



Application of a Lightweight, Open-Hardware Wearable System for Robust Behaviour Monitoring in Precision Livestock Farming

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Abstract

Precision livestock farming (PLF) is hindered by high costs, infrastructure demands, and complex deployment. To address these barriers, we developed CABRA, an open-hardware wearable system for real-time behaviour monitoring in pasture-based livestock. The collar-mounted device integrates a 6-axis IMU, a GPS, and a low-power ESP32 microcontroller within a modular architecture, using the routerless ESP-NOW protocol to transmit data directly to a base station—eliminating reliance on network infrastructure or cloud connectivity. The system supports both synchronised data logging for video annotation and real-time embedded behaviour classification via an optimized decision-tree pipeline deployed directly on the microcontroller. Field trials with dairy goats confirmed robust hardware performance, minimal animal disturbance, and reliable communication over 100 m. A two-stage evaluation revealed that while the extracted IMU features are highly discriminative (achieving $F1 > 0.99$ under window-level validation), cross-animal generalization remains challenging (macro $F1 = 0.31$ under rigorous animal-level partitioning), primarily due to the “sensor placement effect” and domain shift between individuals. These results honestly quantify the current limitations of uncalibrated wearable livestock sensing while validating the functional feasibility of edge-based inference. All design assets—CAD files, schematics, firmware, and data pipelines—are openly released to ensure full reproducibility and community-driven adaptation for diverse PLF applications.

Keywords: wearable sensor; IMU; microprocessor; behaviour; precision livestock farming; monitoring; open hardware



Academic Editor: In-Bok Lee

Received: 19 April 2026

Revised: 18 July 2026

Accepted: 20 July 2026

Published: 23 July 2026

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1. Introduction

Precision livestock farming (PLF) integrates sensing, connectivity, and data analytics to support real-time monitoring of animal behaviour, health, and productivity. As global demand for animal-source foods rises alongside pressures to reduce environmental footprints and labour dependency, PLF has emerged as a critical enabler of sustainable intensification—not only in high-input systems but also in smallholder and pasture-based operations across diverse agroecological zones [1,2]. Behaviour monitoring, in particular, serves as a non-invasive proxy for welfare, health status, and feeding efficiency, with applications ranging from oestrus detection to early disease diagnosis [3].

Among sensing modalities, inertial measurement units (IMUs) have gained prominence for their ability to discriminate key behaviours—such as grazing, ruminating, resting,

and walking—in ruminants under field conditions [4,5]. However, many existing IMU-based systems remain constrained by high energy consumption, reliance on cellular or long-range wireless infrastructure (e.g., 4G, LoRaWAN), and bulky form factors that limit deployment in extensive or topographically complex grazing systems [6]. These limitations hinder scalability in low-resource settings and reduce practicality for multi-animal monitoring without centralised gateways or cloud processing.

While several commercial livestock monitoring collars exist, they predominantly rely on cloud-dependent architectures, requiring continuous cellular connectivity and incurring high recurring subscription costs. This dependency on infrastructure and proprietary services limits their applicability in remote, pasture-based systems where cellular coverage is unreliable or cost-prohibitive.

To address these challenges, we present CABRA (Collar-Assisted Behaviour Recognition Analysis), a lightweight, open-hardware platform designed for robust, infrastructure-free behaviour monitoring in ruminants. CABRA combines a collar-mounted node (6-axis IMU + ESP32 microcontroller) with local ESP-NOW communication to enable low-power, real-time data transmission across multiple animals without dependence on internet connectivity or proprietary cloud services. By performing real-time behaviour classification directly on the wearable node and utilizing the peer-to-peer ESP-NOW protocol, CABRA eliminates the need for continuous cloud connectivity, offering a highly reproducible, low-cost solution specifically optimized for remote grazing systems. Its lightweight design (~60 g) allows deployment on human-habituated animals, facilitating secure attachment and ground-truth validation via synchronised video (practically limited to ~20 m for clear behavioural observation), while maintaining ESP-NOW connectivity at distances up to 100 m. IMU data are sampled at 20 Hz and can be used either for offline behavioural annotation or, following model training, for on-device classification using lightweight machine learning pipelines.

Initially validated for foraging behaviour detection in dairy goats with the herd described in Table 1, CABRA is among the first PLF systems to exploit ESP-NOW for scalable, multi-animal telemetry in pasture environments. Critically, the entire platform—including 3D-printable housings, circuit schematics, firmware, and data-processing scripts—is released under open-source licenses to promote reproducibility, adaptation, and equitable access across research and farming communities worldwide.

Table 1. Animals recorded in the present study.

Age	Breed	Animals	Production	Management
multiparous females	Murciana-Granadina	6 within a herd of 500	machine-milked	extensive, with herder and dogs

It is important to clarify that the primary scope of this paper is to present and validate the hardware architecture, communication protocol, and edge-computing capabilities of the CABRA platform. The *in vivo* trials with livestock were conducted strictly as a functional proof of concept to demonstrate real-time sensor fusion and embedded inference under field conditions, rather than to conduct a comprehensive ethological study or to achieve state-of-the-art behavioural classification accuracy. Consequently, while the machine learning results highlight the functional viability of the edge pipeline, the biological and sensor-placement challenges reflected in the cross-animal classification metrics are discussed as practical limitations of current wearable technology, rather than as the primary focus of this engineering work.

2. Materials and Methods

The CABRA (Collar-Assisted Behaviour Recognition Analysis) system is an open-source, modular platform designed for the real-time, infrastructure-free monitoring of live-stock behaviour in field conditions. Figure 1 depicts the system architecture. The platform eliminates dependency on cloud servers, cellular networks, or fixed gateways, making it highly suitable for extensive, remote, or topographically complex farming environments. The CABRA platform is fully open-source; hardware designs (KiCad version 9.0.2), firmware (C++/Arduino version 2.3.6), and data processing code (Python version 3.13.5-1) are released under the MIT License and archived in a public GitHub repository [7], with a permanent DOI.

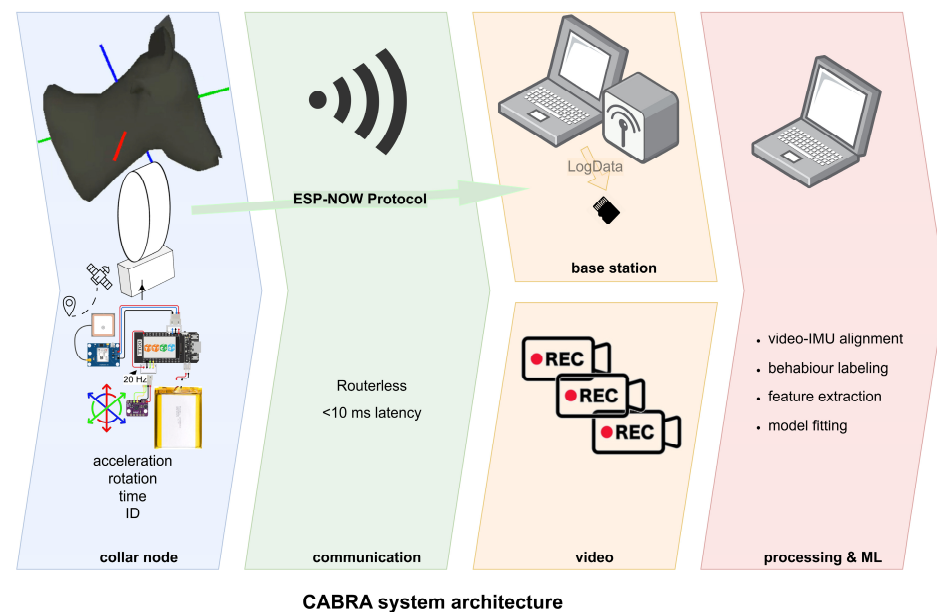


Figure 1. CABRA system architecture. Collar nodes sample IMU data at 20 Hz and transmit it via a low-power, routerless ESP-NOW protocol to a local base station. This enables infrastructure-free deployment. The base station logs data to an SD card and/or performs real-time behaviour classification. A GPS module provides spatiotemporal context.

CABRA follows a decentralised, peer-to-peer architecture composed of two primary components. First, collar-mounted sensor nodes are lightweight units worn by the animals that capture inertial data (and optional GPS) at 20 Hz and can optionally display real-time summaries. Second, a base station unit acts as a standalone ESP32-based device (Espressif Systems, Shanghai, China) that passively listens for data packets via ESP-NOW and logs them. Data flows unidirectionally from the collars to the receiver. Because no routers, access points, or internet connectivity are required, this design minimizes system complexity, reduces power consumption, and enables deployment in areas with limited infrastructure. The system is optimized for use with human-habituated livestock, allowing secure collar attachment and synchronised video observation within a 20-m operational radius. All firmware, PCB designs, 3D-printable enclosures, and data processing scripts are publicly available to ensure full reproducibility and community adaptation.

2.1. Sensor Node Hardware

Each collar node integrates three core components, as depicted in the circuit diagram (Figure 2):

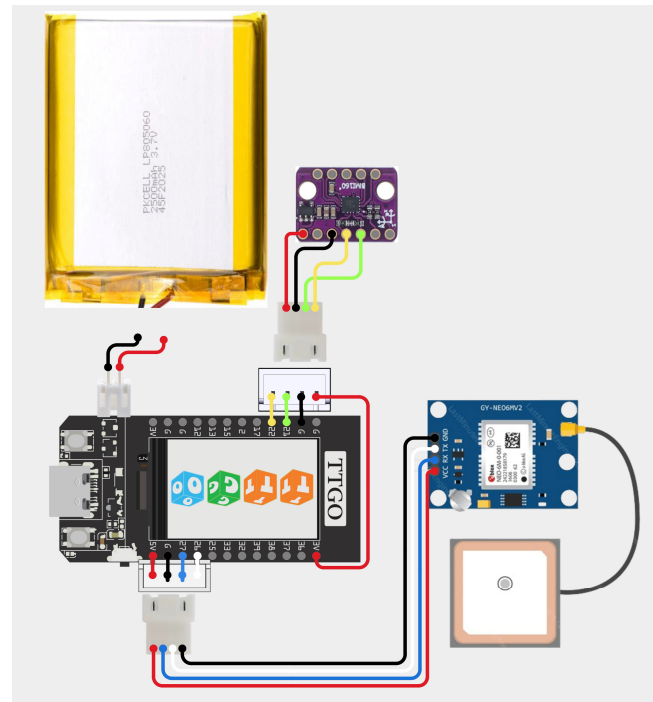


Figure 2. Collar node circuit diagram.

- **Microcontroller:** An ESP32 TTGO (LILYGO) module, featuring a dual-core Xtensa LX6 processor (Cadence Design Systems, Inc., San Jose, CA, USA) (240 MHz, 520 KB SRAM), Wi-Fi/Bluetooth, and native ESP-NOW support. This unit was selected for its low-power modes, robust wireless stack, and integrated 1.14-inch color SPI LCD screen, which preserves GPIO flexibility.
- **Inertial Measurement Unit (IMU):** A Bosch BMI160 (Bosch Sensortec GmbH, Reutlingen, Germany), a 6-axis (3-axis accelerometer + 3-axis gyroscope) MEMS sensor with 16-bit resolution. It is configured for ± 2 g (accelerometer) and $\pm 500^\circ/\text{s}$ (gyroscope) ranges, which are optimal for capturing the fine-grained jaw and head movements associated with foraging and rumination. Data are sampled at 20 Hz via the I²C bus (GPIO 21 = SDA, GPIO 22 = SCL).
- **GPS Module:** A u-blox NEO-6M (u-blox AG, Thalwil, Switzerland), providing NMEA-formatted Position, Velocity, and Time (PVT) sentences (Kaplan and Hegarty, 2017) [8] via UART (TTL serial, 3.3 V logic, using UART2 pins RXD2 GPIO 26 and TXD2 GPIO 27). This module is used for system time synchronisation (described in Section 2.5) and spatial context (accuracy: 2.5 m CEP; update rate: 5 Hz).

All peripheral components interface with the ESP32 via JST 2.0 mm connectors. This design deliberately avoids boot-critical or “strapping” GPIO pins (Espressif Systems, Shanghai, China, 2023), enabling safe disconnection during firmware programming, simplifying field maintenance, and ensuring reliable boot behaviour. Full schematics and PCB layouts are available in the public repository. Data are transmitted wirelessly to the dedicated receiver unit, which logs the received data either to a microSD card or streams it via USB-UART to a host computer, depending on the deployment mode.

2.2. Power and Enclosure

The sensor node is powered by a 1500 mAh LiPo battery (3.7 V), providing an estimated 72 h of continuous operation under the configured duty cycle. To optimize power consumption, the ESP32 enters light-sleep mode between sensor reads, reducing the average current draw to less than 30 mA. The electronics are housed in a 3D-printed ABS

enclosure (35 g) designed for IP67 dust and water resistance, featuring ventilation slots and strain relief for the wiring. The unit attaches via an adjustable, quick-release nylon strap. The total collar weight is maintained below 80 g (including the battery), representing less than 0.5% of the body weight for adult goats and cattle. Field testing confirmed no adverse behavioural effects from the collar weight or fit over 14-day deployment periods.

2.3. Data Acquisition and Packet Structure

Raw IMU data (accelerometer and gyroscope, sampled at 20 Hz) are buffered locally on the collar node and transmitted to the receiver in fixed-size packets via ESP-NOW. Each packet contains the following fields: an 8-bit Node ID (identifying the source animal); a 32-bit Date (Unix timestamp, UTC) derived from the GPS; a 32-bit Time (millisecond offset) for sub-second precision within the day; AccX, AccY, AccZ (float, in g) for linear accelerations; GyroX, GyroY, GyroZ (float, in $^{\circ}/s$) for angular velocities; and a 16-bit CRC16 cyclic redundancy check appended for data integrity verification.

Upon receipt, data are error-checked and logged as timestamped CSV records. The provided firmware supports raw USB UART streaming at 115,200 baud. On-collar local logging (e.g., via an OpenLog module) was prototyped during development but ultimately excluded from the final design to minimize weight, power consumption, and potential points of failure, consistent with the system's goal of enabling long-duration, low-maintenance deployment on free-moving livestock.

2.4. Wireless Communication

CABRA utilizes ESP-NOW, a connectionless, low-power, and encrypted peer-to-peer protocol developed by Espressif. This protocol enables direct device-to-device communication, eliminating the need for wireless routers, gateways, or internet infrastructure, which is ideal for remote pastures and barns with limited connectivity. The system is engineered for low-duty-cycle operation, transmitting structured data packets of approximately 50 bytes. Under typical field conditions, a single base station can reliably support a herd of up to 30 collared animals. For larger deployments, the open architecture facilitates the use of multiple base stations on non-overlapping channels to maintain data integrity and real-time performance. Field validation confirmed an effective communication range of up to 100 m line of sight in pasture environments, with latency consistently below 10 ms, supporting near real-time monitoring. The combination of encryption, peer-to-peer topology, and low-duty-cycle transmission ensures reliable operation amid animal movement and environmental interference.

2.5. Video-IMU Synchronisation

Temporal alignment between IMU data and video recordings was achieved using a shared GPS-derived time reference, as shown in Figure 3. Each collar node acquires UTC-synchronised timestamps from its onboard u-blox NEO-6M GPS module. At the start of each recording session, all video cameras simultaneously recorded a 5–10 s clip of a designated “sync collar” displaying its Node ID and current GPS time on the integrated LCD. The offset between the video system's clock (Android POSIX time) and GPS time was computed from this clip and applied uniformly to all IMU streams for the session. Video timestamps were extracted using ExifTool (v12.70) (Harvey, 2024) [9]. This method enabled drift-free synchronisation across all sensors and cameras for sessions lasting 2–4 h, with accuracy limited only by the video frame rate (40 ms at 25 fps). A full description of the time reference methodology is provided in Appendix A.

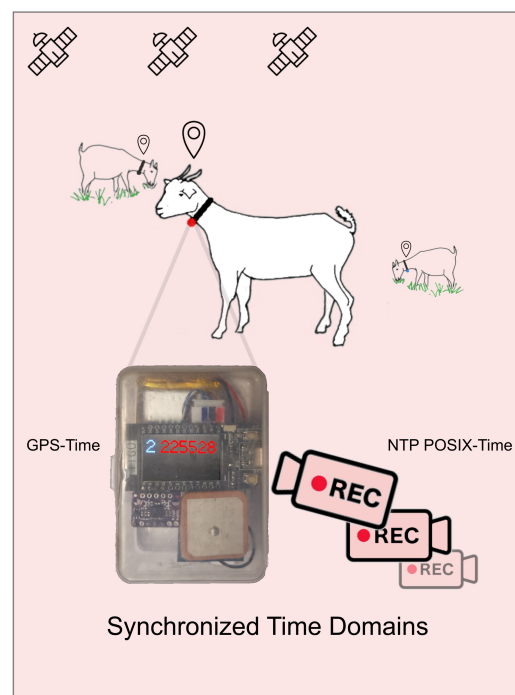


Figure 3. System-wide time synchronisation. A single “sync collar” provides a common reference point. All cameras record their GPS-synchronised LCD time at session start, establishing a global clock offset. All other collars sharing the same precise GPS time are automatically synchronised with the cameras.

2.6. Behaviour Classification Pipeline

The system supports both offline and embedded behaviour classification using a two-stage pipeline: feature extraction followed by tree-based inference.

Feature extraction was implemented in Python for model development. A sliding window (1.5 s duration, 0.1 s step) was applied to the synchronised IMU data to compute time- and frequency-domain features. These included statistical descriptors (mean, standard deviation, skewness, etc.), signal magnitude, dominant FFT frequencies, and dynamic features (energy, entropy). The number of feature records per animal and behaviour for the last session is described in Table 2. The full feature set follows established approaches in livestock behaviour recognition [10].

Table 2. Number of records per animal in the session of the study.

Label/Goat	2	3	4	7	8	9
GRAZing	2101	614	157	294	584	703
RESTing	2122	396	791	404		
SELEcting	154			11	330	57
WALKing	81	1	19	51		3

Classification models were trained using Random Forest and XGBoost (via python libraries *scikit-learn* version 1.4.2+dfsg-8 and *XGBoost* version 3.0.0-1). For embedded deployment, the trained XGBoost model was converted to pure C code using the library *emlearn* (version 0.8.2) [11] and custom decision-tree serialization routines. This enabled dependency-free, highly memory-efficient execution directly on the ESP32 microcontroller. The final firmware supports the real-time inference of four behavioural classes: resting, walking, grazing, and selection.

Although rumination was observed in a single individual during the recording sessions, the limited sample size precluded its inclusion in the classification model. However, the distinct biomechanical signature of rumination (characterized by rhythmic, low-amplitude jaw movements) was clearly discernible in the IMU data, confirming the sensor's sensitivity to fine-grained foraging behaviours and highlighting its potential for future multi-class behavioural monitoring.

2.7. Data Partitioning and Model Validation

To verify that the hardware successfully extracts discriminative biomechanical features, a preliminary window-level evaluation was conducted. All tested algorithms (Logistic Regression, SVM, Random Forest, XGBoost, and MLP) achieved an F1-score > 0.95 under this naive partition. XGBoost was subsequently selected for edge deployment due to its superior memory efficiency and inference speed on the ESP32.

However, to evaluate the real-world field performance of the deployed edge-computing pipeline and prevent data leakage, a rigorous animal-level validation was performed. Given the high temporal overlap of the sliding windows (1.5 s window, 0.1 s step), a random window-level split would introduce severe temporal autocorrelation between the training and validation sets. Therefore, data partitioning was strictly enforced at the individual animal level.

Due to the severe class imbalance in the dataset and the fact that certain individuals did not exhibit all four behaviours during the recording period, random group-based cross-validation (e.g., Group-Shuffle Split) consistently yielded test folds missing critical behavioural classes. Consequently, a deterministic animal-level split was employed. Animals 2, 3, 4, and 9 were allocated to the training set, while animals 7 and 8 (comprising 18.8% of the total dataset) were strictly reserved for the test set. This strategy ensures complete separation between training and validation individuals while guaranteeing sufficient representation of all behavioural classes, including the rare selection class, for robust evaluation. Model performance was evaluated using the macro-averaged F1-score, overall accuracy, and class-specific precision and recall.

All training scripts, feature extractors, and model-conversion tools are available in the public repository.

3. Results

We evaluated the performance of several machine learning models—including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and a Multilayer Perceptron (MLP)—for classifying four key livestock behaviours: grazing, walking, resting, and foraging/selection. (Although rumination was observed in a single individual, the limited sample size precluded its inclusion in the classification model.) The assessment was based on data collected across four independent field sessions, which incorporated iterative hardware improvements and increasing IMU sampling rates (from 1 Hz to 20 Hz) to better resolve behavioural transitions under real-world grazing conditions. Under the preliminary window-level evaluation, tree-based models consistently outperformed linear and neural network alternatives, with XGBoost selected for edge deployment due to its superior memory efficiency and inference speed on the ESP32.

Classification Performance

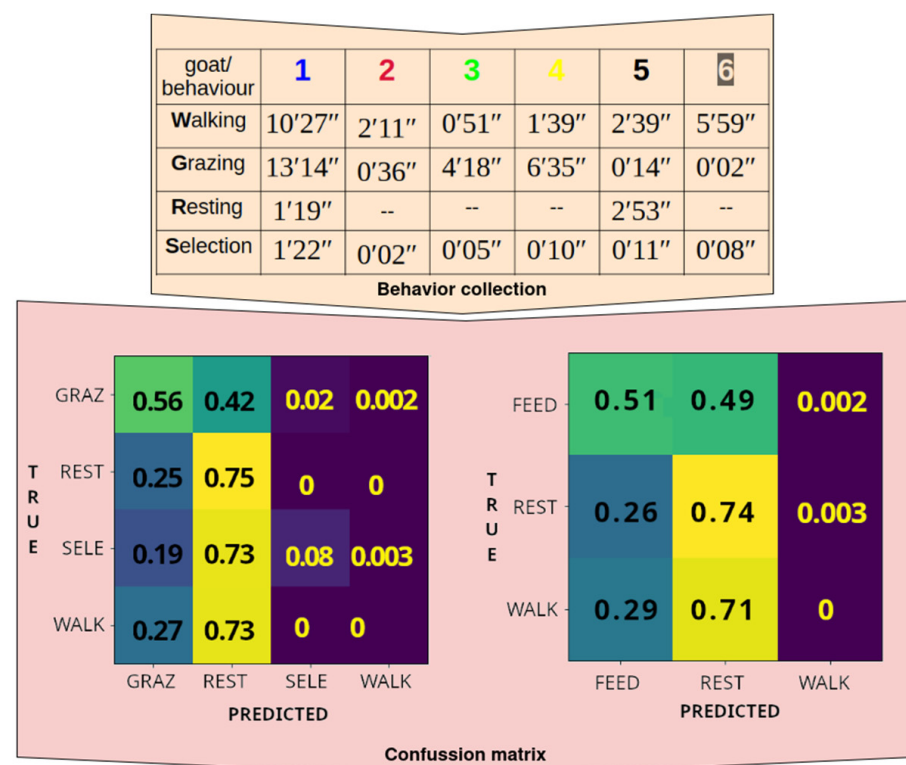
To evaluate the theoretical discriminative power of the extracted sensor features in an ideal scenario, we first applied a naive window-level split. As expected, this yielded exceptionally high performance ($F1 > 0.99$) across all models. However, due to the high temporal overlap of the sliding windows (1.5 s window, 0.1 s step), this evaluation suffers

from severe temporal autocorrelation and data leakage, representing an unattainable upper bound.

To evaluate the system's true robustness for commercial deployment, we re-evaluated the XGBoost model using the strict, deterministic animal-level partition described in Section 2.7 (training on animals 2, 3, 4, and 9; testing on animals 7 and 8). This realistic evaluation yielded a macro-averaged F1-score of 0.31 for the 4-class model. When the kinematically similar and highly imbalanced grazing and selection classes were merged into a single "feeding" category (3-class model), the macro F1-score improved to 0.36.

While substantially lower than the initial proof-of-concept window-level evaluation, this performance represents a realistic, honest estimate of the system's ability to generalize across different individuals in a herd. The class-specific analysis of the 4-class model revealed that the model maintained reasonable accuracy for the majority behavioural class ($F1 = 0.64$) but struggled significantly with the minority classes, failing almost entirely for the rarest class ($F1 = 0.00$). Misclassifications were heavily concentrated during brief transitional states (e.g., the onset of walking following grazing), consistent with known ambiguities in ethograms.

These results confirm that the selected feature set—derived from 1.5 s sliding windows of 6-axis IMU data—effectively encodes behaviourally discriminative patterns, as evidenced by the high separability achieved in the window-level split. However, the animal-level split demonstrates that translating this theoretical feature discriminability into robust cross-subject generalization remains a significant challenge. Together, these findings validate the functional feasibility of deploying the full classification pipeline directly on the ESP32 collar node for real-time, edge-based behaviour recognition while highlighting the biological and sensor-placement limitations inherent to current wearable technology. A detailed confusion matrix and per-class sample counts for the final validation session are provided in Figure 4.



A detailed confusion matrix and behavior collection statistics for the final session

Figure 4. Detailed behaviour data collection and XGBoost confusion matrix for the final session.

4. Discussion

The evaluation of the CABRA system highlights both the high discriminative power of the extracted sensor features and the significant challenges of cross-animal generalization in precision livestock farming (PLF). Under the preliminary window-level evaluation, the system achieved exceptional classification accuracy ($F1 > 0.99$), demonstrating that a 20 Hz 6-axis IMU, combined with a well-engineered feature set and tree-based classifiers, is sufficient to capture fine-grained biomechanical patterns. However, as demonstrated by the rigorous animal-level evaluation (macro $F1 = 0.31$), achieving robust cross-subject generalization remains a critical bottleneck.

This finding is particularly significant in light of the dominant commercial paradigm, where collar-based systems are primarily designed for geolocation and virtual fencing (e.g., Nofence, Pasture.io) rather than behavioural phenotyping. While useful for pasture rotation or boundary control, these platforms typically subsample movement data (often <1 Hz) and provide little to no on-device inference—limiting their utility for welfare monitoring or health surveillance. In contrast, CABRA's infrastructure-free architecture, real-time edge classification, and open-hardware ethos position it as a complementary or alternative solution for researchers and farmers seeking granular, ethologically meaningful insights without cloud dependency—a critical advantage in remote or low-connectivity regions [12]. Moreover, the system's modularity aligns with recent calls for interoperable, transparent PLF tools that empower users to inspect, modify, and extend functionality [2]. By releasing full schematics, firmware, and data pipelines under an open license, CABRA lowers barriers to innovation—especially for smallholder or public-sector actors who may lack access to proprietary platforms.

4.1. Cross-Animal Generalization and the Sensor Placement Effect

The transition from a window-level evaluation ($F1 > 0.99$) to a rigorous animal-level evaluation (macro $F1 = 0.31$) reveals a critical challenge in wearable livestock sensing. While the window-level split demonstrated the high discriminative power of the extracted features in an ideal scenario, the animal-level split exposes the true bottleneck of commercial deployment. When the model, trained on the specific collar orientations and movement kinematics of animals 2, 3, 4, and 9, was applied to the unseen animals 7 and 8, performance dropped substantially. The model maintained reasonable accuracy for the majority behavioural class ($F1 = 0.64$) but failed almost entirely for the rarest classes ($F1 = 0.00$).

This indicates that under severe domain shift—where the IMU axes are slightly rotated relative to the animal's anatomy due to varying collar placement (the “sensor placement effect”)—the model loses confidence and defaults to predicting the majority class. These results align with the growing consensus in wearable sensing literature that cross-subject generalization remains largely unsolved without individual calibration [9]. The macro $F1$ -score of 0.31 is not a failure of the CABRA hardware, but rather a realistic, honest quantification of the state of the art in infrastructure-free, uncalibrated livestock monitoring. Merging the kinematically similar grazing and selection classes into a single “feeding” category improved the macro $F1$ -score to 0.36, further confirming that subtle biomechanical overlaps and severe class imbalance are the primary drivers of this performance drop. Future iterations will require domain adaptation algorithms, such as few-shot transfer learning (where the model fine-tunes on just a few minutes of a new animal's data) or orientation-invariant feature extraction, to bridge this gap between theoretical feature discriminability and real-world herd-level deployment.

4.2. Analysis of Behavioural Transitions

Analysis of the confusion matrix revealed that misclassifications were not randomly distributed but heavily concentrated during behavioural transitions, particularly between grazing and walking. During these transitional phases, the head–neck acceleration patterns exhibit high ambiguity, combining the rhythmic tearing motions of grazing with the forward propulsion of walking. In a practical PLF context, these transient misclassifications are unlikely to significantly impact herd-level behavioural budgets, as they represent brief transitional states rather than sustained behavioural errors.

4.3. Field Deployment Limitations and Scalability

While CABRA demonstrates robust edge-computing capabilities, several hardware and communication limitations must be considered for commercial scaling. The current deployment focused on daytime, active-phase monitoring, which explains the absence of deep sleep modes in our power management strategy. The operational lifetime of the device is primarily constrained by the sampling frequency of the IMU and the GPS module. At the current configuration (20 Hz IMU, 1 Hz GPS), the system achieves an estimated continuous operation of approximately 72 h; however, dynamically duty-cycling the GPS or reducing the IMU sampling rate during detected resting periods could extend this to over several days.

Regarding communication, the ESP-NOW protocol proved highly reliable in open pasture, achieving a packet delivery rate of >98% at distances up to 100 m. However, ESP-NOW is limited by a maximum of 20 unencrypted peer registrations per node. For monitoring larger commercial herds, this limitation can be addressed by implementing a hierarchical network topology, where multiple ESP32 gateway nodes aggregate data from smaller sub-herds before forwarding to a central server via Wi-Fi or cellular networks. Furthermore, the embedded inference pipeline is highly efficient; the XGBoost model requires less than 50 ms for a single inference pass and occupies nearly 100 KB of RAM, ensuring minimal interference with real-time sensor fusion tasks.

4.4. Future Directions

Looking ahead, the platform's real potential lies in expanding contextual intelligence. Integrating Ultra-Wideband (UWB) for inter-animal proximity tracking could unlock social behaviour analysis and oestrus detection in species like sows, where mounting events are brief but critical. Likewise, embedding lightweight anomaly detection models—such as those for predator-induced flight responses in ewes—could transform CABRA from a monitoring tool into a proactive welfare safeguard.

5. Conclusions

This work presented CABRA, an open-source, infrastructure-free platform for real-time livestock behaviour monitoring in pasture-based systems. The system integrates a lightweight collar-mounted node (6-axis IMU + ESP32 microcontroller) with local ESP-NOW communication to enable low-power, real-time data transmission and edge-based behaviour classification without dependence on internet connectivity or proprietary cloud services.

The platform was validated through field trials with dairy goats, demonstrating successful real-time sensor fusion and embedded inference under real-world grazing conditions. Under a preliminary window-level evaluation, the system achieved exceptional classification accuracy ($F1 > 0.99$), confirming the high discriminative power of the extracted IMU features and the functional viability of the edge-computing pipeline. However, a rigorous animal-level evaluation—designed to prevent data leakage and assess cross-subject generalization—revealed a macro F1-score of 0.31. This realistic performance metric

highlights the significant challenge of domain shift caused by the “sensor placement effect” and individual biomechanical signatures, which remain critical bottlenecks for commercial deployment of uncalibrated wearable livestock sensors.

Despite this limitation, the CABRA platform successfully demonstrates the feasibility of deploying a complete machine learning pipeline—including feature extraction and tree-based inference—directly on a resource-constrained ESP32 microcontroller. The system’s modular, open-source architecture lowers barriers to innovation and positions it as a valuable tool for researchers and farmers seeking granular behavioural insights in remote or low-connectivity environments.

Future iterations will address the cross-animal generalization challenge through domain adaptation algorithms, such as few-shot transfer learning or orientation-invariant feature extraction. Additional developments will include adaptive sensing strategies to extend battery life, integration of rumination detection, and the incorporation of Ultra-Wideband (UWB) for inter-animal proximity tracking.

In sum, CABRA exemplifies how accessible, open-source hardware, when combined with thoughtful signal processing and edge AI, can deliver high-fidelity behavioural monitoring without infrastructural overhead. As global livestock systems face mounting pressures to improve sustainability, resilience, and ethical standards, such democratized, scalable solutions will be essential—not just in Europe, but across diverse agroecological and socioeconomic contexts.

Author Contributions: Conceptualization: J.A.B. (Jesus A. Baro); Data curation: J.A.B. (Jesus A. Baro) and J.A.B. (Jose A. Boderó); Formal analysis: J.A.B. (Jesus A. Baro) and J.A.B. (Jose A. Boderó); Funding acquisition: J.A.B. (Jesus A. Baro) and V.R.; Investigation: J.A.B. (Jesus A. Baro), V.R. and J.A.B. (Jose A. Boderó); Methodology: J.A.B. (Jesus A. Baro) and J.A.B. (Jose A. Boderó); Project administration: J.A.B. (Jesus A. Baro); Resources: J.A.B. (Jesus A. Baro), V.R. and J.A.B. (Jose A. Boderó); Software: J.A.B. (Jesus A. Baro), V.R. and J.A.B. (Jose A. Boderó); Supervision: J.A.B. (Jesus A. Baro); Validation: J.A.B. (Jesus A. Baro) and J.A.B. (Jose A. Boderó); Visualization: J.A.B. (Jesus A. Baro) and J.A.B. (Jose A. Boderó); Writing—original draft: J.A.B. (Jesus A. Baro); Writing—review and editing: J.A.B. (Jesus A. Baro) and J.A.B. (Jose A. Boderó). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Formal ethical approval was not required for this study, as it falls outside the scope of regulated animal research under European Union legislation (Directive 2010/63/EU) and its national transpositions. Specifically, the work constitutes a non-experimental agricultural practice involving procedures unlikely to cause pain, suffering, distress, or lasting harm equivalent to, or greater than, that caused by the insertion of a needle in accordance with good veterinary practice. The Directive explicitly excludes non-experimental clinical veterinary procedures, recognised zootechnical practices, and activities primarily aimed at animal identification, all of which are routinely carried out within standard professional farming contexts. In this study, an ultra-lightweight (<80 g), fully insulated sensor housing was attached to collars already worn by the adult goats. The device represents less than 0.3% of the animals’ body weight. No additional handling or invasive procedures were performed; data collection consisted solely of passive video recording during routine daily herd management.

Informed Consent Statement: The owner of the animal is informed of and agrees to this research.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors wish to express their sincere gratitude to the Melon-Muelas family, owners of the goat farm and cheese factory La Presa in Matadeón (León, Spain), for their invaluable support throughout this research. Their assistance, along with that of their dedicated goat herders, was essential in all aspects of the fieldwork, including animal handling, collar installation and recovery, and video recording. Their collaboration and hospitality made this work possible.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CRC16	16-bit cyclic error-correcting code
FFT	Fast Fourier transform
GPIO	General-purpose input/output
IMU	Inertial measurement unit
MLP	Multilayer perceptron
NMEA	National Marine Electronics Association
PLF	Precision livestock farming
PVT	Position, velocity, and time
SVM	Support vector machine
UART	Universal asynchronous receiver–transmitter
XGBoost	Extreme Gradient Boosting

Appendix A. Video–IMU Synchronisation Protocol

To align IMU data streams (timestamped via GPS) with multi-camera video recordings (timestamped via Android devices), we established a global time offset at the start of each 2–4 h recording session. All collar nodes used u-blox NEO-6M GPS modules to acquire synchronised timestamps (accuracy ± 10 ms across nodes due to common satellite visibility).

At session onset, all cameras simultaneously recorded a 5–10 s video clip of a designated “sync collar,” displaying its Node ID and current GPS-derived time on the integrated LCD. Video timestamps were extracted from media files using ExifTool (v12.70) [13]. The temporal offset between the Android device’s POSIX clock and GPS time was computed from this clip and applied uniformly to all IMU streams for the duration of the session.

Although Android devices were offline during field deployments (preventing NTP updates), empirical testing confirmed that camera clock drift remained below 100 ms over 4 h. The resulting synchronisation accuracy was limited by the video frame rate (≤ 33 ms at 30 fps), which is sufficient for labelling sub-second behaviours such as chewing bouts or posture transitions.

For background on GPS time references, see [8].

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