HBC.2022.0062

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KU LEUVEN

VLAIO TETRA
Machine Vision for Quality Control
(MV4QC)

https://www.mv4qc.be

Tussentijdse vergadering IV

Met de steun van VLAIO

Agenda

- Status project
- Toelichting cases fase 2
- Toelichting demonstrator Vives
- Succesverhalen Captic & Innomatic

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Status project - leverbaarheden

- ✓ L1.1 Startvergadering (12/10/2022)
- ✓ L1.2 Rapport die de aanwezige kennis, noden, mogelijke toepassingen, en vijf geselecteerde cases beschrijft (Rapport WP1)
- ✓ L2.1 Rapport die de bestaande technieken bundelt (Rapport WP2)
- ✓ L2.2 Seminarie over de gebundelde technieken (Masterclass op 23-24 oktober)
- ✓ L3.1 Rapport die de praktische kennis bundelt (Rapport WP3)
- ✓ L3.2 Seminarie over de praktische kennis (15/02/2023)
- ❑ L4.1 Vijf uitgewerkte use-cases
- ✓ L4.2 Inschakelen van studenten voor het uitwerken van de use-cases en demonstratoren
- ✓ L4.3 Rapport over de vijf uitgewerkte use-cases
- ❑ L4.4 Twee ontwikkelde demonstratoren (1/2 afgerond)
- ❑ L4.5 Workshop rond de demonstratoren (Workshop op 22 en 23 februari)
- ❑ L5.1 Economische evaluatie en haalbaarheidsstudie
- ❑ L5.2 Rapport over de economische evaluatie en haalbaarheidsstudie
- ✓ L6.1 Cursusmateriaal dat zal ingezet worden binnen het vak ‘Machinevisie’ en Manama ‘AI for Business and Industry’
- ❑ L6.2 Finale begeleidingsgroep vergadering
- ❑ L6.3 Webinar voor doelgroep
- ✓ L6.4 Website

Toelichting cases

Fase 2

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Case 1

Detection of surface damage on flat sheets

Decospan

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Case 1

Detection of surface damage on flat sheets

MCAM

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Covicon – Overzicht cases

Case 1 MCAM

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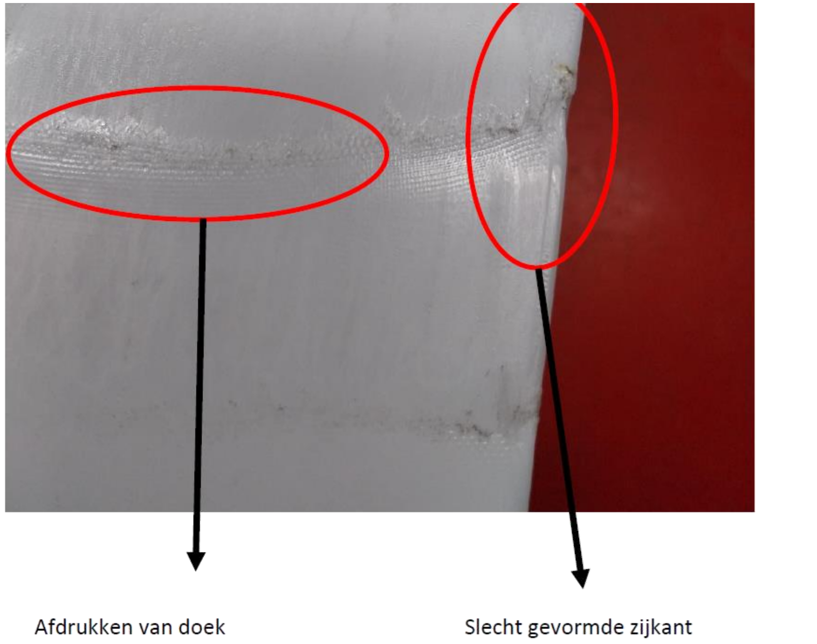
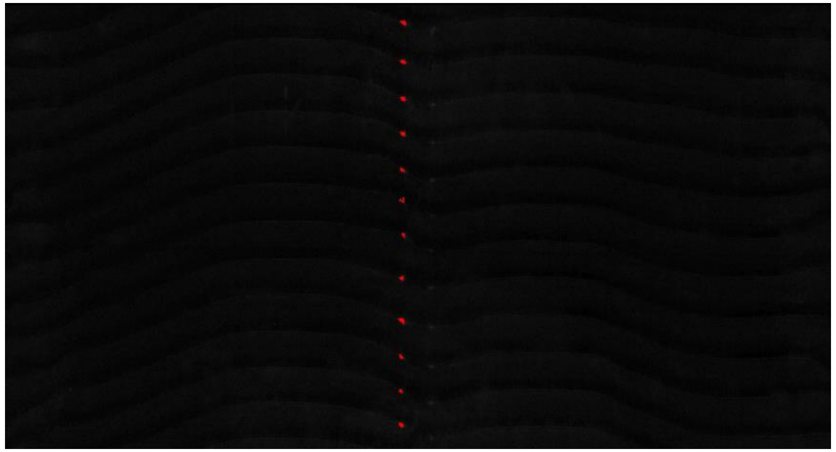
Case 1 MCAM – Probleem & doelstelling

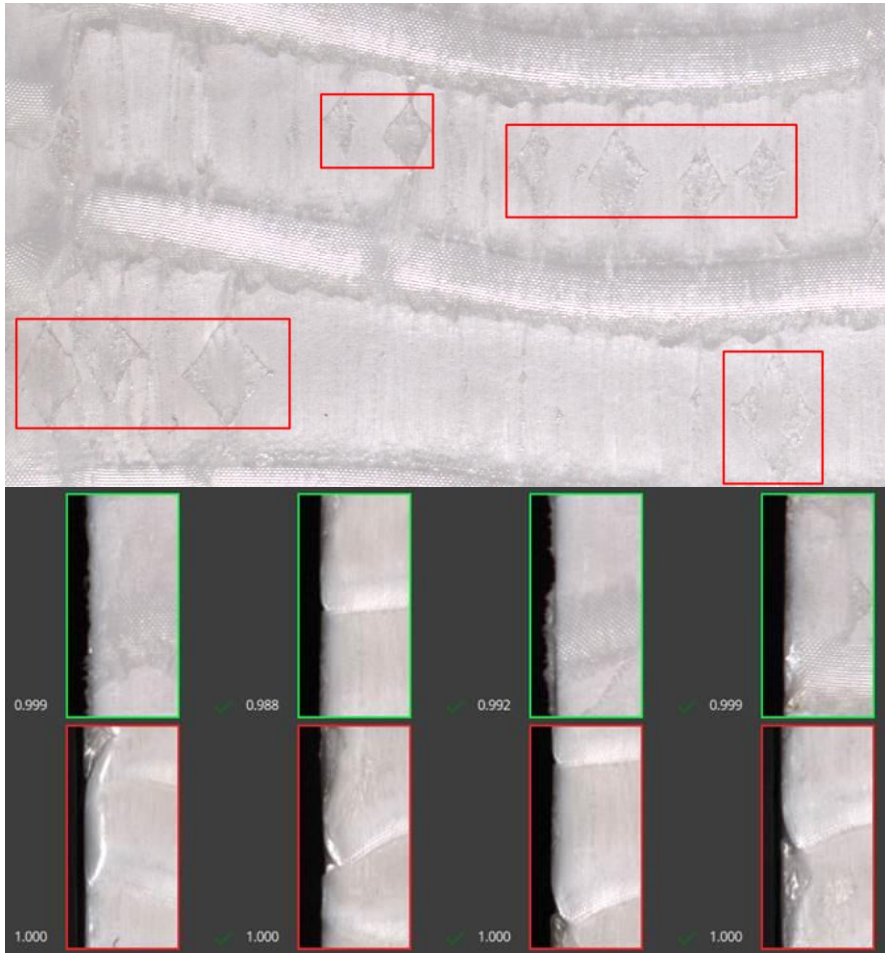
- Extrusie platen vertonen vaak problemen
  - Nepen & inkepingen
  - Brandplekjes
  - Kleeffouten
  - Ongewenste patronen
  - Slecht gevormde zijkanten
- Doelstelling
  - Auto inspectie om zo snel mogelijk in te grijpen



Case 1 MCAM – Van waar komen we?

- Uitgevoerde testen @Covicon
  - Linescan 4k
  - Linelight CCS





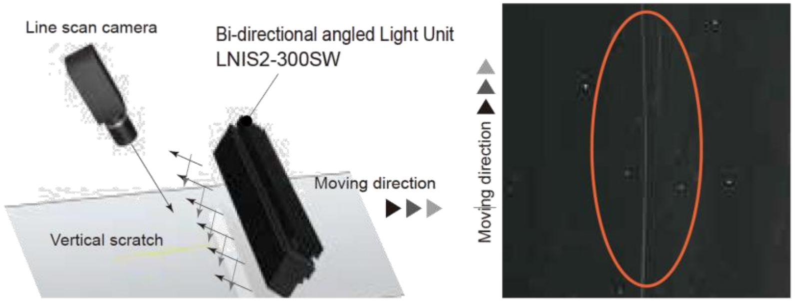
Case 1 MCAM – Mogelijke aanpakken?

- Optie 1
  - Linescan opstelling

  \+ Makkelijk om continue beeld te maken van plaat

  \- Statische opstelling

  \- speciale ‘angled’ belichting nodig (voorbeeld CCS)



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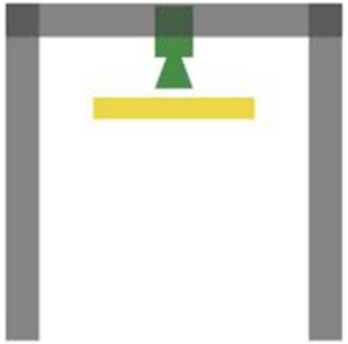
Case 1 MCAM – Mogelijke aanpakken?

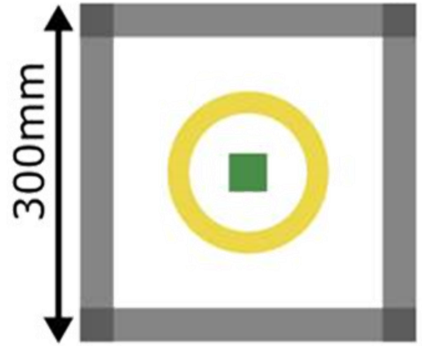
- Optie 2
  - Area scan opstelling
  - Angled light (voorbeeld Keyence)

  \+ Mobiel apparaat

  \+ Makkelijk op fout te plaatsen
  - Gecategoriseerde dataset aanmaken



Zijaanzicht



Bovenaanzicht

Case 1 MCAM – Planning

- W3/4: Opstelling optie 2 uitwerken
  - Rekening houden met finale opstelling
- W6: Opstelling assembleren en on-site gebruiken
- TODO:
  - Beelden verwerken
  - Waar komen we nog te kort?
  - Finale opstelling

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Case 2

Detectie van optimale snijlijn van witloof

Inagro

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The use case:

Optimizing the cutting process of even the most irregular products.

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Determine the ideal cutting line.

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

But

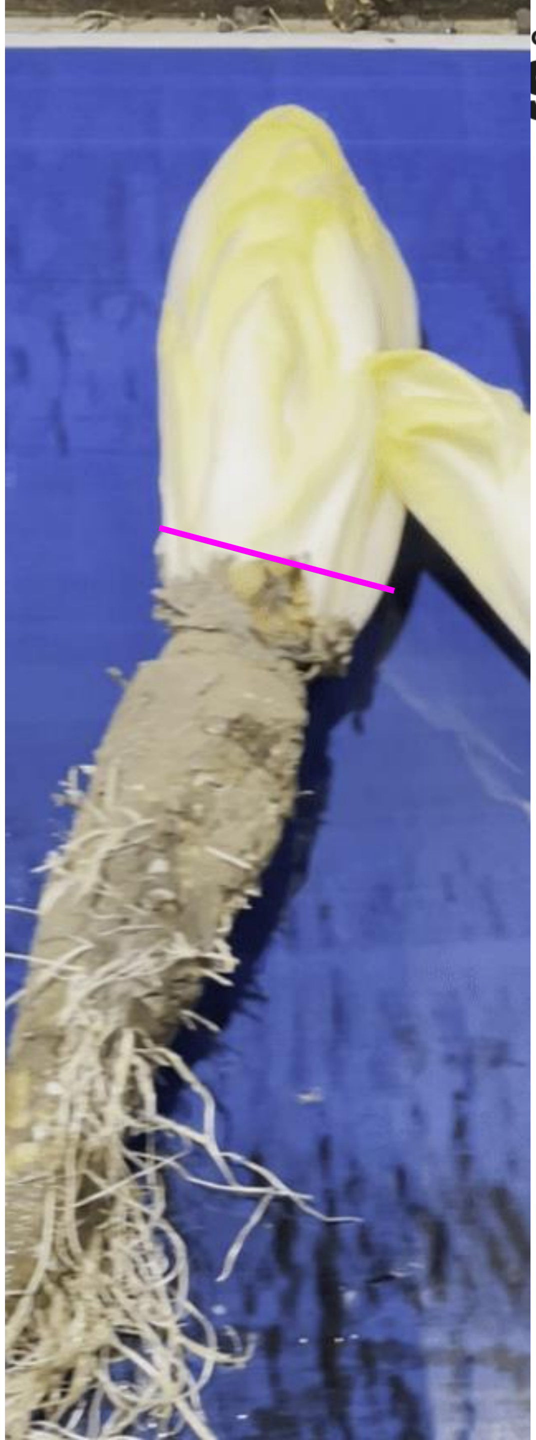
→ How do we find the root?

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

What about:

→ Orientation?

→ Overlap?



Why AI-vision is the ideal approach.

Normal sensors?

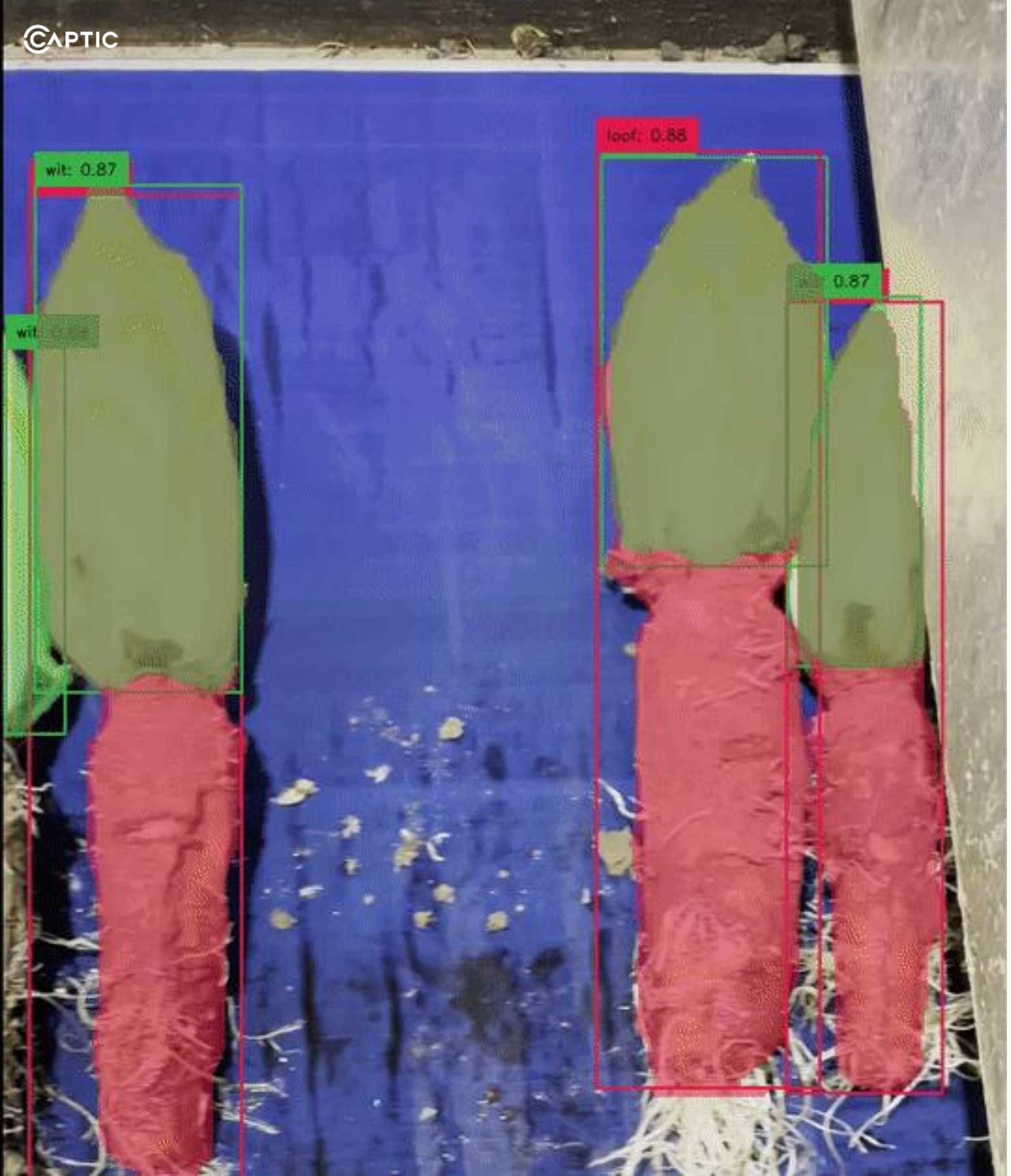
- ❌ Unable to provide the needed information

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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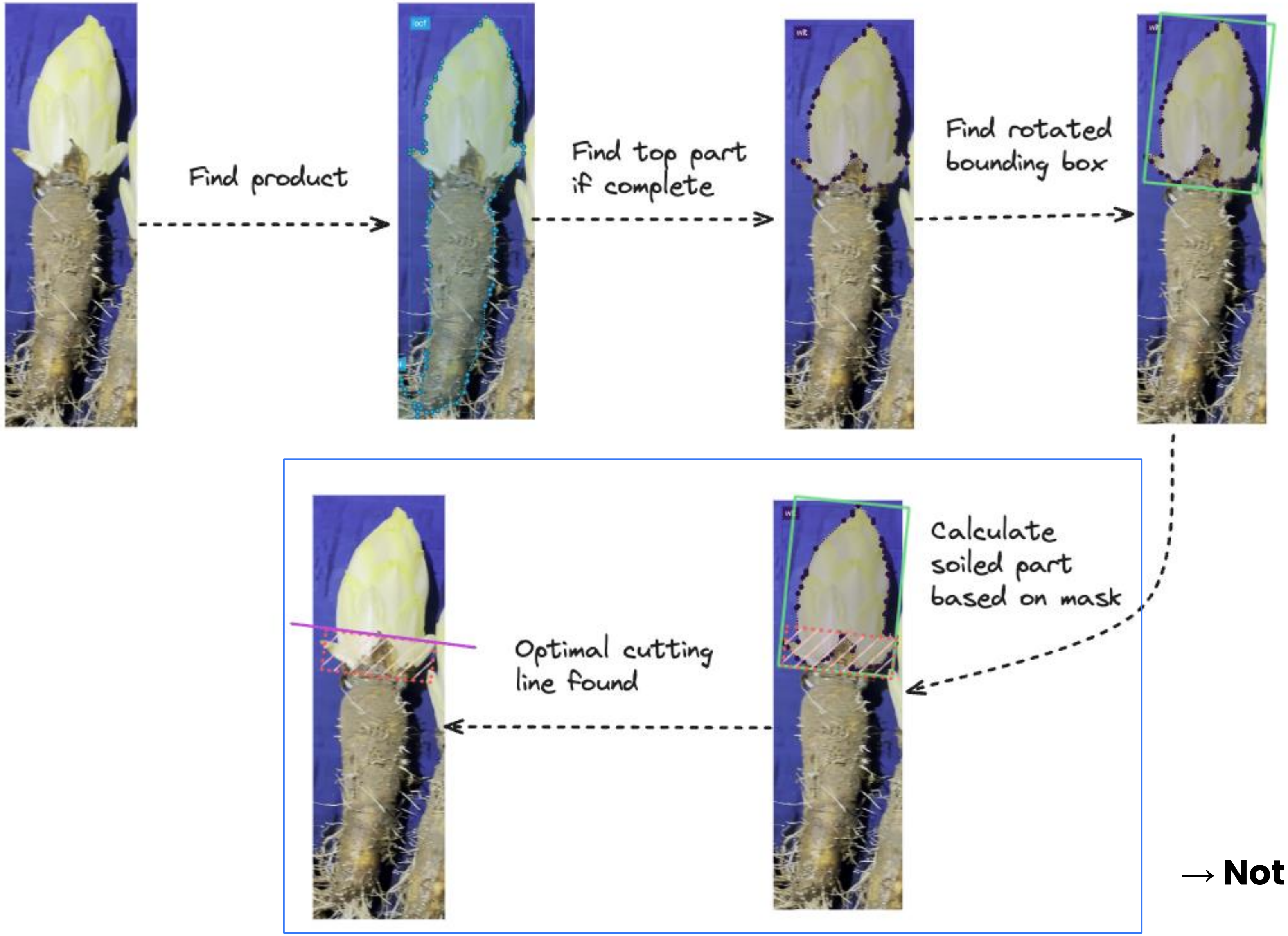
CAPTIC

Our approach.



→ **Not implemented yet**

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CAPTIC

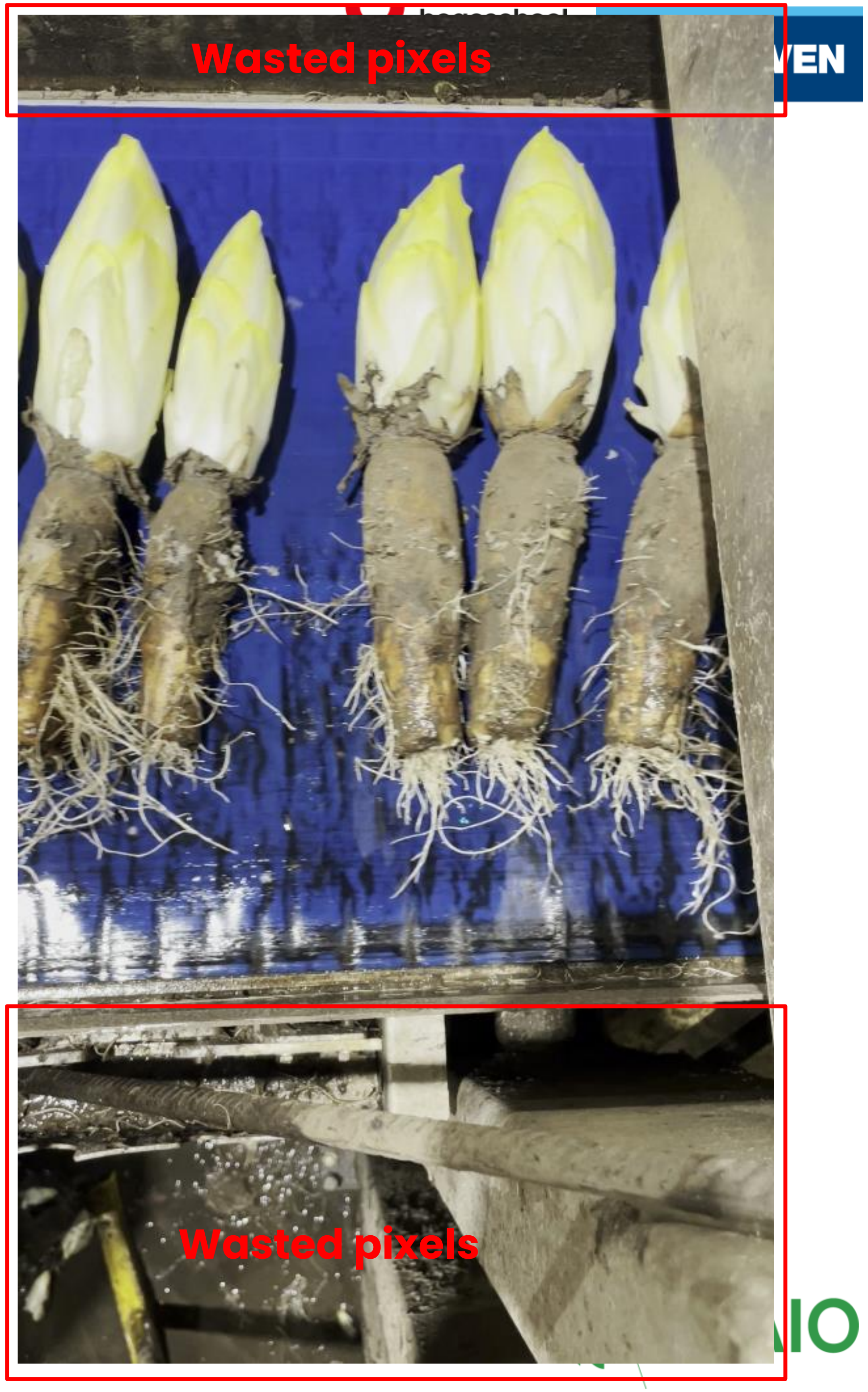
The data we used.

- Two videos
  - 2 min → Used for training
  - 2 min 45 seconds → Used for testing

- 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.

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

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.

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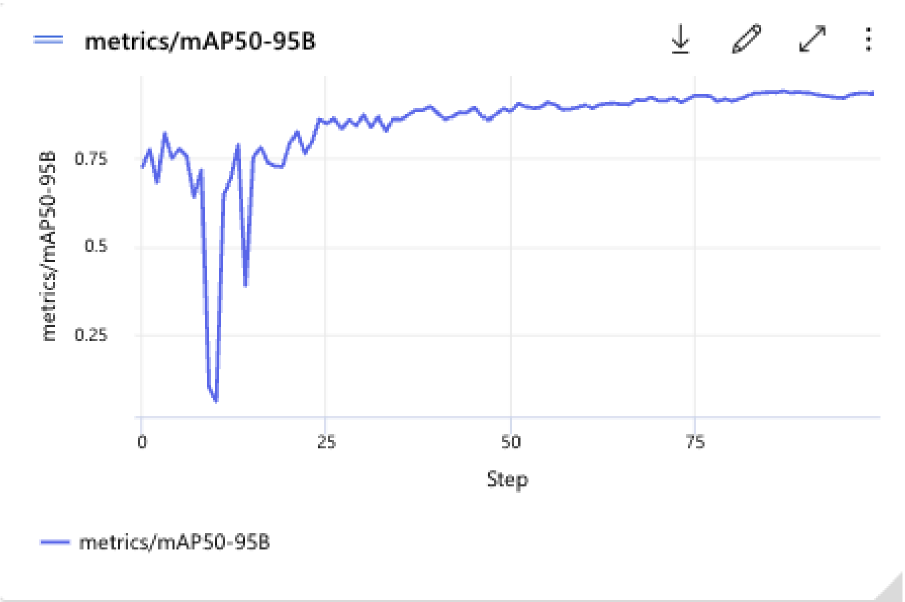
CAPTIC

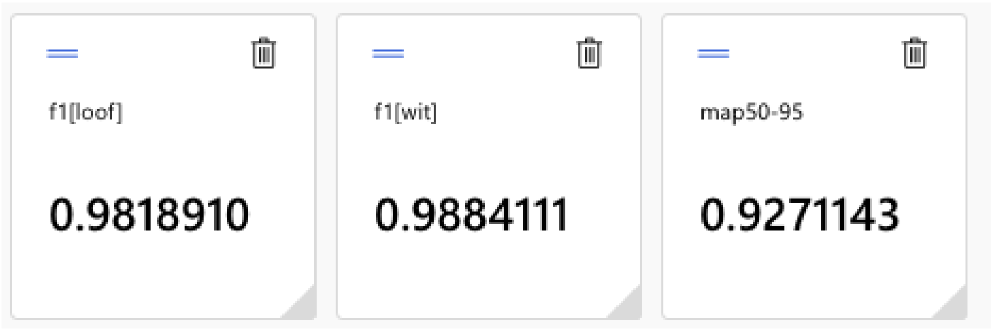
The segmentation model.

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

Azure

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





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

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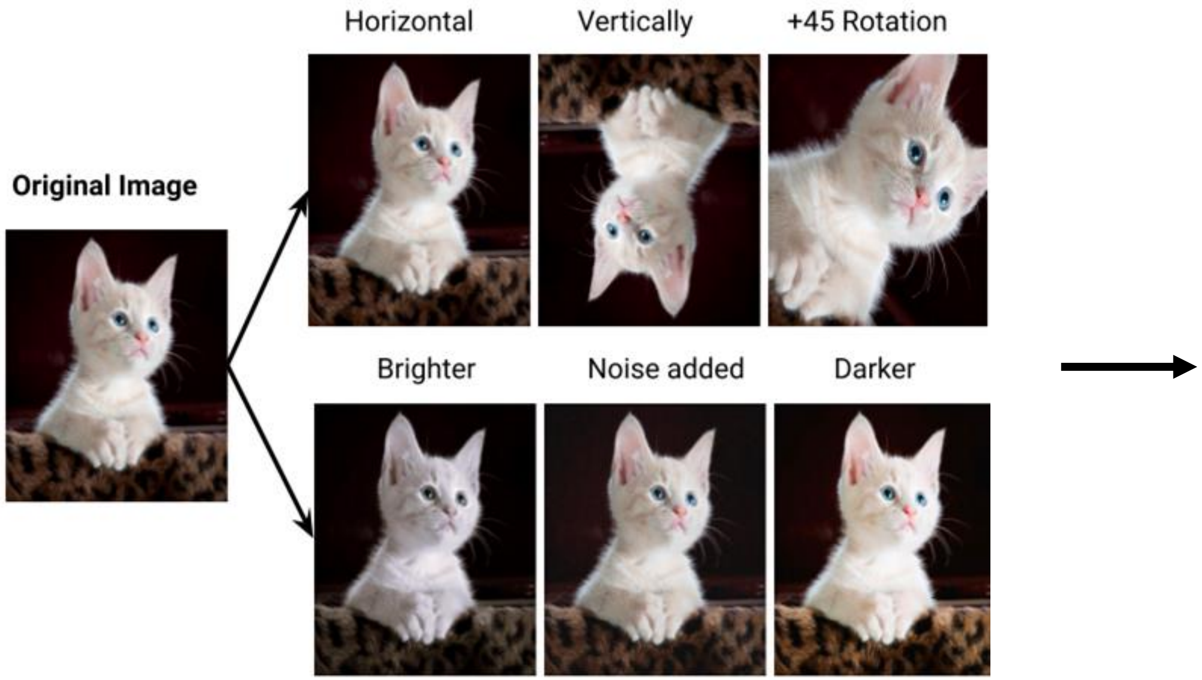
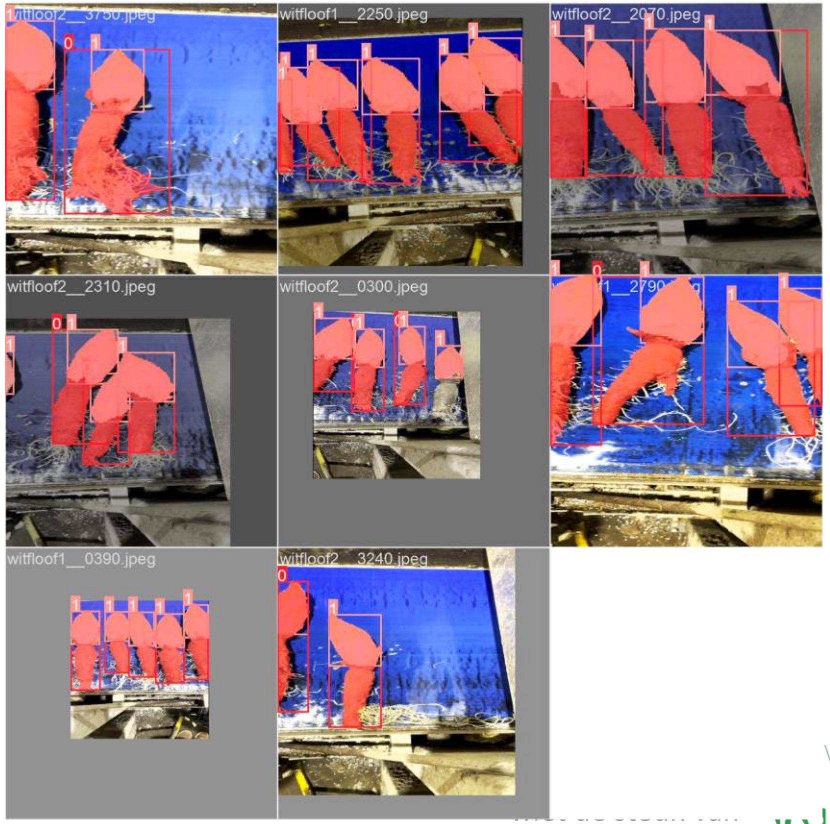
Data augmentation.

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



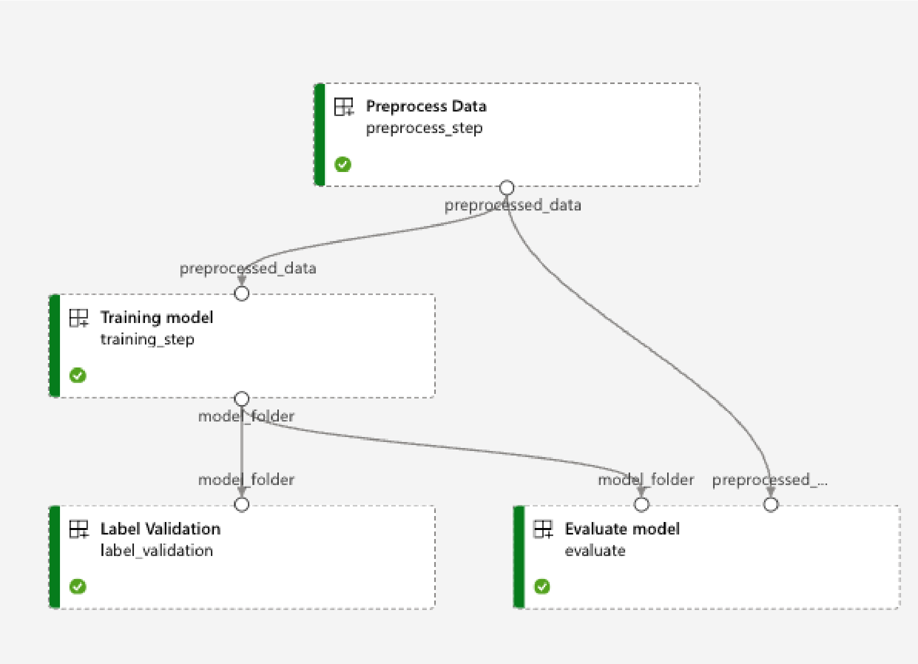


MLOps.

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
- …



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CAPTIC

Next Steps.

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Phase 1: Proving the potential

Can it be solved?

- Build small proof of concept

Next steps:
- Implement cutting line logic
- (Move to production)

→

Phase 2: Going to production

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

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Case 3

Inline determination of the length distribution of fish by category

ILVO

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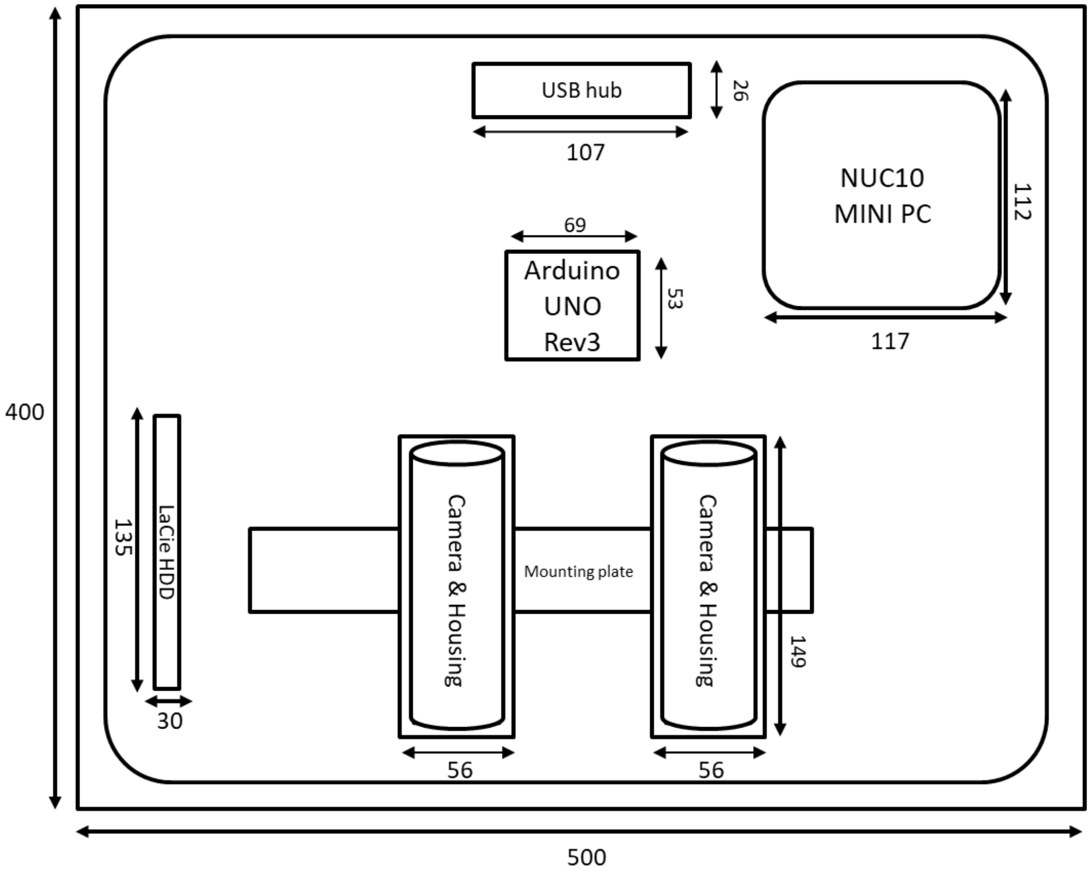
VISIM II: Toepasbaarheid van self-sampling voor het verzamelen van biologische gegevens binnen de Belgische visserijsector ter verbetering van bestandsevaluaties voor commerciële vissoorten

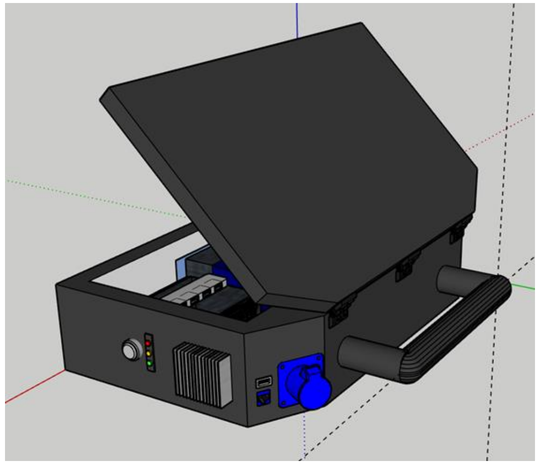
S. Delacauw, S. Vanhoorne, P.-J. De Temmerman, J. Vangeyte, E. Torreele

Medegefinancierd door de Europese Unie

Met de steun van ILVO

1ste Prototype





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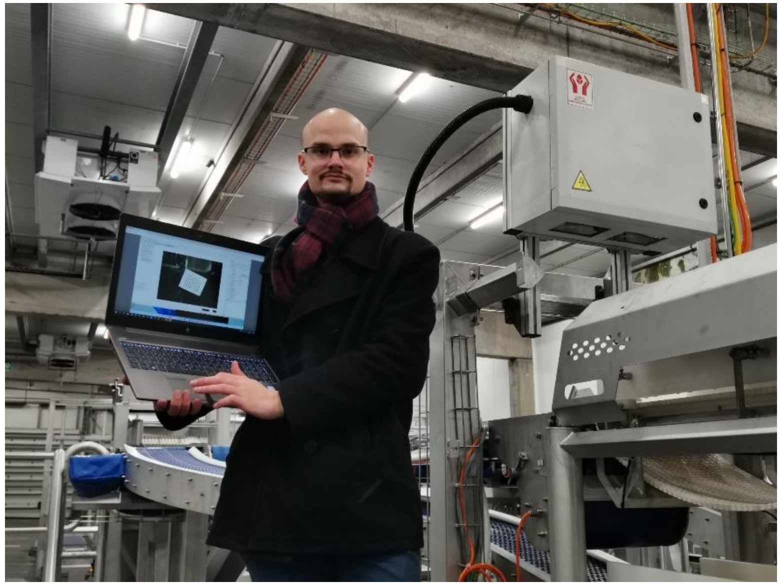

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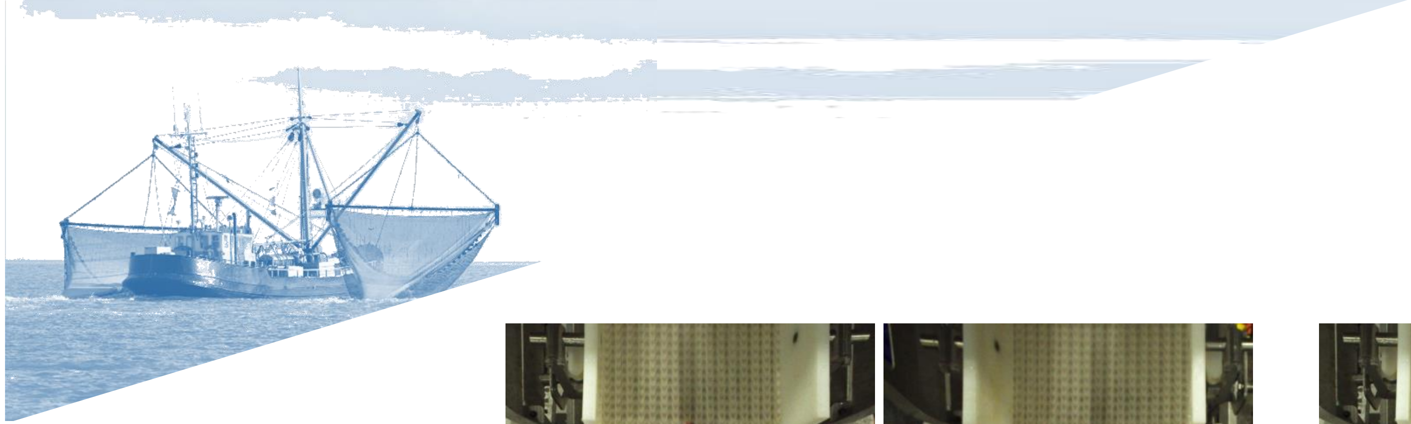

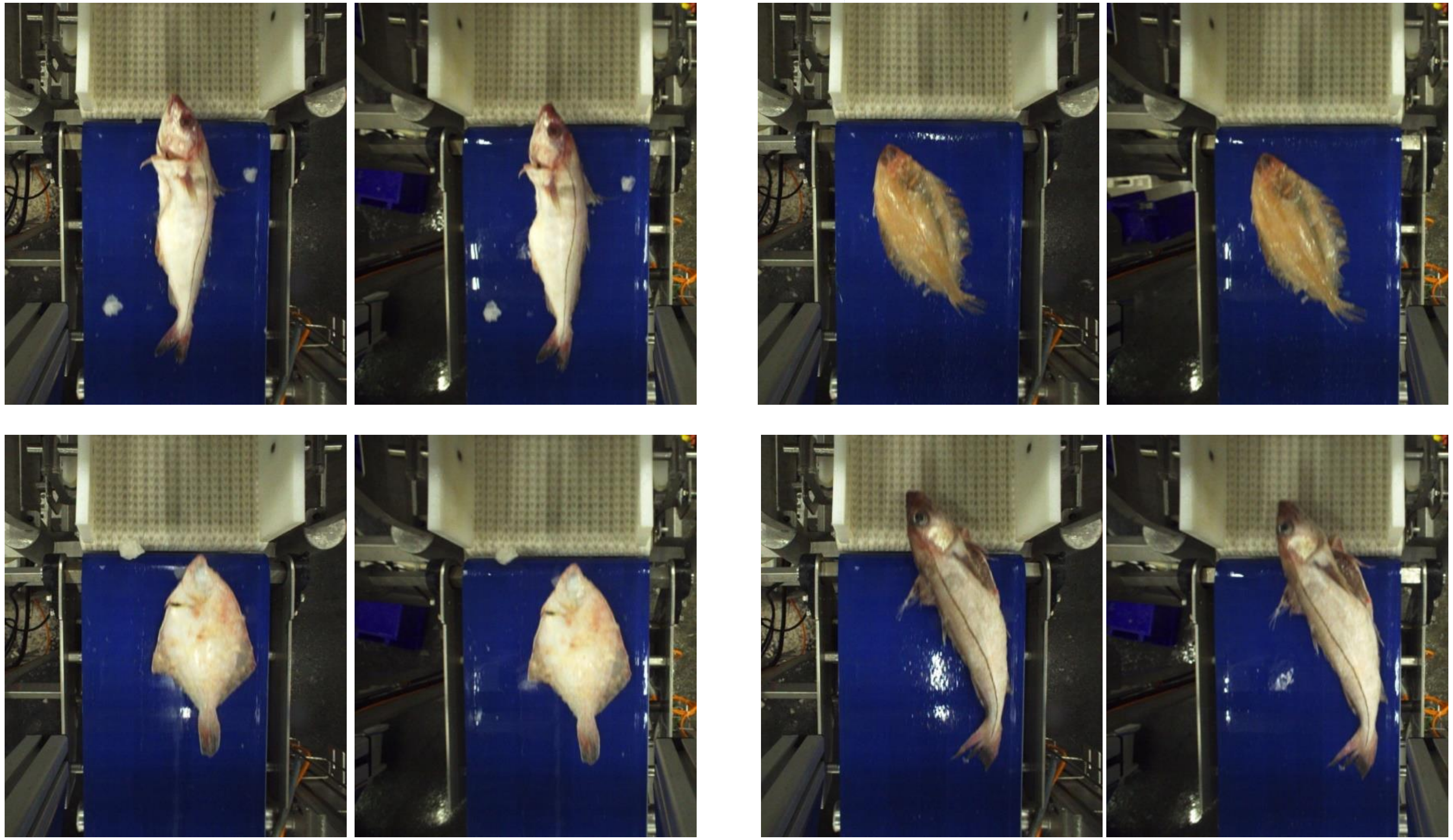

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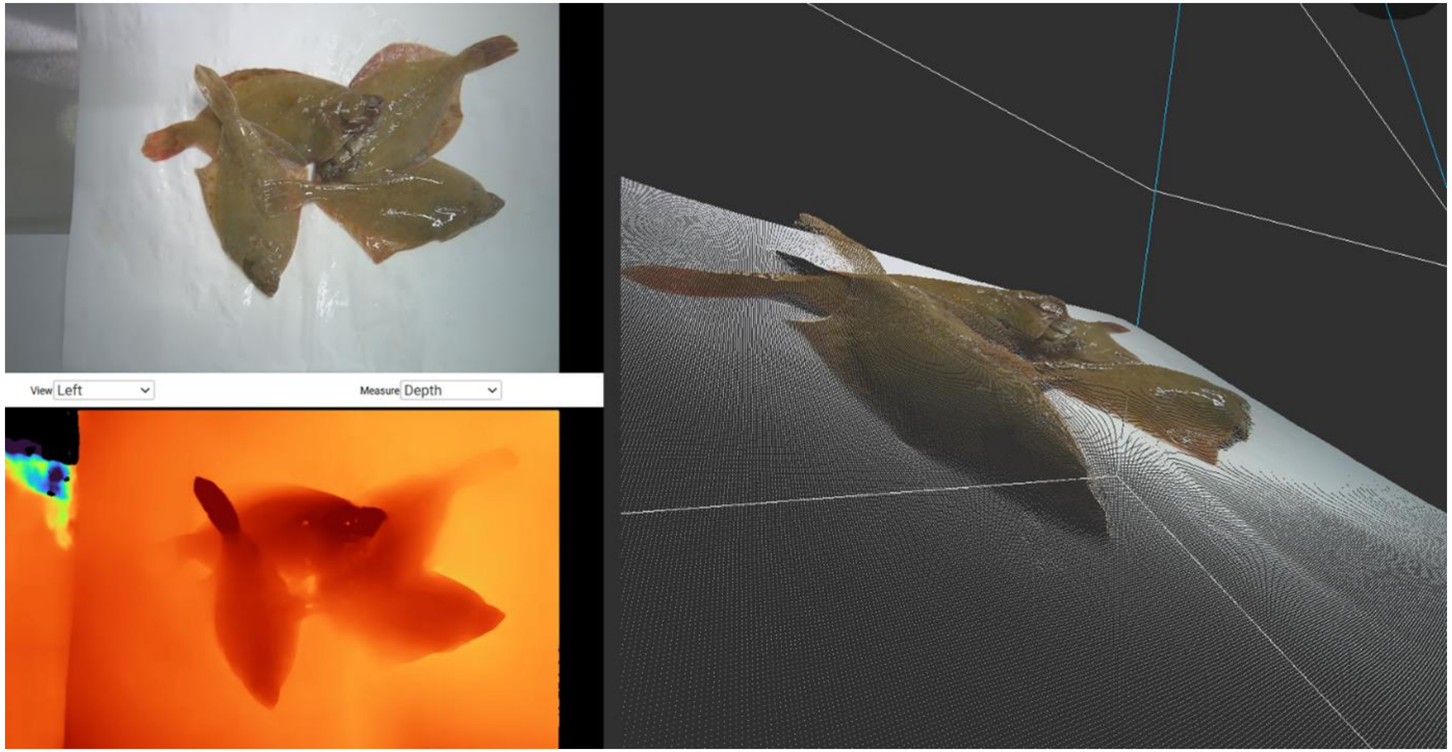
2de Prototype



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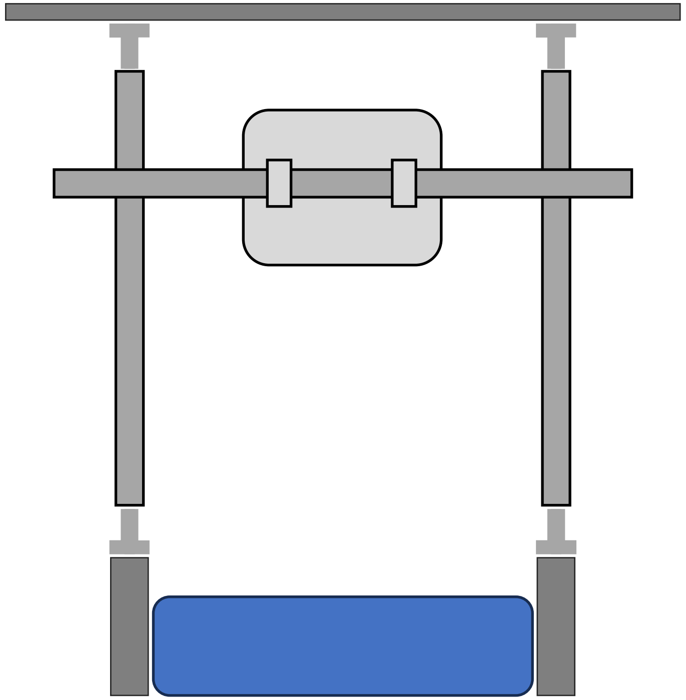
2de Prototype



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2de Prototype

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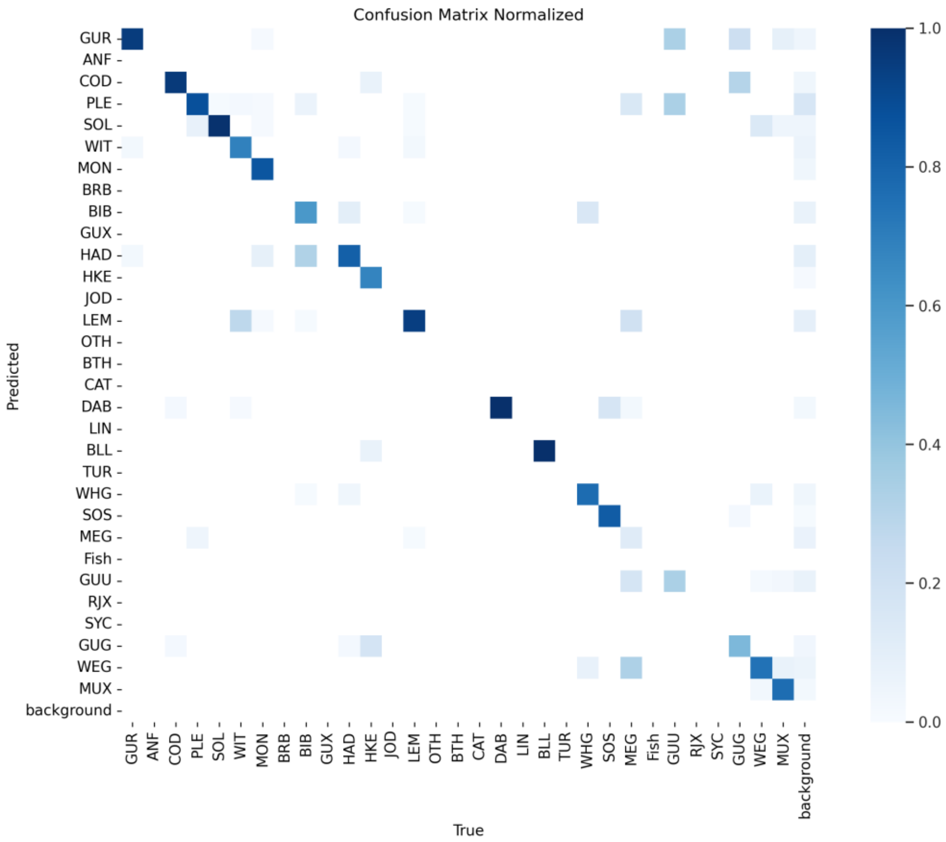
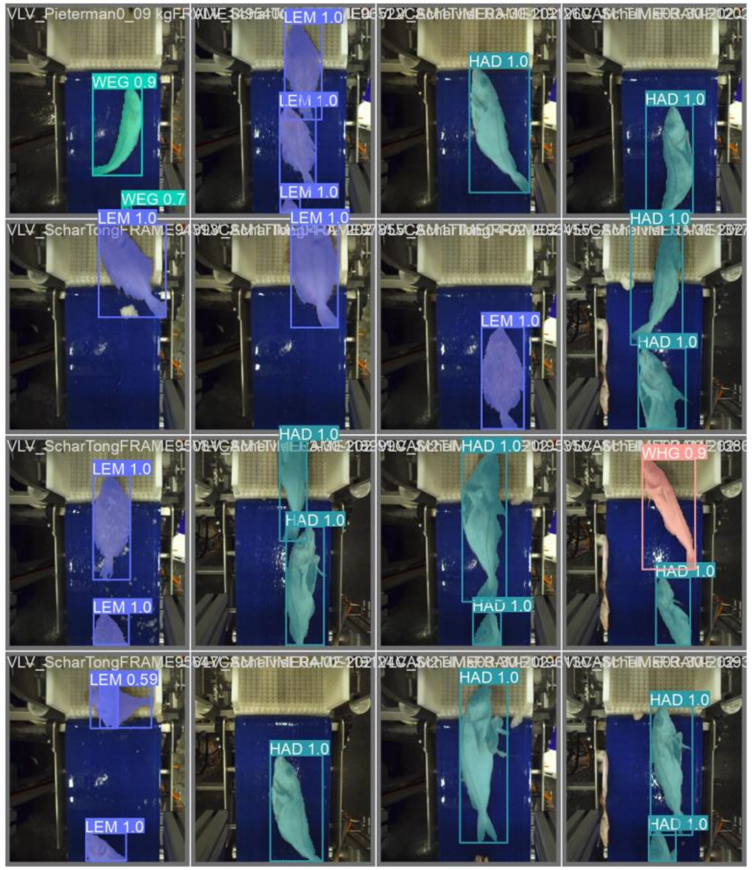
Soortherkenning





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Lengtemetingen

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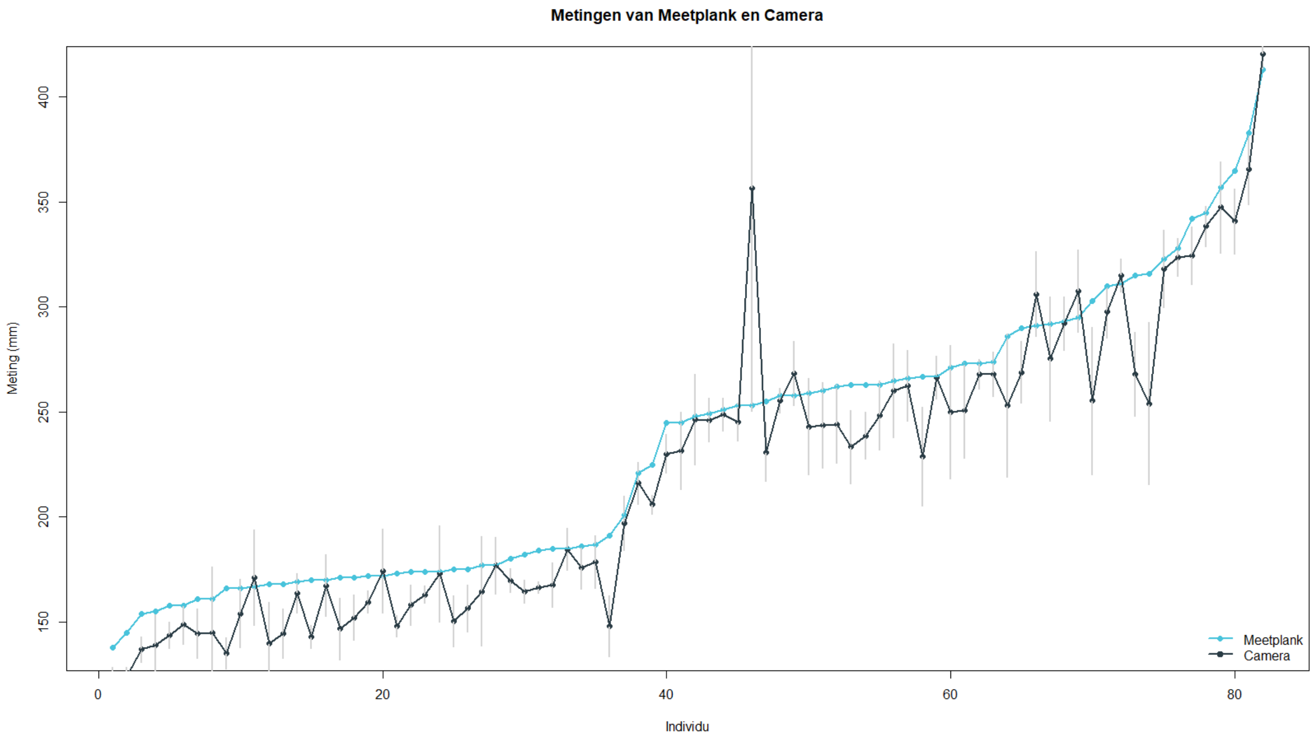
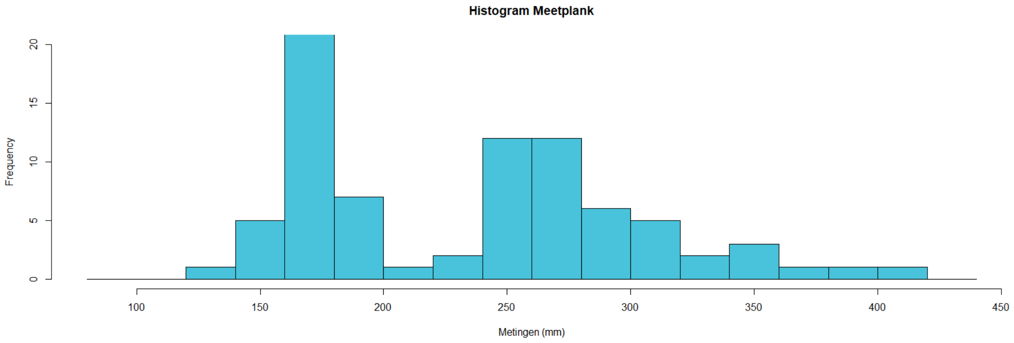
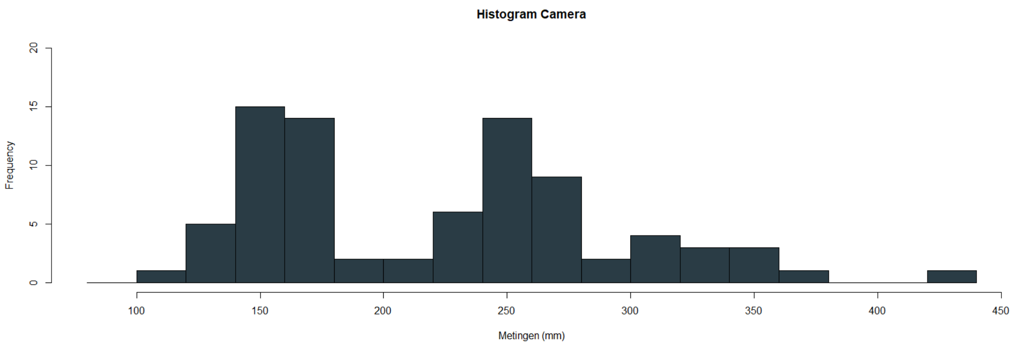
Lengtemeting in mm WHG

Gemiddelde fout:
Absoluut = 16.83 mm
Relatief = 7.55%







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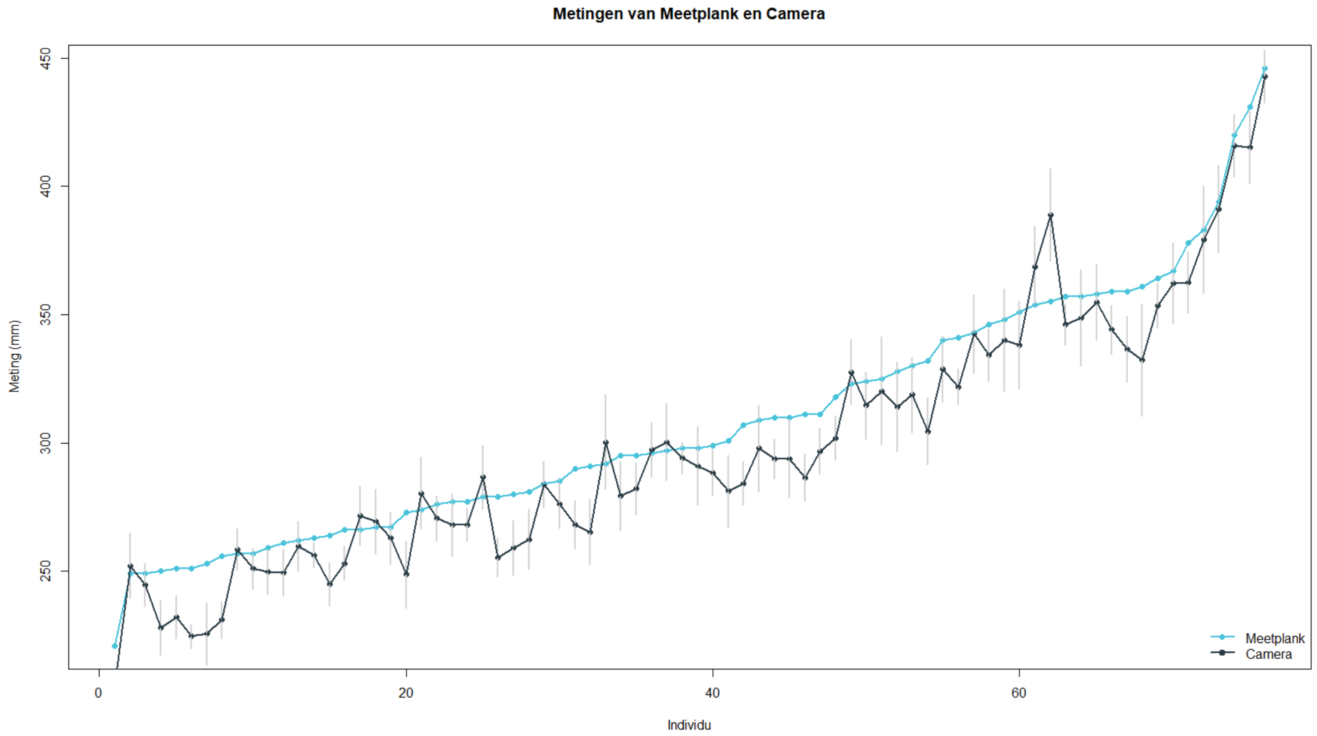
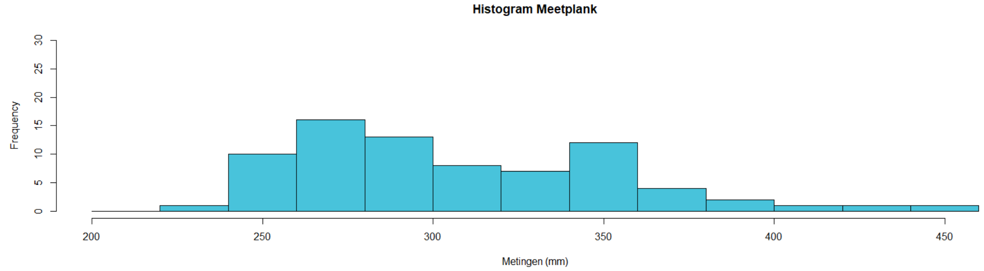
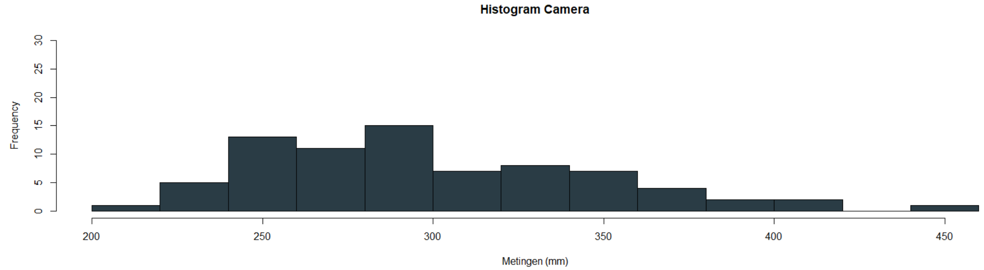
Lengtemeting in mm HAD

Gemiddelde fout:
Absoluut = 12.41 mm
Relatief = 4.13%







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Synthetische data

Synthetische data is informatie die kunstmatig is vervaardigd in plaats van gegenereerd door gebeurtenissen in de echte wereld.

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Synthetische data

Synthetische data is informatie die kunstmatig is vervaardigd in plaats van gegenereerd door gebeurtenissen in de echte wereld.

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Challenges of Collecting (Real) Data

Rare Data

- Difficult to **replicate the state** of the captured objects

- Data is **not available**

- Requires **special conditions** to capture data

Data Privacy

- Risk of breaches leading to **exposure of personal data**

- **GDPR**

Time Consuming

- **Manual process** takes up a lot of precious time

- Extensive **data cleaning** and preprocessing required

- **Iterative process** to ensure quality

Less Precision

- Variability due **to human error** in data collection (needs domain expertise)

- Difficulty in ensuring **data consistency** across different collectors (**ai is biased**)

Big Cost

- **Recurring** labelling **cost per iteration**

- **Investment in technology and personnel** for data collection

Safety

- Risks in **hazardous** or unstable **environments** to collect the data

- Legal implications of collecting data in restricted or **private spaces**

Advantages of Creating Synthetic Data

Generation	Cover All Cases	Parameterized	Unique	Automatic	...
Variation	Materials	Geometry	Lighting	Background	...
Annotations	Consistent	Precise	Fast	Time Saving	...
Workflow	Iterate Faster	Domain Randomization	Improve AI Model	Understand Better	...

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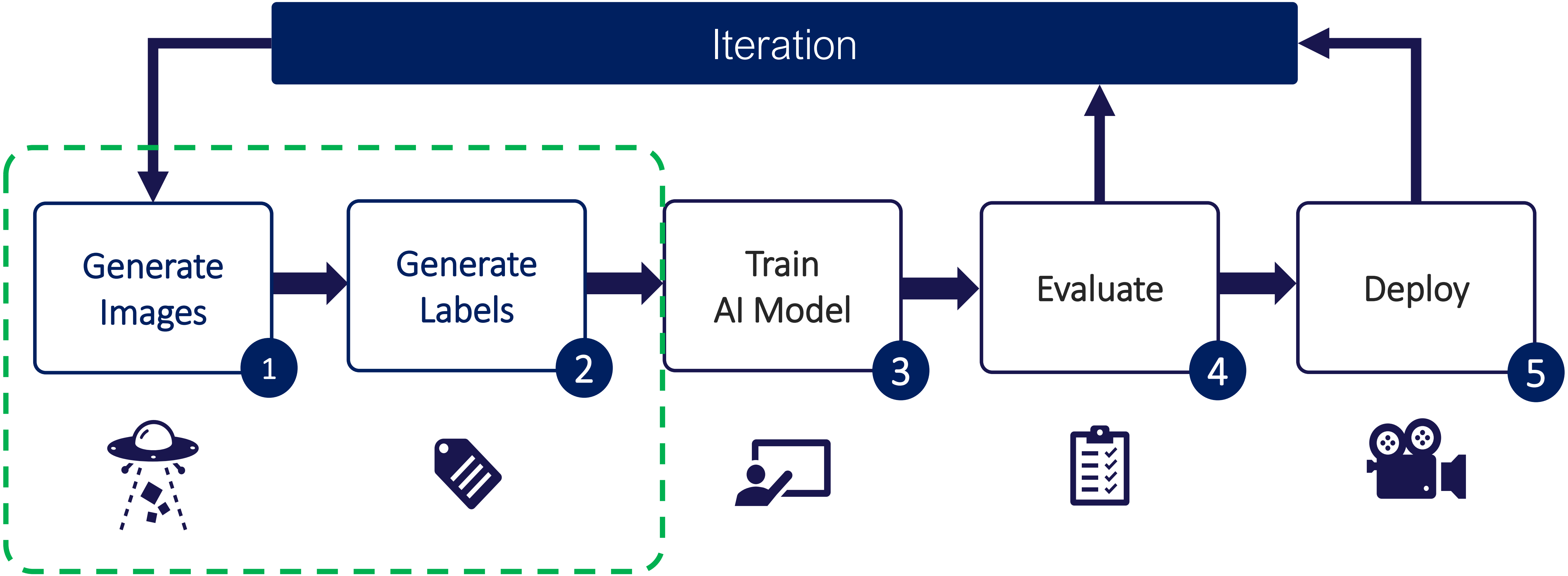
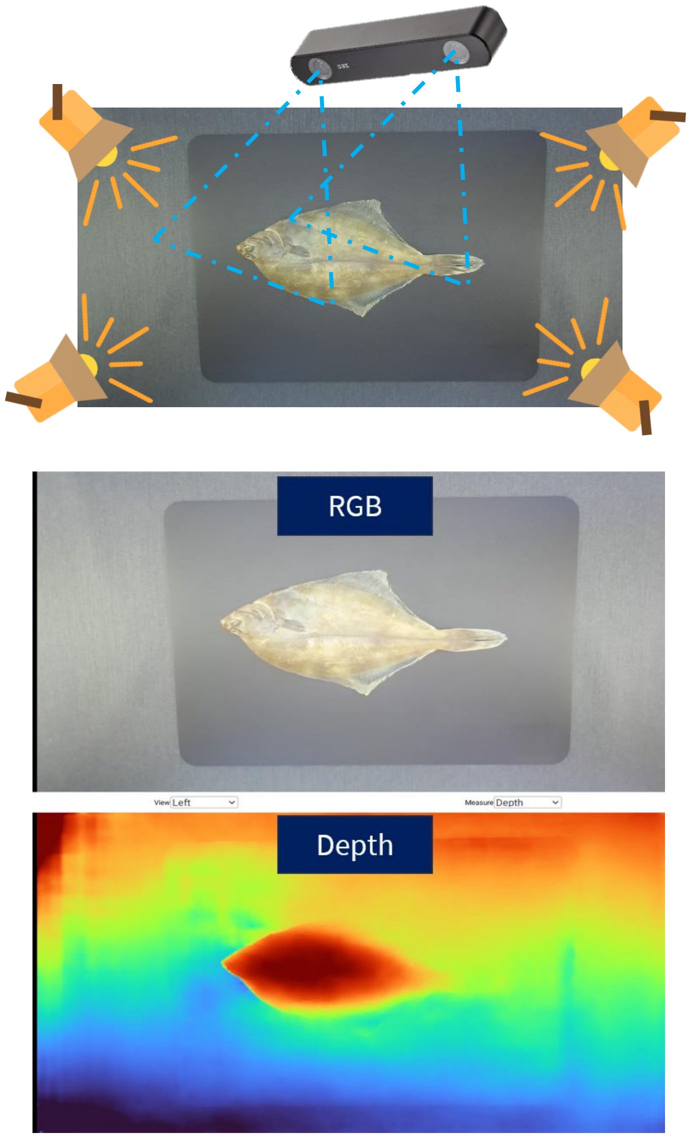
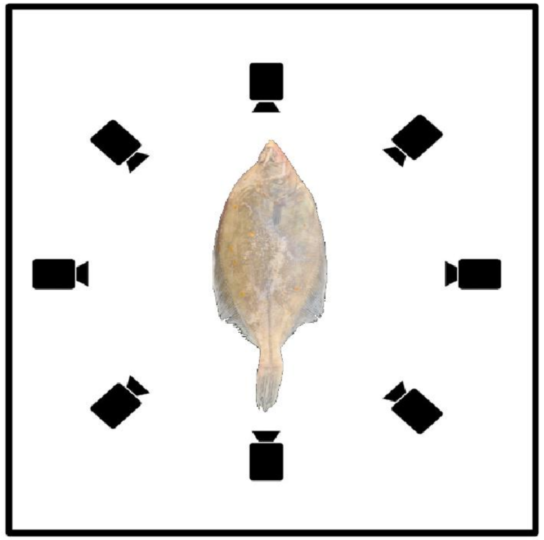
AI Model Training Process – Using Synthetic Data

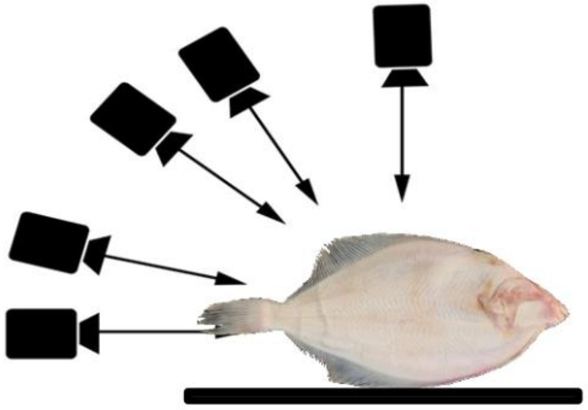


Stereovision

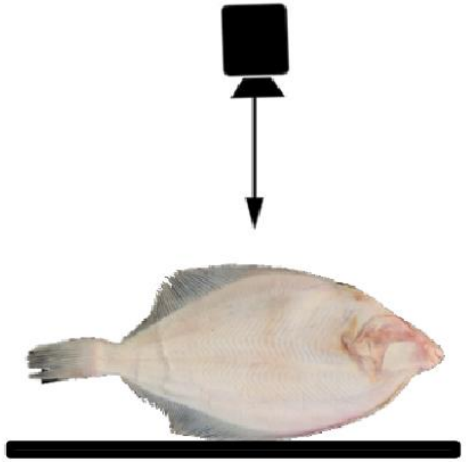


Photogrammetry





1 Image
Generic Shape



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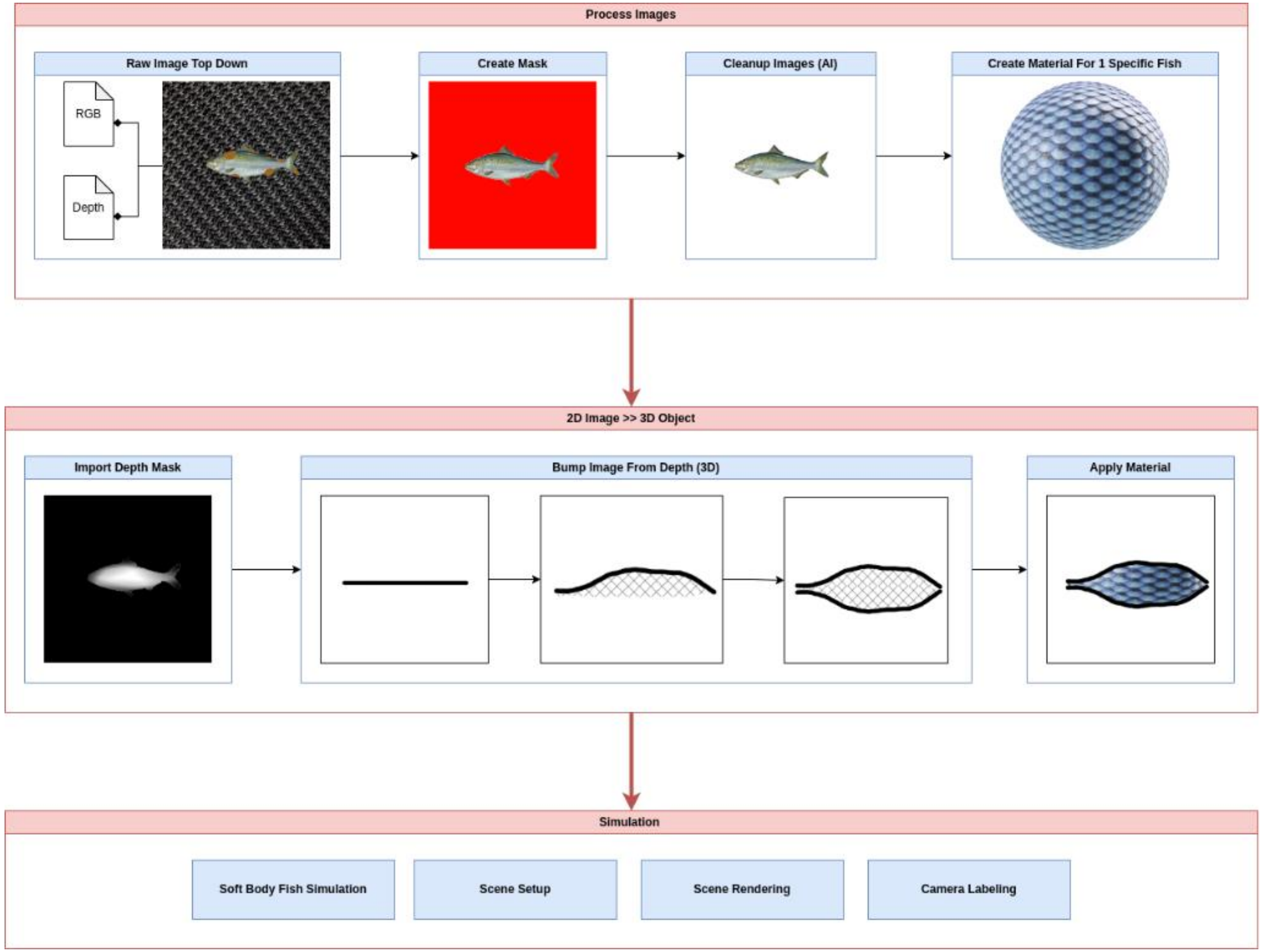
Capture >> Create >> Simulate >> Detect



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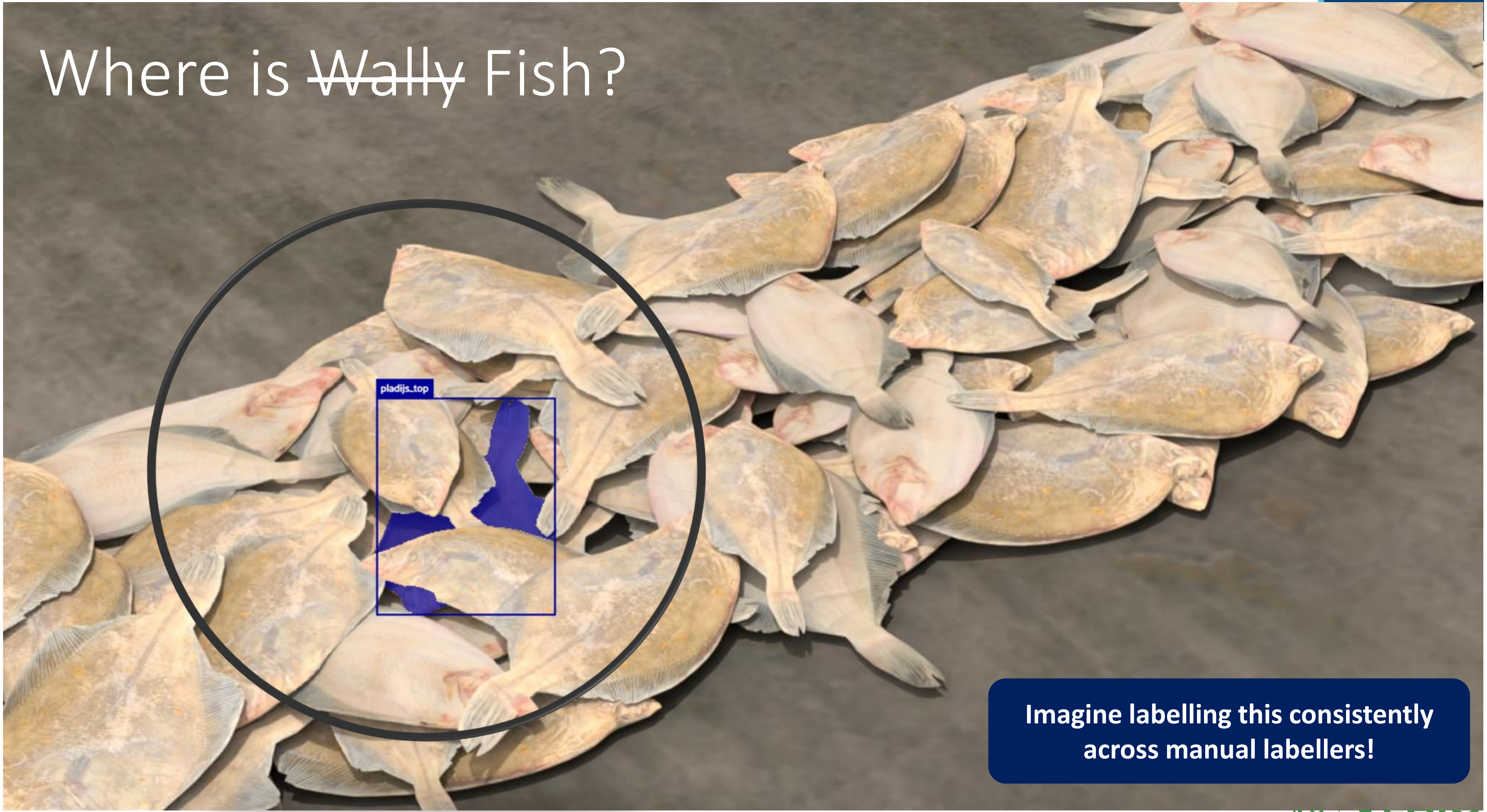
Where is ~~Wally~~ Fish?

Where is ~~Wally~~ Fish?



Imagine labelling this consistently across manual labellers!

Stacking 200 Fish In No-Time

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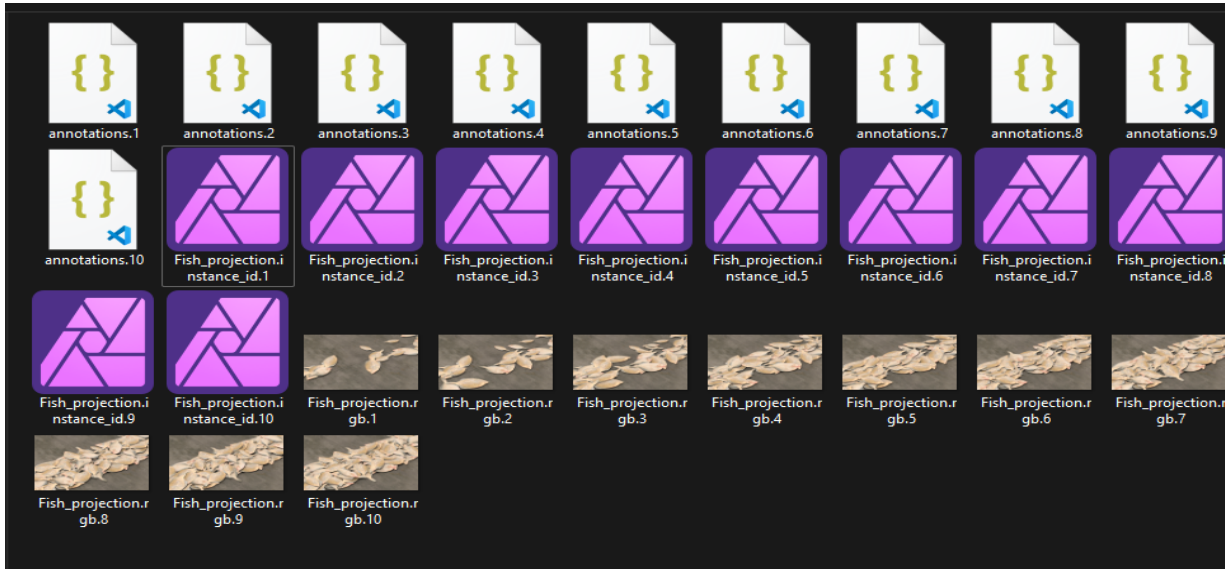
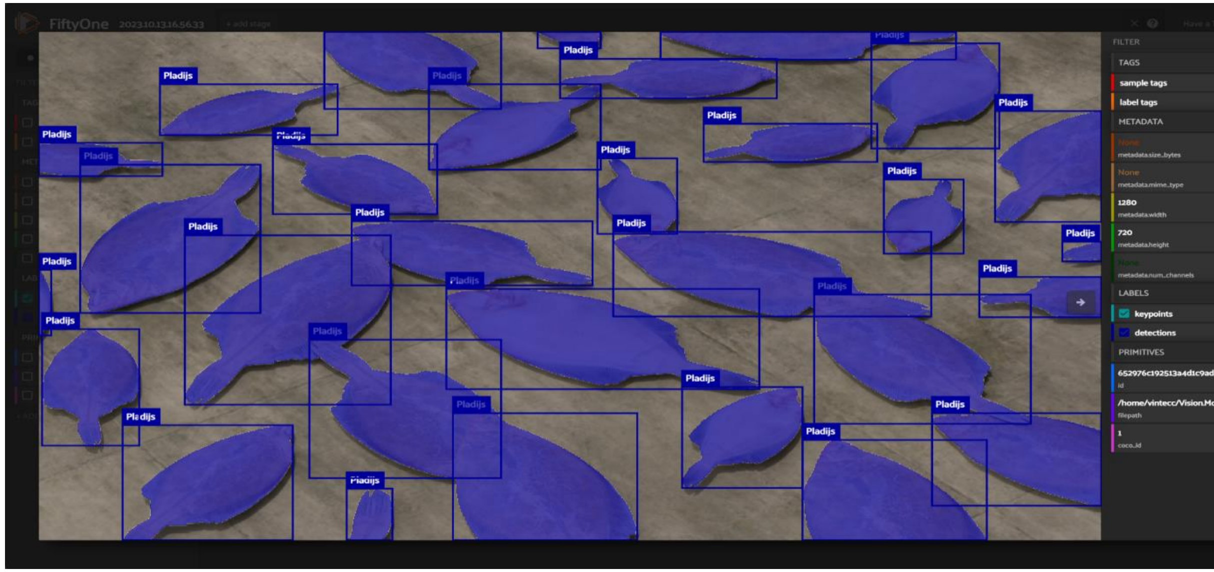
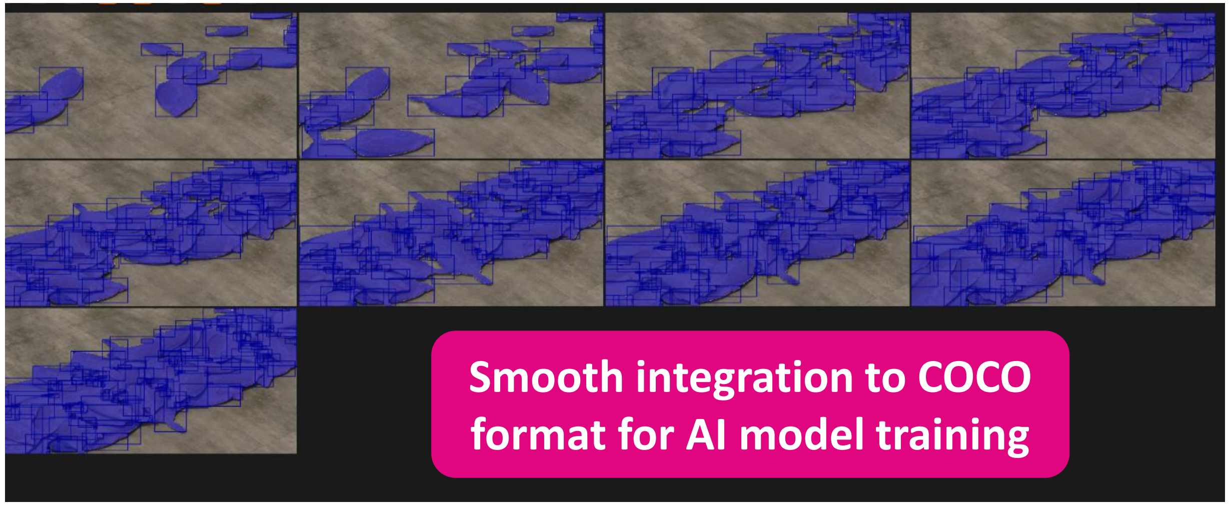
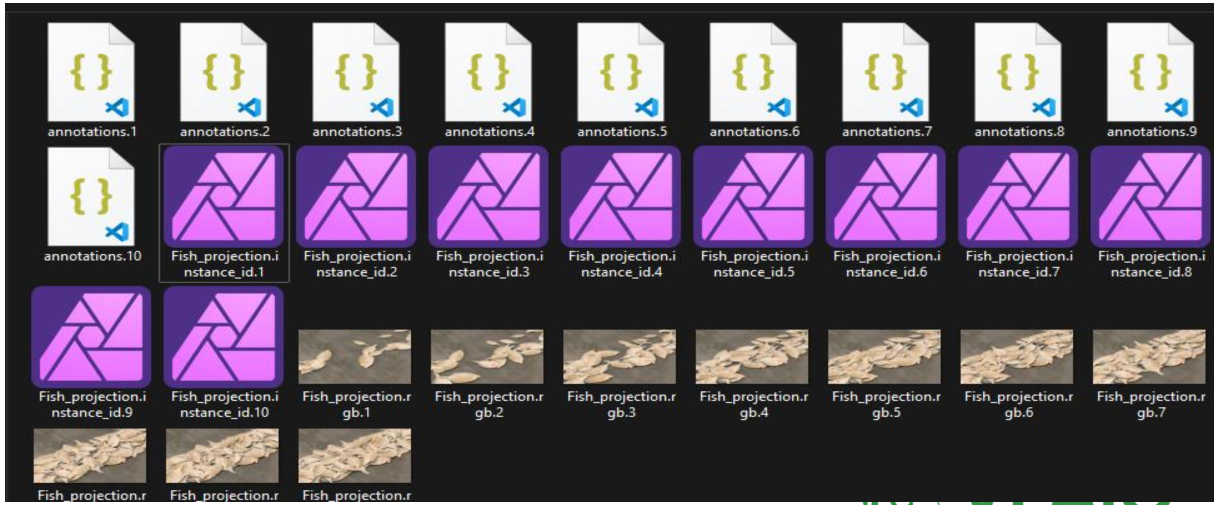
An Automated Pipeline







Smooth integration to COCO format for AI model training



SynFish Project

- Creating synthetic data to optimize automatic recognition, classification and measurements of different kinds of fish breeds

In

- Challenging environments
  - Commercial fishing vessels

Of

- Different kinds of fish breeds
  - Complex, wet, organic, soft body, …
  - Mixed catches of fish stacked on each other
  - Filter out non-relevant object such as starfish, garbage, benthos, wood, ..

To

- Forecast and predict good fishing areas to give better and objective advice to fishers

- Avoid high costs of manual data labelling of very complex data
- Avoid human error & increase data consistency
- Increase monitoring results & gain better data insights
- Accelerate development

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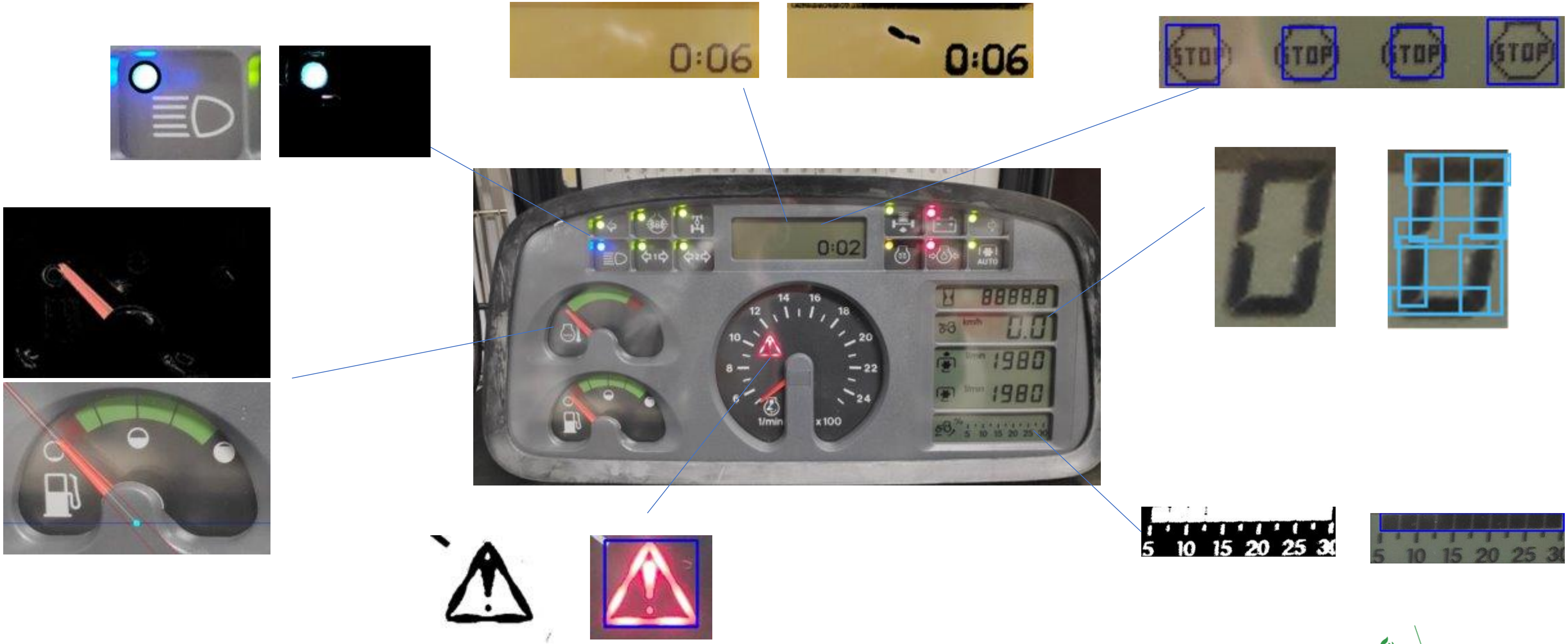
Case 4

Determination of the proper functioning of a LED display

TVH

Met de steun van

Case 4



Case Roles

Case 4

Continued research

Regular
communication

BECKHOFF
New Automation Technology

Building solution

Roles: Beckhoff Automation

BECKHOFF
New Automation Technology

- Continuation of solution development
  - Previous solution as proof of concept
  - Presented their findings to the TVH Management

- Support point for Bechoff hardware and Twincat
  - Providing hardware support
  - Lessons Twincat basics and Twincat Vision

Goal: Create a fully working implementation for TVH while providing research support

Role: Vives-KU Leuven

- Research
  - Hardware: lens/camera/lighting
  - Software: Twincat, Python, ….

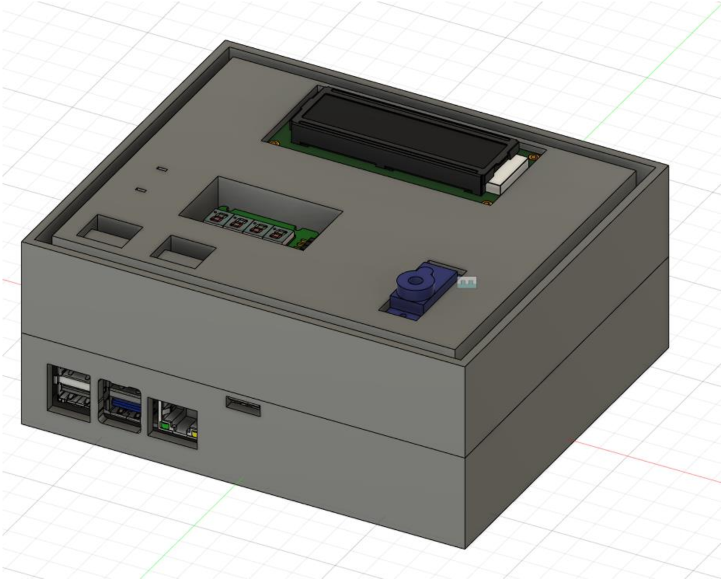
- Demonstrator (Case 4)
  - 1 of multiple
  - Created using Twincat
  - Using similar techniques as in Python

Goal: Acquire and Share obtained knowledge

Demonstrator case 4: Hardware

Created a hardware chassis based on use case 4:

• LED’s	Represents	state LED
• Servo		Gauges
• 4X7 Segment display		Numbers
• LCD screen		Main display



Controlled by a Raspberry PI programmed in Python

Demonstrator case 4: Hardware

Camera and lighting:

- VexG-25M black and white camera
- Led strips in case
- 2 Polarized light bars

PLC:

- Beckhoff CX2043
- Additional Beckhoff components eg: CX2500, CX2100
- Runs the TwinCat Software

Demonstrator case 4: Software

Interface that defines the testing method

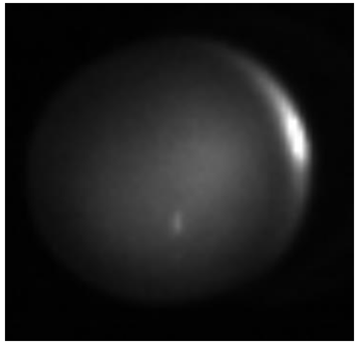
```
IF SUCCEEDED(hr) AND ipImageIn <> 0 THEN
    nNewImageCounter := nNewImageCounter + 1;


    FOR counter :=0 TO 3 BY 1 DO
        eSelectedObject := areaObjects[counter];
        A00_RoiObject();
        hr := F_VN_CopyImage(ipImageIn, workingImages[counter], hr);
        hr := checks[counter].Inspect(
            imageIn             := workingImages[counter],
            stRoiObject         := stRoiObject,
            hrPrev              := hr,
        );
        hr := F_VN_TransformIntoDisplayableImage (workingImages[counter],
                displayImages[counter], hr);


    END_FOR
```

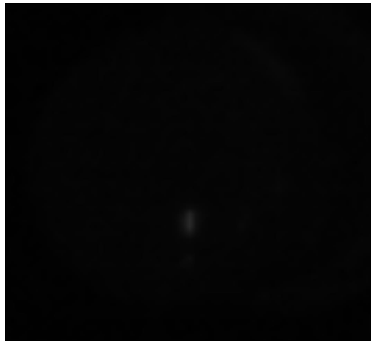
Loop over all testing methods/strategies and execute them on the appropriate location

Demonstrator case 4: Software

Steps to detect LED's:

- Locate LED





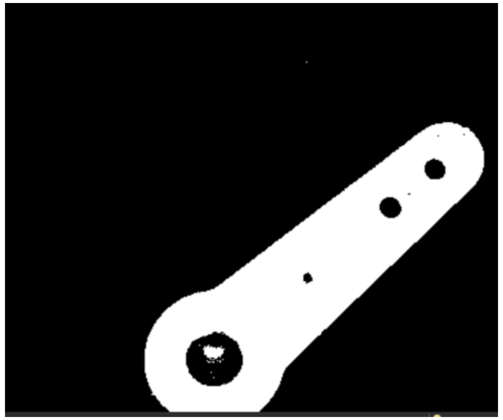
- Threshold the image

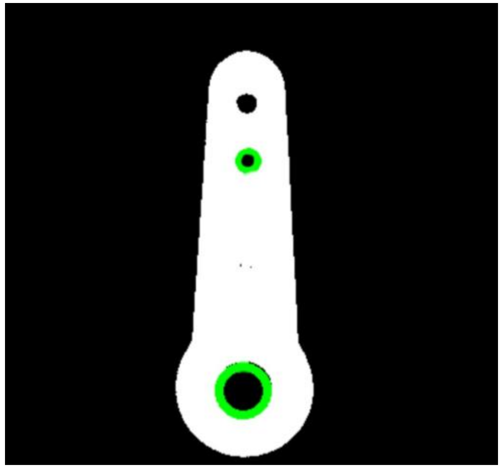
- Contour/circle detection

Demonstrator case 4: Software

Steps to detect Servo position:

- Filter white needle from black background
- Needle has circles
  - Detect circles
  - Need at least 2 to create line
- Connect the centers of the circles to create the midline

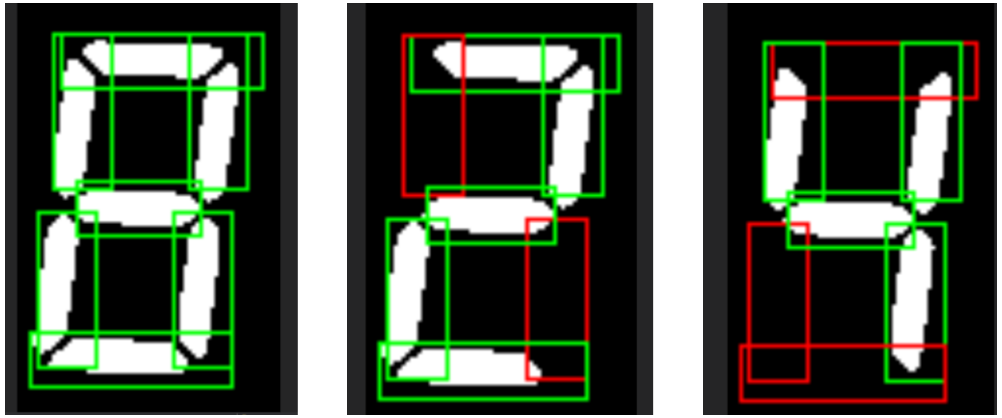




Demonstrator case 4:Software

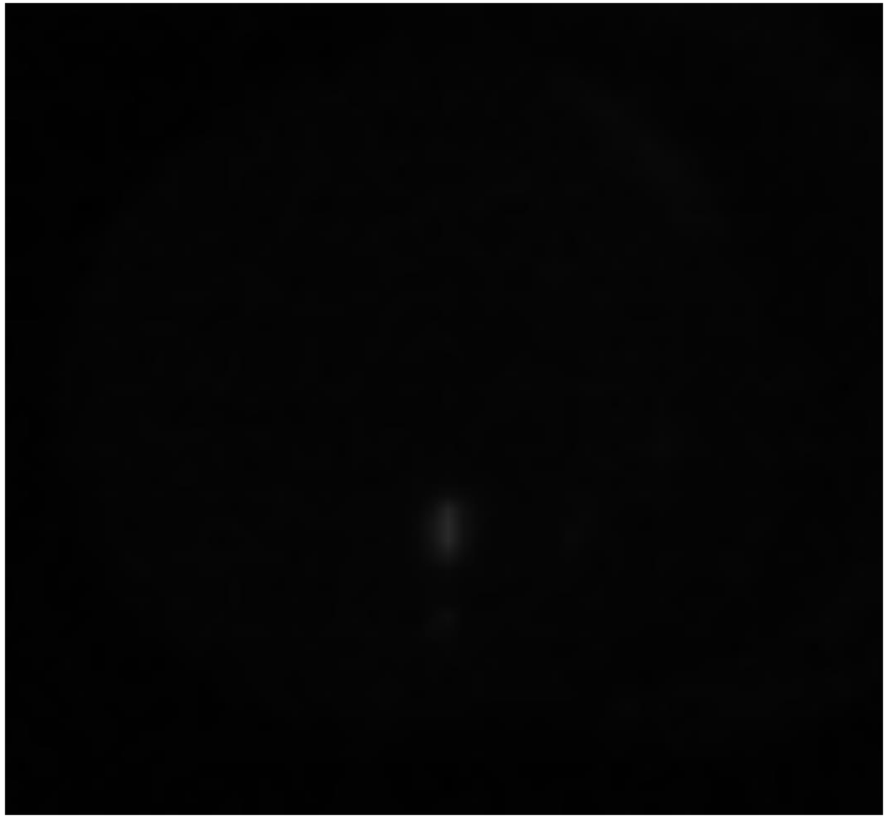
Seven segment

- Split the full display into 4 pieces
- Inspect the 8 segments of each piece
- Map the active segments to a number
- Join the 4 results

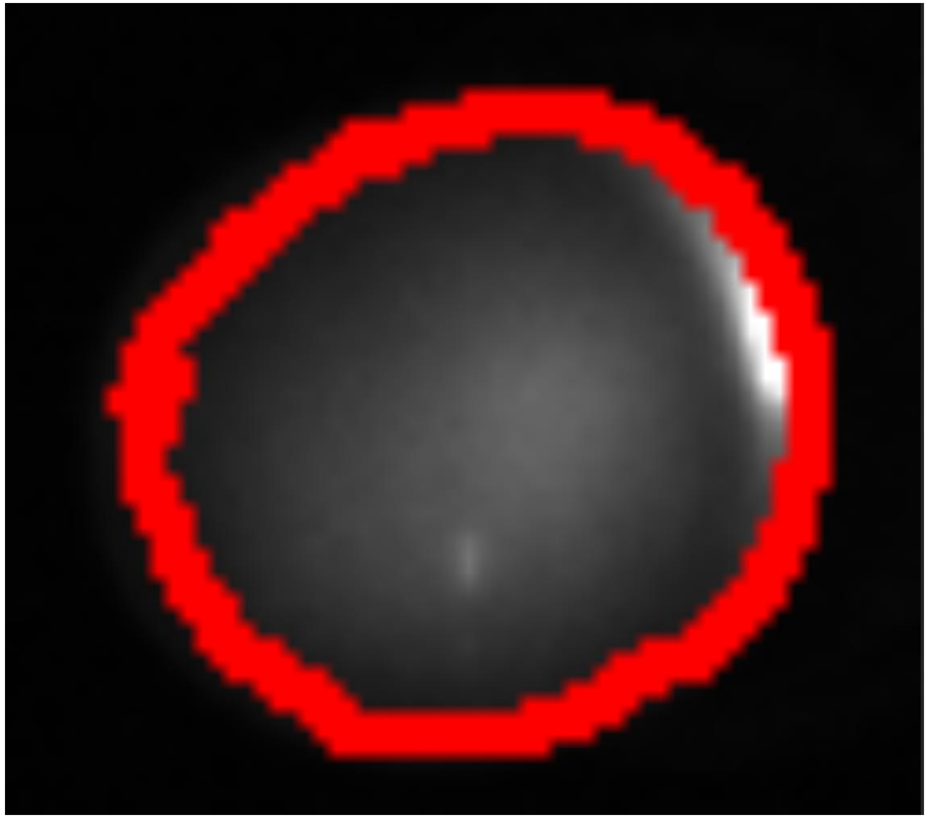


Demonstrator case 4: Results

Led detected when off



When On



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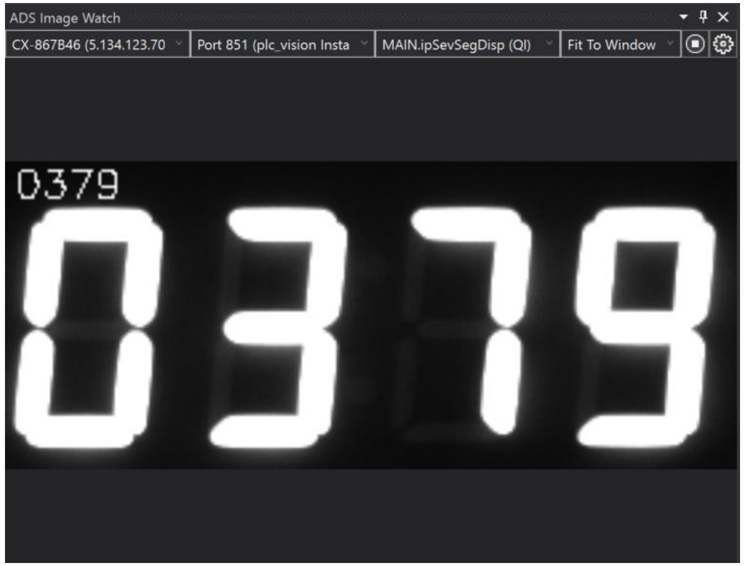
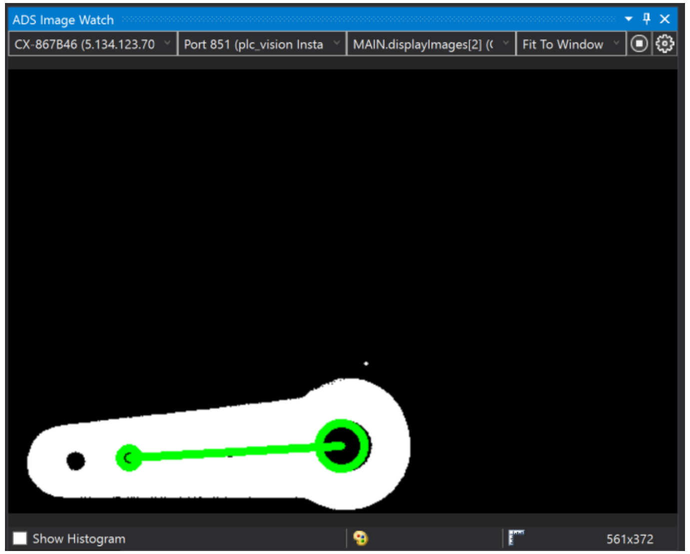
Demonstrator case 4: Results

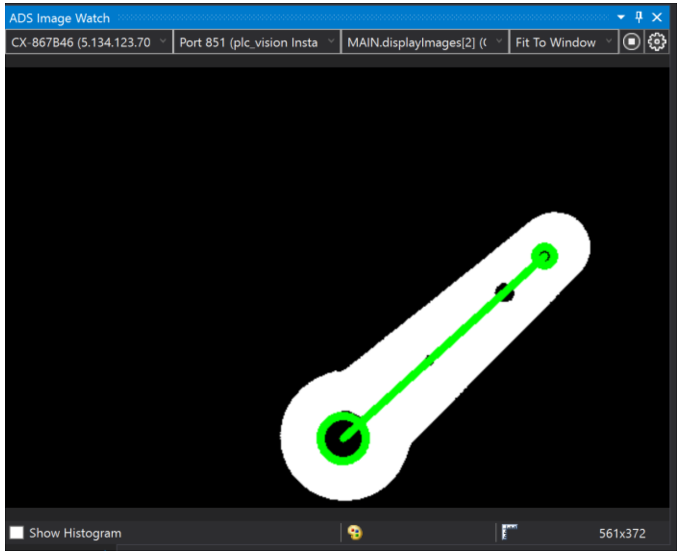
Seven segment detection

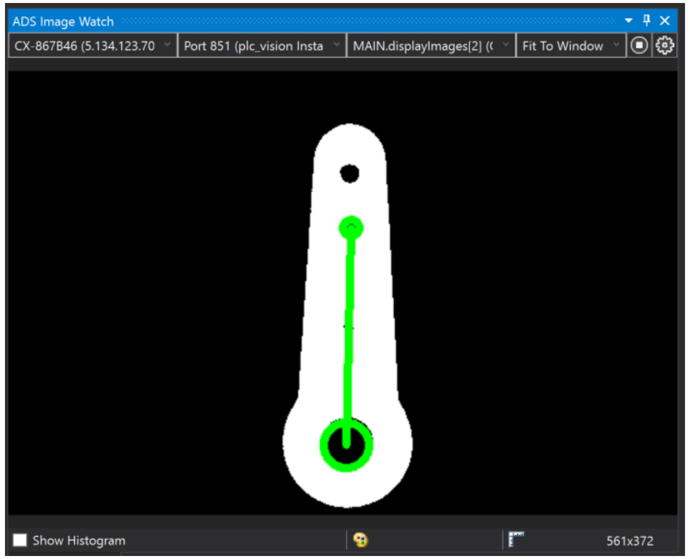


Demonstrator case 4: Results

Servo







Next steps

- Further changes to demonstrator
  - Reflective surface
  - Text recognition using OCR

- Further hardware related research

- Economic analysis

HBC.2022.0062

VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Case 5

Inline determination of the fat absorption of donuts after frying

Vandemoortele

Met de steun van VLAIO

IN-LINE DONUT QUALITY CONTROL

- Industrial Proof-Of-Concept

- January 18th, 2024

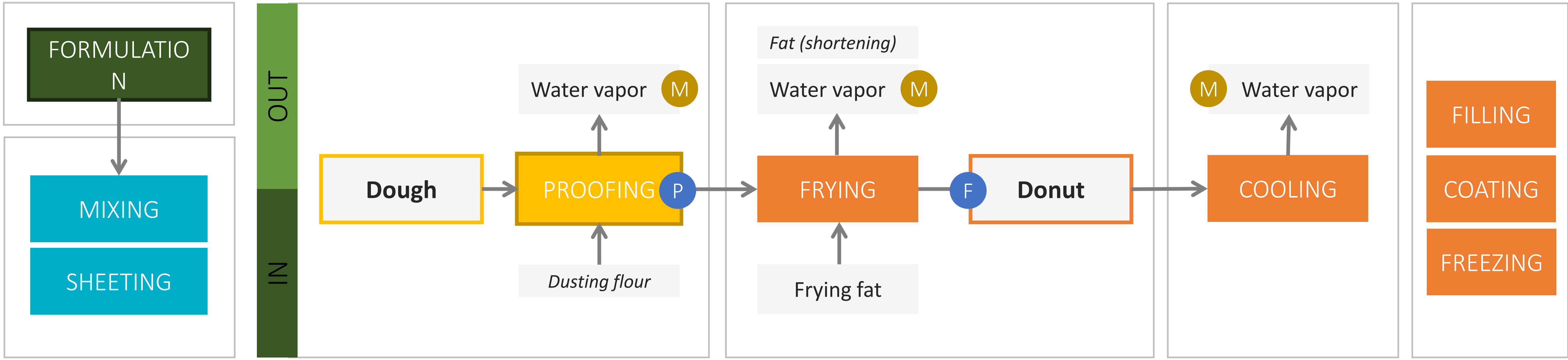
Vandemoortele
shaping a tasty future

Met de steun van VLAIO

PROBLEM STATEMENT

DEEP-DIVE IN FAT ABSORPTION

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



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 variation in weight-based reading is introduced

CONSEQUENCES

Deviating and varying fat absorption values and the unsuccessful attempts to stabilize these have **negative direct and indirect effects** on product quality, and internal and external stakeholder relationships
hindering efficient processing and market growth

FRUSTRATIONS

From production floor over quality to R&D

- Site targets are not achieved consistently
- Contradicting actions due to unclarity about the origin of the issue
- No tools to guarantee more stable values
- Hinders the search for root causes of other quality defects

PRODUCT QUALITY

Reduced quality and increased complaints

- Lowered product quality (mouthfeel, color, shelf-life, …) from fat absorption outside tolerances
- Corrective actions negatively affect overall quality
- Increased scrap levels

ECONOMICAL

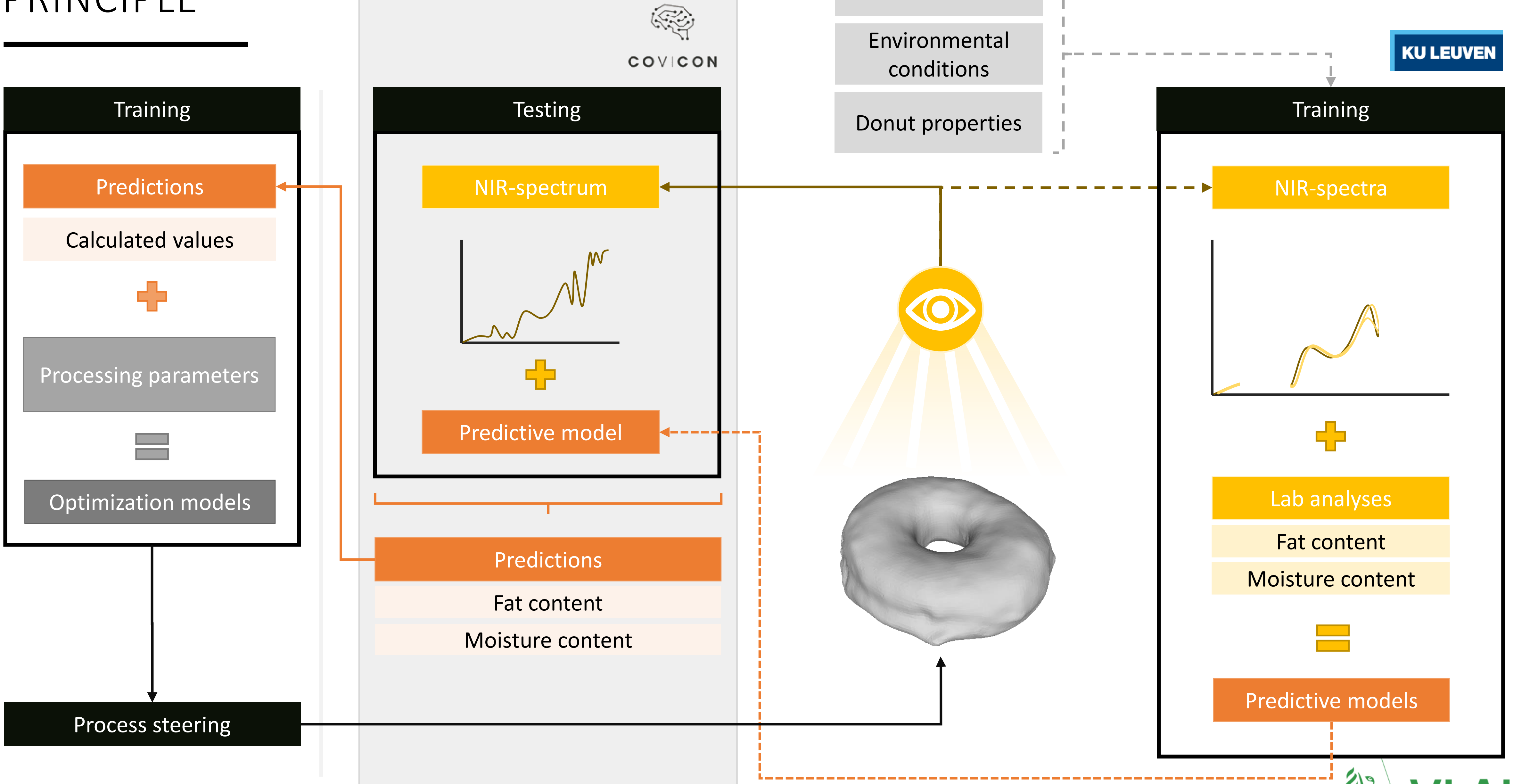
Direct and indirect costs

- Cost of scrap and defective accepted products
- Lowering production efficiency (packaging)
- Poorer customer perception of product quality and increased complaints (weight, quality)
- Invested time of different departments in finding root cause for (fat absorption related) problems

Met de steun van

INDUSTRIAL PROOF-OF-CONCEPT (POC)

PRINCIPLE



Met de steun van

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

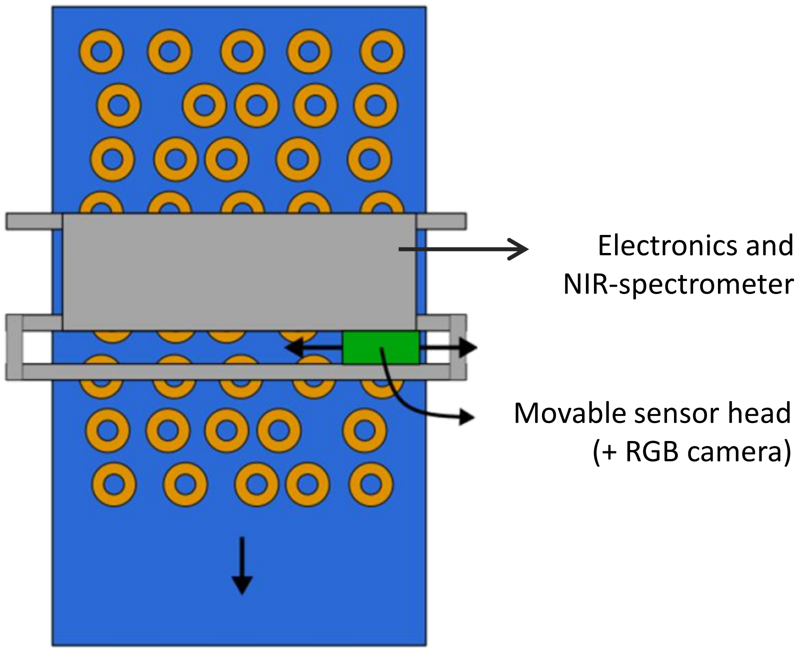
Process steering will require an understanding of the trade-offs between different quality attributes. A combined approach for fat/moisture content, weight and dimensions is preferred.

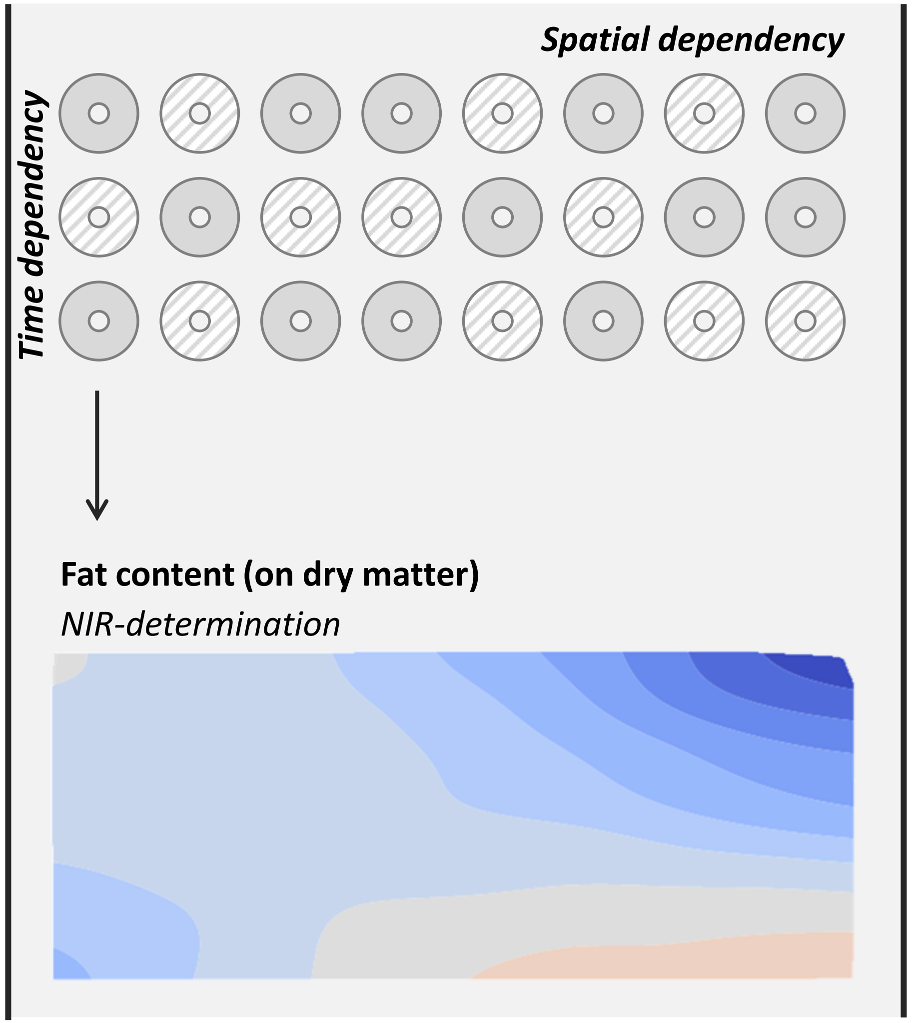
Met de steun van

INDUSTRIAL PROOF-OF-CONCEPT

COVICON

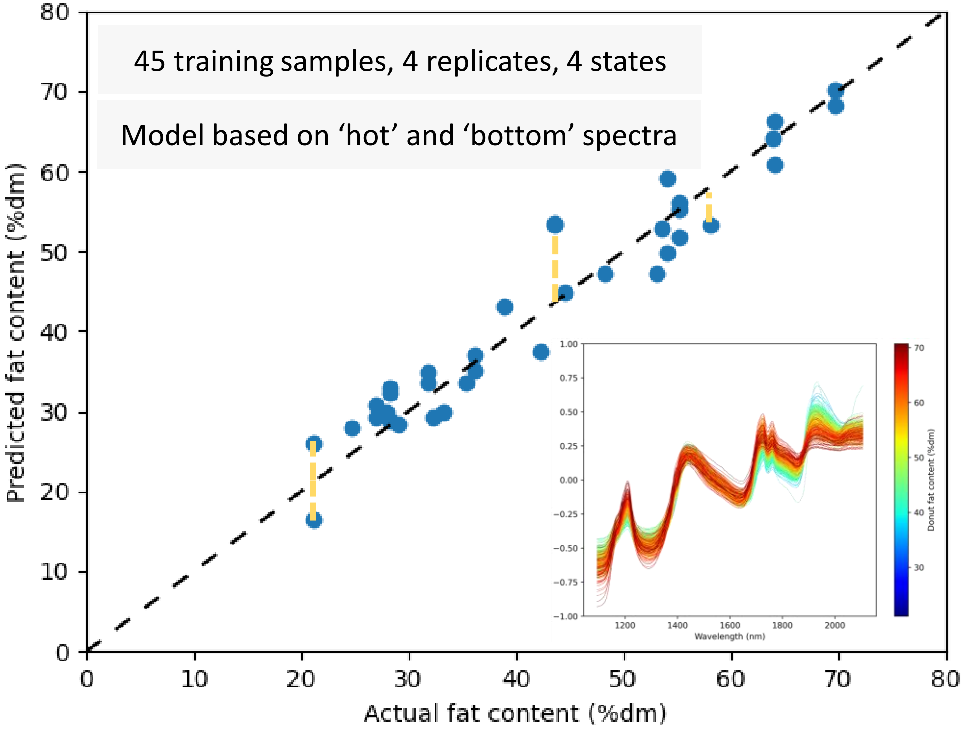
Received a detailed draft for a test installation allowing to investigate feasibility in an industrial setting





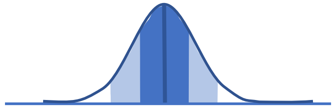
Met de steun van

LAB/INDUSTRIAL PROOF-OF-CONCEPT



$$RMSE_{cv} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} =$$

4.20 %dm



Residuals

single	pooled
4.88 %dm	0.90 %dm

$\pm \sigma$

INDUSTRIAL PoC

Camera speed

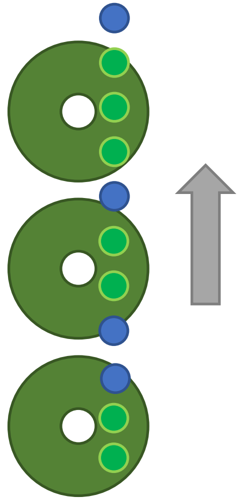
28 measurements/ second

Belt speed

40 mm/second

Donut diameter

< 80 mm



± 40 measurements / donut

Pooling of results (timeframe TBD)

+

More robust model (reference measurements)

CURRENTLY REQUIRED TOLERANCES

Mean value per product type:

- Normal plain donut: 20 %

Relative deviation:

- Nutritional declaration: ± 20 % of mean
- Product quality: ? % of mean

FUTURE TOLERANCES

Mean values per product type: μ %dm
Acceptable absolute deviation: k %dm

Model accuracy (σ_α of residuals) should be below:

- $\sigma_{0.001} = \frac{k}{3.29}$ (0.61 %)
- $\sigma_{0.05} = \frac{k}{1{,}96}$ (1.02 %)

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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.

Another meeting beginning of February

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.

A bunch of internal meetings based on R&D work

Met de steun van

Vandemoortele

VANDEMOORTELE HEADQUARTERS

Ottergemsesteenweg-Zuid 816

9000 Gent, Belgium

www.vandemoortele.com

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VLAIO TETRA
Machine Vision for Quality Control
(MV4QC)

Case 6

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

Ysco

Met de steun van VLAIO

hogeschool vives

KU LEUVEN

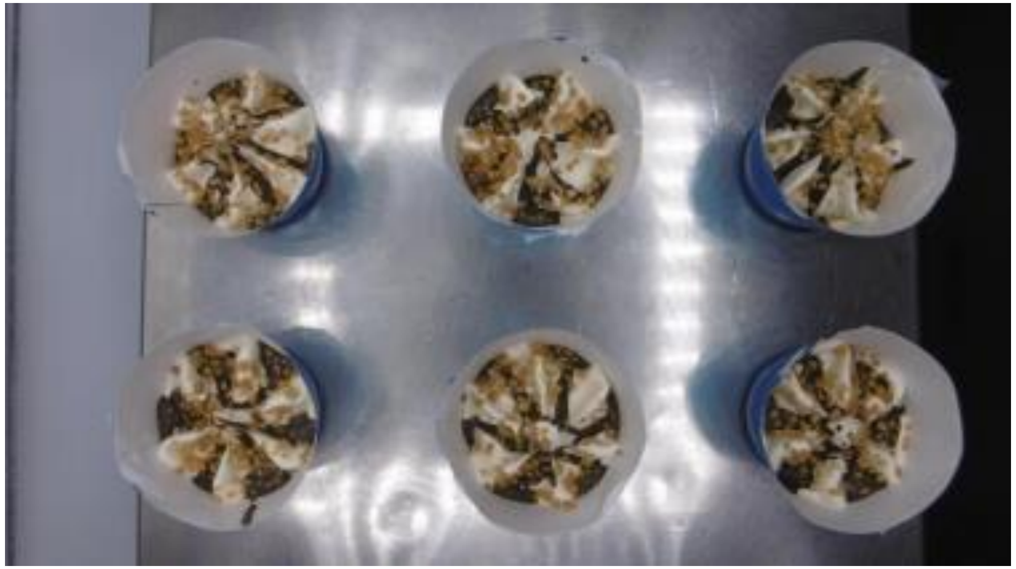
The use case:

Inline Quality Control of ice cream cones.

Met de steun van VLAIO

Context.

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



Conclusions from TETRA's previous research:

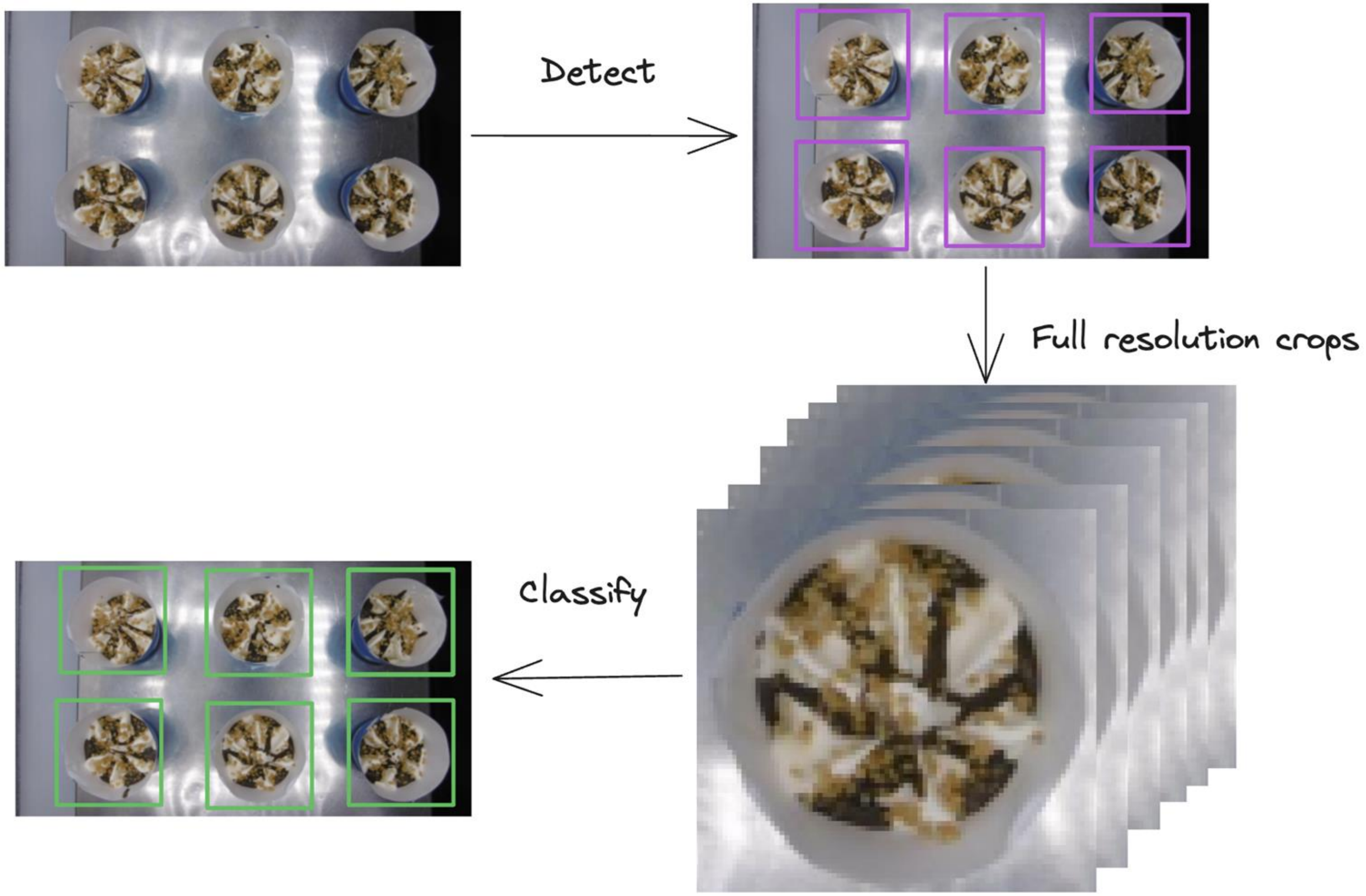
- Both binary classification and multi-label classification showed promising results.
- Size of dataset is rather limited

How we're solving:

Inline Quality Control of ice cream cones.

Met de steun van VLAIO

Our proposed approach.



Plug-and-play in our Captic stack

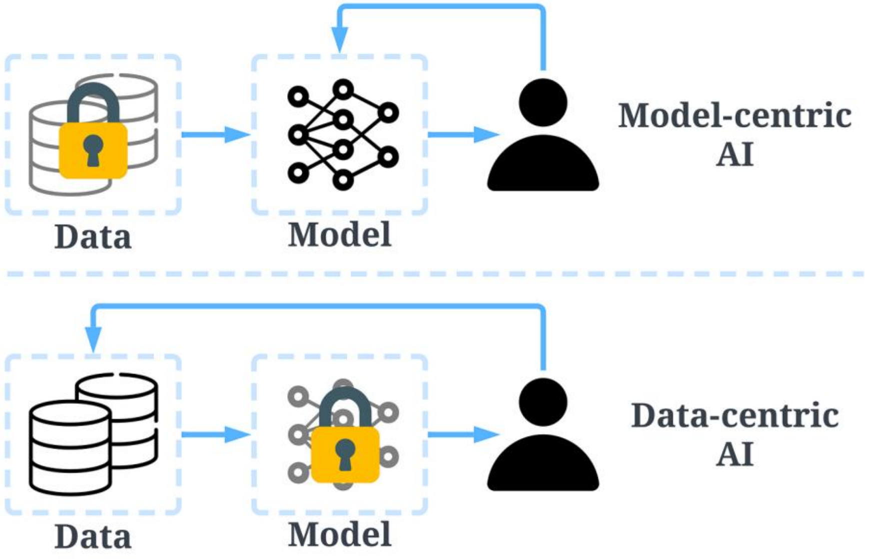
Collecting a big & high-quality dataset.

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



Installation status (1/2).

Currently, both parties are working together to facilitate the Data Collection:

Ysco:

- Adjusted the line to allow inline quality inspection
- Is preparing the frame for installation
- Is providing Captic with the IT/OT details
- Is preparing the required cables

Captic:

- Has ordered and received the hardware components
- Has assembled the Captic system
- Has onboarded the Ysco device in the Captic Cloud

As soon as the preparations by Ysco are finished, Captic will install the system on-site

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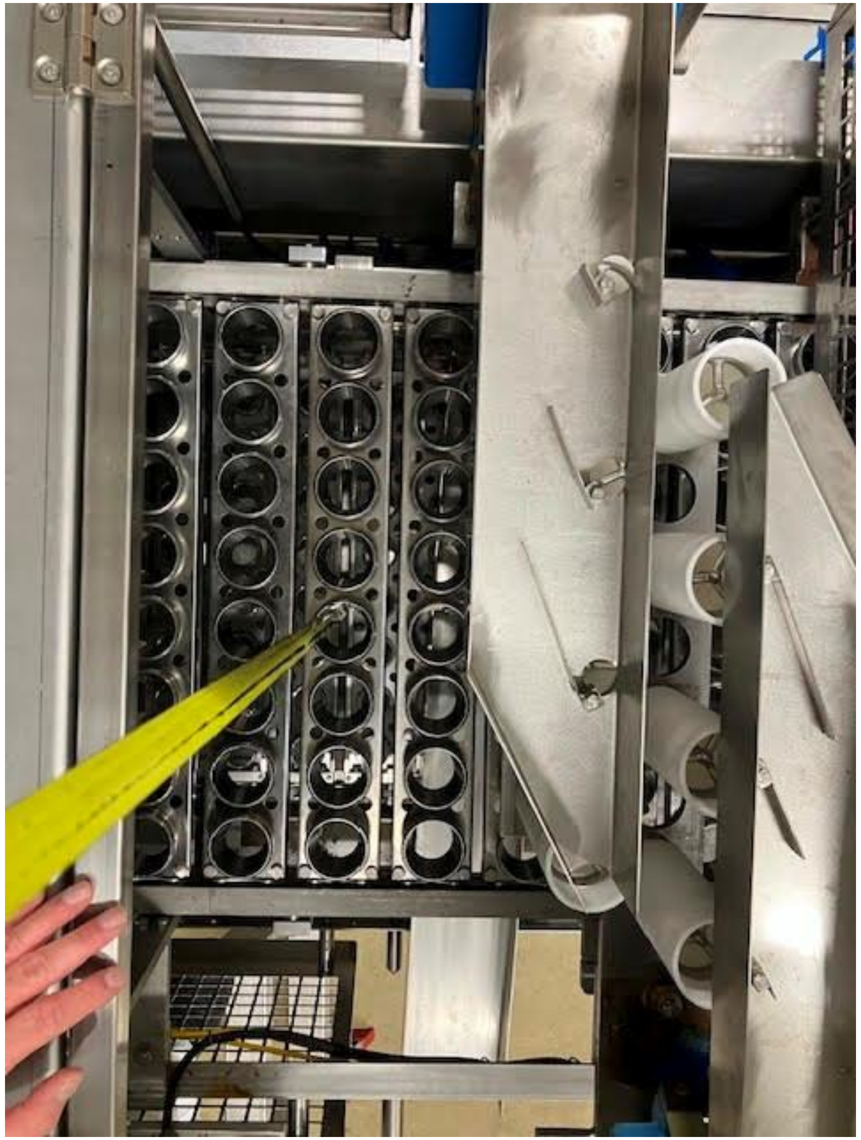
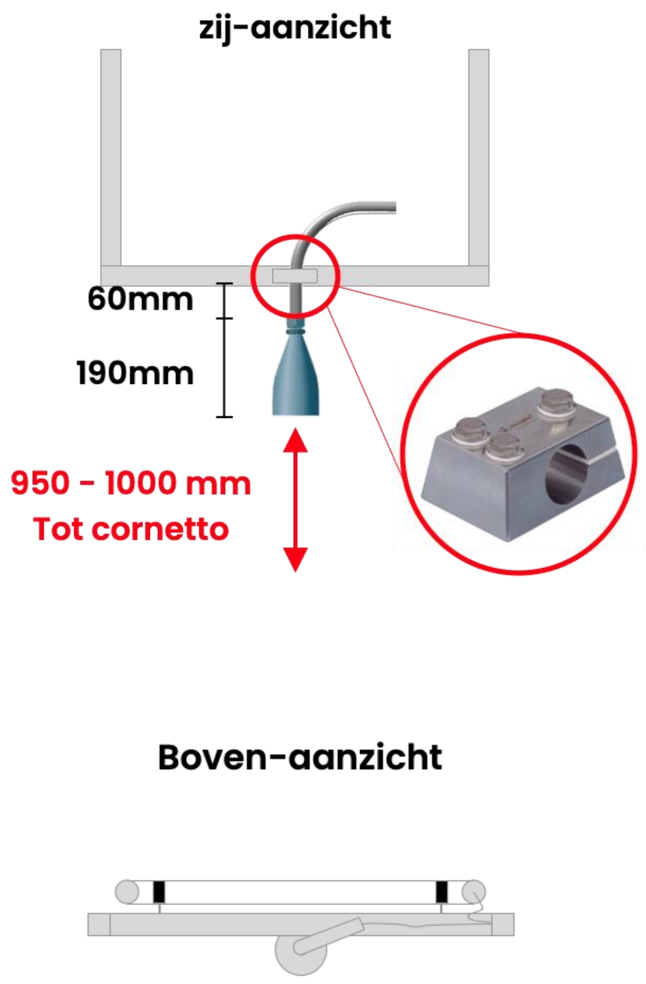
Installation status (2/2).





Met de steun van VLAIO

CAPTIC

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Next Steps.

Phase 1: Proving the potential

Can it be solved?

- Build small proof of concept

✅ Already proven by TETRA's research

→

Phase 2: Going to production

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
- …

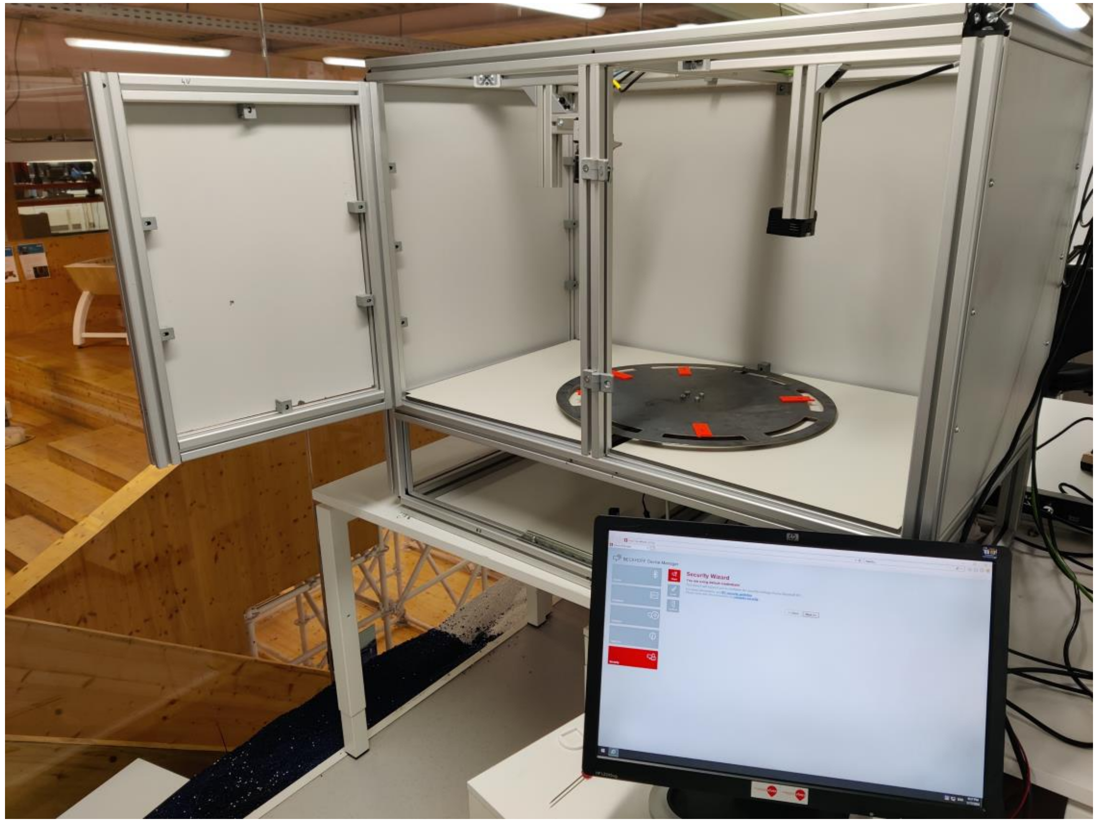
Plug-and-play in our Captic stack

Met de steun van VLAIO

Toelichting demonstrator Vives

Met de steun van VLAIO

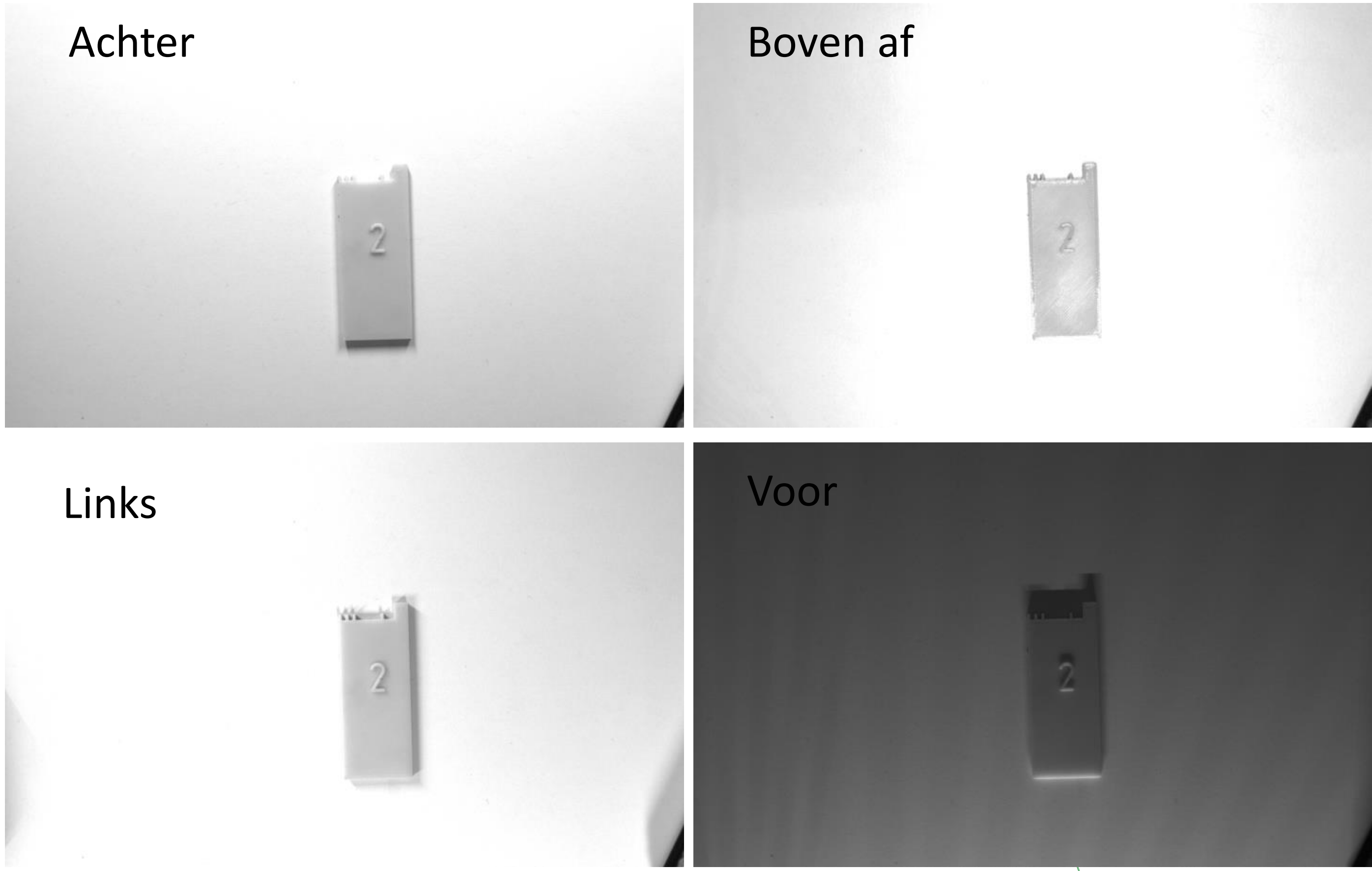
Vives Demonstrator



- Opstelling samengesteld
- Draaitafel voorzien
- Demo op basis van 4 afgewerkt

Vives Demonstrator: belichting

- Automatisch doorlopen van verschillende belichtingen
- Ledstroken als snelle test
- => input naar positie industriële lichten
- Groepen snel wisselbaar



Vives Demonstrator: belichting

- Automatisch doorlopen van verschillende belichting
- Ledstroken als snelle test
- => input naar positie industriële lichten
- Groepen snel wisselbaar

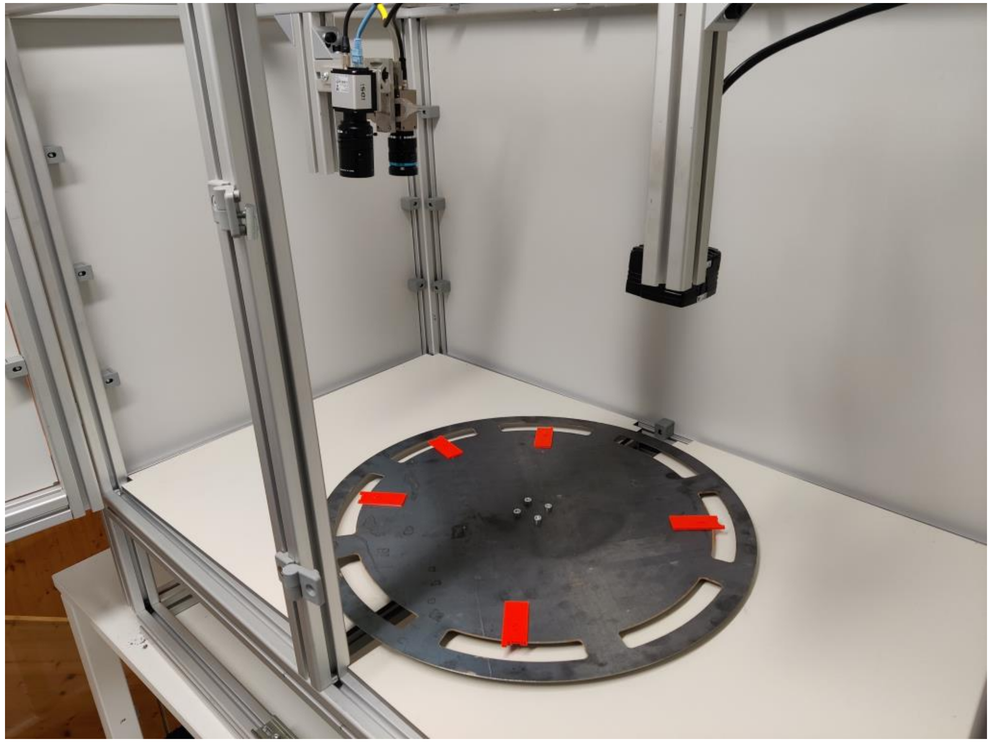
Dark field

Demonstrator gelinkt aan case 4

- Twincat software voorzien
- Demo opstelling voorzien

Draaitafel

- Basisframe draaitafel voorzien
    - Mogelijke toevoeging: Plexiglas bovenlaag
- To:Do: schilderen

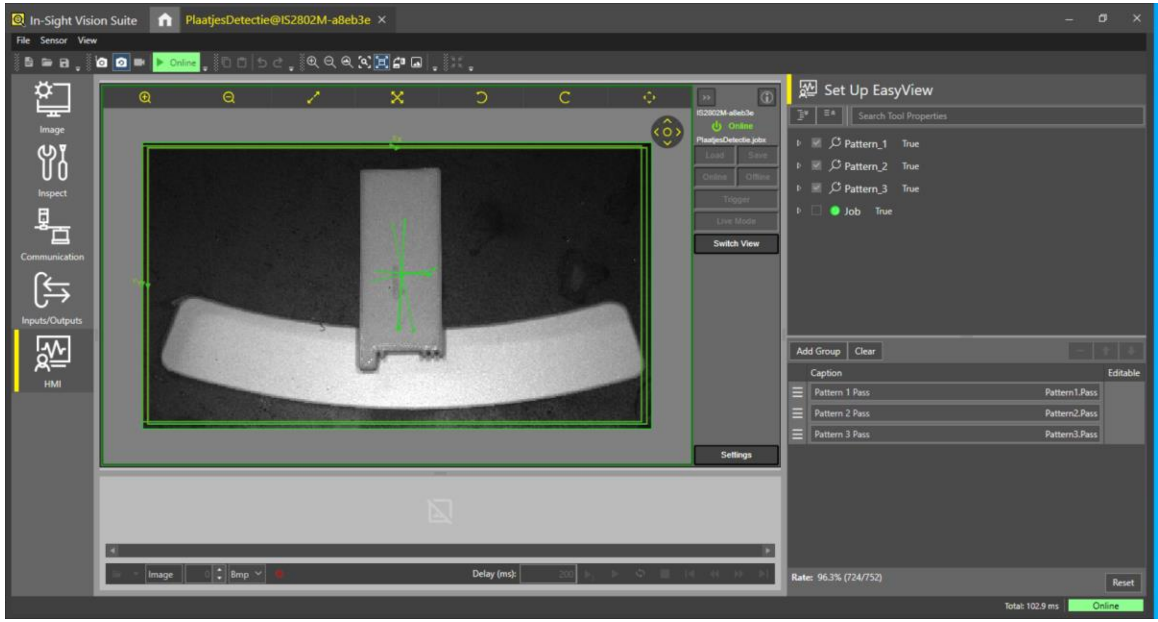


Demo opstelling: Cognex

Basisopstelling voorzien

- Aangesloten op de IPC (PLC):
  - Programmatie via PC met insight vision suit
- Demo programma:
  - Herkenning van verschillende plaatjes
  - HMI voorzien op IPC

- Foto



Nog te ontvangen materiaal

- Belichting met Ethercat interface:
  - Ringlicht
  - Backlight
  - Verwachte levering : Q1:2024

- Camera:
  - VCS2000-0200
  - 167 FPS

Met de steun van VLAIO

Succesverhalen Captic & Innomatic

Met de steun van VLAIO

CAPTIC

10+ years of R&D allowed Captic to harness the power of AI-Vision in food manufacturing, reliably.

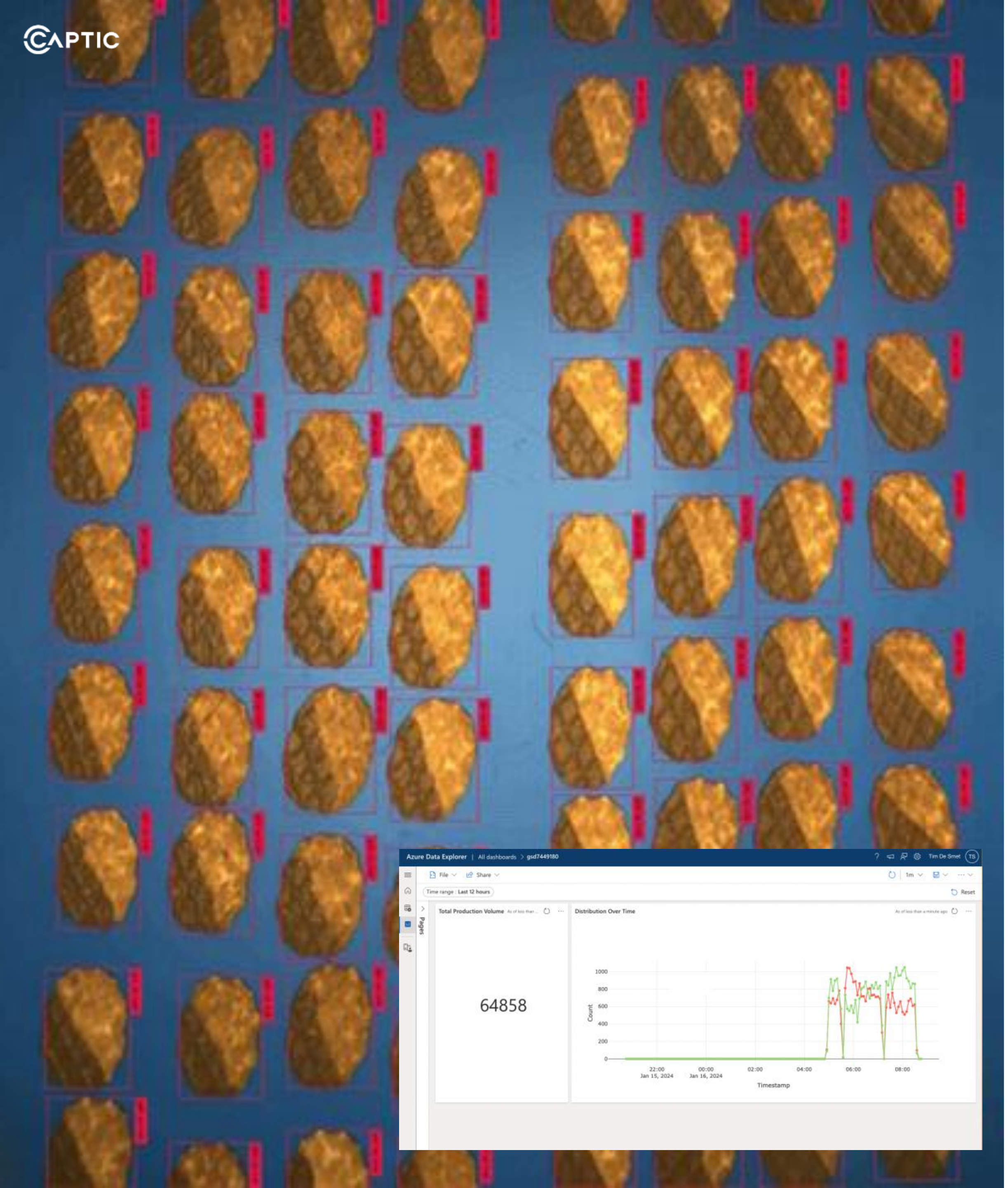
ML6

And more...

CAPTIC

And more...

Met de steun van



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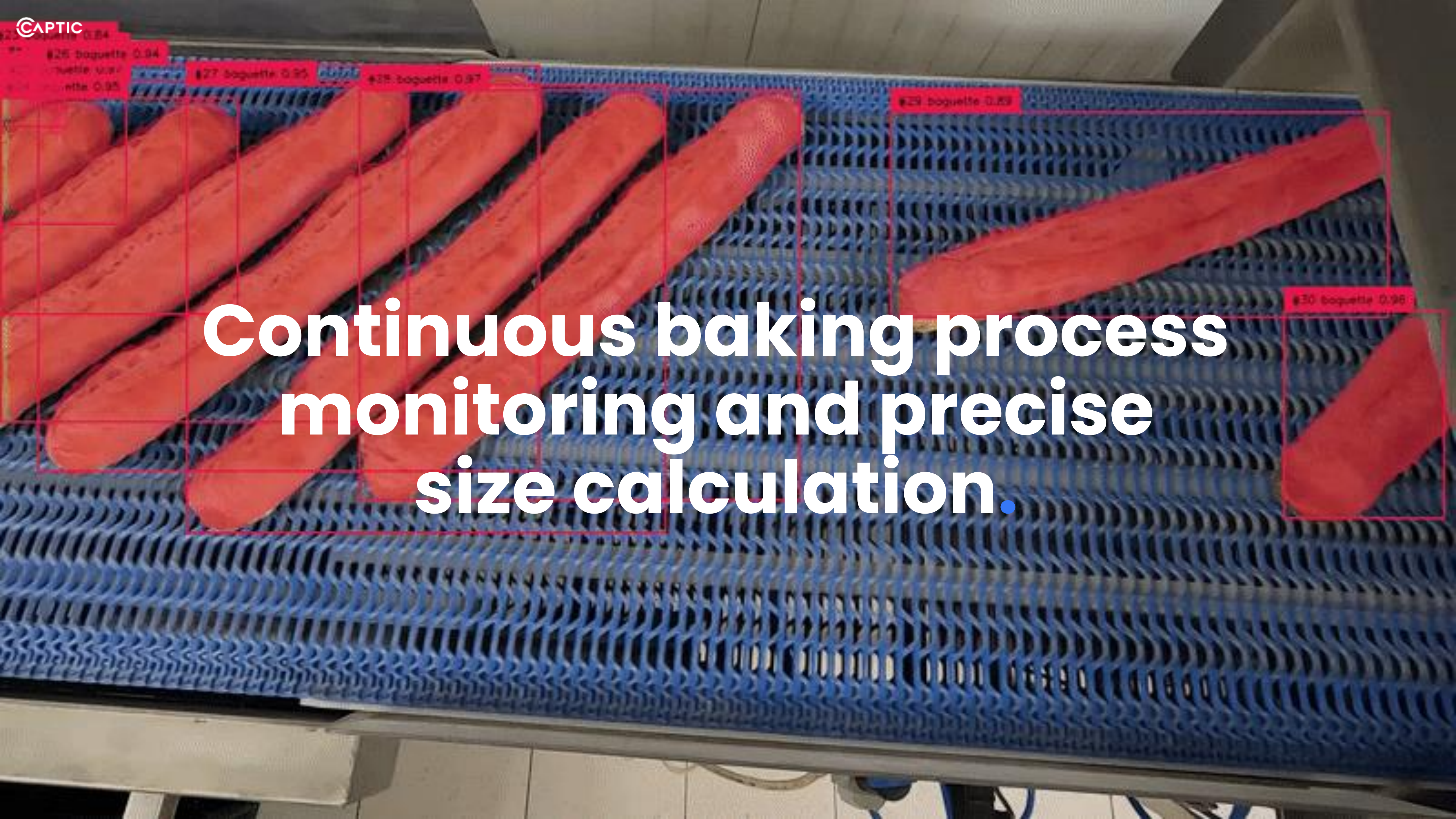
Inline quality control and accurate OEE to ensure production efficiency of complex products.

Met de steun van VLAIO

Real-time process steering through waste line inspection.

Met de steun van



Continuous baking process monitoring and precise size calculation.

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Toxic plant detection to ensure product safety and supplier feedback.

Continuous monitoring for anomalies in bulk product.

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Intelligent package and product inspection with complex checks.

Cross-checking labels, barcodes, BB dates, product, …

Met de steun van VLAIO

Automating laborious, dangerous or dull tasks on irregular items.

Met de steun van VLAIO

Summary.

Captic has proven to be a reliable supplier for AI/3D-Vision applications

Food business? → We can automate manual tasks
→ We can provide detailed insights

Automated packing	OEE	Inline Quality Control	Tray filling	Sorting
Meal prep	Bin picking	Bin picking	Package inspection	Advanced automation

Integrator? → We can enable you to solve a new realm of use cases
through AI and 3D

Machine builder? → We can help you build the new generation of machines

Met de steun van VLAIO

Workshop Machine Vision

- Wanneer? Tweemaal op donderdag 22 en 23 februari (8:30 – 18:00)
- Waar? KU Leuven Brugge – Spoorwegstraat 12, 8200 Brugge
- Prijs? 450 euro basisprijs – 75 euro voor leden TETRA
- Broodjes en koffiepauzes inbegrepen
- Max 1 persoon per bedrijf aan verlaagd tarief
- Inschrijvingen via QR code

Workshop Machine Vision

- 08:30 – 09:00: Ontvangst met ontbijt
- 09:00 – 11:00: Workshop Machine Vision Consultancy
- 11:00 – 11:15: Pauze
- 11:15 – 12:15: Workshops – Wave 1
- 12:15 – 13:00: Lunch met broodjes
- 13:00 – 14:00: Workshops – Wave 2
- 14:00 – 15:00: Workshops – Wave 3
- 15:00 – 15:30: Pauze
- 15:30 – 16:30: Workshops – Wave 4
- 16:30 – 17:30: Workshops – Wave 5

Met de steun van

Workshop Machine Vision

- ‘Cognex Smart camera’
- ‘Omron High-Speed measurement setup’
- ‘Hardware selection’
- ‘Deep Learning met Halcon’
- ‘Vision-Based Robot Picking met een Intel diepte Camera in Python’
- ‘Open Source programmeren met OpenCV en Keras in Python’

Met de steun van VLAIO

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VLAIO TETRA

Machine Vision for Quality Control

(MV4QC)

Inschrijving workshop

Tussentijdse vergadering IV

https://www.mv4qc.be

Met de steun van VLAIO

Hands-on Machine Vision Workshop

- 22^{nd} and 23^{rd} Februari (8:30 – 18:00)
- KU Leuven Brugge – Spoorwegstraat 12, 8200 Brugge