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SmartLivestock Welfare Framework for Continuous Behavioral and Health Monitoring of Farm Animals

Dawakit Lepcha[1*], Dr. Kanchan Thakur[2], Arun Kumar[3]

[1]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.*
Email: ku.dawakitlepcha@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0001-0429-8217
[2]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
Email: ku.kanchanthakur@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0001-9871-6036
[3]Professor, New Delhi Institute of Management, New Delhi, India. Email: arun.kumar@ndimdelhi.org

Key Words	Abstract
Precision livestock farming, Animal welfare, Behavioural monitoring, Wearable sensors, Edge computing, Machine learning.	Continuous welfare assessment on commercial farms is still limited by infrequent and labour-intensive inspection times, which miss the dynamic changes in behaviour and physiology leading up to clinical signs of disease or distress. The SmartLivestock Welfare Framework (SLWF) is introduced which is a four-layer architecture, where a wearable and ambient sensor is combined with an edge device for feature extraction, cloud-based behaviour classification and a decision support system for farmers to continuously monitor the wellbeing status of cattle, sheep and swine without being invasive. These streams of information (tri-axial accelerometer, RFID, acoustics, and thermal imaging) are combined in a Welfare Index to indicate deviations from normal lying behaviour, feeding time, locomotion, and vocalisations that relate to lameness, mastitis, heat stress and parturition. The data flow, latency budgets and alerting logic throughout the architecture is illustrated using a prototype deployment scenario. The framework is placed into the context of the current precision livestock farming (PLF) literature and some barriers are identified, such as the need for validation, the cost of the sensors and the need to standardise the data before it can be adopted on a farm. It proposes a repeatable reference design that can be used by research groups and technology suppliers interested in bridging the gap between research and deployable welfare-monitoring systems.

* Corresponding Author's email: ku.dawakitlepcha@kalingauniversity.ac.in
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Introduction

Animal behaviour is now being recognised as an important non-invasive indicator of animal physical and affective state, a science discipline gaining acceptance. Behaviour is now accepted as a primary indicator of physical and affective state and is a science discipline that is gaining recognition and acceptance in animal welfare science. Traditional welfare audits are carried out every so often by visual inspection, meaning they take a snapshot of an animal's day which can lack the depth of understanding required and depend on the presence of sufficient farm labour and reliability of the observer. Precision livestock farming (PLF) technologies fill this void by installing on or in the animals or their surroundings, providing the ability to monitor the animal's behaviour 24/7, which is not possible with periodic checks made by humans. There are a number of different systems that are proving to have the ability to detect early signs of lameness, oestrus, heat stress and respiratory disease well before they are seen by farm staff, with all of these systems currently being wearable monitors.There are a number of different systems that are proving to have the ability to detect early signs of lameness, oestrus, heat stress and respiratory disease well before they are seen by farm staff, all of which to date have been wearable monitors.

This progress has yet to be reflected in most PLF research, which is primarily focused on an individual modality or species, requiring farmers to manually combine different point solutions. This paper suggests the SmartLivestock Welfare Framework (SLWF), an integrated reference architecture that integrates multi-modal sensing, edge-level processing, cloud analytics and decision support into a unified continuous monitoring pipeline for both cattle, sheep and swine production systems. The rest of the paper summarizes some existing PLF monitoring efforts, outlines the SLWF architecture and the different layers, illustrates a typical deployment scenario with some indicative performance numbers and discusses adoption barriers and potential future research directions.

The rest of this paper is organized as follows. The second section summarizes the most recent research in precision livestock farming and behaviour-based animal welfare monitoring. In Section 3, the proposed SmartLivestock Welfare Framework (SLWF) is presented which has four layers of architecture and key functional components. In Section 4, an illustrative deployment scenario, species specific monitoring targets and implementation challenges are discussed. Lastly, Section 5 wraps up the paper and provides future research directions for improving continuous livestock welfare monitoring.

Related Work

The most validated modality for livestock behaviour classification is currently wearable inertial sensors. Combined offline-online learning is proposed to counteract the sensor drift over long periods of time, and tri-axial accelerometers and gyroscopes mounted on the leg, neck, or ear have been used to classify standing, lying, and locomotion behaviours in sheep in real-time, long-term field conditions (Vázquez-Diosdado et al., 2019). In dairy calves, a systematic review of lying and rest detection using sensors revealed that accuracy values reported depended highly on the location of the sensor and the methodology used for its validation and had to be standardised before wide-spread use (Pesenti Rossi et al., 2024).

The non-contact approach is provided by vision-based approaches. The use of camera-based pipelines to classify dairy cattle behaviour from video has been shown to not require any hardware on the cattle thus it reduces handling stress and equipment costs (McDonagh et al., 2021). Likewise, image-analysis has been employed to count the number of pig locomotion patterns as an indirect pig lameness risk (Kashiha et al., 2014). Automated lying-behaviour measurement systems have been tested for continuous monitoring of comfort and welfare of lactating dairy cows in free-stall barns at the herd-management level (Mattachini et al., 2013). Automated detection of behavioural change in pigs has been demonstrated to be a means of predicting compromise in health and welfare, in addition to the single modality of sensing, as a means to assess welfare based on behaviour rather than physiology (Matthews et al., 2016).

The review of the PLF field highlights that so far the adoption of technology has focused on productivity and health outcomes, and not on a comprehensive notion of welfare that takes into account affective state, and that technology development and implementation needs to be monitored in ways that are collaboratively designed with the welfare scientists themselves and not imposed upon them as part of a productivity-based platform of sensors (Nielsen, 2022). The SLWF proposed in this paper addresses this gap by introducing a composite (multi-species) Welfare Index instead of a single production measure; and by making the architecture sufficiently flexible to accommodate the heterogeneous modalities of sensors surveyed in this paper.

Proposed SmartLivestock Welfare Framework

Architectural Overview

The SLWF is divided into four functional layers: Sensing, Edge Processing, Cloud Analytics and Decision & Alert, which work together to convert raw sensor data into actionable welfare information (Figure 1). They are built to work with any individual hardware vendor chosen, and enable farms to add one layer of the sensors to their existing infrastructure instead of replacing their entire system.

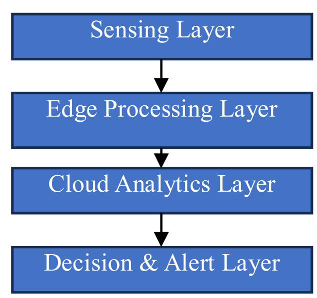

Figure 1: Layered Architecture of the Smartlivestock Welfare Framework

Sensing Layer

The sensing layer includes animal-mounted and ambient devices: tri-axial accelerometers and RFID ear tags for animal identification and movement tracking, acoustic sensors for detecting animal vocalisations and coughing, thermal and RGB cameras for the overall postural and gait analysis of animals. Species and house type dependent accelerometer classification works best on extensively grazed sheep, camera-based works best on intensively housed dairy cows where the hardware are mounted on the animals is more difficult to maintain.

Edge Processing Layer

All raw sensor streams are combined on the farm at a gateway, which filters the signals, extracts features (e.g., step count, lying bout, duration, vocalisation rate), and merges them in a windowed manner and coarse behaviour tags them before they are sent. Edge processing can lower bandwidth usage in low-connectivity rural areas and can enable raising of time-sensitive alerts (such as a parturition event) locally even if there is a cloud connectivity outage.

Cloud Analytics Layer

Aggregated features are sent to a cloud analytics service where supervised machine learning classifiers are used to classify behavioural states and identify anomalies in comparison to each animal's individual baseline. For each modality, outputs are added together to create a composite Welfare Index by assigning a weight to the deviation in each of locomotion, feeding, resting and vocalisation based on their historical association with lameness, mastitis, heat stress and parturition risk.

Decision and Alert Layer

The final layer is to turn the Welfare Index outputs into a dashboard and mobile alerts for the farmer, by urgency and animal identifier. Herd-level reports are also created for veterinary inspection practices, both for immediate use and for long-term welfare checks.

Illustrative Deployment Scenario and Discussion

To illustrate the framework's operation, Table 1 summarises indicative monitoring targets and the behavioural indicators the SLWF is designed to surface for three production systems. These values are drawn from the patterns reported in the reviewed PLF literature rather than from a controlled field trial, and are presented to demonstrate the framework's intended scope rather than as validated performance benchmarks.

Table 1: Indicative Species-Specific Monitoring Targets Under the SLWF

Species	Primary Modality	Key Behavioural Signal	Welfare Concern Flagged
Dairy cattle	Accelerometer + vision	Lying bout duration, gait	Lameness, mastitis
Sheep	Accelerometer + gyroscope	Grazing vs. resting ratio	Heat stress, parasitism
Swine	Vision + acoustic	Locomotion, cough rate	Lameness, respiratory disease

There are three common implementation issues identified in the scenario that are in line with the PLF literature. First, there is inherent variability in sensor validation: reviews of lying-behaviour sensors in calves show that accuracy is heavily dependant on placement and calibration procedures, which means that the SLWF's cloud analytics layer should allow for per-farm baseline recalibration, rather than a single, fixed classifier (Pesenti Rossi et al., 2024). Second, in remote/rural environments or in regions where grazing is more or less extensive, reliance on continuous cloud transmission is limited and so are the local tagging capabilities of the edge-processing layer. Third, cost and burden of animal-mounted hardware support a hybrid (mixed) modality approach that uses vision-based sensing to reduce the need for a universal wearable system (Kashiha et al., 2014; McDonagh et al., 2021).

Another issue addressed in the welfare-science literature is the danger of measuring welfare in terms of output (narrow approach) instead of welfare (broad approach), if monitoring is based on behaviour in relation to productivity output (Nielsen, 2022). The SLWF's Welfare Index is thus extensible; as new classifiers for positive welfare behaviours, such as play or social affiliation, are validated, they can be added to the framework, rather than excluding them from its scope.

Conclusion and Future Work

This paper introduced the SmartLivestock Welfare Framework, a four-layer reference architecture that connects the concept of wearable, acoustic and vision-based sensors, edge processing, cloud-based computing and decision support for farmers to monitor livestock welfare continuously. The framework will be designed as a composite, extensible Welfare Index, rather than a single production metric to help bring sensor research closer to deployable, multi-species monitoring systems. Work in the future will include on-site testing of the composite Welfare Index on various types of farms under clinical and ethological ground truth, edge-model compression for low-connectivity deployments, and creation of data-interoperability standards to enable the framework to accept sensor data from various commercial PLF hardware systems. This paper introduced the SmartLivestock Welfare Framework, a four-layer reference architecture that connects the concept of wearable, acoustic and vision-based sensors, edge processing, cloud-based computing and decision support for farmers to monitor livestock welfare continuously. The framework will be designed as a composite, extensible Welfare Index, rather than a single production metric to help bring sensor research closer to deployable, multi-species monitoring systems. Work in the future will include on-site testing of the composite Welfare Index on various types of farms under clinical and ethological ground truth, edge-model compression for low-connectivity deployments, and creation of data-interoperability standards to enable the framework to accept sensor data from various commercial PLF hardware systems.

References

[1] Kashiha, Mohammad Amin, Claudia Bahr, Sanne Ott, Christel PH Moons, Theo A. Niewold, Frank Tuyttens, and Daniel Berckmans. "Automatic monitoring of pig locomotion using image analysis." *Livestock Science* 159 (2014): 141-148.

https://doi.org/10.1016/j.livsci.2013.11.007

[2] Mattachini, G., A. Antler, E. Riva, A. Arbel, and G. Provolo. "Automated measurement of lying behavior for monitoring the comfort and welfare of lactating dairy cows." *Livestock Science* 158, no. 1-3 (2013): 145-150. https://doi.org/10.1016/j.livsci.2013.10.014

[3] Matthews, Stephen G., Amy L. Miller, James Clapp, Thomas Plötz, and Ilias Kyriazakis. "Early detection of health and welfare compromises through automated detection of behavioural changes in pigs." *The Veterinary Journal* 217 (2016): 43-51. https://doi.org/10.1016/j.tvjl.2016.09.005

[4] McDonagh, John, Georgios Tzimiropoulos, Kimberley R. Slinger, Zoë J. Huggett, Peter M. Down, and Matt J. Bell. "Detecting dairy cow behavior using vision technology." *Agriculture* 11, no. 7 (2021): 675. https://doi.org/10.3390/agriculture11070675

[5] Nielsen, Birte L. "The role of Precision Livestock Farming technologies in animal welfare monitoring: a review." *Veterinarski arhiv* 92, no. 3 (2022): 251-257.

[6] Pesenti Rossi, Gaia, Emanuela Dalla Costa, Sara Barbieri, Michela Minero, and Elisabetta Canali. "A systematic review on the application of precision livestock farming technologies to detect lying, rest and sleep behavior in dairy calves." *Frontiers in Veterinary Science* 11 (2024): 1477731. https://doi.org/10.3389/fvets.2024.1477731

[7] Vázquez-Diosdado, Jorge A., Veronica Paul, Keith A. Ellis, David Coates, Radhika Loomba, and Jasmeet Kaler. "A combined offline and online algorithm for real-time and long-term classification of sheep behaviour: Novel approach for precision livestock farming." *Sensors* 19, no. 14 (2019): 3201. https://doi.org/10.3390/s19143201