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Review

Deep learning-based animal activity recognition with wearable sensors: Overview, challenges, and future directions

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ABSTRACT

Animal behavior, as one of the most crucial indicators of animal health and welfare, provides rich insights into animal physical and mental states. Automated animal activity recognition (AAR) allows caretakers to monitor animal behavioral variations in real time, significantly reducing workloads and costs in veterinary clinics and promoting livestock management efficiency. With recent advances in sensing technologies and smart computing techniques, automated AAR has been increasingly studied, and tremendous successes have been achieved. This paper provides a comprehensive summary of recent research on AAR based on wearable sensors and deep learning algorithms. First, the commonly used sensor types and frequently studied animal species and activities are described. Then, an extensive overview of deep learning-based methods for wearable sensor-aided AAR is presented, according to the taxonomy of deep learning algorithms. We also provide a comprehensive list of publicly available datasets collected via wearable sensor-aided AAR over the past five years. This list can serve as a valuable resource for readers who wish to further explore the field of AAR. In addition, we discuss potential challenges associated with the development of deep learning models for AAR and suggest potential solutions and future research directions for these challenges. In conclusion, this review work provides rich inspiration for the future advancement of robust AAR systems based on wearable sensors and deep learning techniques. When combined with qualitative assessments of veterinary specialists, the accurate and quantitative results obtained by automated AAR systems hold the potential to significantly improve animal health and welfare.

1. Introduction

The behavior of animals provides rich insights into their mental and physical states and is among the most crucial indicators of animals' health, welfare, and subjective states (Eerdekens et al., 2021). However, animal behavior monitoring largely relies on manual observations, which are time consuming, labor intensive, and involve the subjective judgments of individuals (Eerdekens et al., 2021). Therefore, investigating and developing an automated, quantifiable, and precise measurement system for animal behavior, particularly for animal health and welfare monitoring, is vital. Such intelligent animal activity recognition (AAR) systems allow caretakers to continuously and remotely monitor animal behavioral variations, thereby reducing workloads and costs in veterinary clinics and promoting livestock management efficiency (Astill et al., 2020).

Over the past decades, advancements in digital technologies (e.g., computer vision, wearable sensors, and acoustic analysis systems) have driven the rapid development of automated and precise AAR systems. In particular, wearable sensors, such as accelerometers, gyroscopes, magnetometers, pressure sensors, and global navigation satellite systems (GNSSs), have gained popularity in animal monitoring applications due to their light weight, compact size, low power consumption, high reliability, exceptional stability, and effortless integration. Wearable sensors are often integrated into study-specific devices or commercial systems, such as RuuviTag sensors (Arcidiacono et al., 2021), eGrazor and Ceres Tags (Arablouei et al., 2023b; Wang et al., 2023), Axivity AX3 dataloggers (Eerdekens et al., 2020a; Simanungkalit et al., 2021), Whistle Fit (Chambers et al., 2021), and CowView (Veissier et al., 2017). The kinetic characteristics (acceleration, angular velocity, etc.), pressure, and geo-location information of animals with different behaviors can be accurately measured at a certain sampling rate (e.g., 10, 25, 50, and 100 Hz) using these devices, which are generally attached to specific

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animal body parts (e.g., ears, necks, halters, and legs). Subsequently, advanced intelligent computing techniques are used to process and analyze the recorded data to classify various animal behaviors, such as the walking and rumination of cattle (Li et al., 2021b), the trotting and cantering of horses (Eerdekens et al., 2021), and the eating and petting behaviors of dogs (Chambers et al., 2021).

Machine learning, as one of the most promising data processing and analysis techniques, has been widely applied to animal behavioral classification based on data collected using wearable sensors (Brennan et al., 2021; Cabezas et al., 2022; Fogarty et al., 2021, 2020; Price et al., 2022; Simanungkalit et al., 2021; Tran et al., 2021). Machine learning-based data modeling approaches include naïve Bayes, linear regression, support-vector machine, decision tree, linear/quadratic discriminant analysis, and random forest approaches. Generally, to accurately classify animal behaviors through these methods, manual feature extraction and selection are required. However, these processes are time consuming and heavily reliant on expert domain knowledge, which leads to feature engineering challenges (Nweke et al., 2018). Some approaches combining feature extraction with feature selection, such as time series feature extraction based on scalable hypothesis tests (TSFRESH), can automatically capture the most discriminative features for the specific classification task based on specific statistic techniques (Christ et al., 2018; Will et al., 2022). They also provide interpretability and insights by ranking the importance of different features for predicting the target. However, since feature extraction and model development are conducted separately in these methods, handcrafted features may fail to capture complex and general features, resulting in low generalizability (Mao et al., 2021).

Deep learning, a new branch of machine learning, has been successfully adopted in diverse fields owing to its excellent automated feature-extraction ability (Lecun et al., 2015; Mao et al., 2021). Specifically, deep learning involves multiple layers of neural networks and thus enables the learning of features from raw sensor data with less preprocessing than other methods and allows for the hierarchical representation of features from low to high levels (Nweke et al., 2018). The most common deep-learning methods include fully connected feedforward neural networks (FFNNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants (Chen et al., 2021; Nweke et al., 2018; Wang et al., 2019). These methods can be stacked into different layers to form deep learning models that can enhance system performance, flexibility, and robustness. Deep learning models combined with wearable sensors have exhibited promising performance in distinguishing daily animal activities (Eerdekens et al., 2021, 2022; Kleanthous et al., 2022a; Minati et al., 2023; Wu et al., 2022). However, to the best of our knowledge, no study has summarized the application of deep learning techniques in AAR based on wearable sensor data. The existing reviews and survey papers have provided a broad overview of various artificial intelligence technologies for different applications, such as growth estimation, disease monitoring, and animal behavior detection, in the context of smart animal farming (Bao and Xie, 2022; Jukan et al., 2017; Tzanidakis et al., 2023). A few reports have focused on the application of data processing techniques combined with wearable sensors for animal behavior prediction; however, they have typically been limited to either traditional machine learning or specific animals and behaviors (Kleanthous et al., 2022b; Riaboff et al., 2022).

This study is the first to provide a comprehensive review of deep learning- and wearable sensor-based methods for AAR organized with respect to the taxonomy of deep learning algorithms. Moreover, we discuss some challenges associated with the development of deep-learning models for AAR, including annotation scarcity, data privacy, energy efficiency, multimodal fusion, class imbalance, inter-activity similarity, domain generalization, and open-set recognition. Solving these challenges requires dedicated deep-learning models. Hence, we propose some feasible solutions and potential future directions. Overall, we hope that this review work will inspire the development of robust AAR systems using deep learning and wearable sensors.

The remainder of this paper is organized as follows. Section 2 briefly introduces the background of automated recognition for animal activities using wearable sensors. Section 3 presents an extensive overview of deep learning-based methods for wearable sensor-aided AAR, in terms of the taxonomy of deep learning algorithms. The section also provides a comprehensive list of publicly available datasets collected via wearable sensor-aided AAR over the past five years. Section 4 presents some grand challenges and potential research directions in the development of deep learning models for AAR based on wearable sensor data. Section 5 presents our conclusions.

2. Background

Wearable sensors and deep learning techniques are well established in the field of automated AAR. The integration of these technologies facilitates the development of sophisticated systems capable of accurately detecting and classifying various activities, with the potential to revolutionize animal management and promote animal health and welfare (Kleanthous et al., 2022b). Fig. 1 presents a typical flowchart of AAR based on wearable sensors and deep learning methods. Various types of wearable sensors (accelerometers, gyroscopes, etc.) are first mounted on different body parts (ear, neck, etc.) of individual animals (cattle, sheep, etc.) to collect time-series motion signals. These raw sensor data are fed into diverse deep learning models (CNNs, RNNs, etc.) to make inferences about daily life activities (standing, ruminating, etc.). In the following subsection, we introduce the main types of wearable sensors used in AAR-related tasks and commonly studied animals and their activities. In addition, we provide a comprehensive list of publicly available datasets that are collected using wearable sensors for AAR tasks.

2.1. Wearable sensors

Advancements in wearable sensors and communication technologies have significantly enhanced the effectiveness of remote tracking of individual animal behaviors in various environments, and such behaviors can be tracked on a larger scale than was previously achievable (Fan et al., 2022). Herein, we introduce five types of wearable sensors commonly used in AAR-related research: accelerometer, gyroscope, magnetometer, GNSS, and ultra-wideband (UWB). The studies on these wearable sensors are also presented in Table 1.

Accelerometer. The tri-axial accelerometer is the most commonly used sensor in animal behavior monitoring tasks (Fan et al., 2022; Kleanthous et al., 2022b; Riaboff et al., 2022). It can measure acceleration values along three perpendicular spatial axes, enabling the capture of animal motion dynamics. The measurement unit of acceleration is meters per second squared (m/s^2). Attaching multiple accelerometer devices to different parts of an animal is an effective approach for expanding the spectrum of well-predicted behaviors (Riaboff et al., 2022), and it has been demonstrated to enhance recognition performance (Bloch et al., 2023; Eerdekens et al., 2022).

Gyroscope. A tri-axial gyroscope measures orientation and angular velocity along three orthogonal spatial axes. The unit of angular velocity is degrees per second ($^\circ/s$). Gyroscopes are usually integrated with accelerometers and attached to the same location as an accelerometer on animal bodies, such as the neck (Pan et al., 2023), halter (Zhao et al., 2022), back (Kasnesis et al., 2022), tail (Hussain et al., 2022a), or leg (Liseune et al., 2021), and operate at the same sampling rate as an accelerometer, typically ranging from a few Hz to several hundred Hz (Kleanthous et al., 2022b; Riaboff et al., 2022). Gyroscopes can provide information that complements that captured by accelerometers, thereby improving the prediction of some behaviors that are difficult to predict using only accelerometers (Walton et al., 2018).

Magnetometer. The tri-axial magnetometer is another commonly used sensor in AAR tasks. It allows for the detection of changes in the magnetic field at a particular location and the measurement of rotation

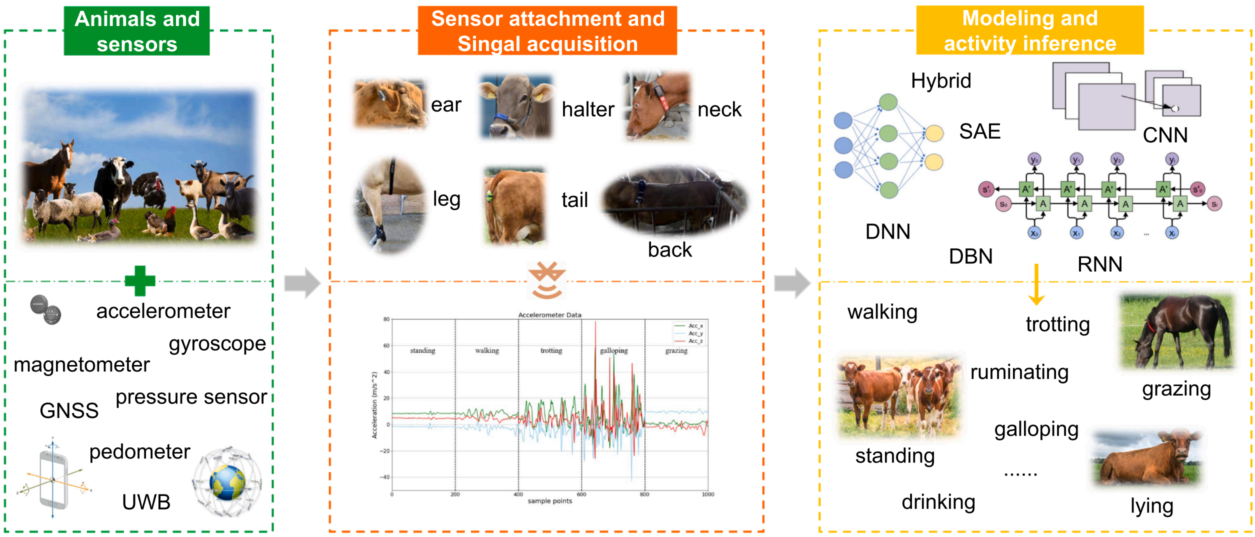

Fig. 1. Animal activity recognition (AAR) based on wearable sensors and deep learning models. Note: Abbreviations used in the Figure: CNN: Convolutional neural network; DBN: Deep belief network; DNN: Deep neural network; GNSS: Global navigation satellite system; RNN: Recurrent neural network; SAE: Stacked autoencoder; UWB: Ultra-wideband.

Table 1
Existing animal activity recognition (AAR)-related studies involving different wearable sensors.

Sensors	Reference
Accelerometer	Arablouei et al. (2021, 2023a, 2023b), Bloch et al. (2023), Chambers et al. (2021), Coelho Ribeiro et al. (2021), Eerdekens et al. (2020a, 2020b, 2021, 2022), Kamminga et al. (2020), Kleanthous et al. (2022a), Li et al. (2021b), Minati et al. (2023), Wang et al. (2023)
Accelerometer and gyroscope	Hussain et al. (2022a, 2022b), Kasnesis et al. (2022), Kim and Moon (2022), Liseune et al. (2021), Mao et al. (2021, Mao et al., 2022b), Pan et al. (2023), Pavlovic et al. (2021), Zhao et al. (2022)
IMU (accelerometer, gyroscope, and magnetometer)	Dominguez-Morales et al. (2021), Hosseininoorbin et al. (2021), Peng et al. (2019, 2020), Shahbazi et al. (2023), Wu et al. (2022)
Accelerometer and GNSS	Arablouei et al. (2023c), Riaboff et al. (2020)
Accelerometer and UWB	Benaissa et al. (2023)

Note: Abbreviations used in the Table: IMU: Inertial measurement unit; GNSS: Global navigation satellite system; UWB: Ultra-wideband.

angle values (i.e., pitch, roll, and yaw). The measurement unit is Tesla (T). A magnetometer is typically assembled with an accelerometer and a gyroscope into an inertial measurement unit (IMU), which can simultaneously capture linear acceleration, angular velocity, and rotation angle. IMUs have been used to obtain a deep understanding of animal behaviors (Dominguez-Morales et al., 2021; Hosseininoorbin et al., 2021; Peng et al., 2020, 2019; Wu et al., 2022). For example, Hosseininoorbin et al. (2021) obtained superior results by using an IMU compared with using an accelerometer, gyroscope, or magnetometer alone or a combination of any two of these devices.

GNSS. The GNSS is a satellite-based navigation system that provides location and time information to users worldwide. It has been combined with motion sensors to track the geo-location and movement patterns of various animals, particularly those grazing outdoors in pastures, to obtain a higher behavioral prediction accuracy than is possible with other methods (Aquilani et al., 2022; Halachmi et al., 2019; Tzanidakis et al., 2023). For example, a recent study examined the use of data from both accelerometers and the GNSS for classifying cattle behaviors (Arablouei et al., 2023c). The use of a combination of data from both sensors resulted in considerably higher prediction accuracy than the use of data from only one sensor, particularly for infrequent but important behaviors such as walking and drinking. Furthermore, the incorporation of the GNSS helps to distinguish between distinct behaviors with similar movement patterns, as these behaviors tend to occur in different functional areas, such as feeding in designated feeding areas and drinking at water troughs (Halachmi et al., 2019).

UWB. The UWB is a radio technology that can use a very low energy level for short-range, high-bandwidth communications over a large portion of the radio spectrum. Real-time location systems based on UWB technology are typically utilized as indoor positioning systems to identify and locate groups of animals in free-stall barns (Benaissa et al., 2023; Pastell et al., 2018; Porto et al., 2014). A recent study incorporated the UWB-based indoor location data with accelerometer data to enhance cattle behavior monitoring systems in a free-stall barn (Benaissa et al., 2023). The novelty of their approach lies in restricting the number of behaviors considered by the accelerometer based on the functional area in which the cow is located (feeding, lying, drinking), effectively reducing the confusion between behaviors (e.g., eating concentrate vs. drinking) with close patterns. In addition, the combination of these two data sources enables the tracking of social interactions among cows, which play a vital role in their health and welfare (Benaissa et al., 2023).

2.2. Animals and animal activities

AAR systems based on wearable sensor data are commonly designed for domesticated animal species, including cattle, sheep, horses, dogs, chickens, and pigs (Halachmi et al., 2019; Jukan et al., 2017; Pan et al., 2023). In the implementation of these systems, the feasibility and economic benefits of wearing wearable sensors on each animal and the potential behavioral changes caused by the added weight and discomfort to the animals have been considered carefully.

Cattle. Cattle, as ruminants, are the most frequently studied animals in the literature on wearable sensor-based AAR owing to their significant economic value in agriculture and large physical size (Halachmi et al., 2019; Riaboff et al., 2022). The common cattle behaviors that have been examined include feeding (eating, grazing, etc.), ruminating, resting (lying, sleeping, etc.), and locomotion (moving, walking, etc.) (Bello et al., 2020; Fan et al., 2022; Riaboff et al., 2022). In addition, maintenance behavior (grooming, itch rubbing, etc.) and social behavior (social licking, attacking, etc.) of cattle has been examined (Hosseininoorbin et al., 2021; Peng et al., 2019; Wu et al., 2022). These activities are typically monitored and statistically analyzed for various applications, such as the early detection of diseases or lameness (Pavlovic et al., 2021; Wu et al., 2022), estrus detection (Pavlovic et al., 2021; Pereira et al., 2020), and the onset of calving (Liseune et al., 2021; Peng et al., 2020). For instance, in Wu et al. (2022), cattle behaviors including feeding, lying, ruminating, itch rubbing, and social licking were monitored using neck-mounted IMU sensors to evaluate skin diseases, because infected cattle have difficulties in feeding and resting and often exhibit abnormal rubbing and scratching behaviors. Liseune et al. (2021) exploited sequential information from neck- and leg-attached sensors to measure six activities (i.e., ruminating, eating, lying, standing up, walking, and inactive behavior) of dairy cattle and thereby predict the moment of calving.

Sheep. Sheep are another ruminant animal typically kept as livestock. Studies on sheep behavior recognition using wearable sensors have focused on activities such as eating, grazing, resting, stationary behavior, standing, walking, trotting, running, and scratching (Kamminga et al., 2020, Kleanthous et al., 2022a). Grazing, which involves feeding on grasses and herbage while standing or walking with the head down, is of great interest in the sheep industry (Kleanthous et al., 2022a). Moreover, changes in physical activities (e.g., lying down, standing, and walking) can signal the occurrence of lameness, a prevalent welfare problem in global sheep farming (Al-Rubaye et al., 2018; Barwick et al., 2018; Walton et al., 2018). In a recent study, walking and scratching were grouped as active behaviors, while standing and resting were grouped as inactive behaviors, to detect potential diseases (Kleanthous et al., 2022a). Evidence has demonstrated that reduced animal activity levels and increased resting levels can be signs of diseases, pain, or heat stress (Aquilani et al., 2022; Fan et al., 2022; Kleanthous et al., 2022a; Price et al., 2022).

Horses. Horses, which are hoofed herbivorous mammals, are also a common research subject in AAR-related studies. Eating remains a frequently studied behavior, as a decrease in voluntary food intake is the most frequently reported symptom of pathogen infection in horses (Fan et al., 2022). Most studies on horse behavior recognition primarily focus on their standing and gaits (e.g., walking, trotting, cantering, and galloping; Dominguez-Morales et al., 2021; Eerdekens et al., 2020a, 2020b, 2021; Kamminga et al., 2020; Mao et al., 2021, 2022b). The presence of a structural or functional disorder in one or more limbs or the back can alter the normal gait, resulting in lameness that is evident when a horse is standing or moving (Weeren et al., 2017). Moreover, lameness is one of the most expensive health problems in the equine industry (Bosch et al., 2018; Weeren et al., 2017). Rare activities, such as rolling, pawing, and flank watching, were considered for the first time in a recent study on wearable sensors (Eerdekens et al., 2020a).

Dogs. Interpreting dog behaviors using activity recognition systems based on wearable sensors has been a subject of substantial research, as dogs play multiple vital roles in human life; for example, they serve as pets and as service and working animals (Jukan et al., 2017; Kasnesis et al., 2022). Recent advances in wearable activity recognition systems have allowed for the expansion of the capabilities of dog activity monitors beyond predicting general activity levels. Activity monitors can now predict when and how long a dog will engage in basic behaviors, such as standing, walking, trotting, running, lying, and resting (Hussain et al., 2022a; Kasnesis et al., 2022; Kim and Moon, 2022), and in a wide variety of actions, such as feeding, drinking, licking, scratching, rubbing, sniffing, and head shaking (Chambers et al., 2021; Eerdekens et al., 2022; Hussain et al., 2022b). The accurate and quantitative detection of these daily activities is helpful in various ordinary contexts, such as animal emotion and health evaluation, medical monitoring, therapeutic intervention, remote control, and health care (Chambers et al., 2021; Hussain et al., 2022b).

Chickens. Wearable sensors have found extensive use in detecting various activity levels and behavioral patterns in chickens, including laying hens and broilers. In laying hen-behavior recognition studies (Derakhshani et al., 2022; Kozak et al., 2016; Shahbazi et al., 2023), daily behaviors were classified into three categories based on their intensity, including low- (static behaviors such as sitting, standing, and resting), moderate- (semi-dynamic behaviors such as eating, drinking, and preening), and high- (highly-dynamic behaviors such as walking, running, and jumping) intensity physical activities. Yang et al. (2021) and Mei et al. (2023) applied accelerometers to identify broiler behaviors that were categorized into two types (i.e., static and dynamic activities), where static activities include sitting, standing, and drinking behaviors, and dynamic activities include feeding, walking, and other behaviors. The real-time monitoring of these bird activities using wearable sensors can aid in detecting abnormal behaviors, promptly alerting potential animal illnesses, and facilitating timely human intervention. For instance, Mei et al. (2023) stated that abnormal behaviors such as prolonged sitting and reduced feeding in broilers can indicate sickness and assist in identifying sick birds.

Pigs. Pigs exhibit various behaviors that are of significant interest in biology and practical breeding (Pan et al., 2023). For example, pigs predominantly spend their time lying down, followed by standing, and the least amount of time walking (Jin et al., 2021). Understanding and analyzing these behaviors is crucial for monitoring their health and providing continuous care. By utilizing wearable sensor-based behavioral monitoring technology, we can offer objective and quantitative assessments of pig behavior. Typical pig behaviors existing works considered for classification include eating, drinking, lying, sleeping, sitting, standing, and moving (Alghamdi et al., 2022; Jin et al., 2021; Pan et al., 2023). In addition, more specific behaviors exhibited by lactating sows, such as nursing and variations of lying postures (i.e., lying on the belly, lying on the right side, and lying on the left side), are crucial areas of exploration and research. These behaviors have received significant attention due to their role in protecting piglets from being accidentally crushed by the sows during parturition (Cornou et al., 2011; Pan et al., 2023; Thompson et al., 2016).

Table 2 presents six above-mentioned animal species (i.e., cattle, sheep, horses, dogs, chickens, and pigs) and their behaviors that have been investigated in recent wearable sensor-aided AAR studies. It can be observed that basic activities such as eating, drinking, lying, resting, standing, and walking have been extensively examined across different animal species. The variations in these behaviors have been validated as indicators of the animals' health states, including sickness, pain, or heat stress (Gougoulis et al., 2010; Kleanthous et al., 2022a; Price et al., 2022; Smith et al., 2015).

3. Overview of deep Learning-based AAR

3.1. Deep learning-based methods for AAR with wearable sensors

This section reviews representative studies published in the past five years on the application of deep learning for wearable sensor-aided AAR. These works were retrieved from international digital libraries, such as Google Scholar, ScienceDirect, the Multidisciplinary Digital Publishing Institute, the Institute of Electrical and Electronics Engineering, and the Web of Science. The search keywords were "animal activity recognition", "animal behavior classification", "cattle", "sheep", "horse", "dog", "chicken", "pig", "wearable sensor", "accelerometer", "gyroscope", "magnetometer", "GNSS", "UWB", "deep learning", and "artificial intelligence". Table 3 lists all of the selected publications according to the categories of deep learning models they have examined (i.e., FFNN, CNN, RNN, and hybrid models). In the following subsections, we will present more details on these studies regarding the types of deep learning models.

3.1.1. FFNN

An FFNN, also known as a multilayer perceptron (MLP), is a type of artificial neural network. As illustrated in Fig. 2, the FFNN typically consists of an input layer, multiple hidden layers, and an output layer, with each layer composed of many interconnected neurons. The output of each neuron in one layer is input to every neuron in the subsequent layer, allowing the network to learn complex non-linear relationships

Table 2
Animal species and their studied activities.

Species	Activities	Reference
Cattle	Eating, drinking, nursing, grazing, ruminating, licking salt, social licking, salting, lying, resting, sleeping, standing up, standing, moving, walking, grooming, headbutting, itch rubbing (leg/neck), urinating, attacking, escaping, being mounted, active behavior, and inactive behavior	Arablouei et al. (2021, 2023a, 2023b, 2023c), Bloch et al. (2023), Coelho Ribeiro et al. (2021), Li et al. (2021b), Liseune et al. (2021), Minati et al. (2023), Hosseininoorbin et al. (2021), Pan et al. (2023), Pavlovic et al. (2021), Peng et al. (2019, 2020), Wang et al. (2023), Wu et al. (2022)
Sheep	Eating, grazing, stationary, walking, trotting, running, active behavior (walking and scratching), and inactive behavior (standing and resting)	Kamminga et al. (2020), Kleanthous et al. (2022a), Monteiro et al. (2022)
Horse	Eating, standing, motionless, walking (natural/rider), cantering, trotting, galloping, rolling, pawing, and flank watching	Dominguez-Morales et al. (2021), Eerdekens et al. (2020a, 2020b, 2021), Kamminga et al. (2020), Mao et al. (2021, Mao et al., 2022b)
Dog	Eating, drinking, object licking, self-licking, lying (with/without head raised), sitting, standing, walking, trotting, running, leaping, sprinting, petting, rubbing, scratching, shaking, sniffing, and nose work	Chambers et al. (2021), Eerdekens et al. (2022), Hussain et al. (2022a, 2022b), Kasnesis et al. (2022), Kim and Moon (2022)
Chicken	Eating, drinking, foraging, sitting, standing, resting, sleeping like resting, neck shortening resting, sleeping, walking, running, jumping, perching, egg laying, side-laying phase of dust bathing, small postural head/shoulder/neck movements, preening, pecking, small wing adjustments, scratching, stretching, head shaking, feather fluffing, searching, wing flapping, controlled aerial ascent/descent, full-body shaking, and shaking phase of dust bathing	Mei et al. (2023), Shahbazi et al. (2023), Yang et al. (2021)
Pig	Eating, drinking, nursing, lying, sleeping, sitting, standing, moving, walking, playing, and exploring	Alghamdi et al. (2022), Jin et al. (2021), Pan et al. (2023)

between inputs and outputs. In addition, an FFNN can handle large datasets and high-dimensional input spaces because it can be easily scaled up by adding more hidden layers and neurons.

Table 4 presents studies in which FFNNs have been used for wearable sensor-aided AAR. Coelho Ribeiro et al. (2021) compared an FFNN with a generalized linear model and a random forest model in terms of cattle grazing behavior detection based on accelerometer data. The random forest model yielded the highest accuracy (76%), followed by the FFNN and the generalized linear model (74% and 59%, respectively). The lower accuracy of the FFNN than the random forest model is attributable to overfitting caused by the large number of parameters used in the FFNN. Hosseininoorbin et al. (2021) and Dominguez-Morales et al. (2021) have examined the performance of FFNNs based on nine-axis motion data from neck-attached IMU sensors, and obtained a favorable F1-score of 89.3% and a high accuracy of 97.96% in recognizing different activities of horses and cattle, respectively. Arablouei et al. (2021) compared an MLP with several machine-learning algorithms (e.g., linear regression, support-vector machine, and decision tree) for identifying cattle behaviors, based on a cattle dataset acquired using neck-attached tri-axial accelerometers. The results demonstrated that the MLP performed the best, with a 93.4% overall accuracy in classifying behaviors, including grazing, ruminating, and resting. According to

Table 3
Deep learning models for AAR with wearable sensors.

Model	Description	Reference
FFNN	Fully connected, feedforward, and multilayer neural network	Arablouei et al. (2021, 2023a, 2023c), Coelho Ribeiro et al. (2021), Dominguez-Morales et al. (2021), Minati et al. (2023), Hosseininoorbin et al. (2021)
CNN	Convolutional, hierarchical, and shared-weight neural network	Bloch et al. (2023), Eerdekens et al. (2020a, 2020b, 2021, 2022), Hussain et al. (2022a), Kasnesis et al. (2022), Kleanthous et al. (2022a), Li et al. (2021b), Mao et al. (2021, Mao et al., 2022b), Minati et al. (2023), Pan et al. (2023), Pavlovic et al. (2021), Shahbazi et al. (2023)
RNN	Recurrent, feedback, and temporal neural network	Hussain et al. (2022b), Peng et al. (2019, 2020), Wang et al. (2023), Wu et al. (2022)
Hybrid	Combination of some deep models	Arablouei et al. (2023b), Chambers et al. (2021), Kim and Moon (2022), Liseune et al. (2021), Zhao et al. (2022)

Note: Abbreviations used in the Table: FFNN: Fully connected feedforward neural network; CNN: Convolutional neural network; RNN: Recurrent neural network.

these findings, Arablouei et al. selected the MLP as the classification model to distinguish more specific cattle behaviors (i.e., walking and drinking) in their subsequent two papers (Arablouei et al., 2023a, 2023c). Arablouei et al. (2023a) developed an end-to-end deep learning model, which consists of infinite-impulse-response and finite-impulse-response filters for feature extraction together with an MLP for classification. This model yielded a high accuracy (95.68%) on the same dataset used in Arablouei et al. (2021). Arablouei et al. (2023c) devised an MLP-based multimodal fusion approach that combines both accelerometer and GNSS data to achieve accurate cattle behavior classification. Experiments were conducted on two new real-world datasets collected using smart cattle collar tags and ear tags, and the method obtained a higher accuracy (88.47%) on the collar-based dataset.

3.1.2. CNN

CNNs, one of the most researched deep-learning algorithms, have been used successfully in a wide range of applications, such as natural language processing, image classification, speech recognition, and time series analysis (Nweke et al., 2018; Wang et al., 2019). Fig. 3 displays the structural diagram of a typical CNN. A CNN is generally designed to automatically learn and extract hierarchical features from raw input data (e.g., sensor values) using multiple layers of convolutional and pooling operations. The convolutional layers apply a set of filters with different kernel sizes and strides to capture local temporal dependencies between neighboring input values. The pooling layers operate by sliding a window over the input feature map and computing a summary statistic (e.g., maximum and average values) within each window to generate a downsampled output feature map, which makes the network translation invariant to changes and variations. Then, the features learned from sensor data are fed into several fully connected layers for final activity classification. In addition, CNNs use weight sharing to reduce the number of parameters in a network, which helps to prevent overfitting and improve model generalization. Owing to these remarkable benefits, CNNs have been increasingly adopted and are the most-used type of deep learning model in the field of wearable sensor-aided AAR.

Table 5 summarizes studies on the use of CNNs for AAR with wearable sensors. CNN-based approaches exhibit excellent performance in the classification of animal behaviors, with accuracies exceeding 90% in most cases. Eerdekens et al. (2020a, 2020b, 2021, 2022) have conducted several studies on the use of CNNs in combination with accelerometer data to recognize the behaviors of horses and dogs. These studies have consistently demonstrated the excellent performance of CNNs, with

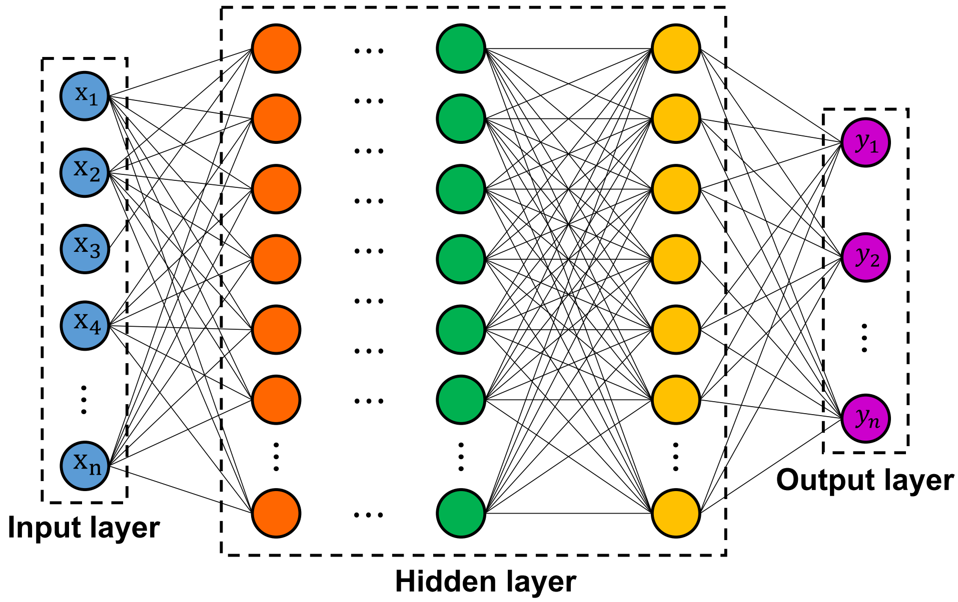

Fig. 2. FFNN structure. The FFNN consists of an input layer, multiple hidden layers, and an output layer, each composed of interconnected neurons.

Table 4
Studies on fully connected feedforward neural network-based methods for AAR with wearable sensors.

Method	Sensor	Placement	Species	Activities	Accuracy (%)
Coelho Ribeiro et al. (2021)	Accelerometer	Halter	Cattle	Grazing, non-grazing	74
Hosseininoorbin et al. (2021)	IMU	Neck	Cattle	Grazing, walking, ruminating (standing), ruminating (lying), standing, lying, drinking, grooming, and others	89.3 (F1-score)
Dominguez-Morales et al. (2021)	IMU	Neck	Horse	Motionless, walking, and trotting	97.96
Arablouei et al. (2021)	Accelerometer	Neck	Cattle	Grazing, ruminating, resting, and others	93.40
Arablouei et al. (2023a)	Accelerometer	Neck	Cattle	Grazing, walking, ruminating/resting, drinking, and others	95.68
Arablouei et al. (2023c)	Accelerometer and GNSS	Neck | ear	Cattle		88.47 (neck) | 75.32 (ear)

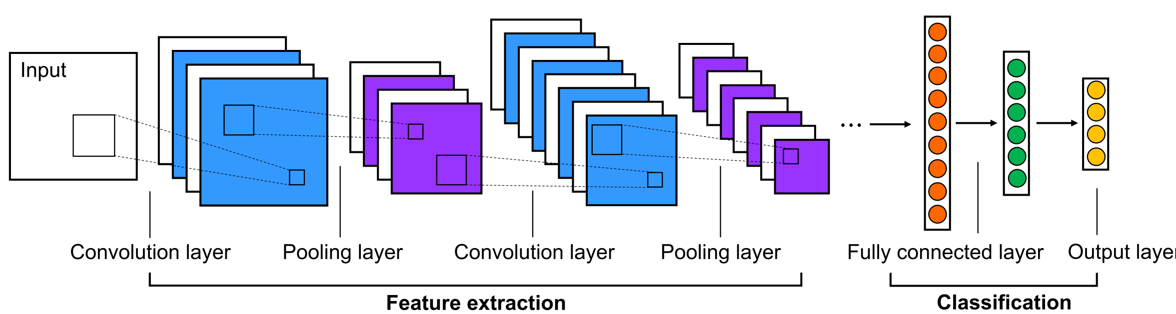

Fig. 3. CNN structure. The CNN comprises a series of convolutional and pooling layers for feature extraction and fully connected layers for classification.

prediction accuracies exceeding 97%. In particular, Eerdekens et al. (2021, 2022) have validated the superior performance of hybrid CNNs with statistical features as input compared with techniques based on raw sensor data, consistent with the findings in Kleanthous et al. (2022a). Kleanthous et al. (2022a) devised three CNN models with distinct architectures to classify sheep activities. The authors employed a feature engineering approach to extract handcrafted features from the raw data for network training. This approach effectively improved model generalization, resulting in higher classification accuracy (98.55%) than the approach based on raw sensor data. In Mao et al. (2021), a new CNN architecture was developed to identify various horse activities using a dataset obtained via neck-fixed accelerometers and gyroscopes. The resulting CNN model obtained a high classification accuracy (90.68%) and was subsequently utilized as the baseline model in two recent studies with different application objectives (Mao et al., 2022b, 2022). Pavlovic et al. (2021) designed a CNN architecture to accurately categorize cattle behaviors using data generated from neck-mounted accelerometer collars. Their CNN architecture underwent a rigorous hyperparameter search process, and the optimal model achieved an impressive overall F1 score of 82%. Their CNN architecture was also applied in a recent study (Bloch et al., 2023), in which it was validated for cattle behavior classification using data collected from both neck- and leg-attached accelerometers, and achieved a high F1 score (93.9%). Li et al. (2021b) investigated the use of CNNs with various data-augmentation techniques to detect cattle behaviors using motion data collected using neck-mounted tri-axial accelerometers. Their CNN

Table 5
Studies on convolutional neural network-based methods for AAR with wearable sensors.

Method	Sensor	Placement	Species	Activities	Accuracy (%)
Eerdekens et al. (2020a)	Accelerometer	Leg	Horse	Standing, walking, trotting, cantering, rolling, pawing, and flank watching	99
Eerdekens et al. (2020b)	Accelerometer	Leg	Horse		99.93
Eerdekens et al. (2021)	Accelerometer	Leg	Horse		99.59
Eerdekens et al. (2022)	Accelerometer	Neck and chest	Dog	Lying, sitting, standing, walking, running, sprinting, eating, and drinking	97.87
Kleanthous et al. (2022a)	Accelerometer	Neck	Sheep	Grazing, active, and inactive	98.55
Mao et al. (2021)	Accelerometer and gyroscope	Neck	Horse	Eating, standing, trotting, galloping, walking with a rider, and natural walking	90.68
Mao et al. (2022b)	Accelerometer and gyroscope	Neck	Horse		–
Mao et al. (2022)	Accelerometer and gyroscope	Neck	Horse		–
Pavlovic et al. (2021)	Accelerometer	Neck	Cattle	Eating, ruminating, and others	82 (F1-score)
Bloch et al. (2023)	Accelerometer	Neck	Cattle	Feeding, ruminating, and others	93.9 (F1-score)
Li et al. (2021b)	Accelerometer	Neck	Cattle	Feeding, walking, salting, ruminating, and resting	94.43
Minati et al. (2023)	Accelerometer	Neck	Cattle	Grazing, moving, resting, ruminating, and salting	96
Kasnesis et al. (2022)	Accelerometer and gyroscope	Back	Dog	Standing, walking, trotting, and running	91.26
Hussain et al. (2022a)	Accelerometer and gyroscope	Neck and tail	Dog	Walking, sitting, down, staying, feeding, sideways, leaping, running, shaking, and nose work	96.85
Shahbazi et al. (2023)	IMU	body	Chicken	Low-, medium-, and high-intensity behaviors	> 99
Pan et al. (2023)	Accelerometer and gyroscope	Neck	Pig	Moving, drinking, eating, nursing, sleeping, and lying	87.33

model achieved a high classification accuracy (94.43%) for cattle behaviors. Minati et al. (2023) utilized the same dataset to develop a CNN with two convolutional layers and obtained a higher classification accuracy (96%). Kasnesis et al. (2022) and Hussain et al. (2022a) have investigated the use of CNNs for recognizing dog activities based on motion data obtained from accelerometers and gyroscopes attached to various body parts, such as the back, neck, and tail. In Kasnesis et al. (2022), a deep late-fusion CNN was designed and yielded a high accuracy (93.68%) in classifying dog activities. In Hussain et al. (2022a), a CNN model with one-dimensional convolution was devised, with features extracted from raw sensor data used as input. This method obtained a high accuracy (96.85%) in recognizing dog behaviors. Recently, CNNs have also been utilized to distinguish behaviors in chickens (Shahbazi et al., 2023) and lactating sows (Pan et al., 2023). In Shahbazi et al. (2023), the CNN model achieved an average accuracy of nearly 100% in classifying activities of individual hens using motion data from body-worn IMU sensors. The high classification accuracy in this study can be attributed to its focus on coarsely categorizing different activity levels in chickens rather than classifying specific behaviors. In Pan et al. (2023), an accuracy of 87.33% was obtained in detecting static behaviors (i.e., nursing, lying, and sleeping) and active behaviors (i.e., eating, drinking, and moving) of lactating sows.

3.1.3. RNN

An RNN is designed to model sequential data, such as natural language text and time series (e.g., sensor data). Unlike feedforward neural networks, RNNs have a feedback loop in their hidden unit, which allows them to maintain a memory (i.e., hidden state) of previous inputs and use it to inform the processing of current inputs (Fig. 4). At each time step, an RNN takes an input vector and combines it with the previous hidden state to produce a new hidden state, which is then used in the next time step. This recurrent connection enables the network to capture the temporal dependencies in the input data. However, RNNs are difficult to train and suffer from the problem of vanishing or exploding gradients, which limits their applicability in modeling long-term activity sequences and temporal dependencies in sensor data. Several variants of RNN have been devised to solve these problems, such as long short-term memories (LSTMs; Hochreiter and Schmidhuber, 1997) and gated recurrent units (GRUs; Chung et al., 2014). An LSTM and a GRU introduce memory cells that can maintain information over long periods and varieties of gates that can control information flow in and out of cells. Compared with an LSTM, a GRU has a simpler structure with fewer parameters, resulting in a simpler training procedure and faster execution speed.

Table 6 summarizes recent studies on RNNs for AAR with wearable sensors. Peng et al. have utilized LTSMs for three cattle-behavior recognition studies based on distinct datasets and targeting different

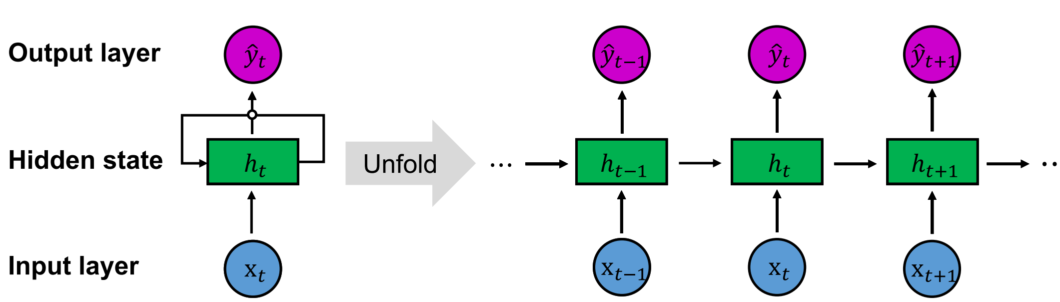

Fig. 4. RNN structure. The RNN has a feedback loop in its hidden unit, which can maintain a memory (i.e., hidden state) of previous inputs and combines it with the current input.

Table 6
Studies on recurrent neural network-based methods for AAR with wearable sensors.

Method	Sensor	Placement	Species	Activities	Accuracy (%)
Peng et al. (2019)	IMU	Neck	Cattle	Feeding, lying, ruminating (lying), ruminating (standing), licking salt, moving, social licking, and headbutting	88.7
Peng et al. (2020)	IMU	Neck	Cattle	Feeding, ruminating (lying), ruminating (standing), lying normal, lying final, standing normal, and standing final	79.7
Wu et al. (2022)	IMU	Neck	Cattle	Feeding, lying, ruminating (lying), itch rubbing (leg), social licking, and itch rubbing (neck)	94.9
Wang et al. (2023)	Accelerometer	Neck | ear	Cattle	Grazing, walking, ruminating/resting, drinking, and others	89.5 (neck) | 80 (ear)
Hussain et al. (2022b)	Accelerometer and gyroscope	Neck and tail	Dog	Walking, sitting, down, staying, feeding, sideways, leaping, running, shaking, and nose work	94.25

applications (Peng et al., 2019, 2020; Wu et al., 2022). These datasets included nine-axial-motion data acquired from collar-attached IMU sensors. Peng et al. (2019) conducted the pioneering research on utilizing LSTMs in wearable sensor-aided AAR tasks. They developed an LSTM model that attained an accuracy of 88.7% in distinguishing eight cattle behaviors, such as feeding, licking salt, and headbutting; thus, the model can be used to assess the health and welfare of cattle. In Peng et al. (2020), the LSTM-based methods achieved an accuracy of 79.7% in identifying seven behaviors prior to calving, such as feeding, lying normally (collected during 72–24 h before calving), and standing normally (collected during 72–24 h before calving). Wu et al. (2022) developed a novel LSTM model called deep residual bidirectional LSTM to classify cattle behavioral patterns for the early identification of bovine dermatomycosis. Their deep residual bidirectional LSTM exhibited a significantly higher classification accuracy (94.9%) than a basic LSTM. Among these three studies, Peng et al. (2019, 2020) compared LSTM models with CNN models and revealed that the former could achieve superior cattle behavior classification performance, consistent with the findings in Wang et al. (2023). Wang et al. (2023) designed multiple LSTM and GRU architectures with varying depths and widths and compared their performances in classifying cattle behaviors with those of two state-of-the-art CNN-based classification models. The experiments were conducted on collar-attached and ear-attached accelerometer data reported by Arablouei et al. (2023c). The considered RNN models achieved comparable or superior accuracy to the CNN models while requiring less computational and memory resources. A two-layer bidirectional GRU model with 128 hidden units exhibited the best performance, with the highest accuracy of 89.5% and 80% on the collar- and ear-based datasets, respectively. The accuracy values were significantly higher than those obtained using MLP models in Arablouei et al. (2023c) (Table 4). Hussain et al. (2022b) employed an LSTM-based method to detect dog activities based on motion data from accelerometers and gyroscopes, which were mounted on the necks and tails of dogs. Their model achieved a good testing accuracy (94.25%) in classifying activities of dogs.

3.1.4. Hybrid model

A hybrid model is a combination of several deep learning models, with the models being combined to improve performance or eliminate the shortcomings of individual models.

Table 7 presents various hybrid deep-learning models for AAR tasks. One emerging hybrid deep-learning model is the combination of CNN and LSTM, i.e., CNN–LSTM model. Liseune et al. (2021) provided a good example of combining CNN and LSTM in cattle-behavior classification tasks, based on motion data from accelerometers and gyroscopes. It was revealed that the CNN–LSTM model outperformed pure CNN and LSTM models. Similar results were also reported in a recent study (Kim and Moon 2022), in which the CNN-LSTM model exhibited a 93.4% accuracy in identifying dog behaviors. Chambers et al. (2021) applied FilterNet, a CNN–LSTM model devised by Chambers and Yoder (2020), to detect daily dog behaviors using neck-mounted accelerometer data. FilterNet displayed high classification accuracies (>94%) for all considered behaviors, such as drinking (99%), eating (94.8%), and object licking (98%). Arablouei et al. (2023b) devised a new hybrid deep-learning method called GRU-MLP to classify cattle behaviors and validated it using previously adopted collar-attached and ear-attached accelerometer data (Arablouei et al., 2023c; Wang et al., 2023). Classification accuracies of 88.1% and 80.6% were obtained on collar- and ear-based datasets, respectively. In particular, this GRU–MLP model exhibited performance comparable with that of the pure GRU model devised in Wang et al. (2023) (Table 6) while requiring significantly smaller numbers of parameters (0.026 vs. 0.496 M) and fewer computational operations (6.4 vs. 101.2 M). The model exhibited this performance mainly because the authors adopted the knowledge distillation technique, in which the residual neural network was taken as the teacher model to improve the performance of the student model, that is, the GRU–MLP model.

3.2. Public datasets for AAR with wearable sensors

Herein, we provide a comprehensive list of publicly available datasets collected via wearable sensor-aided AAR over the past five years (Table 8). Table 8 presents several attributes of the datasets: the species and number of animals; the types, placements, and sampling rates of sensors; considered activities; and the recording duration or number size of annotated samples. To the best of our knowledge, before 2018, only

Table 7
Studies on hybrid methods for AAR with wearable sensors.

Method	Hybrid model	Sensor	Placement	Species	Activities	Accuracy (%)
Liseune et al. (2021)	CNN-LSTM	Accelerometer and gyroscope	Neck and leg	Cattle	Ruminating, eating, lying, standing up, walking, and inactive behavior	–
Kim and Moon, (2022)	CNN-LSTM	Accelerometer and gyroscope	Neck	Dog	Standing, sitting, lying with head raised, lying without head raised, walking, sniffing, and running	93.4
Chambers et al. (2021)	CNN-LSTM	Accelerometer	Neck	Dog	Drinking, eating, object licking, self-licking, petting, rubbing, scratching, shaking, sniffing, and others	> 90
Arablouei et al. (2023b)	GRU-MLP	Accelerometer	Neck | ear	Cattle	Grazing, resting, and others	88.1 (neck) | 80.6 (ear)

Note: Abbreviations used in the Table: GRU: Gate recurrent unit; MLP: Multi-layer perceptron; CNN: Convolutional neural network; LSTM: Long short-term memory.

Table 8
Public datasets[1] on AAR with wearable sensors.

Species	Number of animals	Sensor type	Placement	Sampling rate (Hz)	Activities	Duration/ number	Reference
Goat	5	Accelerometer and gyroscope	Neck	100	Stationary behavior, walking, trotting, running, eating, fighting, shaking, climbing up, climbing down, rubbing, and food fight	143.7 (h)	Kamminga et al. (2018)
Horse	6	Accelerometer and gyroscope	Neck	100	Walking (naturally or with a rider), trotting (naturally or with a rider), grazing, standing, galloping (naturally or with a rider), head shake, scratch biting, rolling, eating, fighting, shaking, jumping, rubbing, and scaredness	93,303 (2-s)	Kamminga et al. (2019)
Cattle	26	Accelerometer (A) and GNSS	Neck	59.5 (A) and 1 (GNSS)	Grazing, ruminating (while lying or standing), resting (lying or standing), and walking	–	Riaboff et al. (2020)
Cattle	6	Accelerometer	Neck	25	Feeding, drinking, grazing, ruminating (standing), salt licking, licking, resting (lying or standing), moving, urinating, attacking, escaping, and being mounted	3.28 (h)	Li et al. (2021b)
Cattle	18	Accelerometer	Neck	10	Eating, ruminating, and others	3,460 (h)	Pavlovic et al. (2021)
Dog	45	Accelerometer and gyroscope	Neck and back	100	Galloping, lying on chest, sitting, sniffing, standing, trotting, and walking	29.48 (h)	Vehkaoja et al. (2022)
Sheep	9	Accelerometer	Neck	12.5	Grazing, active behavior (walking and scratching), and inactive behavior (standing and resting)	> 65 (h)	Kleanthous et al. (2022a)
Sheep	18	Accelerometer	Neck	0.1	Standing, eating, moving, running, and others	1,685,974 (rows)	Monteiro et al. (2022)
Cattle	8	Accelerometer and GNSS	Neck and ear	50 (neck) and 62.5 (ear)	Grazing, drinking, resting, walking, and others	11,962 (5.12-s; neck) and 10,879 (4.1-s; ear)	Arablouei et al. (2023c)
Cattle	21	Accelerometer	Neck and leg	25	Feeding, ruminating, and others	809 (h)	Bloch et al. (2023)

[1] List of links: https://github.com/Max-1234-hub/List-of-public-datasets.

one dataset had been made public, by Kamminga et al. (2017). As shown in the table, the number of publicly released datasets increased over time. Cattle are the most extensively studied species. For all of the datasets, an accelerometer was the adopted wearable sensor, and the neck was the sensor location for data collection, consistent with the statement that most studies have focused on using collar-borne accelerometers (Kleanthous et al., 2022b). This list can serve as a valuable resource for readers who wish to further explore the field of AAR.

4. Challenges and future directions

Despite the increased and successful application of deep learning techniques with wearable sensor data for AAR, some technical challenges associated with deep learning, such as its performance and cost, need to be improved before its practical implementation in commercial animal farming. In this section, we discuss the possible challenges associated with the three main stages (i.e., data acquisition, model development, and activity inference) of AAR tasks (Fig. 5); these challenges are related to annotation scarcity, data privacy, energy efficiency, multimodal fusion, class imbalance, inter-activity similarity, domain generalization, and open-set recognition. Presently, only few or no studies have explored these critical challenges; thus, we propose potential solutions for each of these challenges, to inspire future research directions in automated AAR based on deep learning techniques and wearable sensors.

4.1. Annotation scarcity

The development of deep learning models is heavily reliant on the availability of large, annotated training datasets. However, in practice, such datasets are often scarce owing to the laborious and time-consuming process of data labeling. Additionally, data labeling

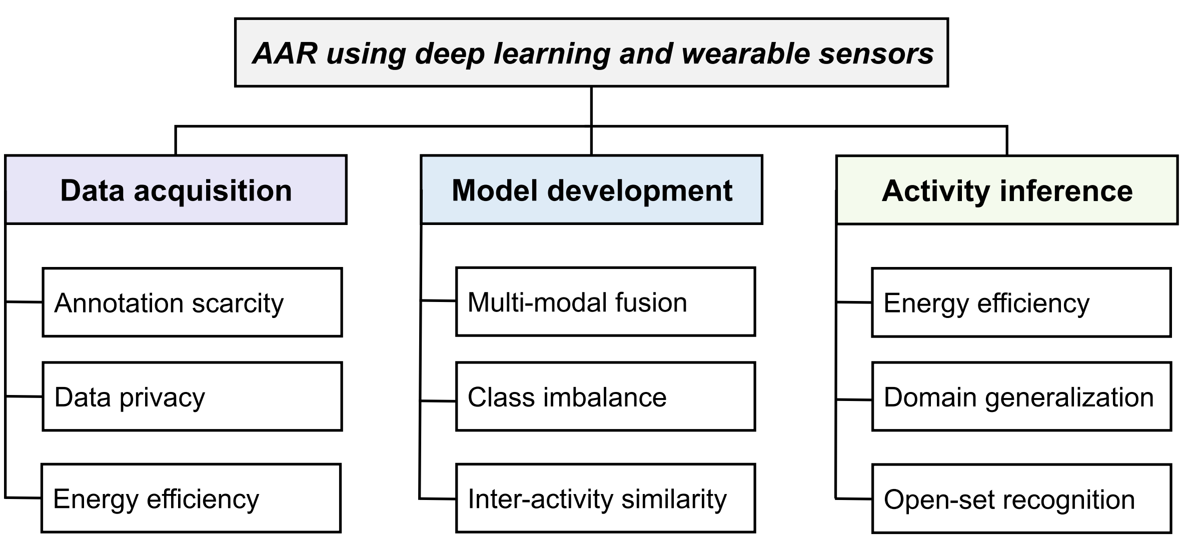

Fig. 5. Challenges associated with the data acquisition, model development, and activity inference stages of AAR.

requires experienced staff with a certain level of knowledge, making it highly challenging to obtain large, annotated datasets. This annotation scarcity can often result in model overfitting and poor generalization performance, limiting the applicability of models in real-world AAR scenarios.

Data augmentation is a low-cost preprocessing technique for creating new samples through the transformation of existing annotated data via rotation, jittering, scaling, noise addition, and other transformation techniques (Shorten and Khoshgoftaar, 2019). Data augmentation has been widely applied in AAR tasks for expanding data sizes and promoting the classification performance of deep learning models (Eerdekens et al., 2020b; Li et al., 2021b; Minati et al., 2023; Pan et al., 2023). However, augmentation techniques tend to be tailored to specific datasets, restricting their generalizability to other datasets. Generative adversarial networks (GANs) are another powerful tool for synthesizing massive fake data from a small amount of real labeled data (Qi and Luo, 2020). The generated data approximate the real data distribution, effectively facilitating the training of models. In addition to a limited amount of annotated data, there is also an extensive amount of unlabeled data in reality. Such data can be utilized by some advanced techniques, such as semi-supervised learning (Presotto, 2021) and active learning (Sun and Hardoon, 2010). Semi-supervised learning only requires less labeled data and massive unlabeled data for training, which exploits labeled data to assign pseudo-labels to unlabeled data. Active learning selects the most informative unlabeled instances for annotation to improve classifier performance with a minimal requirement for human supervision. Transfer learning is also an effective strategy to solve the problem of annotation scarcity, as transfer learning allows models pretrained on large-scale datasets to extract general features that can be fine-tuned on the target dataset with limited labeled data (Bloch et al., 2023). In the extreme case in which there are only a few labeled samples available, few-shot learning is a good option, as it aims to learn a model or an optimizer from a set of base tasks, and the learned model generalizes well to new tasks with few labeled training samples (Snell et al., 2017).

4.2. Data privacy

AAR-related studies have tended to perform model development on a dataset within a single site, and the high performances of their deep learning models have been highly dependent on massive training datasets (Bloch et al., 2023; Kasnesis et al., 2022; Minati et al., 2023; Pan et al., 2023). However, in reality, building a large dataset for one farm or institution is difficult, and limited training data can easily cause model overfitting, resulting in unsatisfactory performance (Mao et al., 2022a; Zhong et al., 2021). Thus, data collaboration across diverse sources (e.g., farms) is increasingly desired for learning a global model (Durrant et al., 2022, Liu et al., 2021). However, constructing a large corpus of centralized datasets across different farms results in data ownership and privacy problems, and poses a significant risk of commercial information leakage for producers and stockholders.

Federated learning, which is a new distributed learning paradigm, has emerged as an attractive approach to mitigate the problem of data privacy (Brendan McMahan et al., 2017). It enables data owners to train a globally shared model by aggregating locally trained models without exchanging their own data, which effectively preserves privacy. Our previous study was the first to validate the effectiveness of federated learning for achieving privacy-preserving AAR by uniting decentralized data across multiple farms (Mao et al., 2022). In addition, data from each source can be protected through homomorphic encryption, which allows any third party to perform computation on encrypted data without the need for decryption, thereby keeping the data secure and confidential (Acar et al., 2018). Furthermore, in recent years, differential privacy has gained attention owing to its ability to provide a strong privacy guarantee for sensitive data in various settings (Hassan et al., 2020). This technique mainly adds random noise to data to prevent the identification of original signals while enabling useful analysis.

4.3. Energy efficiency

Energy efficiency is a non-negligible challenge in the practical deployment of automated AAR systems based on wearable sensors and is a widely studied topic in AAR-related research (Arablouei et al., 2023b; Eerdekens et al., 2021; Mao et al., 2022; Pavlovic et al., 2021). This challenge is typically considered from two perspectives: the power usage of wearable sensors during data acquisition, and the memory and computational cost of deep learning models during activity inference. First, animal activities are generally monitored over a long period (e.g., a few weeks or several months), which requires sensing devices to continuously collect and transmit data (Benaissa et al., 2019b). As most embedded sensing devices are battery-powered, factors affecting the energy consumption and battery life of sensing devices must be carefully considered, such as sampling rate, transmit rate, and routing methods (Benaissa et al., 2019a, 2019b; Eerdekens et al., 2020a). Second, sensing devices for behavior monitoring typically possess low processing and storage capabilities owing to their limited battery life (Benaissa et al., 2019b; Eerdekens et al., 2021), which limits the on-board implementation of deep learning algorithms on wearable sensors. Thus, the memory and computational cost of deep learning models should be constrained to reduce energy usage in microcontrollers.

Most studies have attempted to reduce energy costs during the data acquisition phase by adjusting the configuration parameters of wearable sensors, such as by reducing the sampling rate and the number of logging axes (Benaissa et al., 2019a; Eerdekens et al., 2021; Walton et al., 2018). For example, Walton et al. (2018) found that increasing the sampling frequency from 16 to 32 Hz could reduce the battery life by up to half (1.81 vs. 3.08 years). Another approach is to construct lightweight deep-learning models that are applicable for in-situ implementation on devices during the inference phase. Popular techniques for constructing lightweight deep-learning models include knowledge distillation (Hinton et al., 2015), weight quantization (Gong et al., 2014; Han et al., 2016), and network pruning (Blalock et al. 2020; Pavlovic et al., 2021). These techniques allow for the reduction of the memory footprint and computational complexity of networks. In particular, knowledge distillation can enable the transfer of knowledge from a cumbersome model to a small model that is more suitable for deployment while maintaining desirable performance (Hinton et al., 2015), and this approach was validated in a recent study (Arablouei et al., 2023b). Weight quantization seeks to reduce memory footprint and computational complexity by representing model weights with a smaller number of bits than the original representation. Network pruning involves removing or pruning the connections, weights, or neurons in a neural network. Pavlovic et al. (2021) conducted iterative structured pruning of an original network to reduce its size and computational complexity. As the implementation of the above-described solutions may sacrifice a model's performance, it is crucial to identify a good trade-off between energy efficiency and recognition performance in automated AAR systems.

4.4. Multi-modal fusion

The capability of deep learning models for animal behavior recognition is highly related to the sensor modalities involved. Typically, multiple sensors of different types are attached to an animal's body (e.g., an accelerometer and a gyroscope are mounted on the same location), or sensors of the same type are attached to different locations on an animal's body (e.g., two accelerometers are separately placed at the ear and the neck), to record multi-type data exhibiting diverse modality characteristics. Combining various sensing modalities tends to result in superior performance in animal behavior classification tasks compared with using only one modality (Arablouei et al., 2023c; Eerdekens et al., 2022; Hosseininoorbin et al., 2021; Nweke et al., 2018; Sebastian et al., 2017). However, integrating multimodal data poses a challenge for multimodal fusion in the development of deep learning-based recognition models, as a model may struggle to generalize the different modalities of sensor data (Kleanthous et al., 2022a). A conflicting correlation between multiple modalities can easily interfere with multimodal fusion, resulting in limited recognition performance (Nweke et al., 2018).

Common strategies for multimodal fusion include early fusion, decision fusion, and feature fusion (Liu et al., 2020). The early fusion strategy involves concatenating the input data from multiple modalities into a single vector or tensor and processing them using a unified model. This is the most commonly used method in existing research (Eerdekens et al., 2022; Hosseininoorbin et al., 2021). However, owing to distribution gaps, early fusion is susceptible to interference between multimodal information (Ha and Choi, 2016). The decision fusion strategy combines the outputs or decisions from multiple classifiers at the decision-making stage, using techniques such as majority voting, weighted voting, or stacking, to obtain a final decision that is accurate and robust. However, this scheme is often suboptimal because rich modality information is gradually compressed and lost in separate processes, and the inter-modality correlations are ignored. A better choice is the feature fusion strategy, which involves the fusion of intermediate information from multiple modalities, followed by the generation of a final prediction using classifiers. This strategy avoids the distribution gap problem and achieves inter-modality interaction (Mustaqeem and Kwon, 2021). The feature fusion method has been used to process the multimodal data collected using different sensor types and has confirmed the benefits of multi-modality combination for promoting model performance (Arablouei et al., 2023c; Kasnesis et al., 2022; Kim and Moon, 2022;). Considering the occurrence of redundant or conflicting information in features from different modalities, the attention-based fusion technique has been devised to selectively combine information according to attention mechanisms, that is, according to the importance or relevance of the information to the task at hand (Mao et al., 2021). A recent study compared feature fusion with result fusion and found that the latter outperformed the former (Arablouei et al., 2023c), indicating the need to choose the appropriate multimodal fusion technique for a given situation. In addition, a hybrid fusion technique combining multiple fusion strategies is also a good tool worth exploring, as it has the potential to yield better multimodal fusion performance than a single fusion technique.

4.5. Class imbalance

The frequency and duration of different animal behaviors tend to be inconsistent, owing to animals' specific physiologies, and annotating rare or infrequent behaviors (e.g., the drinking behavior of grazing cattle) is difficult because they occur occasionally or for short durations (Mao et al., 2021). This leads to a disproportion in the number of samples among behavioral classes and induces class imbalance (Li et al., 2021a; Riekert et al., 2020; Sakai et al., 2019). Deep learning methods trained on imbalanced datasets tend to be biased toward majority classes and away from minority classes, which often causes poor model generalizability and high classification error rates for rare categories.

Common techniques for addressing the class imbalance problem include resampling and cost-sensitive learning. Resampling involves either oversampling the minority class or undersampling the majority class to balance the class distribution (Zhang et al., 2021). Cost-sensitive learning is a technique that assigns different misclassification costs to different categories during model training and places a higher penalty on misclassifications in the minority class than on those in the majority class. Cost-sensitive learning can be achieved by adjusting the decision threshold or using class-weighted techniques (Khan et al., 2018). In particular, the basic class-weighted method adds a term for each class that is inversely proportional to the frequency of that class and it has been adopted in several studies (Hussain et al., 2022a, 2022b; Mao et al., 2021). However, these approaches often lack good generalizability to real-world datasets because their training dataset may not accurately represent a true data distribution. Therefore, new techniques that do not rely on class distribution should be further explored, such as focal loss (Lin et al., 2017) and adaptive class suppression loss (Wang et al., 2021). In addition, GANs can also be utilized to address the class imbalance by generating synthetic data for the minority class and combining them with the original data to create a balanced dataset (Suh et al., 2021). GANs can thus learn the underlying data distribution and generate realistic samples that can improve the performance of classifiers trained on imbalanced datasets. In a scenario with extremely imbalanced datasets, the classification tasks can be reformulated as an anomaly detection problem, in which minority-class instances that are dissimilar to the majority class are treated as outliers or anomalies (Gerych et al., 2019). In this context, one-class classification methods can be employed to build a model that learns to capture the characteristics of the majority class and distinguish it from the minority class (Ruff et al., 2018).

4.6. Inter-activity similarity

One of the challenges in AAR tasks is inter-activity similarity; that is, a case in which different animal activities have similar characteristics or movement patterns (Mao et al., 2021; Peng et al., 2020; Zhao et al., 2022). This affects the ability of deep learning models to extract distinguishable features that can uniquely represent activities, leading to high confusion in classifying different activities (Chen et al., 2021). For example, the ruminating behavior for both lying and standing behaviors of cattle can be easily misclassified as feeding, as both behaviors entail a similar chewing movement (Peng et al., 2020). Similarly, a horse's activities of walking with and without a rider are often misclassified as each other, owing to their extreme resemblances in physical movement (Bocaj et al., 2020; Mao et al., 2021). However, there is a lack of studies on how inter-active similarity affects the development of deep learning in AAR based on wearable sensors.

One potential solution is to employ fine-grained activity recognition, which seeks to recognize subtle differences between similar activities by using more detailed features and modeling techniques than other approaches (De et al., 2015). Another approach is context-aware modeling, which sufficiently considers the context of animal activities, such as the time of day, location, or environmental conditions, to enable effective clarification of the purpose of an activity (Yurur et al., 2014). In addition, the simultaneous application of multi-type wearable sensors (e.g., an accelerometer and a geographical positional system (GPS) device) to capture richer information about animals than a single device can effectively help distinguish activities with similar patterns. For instance, the feeding and drinking of cattle have similar movement patterns, and thus a GPS device can be added to record geo-location information, as these two activities are likely to occur in different functional areas, that is, a feeding area and at a water trough (Halachmi et al., 2019).

4.7. Domain generalization

Domain generalization is a challenge in the AAR field. It is the ability of models to generalize well to new and unseen domains, such as different animal species, sensor types, or environmental conditions (Arablouei et al., 2023a; Kleanthous et al., 2022a). In reality, classification models trained on specific domains may exhibit significantly reduced performance when tested on data from a new domain (e.g., different animal species) during the inference phase. This phenomenon, known as domain shift, arises because of the discrepancy between training and test distributions. That is, a model may learn domain-specific features that are not transferable across domains or may overfit the training data, leading to poor performance on new and unseen data and limited applicability in real-world scenarios.

Transfer learning has become a common approach in deep learning to address the problem of domain shift between training and testing data. It can allow for the transmission of the knowledge learned from diverse source datasets to target datasets with different domains and has been investigated by a recent study (Kleanthous et al., 2022a). Specifically, by considering the problem of sensor heterogeneity, Kleanthous et al. (2022a) adopted transfer learning to improve the generalizability of CNN models for sheep activity recognition based on two motion datasets separately acquired using two types of accelerometers (i.e., MetamotionR and Raspberry Pi). However, transfer learning may not be applicable in situations in which the source and target domains are substantially different. That is, a pretrained model may not capture the relevant features in the target domain, and finetuning the model may result in overfitting or underfitting owing to the mismatch between the source and target datasets. In such cases, the domain adaptation technique is a suitable option, as it focuses on adapting a model to a specific target domain by modifying the model to enable it to handle differences between the source and target domains in the feature space, label space, or both (Farahani et al., 2021). Domain-agnostic feature learning is another technique that can enhance a model's generalizability by enabling the model to learn feature representations that are robust or invariant to domain shifts (Saha et al., 2020). That is, it enables a model to effectively capture characteristics shared by the source and target domains by learning domain-invariant features, thus improving its generalizability to new domains.

4.8. Open-set recognition

AAR-related studies have generally developed deep-learning-based classification models on training datasets that only cover a limited set of specific animal activities. However, some rare or infrequent activities, such as head shaking, scratch biting, and rolling, which are important indicators of animal health and welfare, may occur in real-world monitoring scenarios but be absent from training datasets. Thus, during the inference phase, these unseen activities are often misclassified into known activity categories in a training dataset, leading to poor performance and potentially missed opportunities for the early detection of health problems. Consequently, AAR is also characterized by the open-set recognition problem (Geng et al., 2020), which requires models to not only accurately classify known categories but also effectively deal with unknown categories.

An intuitive solution is the threshold-based strategy, which aims to separate known and unknown instances by exerting a threshold over the output probability (Hendrycks and Gimpel, 2017). However, selecting an appropriate threshold can be challenging, as it requires a trade-off between the false-positive and false-negative rates. In addition, generative models can also help solve the open-set recognition problem by modeling the distribution of both known and unknown classes. These models can generate new samples that resemble the known classes and identify samples dissimilar to the known classes as potential outliers and label them as belonging to unknown classes (Perera et al., 2020). Thus, classification performance on the known classes is improved, and the model's robustness is effectively enhanced.

5. Conclusion

Automated AAR based on wearable sensors and deep learning techniques is critical for achieving precise animal monitoring and management. It has the potential to provide rich information on animal health and welfare and offer effective guidance for care actions and environmental improvements. This paper comprehensively summarized recent research on AAR based on wearable sensors and deep learning algorithms. It covered the commonly used sensor types (i.e., accelerometers, gyroscopes, magnetometers, GNSSs, and UWB devices) and frequently studied animal species (i.e., cattle, sheep, horses, dogs, chickens, and pigs) and their activities. An accelerometer is the most frequently used type of sensor in AAR tasks, and most studies have either utilized accelerometers alone or combined them with other sensors to record animal motion data. The majority of studies have chosen the neck as the preferred sensor location, and sensors placed on the neck have been proven to be more accurate in detecting daily animal activities (e.g., feeding, ruminating, resting, and moving) than sensors placed at other locations. Cattle are the most studied animals, mainly because compared with other animals, cattle are larger, so are suitable for wearing sensors, and they have higher economic benefits in agriculture. Moreover, most studies have focused on identifying some common activities, including feeding, drinking, ruminating, resting, and locomotion behaviors. Only a few studies have focused on activities that are rare but important for animal health, such as licking, itch rubbing, scratching, and shaking. These activities should be further investigated in future work.

The applications of different deep learning approaches in AAR based on wearable sensor data were also comprehensively reviewed, according to the taxonomy of deep learning algorithms (i.e., FFNN, CNN, RNN, and hybrid models). CNNs are currently the most widely used models in AAR-related research. They have exhibited excellent performance in most cases, with accuracies higher than 90%. This indicates the promising capability of CNNs for extracting distinguishing motion features of animals. Considering the advantage of RNNs in modeling time series, a few studies have combined a CNN with an RNN to process sequential data from wearable sensors, and the combined model outperformed the single models. Therefore, future research can focus on combining a CNN and an RNN to further explore the effectiveness of this approach. In addition, we provided a comprehensive list of publicly available datasets collected via wearable sensor-aided AAR over the past five years. This list can serve as a valuable resource for readers who wish to further explore the field of AAR.

To provide further insights into the direction of research progress, we presented some potential grand challenges associated with the development of AAR systems based on deep learning and wearable sensors. The challenges are mainly related to annotation scarcity, data privacy, and energy efficiency during data acquisition; multimodal fusion, class imbalance, and inter-activity similarity during model development; and energy efficiency, domain generalization, and open-set recognition during activity inference. In recent years, several studies have investigated the challenges of annotation scarcity, energy efficiency, and class imbalance. However, these studies have often been only preliminary explorations; that is, have used basic methods to deal with challenges. For instance, most studies have only utilized the resampling and class-weighted strategy to deal with the class imbalance problem. Moreover, a very limited number of studies have focused on multimodal fusion, data privacy, and other challenges; thus, these challenges need to be further explored in future work.

In conclusion, this study provides valuable inspiration for investigating automated behavior recognition using deep learning and wearable sensors, which will contribute to the sustainable and profitable development of intelligent animal monitoring systems. Based on accurate and quantitative recognition results of animal activities, farmers or veterinarians can identify deviations from normal behaviors (e.g., the time animals spend lying, standing, or drinking) to qualitatively assess animal health issues and environmental conditions. This enables timely human intervention and necessary adjustments to the animal's environment, thereby significantly benefiting the improvement of animal well-being.

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

No data was used for the research described in the article.

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