Journal of Computer Science and Cybernetics, V.41, N.1 (2025), 33-48
DOI: 10.15625/1813-9663/21637

COWS' BEHAVIOR CLASSIFICATION USING ACCELERATION DATA: A NEW, EFFECTIVE, AND SIMPLE APPROACH

DUC-NGHIA TRAN[1], MANH-TUYEN VI[2], DUC-TAN TRAN[2], VIJENDER KUMAR SOLANKI[3], HA NGUYEN THI THU[2,*], DO VIET MANH[1,4,*]

[1] *Institute of Information Technology, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet Street, Cau Giay District, Ha Noi, Viet Nam*
[2] *Faculty of Electrical and Electronic Engineering, Phenikaa University, Nguyen Trac Street, Ha Dong District, Ha Noi, Viet Nam*
[3] *Department of Computer Science and Enginnering, Stanley College of Engineering Technology for Women, Hyderabad, TG, India*
[4] *Graduate University of Science and Technology, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet Street, Cau Giay District, Ha Noi, Vietnam*

Abstract. Monitoring and classifying cow behaviors provides valuable support for livestock management. This can be done through sensors attached to the pet. Due to their small size, light weight, and high accuracy, accelerometers are well-suited for this purpose. However, the complexity of behaviors, which often involve similar movements, poses challenges in interpreting the sensor data. This paper presents a novel classifier design for cow behaviors based on acceleration data and a specific set of features. By analyzing cow acceleration data, we extracted features for classification with the help of machine learning algorithms. With five features—Mean, Standard Deviation, Root Mean Square, Median, and Range—and a 15-second data window (1 sample/second), the classifier achieved optimal performance when identifying six behaviors: Feeding, Lying, Standing, Lying-standing-transition, Normal-walking, and Active-walking. The results were validated with public acceleration data. The performance of the proposed classifier has been compared with existing models to highlight the research advantages.

Keywords. Cow's behavior, classification, acceleration, wearable sensor.

1. INTRODUCTION

Large-scale dairy farms encounter substantial challenges in ensuring cow welfare and comfort, both of which are critical factors that directly affect milk production. On medium-to-large farms, relying solely on observation to monitor herds proves challenging and can result in financial losses. Given their susceptibility to health issues, dairy cows, as high-value livestock, demand meticulous management.

*Corresponding author.
E-mail addresses: nghiatd@ioit.ac.vn (D.N.Tran); tuyen.vimanh@phenikaa-uni.edu.vn (M.T.Vi); tan.tranduc@phenikaa-uni.edu.vn (D.T.Tran); spesinfo@yahoo.com (V.K.Solanki); 21013386@st.phenikaa-uni.edu.vn (H.N.T.Thu); manhdv@ioit.ac.vn (D.V.Manh)

Cows exhibit behavioral changes when facing with health issues or physiological conditions [1], adjusting their actions in response to stressors like infections, hunger, or alterations in social and environmental factors [2]. As such, behavior is a key indicator of dairy cow health and well-being. Monitoring shifts in daily behaviors can aid in initiating specific management interventions to improve farm operations [3–5].

In recent years, there has been a notable rise in the use of remote monitoring technologies, including GPS trackers, location sensors, and accelerometers, for automated behavior tracking in livestock [6]. A system designed for classifying bull behaviors using video data from camera setups was implemented in [7], focusing on Lying, Standing, Walking, and Mounting. In reference [8], the authors investigate the advantages and difficulties of remotely monitoring cattle behavior using a range of methods, including clinical illness scoring, visual observations, accelerometers, pedometers, feed intake monitoring, GPS, and real-time location systems.

Advancements in sensor technology have led to the development of highly sensitive electronic devices, expanding the capabilities for recording cow activities [9]. Numerous systems employing sensor technology have been created to automatically analyze dairy cow behaviors [10, 11]. Accelerometers, known for their compact size, light weight, and low energy consumption, provide a non-invasive and objective method for monitoring cow behavior in farm environments [6, 12–17].

Compared to traditional herd-based methods, accelerometer-based systems prioritize individual animal well-being and performance. However, identifying specific behaviors from the sensor data remains a significant challenge. Developers face obstacles such as the complexity of certain behaviors, which may involve similar movements, the extraction of relevant features, potential data loss during wireless transmission, and the intensive data processing required to filter out noise [18]. Consequently, the demand for more efficient and precise methods to manage the vast amounts of movement and behavioral data being collected is increasing [19].

Recognizing animal behavior has become a challenging task, prompting various research groups to use wearable sensing technologies to benchmark real-world conditions [10, 20, 21]. Machine learning offers a powerful solution for improving model accuracy, particularly when dealing with dynamic and complex datasets that are influenced by environmental factors [22]. For instance, Martiskainen et al. [23] developed a method utilizing acceleration data and multi-class support vector machines (SVM) to automatically classify various dairy cow behaviors. Likewise, Diosdado et al. [6] employed a decision-tree algorithm to categorize different cattle activities. Additionally, Arcidiacono et al. [14] determined acceleration thresholds to differentiate between Feeding and Standing behaviors in dairy cows housed in a free-stall barn, while also estimating step counts using statistically defined thresholds. In a later study [24], they demonstrated that their updated approach could operate in real-time due to its low sampling frequency (4 Hz) and reduced complexity. The authors also suggested improvements for better classification performance and real-time application.

Recently, Wang et al. [15] presented a Multi-BPAda Boost classification algorithm that classified seven cow behaviors—Feeding, Lying, Standing, Lying-down, Standing-up, Normal-walking, and Active-walking—utilizing data obtained from three-axis accelerometers. While the studies by [6, 14, 15, 23] underscore the potential of machine learning for behavior classification, they either focus on only a few behaviors [6, 14], report low positive predictive value [23], or lack a thorough analysis of the data features [15, 23]. The success of these methods is highly dependent on both the features and window size used, which are tied to the number of samples in the data.

This paper investigates a cow behavior classification model based on data collected from accelerometer sensors attached to the leg. The study also evaluates the model's effectiveness by optimizing feature sets and data windows to improve classification performance. The main challenges encountered during the research are as follows:

- Challenge 1: Selecting features appropriate for accelerometer data. The variations in data for each behavior require suitable features.
- Challenge 2: Processing data to balance classification performance with the optimal computational time of the algorithms.

We evaluated our approach and conducted a comparison with Wang et al.'s work using the same dataset [15]. Furthermore, we compared our method with the research of Martiskainen and Jarvinen [23], which utilized accelerometer data collected from a collar. Our proposed method focuses on improving the classification performance of cow behaviors using accelerometer data. The main contributions of this paper are outlined as follows:

- Contribution 1: This study examines the feasibility of implementing an algorithm to address the behavior classification problem. The Gradient Boosted Decision Tree (GBDT) algorithm proves to be suitable for balancing accuracy and computational efficiency. By leveraging the simplicity of accelerometer data and the effectiveness of GBDT, the system achieves efficient behavior recognition.
- Contribution 2: Optimized activity selection and feature extraction. Six common behaviors Feeding, Lying, Standing, Lying-standing-transition, Normal-walking, and Active-walking were selected. The behaviors Lying-down and Standing-up in the dataset were combined into a single category. This strategic selection enhances the system's classification accuracy and reliability. Moreover, the feature extraction process was adjusted to closely follow the changes in accelerometer data, ensuring the study's efficiency and effectiveness.

In this study, the features Mean, Standard Deviation (SD), Root Mean Square (RMS), Median, and Range were found to be suitable for addressing the challenges in the research. With the current development of IoT systems, a real-time behavior monitoring system, using motion data collected from sensors and a visual interface, can be feasibly built based on the results of this study, as demonstrated in studies [25–27].

The rest of this paper is structured as follows: Section 1 discusses related research and the issues of the proposed system. Section 2 presents the materials of the proposed system. Section 3 presents the methods of the proposed system. The proposed method uses the GBDT classifier for activity recognition in the study. The proposed features are Mean, SD, RMS, Median, and Range. Section 4 evaluate and discuss system performance for the six selected behaviors. Section 5 concludes the paper.

2. MATERIALS

2.1. Conditions for breeding and animal species

In the study by Wang et al. conducted in Nanyang, Henan Province, China [15], five Holstein dairy cows were selected for the experiment based on similar body size and early lactation stage. The cows' legs are equipped with devices that use accelerometers to record their movements. The cows were kept in a designated section of the free-stall barn, which measured 180 m × 31 m. According to the description provided by Wang et al., the barn featured a feeding passage, two rows of self-locking headlocks, and two rows of head-to-head stalls equipped with sand bedding. The roof, made of lightweight colored steel plates, had a symmetrical design with a 1:3 slope. The barn stood 10 m tall, with eaves measuring 4.65 m. The cows were kept in a loose housing area in the middle of the barn, separated by fences. The space included a watering trough, a row of self-locking headlocks, and seven groups of head-to-head stalls.

The cows were milked twice daily using a fish-bone milking machine, and the floors were cleaned daily with a scraper blade. The cows were fed a total mixed ration (TMR) diet and remained healthy, without any signs of serious lameness or conditions that could affect their behavior.

2.2. Data used in this study

We approached the cow behavior classification problem by identifying a learning framework based on studying acceleration data features. This framework was validated experimentally using data extracted from online public datasets provided by Wang et al. [15]. The dataset consists of 3685 records collected from five cows and is publicly available. Since the dataset offers raw data, it was selected for use in our study. To assess performance, we compared our results with the study by Wang et al., focusing on accuracy, sensitivity, and positive predictive value.

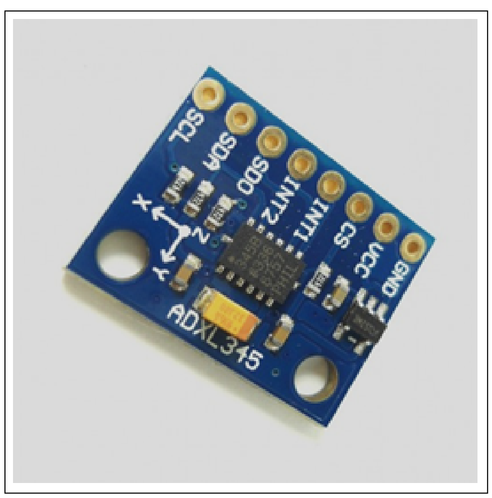

Figure 1: ADXL 345 Accelerometer

In the study of Wang et al. [15], the accelerometer was used to attach to the cow's legs. The cow's leg sensor is a accelerometer ADXL 345 (Figure 1) that collects movement data along the X, Y, and Z axes at a 1Hz sampling rate, with a measurement range of ±8g. It converts analog signals into digital data using a 12-bit A/D converter. Six behavior classes are identified: Feeding (when cows search for or chew food in the feeding area), Lying (resting in a lying position inside the barn), Standing (fully on all fours), Lying-standing-transition (movement between lying and standing), Normal-walking (at least three consecutive limb movements per second), and Active-walking (fast forward movement with long strides, two strides per second).

In [15], the dataset is limited to observations within a 6-second timeframe. As noted in [28], when the sliding window is too brief, it can blur the differences between behaviors. For this research, we tailored the dataset to align with our proposed design. Each labeled observation in the dataset comprises 15 acceleration samples, captured at a 1 Hz sampling rate along three perpendicular axes. Table 1 provides a sample data record with 15 samples/record, while Table 2 offers a detailed breakdown of the behavioral observation component with 15 samples/record.

Table 1: Sample data record

Feeding		
X-axis (g)	Y-axis (g)	Z-axis (g)
-0.9	0.1	0.3
-0.9	0.1	0.3
-0.8	0.1	0.2
-0.9	0	0.2
-0.9	0	0.2
-0.9	0	0.2
-0.9	0	0.2
-0.9	0	0.2
-0.9	0	0.2
-0.8	0.2	1.1
-0.8	0	0.4
-0.8	0	0.4
-0.8	0	0.4
-0.8	0	0.4

Table 2: Behavioral observation components

Behavior pattern	Number of observations
Feeding	613
Lying	731
Standing	451
Lying-standing-transition	629
Normal-walking	738
Active-walking	516
Total	3678

3. METHODS

3.1. Machine learning approaches to cow behavior classification

We propose a behavior classification model using a set of five features (Mean, SD, RMS, Median, and Range). During the recognition of crawling behavior, our approach incorporates a window selection method paired with feature extraction from the acceleration data. We applied a fixed window width of n seconds, where each record i contains n samples, overlapping with the last $n-5$ samples from the preceding record $i-1$. A vector of five features will be extracted from a window. The input of the classifier is trained to recognize behavior using these samples.

From the collected dataset, 60% was randomly designated as the training set, while the remaining 40% was allocated for testing. The classifier was trained using features derived from the measurements (input) that were associated with their corresponding behaviors (output). To evaluate the performance of the proposed method, we implemented different supervised learning algorithms using Python 3.5. The steps involved in constructing the classifier are depicted in Figure 2.

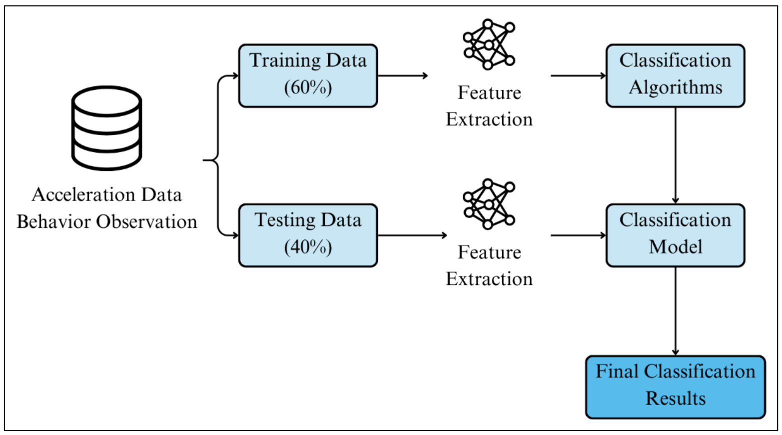

Figure 2: Flow chart of constructive process of the classifier

The performance of classification algorithms is closely related to the characteristics of the data based on the time window. We performed some comparisons with a human action recognition (HAR) problem with wearable devices sampling at higher frequencies (e.g., 50 Hz) [29] than with cow data (1 Hz). The sampling frequency in cows is lower because cows are less active than humans, so we can use a longer sampling window for the cow behavior classification problem.

To analyze the combination with the best results in this study, the classification performance of four separate machine learning algorithms: GBDT, Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN) was evaluated using five characteristics (Mean, SD, RMS, Median, and Range) and different windows (5s, 10s, 15s, 20s). Finally, the overall performance is compared with the results of Wang et al. study [15].

3.2. Feature extraction

In this study, five features are selected including Mean, SD, RMS, Median, and Range. Equations (1–5) represent five feature sets for X-axis data; The formulas for Y-axis and Z-axis are similar.

$$\mathrm{range}(X_j) = \left[\min_{i=1}^{N}\{x_i\}, \max_{i=1}^{N}\{x_i\}\right], \tag{1}$$

$$\mathrm{median}(\mathrm{X_j}) = \frac{x_{[\#N/2]} + x_{[\#N/2+1]}}{2}, \tag{2}$$

$$m(X_j) = \frac{1}{N}\sum_{i=1}^{N} x_i, \tag{3}$$

$$\sigma(X_j) = \sqrt{\frac{1}{N}\sum_{i=1}^{k} (x_i - m)^2}, \tag{4}$$

$$RMS_{X_j} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}, \tag{5}$$

where X represents the data along the X-axis, X_j refers to the j-th record, N is the number of samples in a record (i.e., the window size), x_i denotes the i-th sample of record X_j. The statistical measures are as follows: $m(X_j)$ represents the mean of the values in X_j, $\sigma(X_j)$ is the standard deviation, RMS(X_j) denotes the root mean square, min(X_j) and max(X_j) indicate the minimum and maximum values, respectively. Additionally, range(X_j) is defined as the difference between the maximum and minimum values within X_j.

For research on machine learning, a feature represents a distinct measurable attribute derived from acceleration data. Designing features that are informative, discriminative, and independent is crucial for building effective classification models. The key contribution of this work is the introduction of an efficient feature set tailored for classifying six specific cow behaviors. Properly selected features allow machine learning algorithms to accurately detect the desired patterns. Tables 3–5 display the statistical metrics for six segments within each behavior class. In particular, the computed features for each static behavior (Feeding, Lying, Standing) and dynamic behavior (Lying-standing-transition, Normal-walking, Active-walking) are detailed along the X, Y, and Z-axis.

Table 3: The X-axis acceleration data is calculated by the features

	Feeding	Lying	Standing	Lying-standing-transition	Normal-walking	Active-walking
Mean	-0.82	-0.1	-0.82	-0.01	-0.02	-0.07
SD	0.07	0	0.09	1.05	0.45	1.49
RMS	0.82	0.1	0.82	1.05	0.45	1.49
Median	-0.8	-0.1	-0.8	0	0	-0.2
Range	1.1	0	1.5	4.8	2.3	8

Table 4: The Y-axis acceleration data is calculated by the features

	Feeding	Lying	Standing	Lying-standing-transition	Normal-walking	Active-walking
Mean	-0.02	0.3	-0.02	0.03	0.02	-0.03
SD	0.16	0	0.12	1.05	0.48	1.55
RMS	0.16	0.3	0.12	1.05	0.48	1.55
Median	0	0.3	0	0.1	0	0
Range	2.1	0	1.3	6.1	2.6	8.3

Static behaviors such as Lying exhibit a Mean and RMS close to 0, with SD and Range

Table 5: The Z-axis acceleration data is calculated by the features

	Feeding	Lying	Standing	Lying-standing-transition	Normal-walking	Active-walking
Mean	0.36	-0.6	0.34	0.07	0.04	-0.02
SD	0.09	0	0.07	1.07	0.53	1.56
RMS	0.37	0.6	0.35	1.07	0.53	1.55
Median	0.4	-0.6	0.3	0	0	0.2
Range	0.9	0	0.7	5.9	3	10.4

equal to 0, indicating a state with no significant variation. In contrast, Standing, though also a static behavior, has higher SD and Range values than Lying, particularly on the Z-axis (0.07 and 0.7), reflecting slight movements related to maintaining balance. Feeding displays similar Mean and SD values across the axes as Standing but with a larger Range on the Y and Z axes (2.1 and 0.9), indicating small but consistent movements during feeding.

For the transitional behavior Lying-standing-transition, the Mean is nearly 0 across all axes, but SD and Range are the highest among all behaviors (SD = 1.07, Range = 6.1), highlighting significant variability during the abrupt transitions between Standing and Lying. Normal-walking shows a low Mean, but SD and RMS are at moderate levels (SD 0.5), indicating steady movement with moderate energy. Compared to Normal-walking, Active-walking demonstrates a significantly higher activity level, with the largest SD and Range values (SD = 1.56, Range = 10.4), reflecting faster and more sudden movements.

Comparing the metrics shows that Mean and RMS are suitable for capturing overall movement intensity, while SD and Range emphasize variability in motion, particularly important for fast and irregular behaviors. In these cases, Median proves stable, especially when smoothing out anomalies or noise. Thus, the combined use of these features not only clearly distinguishes between different behaviors but also provides an accurate descriptive model of the kinematics of each activity.

3.3. Evaluation methods

To evaluate the effectiveness of the proposed method, the classification results are presented in the form of a confusion matrix, with the metrics calculated as follows:

$$Acc = \frac{TP + TN}{TP + FP + FN + TN}, \tag{6}$$

$$Sen = \frac{TP}{TP + FN}, \tag{7}$$

$$PPV = \frac{TP}{TP + FP}, \tag{8}$$

$$NPV = \frac{TN}{TN + FN}, \tag{9}$$

where Acc represents accuracy, indicating the correct classification rate, Sen refers to sensitivity, which measures the model's classification capability, PPV stands for positive predictive value, representing the rate of correctly classified positive cases, while NPV refers to negative predictive value, indicating the rate of correctly classified negative cases. True Positive (TP) occurs when an activity takes place, and the model correctly predicts its occurrence. False Positive (FP) happens when no activity takes place, but the model incorrectly predicts that it did. False Negative (FN) occurs when an activity takes place, but the model incorrectly predicts a different activity. True Negative (TN) is when no activity takes place, and the model correctly predicts that no activity occurred.

4. RESULTS AND DISCUSSION

4.1. Experimental results

The performance of four machine learning methods GBDT, RF, KNN, and SVM is compared based on accuracy and sensitivity across five feature sets (Mean, SD, RMS, Median, and Range) and different window lengths (5 seconds, 10 seconds, 15 seconds, 20 seconds). Figure 3 displays the performance outcomes of the classification algorithms tested.

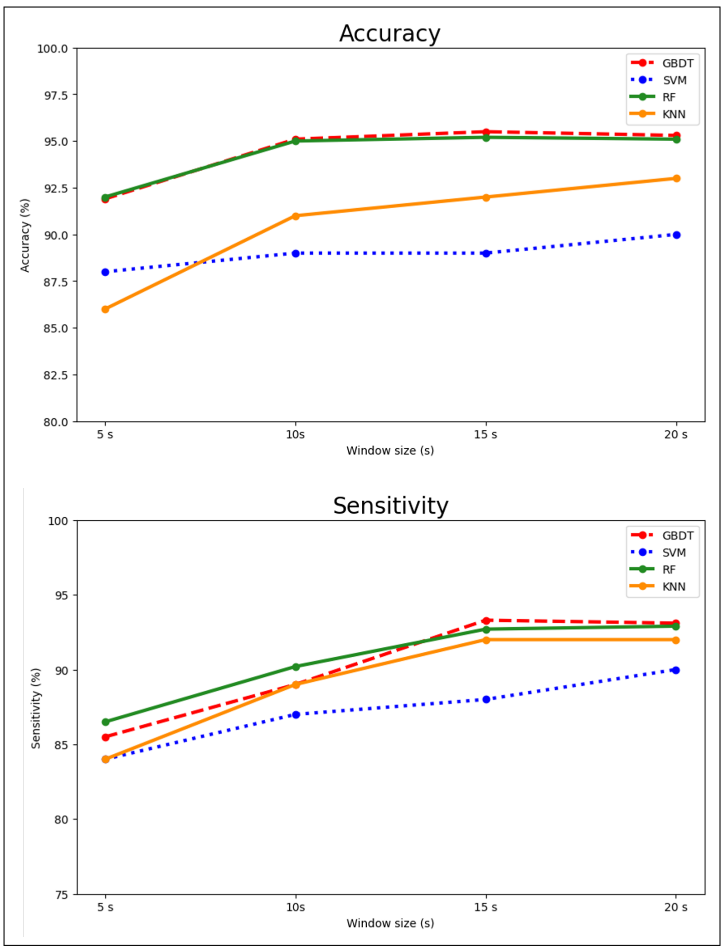

Figure 3: Performance comparison of GBDT, RF, KNN, and SVM

For smaller window sizes, such as 5 seconds, the models generally exhibit lower accuracy and sensitivity. For instance, GBDT and RF achieve 91.9% and 92% accuracy, respectively, while KNN and SVM perform lower, with accuracies of 86% and 88%, respectively. The smaller window sizes may be more sensitive to noise and fluctuations in the data, leading to less stable patterns being captured and, consequently, lower classification performance. Additionally, short windows might fail to encapsulate the full temporal characteristics of the activities, causing misclassifications or incomplete feature extraction.

As the window size increases to 10 and 15 seconds, there is a noticeable improvement in the performance of all classifiers. GBDT reaches 95.5% accuracy and 93.3% sensitivity at a 15-second window, which represents its peak performance. RF follows a similar trend, with its best results (95.2% accuracy, 92.7% sensitivity) also observed at 15 seconds. KNN benefits greatly from larger window sizes as well, showing consistent improvements in both metrics, reaching 92% sensitivity and 93% accuracy at the 20-second window. However, there is a diminishing return for larger windows, particularly beyond 15 seconds. For example, GBDT's performance slightly declines at the 20-second window, dropping to 95.3% accuracy and 93.1% sensitivity. Similarly, RF and KNN show minimal gains or slight drops at 20 seconds compared to 15 seconds. This can be attributed to the possibility of longer windows encompassing more than one activity, leading to mixed or overlapping data points. Moreover, larger windows reduce the number of samples available for training, which could limit the model's ability to generalize effectively.

The results indicate that window size affects classification performance. Selecting an appropriate window size for the experiment can reduce computational complexity and minimize the influence of noise. However, if the window duration is too long, the likelihood of capturing more than one action within a single window increases, and the number of examples available for classification decreases [30]. After taking computational optimization and the characteristics of cow behavior into consideration, we found that the GBDT algorithm, using a 15-second window, achieved the highest overall performance, with an overall sensitivity of 93.3% and an overall accuracy of 95.5%.

4.2. Evaluating the performance of the GBDT model

The results presented in Figure 4 detail the overall results yielded by the GBDT classifier (15 second window). The number of cases that have been identified as positive (modeled behaviors) and negative (other behaviors) is also shown in Figure 4.

As shown in the confusion matrix, the classifier demonstrates a high level of accuracy for certain behaviors, particularly Lying and Normal-walking, where all samples are correctly classified (291/291 and 294/294, respectively). The model also performs well with Active-walking, correctly identifying 202 out of 205 samples. However, there is notable confusion between Feeding and Standing behaviors. Specifically, 52 out of 179 Standing samples were misclassified as Feeding, while 26 out of 244 Feeding samples were misclassified as Standing. This misclassification likely stems from the similarity in postures and movements between these two behaviors. The Lying-standing-transition behavior also shows moderate confusion, with 6 samples being incorrectly classified as Active-walking and 1 sample misclassified as Standing. These results suggest that while the classifier can effectively distinguish between most behaviors, further refinement is necessary, particularly for behaviors with overlapping postural characteristics. Table 6 describes the performance of the GBDT algorithm using four metrics namely Accuracy, Sensitivity, PPV and NPV for all types of behavior.

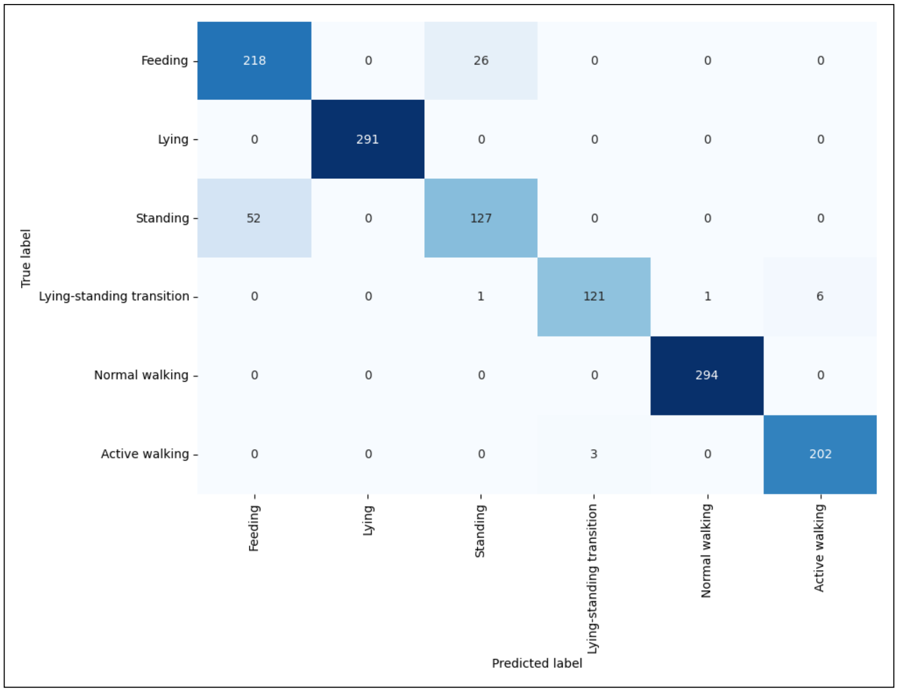

Figure 4: Confusion matrix of dairy cow behavior classification data using GBDT algorithm

Table 6: Performance of the GBDT algorithm using metrics for all behavior types

Behavior Pattern	Algorithm Performance Indicators			
	Accuracy	Sensitivity	PPV	NPV
Feeding	94.19%	89.34%	80.74%	97.57%
Lying	100%	100%	100%	100%
Standing	94.11%	70.95%	82.47%	95.62%
Lying-standing-transition	99.18%	93.8%	97.58%	99.34%
Normal-walking	99.93%	100%	99.66%	100%
Active-walking	99.33%	98.54%	97.12%	99.74%

The GBDT model demonstrated strong overall performances. Accuracy was high for all behaviors, with perfect accuracy for Lying (100%) and excellent values for Normal-walking (99.93%) and Active-walking (99.33%). Sensitivity was also high, exceeding 90% for most behaviors, except for Standing, which had a lower sensitivity of 70.95%, indicating some difficulty in detecting this behavior. PPV varied across behaviors, with perfect values for Lying (100%) and strong results for Lying-standing-transition (97.58%), Normal-walking (99.66%), and Active-walking (97.12%). However, the PPV for Feeding (80.74%) and Standing (82.47%) was relatively lower, suggesting that the model struggled somewhat in correctly predicting positive cases for these behaviors. NPV was excellent for all behaviors, with values above 95%, indicating that the model reliably identified negative cases across all behavior patterns.

4.3. Discussion

The system proposed in this study demonstrates superior performance in classifying cow behaviors through machine learning, leveraging five key features: Mean, SD, RMS, Median, and Range. The GBDT algorithm yields highly significant classification performance (in terms of Sensitivity, Accuracy, NPV, and PPV) for 5 out of the 6 behaviors. The range of behaviors classified in this study is more comprehensive than those addressed in the systems developed by Benaissa et al. [12]. In addition, as presented in Table 6, the GBDT classifier demonstrates significantly better performance compared to the results reported in previous studies [15]. We provide a detailed comparison of overall performance with the study conducted by Wang et al. [15], using the same behavioral dataset. Table 7 presents the comparison results using the macro-average evaluation method, which assesses each class individually, while Table 8 displays the comparison results using the micro-average evaluation method, evaluating all classes collectively.

Table 7: The overall performance indicators calculated using the macro-average

Indicators	Wang et al. [15]	Our work
Accuracy	92.3%	92.93%
Sensitivity	79.1%	92.1%
PPV	82.1%	92.93%
NPV	Not provided	92.1%

Table 8: The overall performance indicators calculated using the micro-average

Indicators	Wang et al. [15]	Our work
Accuracy	86.6%	93.37%
Sensitivity	85.2%	92.1%
PPV	79.8%	92.93%
NPV	Not provided	92.93%

In the study of Wang et al. [15], NPV value was not shown, preventing a direct comparison with our NPV results. Nonetheless, as illustrated in Tables 7 and 8, our NPV values were outstanding: 92.1% using the macro-average evaluation method and 92.93% with the micro-average evaluation method.

When comparing the results between the two studies, our research method produced better outcomes. This was achieved by labeling behaviors more appropriately. During the study, it was observed that the classification performance between the behaviors of Standing-up and Lying-down was relatively low. This is due to the fact that Standing-up and Lying-down share significantly similar data characteristics, which directly leads to confusion in behavior identification. In reality, the frequency of standing and lying down behaviors is nearly equivalent, and there is no practical benefit in distinguishing between the two. Furthermore, when monitoring cow behavior, tracking the total time between Lying and Standing is more practical than focusing on the separate actions of Standing-up and Lying-down. Therefore, the study combined these two behaviors into a single Lying-standing-transition process.

When employing the macro-average evaluation method, our approach surpassed that of Wang et al. [15] in terms of Accuracy (92.93% compared to 92.3%), Sensitivity (92.1%

versus 79.1%), and PPV (92.93% versus 82.1%). Similarly, with the micro-average evaluation method, our performance exceeded Accuracy (93.37% compared to 86.6%), Sensitivity (92.1% versus 85.2%), and PPV (92.93% versus 79.8%). These results indicate that our method achieved better predictions for the most frequently observed classes.

The dataset exhibited an imbalance in the distribution of behavioral data across the classes. Of the 3678 total records spanning six classes (averaging around 613 records per class), the Standing class had only 451 records, while the Active-walking class included 516 records (as shown in Table 2). Due to this imbalance, the micro-average evaluation method is more suitable for assessing the dataset. Under this approach, our method outperformed that of Wang et al. [15] across all evaluation metrics.

In addition, Sensitivity values were generally high, suggesting that the number of false negatives classified as positives was low. The overall performance of the GBDT algorithm, as outlined in Table 6, was robust, with the exception of the Feeding and Standing classes. The study noted that when cows rotated their heads during feeding, the sensor's position would shift, causing misclassifications. Similarly, even when cows were standing, the occasional lowering of their heads led to confusion between Feeding and Standing behaviors. To address this, the authors recommended refining the sensor attachment to minimize these misclassification errors.

While our approach outperformed previous studies in the literature, some limitations persist, particularly in the lower classification accuracy for behaviors such as Standing and Feeding. In studies of cow behavior classification using sensors, the placement of these sensors significantly affects data quality and classification accuracy. For instance, sensors placed on different parts of the body such as the neck, back, or legs can result in variations in movement patterns that impact the ability to distinguish between activities like feeding and standing. Research [16] has shown that placing sensors on the neck can be advantageous for identifying head-related activities, such as grazing or feeding, because these behaviors involve distinct head movements. In contrast, sensors placed on the back or the legs are more effective at tracking overall body movement and posture, which helps classify behaviors like walking, standing, and lying down. The placement of sensors on the neck has been particularly successful in distinguishing feeding from standing, as feeding involves frequent and specific head movements, which are less detectable with back or leg sensors.

Furthermore, in this study, we only applied time-domain features, and the performance achieved was quite good. In the future, the study can be extended to include features such as entropy, which measures the randomness or unpredictability in the data, offering insights into the complexity of activities. Additionally, frequency-domain features, which represent the signal in terms of its frequency components, could be explored to capture patterns that time-domain features might miss, potentially further improving classification accuracy.

In this study, the features Mean, SD, RMS, Median, and Range were found to be suitable for the research objectives. Their computational complexity strikes a good balance between processing time and classification performance. Given the current development of IoT systems, a real-time behavior monitoring system, with motion data collected from sensors and a visual interface, can be feasibly built, as shown in studies [25–27]. Based on our research results, the construction of a real-time cattle behavior monitoring system is entirely feasible. The system is expected to be developed in future research to enable farm managers to receive immediate feedback on livestock conditions and visualize behavior data. This will help farm managers quickly identify trends and make informed decisions.

5. CONCLUSION

In this study, we specifically selected behaviors to label more appropriately and designed an optimized set of features for classifying cow behaviors. A key factor in enhancing classification accuracy was the selection of a 15-second window length. Using the GBDT method, we successfully identified six distinct cow behaviors based on acceleration data: Feeding, Lying, Standing, Lying-standing-transition, Normal-walking, and Active-walking. Our method outperformed the approach introduced by Wang et al. [15] in terms of Sensitivity, Accuracy, PPV, and NPV, which are essential for precise behavior classification. The model was specifically adapted for acceleration data obtained from leg tag sensor systems. However, since our study utilized the dataset from Wang et al. [15], additional validation with new datasets is necessary. Moving forward, we aim to incorporate computer vision techniques to improve the detection of more complex behaviors, such as Feeding and Standing, and further refine classification accuracy.

ACKNOWLEDGMENT

This research was funded by Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number: 02/2022/TN.

REFERENCES

[1] H. W. Neave, J. Lomb, D. M. Weary, S. J. LeBlanc, J. M. Huzzey, and M. A. G. von Keyserlingk, "Behavioral changes before metritis diagnosis in dairy cows," *Journal of Dairy Science*, vol. 101, no. 5, pp. 4388–4399, 2018.

[2] A. Rahman and D. V. Smith, "Cattle behaviour classification from collar, halter, and ear tag sensors," *Information Processing in Agriculture*, vol. 5, no. 2, pp. 124–133, 2018.

[3] E. I. Kaufman, V. H. Asselstine, S. J. LeBlanc, T. F. Duffield, and T. J. DeVries, "Association of rumination time and health status with milk yield and composition in early-lactation dairy cows," *Journal of Dairy Science*, vol. 101, no. 1, pp. 462–471, 2018.

[4] D. Wu, Y. Wang, M. Han, L. Song, Y. Shang, X. Zhang, and H. Song, "Using a CNN-LSTM for basic behaviors detection of a single dairy cow in a complex environment," *Computers and Electronics in Agriculture*, vol. 182, 2021.

[5] G. M. Pereira, J. H. Bradley, and I. E. Marcia, "Validation of an eartag accelerometer sensor to determine rumination, eating, and activity behaviors of grazing dairy cattle," *Journal of Dairy Science*, vol. 101, no. 4, pp. 2492–2495, 2018.

[6] J. A. V. Diosdado and Z. E. Barker, "Classification of behavior in housed dairy cows using an accelerometer-based activity monitoring system," *Animal Biotelemetry*, vol. 3, no. 1, pp. 1–14, 2015.

[7] K. M. Abell, M. E. Theurer, R. L. Larson, B. J. White, D. K. Hardin, and R. F. Randle, "Predicting bull behavior events in a multiple-sire pasture with video analysis, accelerometers, and classification algorithms," *Computers and Electronics in Agriculture*, vol. 136, pp. 221–227, 2017.

[8] M. Benjamin and S. Yik, "Precision livestock farming in swine welfare: A review for swine practitioners," *Animals*, vol. 9, no. 5, 2019.

[9] A. H. Stygar *et al.*, "A systematic review on commercially available and validated sensor technologies for welfare assessment of dairy cattle," *Frontiers in Veterinary Science*, vol. 8, 2021.

[10] M. F. Hansen, M. L. Smith, L. N. Smith, K. A. Jabbar, and D. Forbes, "Automated monitoring of dairy cow body condition, mobility and weight using a single 3D video capture device," *Computers in Industry*, vol. 98, pp. 14–22, 2018.

[11] J. Wang, Z. He, J. Ji, and K. Zhao, "Iot-based measurement system for classifying cow behavior from tri-axial accelerometer," *Ciência Rural*, vol. 49, no. 5, pp. 1–13, 2019.

[12] S. Benaissa *et al.*, "Classification of ingestive-related cow behaviours using rumiwatch halter and neck-mounted accelerometers," *Applied Animal Behaviour Science*, vol. 211, pp. 9–16, 2019.

[13] M. W. Iqbal, I. Draganova, P. C. H. Morel, and S. T. Morris, "Validation of an accelerometer sensor-based collar for monitoring grazing and rumination behaviours in grazing dairy cows," *Animals*, vol. 11, no. 9, 2021.

[14] C. Arcidiacono, S. M. Porto, M. Mancino, and G. Cascone, "A threshold-based algorithm for the development of inertial sensor-based systems to perform real-time cow step counting in free-stall barns," *Biosystems Engineering*, vol. 153, pp. 99–109, 2017.

[15] J. Wang and Z. He, "Development and validation of an ensemble classifier for real-time recognition of cow behavior patterns from accelerometer data and location data," *PLoS ONE*, vol. 13, no. 5, pp. 1–16, 2018.

[16] D.-N. Tran, T. N. Nguyen, P. C. P. Khanh, and D.-T. Tran, "An iot-based design using accelerometers in animal behavior recognition systems," *IEEE Sensors Journal*, vol. 22, no. 18, pp. 17 515–17 528, 15 Sept. 2022.

[17] W. Cheng, F. Cheng, Y. Zhang, X. Wei, Q. Fu, and Y. Zhang, "Automatic recognition of ingestive-related behaviors of dairy cows based on triaxial acceleration," *Information Processing in Agriculture*, vol. 7, no. 4, pp. 427–443, 2020.

[18] L. Riaboff *et al.*, "Evaluation of pre-processing methods for the prediction of cattle behaviour from accelerometer data," *Computers and Electronics in Agriculture*, vol. 165, 2019.

[19] R. Arablouei, L. Currie, B. Kusy, A. Ingham, P. L. Greenwood, and G. Bishop-Hurley, "In-situ classification of cattle behavior using accelerometry data," *Computers and Electronics in Agriculture*, vol. 183, 2021.

[20] R. Arablouei, L. Wang, L. Currie, J. Yates, F. A. P. Alvarenga, and G. J. Bishop-Hurley, "Animal behavior classification via deep learning on embedded systems," *Computers and Electronics in Agriculture*, vol. 207, 2023.

[21] M. Zhang, X. Wang, H. Feng, Q. Huang, X. Xiao, and X. Zhang, "Wearable internet of things enabled precision livestock farming in smart farms: A review of technical solutions for precise perception, biocompatibility, and sustainability monitoring," *Journal of Cleaner Production*, vol. 312, 2021.

[22] F. C. Cairo *et al.*, "Applying machine learning techniques on feeding behavior data for early estrus detection in dairy heifers," *Computers and Electronics in Agriculture*, vol. 179, 2020.

[23] P. Martiskainen and M. Jarvinen, "Cow behaviour pattern recognition using a three-dimensional accelerometer and support vector machines," *Applied Animal Behaviour Science*, vol. 119, no. 1, pp. 32–38, 2009.

[24] C. Arcidiacono, S. M. C. Porto, M. Mancino, and G. Cascone, "Development of a threshold-based classifier for real-time recognition of cow feeding and standing behavioural activities from accelerometer data," *Computers and Electronics in Agriculture*, vol. 134, pp. 124–134, 2017.

[25] M. Vi, D. Tran, V. T. Thuong, N. N. Linh, and D. Tran, "Efficient real-time devices based on accelerometer using machine learning for har on low-performance microcontrollers," *Computers, Materials* & *Continua*, vol. 81, no. 1, pp. 1729–1756, 2024.

[26] V. T. Thuong, D.-N. Tran, D.-T. Tran, B. T. Thu, V. D. Tung, N. T. A. Phuong, P. C. P. Khanh, P. K. Tung, and M.-T. Vi, "Effective human activity recognition through accelerometer data," *Engineering, Technology* & *Applied Science Research*, vol. 14, no. 5, pp. 16 499–16 510, 2024.

[27] N. T. T. Hong, G. L. Nguyen, N. Q. Huy, D. V. Manh, D.-N. Tran, and D.-T. Tran, "A low-cost real-time iot human activity recognition system based on wearable sensor and the supervised learning algorithms," *Measurement*, vol. 218, 2023.

[28] M. Alsaaod, J. J. Niederhauser, G. Beer, N. Zehner, G. Schuepbach-Regula, and A. Steiner, "Development and validation of a novel pedometer algorithm to quantify extended characteristics of the locomotor behavior of dairy cows," *Journal of Dairy Science*, vol. 98, no. 9, pp. 6236–6242, 2015.

[29] K. R. M. Janidarmian, A. R. Fekr, and Z. Zilic, "A comprehensive analysis on wearable acceleration sensors in human activity recognition," *Sensors*, vol. 17, no. 1, pp. 1–26, 2017.

[30] N. Twomey and T. Diethe, "A comprehensive study of activity recognition using accelerometers," *Informatics*, vol. 5, no. 1, pp. 1–37, 2018.

Received on October 01, 2024
Accepted on January 09, 2025