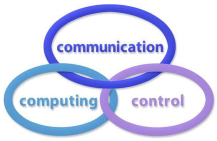
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Animal behavior classification performance in a case deflection of an attached device

Viet-Manh Do, Duc-Tan Tran, Vu Thi Thuong,
Duc-Nghia Tran*, Vijender Kumar Solanki, Valentina E Balas*

Viet-Manh Do
Institute of Information Technology (IoIT),
Vietnam Academy of Science and Technology
(VAST), Hanoi, Vietnam
Graduate University of Sciences and Technology
(GUST), VAST, Hanoi, Vietnam
manhdv@ioit.ac.vn

Duc-Tan Tran
Faculty of Electrical and Electronic Engineering
(FEEE), Phenikaa University, Hanoi 12116, Vietnam
tan.tranduc@phenikaa-uni.edu.vn

Vu Thi Thuong
Faculty of Information Technology and
Communication, Phuong Dong University, Vietnam
thuongvt@dhpd.edu.vn

Duc-Nghia Tran*
Institute of Information Technology (IoIT),
Vietnam Academy of Science and Technology
(VAST), Hanoi, Vietnam
nghiatd@ioit.ac.vn

Vijender Kumar Solanki
Department of Computer Engineering, Marwadi
University,
Rajkot, Gujrat, India
spesinfo@yahoo.com

Valentina E Balas*
Aurel Vlaicu University of Arad, Romania
balas@drbalas.ro

Abstract

Cattle behavior data is core to the assessment of cow health. Behavior recognition systems using accelerometers are an appropriate solution. The accelerometer or accelerometer sensor is affordable and simple to set up, which collects accelerometer data mounted on cattle's leg and collar, using machine learning algorithms to provide high classification performance. In our previous work, a cow behavior classifier was proposed based on synchronized collar and leg-mounted accelerometer data to increase classification performance. In the actual implementation context, we found that cow activity can affect the position of the collar mounted sensor; specifically, this sensor's position can be deflected from the original position, resulting in changes in data obtained from the accelerometer. In this study, we simulated data from the sensor attached to the collar in the case of deflection to evaluate the influence on the results of behavioral classification: lying, walking, feeding, and standing. Using features (mean, RMS, range, and median) with a data window of 16 seconds (one sample/second) and the Random Forest (RF) algorithm, the evaluation results in our test cases with indicators (accuracy, precision, and sensitivity) have a similarity. These results show that the deflection of the collar mounted sensor does not significantly impact the behavioral classification results when applying the proposed classification system.

Keywords: cow, deflection, monitoring, accelerometer, classification, behavior.

1 Introduction

With the rapid advancement of sensor technology, smart sensors are being increasingly integrated into Internet of Things (IoT) systems [1]. Such systems have been widely applied to human monitoring, [2, 3], monitor residential environments for intrusion detection [4], avoid accidents [5, 6]. These technologies are currently also being applied in agriculture and the livestock industry [7]. Where high-tech cattle farming is attracting growing attention and investment. It is well established that automated technologies can provide valuable information about cow health status through behavioral monitoring [8]. Pasture based dairy cow monitoring used to be very difficult in the past, however, with technological advances in data collection tools such as accelerometers and global positioning systems (GPS), now allow multiple variables to be sampled simultaneously with high temporal resolution at the same time [9]. Behavioral monitoring has therefore become a valuable approach for improving herd management, addressing health issues of cows and increasing performance in livestock, behavioral monitoring is a very useful approach [10, 11, 12, 13, 14, 15, 16].

Changes in feeding behavior and activity in cows are commonly used as early indicators of disease and health status [17, 18, 19]. These diseases affect cow behavior, reduce activity, and lead to reduced feed intake [20, 21]. Other factors contributing to behavioral changes include pain, fear, and reproductive behavior [22]. Conducting manual health checks on large herds is time-consuming and labor-intensive, which has motivated the development of behavioral monitoring and evaluation systems for cow's activity [23, 24, 25, 26, 27, 28].

Accelerometer-based monitoring systems have demonstrated the ability to detect and classify cattle behaviors [29, 30, 31]. Machine learning algorithms applied to this problem include both supervised [30, 31] and unsupervised approaches [32, 33, 34, 35]. Based on behavioral activities, activity monitors (usually accelerometers) can be placed on different parts of the animal's body. Some studies are based on neck mounted (collar mounted) accelerometer data [29, 30, 31], others based on leg accelerometer data [36, 37]. The selection mainly depends on the behaviors that are concentrated on, such as leg sensors monitoring positions of standing and lying positions and calculating the number of steps, mounted on the collar to better distinguish feeding behavior.

In the implementation of accelerometers on cows, we observed that cow activity can cause the device to shift from its original position. On the other hand, technicians often find it difficult to attach the device in a precisely controlled orientation. With a composition of three fixed axes (X, Y, Z) to collect acceleration in three directions, so when the sensor is rotated, the obtained accelerometer data will change, then the classification performance will be affected [10]. Sensor deflection has received limited attention in the literature [10, 38]. For example, Arcidiacono et al. [10] proposed a classifier that uses acceleration thresholds on an accelerometer axis to classify standing and feeding behavior. Noted that sensor rotation can cause behavioral feature overlap, leading to reduced classification accuracy.

In our previous work [39, 40], a dual-sensor classification system using synchronized collar-mounted and leg-mounted accelerometers was proposed to improve the recognition of four key cattle behaviors: Feeding, Lying, Standing, and Walking. Building on this foundation, the present study investigates the robustness of this system under collar sensor deflection. espite the growing adoption of accelerometer-based cattle behavior monitoring systems, limited attention has been paid to the influence of sensor deflection on behavioral classification performance. Existing studies have mainly focused on improving classification accuracy under ideal sensor-placement conditions, while the robustness of dual-sensor systems under sensor-misalignment scenarios remains insufficiently investigated. To address this gap, this study systematically evaluates the impact of collar-sensor deflection on a synchronized collar-leg behavior recognition framework. The main contributions of this study are summarized as follows:

(1) A controlled sensor-deflection simulation framework is proposed based on rotation matrices, enabling systematic evaluation of collar sensor misalignment under different rotation angles and deflection proportions.

(2) Seven benchmark datasets representing realistic collar-deflection scenarios are constructed, including combinations of 5° and 10° rotation angles and 10%, 30%, and 50% deflection rates.

(3) The robustness of a synchronized dual-sensor system using collar-mounted and leg-mounted accelerometers is quantitatively evaluated and compared with a collar-only configuration.

(4) Experimental results demonstrate that the proposed dual-sensor system maintains stable clas-

sification performance under all investigated deflection conditions, whereas the collar-only system exhibits progressive degradation as sensor deflection increases.

2 Materials and methods

2.1 Cow monitoring framework

Figure 1 shows a schematic diagram of the proposed cow behavior recognition system. The main components are the two 3-DOF (Degrees of Freedom) accelerometers (2) and (3) mounted on the legs and collar of the cow. These sensors measure static and dynamic acceleration values in three directions namely X, Y, Z (Figure 2) from the leg and collar of the cow (1), their data are synchronized in time. The data obtained from these two sensors will be sent to the digital device (4), where this data will be used to determine the cow's behavior (1) by machine learning algorithms. Then the results of this behavior classification will be sent to the cloud data (7) for storage via the Internet. Users (8) can use computer devices (5), smartphones (6) through the Internet to access and monitor the status of each cow in real time.

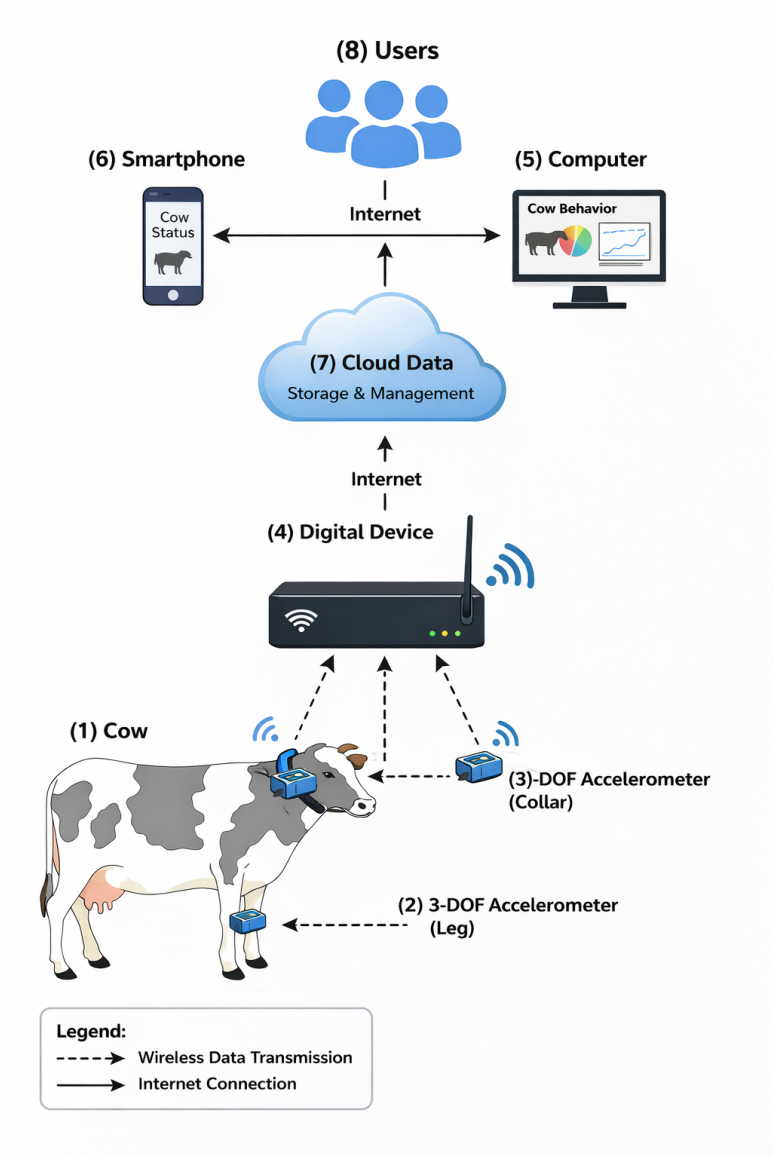


Figure 1: Cow monitoring wireless sensor network (WSN) diagram.

2.2 Deflection sensor simulation

If the cow rotates its head or the device is not worn in the position as designed, the sensor (mounted / attached to the cow's collar) can be deflected. This is shown in Figure 2.

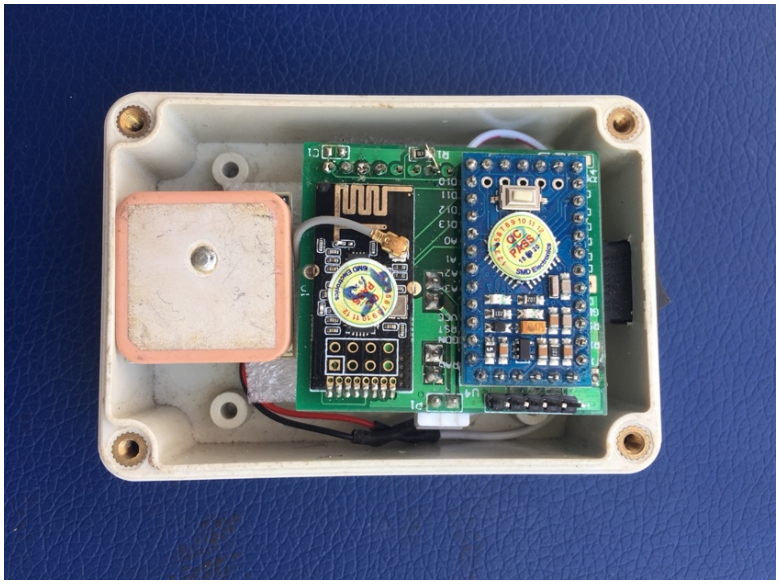


Figure 2: The cow worn deflection collar sensor.

Figure 3 shows the axes of the accelerometer in the initial position. z axis points to the ground. When the cow rotates the head, the sensor will be easily rotated in the z axis, leading to a change in the y and x coordinates. It indicates that when the sensor's z axis is rotated by φ, the x and y axes are also rotated by an angle φ.

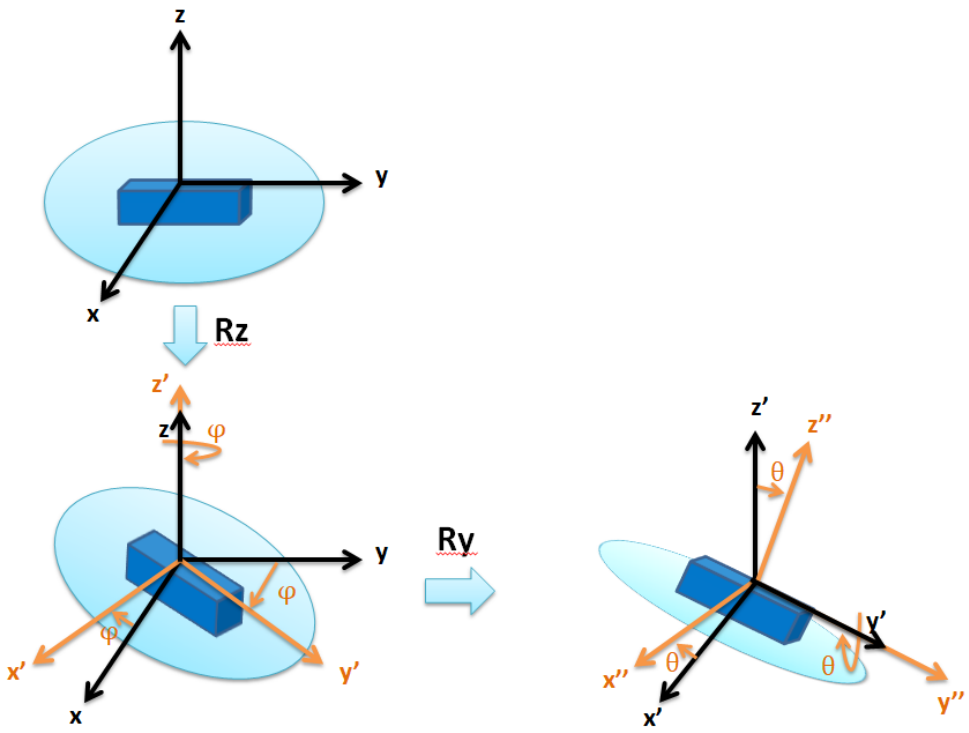


Figure 3: The simulation of the deflection collar sensor.

The inverse rotation is applied as follows:

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} \cos(\varphi) & \sin(\varphi) & 0 \\ -\sin(\varphi) & \cos(\varphi) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} x'' \\ y'' \\ z'' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & 0 & -\sin(\theta) \\ 0 & 1 & 0 \\ \sin(\theta) & 0 & \cos(\theta) \end{bmatrix} \begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} \tag{2}$$

Where φ is the rotation in the z axis, x', y', z' are the new direction of x, y, z when the z axis rotates. We can calculate the value x', y', z' from x, y, z by (1). When the y' axis of the sensor rotates by angle θ, the x' and z' axes are rotated by an angle θ through the rotation $R_{y'}$ (2). We can calculate the value x'', y'', z'' from x', y', z' by (2).

In this study, we tested with $\varphi = 5^\circ$ and $\varphi = 10^\circ$ respectively, with the sensor being rotated by 5% and 10% respectively. Applying formula (1) (2), we built the simulation datasets for the deflection sensor cases.

2.3 Random Forest algorithms for cow behavior classification

Figure 4 illustrates the recognition process of the cow behavior classification system. Accelerometer data collected from the leg and collar mounted sensors were first synchronized and then recalculated to simulate sensor deflection. Four statistical features, namely root mean square (RMS), mean, range, and median, were extracted from the acceleration signals for each data record. Based on direct observations of cow activities, the data were annotated into four behavioral classes: feeding, standing, lying, and walking.

About 60% data was training data; the rest (about 40%) was test data. This division has been proved to be good for the problem of classification of cow behavior [36, 39, 40]. Based on the feature set (section 2.5) and training data (labeled data), the model was trained. The test data was then labeled using a categorical model. These classification results were evaluated by comparing actual observations

The RF algorithm was applied in this work. RF did not use all the training data nor all the attributes of the data to build a decision tree, so each tree (case) might not predict well in order to create a predictive model [38]. Implementation of cases of bad predictions was easy, fast and simple [36]. By iteration, RF trained and combined them to determine the final predictive model. The proposed model uses the Gini measure with 25 decision trees (n). The work was coded on Python version 3.5.

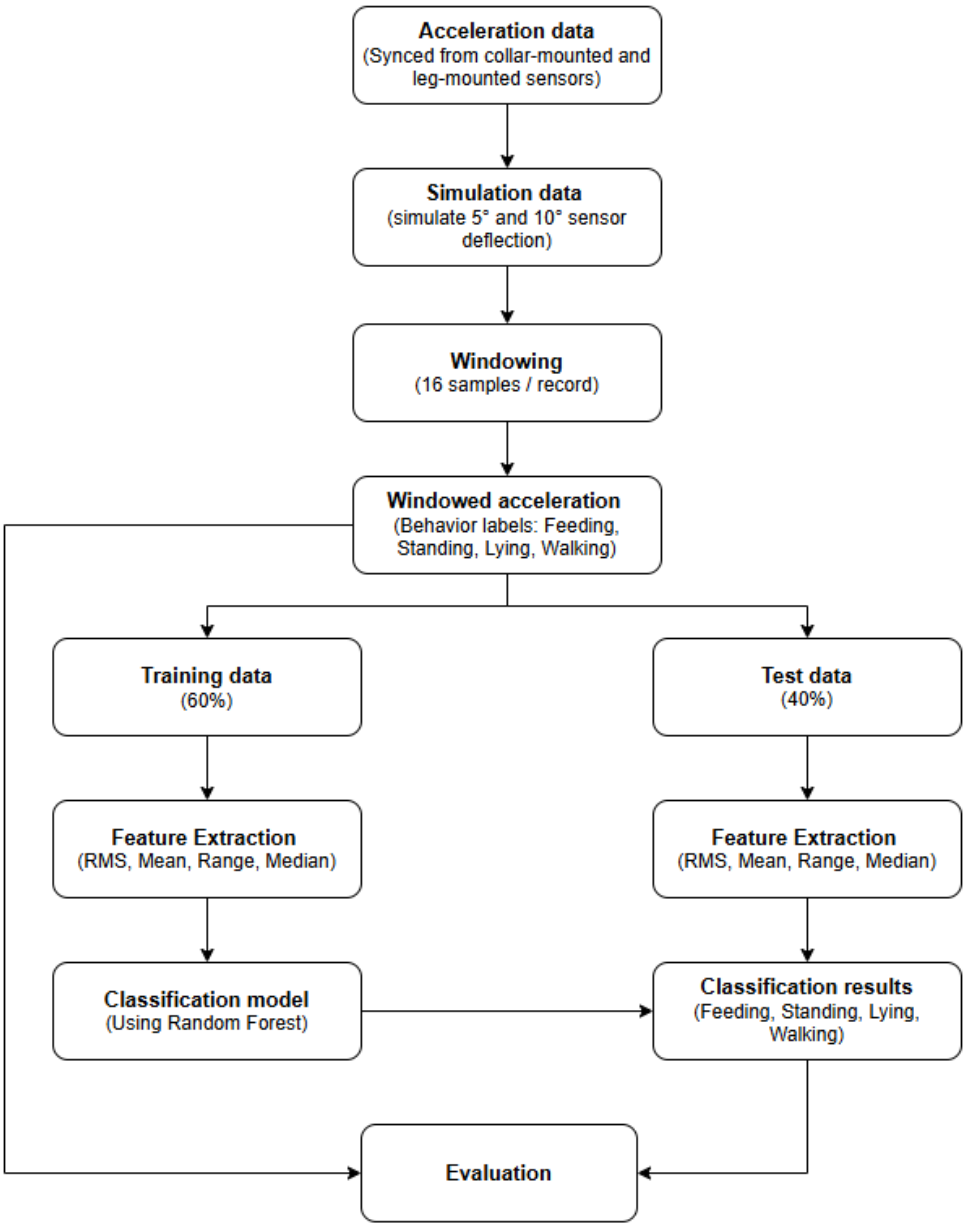


Figure 4: Recognition process of the cow behavior classifier.

RF algorithm was chosen to create the proposed predictive model due to some reasons [39]:

- Data can be lost during the transmission process. RF still performs well in this case (missing data).
- Model overfitting problem may be avoided.
- It works great with acceleration data.

2.4 Collection of acceleration data

The leg-mounted device has been attached to five cows. The sensor receives twenty data samples per axis every second, then sends them to the microcontroller. The raw acceleration data is averaged to smooth and store the data at one sample per second. To exploit the statistical properties of the collected data, 16 samples were concatenated into a window with 10 overlapping samples (Section 2.3). This frame was used to extract four proposed features: RMS, mean, range, and median.

The experiment data of five cows (ID1, ID2, ID3, ID4 and ID5) were collected as section 2.1. The sample rate of raw signals is 20 samples/second. A down sampling signal technique was applied to

average at 1 sample/second. From this dataset, the simulation data were calculated for the case the accelerometer was deflected. The cow behaviors are defined as follows:

- Feeding behavior means cow obtains food.
- Lying behavior means cow is resting in a lying position.
- Standing behavior means cow stands on four legs.
- Walking behavior refers to locomotion in which the cow takes one or more consecutive steps.

An example record of data is shown in Table 1.

Table 1: Sample feeding data collected from leg-mounted and collar mounted accelerometers

Leg			Collar		
Acc x (mg)	Acc y (mg)	Acc z (mg)	Acc x (mg)	Acc y (mg)	Acc z (mg)
-894.70	-156.20	-40.00	-790.20	-281.00	-389.90
-893.22	-156.56	-46.33	-798.10	-265.80	-373.90
-893.30	-154.20	-39.60	-804.00	-216.20	-401.70
-893.70	-164.60	-38.50	-810.78	-170.78	-404.11
-892.30	-158.40	-54.10	-814.10	-172.60	-387.00
-893.80	-154.90	-47.60	-816.60	-181.90	-384.90
-892.67	-153.44	-63.56	-848.90	-125.80	-350.10
-893.60	-144.20	-58.60	-828.44	-173.67	-333.67
-895.80	-144.40	-35.50	-823.10	-191.10	-346.20
-895.80	-139.80	-26.60	-816.90	-179.20	-388.30
-896.63	-132.13	-31.38	-810.20	-199.40	-390.60
-897.36	-130.36	-27.36	-813.60	-197.70	-383.30
-897.00	-127.70	-22.20	-812.22	-199.33	-380.44
-898.10	-126.00	-20.80	-811.20	-199.10	-382.30
-897.44	-125.44	-17.56	-814.70	-199.30	-381.20
-898.50	-121.20	-14.10	-813.00	-202.70	-380.40

Number of observations in the experimental dataset as Table 2. Note that behavior observations number of all datasets (experiment data and simulation data) are the same.

Table 2: The number observations of experiment data

Behavior	Observation count					
	ID01	ID02	ID03	ID04	ID05	All
Feeding	841	561	745	729	801	3677
Lying	689	533	133	619	856	2830
Standing	1329	1489	1098	1311	760	5987
Walking	672	399	337	672	519	2599
Total	3531	2982	2313	3331	2936	

2.5 Feature extraction

In this paper, formulae for three axes are similar. Four features were extracted from each axis as follows: In this paper, formulae for three axes are similar. Four features were extracted from each axis as follows: In this paper, formulae for three axes are similar. Four features were extracted from each axis as follows: In this paper, formulae for three axes are similar. Four features were extracted from each axis as follows:

$$\mathrm{RMS}_{Y_j} = \sqrt{\frac{1}{k}\sum_{i=1}^{k} y_i^2} \tag{3}$$

$$m(Y_j) = \frac{1}{k}\sum_{i=1}^{k} y_i \tag{4}$$

$$\mathrm{Range}(Y_j) = \max_{i=1}^{k}(y_i) - \min_{i=1}^{k}(y_i) \tag{5}$$

$$\mathrm{Median}(Y_j) = \tilde{y} = \begin{cases} y_{\left(\frac{k+1}{2}\right)}, & \text{if } k \text{ is odd} \\ \frac{1}{2}\left(y_{\left(\frac{k}{2}\right)} + y_{\left(\frac{k}{2}+1\right)}\right), & \text{if } k \text{ is even} \end{cases} \tag{6}$$

where:

- RMS_{Y_j}: root mean square of record Y_j, measuring the overall signal energy including both static and dynamic components;
- $m(Y_j)$: mean of record Y_j, capturing the average acceleration reflecting the cow's average posture;
- $\mathrm{Range}(Y_j)$: the difference between the maximum and minimum values within the window, reflecting the peak to peak amplitude of movement;
- $\mathrm{Median}(Y_j)$: the middle value of the sorted samples in record Y_j, providing a robust central tendency estimate that is less sensitive to outliers and transient motion spikes than the mean;
- Y: axis data (X, Y, or Z);
- Y_j: record j;
- k: number of samples per window; in this work $k = 16$;
- y_i: the i-th sample of Y_j;
- $y_{(i)}$: the i-th order statistic (sorted sample) of Y_j.

Note that formulae for the X-, Y-, and Z-axes are similar.

2.6 Evaluation indicators

Accuracy, sensitivity, and precision were used for the evaluation. The formulae for accuracy, sensitivity, and precision are:

$$\mathrm{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

$$\mathrm{Sensitivity} = \frac{TP}{FN + TP} \tag{8}$$

$$\mathrm{Precision} = \frac{TP}{TP + FP} \tag{9}$$

where TP (True Positive): the number of predictions when positive class is predicted correctly; TN (True Negative): the number of predictions when negative class is predicted correctly; FP (False Positive): the number of predictions when negative class is predicted incorrectly; FN (False Negative): the number of predictions when positive class is predicted incorrectly.

3 Results

The test with experiment data and simulation data was implemented to evaluate the impact of deflection sensors. The classifier performance for seven datasets calculated as (7–9):

- Original dataset (experiment data): DT01
- 10% data with 5 degrees rotated (simulation of 10% data): DT02
- 30% data with 5 degrees rotated (simulation of 30% data): DT03
- 50% data with 5 degrees rotated (simulation of 50% data): DT04
- 10% data with 10 degrees rotated (simulation of 10% data): DT05
- 30% data with 10 degrees rotated (simulation of 30% data): DT06
- 50% data with 10 degrees rotated (simulation of 50% data): DT07

The sensor deflection impact was tested in two cases:

- A system used collar mounted sensors (only used acceleration data of a collar sensor on a cow for behavior classification). The results were shown in Figure 5.
- A system used leg-mounted and collar mounted sensors the proposed system (used synchronized acceleration data of leg and collar sensor on a cow for behavior classification). The results were shown in Figure 6.

Figure 5(a) (b) (c) show the comparisons of average accuracy, precision, and sensitivity for the all behaviors respectively in seven cases when the system used collar mounted sensors. Figure 5(a) shows that the average accuracy in seven cases is similar. In Figure 5(b) and Figure 5(c), it is shown that the average precision and sensitivity in the case of DT01 are significantly better than the rest. It means the impact of sensor deflection is significant if the system only uses collar mounted sensors.

Figure 6(a) (b) (c) show the comparisons of average accuracy, precision, and sensitivity for the all behaviors respectively in seven cases when the system used leg-mounted and collar mounted sensors. In Figure 6(a), Figure 6(b) and Figure 6(c), it indicates the average accuracy, precision and sensitivity in seven cases are similar. It means the impact of sensor deflection is not significant if the system uses leg-mounted and collar mounted sensors. These results make sense because of the advantage when using both leg-mounted and collar mounted sensors [39]. Note that in Figure 6(a), Lying and Walking lines overlap, Feeding and Standing lines overlap. The similar things can be found in Figure 6(b) and Figure 6(c). It is not changing the point we concerned.

Table 3 and Table 3 show the results of the average performance in two cases: the system used collar mounted sensors and the system used leg-mounted and collar mounted sensors. Seven datasets in Table 3 have similar accuracy, sensitivity, and precision. In Table 3, DT01 has the highest sensitivity, and precision. So, the same conclusion can be concluded:

- The impact of sensor deflection is significant if the system only uses collar mounted sensors.
- The impact of sensor deflection is not significant if the system uses leg-mounted and collar mounted sensors.

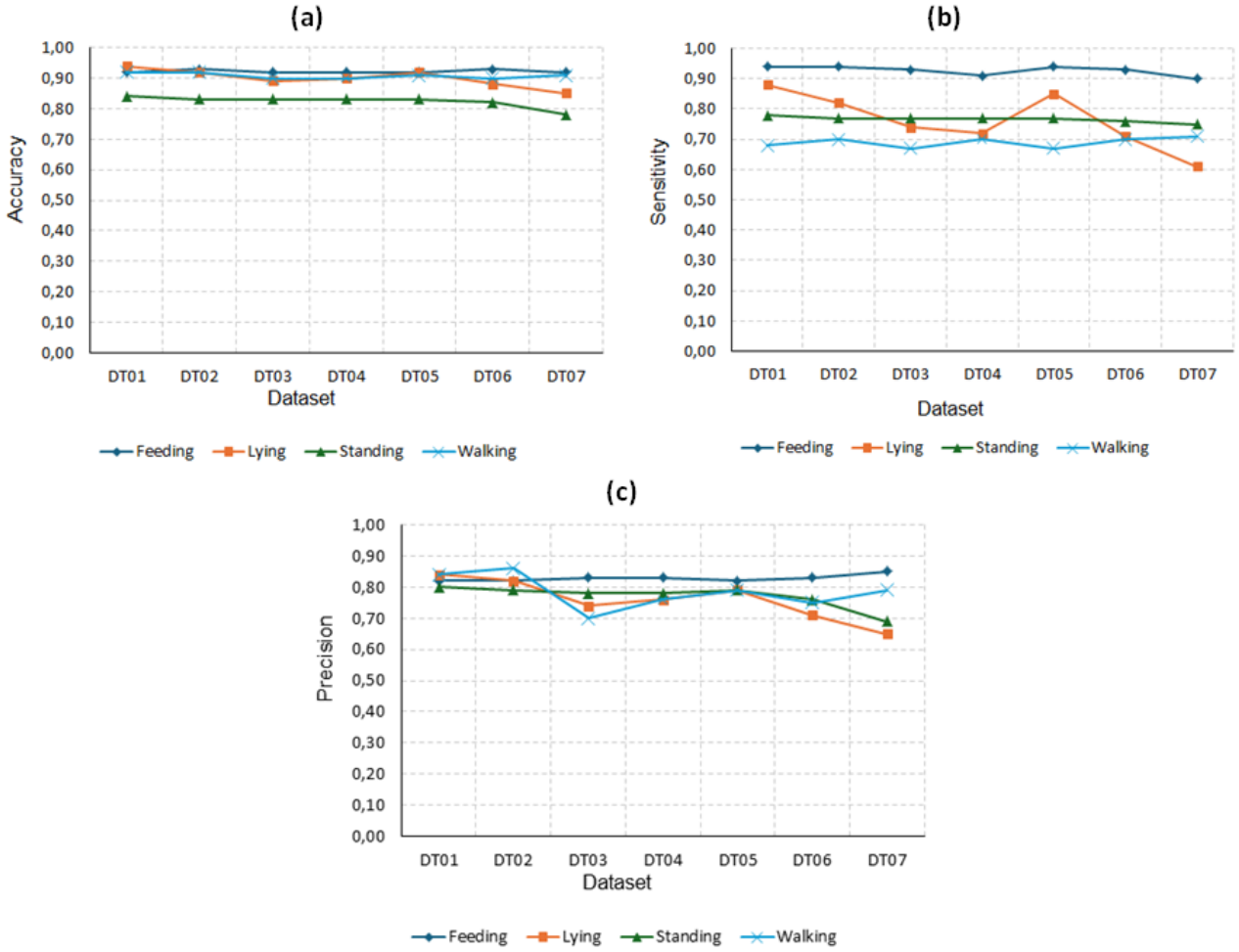


Figure 5: The comparisons of performance for four behaviors of seven datasets when the system used collar mounted sensors: (a) Accuracy; (b) Precision; (c) Sensitivity.

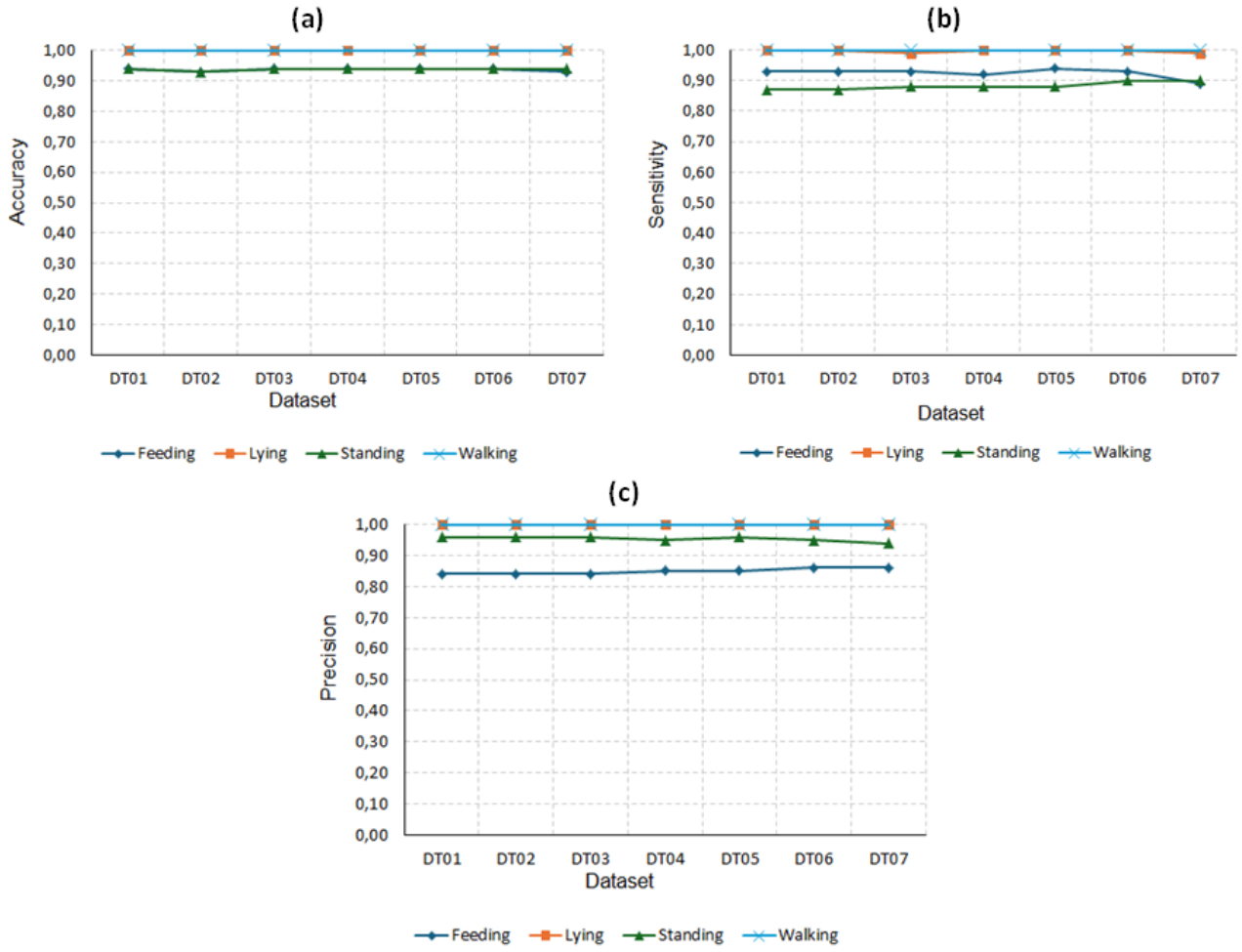


Figure 6: The comparisons of performance for four behaviors of seven datasets when the system used leg-mounted and collar mounted sensors: (a) Accuracy; (b) Precision; (c) Sensitivity.

The average performance when the system used collar mounted sensors

Dataset	Accuracy	Sensitivity	Precision
DT01	0.90	0.82	0.82
DT02	0.90	0.81	0.82
DT03	0.89	0.78	0.76
DT04	0.89	0.78	0.78
DT05	0.90	0.81	0.80
DT06	0.88	0.78	0.76
DT07	0.87	0.74	0.75

Table 3: The average performance when the system used leg-mounted and collar mounted sensors

Dataset	Accuracy	Sensitivity	Precision
DT01	0.98	0.96	0.96
DT02	0.98	0.96	0.96
DT03	0.98	0.96	0.96
DT04	0.98	0.96	0.96
DT05	0.98	0.96	0.96
DT06	0.98	0.96	0.96
DT07	0.98	0.96	0.96

Table 4 presents the per-class classification performance for all five individuals (ID1-ID5) using DT01 (no deflection) and DT07 (the most severe deflection condition) with the dual sensor system.

The results indicate that sensor deflection has minimal impact on classification performance across most behaviors and individuals. For *Feeding*, the overall sensitivity decreases slightly from 0.93 (DT01) to 0.89 (DT07), while precision remains relatively stable at 0.84 and 0.86, respectively. The most notable change occurs in ID3, where sensitivity drops from 0.82 to 0.76, and in ID2, where sensitivity decreases from 0.92 to 0.79. *Feeding* is the behavior most affected by collar sensor deflection because feeding involves continuous head movement and neck rotation, directly affecting the orientation of the collar-mounted accelerometer. As the sensor rotates, the acceleration components measured along the sensor axes change, causing greater variability in the extracted statistical features and increasing the overlap between *Feeding* and Standing patterns. Consequently, *Feeding* exhibits a larger reduction in sensitivity than the other behaviors under severe deflection conditions.

Lying demonstrates the highest stability across both datasets, with accuracy, sensitivity, and precision all maintained at or near 1.00 for every individual. This can be attributed to the static and highly distinctive acceleration pattern associated with the lying posture, which is largely independent of collar orientation and remains easily identifiable even under deflection conditions.

For *Standing*, overall performance remains consistent, with accuracy maintained at 0.94 across both datasets. Sensitivity shows a slight increase from 0.87 (DT01) to 0.90 (DT07), while precision decreases from 0.96 to 0.94. Individual variation is observed; for example, ID5 shows the lowest sensitivity at 0.65 in DT01, increasing to 0.77 in DT07. This reflects the overlap between the acceleration characteristics of *Standing* and *Feeding*. Nevertheless, the overall impact of sensor deflection on *Standing* remains limited.

Walking exhibited the highest robustness among the four behaviors, with accuracy, sensitivity, and precision all maintained at 0.99 or 1.00 across all individuals and both datasets. The strong kinematic signature of walking, characterized by high amplitude periodic acceleration measured by the leg sensor, remains largely unaffected by collar rotation. Consequently, *Walking* is one of the most reliably classified behaviors under all deflection conditions.

In summary, although sensor deflection leads to minor decreases in sensitivity for *Feeding* in certain individuals, the dual sensor system maintains consistently high performance across all behaviors and all five cows. These results confirm the robustness of the proposed system for real world deployment scenarios where precise collar positioning cannot always be guaranteed.

Table 4: Classification performance of all individual cows (ID1-ID5) on datasets DT01 and DT07

COW ID	**Behavior**	**DT01**			**DT07**		
		ACC	SEN	PPV	ACC	SEN	PPV
ID1	Feeding	0.98	0.96	0.98	0.99	0.97	0.98
	Lying	1.00	0.98	1.00	0.99	0.97	1.00
	Standing	0.98	0.99	0.97	0.99	0.99	0.97
	Walking	1.00	1.00	1.00	1.00	1.00	1.00
ID2	Feeding	0.93	0.92	0.77	0.92	0.79	0.77
	Lying	1.00	1.00	1.00	1.00	1.00	1.00
	Standing	0.93	0.90	0.97	0.92	0.91	0.92
	Walking	1.00	0.99	1.00	1.00	0.99	1.00
ID3	Feeding	0.89	0.82	0.84	0.87	0.76	0.82
	Lying	1.00	1.00	1.00	1.00	1.00	1.00
	Standing	0.89	0.89	0.88	0.87	0.89	0.85
	Walking	1.00	1.00	0.99	1.00	1.00	0.99
ID4	Feeding	0.96	0.97	0.87	0.96	0.94	0.89
	Lying	1.00	1.00	1.00	1.00	1.00	1.00
	Standing	0.96	0.93	0.98	0.96	0.94	0.97
	Walking	1.00	0.99	1.00	1.00	0.99	1.00
ID5	Feeding	0.91	1.00	0.75	0.94	0.99	0.82
	Lying	1.00	1.00	1.00	1.00	1.00	1.00
	Standing	0.91	0.65	1.00	0.94	0.77	0.99
	Walking	1.00	1.00	1.00	1.00	1.00	1.00
All	Feeding	0.94	0.93	0.84	0.93	0.89	0.86
	Lying	1.00	1.00	1.00	1.00	0.99	1.00
	Standing	0.94	0.87	0.96	0.94	0.90	0.94
	Walking	1.00	1.00	1.00	1.00	1.00	1.00

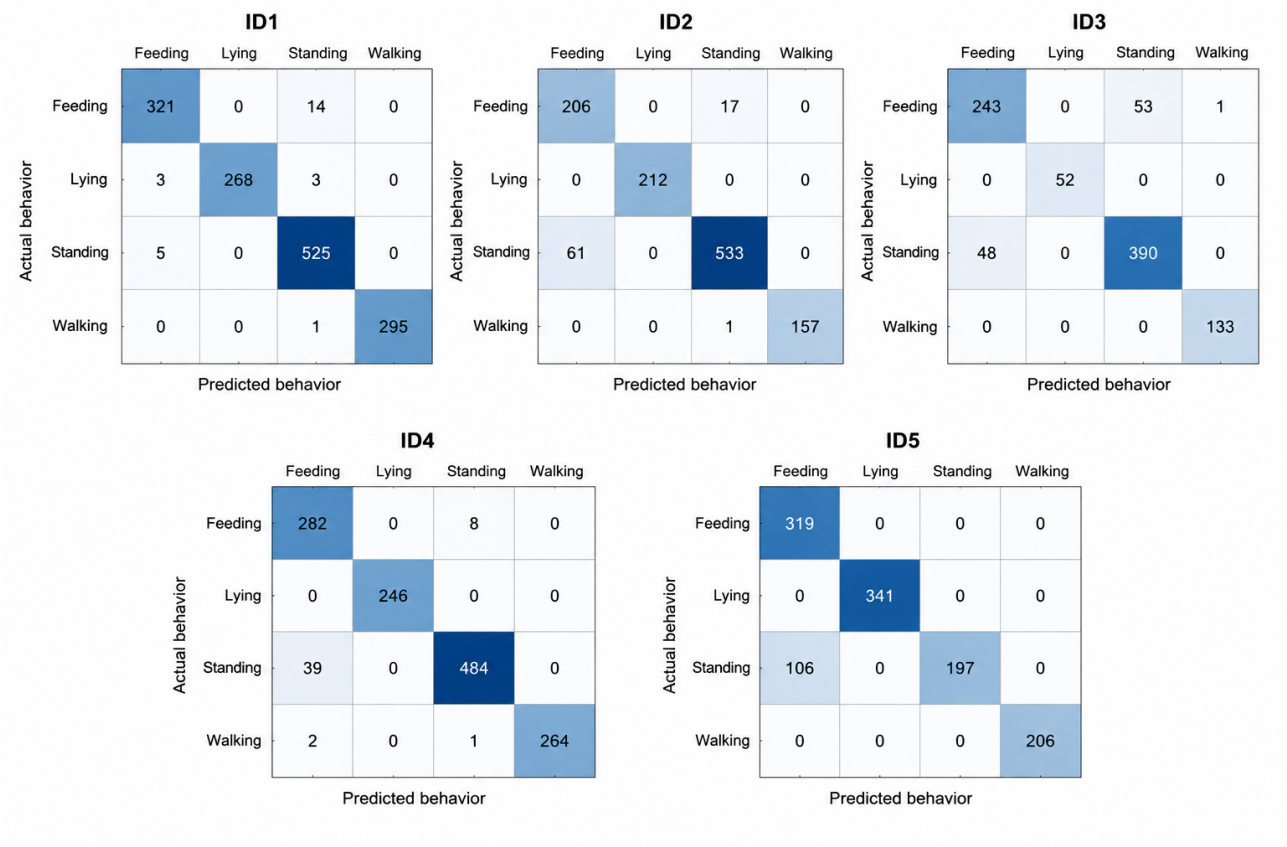


Figure 7: Confusion matrix of the RF algorithm on the DT01 dataset.

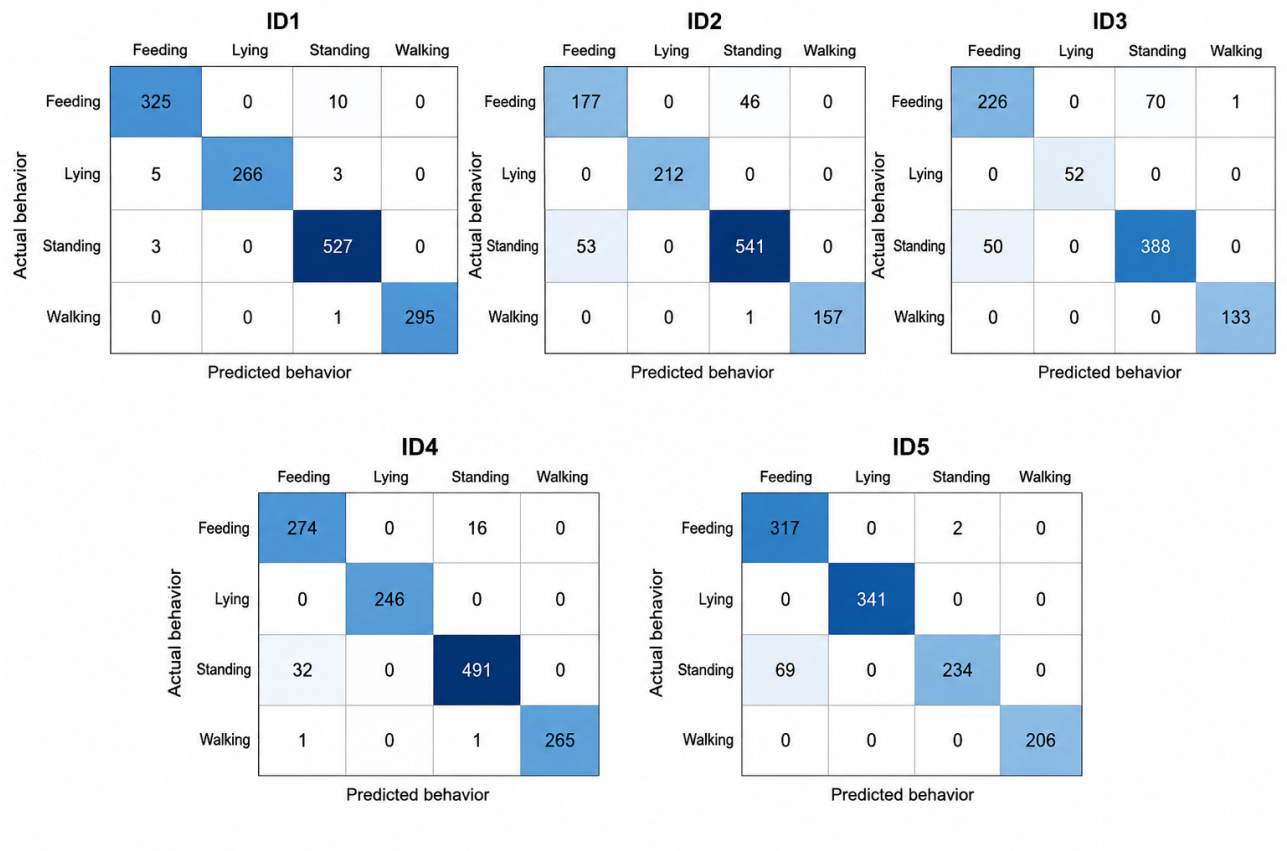


Figure 8: Confusion matrix of the RF algorithm on the DT07 dataset.

Figures 7 and 8 present the confusion matrices obtained from DT01 (no sensor deflection) and DT07 (the most severe deflection condition, where 50% of the samples were rotated by 10°) for all five cows using the proposed dual sensor system.

The confusion matrices reveal that the dominant source of classification error in both datasets is the confusion between *Feeding* and *Standing*. In DT01, the number of *Feeding* samples misclassified as *Standing* ranges from 0 (ID5) to 53 (ID3), whereas the number of *Standing* samples misclassified as *Feeding* ranges from 5 (ID1) to 106 (ID5). Under the severe deflection condition in DT07, the pattern remains largely unchanged. The number of *Feeding* to *Standing* misclassifications decreases slightly in ID1 (14 to 10), but increases in ID2 (17 to 46), ID3 (53 to 70), ID4 (8 to 16), and ID5 (0 to 2). Conversely, the number of *Standing* to *Feeding* misclassifications decreases in most individuals, from 5 to 3 in ID1, 61 to 53 in ID2, 39 to 32 in ID4, and 106 to 69 in ID5, while increasing slightly from 48 to 50 in ID3. These results indicate that sensor deflection mainly affects the decision boundary between *Feeding* and *Standing*, while the overall classification structure remains stable.

Lying exhibits the highest classification accuracy among all behaviors. Perfect classification is achieved for ID2, ID3, ID4, and ID5 in both datasets. For ID1, only six samples are misclassified, including three samples incorrectly classified as *Feeding* and three samples incorrectly classified as *Standing*. Importantly, the confusion pattern remains unchanged between DT01 and DT07, suggesting that the static acceleration characteristics associated with lying are largely insensitive to collar sensor deflection.

Similarly, *Walking* demonstrates strong robustness across both datasets. Misclassification errors are extremely rare and are limited to one or two samples in a few individuals. In DT01, only one *Walking* sample is misclassified as *Standing* in ID1, ID2, and ID4, while two samples are misclassified as *Feeding* in ID4. Nearly identical results are observed in DT07, with only minor variations of one sample. The consistently high classification accuracy of *Walking* can be attributed to its distinctive periodic acceleration pattern captured by the leg-mounted sensor, which is largely unaffected by collar rotation.

Overall, the confusion matrices demonstrate that sensor deflection has only a limited effect on the performance of the proposed dual sensor system. Although minor changes are observed in the classification boundary between *Feeding* and *Standing*, the dominant confusion pattern remains the same in both datasets. In contrast, *Lying* and *Walking* maintain almost identical classification results under both conditions. These findings further confirm the robustness of the proposed system against sensor deflection and support its suitability for practical livestock monitoring applications.

4 Discussion

The parameters and movement patterns of individual cows can influence classification performance. Variations may stem from differences in body size, activity level, or collar attachment position, leading to non-uniform sensor signals across individuals. As observed in the confusion matrices for DT01 and DT07, misclassification between *Feeding* and *Standing* varies considerably across individuals. For example, the number of *Standing* samples misclassified as *Feeding* ranges from 5 in ID1 to 106 in ID5 in DT01, reflecting inherent inter-individual differences in feeding posture and acceleration patterns. Despite this variability, the dual sensor system maintains consistent overall performance across all five cows in both datasets, demonstrating its robustness to individual-level variation.

Versluijs et al. [41] demonstrated high classification accuracy for free-ranging cattle behaviors using collar mounted accelerometers at 10 Hz, but did not address the impact of sensor misalignment on model performance. Oudshoorn et al. [38] reported that firmly attached sensors outperformed loosely attached ones in estimating grazing time (80.4% versus 77.8%), implicitly acknowledging that sensor positioning affects outcomes. Arcidiacono et al.[10] further showed that collar sensor deflection causes behavioral feature overlap, leading to reduced classification performance in threshold-based systems. The present study extends these observations by constructing seven controlled simulation datasets with explicitly defined rotation angles (5° and 10°) and deflection proportions (10%, 30%, and 50%). The experimental results demonstrate that the proposed dual sensor system maintains stable performance with an accuracy of 0.98, sensitivity of 0.96, and precision of 0.96 even when up to 50% of collar sensor

data is affected by misalignment, whereas the collar-only system experiences significant degradation in sensitivity and precision under the same conditions.

The robustness of the dual sensor system against collar deflection can be attributed to the complementary nature of leg and collar acceleration signals. The leg-mounted sensor captures stable postural and locomotion features, particularly the near-zero variance during *Lying* and the high-amplitude periodic pattern during *Walking*, that are independent of collar orientation. When the collar sensor is deflected, its contribution to *Feeding* and *Standing* classification is partially degraded; however, the RF classifier effectively leverages the stable leg sensor features to compensate, maintaining overall accuracy. This implicit feature-level compensation explains why the dual-sensor system achieves consistent performance regardless of deflection angle or proportion, while the collar only system, lacking this redundancy, degrades substantially even under the mildest deflection scenario.

Regarding the influence of rotation angle and deflection proportion, the results reveal an asymmetric pattern between the two configurations. For the collar only system, performance degrades progressively as deflection increases accuracy drops from 0.90 (DT01) to 0.87 (DT07), while sensitivity decreases from 0.82 to 0.74 and precision from 0.82 to 0.75, indicating that a single collar mounted sensor is consistently affected by increasing misalignment. This degradation can be explained by the fact that collar sensor rotation alters the orientation-dependent acceleration components used to characterize Feeding and Standing behaviors. As the deflection angle and the proportion of affected samples increase, the statistical distributions of these behaviors become increasingly overlapped, reducing the discriminative power of the extracted features. Consequently, the RF classifier produces more Feeding-Standing confusion, leading to lower sensitivity and precision. For the dual sensor system, neither the rotation angle nor the deflection proportion produces any meaningful difference; accuracy, sensitivity, and precision remain constant at 0.98, 0.96, and 0.96 respectively across all seven datasets. This complete insensitivity demonstrates consistent robustness across the full range of deflection scenarios tested.

Among the four behaviors, *Lying* and *Walking* demonstrate the strongest robustness to deflection in both sensor configurations. *Lying* is characterized by near zero variance on the leg sensor, producing a highly stable and distinctive signal unaffected by collar rotation. *Walking* produces strong periodic acceleration on the leg sensor that is similarly insensitive to collar orientation. In contrast, *Feeding* and *Standing* share similar posture related acceleration patterns, making them the most susceptible to confusion. As shown in the confusion matrices, this *Feeding Standing* misclassification pattern is present in both DT01 and DT07, confirming that it originates from the inherent similarity of these behaviors rather than from deflection itself.

Recent studies have increasingly explored deep learning and sequence-based approaches, including CNN, LSTM, CNN-BiLSTM, and Transformer-based architectures for livestock behavior recognition. These models can automatically learn temporal dependencies from raw sensor signals and have reported strong classification performance. However, such approaches generally require substantially larger training datasets, higher computational resources, and greater energy consumption than conventional machine-learning methods. In contrast, the objective of this work is to evaluate the robustness of a lightweight dual-sensor classification framework under sensor deflection conditions. Despite using only four statistical features and a Random Forest classifier, the proposed system achieved stable performance across all simulated deflection scenarios, maintaining an average accuracy of 0.98, sensitivity of 0.96, and precision of 0.96. Future work will investigate deep learning and sequence-based models to further assess the trade-off between classification performance, computational complexity, and deployment cost in practical IoT livestock monitoring systems.

This study has several limitations that should be acknowledged. First, the deflection scenarios are simulated using fixed rotation matrices applied to static datasets, whereas real world collar displacement involves dynamic and irregular rotation during activities such as feeding, walking, and lying transitions, which may differ from the controlled angles tested here. Second, the dataset comprises five cows from a single farm, which may limit the generalizability of the findings to other breeds, farm configurations, or device attachment methods. Third, only two rotation angles (5° and 10°) were evaluated; larger deflection angles may produce different degradation patterns. Future work should include experiments with physically displaced sensors under real deployment conditions, a larger and

more diverse animal cohort, and evaluation across a wider range of deflection angles to establish more comprehensive robustness thresholds for practical deployment.

5 Conclusion

From the experiment data collected from the fixed mounted sensor, various datasets were created that simulate the sensor mounted/attached to the collar being deflected. The main contribution of this study is that we have shown that wearing the sensor deflected on the collar has comparable performance to that of a fixed sensor using the proposed system (using the RF algorithm with mean, RMS, range, and median features for synchronized acceleration data). For the system using a collar sensor on a cow, the performance reduces significantly if the device deflects. It means the proposed method can be implemented in practice in terms of not wearing the device in a rigorous position; making it easier to monitor animals such as cows.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors state that they have no conflicts of interest with respect to this study.

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