

Review

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Review

Intelligent Sensing and Application of Animal Behaviors Based on Wearable Sensors: A Review

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Abstract: Accurate, efficient, and timely monitoring of animal behaviors is of great significance to precision livestock farming (PLF). Behavioral monitoring serves as a valuable tool for daily production management for farmers. It can be utilized for assessing animal health, detecting estrus, monitoring parturition, and even estimating feed intake. Non-contact machine vision and contact sensors (such as accelerometers, pressure sensors and position sensors) embedded in wearable devices represent the forefront of current research in behavior monitoring. Due to the continuity and traceability in the contact sensing of wearable sensors, this study focused on contact sensing techniques and reviewed the characteristics of various sensing methods. It addressed challenges in data sorting, advancements in identification algorithms, potential industrial applications following behavior recognition, and the associated challenges and prospects. Current behavior classification algorithms primarily rely on traditional machine learning or deep learning approaches, which exhibit the limitations such as high-frequency data acquisition, complex processing requirements, and low adaptability to the intricate scenarios encountered by wearable devices. As a new frontier in machine learning that is adaptable to application scenarios with limited computational resources, the potential use of Tiny Machine Learning (Tiny ML) in behavior recognition was also analyzed to provide guidance for subsequent research and applications.

Keywords: behavior monitoring; contact sensing; algorithms; tiny machine learning; monitoring applications

1. Introduction

As the demand for meat consumption and protein-rich foods rises, annual meat production has increased from 218 million tons during 1997-1999 and is projected to reach 376 million tons by 2030 [1]. This robust demand has driven the rapid advancement of large-scale and intensive livestock production, promoting the development of intelligent and precision livestock farming (PLF), which relies on the perception and analysis of physiological and behavioral information. Monitoring and analyzing of livestock behavior provide the foundation for production evaluation and assist farmers with daily management. For instance, behavior monitoring aids in calculating the feed intake for conduct nutritional assessments of livestock [2-4], identifying the estrus and parturition in animals [5,6], analyzing health conditions, and providing early warnings for diseases [7-9]. Consequently, behavior monitoring has become a crucial aspect of precision livestock farming and the protection of animal welfare.

Traditionally, monitoring animal behavior has relied on the tracking and observation conducted by researchers using stopwatches, telescopes, counters, and other equipment [10]. However, advancements in technology have made behavior monitoring a prominent research area in recent decades, gradually shifting towards more automated and unattended methods through the use of sensors. This paper analyzed the trends in livestock behavior monitoring of livestock and reviewed the state-of-the-art sensing methods and their applications of behavior monitoring using wearable sensors. Based on the overall analysis of the existing research on livestock behavior monitoring using wearable sensors, this paper systematically reviewed: 1) the characteristics and comparisons of different sensing methods for behavior monitoring; 2) the development of algorithms in behavior classification; 3) the exploring of further application after behavior recognition; and finally 4) summarizes the challenges and future prospects in behavior monitoring of livestock.

2. Hotspots in Behavior Monitoring and Application Research

To address the research focal points on livestock behavior monitoring and its applications, this study examines the relevant literature in the Web of Science database from 2014 to 2024 in April 30, 2024. Keywords encapsulate the essence of a paper, providing a high-level summary of its content [11]. The visualization of these keywords facilitates the identification of popular topics and emerging trends within the field [12]. A higher the frequency of a keyword indicates more active the research in that area. By utilizing the visualization tool CiteSpace, a knowledge graph of keywords is created to illustrate the hotspots in the latest global research on livestock behavior monitoring. The keywords used in the literature search primarily included "behavior" along with "cattle", "sheep", "pigs", "machine vision", "sensors", "feed intake" and "pasture evaluation", among others, yielding a total of 185 papers. Error! Reference source not found. shows the most frequently appearing keywords in literature relating to livestock behavior monitoring over the past decade. These keywords can be categorized into three major directions according to their targeting animal species and behavior type, monitoring techniques, monitoring purpose and application.

2.1 Targeting Animal Species and Behavior Type

The targeted monitored animal species include grazing sheep/goats, grazing or housed cattle, and housed pigs, with a primary focus on observing both normal and abnormal behaviors. Error! Reference source not found. presents the types of target behaviors and their definitions as frequently cited in the literature. The behaviors listed from 'Feeding' to 'Licking/Grooming' are classified as normal behaviors in Table 1, while 'Pawing/Kicking' or 'Fighting' are categorized as abnormal behaviors. Specifically, the most studied normal behaviors include feeding, ruminating, resting, walking, and grazing. Most applications of the related technologies are based on monitoring devices attached to the animals' necks, legs, or ears.

Table 1. Definitions of Livestock Behaviors [13-18].

| Behavior | Definition |
|------------|--|
| Feeding | Behaviors exhibited by animals while eating, such as chewing and swallowing. |
| Resting | The relaxed state of an animal, lying down or remaining still, typically to recover energy. |
| Walking | The behavior of an animal when moving, usually in search of food, water, or other resources. |
| Standing | The animal maintaining a standing posture, which may be for observing the surroundings, waiting, or preparing to move. |
| Rumination | The process in ruminant animals (cattle, sheep) of regurgitating and re-chewing food from the stomach. |
| Grazing | Eating forage at ground level with the head down. |

| | |
|------------------|---|
| Socializing | Interactions between animals, such as sniffing or physical contact, typically seen as social behavior in group-living species. |
| Exploring | The behavior of animals investigating their surroundings by sniffing, licking, or observing, especially in new environments or when encountering novel stimuli. |
| Vocalization | The act of producing sounds to communicate, such as expressing pain or calling for companions. |
| Excretion | The behavior of eliminating waste, including urination and defecation. |
| Parturition | Involving uterine contractions, the expulsion of offspring, and observable behaviors such as restlessness, vocalization, and seeking isolation. |
| Mounting | The noticeable sign of estrus, that a female animal standing for mating or standing to be mounted by other one for a couple of seconds. |
| Mating | the copulatory behavior between a male and female for reproduction, typically occurring during the female's estrus and involving behaviors like mounting and courtship. |
| Licking/Grooming | The behavior of licking either their own body or another animal, usually for cleaning or showing affection. |
| Pawing/Kicking | The behavior of animals pawing the ground or kicking, often due to agitation or aggressive emotions (rare in pigs). |
| Fighting | Intense confrontational behavior between animals, often over resources or status, such as wrestling or headbutting |

2.2. Monitoring Techniques

Generally, behavior monitoring can be categorized into two types of techniques: non-contact techniques (e.g., machine vision or computer vision) and contact techniques (e.g., wearable sensors such as accelerometers). These methods are at the forefront of current research.

The non-contact monitoring techniques are primarily based on machine vision and have made significant advancements in automation and intelligence, making them particularly suitable for use in housed environments [19,20]. In contrast to free-range or grazing systems, intensive housing systems confine animals to a relatively small and controlled living space, which facilitates continuous observation and enables the monitoring of multiple animals from a single camera view [21-23]. However, several challenges remain to be addressed in non-contact monitoring techniques, particularly in complex scenarios involving variable lighting, occlusion, overlapping, and the continuous tracking of animals across different fields of view. Since this paper focuses on contact techniques, a detailed overview of research developments in non-contact monitoring is not included here.

On the other hand, contact-based monitoring techniques (wearable sensor monitoring) provide a direct and continuous method for recording animal behavior and physiological status. These technologies provide high-resolution and high-accuracy data, which aid in a deeper understanding of animal activity patterns and health conditions. For instance, accelerometers can capture movement patterns, sound sensors can analyze vocalizations to identify changes in emotional or physiological states, and location sensors can track movement paths and area usage [24,25].

Either for non-contact or contact-based monitoring techniques, it relies on subsequent algorithms or models for data processing and analyzing to realize behavior recognition and further application. This is generally associated with techniques in statistical analysis, data mining, and artificial intelligence, including machine learning and deep learning. The effective use of these technologies not only improves the accuracy and efficiency of animal behavior monitoring but also provides essential tools for a deeper understanding of behavior patterns, enhancing animal welfare and farm management.

2.3 Monitoring Purposes and Application

From **Figure 1**, the primary purposes of monitoring mainly include “estrus detection”, “tracking”, “weight estimation”, “feed efficiency”, and “lameness detection”, etc. For example, assessing the feeding patterns and feed efficiency is crucial for livestock management and animal welfare. By understanding the dietary needs and habits of livestock, farmers can ensure that livestock receive proper nutrition to maintain health and productivity. Lameness is a clinical symptom associated with many sheep diseases worldwide, which not only adversely affects weight gain, fertility, and birth weight of lambs but also increases the risk of secondary diseases. Barwick et al. [26] used triaxial accelerometers to discriminate lame gait from normal movements in sheep, achieving a maximum recognition accuracy of 87% when the sensor deployed on the legs. Timely and accurate estrus identification is essential for dairy farm management. Wang et al. [27] developed a dual-channel sound detection tag composed of a monaural microphone and an omnidirectional microphone (OM) for estrus identification of cows. By employing a 70-millisecond time window, Mel-frequency cepstral coefficients (MFCC) features, and a BP neural network algorithm, they achieved an accuracy of 97.62% for estrus identification, demonstrating the potential use of acoustic detection as an alternative way for estrus identification. These monitoring purposes enable intelligent application for early warning and analysis in livestock production, providing base data for smart decision-making [28]. Error! Reference source not found.. illustrates the various uses of livestock behavior monitoring mentioned in literature.

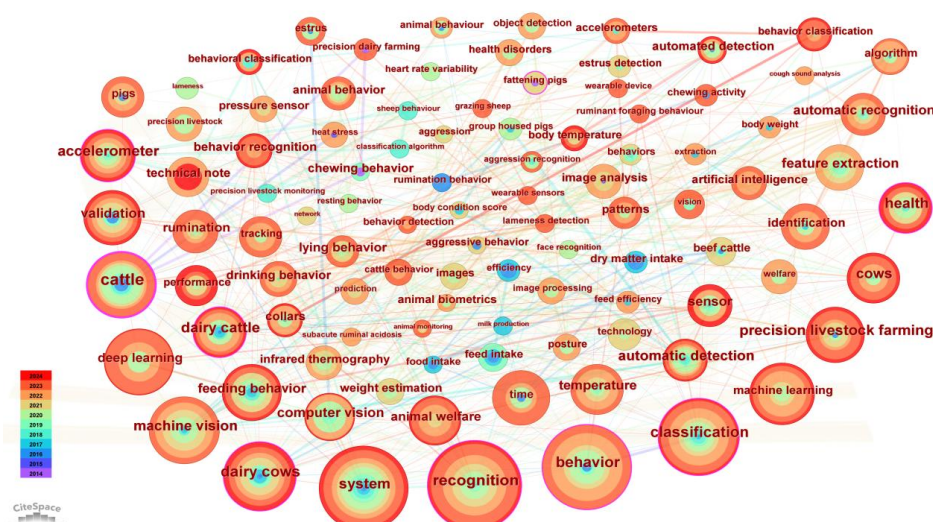


Figure 1. Visualization map of keyword co-occurrence network.

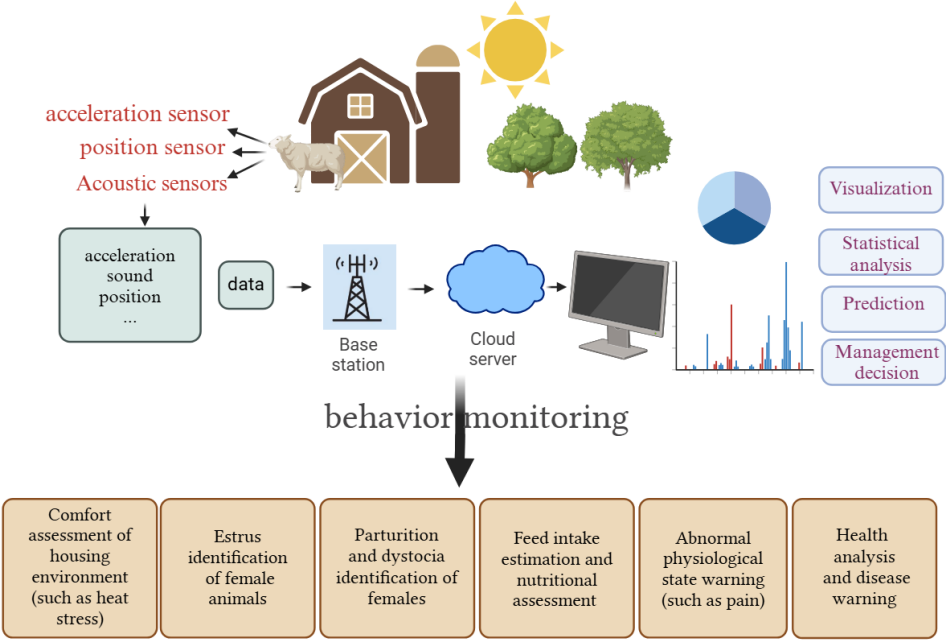


Figure 2. Applications of behavior monitoring for livestock.

3. Behavior Monitoring Based on Wearable Sensors

3.1. Sensing

3.1.1. Sensor Type

Wearable sensors commonly used for monitoring livestock behavior include inertial sensors (IMU, e.g., triaxial accelerometers, gyroscope sensors), pressure sensors, acoustic sensors, as well as positioning sensors such as BeiDou Navigation Satellite System (BDS), Global Positioning System (GPS), or Global Navigation Satellite System (GNSS). This document provides a review of representative studies on sensor technologies, summarizing the key parameters of these sensors in Error! Reference source not found..IMUs play a crucial role in livestock behavior monitoring, with a ccelerometers being the most commonly adopted in research and commercial use. These sensors operate based on the principle that animal motion generates voltage signals proportional to changes in acceleration, reflecting the animal’s three-dimensional movement [44,45]. These sensors can measure real-time changes in animal movement along three axes, such as vertical acceleration (representing standing, lying down, and walking) and angular velocity (indicating turning and tilting). By analyzing data on acceleration and angular velocity, researchers can effectively identify both static behaviors (e.g., standing still, lying down) and dynamic behaviors (e.g., walking, running) of livestock.

Acoustic sensing infers behavior and emotional states by measuring characteristics such as frequency, amplitude, and duration of animal sounds, including vocalizations, breathing, and hoof sounds. For instance, acoustic sensors can capture the sounds of livestock chewing and grazing, extracting features such as waveform, intensity, peak, and duration. When combined with algorithms, these features can accurately monitor and classify mandibular activity events in livestock [46].

Pressure sensing was mainly used to monitor the jaw movement of livestock, and specific to recognize feeding and chewing behaviors of ruminants [47]. The pressure sensor is typically composed of sensitive components (such as resistive strain gauges, piezoelectric elements, etc.). When pressure generated by animals (e.g. chewing), the sensor generates a corresponding electrical signal, which is proportional to the applied pressure. By transmitting these signals to a data

processing unit, real-time recording and analysis of pressure data can be conducted. Zehner et al. [48] assessed the performance of a noseband pressure sensor system, RumiWatch, on measuring ruminating and eating behavior. Showing a consolidated classification of sensor data, the correlations between sensor data and direct behavioral observations were 0.91-0.96 for rumination time, and 0.86-0.96 for eating time. The results showed that this system can provide farmers with sufficiently accurate data on feeding and rumination times, which can be used to support herd management decisions.

Positional sensing primarily tracks animal locations using GPS, Wi-Fi, or Bluetooth technologies, thereby inferring movement patterns and activity ranges. Currently, BDS/GPS technology is increasingly used in field monitoring [49-51]. By analyzing the movement paths of livestock on pastures, researchers can assess activity levels, resting areas, and social behaviors. This information aids in understanding the foraging, social, and resting habits of grazing livestock (mainly cattle and sheep).

With technological advancements and the increasing demand for comprehensive management, single-type sensors are increasingly insufficient for complex monitoring needs. Different types of sensors each have their advantages. With technological advancements, researchers have begun to explore the integration of multiple sensors. Combining the motion information from accelerometers, emotional signals from acoustic sensors, and spatial movement data from positional sensors enables more accurate identification of various animal behaviors, such as feeding, resting, estrus, and social activities [52-54]. For example, while GPS technology can provide the location of livestock, it may be challenging to distinguish specific behavioral patterns, such as distinguishing between foraging, resting, and social interactions. Therefore, combining data from other sensors or observations is necessary for a more accurate interpretation of animal behavior. Brennan et al. [39] combined GPS trackers with three-axis accelerometers to monitor seasonal grazing behaviors in cattle. Meanwhile, the integration of multiple sensors also presents challenges, particularly the conflict between low data acquisition frequency and long battery life. For wearable devices, there is normally limited resources for computing and power supply. It is essential to balance between the need for prolonged device operation with achieving high precision in detection.

Table 2. Key Parameters of Different Sensors(Single-Sensor).

| Sensing Method | Sampling Frequency | Deployment Location | Behavior Categories Identified | Time Window Size | Recognition Accuracy | Sample Size | Reference |
|----------------|--------------------|---------------------|---|------------------|----------------------|---|-----------|
| ACC | 62.5 Hz | Jaw | grazing, rumination, resting | 5s | 93% | 3 non-lactating Sarda ewes; 675 minutes of collected data | [29] |
| ACC | 12 Hz | Ear | grazing, standing, walking | 10s | 94-99% | 10 Merino sheep; 2956 10-second segments | [24] |
| ACC | 50 Hz | Neck | grazing, walking, rumination, resting, drinking | 5.12s | 90% | 10 Angus breed cattle; 24,525 data samples | [30] |
| ACC | 50 -62.5 Hz | Neck, Ear | feeding, walking, resting, ruminating | 4.1s-5.12s | 80.9%-87.4% | 27 cows; 187,937 data samples | [30] |

| | | | | | | | |
|------|-----------------|-----------------------|---|-------------|----------------|---|------|
| ACS | 44.1kHz | Forehead | grazing, ruminating | 5 mins | 76.5%-83.3%- | 5 dairy cows;total of 137 hours | [31] |
| ACS | 44.1kHz | Neck | mouth open, mouth closed, mixed mouth movements | 256 points | 99.5% | 10 dairy cows;709 vocal | [32] |
| ACS | 11.69Hz-35.08HZ | Forehead | bites, exclusive chews, chew-bite combinations, exclusive sorting | 2048 points | 89.62% - 95.9% | 10 Holstein cows; 60 audio data | [33] |
| PRS | 2Hz | Reticulorumen | ruminating, eating, drinking, sleeping | 120 s | 98% | four rumen-fistulated cows | [34] |
| PRS | 17Hz | Lumbar Intervertebral | the intradiscal pressure signal of an anesthetized sheep | \ | \ | 1 female merino ewe;2 hours respiratory rate data | [35] |
| GNSS | \ | Neck | behaviors during estrus and non-estrus | \ | 90-94% | 8 ewes and 40 experienced ewes ; 8 days data | [36] |
| GPS | \ | Neck | sheep feeding patterns and pasture grazing behavior | \ | \ | 7 ewes, 350 sheep; 3 years data | [37] |

ACC = accelerometer, ACS = acoustic sensors, GYR = gyroscope, PRS = pressure sensors, GPS = global positioning system, GNSS = global navigation satellite system, IMU = inertial measurement unit.

Table 3. Key Parameters of Different Sensors(Multi-sensor fusion.

| Sensing Method | Sampling Frequency | Deploym ent Location | Behavior Categori es Identifie d | Time Windo w Size | Recogniti on Accuracy | Sample Size | Equipm ent Duratio n | Referen ce |
|----------------|--------------------------|----------------------|---|-------------------|-----------------------|---|----------------------|------------|
| ACC,UR | 50 Hz | Neck | grazing, eating, walking, running, standing | 20ms | 95% | a sheep herd over 3 days of grazing;12, 968 data points | \ | [38] |
| ACC, GPS | 60 Hz (GPS), 12 Hz (ACC) | Neck | grazing or non-grazing (walking, standing, ruminati ng, drinking) | 1min2 1s | 88.8% | 45 one-year-old cattle; 3 months;5,2 61 datasets | \ | [39] |
| PRS, IMU | 30 Hz(PRS), 200Hz(IMU) | Claws of hind limbs | gait analysis | \ | \ | ten dairy cows | 4h | [40] |

| | | | | | | | | |
|-------------|---------------------------|---------------------------------|---|----|-----------------|---|----------|------|
| ACC, GYR | 16Hz | Ears and collar | walking, standing, lying down | 7s | 95% | 30 datasets from 6 sheep | 2.4 days | [41] |
| ACC, GYR | 16Hz | Ears | walking, standing, lying down | 7s | 80% | 10 non- lame sheep and 13 lame sheep ;20,104 samples | \ | [42] |
| ACC, GYR | 20Hz | Neck | walking, standing, grazing, lying down, running feeding, ruminati ng, | 3s | 87.8% | 3 sheep;67.5 hours data | \ | [18] |
| IMU、G PS | IMU (20Hz) 、 GPS (1Hz) | Chin, neck, and hind legs | walking, standing, lying down | 5s | 98.9%- 99.9% | 22 sheep; over 2-3 days | \ | [43] |

ACC = accelerometers, UR = ultrasonic transducer, ACS = acoustic sensors, GYR = gyroscope, PRS = pressure sensors, GPS = global positioning system, GNSS = global navigation satellite system, IMU = inertial measurement unit.

Table 4. Machine learning in livestock behavior recognition.

| Model | Behavior | Accuracy | DataSet | Applications | Reference |
|---|--|----------|------------------------|--|-----------|
| FMM, DT | standing,lying,transitional behaviors | 99% | 8 cows | identification of multiple behaviors of cows | [91] |
| KNN, RF, GBDT, SVM, LVQ, KNN-RF | feeding, ruminating, running, walking, resting, drinking, head shaking | 80%-99% | 3 cows 3 days | identification of multiple behaviors of cows | [92] |
| K-means, interval thresholding classification | standing, walking, running | 96.21% | 107,450 | identification of ram's locomotor behavior | [93] |
| RF | lying,grazing, walking,standing,chewing, social,ruminating, resting | 76%-94% | 12 cows 136 minutes | prediction of cow lying behavior in pastures | [94,95] |
| BP neural network | acoustic signals in ewes under stressful behavior | 93.8% | 1,200 | recognizing their vocal signals of ewes | [96] |
| KNN | ruminating | 93.7% | 5 cows | monitoring of cow ruminant behavior | [97] |

| | | | | | |
|--------------|--|---------|--------|--|---------|
| K-means, SVM | standing, walking, feeding | 79%-93% | 71,594 | sheep behavior recognition | [64] |
| CDA, DA | grazing, ruminating, other | 88%-90% | 69,975 | behavior of grazing animals distinguish between vocal and limp gait movements in sheep | [62,66] |
| QDA | lame walking, grazing, standing, walking | 82%-87% | 4,419 | | [24] |

SVM = Support Vector Machine CDA = Classical Discriminant Analysis DA = Discriminant Analysis QDA = Quadratic Discriminant Analysis RF = Random Forest FMM = Finite Mixture Models DT = Decision Tree KNN = K-Nearest Neighbors GBDT = Gradient Boosting Decision Tree LVQ = Learning Vector Quantization.

Table 5. Group Synthesize Calculation Method in livestock behavior recognition.

| Model | Behavior | Accuracy | DataSet | Applications | Reference |
|------------------------|--|------------------|--------------------------------|---|-----------|
| FA, SVM | feeding, ruminating, drinking | 98.02% | 4,200,000 pieces of data | cow behavior monitoring | [98] |
| GA, SVM | walking, lying, drinking, feeding, ruminating / bite, chewing, chew-bite,selecting | 97.88% 95.66% | 29,150 pieces of data, 10 cows | behavioral monitoring of ewes | [19,33] |
| HMM, BP neural network | coughing signals | 95.04% | 900 | monitoring the coughing of captive sheep | [58] |
| Bidir-LSTM | feeding, lying, rumination (lying), rubbing (legs), social licking, rubbing (neck) | 94.9% | 1066 hours | detect important physiological states in cattle | [99] |

HMM = Hidden Markov Model FA = firefly algorithm GA = Genetic Algorithm SVM = Support Vector Machine LSTM = Long Short-Term Memory Bidir-LSTM = Bidirectional LSTM.

Table 6. Deep learning in livestock behavior recognition.

| Model | Behavior | Accuracy | DataSet | Applications | Reference |
|-----------------------------------|---|----------|------------------------|--|-----------|
| GAN, TCN | lying, standing, walking, running, jump, run around | 97.15% | 211,000 pieces of data | Recognizing the locomotor behavior of dairy goats | [100] |
| BP neural network, FCN, CNN | grazing | 83%-94% | 30,000 pieces of data | estimating the distribution of grazing area intake | [56] |
| An end-to-end deep neural network | grazing | 93.93% | 24,525 pieces of data | animal behavior classification | [13] |
| CNN, TL | feeding, ruminating, other | 93.9% | 21 cows 3 days | recognition of the feeding behavior of cows | [101] |
| Conv1D, Conv2D, | bite, chewing, chew-bite | 93% | 3 cows | classifying chewing events in grazing | [102] |

| | | | | | |
|---------------|--|--------|-----------------------|--|-------|
| LSTM | | | | cattle by acoustic signals classifying chewing events in grazing cattle by acoustic signals | |
| CBIA | bite, chewing, chew-bite | 90% | 2 cows 6 days | [103] | |
| LSTM-RNN, CNN | feeding, lying, ruminating, salt licking, moving, social licking, headbanging | 88.7% | 11,391 pieces of data | classification of cattle behavioral patterns | [104] |
| FCN | lying down and ruminating, lying, feeding, Leg rubbing, self licking, neck rubbing, social licking | 83.75% | 20,000 pieces of data | classification of cattle behavioral patterns | [105] |

FCN = Fully Convolutional Network CNN = Convolutional Neural Network LSTM = Long Short-Term Memory RNN = Recurrent Neural Network TL = Transfer Learning CBIA = Chew-Bite Intelligent Algorithm GAN = generative adversarial network TCN = temporal convolutional network.

3.1.2. Sampling Frequency

The sampling frequency of different types of sensors significantly affects the accuracy of animal behavior monitoring and energy consumption. An appropriate sampling frequency can reduce energy consumption while maintaining high accuracy [19,41,55-57].

For accelerometers, data sampling frequencies commonly range from 1 Hz to 50 Hz. Research by Walton et al. [41] indicated that the high sampling frequencies, such as 32 Hz, provide more detailed information on behavioral changes and are suitable for capturing complex behavioral features. However, this comes at the cost of increased energy consumption and data processing requirements. At a sampling frequency of 32 Hz with a 7-second time window, behavior classification in sheep achieved 95% accuracy and an F-score of 91%-97%. In comparison, a sampling frequency of 16 Hz resulted in a slight decrease in accuracy to 91%-93% and an F-score ranging from 88%-95%. While the energy consumption was approximately 10 μ A h for 16 Hz compared to 17 μ A h for 32 Hz, demonstrating a good energy efficiency ratio.

Different behaviors may require different sampling frequencies for optimal classification results. For instance, Fogarty et al. [55] used a 12.5 Hz sampling frequency with a 10-second time window for classifying sheep behavior. They found lower classification accuracy for certain behaviors, such as lying and standing, but higher accuracy for walking behavior. When choosing the proper sampling frequency of sensors, it should consider the dynamics and complexity of the target behaviors. For dynamic behaviors such as walking and running, a higher sampling frequency may be necessary to capture rapidly changing features, whereas a lower frequency might suffice for static behaviors such as standing and lying down.

For acoustic and positional sensors, existing literature suggests that acoustic sensors typically operate within a frequency range of 16 kHz to 44.1 kHz [58-61]. Due to the high sampling frequency, devices incorporating acoustic sensors require careful consideration of battery life. Positional sensors, which are often used in conjunction with accelerometers, do not have specific sampling frequency requirements and are generally set to meet the needs of battery life and tracking. Limited literature can be found on the sampling frequency of pressure sensors for behavior monitoring. According to unpublished data from the authors, a sampling frequency of 1 Hz is good enough to recognize the chewing behavior of cattle, but the sampling frequency needs to rise to 5 Hz to obtain satisfactory accuracy for calculating the chewing bouts.

3.1.3. Sensor Deployment Position

A proper sensor deployment position significantly affect the effectiveness of behavior monitoring. Differing for varied monitoring purposes, the adopted deployment positions of wearable devices include the animal's ears, forehead, jaw, neck, back, legs, and root of the tail [24,26,55,62,63]. Among these, the neck, legs, and jaw are the most commonly used in behavior monitoring.

Attaching accelerometers to the neck is a common practice to measure the activities of ruminants. Research by Guo et al. [63] and Cao et al. [64] showed that accelerometers placed on the neck of sheep generally provide superior identification efficiency compared to the position near the front legs or on the back, and the recognition accuracy for grazing behavior exceeding 97%. However, while the sensor is positioned on the neck, it is easy to shift under free-range conditions [65]. It is needed to assess whether this would or would not affect the precise recognition of behavior in practical use. Additionally, the ears may be an alternative position. Results from Barwick et al. [26] indicate that accelerometers attached to the ears can differentiate lameness from grazing, standing, and normal walking. Integration with ear tags may be a potential use for ear-mounted sensors to monitor behaviors. While it should be noticed that it is easy to generate inertial noise, which would address potential data quality issues because there is no fixed point on the ear and the sheep moves fast [10]. Furthermore, deploying three-axis accelerometers or pressure sensor on the jaw provides the benefit of capturing detailed movements of mouth, enabling monitoring of fine feeding behaviors such as biting and chewing [62,66].

Acoustic sensors are typically mounted on the neck or forehead. For example, Shorten and Hunter [32] used a WS-853 digital recorder attached to the neck of dairy cows, achieving an overall accuracy of 99.5% in recognizing three different cow vocalization classes, which were open mouth, closed mouth, and mixed mouth (closed mouth followed by open mouth). Position sensors generally do not have specific placement requirements, as long as they do not interfere with normal animal activities and data collection. Currently, most positional sensors are integrated with other sensors, with the primary concerns on the placement of the other sensors.

Sensors mounted on the legs provide higher accuracy for posture and gait-related behavior recognition. When deploying three-axis accelerometers, the legs are the most stable location due to their rigid support. However, from an application perspective, the legs are not the optimal position [24,55]. This is because the leg-mounted sensors are only advantageous for recognizing lameness. Its recognition accuracies lowered for other behavior classifications compared to ear-mounted sensors and were not conducive to multifunctional integration applications.

3.2. Algorithms for Behavioral Recognition

Models are essential for data processing and behavior recognition. In general, models for behavior monitoring on the basis of on-animal sensors follow the framework, including data pre-processing, algorithm selection for behavior classification, as well as model tuning and evaluation (as shown in Error! Reference source not found.). Since the early stage of research to now, machine learning has emerged as the predominant approach [3,8,67]. This is due to the consistent performance and relatively modest requirements for data volume, establishing machine learning as the mainstream methodology in the field [68]. As a technical improvement, deep learning has progressively emerged as a focal point of research, especially in image analysis, due to their potent ability to learn features and their superior performance in the analysis of intricate data sets. Hence, algorithms for behavior recognition undergo a progress from the predominance of traditional machine learning approaches to the burgeoning ascendancy of deep learning methodologies, as well as the combination of both.

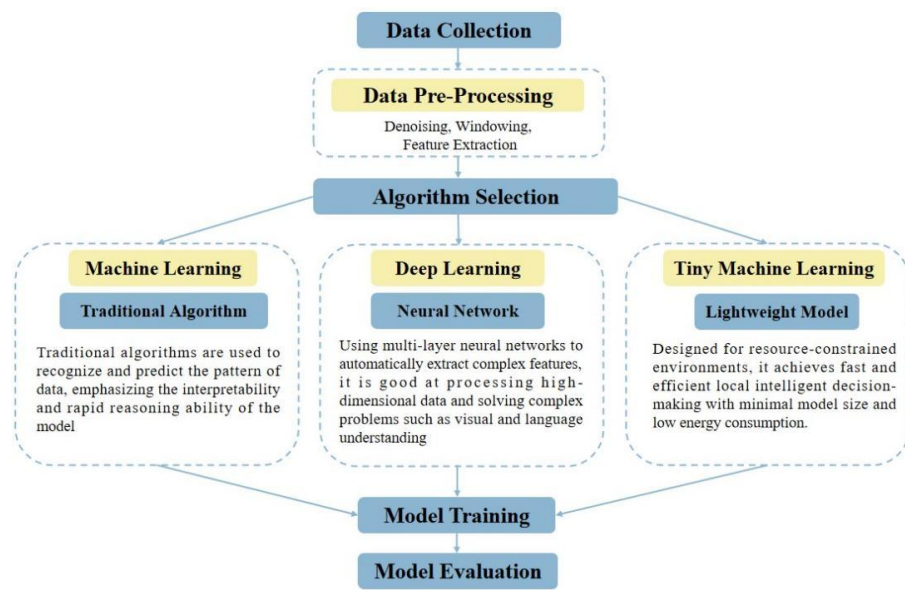


Figure 3. Overall framework for behavior recognition.

In addition to deep learning and traditional machine learning, a relatively new approach, tiny machine learning (Tiny ML), is emerging in many fields with its unique advantages, especially in the application of edge devices like wearable sensors [69-71]. The deployment of models on device-side through Tiny ML techniques significantly diminishes power consumption, compacts model dimensions, and ensures swift response times [72]. Although the field of Tiny ML remains in its nascent phase, it paves the way for novel applications in the realm of real-time monitoring and edge intelligent computing due to its advantages in conditions with limited resources. This suggests a promising trajectory for future integration within the domain of animal behavior recognition. This section introduced and compared the algorithms or methods used in the literature for data preprocessing and classification in behavior monitoring and discussed Tiny ML as an alternative way for behavior classification.

3.2.1. Data Preprocessing

Data preprocessing is essential before implementing behavior recognition algorithms, as it augments the algorithms' performance by refining data quality, standardizing data formats, and diminishing dimensionality. Furthermore, the processes of data cleaning and denoising are instrumental in bolstering the generalization capabilities of the algorithms. Concurrently, feature extraction plays a pivotal role in directing the algorithms' attention to the most salient information pertinent to behavior recognition.

Denoising

Data collected by sensors in open environments invariably contains a certain degree of noise [73]. Therefore, the filtration and denoising of sensor data constitute an essential preliminary step in the construction of behavior recognition models [74]. The application of denoising techniques is necessary for refining the integrity of signal data within the context of behavior recognition algorithms. It serves to attenuate the computational burden by eliminating non-essential processing demands, thereby enhancing algorithmic efficiency. Concurrently, it reinforces the model's resilience to fluctuations in environmental conditions, a critical factor in preserving the model's predictive accuracy. Furthermore, denoising standardizes the data, which is instrumental in curbing the potential for overfitting, a common impediment to the generalizability of machine learning models [75]. The application of denoising techniques on behavior recognition is predominantly concentrated within the realms of the time domain, frequency domain, and time-frequency domain, extending

their utility to the processing of waveforms, spectral data, and acoustic spectrograms [73]. Denoising strategies encompass a spectrum of techniques, with common practices including low-pass, band-pass, and high-pass filtering to attenuate unwanted noise components. In [76], low-pass filters with cutoff frequencies of 5 Hz and 10 Hz were used, as well as a high-pass filter with a cutoff frequency of 0.3 Hz without filtering. Sophisticated methodologies, such as optimal Finite Impulse Response (FIR) filters, spectral decimation, Minimum Mean Square Error Short-Time Spectral Amplitude Estimator (MMSE-STSA), and wavelet-based denoising, are deployed to further refine the signal-to-noise ratio [77]. Additionally, Wiener filtering and Singular Spectrum Analysis (SSA) have demonstrated particular efficacy in the context of bioacoustic signal processing, showcasing their utility in enhancing the clarity and integrity of acoustic data [73]. The selection of a denoising method should be adapted to the specific animal species and the objectives of the study [73]. Riaboff et al. [76] demonstrated the importance of choosing the filtering approach in a study recognizing cattle behavior. They found that high-pass filtering of acceleration signals significantly degraded classification performance, resulting in a 5% decrease in accuracy (from 92% to 87%) and a 6% decrease in the F-score (from 93% to 87%).

Windowing

Raw sensor data, which constitutes a continuous stream of information, can be effectively managed by partitioning it into manageable segments. This segmentation is crucial for capturing the nuances of local dynamics, simplifying computational demands, and responding to the fluidity of behavioral changes [78]. The strategy of employing static time windows, which are either mutually exclusive or exhibit overlap, presents distinct advantages. Non-overlapping windows provide discrete snapshots of behavior, while overlapping ones enhance the likelihood of capturing transitional phases [79]. It can be observed that window size typically ranges from 3 to 10 seconds and is selected by the particular requirements of the specific recognition task and the sampling frequency of sensors [45,80,81]. Shorter windows may be suitable for quickly identifying short-lived activities, while longer windows may be used to analyze more persistent or complex behavior patterns.

In the study by Nóbrega et al. [38], a 0.5-second window was employed to segment data sampled at 50 Hz and effectively captured the nuances of movement and rapid acceleration. It achieved a commendable accuracy of 91.78% in discerning behaviors such as infracting, moving, running, and standing of sheep using a decision tree algorithm. In contrast, Fogarty et al. [82] compared window sizes of 3, 10, and 30 seconds for data sampled at 12.5 Hz. Their findings suggest that larger windows are conducive to identifying behaviors that evolve over time, such as the shift from inactivity to activity. Employing a 30-second window, it attained an accuracy of 98.1% using the CART algorithm in recognizing general activities (active and inactive). This suggests that a longer time window helps to more accurately identify behavioral patterns that may take some time to unfold, such as transitions from a stationary to an active state. In contrast, an accuracy of 90.6% in discerning body postures using the Linear Discriminant Analysis (LDA) algorithm at a 30-second window [82]. These results indicate the importance of selecting an appropriate time window as a key determinant in the accuracy of behavior recognition.

Feature Extraction

Feature extraction is a vital technique used to enhance model performance. It refines the data representation by extracting and constructing new features from raw data to optimize the model's capacity to discern underlying patterns and relationships [83]. In animal behavior recognition, this process is particularly important because it allows the model to understand and interpret complex patterns in the data in greater depth. Feature extraction improves the predictive power of models by reducing data dimensionality, capturing dynamic behaviors in time series, and enhancing the robustness of models to noise and outliers [84]. In addition, the flexibility of feature extraction allows researchers to explore the best representation of the data by trying different combinations of features,

thus providing a solid foundation for building efficient and accurate classification models [85]. When performing feature engineering, it is usually approached from the time domain and the frequency domain to ensure that the intrinsic properties and dynamic behaviors of the data can be comprehensively captured.

Time-domain features can effectively reflect the dynamic fluctuations and evolving attributes of signals such as trends and periodic patterns. In time-domain analysis, feature extraction is concentrated on extracting information directly from time-series data, including but not limited to statistics (such as mean, variance, skewness, kurtosis), time-delay correlations (such autocorrelation coefficient), and other relevant features that can provide deeper insights into the data's temporal dynamics [86]. The time-domain features usually adopted in animal behavior recognition can be found in Kleanthous et al. [87]. After feature extraction, it commonly follows feature dimensionality reduction or feature selection to remove irrelevant or redundant features and thereby improve the performance or interpretability of the model. Dimensionality reduction can be realized through methods such as principal component analysis (PCA) or LDA, and feature selection mainly includes filter, wrapper, embedded, and hybrid methods [84,87]. In the study of Guo et al. [63], 55 features were computed, including time-domain features such as maximum, minimum, mean, standard deviation, peak-to-peak, average frequency, energy, entropy, skewness, and kurtosis, and probabilistic principal component analysis (PPCA) was used for dimensionality reduction. The identifying accuracy of grazing behaviors exceeded 95%. to reduce the feature space even when the 55 features were reduced to two principal components.

Conversely, frequency domain analysis centers on the transformation of time-domain signals into their frequency-domain counterparts. This process entails the application of various techniques to dissect the frequency components of the signals, thereby revealing insights into their cyclical behaviors and underlying structures. Methodologies usually adopted for the transformation include the Fourier Transform (FT), the Short-Time Fourier Transform (STFT), and the Wavelet Transform (WT) [88]. FT decomposes signals into their constituent frequencies. STFT is useful for non-stationary signals to analyze frequency content over time. WT offers time-frequency resolution and is adept at handling signals with varying frequencies over time. Frequency domain features help to reveal the distributional traits of data across various frequencies, which is invaluable for accurately locating and examining periodic patterns, identifying harmonic components, and characterizing noise elements within the data [89]. For example, Chen et al. [47] extracted the frequency-domain feature based on the FFT to recognize the feeding behaviors of cattle using noseband pressure. An accuracy of 96.6% is achieved using the XGB model.

3.2.2. Behavior Classification

Machine Learning Algorithm

Machine learning can effectively extract dynamic features, and has a relatively high interpretability at a low computational cost [90]. Various supervised machine learning algorithms have been used, and LDA, Quadratic Discriminant Analysis (QDA), Random Forest (RF), Classification and Regression Trees (CART), AdaBoost, as well as Extreme Gradient Boosting (XGB) are the most often adopted algorithms that have been used for animal behavior classification [87]. Learning algorithms are shown in Table 3.

Different machine learning algorithms have different application scenarios in recognizing animal behaviors. K-means clustering algorithm is widely used to distinguish between the static and dynamic behaviors of cows [64]. LDA has the advantages in terms of dimension reduction and sparsity reduction, which can better capture key features and patterns in animal behavior by projecting a few non-zero features per sample into a low-dimensional space [93]. QDA is an extension of LDA that allows each category to have its own covariance matrix, which allows QDA to more flexibly model the distribution of the data, especially when the categories have different shapes and scales [55]. However, LDA and QDA can only discriminate a few behaviors, while their accuracy

reduced performing to multi-behavior discrimination [24,93]. Consequently, it has progressively adopted diverse ensemble algorithms, including classification trees, RF, SVM, and artificial neural network models like multi-layer perceptrons (MLP). Showing a good performance and generalization capability, the algorithms on the basis of tree models (e.g., RF, CART, XGB) have become the principal methods on behavior classification [58,98,100]. Similarly, the more behaviors discriminated simultaneously, the lower the accuracy is observed. For example, Kleanthous et al. achieved an accuracy of 99.43% to classify four behaviors of grazing, walking, scratching, and inactive in sheep using the Random Forest algorithm based on acceleration data [67]. While the accuracy decreased to 96.47% when classifying five behaviors of grazing, walking, scratching, lying, standing of sheep [106]. Meanwhile, deep learning approaches or the integrative approaches of multi-algorithm cascaded classification to further improve the accuracy of behavior classification.

Algorithm Assembling and Deep Learning

Algorithm assembling can make full use of the advantages of various algorithms, improving the overall performance over a single algorithm. Some combination algorithms are shown in Table 4. Hidden Markov Model (HMM) deals with time-varying characteristics in time series data, adding temporal continuity to separate time windows [107]. It was applied to correct the recognized behaviors with the state transition probability matrix after behavior classification using XGB or RF [108]. Results from Ding et al. demonstrate that the accuracy would be greatly enhanced (about 5-10%) after applying the HMM-Viterbi algorithm integrated with XGB to identify the chewing and ingesting behaviors from jaw movement through a triaxial accelerometer [109]. For another example, K-Means clustering algorithm for behavioral categorization and the SVM algorithm to identify different feeding stages to improve the classification accuracy of fine feeding movement such as chewing [3,9]. Besides algorithm assembling of traditional machine learning approaches, deep learning is capable of automatically learning and extracting complex features from data to improve the accuracy and robustness of behavioral classification.

In theory, deep learning is a subset of machine learning that automatically extracts complex features of data by utilizing multi-layer neural networks. Developed in part to improve computational efficiency and handle more complex data patterns, the deep learning algorithm in behavior recognition is shown in Table 5, deep learning demonstrates its advantages in understanding complex behavioral patterns by increasing the depth and width of the model to learn more abstract feature representations [90,110]. For example, Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) have been used to detect cattle behavior by collecting behavioral data through wearing IMU sensors, extracting and fusing features from different parts of the body, and realizing high-precision behavioral analysis and individual identification [68]. Recurrent Neural Network (RNN) and its variant LSTM are suitable for recognizing long term dependencies in sequential data such as consecutive actions or behavioral patterns such as walking, running, etc., and achieved an accuracy of 92.6% [68]. When dealing with fixed-length time-series data, one-dimensional CNN are able to extract local temporal features and are suitable for recognizing behaviors with specific patterns, achieving an accuracy of 93% [102]. Although deep learning shows great potential for automatic feature extraction, it requires a large amount of computational resources and data to train the model [90]. Therefore, it normally served as cloud machine learning, and the success of deep learning models often comes at the cost of high computation, which is not feasible for using edge device. The choice between traditional machine learning or deep learning approaches in behavioral recognition research and applications usually depends on the specific task requirements, the nature of the data, and the available computational resources [90].

3.2.3. Promising Use of Tiny Machine Learning

Tiny ML is a new frontier of machine learning and represents an adaptive approach tailored for environments with limited computational resources [111]. It targets predominately to battery-

operated embedded edge devices and has many practical applications including personalized healthcare, wearable or IoT devices, smart home, ecology and agriculture [112]. As shown in Error! Reference source not found., Tiny ML consists the three key elements of software, hardware, and algorithms, which can be accommodated in Linux, embedded Linux, and cloud-based software [72]. Tiny ML requires specific libraries and software platforms to support its use. The existing software tool includes uTensor[113], Edge Impulse[114], NanoEdge AI Studio[115], STM32Cube.AI[116], etc. By implementing the Tiny ML framework on an Arduino Uno board, it can be demonstrated that complex models like neural networks, SVM, decision trees (DT), and RF are still feasible on resource-constrained devices with accuracy close to that of standard models [117].

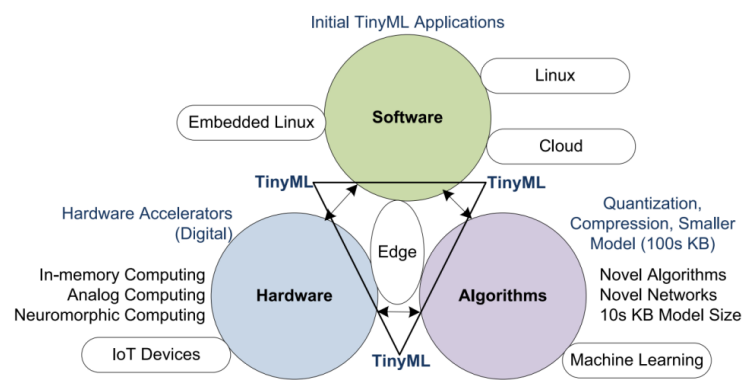


Figure 4. Composition of Tiny ML (Ray, 2022 [72])

Although Tiny ML is not yet used in the field of animal behavior monitoring to the knowledge of authors, it has been used in human wearable devices such as the computationally intensive nature of current state-of-the-art neural network implementations [69]. In the agricultural sector, Tiny ML is also applied in the fields of environmental prediction, energy saving, and precision agriculture to protect the ecology and promote sustainable agriculture [70,71]. Within the domain of livestock behavior monitoring, Tiny ML may facilitate the execution of real-time behavioral analyses directly on embedded systems. This is achieved by meticulously crafting and optimizing model architectures, leveraging deep compression techniques to ensure that these models, despite their compact form, can closely emulate the efficacy of their more intricate counterparts. The implementation of Tiny ML on such devices allows for immediate recognition of behaviors, significantly minimizing the latency associated with data transmission and cloud-based processing. Consequently, Tiny ML may be a promising solution for enhancing the efficiency and responsiveness of on-site monitoring of animal behaviors.

4. Application with Behavioral Monitoring

4.1. Feed Intake Estimation

Feed intake is an important indicator that helps optimize daily management and improve production efficiency of livestock [118]. Contact sensors, such as acceleration sensors installed on the neck or jaw of cattle, can estimate feeding information such as feed intake, feeding rate, and feeding duration, by monitoring the animal's feeding behavior in real time [2,109]. Compared to the trough scale, on facility modifications are required using this approach, and it can be integrated for multi-function use (e.g., estrus alarm, early detection of health problems in animals) using the continuous data stream provided by one set of sensors. In addition, analyzing the amount of feed intake and behavioral patterns of animals with wearable sensors can subsequently assess the grazing capacity of meadows for proper use of pasture and improve the production efficiency of grassland [10].

Existing feed intake estimation models were mostly achieved by mathematical model fitting, i.e., static models. From early studies, feed intake of grazing livestock is typically estimated through identified grazing behavior by the regression of behavior indicators such as chewing bouts, bite rate, feeding duration, ruminating duration, etc. [65,119,120] For example, Shangru et al. detected the feeding time and rumination time of 10 cows with wearable collars to estimate their feed intake using different algorithms including linear regression (LRM), ANN, SVM, and KNN [4]. Indicating a nonlinear relationship between feed intake and feeding time and ruminating time, LRM showed an R^2 of 0.73, while the other models showed the R^2 greater than or equal to 0.82. For another example, Davison et al. estimated the feed intake of eighty cows using four modeling approaches, including proportion of total feeding time of individual animals (GRP), multiple linear regression (REG), RF and SVM [121]. The RMSE of dry matter intake (DMI) estimation of the REG, RF, and SVM ranged from 1.15-1.61 kg, whereas a higher error was observed using GRP due to the fact that it did not capture the individual feeding patterns.

Estimating feed intake of livestock using behavior quantification indicators is often limited by the segmentation and accuracy of dynamic quantification of feeding behaviors, especially when dealing with complex feeding behaviors such as mixed movements of feeding, chewing, and swallowing [3]. Hence, behavior monitoring needs to be further promoted to synchronization recognition of multi-category behaviors (fine behaviors like chewing, biting, and regular behaviors like feeding, ruminating) and the quantification of behavior indicators. Furthermore, in combination with positional sensing, especially for grazing animals, the movement patterns of animals in an enclosure or feeding area can be analyzed and fused with data on feeding behavior to improve the accuracy of feed intake estimation. For example, the duration and intensity of feeding behavior can be inferred by analyzing the duration of an animal's residence time and activity patterns near the feed trough [3].

4.2. Estrus and Parturition Alarming

Behavioral monitoring is a useful tool in reproduction management of livestock for early identification of estrus and parturition. Contact sensors can provide a rich data stream over relatively long periods of time to capture their behavioral movements and sound, which in turn can be used to assess the physiological status of animals [122]. For example, Talukder et al. measured the activity and rumination of lactating cows by wearing accelerometers and microphones to identify factors associated with estrous events using a multivariate logistic generalized linear mixed model [5]. Assessing the overall utility by plotting of the ROC curve and calculating area under the curve (AUC), results showed that AUC was 0.82 for activity level, 0.54 for rumination level, and 0.75 for the combination of activity and rumination. This indicates that the activity level generated a more accurate estrus alarming. In the study of Silper et al. [6], the activities of cows were detected by two contact sensors (Heatime and IceTag) to detect signs of estrus at a high activity level. At a baseline of 87 ± 28 steps per hour, IceTag recorded 371 ± 91 steps per hour during estrus. Compared to which is a $360 \pm 170\%$ increase in activity relative to walking activity, it resulted in a positive estrus alarming of 98.7%. While the Heatime recorded an estrus intensity of 77.3 ± 19.5 peak exponential values, resulting in a positive estrus alarming of 84.7%.

Acoustic sensing plays an important role in livestock estrus monitoring, although for some reason it has not yet been commercially used in production. Researches showed that characteristics of sound such as intensity and frequency changes in estrus for cows and ewes [123,124]. Combined with machine learning algorithms such as K-Means clustering and SVM, automated estrus status recognition can be achieved. One of the reasons why acoustic sensing has not been widely used in production is due to the relatively large requirement of computation resources of acoustic analysis and the difficulty of implementation in edge devices. The further application of Tiny ML may be a solution in these resource-constrained scenarios [111].

Aside from estrus alarming, behavior monitoring can also be used for parturition warning [125]. This would be important for grazing animals, as it could help to reduce the mortality of newborn

animals. For example, Smith et al. tried to identify the parturition of pregnant ewe's based on the changes of their activity levels by either Maximum Mean Discrepancy (MMD) or the Earth Mover's Distance (EMD)[126]. Results from 76 pregnant ewes showed that these algorithms can estimate the birth of lambs, with 84% of parturition events falling within 12 hours of the actual birth time. While their study also showed that models need to be developed over sufficiently long periods ($2\text{ h} \leq \text{time period} \leq 6\text{ h}$) to capture the feature and enhance the model performance.

4.3. Assessing Animal Health and Welfare

The health status of animals is crucial in farm management, not only affecting productivity but also being an important consideration for animal welfare. Behavioral changes are good indicators of abnormalities caused by internal or external stimuli in animals. It helps to detect early signs of disease, and by identifying abnormal behaviors such as loss of appetite, reduced activity, or changes in social behavior, potential health problems can be detected early for timely intervention [7,9]. A study by Wang et al. indicated that pig behavior and vocalizations can be monitored in real time and translated into key health indicators, enabling early detection and intervention of diseases, and improving productivity and animal welfare in pig farms [9]. In addition, combining multiple sources of data such as accelerometers, temperature sensors, and heart rate monitors allows for the construction of more comprehensive health status metrics that can be used to identify health abnormalities in animals in real time through anomaly detection algorithms [127]. In this context, contact sensors provide a useful tool for the assessment of animal health and welfare.

Lameness is a common disease in ruminants caused by hoof lesions, limb lesions, or defects in locomotor and results in loss of animal production. A study from Norring et al. showed that cows with more severe lameness had shorter feeding times per day (lameness scores of 2, 3, and 4, 104 ± 4 min, 101 ± 4 min, and 91 ± 4 min/day, respectively) and consequently reduced the milk yield of cows [128]. Hence, lameness identification helps reduce the production loss, and this can be realized through behavior monitoring using contact sensors [8]. For example, Chapinal et al. investigated the effectiveness of acceleration of the legs and back of dairy cows to detect changes in gait or locomotion associated with lameness [129]. Results showed that the asymmetry of variance of acceleration within a pair of legs was correlated, and accelerometers attached to a leg would be a promising tool for lameness detection on farm.

Diseases for the digestive system, such as subclinical ketosis and subclinical acidosis, affect a large percentage of dairy cows and have a negative impact on their performance [130]. Results from Antanaitis et al. showed that cows with subclinical ketosis (SCK) or subclinical acidosis (SCA) would significantly decrease 17.47% of the rumination time, and 36.84% of the eating time, 38.10% of the eating chews, and lead to a 27.36% reduction in the overall activity levels compared to the healthy cows [131]. This indicates the promising application of behavior monitoring for early detection and effective management of SCK and SCA on dairy cow health [132].

Besides these examples mentioned above, there may still be some other potential application scenarios for assessing animal health with behavior monitoring. However, health assessment with behavior monitoring still faces many challenges. First, data complexity and noise handling are key issues, especially when fusing multiple sensors and cross-analyzing data from multiple sources. Second, how to translate the monitoring results into practical health management strategies and how to maintain the consistency and accuracy of monitoring across environments and species are also needed to be further studied.

5. Challenges and Prospects

5.1. Current Challenges

Significant progress has been achieved in monitoring and application of livestock behavior based on contact sensors, whereas numerous challenges remain to be addressed.

Firstly, the processing and interpretation of data remain complex and not feasible for edge computation in practical use. The algorithms are generally established with manual feature extraction and are based on fixed rules or training datasets, but often have limitations in the segmentation of dynamic behaviors and the adaptability to complex scenes [31,133]. In the scene of wearable devices, optimized or miniaturized algorithms should be established to adapt to the limited computing resources of wearable devices. Although the new method Tiny ML technology can execute machine learning models on low-power devices, significantly improving the energy efficiency and response speed of the system [7,72]. It's still an urgent issue about how to achieve a balance between real-time preprocessing, feature extraction, and model selection of data to ensure recognition accuracy and reduce computational complexity [7].

Secondly, while many researchers use three-axis acceleration sensors to identify livestock behavior, most of the models have not been systematically assessed and validated with embedded systems in practical application, including the effectiveness of behavior recognition and the power consumption or maximum endurance [134]. Existing behavior identification models rely on high frequency data acquisition and large-scale data transmission. This would result in high power consumption and short endurance of wearable devices. Algorithms for precision behavior recognition at a low frequency of data acquisition are needed to reduce resource loss in data transmission and storage and maintain the identification accuracy.

Finally, the reliability and cost of wearable devices pose another challenge. The durability under different environmental conditions, along with their installation and maintenance costs of wearable devices, have hindered their widespread application. For example, sensors may affect the accuracy and consistency of data due to wear, tear, and self-cleaning of animals or harsh weather conditions. In addition, the integration of sensors and the fusion of data, especially in the case of multimodal data, require more advanced algorithms to reduce noise, improve the efficiency of feature selection, and ensure consistency across sensor data [8,135].

5.2. Future Research Prospects

Despite the above challenges, looking into the future, there is a considerable prospect for livestock behavior monitoring and application based on wearable sensors or devices. The integrated use of sensors will promote the multi-function application and improve the accuracy of behavior monitoring. For example, studies can explore more sensor fusion strategies, such as combining physiological parameters (such as heart rate and body temperature) with motion characteristics to achieve a more comprehensive health assessment [127].

In terms of model construction, the aforementioned literature mentioned above indicates that the classification accuracy of routine livestock behavior is relatively high. However, when applying features of daily behavior, the performance is not as satisfactory as expected with the increase in the number of test samples. Predicting individual characteristics of complex behaviors typically exhibits lower efficiency and weaker model robustness. Therefore, in future research, strategies such as enhancing data diversity, integrating multimodal data, applying data augmentation techniques, introducing robustness regularization, and implementing cross-domain transfer learning could be considered to enhance the model's predictive efficiency and robustness for individual characteristics of complex behaviors, thereby advancing the model's generalization capabilities and stability. In addition, optimized or compressed models suitable for edge computing of wearable devices are needed, as mentioned above.

Translating behavior monitoring results into practical management decisions is a hot topic in current research. Although changes in behavior patterns can indicate an animal's health or productivity, translating this information into specific, actionable advice can be challenging for farmers. Interdisciplinary collaboration, such as the integration of biology, computer science, and engineering, is crucial for developing refined management strategies based on monitoring results. For example, the Five Domains Model proposed by Fogarty et al. [136] can be used as a framework

for evaluating animal welfare, but further research and development are still needed to integrate sensor data with each domain of the model.

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