Smart Milk Yield Monitoring System for Dairy Farm Applications

Original Scientific Paper

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Abstract *– Effective management of individual dairy cow milk yield plays an important role in extending herd longevity and increasing average annual productivity. This paper proposes a smart monitoring and management system designed to track the daily milk yield of individual dairy cows. The proposed system was built based on the Internet of Things (IoT) technology and integrated deep learning models. The proposed system comprises the following main components: an improved RFID tag with energy-harvesting capability integrated with a triaxial accelerometer for behavior monitoring ("Resting," "Grazing," "Moving," and "Milking") and automatic management of cow identification (ID); an electronic weighing unit that can be interfaced with an IoT Node for recording milk yield data; an RFID reader equipped with a 12 dBi antenna for retrieving ID and behavioral data; and a Raspberry-based device embedded with a pre-trained deep learning model that accurately identifies the cow currently positioned at the milking station and integrates this information with milk yield data for transmission to a central server. A Bidirectional Long Short-Term Memory (Bi-LSTM) deep learning model is employed to train and classify dairy cow behaviors during the milking process based on sensor data and the Received Signal Strength Indicator (RSSI), enabling accurate identification of the target cow among neighboring individuals. The system has been deployed and evaluated in a practical environment at the Tan Tai Loc dairy farm (Soc Trang province, Vietnam). Experimental results showed that the trained model can achieve 98% accuracy in behavior recognition and 99.38% accuracy during three months of real-world deployment at the farm. The experimental results demonstrate that the proposed system has potential for practical application, contributing to improved efficiency, enhanced management, and the advancement of smart dairy farm operations in the future.*

Keywords: *Radio Frequency Identification (RFID); Received Signal Strength Indicator (RSSI); Bidirectional Long Short-Term Memory (Bi-LSTM); Milking behavior; Smart Milk Yield Monitoring System*

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1. INTRODUCTION

Optimizing daily milking schedules is crucial for maximizing milk yield and extending the productive lifespan of dairy cows [1-4]. Real-time monitoring of milking not only supports early detection of changes in individual cows' health and behavior but also enables timely interventions for improved farm productivity [5]. Precise daily milk yield tracking is therefore essential for effective animal health management and production efficiency.

In Vietnam, many dairy farms still rely heavily on manual milking and subjective estimates by farmers to measure milk yield for each cow [2], [6,7]. This traditional approach introduces several limitations in accuracy and data recording. Manual weighing and recording, often employing mechanical or electronic scales and handwritten IDs, are error-prone due to operator inconsistency, unstable conditions, and potential confusion when linking each data of the cow, issues amplified on large-scale farms or during simultaneous tasks. These shortcomings reduce management effectiveness and hinder decisions in milk production.

With the advent of the IoT, wireless sensor nodes have become increasingly feasible for livestock monitoring because of their sensing and wireless data transmission capabilities [8]. Nevertheless, the need for periodic battery replacement or recharging remains a challenge. To address this, wireless power transfer (WPT) technology has emerged as a promising solution, allowing sensor nodes to harvest energy wirelessly from the environment and reducing the need for frequent battery changes [9]. Various WPT technologies have been applied as battery alternatives in livestock monitoring systems, including near-field inductive coupling, near-field communication (NFC), and long-range WPT methods [10-12].

This study proposes a semi-automated milking monitoring system that incorporates an energy-harvesting electronic tag based on RFID technology to track movement activity and enable automatic identification of individual dairy cows on the farm [13]. In general, two primary approaches are employed for monitoring animal behavior: vision-based methods and sensor-based methods [14-18]. However, vision-based systems often encounter significant challenges in automatically tracking individual animals in real-world farm environments. In contrast, modern sensor technologies, particularly triaxial accelerometers, now provide a practical and effective solution for monitoring the activity of individual livestock [19]. Martiskainen et al. (2009) demonstrated the feasibility of accelerometer-based cattle behavior recognition using handcrafted features and SVM classification [20]. Although effective for identifying basic behaviors, this approach relies heavily on manual feature engineering and battery-powered sensors, which limit its scalability, adaptability, and suitability for long-term deployment. Subsequently, video-based methods, such as the multiview action-recognition framework proposed by Fuentes et al. (2023), enhanced robustness to occlusion in enclosed barns, but they require substantial power, consistent lighting conditions, and high computational resources, making them impractical for large herds or outdoor environments [16].

To enhance the accuracy of automatic cow identification during milking, we suggest integrating motion-behavior tracking data with Received Signal Strength Indicator (RSSI) measurements obtained from wearable tags. These two parameters serve as inputs to a pre-trained machine learning (ML) model. ML techniques have demonstrated strong performance in identifying behavioral patterns that are difficult to detect using conventional analytical methods [21]. Their applications in farm management, such as behavior prediction, anomaly detection, and disease forecasting, are becoming increasingly effective [22]. With recent advances in computational power, deep learning (DL), a specialized subset of ML, can address complex problems involving large-scale datasets more efficiently than traditional approaches [23]. Prominent adopted DL architectures include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks; CNNs are better suited for image data, whereas RNNs and LSTMs are more appropriate for time-series data [24-26].

To recognize cow behaviors, this study applies deep learning using a Bi-LSTM model. The Bi-LSTM improves upon the traditional LSTM by learning both forward and backward temporal dependencies, enhancing behavior recognition in complex situations such as distinguishing milking from routine activities. Compared with existing methods, the Bi-LSTM delivers higher accuracy and more efficient real-time processing [27]. When deployed in the semi-automated milking system, the proposed study uses a Bi-LSTM network to train and classify cow behaviors, particularly the milking activity, based on accelerometer and RSSI data. The recognition algorithm leverages accelerometer measurements combined with RSSI to classify four primary behaviors: milking, grazing, moving, and resting. Each behavior exhibits distinct acceleration signatures; however, there is some overlap between resting and milking due to similar movement patterns. To improve accuracy, RSSI is used as a spatial indicator. For behaviors such as grazing, moving, or resting, RSSI tends to fluctuate because cows move freely around the farm. In contrast, milking occurs at a fixed location near the RFID antenna where RSSI is more stable and stronger. Nevertheless, cows that are not being milked may sometimes pass by or stop near the antenna, which can raise RSSI and cause confusion if relying on RSSI alone. Combining accelerometer and RSSI data substantially reduces such errors. To evaluate system feasibility, a wearable sensor module with energy-harvesting capability was designed and prototyped. Field experiments were subsequently conducted at a dairy farm in Soc Trang Province, Vietnam, using a cohort of 20 dairy cows.

The main contributions of this study are summarized as follows:

i. An improved self-powered wearable sensor tag is proposed to monitor dairy cow behavior, employing long-range RF energy harvesting at 915 MHz, together with a detailed analysis of system architecture and energy-harvesting performance.

ii. A Bi-LSTM deep learning model is developed to recognize milking behavior by integrating accelerometer signals with RSSI measurements.

iii. A semi-automated milk-yield monitoring system is implemented and evaluated under real farm conditions, accompanied by a comprehensive analysis of its operational performance.

In the remainder of this paper, Section 2 presents the system architecture, focusing on the design of the wearable inertial sensor tag; Section 3 introduces the structure of the Bi-LSTM deep learning model; Section 4 describes the field experiments, the data collection procedures, and the training of the Bi-LSTM model. This section also explains how the classified behaviors are applied to automate milk-yield monitoring. Finally, Section 5 concludes the paper and discusses future work.

2. SYSTEM DESIGN

On small-scale dairy farms in rural Vietnam, typically with 10 to 20 cows, daily milking is commonly performed using manual milking machines. However, the milk yield of each cow is inconsistently recorded, resulting in lower average annual productivity and shorter productive lifespans for dairy cows. Implementing an automated milk-yield management system faces a key challenge: accurately identifying the ID number of the cow being milked, as signal interference often occurs when other cows move nearby.

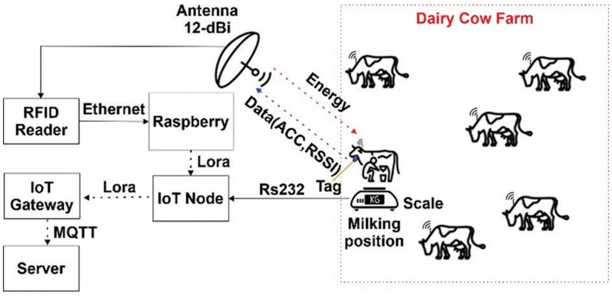


Fig. 1. Diagram of the individual milk yield management system

To overcome this challenge, this study proposes an individual milk-yield management system for dairy cows, the overall structure of which is depicted in Fig. 1. The proposed system comprises four key hardware components:

i. An energy-harvesting wearable tag that stores the unique ID of each cow and integrates a triaxial accelerometer (ACC). When worn around the neck, the tag enables the monitoring of basic behaviors such as chewing, walking, and resting.

ii. An electronic milk-weighing scale that consistently transmits milk-weight measurements via an RS232 interface to an IoT node. The scale, which has a maximum capacity of 50 kg, is connected to a manual milking machine.

iii. A UHF RFID reader (Impinj Speedway R420), equipped with a 12-dBi antenna, capable of reading accelerometer-tag data at high speed (up to 2,000 tags per second), recording RSSI values, and simultaneously supplying wireless power to the tags for energy harvesting.

iv. An individual cow identification module, implemented on a Raspberry Pi 3, which executes a pre-trained behavior-recognition algorithm using RSSI and ACC data.

With the proposed architecture, the system can accurately identify the ID of the cow being milked, enabling the corresponding data to be transferred to the IoT node. The identified ID is then combined with real-time milk weight data from the scale, encapsulated, and forwarded to the server via an IoT gateway for monitoring and management.

The central component of the proposed system is the wearable sensor tag, which consists of two primary components: an energy harvesting unit and a sensing module, as shown in Fig. 2. The red lines in the functional diagram represent the energy flow within the device, illustrating how energy is harvested and delivered to power the sensing module. The module integrates a triaxial accelerometer, a low-power microcontroller unit (MCU), and a UHF transceiver. The blue lines denote the signal flow: the MCU collects data from the accelerometer and transmits it to the transceiver, which subsequently forwards the necessary information to the RFID reader.

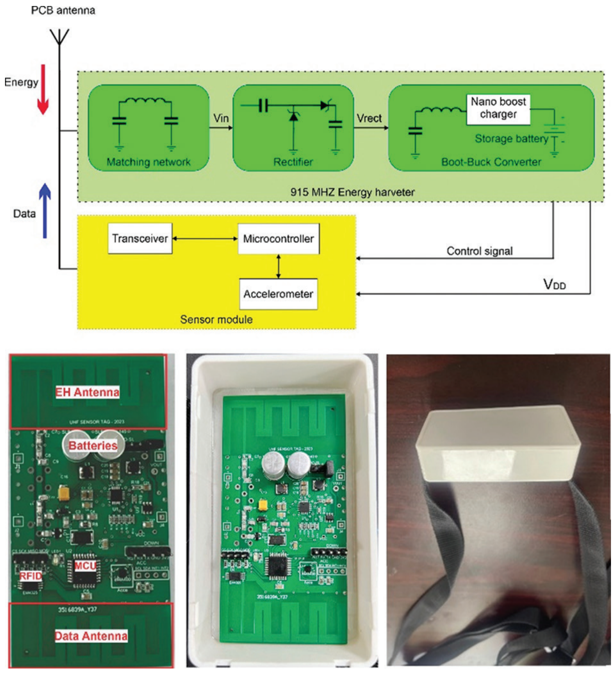


Fig. 2. The proposed sensor tag

In this study, the energy harvesting unit adopts Radio Frequency Energy Harvesting (RFEH) technology, in which RF waves are captured and converted into usable electrical energy [28]. The present design extends and enhances the architecture introduced in our previous work [11]. At the core of the harvester is an Inverted-F Antenna (IFA), as detailed in [29], which was selected due to its compact form factor and high energy collection efficiency in the UHF band. To maximize power transfer from the antenna to the rectifier circuit, a Pi-matching network is incorporated for impedance matching between components [30]. The voltage rectifier employs a single-stage Dickson charge pump with low-forward-voltage Schottky diodes (SMS-7630 from Skyworks Technologies), resulting in low power losses and high energy conversion efficiency. A notable enhancement in this design is the replacement of the traditional 200 mF supercapacitor with a rechargeable SLB08115L140 battery (NICHICON, Japan), which extends the operational time of the sensor. The power management unit consists of a buck-boost energy control circuit (BQ25570, Texas Instruments) coupled with an ultra-low-leakage load switch (nRF-PPK2, Nordic Semiconductor, Switzerland), enabling stable and energy-efficient operation of the entire tag in the absence of external power sources. The accelerometer module was also enhanced compared with the previous study by replacing the previously used ADXL362 sensor with the BMA400 (Bosch, Germany), which provides lower power consumption and higher accuracy for monitoring cattle movement. Additionally, the earlier STM32L432 MCU was substituted with the Atmega328P (Atmel, USA), a low-power, cost-effective MCU widely used in embedded applications [11].

The EM4325 RFID transceiver is retained to ensure effective communication and data transfer in the UHF band. Moreover, a TPS22916 ultra-low-leakage load switch (Texas Instruments) has been integrated to isolate the UHF transceiver from the power source after the sensor data are transmitted, allowing the transceiver to enter passive mode and further conserve energy. To distinguish the data communication link from the energy harvesting link, a dedicated antenna has been added for data transmission between the sensor circuit and the reader. This secondary antenna shares the same structure as the harvesting antenna and is directly connected to the transceiver. The complete prototype of the sensor tag is shown in Fig. 2.

To overcome the limitations of energy harvesting, a specialized operational scheme was implemented for the sensor module, as previously introduced in [11]. Specifically, the module operates in two distinct phases within each operational cycle: the activity phase and the sleep phase. During the active phase, the triaxial accelerometer collects motion data from the cow and transmits it to the MCU for preliminary processing. The processed data is then transferred to the UHF transceiver before wirelessly forwarded to the RFID reader. While the accelerometer and the MCU are active, the transceiver is maintained in the sleep state to minimize power consumption.

In the subsequent sleep phase, all components of the sensor module are configured to enter standby or low-power modes, thereby substantially reducing overall current consumption. The UHF transceiver remains in sleep mode throughout this phase. The MCU stays idle, awaiting an interrupt signal from the Real-Time Clock (RTC) that triggers a new operational cycle. This interrupt is generated at intervals equal to the sampling frequency of the accelerometer, set to 10 Hz.

The current consumption of the sensor module is denoted as I_{ACT} and I_{SL}, corresponding to the current drawn during the active and sleep phases. The average current consumption of the sensor module over one complete cycle can be expressed using the following formula:

$$I_{AVG} = \frac{I_{ACT} \times T_{ACT} + I_{SL} \times T_{SL}}{T_{ACT} + T_{SL}} \tag{1}$$

where T_{ACT} and T_{SL} represent the durations of the active and sleep phases, respectively, within a single operational cycle.

Based on the findings reported in, the following values were determined: I_{ACT} = 379.6 μA, I_{SL} = 0.785 μA, T_{ACT} = 16 ms, and T_{SL} = 100 ms. All current measurements were conducted at a supply voltage of 3.3 V. Substituting these values into Equation (1), the average current consumption I_{AVG} of a sensor module is approximately 53.04 μA [11].

Once the sensor module's current profile is characterized, it is possible to estimate the required storage capacity of the energy harvesting unit. The storage element must be appropriately sized to enable continuous sensor operation under intermittent power harvesting conditions. In general, the minimum required energy storage capacity can be estimated using the following expression:

$$C_{store} = \frac{\Delta T \times I_{AVG}}{\Delta V_{CAP}} \tag{2}$$

In this equation, I_{AVG} represents the average current consumption of the sensor module, ΔT denotes the operating duration of the module, and ΔV_{CAP} corresponds to the voltage drop across the storage element during this period.

In the worst-case scenario, the storage element must supply sufficient energy for a single operational cycle of the sensor module. Under this condition, the voltage drop across the storage component is defined as: $\Delta V_{CAP} = \Delta VH_{Thres} - \Delta VL_{Thres}$ = 1.3 V, and the operating duration is: ΔT = 116 ms. Using the previously calculated average current consumption of I_{AVG} = 53.04 μA, the minimum required storage capacitance C_{store} is approximately 4.7 μF.

The SLB08115L140 is a lithium titanate rechargeable battery manufactured by Nichicon. It has a diameter of 8.0 mm, a height of 11.5 mm, a nominal voltage of 2.4 V, a capacity of 14 mAh, and a maximum discharge current of 280 mA. This battery is designed for applications that require rapid charge/discharge cycles and stable performance at low temperatures. With the fast-charging capability and high efficiency, it is well-suited for IoT devices, energy harvesting systems, and other high-reliability applications.

Fig. 3 compares the discharge duration of the sensor module using the proposed battery with supercapacitors of 50 mF, 100 mF, 150 mF, and 200 mF. The durations for which these supercapacitors maintained a voltage level of 2 V were 712 seconds (50 mF), 2,995 seconds (100 mF), 5,832 seconds (150 mF), and 10,320 seconds (200 mF), respectively. In contrast, the lithium battery sustained a voltage close to 2.4 V over a period comparable to that of the 200-mF supercapacitor. The battery voltage started to drop significantly at around 700,000 seconds (194 hours) and reached 1.8 V after 1,125,503 seconds (312 hours). These results demonstrate that using a lithium battery can significantly extend the operational time of the sensor module up to 312 hours (approximately 13 days) before the supply voltage drops below the lower threshold.

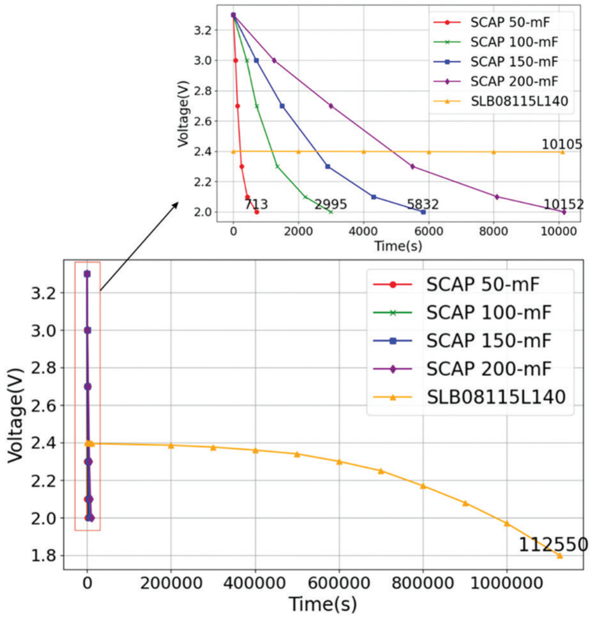


Fig. 3. Comparison of the discharge times of capacitors [11] and the SLB08115L140 battery

3. THE BI-LSTM

To automatically recognize the cow being milked, the proposed system employs a pre-trained deep learning model that takes triaxial acceleration data and RSSI values as inputs. After collection, these data are restructured using the sliding window method, a widely used technique in supervised learning tasks involving time-series data [11]. In particular, the input data are segmented into fixed-length, overlapping windows. The overlap between consecutive windows helps maintain the relevant information across adjacent data segments. A previous study [20] investigated window sizes of 3, 5, and 10 seconds to detect cattle behavior.

In this study, we propose using a Bidirectional Long Short-Term Memory (Bi-LSTM) network as the deep learning algorithm for detecting cow behaviors. The Bi-LSTM is an extension of the traditional LSTM architecture, which is a type of recurrent neural network (RNN) designed to model and predict sequential data, particularly time-dependent sequences such as text, audio, and other time-series data. First introduced by Graves and Schmidhuber [31], the Bi-LSTM enhances the capability of standard LSTM by enabling the model to learn from past and future contexts within a sequence. Whereas a conventional LSTM processes input data in one direction (typically forward in time), a Bi-LSTM employs two LSTM layers that operate in opposite directions: one forward and one backward. This bidirectional structure allows the model to capture more comprehensive temporal dependencies, making it particularly effective in tasks in which context information from both directions is essential for accurate prediction or classification.

The forward and backward LSTM layers in the Bi-LSTM allow the model to receive and transmit information in both temporal directions of the sequence. Specifically, at the time t, the input x_t is processed by the forward LSTM layer to produce the output h_f^t, while simultaneously being fed through the backward LSTM layer to yield h_b^t. The final output of the Bi-LSTM at time t is formed by combining these two outputs, h_f^t and h_b^t, as expressed in the following equations [32]:

$$h_t^f = f\left(W_{xh}^f x_t + W_{hh}^f h_{t-1}^f + b_h^f\right) \tag{3}$$

$$h_t^b = f\left(W_{xh}^b x_t + W_{hh}^b h_{t+1}^b + b_h^b\right) \tag{4}$$

In these equations, W denotes the weight matrices (e.g., W_{xh} is the weight matrix connecting the input to the hidden layer), b represents the bias vectors (e.g., b_h is the bias vector of the hidden layer), and f is the activation function of the hidden layer. The output y_t of the Bi-LSTM network is then given by:

$$y_t = g(W_{hy}^f h_t^f + W_{hy}^b h_t^b + b_y) \tag{5}$$

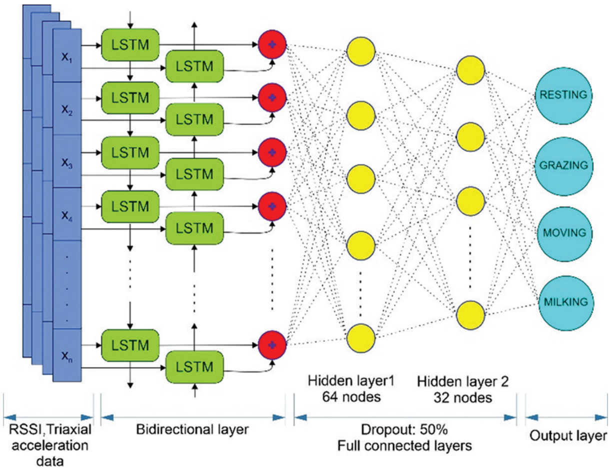


Fig. 4. Architecture of the proposed Bi-LSTM model

In this study, a deep learning-based behavior classification system is developed using a Bi-LSTM network, as shown in Fig. 4. Each LSTM layer in the Bi-LSTM architecture is configured with 64 units, enabling the model to effectively process bidirectional temporal patterns in the input data. To reduce the risk of overfitting, a dropout rate of 0.5 is applied to the LSTM layers during training. The outputs from the forward and backward layers of the Bi-LSTM are then concatenated and fed into two fully connected hidden layers: the first containing 64 neurons and the second containing 32 neurons. Network weights are updated using the backpropagation algorithm.

The output layer of the model consists of four neurons corresponding to the four classified cow behaviors: "Resting," "Grazing," "Moving," and "Milking." The hidden layers employ the ReLU activation function to enhance non-linearity, while the output layer uses the Softmax function to transform the outputs into probabilities, allowing the system to identify the most likely behavior for each cow.

4. EXPERIMENTAL RESULTS

4.1. EXPERIMENTAL SETUP AND TRAINING DATA COLLECTION

To collect data for training the proposed Bi-LSTM behavior classification model, an on-farm experiment was carried out at the Tan Tai Loc dairy farm, located in My Xuyen District, Soc Trang Province, Vietnam (coordinates 9°31′42.1″N, 105°54′08.7″E). Fig. 5 illustrates the overall configuration of the designed system, and Fig. 6 presents the primary components deployed during the experiment.

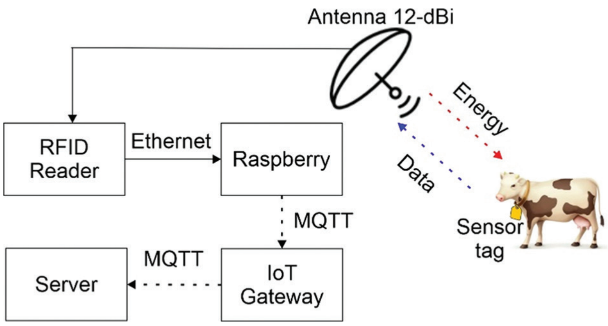


Fig. 5. The proposed model for collecting the training dataset

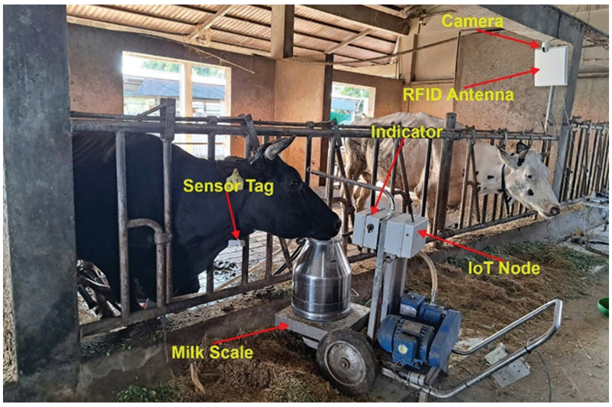
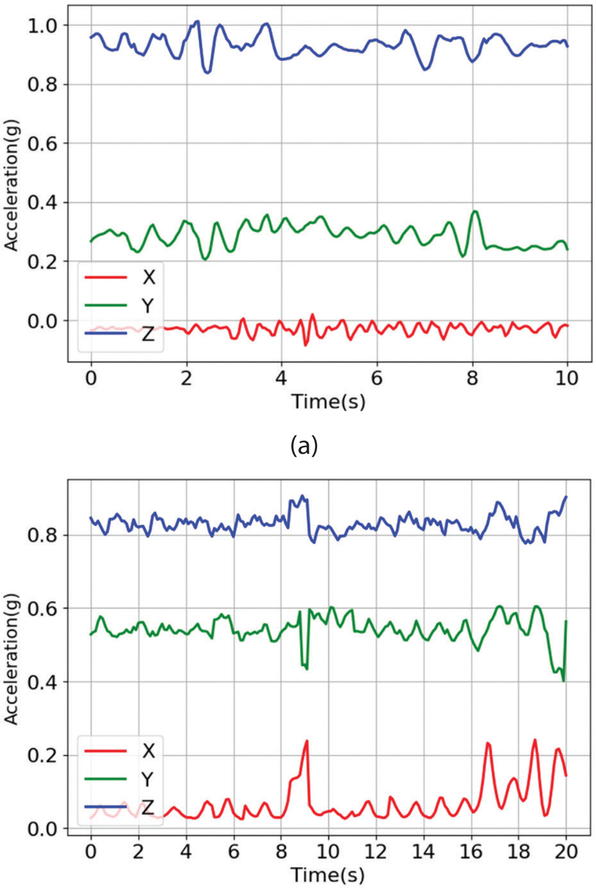


Fig. 6. Experimental setup at the Tan Tai Loc dairy cow farm

Two healthy dairy cows were housed in a 4 × 15-meter barn throughout the data acquisition period. An Impinj Speedway R420 RFID reader with two 12 dBi antennas was installed diagonally at opposite corners of the barn to transmit RF energy to the sensor tags attached to the cows' necks. A server was connected to the reader to collect data from the sensors. To ensure data consistency, all devices were securely mounted to keep the orientation of the sensor tags unchanged during the entire experiment. A CA-H200CX camera (Keyence, Japan) was installed to record the behavior of each cow. The milking area was permanently arranged at the left corner of the barn, adjacent to the RFID reader and antennas.

With this configuration, the ID number, RSSI values, and triaxial acceleration data from each cow were regularly recorded. Each day, the farmer performed milking at two fixed times, 9:00 a.m. and 3:00 p.m., corresponding to two data acquisition sessions for the milking behavior. During the remaining periods, the system continuously collected data associated with resting and locomotion behaviors. Previous studies have employed a wide range of sampling frequencies for livestock behavior monitoring, ranging from high rates above 50 Hz [33] to medium rates around 25 Hz [34-36]. To achieve an optimal balance between the sampling interval and device energy consumption, this study adopted a sampling frequency of 10 Hz. Fig. 7 and 8 illustrate representative samples received from neck-mounted sensor tags corresponding to the four behavioral states of the cows.



(a)

(b)

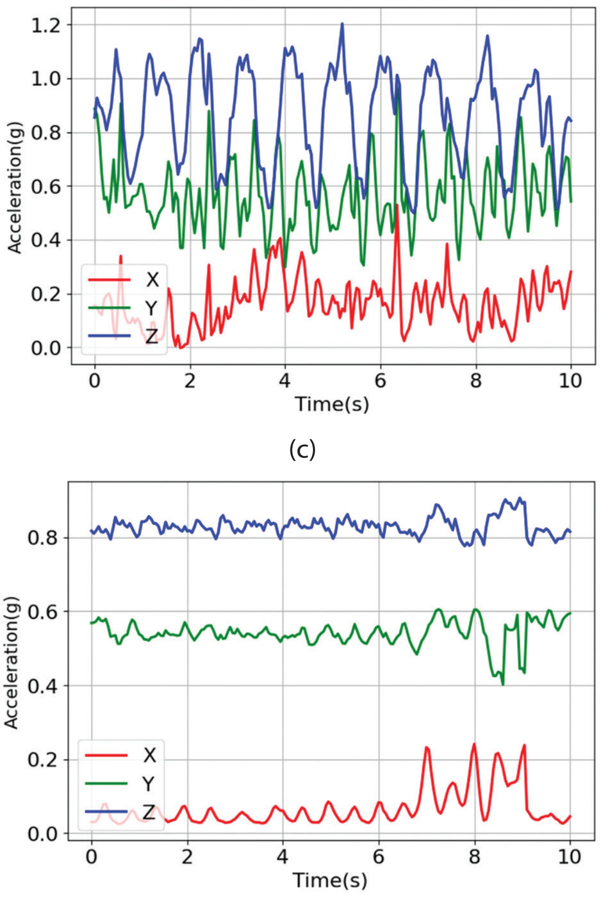


Fig. 7. Recorded waveforms of four behaviors of dairy cows: (**a**) Resting, (**b**) Grazing, (**c**) Moving, (**d**) Milking

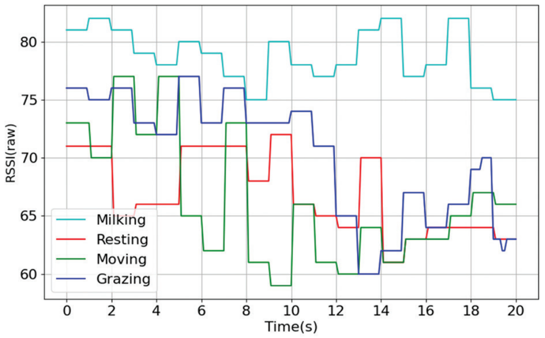


Fig. 8. Recorded waveforms of RSSI values of dairy cows from sensor tags in four different behaviors

After the complete dataset was collected, the labeling of the four distinct behaviors was carefully performed by cross-referencing the recorded timestamps with the corresponding video observations. The results are presented in Table 1.

In this study, the dataset collected from each cow was randomly divided into two subsets: a training set and a testing set, following a split ratio of 80:20. During training, the batch size was set to 32, and the number of epochs was configured at 5,000. The cross-entropy loss function was employed, and the Adam optimizer was used to train the model. To minimize overfitting during model evaluation, a cross-validation technique was incorporated, which also facilitated the optimization of hyperparameters for the deep learning model.

Table 1. Distribution of collected samples across the four behaviors

Label	Number of samples	Description
Resting	150130	A dairy cow lies or sleeps
Moving	50199	A dairy cow moves from one position to another continuously
Grazing	81811	A dairy cow eats food without raising its head
Milking	57768	The cow is tied and milked by the farmer

More specifically, five-fold cross-validation was used to evaluate the performance of the Bi-LSTM model under various parameter configurations for both the Bi-LSTM layer and the subsequent two hidden layers. The average accuracy across five folds was computed to identify the optimal model architecture. In addition, an early stopping technique was implemented to choose the model weights yielding the best performance. All procedures for model development, training, and evaluation were carried out using Python.

4.2. BI-LSTM MODEL PERFORMANCE

The accuracy of the Bi-LSTM behavior classification model can be accessed using a confusion matrix. A confusion matrix is a visual analytical tool commonly used in multi-class classification problems, which provides detailed insights into model performance. It consists of two dimensions: one representing the ground truth classes and the other representing the predicted classes generated by the model. Fig. 9 presents the confusion matrix for the Bi-LSTM model. According to the results, the Bi-LSTM model exhibits a very low misclassification rate for the behaviors "Grazing", "Moving", and "Resting", each with an error rate of 2%. Notably, the behavior "Milking" shows the lowest error rate, at only 1%.

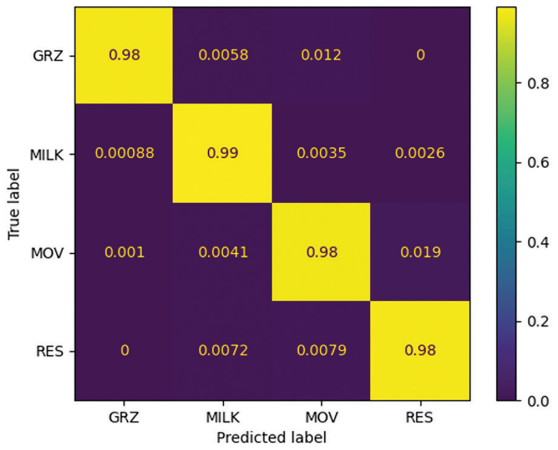


Fig. 9. Confusion matrix of the proposed Bi-LSTM model, in which GRZ, MILK, MOV, and RES stand for grazing, milking, moving, and resting behaviors, respectively

In addition, a classification report was generated to evaluate the overall performance of the Bi-LSTM model using standard metrics, including precision, recall, and F1-score. Specifically:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

where TP (True Positive) is the number of correctly predicted positive samples and FP (False Positive) denotes the number of negative samples incorrectly classified as positive. Precision measures the proportion of correctly predicted positive samples among all predicted positives, indicating the model's reliability when predicting a positive instance.

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

Here, FN (False Negative) refers to the number of positive samples that were missed (classified as negative). A higher recall indicates fewer missed positive cases.

$$F1 - Score = \frac{2 \times (Precision \times \mathrm{Recall})}{\mathrm{Precision} + \mathrm{Recall}} \tag{8}$$

The F1-score provides a measure that reflects whether a model is both accurate (high Precision) and comprehensive (high Recall). A high F1-score, therefore, introduces a consistently strong classification performance across both aspects — it predicts correctly and catches most of the true cases.

Table 2 summarizes the classification report of the experiment. The results show that all metrics exceed 98%, in which the overall accuracy of the model reaches 98%. These results demonstrate that the proposed Bi-LSTM model achieves very high classification performance and can effectively distinguish the primary behaviors of dairy cows. By incorporating each cow's identification data, the Bi-LSTM-based system is capable of reliably determining which cow is being milked in real farm environments, even when neighboring cows may introduce potential signal interference.

Table 2. Classification Report of the proposed Bi-LSTM model for dairy cow behavior recognition

Label	Precision	Recall	F1-score
Grazing	0.99	0.98	0.99
Milking	0.98	0.99	0.98
Moving	0.97	0.98	0.97
Resting	0.99	0.98	0.99
Accuracy		**98%**	

Another important indicator of model performance and generalization capability is the training and validation loss curves. As illustrated in Fig. 10, both losses decrease steadily and stabilize below 0.1 until approximately the 460th epoch, suggesting that the training process is proceeding effectively. After this point, the validation loss starts to exceed the training loss by approximately 0.03, indicating mild overfitting. With the relatively low degree of overfitting, the model can be concluded to exhibit satisfactory generalization performance.

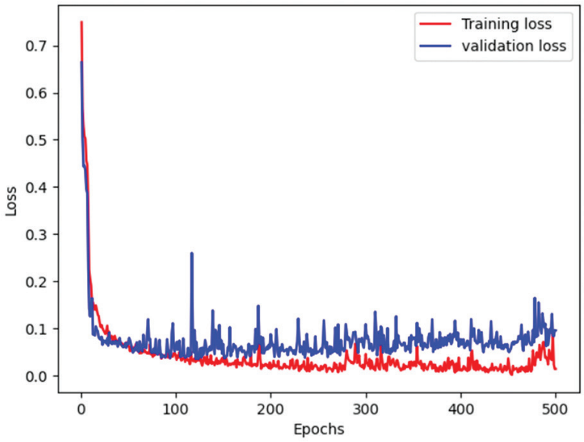


Fig. 10. Training and validation loss curves

4.3. PERFORMANCE OF INDIVIDUAL MILK-YIELD MANAGEMENT SYSTEM

To evaluate the performance of the proposed individual milk-yield management system, an extended on-farm experiment was conducted using a full cohort of 20 dairy cows, following the system architecture illustrated in Fig. 1. In this setup, each cow is equipped with a neck-mounted sensor tag that transmits triaxial acceleration data, RSSI values, and its identification code (ID) to the RFID reader positioned within the monitoring area. A Raspberry Pi module embedded with the pre-trained Bi-LSTM model is employed to collect these sensor signals and subsequently classify cow behaviors in real time, enabling the system to accurately determine which cow is being milked. The identified cow ID is then forwarded to the IoT node via LoRa-based wireless communication. Once milking is completed, the operator presses the "Complete" button on the IoT node to transmit the detected ID and the measured milk yield (recorded by the weighing sensor through an RS232 communication interface) to the IoT gateway. Finally, all data are forwarded to the central storage server via the MQTT protocol.

The semi-automatic milking system was deployed at Tan Tai Loc dairy farm for a period of three months. During this time, the dairy cows were housed in the same barn illustrated in Fig. 6 for continuous monitoring under real operating conditions. Table 3 summarizes the results obtained from the deployment.

Table 3. Performance of cow identification

Month of deployment	Number of milking sessions	Correctly identified cow IDs	Incorrectly identified cow IDs
1st	1190	1182	8
2nd	1188	1183	5
3rd	1194	1185	9
Total	3572	3550	22
Rate		99.38%	0.62%

During the milking process, some individual cows (e.g., the white cow in Fig.6) were occasionally observed to inadvertently move into the vicinity of the antenna, resulting in the RSSI values that were comparable or even higher than those of the cow being milked. However, the system could accurately distinguish these exceptional cases because the milking cow exhibited both low acceleration and relatively stable RSSI patterns, indicating a stationary state. The simultaneous integration of both these data, therefore, significantly enhances the robustness of behavior recognition. In the real-world deployment, the system achieved an identification accuracy of up to 99.38% for the "Milking" behavior, confirming the effectiveness and high reliability of the proposed method.

Table 4. Comparison of Related Studies on Dairy Cow Behavior Recognition Using Accelerometer Sensors

No	Reference (Year)	Sensor Type	Behaviors	Key Features	Accuracy / F1-score
1	Bloch et al. (2023)	3-axis ACC	Feeding behaviors	CNN + Transfer Learning	Acc=93.9%
2	Balasso et al. (2023)	3-axis ACC	Standing, moving, feeding, ruminating, resting	CNN	F1=0.96
3	Proposed System (2025)	ACC + RSSI	Grazing, resting, moving, milking	(ACC + RSSI), real-time ID tracking	Acc = 98 %, F1 = 0.98

We further compared the experimental findings of this study with some recent deep learning-based approaches for livestock behavior recognition. Bloch et al. (2023) [33] employed a CNN model combined with transfer learning to classify feeding and non-feeding behaviors based on triaxial accelerometer data, achieving an overall F1-score of 93.9%. Similarly, Balasso et al. (2023) [37] utilized a 1D-CNN to analyze tri-axial accelerometer data and successfully identified five activity states with an average F1-score of 0.96. In contrast, the proposed system integrates both accelerometer and RSSI measurements within a Bi-LSTM deep learning framework, enabling the model to capture both motion dynamics and spatial proximity information during the milking process. This multimodal fusion significantly enhances classification robustness, particularly in distinguishing between cows in close proximity—an inherent limitation of accelerometer-only methods. Consequently, the proposed Bi-LSTM + RSSI model achieved the highest performance among the reviewed methods, with an accuracy of 98 % and an F1-score of 0.98, demonstrating its strong potential for reliable real-time deployment in smart dairy farming environments.

5. CONCLUSION

The study successfully developed an intelligent system that enables monitoring of the milk yield from individual dairy cows while also improving the lifespan of the sensor tags. The system allows daily monitoring of milk production in a herd of 20 cows. By integrating an improved Bi-LSTM deep learning algorithm that utilizes two types of data—RSSI signals and accelerometer readings—the system can accurately identify the specific cow being milked while effectively filtering out noise from other cows moving in the surrounding area. Identification information of each cow is automatically stored on a central server via an Internet connection. The ID recognition system achieved an accuracy of up to 98% during model validation and nearly 100% in real-world deployment. These results demonstrate that the developed system has strong potential for wide application in modern dairy farms, supporting precise daily control of milk yield, enhancing herd productivity, and prolonging the milking lifespan of dairy cows.

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