Zero-Defects Manufacturing (ZDM) workshop

OPTIMAI

[4ZDM Cluster]

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OPTIMAI

Manufacturing Processes through Artificial Intelligence and Virtualization

https://optimai.eu/

Outline

- Achievements:
- Defect detection
- Automatic Calibration

Use case: Defect detection

MICROCHIP pilot site

PCB manufacturing

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MICROCHIP – pilot site

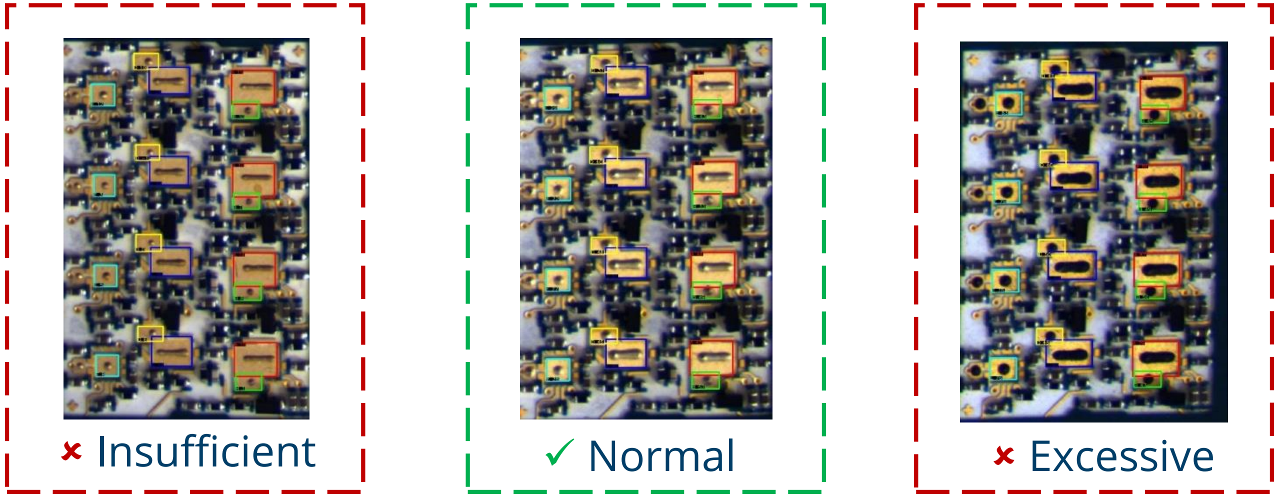
Product: Printed Circuit Boards (PCBs)

Use case: Defect detection

Industrial process/workstation: Glue/epoxy glue dispensing

Problem formulation:

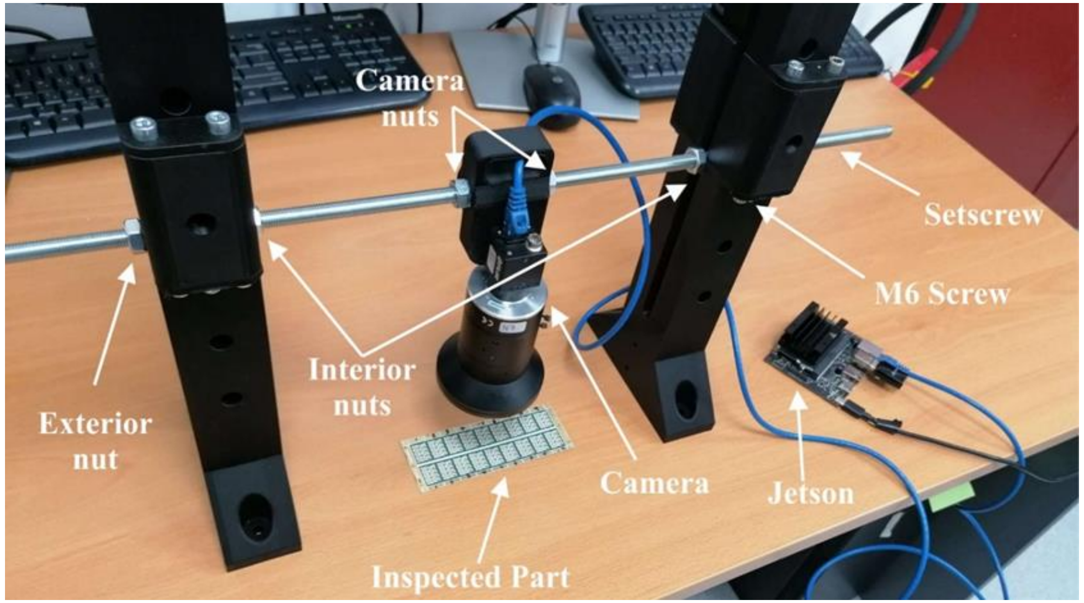
➢The identification of such defects requires **manual inspection**, which is a time consuming and depends on operator’s experience.



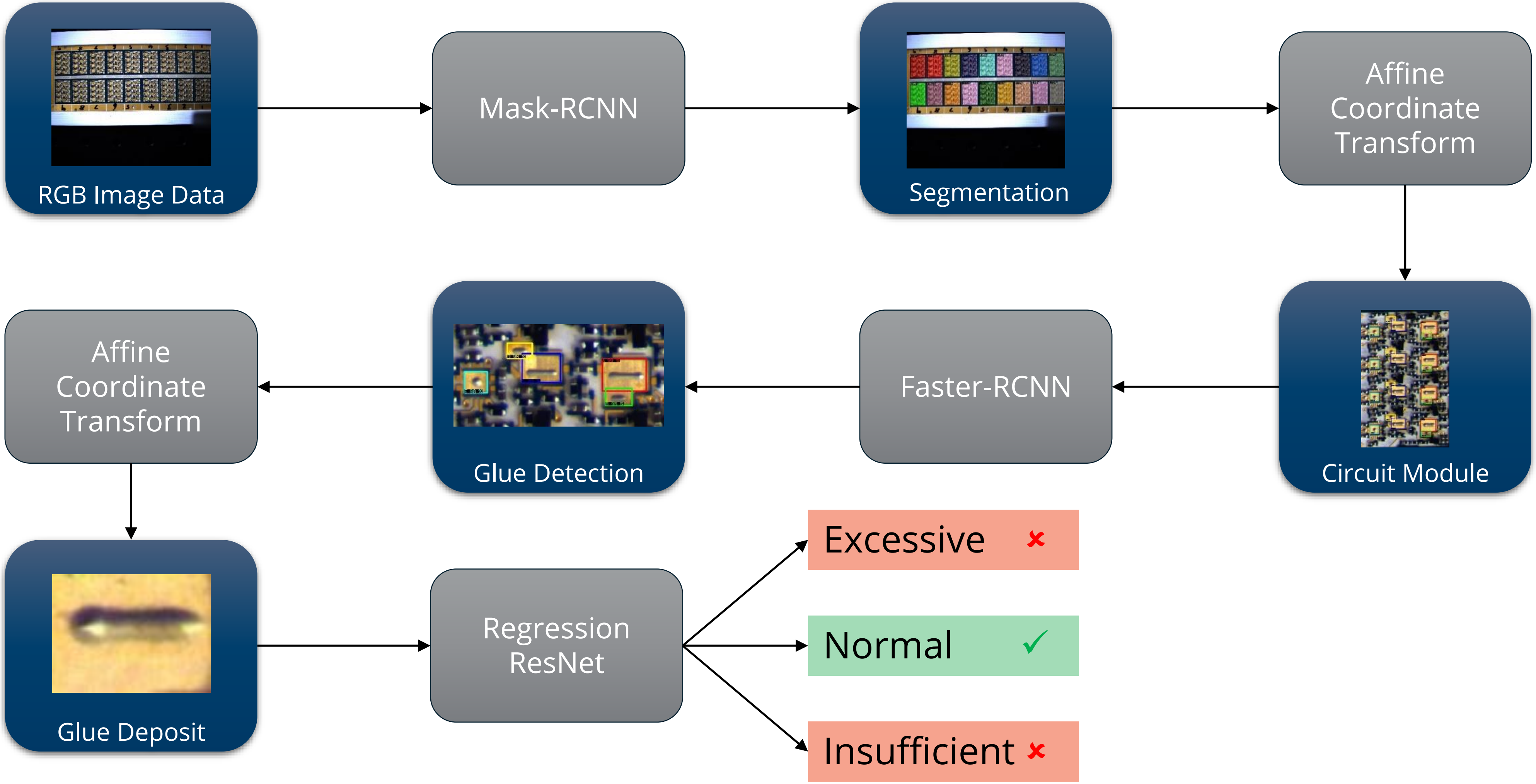
Defects generated during dispensing process

OPTIMAI defect detection

- 3D printed adjustable structure
- Machine vision camera
- Computational unit (e.g. Jetson)



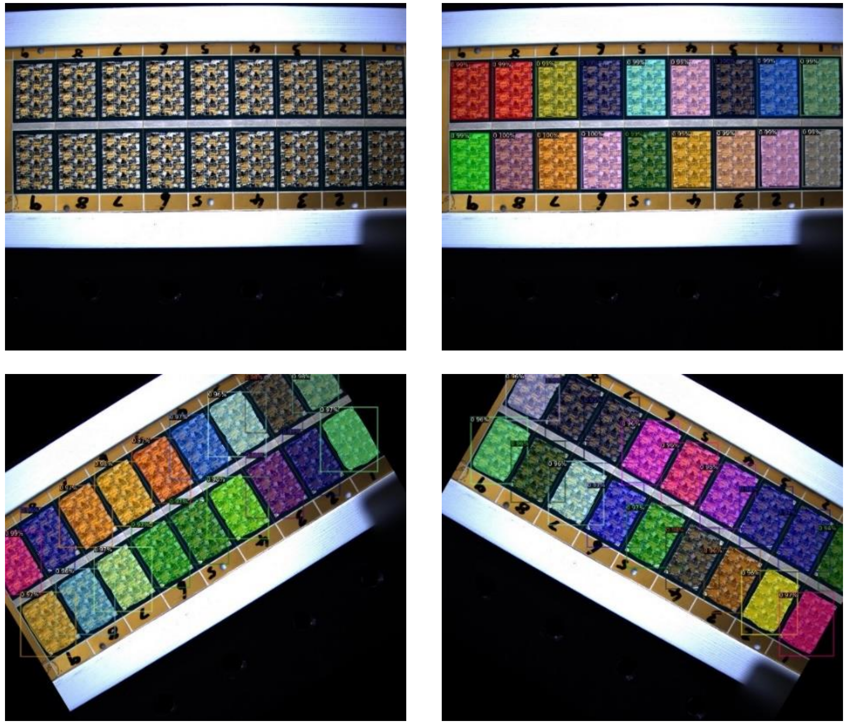
Defect Detection Process



Results

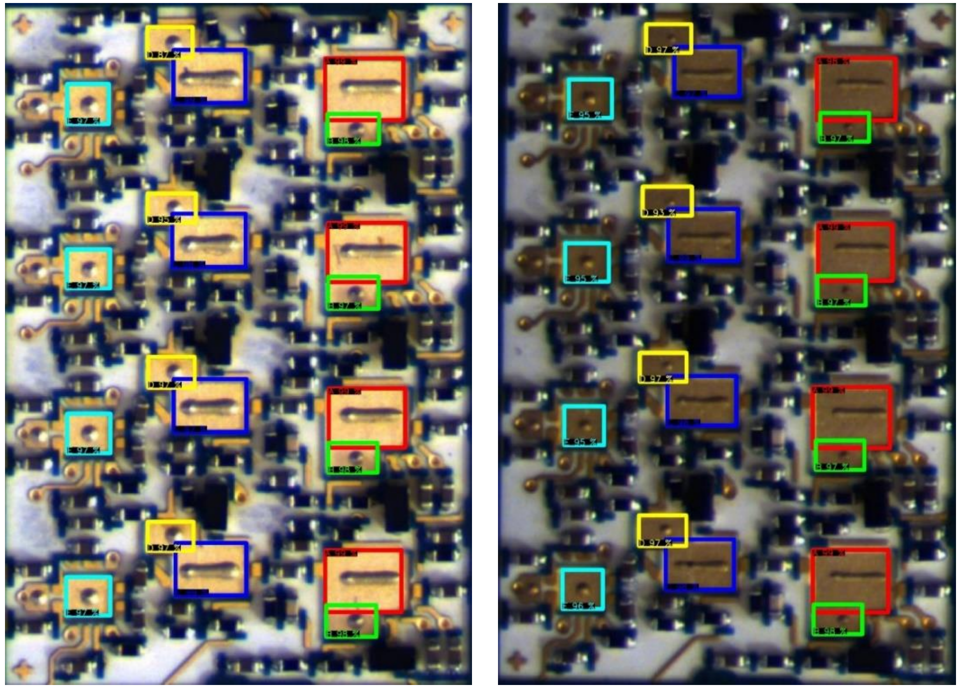
➢ Module Segmentation

- Segmentation is achieved using Mask-RCNN
- Results are accurate irrespective of orientation-occlusion



➢ Glue Detection

- Detection is performed using Faster-RCNN
- Glue deposits are detected despite the variability in volume and illumination



Use case: Automatic calibration

KLEEMANN pilot site

Lift control valve block calibration

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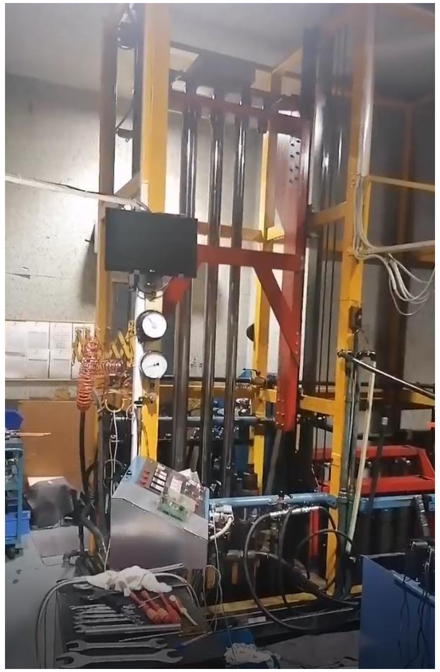
KLEEMANN – pilot site

KLEEMANN
Valve block that
controls the lift



Product: Lift manufacturing

Use case: Automatic Calibration

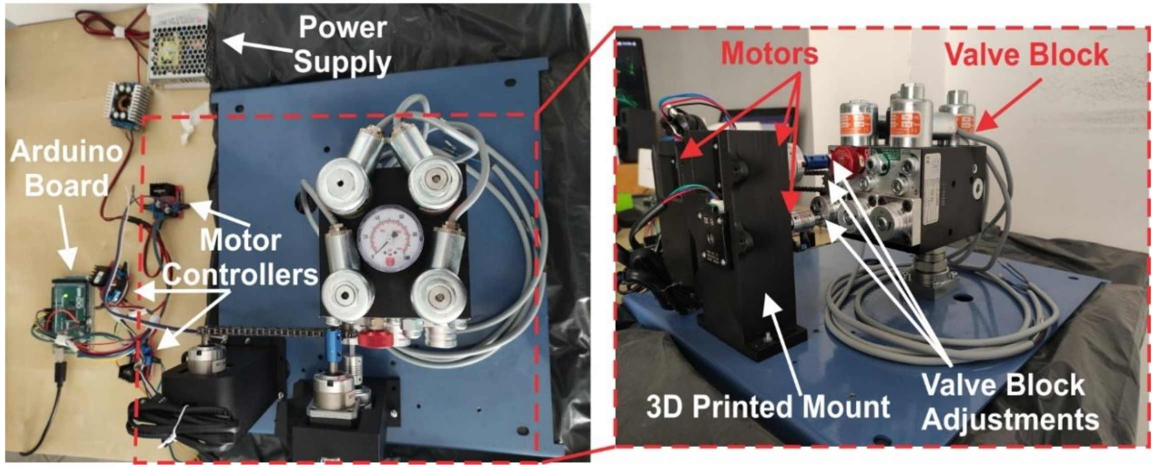
Industrial process/workstation: Calibration of the valve block, responsible for the movement of the elevator lift.

Problem formulation:

- The quality of an elevator lift (accelerations and velocities) is associated with the comfort of the users in the interior of the cabin
- Its calibration is a time-consuming process that is conducted manually by an operator based on his experience
- A solution is proposed using an affordable experimental equipment in order to automatically calibrate elevator control valve block securing a stable and efficient performance of the lift itself.

Hardware setup

- The presented solution is consisted of a 3D-printed mount-device, three step motors, three controllers of the motors, one Arduino Megaboard, a computational unit, a power supply and a web camera
- The **webcam** receives the RGB data during the operation of the lift.
- In the **computational unit**, those data are being analysed to compute the current velocity of the lift.
- AI algorithms are deployed to find the adjustments need to be executed in the motors.
- Arduino board that executes the commands to the **step-motors** to rotate properly the screws of the block.



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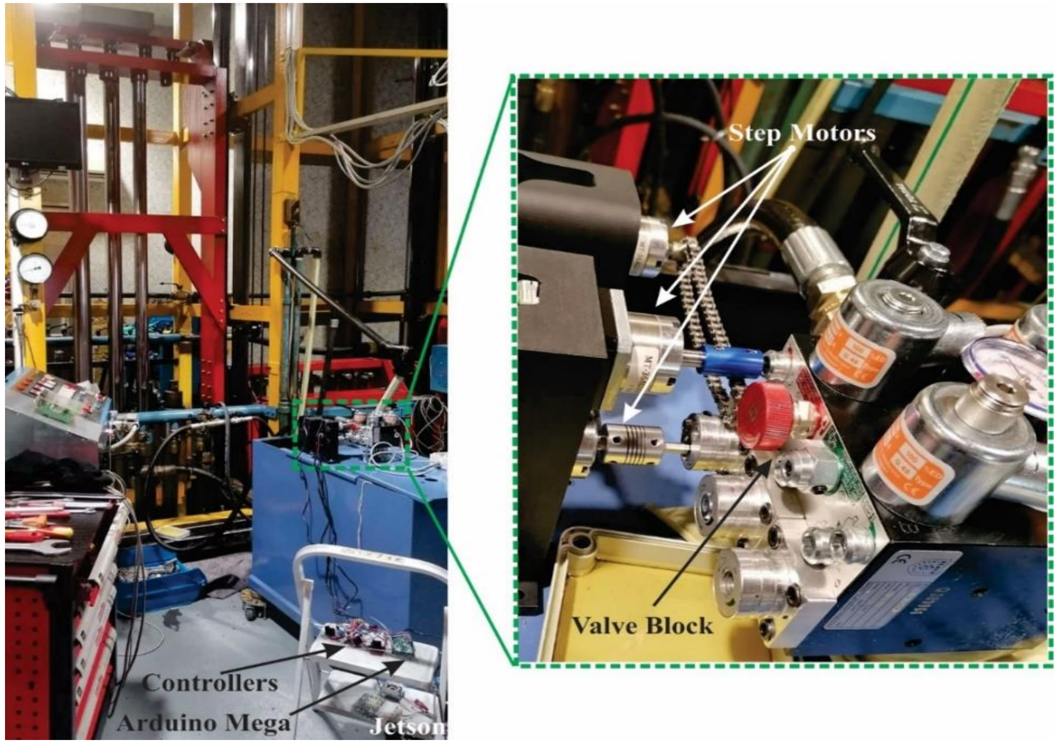
Software Development and Integration

- A **Reinforcement Learning (RL)** framework is developed to tune the parameters of the valve-block

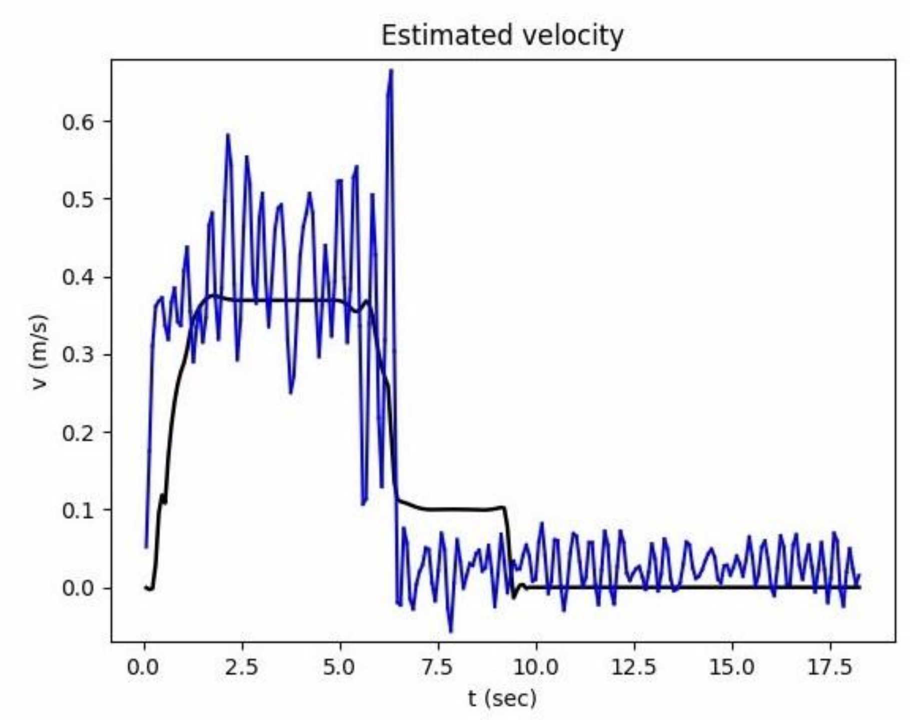
- **Training** of the RL agent is achieved through Temporal Difference (TD) Q-Learning, whereas memory replay and target network techniques are also utilized to optimize performance

- The reward function is chosen as the negative squared distance between the desired and estimated velocity, such that the maximization of cumulative future rewards is equivalent to the minimization of the mean square approximation error.

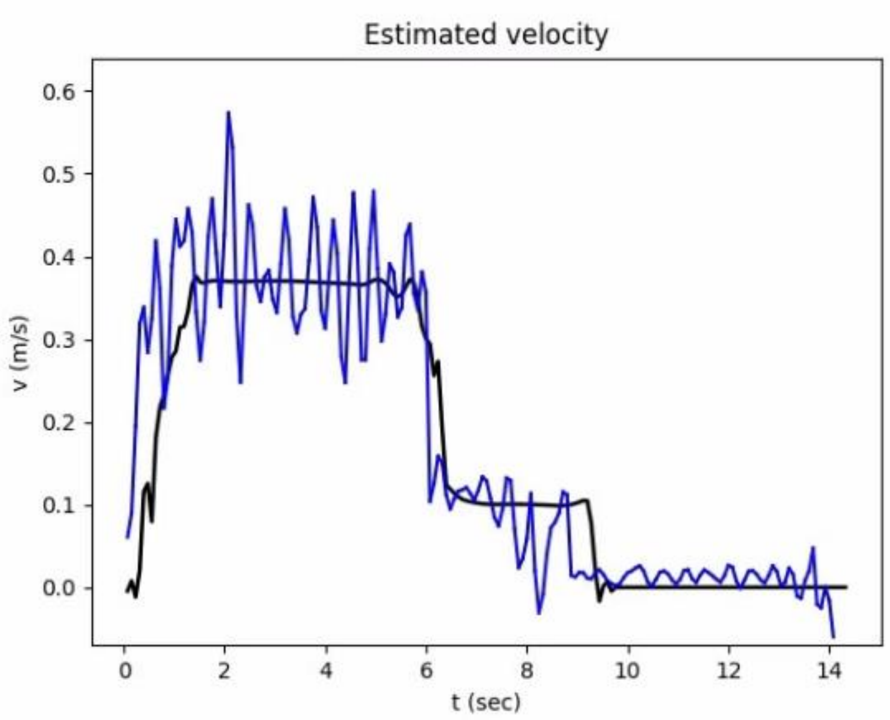


Results

Current Status



Automatic Calibration



Use case: Defect detection

TELEVES pilot site

Antenna manufacturing

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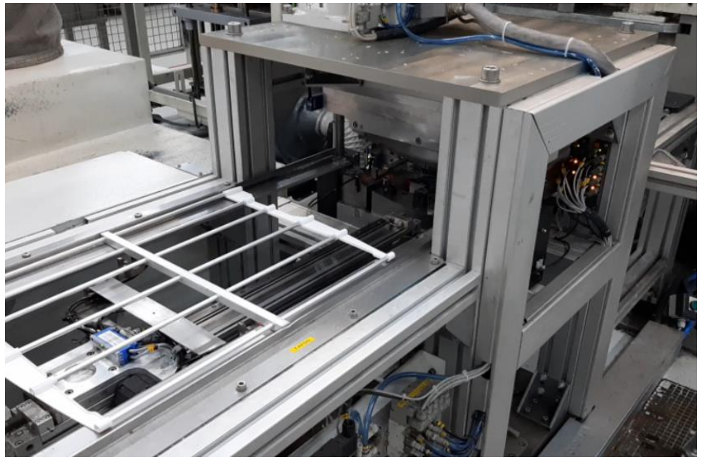
TELEVES – pilot site

Product: Antenna

Use case: Defect detection

Industrial process/workstation: Hydraulic press

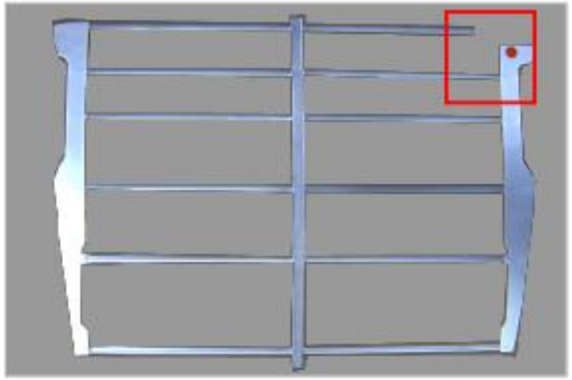


TELEVES hydraulic press cell

Problem formulation:

- The quality inspection is conducted manually and depends on operator’s experience.
- Automatic location of defects in real-time is crucial for the production, to avoid defect propagation/production stoppages.

Non-defective

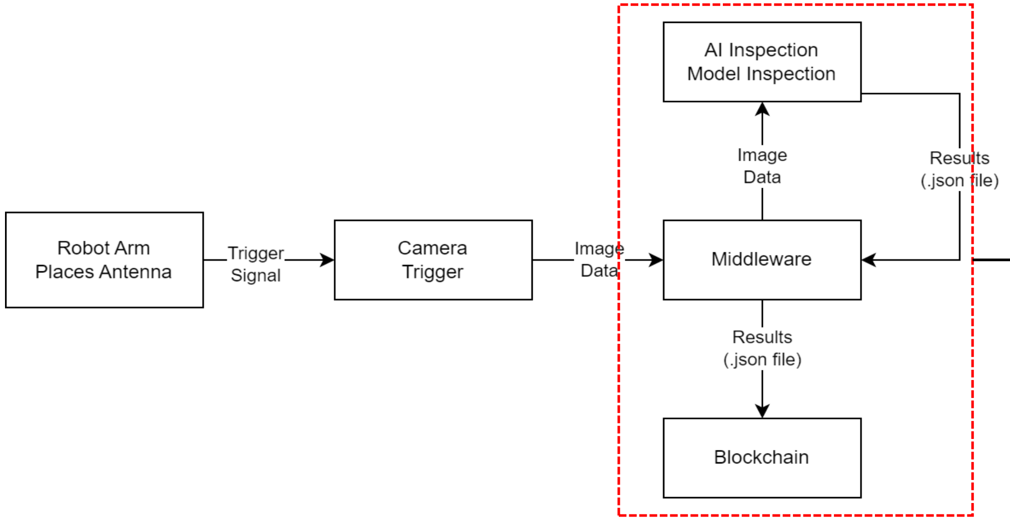


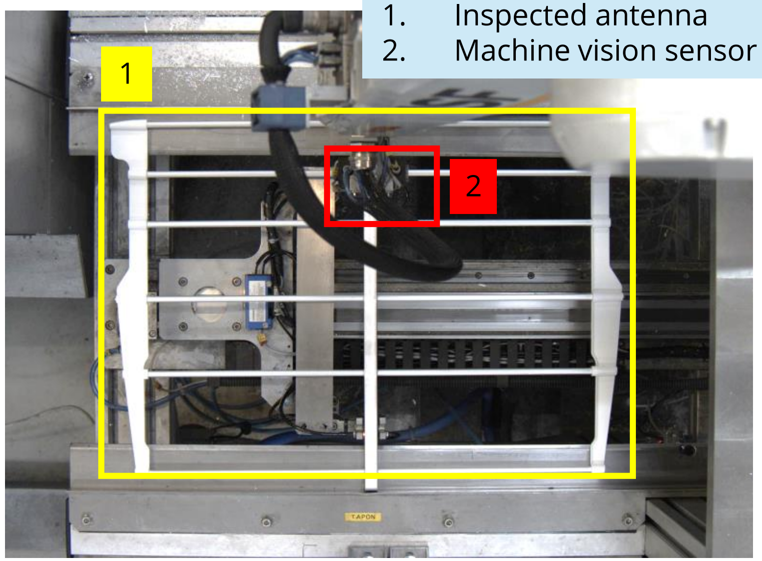
Defective

Defects generated during pressing – geometric deviations & cracks

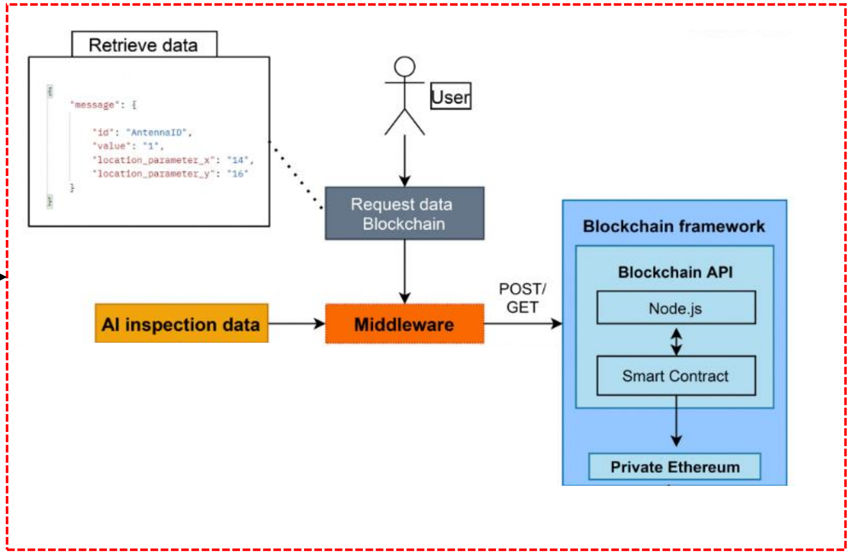
Shopfloor installation

› Pipeline of the AI-based defect inspection system





1. Inspected antenna
2. Machine vision sensor



1. A robot arm places the antenna under the **machine vision sensor** for inspection.
2. The robot arm and the sensor are **synchronized** using a hardware triggering mechanism.
3. The antenna's image is acquired by the sensor.
4. The AI model performs a **patch-based analysis** on the image
5. The AI results include **localized information** about the defects on the image.
6. The AI results are recorded using the **Blockchain paradigm** in private Ethereum.
7. The inspection results can be retrieved in a trustworthy and reliable manner.

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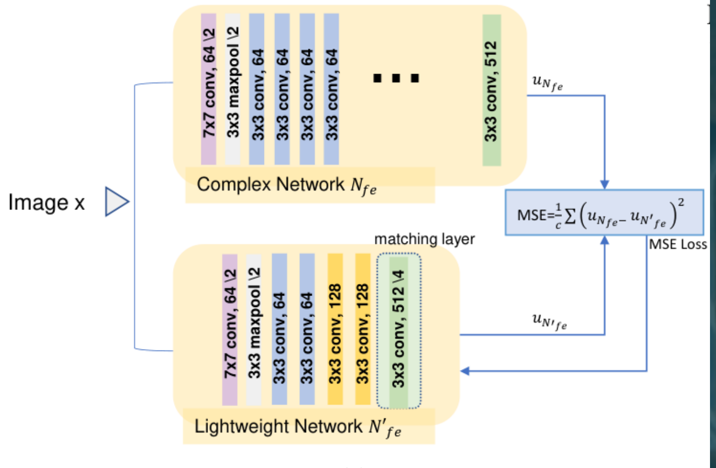
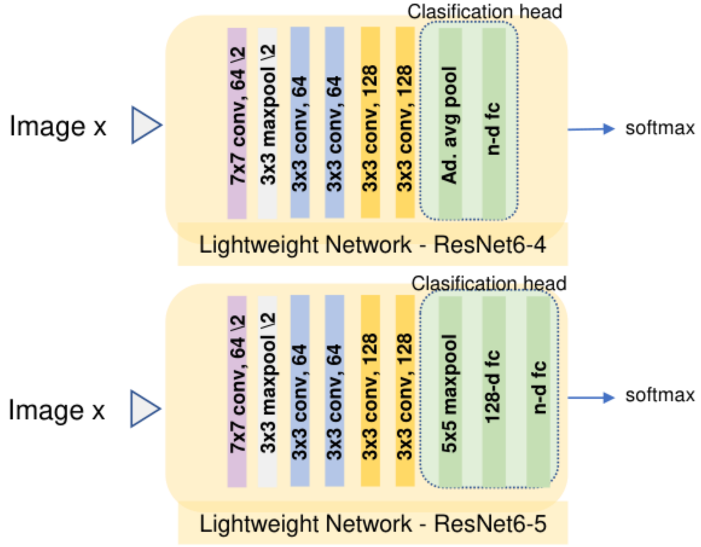
Proposed Methodology

- A real-time solution based on lightweight Deep Residual Networks.
- A **two-stage training** strategy is used to:
  - Boost performance of the baseline classifiers.
  - Lower the inference times.
- **1st stage:** Shallow version of ResNet, ResNet-18
- **2nd stage:** Removed most of the late layers resulting in a lightweight ResNet – 6.
  - *Explored a modification of the classification head of ResNet-6 to improve results.*
- Blockchain AI paradigm to record inspection results in an immutable and verifiable manner in an IoT environment.



(a)



(b)

Results

- Quantitative analysis of defect inspection
  - The proposed method **improves the performance of baseline transfer learning methods by 10%** in F1-score while **lowering inference times by 2.2x**

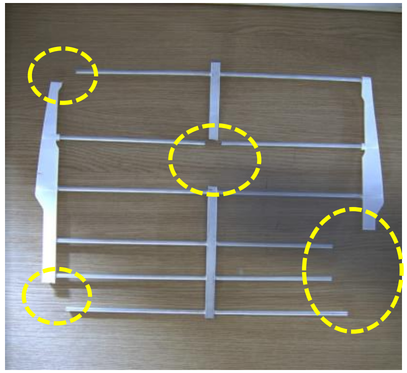
	Model	Precision %	Recall %	F1-score %	MCC
baseline learning methods	ResNet6-1	39.1	17.1	23.8	0.093
	ResNet6-2	86.4	47.9	61.6	0.558
	ResNet6-3	94.3	56.8	70.9	0.666
	ResNet6-4	100	61.6	76.2	0.732
proposed	ResNet6-5	97.1	69.1	80.8	0.768
complex network	ResNet18	95.0	78.7	86.1	0.821

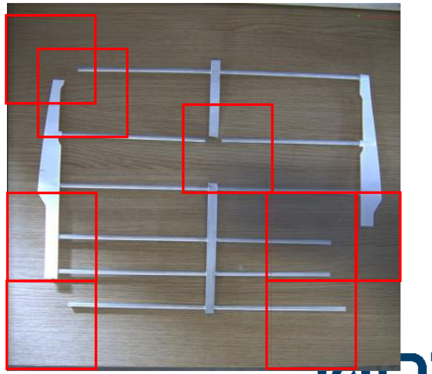
10% better performance (compared to ResNet6-3)

proposed

2.2x lower latency (compared to ResNet18)

- Qualitative analysis of defect inspection
  - On the left, the defect regions on the antenna image
  - On the right, the patch-based defect detections





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Thank you

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