Lightweight Heat Stress Detection for Cow Health Monitoring

Aakanksha Dutta[1], Elvis Imamura[1], Eva Salmone[1], Sreejato Chatterjee[1], Duole Hong[1]
Sponsors: John Balbian[2], Emmanuel Mounier[2], Utsav Uts[2], **Instructor:** Ajay Anand[1], Cantay Caliskan[1]
[1]University of Rochester Goergen Institute for Data Science & AI, [2]Zalliant

MELIORA
University of Rochester
Goergen Institute for Data Science & Artificial Intelligence

Introduction

Background: Cattle health monitoring is vital for agricultural productivity and economic stability. Traditional manual observation often detects illness only after symptoms progress, leading to high mortality and costly, late-stage interventions. Zalliant addresses this by using rumen boluses (sensors) to continuously monitor internal temperature, shifting herd management from reactive to proactive.

Our Goal: Our work focuses on improving Zalliant's existing temperature-based alert system by evaluating whether more efficient, data-driven methods can enhance performance while reducing cost. A key goal of this project is to assess the feasibility of machine learning approaches within Zalliant's workflow.

We aim to answer a central question:
Can we develop a model that improves or matches the current detection performance while operating at a low cost?

Dataset

Raw Data: Rumen Temperature Data
- 20 cows – 10 from each farm, with and without alerts
- 30-day span
- Time series has gaps as sensor data may not always be capturable

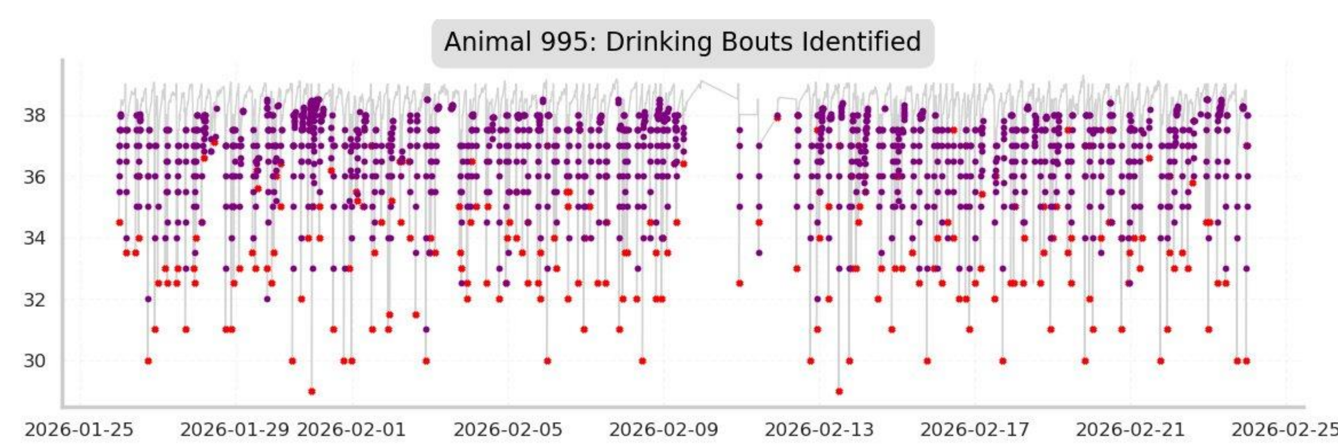
Data Source: CowMonitor.com
- Grace-Way Farms (New York, USA)
- Voltaurin (South France)

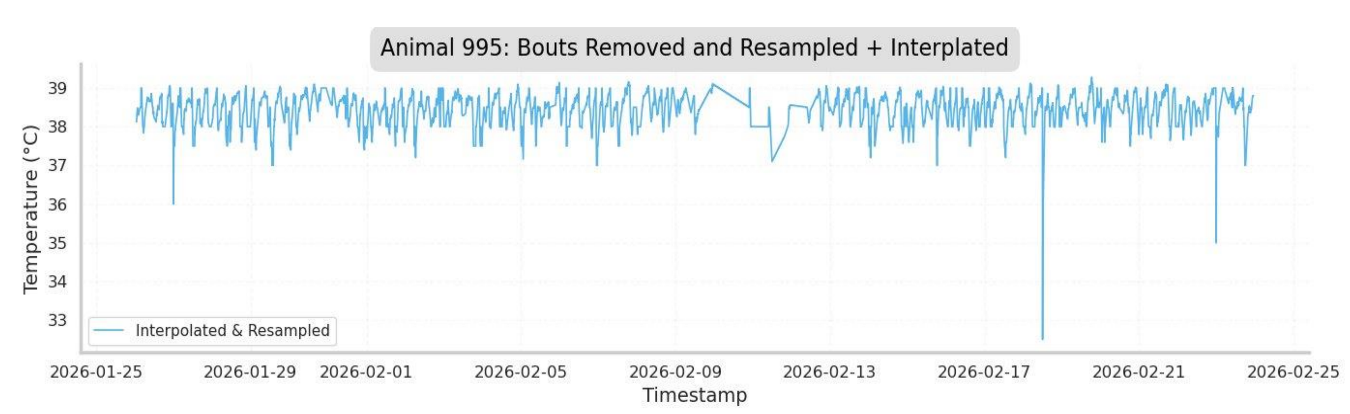
Variable	Description
animal_id	Unique identifier assigned to each cow
temperature	Primary signal: rumen temperature captured by bolus sensor, updated every 5 minutes
device_id	Unique identifier for each bolus device
timestamp (UTC)	Date and time associated with each observation
alert	Boolean flag triggered when the current detection system identifies a potential health event
communication_flag	Boolean flag indicating connectivity issues between sensor and network

Method

1. Baseline Reconstruction

Goal: *Estimate cow's normal temperature pattern ("blue line")*
- Detect drinking bouts (sharp temporary drops)
- Remove distorted readings
- Interpolate missing sections
- Create smoothed baseline trajectory

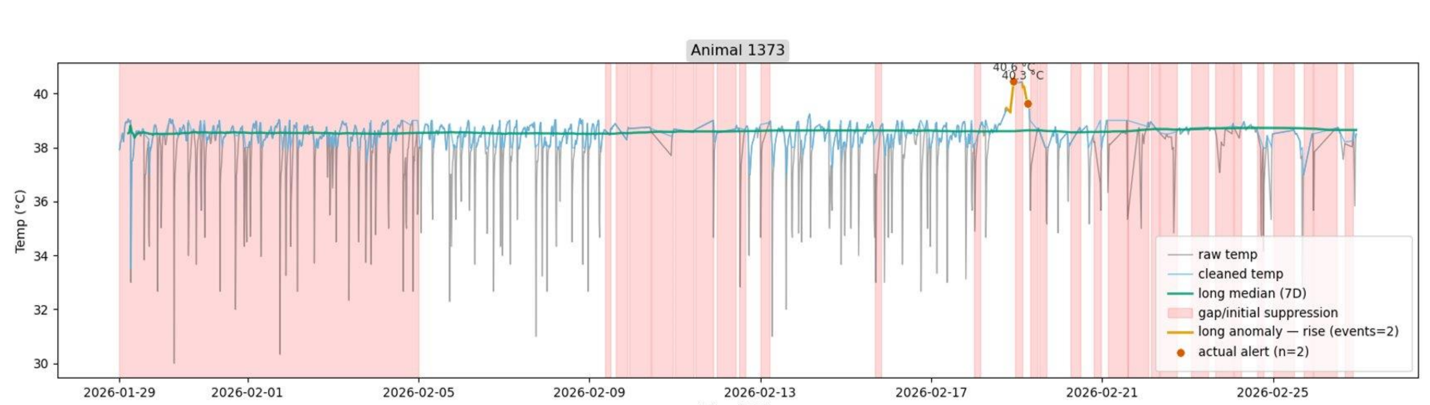




2. Context-Aware Detection

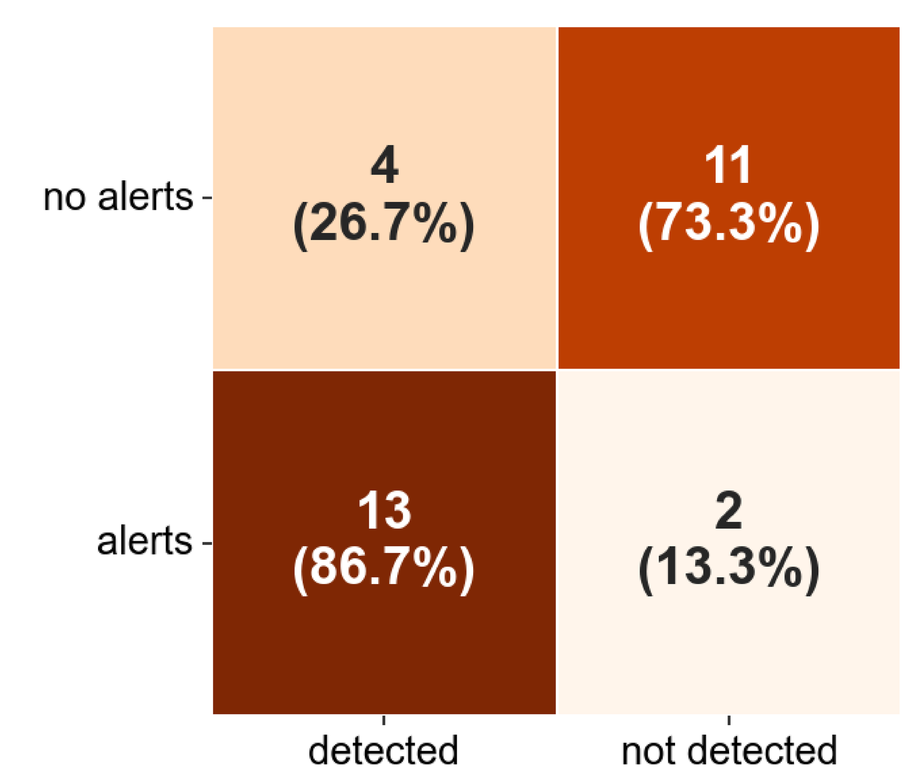
Instead of asking "Is this temperature high", we ask: "Is this unusually high for this cow right now?

Method:
- Detects anomalies using the distribution of deviations (outliers)
- Uses two rolling windows:
  - Baseline Window: Get baseline using rolling median and the deviations
  - Scale Window: Models historical deviations to get "usual fluctuation"
- Flags alerts only when:
  - A deviation is unusual compared to past deviations
  - It persists over time



Results

Test Set :
- 30 cows – 20 from dairy & 10 for beef
- 50:50 split between cows with alerts & without alerts.



Accuracy	0.8
Precision	0.747
Recall	0.867
F1 Score	0.813

Earlier Detection
- Match our alerts with Zalliant's by filtering for high alerts and linking only nearby alerts as the same event.
- Median Early Detection = **9 hours** earlier than current alerts!

Performance Metrics by Sampling Rate			
Sampling Rate	5 min	10 min	15 min
Accuracy	0.85	0.9 +6%	0.8 -6%
Precision	0.86	0.88 +2%	0.7 -18%
Recall	0.75	0.88 +17%	0.88 +17%
Specificity	0.92	0.92	0.75 -18%

Conclusion

Takeaway: We developed a lightweight, context-aware event detection model using rumen temperature sensing data, outperforming machine learning approaches under real-world conditions with noisy and limited labeled data. Our method performs strongly while remaining interpretable and robust to natural temperature variation, sensor gaps, and operational constraints.
Impact: Compared to Zalliant's current detection methods, our model identifies heat stress events ~9 hours earlier. This enables farmers to respond before visual symptoms appear, reducing productivity losses and promoting improved cattle health.
Cost Efficiency: Our models maintain performance at lower sampling frequencies, allowing sensors to collect data every 15 minutes, 3 times longer than the current 5-minute sampling period. This potentially increases bolus battery lifespan by up to 300%, decreasing hardware-related costs by 50%.

Acknowledgements

We would like to extend a thank you to the team at Zalliant—John Balbian, Utsav Uts, and Emmanuel Mounier, for their guidance and support throughout this project. We would also like to thank Professor Caliskan for his continuous mentorship and feedback.

References

1. Knight, Russel. Cattle & Beef – Sector at a Glance. USDA Economic Research Service. https://www.ers.usda.gov/topics/animal-products/cattle-beef/sector-at-a-glance. Accessed March 17, 2026.
2. Rollin E, Dhuyvetter KC, Overton MW. The cost of clinical mastitis in the first 30 days of lactation: An economic modeling tool. Prev Vet Med. 2015 Dec 1;122(3):257-64. doi: 10.1016/j.prevetmed.2015.11.006. Epub 2015 Nov 7. PMID: 26596651.
3. Kleen, J. L., & Guatteo, R. (2023). Precision Livestock Farming: What Does It Contain and What Are the Perspectives? Animals, 13(5), 779. https://doi.org/10.3390/ani13050779

An image of Zalliant's bolus used to capture the temperature data. The device is swallowed by the cow and remains in the rumen (stomach) for the lifetime of the device.