Leveraging AI-Derived Digital Phenotypes for Precision Monitoring of Dairy Cattle Production, Health, and Behavior

Haipeng Yu

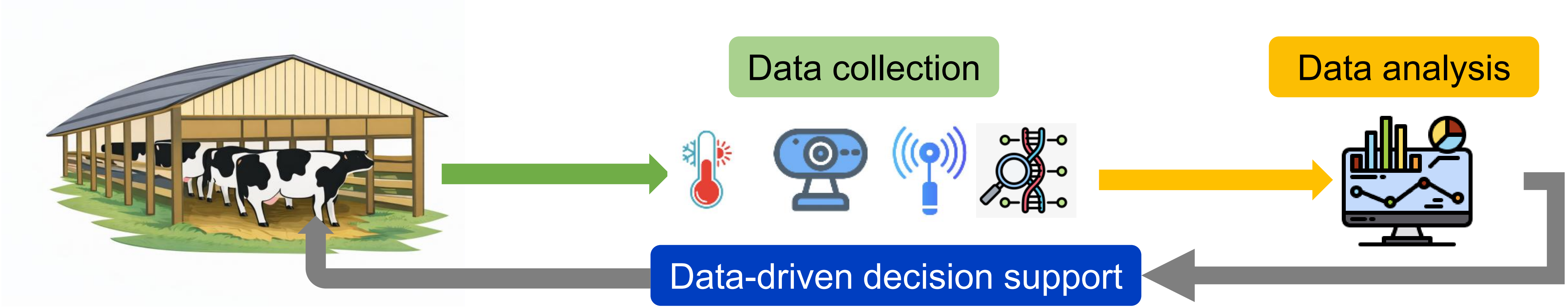
Assistant Professor - Artificial Intelligence in Animal Omics Sciences

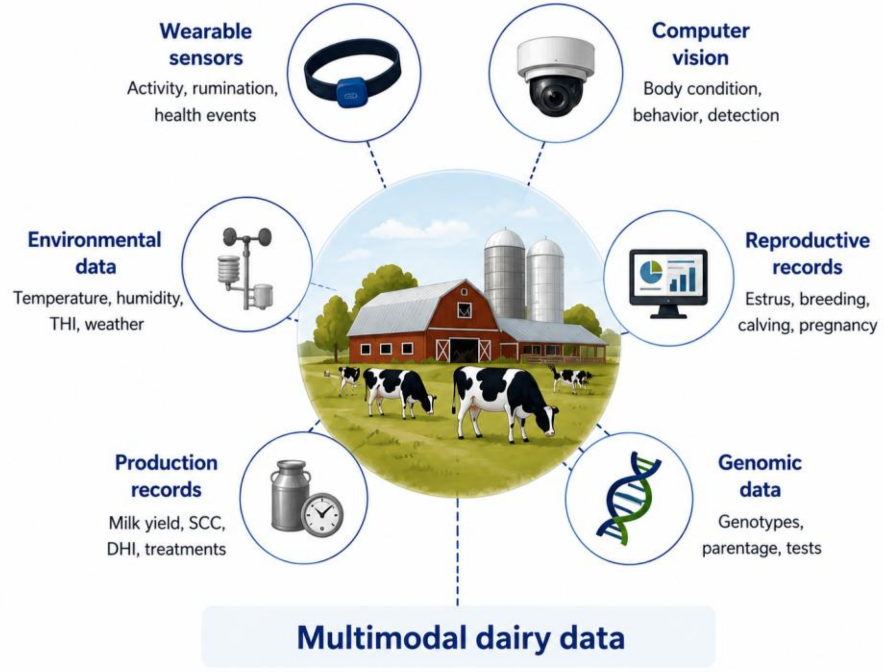
Department of Animal Sciences, University of Florida

2026 ASAS-NANP Symposium: Mathematical Modeling in Nutrition

UF | UNIVERSITY of FLORIDA

AI-derived digital phenotypes for precision dairy monitoring



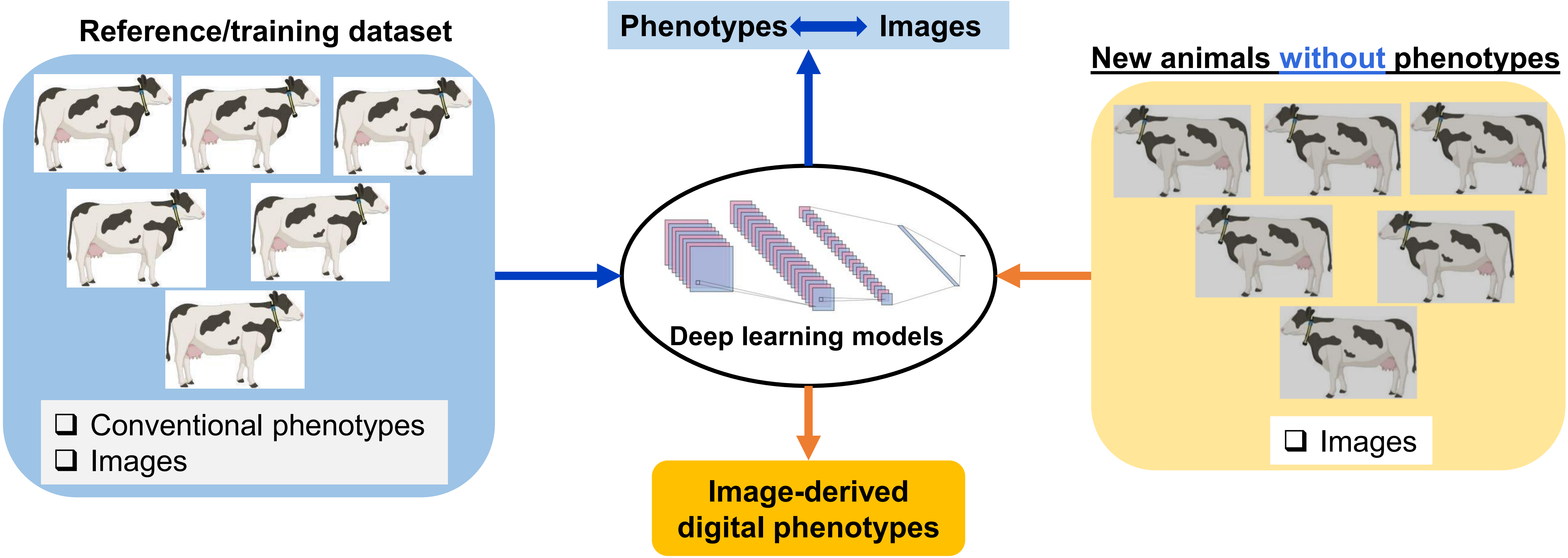


Some key challenges in AI-derived digital phenotyping

- ❑ Limited labeled data
- ❑ Integrating heterogeneous dairy data
- ❑ Deriving biologically meaningful behavioral phenotypes

Challenge 1: Limited labeled data

Generating digital phenotypes from images



Accurately estimating image-derived phenotypes requires a large reference dataset!

Small farms often **lack sufficient reference data**, which can lead to **inaccurate** digital phenotypes and **affect** downstream analysis.

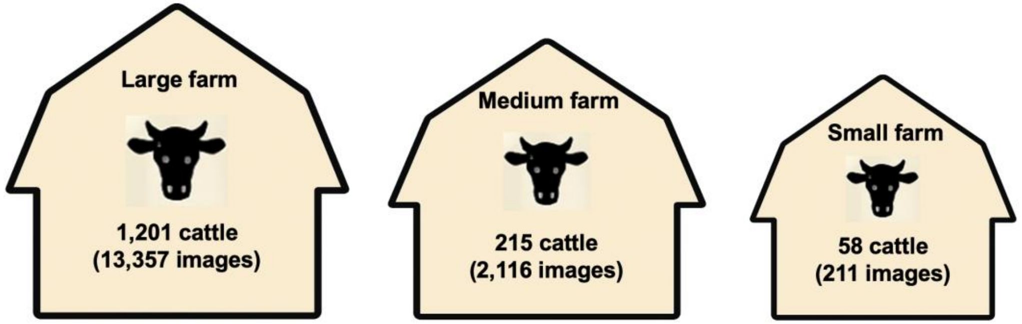
Project 1: Transfer learning for body weight prediction in small dairy farms

Objectives:

- ❑ Investigate the impact of using large farm data (via transfer learning) on image-based body weight (BW) prediction in small farms
- ❑ Compare body weight prediction performance using depth images versus 3D point cloud data

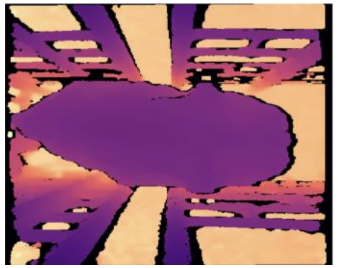
BW and image data:

Jin Wang

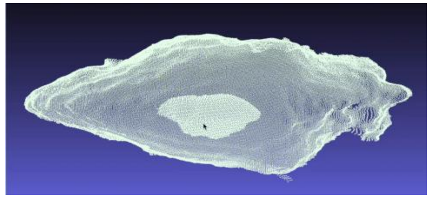


Three farms
(1,474 cows, 15,684 images)

- ❑ Depth image

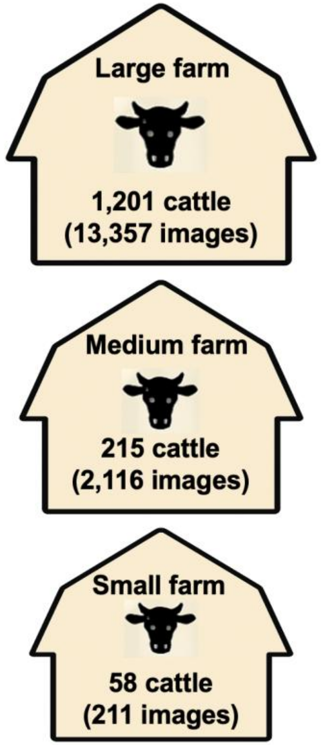


- ❑ 3D point cloud data

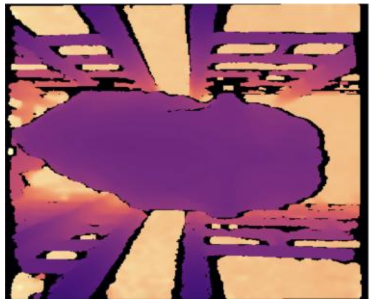


- ❑ Scale-based BW

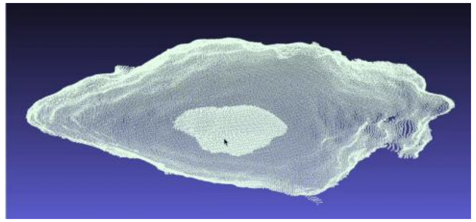
Overview of the study



- ❑ Depth image



- ❑ 3D point cloud data

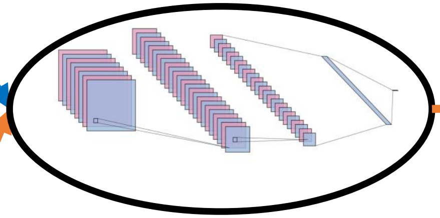


- ❑ Scale-based BW

Small-farm-only* *learning

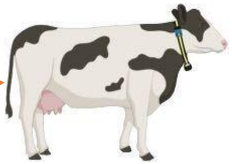
Training data:
Small farm training

Training data:
***Large/medium* + *small* farm training**



Deep learning models

Small-farm test set



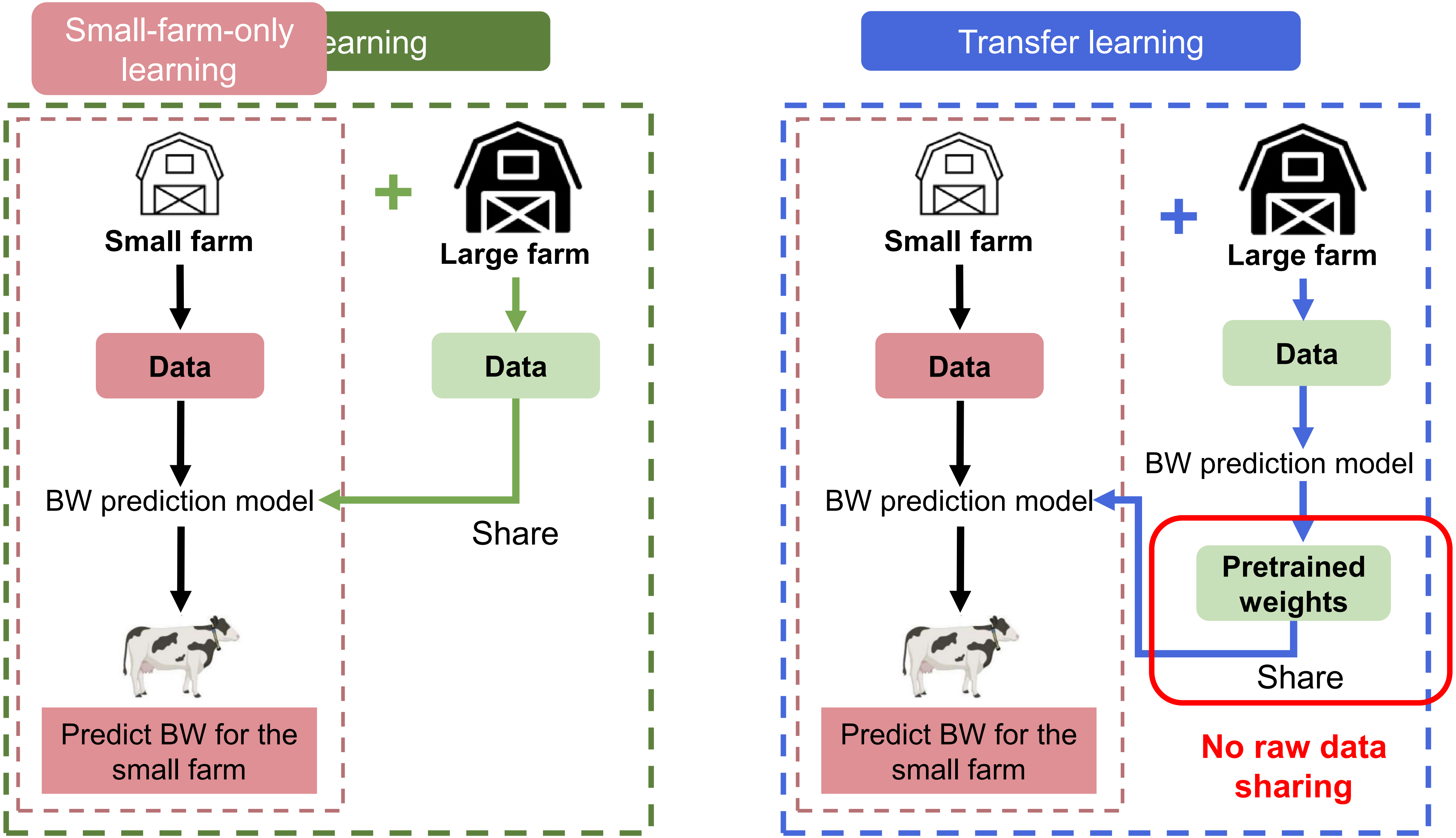
$\widehat{BW}$

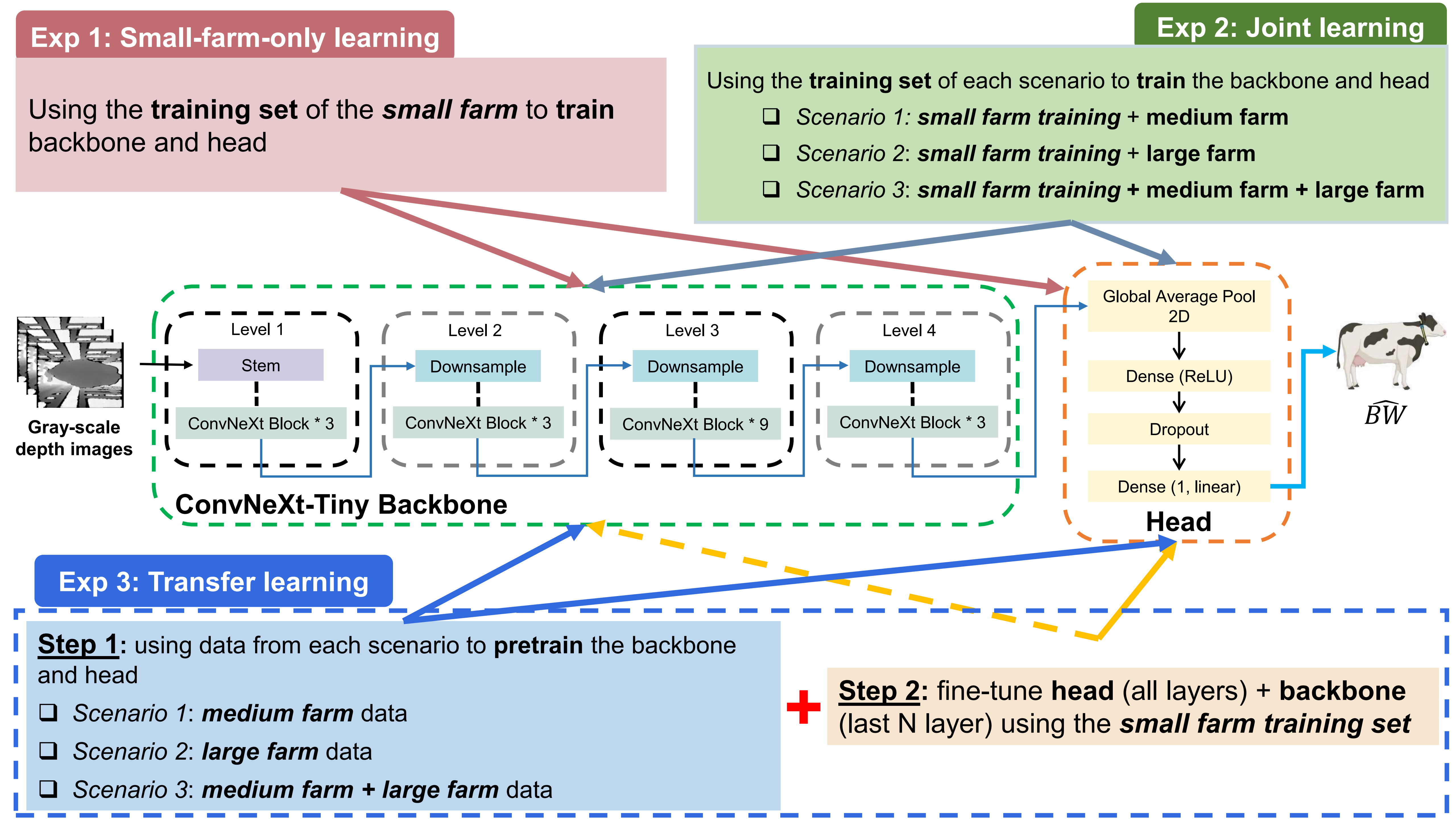
$$\mathbf{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

$$\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Joint/transfer* *learning* *targeting* *only small farm

Small-farm-only learning, joint learning, and transfer learning




Exp 1: Small-farm-only learning
Using the training set of the small farm to train backbone and head
Exp 2: Joint learning
Using the training set of each scenario to train the backbone and head
Scenario 1: small farm training + medium farm
Scenario 2: small farm training + large farm
Scenario 3: small farm training + medium farm + large farm
Gray-scale depth images
Level 1
Stem
ConvNeXt Block * 3
Level 2
Downsample
ConvNeXt Block * 3
Level 3
Downsample
ConvNeXt Block * 9
Level 4
Downsample
ConvNeXt Block * 3
ConvNeXt-Tiny Backbone
Global Average Pool 2D
Dense (ReLU)
Dropout
Dense (1, linear)
Head
$\widehat{BW}$
Exp 3: Transfer learning
Step 1: using data from each scenario to pretrain the backbone and head
Scenario 1: medium farm data
Scenario 2: large farm data
Scenario 3: medium farm + large farm data
+
Step 2: fine-tune head (all layers) + backbone (last N layer) using the small farm training set

Small farm BW prediction using joint learning and transfer learning

Strategy	External data scenario	R^2			
		Depth image model		PC model	
		ConvNeXt	MobileViT	PointNet	DGCNN
Single-source	No external data	0.30 (0.03)	0.56 (0.10)	0.37 (0.09)	0.39 (0.11)
Joint learning	Medium-farm	0.64 (0.06)	0.75 (0.02)	0.46 (0.05)	0.75 (0.05)
	Large-farm	0.57 (0.05)	0.78 (0.02)	0.68 (0.04)	0.77 (0.01)
	Medium + Large farm	0.65 (0.04)	0.76 (0.03)	0.73 (0.03)	0.74 (0.03)
Transfer learning	Medium-farm	0.46 (0.05)	0.68 (0.07)	0.70 (0.01)	0.70 (0.03)
	Large-farm	0.51 (0.01)	0.78 (0.03)	0.71 (0.02)	0.77 (0.02)
	Medium + Large farm	0.67 (0.05)	0.82 (0.02)	0.68 (0.04)	0.79 (0.03)

Summary

- ❑ Transfer learning consistently improved body weight prediction for a small dairy farm with limited training data.

- ❑ Transfer learning achieved performance comparable to or better than joint learning, enabling cross-farm knowledge transfer without sharing raw data.

- ❑ Both depth images and point cloud data were effective under transfer learning, with no clear advantage of one modality over the other.

Challenge 2: Integrating heterogeneous dairy data

Traditional data

- Farm/ management records
- Production records
- Reproductive records

Digital data

- Wearable sensors
- Computer vision
- Environmental data
- Genomic data

AI

AI algorithms provide an opportunity to integrate traditional and emerging digital data to support decision-making

Project 2: Multimodal integration for postpartum disease prediction

Early detection of postpartum diseases in dairy cattle is essential for improving health, welfare, and productivity.

Routine clinical evaluations are subjective and may **delay diagnosis**.

Wearable sensors enable early disease detection, **but** most studies rely solely on sensor-derived information.

Imbalanced datasets limit disease prediction performance.

Angelo De Castro

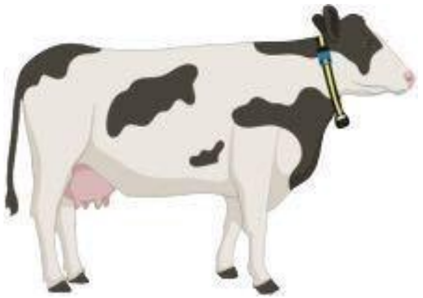
Objectives

- Develop a **multimodal deep learning (DL) model** that integrates time-series sensor and phenotypic data for early postpartum disease prediction.
- Evaluate the impact of **representation learning** and **class-imbalance mitigation** strategies on disease prediction performance.

Multimodal data for postpartum disease prediction

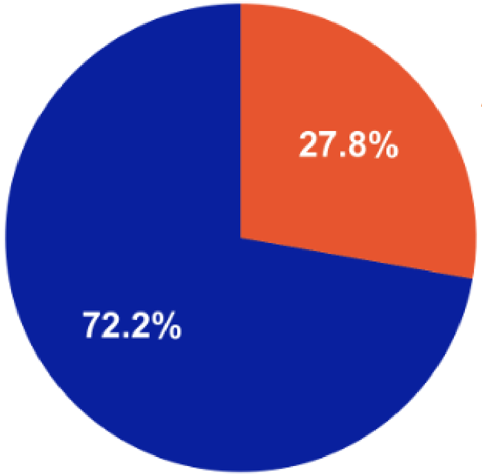
Time-series data:
- ❑ Rumination
- ❑ Activity
- ❑ Days in Milk
- ❑ Temperature-humidity index

Single-time-point data:
- ❑ Parity
- ❑ Calving problems
- ❑ Calving cohort
- ❑ Calf sex
- ❑ Calving ease score



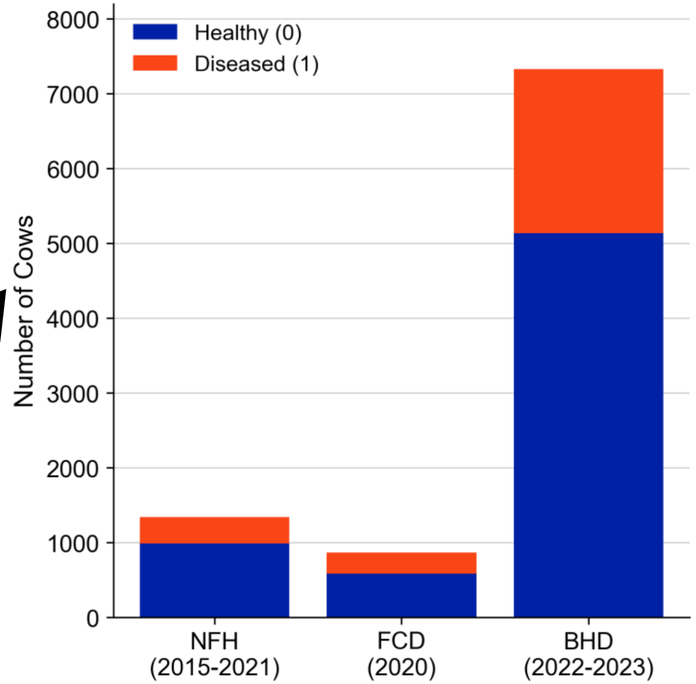
Postpartum disease data
(N = 9,540 cows)

Healthy (0)
6,888 cows

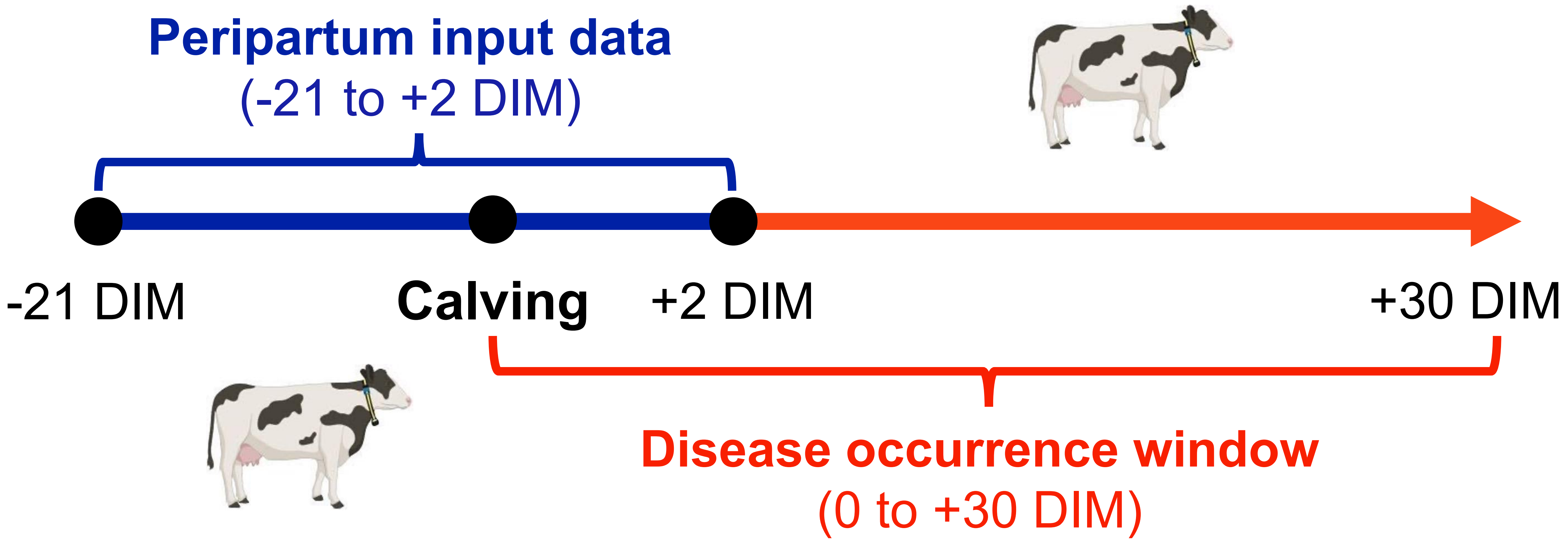


2,652 cows
Diseased (1)

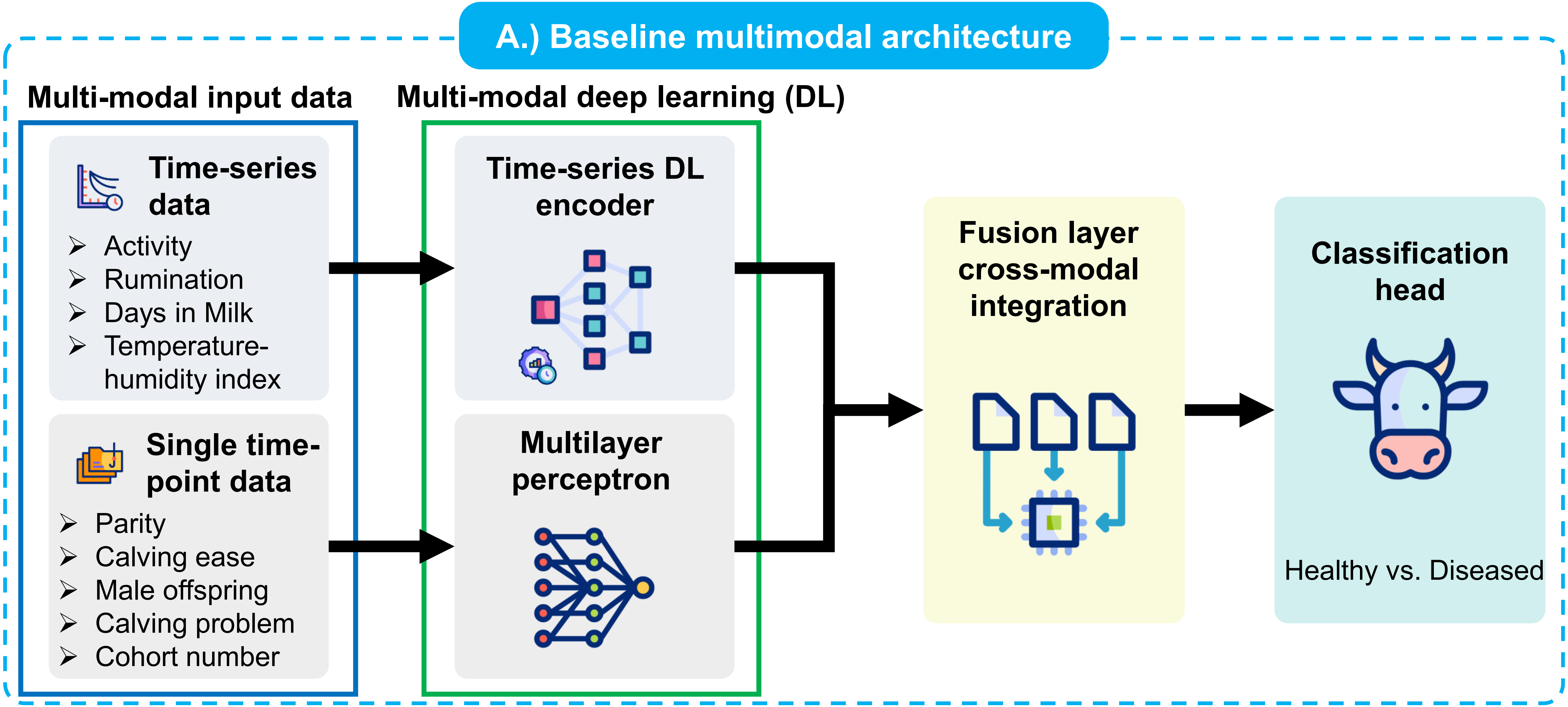
Disease distribution across three farms



Postpartum disease prediction design

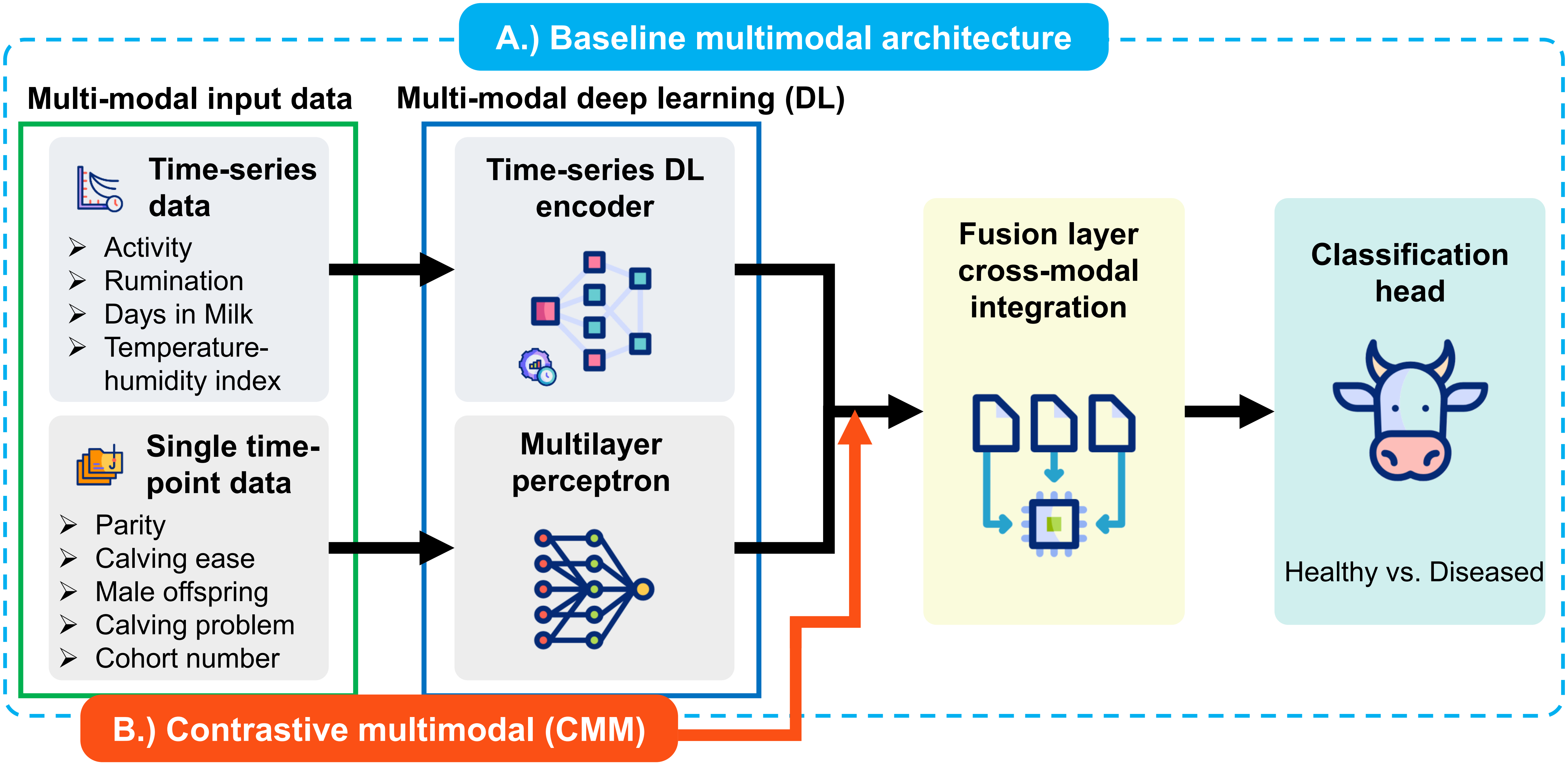


Baseline multimodal architecture

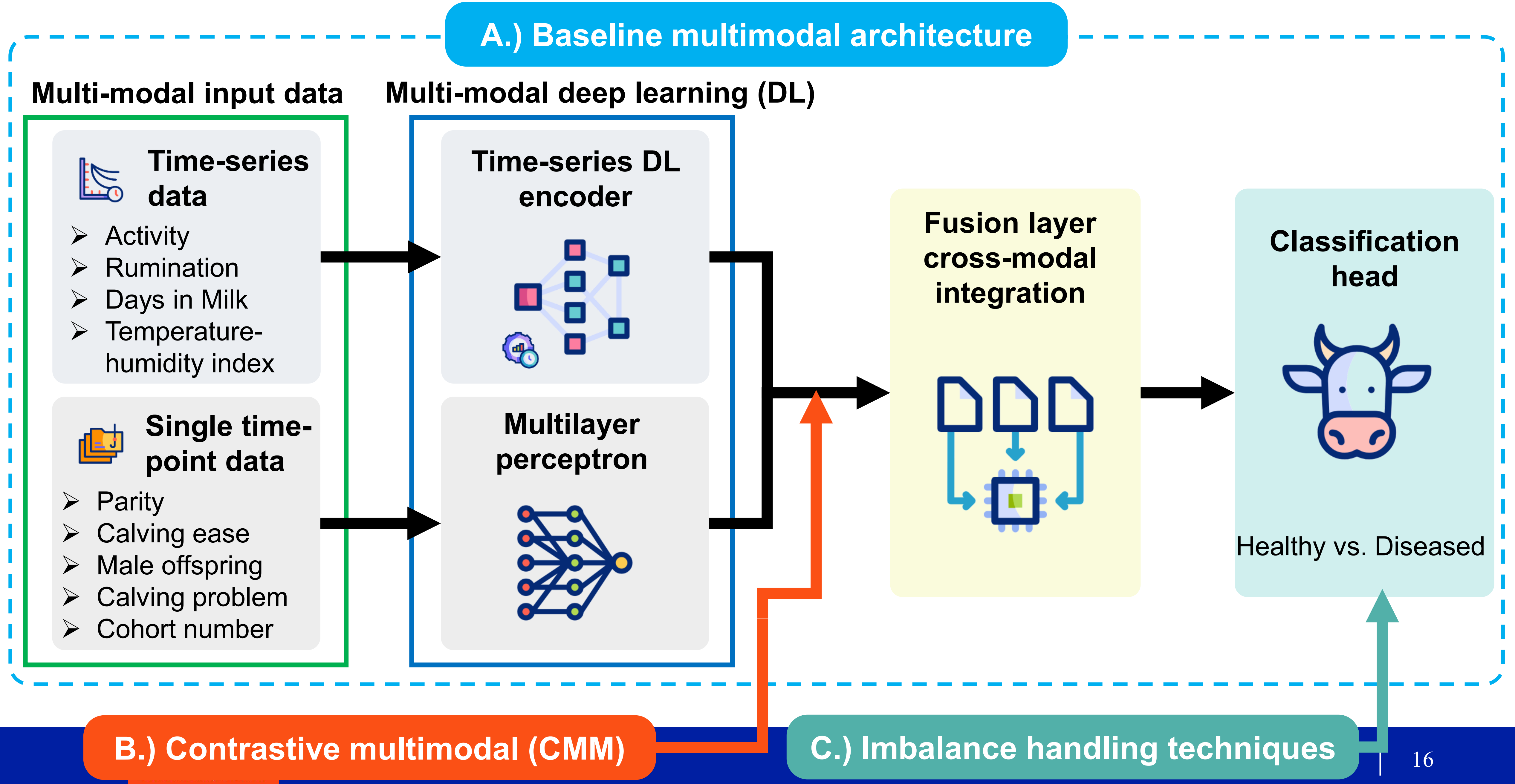


- Three time-series DL encoders: **LSTM, TCN, and Transformer.**

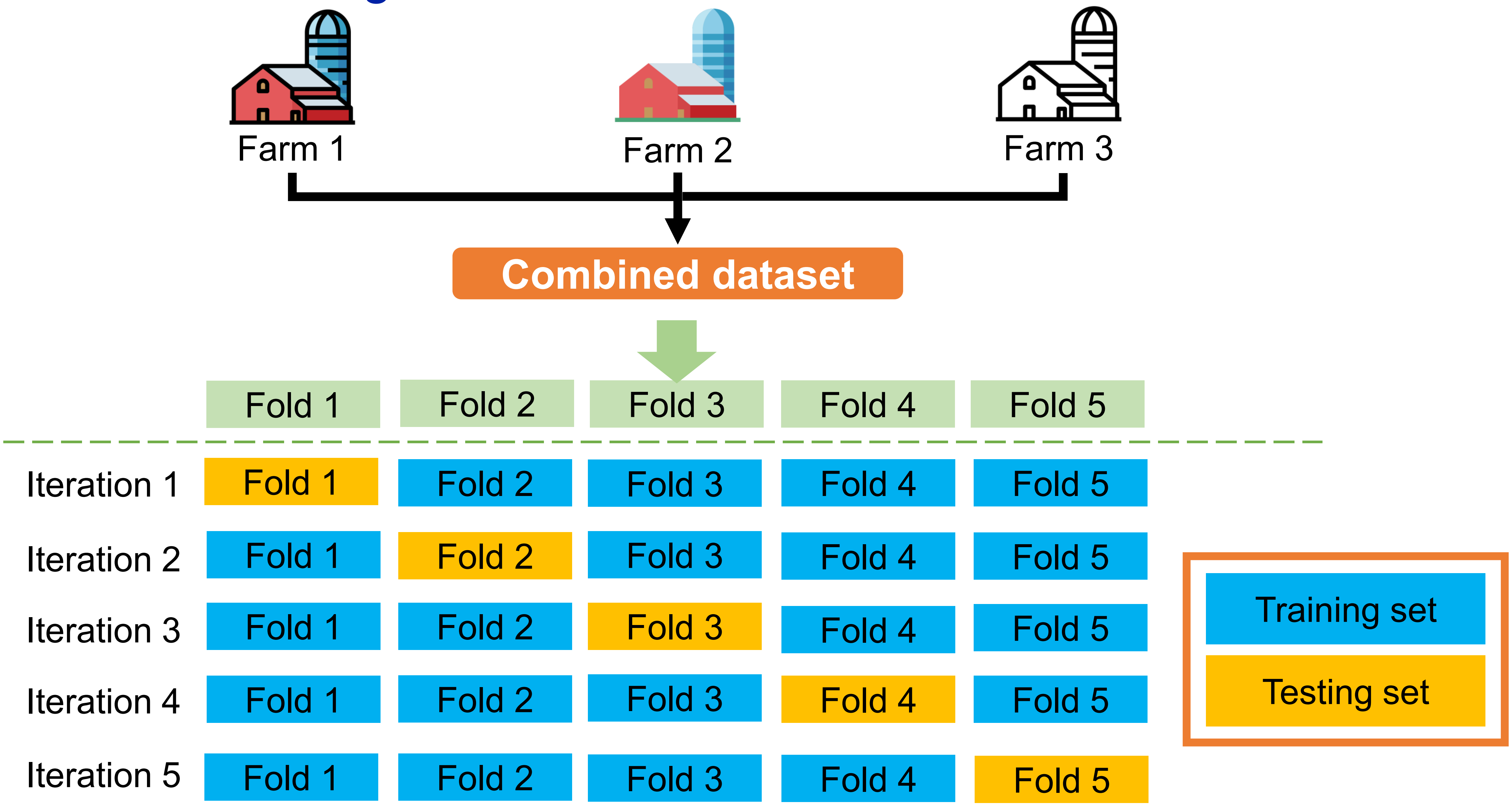
Adding representation learning



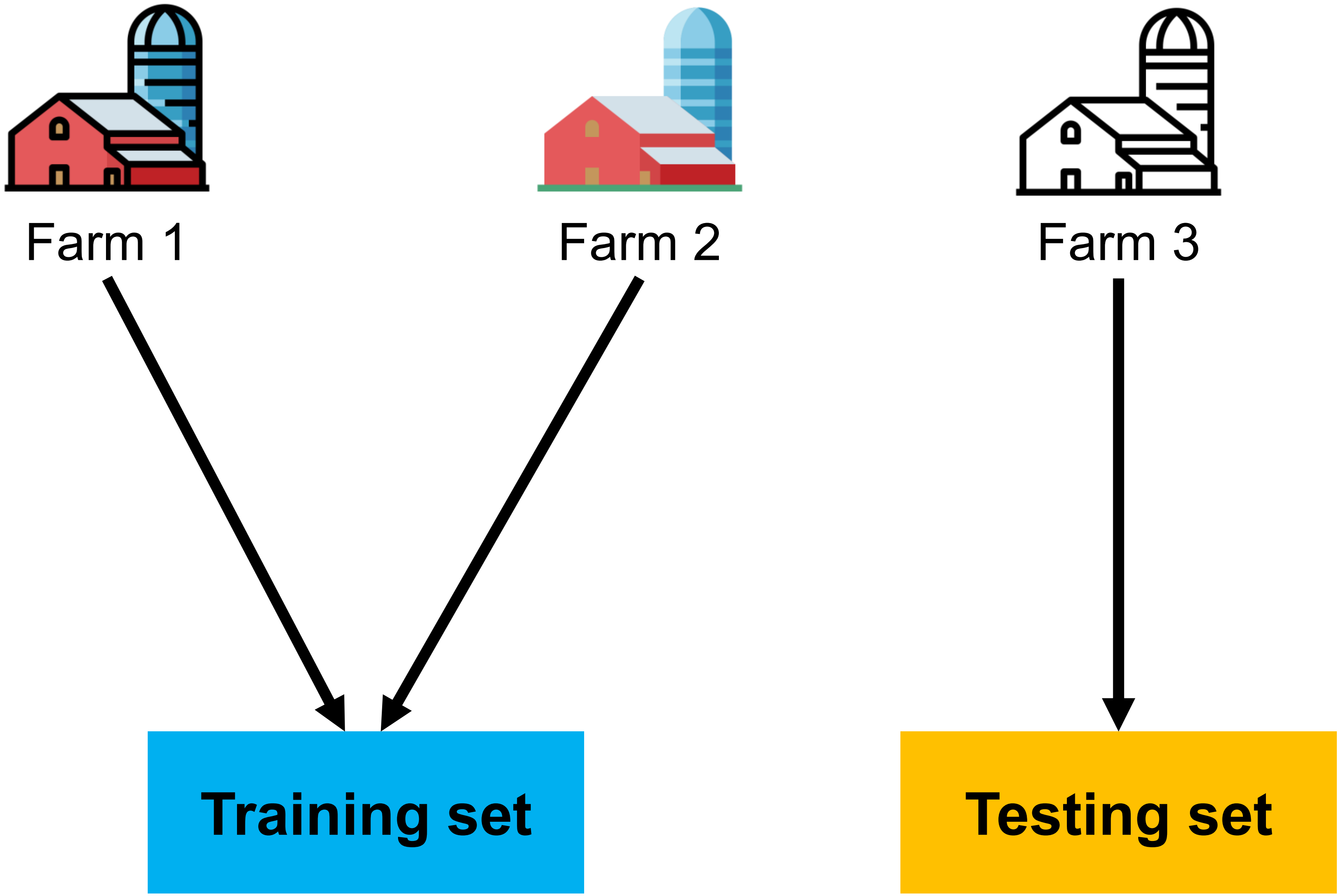
Adding class imbalance handling



Cross-validation design: 5-fold CV



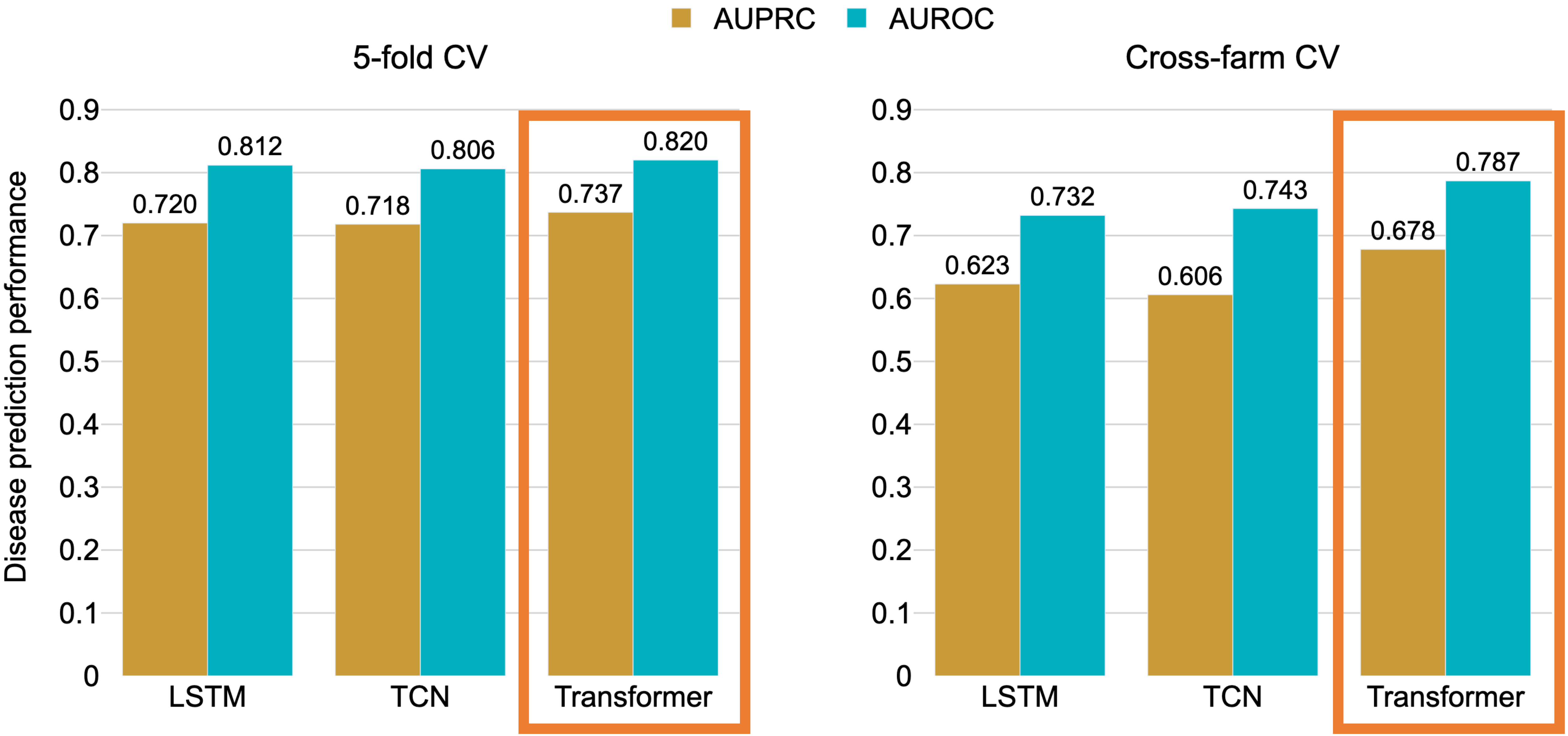
Cross-validation design: cross-farm CV



Results: prediction performance across model designs

Configuration	Encoder	5-fold CV		Cross-farm CV	
		AUPRC	AUROC	AUPRC	AUROC
Baseline	LSTM	0.651 (0.007)	0.772 (0.007)	0.556	0.735
	TCN	0.631 (0.008)	0.757 (0.007)	0.527	0.678
	Transformer	0.676 (0.003)	0.781 (0.006)	0.583	0.715
Baseline + CMM	LSTM	0.674 (0.004)	0.784 (0.005)	0.600	0.703
	TCN	0.667 (0.009)	0.785 (0.010)	0.587	0.713
	Transformer	0.687 (0.003)	0.793 (0.004)	0.620	0.719
Baseline + CMM + Focal loss	LSTM	0.720 (0.002)	0.812 (0.004)	0.623	0.732
	TCN	0.718 (0.006)	0.806 (0.002)	0.606	0.743
	Transformer	0.737 (0.007)	0.820 (0.006)	0.678	0.787
Baseline + CMM + Positive weighting	LSTM	0.706 (0.003)	0.804 (0.003)	0.600	0.720
	TCN	0.697 (0.002)	0.800 (0.005)	0.597	0.767
	Transformer	0.714 (0.004)	0.810 (0.004)	0.651	0.748
Baseline + CMM + Weighted sampling	LSTM	0.698 (0.005)	0.787 (0.006)	0.585	0.690
	TCN	0.693 (0.003)	0.804 (0.004)	0.585	0.723
	Transformer	0.704 (0.005)	0.807 (0.006)	0.605	0.729

Results: prediction performance across three deep learning encoders



Summary

We developed multimodal deep learning models that integrate time-series and single-time-point data to effectively predict postpartum diseases in dairy cattle.

Contrastive multimodal representation learning (CMM) improved multimodal feature learning by aligning representations across data modalities.

Class imbalance handling strategies improved prediction of minority disease cases, and the combined framework achieved the highest performance (AUPRC = 0.74).

Our proposed multimodal integration provides an opportunity to enhance early disease detection and advance the use of digital phenotypes in dairy cattle.

Challenge 3: Deriving biologically meaningful behavioral phenotypes

- **Social behavior** influences welfare, health, and productivity in dairy cattle.
- Human observation is **labor-intensive** and prone to **observer bias**.
- **Computer vision** offers opportunities for continuous, automated monitoring of social behavior.
- **Computer vision-based** social network analysis **remains underexplored** in dairy cattle.

Angelo De Castro

Project 3:

Develop and evaluate a **computer vision approach** for **automated social network analysis** in group-housed dairy calves.

Overview of the study

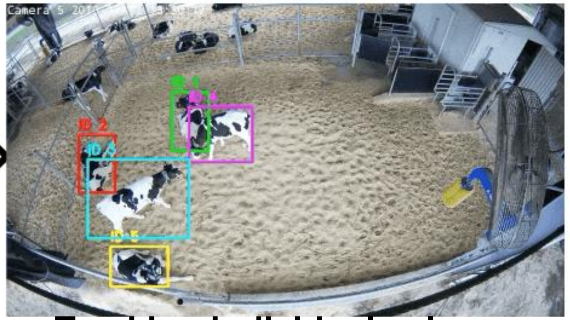
Video data

Continuous video recording of group-housed dairy calves

Step 1: Dairy calf detection

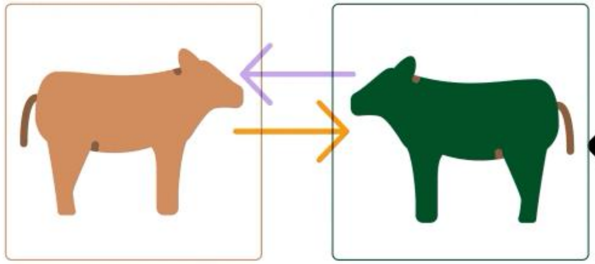
Detecting calves in each frame using the YOLOv8 model

Step 2: Dairy calf tracking



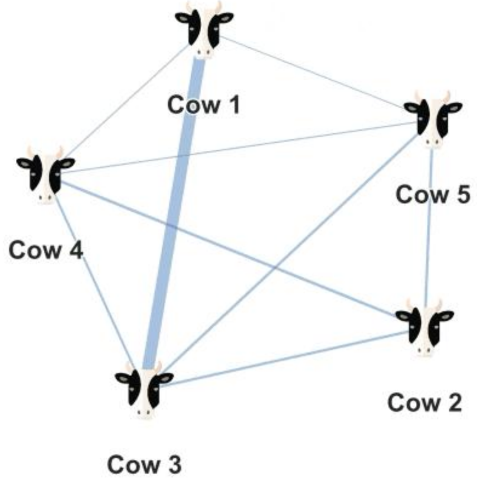
Tracking individual calves across frames using ByteTrack tracker

Step 2.1: Interaction detection

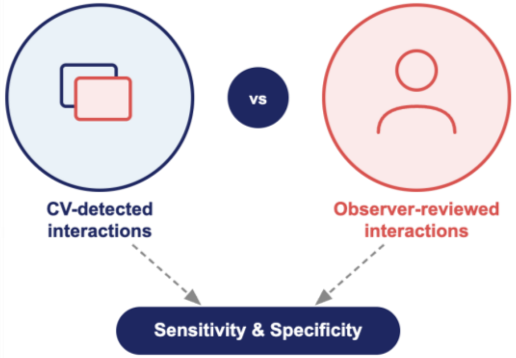


Detecting interactions using (a) one-body length and (b) bounding box overlap

Step 3: Social network analysis



Step 4: Case study evaluation



Experimental setup

Five group-housed Holstein heifer calves (28-42 days old) at the UF Dairy Unit

~3 m overhead top-down camera, 7 fps, **continuous video recording**

Selected video segments used for model development and evaluation

Dataset	Pen	Duration	Description
★ Training video	Pen 1	~60 min	Training (20 min) and evaluation (40 min)
★ Testing video	Pen 1	~171 min	Same calves, ***same pen***, different day
★ Testing video	Pen 2	~148 min	Same calves, ***different pen***, different day

Pen 1

Pen 2

Step 1: Dairy calf detection

Detects and localizes each calf in every frame using bounding boxes and confidence scores.

8,676 frames from Video 1 manually annotated using CVAT

Pre-trained **YOLOv8** model fine-tuned using 8,676 manually annotated calf images

Training set
8,676 frames from video 1

Testing set
16,801 frames from video 1

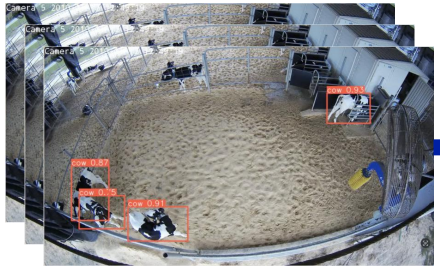
YOLOv8

Trained model

Evaluate detection performance

Step 2: Dairy calf tracking

Dairy calf detection outputs



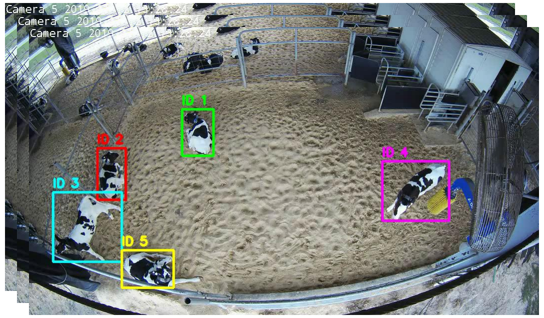
ByteTrack tracking algorithm

Kalman filter
Predicts calf positions

→ **Match detections**
Link detections to existing tracks

→ **Assign IDs**
Unique ID for each calf

Tracking output

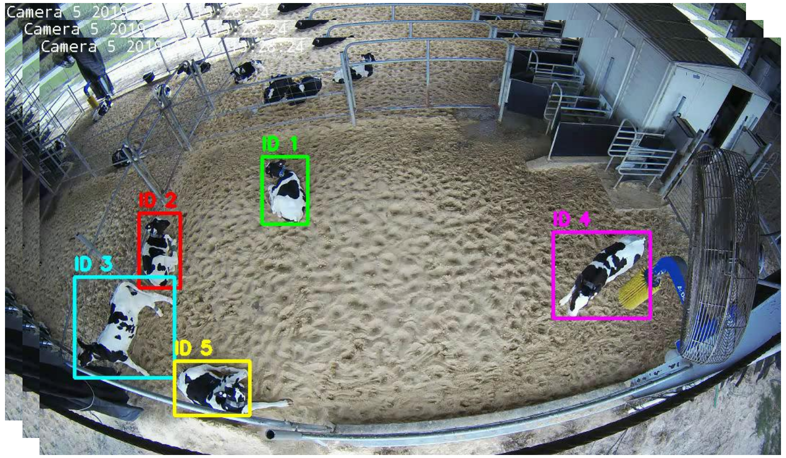


Dairy calf tracking outputs
Frame number
Track ID
Bounding box coordinates

- ❑ Continuous tracking across video frames
- ❑ Persistent calf IDs during occlusion
- ❑ Outputs used for interaction detection in Step 2.1

Step 2.1: Dairy calf interaction detection

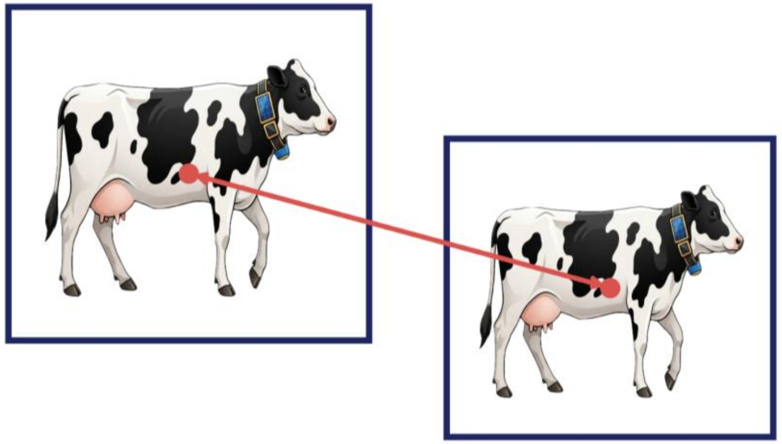
Dairy calf tracking outputs
Frame number
Track ID
Bounding box coordinates



Tracking video

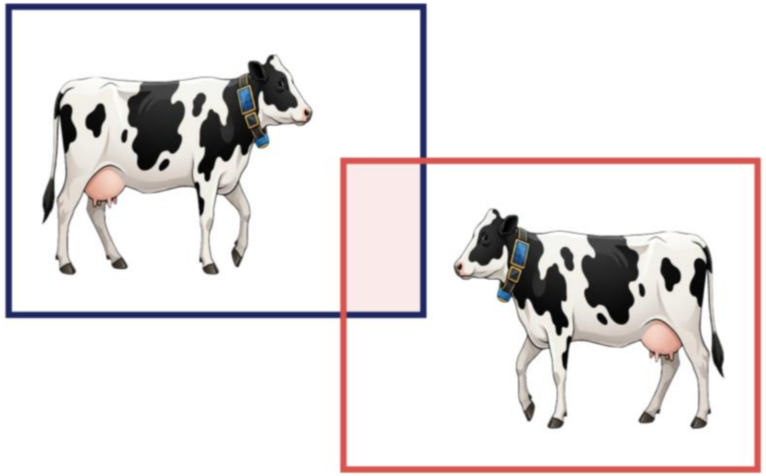
Interaction detection criteria

Proximity-based interaction



Centroid distance ≤ minimum calf body length of each pair

Contact-based interaction



Bounding box overlap > 0

Step 3: Social network analysis (SNA)

Group-by-individual (GBI)

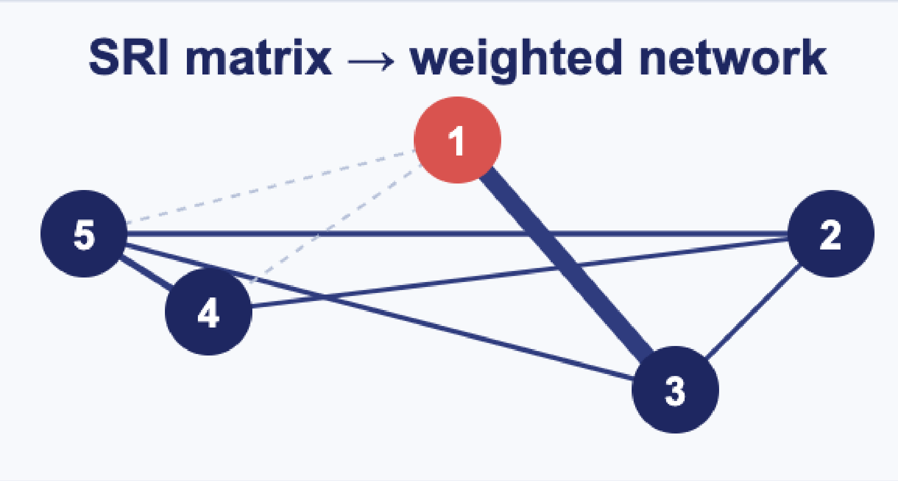
- Records whether pairs of calves were grouped together in each frame
- **1** = grouped together, **0** = not grouped together

Simple ratio index (SRI)

- Quantifies the proportion of observations in which two calves were grouped together.
- Serves as the edge weight in the social network.

	1	2	3	4	5
1	0.000000000	0.0000000	0.47293210	0.009493481	0.001460376
2	0.000000000	0.0000000	0.10744183	0.099901800	0.113238802
3	0.472932100	0.1074418	0.00000000	0.063320781	0.103006828
4	0.009493481	0.0999018	0.06332078	0.000000000	0.150595809
5	0.001460376	0.1132388	0.10300683	0.150595809	0.000000000

Social network metrics



Group-level

- Density
- Modularity
- Community structure (Louvain)
- Clustering coefficient

Step 4: Case study evaluation

Video 2 – same animals, **same pen**, different day

Video 3 – same animals, **different pen**, different day

Comparison between CV- and observer-identified interactions

CV-detected interactions **vs.** **Observer-reviewed interactions**

Sensitivity and specificity

- Videos 2 and 3 were sampled at 1-minute intervals for **case study evaluation**
- Each calf pair was assessed by a **trained observer** using both interaction criteria

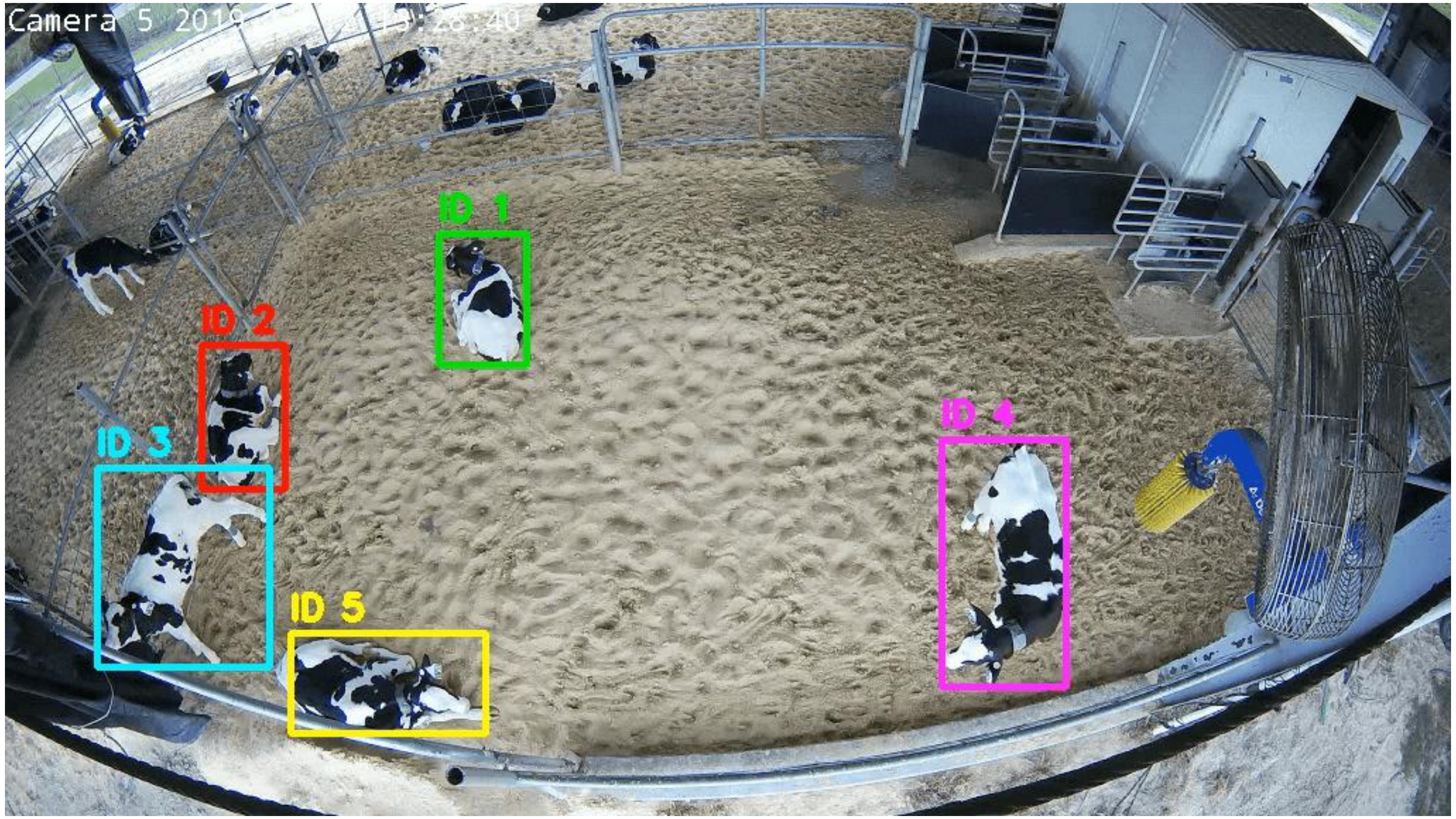
Results: Calf detection and tracking performance

Detection performance

Metric	Result
F1 score	0.985
mAP@0.5	0.994

Tracking performance

Metric	Result
MOTA	0.981
MOTP	0.127
IDsw	0

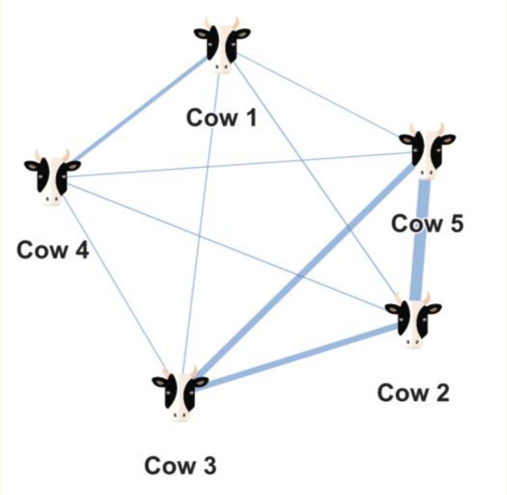


The model **accurately detected and tracked** dairy calves under group-housed pen conditions.

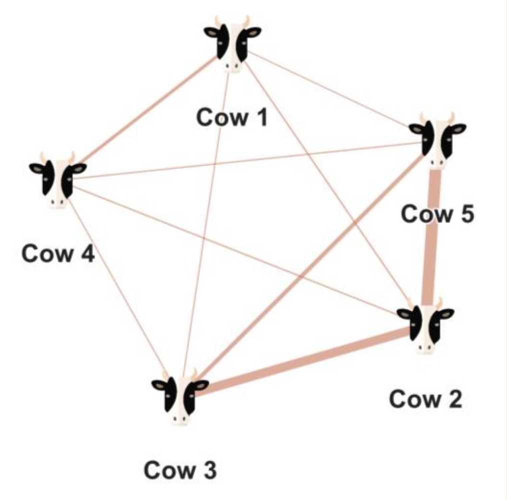
Results: Social network analysis

Testing video 2

Proximity-based interaction



Contact-based interaction



Proximity-based interaction

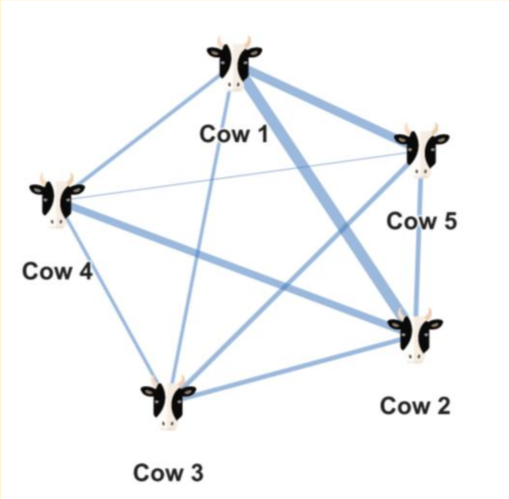
Video 2	Network metric	Video 3
1.0	Density	1.0
1.0	Clustering coefficient	1.0
0.20	Modularity	0.0
2	Community structure (Louvain)	1

Contact-based interaction

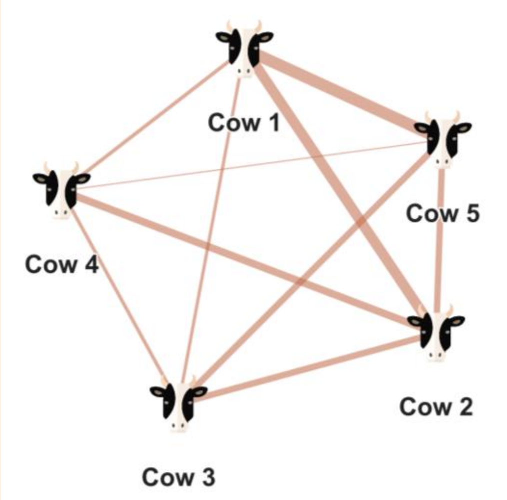
Video 2	Network metric	Video 3
1.0	Density	1.0
1.0	Clustering coefficient	1.0
0.15	Modularity	0.0
2	Community structure (Louvain)	1

Testing video 3

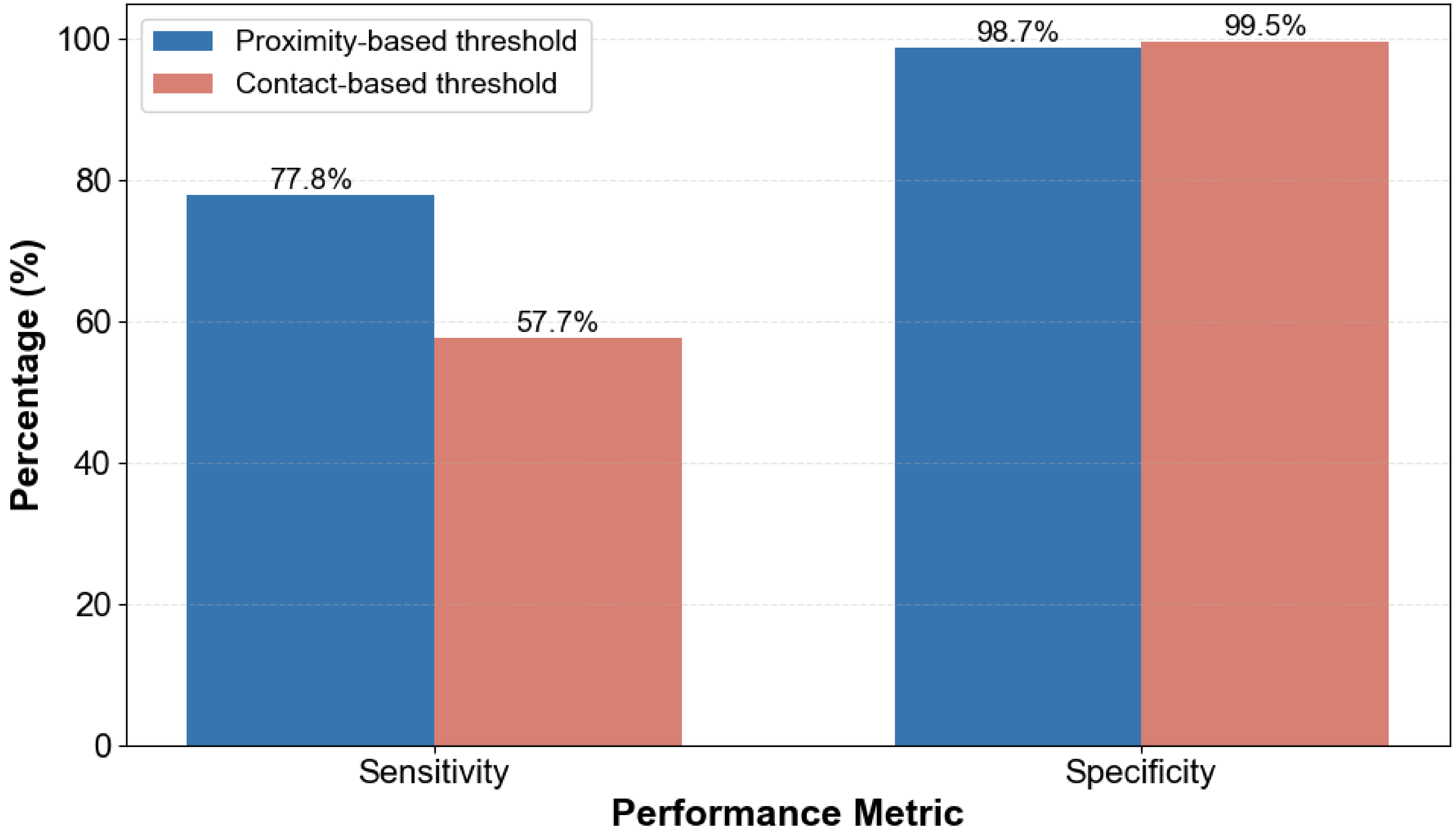
Proximity-based interaction



Contact-based interaction



Results: Case study evaluation



❖ The proximity-based threshold **detected more true interactions (human-reviewed interaction)** than the contact-based threshold.

Summary

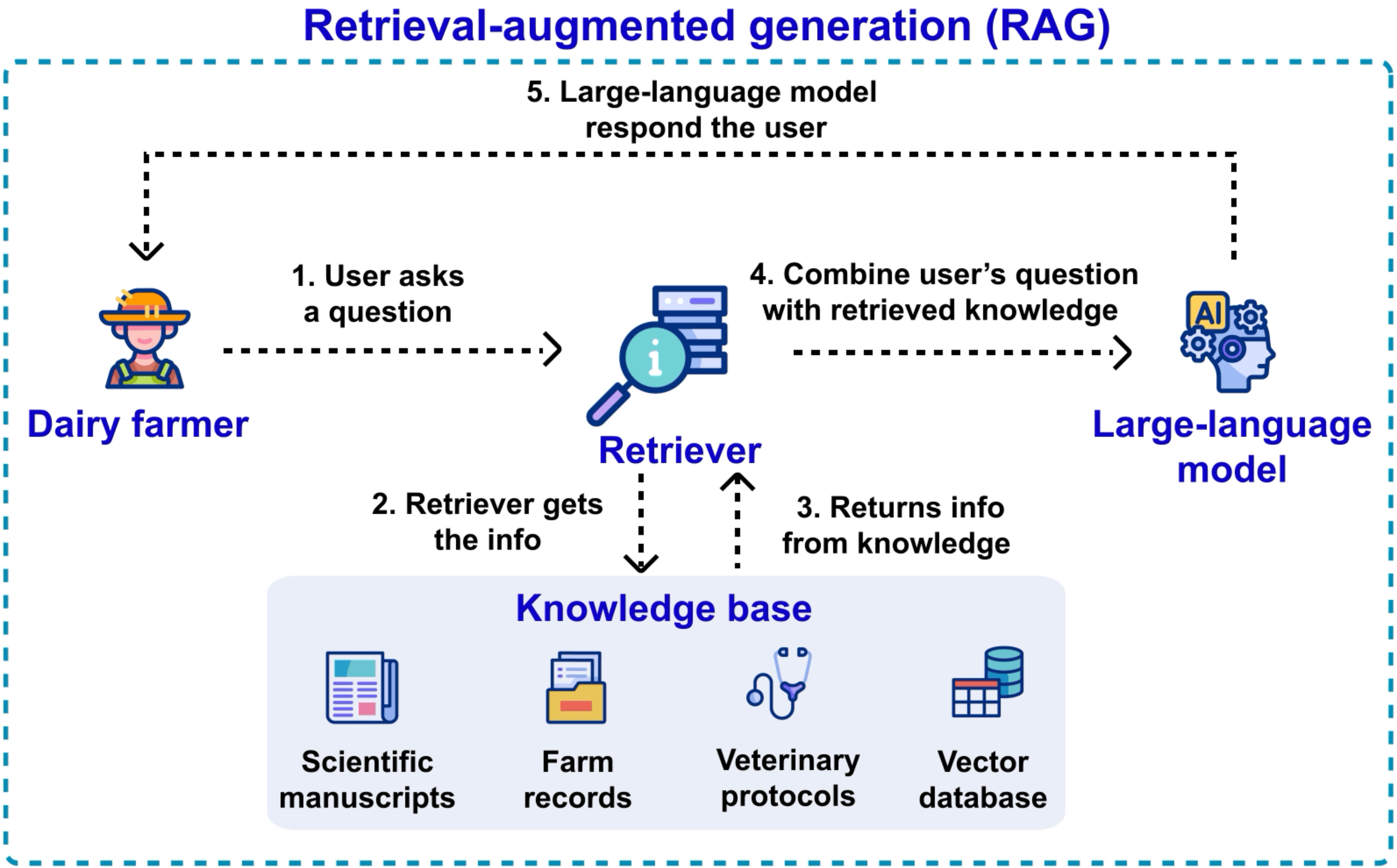
The proposed computer vision framework **enabled automated** quantification of **social interactions** and **social network structure** in group-housed dairy calves.

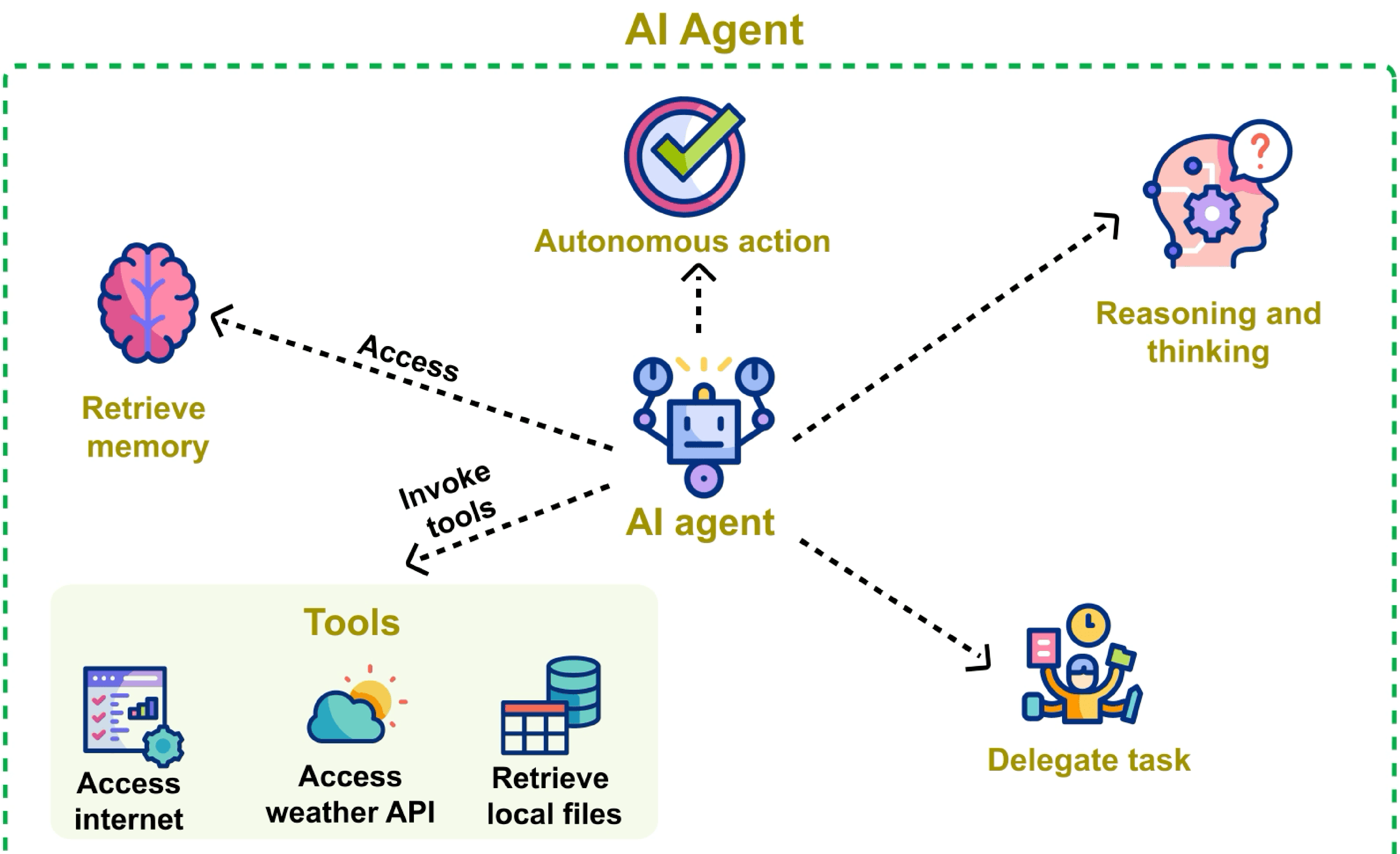
The proximity-based interaction criterion achieved higher sensitivity than contact-based interaction (**77.8% vs. 57.7%**), while both maintained **high specificity** (>98%).

Differences in social network structure were detected between the two evaluated housing environments.

Future work will extend the framework by **incorporating behavior classification** to capture both social relationships and behavioral context.

Looking ahead: From prediction to intelligent decision support




AI Agent
Autonomous action
Reasoning and thinking
Retrieve memory
Access
AI agent
Invoke tools
Tools
Access internet
Access weather API
Retrieve local files
Delegate task

Thank you!

Animal
Omics Sciences
Lab

Artificial Intelligence in Animal Omics Sciences Lab @ UF

UF | IFAS
UNIVERSITY *of* FLORIDA