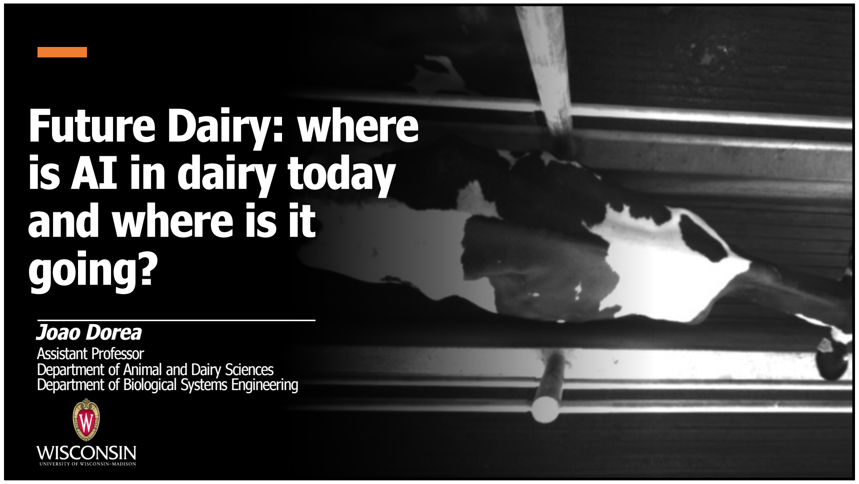


Future Dairy: where is AI in dairy today and where is it going?

Joao Dorea
Assistant Professor
Department of Animal and Dairy Sciences
Department of Biological Systems Engineering
WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

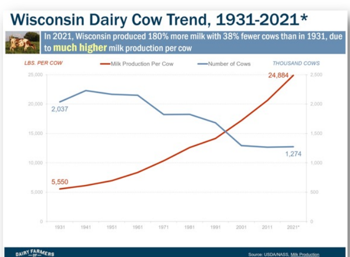
1

Outline

- **What is AI?**
- **Why is AI important for dairy systems?**
- **Applications of AI in dairy farms :**
  - **Computer Vision**
    - Identification, Diseases, Heat-Stress, Locomotion
- **Final Considerations**

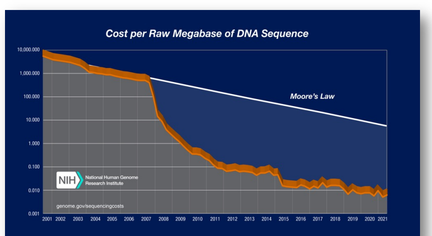
2

Genomics: Amazing Progress!



Genomics, Transcriptomics, Proteomics, Metabolomics, Epigenomics, Microbiomics, etc.

Costs to genotype drastically decreased over time!

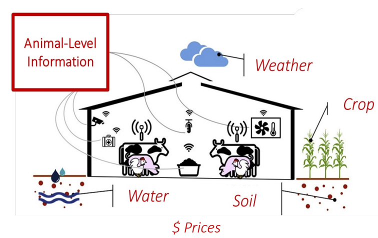


High-Throughput Phenotyping
"Phenomics"

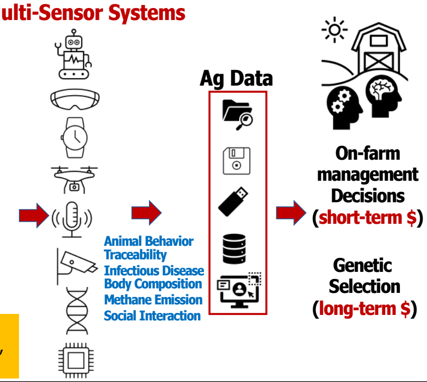
3

Sensing Technologies: Individual Animal Data

- For large-scale phenotyping (what is it?):
"sensing technology is the solution"

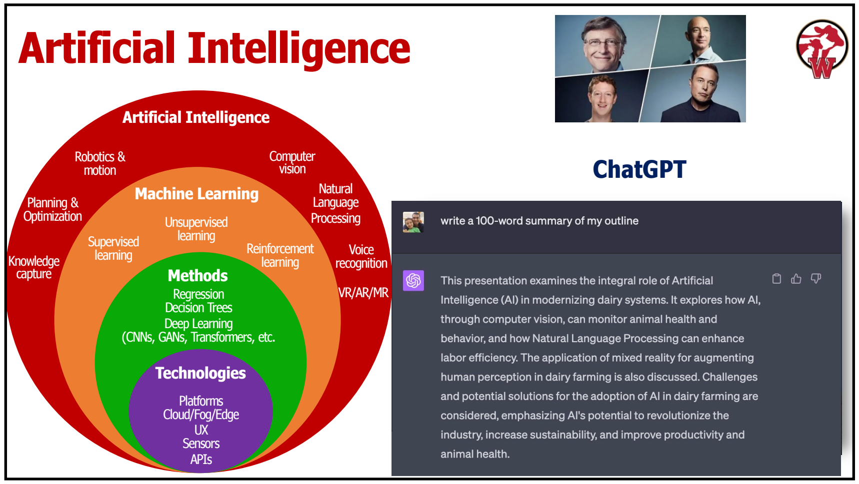


Multi-Sensor Systems

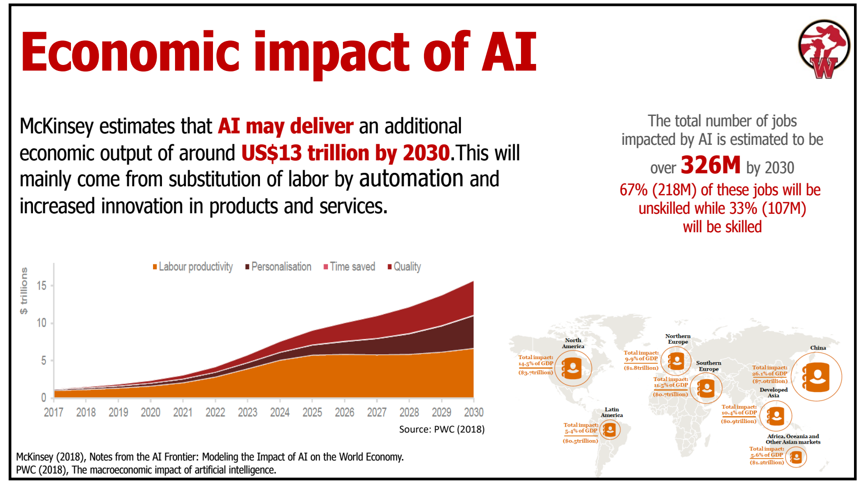


The total **farm employment**—hired workers and self-employed and family workers—**fell by 81%** between 1948 and 2017 (USDA, ERS, 2020).

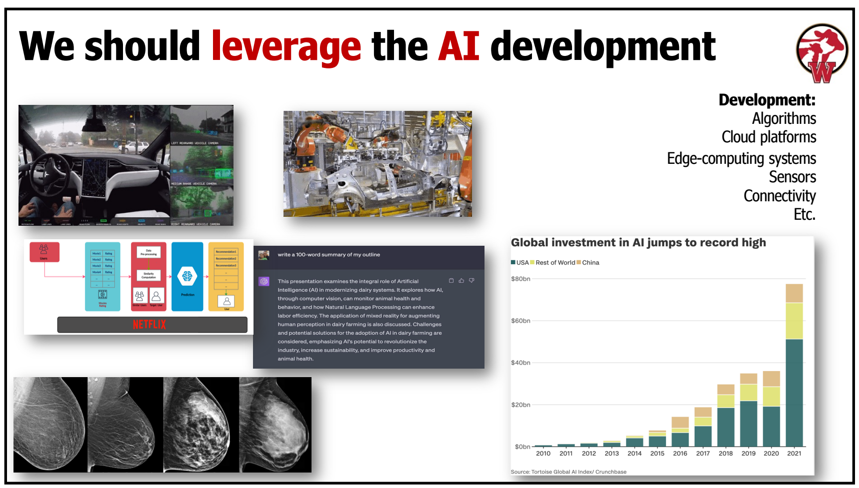
4


Artificial Intelligence
Artificial Intelligence
Robotics & motion
Computer vision
Planning & Optimization
Machine Learning
Natural Language Processing
Unsupervised learning
Supervised learning
Reinforcement learning
Voice recognition
Knowledge capture
Methods
Regression
Decision Trees
Deep Learning
(CNNs, GANs, Transformers, etc.
VR/AR/MR
Technologies
Platforms
Cloud/Fog/Edge
UX
Sensors
APIs
ChatGPT
write a 100-word summary of my outline
This presentation examines the integral role of Artificial Intelligence (AI) in modernizing dairy systems. It explores how AI, through computer vision, can monitor animal health and behavior, and how Natural Language Processing can enhance labor efficiency. The application of mixed reality for augmenting human perception in dairy farming is also discussed. Challenges and potential solutions for the adoption of AI in dairy farming are considered, emphasizing AI's potential to revolutionize the industry, increase sustainability, and improve productivity and animal health.

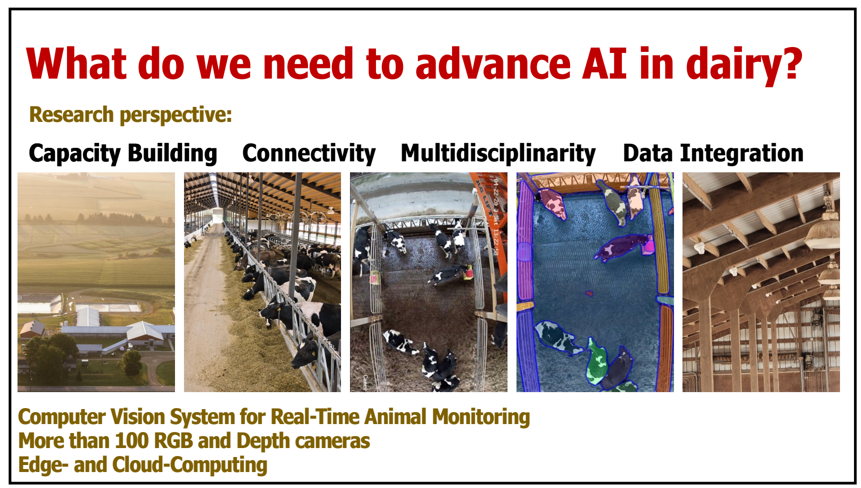
5


Economic impact of AI
McKinsey estimates that AI may deliver an additional economic output of around US$13 trillion by 2030.This will mainly come from substitution of labor by automation and increased innovation in products and services.
The total number of jobs impacted by AI is estimated to be over 326M by 2030
67% (218M) of these jobs will be unskilled while 33% (107M) will be skilled
Labour productivity
Personalisation
Time saved
Quality
$ trillions
15
10
5
0
2017 2018 2019 2020 2021 2022 2023 2024 2025 2026 2027 2028 2029 2030
Source: PWC (2018)
McKinsey (2018), Notes from the AI Frontier: Modeling the Impact of AI on the World Economy.
PWC (2018), The macroeconomic impact of artificial intelligence.

6


We should leverage the AI development
Development:
Algorithms
Cloud platforms
Edge-computing systems
Sensors
Connectivity
Etc.
Global investment in AI jumps to record high

7


What do we need to advance AI in dairy?
Research perspective:
Capacity Building
Connectivity
Multidisciplinarity
Data Integration
Computer Vision System for Real-Time Animal Monitoring
More than 100 RGB and Depth cameras
Edge- and Cloud-Computing

8

Artificial Intelligence in Dairy Systems

Our Goal:

-Optimize farm management decisions:
  - Nutrition and Health (others…)

-Improve labor efficiency

-Important for animal breeding programs

Today's Example:

Computer vision:
Identification, Diseases, Locomotion

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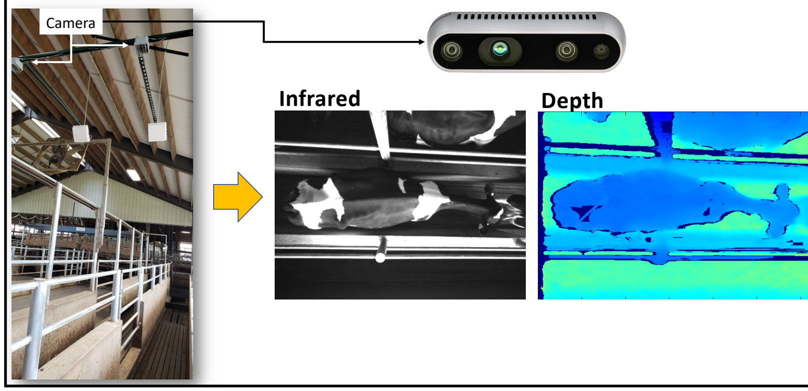
Implementing AI in Livestock Operations



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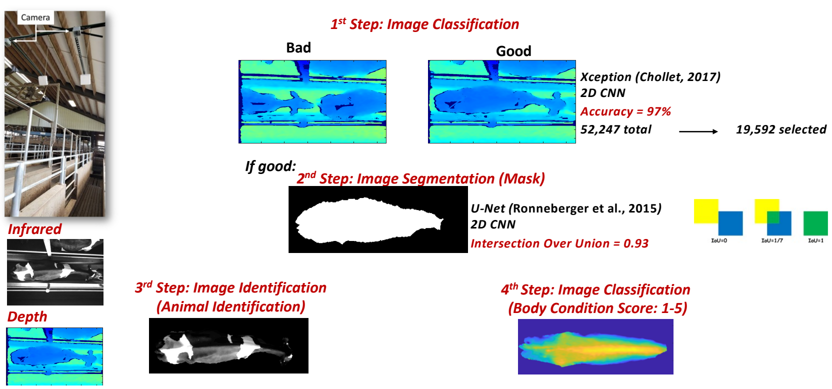
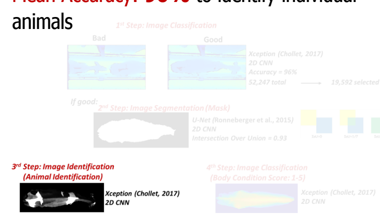
Automation: Cloud-Computing Framework

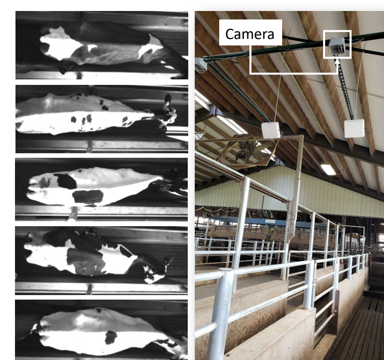


11

Animal identification using 2D images

- 92 lactating dairy cows;
- Training set: 16,055 images automatically acquired at UW-Madison;
- Testing set: 3,680 images test
- Deep Learning (CNN; Xception)
- Mean Accuracy: **96%** to identify individual animals





Ferreira et al., 2023

12

Animal identification using 2D images

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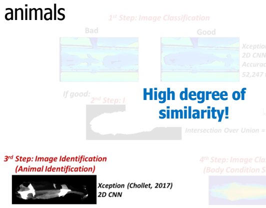

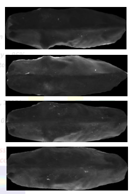

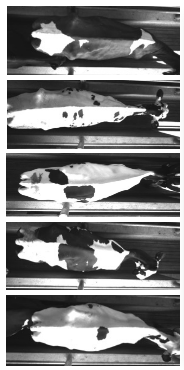

Ferreira et al., 2023

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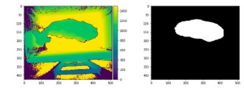
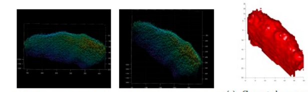
Animal Identification: 3D representation

3D images:
Voxels (VoxNet; Maturana and Scherer, 2015)
Point cloud (PointNet; Qi et al., 2016)

2D images:
Depth images
(VGG16, Xception, Inception v3)



(a) Original depth frame (b) Output from Mask R-CNN



(c) Generated point cloud (d) Augmented point cloud (e) Generated occupancy grid

RO = Random
CO = Chronological

Train-test split	Data representation	Architecture	F_1 score
RO[1]	DI[3]	VGG16	0.888
RO[1]	DI[3]	Inception v3	0.904
RO[1]	**DI[3]**	**Xception**	**0.959**
RO[1]	PC[4]	PointNet	0.669
RO[1]	OG[5]	VoxNet	0.880
CO[2]	DI[3]	VGG16	0.718
CO[2]	DI[3]	Inception v3	0.750
CO[2]	**DI[3]**	**Xception**	**0.804**
CO[2]	PC[4]	PointNet	0.429
CO[2]	OG[5]	VoxNet	0.656

How frequent should I retrain the algorithms?

F1-score

Time interval	Xception	PointNet	VoxNet
No skipping	**0.917**	0.533	0.917
1 week	**0.846**	0.551	0.831
2 weeks	**0.835**	0.441	0.806
3 weeks	**0.856**	0.282	0.792

Ferreira et al., 2022

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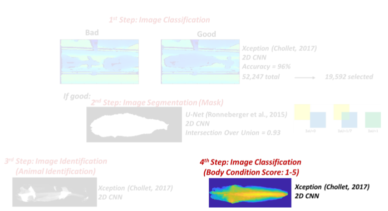
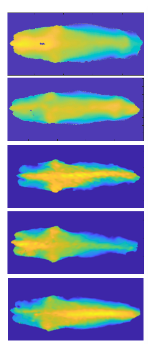
Body Condition Score using 3D images

- 59 lactating dairy cows
- Train: 11,943 images
- Test: 651 images
- Deep Learning (CNN; Xception)
- Accuracy (0.25-error): **81%** to classify BCS
- Accuracy (0.5-error): **96%** to classify BCS





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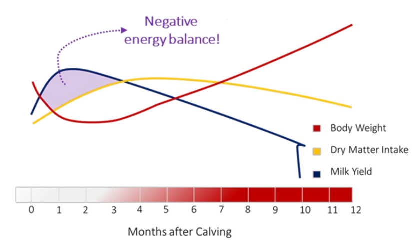
Problem: Health Disorders During Transition Period

- **The transition period is responsible for 67% of all cases of disease in dairy cows** ***(Carvalho et al., 2019);***

3 weeks pre- until 3 weeks post-calving



- **The severity of NEB can increase the risk of various peripartum disorders, including ketosis, hypocalcemia, retained placenta, metritis, endometritis, and displaced abomasum;**

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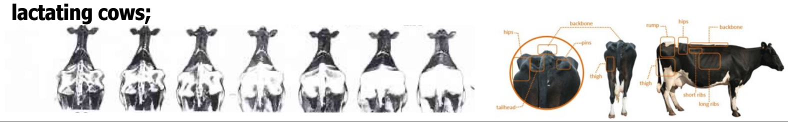
Economic Losses

- **Average cost per case:**
  - **- retained placenta: from $257 to $414** *(Liang et al., 2017; Gohary et al., 2018)*
  - **- metritis: $241 to $513** *(Liang et al., 2017; Perez-Baez et al., 2020)*
  - **- subclinical ketosis: from $169 to $359** *(Mostert et al., 2018; Raboissan et al., 2015)*
  - **- clinical ketosis can cost up to $1,673** *(Steeneveld et al., 2020)*
- **Large economic losses on dairy farms: treatment costs, reduced productive and reproductive performance and increased culling;**
- **Body condition score (BCS) is commonly used as a tool to assess risk of NEB in lactating cows;**



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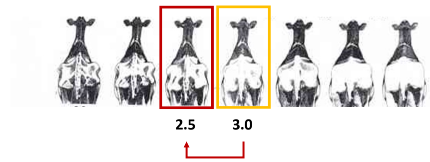
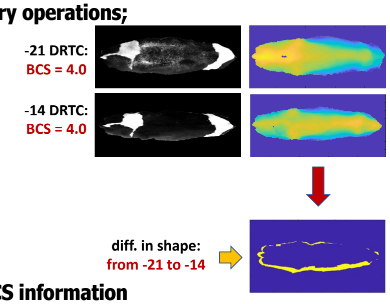
Subjective and Labor-Intensive

- **BCS is a subjective measurement on a 5-point scale that is difficult to measure consistently and systematically in large dairy operations;**





- **It requires a trained evaluator to collect BCS information**

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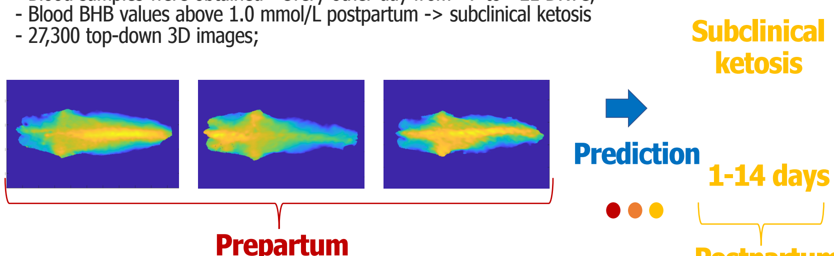
Early detection of subclinical ketosis in dairy cows

- Goal: Use prepartum 3D images to predict subclinical ketosis (1-14 DIM)
- **21, 14 and 7 days prior to calving;**
- 76 Holstein cows were individually collected (40 SCK and 36 non-SCK);
- Blood samples were obtained ~every other day from −7 to +21 DRTC;
- Blood BHB values above 1.0 mmol/L postpartum -> subclinical ketosis
- 27,300 top-down 3D images;



Ferreira et al., 2022 – ADSA

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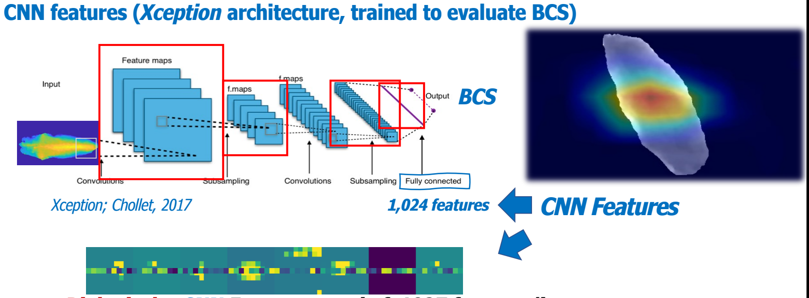
Early detection of subclinical ketosis in dairy cows

For each image:

- **Biological features (mask size, surface area, volume)**
- **CNN features (*Xception* architecture, trained to evaluate BCS)**



***Biological* + *CNN* Features: total of 1027 features/image;**

20

Early detection of subclinical ketosis in dairy cows

- **PLS-DA achieved a mean precision of 0.65, recall of 0.91, and F1-score of 0.75:**

Features	Algorithm	Precision (mean ± stdev)	Recall (mean ± stdev)	F1-Score (mean ± stdev)
BCS only	GBDT	0.503 ± 0.160	0.828 ± 0.205	0.611 ± 0.150
BCS only	PLS-DA	0.534 ± 0.148	0.963 ± 0.078	0.678 ± 0.125
Our features	GBDT	0.630 ± 0.094	0.908 ± 0.106	0.739 ± 0.086
Our features	**PLS-DA**	**0.650 ± 0.090**	**0.912 ± 0.102**	**0.754 ± 0.081**

+11 %

~65% of detected cows actually got sick

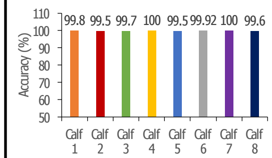
~91% of sick cows were early detected

False positives are better than false negatives!

21

Monitoring Feeding Behavior

- 1,546 images were used to train a deep learning algorithm for object detection (**YOLOv3**);
- 663 extra images were used for testing



The R^2 between observed and predicted:
- **Total eating time:** 0.99
- **Visit duration:** 0.77
- **Interval between visits:** 0.70
- **Visits:** 0.55

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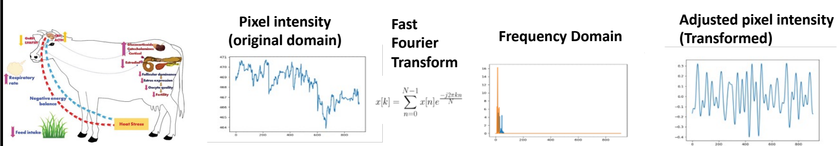
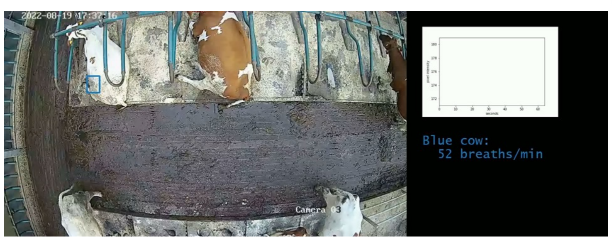
Monitor Respiration Rate



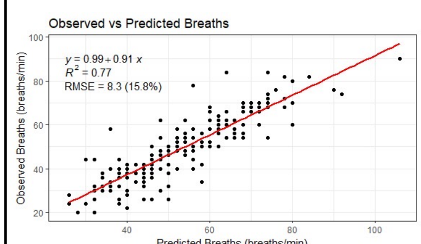


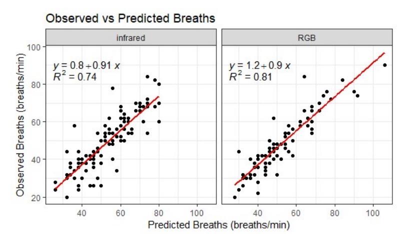
Mantovani et al., 2023 - JDS

23

Predictive Performance – Respiration Rate

- 168 videos (30-seconds segments) from 32 lactating cows
- Infrared images (night period)
- RGB images (day period)





Mantovani et al., 2023 - JDS

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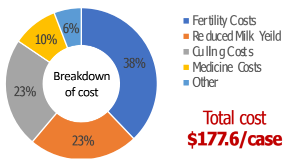
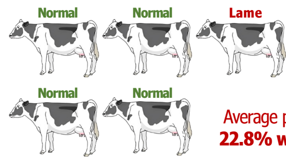
Impact of lameness

Lameness is **the third largest cause of economic losses** in the dairy industry after mastitis and reproductive disorders, estimated to cause an annual loss of **over 11 billion US dollars** globally.



Total cost
$177.6/case



Average prevalence
22.8% worldwide

Ózsvári et al. (2017), Goldman Sachs (2016), Willshire et al. (2009), Cha et al. (2010), Thomsen et al. (2023)

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Problems of visual mobility scoring

Category of score	Score	Description of cow behaviour
Good mobility		
	0	• Walks with even weight-bearing and rhythm on all four feet, with a flat back • Long, fluid strides possible
Imperfect mobility		
	1	• Steps uneven (rhythm or weight-bearing) or strides shortened; affected limb or limbs not immediately identifiable
Impaired mobility		
	2	• Uneven weight-bearing on a limb that is immediately identifiable and/or obviously shortened strides (usually with an arch to the centre of the back)
Severely impaired mobility		
	3	• Unable to walk as fast as a brisk human pace (cannot keep up with the healthy herd) • Lame leg easy to identify – limping; may barely stand on lame leg/s; back arched when standing and walking • Very lame

Using visual mobility scoring resulted in:

- ✓ The majority of farmers were about three times less likely than skilled personnel to detect the lame cows (0~20% vs. 1.2~64%)
- ✓ Even among trained personnel, there was variability in inter-rater agreement (weighted kappa of 0.42~0.73)
- ✓ Training had limited effectiveness in improving score agreement (inter-rater weighted kappa of 0.48 before and 0.52 after training)

AHDB (2020), Sadiq et al. (2019), Rutherford et al. (2009), Thomsen et al. (2008)

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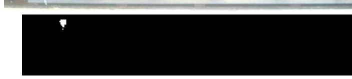
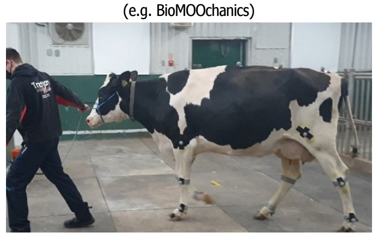
Technologies for objective mobility analysis / scoring

Pressure mapping system
(e.g. Gaitwise)



Large installation space
High system cost

Attaching markers and motion tracking
(e.g. BioMOOchanics)



Labor intensive
Time consuming

Mertens et al. (2012), https://www.cowlifemcgill.com/

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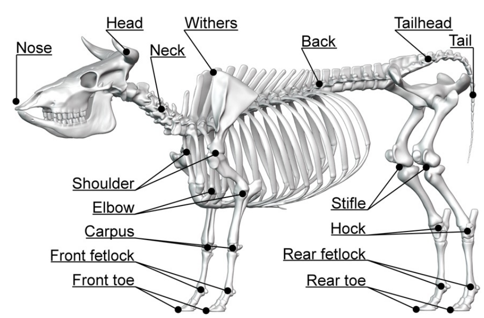
AiPEC (AI-based pose estimation system for cattle)

- **25 keypoints**
- **Real time**
- **Multiple animals**
- **Markerless**



Training dataset
9,003 images

Training epoch
3,750 epochs

Test dataset
970 images (1,432 animals)

Performance
8.79 ± 2.20 pixels
(Average Euclidean distance between the ground truth keypoints and the predicted keypoints)

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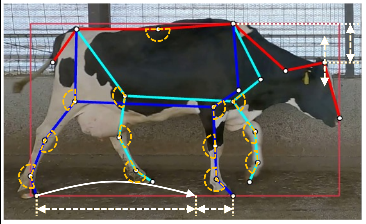
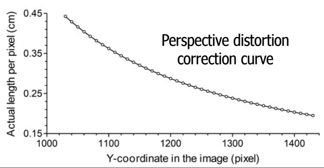
Analysed mobility variables





Variables	Description
Head bob	Vertical movement of the head
Head position	Vertical distance between the heights of the head and the withers
Stride length (cm)	Horizontal distance between two consecutive toe landings of the same toe
Tracking-up (cm)	Horizontal distance between front toe landing and ipsilateral rear toe landing
Stride duration (s)	Time interval between two consecutive toe landings of the same toe
Stance duration (s)	Time interval between toe landing and following toe off
Swing duration (s)	Time interval between toe off and following toe landing
Stance phase (%)	Stance duration / stride duration
Swing phase (%)	Swing duration / stride duration
Walking speed (m/s)	Stride length / stride duration
Back angle (°)	Ventral angle at the back
Elbow joint angle (°)	Anterior angle at the elbow joint
Stifle joint angle (°)	Posterior angle at the stifle joint
Carpus joint angle (°)	Posterior angle at the carpus joint
Hock joint angle (°)	Anterior angle at the hock joint
Front fetlock joint angle (°)	Posterior angle at the front fetlock joint
Rear fetlock joint angle (°)	Posterior angle at the rear fetlock joint

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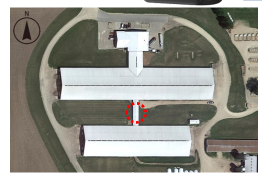
Experiment overview



Video recording & selection
204 video clips

Anotate mobility score
Score 0 (Good): 64
Score 1 (Imperfect): 65
Score 2 (Impaired): 57
Score 3 (Severe): 18

Pose estimation
Time series XY-coordinate data

Quantitative mobility analysis
10 spatial and temporal variables
7 joint angle related variables

Objective mobility scoring
Machine learning (Random Forest)

Training dataset (80%)

Test dataset (20%)

Classification model (Score 0, 1, and 2+3)

Cross validation (Repeated 10 times)

Performance evaluation
(Sen, Spe, PPV, NPV, Acc, Wt. kappa, AUC-ROC)

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Measurements of variables derived from pose estimation

Variables	Mobility score				Previous reports
	Score 0	Score 1	Score 2	Score 3	Healthy cow
Head position	-0.26 ± 0.14	-0.33 ± 0.19	-0.38 ± 0.18	-0.46 ± 0.20	–
Head bob	0.80 ± 0.65	1.00 ± 0.74	1.37 ± 1.12	2.19 ± 2.31	–
Stride length (cm)	161.7 ± 8.1	157.9 ± 8.2	152.0 ± 10.7	147.0 ± 11.4	1.5 to 1.69 m
Tracking-up (cm)	4.0 ± 2.2	9.3 ± 5.0	10.9 ± 6.6	15.9 ± 7.8	4 to 6.5 cm
Stride duration (s)	1.25 ± 0.09	1.31 ± 0.11	1.34 ± 0.13	1.39 ± 0.21	1.22 to 1.5 s
Stance duration (s)	0.83 ± 0.07	0.89 ± 0.10	0.91 ± 0.11	0.95 ± 0.18	0.66 to 0.85 s
Swing duration (s)	0.42 ± 0.02	0.43 ± 0.02	0.43 ± 0.03	0.43 ± 0.04	0.38 to 0.46 s
Stance phase (%)	66.1 ± 1.6	67.4 ± 1.8	68.1 ± 1.7	68.4 ± 2.7	64.2 to 66.9%
Swing phase (%)	33.9 ± 1.6	32.6 ± 1.8	31.9 ± 1.7	31.6 ± 2.7	33.0 to 35.7%
Walking speed (cm/s)	129.4 ± 10.7	121.0 ± 11.1	114.4 ± 12.7	108.6 ± 19.7	1.1 to 1.4 m/s
Back angle (°)	183.0 ± 3.0	180.6 ± 2.4	179.2 ± 3.6	176.4 ± 3.7	183.0°
Elbow joint angle ROM* (°)	52.9 ± 4.5	53.0 ± 4.5	52.5 ± 4.8	52.9 ± 7.0	40 to 47°
Stifle joint angle ROM (°)	40.2 ± 3.5	39.9 ± 3.7	39.1 ± 4.6	39.8 ± 3.9	40 to 44°
Carpus joint angle ROM (°)	65.2 ± 6.4	63.6 ± 6.8	64.1 ± 7.3	59.9 ± 7.8	48 to 52°
Hock joint angle ROM (°)	43.0 ± 3.1	42.5 ± 3.5	42.2 ±3.2	42.2 ± 3.6	30 to 41°
Front fetlock joint angle ROM (°)	92.9 ± 5.8	90.6 ± 7.3	86.7 ± 7.8	81.8± 5.3	66 to 106°
Rear fetlock joint angle ROM (°)	82.8 ± 6.5	82.4 ± 6.2	81.2 ± 6.3	79.6 ± 5.9	69 to 98°

*ROM: Range of motion

Maertens et al. (2011), Van Nuffel et al. (2013), Herlin and Drevemo (1997), Meyer et al. (2007), Alsaaod et al. (2017)

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Performance of machine learning classification model

Based on the 10-fold cross validation

Mobility score	Number of cattle	Sensitivity (%)	Specificity (%)	Pos Pred Value (%)	Neg Pred Value (%)	Accuracy (%)	Weighted kappa	AUC-ROC*
0	64	76.3 (69.1 – 83.5)	86.6 (84.4 – 88.9)	72.4 (66.8 – 78.0)	88.6 (84.3 – 92.8)	83.4 (80.4 – 86.5)	0.69 (0.62 – 0.76)	0.86 (0.84 – 0.89)
1	65	59.0 (48.0 – 70.0)	82.6 (79.6 – 85.6)	61.7 (57.2 – 66.2)	80.9 (76.6 – 85.2)	74.9 (72.3 – 77.5)		
2 + 3	75	76.8 (70.8 – 82.8)	86.8 (82.7 – 91.0)	76.4 (69.2 – 83.5)	87.2 (83.4 – 90.9)	83.2 (79.7 – 86.6)		

*Area Under the Receiver Operating Characteristic Curve

- ✓ The weighted kappa coefficient of 0.69 is comparable to or higher than the inter-rater agreement of the visual mobility scoring (0.65 across a 3-level scale)
- ✓ The AUC-ROC of 0.86 indicates that the present classification model has excellent discriminating ability among different mobility classes

Schlageter-Tello et al. (2014), Mandrekar et al. (2010)

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Examples of applications of AiPEC

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Limitations of the present approach

Overlapping

Meandering

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New Strategy

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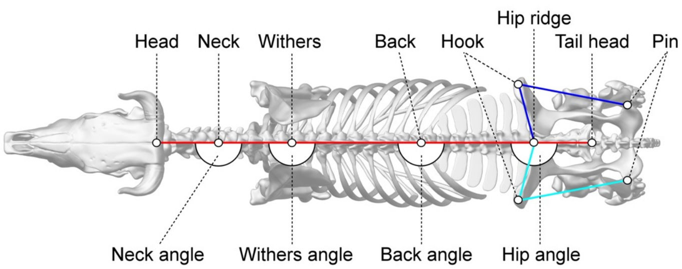
Keypoints



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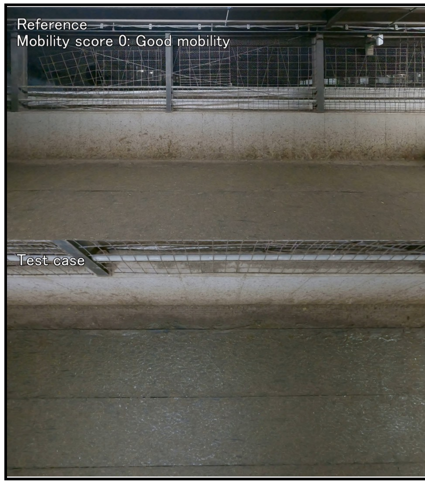

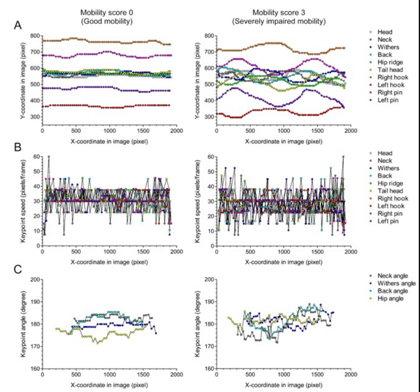

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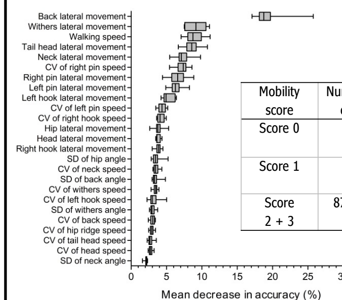
Preliminary Results



Mobility score	Number of cattle	Sensitivity (%)	Specificity (%)	F1-score (%)	**Accuracy (%)**	AUC-ROC[1]
Score 0	78	87.2 (80.7 – 93.7)	94.7 (92.0 – 97.5)	88.2 (83.8 – 92.5)	**92.1 (89.1 – 95.1)**	0.888 (0.866 – 0.910)
Score 1	71	54.4 (43.1 – 65.6)	84.2 (79.5 – 88.8)	55.4 (45.5 – 65.2)	**76.0 (71.1 – 80.8)**	
Score 2 + 3	87 + 20	81.6 (74.9 – 88.2)	82.3 (73.5 – 91.1)	79.1 (74.8 – 83.5)	**82.3 (77.3 – 87.3)**	

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Final Considerations

- **Digital technologies** are **crucial** to collect cheaper, precise, and real-time phenotypes
- **Animal-level** information is a **very important component** of any integrated databases
- Leverage **Artificial Intelligence** Systems: Applications in Livestock (**Dairy and Beef**)
- It is not about new questions only! It is about **unanswered questions**!
- **Digital Agriculture**: undergrad and grad courses (livestock, crop, water, soil - data management, storage, and analyses – cloud computing)
- **New generation** of students/professionals
- **Multidisciplinary teams:** Collaboration across campus

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Acknowledgments

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DAIRY INNOVATION HUB

PURINA

HT CENTER FOR HIGH THROUGHPUT COMPUTING

NVIDIA

Microsoft

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Combining high-throughput phenotyping and genomics

-Data Integration:
Body growth + Mammary gland development + Genomic information
-From birth to first lactation (240 animals):

Cloud ➡ **20 TB/mo**

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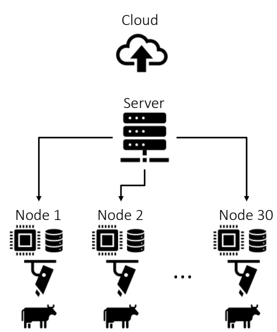
Edge-Computing System

- Edge-computing system with **29 edge devices** (3D cameras) ;
- Deployed in **November 2021**;
- During this period, **~130 TB** of daily images from 200 dairy heifers were generated;
- Each camera generates **~10.3 GB per day**;
- **Compressed** in a single file, which result in approximately **300 GB per day**;
- To upload such amount of data to a cloud system in a **24-hour period**, an average of **30 mbps** network bandwidth would be **required**.
- Farm pays for 25 mbps, but only gets **~5-10 mbps**
- It would take **4 days and 6 hours** if network bandwidth is **7 mbps**

Analytical strategy to overcome!



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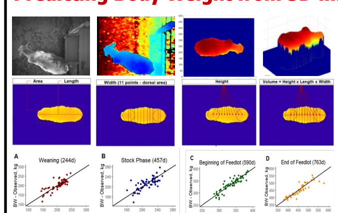
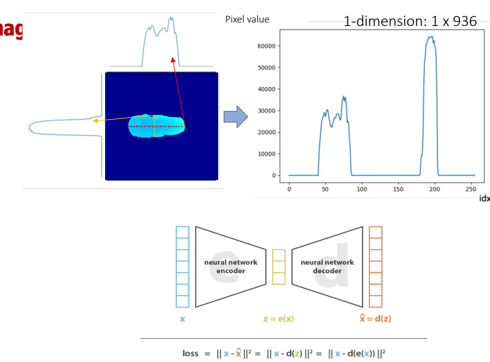
We cannot transfer 20 TB of data/mo

Reducing Data Dimension - Autoencoders

Predicting Body Weight from 3D imag



Cattle: Cominotte et al., 2020 – *Livestock Science* 232:103904
Pigs: Fernandes et al., 2019 – Journal of Animal Science 97:496-508
Other groups



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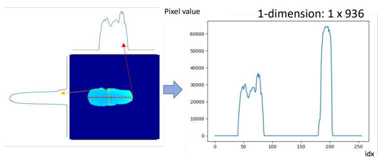
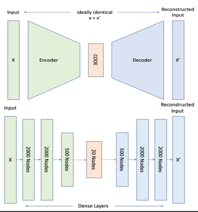
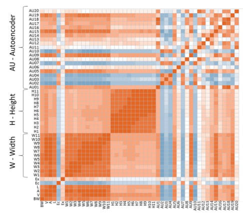
Reducing Data Dimension - Autoencoders







Prediction of Calf BW
Independent Testing Set:

	Partial Least Squares	
	Biological Features	Autoencoders Features
R^2	0.81	0.78
CCC	0.88	0.88
RMSEP, kg	6.50	6.90

Reduction in size:

From: 600 KB (depth image) – Biological Feat.

To: 0.21 KB (single vector) – Autoencoder Feat.

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