

A.I. IN PRODUCTION

THE ROAD TO PROCESS
OPTIMALISATION WITH A.I.

A.I. LAB — PERRON038

6 March 2025



INTRODUCTION

Name: **Arend Lutén**

Age: 42 years

Home: Area of Zwolle - NL

Education

Bachelor Software Engineering Zwolle - 2006

Vocational education Electrical Engineering - 2002

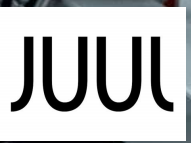
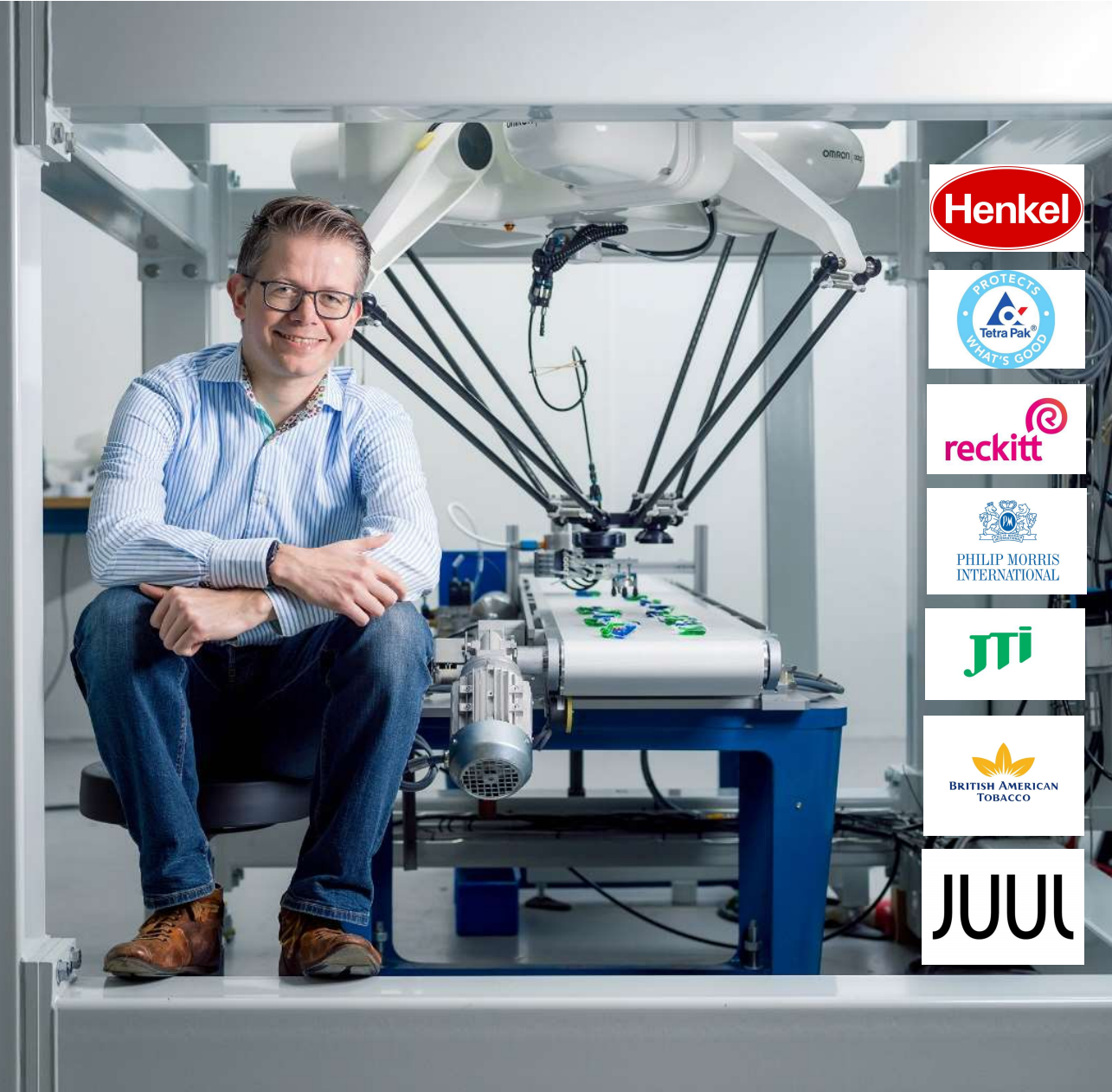
Work Experience:

Tembo Kampen NL 2007 - now

- A.I. lab Perron038 2023 - now
- R&D Innovation lab Perron038 2019 - now
- Lead Developer HMI* 2008 - now
- Software Developer OEE** 2007 - 2010

Hobbies:

Keyboard player, Beekeeper, Running,
3D printing



*Human Machine Interface **Overall Equipment Effectiveness



A.I. IN PRODUCTION

- Introduction Tembo & Perron038
- How can we make a machine smarter?
- Case study: Genesis
A.I. Driven quality check
- Case study: Salome
A.I. Driven Process optimization
- Conclusion

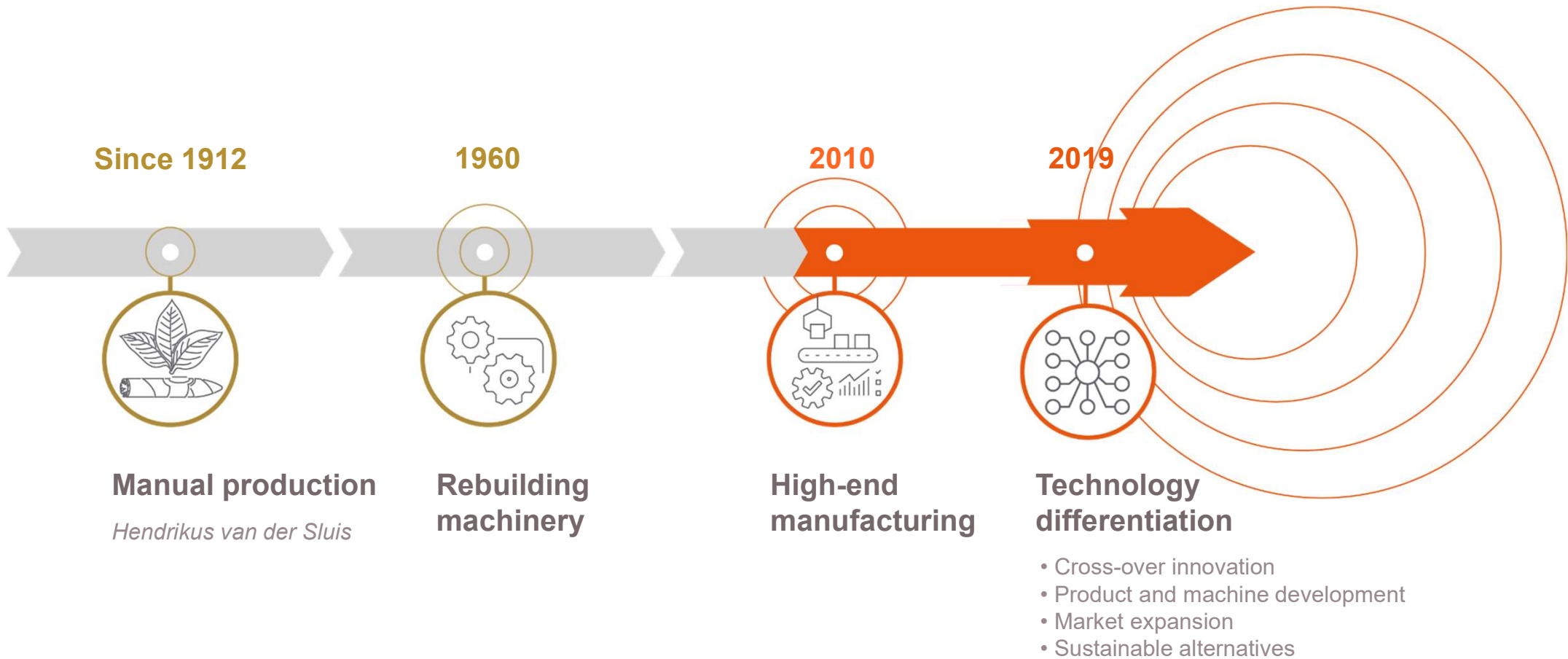
About our name

Tembo means elephant

It refers to De Olifant, our founding company – an authentic cigar factory located in Kampen, the Netherlands.



Our transformation



Tembo markets and solutions

Global services technology hubs



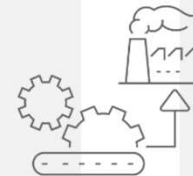
Innovation



Digitalisation



Packed drinks
Changing legislation



Detergents
Changing consumer
needs



Next generation
Sustainable choices

Tembo at a glance



1.200
employees

100 Nations

100%
family-owned
since 1912



2.000+
Installed based solutions

± 200 mil €
Annual revenue

18
Companies
Located in 10 countries
Worldwide

**Work with
Joy and
Pride**

Creating the next. Together.

 Tembo

Innovation Eco-system

Close collaboration

This means we can access cutting-edge knowledge across a wide range of different technologies, which is a big advantage to help our customers and partners respond immediately to changes in their market.



We collaborate with universities, RTOs, and innovation networks:

UNIVERSITY
OF TWENTE.

RWTHAACHEN
UNIVERSITY

uni.lu
UNIVERSITÉ DU
LUXEMBOURG

hogeschool
Windesheim

Fraunhofer

ESCF
European Supply
Chain Forum

INC
INVENTION
CENTER



FACTORY NEXT

Discover | Develop | Deliver



GOAL

Making new technology accessible

- Test before invest
- Incidental use

METHOD

- Gaining new knowledge and developments (events, academy)
- Prototyping
- Joint project
- Self-development or research

FACTORY NEXT



Digital Manufacturing



Robotics & Logistics



Vision & Optics



Artificial
Intelligence



Additive
Manufacturing

Co-developed by



AWL.

 **Tembo**

 **Tembo**



HOW CAN WE MAKE A MACHINE SMARTER?



HOW CAN WE MAKE A MACHINE SMARTER?

Introduction

- Understand technology innovation via TOE-framework
- What can A.I. do in the industry?
- Process to integrate A.I. in a machine
- How can data & A.I. be adapted to a machine

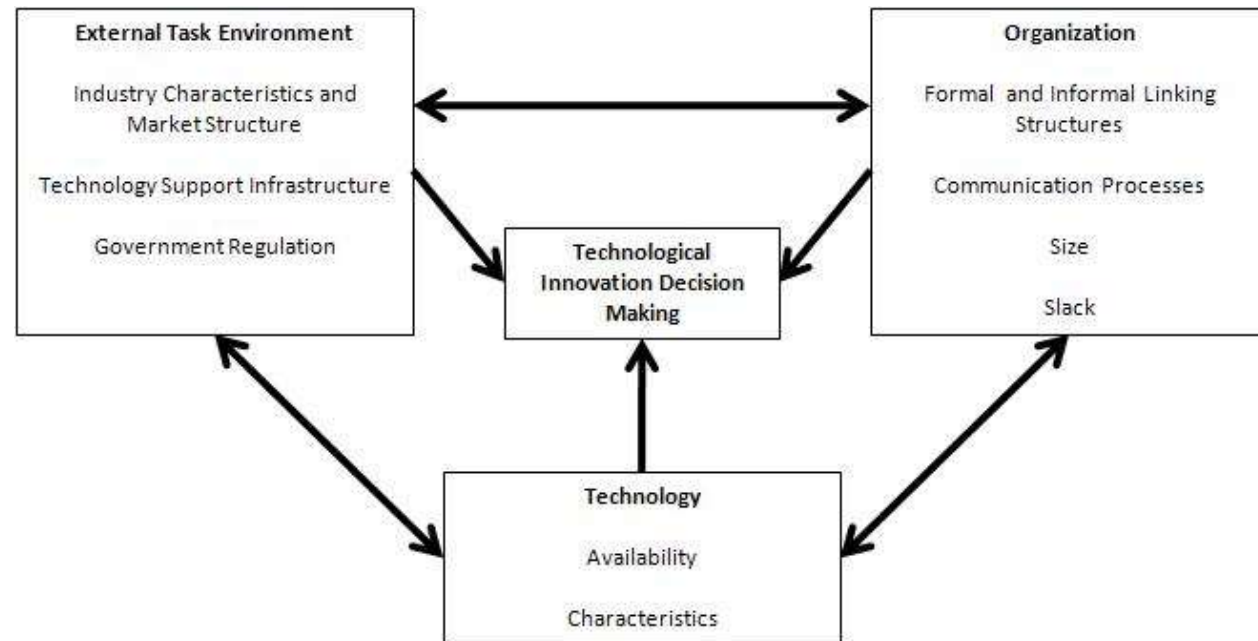


INNOVATION VIA T.O.E. FRAMEWORK

The technology-organization-environment (TOE) framework was created by Tornatzky and Fleisher (1990). It describes factors that influence technology adoption and its likelihood.

TOE describes the process by which a firm adopts and implements technological innovations is influenced by the technological context, the organizational context, and the environmental context.

Data driven & A.I. applications needs to be adapted in multiple domains.



WHAT CAN MACHINE LEARNING DO IN THE INDUSTRY

From technology point of view

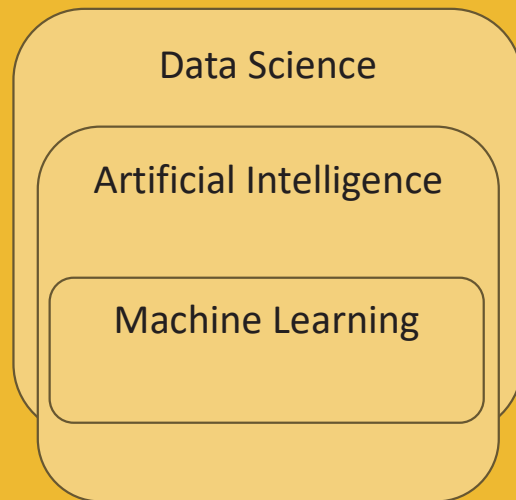


Machine Learning is a branch of A.I. and can help us with:

1. Predictive maintenance
2. Quality control
3. Robotics & Automation (adapting to environment)
4. Process optimization
5. Supply chain optimization
6. Energy management
7. Safety monitoring
8. Data analytics and visualization
9. Human machine interaction with Natural Language Processing
10. Training and Simulation

WHAT CAN MACHINE LEARNING DO IN THE INDUSTRY

From technology point of view



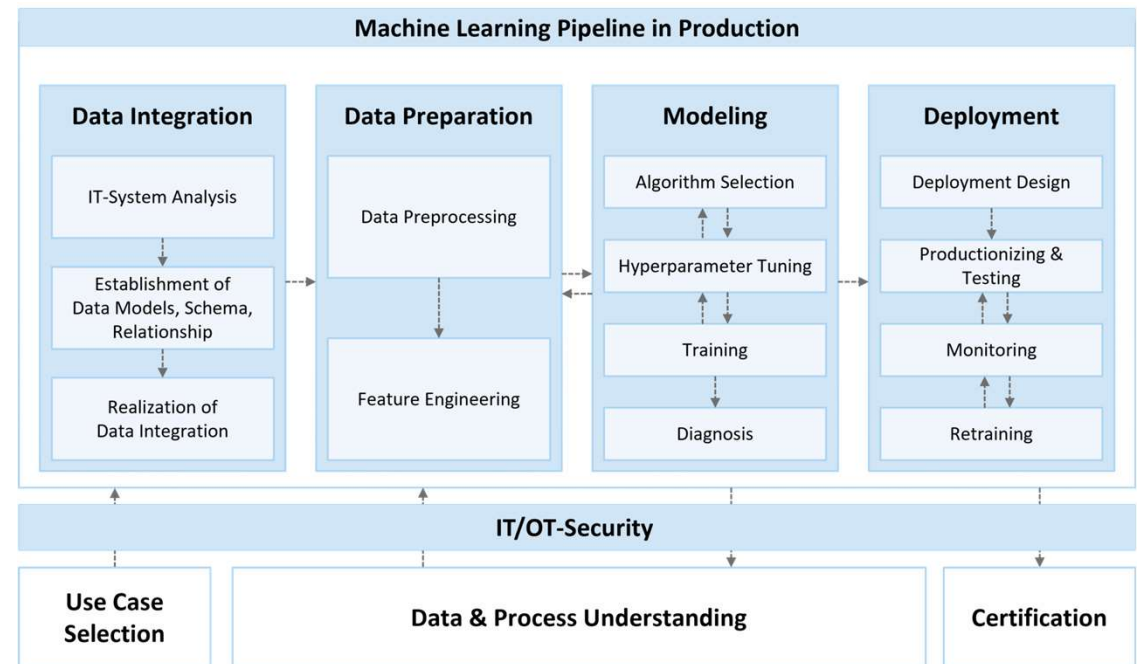
What is Machine Learning?

*“Arthur Samuel, a pioneer in the field of artificial intelligence and computer gaming, coined the term “Machine Learning”. He defined machine learning as – a “Field of study that gives computers the capability to learn without being explicitly programmed”. In a very layman’s manner, **Machine Learning(ML) can be explained as automating and improving the learning process of computers based on their experiences without being actually programmed i.e. without any human assistance.**”*

Get to know of what is available

PROCESS TO INTEGRATE M.L. IN A MACHINE

From organizational point of view



Get skills in organization

WHAT CUSTOMER WANT

From environment point of view



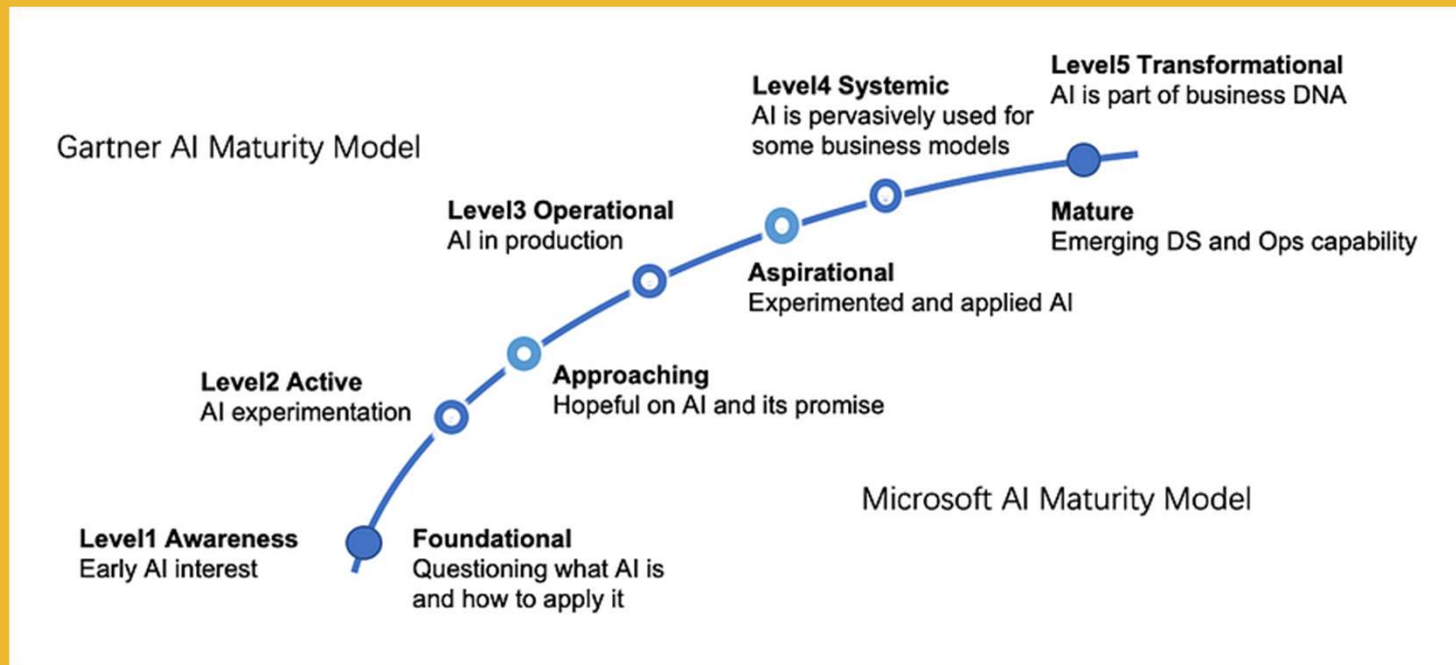
- See anomaly in data => Production stability
- Predict maintenance => achieve higher uptime, less costs maintenance
- Quality control => Higher quality, less rejects/waste
- **Lower cost per unit**

**Get to know the voice of the customer
and the business value**

HOW CAN WE MAKE A MACHINE SMARTER?

==

HOW CAN WE MAKE YOU SMARTER



PRODUCE SMARTER

ADVANCE IN PHASES



Phase 1: Initiation

- Business case
- Process mapping to sensors
- Infrastructure data collection
- (Fault) Data collection
- Manual analysis

Phase 2: Development

- Basic ML models (e.g. classification)
- Correlation
- Condition monitoring
- Dashboard analysis

Phase 3: Intermediate

- Model tuning
- Simulation testing
- Automated Quality Checks
- Initial maintenance scheduling

Phase 4: Advanced

- ML Deployment in Automation
- Multi sensor analysis
- AI-Driven Process Adjustment
- Real-time Predictions

Phase 5: Expert

- Full Automation
- Real-time Continuous Improvement
- Adaptive Quality Standards



MATURITY WITH CHALLENGES

Process and Industry Characteristics

- High data and information confidentiality
- Conservative industry with highest demands on reliability
- Increasing need for efficiency improvement and cost reduction
- Lack of IT and data science expertise
- Need for context-aware provision of comprehensible information
- Evolving process dynamics due to e.g., wear and tear
- Highly individualised and specialised real-world processes

Data Characteristics

- Data tends to be highly imbalanced
- High complexity and low signal-to-noise-ratio
- Inhomogeneous multi-variate and multi-modal data sources
- Poor data quality due to challenges in data integration and management
- High measuring and labeling efforts for defining target variables

ML-Model Characteristics

- Non-deterministic behavior lacking functional provability
- Intransparent model functionality
- Lack of robustness and safety
- Vulnerable against erroneous or manipulated data
- Susceptible to data drifts (dynamically changing data)
- Poor generalizability across processes and tasks
- High development, implementation and maintenance costs

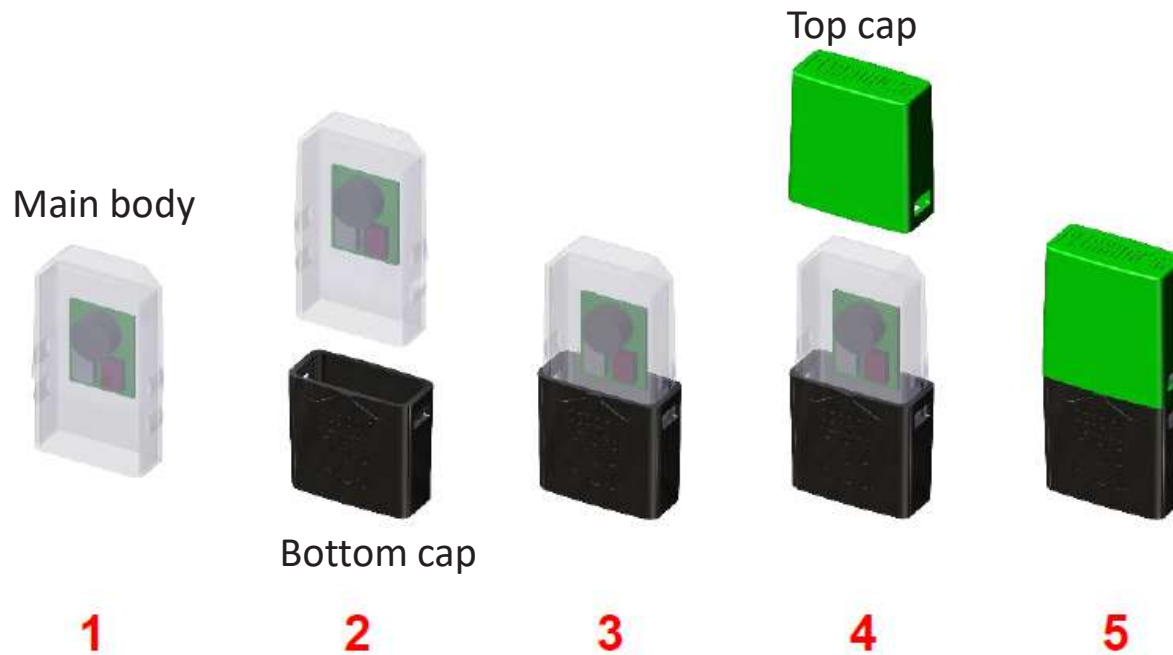
CASE STUDY: AI DRIVEN QUALITY CHECK









CASE STUDY: AI DRIVEN QUALITY CHECK

GENESIS - PRODUCT

Genesis assembles a LED-pod as test product to gather data for ML.

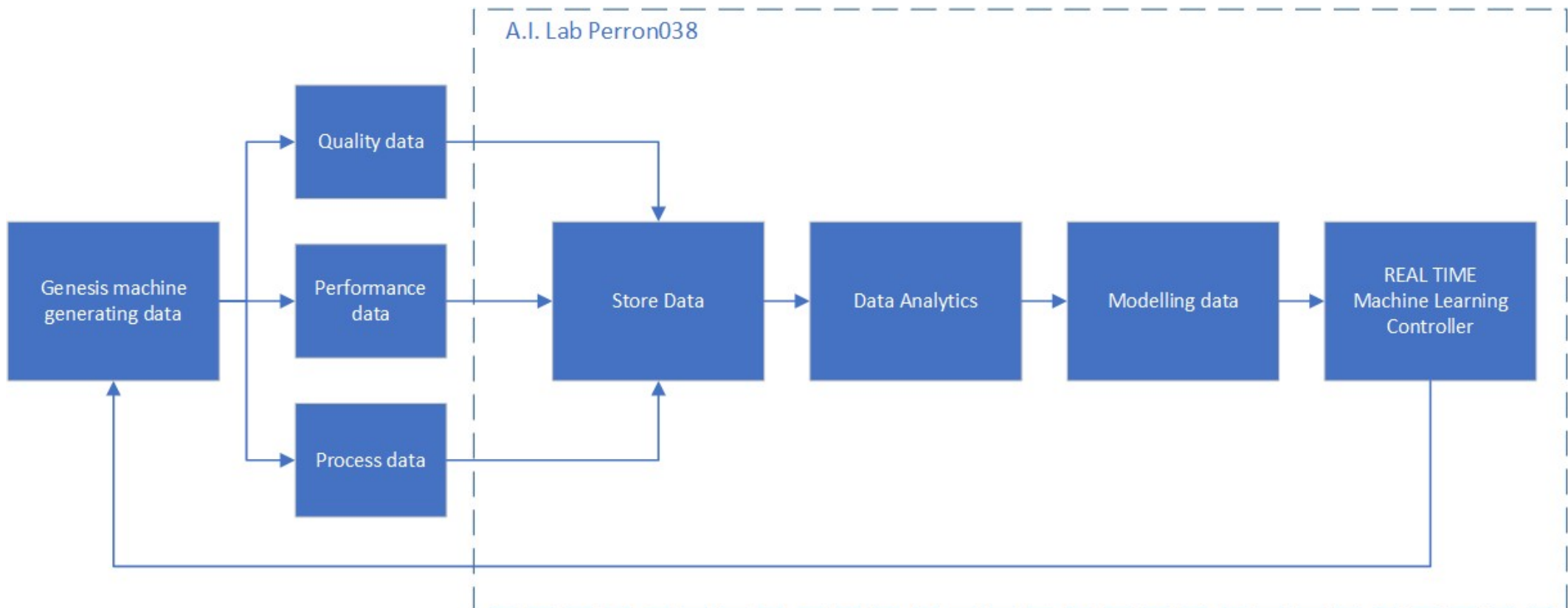


GENESIS — PRODUCT TRANSPORT VIA PUCKS

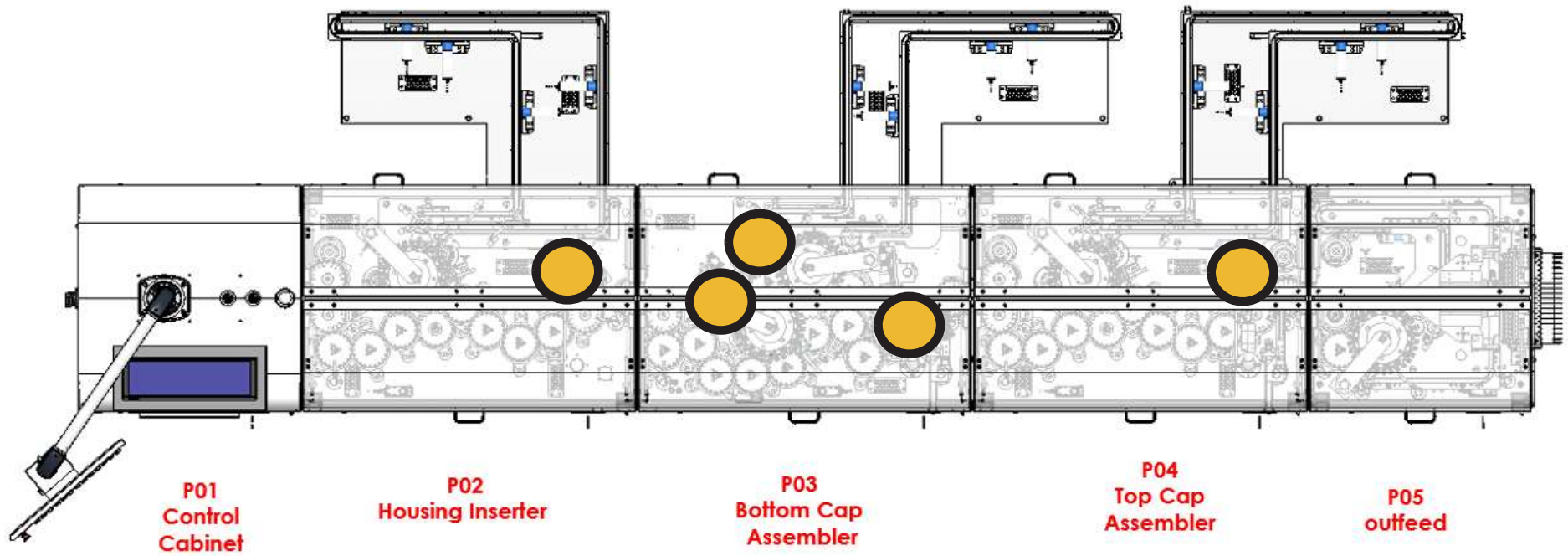
MODULE	P02	P03	P04	P05
Main				
Sub				

These pucks will wear out

GENESIS — DATA COLLECTION VIA SENSORS



GENESIS — QUALITY DATA



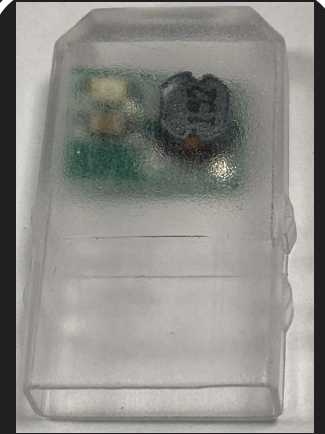
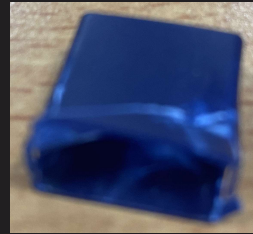
 Location of vision sensor

CASE STUDY: AI DRIVEN QUALITY CHECK

Damaged LED housing

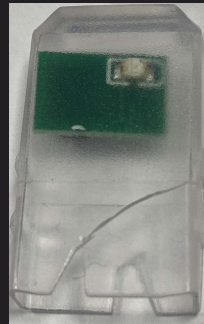
- **End of line quality cost**
→wasting good parts due to assembly with a bad part
- **Possible crash while assembly**
→ stops the machine i.e. OEE loss + can cause damage to machine
- If goes undetected through production, then we get **dissatisfied customers**

Crashed cap
due to
damaged
LED housing

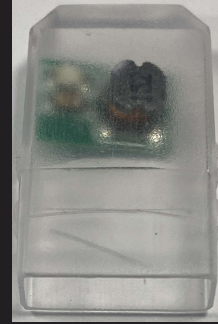


Good part

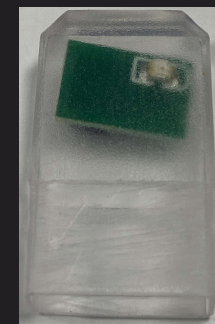
Bad parts



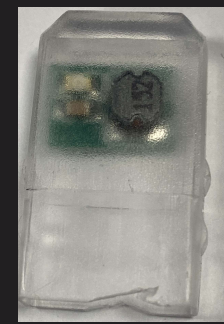
Crack



Scratch

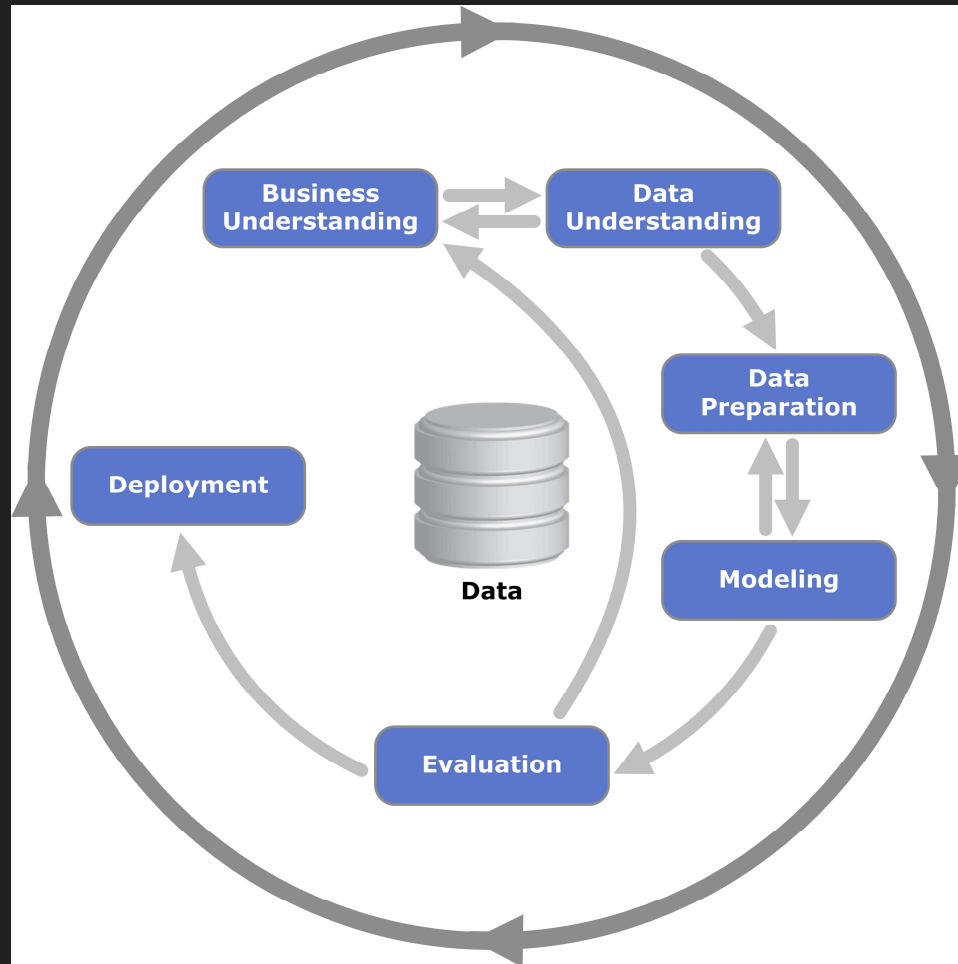


Wear



Chip-off

CRISP-DM (CROSS INDUSTRY STANDARD PROCESS FOR DATA MINING)



BUSINESS UNDERSTANDING (IMPACT)

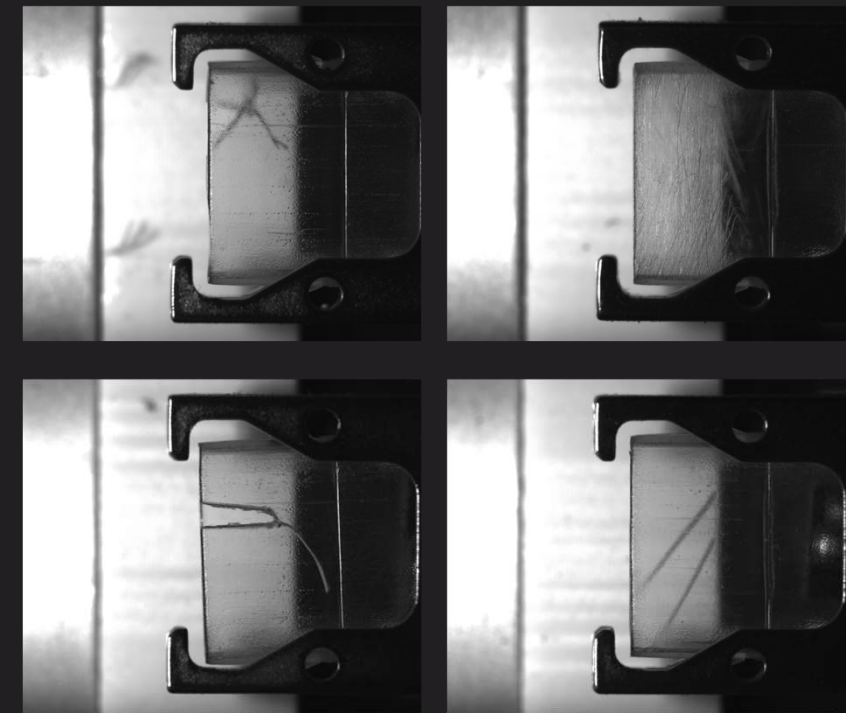
END OF LINE QUALITY COSTS		
Without AI model		
damaged housing /1000 pieces	5	pieces
Production speed	100	pieces /min
total parts in one shift	48000	pieces
end of line rejects in one shift due to damage housing	240	pieces
cost of throwing away one good top and bottom cap	0.1	€
End of line quality cost/shift	24	€
End of line quality cost per year (24/7 production)	25920	€
After implementing 95% accurate AI Model detecting and rejecting damaged LEDs		
Rejects/shift (95% reduction)	12	pieces
End of line quality cost/shift	1.2	€
End of line quality cost per year (24/7 production)	1296	€
Yearly saving/machine	24624	€

MACHINE AVAILABILITY (OEE)		
Without AI model		
damaged housing /1000 pieces	5	pieces
probability of crash	1 crash/30 damaged LEDs	
total possible crashes in one shift	8	crashes
Time to return/crash (removing broken parts and restarting)	2	mins
Machine unavailability due to crashes	16	mins
production loss due to machine unavailability	1600	pieces/shift
production loss in a year/machine	1728000	pieces
After implementing 95% accurate AI Model detecting and rejecting damaged LEDs		
possible crashes in a shift	0.4	crashes
production loss due to machine unavailability/shift	80	pieces
production loss in a year/machine	86400	pieces
Yearly production gain/machine	1641600	pieces

Lower risk by 95% of breaking the machine & Good quality products → Happy customer

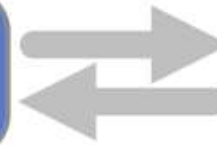
DATA UNDERSTANDING (FEASIBILITY)

- DEFECTS: Cracks, Scratches, Wear, Edge chip offs
- Features are Prominent which means
 - Modeling efforts will be low
 - Data Labelling efforts will be low
 - Data volume requirement will be low
- Vision sensor already present checking the presence of part i.e. data is available
- AI inference engine and beckhoff edge computer is already available
- Estimated efforts for model development ~5PD
- Estimated efforts for deployment ~5PD
- **Total cost of implementation = 10x1200 = 12000€**



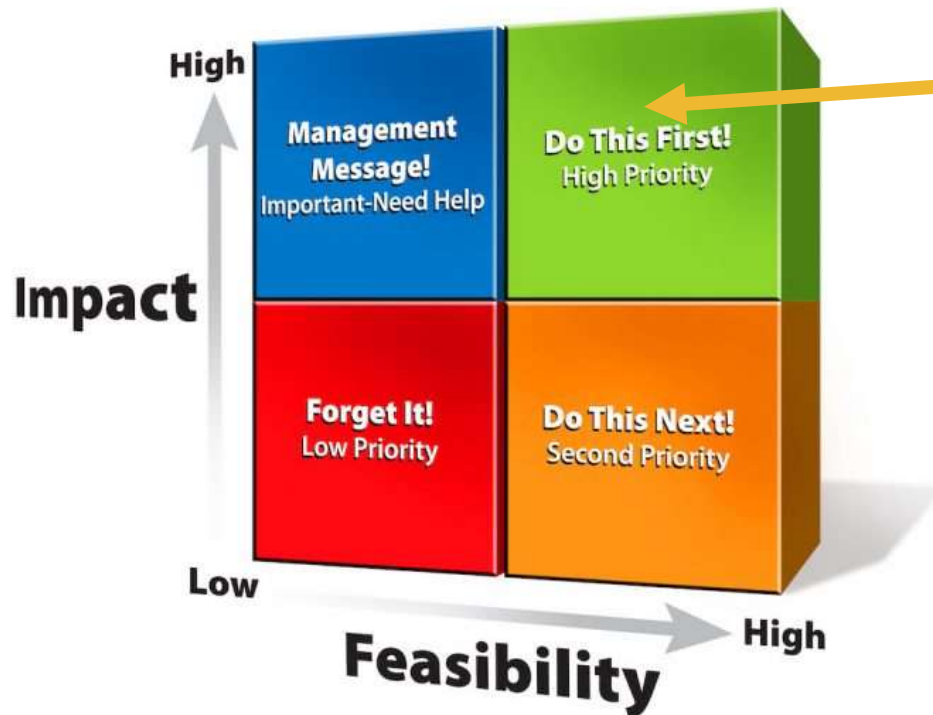
IMPACT VS FEASIBILITY

Business Understanding



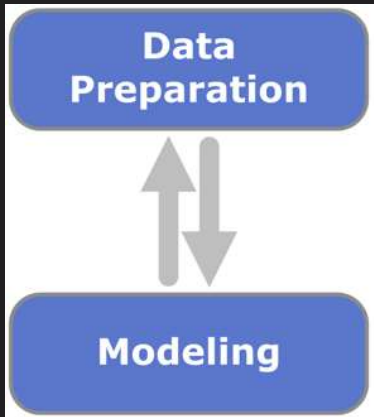
Data Understanding

Impact/Feasibility Matrix

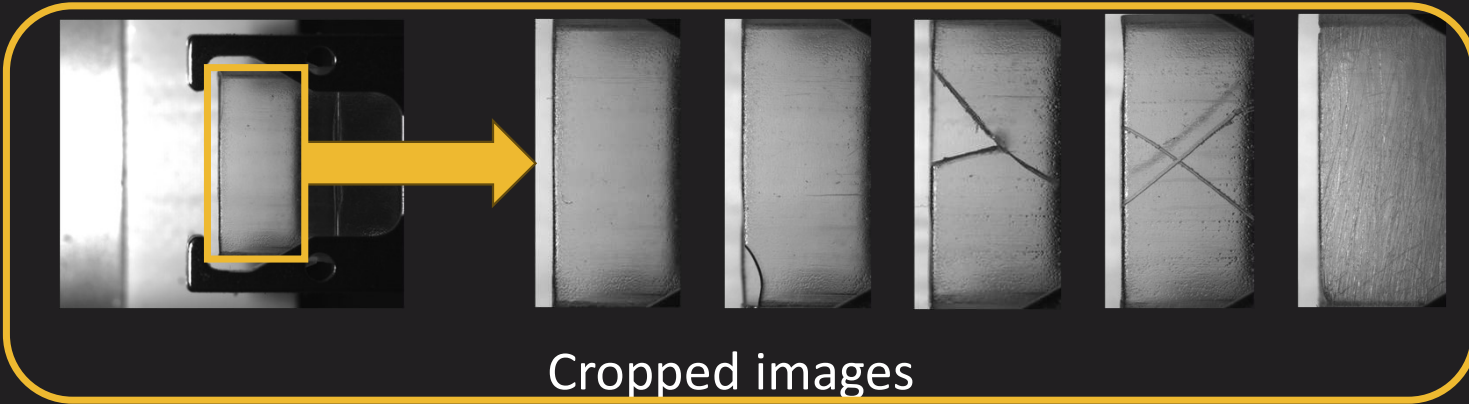


AI DRIVEN
QUALITY CHECK

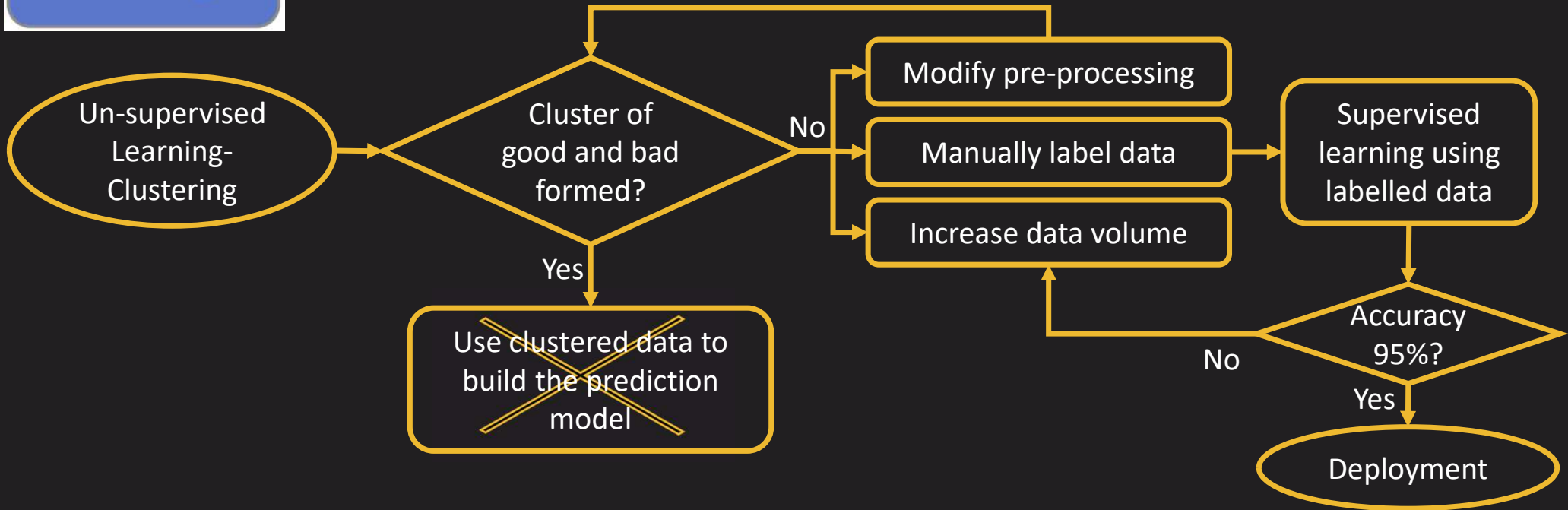
DATA PREPARATION



Data Volume
250 good
80 bad



Cropped images



DATA MODELING

UNSUPERVISED LEARNING - CLUSTERING

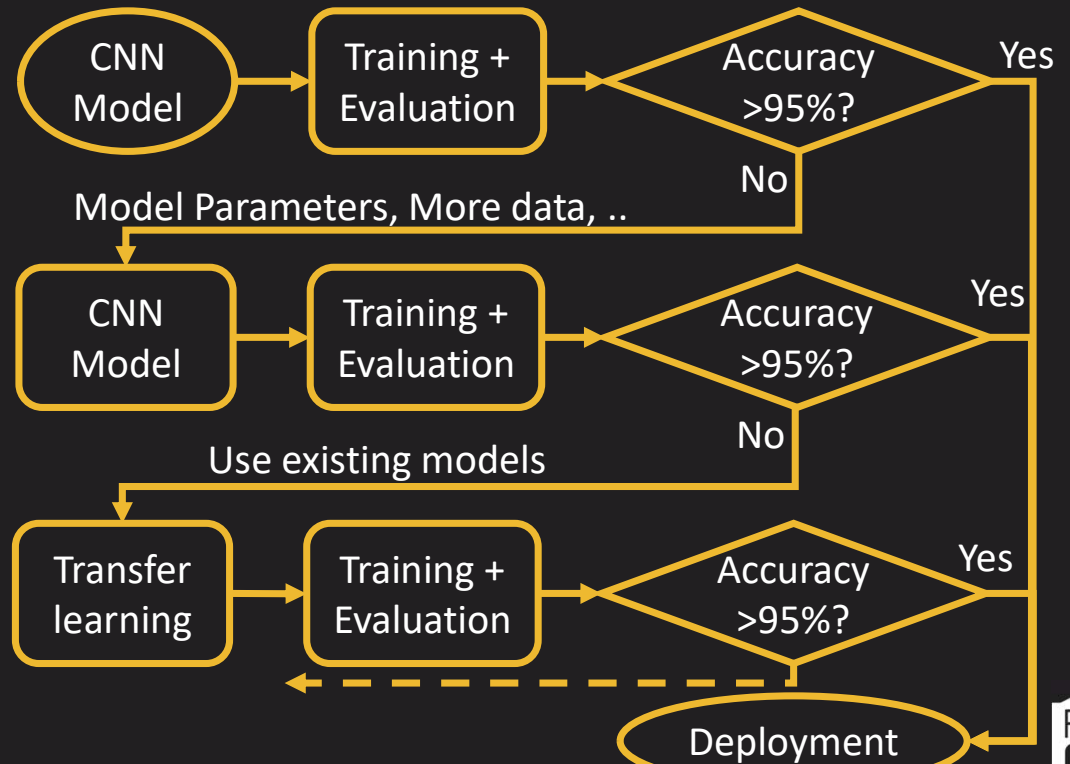
- **Models:** Agglomerative Clustering, Kmeans, Gaussian Mixture
- **OpenCV pre-processing:** Cropping parameters, Edge detection, contrast enhancement
- PCA used for dimensionality reduction
- Filtering techniques tried

RESULT: None of the methods yielded clusters of good and bad products

REASON: Data volume was low especially the bad product data

LEARNING (Iterative)

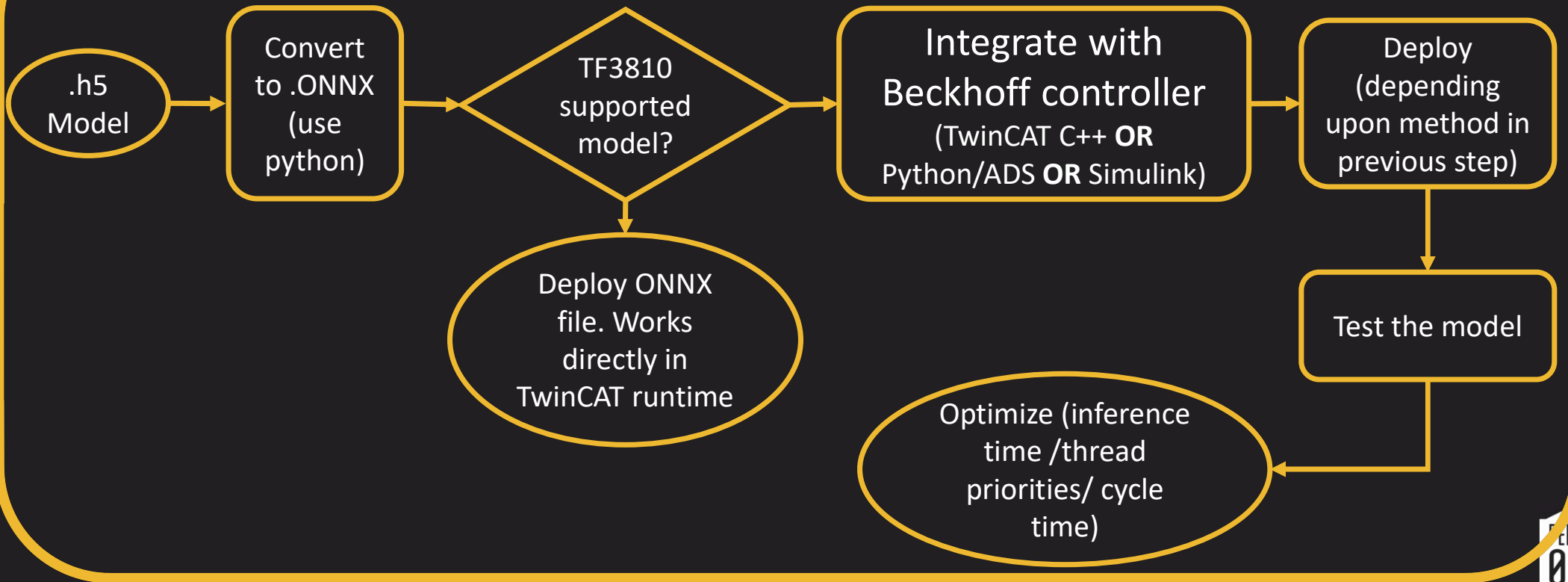
Binary SUPERVISED class data "Good" & "Bad"



DEPLOYMENT

Deployment was not done in this use case. However, the workflow for deployment is given below.

Beckhoff/TwinCAT



CASE STUDY: PROCESS OPTIMALISATION SALOME



LAUNDRY POD PRODUCTION MACHINE

PRODUCT



Concept 4A	[1] White	[2] Blue	[3] Red	Validation
48.82 x 39.65 mm				
14.79 ml / 12.86 ml				
±2 mm inner seal				
	Powder	Liquid	Liquid	
Depth	13.25 mm	11 mm	7.25 mm	✓
Headspace	1 mm	1.5 mm	1.5 mm	✓
Cavity Volume	7.61 ml	6.28 ml	0.9 ml	✓
Fill Volume	6.93 ml	5.28 ml	0.65 ml	✓
Stretch	2.5	2.28	2.28	✓

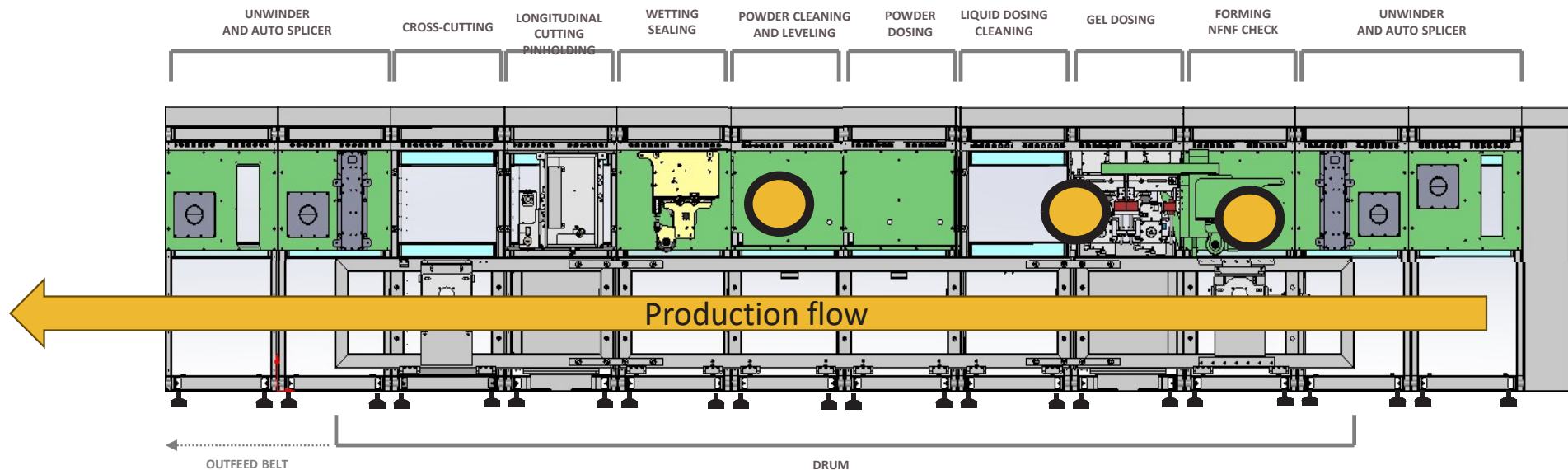


PRODUCTION FLOW SALOME

MODULAR PLATFORM — EACH MODULE A PROCESS STEP



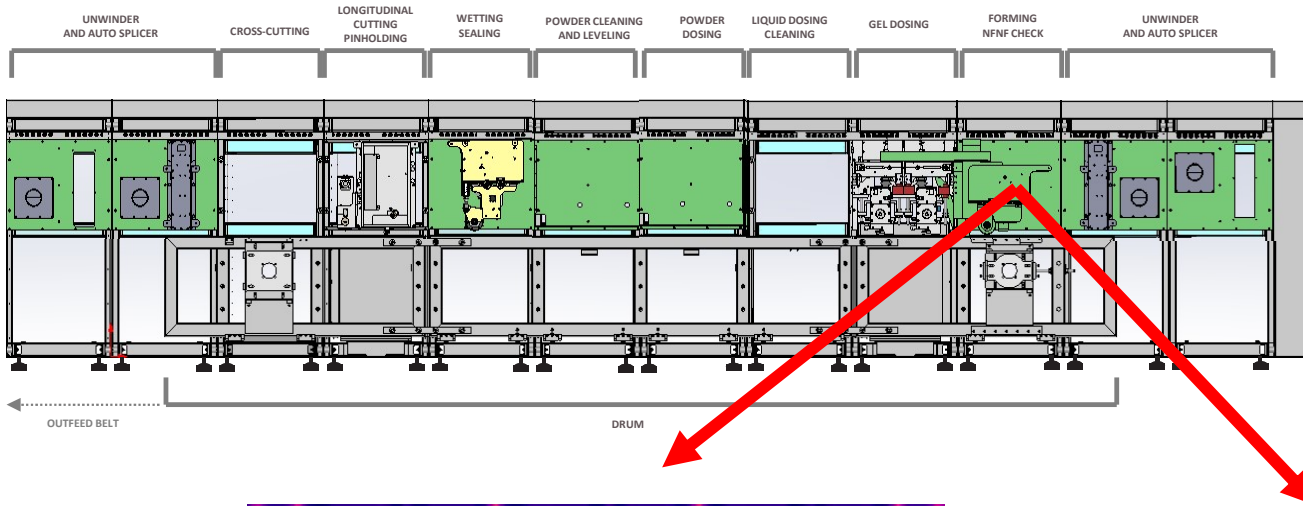
Location of vision sensor



- Drum exists of 200+ beams
- One beam has 36 cavities
- Theoretical output is 2000 p/m

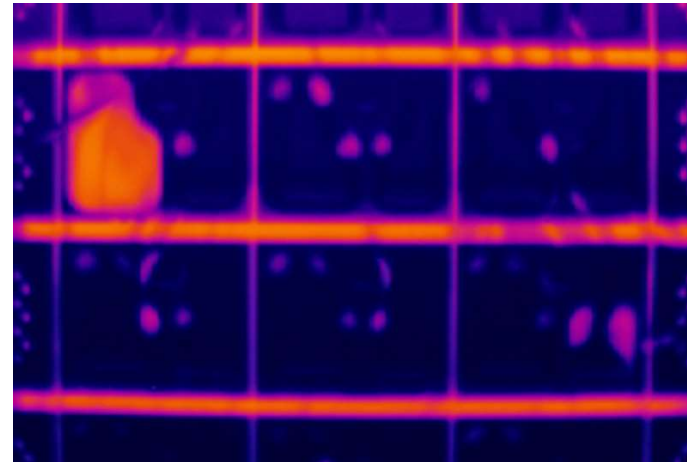
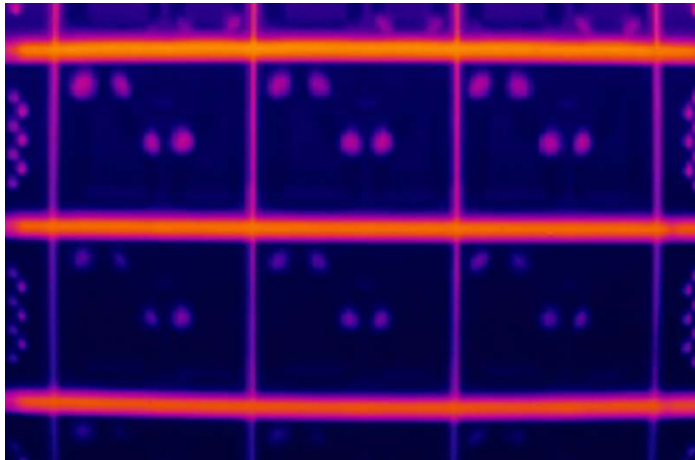
THERMOFORMING INSPECTION USING THERMAL CAMERAS (NO FORM NO FILL)

VISION CHECK IN PROCESS



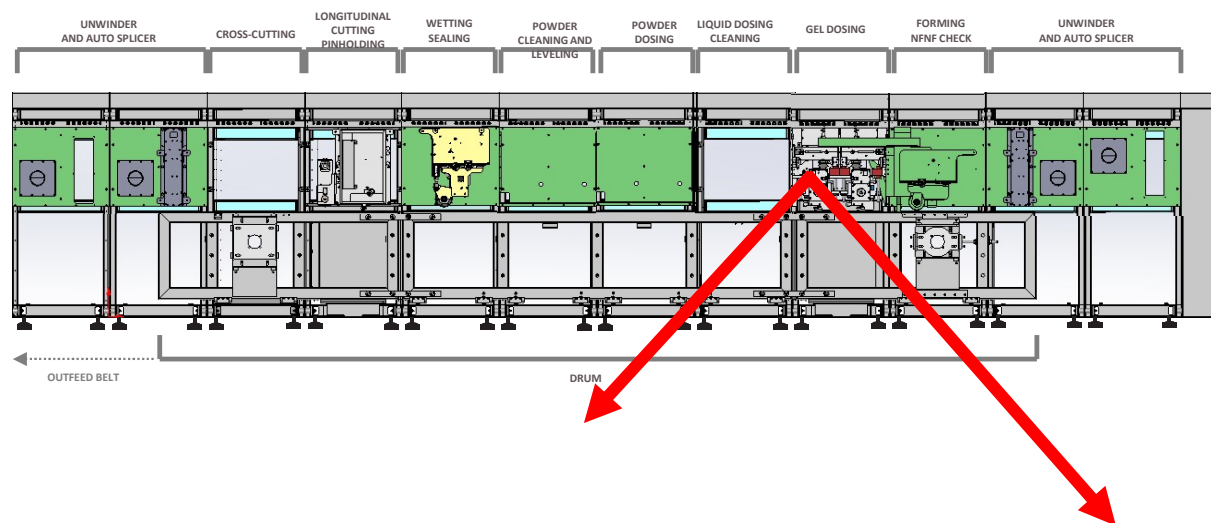
Thermoforming inspection using thermal cameras (thermal process)

- Vacuum loss (e.g., due to wrinkles in the foil)
- Heating roll not (homogeneously) at temperature
- Inferior foil or defective spots in foil
- Holes in foil / inclusions in foil
- Incorrect environmental factors (temperature / humidity)
- Etc.



LIQUID DOSING AND SEAL INSPECTION (LIQUID CHECK / SEAL CHECK)

VISION CHECK IN PROCESS

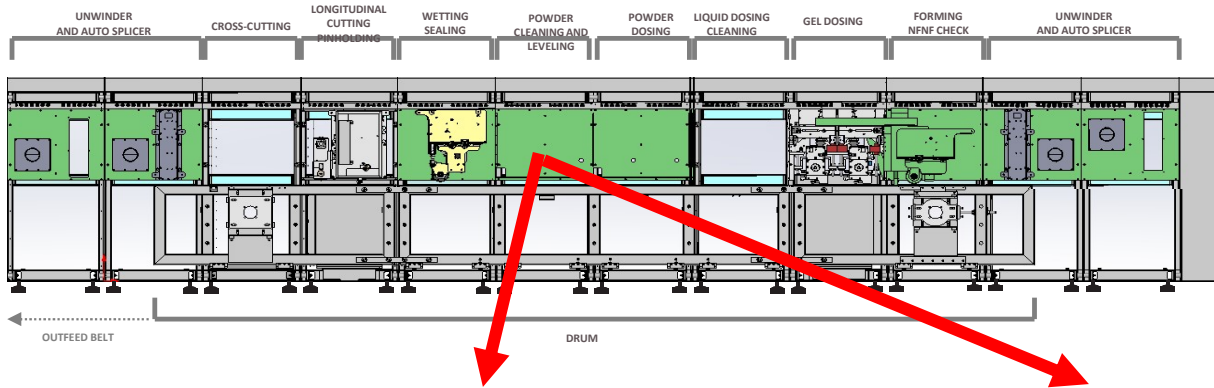


Liquid / gel dosing and seal contamination

- Stringing of liquid / gel
- Unfilled compartments
- Color deviations
- Liquid / gel droplets outside the filling area
- Overflow / underflow of liquid / gel
- Position measurement of the drum
- Etc.

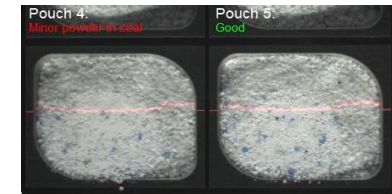
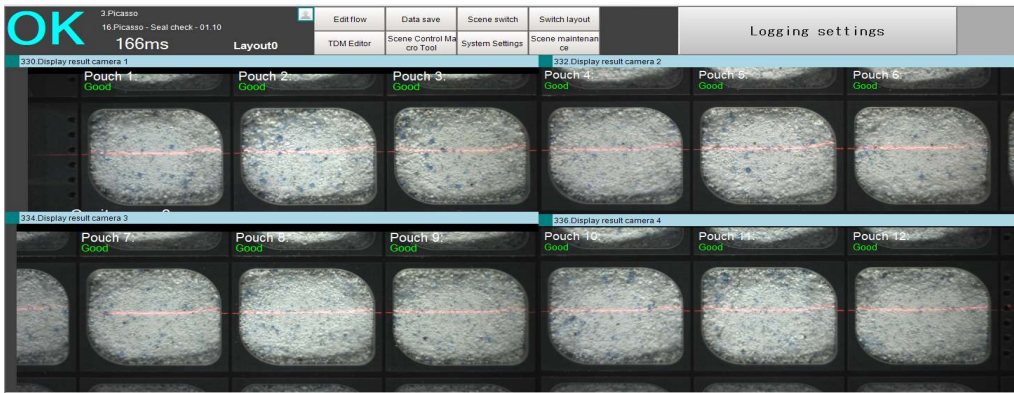
POWDER DOSING AND SEAL AREA INSPECTION (POWDER CHECK / SEAL CHECK)

VISION CHECK IN PROCESS



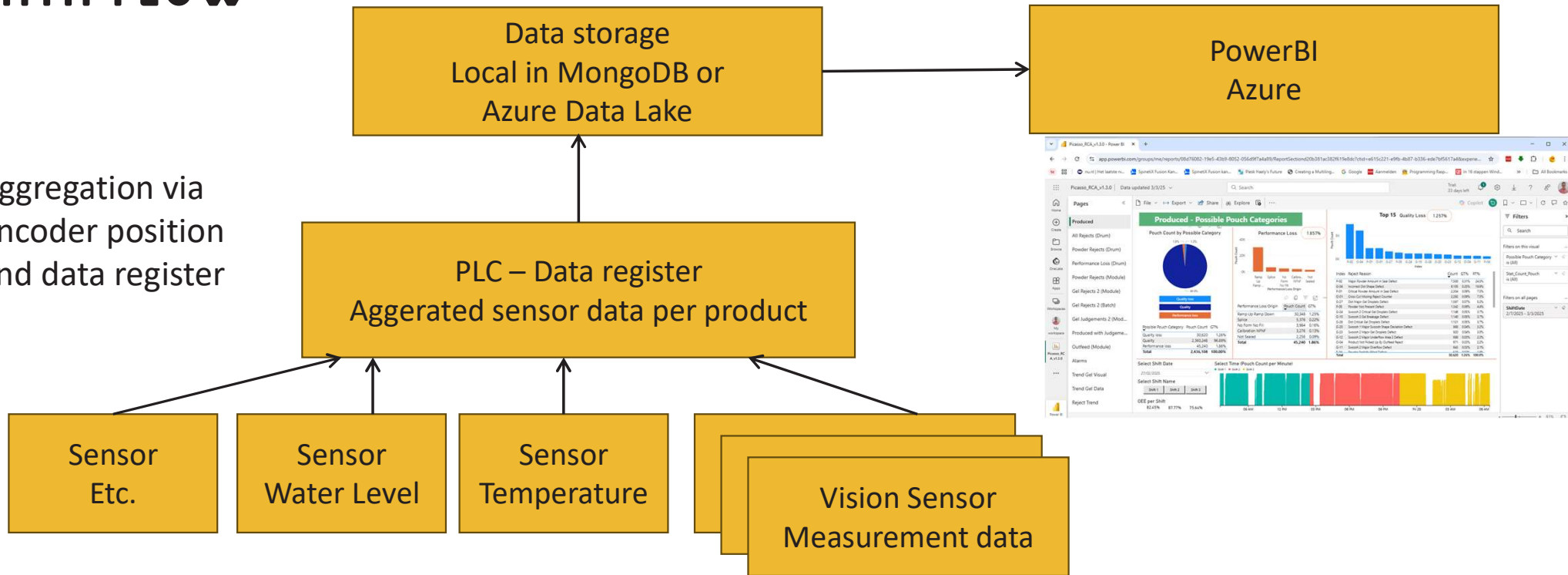
Powder dosing and seal contamination

- Overfill / underfill using 2.5D laser measurement
- Powder contamination on the seal area
- Position measurement of the drum
- Etc.



DATA ACQUISITION DATA FLOW

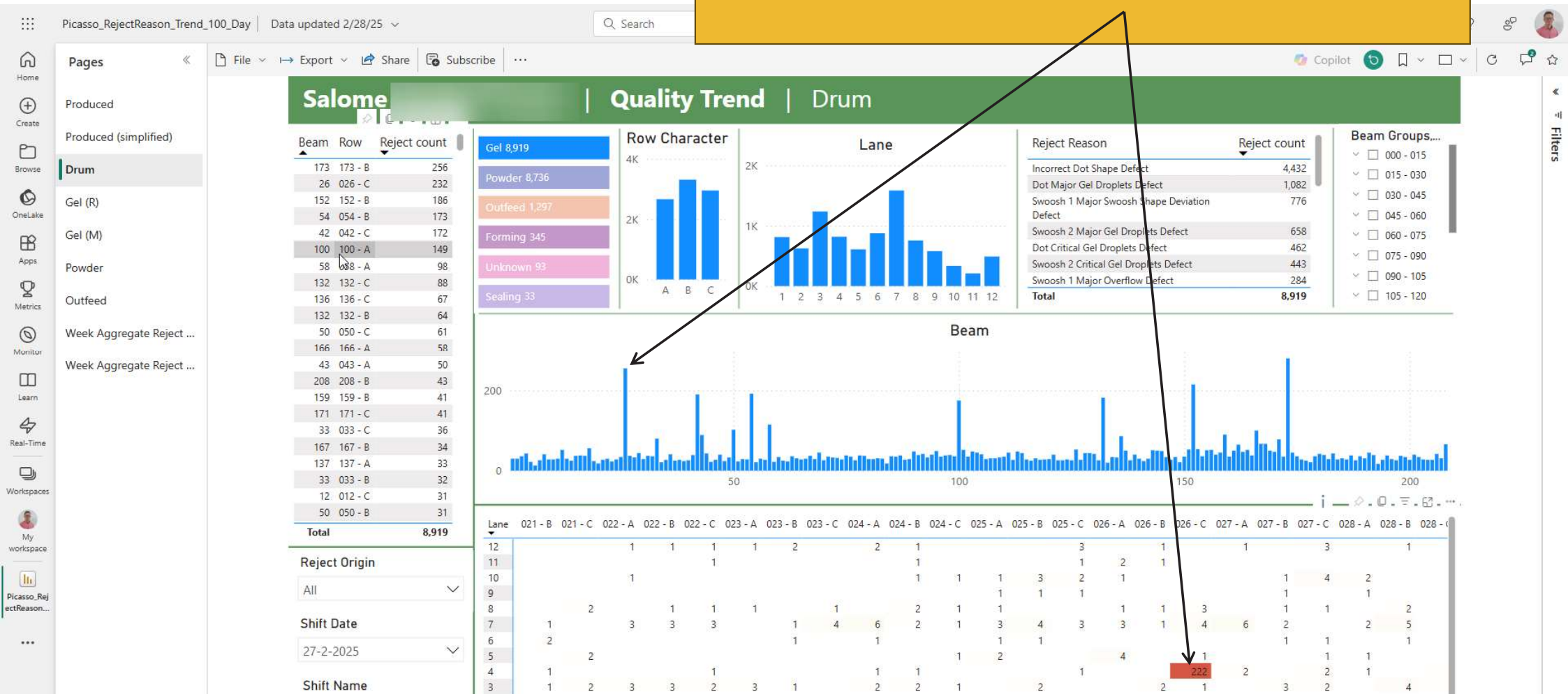
Aggregation via
encoder position
and data register



DATA INTERPRETATION

HEAT MAP REJECT DRUM - POWERBI

1 Cavity Beam has anomaly on gel defects.
Problem related to cavity??



MEASURE CAVITY PROBLEMS WITH A.I.

RESEARCH VISION SENSOR WITH A.I. - CAVITY ERRORS ARE DETERMINED AS FALSE GEL DEFECTS BY CLASSIC VISION

Example pictures of damaged cavities

Damaged cavities will lead to false rejects – Can we early detect these problems?



MEASURE CAVITY PROBLEMS WITH A.I.

RESEARCH VISION SENSOR WITH A.I. - RECOGNIZE DROPLETS

Example pictures of droplets

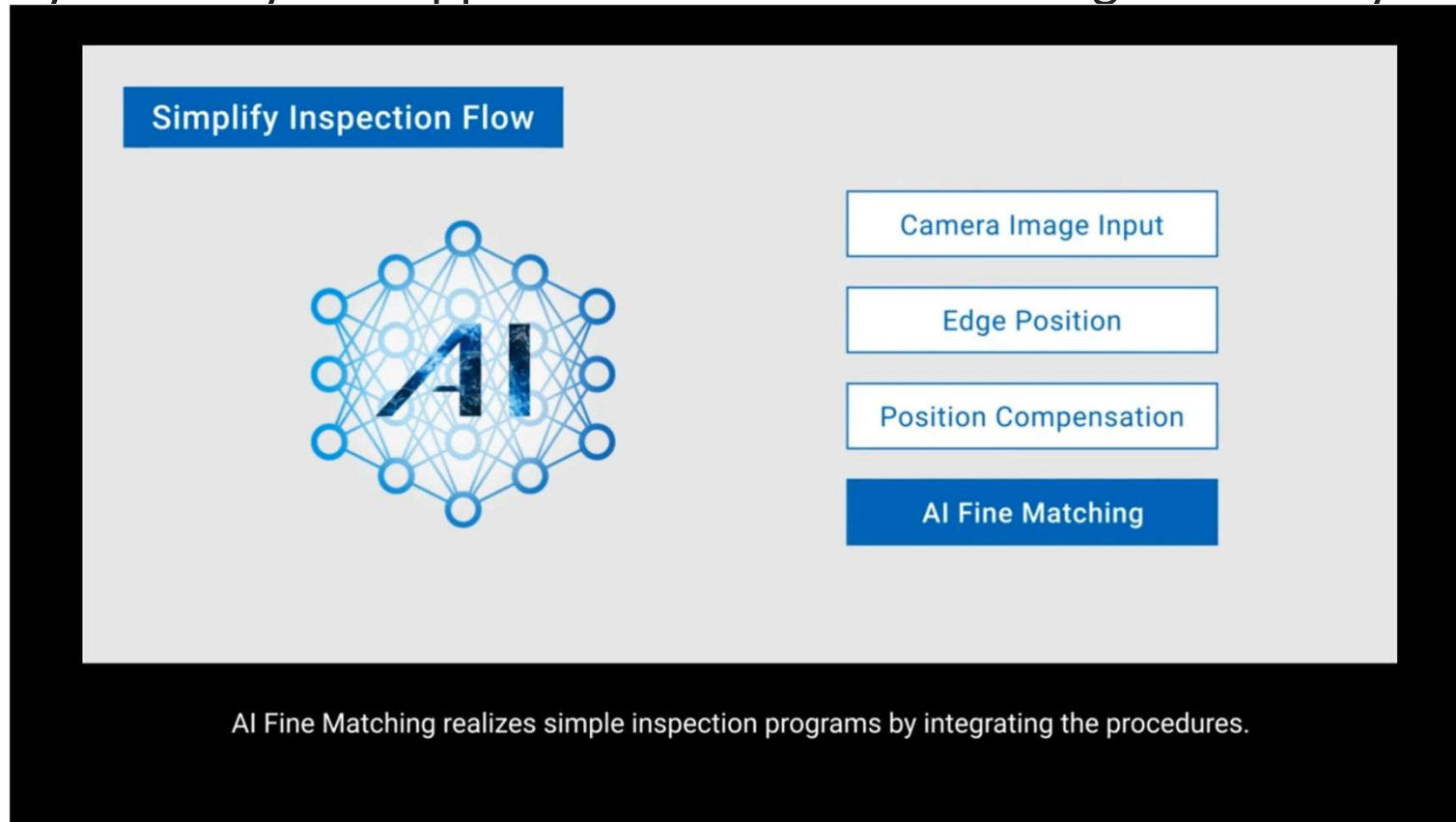
Droplets will lead to seal issues



MEASURE CAVITY PROBLEMS WITH A.I.

A.I. FUNCTIONALITY INTEGRATED IN VISION SENSOR

Keep an eye out to your suppliers and their tools to integrate A.I. in your solution



Source: <https://www.youtube.com/watch?v=I3VayFIB618&t=242s>

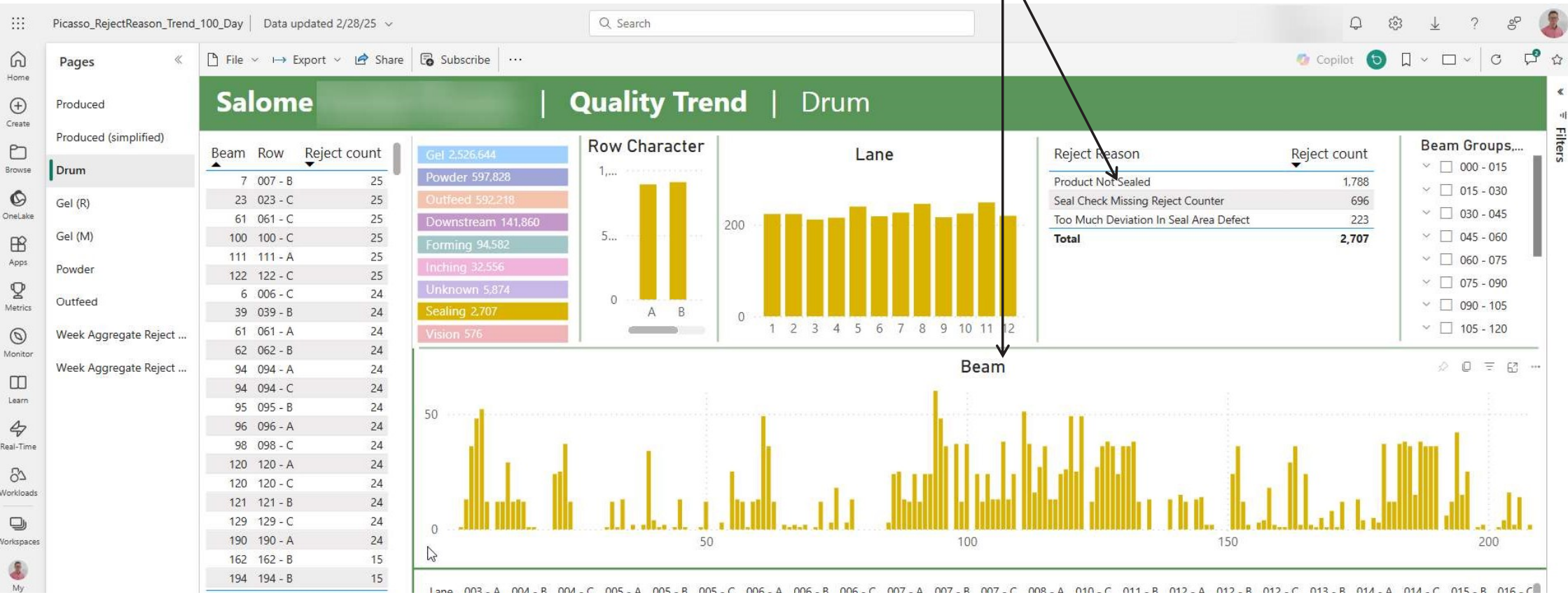
Or model can be trained via OPENVINO



DATA INTERPRETATION

HEAT MAP REJECT DRUM - POWERBI

Seal problems are visible over whole drum
Problem related other parameters?

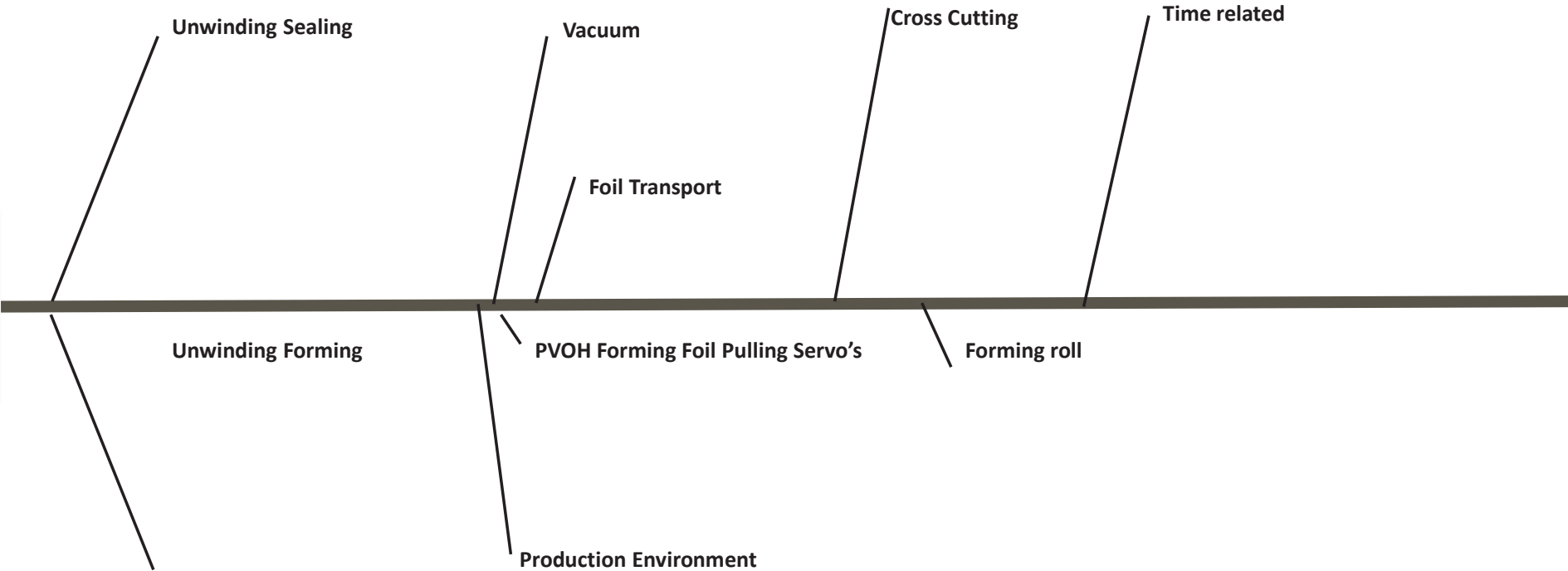


MEASURE PVOH FOIL SEALING BEHAVIOR

DETERMINE OPTIMAL SETTINGS == DETERMINE IMPACT



Minimum rejects



MEASURE PVOH FOIL SEALING BEHAVIOR

BRAINS PROJECT WORK IN PROGRESS

“Tembo’s use case richt zich op de uitdaging van variërende afdichtingssterkte die leidt tot lekkende pods, waardoor het systeem moet worden stilgelegd en gereinigd. Hun benadering richt zich op twee hoofddoelen: het optimaliseren van parametercontrole om lekken te minimaliseren door het bepalen en meten van beïnvloedende parameters, en het verkleinen van de machinevoetafdruk door het optimaliseren van relevante ontwerpvariabelen en procesparameters.”

<https://www.tembo.eu/news-plus-stories/het-brains-project>

BRAINS wordt mede mogelijk gemaakt door een bijdrage van het European Fund for Regional Development of the European Union met steun van Universiteit Twente



MEASURE PVOH FOIL SEALING BEHAVIOR

RANDOM FIELD

With the Random Field model, we try to find the optimal settings to find the optimal process parameters for a successful seal.

- Choose sensors on demonstrator
- Acquire data
- Change parameters
- Find relations between parameters
- Train model

More information: <https://linkmagazine.nl/de-kunst-van-werken-met-ai-in-de-industrie/?v=1a13105b7e4e>



OTHER A.I. IN PRODUCTION ACTIVITIES FROM PARTNERS OF PERRON038

OR VISIT OUR 'KENNISEVENT — TOEPASSING VAN AI VOOR KWALITEITSCONTROLE ON 21 MARCH 2025' (1)

- AWL – Visual Weld quality inspection (2)
- Zuidberg – Quality inspection assembly process
- Windesheim – Sensor Fusion welding process (in combination with AWL)
- VMI – Anomaly inspection rubber (3)
- VMI – Regression rubber assembly

INFORMATIE



DATUM EN TIJD

21 maart om 10:00 - 17:00



LOCATIE

Perron038

Hanzelaan 95B

Zwolle, 8017 JE Nederland

(1)Source: <https://www.perron038.nl/evenement/kennisevenement-toepassing-van-ai-voor-kwaliteitscontrole/>

(2)Source: <https://linkmagazine.nl/de-kunst-van-werken-met-ai-in-de-industrie/?v=1a13105b7e4e>

(3)Source: <https://linkmagazine.nl/met-ai-model-zet-vmi-belangrijke-stap-richting-zelfsturende-machines/?v=1a13105b7e4e>



PRODUCE SMARTER

TAKEAWAY



- **Using Data to Drive Process Improvements:**
 - Quality Inspection
 - Process Optimization
 - Predictive Maintenance
 - Data Analytics and Visualization

- **Achieving Impact on *OEE with ML and AI Optimization:**
 - Enhance Product Quality
 - Stabilize Production Processes
 - Minimize Downtime
 - Perform Root Cause Analysis

*OEE = Overall Equipment Effectiveness

WHAT YOU NEED FOR AI - TAKEAWAY

If you want to automate a process, or answer a complex question using a machine (and this can be any form of AI but also does not need to be), you need to

1. Design the format or shape of an algorithm that is capable of translating that input into a good output

Understanding of your
problem

Experience in designing
algorithms & automation

2. Find the parameters inside that algorithm that will correctly fit the algorithm onto your problem.

Understand how machines
learn

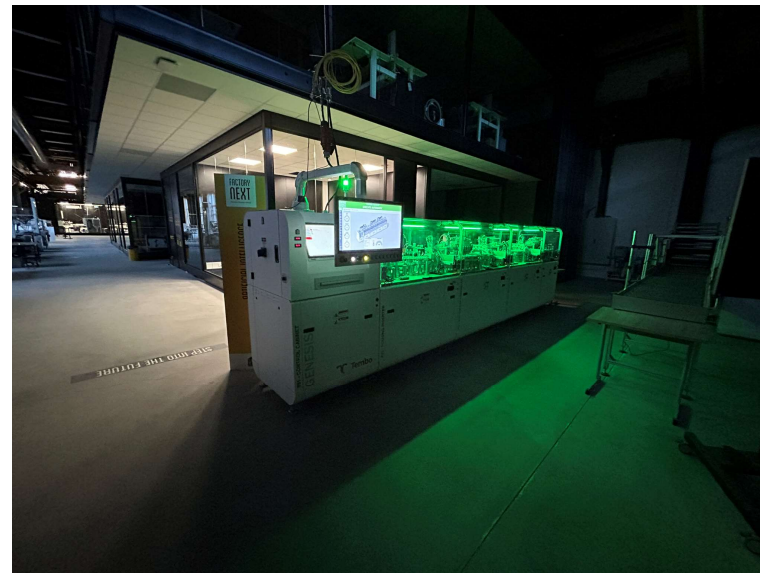
Have good quality data

Have a good digital
infrastructure

MACHINES THAT MAKES USE OF A.I. . . . TAKEAWAY

- Achieve a higher production stability – They see anomalies and can act on it
- Predict maintenance - achieve higher uptime, less costs maintenance
- Quality control - Higher quality, less rejects/waste

. CAN RUN DAY AND NIGHT



THANK YOU

FACTORY
NEXT

Discover | Develop | Deliver

CONTACT US FOR MORE

PERRON038 — MAAK DE TOEKOMST

TEMBO — CREATING THE NEXT TOGETHER



FACTORY
NEXT

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