Computers and Electronics in Agriculture 214 (2023) 108181

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Digital twin perception and modeling method for feeding behavior of dairy cows

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ARTICLE INFO

Keywords:
Digital twin
Indoor positioning
IMUs
Dairy cow
Deep learning

ABSTRACT

The digital twin of cows holds significant promise for advancing animal welfare and production efficiency. This paper aims to propose an architecture for digital twins of cows that covers their entire lifecycle. A digital twin solution has been developed that utilizes indoor positioning data and inertial measurement unit (IMU) data to construct a cow's digital shadow. As an example, the paper utilizes the classification of cow feeding and non-feeding behaviors to study the digital twin perception and modeling methods. A custom-made collar integrated with utilized ultra-wideband (UWB) chips and inertial measurement units (IMUs) was utilized to collect real-time location and neck movement data from five healthy non-lactating Holstein cows. The collected data was transmitted via UWB signals to the positioning anchor and subsequently forwarded to a local server. To classify the feeding and non-feeding behaviors of the cows, three methods were employed: Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Long Short-Term Memory (LSTM). According to the experimental results, all three classification methods were effective, however, LSTM outperformed the others. Employing solely IMU data and implementing the LSTM, the precision of identifying bovine foraging behavior reached 91.05%, with concomitant precision and recall rates of 92.23 and 91.35%, respectively. Through an integration of the data from indoor position detection and IMU devices and the employment of LSTM, the accuracy of identification increased to 94.97%, with a precision rate of 99.99% and a recall rate of 93.86%. The trial of the digital twin solution demonstrated the rationality and technical feasibility of the digital twin architecture, which holds significant reference value for the development of animal digital twins in the animal husbandry industry.

1. Introduction

Digital twin technology is characterized by a physical entity and its corresponding virtual replica, with data connections between them. An increasing number of individuals utilize digital twin technology as a way to enhance the performance of physical entities through the use of computing technology, utilizing its virtual counterpart to achieve these calculations (Jones et al., 2020). Kritzinger et al. (2018) divided digital twin integration into three categories according to the level of integration: digital model, digital shadow, and digital twin. A digital model is a numerical representation of the physical object, and does not involve any automatic data exchange between physical and numerical objects. A digital shadow is an automatic, one-way data transfer between an existing physical object and its digital replica. Digital twin, on the other hand, refers to bidirectional data flow between physical and digital objects, with full integration. The implementation of digital twin in animal husbandry can promote the realization of smart agriculture concepts. Ranches of the future will rely on real-time data processed through artificial intelligence analyses, which can lead to better business decisions, improved animal health and welfare, and maximized agricultural resource returns (Verdouw et al., 2021). Currently, digital twinning technology can support personalized management of complex systems, integrate information, quantify uncertainty, simplify work, and facilitate access control (Pylianidis et al., 2021). However, the use of digital twinning technology in agriculture is not yet widespread.

Precision livestock farming (PLF) is a pioneering technology in the digital twin of animal husbandry (Neethirajan & Kemp, 2021). In previous works, identifying behavioral characteristics of cows has been a significant focus, as these factors have been found to effectively gauge a cow's production and health. Notably, feeding behavior is seen as the

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https://doi.org/10.1016/j.compag.2023.108181
Received 23 May 2023; Received in revised form 21 August 2023; Accepted 24 August 2023
Available online 29 September 2023
0168-1699/© 2023 Published by Elsevier B.V.

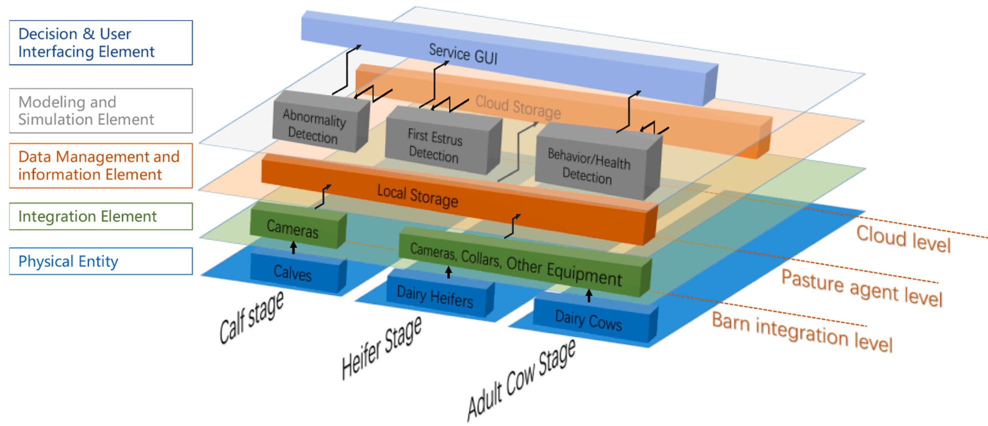


Fig. 1. Digital twin architecture for dairy cows.

primary behavioral response to cold stress in cows. Cows will adjust their dry matter intake automatically during cold weather, in order to boost their heat production and maintain body thermal balance (Mader et al., 2011). Initially, researchers typically relied on observing or recording cow behavior via video to identify changes (Müller & Schrader, 2003). Technological advancements in the last two decades, such as the development of sensors, networks, cloud computing, and artificial intelligence, have significantly improved the effectiveness of information collection and analysis resulting in the rapid growth of PLF (Tedeschi et al., 2021). Homer et al. (2013) utilized ultra-wideband (UWB) radio technology to identify the onset of estrus in cows and immediately report its occurrence. In the realm of cow behavior detection, the UWB positioning technology presents notable merits characterized by its high accuracy, robustness, and capacity to monitor intricate locomotion patterns within intricate settings. Grinter et al. (2019) conducted a study that utilized animal sensors to monitor activities of lactating cows, including rumination, feeding, and resting. To classify cow behavior patterns, Peng et al. (2019) gathered monitoring data using inertial measurement units (IMUs). Shen et al. (2020) employed machine learning algorithms to identify cow feeding behavior through the interpretation of data collected by a three-axis accelerometer sensor. To detect calving and estrus behavior in cows, Benaissa et al. (2020) utilized indoor positioning sensors coupled with acceleration sensors. Wang et al. (2022) employed machine learning methods to identify the onset of estrus in cows. The data was gathered from neck tags that collected acceleration and location information. Riaboff et al. (2021) investigated the identification of lame behavior in cows through the analysis of acceleration and GPS sensor data collected on farms. In proposing a new method for predicting cow behavior, Shakeel et al. (2022) suggested the use of microchips that cows would swallow to collect acceleration data, which would then be used in their behavior recognition and computation scheme (BRCS). Although the studies mentioned above demonstrate the importance of UWB positioning technology and IMUs in collecting cow behavior data, they solely focus on identifying singular aspects of behavior feature recognition, thus lacking comprehensive research and general methods.

The method of perceiving and recognizing cow behavior described above has provided the technical foundation for digital twin. Currently, the dairy industry is shifting towards larger scale, more intensified and standardized production. Digital twin-related technologies are used to achieve comprehensive physiological monitoring and modeling of cows (Purcell & Neubauer, 2023), in order to construct virtual cows without disturbing actual cows and make dairy farming more controllable. This technology has the capacity to facilitate decision-making processes, such as disease prediction, feeding management, and health assessment. With the ability to reduce cow stress, improve management levels, and promote animal welfare (Tao et al., 2022).

This study proposes a novel architecture for creating a digital twin of cows and implements a solution for constructing their digital shadow. By utilizing an innovative intelligent collar that incorporates UWB chips and IMUs, this research gathers data on the position and movement of cows. The UWB anchors are employed to receive data transmitted by the collar. To achieve accurate recognition of feeding and non-feeding behaviors of cows, Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Long Short-Term Memory (LSTM) models are used to analyze the behavior data collected by the collar. Furthermore, this study successfully integrates elements of perception, data management, and modeling into the digital twin architecture, and conducts an initial exploration of simulation and visualization user interfaces.

2. Materials and methods

2.1. Digital twin architecture for dairy cows

This study proposes a digital twin architecture for cows to manage dairy cow production and improve animal welfare. The architecture, depicted in Fig. 1, is divided into three levels, namely the barn integration level, the pasture agent level, and the cloud level, based on the reliability of the data. Also, cows are categorized into three stages, which include the calf stage, heifer stage, and adult cow stage. The architecture is functionally divided into five layers, which comprise the physical entity layer, the integrated layer, the data management and information layer, the modeling and simulation layer, and the decision and user interfacing layer. Camera-based monitoring is employed for the behavior and health of the calf stage. This primarily involves observing the calf's mental state, fecal, milk and food intake, enabling early detection of abnormality. In contrast, visual or sensor information is collected through cameras, smart collars, and other devices to analyze estrus and other behaviors during the heifer and adult cow stages. This architecture enables a focus on the initial estrus in heifers, while the daily behaviors of adult cows provide insights into both estrus and health conditions. It provides decision support for pasture managers via a visual user interface. The video is stored on the pasture server, while sensor information and the derived secondary features of the video are stored and modeled on the cloud. Lastly, the rendering of visualizations is conducted by relevant servers and hosts at the pasture agent level.

To establish a digital twin of dairy cows within this architectural framework, the initial phase encompasses the integrated layer, which facilitates the real-time collection and integration of data from physical dairy cows through the utilization of cameras, collars, and other sensor devices. The following phase involves the data management and information layer, which is accountable for representing and storing the acquired data. Next, the modeling and simulation layer generates models and performs simulations of the physical dairy cows, utilizing

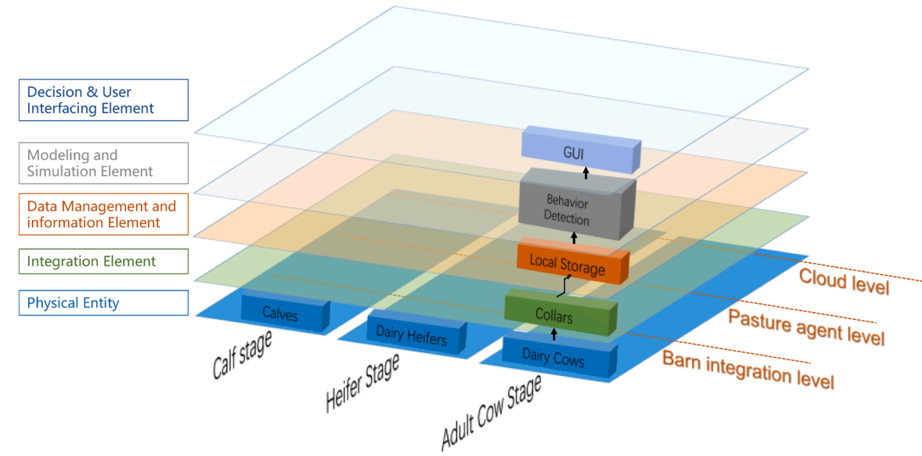


Fig. 2. Digital twin architecture implemented in this study.

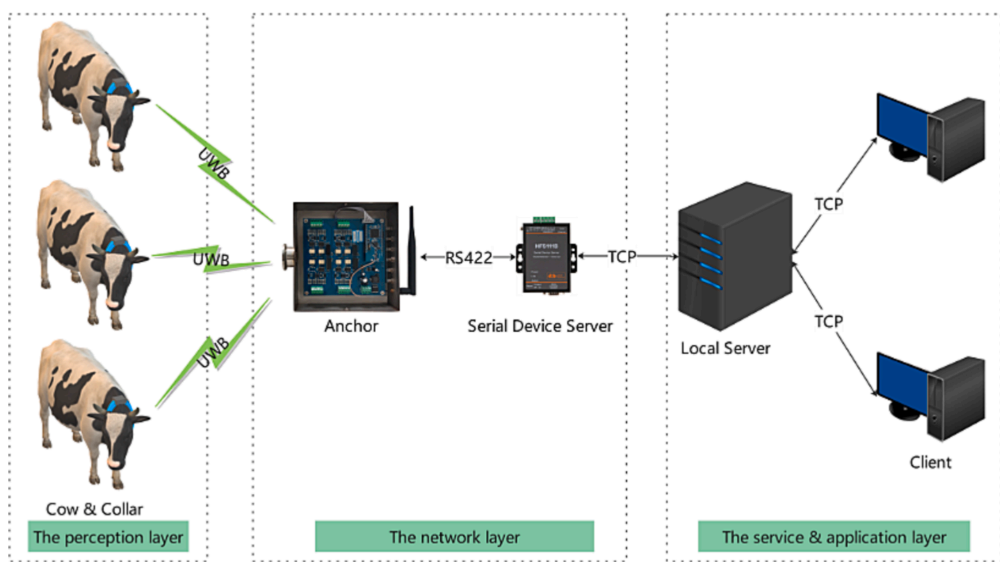


Fig. 3. The overall structure of the cow behavior monitoring system.

the data that has been collected. Lastly, the decision and user interfacing layer provides ranch managers with essential decision support and visualization tools which assist in tasks such as the analysis of historical and real-time data to manage individual dairy cows effectively.

This study primarily focuses on the adult cow stage in the life cycle of dairy cows, which is illustrated in Fig. 2. The collars, anchors and other devices utilized within the barn are among the barn integration level perception layer devices. The server belongs to the local server of the pasture agent level, executing part of the data classification algorithm and data modeling functions. The client program endeavors to project the cows' position and status in a 2D form, corresponding to the decision and visualization layer. By implementing the functionalities of the architecture in Fig. 1, the rationality and technical feasibility of the digital twin architecture for dairy cows are established.

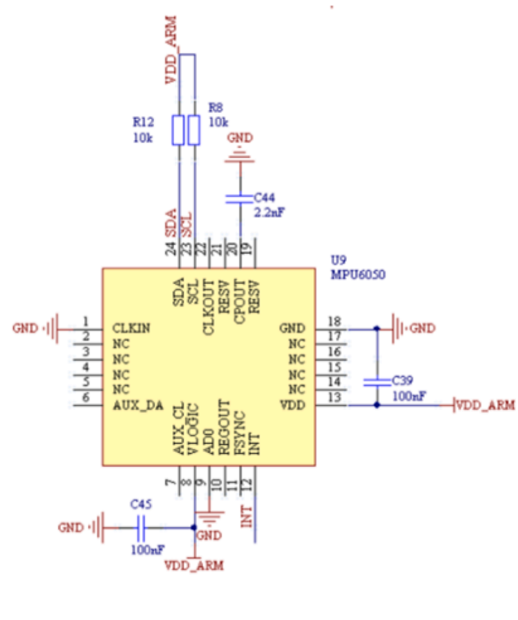
2.2. Experimental setup

This study utilizes neck-based IMU and indoor positioning data to precisely detect feeding and non-feeding behavior in cows. The experimental device's hardware platform consists of specially designed collars, anchor points, a serial device server, and an application server. The collar incorporates a three-axis accelerometer, a three-axis gyroscope, and an UWB chip to collect data on motion and transmit it to anchor points. Similarly, the anchor points integrated with an UWB chip and RS422 communication module execute data reception, initial calculation, and forwarding to the application server. Fig. 3 depicts the system's overall structure, where the collar placed on the cow's neck wirelessly communicates with the anchor points via UWB signals. The anchor points, serial device server, and client connect to one another via twisted pairs to form a network.

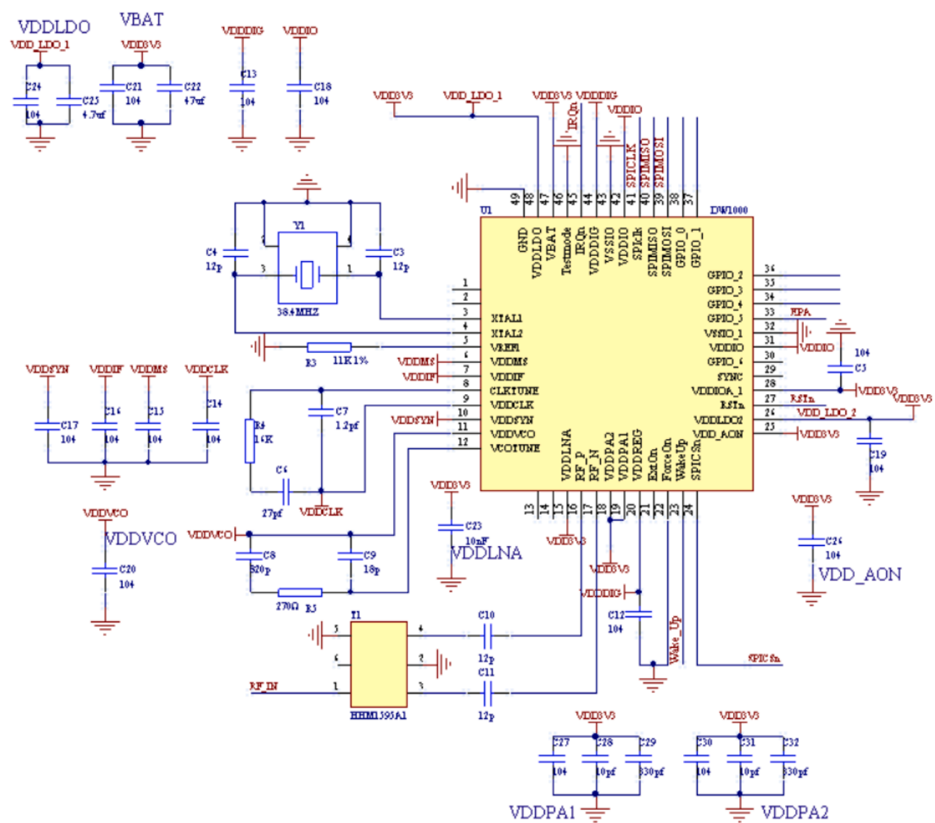
The software platform includes four components: The Collar

Table 1
Header format of communication protocol between anchor points and server.

Type	Packet ID	Packet length	Packet type	Destination address	Source address	Sequence number	Reserved	Checksum
Number of bytes	2	1	1	2	2	2	1	1
Details	0x4454	0x0-0xff	0x11	0xffff	0x0000	0x0000-0xffff	0x00	0x1F



(a)



(b)

Fig. 4. (a) IMU sensor circuit and (b) UWB circuit on the collar.

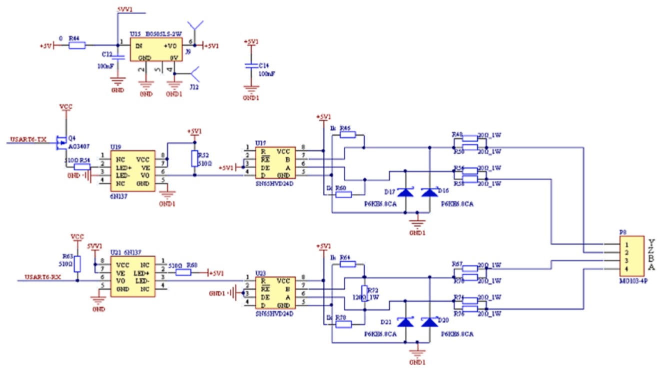


Fig. 5. RS422 circuit on the anchor point.

Processing Program, Anchor Point Forwarding Program, Server Program, and Visualization User Interface Program. The Collar Processing Program collects and sends real-time cow IMU data and positioning beacons to anchor points. The Anchor Point Forwarding Program receives the data, calculates the absolute time difference of the beacons' arrival at each anchor, and forwards the results to the Server. The Server Program receives all data and completes storage and calculation. The Visualization User Interface Program mainly completes the query and display of server results, as well as the maintenance of basic data. The Anchor and Server communicate via TCP, and the Communication Protocol Data Header Format of the application layer is listed in Table 1. In order to complete the transmission and function of different data, there are a total of seven different formats of Data Packets based on the following header.

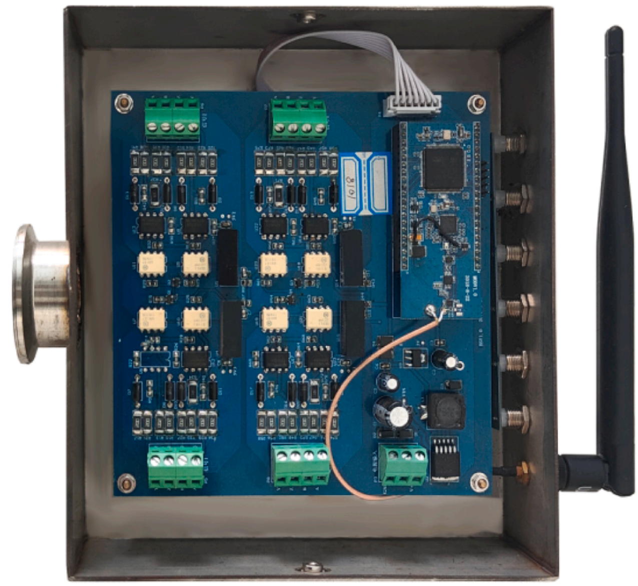
2.2.1. Data collection collar

The collar is composed of four main sections: a microprocessor section featuring an STM32F103CBU6 model, an IMU sensor section that utilizes the MPU6050 model, an ultra-wideband positioning section containing the DW1000 model, and a power circuit section. The microprocessor section is responsible for collecting, processing, and transmitting data obtained from the IMU sensor to the wireless ultra-wideband circuit. As illustrated in Fig. 4(a), the IMU sensor section is shown to sense and quantify physical motion, and transmit the data to the microprocessor unit. Furthermore, Fig. 4(b) exemplifies the circuit diagram of the ultra-wideband positioning section, which sends location beacon and motion sensor data. The power circuit section stabilizes the 3.6 V lithium battery voltage to 3.3 V, providing power to each circuit section.

2.2.2. Anchor point

An anchor point is comprised of four main sections: a microprocessor section utilizing the STM32F407VET6 model, an UWB positioning section containing the DW1000 model, an RS422 communication section with the SN65HVD24P model, and a power circuit section. Fig. 5 illustrates the circuit diagram for the RS422 communication section. The STM32 microprocessor wirelessly exchanges data with the cow collar via the UWB positioning circuit, and calculates the absolute time difference when the collar's location beacon arrives. Simultaneously, the RS422 communication circuit realizes bidirectional data communication with the server. Lastly, the power circuit section stabilizes the input 12 V DC voltage to 5 V and 3.3 V, and provides power to each circuit section.

The anchor was placed in a metal casing (190 × 175 × 60 mm), displayed in Fig. 6(a). During testing, the anchor covered by a stainless-steel cover connected to an external antenna via a signal cable. The collar, weighing 93 g was designed with a 3D-printed shell, electronic parts, and a battery, measures 74 × 54 × 26 mm. Fig. 6(b) shows a physical image of the cow collar, with the top showing the internal structure and outer casing, and the bottom showing the collar with the strap attached. The collar and battery weigh a total of 93 g and are placed in the middle of a 3D printed box (74 × 54 × 26 mm).



(a)

(b)

Fig. 6. (a) Physical image of the anchor point and (b) the collar.

2.2.3. Measurement system

During the experiment, the collar was securely fastened to the top of the cow's neck by means of a strap, with its position indicated in Fig. 7. The collar gathers acceleration and angular velocity data from the cow at a sampling frequency of 4 Hz, as well as position information at a rate of 1/3Hz, both of which are transmitted to the anchor point via the UWB signal.

The study area, spanning 18.4 m × 8.4 m, was divided into two 9 m × 8 m grids and were fitted with six anchor points. Positioned at a height

Fig. 7. The collar and sensor position.

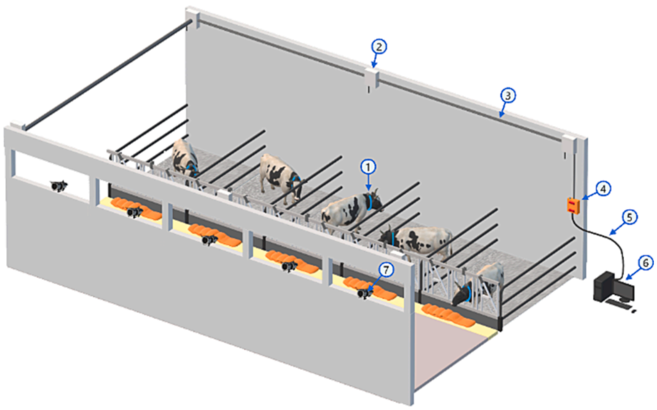


Fig. 8. Schematic diagram of the measurement system. collar (1), anchor (2), RS422 bus (3), HF4111B (4), twisted pair (5), server (6), camera (7).

of 3 m above ground level, with the antenna facing downwards and 20 cm away from walls, each anchor point facilitates clock synchronization and data transmission through connection via a RS422 bus. A master anchor point from the six established was connected to the HF5111B serial port device server outside of the study area by means of RS422. The serial port device server utilizes full-duplex communication with the farm server via TCP protocol, and is linked via twisted pair. The anchor points collect location data and IMU data, transmitted to the serial port device server through the RS422 bus before being sent to the farm server via TCP protocol. To ensure the security of the farm server, it is positioned within an adjacent barn devoid of livestock. Fig. 8 illustrates the measurement system which encapsulates the experiment.

Prior to entering the farm, the equipment was debugged for three months, and the static positioning accuracy and error of the cow collar obtained by the TDoA algorithm were 0.15 ± 0.04 m, while the dynamic positioning accuracy and error were 0.28 ± 0.09 m. Before the equipment started working, the anchor point timing was synchronized with the National Internet Time Service (National Time Service Center, Xi'an, China) through server settings. The coordinates of the feeding area in the cowshed were measured and recorded in the system during this research. Based on the real-time location data, the system can determine whether the cow is present in that specific area. The acceleration and angular velocity data from the cow collar were sampled at a frequency of 4 Hz. Data sets were created every 90 s and sent back to the server. Each dataset consists of 360 lines of data. Each line includes the collar ID, time, packet number, acceleration information in three dimensions, and angular velocity information. The server stores this information in separate CSV files, organized by date and collar number. The location data is uploaded every three seconds, including the absolute time difference between the arrival times of the beacon at the six anchor points. The server calculates precise location data and stores the collar ID, location information, and time in the Oracle database.

2.3. *Experiment and data processing*

From May 27th to June 13th, 2022, this study conducted on-site experiments at the A'cheng Experimental Base of Northeast Agricultural University. Throughout the experimental process, the study followed the "Regulations for the Administration of Experimental Animals in the People's Republic of China.".

2.3.1. *Experimental objects*

Five healthy non-lactating Holstein cows, 3 ± 0.5 years old and weighing 410 ± 40 kg each were used as experimental subjects. The cows were housed individually in enclosed spaces of size 5 m × 3 m × 1.5 m with iron fences. The cows were fed twice daily at 4:00 and 15:00 with a concentrate-to-hay ratio of 3:7. The concentrate is composed of corn (32.5%), corn protein feed (15%), corn germ meal (12%), peanut hulls (15%), soybean dregs (10%), DDGS (8%), molasses (4.5%), limestone (1%), salt (0.8%), baking soda (0.5%), magnesium oxide (0.5%), and premix (0.2%). The hay is cut into pieces with 48% longer than 19 mm, 22% between 8 and 19 mm, 18% between 1.2 and 8 mm, and 12% smaller than 1.2 mm. At each feeding, the cows were given 3 kg of concentrate and 7 kg of hay. The cows had access to drinking water throughout the experiment.

2.3.2. *Visual observation for feeding behavior*

To analyze cow behavior, five network cameras (CS-C1C, HIKVISION) were positioned 2.6 m high on the steel beams in the cowshed, 3 m away from the feeding area to record individual cow behavior. Each camera has a 128 GB Micro SD memory card. The video data is copied to a server and wiped from the SD card data weekly during the cows' non-feeding period. The video data had a resolution of 1920 × 1080, clearly capturing experimental subjects and areas of interest. The videos helped in identifying cow behaviors such as feeding, drinking, and rumination. Three experienced caretakers monitored the videos to record details of the cow's feeding behavior, which was then averaged.

2.3.3. *Data pre-processing*

This study successfully collected acceleration, angular velocity, and position data from five experimental subjects. 1,381,800 items of positioning data and 16,582,270 items of acceleration and angular velocity

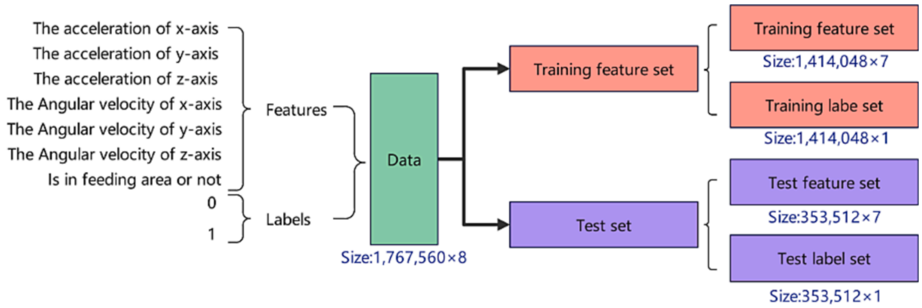


Fig. 9. Dataset structure.

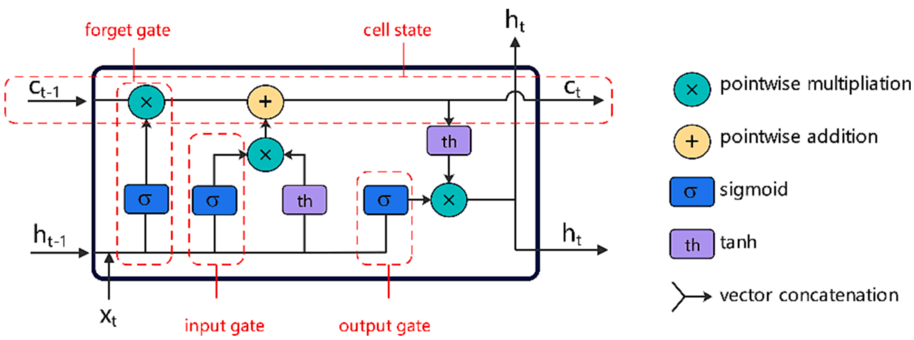


Fig. 10. LSTM memory cell structure.

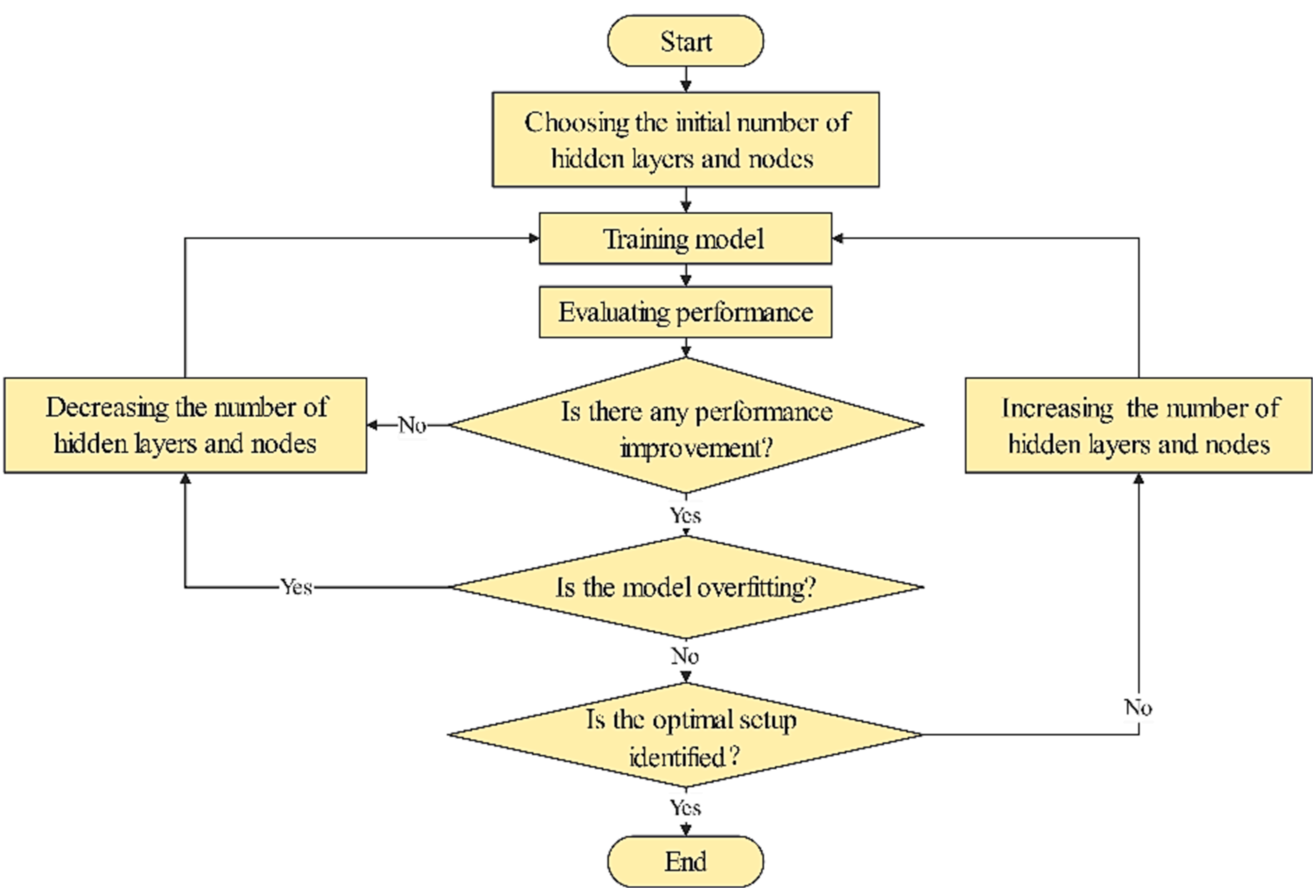
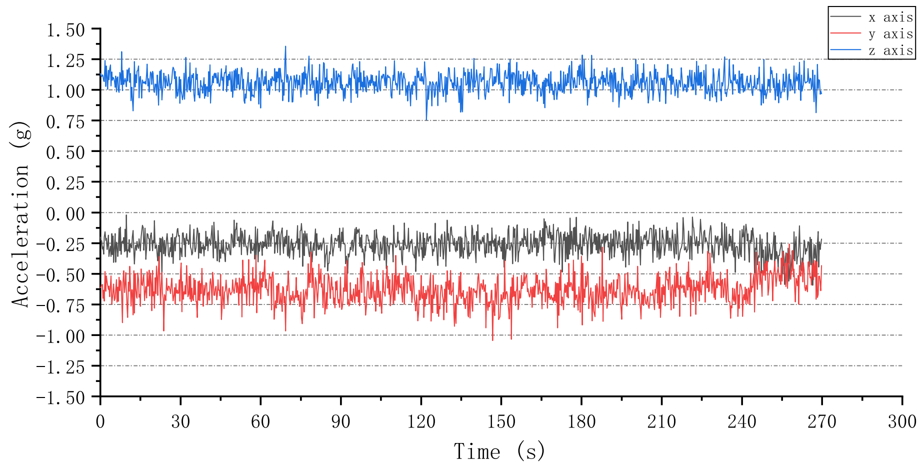
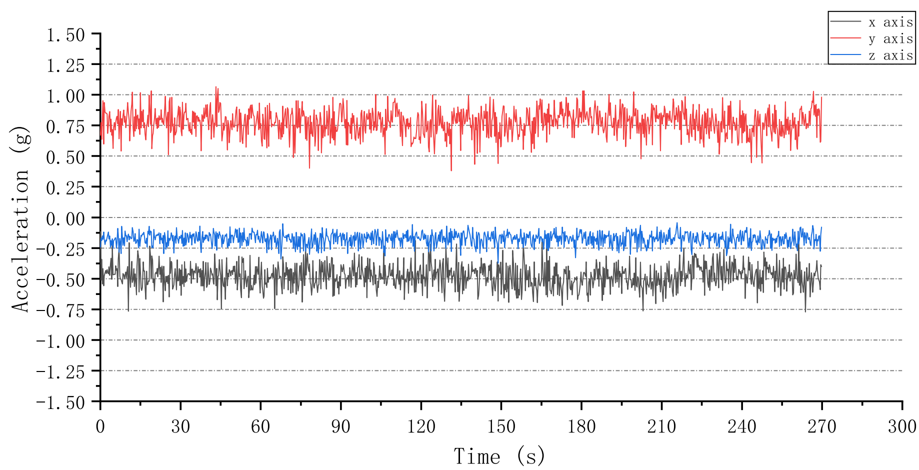


Fig. 11. Optimal hidden layers and nodes decision flowchart.



(a)



(b)

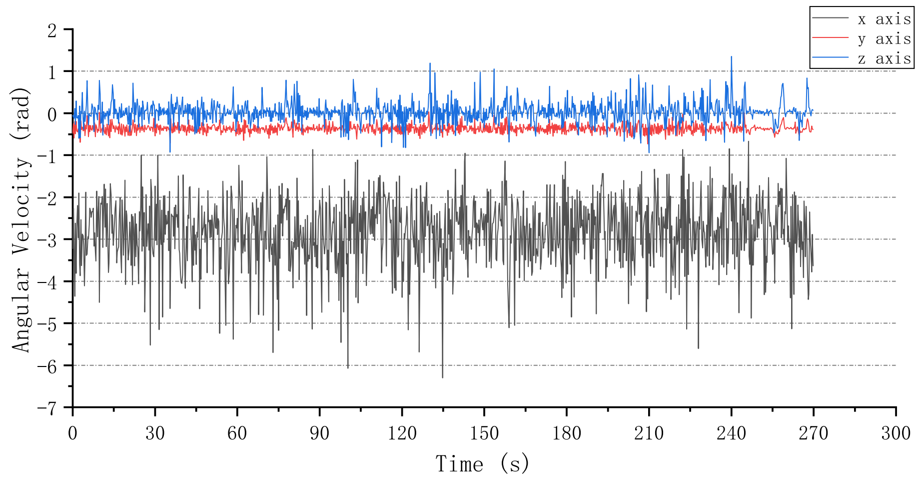
Fig.12a. (a) Feeding and (b) non-feeding acceleration waveforms.

sensor data were collected from the cows. The two types of data were aligned based on millisecond-accurate time measurements. The coordinate range of the feeding area for cows was defined through measurement, and the two-dimensional position coordinates of the cows were then transformed into binary data. A value of “1” represented that a given collar’s position was within the feeding area, while a “0” indicated that it was not. Data collected during feeding times were labeled “1”, while data taken during non-feeding moments were labeled as “0”, based on video observations. The collected motion sensor data were normalized with respect to their maximum values. The resulting maximum-normalized data lied in the range of [0,1]. Data were recorded from a total of 5 cows, of which 4 were utilized in training the model while data from the remaining cow served to evaluate the model’s performance as a test set. The data collected consisted of three-dimensional accelerations, three-dimensional angular velocities, information regarding the collar position with respect to the feeding area, and labeled data. Training the algorithm directly on the collected data without adjusting the ratio of feeding and non-feeding data could result in a bias towards the non-feeding state. This is because the data collected for the non-feeding state was substantially larger in comparison to the feeding data. To combat this possibility, the non-feeding state data was pruned until the ratio of feeding data to non-feeding data was 1:1. Please refer to Fig. 9 for a representation of the division of data in the training and testing sets.

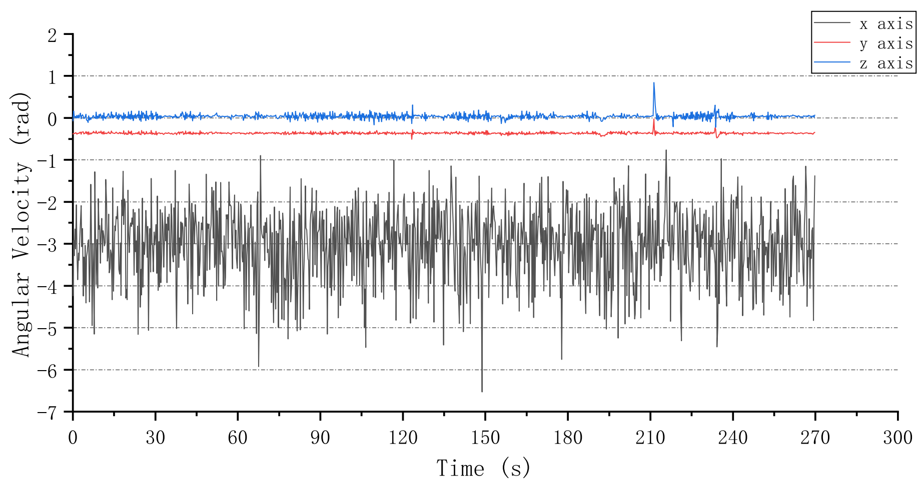
2.4. Classification algorithms

Machine learning is a powerful technique, which enables the discovery of hidden information within large and intricate data sets (Nobrega et al., 2020). Commonly utilized machine learning methods for classification of sensor data comprise SVM, KNN, Decision Trees (DT), and random forests. Each method exhibits distinctive capabilities in various classification assignments. Shen et al. (2020) employed KNN, SVM, and PNN classification algorithms to identify the feeding behavior of cows, with KNN achieving the highest classification accuracy. Benaissa et al. (2019) utilized DT and SVM algorithms to analyze accelerometer and pressure sensor data obtained from RumiWatch. The authors sought to classify feeding-related behaviors of cows, and found that SVM exhibited a higher degree of classification accuracy.

The LSTM network, introduced by Hochreiter and Schmidhuber (1997) to address long-term dependencies, has gained prominence in the field of artificial intelligence for its adeptness in extracting temporal features (Liu et al., 2022). Comprising input, hidden, and output layers, LSTM employs memory cells as its fundamental hidden layer units. Its standard structure, illustrated in Fig. 10, involves key components: h_{t-1} as the prior memory cell output, c_{t-1} as the previous memory cell state,



(c)



(d)

Fig. 12c. (c) Feeding and (d) non-feeding angular velocity waveforms.

h_t as the current memory cell output, c_t as the current memory cell state. Additionally, circles indicate point vector computations such as dot products and vector addition, while line mergings represent connections, and line crossings denote content replication and relocation to different locations.

The determination process of LSTM hidden layers and nodes count is illustrated in Fig. 11. The LSTM architecture employed in this study includes 10 hidden layers, each of which containing 10 nodes, with the Sequence length and Time steps set to 12 respectively. A threshold value of 0.5 is used to determine the binary classification task: predictions above or equal to the threshold are classified as 1, while the predictions below it are classified as 0.

To enhance the accuracy of digital shadow of dairy cows, this study employed SVM and KNN as machine learning algorithms to classify their feeding and non-feeding behaviors. The performance of the three algorithms was compared against each other.

2.5. Indices of performance

This study evaluated the classification performance of different algorithms on feeding behavior by determining the accuracy, precision, recall, specificity, and F1 score. These parameters are more effective when closer to 1. The definitions of each parameter are given below:

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$precision = \frac{TP}{TP + FP} \quad (2)$$

$$recall = \frac{TP}{TP + FN} \quad (3)$$

$$specificity = \frac{TN}{TN + FP} \quad (4)$$

$$F1\,score = \frac{2 \times precision \times recall}{precision + recall} \quad (5)$$

The parameters TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) in the above five formulas are defined below:

TP: The behavior is actually feeding, and the algorithm predicts it to be feeding.

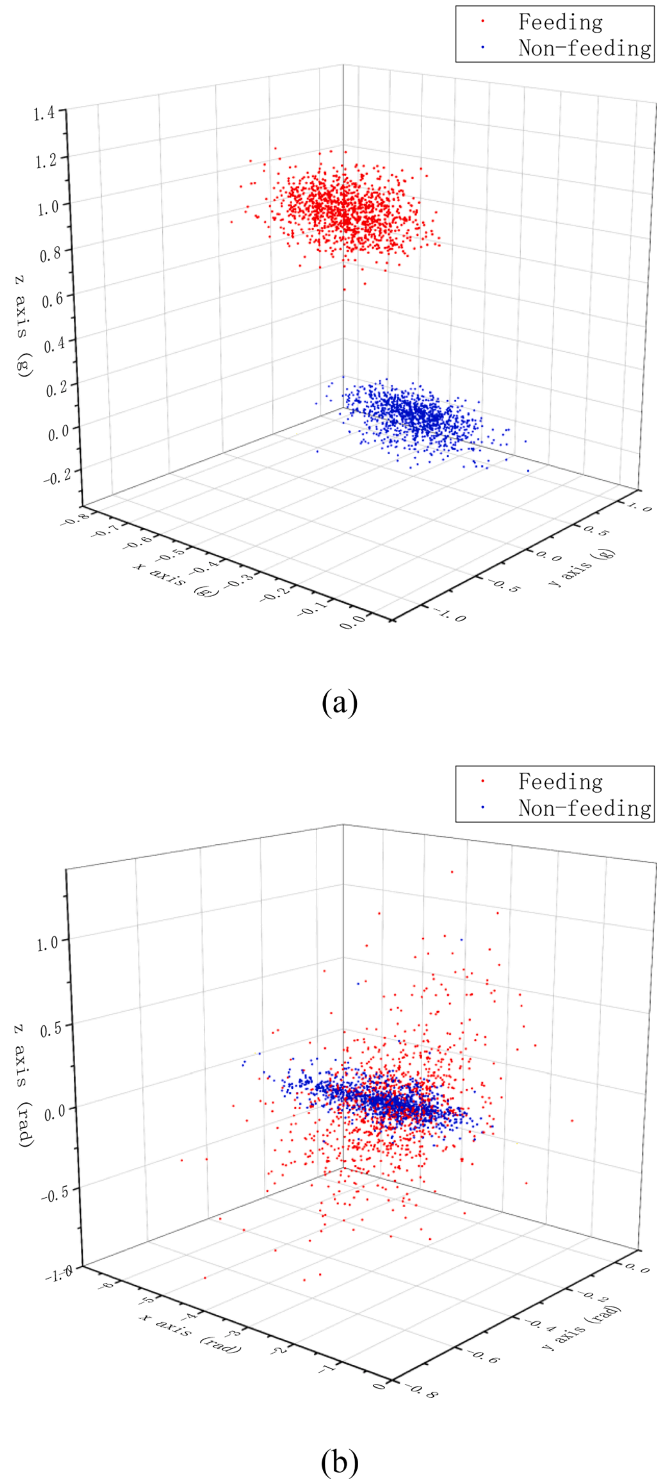


Fig. 13. (a) Scatter plot based on three-axis acceleration and (b) three-axis angular velocity.

TN: The behavior is actually not feeding, and the algorithm predicts it to be not feeding.
FP: The behavior is actually not feeding, but the algorithm predicts it to be feeding.
FN: The behavior is actually feeding, but the algorithm predicts it to be not feeding.

3. Results and analysis

3.1. Relationships between IMU data and feeding behavior

The study found significant differences in acceleration and angular velocity data between cows' feeding and non-feeding behaviors, as observed through collar-collected data. Fig. 12 displays waveform data for the acceleration and angular velocity of cows during feeding and non-feeding periods. Specifically, Fig. 12(a) illustrates the significant acceleration value fluctuations in three directions during feeding periods, which result from the cows' frequent large amplitude movements in various directions. The x-axis fluctuation ranges from 0 g to − 0.75 g, the y-axis fluctuation ranges from − 0.25 g to − 1.1 g, and the z-axis fluctuation ranges from 0.75 to 1.35. By contrast, the cows exhibit less movement and lower acceleration values during non-feeding periods. The range of x-axis fluctuation is between − 0.2 g and − 0.75 g, the range of y-axis fluctuation is between 0.35 g and 1 g, and the range of z-axis fluctuation is between 0 g and 0.3 g. The angular velocity waveform also exhibits significant differences between feeding and non-feeding behaviors. During feeding periods, x-axis and z-axis angular velocity fluctuate greatly, with the range of x-axis fluctuation between − 1 and − 6.1 rad, while the y-axis fluctuates less, with the range between − 0.5 and 0 rad, as illustrated in Fig. 12(c). During non-feeding periods, cows exhibit greater variation in angular velocity along the x-axis than along the y and z-axes. Specifically, the range of x-axis angular velocity fluctuation is between − 1 and − 6 rad, the range of y-axis angular velocity fluctuation is between 0 and − 0.5 rad, and the range of z-axis angular velocity fluctuation is between − 0.5 and 0.5 rad. In conclusion, the acceleration and angular velocity waveforms exhibit significant differences between feeding and non-feeding behaviors of cows..

This study plotted the three-axis acceleration of feeding and non-feeding behaviors as a three-dimensional scatter plot. Fig. 13(a) reveals significant differences between feeding and non-feeding behaviors in the value of z-axis acceleration data, indicating the cow's larger up-and-down head movement during feeding. Fig. 13(b) displays the three-axis angular velocity of feeding and non-feeding behaviors as a three-dimensional scatter plot. Feeding behavior and non-feeding behavior exhibit significant changes along the x, y, and z-axes, with the cow's head movements being more intense during feeding. Consequently, the angular velocity scatter of non-feeding behavior is almost submerged in the scatter of feeding behavior, which is dominated by the larger amplitude of the cow's head movements. Thus, the three-axis acceleration and angular velocity effectively distinguish between feeding and non-feeding behaviors.

3.2. Results of indoor localization

The TDoA algorithm was used to calculate the location information in this experiment, utilizing the absolute time difference between the signal's arrival at two anchor points to determine the test node's position. Compared to the ToA method, the TDoA positioning method has a significant advantage as it does not require synchronization between the test node and each anchor point's clocks. This greatly relaxes the application conditions and simplifies the system structure in practical engineering (Wang et al., 2021). Formula (6) shows the TDoA algorithm equation for the three base stations.

$$\sqrt{(x-x_1)^2+(y-y_1)^2}-\sqrt{(x-x_3)^2+(y-y_3)^2}=c(t_1-t_3)$$

$$\sqrt{(x-x_2)^2+(y-y_2)^2}-\sqrt{(x-x_3)^2+(y-y_3)^2}=c(t_2-t_3) \tag{6}$$

The variables x and y represent the coordinates of the test node, while x_i and y_i represent the coordinates of the anchor points, The arrival time at each anchor point is represented by t_i (where $i=1,2,3$).

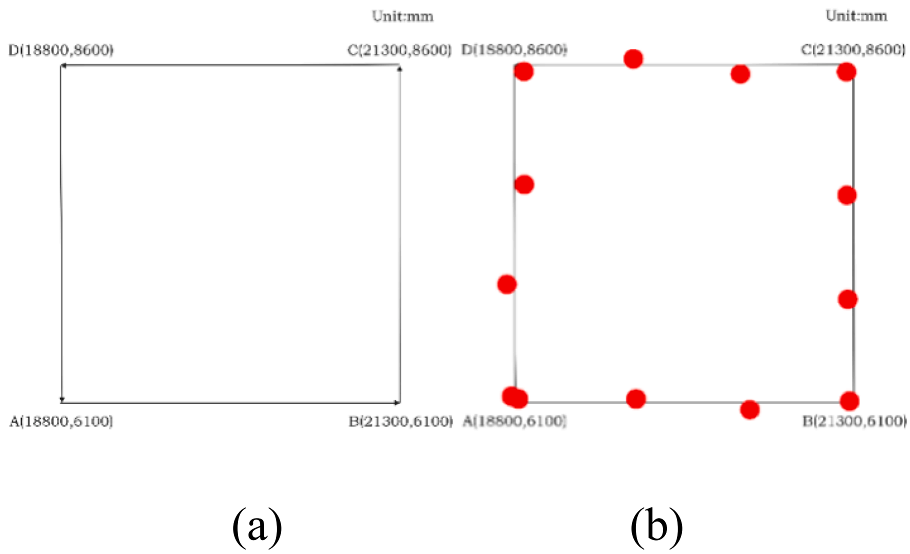


Fig. 14. (a) Coordinate mapping of the track and (b) the actual positioning of the track.

The speed of light is represented by c. By computing this equation, the two-dimensional coordinates of the test node can be obtained.

During the experiment, the test node sent a timestamp to each anchor point every 3 s. The anchor points then send the absolute time difference to the master anchor point, which forwards it to the server. The server uses the TDoA algorithm to calculate the cow's position information and obtain the real-time location. To verify the dynamic positioning accuracy of the measurement system in the cowshed environment, an area with four fixed points was measured and identified in a cow-free area, with coordinates shown in Fig. 14(a). The experimenters lifted the test node above their head and walked through the four points in sequence (ABCDA), and the system's actual trajectory is shown in Fig. 14(b). The trajectory demonstrates the system's good accuracy and real-time tracking performance since it closely follows the actual route when the test node is moved.

3.3. Analysis and realization of cow feeding behavior verification

To classify feeding and non-feeding behaviors, the preprocessed data of four dairy cows was used as the training set and another dairy cow's data was used as the test set, employing SVM, KNN, and LSTM algorithms. Initially, the algorithms utilized the IMU data only, while positional data was integrated and reclassified later. The evaluation metrics for the IMU data are presented in Fig. 15(a), while the metrics for the integrated IMU data and positional information are shown in Fig. 15(b). The addition of positional information improved the system's classification performance compared to using only IMU data. Among the three algorithms, LSTM achieved the highest accuracy of 94.97%, precision of 99.99%, recall of 93.86%, specificity of 99.99%, and F1 score of 95.21% when positional information was included. SVM and KNN's models achieved less than 92% in each classification metric, as shown in Table 2, suggesting deep learning models outperformed traditional machine learning algorithms for behavioral analysis of dairy cows. It is essential to note that the collar's wearing position varied slightly among the different cows during the experiment, which might have impacted SVM and KNN's performance metrics.

The performance of the algorithm was further validated by applying the LSTM algorithm's model to all dairy cows, and evaluating the classification effect of different cows. The precision, recall, specificity, F1 score, and accuracy obtained are presented in Table 3, which shows stable classification performance of the model on the various dairy cows in the experiment.

3.4. Digital twin of dairy cows

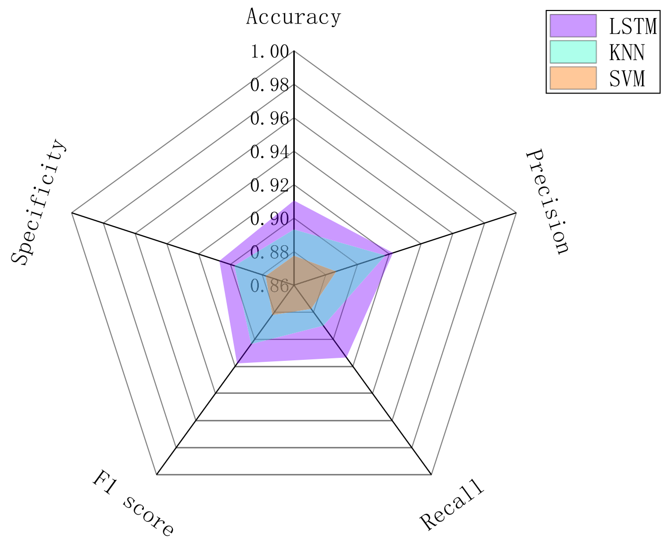
To create a digital twin of dairy cows, the client program was developed to visualize their location and status. Every three seconds, the client program retrieves real-time collar position data from the server database and displays it on the visualization interface. Fig. 16 displays a screenshot of the user interface, which presents the real-time location of dairy cows on the barn floor plan. The outer segments represent concrete walls, while the inner segments depict iron cattle shed fencing. The green squares represent anchor points, while the enclosed green lines depict feeding areas. As the collar is worn on the cow's upper neck, the collar's position represents the cow's neck position. The red circle indicates the position of a non-feeding cow, while the yellow circle indicates a feeding cow's location. This approach enables the establishment of the dairy cows' digital twin. Through the server program, the feeding start time and duration can be recorded, reflecting the cows' health status and stress level. If the cows display abnormal behavior, the server program's decision-making layer can issue alerts and notify veterinarians through the client program, speeding up the response to abnormal situations and improving animal welfare.

4. Discussion

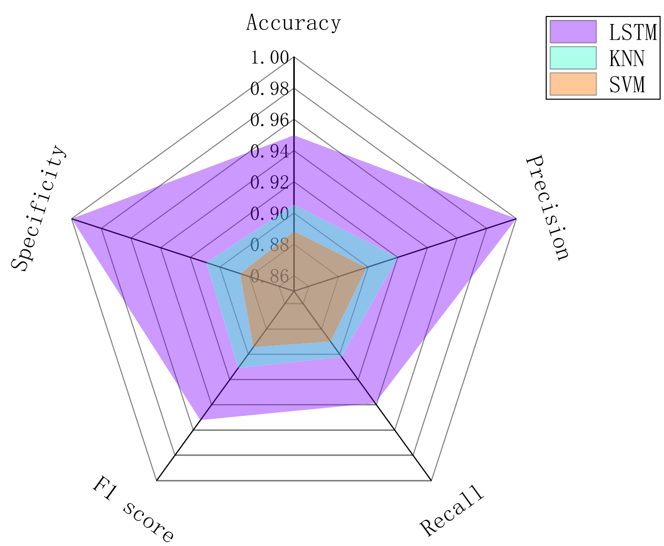
4.1. A new method for creating digital twin of dairy cows

This paper proposes a digital twin architecture designed for dairy cows. It is implemented through a custom-made collar and related software. The implementation consists of an integration layer, a data management and information layer, a model and simulation layer, and a partial decision-making and visualization layer. By effectively integrating established and emerging technologies, this architecture extracts information from both visual and sensor data to construct a multidimensional digital twin of cows. Notably, this approach demonstrates a high degree of reliability and scalability. The application of a layered design philosophy contributes to a reduction in inter-layer coupling, thereby enhancing the overall robustness of the system. Consequently, this comprehensive architecture yields practical and feasible solutions for the implementation of digital twinning in the context of dairy cows.

In this study, cow location data in real-time was collected utilizing UWB technology, while the acceleration and angular velocity data of various cow behaviors were collected through the implementation of IMU sensors. The experimental setup in the current study involved developing a collar to collect and transmit beacon and sensor data from



(a)



(b)

Fig. 15. (a) Performance on the IMU data validation set and (b) IMU & location data validation set.

Table 2
Performance of SVM, KNN and LSTM algorithms on the validation set.

Algorithms		Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)	Specificity (%)
IMU data	SVM	87.77	88.66	87.76	88.21	87.78
	KNN	89.33	91.75	89.00	90.36	89.74
	LSTM	91.05	92.23	91.35	91.79	90.70
IMU & location data	SVM	88.83	89.90	89.00	89.45	88.64
	KNN	90.53	92.00	90.20	91.09	90.91
	LSTM	94.97	99.99	93.86	95.21	99.99

Table 3
Performance of algorithms on different experimental subjects.

Experimental objects	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)	Specificity (%)
Cow 1	94.99	99.99	93.89	95.23	99.99
Cow 2	94.97	99.99	93.86	95.21	99.99
Cow 3	94.98	99.97	93.90	95.22	99.97
Cow 4	95.16	99.98	94.18	95.38	99.98
Cow 5	95.25	99.98	94.34	95.47	99.98
Average	95.07	99.98	94.03	95.30	99.98

the cow, implementing an anchor point program to receive and transfer data to the server, utilizing a server program to perform location calculations and machine learning algorithm analysis to detect feeding and non-feeding behaviors of dairy cows, and creating a client software to display the real-time location and status of the cows. A digital twin of the dairy cows was created by classifying the collected data using recognition algorithms and visualizing them. The data collected as part of this study provided a foundation for analyzing the behavior of other dairy cows in future research. Especially, dividing the barn areas and collecting real-time location information significantly improved the performance of dairy cow behavior recognition. In this context, the UWB and IMU chips constitute the integration elements, the software managing this data pertains to the data management and information elements, the algorithm for recognizing cow feeding behaviors falls under the modeling and simulation elements, and the user interface resides within the decision and user interface elements. Employing adult cows as the subjects of investigation, the construction of the bovine digital twin has been achieved at both the barn integration level and the pasture agent level.

The proposed digital twin platform has several distinct features, including low costs, high accuracy, easy deployment, and comprehensive multi-dimensional perception. By only requiring a collar, cows experience less stress, improving their welfare. The data communication architecture of this software and hardware platform enables easy network access and data transfer to the cloud, allowing for simple data storage and analysis using cloud resources. This paper solely investigated the feeding and non-feeding behaviors of dairy cows, without fully realizing the potential of the proposed solution. Subsequently, this platform can be utilized to sense and model a range of cow behaviors. A relationship-based model connecting behavior with estrus, health, and productivity can be developed to construct a digital shadow, ultimately improving animal welfare. The detection of these behaviors and states plays a crucial role in the creation of a digital twin of dairy cows. In the future, a comprehensive digital twin of dairy cows can be developed by upgrading visualization interfaces and combining the perception of multiple states of dairy cows.

4.2. Benefits of integrating indoor positioning data and IMU data in classifying dairy cow behavior

This study utilized a methodology combining Inertial Measurement Unit (IMU) and indoor positioning data to classify dairy cows' behaviors associated with feeding and non-feeding activities. Indoor positioning data provided accurate cow location information to indicate whether the cows were in the feeding area. Combining this data for dairy cows resulted in significantly enhanced performance metrics compared to relying solely on IMU data. The improved performance metrics were observed across various evaluation metrics including accuracy, precision, recall, and specificity. The utilization of indoor positioning data was found to significantly improve the classification of area-related behaviors of dairy cows. Indoor positioning data can provide assistance in the accurate characterization of several behaviors including rumination, drinking, lying down, and estrus detection, in addition to feeding and non-feeding behaviors.

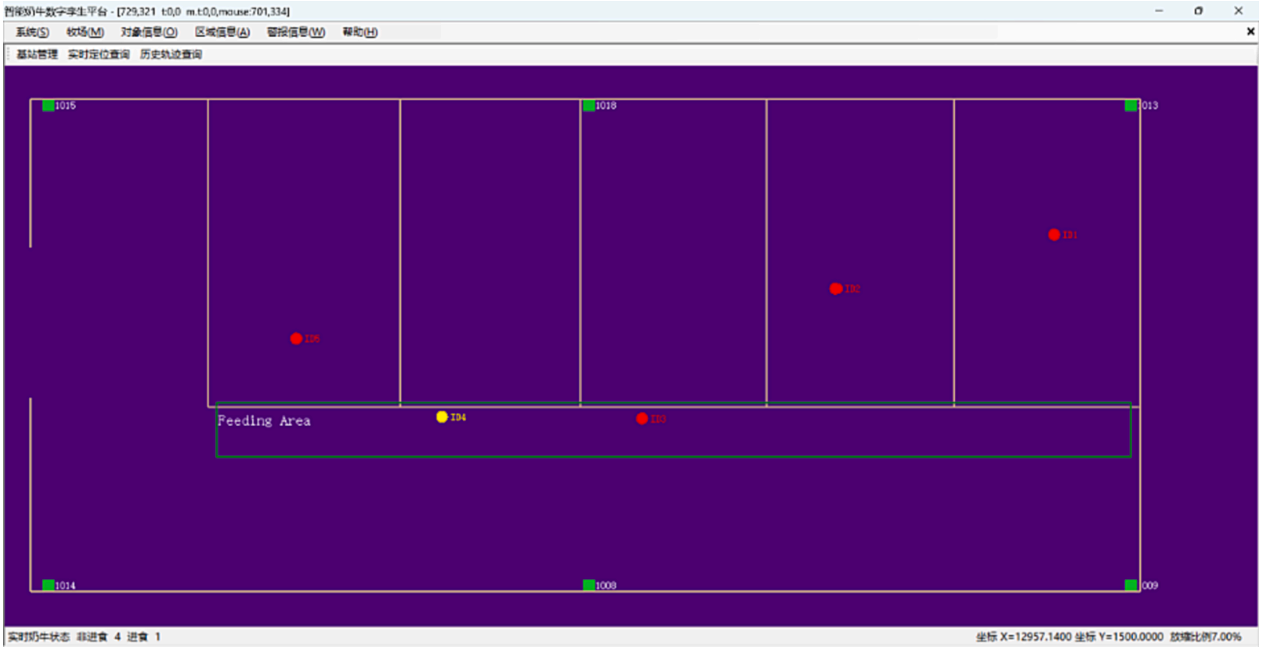


Fig. 16. Visualization of dairy cows' position and status.

The limited sample size in this study may introduce potential behavioral variations among different individual dairy cows, which could impact the accuracy of the classification. Further efforts are warranted to amass a larger dataset encompassing diverse sensor-equipped cows, thereby enhancing the model's performance.

4.3. Comparison with previous research

The application of digital twins in the livestock industry is still at an early stage of development. Previous studies have primarily focused on precision livestock farming, examining specific cow behaviors or addressing particular concerns. While their research can serve as technical reference points or typical applications under the digital twin architecture, it is important to note that only a limited number of comprehensive digital twin solutions for cows have been proposed.

The researchers Achour et al. (2020) utilized an overhead camera position on the cow's head, while implementing a CNN algorithm to identify cow individuals and their feeding and standing behaviors. The accuracy and precision of object recognition achieved were 92.61% and 97.13%, respectively. To execute this method, significant computing and storage resources are required. It should be noted that the camera must be positioned directly above the detected object. Each detected object also requires a single camera, which escalates expenses. This study utilized a low-cost solution consisting of collars and anchor points. Through our implementation of this solution, we were able to maintain relatively low operating costs.

The researchers Benaissa et al. (2020) implemented a combination of indoor positioning and accelerometer sensors to detect cow estrus and calving. They mounted an indoor positioning sensor and an accelerometer sensor on the cow's neck. Additionally, the cow's right hind leg was fitted with a second accelerometer sensor. Using multiple sensors increases the stress response of cows, and this can affect animal welfare. This study proposes the usage of a single collar to detect the feeding and non-feeding behaviors of cows. This method removes the need to wear multiple sensors, thereby reducing the stress on the cows.

The researchers Scheurwater et al. (2021) monitored the cow's reticulum pressure and used the random forest algorithm to detect rumination reactions with an accuracy of 0.98, sensitivity of 0.95, and specificity of 0.99. The peak detection algorithm achieved a detection accuracy of 0.92, sensitivity of 0.97, and specificity of 0.90. Furthermore, they proved it theoretically that the random forest algorithm can detect eating, drinking, and sleeping behaviors from the same data with all measured performances over 0.90. The experimental subjects had fistulas, and implementation may be challenging. This study proposes that healthy cows can wear the devices, making the implementation less complicated.

The researchers Shen et al. (2020) used three-axis accelerometer data to classify cow feeding, rumination, and other behaviors, achieving a 92.8% precision when the data segment length was 256. Cows tend to feed in specific areas of the barn, prompting this study to use indoor positioning data to improve feeding and non-feeding recognition accuracy and precision. By analyzing location and IMU data, the LSTM neural network method was utilized to achieve a 99.98% accuracy rate for feeding behavior classification. This study also reported a 7.28% increase in the accuracy rate, compared to Shen et al.'s research.

5. Conclusion

This study presents a digital twin structure for cows, employing a collar equipped with an UWB chip and IMU sensors, together with a local server and a client, to develop an individualized digital twin solution. The LSTM algorithm is utilized to achieve an accurate identification of feeding and non-feeding behaviors of cows through the collection of real-time location and motion sensor data from the cow's neck. The digital twin system creates a virtual representation of the cow, displaying the cow's location and status through the cooperating client program. The study indicates that utilizing the custom-made collar, anchor points, and local server combination leads to an accuracy rate of 95.07% when identifying feeding and non-feeding behaviors of cows, which is 3.92% higher than when only IMU data is used. The client program presents the identification results in a user-friendly interface, providing veterinarians and management personnel with an intuitive method of monitoring the cow's location and feeding status. Additionally, alerts can be issued for unusual situations, reducing response time in emergencies and improving overall management efficiency.

The digital twin architecture proposed in this article is significant in terms of reference value for developing digital twins of livestock animals. The digital twin solution developed and tested in this study confirms the rationality and technical feasibility of the digital twin architecture. This provides a solution for the exploration of digital twins for cows, specifically their digital shadow construction. This is a valuable investigation into digital twins for cows.

CRediT authorship contribution statement

Yi Zhang: Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Yu Zhang:** Conceptualization, Methodology, Data curation, Writing – review & editing, Supervision. **Meng Gao:** Methodology, Data curation, Validation. **Baisheng Dai:** Methodology, Funding acquisition. **Shengli Kou:** Resources, Validation. **Xinjie Wang:** Software. **Xiao Fu:** Validation. **Weizheng Shen:** Conceptualization, Funding acquisition, Data curation, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was financially supported by the National Natural Science Foundation of China (Grant No. 32072788); Key Research and Development Program of Heilongjiang Province of China (Grant No. 2022ZX01A24); "Supported by the earmarked fund for CARS36"; The authors are grateful to anonymous reviewers for their comments.

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