Symposium
Machine Vision for Quality Control

WiFi

Website

TETRA Machine Vision for Quality Control (MV4QC)

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KU Leuven Bruges – M-Group

- 8 professors
- 1 research manager
- 1 project office manager
- 6 post-docs
- > 40 junior researchers
- 2 ATP test engineers

Mechanical Engineering

Electrical Engineering

Computer Science

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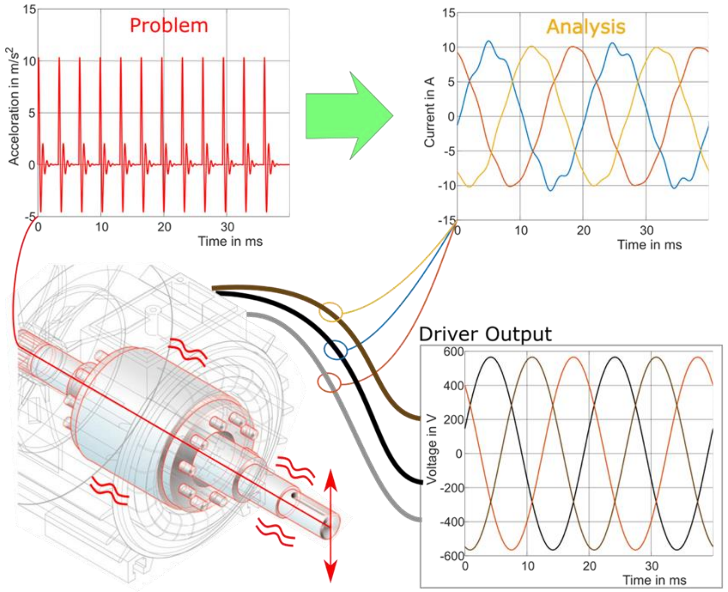
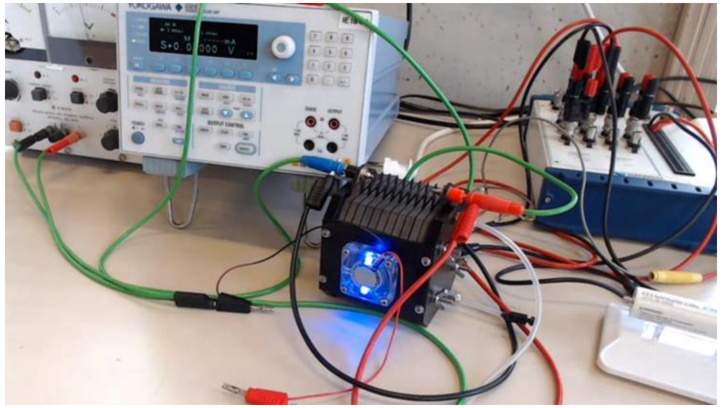
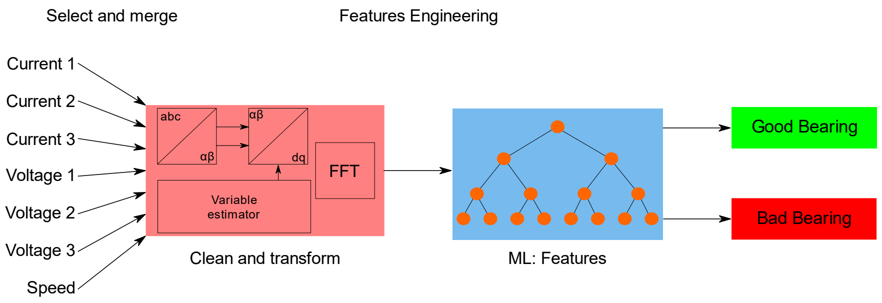
The Ultimate Machine

- EMC test chambers
- Climate chambers
- Fuel cells
- Smart conditioning monitoring
- Edge computing







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The Ultimate Factory

- Data-driven process optimisation
- Autonomous systems
- Quality control

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AI for complex mechatronic systems and processes

OPTIMISATION

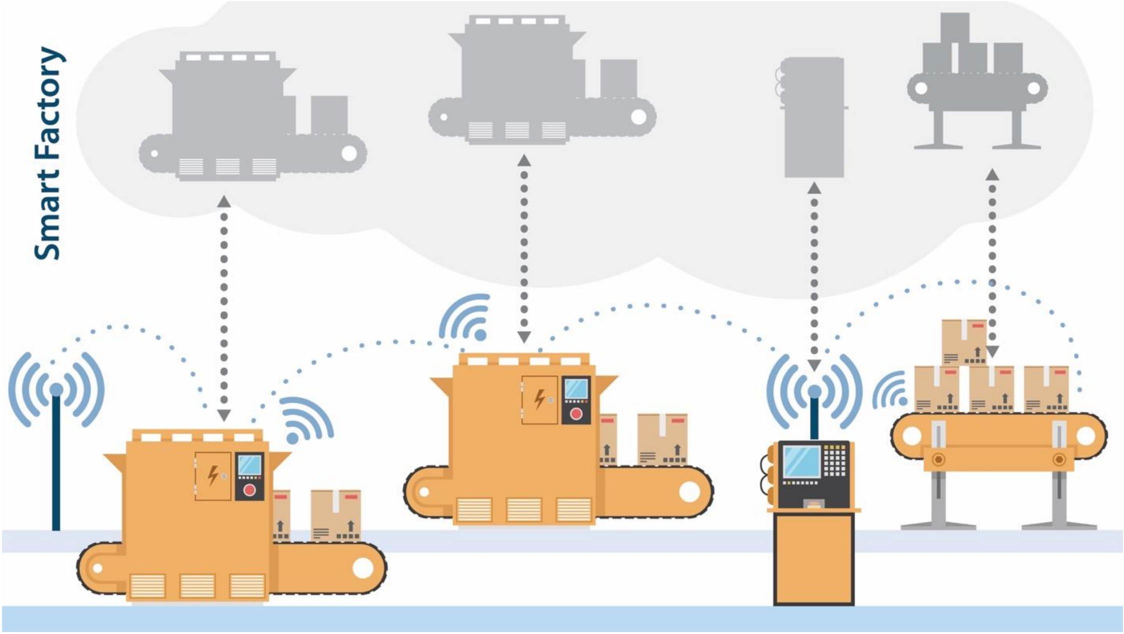
How can unwanted effects be mitigated?

- Link between process parameters & conditions and product quality

MONITORING

What is going wrong and what is the underlying reason?

- Abnormal machine behavior
- Product quality defects



CONTROL

How can the parameter tuning be automated?

- Realise a stable system behavior

TRANSVERSAL ASPECTS: SAFETY, ROBUSTNESS, EFFICIENCY

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Hogeschool VIVES

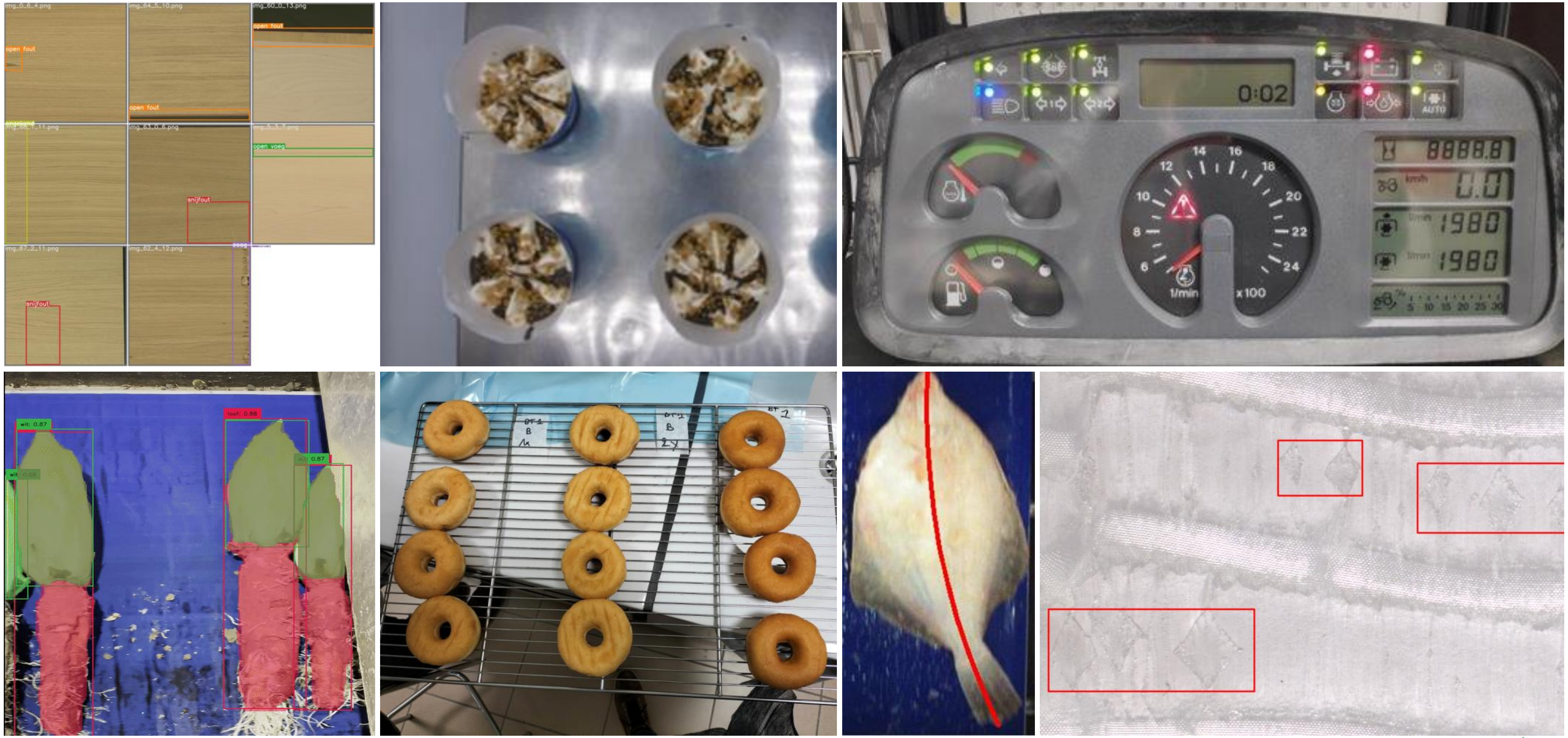
Research group Smart Automation

- Adaptation to Industry 4.0
- Implementation of classical machine vision algorithms and hardware
- Connection with education: Professional Bachelor EM – Automatisation

Manufacturing lab Kortrijk

- Product design and building
- Prototyping
- Extensive machine park
- Building of demonstrators

TETRA “Machine Vision for Quality Control”



TETRA Project – Doelstellingen

Doelstelling

Het faciliteren van de implementatie van machinevisie voor kwaliteitscontrole voor bedrijven door het verzamelen, structureren en beschikbaar stellen van de beschikbare kennis en innovatie op een pragmatische manier.

- **Doelstelling 1**: Het verkrijgen van een overzicht van de bestaande kennis, potentiële toepassingen en kennisbehoeften + definitie van vijf use cases.
- **Doelstelling 2**: Het verzamelen en structureren van de bestaande hardware- en softwaretechnieken voor machine vision voor kwaliteitscontrole.
- **Doelstelling 3**: Het verzamelen en structureren van de praktische kennis met betrekking tot de bestaande technieken.
- **Doelstelling 4**: Het ontwikkelen van gedefinieerde use cases.
- **Doelstelling 5**: Het ontwikkelen van twee demonstratoren voor de demonstratie van de projectresultaten.
- **Doelstelling 6**: Het evalueren van het economische potentieel van de gedefinieerde use cases.
- **Doelstelling 7**: Het verspreiden van de opgedane kennis naar de doelgroep in de vorm van seminars, workshops, onderwijs, enz.

TETRA Project – Outputs

Rapporten:

- ✓ Overzicht van beschikbare kennis en noden vanuit de industrie
- ✓ Syllabus "Machine Vision - A starters guide on machine vision for quality control."
- ✓ Jupyter Notebooks
- ✓ Economische evaluatie

Demonstratoren:

- ✓ Demonstrator KU Leuven (OMRON, Cognex, CCS, IDS, Intel)
- ✓ Demonstrator VIVES (Beckhoff Automation)

Evenementen:

- ✓ Seminarie "Do's and don'ts in machine vision for quality inspection" (Februari 2023)
- ✓ Masterclass Machine Vision (PUC) (Oktober 2024)
- ✓ Workshop "Hands-On Machine Vision Workshop" (Februari 2024)
- ✓ Workshop "Beginner's guide on machine vision" (Mei 2024)
- ✓ Machine Vision Seminars (Captic – CCS – Pickit3D) (Mei 2024)
- ✓ **Symposium over Machinevisie voor kwaliteitscontrole** **(Vandaag)**
- ✓ Masterclass Machine Vision (PUC) (21 en 22 november 2024)

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Agenda

13:30 – Uiteenzetting van de projectresultaten:

- Defect detectie op houten platen (Decospan) door masterstudent **Karel Debedts (student KU Leuven)**
- Defect detectie op geëxtrudeerde kunststoffen platen (Mitsubishi Chemical Advanced Materials) door **Jonas Wittouck (Covicon)**
- Bepalen van de optimale snijlijn van witloof (Inagro) door **Jonathan Kesteloot (Captic)**
- Detectie van toppings op Cornetto's (Ysco) door **Jonathan Kesteloot (Captic)**
- Bepalen van de lengtedistributie van vissen per soort (ILVO) door **Sam Vanhoorne (ILVO)** en **Glenn Aesaert (Vintecc)**
- Detectie van de goede werking van een LED-display voor vorkheftrucks (TVH) door **Julia Otero Jiménez (Beckhoff Automation)**
- Bepalen van het vetgehalte in donuts (Vandemoortele) door **Arne De Temmerman (doctoraatsonderzoeker KU Leuven)**

15:30 – Pauze / postersessies / demo's / labo rondleidingen

17:00 – Keynote door **Lien Smeesters (B-Phot)**

18:00 – Netwerking & dinner

VLAIO TETRA
Machine Vision for Quality Control
(MV4QC)

Defect detectie op houten platen

Decospan

- Karel Debedts (KU Leuven) -

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Inhoudstafel

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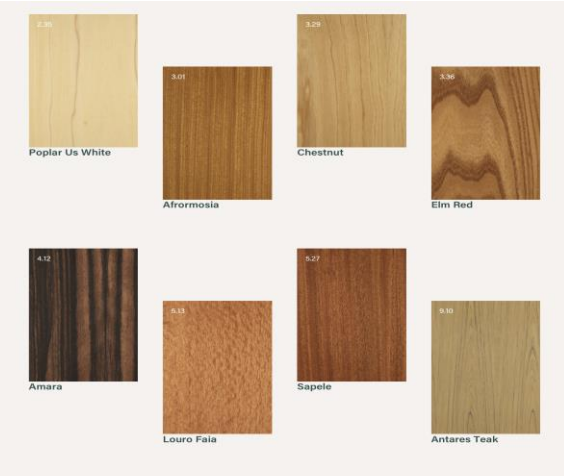
Context

Decospan

- Een Europese marktleider in de verwerking van fineerhout
- Hoofdkantoor te Menen
- 3e generatie familiebedrijf
- 900 werknemers
- 100+ houtsoorten
- Omzet > 200 miljoen



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Context

Fineer

Muren en meubilair

Vloeren

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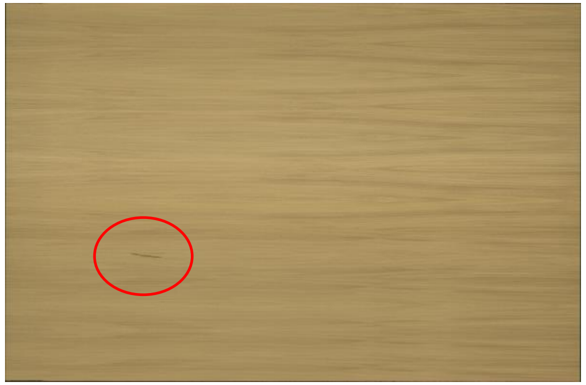
Probleemstelling

Kwaliteitsinspectie

Huidige situatie:

- Op het einde van productielijn voert operator manuele inspectie uit
    - Lijn verplaatst platen met een hoge snelheid
    - Oppervlaktefouten zijn relatief klein



Gevolg:

- Jaarlijks 4627 defecte platen
- Waarvan 1352 bij klant terecht komen
- Jaarlijkse logistieke kost van €60 000
- Schade aan reputatie & klanttevredenheid

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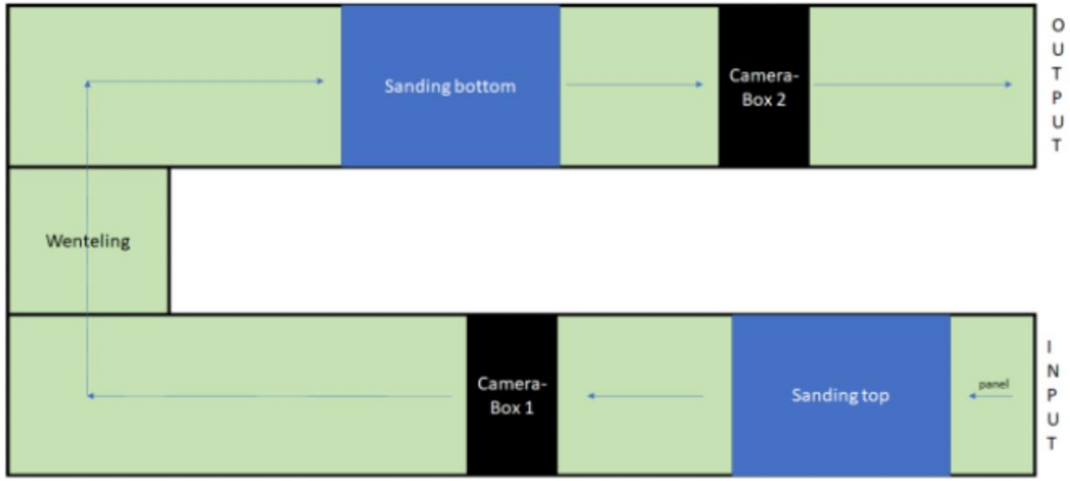
Doelstelling

"Het ontwikkelen en valideren van een visueel detectie systeem om defecten in fineerplaten te detecteren en te classificeren"



Vereisen Decospan:

- Accuracy > 90%
- Snelheid < 3s

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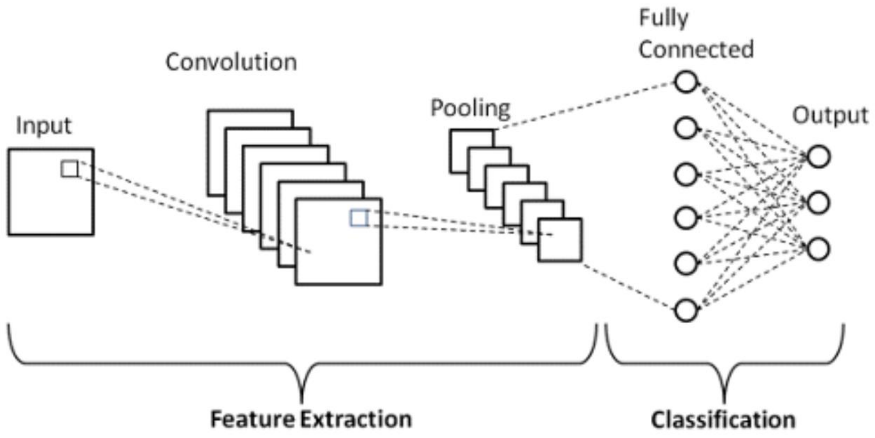
Literatuurstudie

- Deep learning

  - Lagere kost
  - Hogere accuracy
  - Veilig
  - Flexibel

=> Hardware vs Software



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Dataset

371 afbeeldingen

Manueel geannoteerd met LabelMe

- Beperkt aantal afbeeldingen
- Hoge resolutie afbeeldingen
- Onevenwichtige dataset

$\neq$ Vereisten CNN

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Dataset: beperkt aantal afbeeldingen

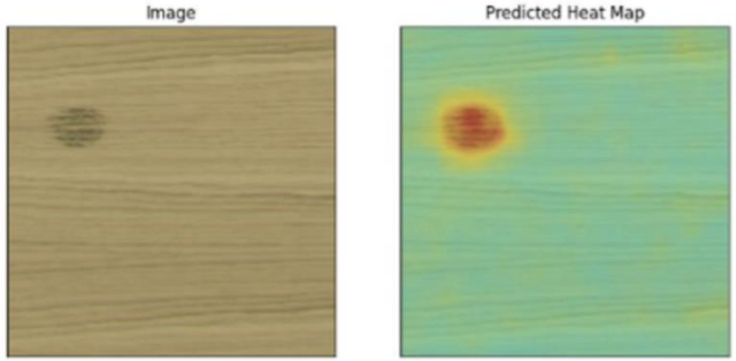
Het maken van een dataset is **niet** low effort:

1) Foutieve platen komen beperkt voor (0.5%) + zijn moeilijk te detecteren
2) Labelen is tijdintensief en vergt expert knowledge

→ Nood aan low effort methode voor efficiënte generatie dataset

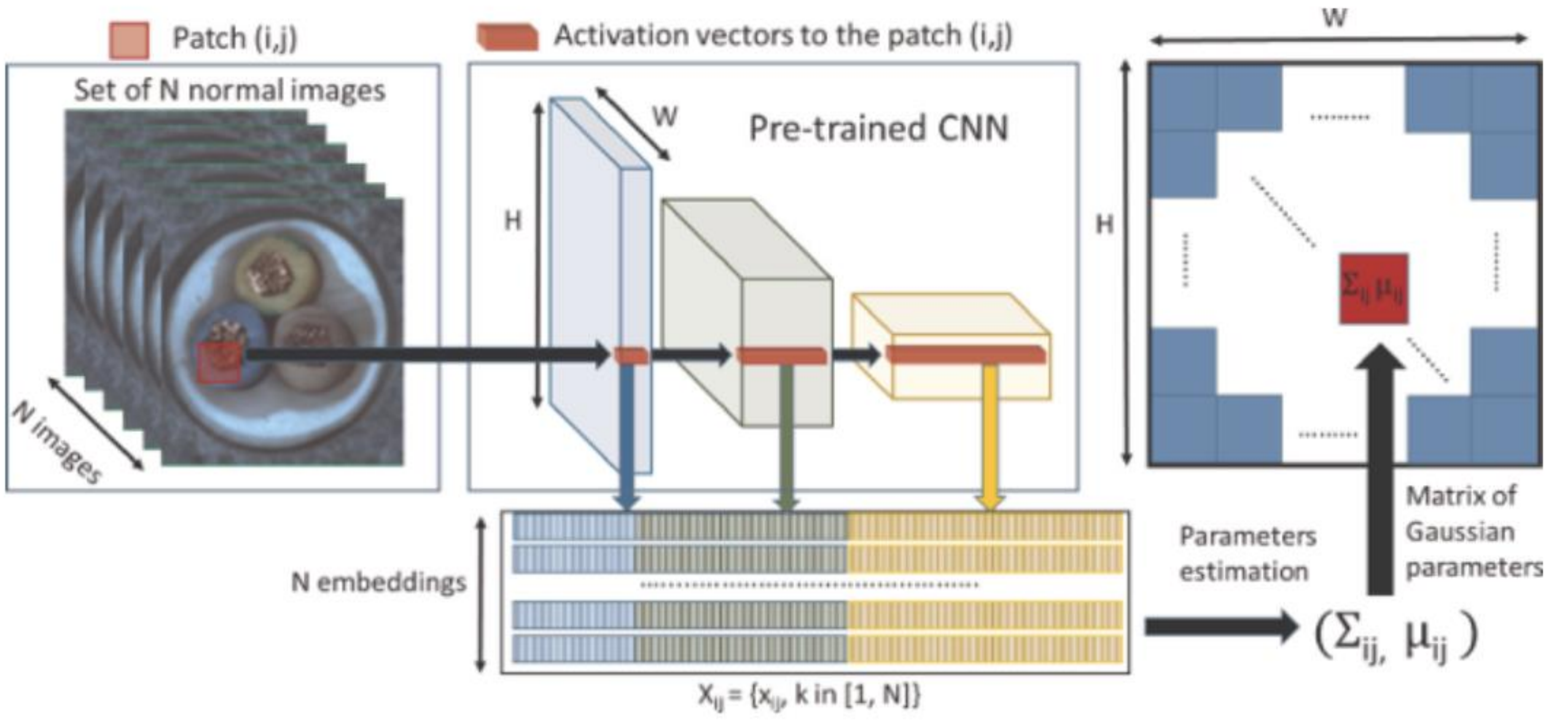
Unsupervised Anomaly Detection:

Een model, enkel getraind op foutloze platen, duidt foutieve regio's aan op nieuwe, ongeziene platen.



Unsupervised Anomaly Detection: PaDiM

- De “one-size-fits-all” oplossing?



Dataset

- Beperkt aantal afbeeldingen
- **Hoge resolutie afbeeldingen**
- Onevenwichtige dataset

≠ Vereisten CNN

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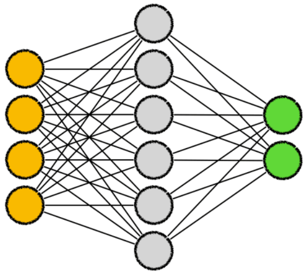
Dataset: hoge resolutie afbeeldingen

Plaat

15879 x 7949

SAHI

ResNet



224 x 224

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Dataset: hoge resolutie afbeeldingen

Slicing aided hyperinference (SAHI)

- Overlapping sliding windows
- Enable small object detection

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Dataset

- Beperkt aantal afbeeldingen
- Hoge resolutie afbeeldingen
- **Onevenwichtige dataset**

$\neq$ Vereisten CNN

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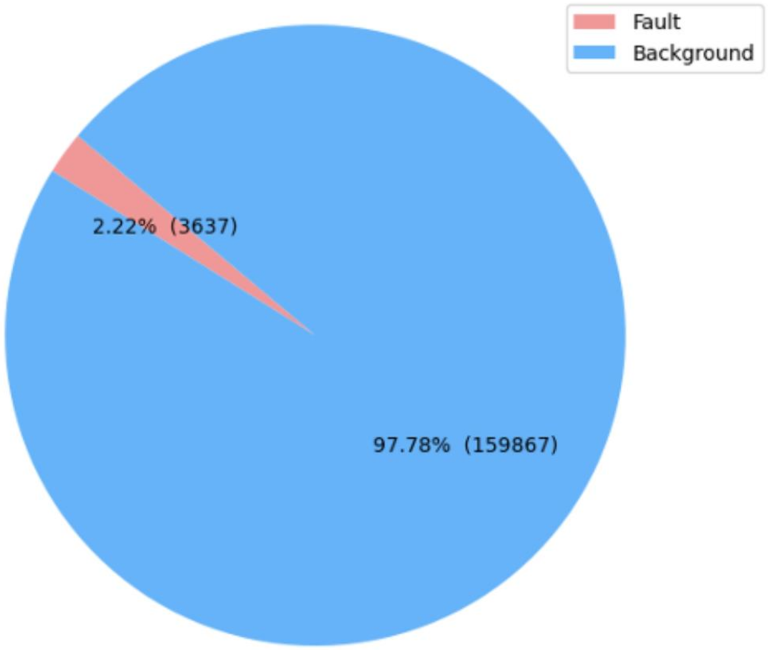
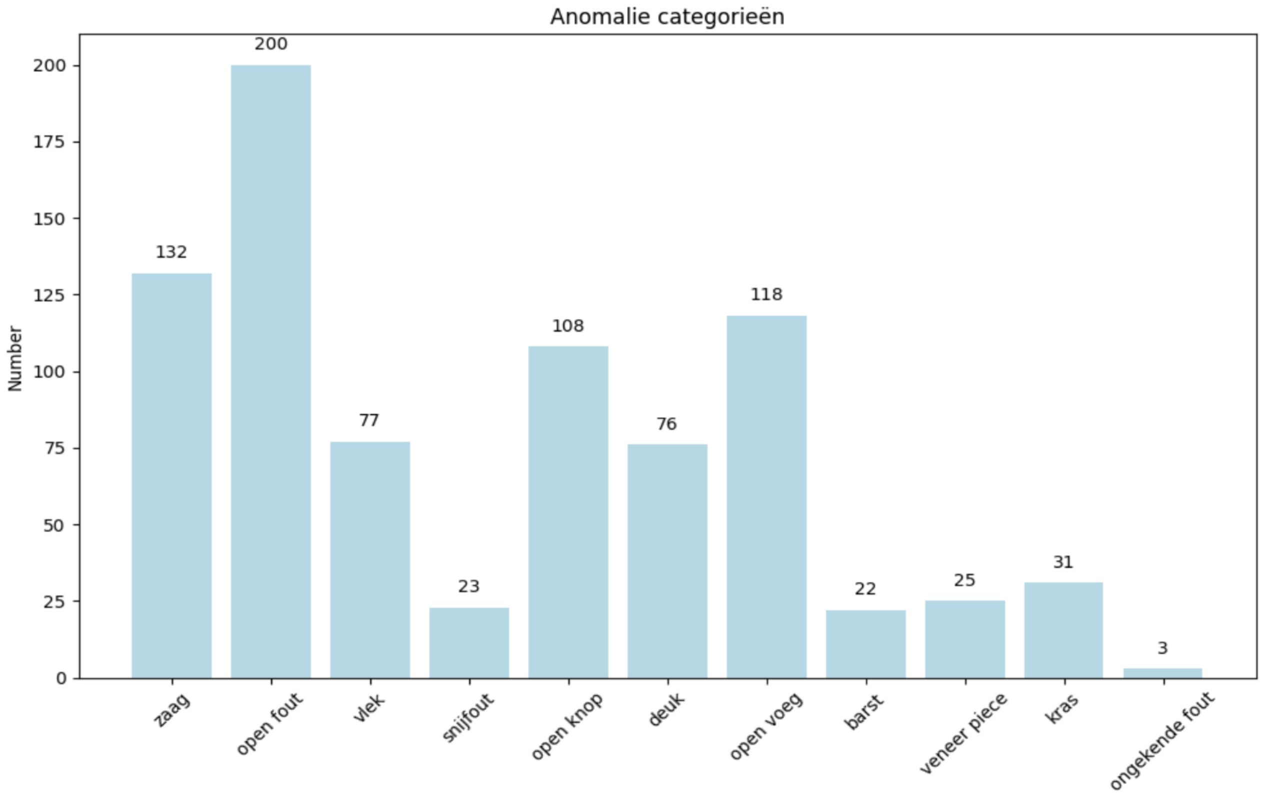
Dataset: onevenwichtig

Background vs faulty windows



Type fout



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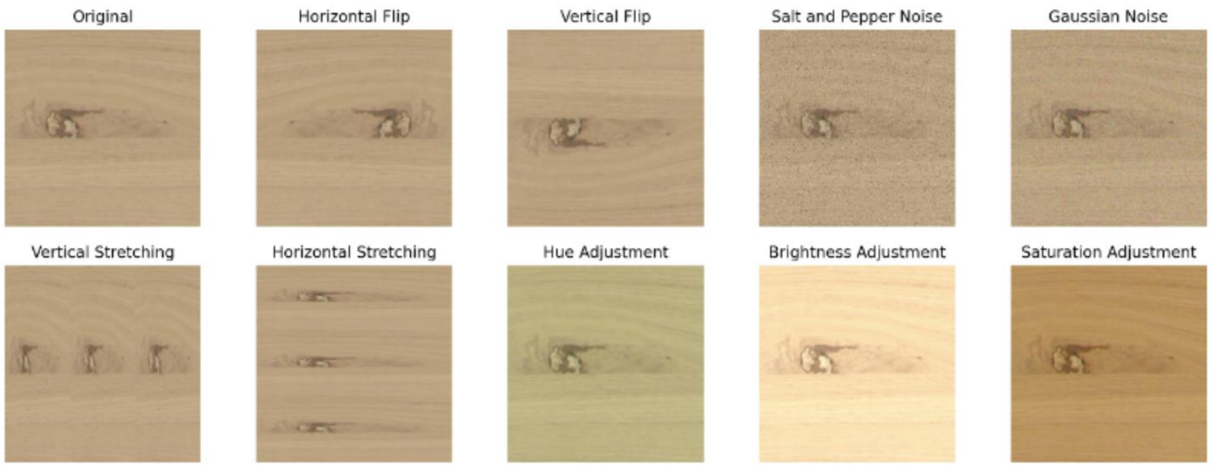
Dataset: onevenwichtig

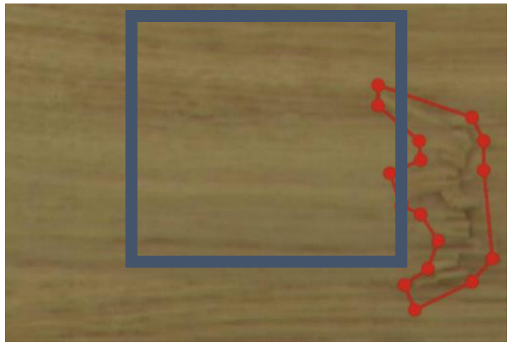
Augmentaties



Undersampling

Training

Vergelijking performantie state-of-the-art modellen

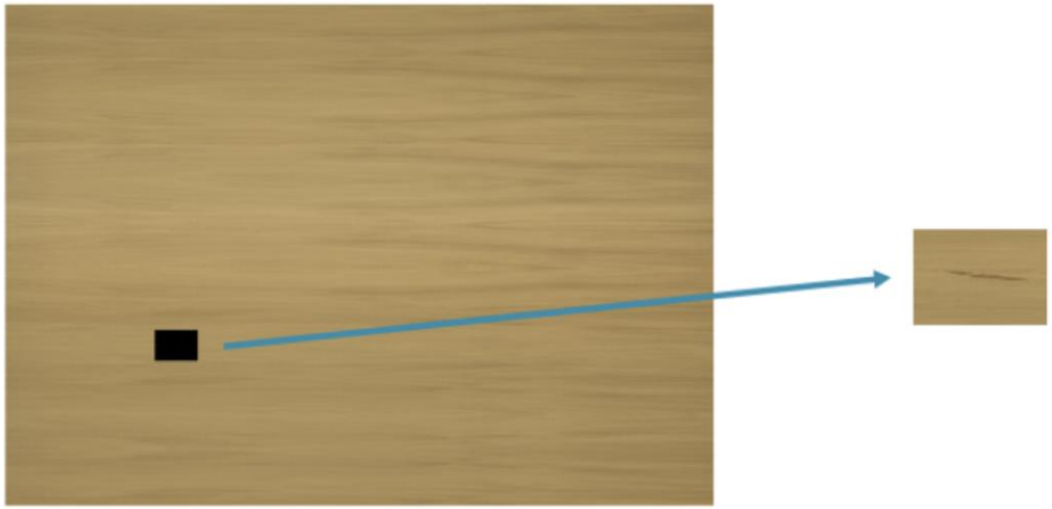


Soorten modellen:

- Binaire classificatie
  - ResNet, Yolo, AlexNet, GoogLeNet, VGG, PaDiM, …
- Multi-class classificatie
  - ResNet, Yolo, Mask-RCNN, Paligemma, …

Methodologieën:

- Model per houtsoort
- Training op enkel fouten
- Cut-out methode
- Training op 5 foutcategorieën



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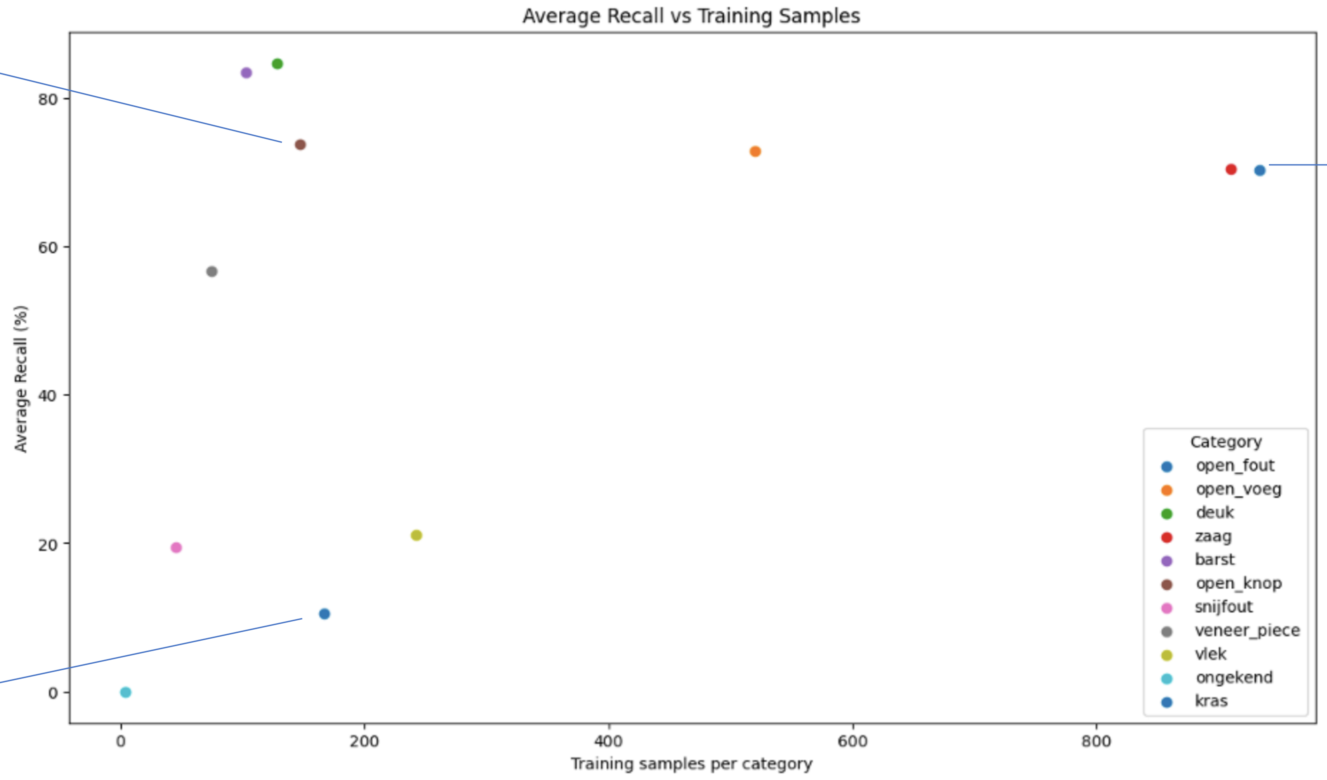
Training: inzichten

Meer samples = hogere recall

Open knop



Open fout

Kras

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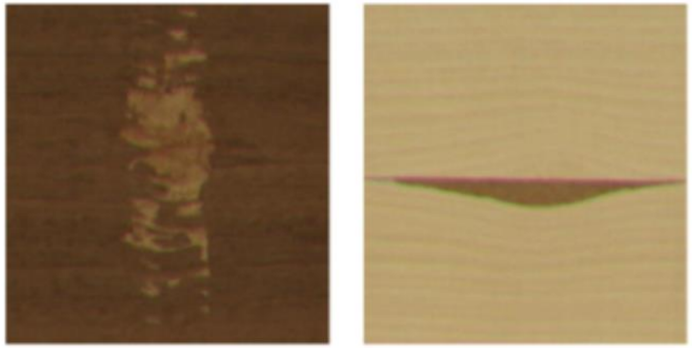
Training: inzichten

Effect van trainen per houtsoort sterk afhankelijk van visibiliteit fouten tov houtsoort.



Open fout

Fineer stuk

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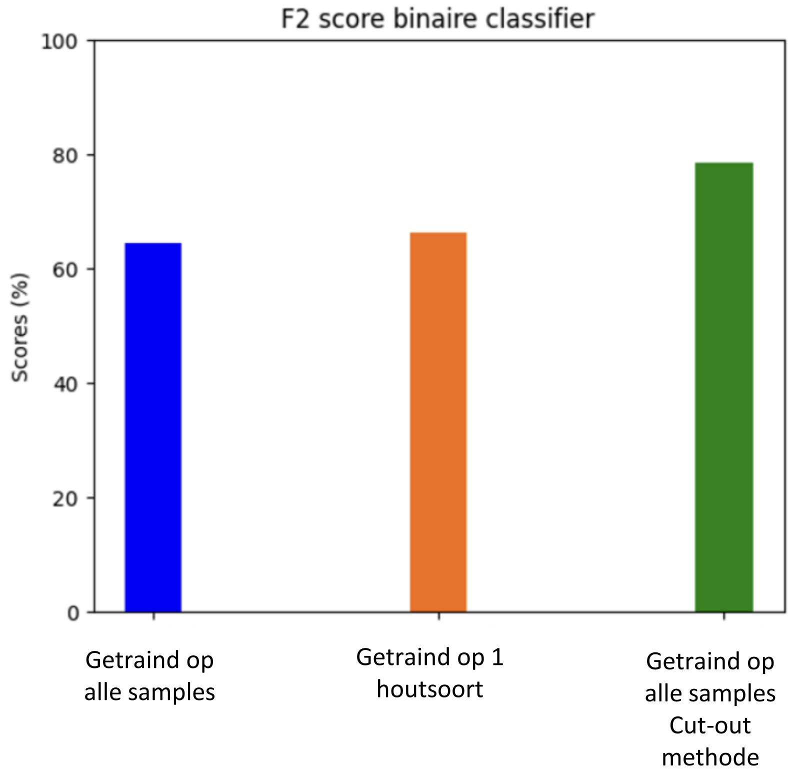
Training: inzichten

Cut-out methode verbetert performantie aanzienlijk.

Terwijl de beperkt verbeterde performantie van een model per houtsoort praktisch onhaalbaar is.



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Training: inzichten

Trainen op 5 foutcategorieën biedt geen performantie voordeel.

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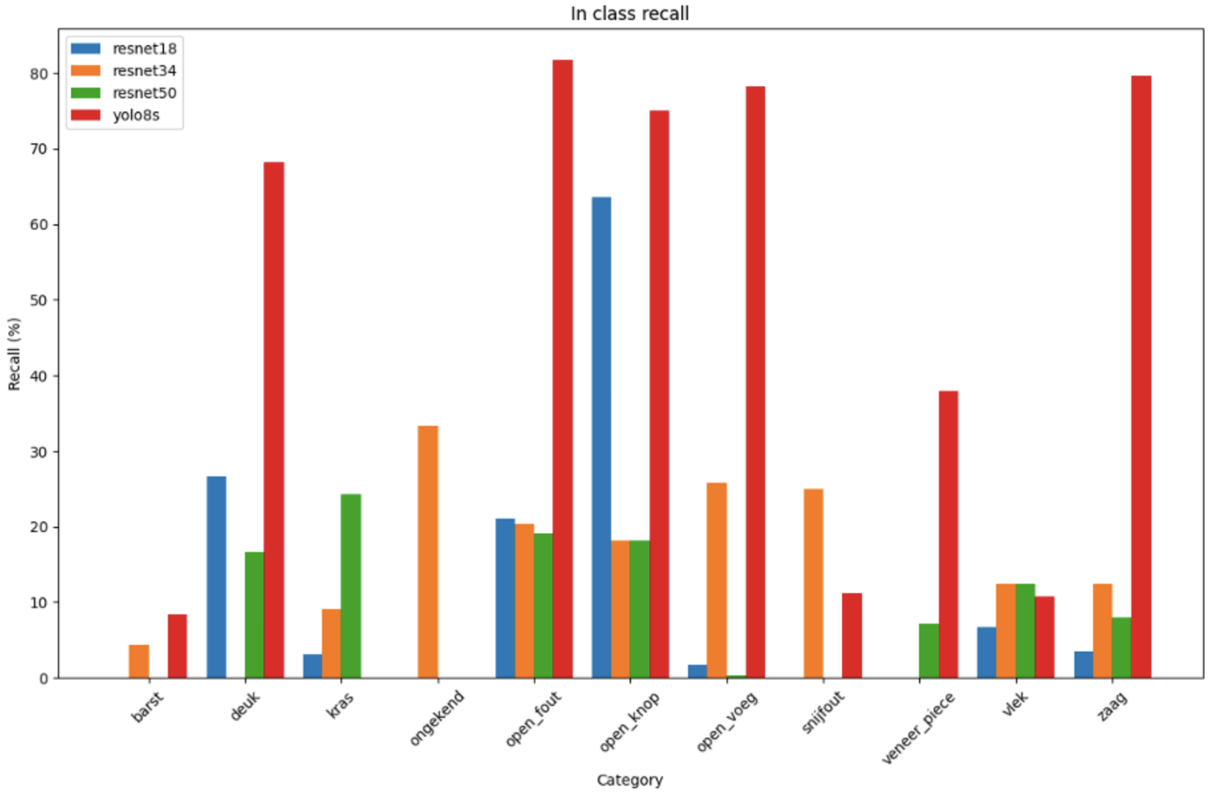
Training: inzichten

Omdat Yolo segmentatie gebruikt, is het beter in staat fouten te classificeren.



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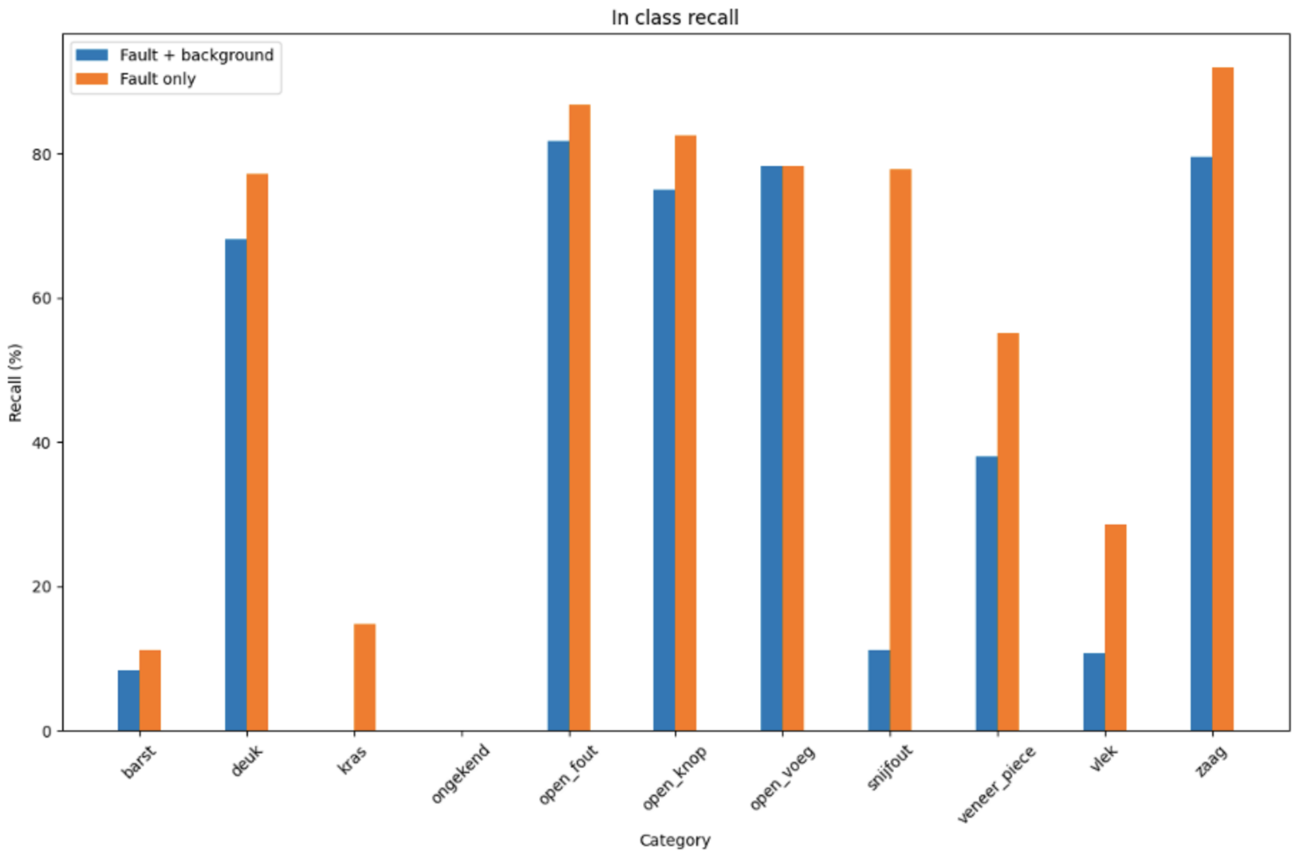
Training: inzichten

Yolo trainen op enkel fouten verhoogt de performantie.



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Resultaten

Binaire classificatie

- Getraind op alle houtsoorten
- Cut-out methode
- ResNet 18 backbone

Accuracy	98,9%
Recall	75,9%
Precision	90,8%

Multi-class classificatie

- Getraind op enkel fouten
- Yolov8s

Accuracy	72,7%

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Inhoudstafel

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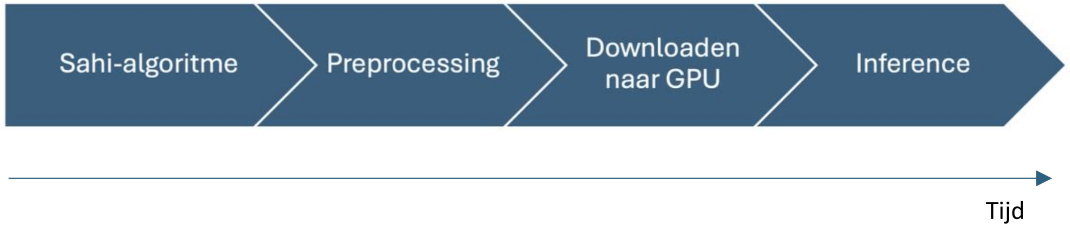
Inferentie



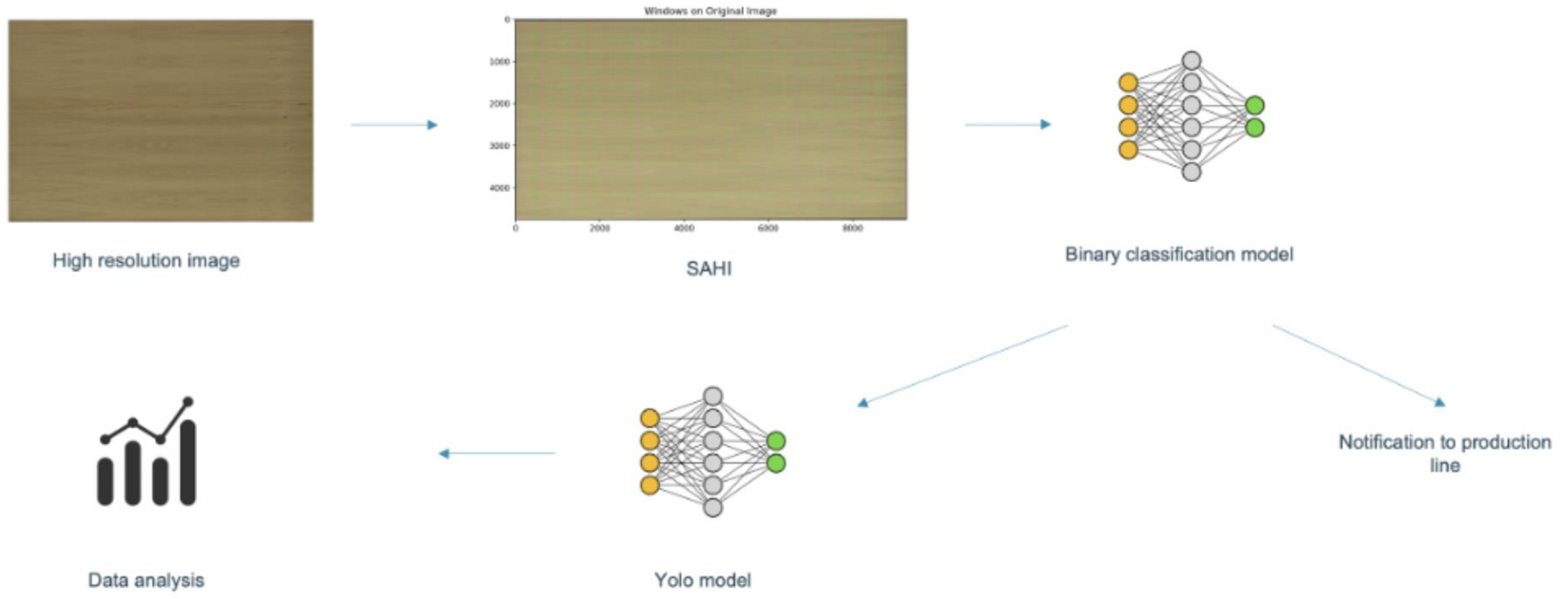
Type	Totale inferentietijd voor 924 windows [s]	
	Alienware	Jetson
Binaire classificatie	1.245	1.204
Multi-class classificatie	9.027	32.003

Proposed solution

- 2 stage approach

  →Yolo model krijgt enkel foutieve windows

  - Hogere performantie
  - Multi-class classificatie terug mogelijk binnen de realtime constraint



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Financiële analyse

0.5% van totale productie is uitval, waarvan de operator 71% zelf detecteert.

Tabel 4.26 Vergelijking van kosten tussen manuele inspectie en AI-systeem.

Systeem	**Platen bij klant**	**Kost door klant**
Manuele inspectie	1352	€ 59 457
AI-systeem	463	€ 20 348
Verschil	889	€ 39 109

Key points:

- Investeringkost: €64 255
- Terugverdientijd: < 2 jaar
- Netto rendement: 32,8% / jaar

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Future work

- Meer samples verzamelen & hertrainen modellen
- Het implementeren in de productielijn en het programmeren van een visuele weergave voor de operator.
- Het opslaan van resultaten in een algemene databank voor verdere data-analyse
- Verder onderzoek naar unsupervised anomaly detection
- Onderzoek naar LLM & Transformer networks

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VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Defect detectie op geëxtrudeerde kunststoffen platen

Mitsubishi Chemical Advanced Materials

- Jonas Wittouck (Covicon) -

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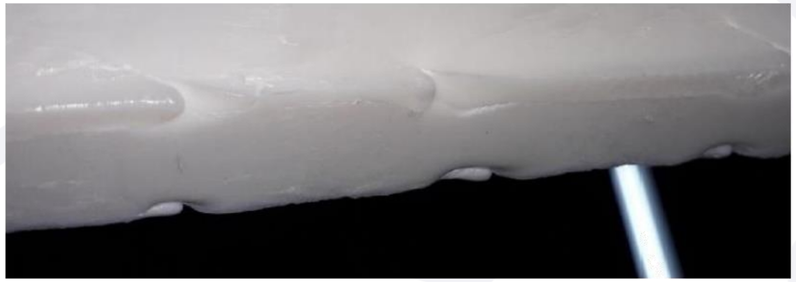
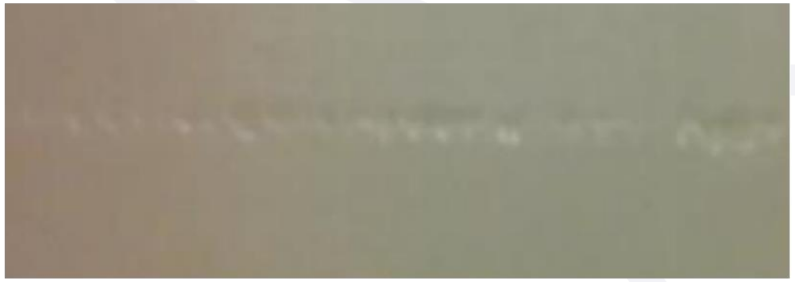
Introduction

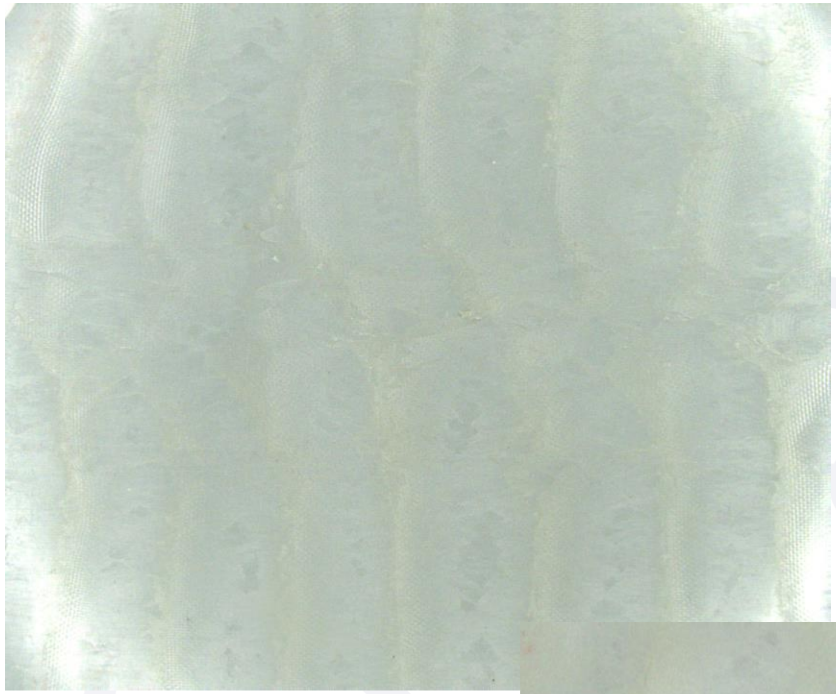
- Several defects occur when extruding polymer sheets
  - Stick defects
  - Damage on the sides
  - Color deviations
  - Pits
  - …
- Goal
  - Automated quality control

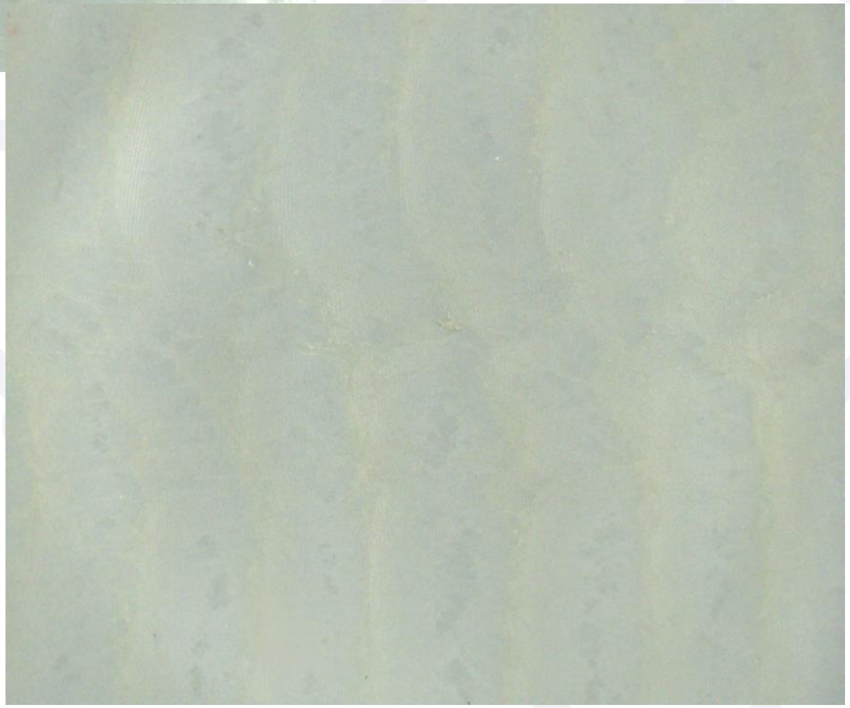




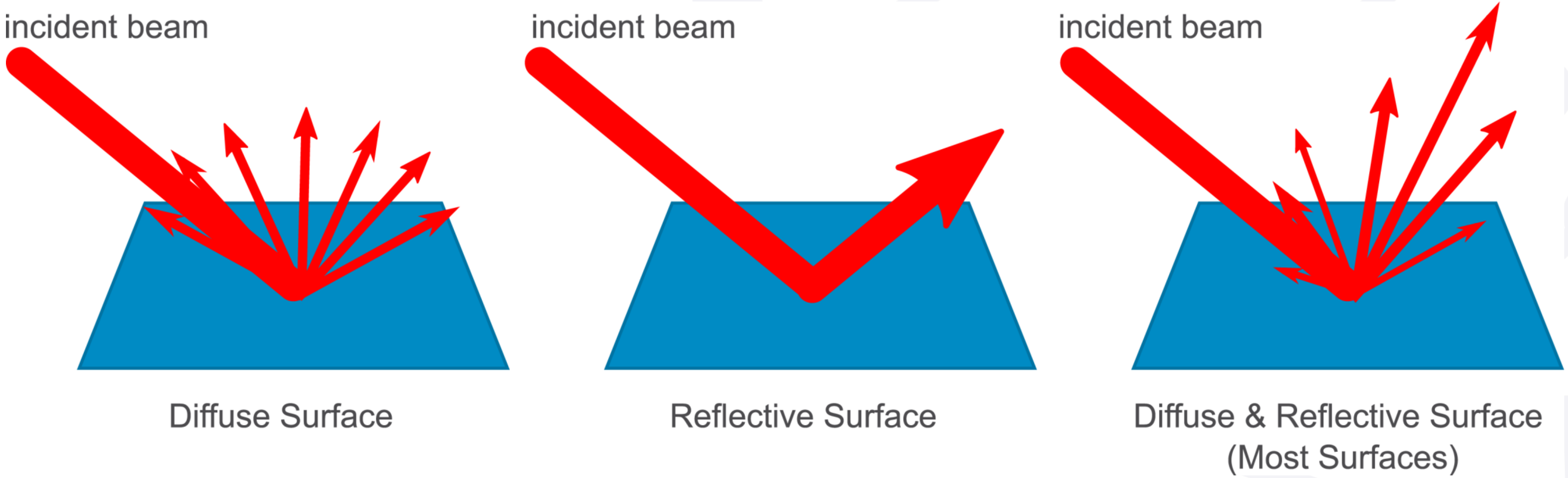
Difficulties

- Reflective material
- Different kinds of material
  - POM
  - PET
  - …
- Small details
- Strong variation in texture



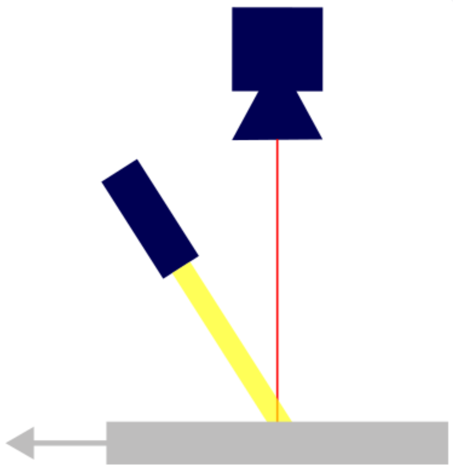


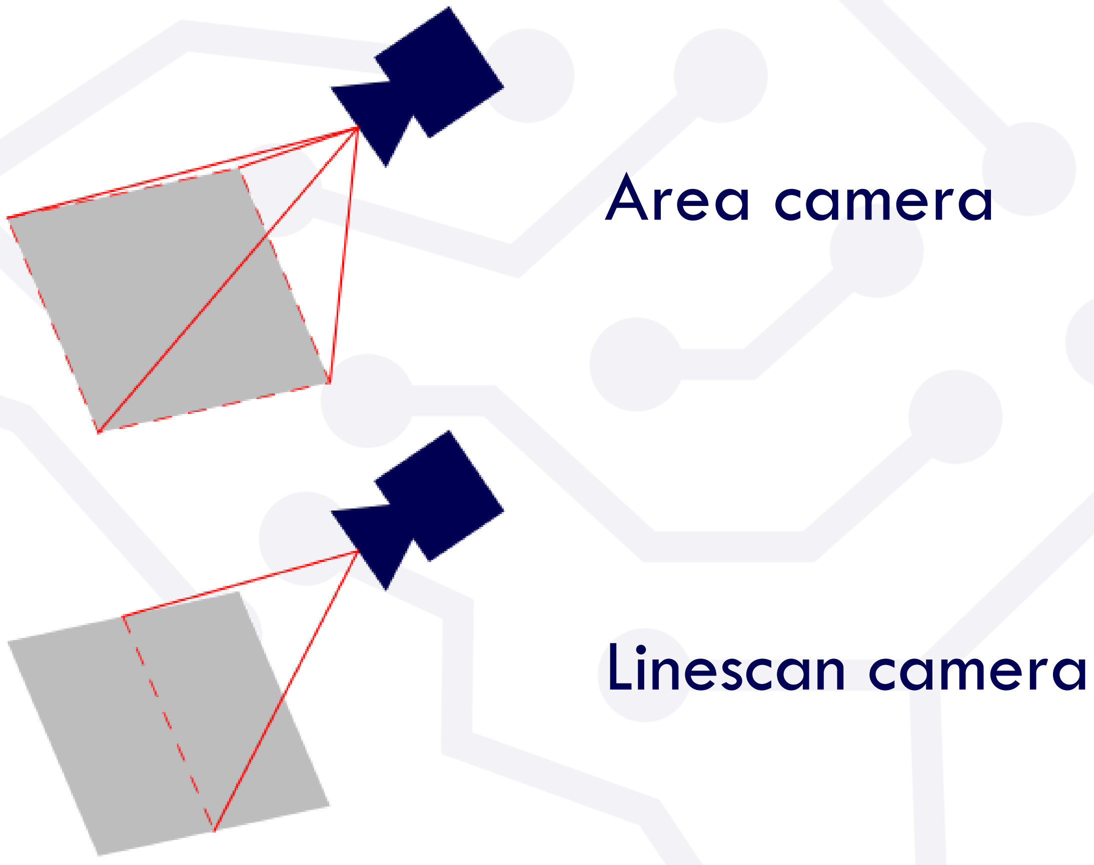
What is reflection?



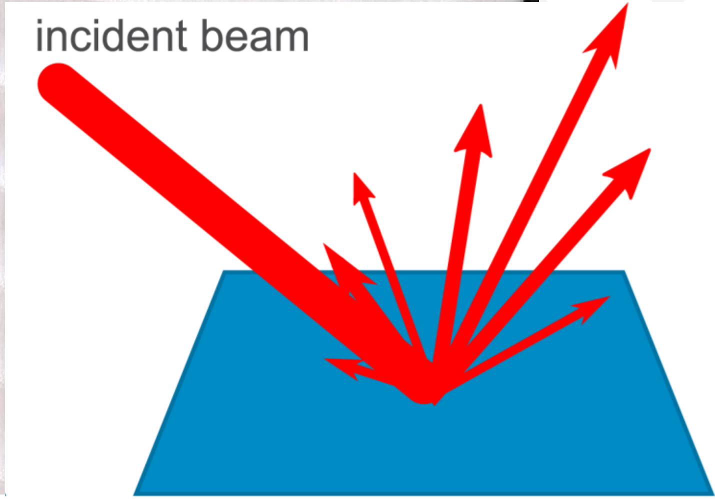
Initial tests – what can we see?

- In house demo setup
  - Linescan RGB camera
    - 0,2mm/px
  - Barlight
- No reflection problems

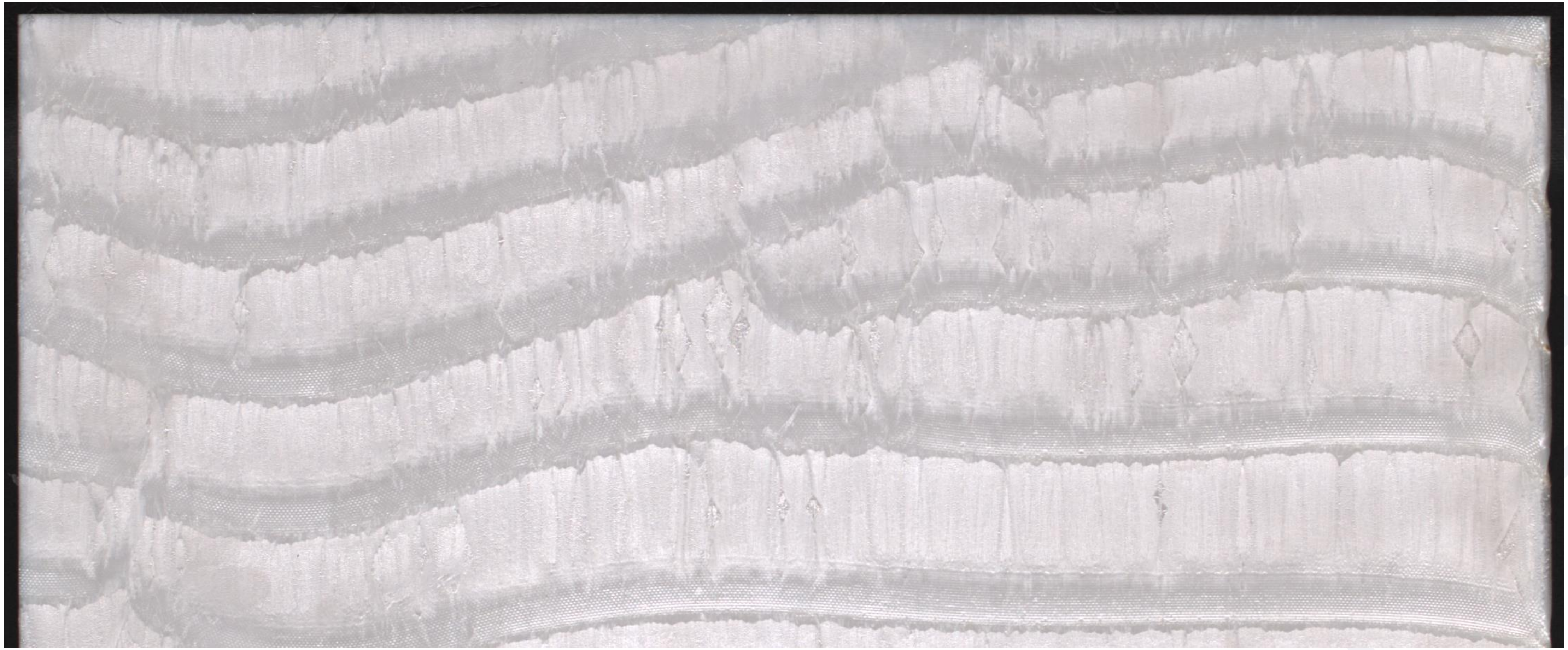




Initial tests – what can we see? (2)

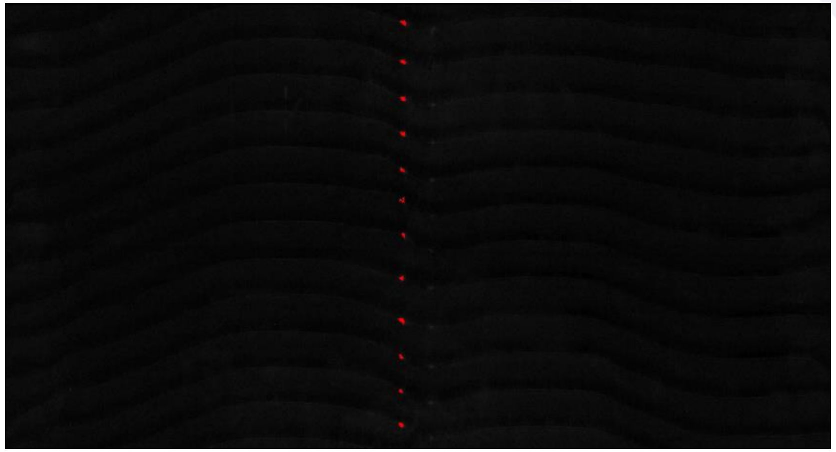


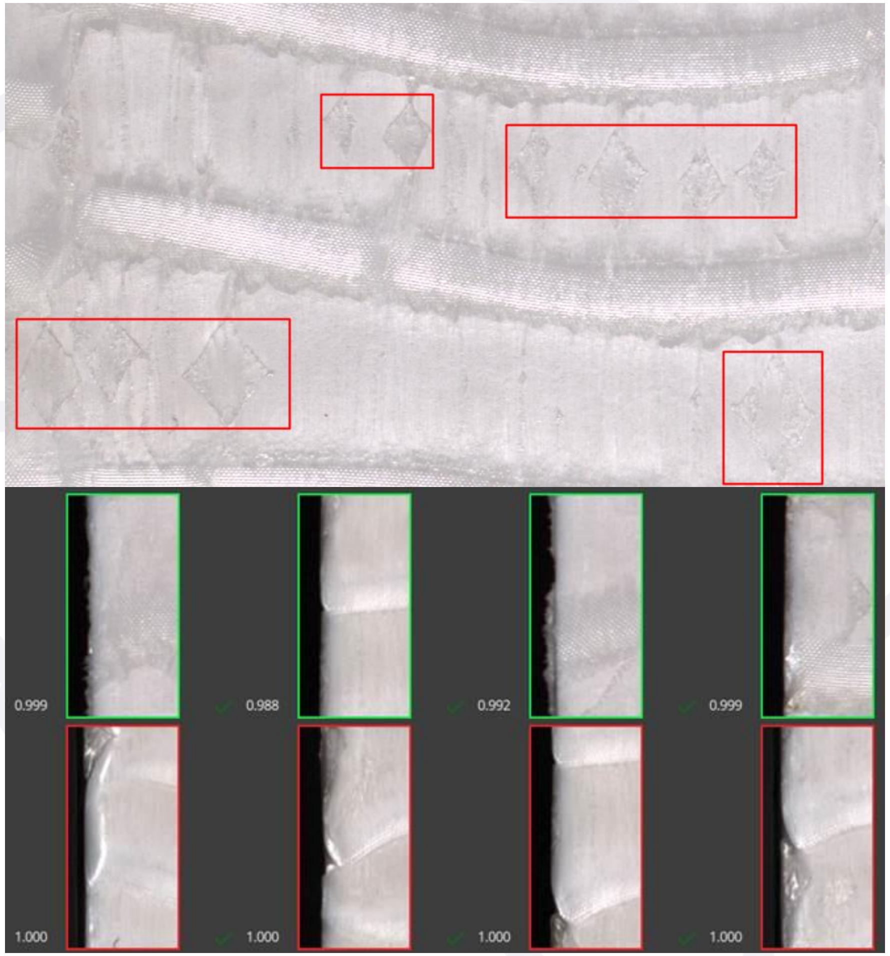
Diffuse & Reflective Surface
(Most Surfaces)



Software solutions

- Sticky marks: visible
- Damaged border detection with classification (ResNet18)
- Other contamination detection with traditional techniques



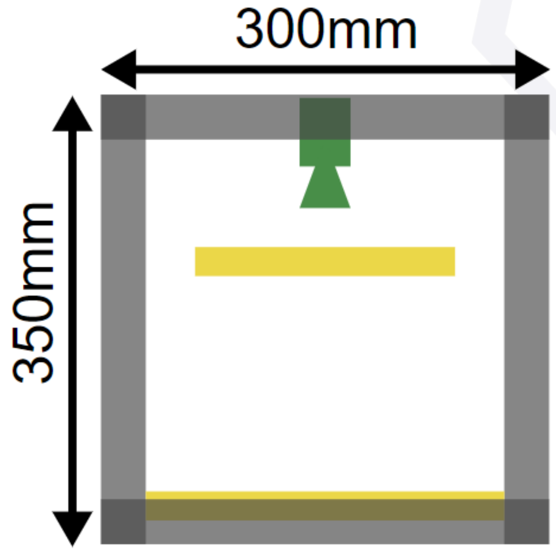


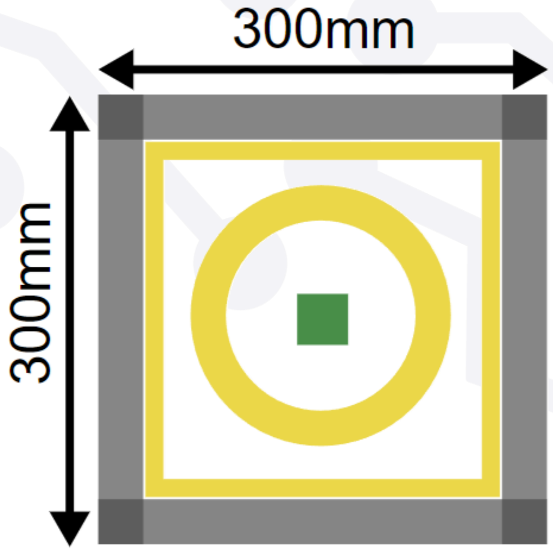
Can we look through?

- PET-plate - 20mm thick – strong white led light
- Only red comes through -> Would IR be a solution?
  - Pits and crasks: yes
  - Color changes: no
  - Only for white PET plates
- IR sensor are less light sensitive

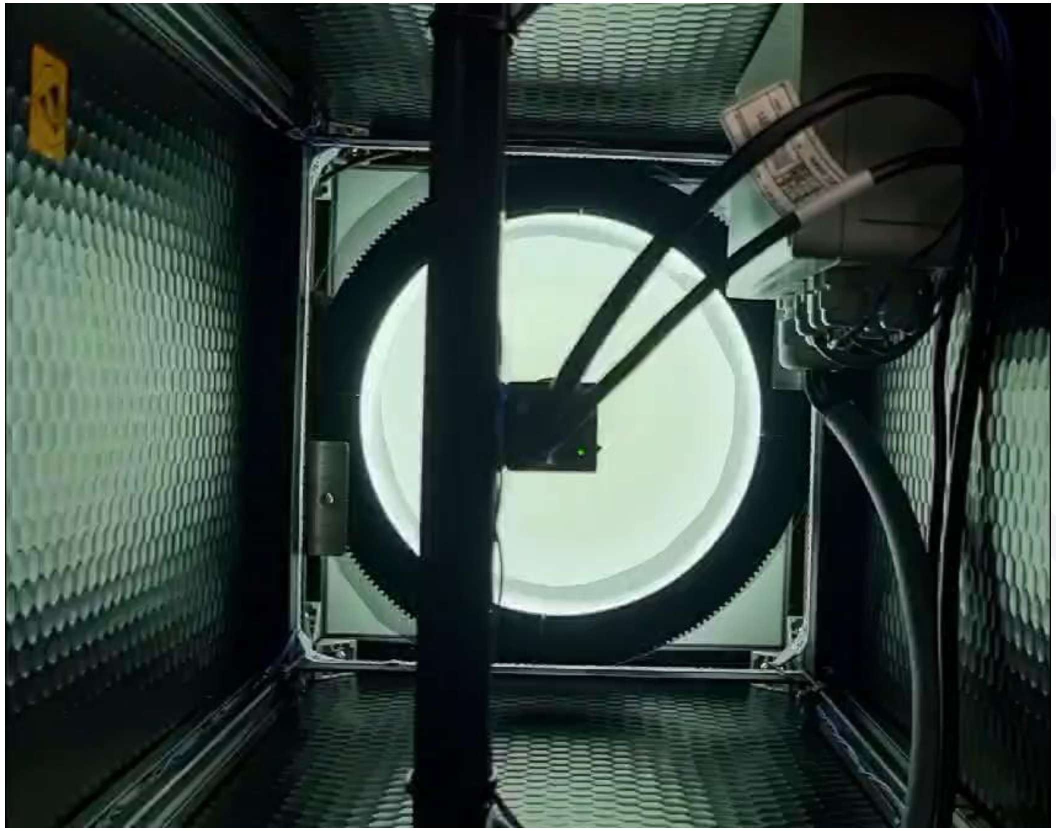
Mobile setup for data acquisition

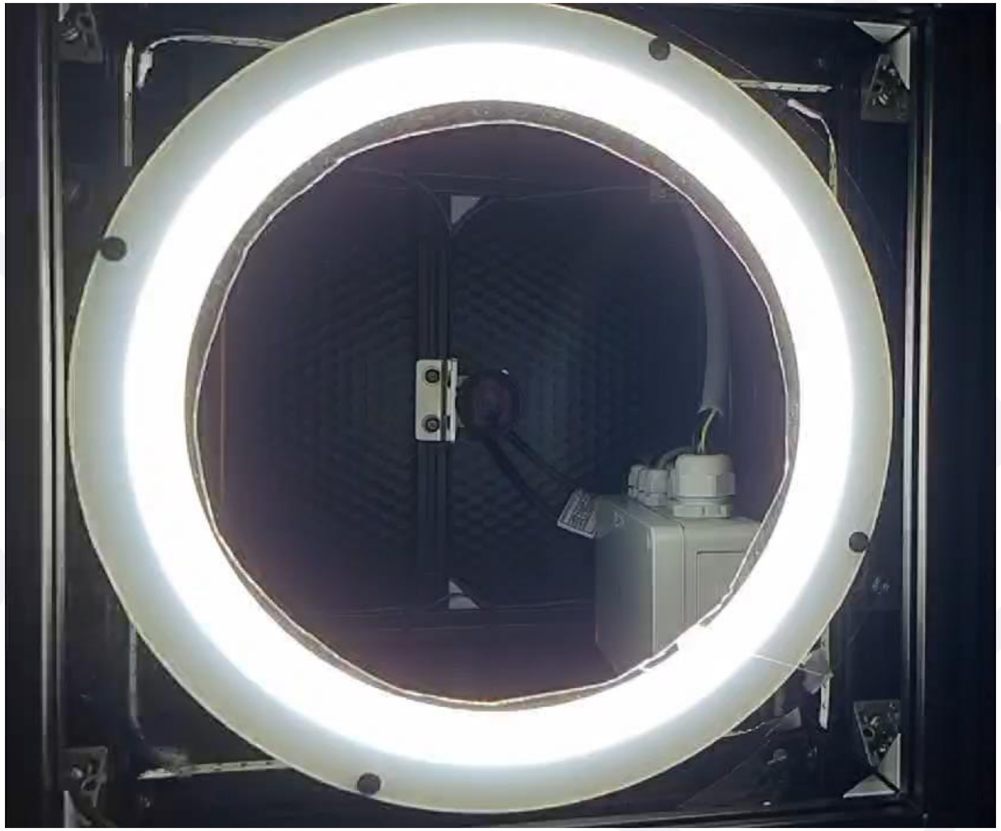
- Acquire data on multiple installations
- 4 darkfield light sources
- polarizer



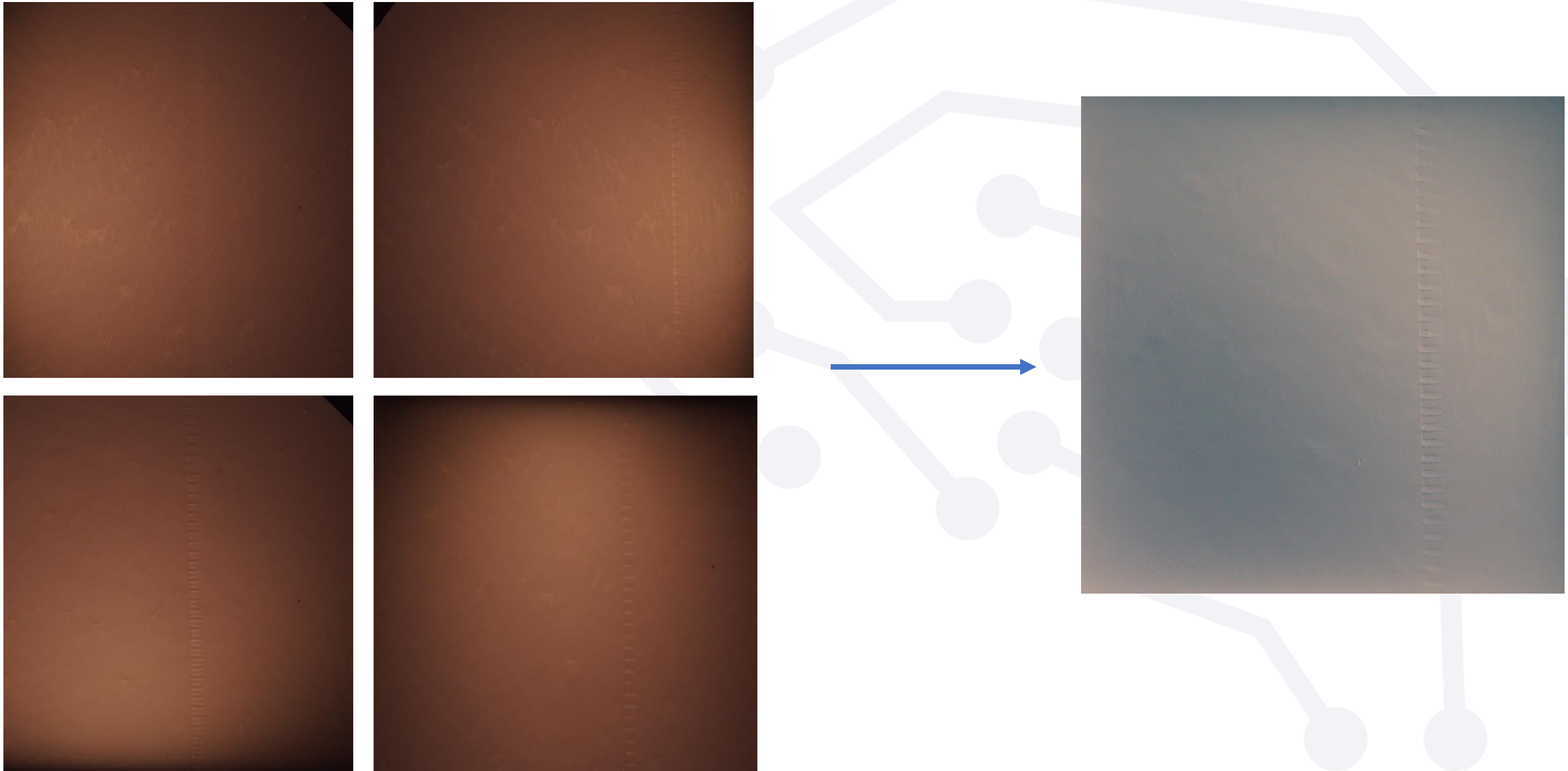


Mobile setup for data acquisition

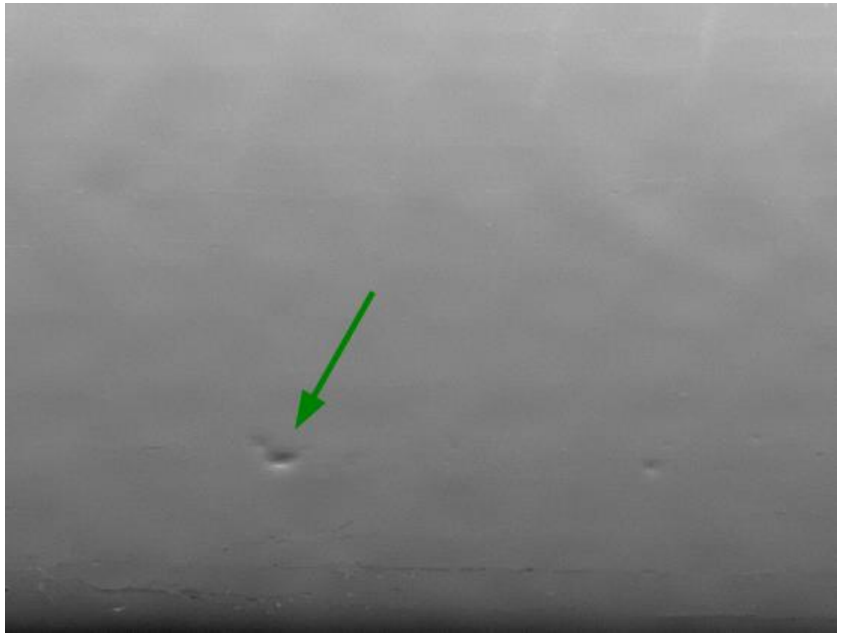




From 4 images to one

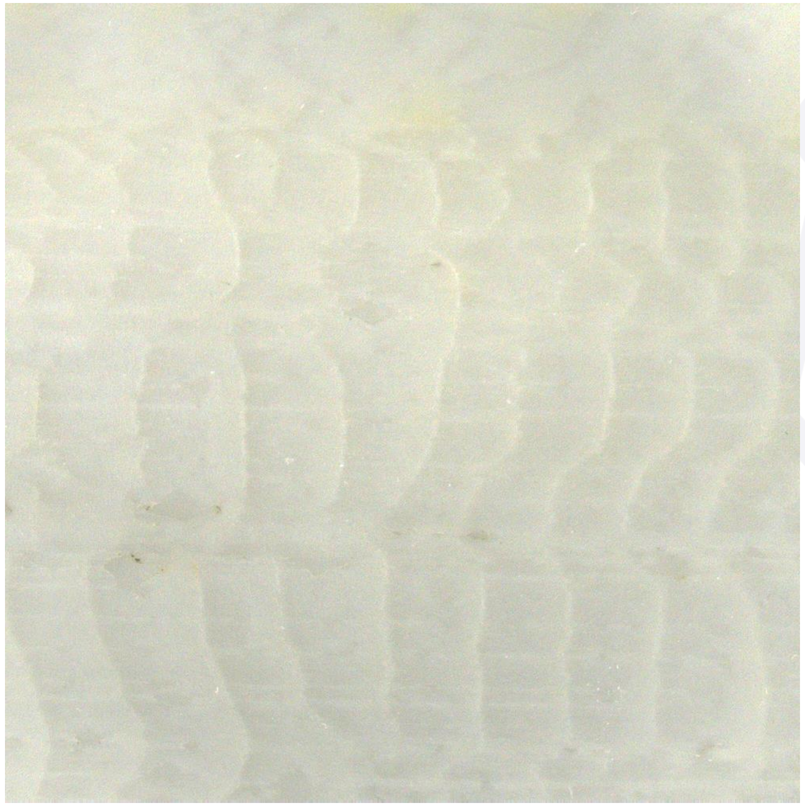


Some results (1)



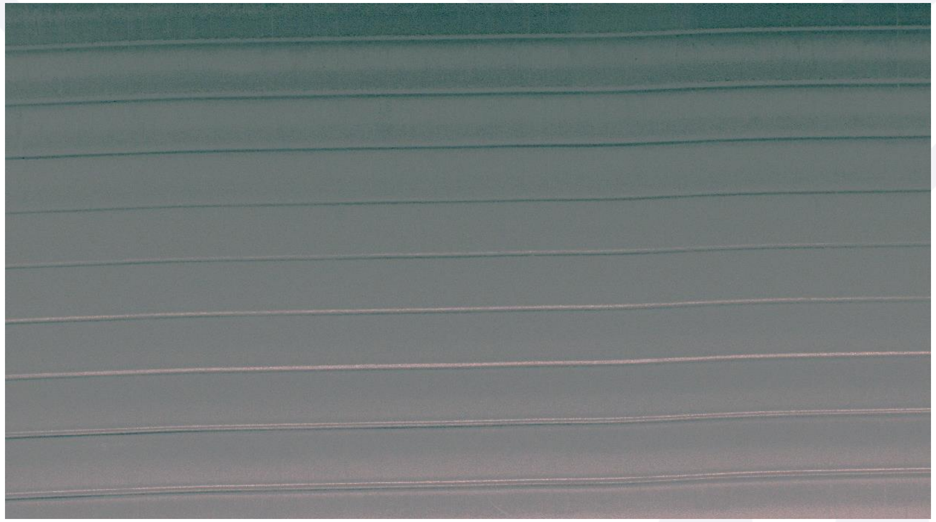
Some results (2)

Some results (3)



To be continued

- MCAM has acquired images for multiple weeks
  - Software solutions to be developped
- New iteration to improve the contrast
- Known problems:
  - notch in pom plate not visible -> solution position lights



Demo

- Live demo @ Covicon's booth
  - Pits and small brown spots

VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Bepalen van de optimale snijlijn van witloof

Inagro

- Jonathan Kesteloot (Captic) -

With the support of VLAIO

AI-Driven Robotics & Inspection Against Labor Scarcity.

What we do, **why** we do it **and how** we do it.

CAPTIC

With the support of VLAIO

Building on a decade of R&D, Captic now delivers **the incredible power of AI** to industry leaders.

ML6

Pfizer
P&G
BEKAERT
gsk
wienerberger
ASML
balta
HOLCIM

And more...

CAPTIC

WHAT'S COOKING?
ELECTROTECHNIEK DECALF
Milcobel
ANTARCTIC FOODS
BISCUITERIE JULES DESTROOPER BELGIUM SINCE 1886
AnnaFaggio
WYZO
Belgian Pork Group

And more...

With the support of
VLAIO

Current challenges in manufacturing.

- Increasing wage costs
- Constant recruiting effort
- Aging workforce = lost experience
- Constant planning effort
- Hard to provide meaningful work

- Bottlenecks in the process
  - Limiting quality
  - Limiting throughput
- Unclear production figures

- Energy waste
- Water waste
- Food waste

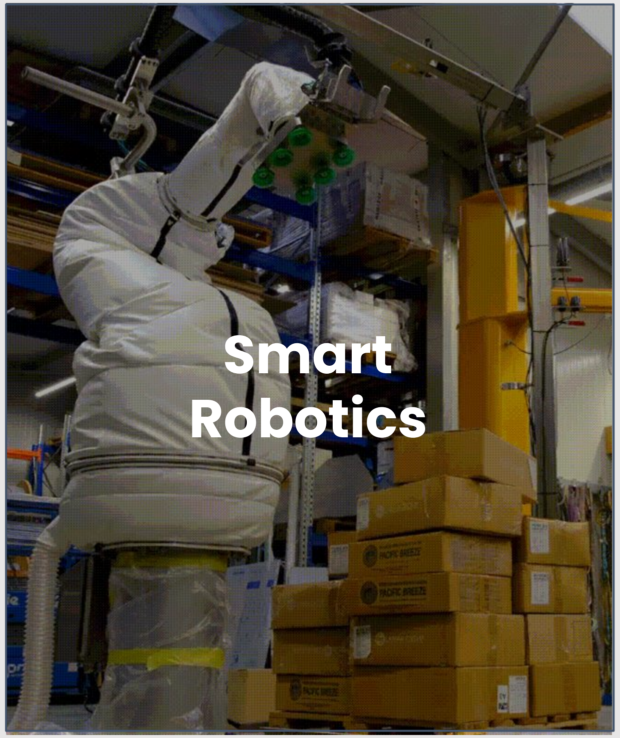
So what if...

You could produce more with fewer people.

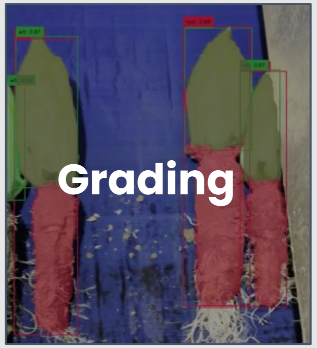
You could limit mistakes during production.

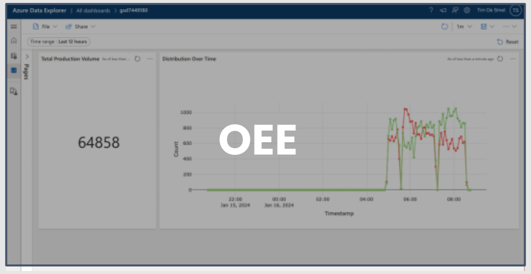
To do so, leverage the incredible power of Captic's AI technology.

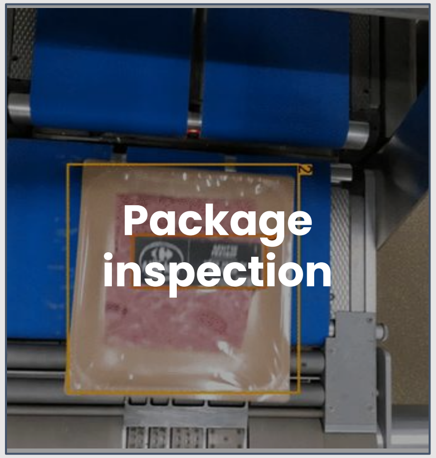
Produce more with fewer people



Make fewer mistakes







Case 2
Inagro.

How Captic is tackling the use case.

inagro × CAPTIC

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hogeschool vives

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The use case:

Optimizing the cutting process of even the most irregular products.

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CAPTIC

Determine the ideal cutting line.

The ideal cutting line is located 2mm above the root.

But

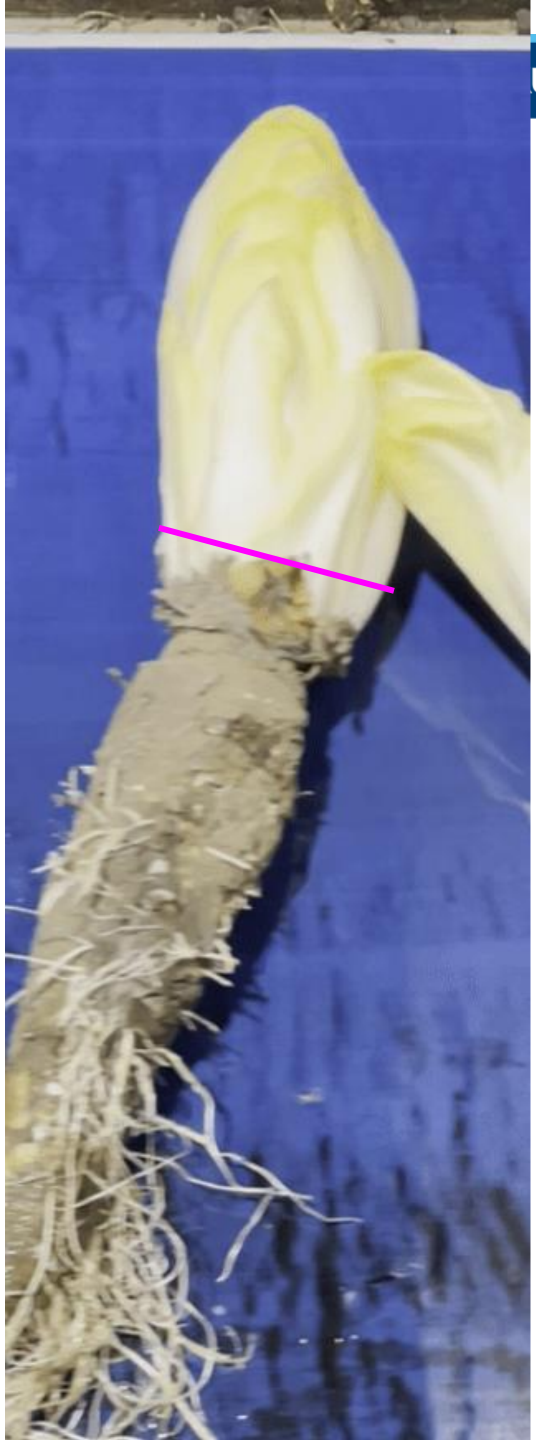
→ How do we find the root?

→ How do we know if the top part is attached to the root?

What about:

→ Orientation?

→ Overlap?



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VLAIO

Why AI-vision is the ideal approach.

Normal sensors?

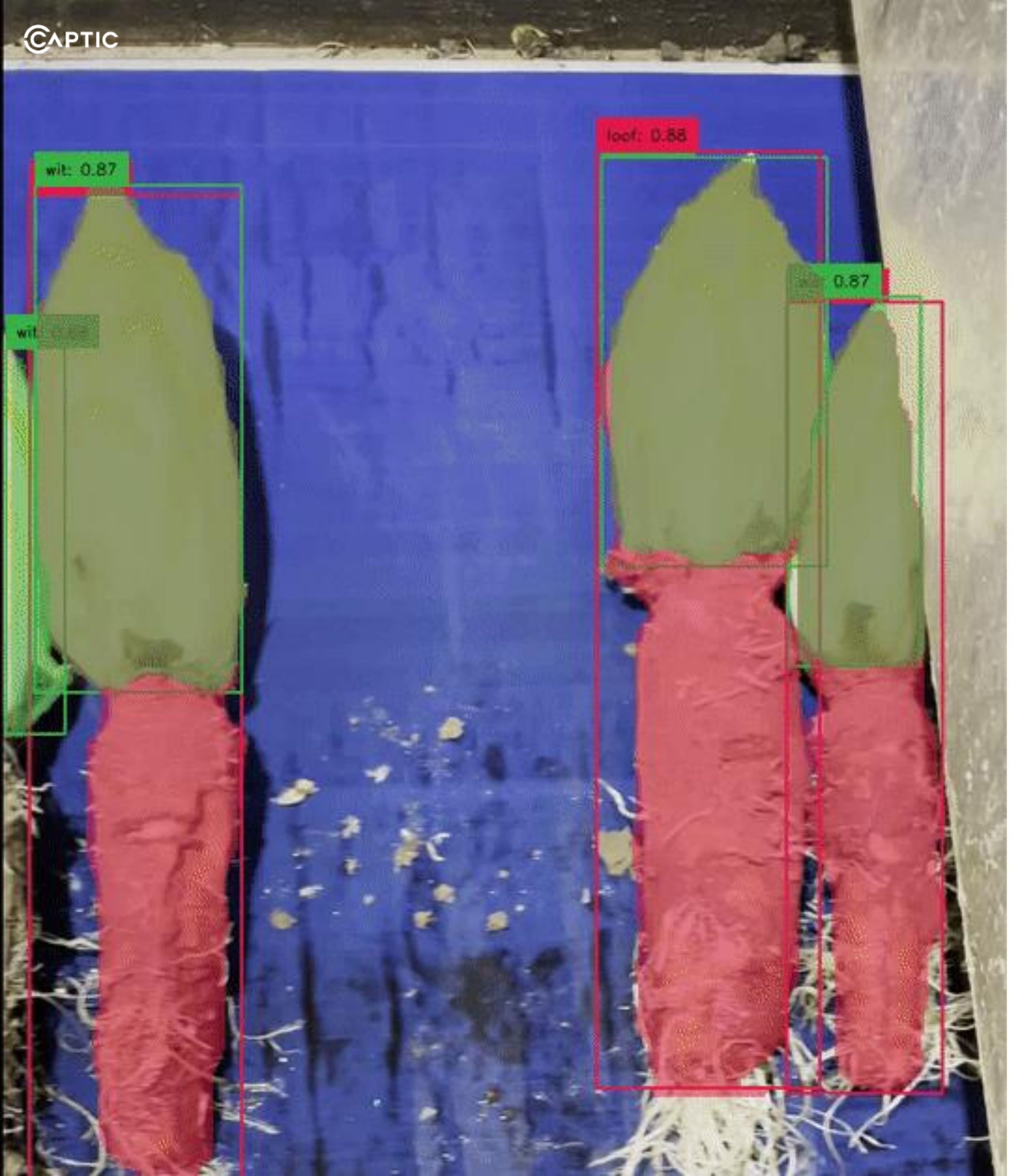
- ❌ Unable to provide the needed information

Classical computer vision? (= rule-based approaches**)**

- ❌ Unable to handle the variety in product

The visual “skills” of a human are needed

- ✅ AI outperforms humans and learns to cope with variability



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How we’re solving:

Optimizing the cutting process of even the most irregular products.

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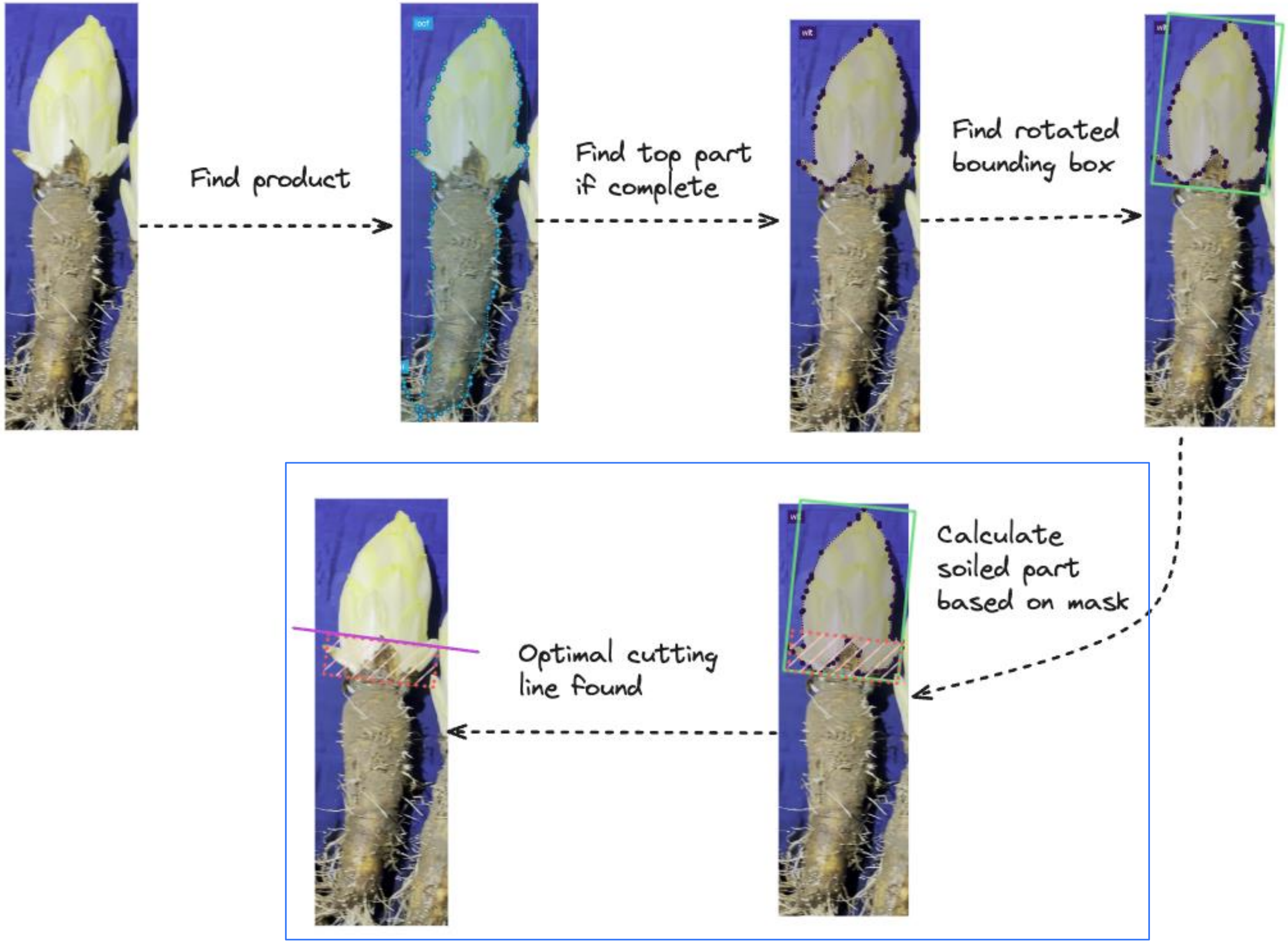
CAPTIC

Our approach.



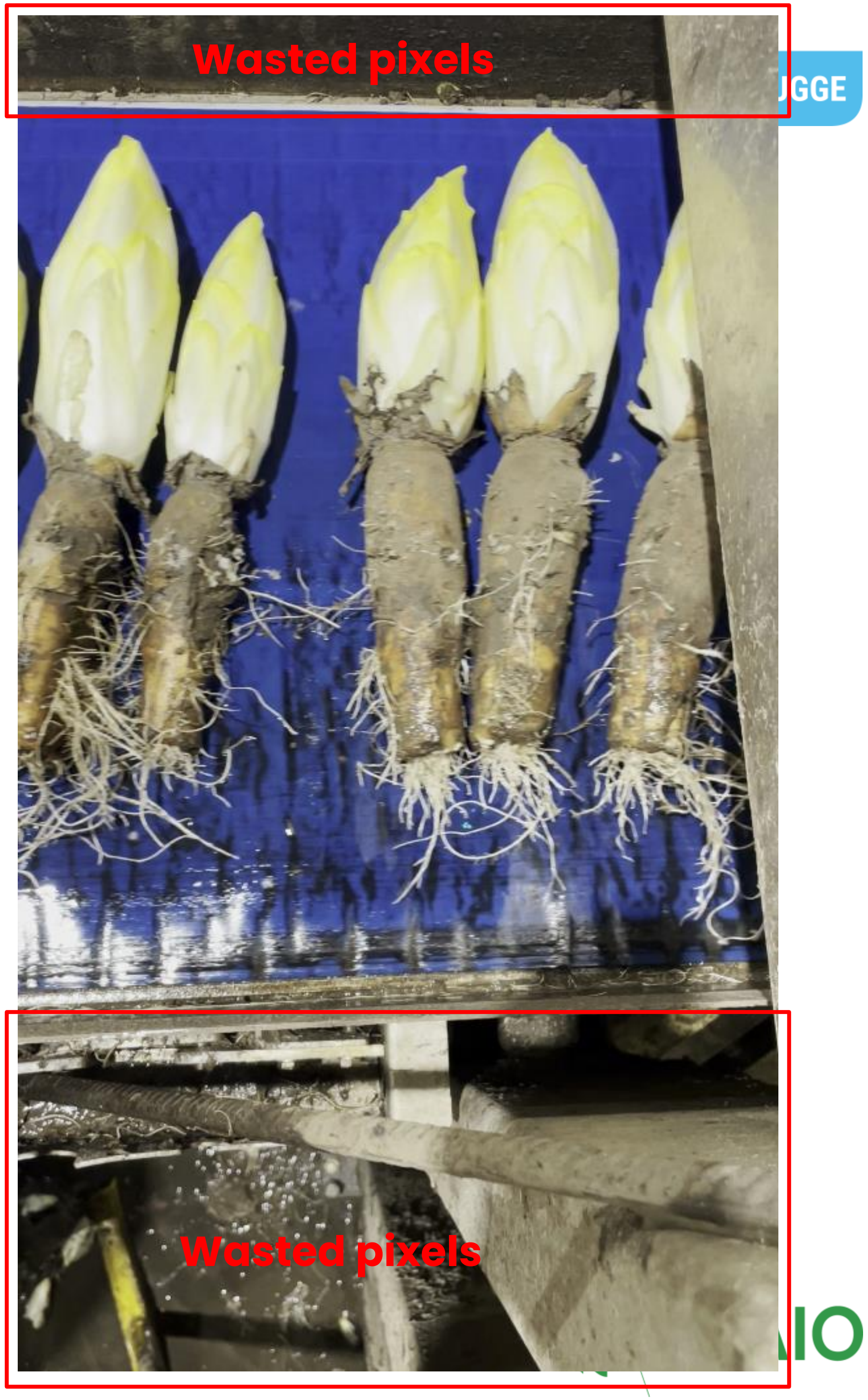
ort of VLAIO

The data we used.

- Two videos
  - 2 min training → Used for
  - 2 min 45 seconds testing → Used for
- Recorded with iPhone
  - 1080×1920
  - Low quality
    - Not centered
    - Not stable
    - ...

Result: 103 uniform sampled Images (no cropping applied)

Note: Our AI is powerful enough to cope with these suboptimal conditions, but could perform even better with optimized data



CAPTIC

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Labelling the data.

Old way of working:

Manual segmentation labelling is very slow

→ key points need to be drawn to indicate the edges

This would take about 4.5 hours of work for 100 images

When looking at a production dataset (+10k) images that would result in about 50 days of manual labor

New way of working:

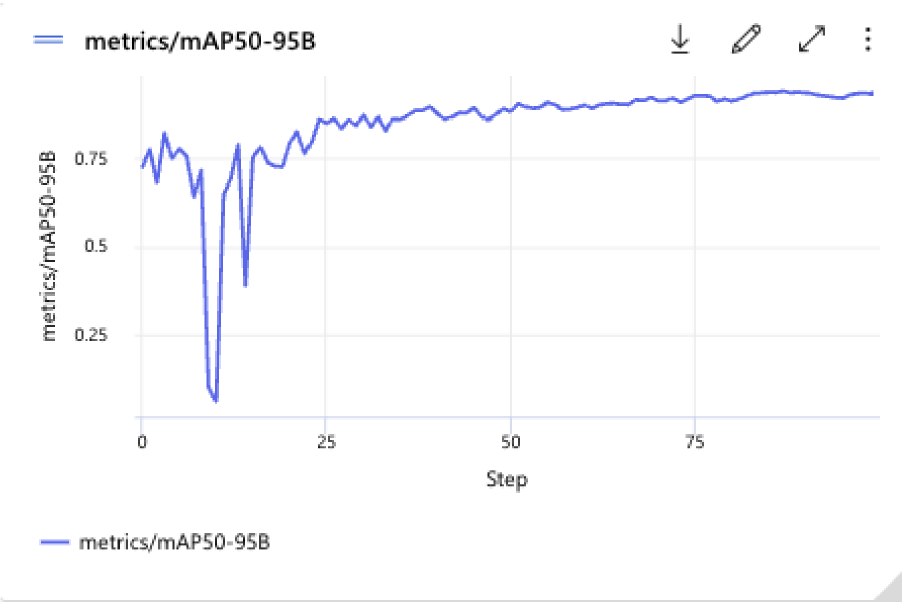
At Captic, we're leveraging state-of-the-art techniques to speed this up dramatically: pixel clustering, model assisted labeling using Large Vision Models and human-in the loop.

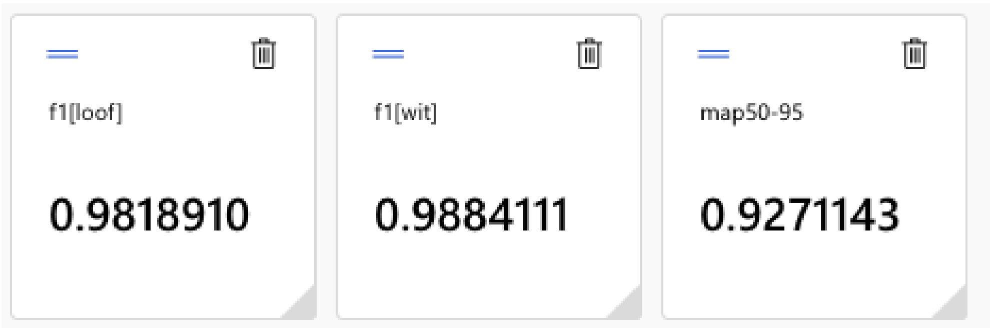
The segmentation model.

We used one of our segmentation models that is based on the Yolov8 architecture

- Real-time capabilities
- Input size: 640 x 640
- 100 epochs

Azure





Note: Erratic pattern indicates further optimization is possible, collection of more data is the logical next step

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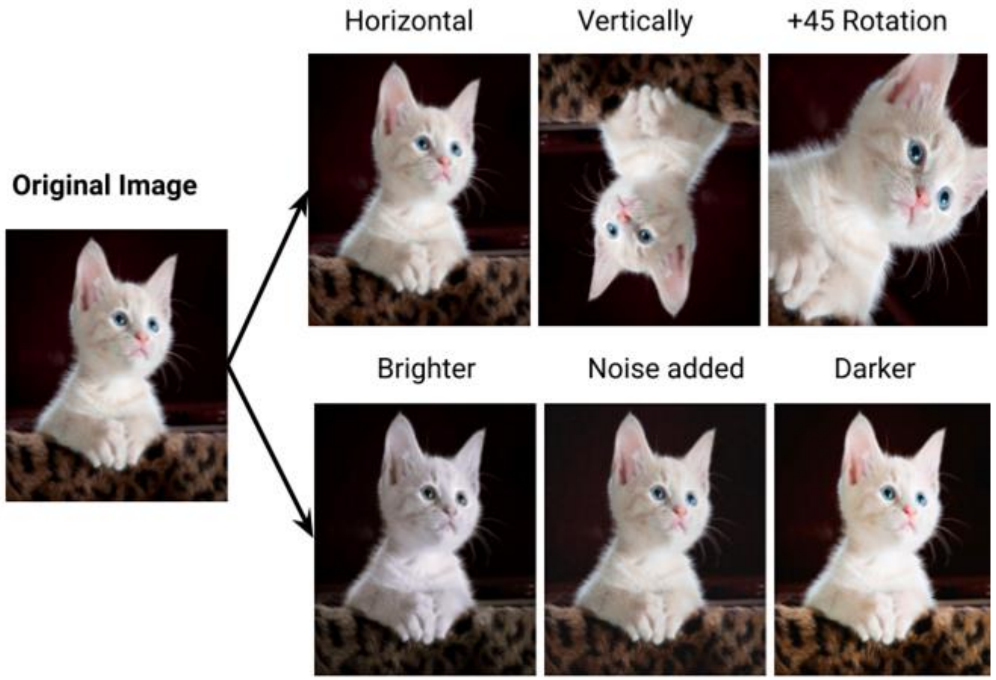
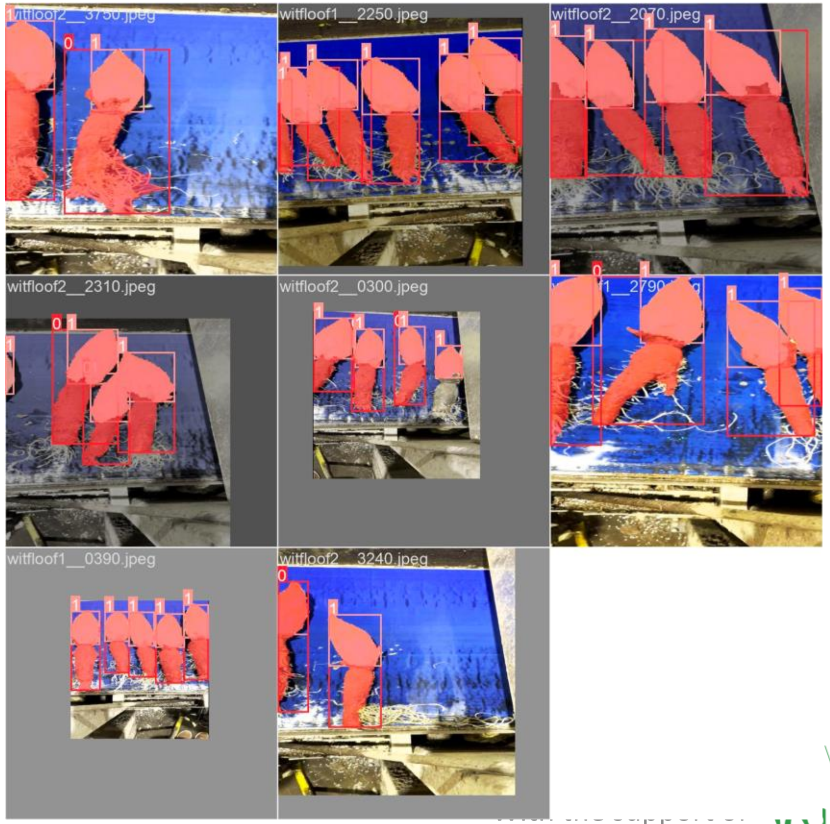
Data augmentation.

The Captic AI core artificially creates additional data based on the images in the dataset using basic techniques such as:





End results:



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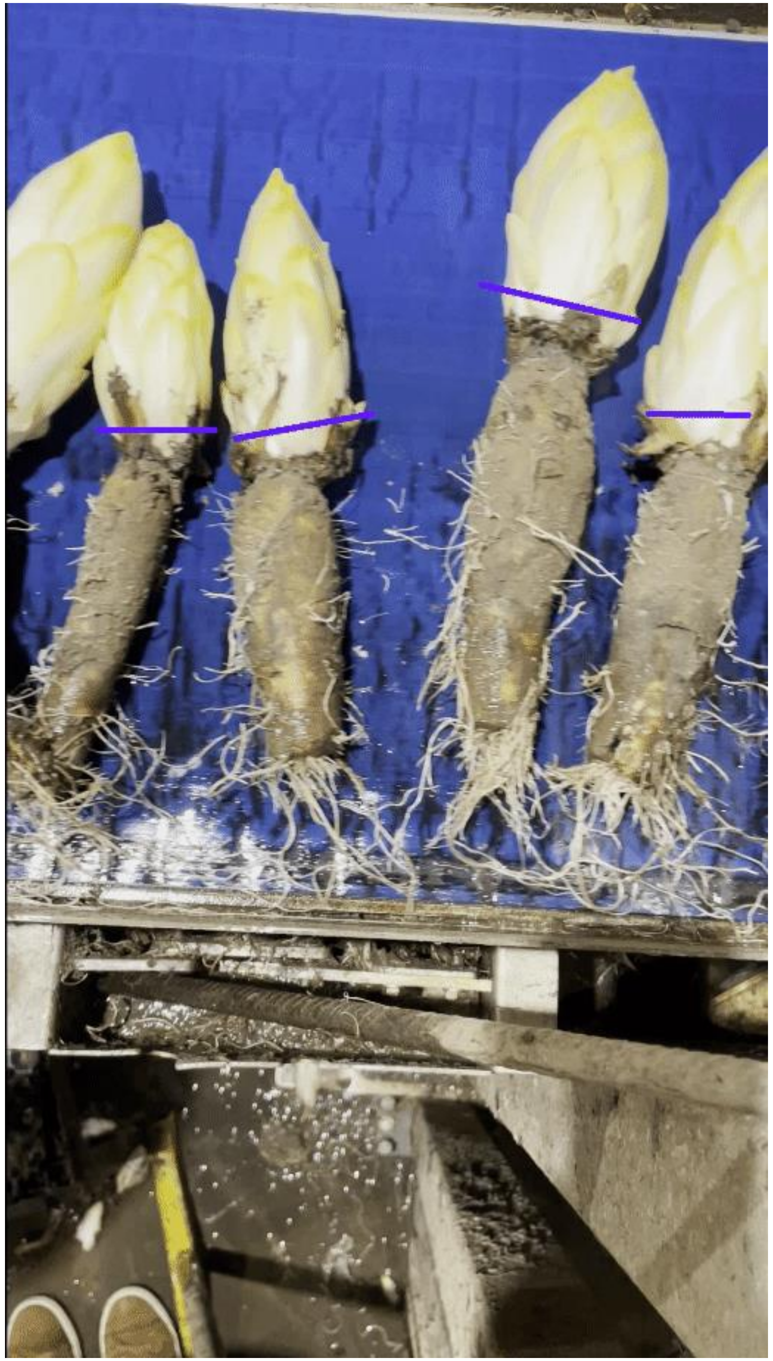
CAPTIC

End results:



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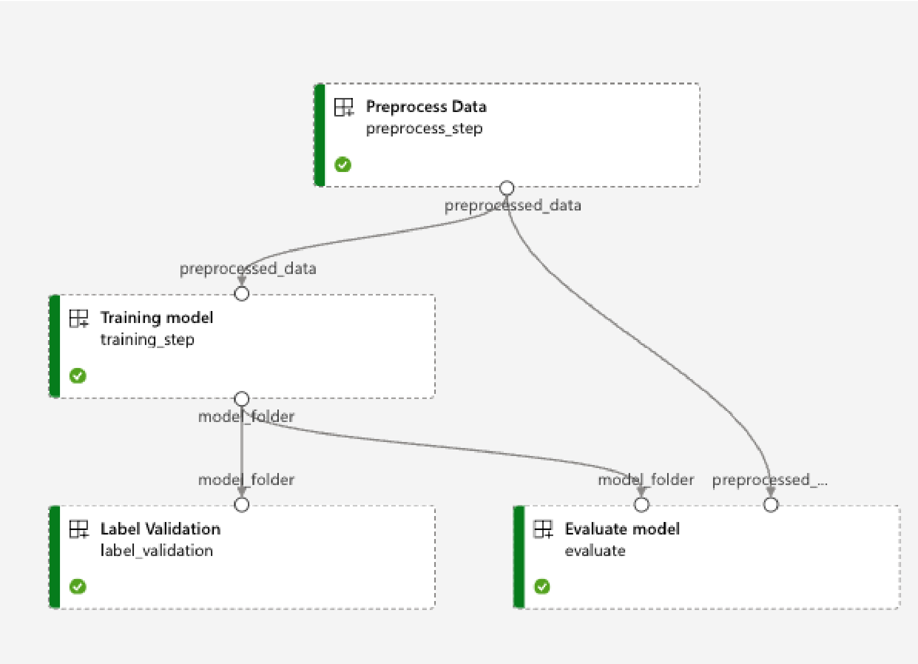
MLOps.

Even though it's a PoC, the Captic AI core ensures that MLOps best practices are adhered to automatically (traceability, reproducibility, security, …). This ensures and enhances the speed at which we can iterate on models and improve the eventual result.

The core leverages:

- Registered datasets
- ML pipelines
- Model registries
- …



With the support of VLAIO

Next Steps.

Tetra: Proving the potential

Can it be solved? → YES!

Phase 2: Going to production, if business case makes sense.

How do we leverage the solution in a robust and safe way?

- Hardware selection and installation
- Rugged and food safe design
- Continuous data collection
- Continuous data labelling
- Model optimization for production
- Robust deployments on-site
- IoT Device security
- Hardware monitoring
- Model performance monitoring
- Continuous retraining in the cloud
- Robotics integrations
- MES integrations
- Dashboarding
- …

Plug-and-play in our Captic stack

With the support of VLAIO

VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Detectie van toppings op Cornetto's

Ysco

- Jonathan Kesteloot (Captic) -

With the support of VLAIO

Case 6
Ysco.

How Captic is tackling the use case.

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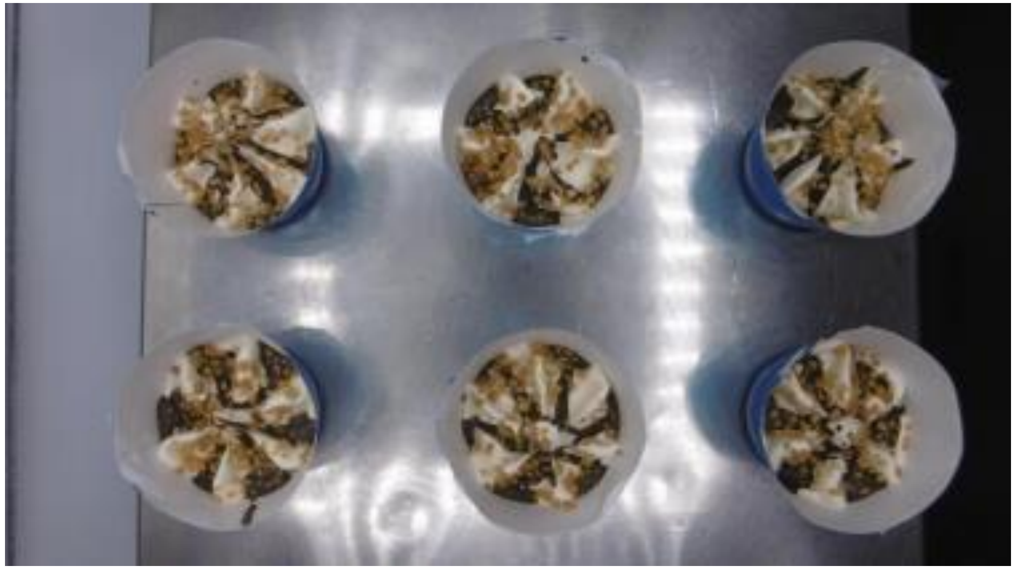
How we're solving:

Inline Quality Control of ice cream cones.

With the support of VLAIO

Context.

Detection of a sufficient presence of nuts and sauce on Cornetto's

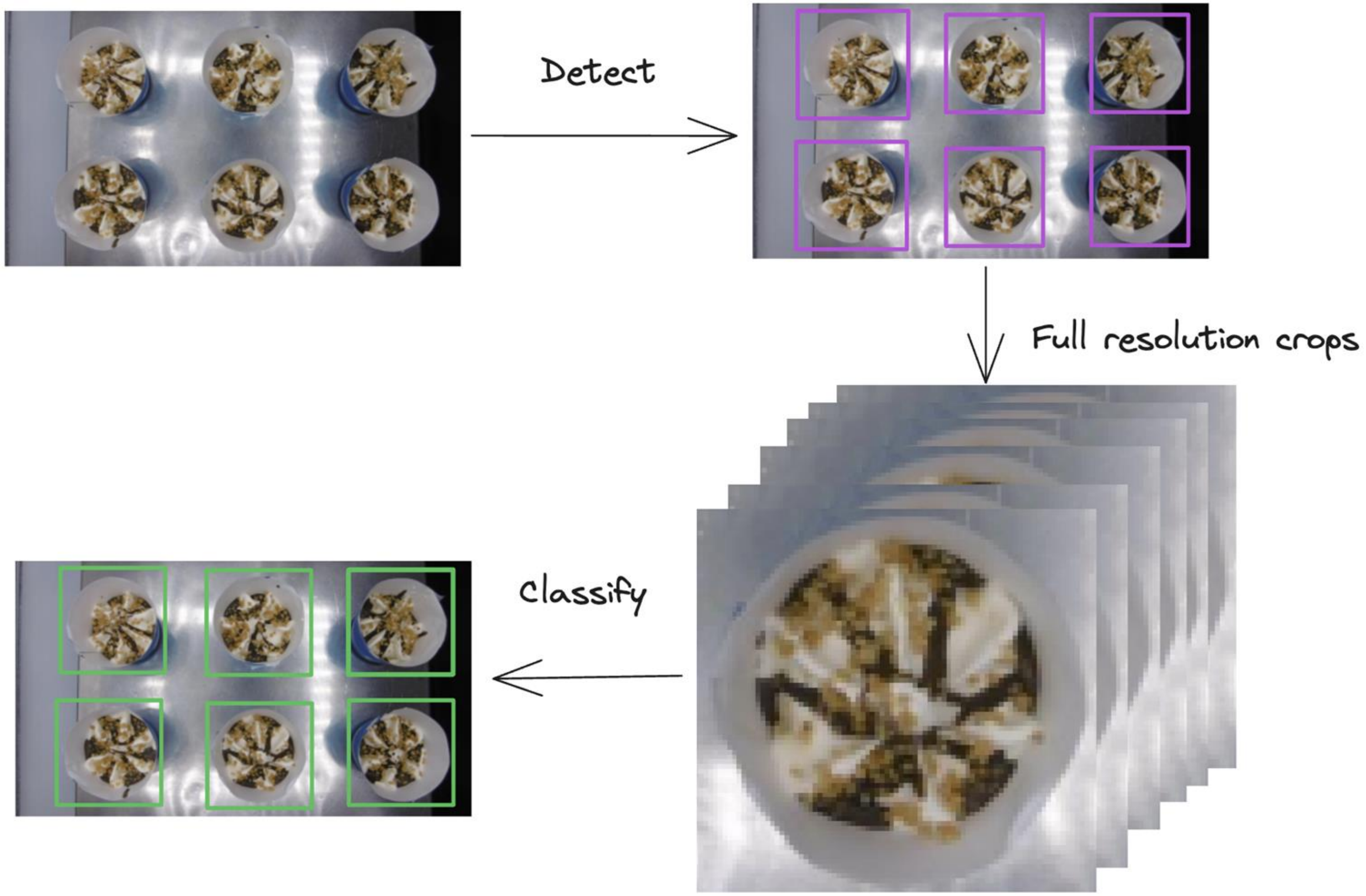


Conclusions from TETRA's previous research:

- Both binary classification and multi-label classification showed promising results.
- Size of dataset is rather limited

CAPTIC

Our proposed approach.



Plug-and-play in our Captic stack

With the support of VLAIO

Collecting a big & high-quality dataset.

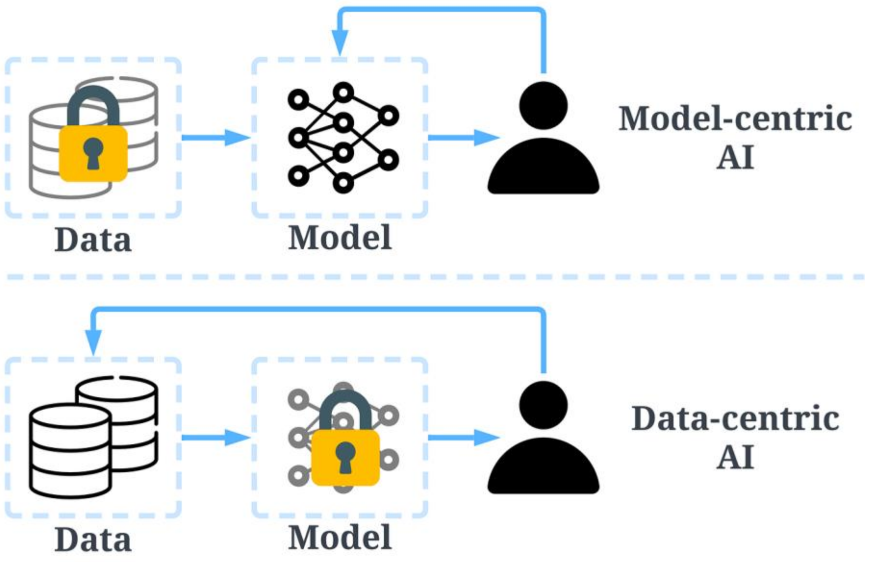
Current dataset:
- 41 images
- 246 samples

We want to collect a few thousand images with real defects from production

→ **Continuous data collection** is part of our Captic stack, so it made sense to install a real setup on site

Our stack will also help speed up any required labelling effort

Academic research



Needed in production

The hardware setup.

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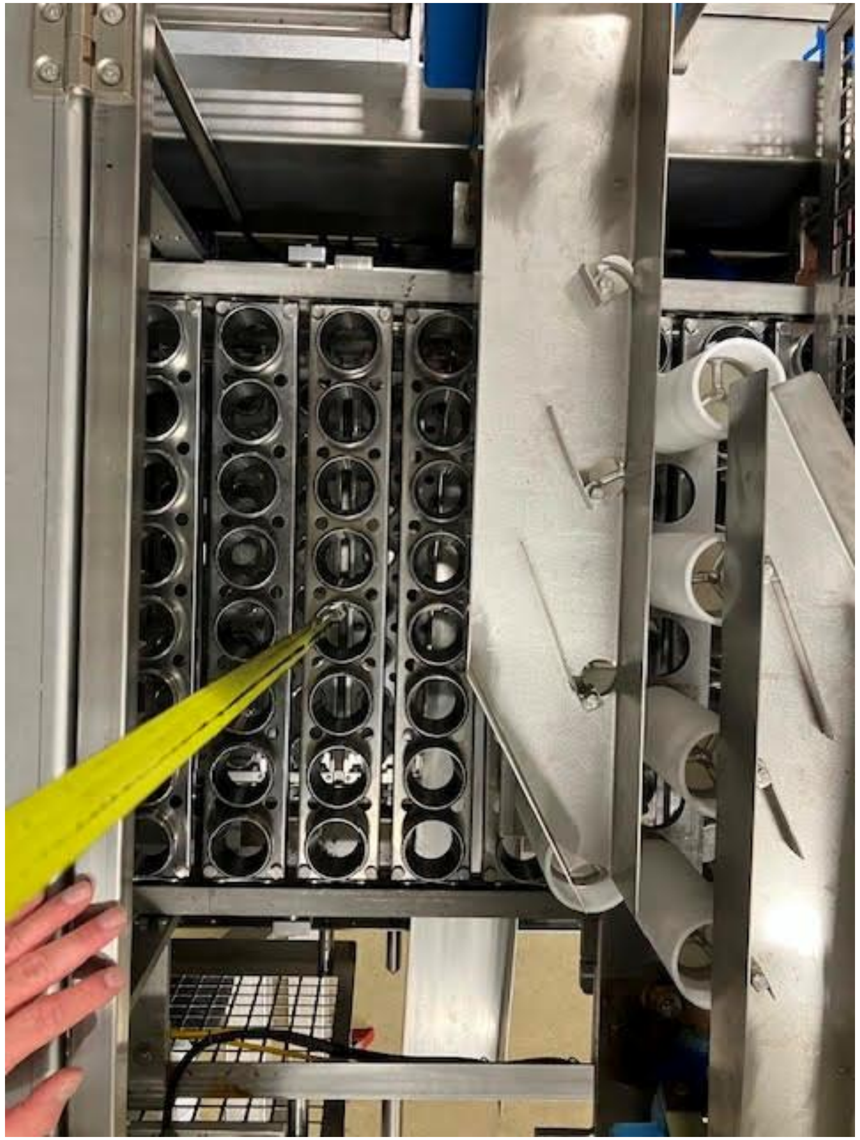

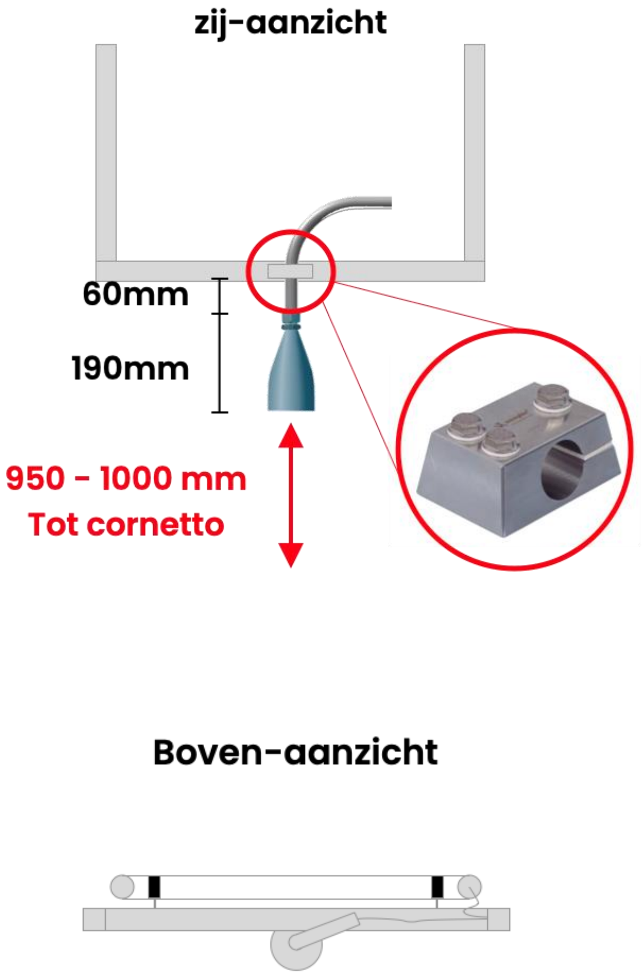

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CAPTIC

The hardware setup.

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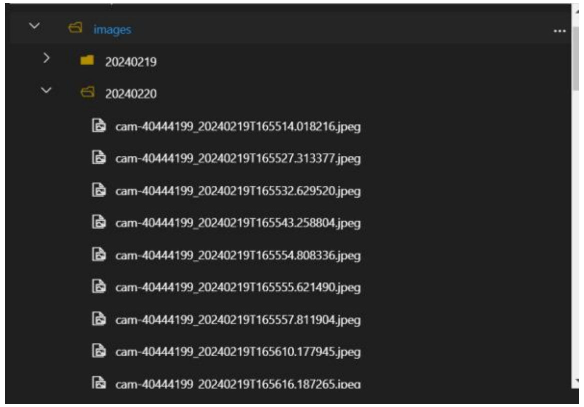
VLAIO

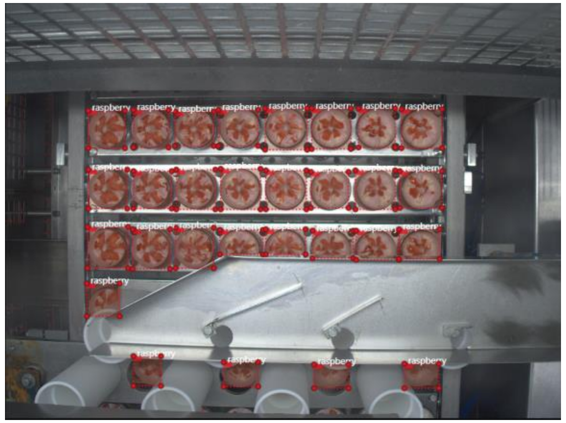
CAPTIC

The process.

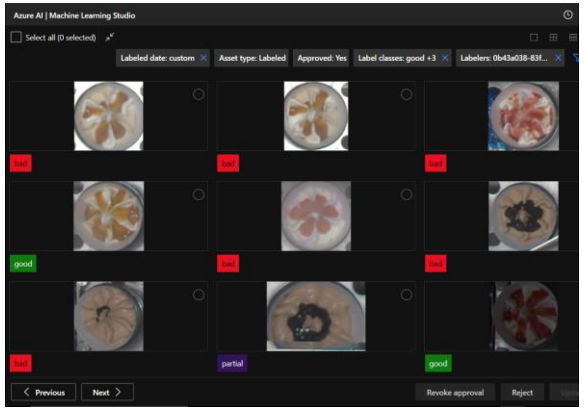
1. **Data collection.**



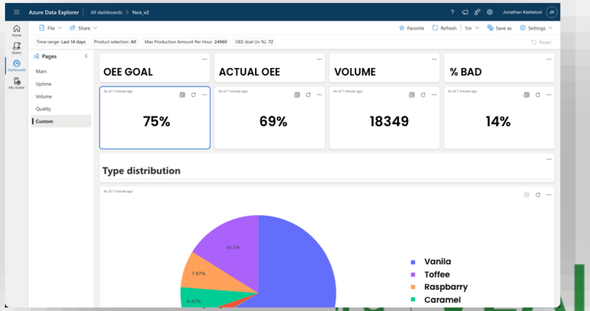
2. **Flavour detection.**



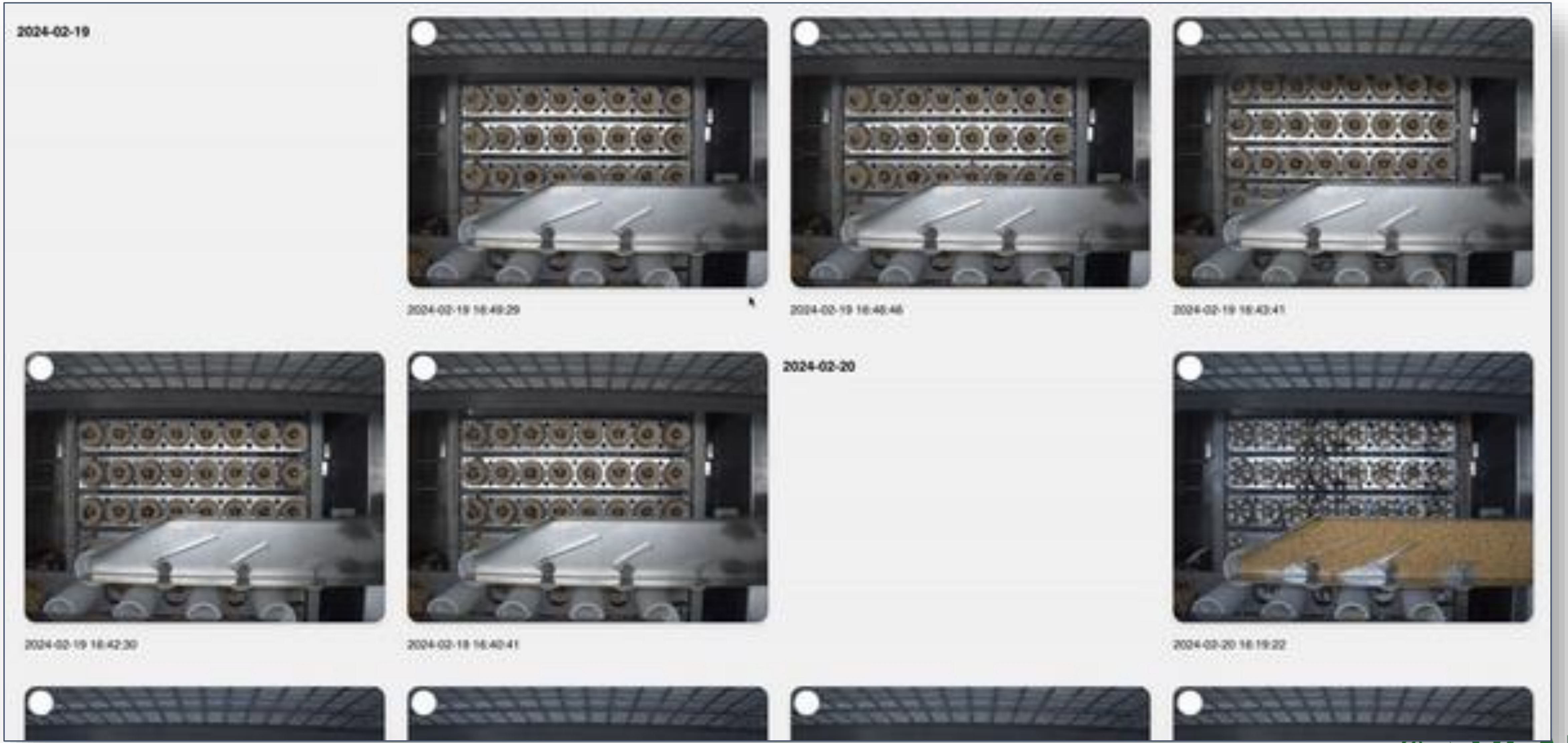
3. **Quality control. (QC)**



4. **Insights & dashboarding.**



Step 1: Continuous data collection.



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Step 1: Continuous data collection – Crops

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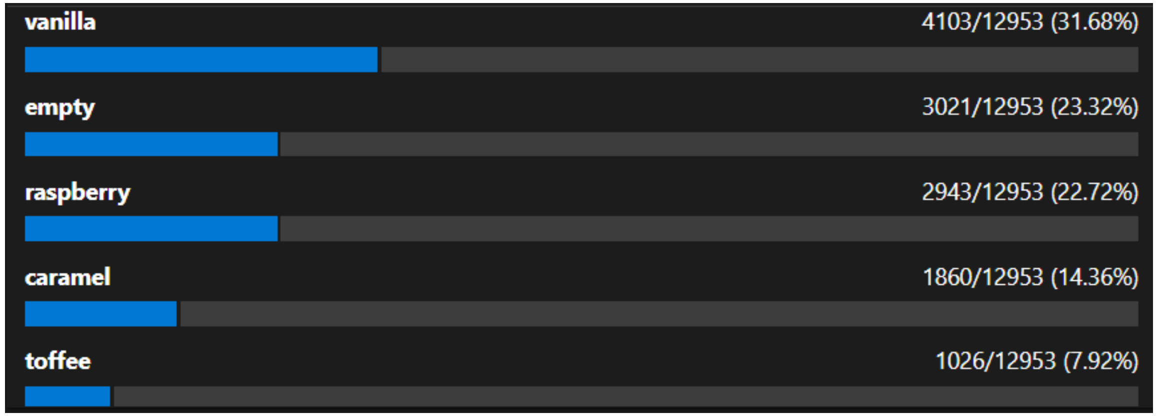
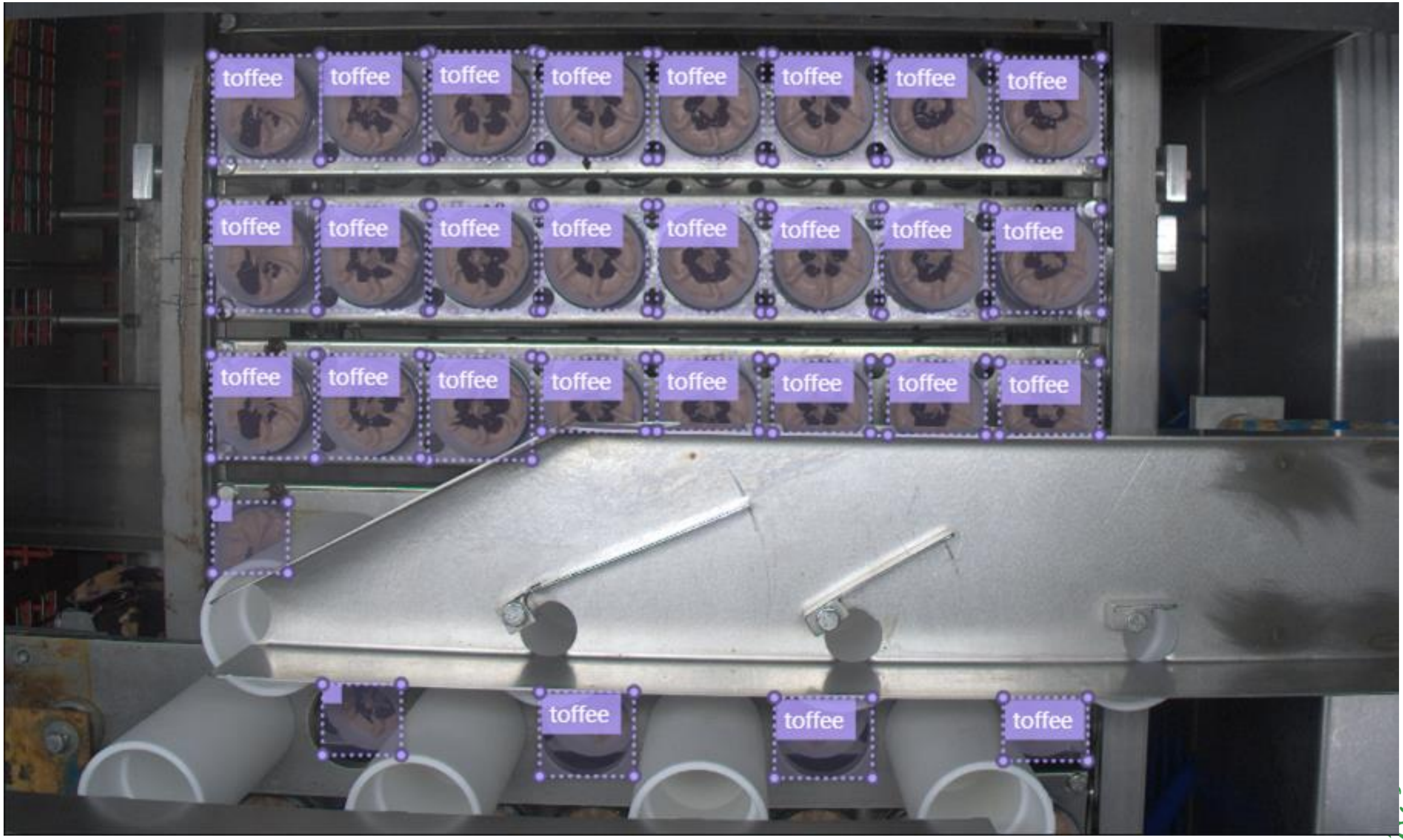
Step 2: Data labeling - Type.

Type detector:
Model trained on balanced dataset of 1000 examples per type.



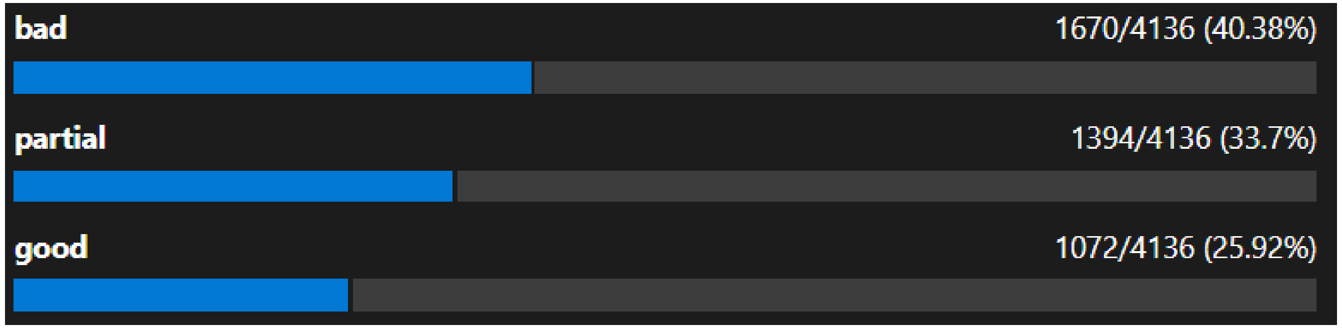
With the support of VLAIO

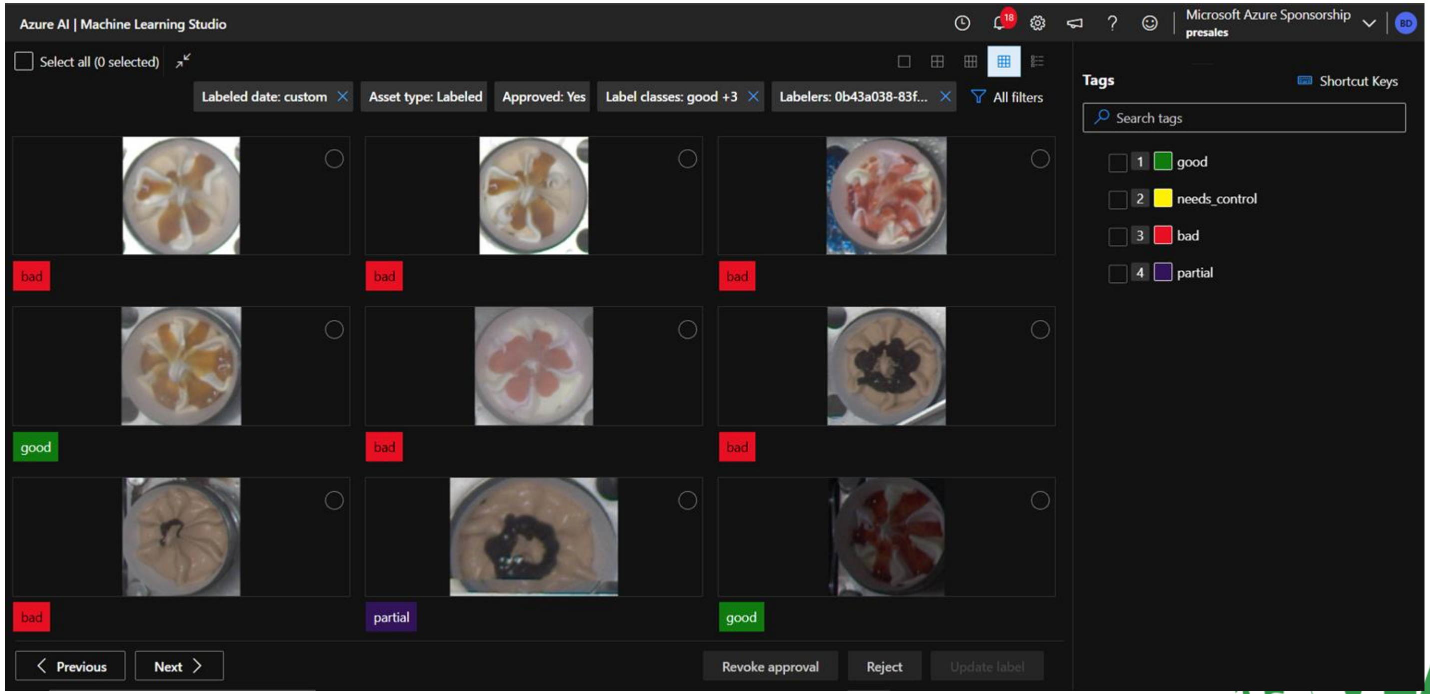
Step 2: Data labeling - Type.



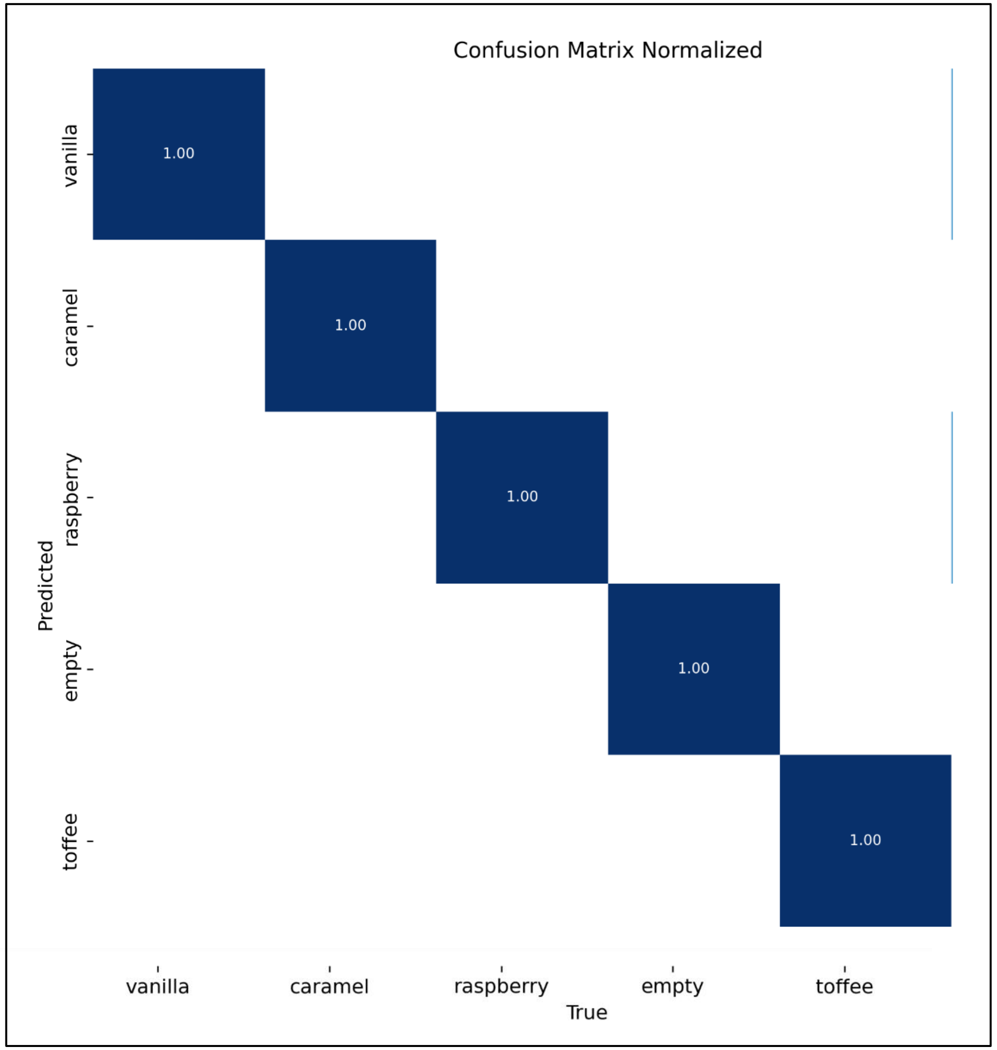
Step 2: Data labeling – Crops.

Quality control:
Model trained on balanced dataset of 1000 examples per type.





Step 3: Model training.



The model can accurately distinguish between the different flavours:

- Vanilla,
- caramel,
- raspberry,
- empty,
- toffee.

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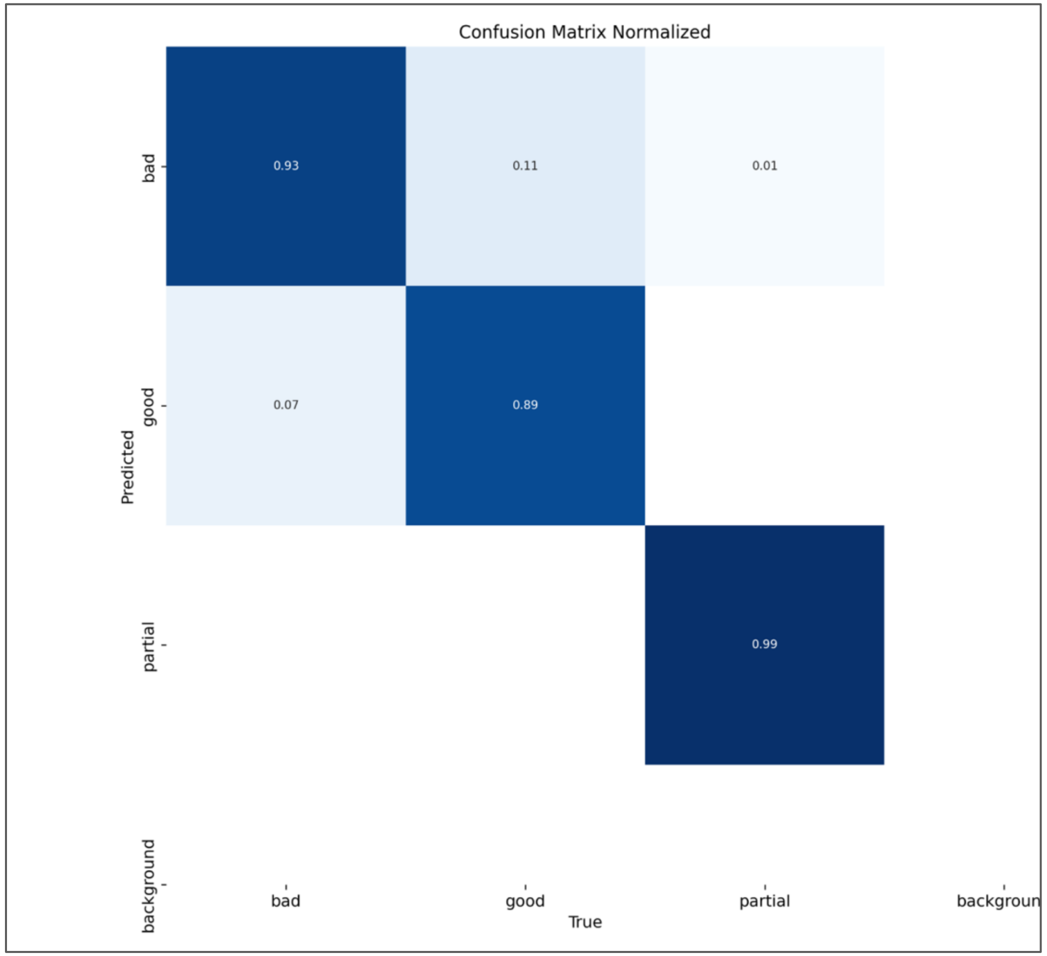
Step 3: Model training.



Distinguishing between good and bad is more subjective than classifying different flavors. However, the confusion matrix on the left indicates that the model is beginning to grasp the distinction between good and bad ice cream cones.

Overall, we've trained one quality model with three classes:

- Good
- Bad
- Partial

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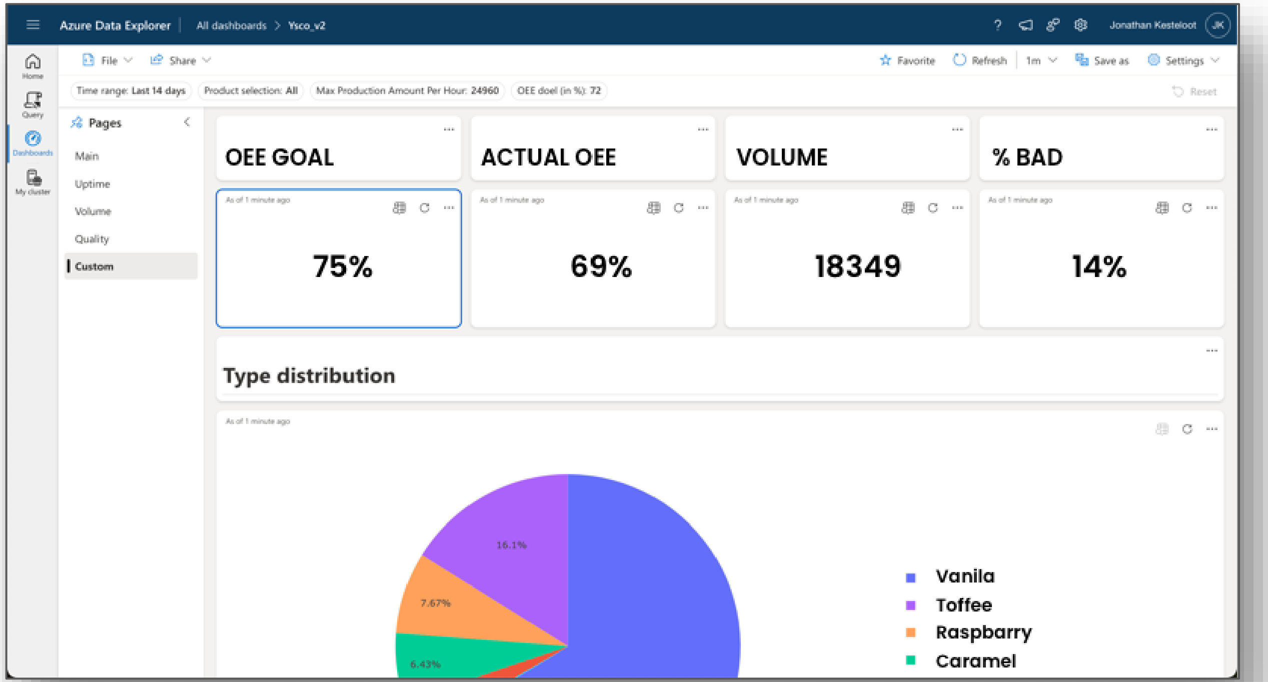
End result.

Production continuously monitored

Results visualised in a custom dashboard



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Next Steps.

Tetra: Proving the potential

Can it be solved? → YES!

Ysco is heavily investing in the safety of its operators, but this can make it more challenging for them to observe what's happening directly on the line. As a solution, cameras offer an excellent way to continuously monitor production and deliver valuable insights into real-time operations.

→

Phase 2: Going to production,

Moving the setup to a different location

The visual appearance of the ice cream cones is important, but there are other issues that may arise earlier in the process. As a result, we have relocated the setup to prioritize addressing these issues first.

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The possibilities are endless.

With the support of

VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Bepalen van de lengtedistributie van vissen per soort
ILVO

- Sam Vanhoorne (ILVO) -
- Glenn Aesaert (Vintecc) -

With the support of VLAIO

VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Bepalen van de goede werking van een LED-display

TVH

- Julia Otero Jiménez (Beckhoff Automation) -

With the support of VLAIO

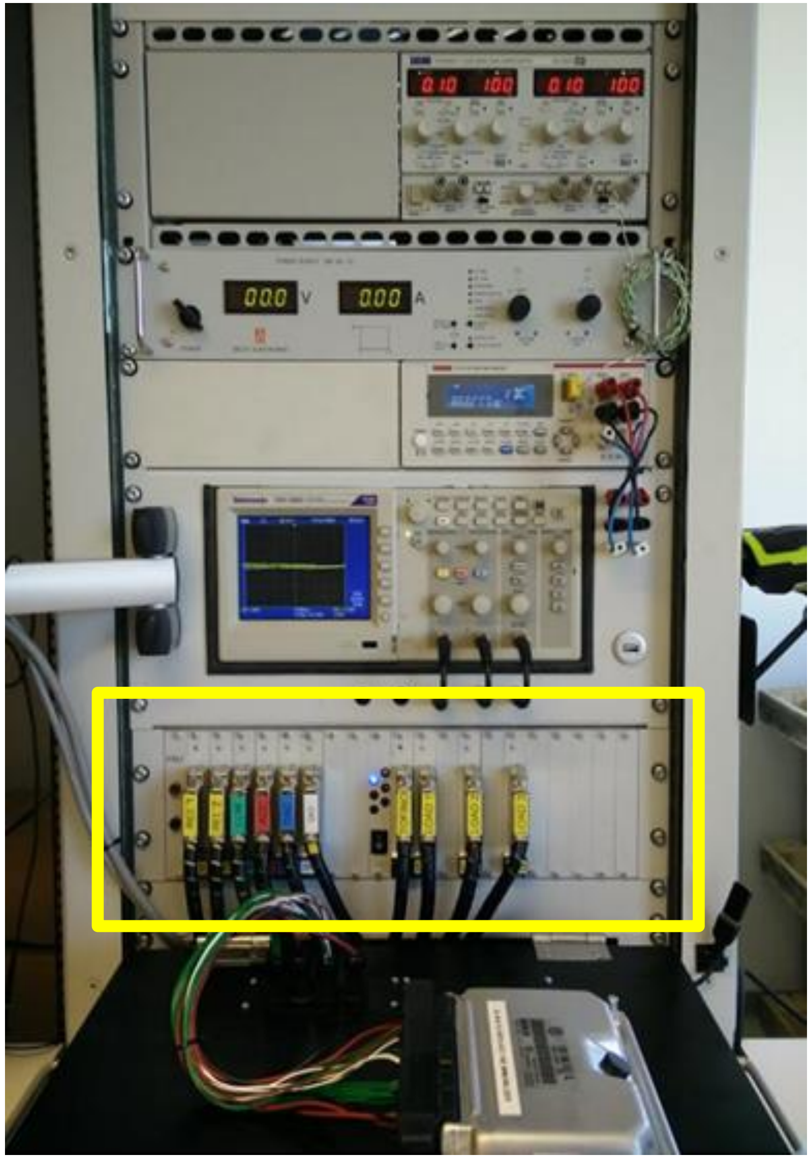
Context

- Een operator start de test
- De operator :
  - Controleert visueel (OK/NOK)
  - Bevestigt handmatig

Geautomatiseerd visie-systeem

Hudige systeem

BECKHOFF



TCP/IP

CAN

Externe PC met LabVIEW™

Systeemvereisten

BECKHOFF

Communication

- Meerdere communicatieprotocollen
  - CAN
  - TCP
- Integratie of communicatie met LabVIEW™

Displays

- Meerdere soorten displays

Optioneel

- Extra IO interfaces

Visie

- Reflecterend oppervlak
- Klassieke Machine Visie is voldoende

TVH®

Beckhoff solution | Technology architecture

BECKHOFF

Voorstel en proof of concept

- Beckhoff Hardware/Software
  1. ~~Huidige system~~
  2. + Visie systeem
- Software Demo
  - TwinCAT 3
  - Vision + OOP
  - CAN communicatie
  - JSON handling
  - OPC-UA

TVH®

Visie systeem | Hardware architectuur

BECKHOFF

AV Mako G-319C

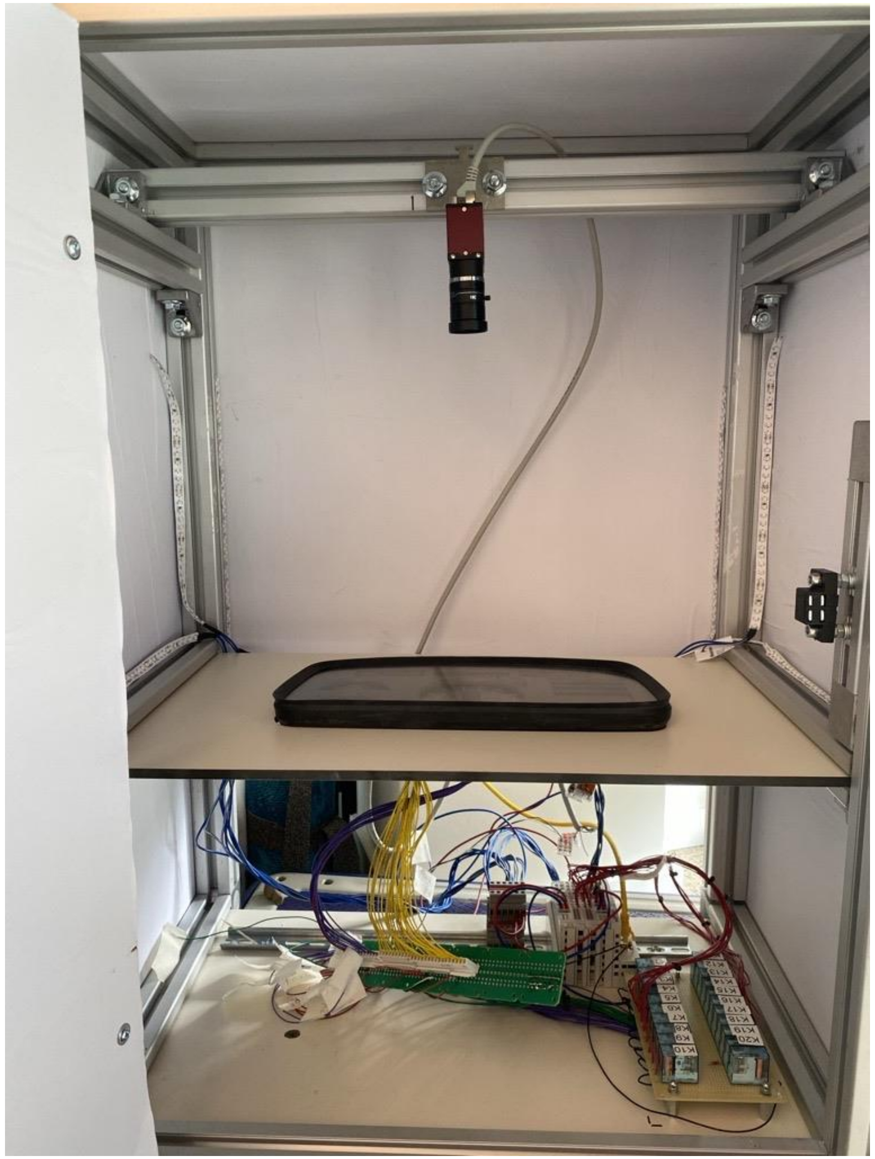
- Area scan camera
- GigE Vision
- 3 MP
- Color
- PoE

Computar M0824-MPW2

- f 8mm

Ohmeron LS5M09-600

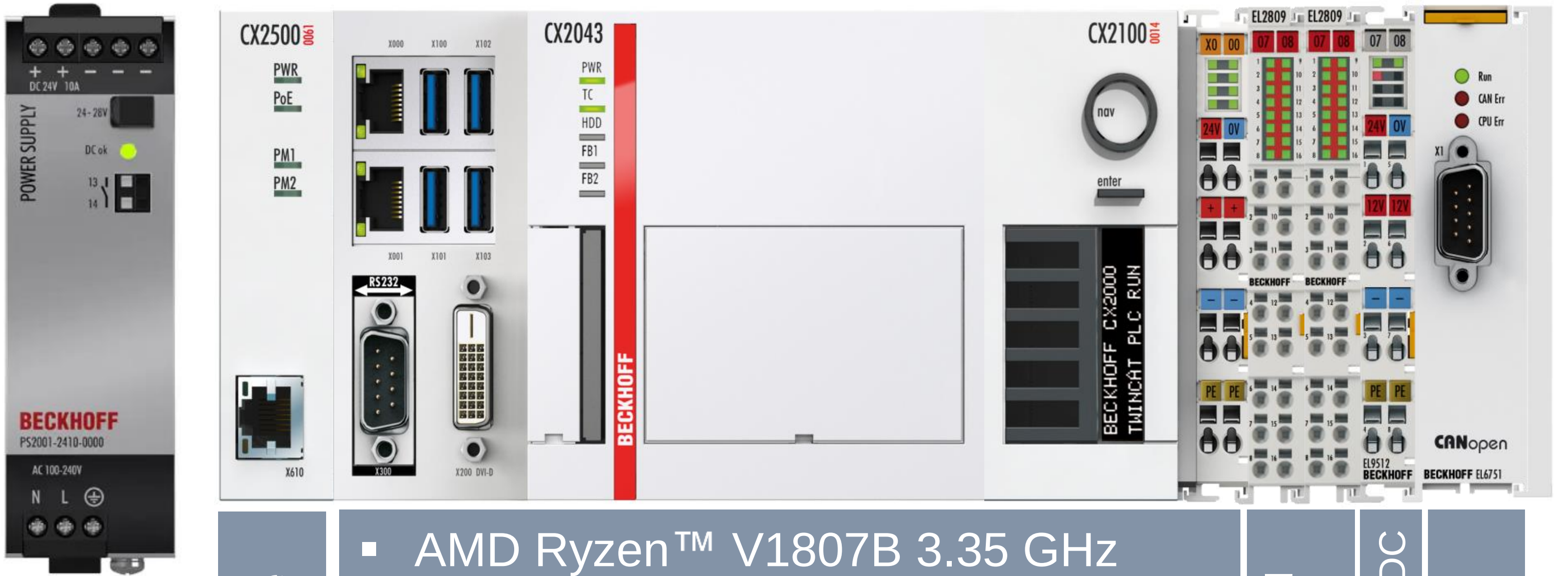
- Cool white 6000K
- 24V DC



Beckhoff solution | Hardware architectuur

BECKHOFF

Power Supply	CX2043 | Embedded PC	EtherCAT Terminals



PS 2001-2410-000 | Power supply 24 V DC 10A

CX2500-0061 | PoE module

- AMD Ryzen™ V1807B 3.35 GHz
- 4 cores
- 8/16/32 GB RAM
- Windows 10 IoT Enterprise 2021 LTSC 64 bit
- 2 x RJ45 1Gbit/s
- E-bus connection

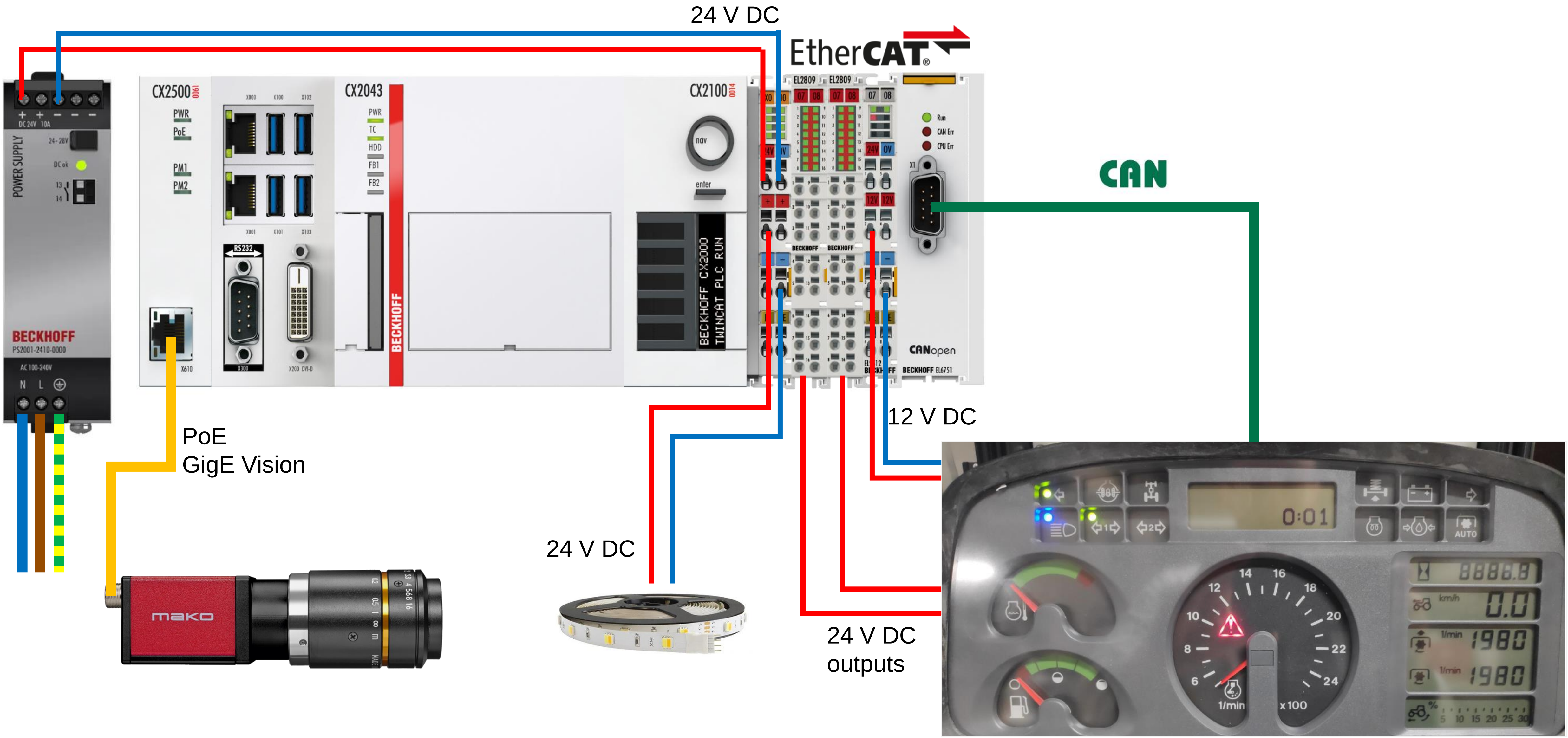
EL2809 | 16-channel digital output 24 V DC, 0.5 A

EL9512 | Power supply 12 V DC

EL6751 | CANopen master/slave

Beckhoff solution | Hardware architectuur

BECKHOFF



Beckhoff solution | Software architectuur

CX2043 | Embedded PC | Windows 10

OS Windows 10

TwinCAT 3 Runtime

- TwinCAT PLC
- TwinCAT Vision
- TwinCAT HMI

Beckhoff solution | Software architectuur

BECKHOFF

CX2043 | Embedded PC | Windows 10

OS Windows 10

TwinCAT 3 Runtime

- (TwinCAT PLC)
- (TwinCAT Vision)
- (TwinCAT HMI)

ADS
OPC-UA
…

LabVIEW™ Runtime

Beckhoff solution | Software architectuur

BECKHOFF

CX2043 | Embedded PC | Windows 10

OS Windows 10

TwinCAT

TwinCAT 3 Runtime

Sequence

Pamameters

DisplayTypeXY.json

TVH

Sequence
Pamameters

DisplayTypeXY.json

Sequence_XXX.json

Schema: <No Schema Selected>


```
{
    "Config": {
        "ID": "Sequence_XXX",
        "Description": "Test sequence for panel XX",
        "StartObject": "DisplayOn"
    },
    "DisplayOn": {
        "ID": "SetOutput",
        "Description": "Switch On display",
        "Offset": 0,
        "State": true,
        "NextObject": "WaitAfterDisplayOn"
    },
    "WaitAfterDisplayOn": {
        "ID": "IdleTime",
        "Description": "Idle Time After Switching On Display",
        "IdleTime": 3000,
        "NextObject": "DetectIndicatorLeft"
    },
    "DetectIndicatorLeft": {
        "ID": "DetectLamp",
        "Description": "Detect and check indicator left lamp on display",
        "nLamp": 1,
        "stItemRoi": {
            "nX": 180,
            "nY": 50,
            "nWidth": 140,
            "nHeight": 90
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        "aColorUpperBounds": [ 255.0, 255.0, 190.0, 0.0 ],
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        "fMinAreaLamp": 100.0,
        "fMaxAreaLamp": 500.0,
        "Detected": false,
        "NextObject": "SwitchIndicatorLeftOff"
    },
    "SwitchIndicatorLeftOff": {
        "ID": "SetOutput",
        "Description": "Switch off indicator left lamp",
        "Offset": 1,
        "State": false,
        "NextObject": "DetectIndicatorRight"
    },
```
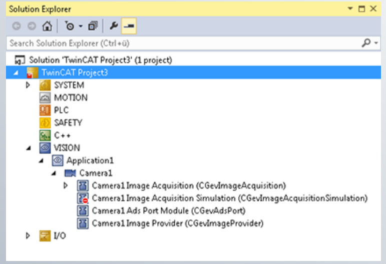
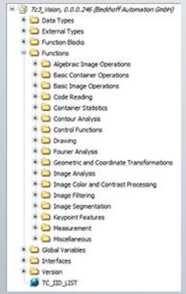

Beckhoff solution | Software applicatie : TwinCAT Vision

BECKHOFF

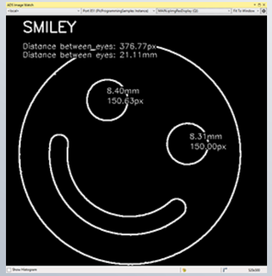
System Manager

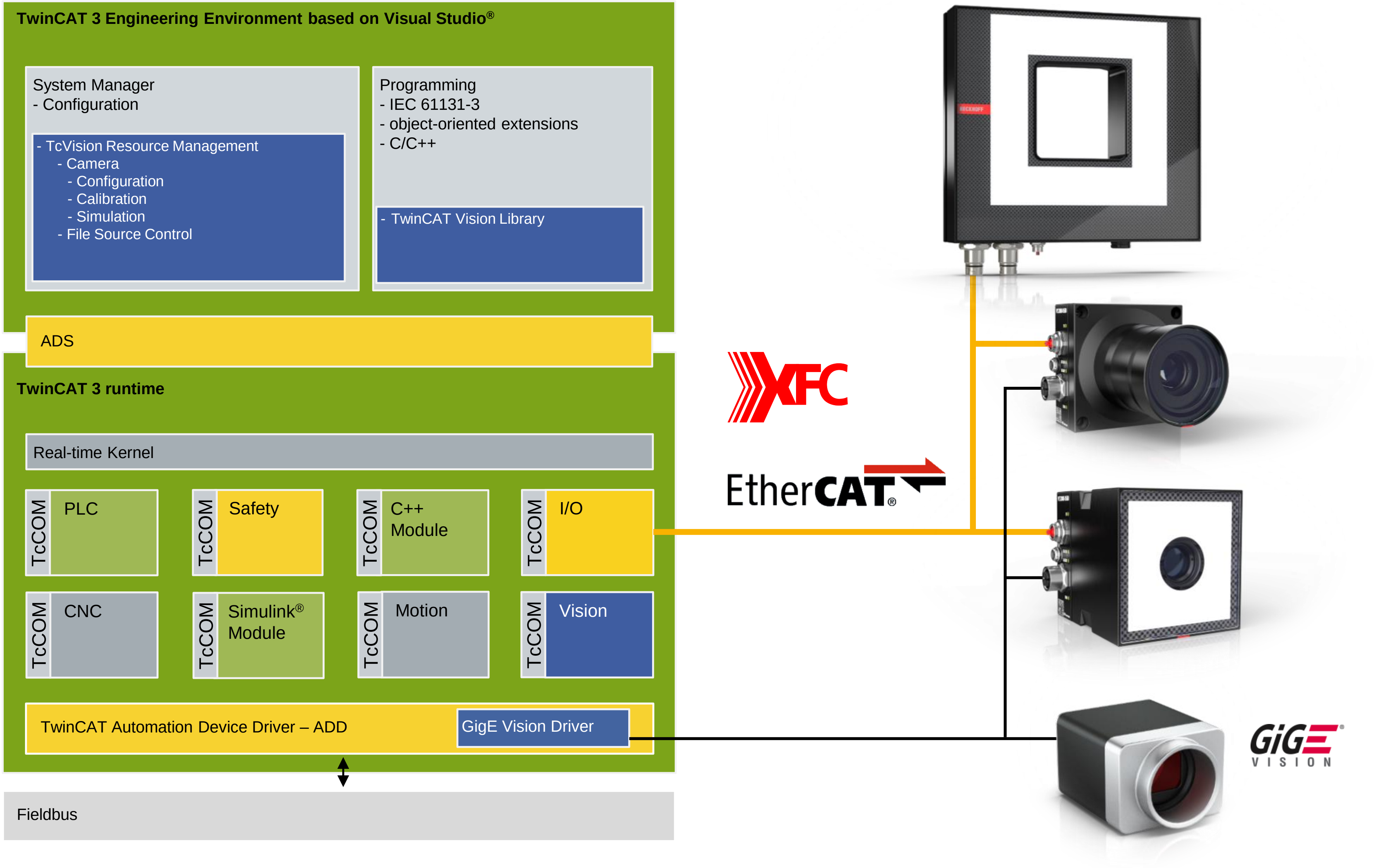


TwinCAT Vision Library



ADS Image Watch





Beckhoff solution | Software applicatie

BECKHOFF

Visie analyse / strategie

- Selectie van verschillende ROIs om een bepaalde type visie applicatie uit te voeren
  - Geïntegreerd met OOP → meer flexibiliteit
  - Parameters geïntegreerd in een JSON document

Voorbeeld

- Applicatie ROI 1 : Lamp detectie
- Applicatie ROI 2 : Lamp detectie
- Applicatie ROI 3 : Meter detectie
- Applicatie ROI 4 : Tekst detectie


```
"DetectFullBeamLight": {
    "ID": "DetectLamp",
    "Description": "Detect and check indicator full beam light lamp on display",
    "nLamp": 8,
    "stItemRoi": {
        "nX": 210,
        "nY": 120,
        "nWidth": 130,
        "nHeight": 100
    },
    "aColorLowerBounds": [ 80.0, 130.0, 200.0, 0.0 ],
    "aColorUpperBounds": [ 255.0, 255.0, 255.0, 0.0 ],
    "bCircularLamp": true,
    "fMinAreaLamp": 100.0,
    "fMaxAreaLamp": 400.0,
    "Detected": false,
    "NextObject": "SwitchIndicatorFullBeamLightOff"
},
```

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Voorbeeld

- Applicatie ROI 1 : Lamp detectie
- Applicatie ROI 2 : Lamp detectie
- Applicatie ROI 3 : Meter detectie
- Applicatie ROI 4 : Tekst detectie


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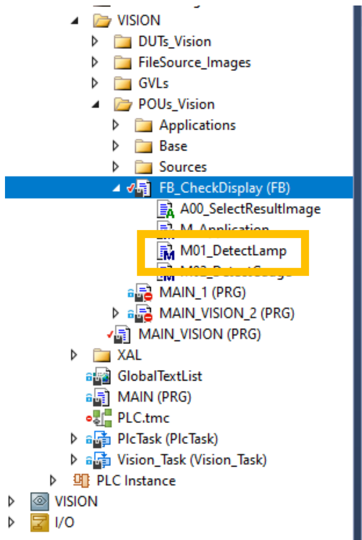
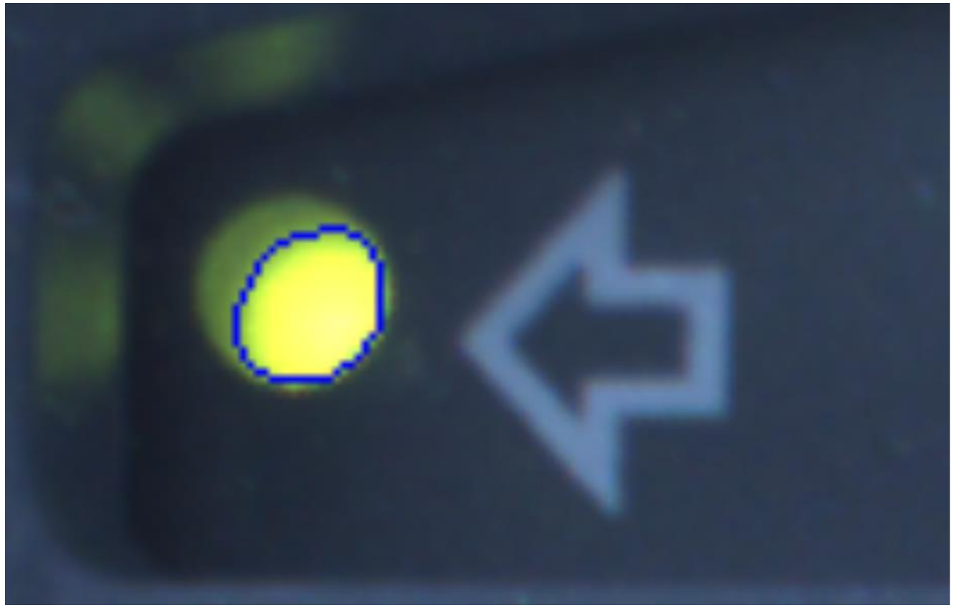



```
// Return pending state
M_Application       := S_PENDING;

IF FAILED(hrPrev) THEN
    M_Application := hrPrev;
    RETURN;
ELSE
    hr := s_ok;
END_IF

IF ipSrcImage = 0 THEN
    M_Application := Tc2_System.E_HRESULTAdsErr.INVALIDPARM;
    RETURN;
END_IF

hr := F_VN_ConvertColorSpace(ipSrcImage, ipSrcImage, TCVN_CST_Bayer_RG_TO_RGB, hr);
hr := F_VN_RotateImage(ipSrcImage:= ipSrcImage, ipDestImage:= ipSrcImage, eAngle:= TCVN_RA_180_DEG, hrPrev:= hr);
hr := F_VN_CopyImage(ipSrcImage, ipDestImage, hr);

// ***********  APPLICATION ***************

CASE eDisplayItem OF

    E_DisplayItems.Overview :
        ;

    E_DisplayItems.Lamp :
        hr := M01_DetectLamp(ipSrcImage,ipImageWorkInt, ipDestImage, stDetectLamp, hr);

    E_DisplayItems.Gauge :
        hr := M02_DetectGauge(ipSrcImage, ipDestImage, ipImageWorkInt, stDetectGauge, hr);

END CASE
```

Voorbeeld

- Lamp detectie
  - Color segmentation
  - Blob detection

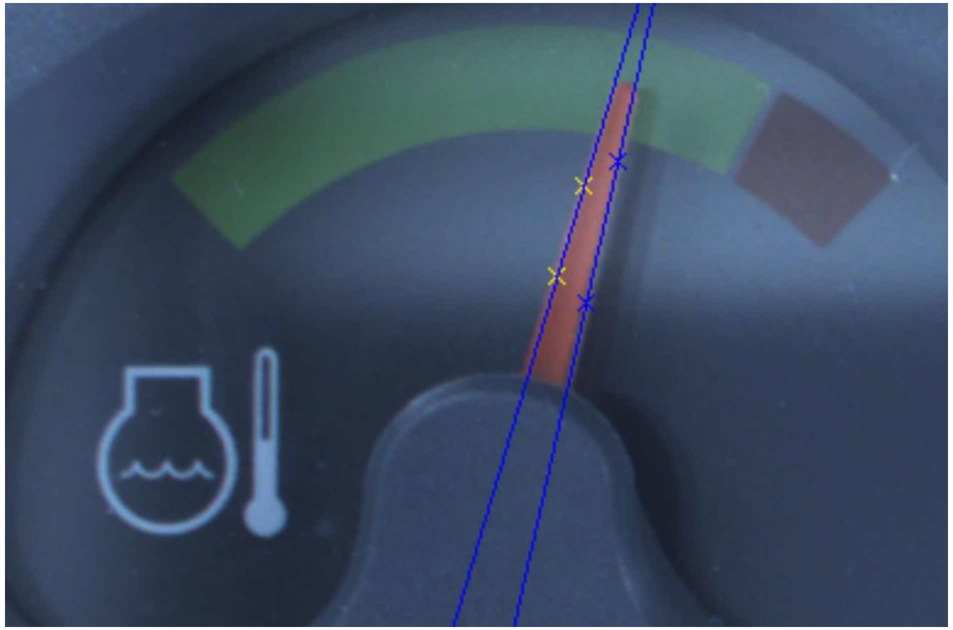
```
hr := F_VN_CheckColorRange( ipWorkImageInt, ipWorkImageInt,
                            stDetectLamp.aColorLowerBounds, stDetectLamp.aColorUpperBounds,hr);

hr := F_VN_CopyImage(ipWorkImageInt, ipWorkImage, hr);

stBlobParams.bFilterByArea := TRUE;
stBlobParams.bFilterByCircularity := stDetectLamp.bCircularLamp;
stBlobParams.fMinArea := stDetectLamp.fMinAreaLamp;
stBlobParams.fMaxArea := stDetectLamp.fMaxAreaLamp;

hr := F_VN_DetectBlobs(ipWorkImageInt, ipLampContour, stBlobParams, hr);
```



Voorbeeld

- Meter detectie
  - Kleur segmentatie
  - Blob detectie
  - Polygoonbenadering
  - Twee lijnen extraheren

```
hr := F_VN_CheckColorRange( ipImageWorkInt_1, ipImageWorkInt_1,
                            stDetectGauge.aColorLowerBounds, stDetectGauge.aColorUpperBounds, hr);

stBlobParams.bFilterByArea := TRUE;
stBlobParams.fMinArea := 500;
stBlobParams.fMaxArea := 3000;
stBlobParams.fMinThreshold := 70;

hr := F_VN_DetectBlobs(ipImageWorkInt_1, ipContours, stBlobParams, hr);

hr := F_VN_GetNumberOfElements(ipContours, nNumberOfElements, hr);

IF nNumberOfElements >= 1 AND nNumberOfElements <=5 THEN

    hr := F_VN_GetAt_ITcVnContainer(ipContours,ipContour, 0, hr);

    hr := F_VN_ApproximatePolygon(ipContour, ipArrowContour, 0.5, TRUE, hr);

    hr := F_VN_GetNumberOfElements(ipArrowContour, nNumberOfArrowElems, hr);

    // Find two lines from polygon points :
```



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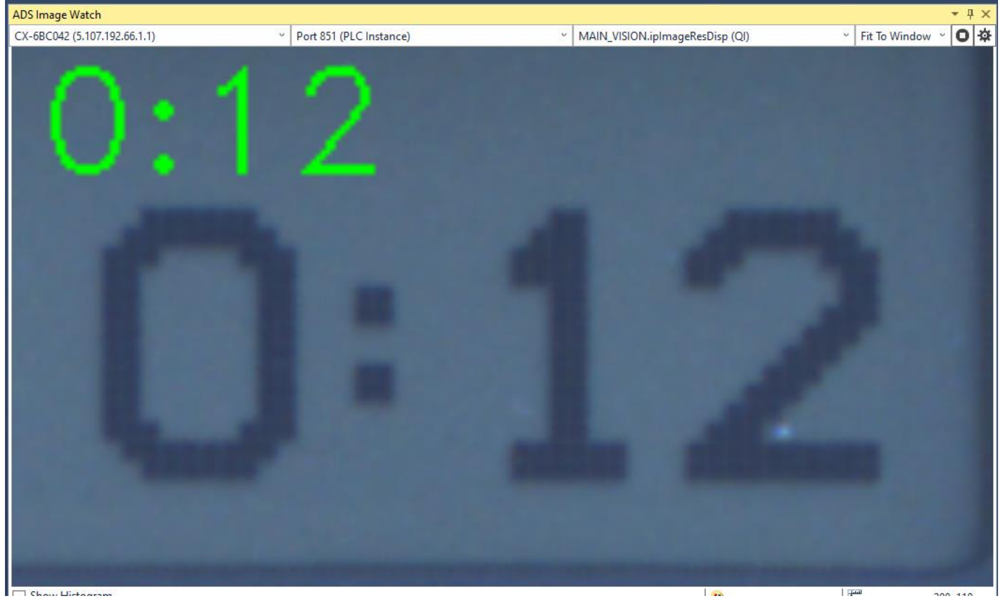
Voorbeeld

- Tekst detectie
  - Thresholding
  - OCR functie
  - Tekst extraheren

```
// Invert image depending on bright or dark text color
hr := F_VN_Threshold(ipWorkImageInt, ipWorkImageInt, 70, 255, TCVN_TT_BINARY_INV, hr);

// Remove border objects
hr := F_VN_BrightBorderObjects(ipWorkImageInt, ipThreshBorder, hr);
hr := F_VN_SubtractImages(ipWorkImageInt, ipThreshBorder, ipWorkImageInt, hr);

hr := F_VN_CopyImage(ipWorkImageInt, ipWorkImage, hr);

// Read characters
hrOCR := F_VN_OCR(
                ipSrcImage      := ipWorkImageInt,
                eModel          := ETcVnOcrModelType.TCVN_OMT_NUMBERS_SC,
                ipCharacters    := ipCharacters,
                hrPrev          := hr);

// Check if characters were found
hr := F_VN_GetNumberOfElements(ipCharacters, nNumberOfElements, hr);
IF SUCCEEDED(hrOCR) AND nNumberOfElements > 0 THEN
    // Export character to string
    hr := F_VN_ExportSubContainer_String(ipCharacters, 0, sText, 255, hr);
    nStringLenght := LEN(sText);

    // Write text result to filtered and original image
    hr := F_VN_PutText(sText, ipDestImage, 5, 25, TCVN_FI_HERSHEY_DUPLEX, 1, aColorGreen, hr);
END_IF
```



Demo

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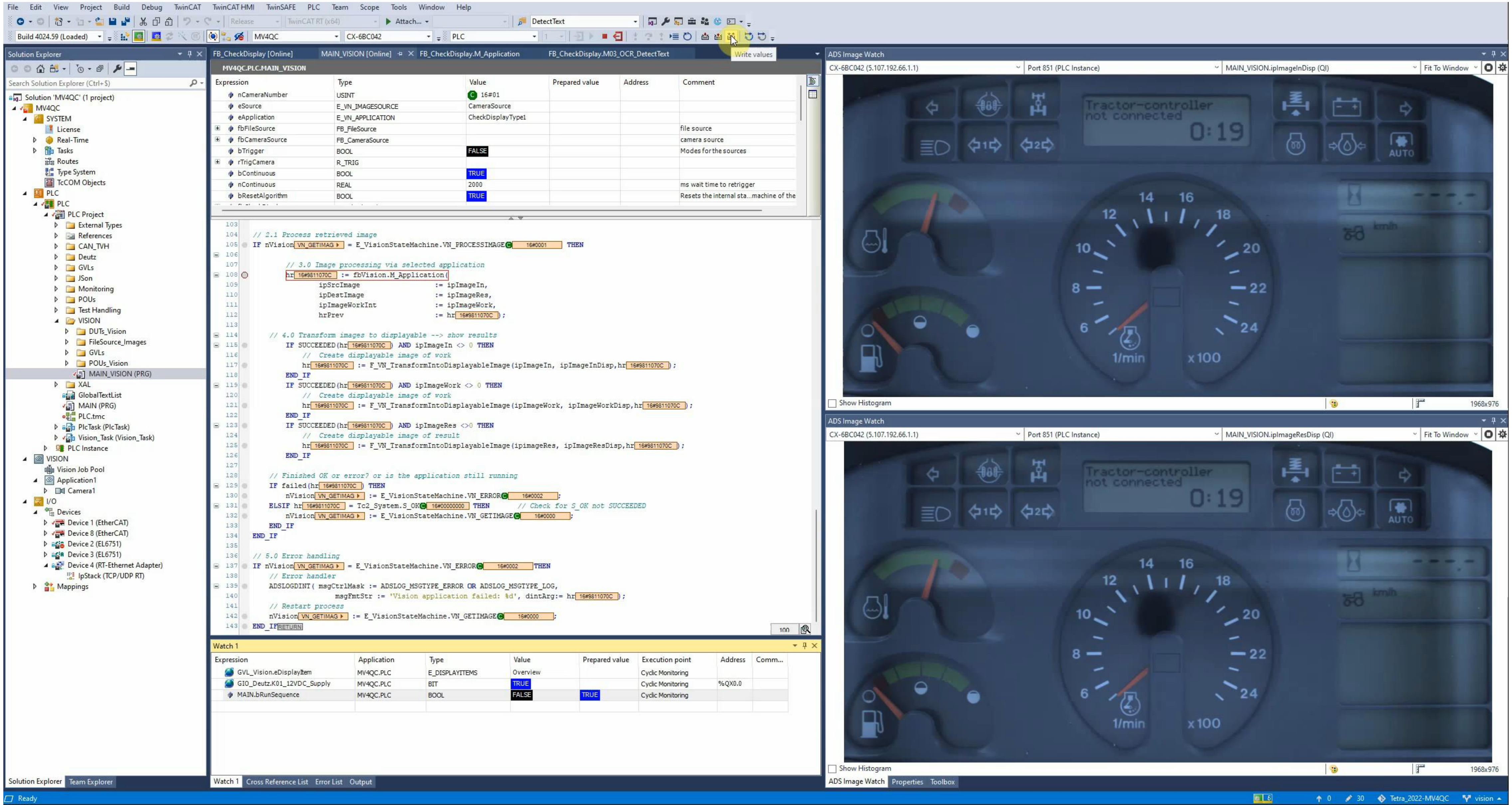

Contact

BECKHOFF

Beckhoff Automation bv
Hoofdkantoor België
Klaverbladstraat 11.2/2
3560 Lummen

Kantoor West
Blokkestraat 41A
8550 Zwevegem

Phone: +32 13 25 22 00
E-Mail: info@beckhoff.be
Web: www.beckhoff.com/nl-be/

VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Bepalen van het vetgehalte in donuts

Vandemoortele

- Arne De Temmerman (KU Leuven) -

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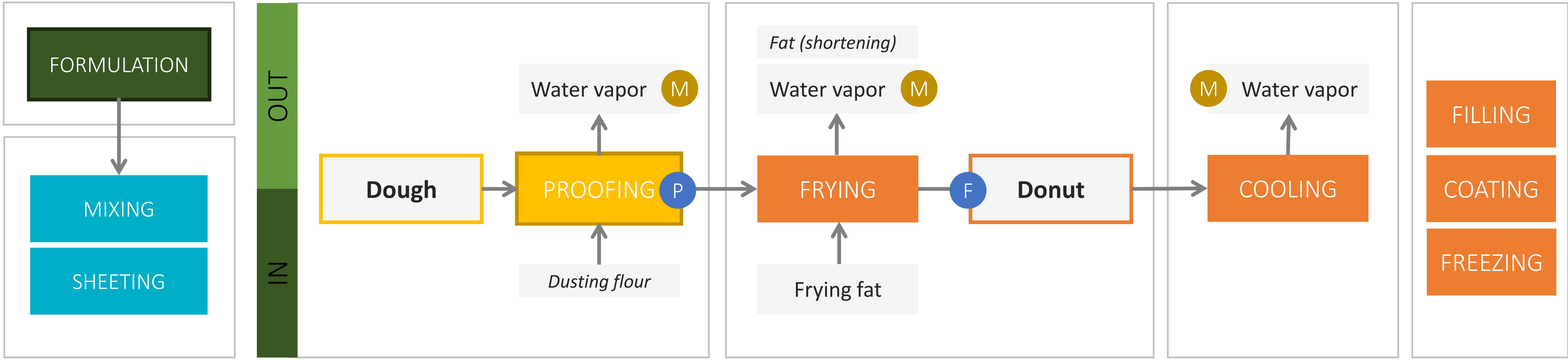
DEEP-DIVE IN FAT ABSORPTION

$$LSL \leq \frac{F - P}{F} \times 100 = FA\ (\%) \leq USL$$



WEIGHT-BASED FAT ABSORPTION MEASUREMENT

- Doesn't incorporate additional (interaction) effects
- Highly sensitive to operator execution

➔ Insufficiently accurate for monitoring or immediate adjustment of process parameters

ACTIONS WHEN DEVIATION IS OBSERVED

- Combined effect on fat absorption and other quality attributes (e.g., volume)
- Additional offvariation in weight-based reading is introduced

With the support of VLAIO

Problem statement

- **Deviating and varying fat absorption** values have **negative effects** on product quality.
  - Product weight is critical for customer (retailers)
  - Variations in the fat quantity and type result in a different end user experience
- The multistage manufacturing process is highly **susceptible to initial process parameters** and **environmental changes**.
- **Quality system requirements:**
  - Non-destructive
  - Non-contact
  - Large-volume
  - Accurate
  - Fast

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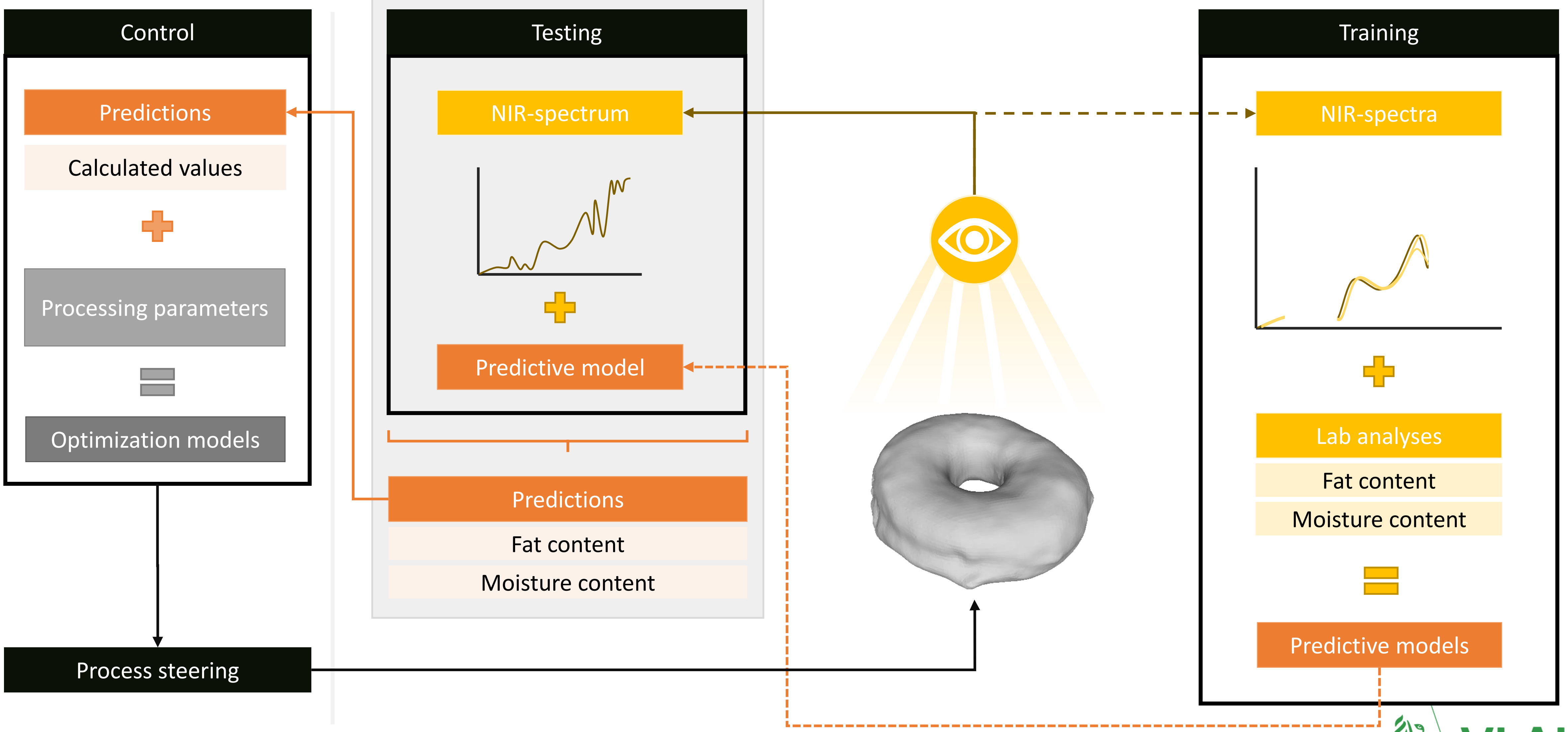
Principle



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Spectrometry setup

- 256 spectral bands of < 7.9 nm
- NIR spectral range between 1100 and 2100 nm
- Sample distance between 0-50 mm

Fig. 3: PAS-H-B01 contact sensor head

Fig. 2: Polytec Advanced Spectrometer (PAS) - 2120 NIR spectrometer

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Non-corrected NIR-Dataset

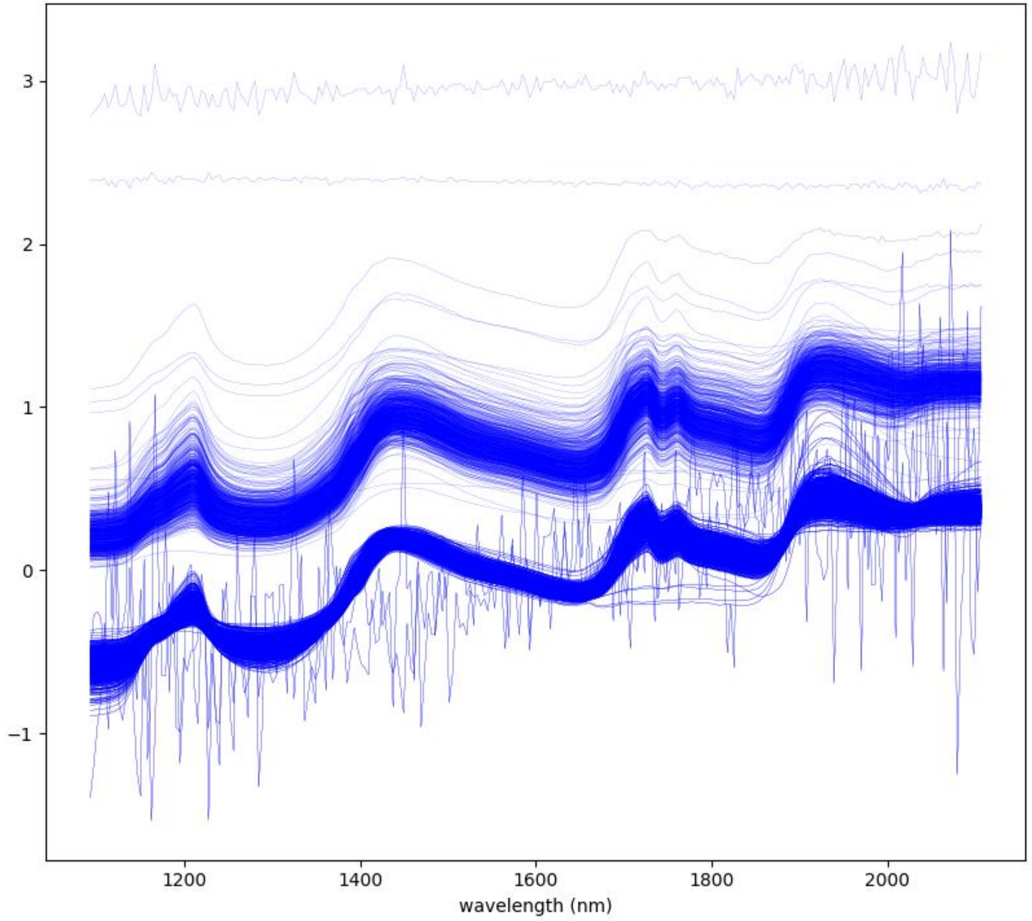

Fig. 4: Non-corrected response spectra

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Spectral alignment, normalisation and outlier filtering

Caused by:
- Misalignment over the sensor
- Variation of sample texture
- Variation of sample transparency

Alignment and normalisation with:
- Multiplicative scatter correction (MSC)
- Standard Normal Variate (SNV)

Filtered by a combination of:
- MSE (Mean Squared error)
- Mahalanobis distance
- Cosine similarity

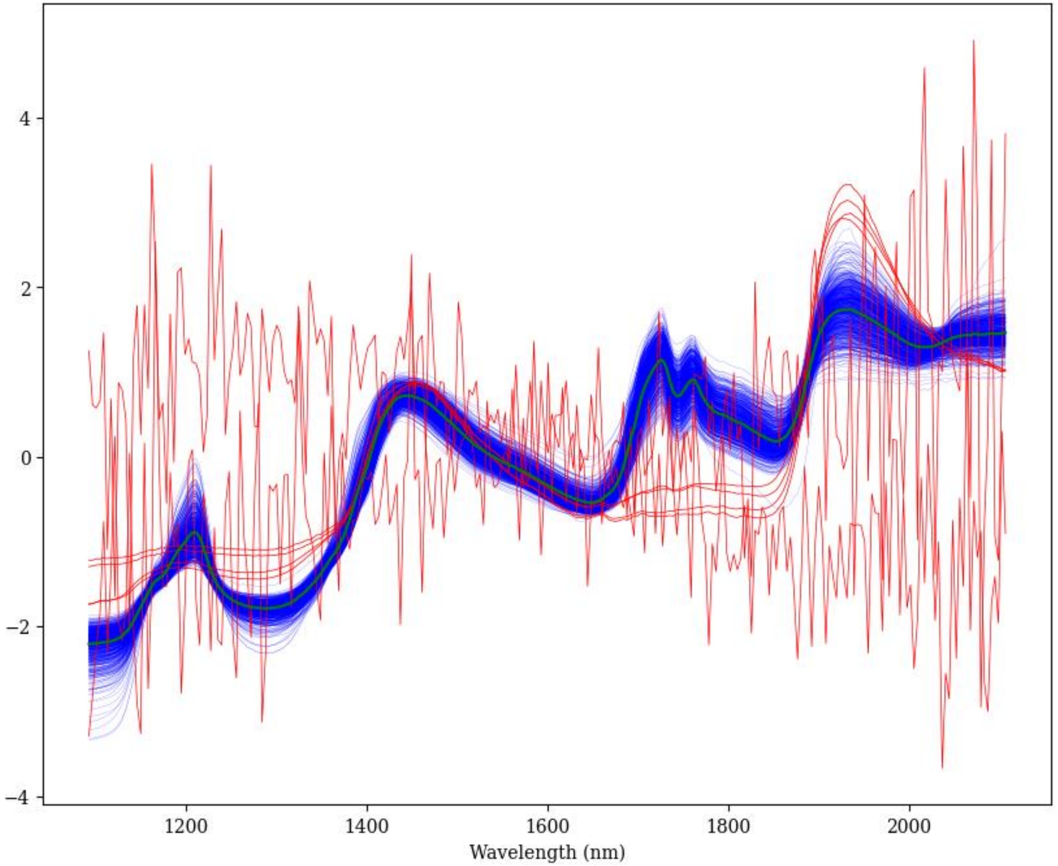

Fig. 6: FFC & SNV corrected spectra (blue) with removed outliers (red)

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Resulting spectra

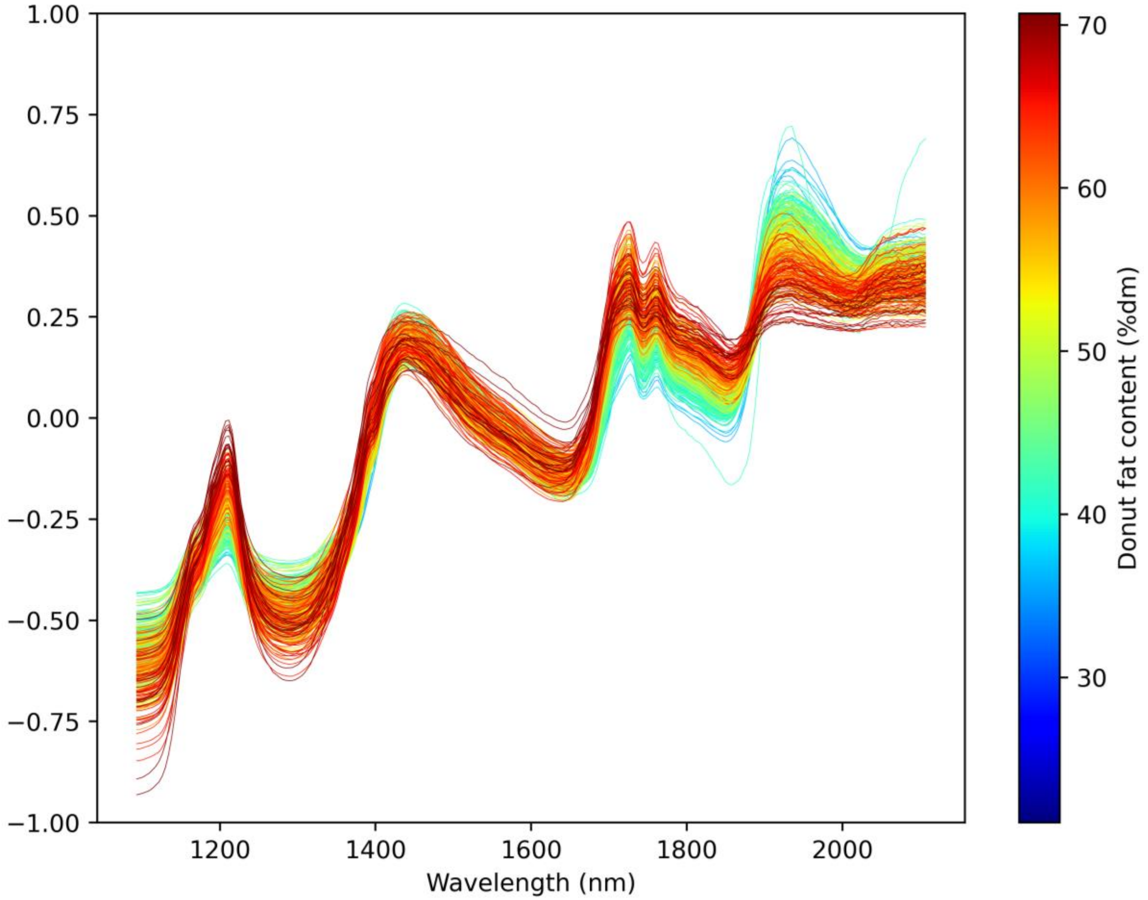

Fig. 7: Hyperspectral response between 1100 and 2100 nm colored by the dry mass percentage of fat content

Fat & Moisture prediction - models

Partial least-squares regression (PLS-R-10)

P. Geladi and B. R. Kowalsk

Least-squares support vector machine (LS-SVM)

J. A. Suykens, L. Lukas, and J. Vandewalle

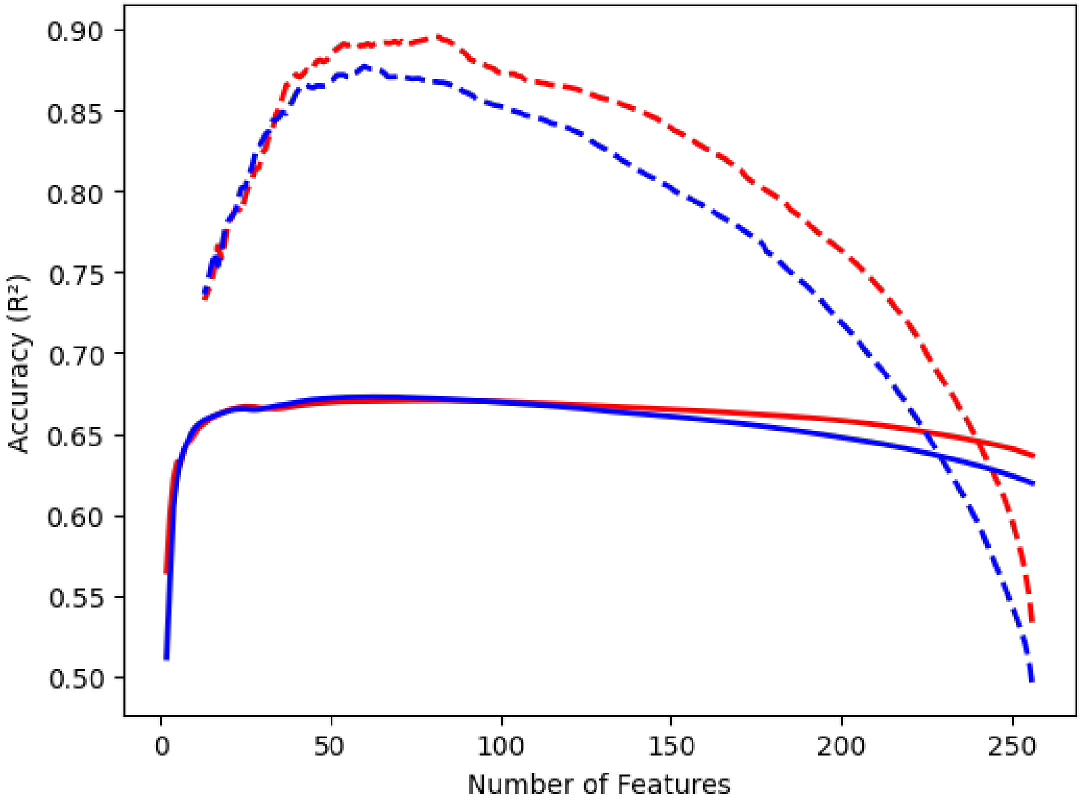

Fig. 11: Comparison of the accuracy between PLS-R (dashed) and LS-SVM (full) for both the fat (red) and moisture (blue) content.

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Fat & Moisture prediction - results

Reference method (Lab NIR model)

$RMSE_{CV}$ = 1.44 (fat)

Hyperspectral analysis

$RMSE_{CV}$ = 4.20 (fat)

$RMSE_{CV}$ =1.83(moisture)

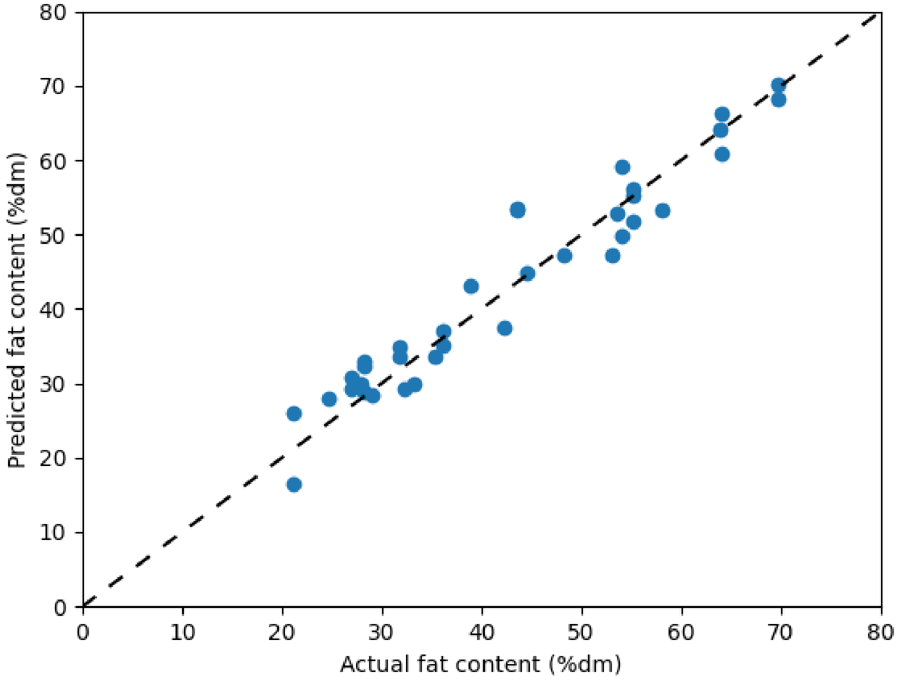

Fig. 12: The prediction of the best performing model, PLRS (SNV+ SD), plotted against the actual fat content

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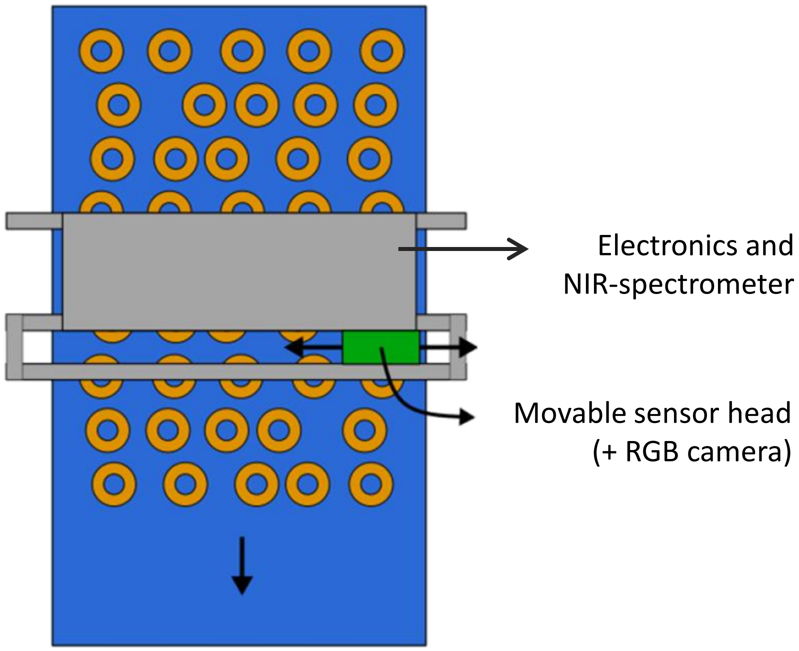
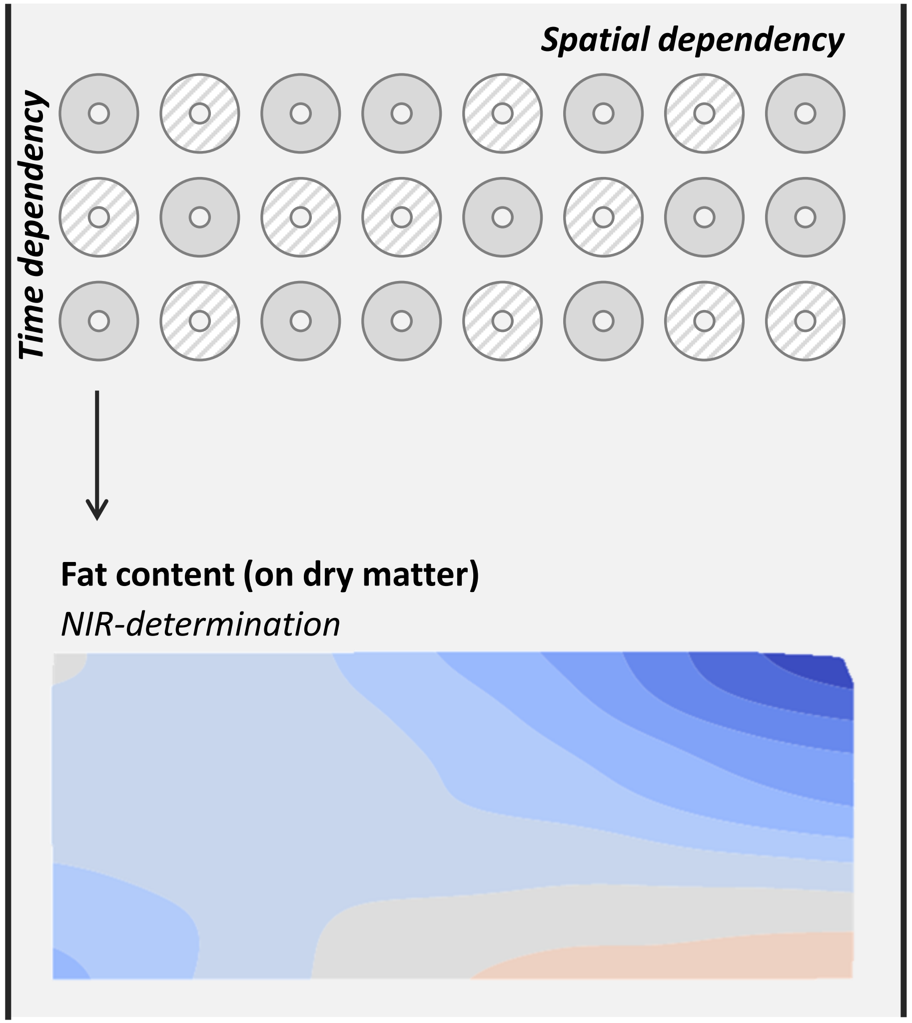
INDUSTRIAL PROOF-OF-CONCEPT

COVICON

Received a detailed draft for a test installation allowing to investigate feasibility in an industrial setting





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INDUSTRIAL PROOF-OF-CONCEPT

RESEARCH STATE

PRODUCTION STAGE

Dimensions and configuration of the (temporary) installation

Concerns about the size of the installation, the hygienic design and robustness. Questions about the installation's requirements in terms of position over the conveyor belt.

Accuracy of the methodology

Different properties considered and poor overall understanding of the current accuracy makes the site hesitant for an investment. Difficult to translate to benefits.

Current and future needs

Process steering will require an understanding of the trade-offs between different quality attributes. A combined approach for fat/moisture content, weight and dimensions is preferred.

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Follow-up projects

Machine Learning Operations

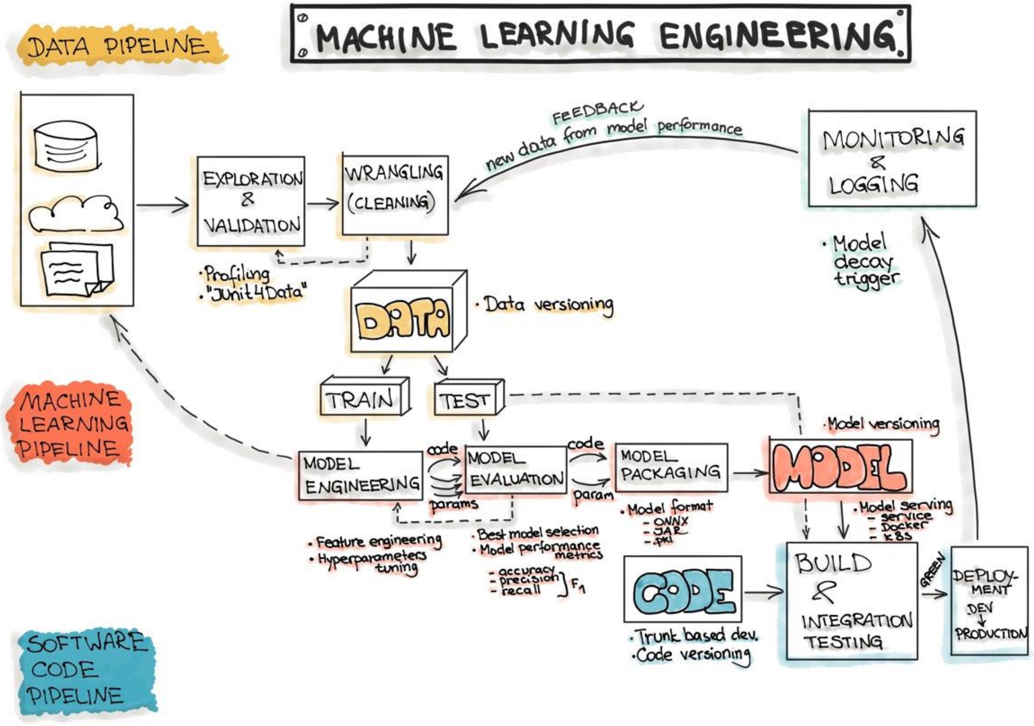
MLOps = Paradigm used to **create** and **maintain** a machine learning model that will be deployed in **production**

MLOps

ML
(Machine Learning)

+

DevOps



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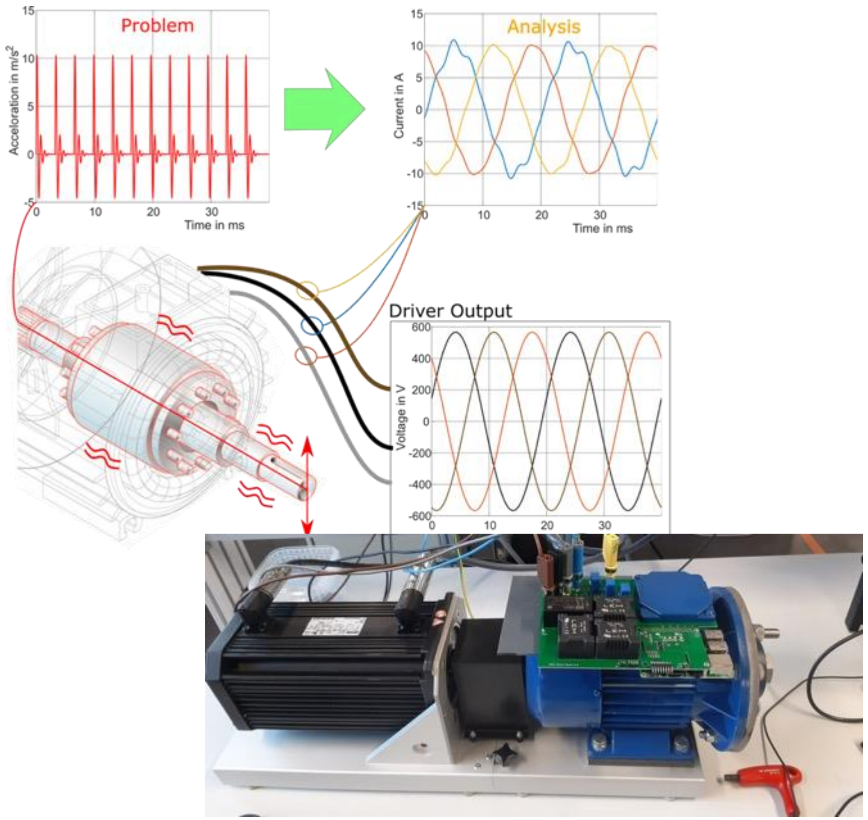
Machine Learning Operations

Ongoing VLAIO TETRA project on Machine Learning Operations for Edge Condition Monitoring

- Frequent user group meetings and workshops
- Possibility to bring in company use case
- Knowledge exchange with a user group of >15 companies across different sectors.



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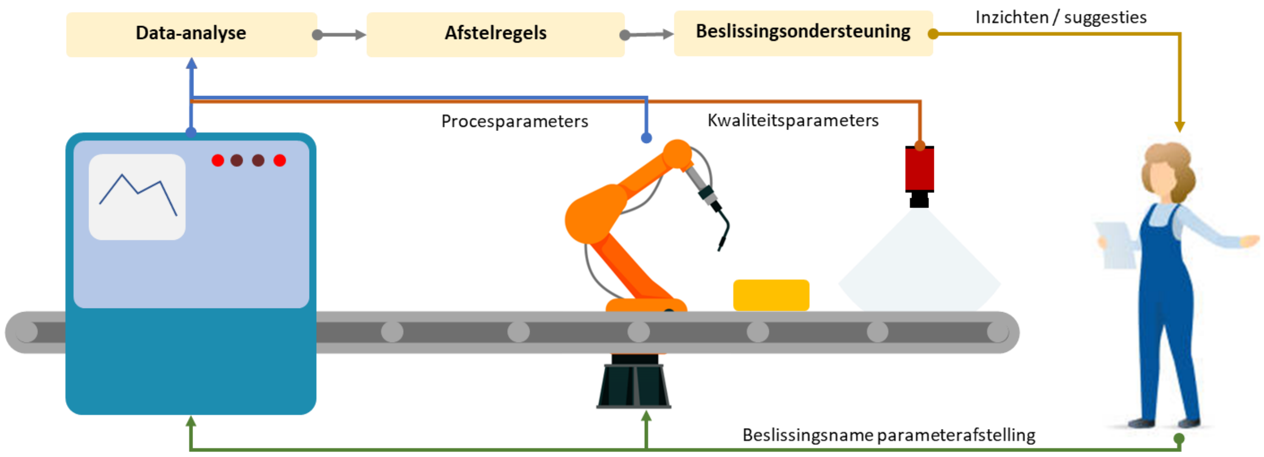
COOCK+ DeciQual

Data-gedreven beslissingsondersteuning voor kwaliteitscontrole en procesoptimalisatie

- Bepalen van invloeden van procesparameters op kwaliteitsparameters
- Communiceren van inzichten naar de operator
- Ondersteunen van operatoren in (optimale) procesafstelling



Sectoren:
Voeding – Kunststofverwerking - Machinebouw

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Do you recognize similar challenges in your own company context?

Get in touch:

Mathias.Verbeke@kuleuven.be

Jonas.Lannoo@vives.be

hogeschool vives

KU LEUVEN BRUGGE

Thanks to

ACTEMIUM

ALTACHEM LINDAL GROUP

BECKHOFF

Ysco

CAPTIC

cataél PARTNERS IN AUTOMATION

COVICON

CTRL engineering

DEPREZ HANDLING SOLUTIONS Taking better care of goods

Milcobel

iDS

inagro

ILVO

Innomatic industrial resolution

ISOTRON OUR HEARTS BEAT AUTOMATION

KOMOTION FAR MORE THAN AUTOMATION

L.E.T. group

marelec A DURAVANT COMPANY

Melexis INSPIRED ENGINEERING

MITSUBISHI CHEMICAL GROUP Advanced Materials

DECOSPAN Wood Solutions

TVH

Vandemoortele shaping a tasty future

vintecc CREATING SMARTER MACHINES

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Thanks to

Onderzoekers:

- Matthias De Ryck (KU Leuven Brugge)
- Arne De Temmerman (KU Leuven Brugge)
- Quinten Danneels (KU Leuven Brugge)
- Peter Vanbiervliet (Hogeschool VIVES Kortrijk)
- Shan Rizvi (Hogeschool VIVES Kortrijk)

Promotoren:

- Mathias Verbeke (KU Leuven Brugge)
- Jonas Lannoo (Hogeschool VIVES Brugge)

Pauze / Postersessies / Demo's / Labo rondleidingen

Labo rondleidingen:

- Groep 1 – 16:00
- Groep 2 – 16:15
- Groep 3 – 16:30

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Symposium
Machine Vision for Quality Control

WiFi

Website

TETRA Machine Vision for Quality Control (MV4QC)