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# Leveraging artificial intelligence to optimize farm management decisions

#### Artificial Intelligence in Agriculture

https://dorealab.cals.wisc.edu

Joao Dorea Associate Professor Department of Animal and Dairy Sciences Department of Biological Systems Engineering

#### Genomics: Amazing Progress!





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

#### Costs to genotype drastically decreased over time!





High-Throughput Phenotyping "Phenomics"

# Sensing Technologies: Individual Animal



Multi-Sensor Systems



On-farm management Decisions (short-term \$)

Genetic Selection (long-term \$)

#### Implementing AI in Livestock Operations



#### Implementing AI in Livestock Operations



# Automation: Cloud-Computing Framework

![](_page_5_Picture_1.jpeg)

![](_page_5_Picture_2.jpeg)

#### Infrared

![](_page_5_Picture_4.jpeg)

Depth

![](_page_5_Picture_6.jpeg)

1<sup>st</sup> Step: Image Classification

![](_page_5_Figure_8.jpeg)

If good:

#### 2<sup>nd</sup> Step: Image Segmentation (Mask)

![](_page_5_Picture_11.jpeg)

U-Net (Ronneberger et al., 2015) 2D CNN Intersection Over Union = 0.93

![](_page_5_Figure_13.jpeg)

3<sup>rd</sup> Step: Image Identification (Animal Identification)

![](_page_5_Picture_15.jpeg)

#### 4<sup>th</sup> Step: Image Classification (Body Condition Score: 1-5)

![](_page_5_Picture_17.jpeg)

# 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

![](_page_6_Picture_6.jpeg)

#### 2<sup>nd</sup> Step: Image Segmentation (Mas

![](_page_6_Picture_8.jpeg)

![](_page_6_Picture_9.jpeg)

#### 3<sup>rd</sup> Step: Image Identification (Animal Identification)

![](_page_6_Picture_11.jpeg)

Xception (Chollet, 2017) 2D CNN

#### 4<sup>th</sup> Step: Image Classification (Body Condition Score: 1-5)

Xception (Chollet, 2017) 2D CNN

![](_page_6_Picture_15.jpeg)

#### Ferreira et al., 2023 – Scientific Reports

# Animal identification using 2D images

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(Animal Identification)

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![](_page_7_Picture_6.jpeg)

Xception (Chollet, 2017)

2D CNN

![](_page_7_Picture_7.jpeg)

![](_page_7_Picture_8.jpeg)

: Image Class Condition Sco

![](_page_7_Picture_10.jpeg)

Ferreira et al., 2023 – Scientific Reports

# Animal Identification: 3D representation

![](_page_8_Picture_1.jpeg)

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

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

	Train-test split	Data representation	Architecture	$F_1$ score
	RO <sup>1</sup>	$\mathrm{DI}^3$	VGG16	0.888
	RO <sup>1</sup>	$\mathrm{DI}^3$	Inception v3	0.904
	RO <sup>1</sup>	DI <sup>3</sup>	Xception	0.959
	RO <sup>1</sup>	$\mathrm{PC}^4$	PointNet	0.669
RO = <i>Random</i>	RO <sup>1</sup>	$OG^5$	VoxNet	0.880
CO - Chronological	$\rm CO^2$	$\mathrm{DI}^3$	VGG16	0.718
	$\rm CO^2$	$\mathrm{DI}^3$	Inception v3	0.750
	CO <sup>2</sup>	$\mathrm{DI}^3$	Xception	0.804
	$\rm CO^2$	$PC^4$	PointNet	0.429
	$\rm CO^2$	$OG^5$	VoxNet	0.656

![](_page_8_Figure_5.jpeg)

Time interva	l 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 – Computer and Electronics in Agriculture

How frequent should I retrain the algorithms?

### Animal Identification: Keypoints

#### Animal Identification

- Keypoint model (Newell et al., 2016)
- 4,319 top-down view images
- **SNN** animal identification
- 11,499 top-down view images
- 41 dairy cows, 5 different days; BW and HH prediction
- 1,592 top-down view images
- 87 beef-on-dairy, 5 months

![](_page_9_Picture_9.jpeg)

Figure 1: Predicted keypoints strategy 1, 2 and 3. The images were generated using the testing set

#### Animal Identification: Keypoints

![](_page_10_Figure_1.jpeg)

Figure 2: Description of measurement sites for Euclidean distance as a Feature

F1, F2, F3, F4, F4, F5, F6, F7, F8, F9, F10, F11, F12, F13, F14, F15, F16, F17, F18 and F19 represents the Euclidean distance between the following points + all nineteen distances standardized as percentage of the sum of all distances, respectively:  $1 \rightarrow 2$ ;  $3 \rightarrow 4$ ;  $5 \rightarrow 6$ ;  $1 \rightarrow 3$ ;  $2 \rightarrow 4$ ;  $3 \rightarrow 6$ ;  $4 \rightarrow 6$ ;  $3 \rightarrow 5$ ;  $4 \rightarrow 5$ ;  $1 \rightarrow 6$ ;  $2 \rightarrow 6$ ;  $1 \rightarrow 5$ ;  $2 \rightarrow 5$ ;  $6 \rightarrow 7$ ;  $7 \rightarrow 8$ ;  $1 \rightarrow 8$ ;  $2 \rightarrow 8$ ;  $8 \rightarrow 9$ ;  $9 \rightarrow 10$ 

#### Model performance on closed set

Accuracy, precision, F1 scores, and recall calculated at the frame level and using mode prediction to identify individual cows in closed-set scenarios

SNNs		Test				
Method	N°	Accuracy	Precision	F1 - Score	Recall	
Keypoint Prediction m	ajority vote					
Strategy 1	188	96.3	96.3	95.9	96.0	
Strategy 2	188	93.1	93.4	92.5	92.6	
Strategy 3	188	81.9	84.2	80.9	81.6	

#### Artificial Intelligence: Sensor System Computer Vision System at Marshfield – WI (Heifers)

- Edge-computing system with 30 edge devices (3D cameras);
- Each camera generates  $\sim 10.3$  GB per day;
- Until last month: 451.1 TB of data (images)

![](_page_12_Figure_4.jpeg)

#### Using keypoints for body biometrics

![](_page_13_Figure_1.jpeg)

Relationships between predicted and observed variables.

#### Using keypoints for body biometrics

![](_page_14_Figure_1.jpeg)

Relationships between predicted and observed variables

### Automation: Cloud-Computing Framework

![](_page_15_Picture_1.jpeg)

![](_page_15_Picture_2.jpeg)

#### Infrared

![](_page_15_Picture_4.jpeg)

Depth

![](_page_15_Picture_6.jpeg)

![](_page_15_Picture_7.jpeg)

# Body Condition Score using 3D images

![](_page_16_Picture_1.jpeg)

- 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

![](_page_16_Figure_8.jpeg)

3<sup>ra</sup> Step: Image Identificatio (Animal Identification)

![](_page_16_Picture_10.jpeg)

Xception (Chollet, 2017) 2D CNN

#### (Body Condition Score: 1-5)

Xception (Chollet, 2017) 2D CNN

![](_page_16_Picture_14.jpeg)

# Subjective and Labor-Intensive

![](_page_17_Picture_1.jpeg)

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

![](_page_17_Figure_3.jpeg)

• It requires a trained evaluator to collect BCS information

![](_page_18_Picture_1.jpeg)

- Goal: Use prepartum 3D images, wearable sensor, and text to predict subclinical ketosis
- 21, 14 and 7 days prior to calving;
- 92 Holstein cows were individually collected (37 SCK and 55 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
- 52,450 top-down 3D images;

![](_page_18_Figure_8.jpeg)

Ferreira et al., 2024 – submitted

Subclinical

Ferreira et al., 2024 – submitted

#### Early detection of subclinical ketosis in dairy cows

For each image:

CNN features (Xception architecture, trained to evaluate BCS)

![](_page_19_Figure_4.jpeg)

![](_page_20_Picture_1.jpeg)

1-6

75

100 125 150 175 200

For each image: Biological features (depth vectors)

![](_page_20_Figure_3.jpeg)

BCS=2.25

![](_page_21_Picture_1.jpeg)

![](_page_21_Figure_2.jpeg)

Merging Structured and unstructured data

Ferreira et al., 2024 – submitted

![](_page_22_Figure_0.jpeg)

Ferreira et al., 2024 – submitted

![](_page_23_Picture_1.jpeg)

![](_page_23_Figure_2.jpeg)

![](_page_23_Figure_3.jpeg)

![](_page_23_Picture_4.jpeg)

![](_page_24_Figure_0.jpeg)

![](_page_25_Picture_1.jpeg)

![](_page_25_Figure_2.jpeg)

DATE	EVENT	REMARKS	DETAILS	RESPONSIBLE <sup>1</sup>	DIM	PEN
9/14/2019	FRESH	9762/92	Heifer 9762 Live		-	26
9/17/2019	LAME	EXD1.21	FOOT ROT EXED		3	9
12/5/2019	BRED	511H12240	Open (O), Double Ovsynch (D)	Rafael	82	34
1/6/2020	RECHK	LOSING?	-		114	34
1/13/2020	OPEN	LUT2CLEA	-		121	34
1/20/2020	NOTES	CIDR	-		128	34
1/27/2020	OK	LUT	-		135	34
1/30/2020	BRED	629H18813	Open (O), LUT (L)	Joao	138	34
3/2/2020	OPEN	LUT	-		170	34
3/5/2020	BRED	11AN1212	Open (O), Resynch 25 (T)	Rafael	173	34
4/6/2020	OPEN	CL RIGHT			205	34
4/9/2020	BRED	29AN1993	Open (O), Resynch 25 (T)	Joao	208	34
5/11/2020	OPEN	LUT	-		240	34
5/14/2020	BRED	829AN1868	Pregnant (P), Resynch 25 (T)	Joao	243	34
6/15/2020	PREG	ROCL	-		275	34
6/29/2020	PREG	ROCL	-		289	34
7/1/2020	MOVE	TOMARS	-		291	34
7/17/2020	LAME	LATDRH	Dig Derm - Wa		307	94
7/20/2020	PREG	HEIFER	-		310	94
9/14/2020	PREG	123 Days	-		366	94
12/27/2020	MOVE	F094T168	94 → 168		470	94
12/30/2020	DRY	SPCDC	SPECTRA-DC.IM		473	168
1/6/2021	MOVE	TO ARL	-		480	168
1/26/2021	MOVE	CLOSEUP	-		500	38
1/26/2021	ONEXP	HMW618	-		500	26
2/2/2021	NOTES	URINE 5.5	-		507	26

#### (a) CSV file containing all the notes taken during the previous lactation

The chronological report of events for the cow described in the CSV is as follows: 1. \*\*September 14, 2019\*\*: The cow entered the herd as a fresh heifer (9762/92). This event happened in pen 26. 2. \*\*September 17, 2019\*\*: The cow was diagnosed as lame due to foot rot (EXD1.21) on day 3 of lactation in pen 9. \*\*December 5, 2019\*\*: The cow was bred by Rafael using semen from bull 511H12240 with the method "Open (0), Double Ovsynch (D)" on day 82 of lactation in pen 34. 4. \*\*January 6, 2020\*\*: A recheck (RECHK) indicated a possible issue ("LOSING?") on day 114 in pen 34. 5. \*\*January 13, 2020\*\*: The cow was confirmed open with a treatment of LUT2CLEA on day 121 in pen 34. 6. \*\*January 20, 2020\*\*: Notes indicate a CIDR intervention on day 128 in pen 34. \*\*January 27, 2020\*\*: The cow was OK'd following LUT treatment on day 135 in pen 34. 8. \*\*January 30, 2020\*\*: The cow was bred by Joao using semen from bull 629H18813 with the method "Open (O), LUT (L)" on day 138 in pen 34. 9. \*\*March 2, 2020\*\*: The cow was confirmed open following LUT treatment on day 170 in pen 34. 10. \*\*March 5, 2020\*\*: The cow was bred by Rafael using semen from bull 11AN1212 with the method "Open (0), Resynch 25 (T)" on day 173 in pen 34. 11. \*\*April 6, 2020\*\*: The cow was confirmed open with a note of "CL RIGHT" on day 205 in pen 34. 12. \*\*April 9, 2020\*\*: The cow was bred by Joao using semen from bull 29AN1993 with the method "Open (0), Resynch 25 (T)" on day 208 in pen 34 13. \*\*May 11, 2020\*\*: The cow was confirmed open following LUT treatment on day 240 in pen 34. 14. \*\*May 14, 2020\*\*: The cow was bred by Joao using semen from bull 829AN1868 with the method "Pregnant (P), Resynch 25 (T)" on day 243 in pen 34. 15. \*\*June 15, 2020\*\*: Pregnancy confirmed (ROCL) on day 275 in pen 34. 16. \*\*June 29, 2020\*\*: Another pregnancy check confirmed (ROCL) on day 289 in pen 34. 17. \*\*July 1, 2020\*\*: The cow was moved to Mars on day 291 in pen 34. 18. \*\*July 17, 2020\*\*: The cow was diagnosed as lame due to digital dermatitis (Dig Derm - Wa) on day 307 in pen 94. 19. \*\*July 20, 2020\*\*: Pregnancy confirmed with a note of "HEIFER" on day 310 in pen 94. 20. \*\*September 14, 2020\*\*: Pregnancy progression noted as 123 days on day 366 in pen 94. 21. \*\*December 27, 2020\*\*: The cow was moved from pen 94 to 168 on day 470. 22. \*\*December 30, 2020\*\*: The cow was dried off with SPECTRA-DC.IM on day 473 in pen 168. 23. \*\*January 6, 2021\*\*: The cow was moved to ARL on day 480 in pen 168. 24. \*\*January 26, 2021\*\*: The cow was moved to the close-up pen on day 500 in pen 38 and also noted for on-experiment with HMW618 in pen 26. 25. \*\*February 2, 2021\*\*: Notes indicate a urine pH of 5.5 on day 507 in pen 26. This report tracks the cow's journey through various health checks, breeding attempts, pregnancy confirmations, and management changes throughout her lactation period.

The cow's current lactation, for which we want to predict the risk of subclinical ketosis, started on February 13, 2021.

![](_page_26_Picture_1.jpeg)

![](_page_26_Figure_2.jpeg)

DATE	EVENT	REMARKS	DETAILS	RESPONSIBLE <sup>1</sup>	DIM	PEN
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1/26/2021	MOVE	CLOSEUP			500	38
1/26/2021	ONEXP	HMW618			500	26
2/2/2021	NOTES	URINE 5.5	-		507	26

#### (a) CSV file containing all the notes taken during the previous lactation

The chronological report of events for the cow described in the CSV is as follows:

```
"Soptember 14, 2019": The cow stered the herd as a fresh helfer (976/29). This event happend in pen 26.
"Soptember 17, 2019": The cow stered the herd as a fresh helfer (976/29). This event happend in pen 36.
"December 5, 2019": The cow stered by Bafael using seem from bull S1H12240 with the method "Open (0), Double Ovsynch (D)" on day 82 of lactation in pen 94.
"January 10, 2020": The cow uss confirmed open with a treatment of UUTXLIS on day 11 in pen 34.
"January 20, 2020": The cow uss confirmed open with a treatment of UUTXLIS on day 121 in pen 34.
"January 20, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"January 30, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"March 5, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"March 5, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"March 5, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"March 5, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"March 5, 2020": The cow uss confirmed open following UUT treatment on day 35 in pen 34.
"March 1, 2020": The cow uss confirmed open following UUT treatment on day 36 in pen 34.
"March 1, 2020": The cow uss confirmed open following UUT treatment on day 36 in pen 34.
"March 1, 2020": The cow uss confirmed open following UUT treatment on day 36 in pen 34.
"March 1, 2020": The cow uss ford 10 acounting UUT treatment on day 30 in pen 34.
"March 1, 2020": The cow uss ford 10 acounting UUT treatment on day 30 in pen 34.
"Nume 15, 2020": The cow uss ford 10 acounting UUT treatment on day 30 in pen 34.
"Num 15, 2020": The cow uss ford 10 acount 10 and 20 in pen 34.
"Num 15, 2020": The cow
```

This report tracks the cow's journey through various health checks, breeding attempts, pregnancy confirmations, and management changes throughout her lactation period.

The cow's current lactation, for which we want to predict the risk of subclinical ketosis, started on February 13, 2021.

#### (b) Free text generated from the CSV file using OpenAI's chat completion API

![](_page_26_Figure_10.jpeg)

CSV files of notes recorded during previous lactation and dry period

Text containing notes recorded during previous lactation and dry period (notes text) 1,536-dimensional text embeddings (notes)

#### Few Considerations:

The resulting model achieved an average  $F_1$  score of 0.68 and average Accuracy of 76.1% (using Random Forest) –

\*early detection of subclinical ketos (at least 7 days in advance)

Unstructured vs Structured data:

average F1 score = 0.60 vs 0.65

average accuracy = 70% vs 74%

\*embedding model not fine-tuned in our data(text) context

Adding unstructured notes increased the average F1-score and accuracy of the model

\*relevant information on the notes

![](_page_27_Figure_10.jpeg)

Feeding behavior, cow activity,

and cow history variables

![](_page_27_Figure_11.jpeg)

Feeding behavior, cow activity,

and cow history text (template text) 1.536-dimensional text embeddings

(feeding behavior, cow activity, and cow history)

# 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

![](_page_28_Figure_4.jpeg)

#### The R<sup>2</sup> between observed and predicted:

- Total eating time: 0.99
- Visit duration: 0.77
- Interval between visits: 0.70
- Visits: 0.55

![](_page_28_Picture_10.jpeg)

Assessing optimal frequency for vision systems developed to mon of group-housed Holstein heifers

T. Bresolin, <sup>(3)</sup> R. Ferreira, <sup>(3)</sup> F. Reyes, <sup>(3)</sup> J. Van O Department of Animal and Dairy Sciences. University of Wisco

![](_page_28_Picture_13.jpeg)

eating: 1 lying: standing: 1 drinking: "" mounting:

![](_page_28_Picture_15.jpeg)

### Animal Health: Heat-Stress

![](_page_29_Picture_1.jpeg)

![](_page_29_Picture_2.jpeg)

https://doi.org/10.3168/jdsc.2023-0442 Short Communication Health, Welfare, and Behavior

### Predicting respiration rate in unrestrained dairy cows using image analysis and fast Fourier transform

Raphael R. Mantovani,<sup>1</sup> Guilherme L. Menezes,<sup>1</sup> and João R. R. Dórea<sup>1,2</sup>\* O

![](_page_29_Figure_6.jpeg)

Mantovani et al., 2024

### Animal Health: Heat-Stress

![](_page_30_Picture_1.jpeg)

![](_page_30_Figure_2.jpeg)

![](_page_30_Figure_3.jpeg)

![](_page_30_Figure_4.jpeg)

![](_page_30_Figure_5.jpeg)

Adjusted pixel intensity (Transformed)

![](_page_30_Figure_7.jpeg)

![](_page_30_Picture_8.jpeg)

![](_page_30_Picture_9.jpeg)

Blue cow: 52 breaths/min

Mantovani et al., 2024

# Predictive Performance – Respiration Rate

JDS https://doi.org/10.3168/jdsc.2023-0442 Communications® Short Communication Health, Welfare, and Behavio

#### Predicting respiration rate in unrestrained dairy cows using image analysis and fast Fourier transform

Raphael R. Mantovani,<sup>1</sup> © Guilherme L. Menezes,<sup>1</sup> © and João R. R. Dórea<sup>1,2</sup>\* O

- 168 videos:(30-seconds segments)from 32 cows
- 42 videos from 25 calves
- Infrared images (night period)
- RGB images (day period)

![](_page_31_Figure_8.jpeg)

![](_page_31_Figure_9.jpeg)

![](_page_31_Figure_10.jpeg)

#### Predicted vs. Observed Breaths - Cows (b) R-squared = 0.79110 RMSEP = 8.14 - (16.56 %) 100 90 80 70 60 50 40 30 20 y = -0.44 + 0.93 x10 100 110 10 20 70 90

#### Predicted vs. Observed Breaths - Calves

![](_page_31_Figure_13.jpeg)

#### Locomotion Problems

![](_page_32_Picture_1.jpeg)

Computers and Electronics in Agriculture Volume 217, February 2024, 108573

![](_page_32_Picture_3.jpeg)

Leveraging computer vision-based pose estimation technique in dairy cows for objective mobility analysis and scoring system

<u>Shogo Higaki <sup>a b</sup></u>, <u>Yoshitaka Matsui <sup>c</sup></u>, <u>Masafumi Miwa <sup>d</sup></u>, <u>Takashi Yamamura <sup>e</sup></u>, <u>Takuo Hojo <sup>f</sup></u>, <u>Koji Yoshioka <sup>g</sup></u>, <u>Alysia Vang <sup>b</sup></u>, <u>Ariana Negreiro <sup>b</sup></u>, João R.R. Dórea <sup>b</sup> 久 函

![](_page_32_Picture_6.jpeg)

Training dataset = 9,003 images (9,000 animals)

Test dataset = 970 images (1,432 animals)

Performance =  $8.79 \pm 2.20$  pixels (Euclidean distance)

![](_page_32_Figure_10.jpeg)

#### Mobility variables

![](_page_33_Picture_1.jpeg)

Computers and Electronics in Agriculture Volume 217, February 2024, 108573

c 0

Leveraging computer vision-based pose estimation technique in dairy cows for objective mobility analysis and scoring system

<u>Shogo Higaki <sup>a b</sup>, Yoshitaka Matsui <sup>c</sup>, Masafumi Miwa <sup>d</sup>, Takashi Yamamura <sup>e</sup>, Takuo Hojo <sup>f</sup>, Koji Yoshioka <sup>g</sup>, Alysia Vang <sup>b</sup>, Ariana Negreiro <sup>b</sup>, João R.R. Dórea <sup>b</sup> 久 函</u>

![](_page_33_Picture_5.jpeg)

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

#### Experiment overview

![](_page_34_Figure_1.jpeg)

#### Performance of machine learning classification model

#### Based on the 10 repeated holdout validation sets

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)		
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)	<b>0.69</b> (0.62 - 0.76)	<b>0.86</b> (0.84 – 0.89)
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

#### Examples of applications of AiPEC

![](_page_36_Picture_1.jpeg)

#### Limitations of the present approach

Overlapping	Meandering

![](_page_38_Picture_0.jpeg)

![](_page_38_Picture_1.jpeg)

#### Top-down view keypoints

![](_page_39_Figure_1.jpeg)

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![](_page_40_Figure_0.jpeg)

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#### Preliminary Results

![](_page_41_Figure_1.jpeg)

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

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# Final Considerations

![](_page_42_Picture_1.jpeg)

- Digital technologies are crucial to collect cheaper, precise, and real-time phenotypes
- Animal-level information is a very important component of any integrated databases
- Digital Agriculture: undergrad and grad courses (livestock, crop, water, soil data management, storage, and analyses cloud computing)
- New generation of students/professionals
- Multidisciplinary teams

# Acknowledgments

![](_page_43_Picture_1.jpeg)

![](_page_43_Picture_2.jpeg)

United States Department of Agriculture National Institute of Food and Agriculture

> Data Science Institute UNIVERSITY OF WISCONSIN-MADISON

![](_page_43_Picture_4.jpeg)

![](_page_43_Picture_5.jpeg)

DAIRY INNOVATION HUB

![](_page_43_Picture_7.jpeg)

![](_page_43_Picture_8.jpeg)

![](_page_43_Picture_9.jpeg)

![](_page_44_Picture_0.jpeg)

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# Thank you!

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