The Manufacturing Partnership Day
7-8/5/2024, Brussels, Belgium

Transitioning from ZDM to Industry 5.0: An applied approach

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CERTH

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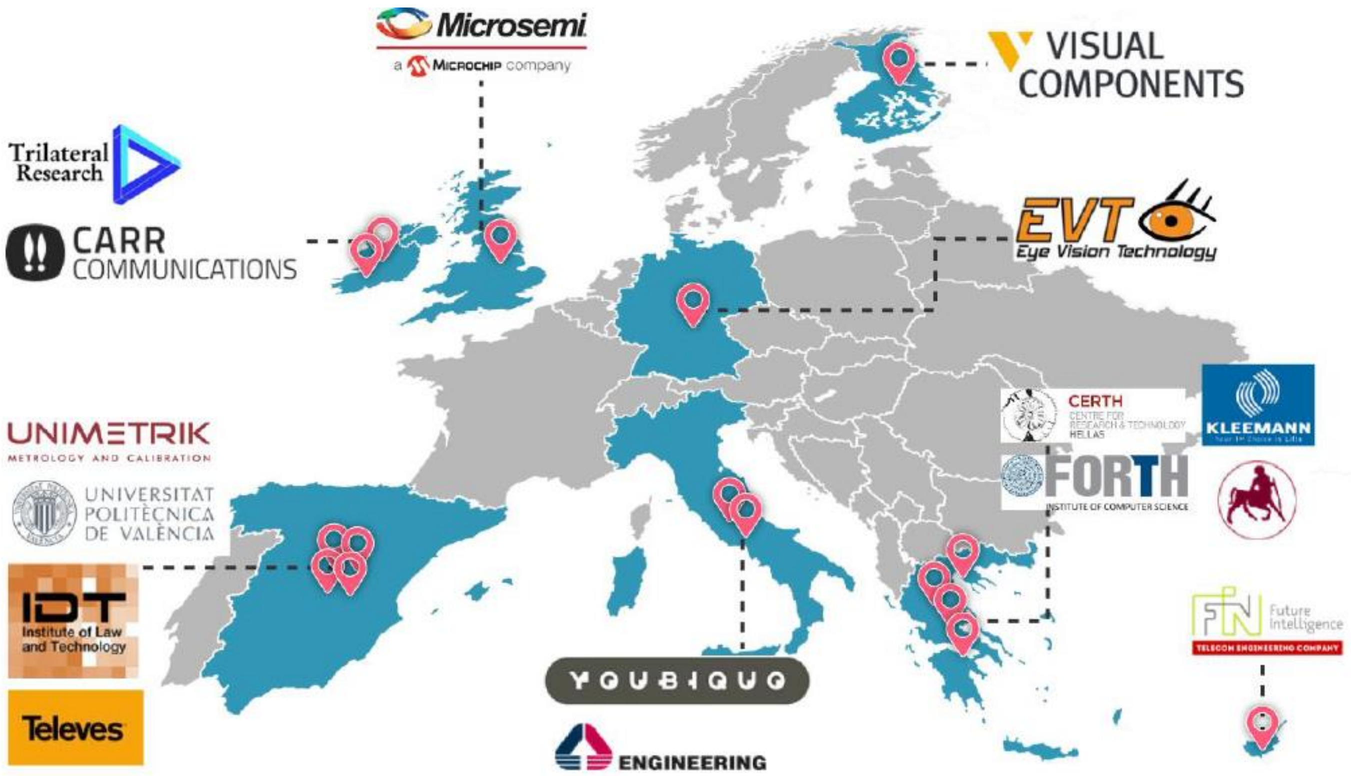
OPTIMAI

Presentation outline

- OPTIMAI overview
- From ZDM to Industry 5.0
- Defect detection and prediction
- DSS and actuation
- “XRay” Vision and XR for human-machine collaboration

OPTIMAI overview

The Consortium



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- 16 Partners
- 8 European Countries

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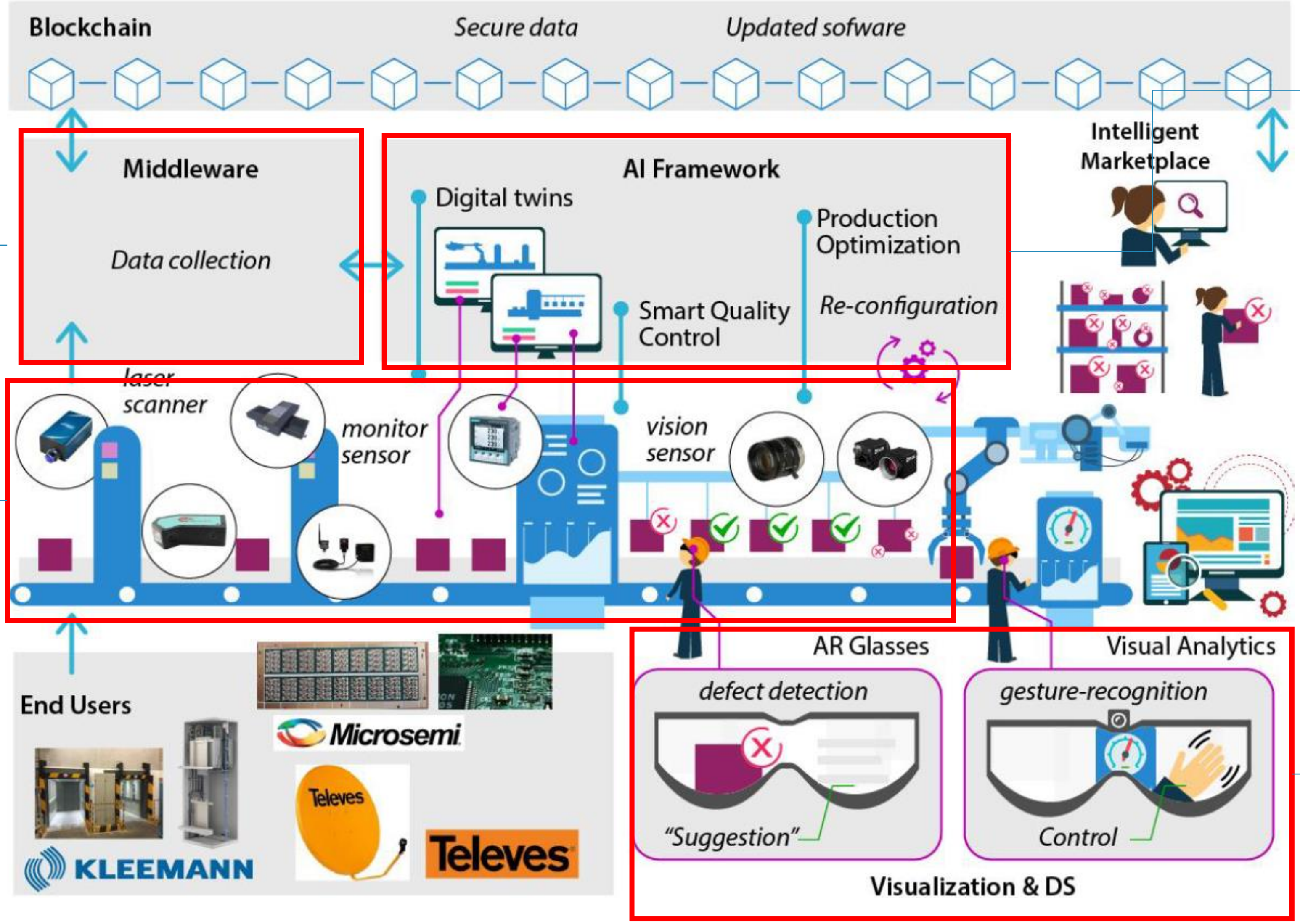
OPTIMAI Concept

- Middleware layer for real-time data collection.
- Production instrumentation with smart sensors.

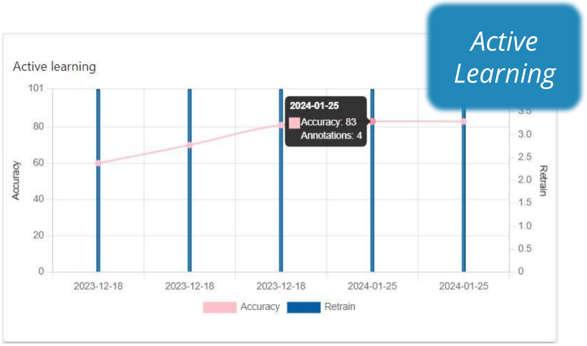


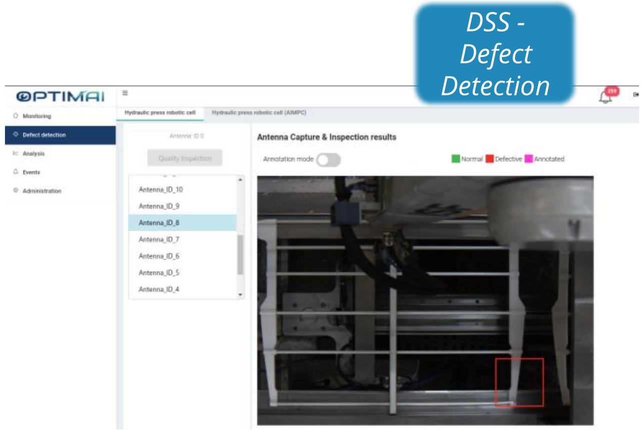
- AI methods for early detection.
- Digital Twins for production optimization and reconfiguration.
- Human-machine collaboration through XR technology and "XRay" vision.

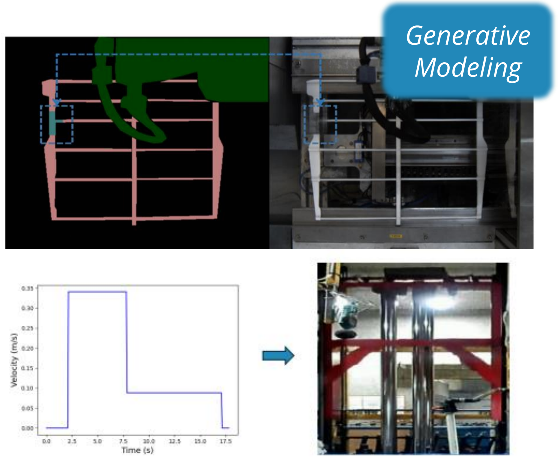
From ZDM to Industry 5.0

From ZDM to Industry 5.0

- **Bridge defect detection & prediction**
  - Deep Learning models for real-time defect detection & prediction
  - Closed loop control for ZDM via Reinforcement Learning
  - Generative modelling for Digital Twins generation.
- **DSS and Actuation**
  - DSS for real-time monitoring and defect detection.
  - Smart Actuation keeping Human-in-the-Loop.
- **Active Learning**
  - Active Learning for fast deployment, dealing with data scarcity.
- **XR and “XRay” Interfaces**
  - XR as an enabler for human-machine interaction and production (re)-configuration.
  - "XRay" vision providing insights into component integrity and potential defects.







Input curve

Generated data

(Semi)-automatic calibration of valve block in elevator manufacturing – KLEEMANN pilot

- Production (Re)-configuration
- XR for human-machine collaboration
- Defect Detection
- Decision Support System

Production (Re)-configuration

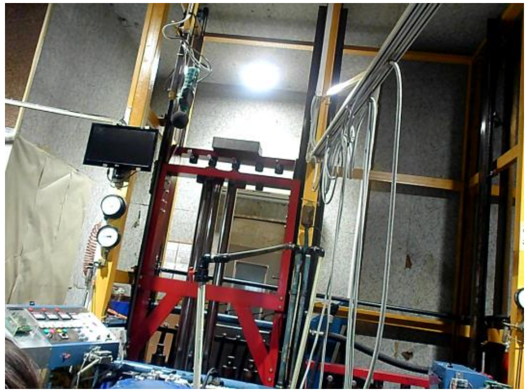
Applied in Elevator Manufacturing

KLEEMANN
Production (Re)-configuration - Use Case Description

Valve Block: The hydraulic Elevator Control Valves (EVs) control the movement of the elevator.

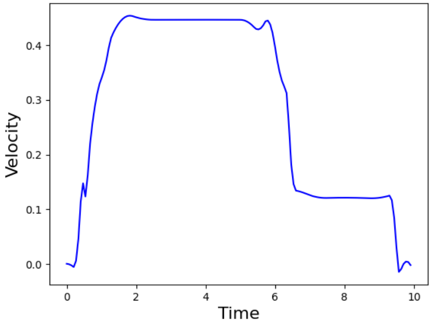
KLEEMANN
Valve block that controls the lift

Testing workstation: EVs are connected to weights that simulate the movement of the elevator.



KLEEMANN
Testing workstation

- An **experienced operator manually adjusts** the valves to achieve the desired motion.
- The **intended movement** depends on the type of the elevator, maximum load, user requirements, etc.



KLEEMANN
Elevator velocity reference curve

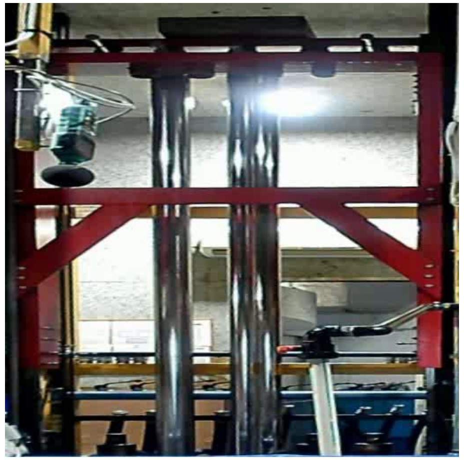
KLEEMANN
Optimal downward movement

KLEEMANN

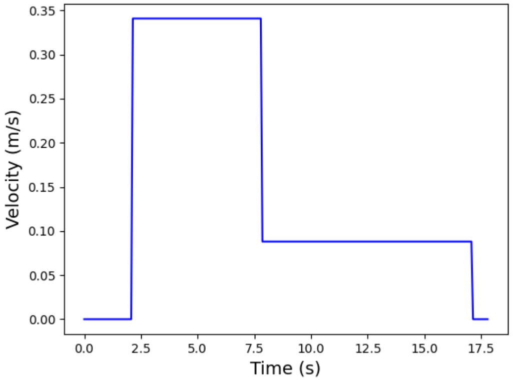
Production (Re)-configuration - Digital Twinning

- We create a **Digital Twin (DT)** of the process using **Generative AI** by simulating the movement given the velocity curve.
- To this end, we develop a **Soft Sensor (SS)** that acts directly on the captured RGB frames using **Deep Learning (DL)** to collect training data.
- A **lightweight residual architecture** is used to achieve real-time soft sensing performance.

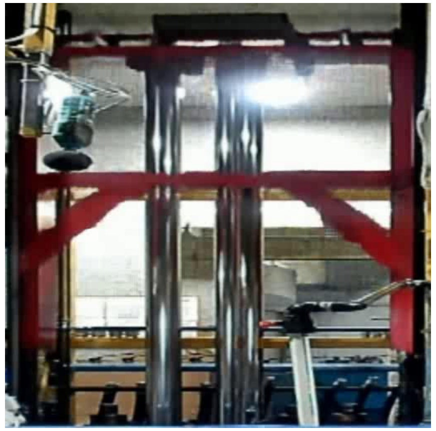
Initial frames



Transformed frames



Input curve

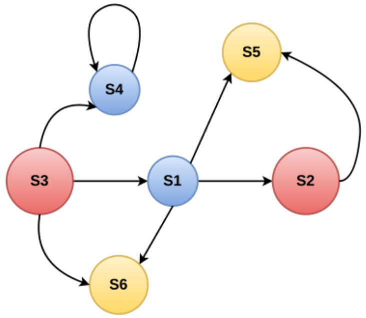


Generated data

OPTIMAI

KLEEMANN

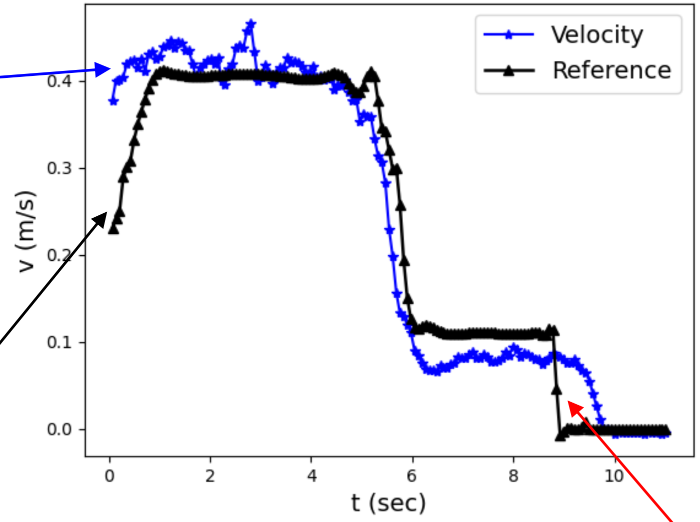
Production (Re)-configuration - Reinforcement Learning (RL)

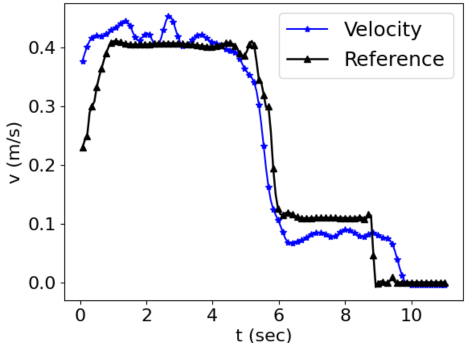


- We use **Reinforcement Learning (RL)** to automatically calibrate the parameters of the valve block.
  1. The **DIgital Twin** of the process is used for data augmentation.
  2. The **Soft Sensor** is used to estimate the reward in real time.

Current velocity – soft sensing output

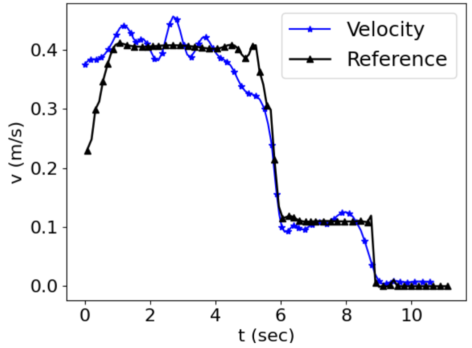
Intended velocity based on client's order





Initial curve

RL Agent



Calibrated curve

R = - (Velocity – Reference)2

OPTIMAI

XR interfaces for human-machine collaboration

Applied in Elevator Manufacturing

KLEEMANN

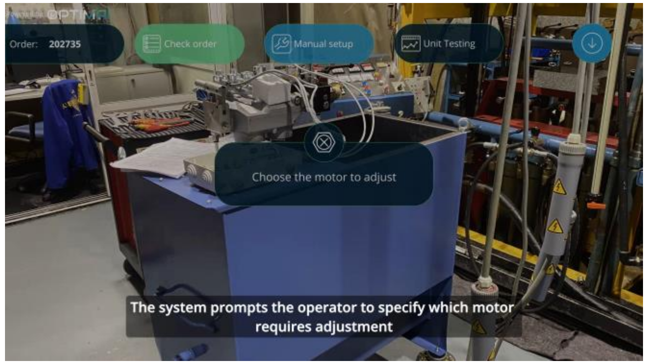
(Semi) Automatic Calibration - Gesture Based Production Configuration

Client order validation scenario

- Cross-check between the produced parts and the parts referred to the client's order
- Visualized list of parts for validation and order status

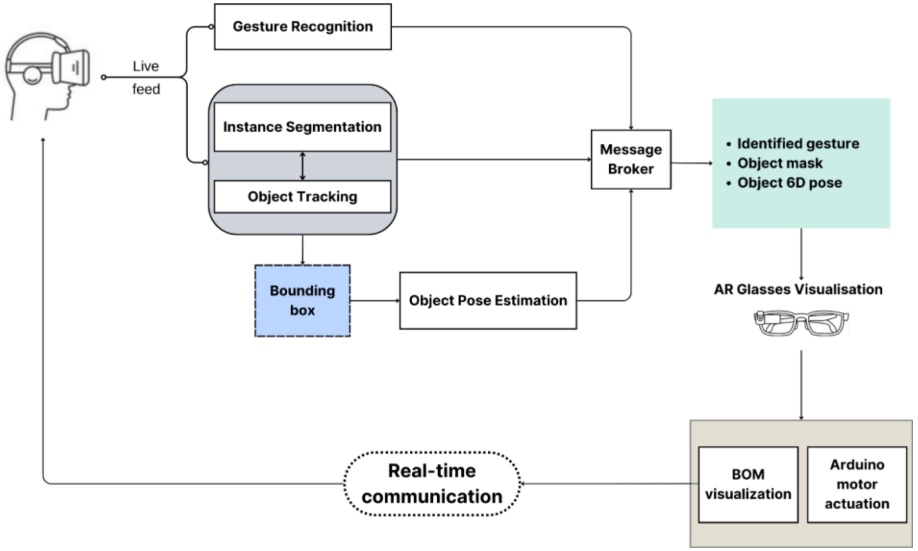
Valve block calibration scenario

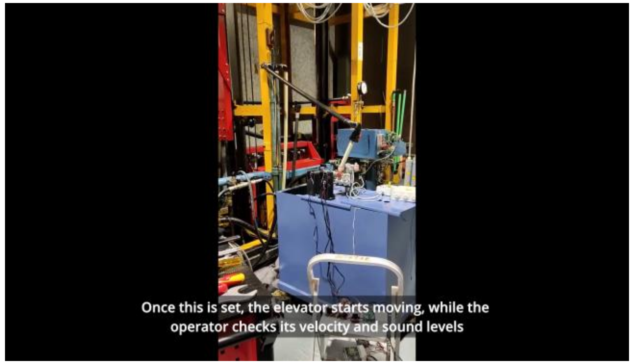
- **Numbers 1-3:** Used to identify which motor to move
- **Scroll hand left/right:** used to choose the direction of the motor movement
- **Static fist:** stop calibration for the chosen motor
- **OK:** calibration complete



Identify motor & choose direction

Bill of materials visualization (BoM)





Arduino motor actuation

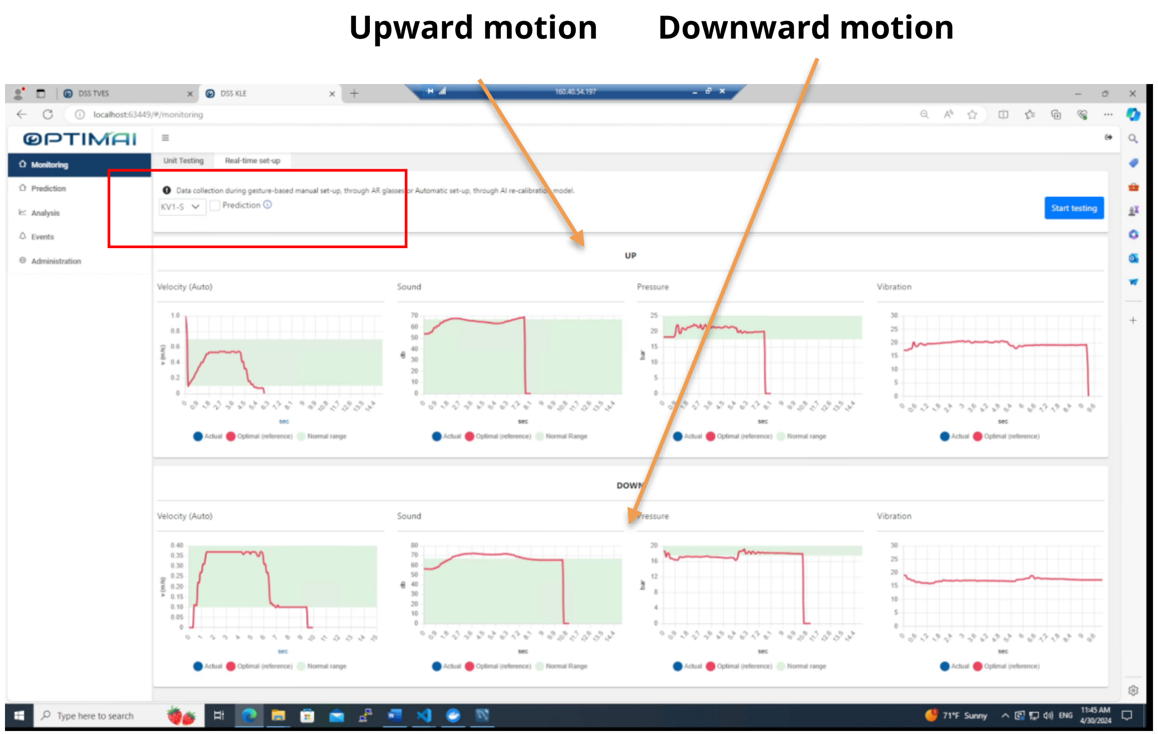
Decision Support System

Applied in Elevator Manufacturing

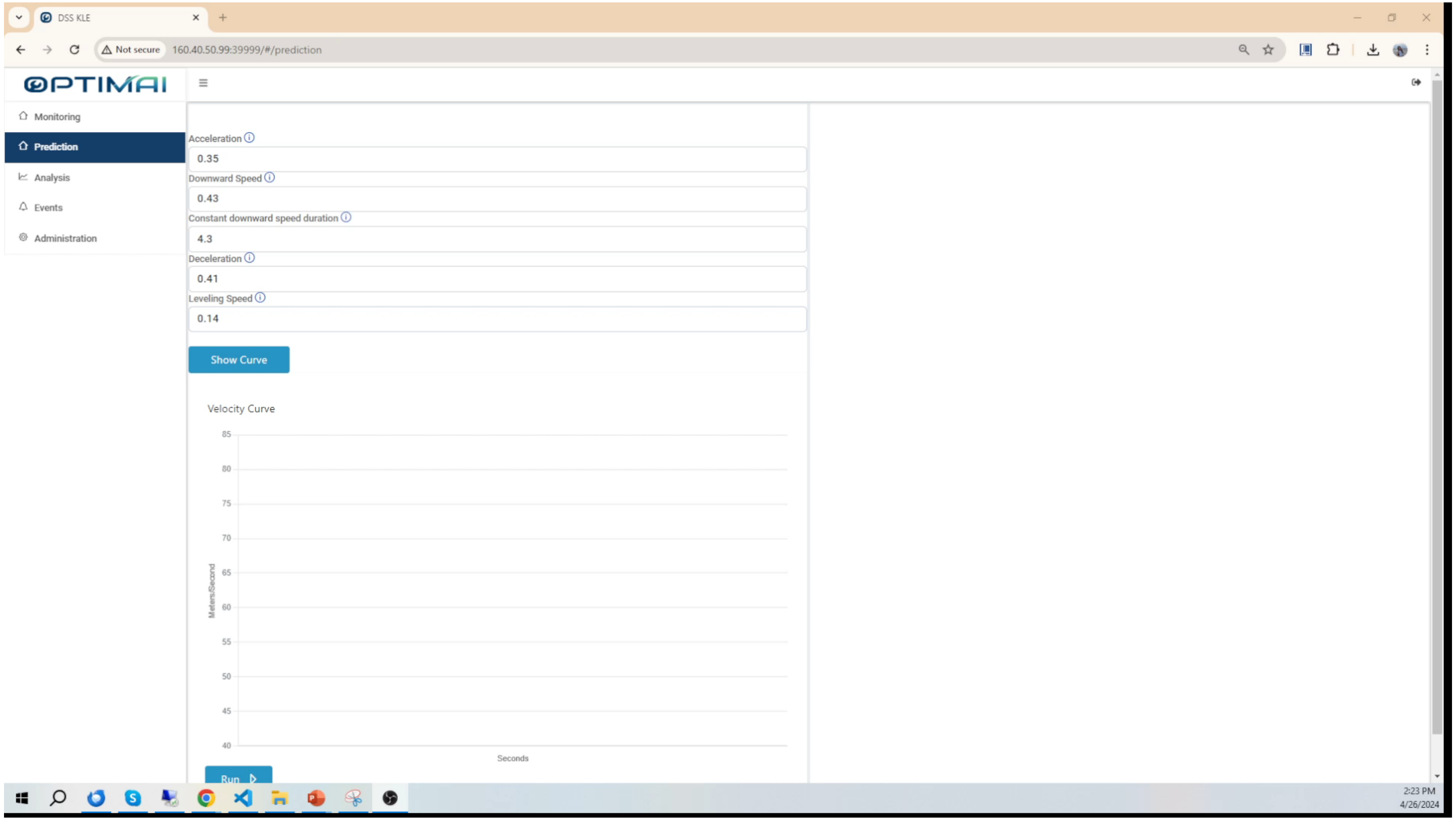
KLEEMANN
DSS - Monitoring

The users monitor data streams in real-time.

- Users have the flexibility to incorporate **Predictions** as reference into their testing
- In the example, after completion of the **first testing stage** (upward motion), the defect detection outcome is displayed, classifying the result as either "**Normal**" or "**Abnormal**"
- This classification provides users with insights into the testing outcome, facilitating informed **decision-making**



KLEEMANN
DSS - Prediction



Controlling glue dispensing in micro-electronics – MICROCHIP pilot

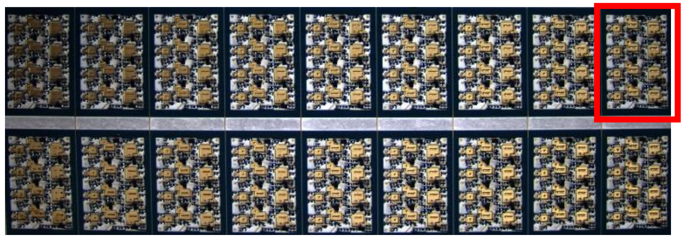
- Defect Detection
- XR Interfaces
- Decision Support System

Defect Detection

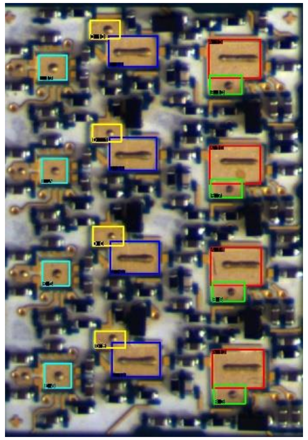
Applied in Microelectronics

MICROCHIP
Defect Detection - Use Case Description

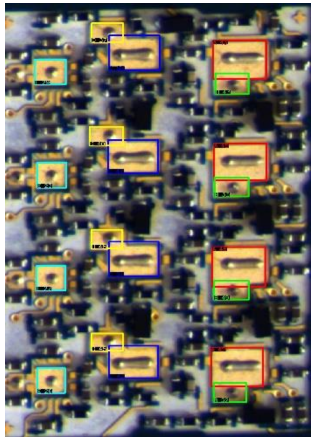
- An industrial process that generates defects is the dispensing of glue on **Printed Circuit Boards (PCBs).**
- The defects are the dispensing of insufficient or excessive amount of glue.
- **Problem**: Identification of such defects is a time-consuming and error-prone process.



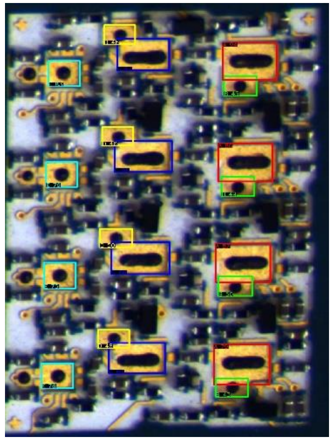
Printed Circuit Board (PCB) with 18 circuit modules



✖ Insufficient



✓ Normal

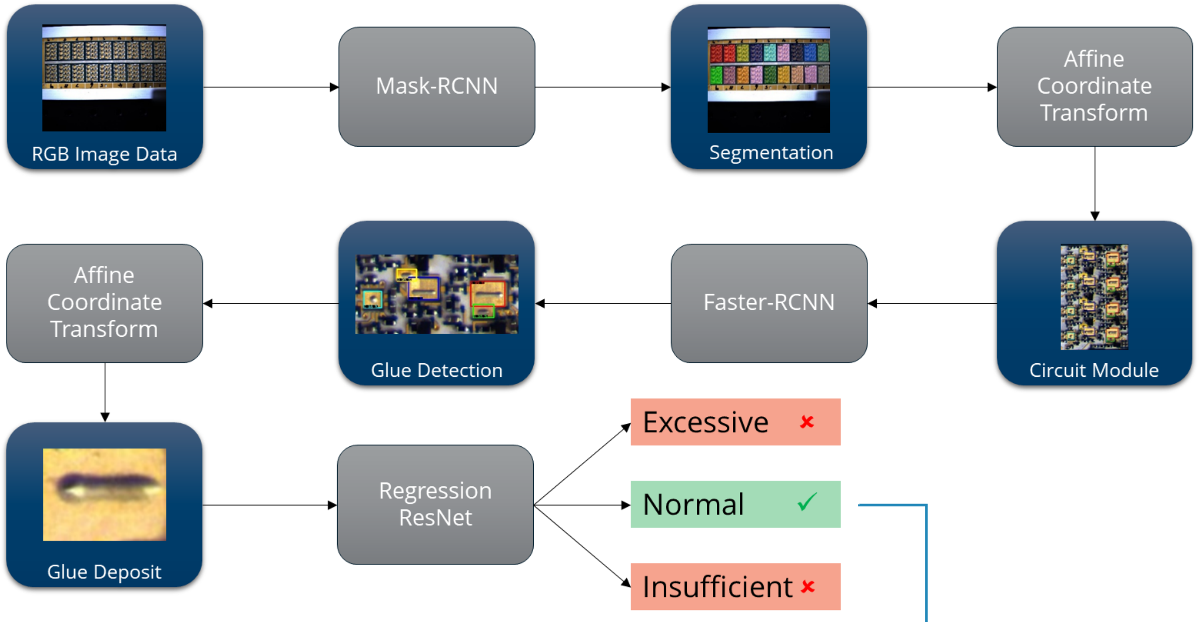


✖ Excessive

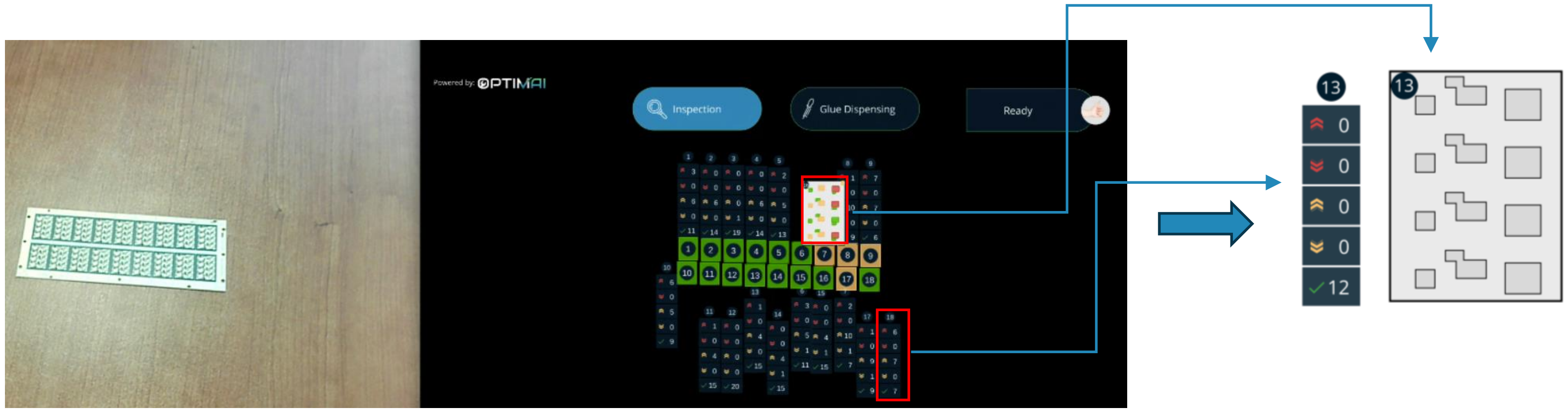
- **Solution**: Develop an automatic inspection system that uses RGB images.

A. Evangelidis, N. Dimitriou, L. Leontaris, D. Ioannidis, G. Tinker and D. Tzovaras, "A Deep Regression Framework Toward Laboratory Accuracy in the Shop Floor of Microelectronics," in IEEE Transactions on Industrial Informatics, vol. 19, no. 3, pp. 2652-2661, March 2023.

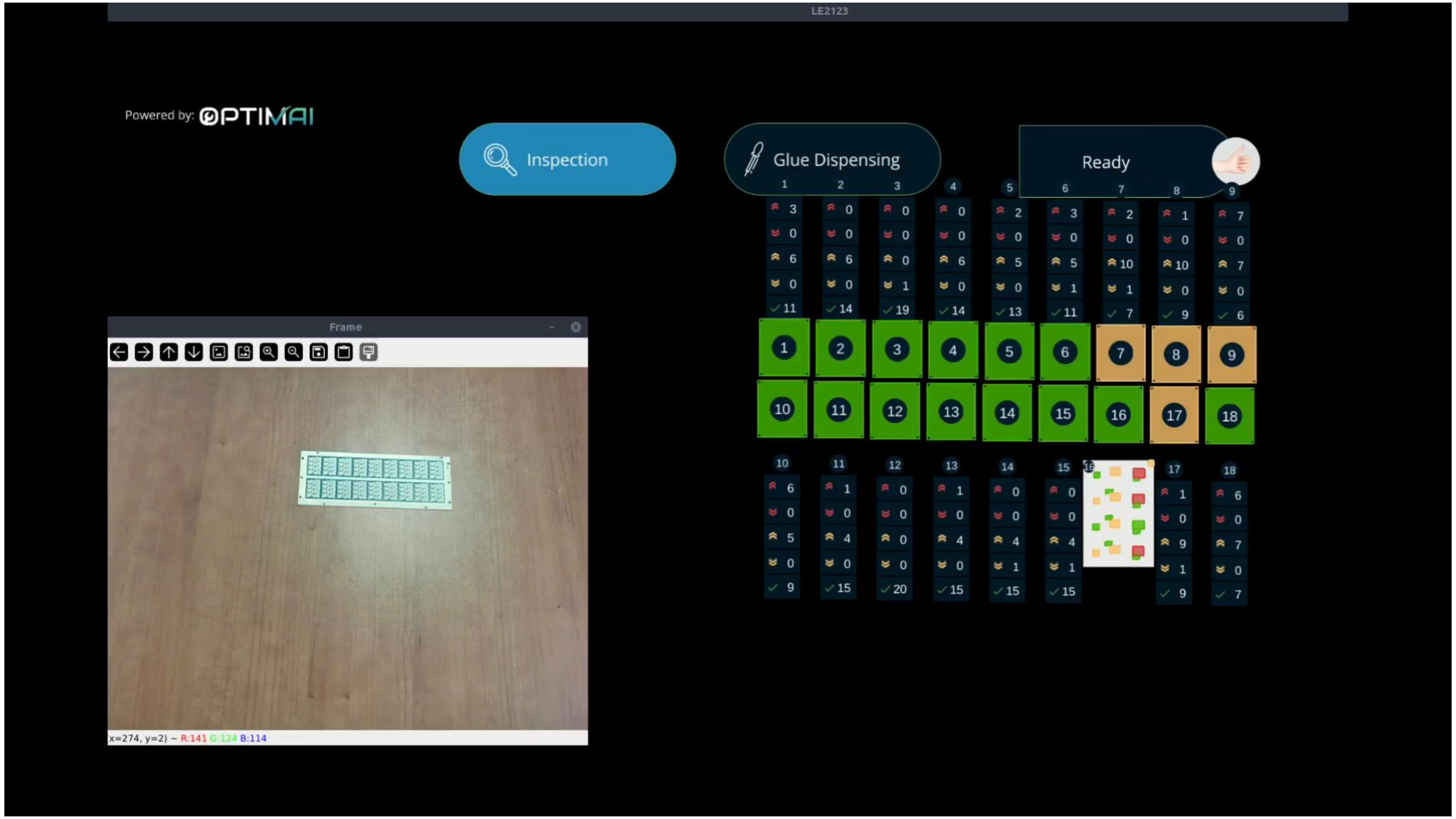
MICROCHIP
Defect Detection – XR Visualization



- **Low LoD widget (Left image)** :
  - excessive and rejectable
  - insufficient and rejectable
  - excessive and acceptable
  - insufficient and acceptable
  - normal
- **High LoD widget (Right image)**:
  - representation of glue positions
  - glue's quantity is represented by color (green, yellow, red)



MICROCHIP
Defect Detection – XR Visualization

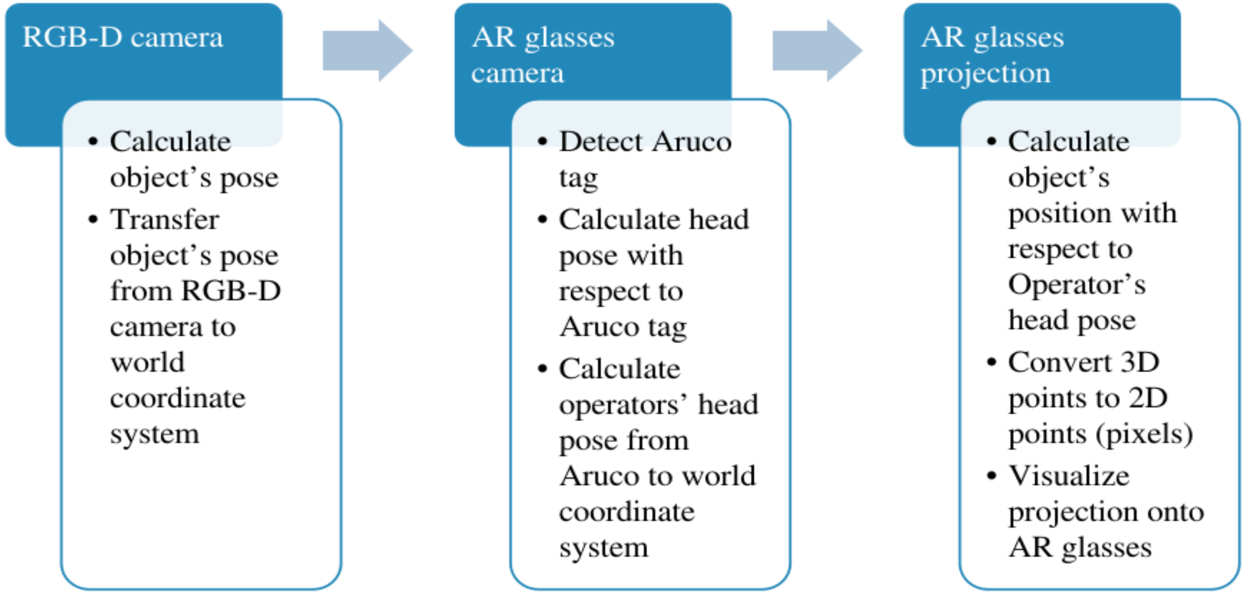


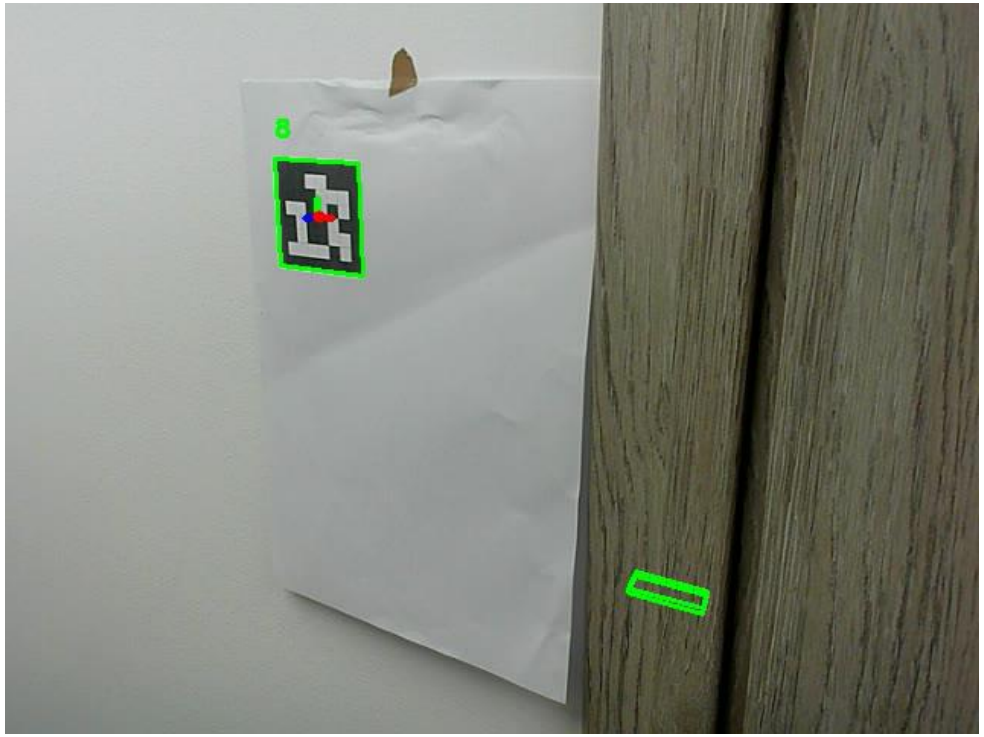
“XRay” Vision

Applied in Microelectronics

MICROCHIP
“XRay” Vision - Overview

- **Functionality:** a) real-time inspection of sealed machines, b) minimization of human intervention in difficult to reach areas, c) minimization of unneeded stoppages
- **Sensors:** AR glasses camera and RGB-D camera
- **Input:** RGB image and depth data
- **Output**: The projected 3D bounding box of the object onto the AR glasses



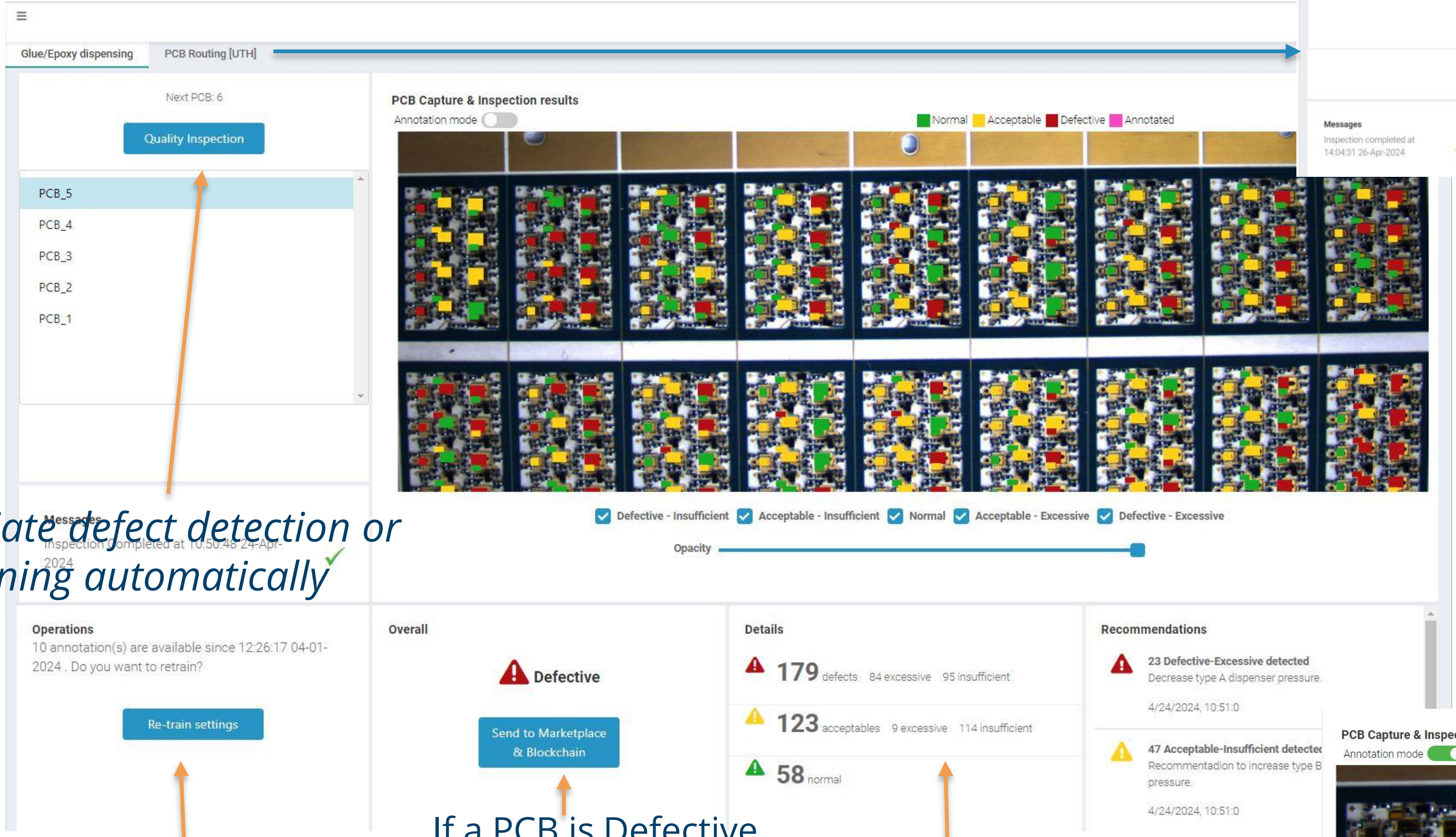


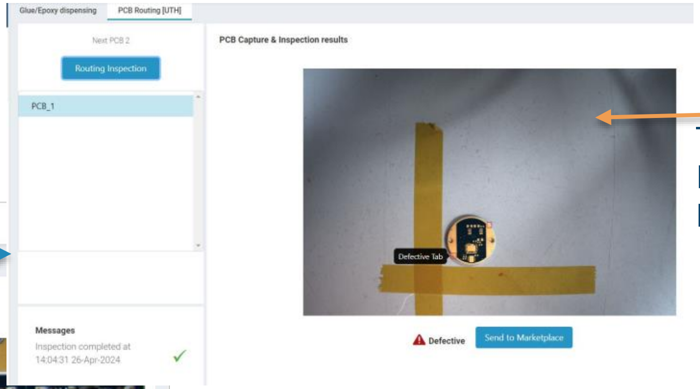
Decision Support System

Applied in Microelectronics

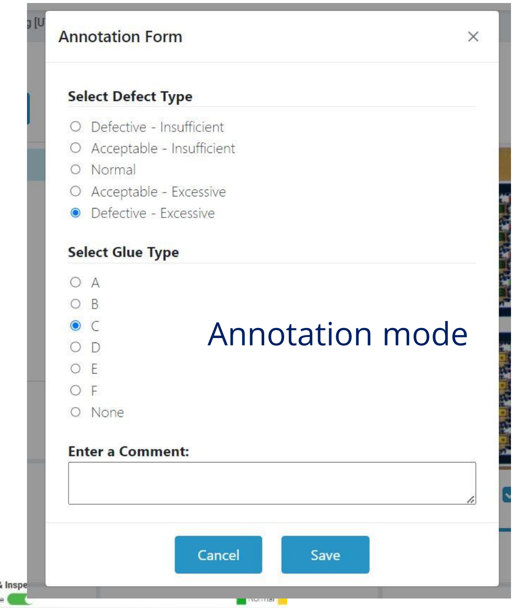
MICROCHIP

DSS - Defect Detection

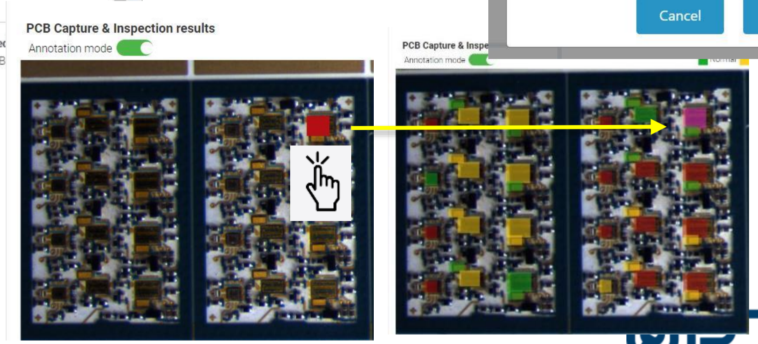




The second Tab of the Defect Detection **PCB Routing**



Annotation mode



Initiate defect detection or running automatically

Retrain AI model

If a PCB is Defective, the user can send it to the Marketplace (for scrap) and store the data to the Blockchain

Results

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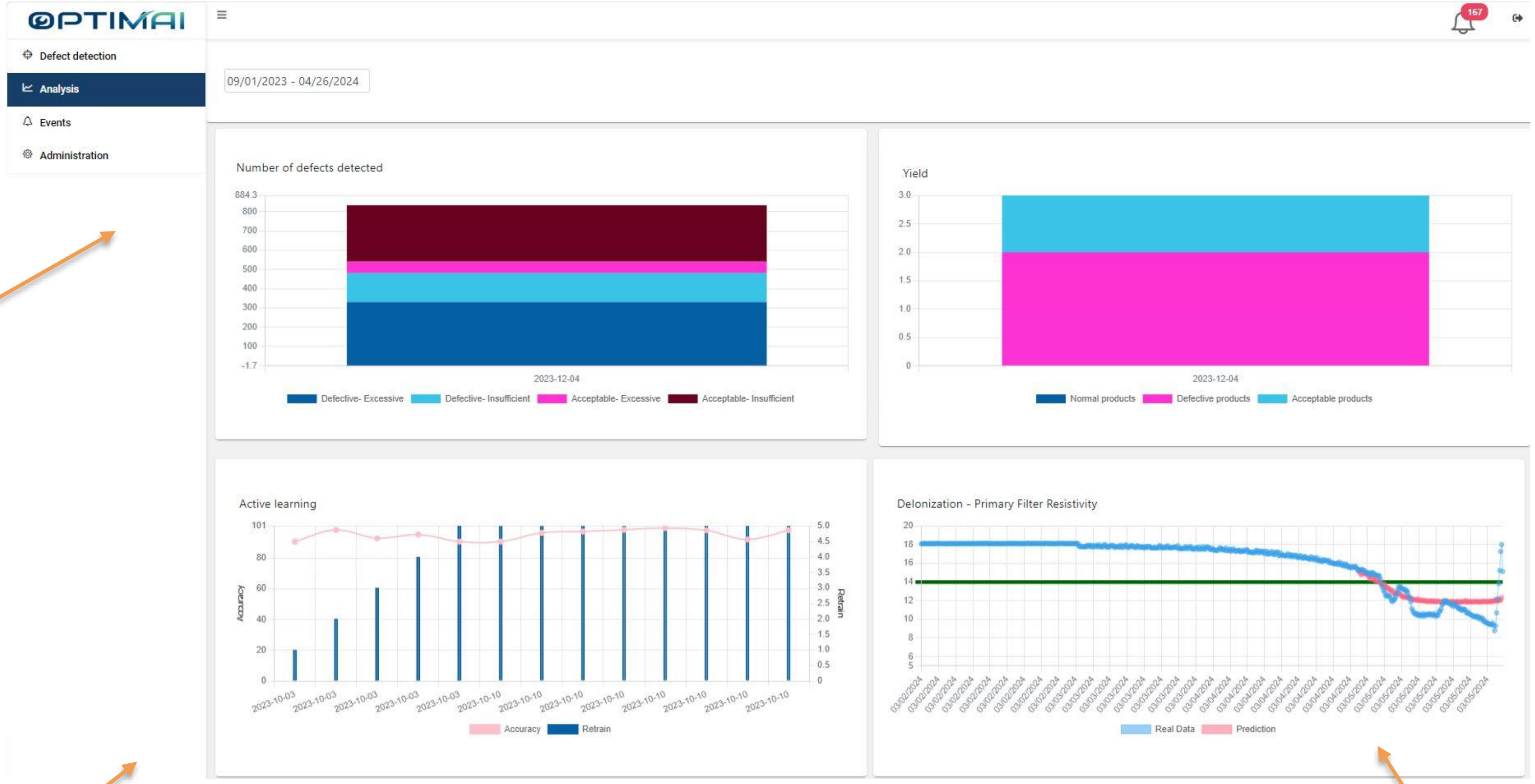
MICROCHIP

DSS - Analysis

Yield

Defect detections



Active Learning model performance gain from retraining

Shopfloor sensors monitoring

Antenna bending – TELEVES pilot

- Defect Detection & Prediction
- Decision Support System & Actuation

Defect Detection

Applied in Antenna Manufacturing

TELEVES
Use Case Description

› The **problem**

› During antenna manufacturing, **geometric deviations & cracks** are generated.

› Data from defective antennas are **scarce.**

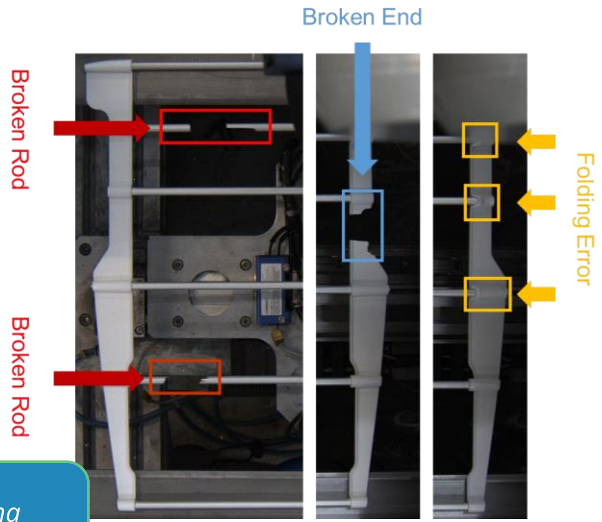
➢ **What we do:**

➢ We use **a DL model to inspect RGB images**, passing through the production line

➢ We use **Generative Adversarial Networks** to combat data **scarcity** and train inspection networks

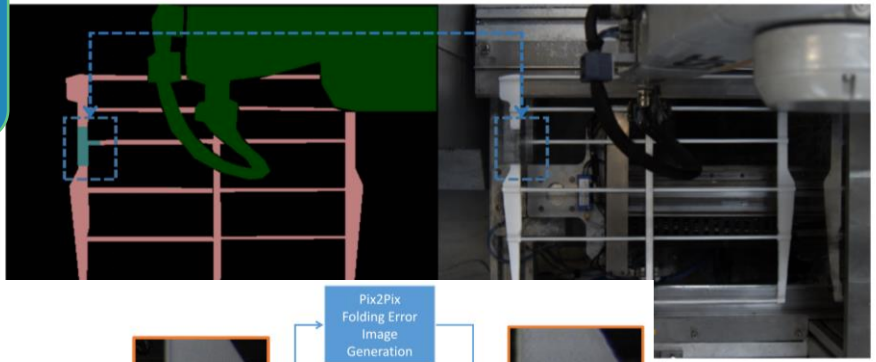
➢ We achieved **20% increased performance** in under-represented classes

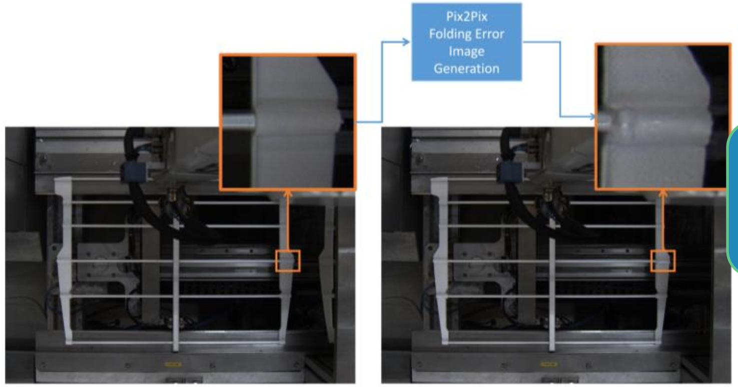
Hydraulic press cell



Antenna defects

Broken End and Broken Rod Defect Generation using GANs





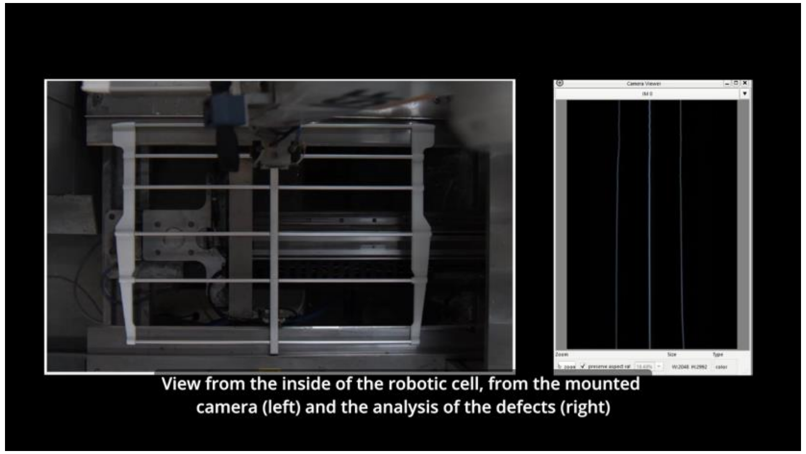
Folding Error Image Generation Using GANs

OPTIMAI

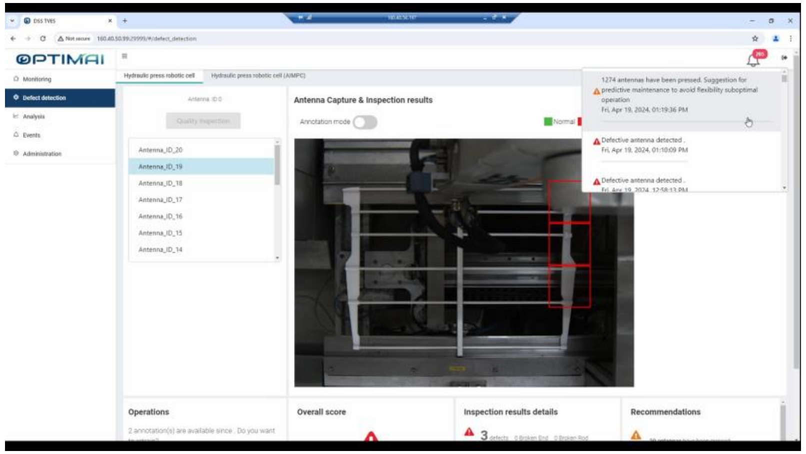
TELEVES
Defect Detection

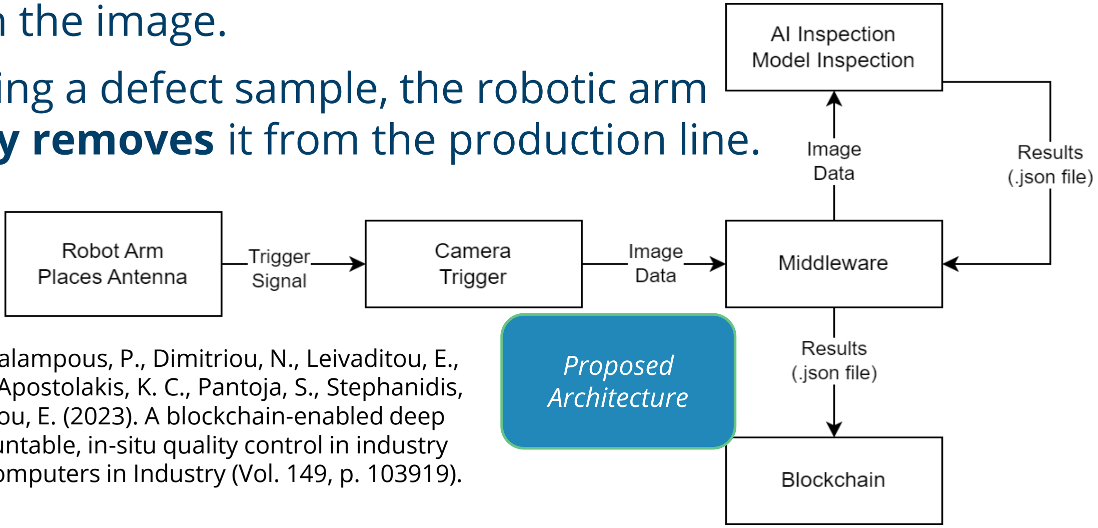
- The proposed architecture follows the procedure below
  1. A robot arm places the antenna for inspection.
  2. **Two machine vision sensors** capture images **above and below** the antenna.
  3. The robot arm and the sensor are **synchronized** using a hardware triggering mechanism.
  4. The antenna's images are acquired by the sensors.
  5. The AI model performs an **analysis.**
  6. The AI results include **localized information** about the defects on the image.
  7. Upon identifying a defect sample, the robotic arm **automatically removes** it from the production line.

Antenna line monitoring – two machine vision sensors


View from the inside of the robotic cell, from the mounted camera (left) and the analysis of the defects (right)

DSS visualization





Proposed Architecture

Leontaris, L., Mitsiaki, A., Charalampous, P., Dimitriou, N., Leivaditou, E., Karamanidis, A., Margetis, G., Apostolakis, K. C., Pantoja, S., Stephanidis, C., Tzovaras, D., & Papageorgiou, E. (2023). A blockchain-enabled deep residual architecture for accountable, in-situ quality control in industry 4.0 with minimal latency. In Computers in Industry (Vol. 149, p. 103919).

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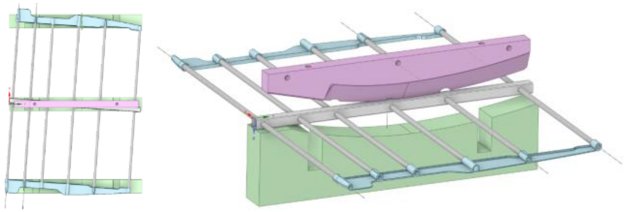
Defect Prediction

Applied in Antenna Manufacturing

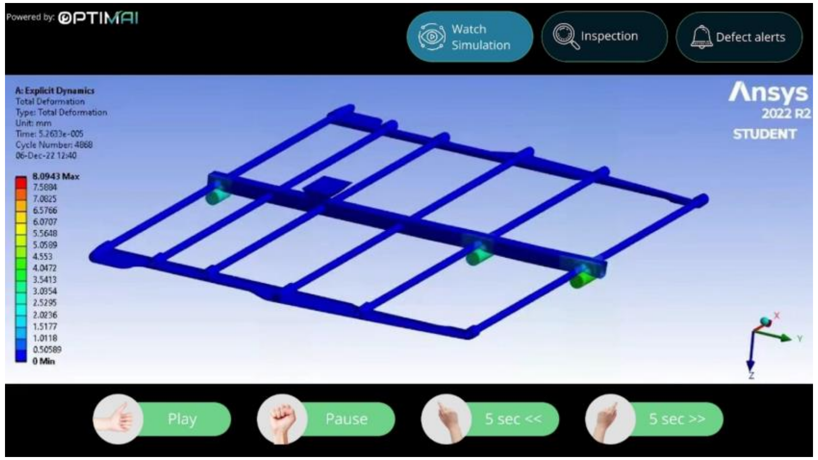
TELEVES
Defect Prediction

- **Problem:** The cause of the defects is the **misplacement of the antenna body on the bending surface**
- This process can lead to **excessive stress and strain development** that can cause **cracks** on the antenna
- The prediction of such defects required the **use of expensive and time-intensive simulation software**
- **Solution:** Developed an prediction system that utilizes a Convolutional Neural Network (CNN) to **synthesize simulations** similar to the ones produced by a typical simulation software
  - **Knowledge distillation** from Finite Element Method (FEM) to CNN
  - This drastically **reduces simulation time and cost, from 5-6 hours** to **close to 10 seconds**.
  - Through XR the user can **compare real and simulated** defects for enhanced decision-making
  - We create **Digital Twins** of antenna manufacturing with **Generative AI**



Real Simulation | Predicted

Simulation results through XR interface



Decision Support System and Active Learning

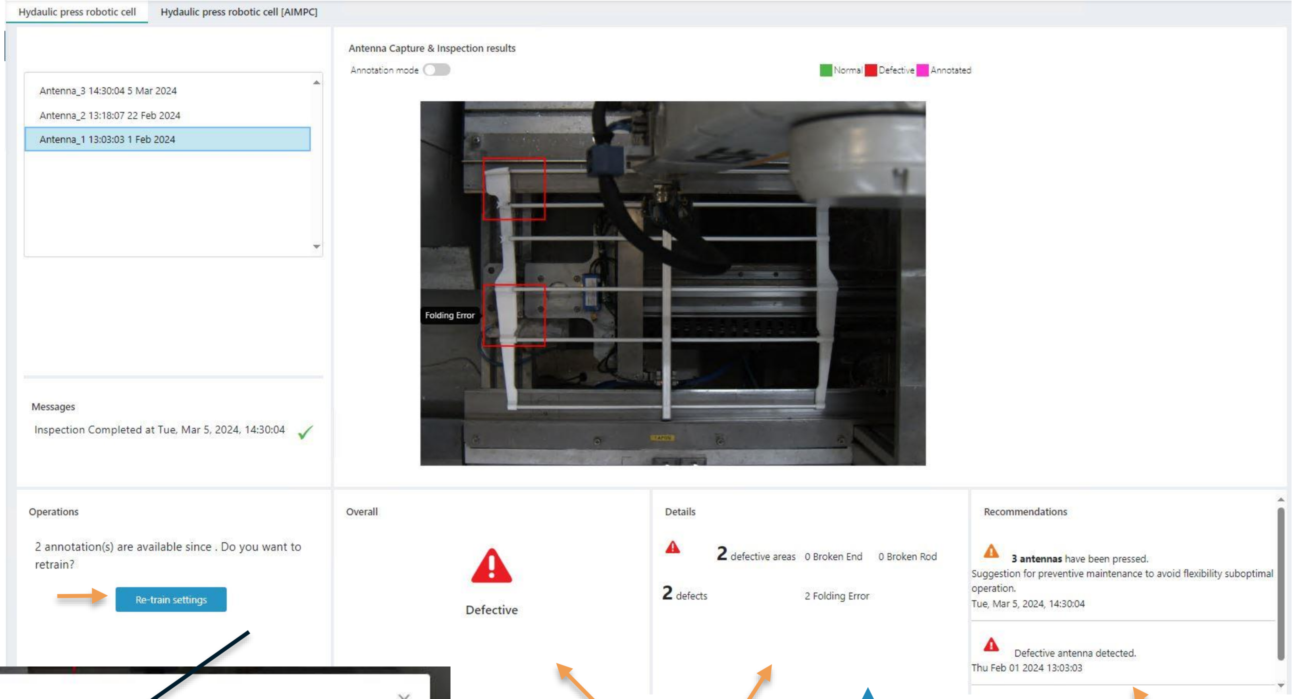
Applied in Antenna Manufacturing

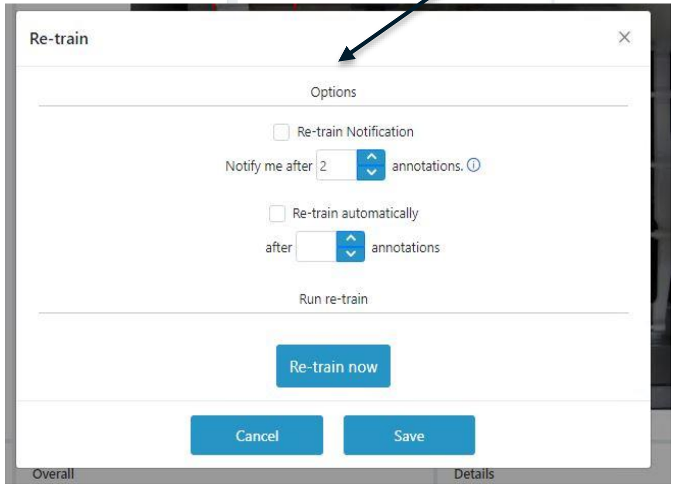
TELEVES
DSS and XR interface

DSS and Actuation

Defect Detection

Retrain AI model





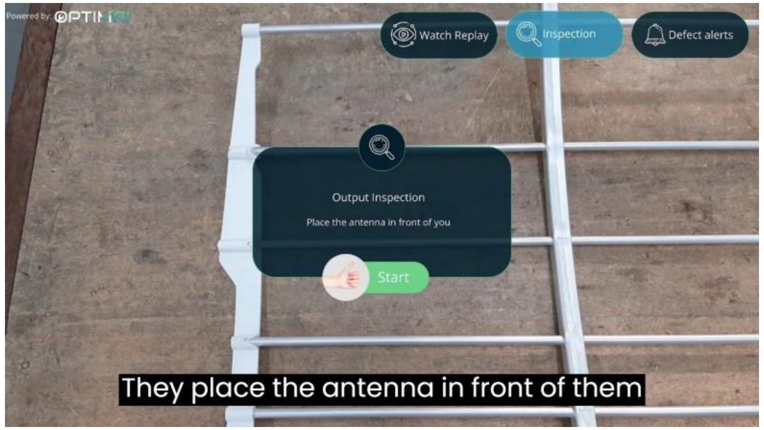
Results

Details: Number of defective Areas, Number of Defects, Categories of Defetcs

Recommendations - The end user gets recomendations to act when a defect antenna is found

XR interface – auto inspection

XR interface – manual inspection



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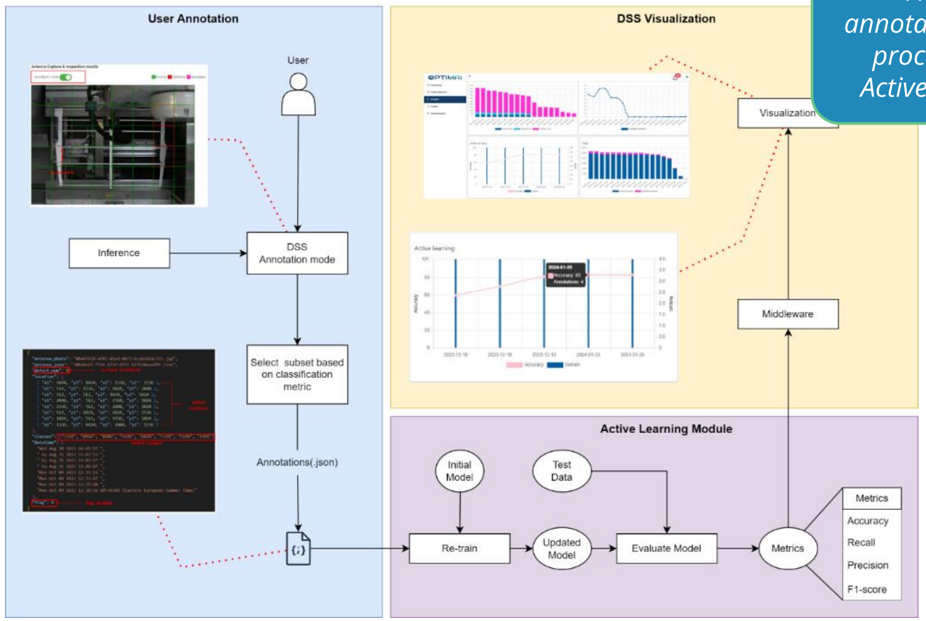
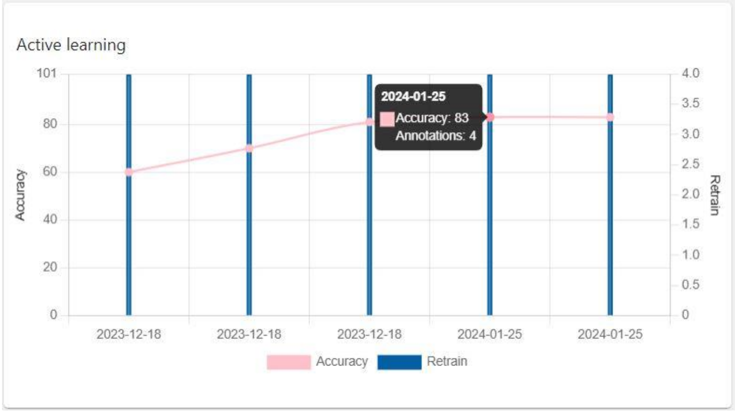
TELEVES
Active Learning

- The active learning can be divided into 3 main sections
  1. **User Annotation**: The end-user, via the DSS annotation mode, examines the model's results and selects a subset of the inspected samples. The selected subset is manually annotated by the end-user and forwarded to the active learning module.
  2. **Active Learning (AL) Module**: The re - annotated results are used to retrain the antenna inspection model.
  3. **DSS Visualization**: The evaluation metrics from the active learning module are displayed through the visualizations in the DSS Analysis tab.

Flowchart of the annotation and retraining processes used in the Active Learning module



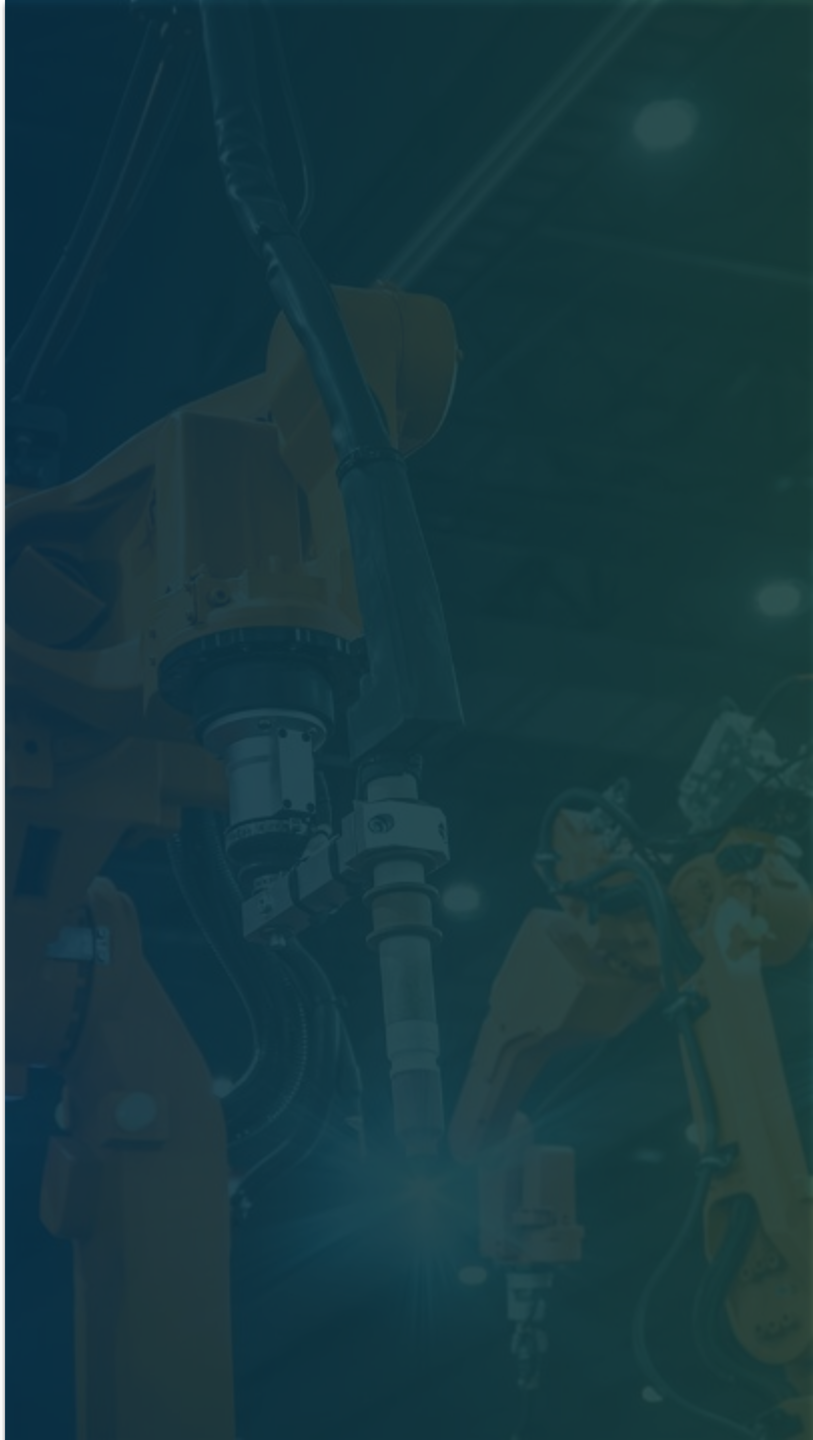


Through AL performance increases from 60% to 83%

Conclusions

Conclusions

- Reduced instrumentation complexity and cost through **soft sensing.**
- Exploited **Generative AI** to create **Digital Twins** and optimize production.
- Reduced human intervention and unneeded stoppages with **“XRay” vision**.
- **Human-machine collaboration** for continuous production improvement through a DSS.
- Capturing human expertise with **Active Learning** to accelerate AI training.
- Enhance workers abilities and improve working conditions with XR.



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https://www.linkedin.com/company/optimai-project/

OPTIMAI H2020
https://www.youtube.com/channel/UCgn6kut1if7_mAsDbSR0xMw

Thank you

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