

Monitoring cattle behavior using deep learning: An LSTM-based approach with accelerometer data

Tran Duc Nghia¹, Vi Manh Tuyen^{2,3}, Tran Binh Duong⁴, Hoang Minh Thang⁵,
Pham Quang Huy⁶, Do Viet Manh^{1,3*}, Tran Duc Tan^{2*}

¹Institute of Information Technology, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet, Cau Giay, Hanoi, Vietnam;

²Faculty of Electrical and Electronic Engineering, Phenikaa University, Yen Nghia, Ha Dong, Hanoi, Vietnam;

³Graduate University of Sciences and Technology, Vietnam Academy of Science and Technology, 18 Hoang Quoc Viet, Cau Giay, Hanoi, Vietnam;

⁴Vietnam Paper Corporation, 25A Ly Thuong Kiet, Hoan Kiem, Hanoi, Vietnam;

⁵MobiFone Corporation - MobiFone Northern Network Center, 1 Pham Van Bach, Cau Giay, Hanoi, Vietnam;

⁶Electric Power University, 235 Hoang Quoc Viet, Bac Tu Liem, Hanoi, Vietnam.

*Corresponding authors: manhdv@ioit.ac.vn, tan.tranduc@phenikaa-uni.edu.vn

Received 09 Mar. 2025; Revised 07 May 2025; Accepted 09 May 2025; Published 25 May 2025.

DOI: <https://doi.org/10.54939/1859-1043.j.mst.103.2025.102-109>

ABSTRACT

Behavior data analysis is a crucial factor in the early detection of cow health issues, thereby optimizing farming processes and improving productivity in large-scale farms. Accelerometers, attached to the neck or legs of cows, collect movement data, providing a foundation for analyzing animal behavior. Previous studies have proposed cow behavior classification systems based on accelerometer data combined with machine learning algorithms. However, with the advancement of deep learning, the application of Long Short-Term Memory (LSTM) networks can significantly enhance classification performance. In this study, we utilize an LSTM network to classify four primary cow behaviors: Eating, Lying, Standing, and Walking. The LSTM model effectively processes time-series data by retaining essential information while filtering out unnecessary data. Experimental results demonstrate that the model achieves high classification performance, with an average accuracy of approximately 90% across all behaviors, outperforming traditional machine learning algorithms. This research can be implemented in smart farms, integrating with IoT technology to automate livestock monitoring and management efficiently.

Keywords: Accelerometer; Behavior classification; LSTM; Monitoring.

1. INTRODUCTION

Nowadays, with advances in sensor technology, smart sensors are being integrated into many "Internet of Things" (IoT) systems [1]. Many systems are designed to collect data to classify human behavior [2], monitor human living environments such as detecting intruders [3], preventing accidents [4], etc. In the field of agriculture, specifically dairy farming, the current trend in developed countries is to reduce the number of dairy cows while increasing milk production. For instance, in the UK, while the number of dairy cows declined from over 3.2 million in 1980 to less than 1.9 million in 2019, milk production saw an increase during the same timeframe [1]. This increase in productivity is achieved through improvements in the application of technology in livestock farming, including behavior monitoring. Valuable information about a cow's health status can be analyzed through monitoring its behavior [5]. To manage and improve cattle health issues to enhance farming efficiency, monitoring behavioral activities is a very useful approach [6-8].

Changes in activity and behavior, such as eating in cows, are often used to predict diseases and

health conditions [9, 10]. Diseases in cows affect their behavior, leading to reduced activity and loss of appetite [11,12]. Other factors that can cause behavioral changes include pain, fear, and reproduction [13]. Implementing procedures and testing during health examinations in a large herd of cows requires significant time and effort. This drives the development of monitoring systems to assess cow behavior [6, 14].

Behavior classification requires durable, accurate, and integrable sensors. These are typically mounted on the neck [6, 15], head [16], or legs [17, 18]. Neck and ear sensors effectively capture feeding behavior, while leg-mounted sensors are used for detecting standing, lying, and walking patterns [19, 20]. While traditional machine learning (ML) approaches have been commonly applied [6, 18], recent studies show that deep learning models, such as RNN/LSTM, can achieve better classification performance. For instance, Peng et al. [21] used an LSTM-based model to classify eight cow behaviors from neck-mounted accelerometer data.

Building upon this, our previous work proposed an ML-based behavior recognition system using triaxial acceleration data from neck-mounted sensors to classify four behaviors: walking, lying, standing, and feeding [22]. In this study, the classification performance of these behaviors is evaluated using an LSTM deep learning model and compared with traditional ML methods. Experimental results demonstrate that the LSTM model outperforms ML algorithms on the same dataset [22].

2. MATERIALS AND METHODS

2.1. Cow behavior recognition system

The cow behavior recognition system comprises four layers, as shown in figure 1. In Layer 1, each cow is equipped with two 3-axis accelerometer sensors mounted on the neck and leg (figure 2) to collect data related to eating, lying, standing, and walking behaviors. These sensors also capture GPS location, battery level, and timestamps. Data is wirelessly transmitted to Layer 2 for behavior classification, then sent to cloud storage (Layer 3) and accessed by users through web or mobile applications (Layer 4). The system design is based on the IoT framework proposed in [22].

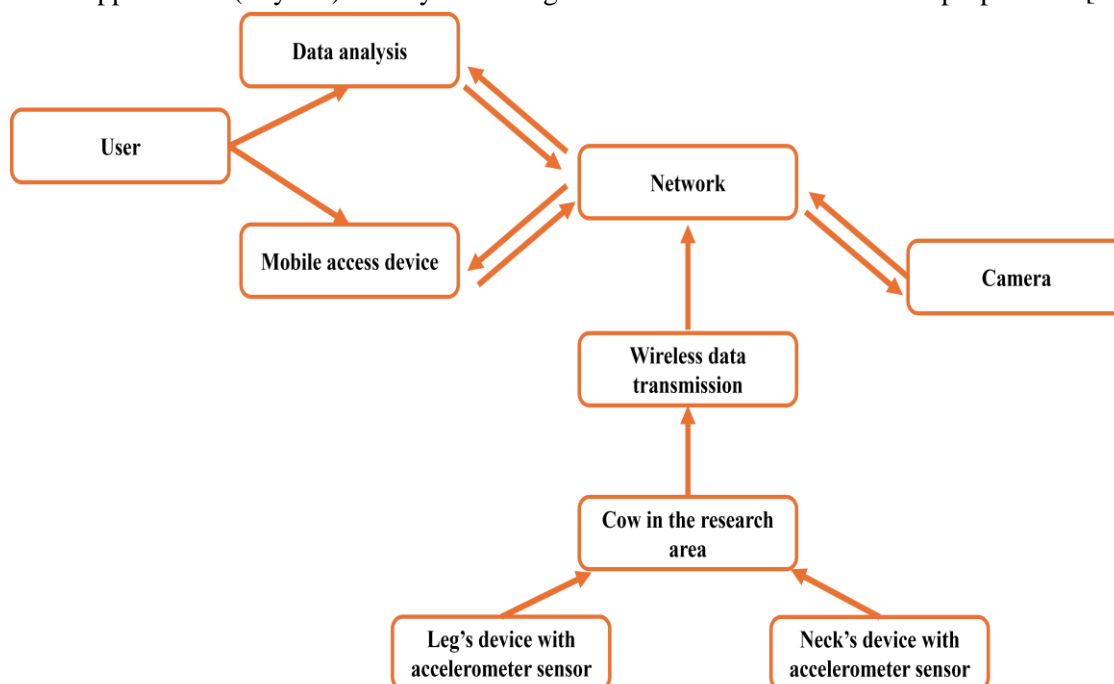


Figure 1. Components of the cow behavior classification system.

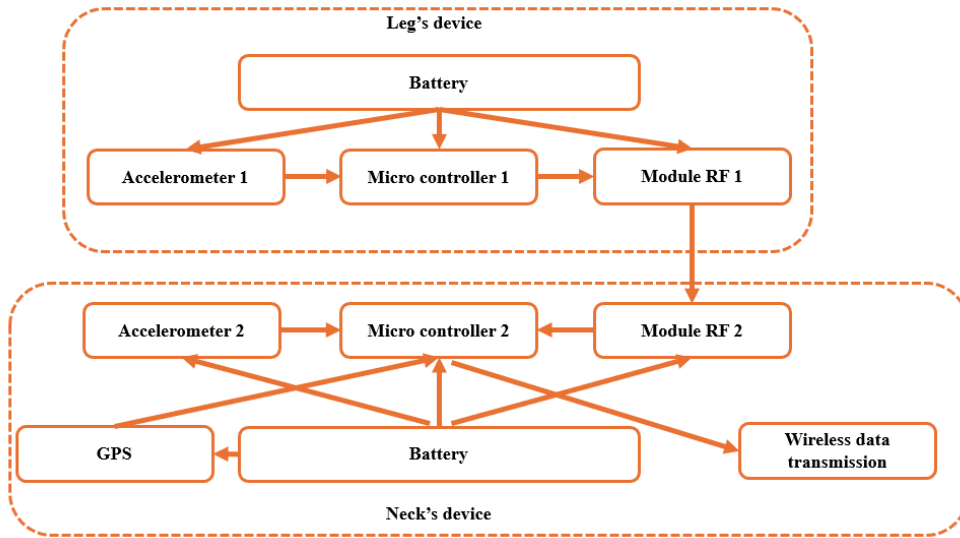


Figure 2. Data collection device mounted on cow in Layer 1.

2.2. Behavior classification process

The process of the cow behavior classification system is shown in figure 3 below.

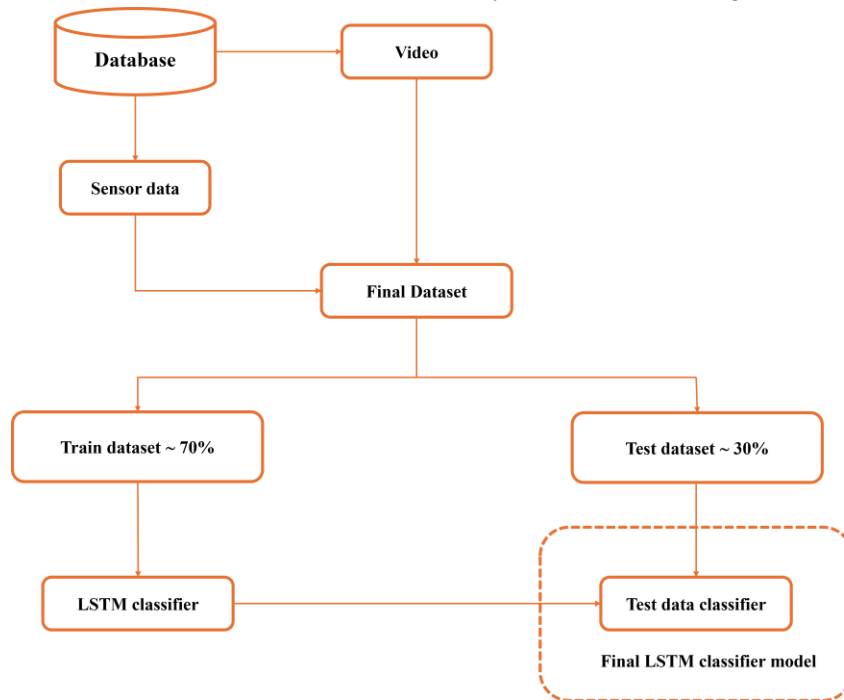


Figure 3. Cow behavior classification process.

Accelerometer data collected from sensors mounted on the cow’s neck is segmented into fixed-length records of 15 seconds using a 5-second sliding window with overlap. All records are normalized, labeled based on video observations, and split into training (70%) and testing (30%) sets. The data processing procedure follows the methodology described in [22]. The classification model is trained using the LSTM algorithm [13] with the training dataset. The classification results from the test dataset are evaluated by comparing them with actual observations (ground truth labels) to assess the model’s performance.

2.3. Acceleration data collection

Data was collected from five cows under normal conditions, with no behavioral restrictions. Sensors were mounted on the neck and leg and synchronized during data acquisition. The behaviors of the cows in this study are described as follows:

- Eating: The cow consumes food.
- Lying: The cow is lying down, with its legs and belly in contact with the ground.
- Standing: The cow is standing on all four legs.
- Walking: The cow is moving using its legs.

The number of behavior samples is 18,230 labeled records used for training and testing [22].

2.4. Feature extraction

In this study, the two features we used are the root mean square (RMS) value and the mean value, as defined by the following formulas (1) and (2):

$$RMS_{Y_t} = \sqrt{\frac{1}{N} \sum_{k=1}^N y_k^2} \quad (1)$$

$$m(Y_t) = \frac{1}{N} \sum_{k=1}^N y_k \quad (2)$$

Where: RMS_{y_t} is the root mean square value of the record Y_t , $m(Y_t)$ is the mean value of the record Y_t , Y is y-axis data, Y_t is the record t with N samples, y_k is the k-th sample of record Y_t .

The formula for the x-axis and z-axis is similar.

2.5. Deep learning model: LSTM

An LSTM model with two stacked layers containing 64 and 32 hidden units is used to classify cow behaviors from time-series accelerometer data. Batch Normalization and Dropout (rate = 0.3) are applied between layers to enhance stability and prevent overfitting. The output is flattened and passed through a Dense layer with 4 units corresponding to the behaviors: Eating, Lying, Standing, and Walking, with Softmax activation for multi-class classification.

The model is trained using the Adam optimizer (learning rate = 0.001), categorical cross-entropy loss, batch size of 64, and 200 epochs. The total number of parameters is approximately 17,000–20,000, making the model lightweight and suitable for real-time deployment in livestock monitoring systems.

2.6. Evaluation indicators

The evaluation indicators Accuracy, Sensitivity, and Positive Predictive Value (PPV) calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (3)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (4)$$

$$PPV = \frac{TP}{TP + FP} \quad (5)$$

Where:

- TP (True Positive): The number of intentions correctly labeled compared to observations.
- FN (False Negative): The number of intentions incorrectly labeled as other intentions.
- FP (False Positive): The number of other intentions incorrectly labeled as the intention under consideration.
- TN (True Negative): The number of other intentions correctly labeled compared to observations.

3. RESULTS AND DISCUSSIONS

The proposed application of the LSTM model in cow behavior classification demonstrates significant improvement in performance compared to traditional machine learning approaches, specifically Random Forest (RF) the best-performing ML model for this dataset as reported in [22].

As presented in table 1, the LSTM model achieved high classification accuracy across four behaviors: Feeding (91%), Lying (90%), Standing (78%), and Walking (88%). Corresponding sensitivities were 85%, 81%, 73%, and 69%, while PPVs were 85%, 71%, 73%, and 77%, respectively, as detailed in table 2. The confusion matrix further indicates that Feeding behavior had the highest correct classification rate (1129/1326), whereas Standing was most often confused with other behaviors, particularly Lying (145 instances) and Walking (253 instances), explaining its relatively lower performance.

Table 1. Confusion matrix on the dataset of five individual cows.

Dataset		Predicted behavior				Total
		Feeding	Lying	Standing	Walking	
Observed behavior	Feeding	1129	2	153	42	1326
	Lying	14	723	241	42	1020
	Standing	187	145	1572	253	2157
	Walking	4	27	186	746	963
Sum		1334	897	2152	1083	5466

Table 2. Experimental results.

Behavior	Acc	Sen	PPV
Feeding	91%	85%	85%
Lying	90%	81%	71%
Standing	78%	73%	73%
Walking	88%	69%	77%
Average	86,6%	77%	76,5%

Comparative analysis between LSTM and RF is illustrated in figures 4(a-c). Regarding classification accuracy (figure 4a), the LSTM model consistently yields higher results across all behaviors. For Feeding, LSTM achieves an accuracy of 91%, exceeding the 84% recorded by RF. Similarly, LSTM attains 90% for Lying, whereas RF only reaches 80%. In the case of Standing, the improvement is more substantial, with LSTM reaching 78% in contrast to RF's 66%. For Walking, the LSTM model delivers an accuracy of 88%, outperforming the 79% achieved by RF. These results indicate that LSTM not only maintains consistent performance but also offers improved classification in both frequent and transitional behaviors.

In terms of sensitivity (figure 4b), LSTM again surpasses RF in nearly all categories. The model reaches 94% sensitivity for Feeding, significantly higher than the 85% obtained by RF. For Lying, LSTM achieves 92%, while RF achieves only 81%. Similarly, Standing behavior is better captured by LSTM with 80% sensitivity, compared to 70% for RF. The only exception is observed in walking behavior, where RF slightly outperforms LSTM at 86% compared to 83%. However, this small difference does not impact on the overall advantage demonstrated by LSTM.

With respect to positive predictive value (figure 4c), LSTM continues to show superiority. It records a PPV of 91% for Lying, compared to 82% for RF. For Standing, the values are 79% for

LSTM and 68% for RF, while in Walking, LSTM reaches 87% and RF 78%. Although RF yields a slightly higher PPV for Feeding-87% compared to 84% from LSTM-this marginal difference is outweighed by the consistent improvements seen in the remaining behaviors.

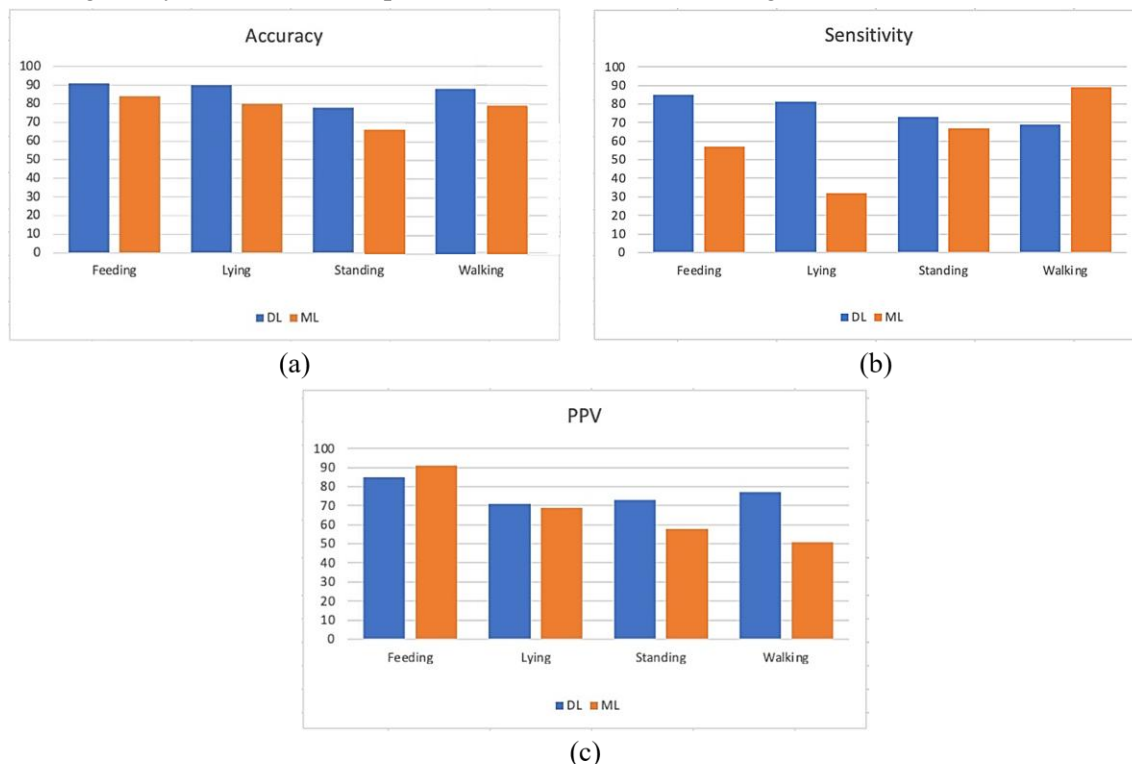


Figure 4. Classification performance of the LSTM model and Random Forest (the best machine learning model for this dataset [22]).

In the study by Peng et al. [21], an accelerometer sensor attached to the cow's neck was used to classify eight behaviors. With a 3.2-second data window, the classification model using the RNN/LSTM algorithm achieved 88% accuracy, 88% sensitivity, and 88% PPV. Their study also demonstrated that the LSTM-RNN model outperformed the CNN model in classification performance.

Overall, if the real-time factor is not considered in the behavior classification process, the study's results confirm that the LSTM (Deep learning) outperforms the RF (ML) in most classification metrics. However, the slightly lower specificity in Walking behavior suggests that relying solely on temporal dependencies may not be sufficient for optimal classification of this behavior. Enhancing the feature extraction process or integrating hybrid modeling approaches could further improve performance. Our future research will expand to larger, more diverse datasets and investigate the application of hybrid models to improve classification accuracy.

4. CONCLUSIONS

In this study, we demonstrated that using the LSTM model provides higher classification performance compared to machine learning models when utilizing the dataset obtained from sensors worn on the cow's neck. We conducted experiments on machine learning algorithms and the LSTM model using the same dataset collected from five cows, and the classification results of the LSTM model achieved ideal outcomes. Specifically, the accuracy for eating behavior was 91%, Lying was 90%, Standing was 78%, and Walking was 88%. The sensitivity for Eating behavior was 85%, Lying was 81%, Standing was 73%, and Walking was 69%. The PPV for Eating

behavior was 85%, Lying was 71%, Standing was 73%, and Walking was 77%. Future studies will experiment with other deep learning methods, such as Transformer or CNN-LSTM, to assess their potential for improving classification performance. Additionally, integrating data from various types of sensors, such as motion sensors and biometric sensors, could enhance the accuracy and applicability of the system in smart livestock farming.

Acknowledgement: *This research is funded by the Institute of Information Technology (IoIT-VAST) under grant number CSCL02.02/24-25.*

REFERENCES

- [1]. S. S. Goel, A. Goel, M. Kumar, G. Moltó, "A review of Internet of Things: qualifying technologies and boundless horizon", *J. Reliab. Intell. Environ.*, vol. 7, pp. 23-33, (2021).
- [2]. C. Demongivert, K. Bouchard, S. Gaboury, B. Bouchard, M. Lussier, C. Parenteau, C. Laliberté, M. Couture, N. Bier, S. Giroux, "A distributable event-oriented architecture for activity recognition in smart homes", *J. Reliab. Intell. Environ.*, vol. 7, pp. 215–231, (2021).
- [3]. P. K. Keserwani, M. C. Govil, E. S. Pilli, P. Govil, "A smart anomaly-based intrusion detection system for the Internet of Things (IoT) network using GWO-PSO-RF model", *J. Reliab. Intell. Environ.*, vol. 25, pp. 3-21, (2021).
- [4]. J. A. Onesimu, A. Kadam, K. M. Sagayam, A. A. Elngar, "Internet of things based intelligent accident avoidance system for adverse weather and road conditions", *J. Reliab. Intell. Environ.*, (2021).
- [5]. Charlton, G. L., V. Bouffard, J. Gibbons, E. Vasseur, D. B. Haley, D. Pellerin, J. Rushen, A. M. de Passillé., "Can automated measures of lying time help assess lameness and leg lesions on tie-stall dairy farms?", *Appl. Anim. Behav. Sci.*, vol. 175, pp. 14-22, (2013).
- [6]. C. Arcidiacono, S. M. C. Porto, M. Mancino, G. Cascone, "Development of a threshold-based classifier for real-time recognition of cow feeding and standing behavioral activities from accelerometer data", *Comput. Electro. Agric.*, vol. 134, pp. 124–134, (2017).
- [7]. H. C. Weigele, L. Gyax, A. Steiner, B. Wechsler, J. B. Burla, "Moderate lameness leads to marked behavioral changes in dairy cows", *J. Dairy Sci.*, vol. 3101, pp. 2370–2382, (2018).
- [8]. G. M. Pereira, J. H. Bradley, I. E. Marcia, "Validation of an eartag accelerometer sensor to determine rumination, eating, and activity behaviors of grazing dairy cattle", *J. Dairy Sci.*, vol. 101, pp. 2492–2495, (2019).
- [9]. I. Halachmi, "Precision livestock farming applications.", Wageningen Academic Publishers, vol. 10:9, pp. 1482–1483, (2016).
- [10]. K. Fogsgaard, C. Røntved, P. Sørensen, M. Herskin, "Sickness behavior in dairy cows during *Escherichia coli* mastitis", *Int. J. Dairy Sci.*, vol. 95, pp. 630–638, (2012).
- [11]. T. Halasa, K. Huijps, O. Østerås, H. Hogeveen, "Economic effects of bovine mastitis and mastitis management: a review.", *Veterinary Quarterly*, vol. 29:1, pp. 18–31, (2011).
- [12]. P. Sepulveda-Varas, K. L. Proudfoot, D. M. Weary, M. A.G. von Keyserlingk, "Changes in behaviour of dairy cows with clinical mastitis", *Appl. Anim. Behav. Sci.*, vol. 175, pp. 8–13, (2016).
- [13]. H. M. Zebari, S. M. Rutter, E. C. L. Bleach, "Characterizing changes in activity and feeding behaviour of lactating dairy cows during behavioural and silent oestrus", *Appl. Anim. Behav. Sci.*, vol. 206, pp. 12–17, (2018).
- [14]. R. Dutta, D. Smith, R. Rawnsley, G. Bishop-Hurley, J. Hills, G. Timms, D. Henry, "Dynamic cattle behavioral classification using supervised ensemble classifiers", *Comput. Electron. Agric.*, vol. 111, pp. 18–28, (2015).
- [15]. J. A. Vázquez Diosdado, Z. E. Barker, H. R. Hodges et al., "Classification of behavior in housed dairy cows using an accelerometer-based activity monitoring system", *Anim. Biotelemetry*, vol. 3, no. 15, (2015).
- [16]. K. Abell, M. Theurer, R. Larson, B. White, D. Hardin, R. Randle, "Predicting bull behavior events in a multiple-sire pasture with video analysis, accelerometers, and classification algorithms", *Comput. Electron. Agric.*, vol. 131, pp. 221–227, (2017).

- [17]. J. Wang, 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, (2018).
- [18]. C. P. K. Phung, D. T. Tran, V. T. Duong, H. T. Nguyen, D. N. Tran, "The new design of cows' behavior classifier based on acceleration data and proposed feature set", Math. Biosci. Eng., vol. 17, no. 4, pp. 2760-2780, (2020).
- [19]. B. D. Robért, B. J. White, D. G. Renter, R. L. Larson, "Determination of lying behavior patterns in healthy beef cattle by use of wireless accelerometers", Am. J. Vet. Res.; vol. 72, pp. 467–473, (2011).
- [20]. P. Martiskainen, M. Jarvinen, "Cow behavior pattern recognition using a three-dimensional accelerometer and support vector machines", Appl. Anim. Behav. Sci., vol. 119, pp. 32–38, (2009).
- [21]. Y. Peng, N. Kondo, T. Fujiura, T. Suzuki, W. Hidetsugu, Y. Yoshioka and E. Itoyama, "Classification of Multiple Cattle Behavior Patterns Using a Recurrent Neural Network with Long Short-Term Memory and Inertial Measurement Units," in Computers and Electronics in Agriculture, vol. 157, pp. 247-253, (2019), doi: 10.1016/j.compag.2018.12.023.
- [22]. 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" in IEEE Sens. J., (2021), doi: 10.1109/JSEN.2021.3051194.

TÓM TẮT

Giám sát hành vi bò sử dụng học sâu: Phương pháp dựa trên mạng LSTM và dữ liệu gia tốc

Việc phân tích dữ liệu hành vi là yếu tố quan trọng giúp phát hiện sớm các vấn đề về tình trạng sức khỏe của bò, từ đó tối ưu hóa quy trình chăn nuôi và nâng cao năng suất tại các trang trại lớn. Gia tốc kế (cảm biến gia tốc) được gắn trên cổ hoặc chân bò giúp thu thập dữ liệu chuyển động, tạo cơ sở cho việc phân tích hành vi của động vật. Trong các nghiên cứu trước đây, hệ thống phân loại hành vi của bò đã được đề xuất dựa trên dữ liệu gia tốc kết hợp với các thuật toán học máy. Tuy nhiên, với sự phát triển của học sâu, việc áp dụng mạng bộ nhớ dài-ngắn hạn (LSTM) có thể cải thiện đáng kể hiệu suất phân loại. Trong nghiên cứu này, chúng tôi sử dụng mạng LSTM để phân loại bốn hành vi chính của bò: ăn, nằm, đứng và đi. Mô hình LSTM có khả năng xử lý dữ liệu chuỗi thời gian hiệu quả nhờ cơ chế ghi nhớ thông tin quan trọng và loại bỏ dữ liệu không cần thiết. Kết quả thử nghiệm cho thấy mô hình đạt hiệu suất phân loại cao, với độ chính xác trung bình xấp xỉ 90% cho tất cả các hành vi, cao hơn so với các thuật toán học máy trước đó. Nghiên cứu này có thể được triển khai trong các trang trại thông minh, kết hợp với công nghệ IoT để tự động hóa việc giám sát và quản lý đàn gia súc một cách hiệu quả.

Từ khoá: Cảm biến gia tốc; Phân loại hành vi; LSTM; Giám sát.