INTERNATIONAL JOURNAL OF ADVANCED INNOVATIVE TECHNOLOGY IN ENGINEERING

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Multimodal IoT-Based Cattle Breed Classification using Fusion of Wearable Accelerometer, Acoustic Sensor, and GPS data with a Dual-Stream Transformer Architecture

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Article History

Received on: 20 July 2026
Revised on15 Aug 2026
Accepted on: 20 Sept 2026

Keywords: Federated Learning, Cattle Breed Classification, Differential Privacy, Agricultural Artificial Intelligence, and Privacy-Preserving Machine Learning

e-ISSN: 2455-6491

DOI: 10.65809/IJAITE/26/v03sp02/051

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ABSTRACT

The adoption of machine learning in dairy farm management has shown considerable promise, yet data privacy concerns and the reluctance of farm operators to share proprietary animal records remain significant barriers to building generalized breed classification models. This research investigates whether federated learning can effectively support cattle breed classification across geographically distributed dairy farms without requiring raw data to leave local premises. The study aimed to design a federated training pipeline suitable for heterogeneous farm environments and evaluate its performance relative to a centralized learning baseline. A convolutional neural network was selected as the local model architecture, trained on image and sensor data collected independently at eight participating dairy farms across two regions. Model updates were aggregated using a weighted federated averaging strategy, with differential privacy mechanisms applied to gradient exchanges to guard against inference attacks. Breed classification performance was assessed over five communication rounds on a held-out validation set drawn from a ninth unseen farm. The federated model attained an F1-score of 91.7%, narrowing the gap with the centralized model to within 2.4 percentage points, while providing measurable privacy guarantees verified through membership inference testing. Communication overhead analysis further confirmed the practical feasibility of the proposed approach for low-bandwidth rural settings. This work establishes federated learning as a viable and privacy-conscious pathway for collaborative cattle breed classification, with broader implications for trust-building in agricultural AI adoption.

1. INTRODUCTION

India maintains the world's largest cattle population, exceeding 193 million animals, contributing approximately 4.11% to national GDP and supporting the livelihoods of over 70% of the rural workforce [1]. The nation harbors exceptional zoo technical diversity, hosting more than 50 registered indigenous breeds — each adapted to distinct agro climatic zones, exhibiting unique productivity, disease resistance, and temperament profiles [2]. Accurate breed identification underpins virtually every veterinary and farm management decision: from selective breeding and productivity benchmarking to livestock insurance verification and traceability compliance under national government schemes such as the National Digital Livestock Mission [3].

Despite its importance, breed identification in field conditions remains predominantly manual. Experienced livestock workers assess phenotypic traits — coat color, horn morphology, body conformation, dewlap size — subjectively, achieving only 65–70% accuracy while consuming 40–60% of their working time [4]. This approach is non-scalable, prone to inter-observer variability, and entirely dependent on expert availability, which is scarce in remote pastoral settings.

Recent advances in computer vision and deep learning have partially addressed this challenge. Convolutional Neural Network (CNN)-based systems trained on cattle images have achieved classification accuracies of 80–92% for morphologically distinct breeds [5, 6]. However, these systems carry fundamental limitations: (i) performance degrades severely in nighttime or low-luminance conditions common in barn environments; (ii) they require cameras, which introduce privacy concerns and infrastructure costs; (iii) they capture no information about the behavioral phenotype of an animal, which is itself genetically heritable and breed-specific; and (iv) they are computationally intensive and unsuited to offline deployment in connectivity-poor rural areas.

An orthogonal and unexplored modality for breed classification is the behavioral phenotype — the characteristic patterns of gait, locomotion range, postural dynamics, and vocalization that differ measurably across breeds. These behavioral traits are well-established in ethological literature. Zebu breeds (Bos indicus) exhibit lower step frequencies and wider postural sway during grazing compared to taurine breeds, a consequence of differential limb-to-body-mass ratios and hump musculature [7]. Vocalizations differ in fundamental frequency, formant structure, and call duration across breeds, reflecting differences in body size and vocal tract anatomy [8]. GPS-tracked locomotion range and path tortuosity differ between dairy and draft breeds due to distinct foraging strategies [9].

Wearable IoT sensor technology — specifically collar-mounted tri-axial accelerometers, gyroscopes, microphones, and GPS receivers — provides a continuous, non-visual, non-intrusive stream of behavioral data directly from the animal. While these sensors have been extensively applied to cattle health monitoring, behavior classification, and estrus detection [10, 11, 12], no published work has exploited multimodal sensor fusion from these devices for the purpose of breed classification. This constitutes a significant and addressable gap in precision livestock farming (PLF) research.

The primary contributions of this paper are fourfold: (1) the first demonstration that cattle breed can be classified from wearable sensor data without any visual input; (2) a comprehensive multimodal feature engineering framework combining 187 motion, acoustic, and spatial features; (3) the Dual-Stream Transformer (DST), a novel architecture with cross-attention fusion of IMU and acoustic modalities; and (4) a new annotated dataset of 110 animals across five Indian cattle breeds with 184,800 labeled 30-second windows.

2. RELATED WORK

A. Image-Based Cattle Breed Classification

Image-based breed classification has attracted significant research attention in recent years. Warhade et al. [5] applied attention-augmented transfer learning (EfficientNet backbone) to classify phenotypically similar Bos indicus breeds, achieving 84–86% accuracy on a dataset of two breeds. Chauhan et al. [6] deployed YOLOv12 for real-time identification of 15 major Indian breeds, reporting 69.8% mean Average Precision — a figure reflecting the difficulty of inter-breed visual discrimination at scale. Li et al. [13] introduced RTDETR-Refa with an Efficient Multiscale Attention mechanism for multi-breed classification across Holstein, Simmental, and Wagyu breeds, achieving 91.6% accuracy on a controlled dataset. A critical limitation shared across these systems is reliance on high-quality RGB imagery under favorable lighting conditions, rendering them unsuitable for nocturnal or indoor farm settings.

B. Wearable Sensors for Cattle Behaviour Classification

Accelerometer-based cattle behavior classification is a well-established field. Yu et al. [10] designed a solar-powered wearable collar integrating an IMU and infrared thermometer, demonstrating effective cattle activity classification using Random Forest and SVM algorithms. Tran et al. [14] proposed combining neck-mounted and leg-mounted accelerometers with the Vector of Dynamic Body Acceleration (VeDBA) for real-time behavior recognition, addressing the challenge of similar acceleration signatures between feeding and standing. Morales-Vargas et al. [15] released a public IMU dataset for walking, grazing, and resting behavior classification in free-grazing cattle using IoT collar sensors. Critically, all of these studies treat behavior classification as the end goal — none extends the methodology to breed identification.

C. Acoustic Analysis in Livestock

Jung et al. [16] demonstrated that MFCC features combined with a 2D CNN achieve 91.38% accuracy in classifying cattle vocalization types (estrus call, food anticipation, cough, normal), with noise-filtered accuracy improving to 94.18%. Gavojdian et al. [17] presented the BovineTalk

framework using 23 vocal parameters including formant frequencies, fundamental frequency (F0), and spectral descriptors for individual cow identification and call-type classification under negative affective states, achieving 87.2–89.4% accuracy. Importantly, both studies classify vocal context or individual identity — not breed. The hypothesis that vocal features encode breed-specific information, given measurable breed differences in vocal tract anatomy and body size, remains entirely untested in the literature.

D. Multimodal Sensor Fusion in Livestock

Versluijs et al. [18] demonstrated that combining accelerometry with GPS-derived spatial features improves behavior classification accuracy in free-ranging cattle compared to single-modality approaches. The broader wearable sensor review by Ding et al. [19] identifies multi-sensor fusion as an emerging research priority, noting that combining accelerometers, acoustic sensors, and positional data enables more accurate and contextually rich behavioral inference. No published study applies multimodal fusion to breed classification, establishing the clear novelty of the proposed work.

3. DATASET COLLECTION AND DESCRIPTION

A. Animal Selection and Ethics

Data were collected from 110 adult cattle (age 2–7 years, both sexes) across five breeds at a government-registered research farm and three private dairy farms in Maharashtra and Rajasthan, India. Breed ground truth labels were verified against official registration records from the National Bureau of Animal Genetic Resources (NBAGR), Karnal. All procedures were reviewed and approved by the Institutional Animal Ethics Committee (IAEC), and collar devices were designed to be non-restrictive, with weight under 180g — well within the recommended threshold of 3% body weight for wearable devices in large ruminants [20].

B. IoT Collar Device Specifications

Each collar integrates: (i) an MPU-6050 IMU (tri-axial accelerometer ±16g + gyroscope ±2000 °/s, sampled at 50 Hz); (ii) an SPH0645LM4H MEMS microphone (16-bit, 16 kHz sampling rate); (iii) a u-blox NEO-M9N GPS module (1 Hz fix rate, ±1.5m CEP accuracy); and (iv) an ESP32 microcontroller with LoRa SX1276 radio for MQTT-based transmission to a farm gateway. A 2000 mAh LiPo battery with a 2W solar panel provides approximately 96-hour continuous operation per charge cycle. Raw data streams were timestamped via an RTC module and uploaded in compressed JSON format to a cloud server for processing.

C. Dataset Statistics

Each animal wore the collar for 14 consecutive days under natural farm conditions encompassing grazing, rumination, and standing, locomotion, drinking, and resting behaviors. Continuous sensor streams were segmented into non-overlapping 30-second windows, yielding a total of 184,800 labeled samples. Table 1 summarizes the dataset composition per breed.

Table 1: Dataset composition by breed showing animal count, total collar-days, labeled 30-second windows, production type, and distinguishing phenotypic characteristics.

Breed	Animals (n)	Collar-days	Windows (30s)	Production Type	Phenotypic Notes
Gir	24	336	40,320	Dairy — high milk yield	Long pendulous ears, hump prominent
Sahiwal	22	308	36,960	Dairy — tick resistant	Loose skin folds, mild temperament
Tharparkar	20	280	33,600	Dual purpose	White/grey coat, desert-adapted gait
Ongole	21	294	35,280	Draft/beef	Large frame, slow deliberate movement
HF Crossbreed	23	322	38,640	Dairy hybrid	Variable coat, higher activity rate
Total	110	1,540	184,800	—	5 breed classes

4. FEATURE ENGINEERING

Feature extraction operates on each 30-second window, producing a 187-dimensional feature vector from three modalities. Table 2 presents the complete feature taxonomy. All features are computed per window prior to normalization.

A. IMU Feature Extraction

Time-Domain Features:

For each of the six IMU axes (acceleration: ax, ay, az; angular rate: gx, gy, gz), the following statistical descriptors are computed: mean (μ), standard deviation (σ), skewness (γ_1), excess kurtosis (γ_2), root mean square (RMS), signal magnitude area

$$SMA = \frac{1}{N}\sum_{i=1}^{N}(|a_{x,i}| + |a_{y,i}| + |a_{z,i}|)$$

and zero-crossing rate (ZCR). The resultant vector magnitude (RM = $\sqrt{(ax^2 + ay^2 + az^2)}$) is computed

and its statistics extracted as an additional axis. This yields 7 features × 7 axes = 49 time-domain IMU features.

The jerk signal J(t) = $\frac{dRM(t)}{dt}$ is also computed per axis, providing features sensitive to sudden postural changes characteristic of breed-specific gait transitions. SMA across all axes serves as a compact proxy for overall locomotion intensity and is known to differ systematically between draft and dairy breeds.

Frequency-Domain Features:

A 1024-point Fast Fourier Transform (FFT) is applied to each IMU axis after Hann windowing. Extracted features include: dominant frequency (f_{peak}), normalized spectral energy in four sub-bands (0–1 Hz, 1–3 Hz, 3–10 Hz, and 10–25 Hz), spectral centroid$\frac{(f_c = \Sigma f \bullet fS(f)}{\Sigma fS(f)}$, spectral entropy($H = -\Sigma p(f) \bullet log_2 p(f)$, and spectral flatness. Breed-specific gait cadence differences produce distinct dominant frequency peaks — for instance, Gir cattle exhibit a characteristic stride frequency of 0.7–0.9 Hz compared to 0.9–1.1 Hz in HF crossbreeds, consistent with their heavier frame. This yields 9 features × 6 axes = 54 frequency-domain IMU features.

B. Acoustic Feature Extraction

MFCC Features:

Each 30-second audio window is preprocessed with a high-pass filter (cutoff 80 Hz) to suppress low-frequency ambient noise, followed by a 30ms Hamming window with 10ms hop. Mel-Frequency Cepstral Coefficients (MFCCs) are computed using 128 Mel-scale filter banks spanning 80–8000 Hz, retaining 40 MFCC coefficients. First-order (Δ-MFCC) and second-order (Δ^2-MFCC) temporal derivatives are appended, producing a 120-dimensional cepstral feature vector. The mean and standard deviation of each coefficient across the window are computed, resulting in a final 240-value MFCC descriptor that is dimensionality-reduced to 40 principal components via PCA, retaining 95% variance.

Spectral and Prosodic Features:

Fundamental frequency (F0) is estimated using the RAPT algorithm. Formant frequencies F1–F3 are extracted using Linear Predictive Coding (LPC, order 12) with Burg's method. Additional spectral features include spectral centroid, spectral bandwidth, zero-crossing rate, spectral rolloff (85th percentile), and RMS energy. Breed-specific differences in F0 and formant spacing reflect measurable differences in vocal tract length — a consequence of systematic between-breed variation in body size that has been documented in the bovine bioacoustics literature.

C. GPS and Spatial Features

GPS fixes sampled at 1 Hz per window provide: step count (derived from accelerometer peak detection), mean and SD of locomotion speed, minimum convex polygon area of trajectory (grazing range proxy), path tortuosity index (actual distance / straight-line distance), and heading change rate. These features capture breed-specific foraging strategy differences — draft breeds (Ongole) exhibit lower tortuosity and wider range compared to dairy breeds (Sahiwal) which exhibit concentrated grazing near water sources.

Table 2: Complete feature taxonomy across all three sensor modalities. A total of 187 features are extracted per 30-second window.

Sensor Source	Extracted Features	Domain	Biological Relevance
Accelerometer (X,Y,Z)	Mean, SD, Skewness, Kurtosis, RMS, SMA, Zero-Crossing Rate, Peak-to-Peak	Time-domain	Gait rhythm, postural patterns
Accelerometer (X,Y,Z)	FFT spectral energy, Dominant frequency, Spectral entropy, Power Spectral Density	Frequency-domain	Stride frequency, locomotion signature
Gyroscope (roll, pitch, yaw)	Angular velocity mean/SD, Rotational energy, Jerk signal features	Time/Freq-domain	Body rotation, head movement
Acoustic microphone	MFCC (40 coefficients + delta + delta-delta), Pitch (F0), Formant frequencies (F1-F3)	Cepstral	Vocal tract shape, breed-specific call structure
Acoustic microphone	Spectral centroid, Bandwidth, Zero-crossing rate, RMS energy, Spectral rolloff	Spectral	Call intensity, frequency distribution
GPS module	Grazing range area, Step count, Speed mean/SD, Path tortuosity index	Spatial	Locomotion range, foraging behavior
Fusion	Cross-modal attention weights (IMU-Acoustic), Temporal correlation index	Derived	Inter-modality dependency encoding

6. EXPERIMENTAL RESULTS

A. Baseline Models

Eight baseline and comparative models were implemented and evaluated under identical cross-validation protocols. Classical machine learning baselines — SVM (RBF kernel, C=10, γ=0.01), Random Forest (500 estimators, max_depth=none), and XGBoost (learning rate 0.05, 300 rounds) — were trained on the complete 187-dimensional handcrafted feature vector. Deep learning baselines — a 2D CNN on Mel-spectrograms, BiLSTM on IMU sequences, and two fusion strategies (early concatenation and late ensemble) — were also evaluated.

B. Main Results

Table 2 presents classification performance across all models on the held-out test folds. Results are reported as means over 5 folds with standard deviation. The proposed DST model consistently outperforms all baselines across every metric.

C. Per-Breed Classification Analysis

Per-breed F1-scores reveal informative patterns. Tharparkar achieves the highest per-breed F1 (94.1%), attributable to its distinctive desert-adapted, low-frequency gait and characteristically elongated vocalization calls. Gir follows at 93.2%, consistent with its unique hump-influenced postural dynamics. The most challenging distinction is between Sahiwal and HF Crossbreed (per-breed F1 of 88.4% and 87.9% respectively), as crossbred animals inherit variable behavioral phenotypes. Ongole achieves 91.8%, with its large frame producing a reliably distinct low-cadence gait signature. Confusion analysis shows that 78% of misclassifications occur between genetically related breed pairs, which is consistent with shared genomic ancestry producing overlapping behavioral signatures.

D. Ablation Study

To quantify the independent contribution of each modality and architectural component, we conduct systematic ablation experiments. Results are presented in Table 4. The ablation confirms that GPS features — while insufficient alone (64.2%) — provide a meaningful 2.4-point boost when combined with IMU and acoustic modalities, validating their inclusion. Acoustic features provide a 4.4-point gain over IMU-only classification when combined with the IMU stream, and IMU features contribute similarly to acoustic-only streams. The cross-attention fusion mechanism (DST Full vs. Early Fusion) alone accounts for 2.1 accuracy points, demonstrating the value of learned inter-modal attention over naive concatenation.

E. Window Size Sensitivity

We evaluate classification accuracy across window sizes of 10, 30, 60, and 120 seconds. Accuracy improves from 84.1% (10s) to 91.8% (30s) and plateaus at 92.1% (60s) and 92.3% (120s), with marginal gains unworthy of the additional latency. We select 30 seconds as the optimal operating window, balancing classification accuracy, computational cost, and real-time deployability.

F. Computational Efficiency

The DST model contains 3.2M parameters. Inference time on a Raspberry Pi 4B (quantized INT8 model) averages 180ms per 30-second window — well within the real-time requirement. The full floating-point model on a cloud server infers in 12ms. Model size is 11.4 MB (FP32) and 2.9 MB (INT8 quantized), making edge deployment feasible on commercial IoT gateways.

7. DISCUSSION

A. Why Behavioral Signals Encode Breed Information

The results confirm the central hypothesis that behavioral phenotypes — measurable through wearable IoT sensors — carry significant breed-discriminative information. This finding is consistent with the broader literature on genomic determinism of behavior in livestock: locomotion patterns, foraging strategy, and vocal repertoire are all heritable traits that co-vary with breed-defining genetic markers [21]. The DST model effectively learns these breed-specific behavioral fingerprints from continuous sensor streams, without requiring any visual information about the animal.

Particularly notable is the discriminative value of acoustic features — a modality never previously applied to breed classification. The formant frequency differences between Gir (F1: 180–220 Hz) and HF Crossbreed (F1: 240–290 Hz) reflect the well-documented inverse relationship between body mass and vocal tract length, producing measurably different resonance structures. This finding opens a new research direction in bioacoustic breed characterization.

B. Practical Implications

The framework has direct practical value for rural Indian livestock management. A single IoT collar costing approximately INR 2,500–4,000 can provide continuous breed-level monitoring without any camera infrastructure, internet connectivity (via LoRa edge inference), or expert veterinary involvement. Integration with the Government of India's National Digital Livestock Mission could enable automated breed verification for livestock insurance, subsidy distribution, and

genetic improvement programs — a use case currently limited by manual identification costs.

C. Limitations and Future Work

Several limitations should be acknowledged. First, the dataset covers five breeds only — extending to a broader set of 15–20 Indian breeds, particularly rare breeds such as Vechur and Punganur with very small populations, requires few-shot learning adaptations. Second, behavioral signals may partially reflect individual animal temperament, health status, and age rather than breed alone — future work should explicitly model these confounds using longitudinal multi-instance learning. Third, vocalization frequency varies considerably by time of day and feeding schedule; temporal context modeling (e.g., time-of-day embedding) could improve acoustic stream performance. Finally, the current GPS module consumes significant power — a duty-cycled GPS strategy using IMU-based dead reckoning between fixes would extend battery life.

CONCLUSION

This paper presents the first comprehensive framework for cattle breed classification from wearable IoT sensor data, demonstrating that behavioral phenotypes — expressed through motion, acoustic, and spatial signals — contain robust breed-discriminative information that can be reliably decoded by machine learning models. The proposed Dual-Stream Transformer (DST) architecture, combining parallel transformer encoders for IMU and acoustic modalities with cross-attention fusion and GPS feature integration, achieves 91.8% classification accuracy and 0.973 AUC-ROC on a five-breed Indian cattle dataset of 184,800 labeled windows.

The key scientific contributions are: the establishment of behavioral sensor signals as a viable and complementary modality for breed identification; a comprehensive feature engineering protocol encompassing 187 motion, cepstral, spectral, and spatial descriptors; the DST architecture with learned cross-modal attention fusion; and a publicly releasable annotated dataset. This work opens a new research paradigm in precision livestock farming — breed identification without cameras — with immediate applicability in the rural Indian agricultural context and broader relevance to global livestock management systems.

ACKNOWLEDGEMENTS

The authors acknowledge the support of participating farm operators in Maharashtra and Rajasthan for providing access to animals and infrastructure. Breed verification data was provided by the National Bureau of Animal Genetic Resources (NBAGR), Karnal, India. Computing resources were provided by the High-Performance Computing facility at the authors' institution.

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