Data Science for Next Level Dairying

HDRF Next Generation Dairying Conference

November 19th, **Claudia Kamphuis** – senior researcher WLR, coordinator Expertise Team Data Science

Wageningen University and Research

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Road map of this presentation

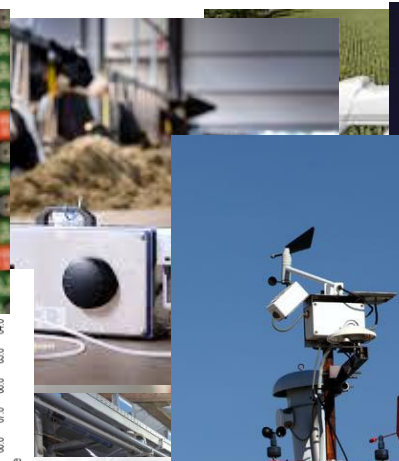
Data (Science) in the Dairy Domain

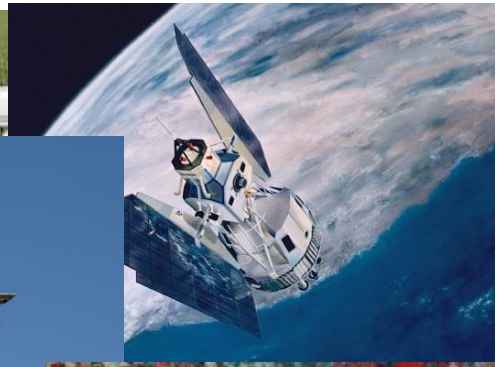
Sweet spot examples (at WUR)

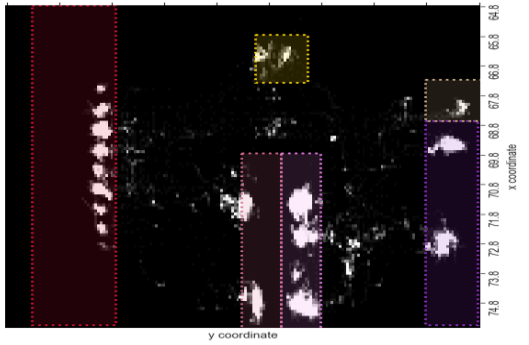
- Large scale real-time data collection
- Digital twins
- Artificial Intelligence for behaviour analysis

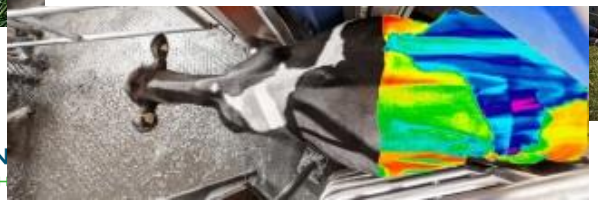
Take-home message

Data in the Dairy Domain









Data in the dairy domain

Due to increasingly tech-saffy livestock domain

Volume

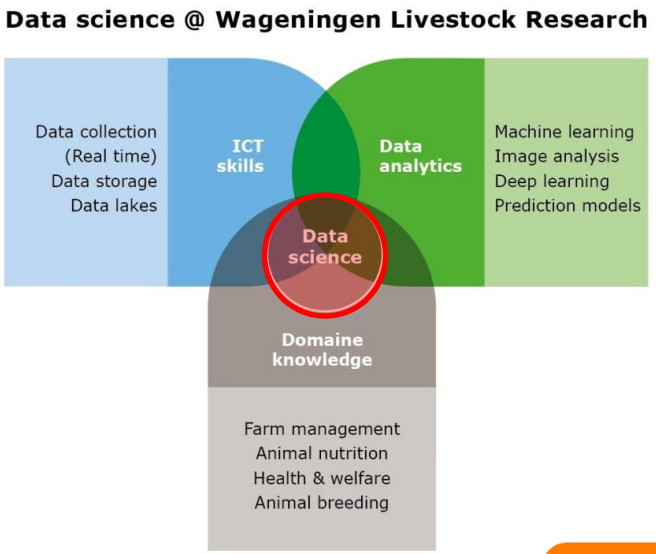
Variety

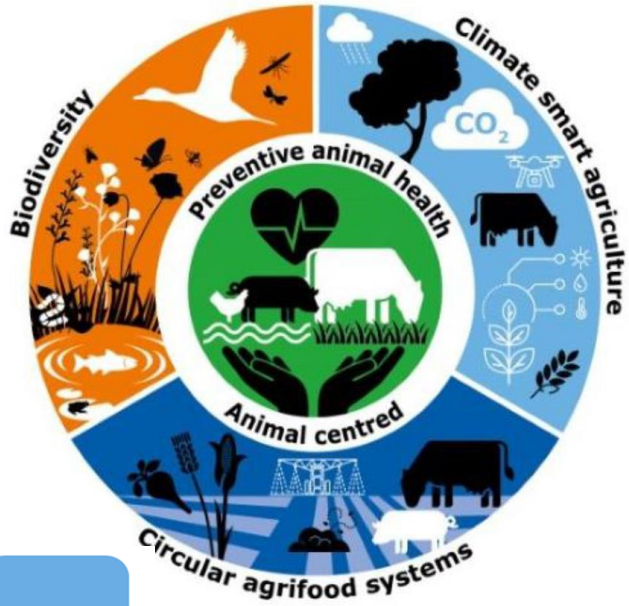
Veracity

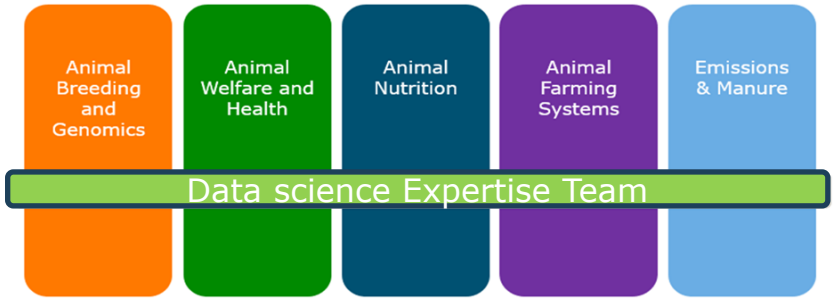
Bringing challenges before we can create value

Data Science can help

Data Science in the Dairy Domain







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Take-home message

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Acknowledgements to financers
KB Data Driven and High Tech
Next Level Animal Sciences
SSN – Dairy Campus Innovation Fund
Ministry of LVVN
Noldus Technology

And many MANY people doing all the work
Ina Hulsegge, Marjaneh Taghavi, Wijbrand Ouweltjes, Rodania Bekhit, Yvette de Haas, Roel Veerkamp, Bert Klandermans, Gerrit Seiger, Anouk van Breukelen, Frits van Evert

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Take-home message

Large-scale real-time collection and storage of methane emissions

Why?

NL has committed itself to the climate agenda: reduce methane emissions by 49% in 2030

Livestock sector committed to this reduction too

Necessary for strategies to reduce methane emissions in livestock sector, e.g., through breeding

For breeding: lots of cow-individual data required, how to do this?

Large-scale real-time collection and storage of methane emissions

Sensor ‘Sniffer’

Relatively cheap continues measurements CH4 and CO2

Not measured = from which cow?

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100years 1918 — 2018

Large-scale real-time collection and storage of methane emissions

Sniffer

Data push

Data logger

WiFi

Data pull

Computer at WUR

Data push

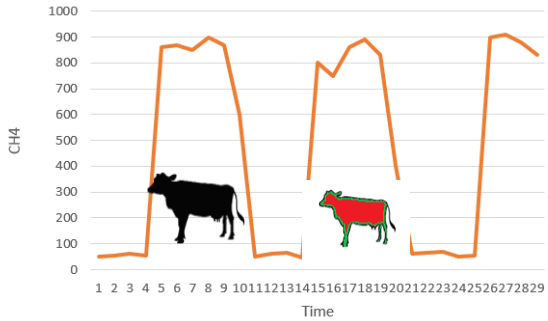
Storage drive

Data pull

Quality check and analysis

But

Difficult to combine sensors due to error-prone key identifiers



Large-scale real-time collection and storage of methane emissions

But

Difficult to combine sensors due to error-prone key identifiers

Difficult to upscale to more farms

costs are relatively high, and depends on WIFI coverage

Data quality check done after data storage

risk of losing data if not done regularly

Large-scale real-time collection and storage of methane emissions

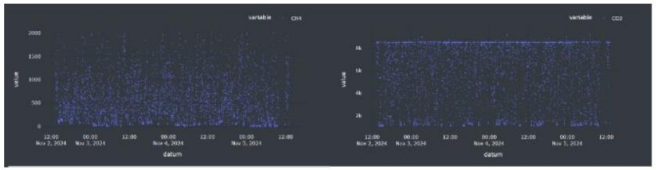
Data pull

IoT

Data push
Every 3 minutes

Azure

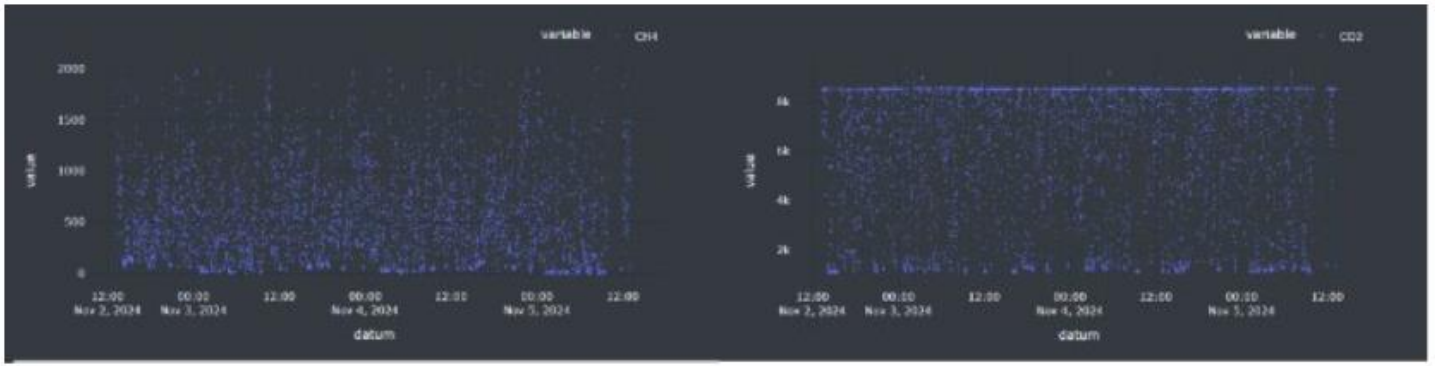
Alert via email when
no batch
no values in batch
Strange values



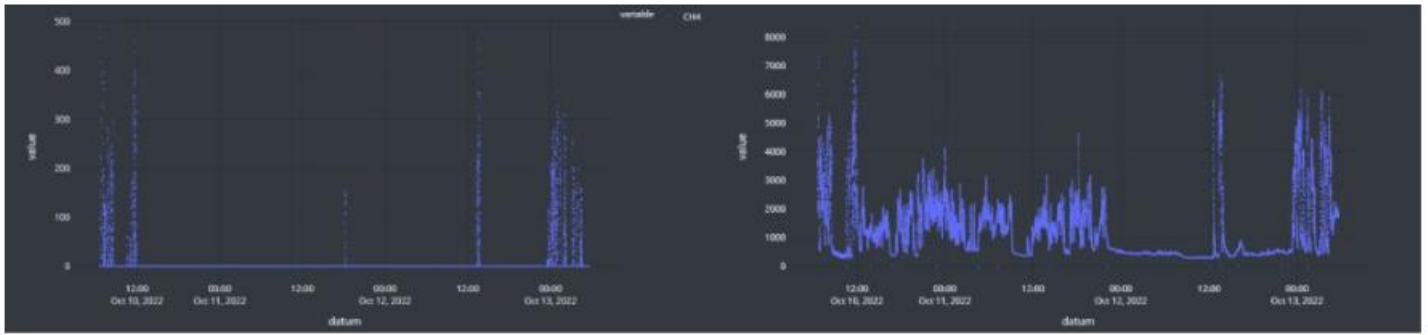
Real-time Visualisation of data

Data pull

Large-scale real-time collection and storage of methane emissions



Desired data



Undesired data due to, e.g., blocked tube or filter

Large-scale real-time collection and storage of methane emissions

Large-scale phenotyping made possible

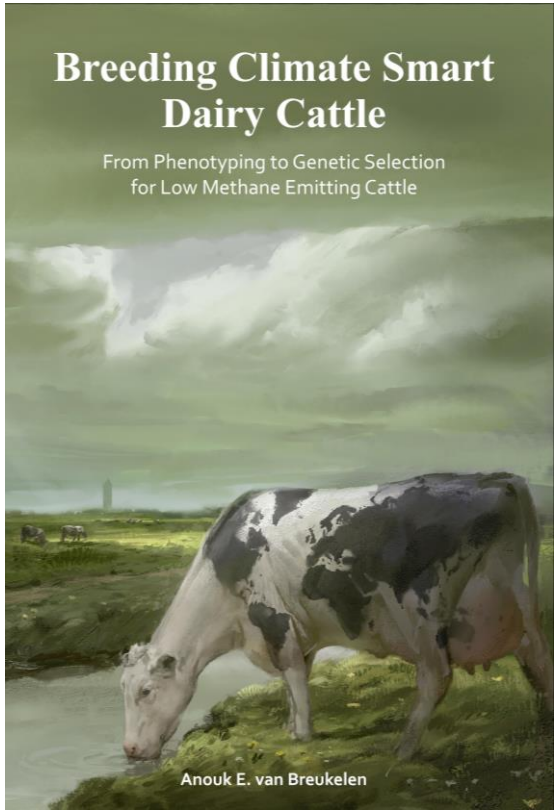
	N farms	N cows	N records
Weekly mean CH_4	72	7,139	74,569

Heritability weekly CH_4 = 0.17 ± 0.04

Genetic correlation with GreenFeed = 0.76 ± 0.15

Low and non-significant correlations with other production and health traits

Large-scale real-time collection and storage of methane emissions



Dutch breeding company will bring out a new breeding value for methane emission based on this work, early next year

Which was not possible without this new way of data collection

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Take-home message

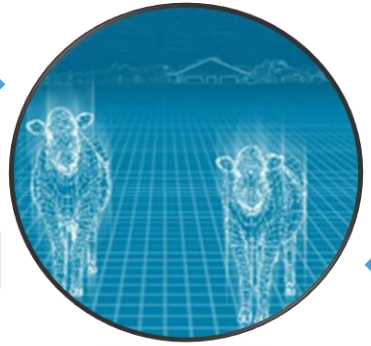
Digital Twin of a dairy farm – key aspects of a twin

Updated by real-time (sensor) data
provides immediate feedback

Models the individual, enables simulation
Is modular, multi-scale, predictive

Provides basic user interaction

Facilitates communication



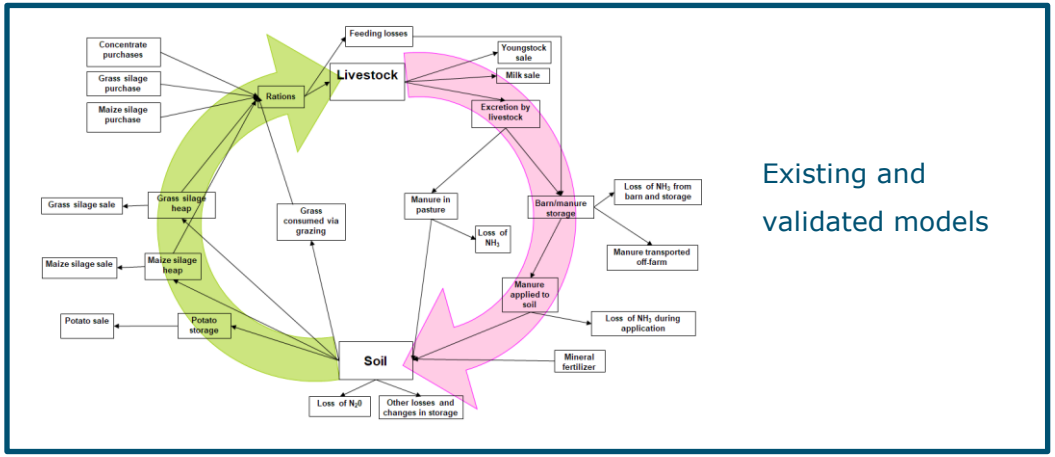
Provides actionable knowledge

(near) Real-time farm and field specific data that feed the digital version containing different models

Inputs

Core of Digital Twin: Twinning N status

Framework to let different models communicate
Models are modular and flexible
Simulating Nitrogen situation
Data assimilation to synchronize status of digital version with reality



Existing and validated models

(near) Real-time farm and field specific data that feed the digital version containing different models

Inputs

Core of Digital Twin: Twinning N status

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Simulating Nitrogen situation
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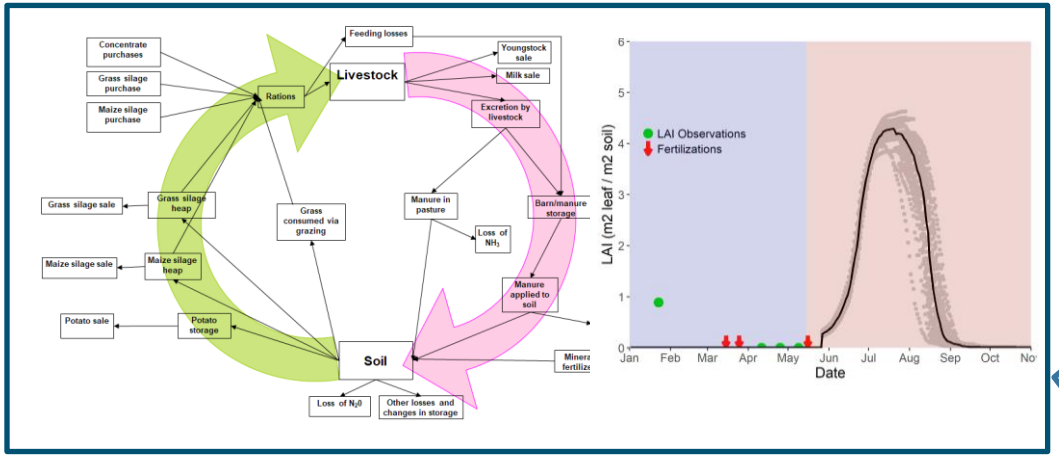
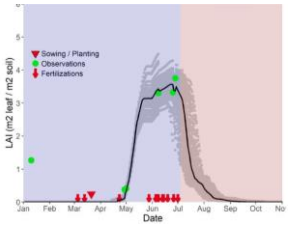
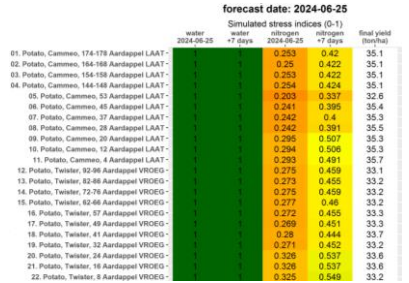


Outputs

Output of those models providing real-time feedback through e.g., visualisation

Information / Alerts





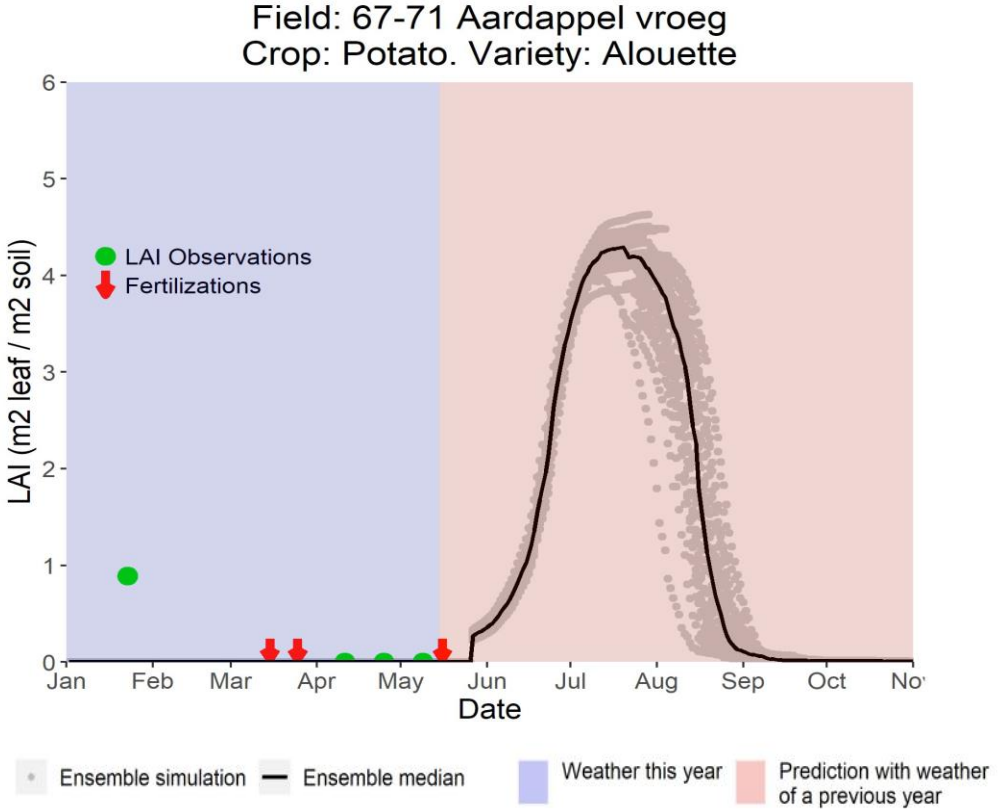
Decisions, and actions

Inputs

The DFF in use on Boerderij van de Toekomst and Van den Borne

BvdT Lelystad

van den borne aardappelen



The DFF in use on Boerderij van de Toekomst and Van den Borne

BvdT Lelystad

van den borne aardappelen

	forecast date: 2024-06-25					forecast date: 2024-06-26				
	Simulated stress indices (0-1)					Simulated growth conditions (1=very good)				
	water 2024-06-25	water +7 days	nitrogen 2024-06-25	nitrogen +7 days	final yield (ton/ha)	water 2024-06-26	water +7 days	nitrogen 2024-06-26	nitrogen +7 days	final yield (ton/ha)
01. Potato, Cammeo, 174-178 Aardappel LAAT	1	1	0.253	0.42	35.1	1	1	1	1	64.1
02. Potato, Cammeo, 164-168 Aardappel LAAT	1	1	0.25	0.422	35.1	1	1	1	1	63.7
03. Potato, Cammeo, 154-158 Aardappel LAAT	1	1	0.253	0.422	35.1	1	1	1	1	63.8
04. Potato, Cammeo, 144-148 Aardappel LAAT	1	1	0.254	0.424	35.1	1	1	1	1	63.8
05. Potato, Cammeo, 53 Aardappel LAAT	1	1	0.203	0.337	32.6	1	1	1	1	63.5
06. Potato, Cammeo, 45 Aardappel LAAT	1	1	0.241	0.395	35.4	1	1	1	1	63.6
07. Potato, Cammeo, 37 Aardappel LAAT	1	1	0.242	0.4	35.3	1	1	1	1	63.7
08. Potato, Cammeo, 28 Aardappel LAAT	1	1	0.242	0.391	35.5	1	1	1	1	63.5
09. Potato, Cammeo, 20 Aardappel LAAT	1	1	0.295	0.507	35.3	1	1	1	1	57.6
10. Potato, Cammeo, 12 Aardappel LAAT	1	1	0.294	0.506	35.3	1	1	1	1	57.6
11. Potato, Cammeo, 4 Aardappel LAAT	1	1	0.293	0.491	35.7	1	1	1	0.928	42.1
12. Potato, Twister, 92-96 Aardappel VROEG	1	1	0.275	0.459	33.1	1	1	1	1	56.8
13. Potato, Twister, 82-86 Aardappel VROEG	1	1	0.273	0.455	33.2	1	1	1	1	56.9
14. Potato, Twister, 72-76 Aardappel VROEG	1	1	0.275	0.459	33.2	1	1	1	1	56.5
15. Potato, Twister, 62-66 Aardappel VROEG	1	1	0.277	0.46	33.2	1	1	1	1	56.8
16. Potato, Twister, 57 Aardappel VROEG	1	1	0.272	0.455	33.3	1	1	1	1	56.9
17. Potato, Twister, 49 Aardappel VROEG	1	1	0.269	0.451	33.3	1	1	1	1	56.5
18. Potato, Twister, 41 Aardappel VROEG	1	1	0.28	0.444	33.7	1	1	1	0.944	42.7
19. Potato, Twister, 32 Aardappel VROEG	1	1	0.271	0.452	33.2	1	1	1	1	56.8
20. Potato, Twister, 24 Aardappel VROEG	1	1	0.326	0.537	33.6	1	1	1	1	48.7
21. Potato, Twister, 16 Aardappel VROEG	1	1	0.326	0.537	33.6	1	1	1	1	49.3
22. Potato, Twister, 8 Aardappel VROEG	1	1	0.325	0.549	33.2	1	1	1	1	49.2

The DFF in use on De Marke

Data from different sources into a DFF data base

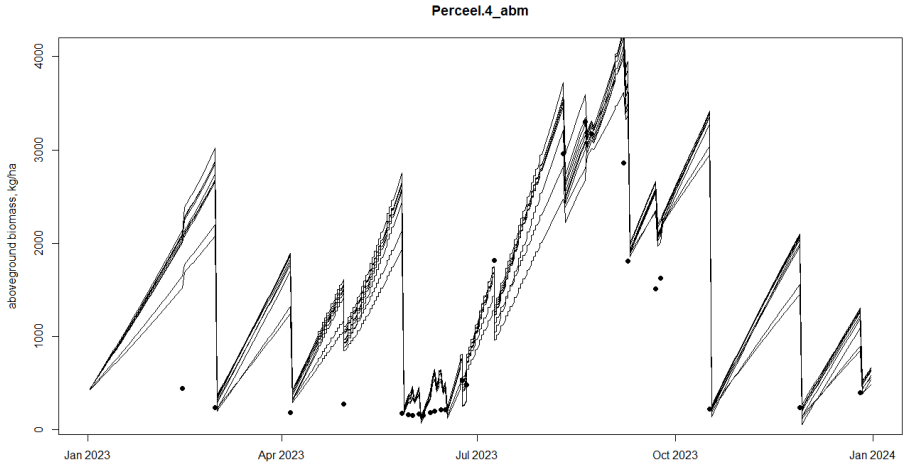
Weather at field level, sentinel, Dacom, national soils, Eurofins, cow data

Models in the CORE of the DFF

grass growth model, cow production model, ration model, water balance model

Simulating grass growth, with data assimilation for e.g., harvest events

using high growth rate uncertainties (bigger perturbations, e.g., drought)



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100years
1918 — 2018

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Take-home message

Artificial intelligence for behaviour analyses

Dot on the horizon:

Longitudinal continuous non-invasive measurements of health and welfare of a large group of animals

Use Case:

Behaviour related to **Locomotion** using computer vision in a 'real' environment

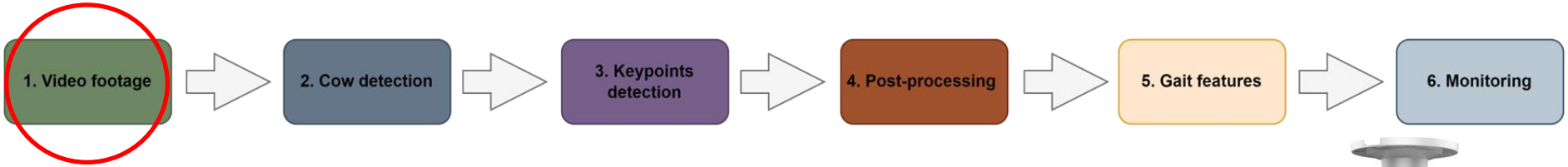
WLR - Dairy Campus

Individual animal – locomotion scoring
One camera

Individual animal in a group – behavior related to locomotion. Multiple cameras

Artificial intelligence for behaviour analyses

For an individual animal



One RGB-camera at exit lane milking parlour

25 fps, 100 Holstein cows, 2/day, 6hr/day

Manual selection of video clips of 24 cows for step 2

afternoon and morning, cows passing calmly, variation in coat pattern

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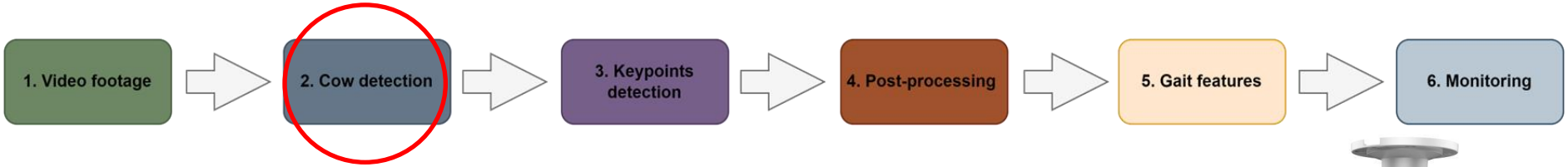
Artificial intelligence for behaviour analyses

For an individual animal



One RGB-camera at exit lane milking parlour

25 fps, 100 Holstein cows, 2/day, 6hr/day

Manual selection of video clips of 24 cows for step 2

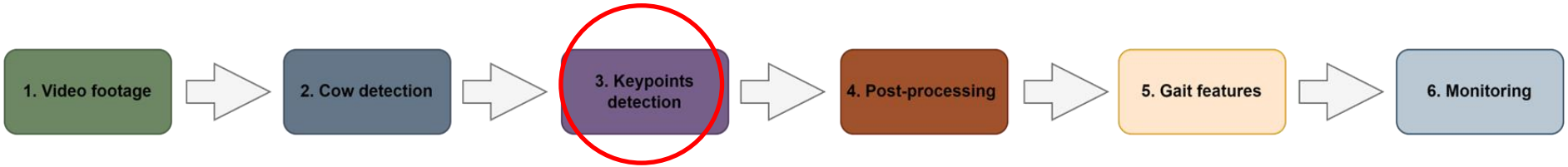
afternoon and morning, cows passing calmly, variation in coat pattern

Trained Yolov8 object detector on 200 frames

mean average precision: 0.95

Artificial intelligence for behaviour analyses

For an individual animal



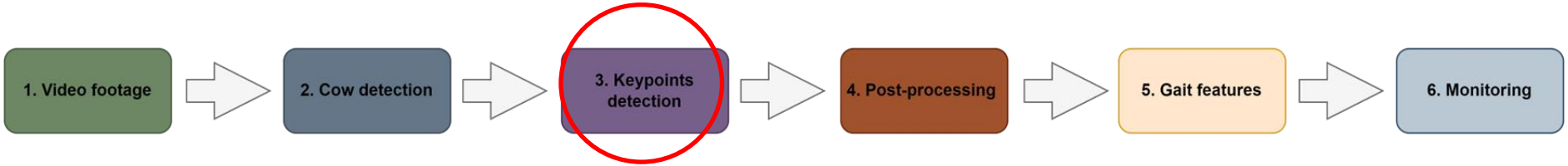
Key point detection using T-leap model (Russello et al., 2022)

- Used the temporal information to detect the key-points,
- Validated on artificially occluded data
- Retrained for indoor situation

Russello et al. 2022

Artificial intelligence for behaviour analyses

For an individual animal

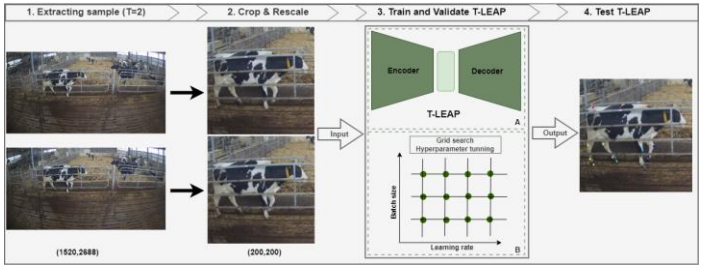


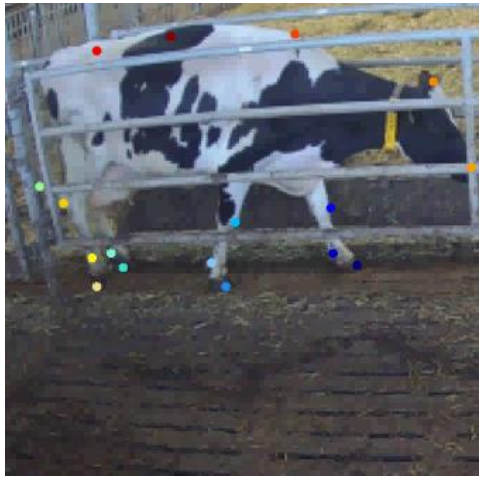
Key point detection using T-leap model (Russello et al., 2022)

Used the temporal information to detect the key-points

validated on artificially occluded data

Retrained for indoor situation, 17 key points

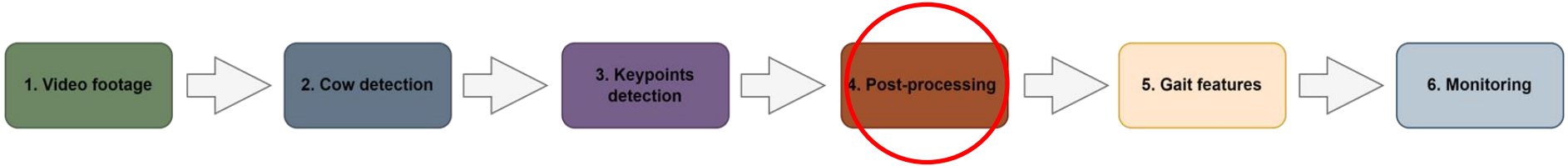


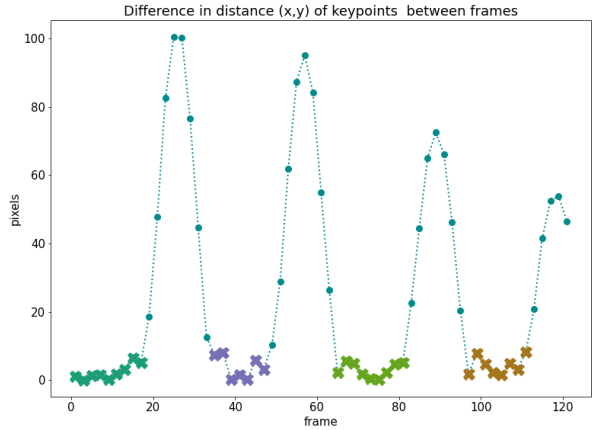


Taghavi et al. 2023

Artificial intelligence for behaviour analyses

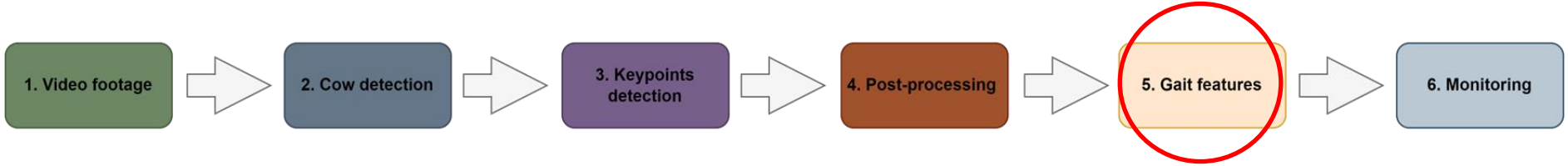
For an individual animal

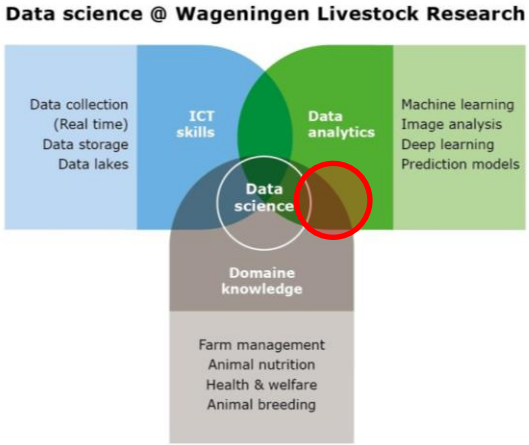




Artificial intelligence for behaviour analyses

For an individual animal



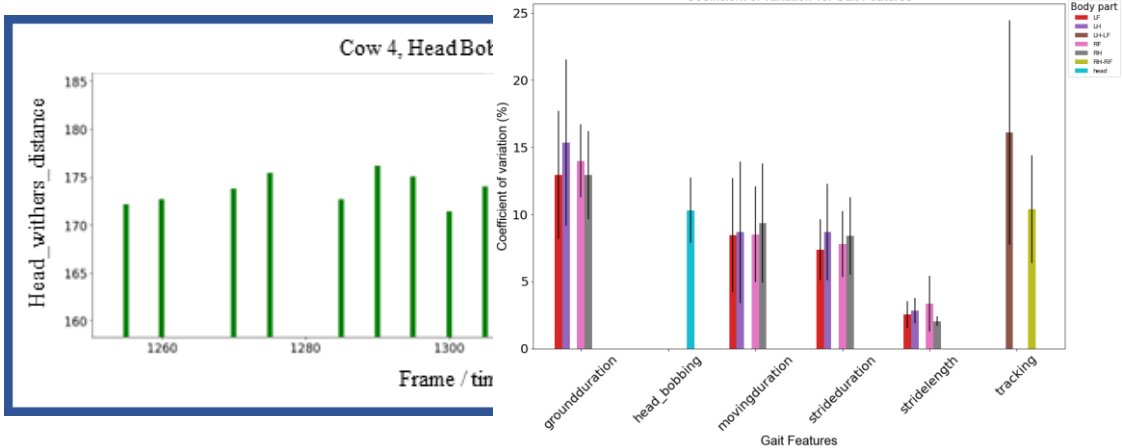


Gait feature	Involved key points	Calculation x,y	t-dimension
Stride length	All hoofs	Leg positions	• Stable leg position • Distance between steps- pixels wise
Stride duration	All hoofs	Leg positions	• Stable leg position • Distance between steps- time wise
Ground duration	All hoofs	Leg positions	• Stable leg position
Moving duration	All hoofs	Leg positions	• Moving leg
Tracking up	Front hoofs, hind hoofs	Leg positions	• Distance of the footprints of the same side (left/ right)
Head bobbing	Nose, forehead, withers	Distance head to withers (vertical)	• Amplitude

Artificial intelligence for behaviour analyses

For an individual animal

1. Video footage → 2. Cow detection → 3. Keypoints detection → 4. Post-processing → 5. Gait features → 6. Monitoring



Prediction model for locomotion scoring using gait features and key points

Repeatability analysis: consistency of gait features in healthy cows (n = 15, 15 weeks, one video per week)

Artificial intelligence for behaviour analyses

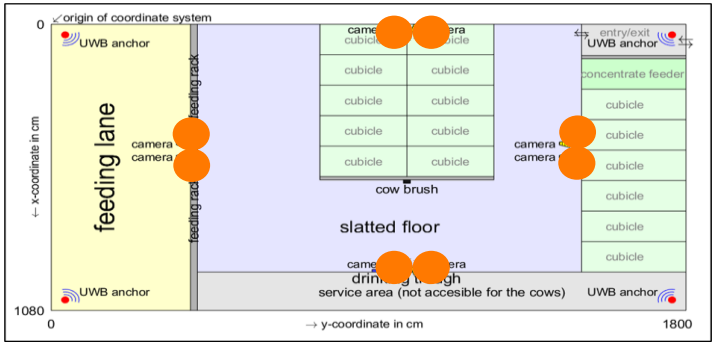
For an individual animal *housed in a group*

8 cameras (Noldus technology)

In stereo

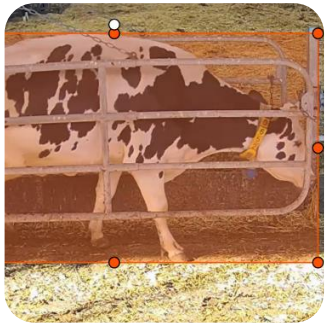
Birds view

16 animals



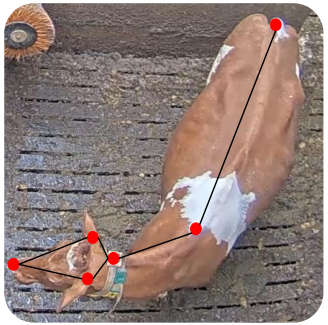
Artificial intelligence for behaviour analyses

For an individual animal *housed in a group*



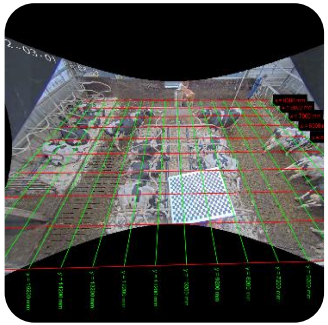
Step 1

Object detection and tracker Yolov8



Step 2

Keypoint detection (MMPose, 4 key points)



Step 3

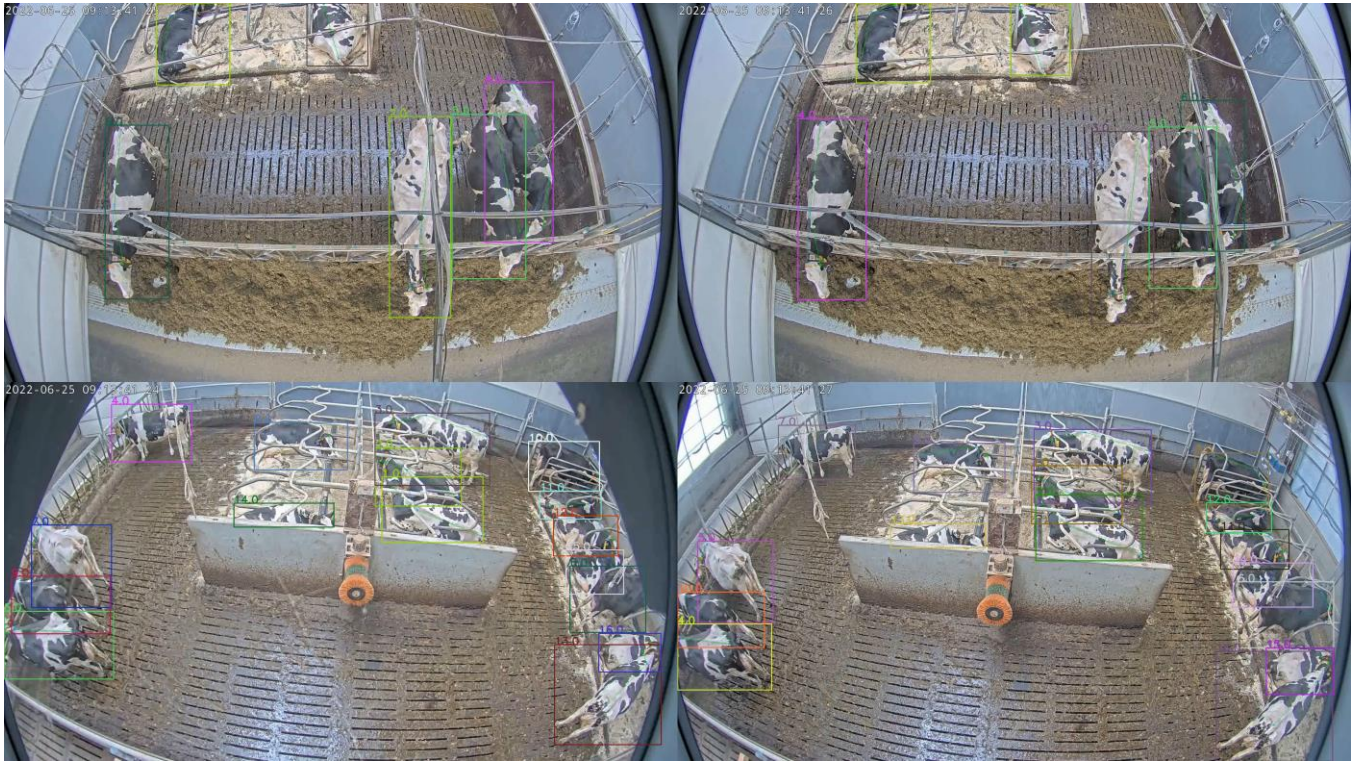
Integration of multiple views

2D to 3D key point tracker

Step 4

Behavior recognition (patterns)

Artificial intelligence for behaviour analyses



Step 4

Behavior recognition (patterns)

Artificial intelligence for behaviour analyses

For an individual animal *housed in a group*

Step 4

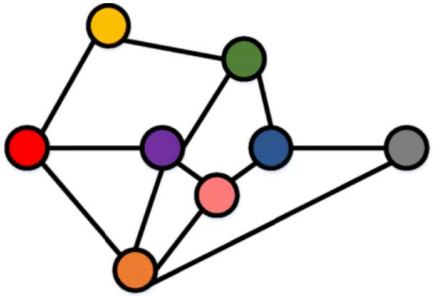
Behavior recognition (patterns)

The time it takes for a cow to **get up** or **lie down**

Involves

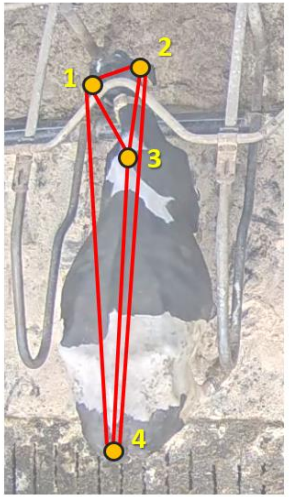
Recognize and classify the actions using (2D / 3D) key points

Assess the time it takes



GNN

In Non-Euclidean Space



Artificial intelligence for behaviour analyses

For an individual animal *housed in a group*

Step 4

Behavior recognition (patterns)

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Recognize and classify the actions using (2D / 3D) key points

Assess the time it takes

2D

Train	Val	Test
90.5%	80%	79.3%

Test	
Else	8/9
Down	7/10
Up	8/10

Data size

- Training: 274
- Validation: 42
- Test: 29

3D

Train	Val	Test
91.2%	79.2%	75%

Test	
Else	4/7
Down	8/8
Up	6/8

Data size

- Training: 147
- Validation: 24
- Test: 24

Artificial intelligence for behaviour analyses

For an individual animal *housed in a group*

The time it takes for a cow to **get up** or **lie down**

Road map of this presentation

Data (Science) in the Dairy Domain

Sweet spot examples (at WUR)

- Computer vision and Artificial Intelligence
- Large scale real-time data collection
- Digital twins

Take-home message

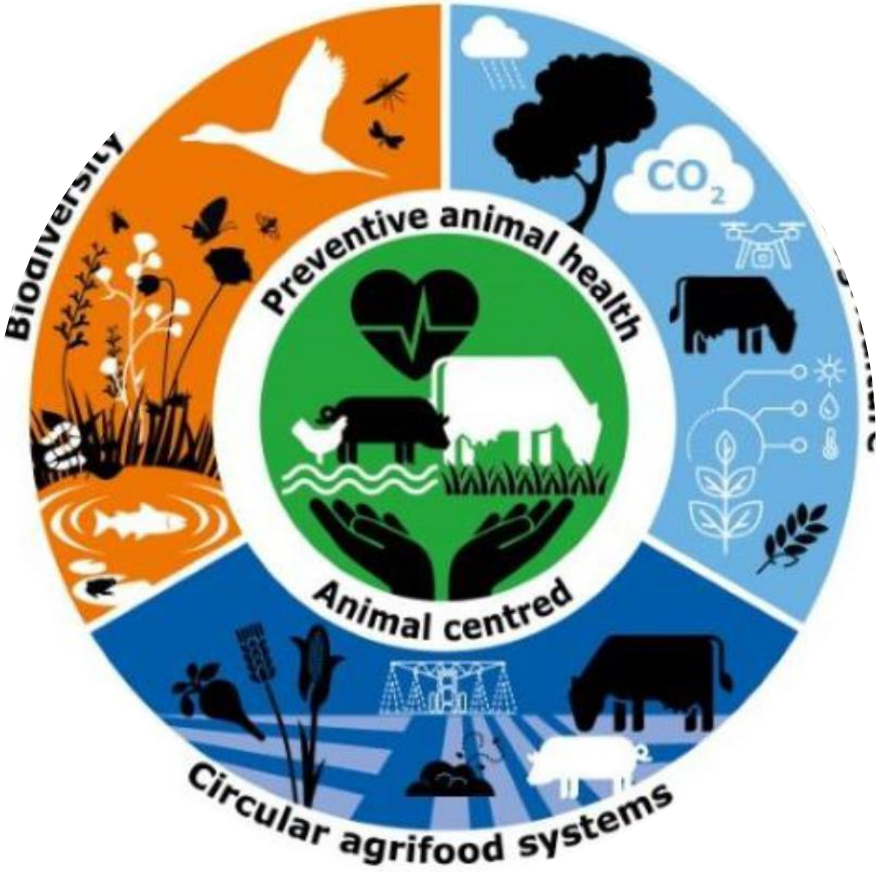
Take home message

Data Science is the sweet spot

Contributes to solving complex challenges

Success lies in connecting technical solutions with our domain

Most important are people, communication, understanding, and patience



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