus.
- → Pickup SSD at Technopark

## Challenge Components:

- → Build a CV pipeline that
  - 1. Based on CAD data of each part / assembly stage creates a rendered dataset to train models for the following step
  - 2. Segments all relevant assembly parts in a live video stream in real time
  - 3. Performs anomaly detection on single parts and sub-assemblies
  - 4. Anomaly detection on subassembly: wrong assembly!
  - 5. Rejects frames in which no inspection can be performed reliably due to occlusion, motion blur etc,

# 07 DSL Challenge



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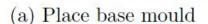
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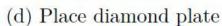




(b) Place axle

(c) Place centre mould







(e) Place cover



(f) Screw first location

# 07 DSL Challenge



## **Evaluation Metrics:**

- 1. Accuracy of recognized assembly status
- 2. Accuracy of segmentation (mIOU)
- 3. Detection rate of anomalies (screw missing, flipped part) (AUROC/PRO)

# **Successful Project:**

- → Can discern assembly status on real data
- > Rejects obvious disturbances / occlusions (e.g. hand covers assembly group
- → Can pinpoint anomalies robustly: rotation, position, illumination invariant, robust against slight variation in part appearance
- → Well-documented and reasonable code

# SotA: Datasets exist, but do not accurately represent real application scenarios



Data set	Visual sensors	Assembly task	Reflective components	Cabling tasks	Symmetric base	Fine-grained labelling
Assembly101 <sup>15</sup>	Eight RGB cameras (static mount), four monochrome cameras (head mount)	Toy cars	No	No	No	Yes
Wooden box <sup>16</sup>	Two RGB cameras (static mount)	Wooden box	No (screws)	No	Yes	No
MECANO 17,18	RealSense300 (RGB + depth, head mount), Pupil Core (gaze signals, head mount)	Toy motorbike	No	No	No	Yes
IKEA ASM <sup>19</sup>	Three Azure Kinect V2 (RGB + depth, static mount)	Ikea furniture	No	No	Yes	Yes
IKEA FA <sup>20</sup>	One RGB camera (static mount)	Ikea furniture	No	No	Yes	No
IKEA Ego 3D <sup>21</sup>	HoloLens 2 (RGB + point cloud, head mount)	Ikea furniture	No	No	Yes	Yes
HA4M <sup>22</sup>	One Microsoft Azure Kinect (RGB + depth + IR + point cloud, static mount)	Generic assembly tasks	No	No	Yes	Yes
HA-VID <sup>23</sup>	Three Azure Kinect (RGB + depth, static mount)	Generic assembly tasks	No (screws, nuts)	No	Yes	Yes
MA-3 dataset (ours)	Two RGB cameras, 1 depth camera (all static mount)	Three manually assembled products	Yes	Yes	Yes	Yes



# Contribution: Dataset including specific application hurdles for computer vision approaches in manual assembly + benchmark



# Challenges

- High operator-induced variance in task execution
- Reflective components
- Cabling tasks
- Symmetric parts (base plate)
- Fine-grained task distinction (e.g., screw coordinates)

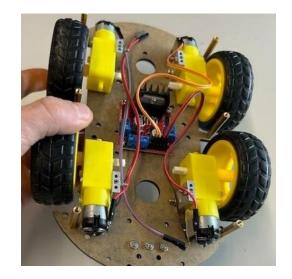
### **Belt sander**



- Task execution variance
- Fine-grainde task distinction

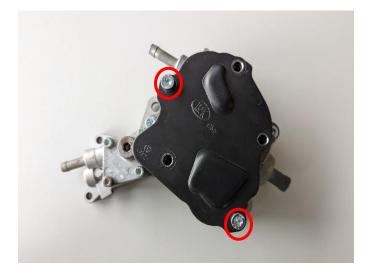
## Robot car

Use cases



- Task execution variance
- Finegrainde task distinction
- Symmetric parts
- Cabling task

## Vaccum pump



- Task execution variance
- Finegrainde task distinction
- Reflective parts



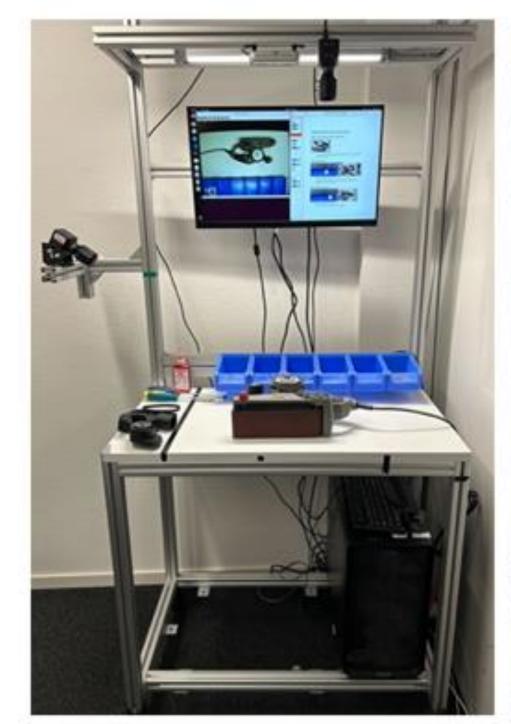
# Methods: Dataset collection + benchmark

## **Data collection**

- 2 RGB cameras, 1 depth camera
- 20 participants, 3 recordings per use case
- Labelling with ground truth (79 distinct classes)
  - Action class + specifier, e.g., screw\_screw1

## **Benchmark**

- 4 Computer vision approaches
- F1-scores
- Reverse Leave-one-out

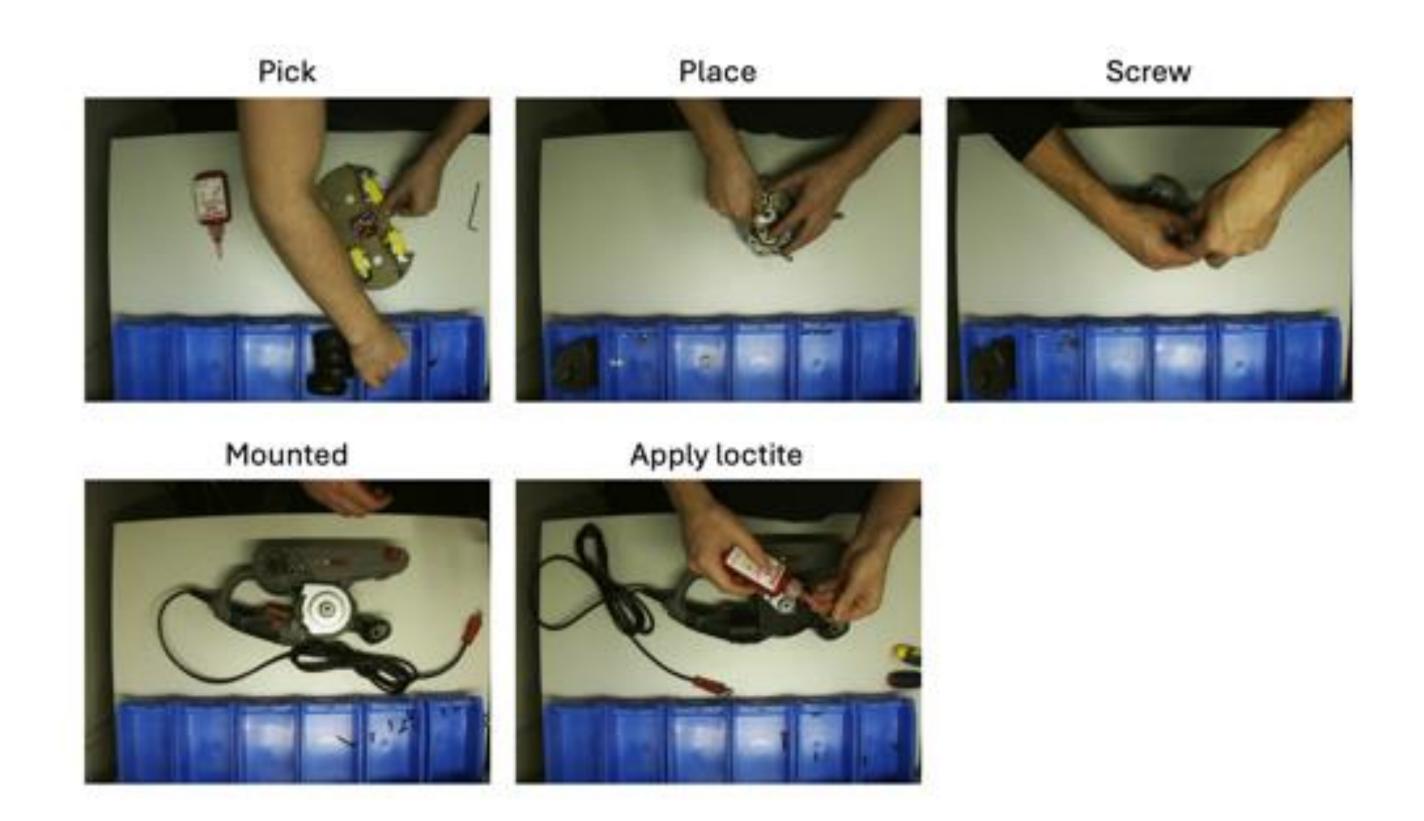








# **Action class overview**





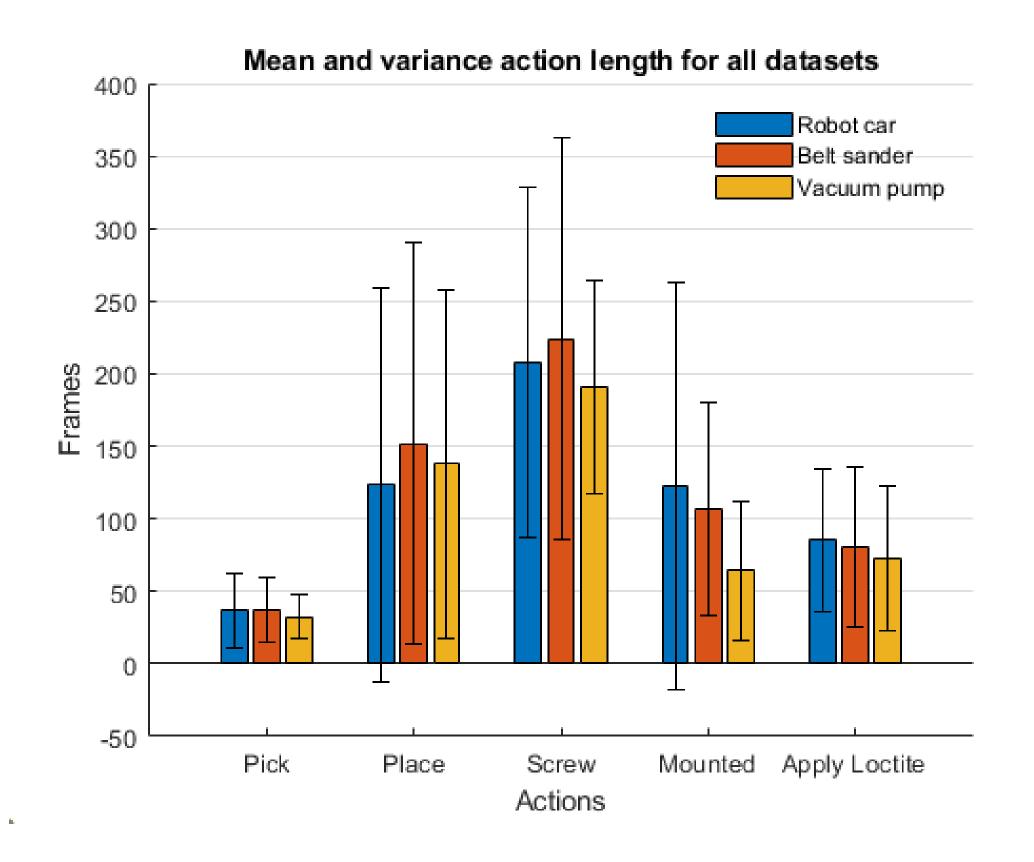
# **Technical validation**

## **Dataset overview**

- 18 hours, 9 minutes of assembly activity
- Recorded in 540 videos

## **Benchmark**

- Overall performance
- Confusion matrix for one computer vision approach
- Results Reverse Leave-One-Out for one approach







# **Technical validation**

Action	Instances	Mean Length (frames)	Variance (frames)	Min Length (frames)	Max Length (frames)
pick	1732	35.59	21.73	10	238
place	1286	134.43	133.01	10	1556
screw	961	208.65	116.6	12	904
mount	4015	100.26	104.15	9	1072
apply_loctite	801	79.15	51.78	10	339



# **Technical validation**

F1-score of various models over all datasets								
Models	Average	Robot car	Belt sander	Vacuum Pump				
YOLOv8m-cls	0.731	0.610	0.801	0.781				
EfficientNetB4	0.796	0.677	0.885	0.825				
UniFormerV2	0.795	0.656	0.905	0.824				
CSN-r50	0.808	0.656	0.909	0.858				
CSN-r152	0.790	0.625	0.888	0.858				

# 08 Next steps



- → Get familia with dataset and theory
- → Define focus areas
- → Reach out if further inputs are needed (best via mail)



# Thank you!

Please get in touch with us. Any day, any time!

+41 44 556 58 76

Reach us via mail to schedule a meeting: jonas@sentinus.ch

# Supported by:















