Keypoint-Based Nest-Building Behaviour Detection in Sows Using Top-View Video Analysis

29.06.2026 | Sehrish Malik | Researcher at Topigs Norsvin

AI4AS Conference

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Nest-building behaviour in Sows

- **Nest-building** is a complex maternal behaviour
  - driven by hormonal changes,
  - occurs 1-2 days before farrowing,
  - involves gathering and arranging materials (straw, grass),

- Important for
  - understanding pre-farrowing activity,
  - and assessing maternal readiness.

- ***This behaviour varies in intensity and timing across sows***

Why detect nest-building behaviour matters?

- If behaviour is expressed:
  - Reduced stress
  - Improved maternal behaviour
  - Better hormonal balance

- If behaviour is restricted:
  - Increased stress and frustration
  - Disrupted physiology

- **Nest-building behaviour is a key indicator of sow welfare and maternal readiness.**

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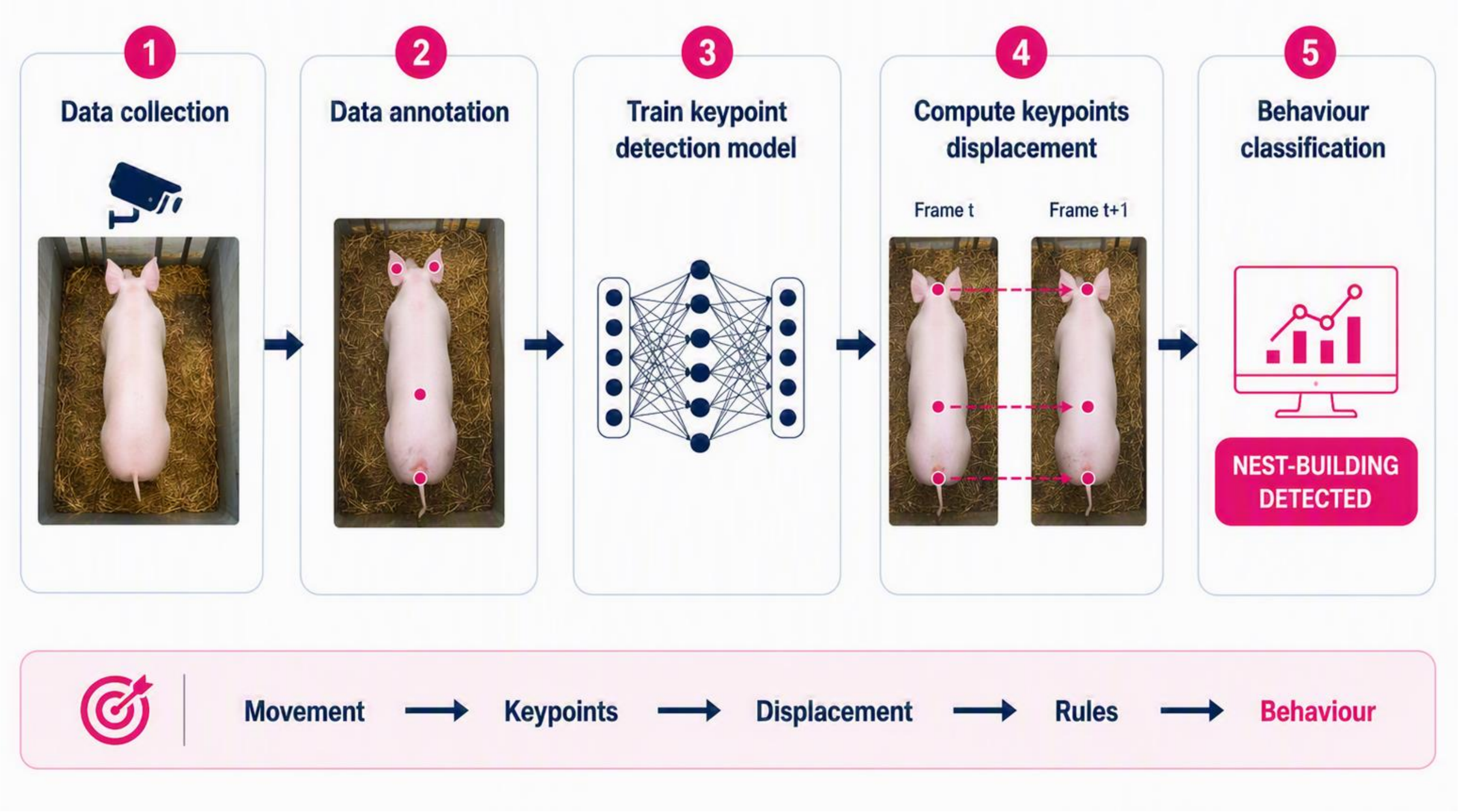
Why automate Nest-building detection?

- Limitations of manual observation
  - Labour-intensive and time-consuming
  - Observer bias
  - Limited temporal coverage
  - Difficult to quantify manually at scale

- Video-based automated detection enables
  - Continuous monitoring
  - Scalable across animals
  - Objective and consistent measurement
  - Supports data-driven decisions

Our Approach: Keypoint displacement based nest-building behaviour detection



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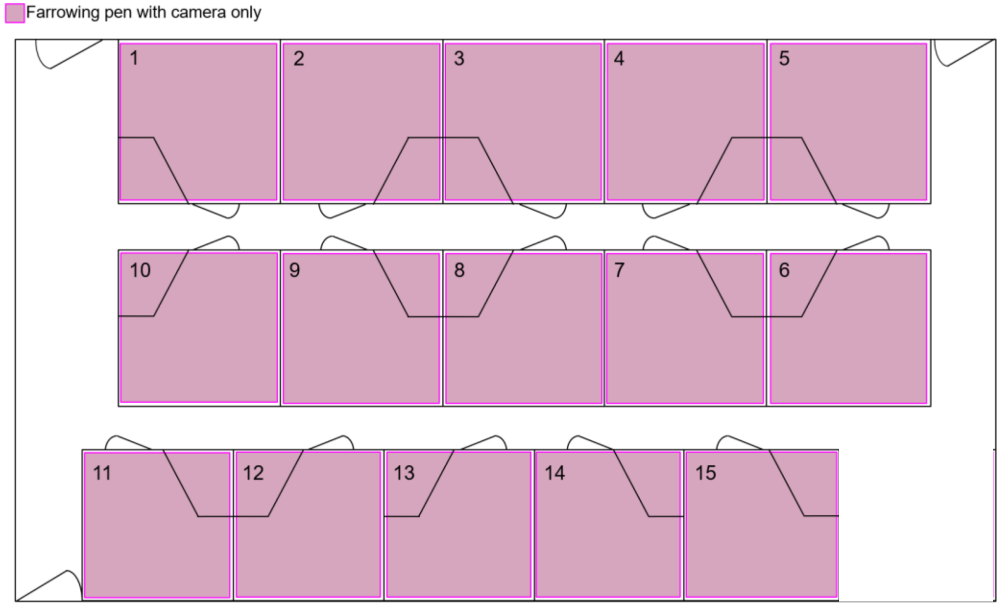
Data Collection and Ground Truth

- Dataset
  - 15 sows (Oct 2025)
  - 12–1 h pre-farrowing window
- Video-based ground truth
  - 83 nest-building intervals
  - Daytime only (controlled lighting)
- Challenge
  - Night-time variability excluded

Sows pen top-view video



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Data Preparation for Keypoint Model Training

- Extracted 1000 frames from videos data.

- 200 images from each posture
  - Standing
  - Kneeling
  - Sitting
  - Sternal lying
  - Lateral lying

Standing

Kneeling

Lateral lying

Sternal lying

Sitting

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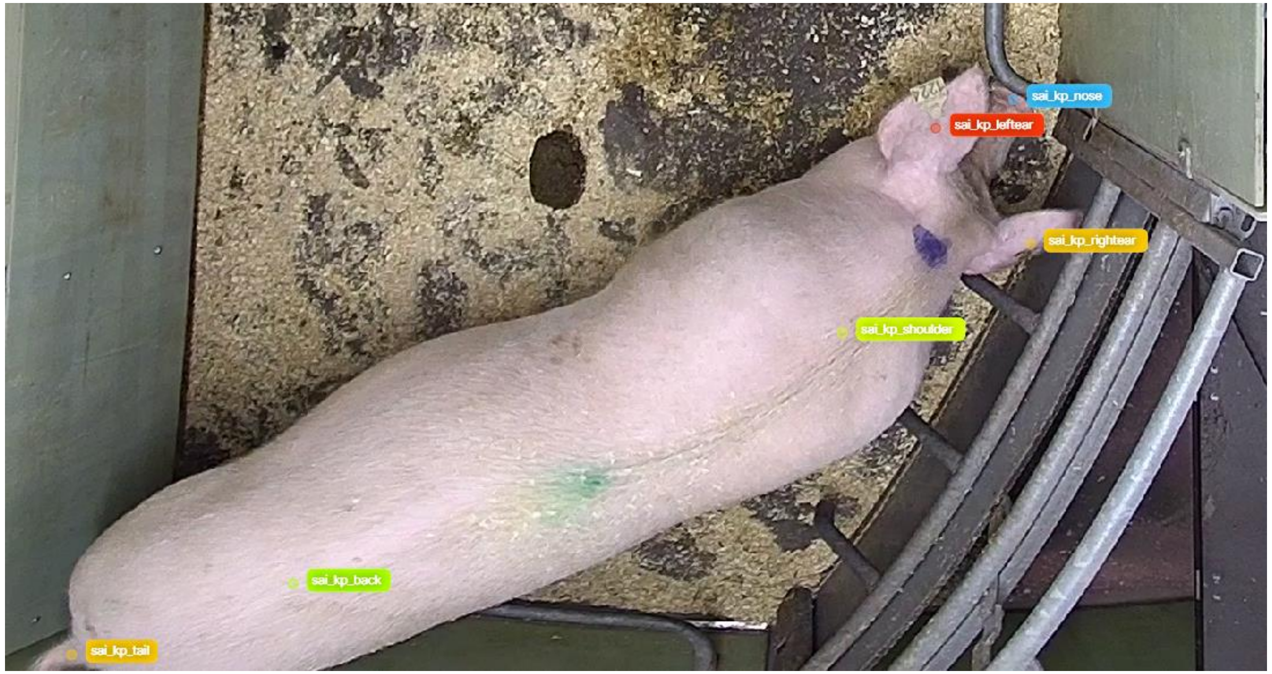
Sow Keypoints Annotation

6 on-body keypoints from top view

- Tail
- Back
- Shoulder
- Nose
- Left ear
- Right ear



- Coco format – (x-axis ,y-axis ,visibility)

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Keypoints Detection Model

- YOLOv11 pose model
  - Precision: 0.9997
  - Recall: 0.9951
  - mAP@0.5: 0.995
- Robust and accurate keypoint detection.
- Real-time capable: ~7.7 ms per frame

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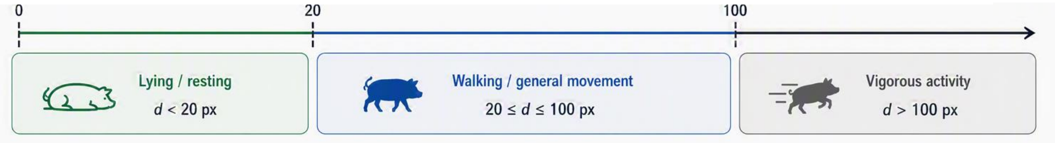
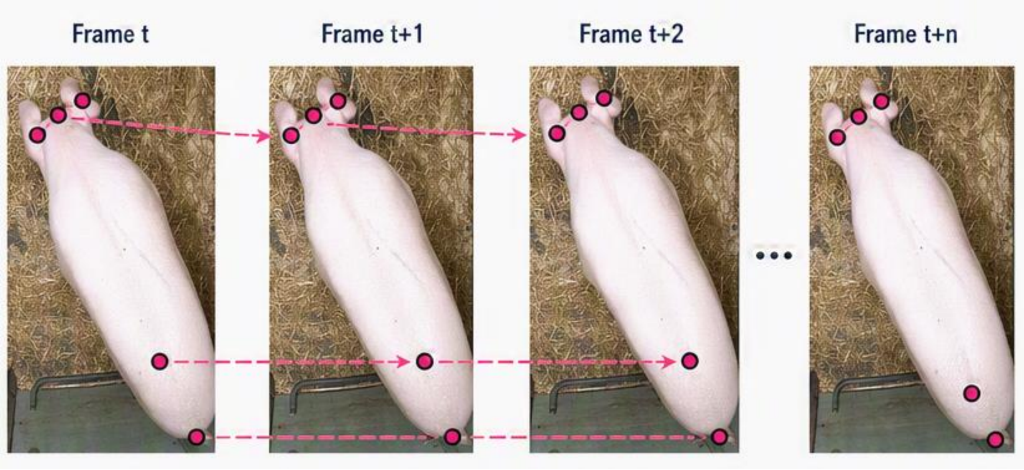
Keypoints Displacement enables rule-based behaviour classification

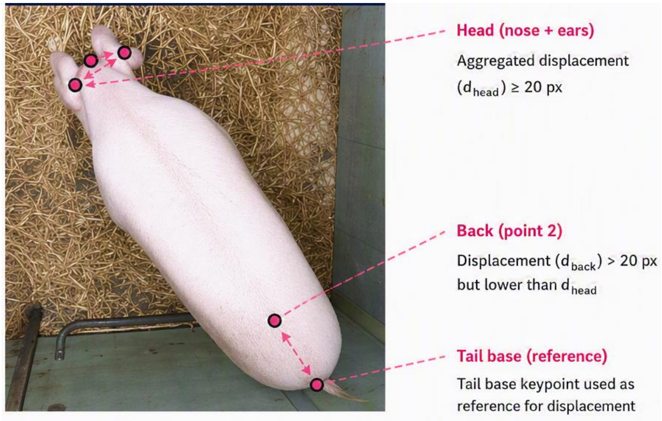
- Keypoints displacement over video frames was quantified and validated against ground-truth sow activities.
- Movement thresholds were derived to enable automated rule-based extraction of behaviour patterns.
- Observed pixel displacement-based activity mapping:





- Nest-building classification:

$$D_{head} \geq 20 \text{ px} \quad \text{and} \quad 20 < D_{back} < D_{head}$$



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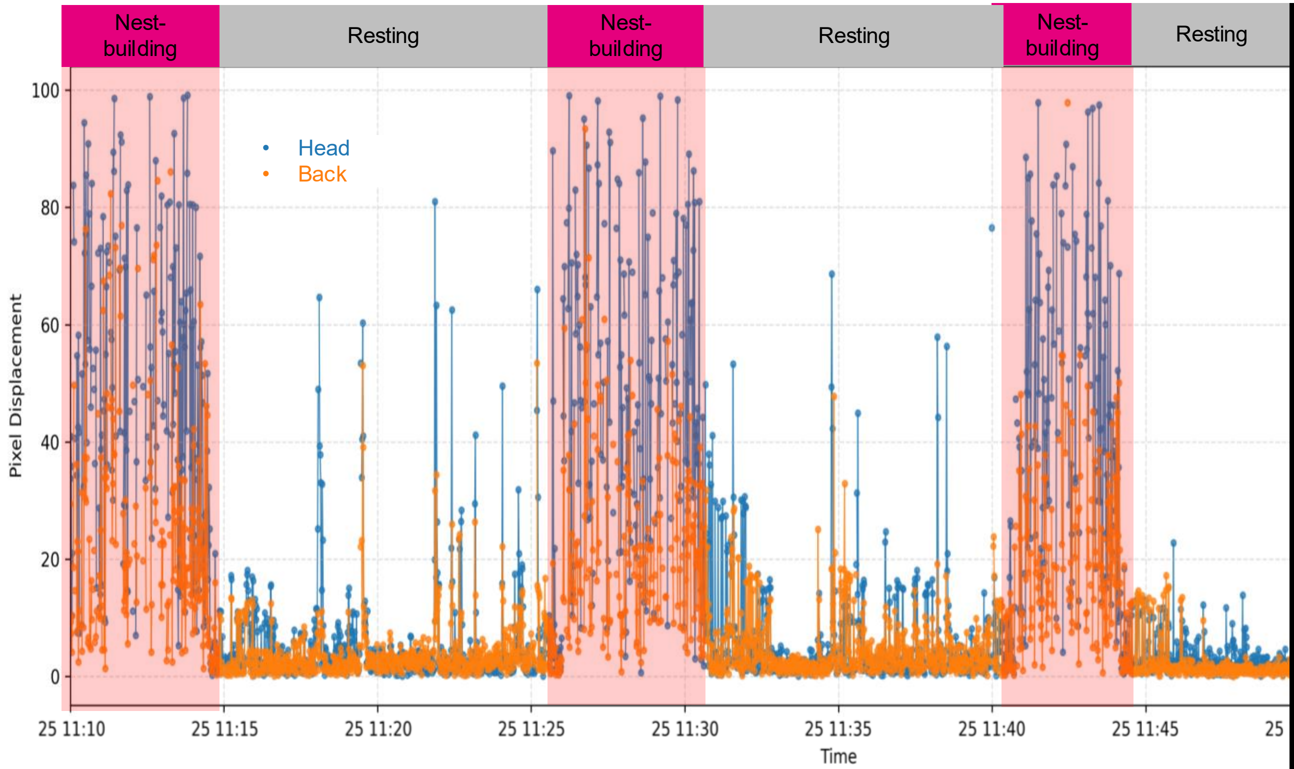
Automated Nest-building Behaviour Detection

Using keypoints displacement Classification



F1 score = 0.70

- ✓ High recall (0.84)
- Moderate precision (0.60)
  → False positives: eating and sitting activities

Baseline: accelerometer-based nest-building detection

- Common approach in precision livestock systems
  - Smart eartags with accelerometer
  - Measures overall body motion along x, y, z axes

➢ ***Question:*** Does keypoint-based video detection improve performance when compared to the baseline?

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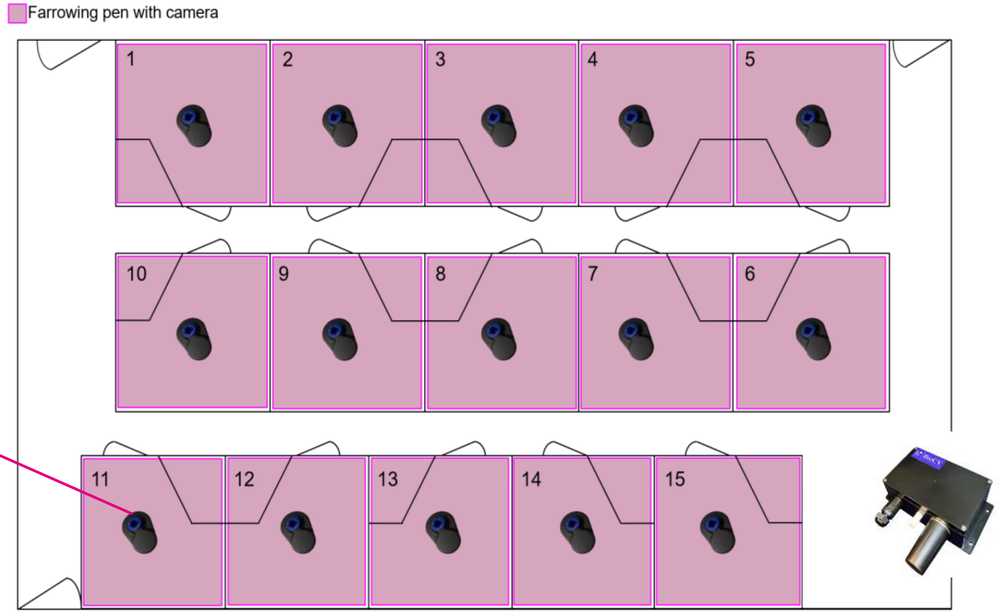
Baseline Setup

- Smart eartags attached to sows
- Accelerometer sensor (movement)
- Data collected during farrowing period



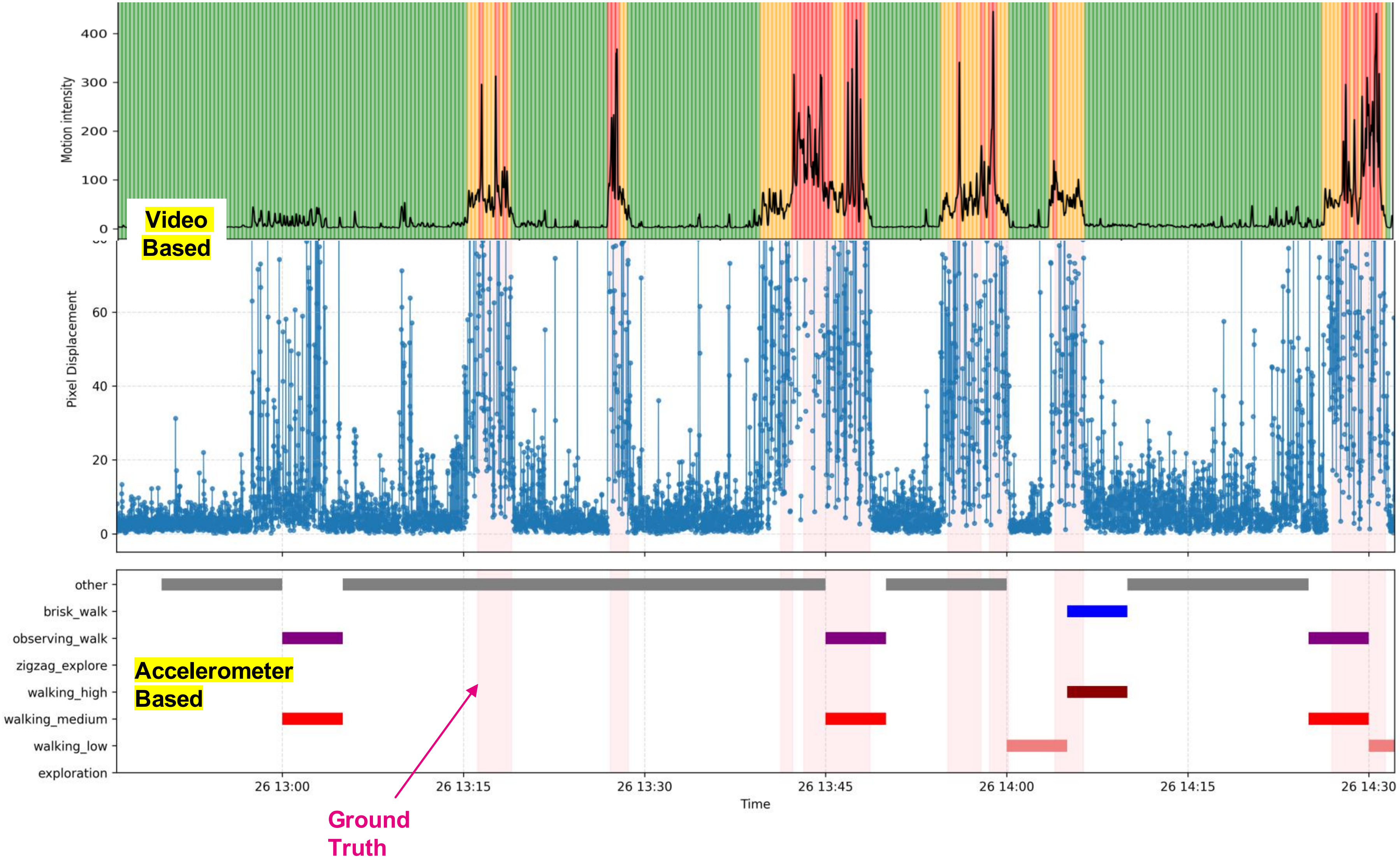
Biotags – Smart eartags

- Sends sow activity (x,y,z) data to the receiver node

BioNode – Receiver node

- Receiver node for data from smart eartags

Video (keypoints) vs accelerometer baseline



- ✓ Evaluated on the same dataset and ground truth
- ✓ Reliable detection of low-activity states (e.g., resting)
- ⚠ Nest-building signals highly overlap with other movement patterns.
  - ➢ Low separability between behaviours

F1 score	Accelerometer	Keypoints
	0.589	0.70

Keypoint-based detection provides more specific and interpretable behaviour signals.

Summary of results and contributions

- **Method Contribution**
  - Behaviour detection using keypoint displacement thresholds
  - Rule-based, interpretable mapping from movement → biologically meaningful behaviour
- **Key results**
  - F1 = 0.70 (keypoints) vs 0.589 (accelerometer)
    - Accelerometer-based methods capture overall activity intensity (from low to high),
    - while keypoint-based analysis provides behaviour-specific and interpretable detection of body-part movements.
- **Limitations**
  - Similar movement patterns across behaviours lead to confusion and false positives

Future directions

Challenge: Movement-based rules struggle to separate behaviours with similar motion patterns

- Direction 1: Context-aware filtering
  - Filter feeder-related activity
  - Exclude irrelevant regions

- Direction 2: Behaviour context modelling
  - Integrate posture information
  - Combine keypoints with posture cues

Conclusive Remarks:
Video-based automated analysis unlocks richer, structure-aware information, offering strong potential for detailed behaviour-specific detection and scalable on-farm monitoring and welfare assessment.

Thank you ☺

Questions ?