A Survey on Deep Learning for Human Activity Recognition

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Human activity recognition is a key to a lot of applications such as healthcare and smart home. In this study, we provide a comprehensive survey on recent advances and challenges in human activity recognition (HAR) with deep learning. Although there are many surveys on HAR, they focused mainly on the taxonomy of HAR and reviewed the state-of-the-art HAR systems implemented with conventional machine learning methods. Recently, several works have also been done on reviewing studies that use deep models for HAR, whereas these works cover few deep models and their variants. There is still a need for a comprehensive and in-depth survey on HAR with recently developed deep learning methods.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing;**

Additional Key Words and Phrases: Machine learning, deep learning, activity recognition, mobile sensing, deep models

ACM Reference format:
Fuqiang Gu, Mu-Huan Chung, Mark Chignell, Shahrokh Valaee, Baoding Zhou, and Xue Liu. 2021. A Survey on Deep Learning for Human Activity Recognition. *ACM Comput. Surv.* 54, 8, Article 177 (October 2021), 34 pages.
https://doi.org/10.1145/3472290

Jianga Shang, China University of Geoscience (Wuhan), China, has been added as an author for this paper after it was accepted.

This study is jointly supported by the National Natural Science Foundation of China (No. 42174050 and No. 42171427), National Key Research and Development Program of China (No. 2016YFB0502200), Guangdong Basic and Applied Basic Research Foundation (No. 2019A1515011910), and Shenzhen Scientific Research and Development Funding Program (No. JCYJ20190808113603556).

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0360-0300/2021/10-ART177 $15.00
https://doi.org/10.1145/3472290

1 INTRODUCTION

The knowledge of human activity is crucial for a lot of applications and services such as health monitoring, fitness, home automation, augmented reality, traffic scheduling and control, precise advertising, and security [110]. For example, the record of a person's daily activities can be used to calculate the calorie he has consumed on a day, which can further suggest proper diet for him to keep healthy and fit; detecting the fall activity of elderly people can be used to trigger emergency assistance to avoid causing severe accidents.

Human activity can be recognized by applying conventional machine learning methods. However, conventional machine learning methods for **Human Activity Recognition (HAR)** require to design and select relevant features. This process involves laborious human intervention and expert knowledge, and the designed and selected features might still achieve suboptimal performance. To relieve the burden of hand-engineering features, deep learning methods have been proposed in recent years [112, 207]. Deep learning methods are very useful for HAR and can benefit HAR from several aspects. First, it relieves the effort of manually designing features, which often requires expert knowledge. Second, it has shown better accuracy in HAR than conventional methods [69, 160, 260]. Third, it has the ability to learn from unlabeled data, which is important and useful for HAR, since it is unpractical to obtain a large amount of labeled activity data. Fourth, it has the powerful capability of learning useful features from raw data and can deal with activity-related data from different people, different device models, and varying device poses.

The relationship of deep learning, machine learning, and artificial intelligence is demonstrated in Figure 1. Deep learning is a subset of machine learning methods, and has multiple levels of representations. Deep learning networks are artificial neural networks with more than one hidden layer, and therefore deep learning networks are also known as deep neural networks. In Reference [40], the authors categorized deep learning models as deep networks for supervised learning, deep networks for unsupervised learning, and hybrid approaches. In this work, we adapt the categorization in Reference [40] and divide deep learning models into deep generative models, deep discriminative models, and deep hybrid models. Deep generative models aim to learn useful representations of data via unsupervised learning or to learn the joint probability distribution of data and their associated classes [184]. Popular generative models are **Restricted Boltzmann Machines (RBMs)** [86], autoencoders [216, 219], **Generative Adversarial Networks (GANs)** [65], and their variants. Discriminative models aim to learn the conditional probability distribution of classes on the data, in which the label information is available directly or indirectly [239]. Popular deep discriminative models are **Convolutional Neural Networks (CNNs)** [62, 106, 178], **Recurrent Neural Networks (RNNs)** [20, 186], and their variants. Deep hybrid models combine a generative model and a discriminative model where the outcome of the generative model is often used as the input to the discriminative model for classification or regression [52]. These models were originally proposed for processing images, video, speech, and audio, but they can also be applied to other domains such as activity recognition [150, 181, 244] and indoor localization [67, 71].

So far, there have been several surveys on HAR in the literature. Poppe [164] reviewed research works on vision-based human action recognition and discussed different image representation methods as well as action classification methods. Aggarwal and Ryoo [3] presented an approach-based taxonomy for HAR and discussed recognition methods, including space-time approaches, sequential approaches, and hierarchical approaches, for simple human actions and high-level activities (e.g., human–human interactions and human–object interactions, group activities). Chen et al. [34] surveyed various aspects of sensor-based activity recognition, mainly including data-driven and knowledge-driven methods for activity monitoring, modeling, and recognition. Incel et al. [93] provided a taxonomy of activity recognition on smartphones, introduced the process

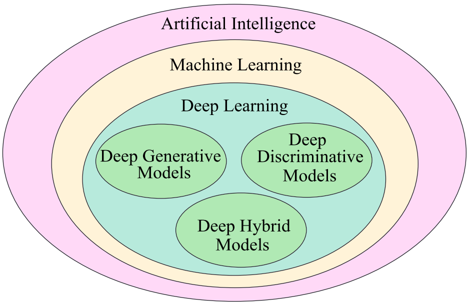


Fig. 1. The relationship of deep learning, machine learning, and artificial intelligence.

and challenges of HAR on phones, and reviewed HAR works based on location, motion, and other contextual information. Lara and Labrador [110] conducted a survey on HAR with wearable sensors, and discussed different types of activities, the design issues and recognition methods of HAR. Specifically, they evaluated 28 systems in terms of recognition accuracy, energy consumption, obtrusiveness, and flexibility. Wang and Zhou [227] surveyed radio-based HAR methods, mainly including Zigbee-based, WiFi-based, and **Radio Frequency Identification– (RFID)** -based methods. Shoaib et al. [196] reviewed HAR systems that are implemented on smartphones and use only on-board phone sensors. Yousefi et al. [244] conducted a survey on HAR using WiFi **Channel State Information (CSI)**. Mukhopadhyay [141] reviewed relevant technologies and methods of human activity monitoring with wearable sensors. Bulling et al. [27] provided a tutorial on HAR with conventional machine learning methods based on wearable inertial sensors. Guo and Lai [74] conducted a survey on human action recognition with still images. While these existing survey works have reviewed many HAR methodologies and systems from different perspectives, they focused mainly on the taxonomy of HAR and reviewed the state-of-the-art HAR systems implemented with conventional machine learning methods.

In this article, we review systematically the techniques and methods related to HAR with deep learning. This study first presents a taxonomy of human activity, and then introduces commonly used sensors, preprocessing techniques, deep model building, and evaluation techniques. Although several recent works [151, 224, 250] have reviewed some works using deep models for activity recognition, they cover few deep models and do not involve preprocessing techniques nor the evaluation methods and metrics. There is still a need for a complete, comprehensive survey on HAR with recently developed deep learning methods, which is the main motivation of this work.

This survey is structured as follows: Section 2 introduces the human activity types and sensors that have been studied in the literature. Section 3 provides an overview of deep learning models for HAR. In Section 4, commonly-used data preprocessing techniques for deep learning are introduced. Section 5 presents core deep models and their variants, as well as their applications in HAR. Section 6 introduce evaluation methods, metrics, and public datasets, respectively. Finally, we conclude this article in Section 7 and give open research challenges.

2 BASICS OF HUMAN ACTIVITY RECOGNITION

2.1 Activity Category

While describing a specific human motion that has been done, it is common that one may find confused of choosing the appropriate term. Action, activity, and behavior are all frequently used candidates. Though they may seem to be similar, referring to the Oxford English Dictionary: *Action* means something that is done; *Activity* represents the state of being actively occupied, brisk,

Table 1. Categories of Activities Studied in the Literature

Category	Specific Activities
Locomotion	Walking, running, jogging, lying, standing, sitting, going upstairs/downstairs, and so on
Transport mode	Cycling, riding a bus, driving, traveling with a vehicle, and so on
Phone usage	Texting, making a call, using an app, browsing the web, checking the email, and so on
Entertainment	Playing soccer, playing basketball, attending a party, gaming, and so on
Health-related activity	Falls, respiration, rehabilitation activities, smoking, and so on
Daily activity	Sleeping, using computer, shopping, eating, attending a meeting, having a conversion, going to work, and so on
Gesture	Body gestures, arm gestures, hand gestures, head gestures, body languages, sign languages, and so on
Emotion	Angry, disgust, fear, happy, sad, surprise, neutral, and so on
Security	Presence, attacking, abnormal activities, and so on

This table is adapted from Reference [93].

or vigorous action; whereas *Behavior* depicts the manner of conducting oneself in the external relations of life. Each of them has its particular meaning and can derive different sets of jargon.

In philosophy and sociology, the three terms can be further defined. Max Weber described the connection between action and social action [30]. He believes action is motivated by an actor's feelings or experiences and is done on purpose. However, behavior can only be considered as a reflection of cues or impulses. Campbell [30], citing Weber's work, sees that action is an intentional activity, whereas behavior is an activity done without purposes or intentions. Action requires consciousness of the actor, which means the actor is intended to perform a certain activity, yet behavior requires a cue or stimulus to trigger. The relationship is thus clear. Action can be considered as a proactive activity, and behavior can be seen as a reactive activity. Beyond the two is the term activity, which is the super-set of both.

In addition, activity can be categorized into different levels, from low to high, according to its complexity [138]. For the sake of unambiguity, in this article, we do not differentiate activities of varying levels. Instead, we extend the taxonomy of activity in Reference [93], and categorize human activities into different types according to application domains. Table 1 shows the main categories of activities that are studied in the literature, including locomotion (e.g., walking, standing, running), transport mode (e.g., cycling, driving), phone usage (e.g., texting, making a call), entertainment (e.g., playing basketball, attending a party), health-related activities (e.g., falls, respiration), daily activities (e.g., sleeping, eating, going to work), gesture (e.g., hand gestures, arm gestures), and security (e.g., presence, attacking).

2.2 Sensors Used for HAR

There are a variety of sensors that can be used for HAR, which are mainly categorized as ambient sensors, wearable sensors, and other sensors.

2.2.1 Ambient Sensors. Ambient sensors require to be installed at fixed locations to recognize activities, which usually contain a server (e.g., WiFi access point) and a client (e.g., WiFi receiver in a smartphone). For simplicity, we call both servers and clients as sensors without distinguishing them. Ambient sensors that have been used for HAR mainly include **Global Navigation Satellite System (GNSS)**, Cellular, WiFi, Zigbee, FM (Frequency Modulation), and RFID.

- **GNSS**. The GNSS module built in smart devices can be used for positioning as well as activity detection. By using the location, moving speed, and number of available satellites provided by the GNSS, it is possible to recognize locomotion, transportation mode, and daily activities. For example, Liao et al. proposed a discriminative relational method for recognizing human activities solely using GPS data based on the **Relational Markov Networks (RMN)** framework. The proposed method performed efficient inference and learning with MCMC algorithms in extended RMNs [124]; Zhen et al. proposed a method based on supervised learning for inferring people's motion modes from GPS logs, such as the modes of walking and driving [258]; and Zheng et al. reported on an automatic inference inferring approach for transportation modes using supervised learning from raw GPS logs. The proposed method enabled to identification the modes of walk, driving, bus and bike, containing three parts, i.e. a change point-based segmentation method, an inference model using and a graph-based post-processing algorithm [257].
- **Cellular**. A cellular network is a communication network that is commonly used in mobile phones. Popular cellular technologies include GSM, CDMA, GPRS, UMTS, LTE, and so on. By measuring the **Received Signal Strength (RSS)** between the cellular receiver and transmitter, one can recognize different activities such as transport mode, daily activies. For instance, Sohn et al. investigated a system to recognize high-level properties of user mobility and daily step count based on coarse-gained GSM data from mobile phones [200]; Anderson and Muller developed a method to identify activities (e.g., walking, traveling in a motor car and remaining still) based on information readily available on a typical GSM cell phone, which can realize a context awareness level similar to that of an accelerometer [9].
- **WiFi**. WiFi is a local-area wireless communication technology that sends signals from a transmitter to a receiver. The available measurements of WiFi for HAR include RSS, CSI, and **Round Trip Time (RTT)**. Due to the ubiquity of WiFi infrastructures in urban and indoor environments, it has been widely used for positioning and activity recognition. For example, Sigg et al. investigated the use of WiFi RSS at a mobile phone for the recognition of situations, activities, and gestures [197]. Wang et al. proposed a device-free activity recognition system with deep learning approach based on CSI information [222]. In recent years, many works have used WiFi CSI for recognizing gestures [2, 248] and other types of activities [150, 223, 236, 242].
- **Zigbee**. Zigbee is a communication technology that is intended to be simpler and less expensive than Bluetooth, and WiFi. It uses IEEE 802.15.4 protocols to create personal area networks with small, low-power digital radios. Scholz et al. showed the general feasibility of activity recognition using Zigbee RSS on simple transceiver hardware [188]. Qi et al. developed RadioSense, a prototype system that exploits wireless communication patterns for activity recognition [167].
- **FM**. FM radio is a technology that conveys information by varying the frequency of a carrier wave. Shi et al. demonstrated that human activity recognition can be done with ambient FM-radio signals. They used fluctuations in the ambient signals of FM radio stations to distinguish empty room, opened door, and walking person [194, 195].
- **RFID**. RFID is a commonly-used technique to automatically identify and track tags by detecting the electromagnetic pulse from a nearby reader. It can be used for HAR, since the movement of human would change the single strength received by the reader. Li et al.

present a system for activity recognition from passive RFID data using a deep convolutional neural network [118]. Liu et al. proposed to use RF tag arrays and data-mining techniques for activity monitoring [127]. Wang et al. quantified the correlation between RF phase values and human activities by introducing TACT and modeling intrinsic characteristics of signal reflection in contact-free scenarios [233]. Fan et al. introduced an advanced RFID activity identification framework, DeepTag, which used a deep learning-based approach that combined a convolutional neural network and **Long Short-term Memory (LSTM)** network for activity identification in multipath-rich environments [56].

The advantages of using ambient sensors for HAR include non-intrusiveness toward users, and support multi-occupant activity detection. However, they have poor coverage and the achieved accuracy is influenced by many factors (e.g., people movement, obstacles).

2.2.2 Wearable Sensors. Wearable sensors are the sensors that are easy to carry and are usually built in smart devices. Common wearable sensors used for HAR are accelerometer, gyroscope, magnetometer, barometer, camera, acoustic sensor, light sensor, and biosensor.

- **Accelerometer**. An accelerometer is a tool used to measure the acceleration of a body in its own instantaneous rest frame. It has been integrated into most modern smart devices (e.g., smartphones, smart watches). Ravi et al. illustrated their efforts on users' activity recognition from a single triaxial accelerometer worn near the pelvic region [175]. Chen et al. introduced a deep learning-based system called METIER for activity recognition, which was evaluated on several accelerometer-based datasets [35]. Pei et al. also presented a deep learning-based system, called MARS, for recognizing different locomotion activities using several inertial measurement units that are placed on different parts of the body [160].
- **Gyroscope**. A gyroscope is a device that measures orientation and angular velocity, which is often used with an accelerometer. Pei et al. utilized the gyroscope accelerometer data to distinguish different locomotion activities [159]. Gu et al. developed a deep learning method for locomotion activity recognition by utilizing multiple sensors data built in most smart devices [70]. Zhou et al. proposed a convolutional neural network-based method for pedestrian activity recognition using a gyroscope and other sensors [260].
- **Magnetometer**. A magnetometer is a device used for measuring magnetic fields, which is also often used with a accelerometer. It has been widely used for activity recognition in many works [70, 159, 260].
- **Barometer**. A barometer is a device that measures the air pressure in a certain environment. Gu et al. used the barometer data for recognizing going upstairs, going downstairs, taking an elevator upward or downward [68, 69, 193]. Ye et al. proposed a barometer-based floor localization system, which uses the barometer of a smartphone to identify the floor of a mobile user in a multi-floor building [243].
- **Camera**. A camera is an optical instrument that captures images, from which a lot of activity types can be recognized. Nagarajan et al. introduced an environmental affordance model that learns directly from the egocentric video, primarily gaining a human-centered model of physical space (e.g., kitchen) that captures the primary spatial zones of interaction and the likely activities they support [145]. Tang et al. studied the RGB-D egocentric action recognition problem. The self-generated egocentric video is generated by wearable sensors, and the deep neural network method was used to explore the shared information and features of different modes [211]. Wang et al. proposed a novel symbiotic attention framework leveraging privileged information for egocentric video recognition [231].

- **Acoustic sensor**. An acoustic sensor is used to measure sound levels. Wang et al. proposed a contact-free acoustic gesture recognition system that adopts a frequency-hopping mechanism to mitigate frequency selective fading and avoid signal interference [232]. Ling et al. proposed an ultrasonic finger motion perception and recognition system based on **Channel Impulse Response (CIR)**. The system uses CIR measurements as gesture recognition features and utilizes a CNN model to classify the acquired images into different gestures [125]. Sun et al. proposed a system that supports fine-grained gesture-sensing on the back of mobile devices based on acoustic signals, which uses both the structure-borne and the air-borne acoustic signals to measure touch gestures [204].
- **Light sensor**. A light sensor is a photoelectric device that converts light energy into electricity, which has been integrated into many smart devices. Zhou et al. designed a system called IODetector to implement indoor/outdoor environment detection using the smartphone built-in light sensor [261]. Choudhury et al. proposed an automatic activity recognition system using light sensors [44].
- **Biosensor**. A biosensor is an analytical device used to evaluate and record the electrical activity of the human's muscles, heart, and so on. Popular biosensors are Electromyography and Electrocardiography, which measure the electrical activity of muscles, and that of the heart, respectively. Song et al. proposed an end-to-end spatial and temporal attention model for human action recognition from skeleton data [201]. Zheng et al. used machine learning methods to study emotion recognition over time in stable patterns of **Electroencephalogram (EEG)** patterns [255].

Compared to ambient sensors, wearable sensors do not suffer the coverage problem, and can achieve a higher accuracy as the user usually carries the sensors. However, wearable sensors can only detect the activity of the person who carries them, and do not support multiple person detection. Apart from ambient sensors and mobile sensors, there are some other sensors, such as event camera, which can also be used for HAR.

2.2.3 *Other Sensors.*

- **Event camera**. An event camera is a relatively new sensor that captures the brightness change of the scene. Different from conventional cameras, which output synchronous frames, event cameras output asynchronous events. Amir et al. proposed an event-based gesture recognition system using a TrueNorth neurosynaptic processor [8]. Miao et al. introduced several event-based datasets for pedestrian detection, action recognition, and fall detection [134].

Table 2 summarizes the sensors that have been used for HAR in the literature.

3 OVERVIEW OF DEEP LEARNING FOR HAR

In this section, we provide an overview of using deep learning methods for HAR. As shown in Figure 2, there are four components for deep learning–based HAR systems. First, data are collected from a variety of sensors, and these data can be images, WiFi CSI, accelerations, gyroscope readings, barometer readings, sound, biosensor readings, and so on. Second, the input data are preprocessed using certain techniques such as scaling, **Principal Component Analysis (PCA)** whitening, **Zero-phase Component Analysis (ZCA)** whitening, or denoising. Third, the preprocessed data are fed to model building component where different deep models (e.g., RBM, autoencoder, RNN) can be chosen to learn useful features. This is followed by a classifier at the top layer (e.g., softmax classifier, SVM). Once we build a model, we can train it with the input data. During

Table 2. Sensors used for HAR in the Literature

Sensor	Reference	Activity Category
GNSS	[124, 257, 259]	Locomotion, transportation mode, daily activity
Cellular	[9, 200]	Locomotion, transportation mode, daily activity
WiFi	[2, 150, 197, 222, 236, 242, 248]	Locomotion, transportation mode, daily activity, gestures
Zigbee	[167, 188]	Locomotion activity
FM	[194, 195]	Locomotion, daily activity
RFID	[56, 118, 127, 233]	Locomotion, daily activity, security
Accelerometer	[35, 160, 175]	Locomotion, phone usage, entertainment, gesture, transportation mode, daily activity
Gyroscope	[70, 159, 260]	Locomotion activity
Magnetometer	[70, 159, 260]	Locomotion activity
Barometer	[68–70, 193, 243]	Locomotion activity
Camera	[145, 145, 201, 211, 211, 231]	Locomotion, entertainment, daily activity, health-related activity, gesture, security
Acoustic sensor	[125, 198, 204, 232]	Locomotion, transportation mode, daily activity
Light sensor	[44, 261]	Locomotion activity, gesture
Biosensors	[201, 255]	Locomotion, health-related activity, emotion, daily activity
Event camera	[8, 134]	Gesture, locomotion activity

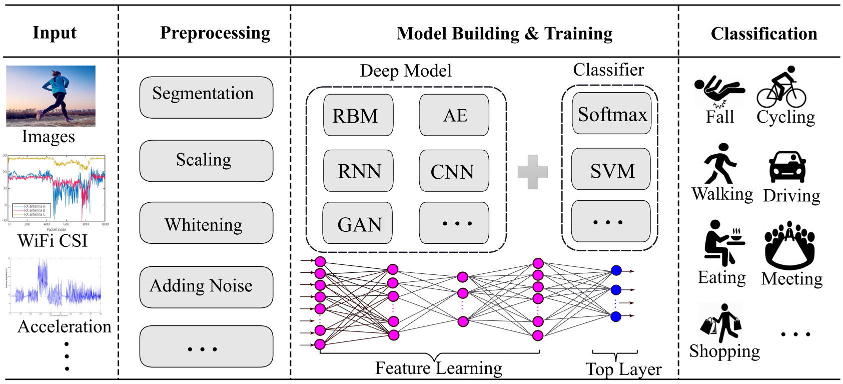


Fig. 2. Overview of deep learning for HAR.

the training process, the network parameters such as weights are optimized. Finally, we can use the trained model to predict the activity of upcoming data.

In the following, we will elaborate the techniques related to preprocessing, model building, and evaluation.

4 PREPROCESSING TECHNIQUES

Before we feed data to a deep model, certain preprocessing techniques are required to be used to obtain satisfactory performance. The main preprocessing techniques include segmentation, scaling, one-hot encoding, dealing with missing data, transformation, adding noise, and denoising. We will introduce each of them in the following.

4.1 Segmentation

Depending on the used sensor data, segmentation might be necessary to be conducted on the data before feeding it to a deep model. For image-based HAR, it is feasible to recognize activities such as gestures and walking from a single image. However, we cannot recognize activities from a single accelerometer reading, barometer reading, WiFi CSI, and so on. This is because a single data sample (except an image) cannot capture the characteristics of an activity. Therefore, we need to segment these data into sequences using a fixed time window (e.g., 2 s), on which we can build models for HAR. Note that when combining data from different sensors for conducting HAR, we need to align them to the same time window as the sampling frequency for different sensors might be different. It is also usually required by some deep models (e.g., autoencoder) to stabilize the number of input samples within a time window through interpolation (e.g., spline interpolation), since the sampling rate for the same sensor may not be stable [70]. In recent years, some time-aware models have been proposed to deal with irregular time intervals in data [18].

4.2 Scaling

Raw data are usually not useful enough for machine learning methods unless the raw attributes have a meaning in the original domain [60]. To enable deep models to achieve desirable performance, we usually require to rescale the raw data to a certain range, since deep models are usually preferable to work on inputs of small values (e.g., between 0 and 1). If the input values of a model are too large, then the model tends to learn large weight values, which increases the computational cost and may lead to overflow on digital computers [64]. Two common scaling techniques are normalization and standardization.

Normalization is a technique that rescales the data from the original range to the range between 0 and 1. Let $\boldsymbol{x}$ indicate an input vector of sensor readings, which usually corresponds to one column of the input matrix. The normalization process is mathematically expressed as follows:

$$\boldsymbol{x}' = \frac{\boldsymbol{x} - min(\boldsymbol{x})}{max(\boldsymbol{x}) - min(\boldsymbol{x})}, \tag{1}$$

where *min* and *max* are the functions to calculate the minimum and maximum values of the input vector, respectively. The resulting vector $\boldsymbol{x}'$ ranges from 0 and 1. However, normalization may not work well in some cases where the maximum or minimum value of the vector is not available or there are extreme outliers [60]. For simplicity, we also use $\boldsymbol{x}'$ to represent the resulting vector after a manipulation in the following.

Standardization is another popular scaling technique, which is less influenced by the presence of outliers. It is mathematically described as

$$\boldsymbol{x}' = \frac{\boldsymbol{x} - \mu_x}{\sigma_x}, \tag{2}$$

where μ_x and σ_x are the mean and standard deviation of the values of the input vector $\boldsymbol{x}$. After the standardization manipulation, the resulting data have a mean of 0 and a standard deviation of 1. If the mean and standard deviation of the corresponding probability distribution are not available, then the sample mean and standard deviation will be used instead [60].

4.3 Label Encoding

Activity labels, such as walking and shopping, are usually categorical, but deep models cannot work on the categorical labels efficiently, and require all the input data to be numeric. To do that, we can simply encode each label as an integer. However, integer encoding may not perform well as the model may try to learn a natural ordering relationship in categories. To avoid this, a more common way is to encode the label with one-hot encoding [142]. In the one-hot encoding, an identity matrix with the size equal to the number of activity categories is used. Each row represents an activity, and has and only has one element with the value of 1 that indicates the activity.

4.4 Dealing with Missing Data

Missing data can lead to efficiency loss, biased results, and complexity increase [60]. There are different ways to deal with missing data. A simple way is to discard the samples with missing values in their attributes or even to delete the entire attribute if any of samples has a missing value. However, this may significantly reduce the amount of training data if the number of samples with missing values is large, which will decrease the performance of the classifier trained on it. An alternative way is to replace the missing values with the mean/median of the non-missing values in the same attribute. While it is easy and fast, it does not consider the correlations between attributes. A more sophisticated way is to do imputation that replaces missing values with the values estimated by imputation methods. The commonly used imputation methods include K-nearest neighbors [55], maximum likelihood imputation [60], singular value decomposition [215], and fuzzy k-means clustering [116]. More details of imputation methods can be found in the book [60].

4.5 Transformation

It is often advantageous to conduct certain transformations on the input data before using them to train a deep model. The transformations are usually used to reduce the correlations in the input data. Popular transformations include PCA whitening, ZCA whitening, and spectrogram analysis.

4.5.1 PCA Whitening. Whitening (or sphering) is a linear transformation that converts the input vector into another vector with the unit diagonal white covariance, which can be viewed as a generalization of standardization [101]. PCA whitening is one of commonly-used preprocessing methods reduce the redundant information in the input data so that the deep models can learn features more efficiently [122, 146]. Since PCA whitening is based on the PCA method, it enables us to obtain whitened data with lower dimensionality than the original input by simply keeping top k components [147, 220].

4.5.2 ZCA Whitening. ZCA whitening is another popular preprocessing method to reduce the correlations in the input data. ZCA whitening is related to PCA whitening [101], and the ZCA whitening matrix is obtained by multiplying an orthogonal matrix with the PCA whitening matrix. Different from PCA whitening, ZCA whitening does not reduce the dimensionality of inputs. ZCA whitening has been widely used in image processing [39, 105, 122, 146], and activity recognition [70]. Apart from PCA whitening and ZCA whitening, there are other whitening methods such as Cholesky whitening, ZCA-cor whitening, and PCA-cor whitening [101].

4.5.3 Spectrogram Analysis. As many types of sensor data for HAR (e.g., accelerometer readings) are usually time series, spectrogram analysis might be helpful in capturing variations in the input data. A spectrogram is a representation of the frequency spectrum of the input signal as it varies with time, which can be generated by the Fourier transform [25] or a wavelet transform [191]. In the spectrogram analysis using short-time Fourier transform, the spectrogram can be considered as the squared amplitude of a time-frequency transformation of the signal (e.g., a time-frequency energy density function) [191]. Spectrogram analysis has been used extensively in the fields of speech processing [254], image processing [228], music [81], and others. In Reference [6], the spectrogram of an accelerometer signal has been used for deep learning-based activity recognition and witnessed better classification accuracy and lower computational complexity. In Reference [70], apart from spectrogram analysis, more frequency-related transformations have been conducted for activity recognition, including fast Fourier transform, power spectral density, discrete cosine transform, and cepstrum analysis. It concludes that using spectrogram can result in better accuracy on accelerometer data-based classification, but other transformations do not lead to a better accuracy than the original data.

4.6 Adding Noise

Adding noise to input data is a commonly used way to help deep learning models learn good representations that are rather robust under corruptions of the input. There are three popular types of noise used for preprocessing sensor data [219]: (1) additive Gaussian noise where a Gaussian noise term is added to the input; (2) masking noise where a fraction of the input's elements is set to zero; (3) salt-and-pepper noise where a fraction of the input's elements is assigned to their maximum or minimum value. Additive Gaussian noise is a common noise model for real-valued inputs, while the salt-and-pepper noise is considered when input domains are binary or near binary. Masking noise is often regarded as turning off components, which numerically means forcing components to zero so that these components are ignored in the computations of downstream neurons. Note that these noise can be added not only to the inputs, but also to activations, weights, gradients, and outputs. These operations are usually helpful for deep models to achieve good accuracy on the HAR task.

4.7 Denoising

Denoising is to remove or reduce the noise in the input data so that the model can achieve better recognition accuracy. A commonly used denoising method is to apply filters (e.g., low-pass filters, median filters, Kalman filters) to the input data. For example, low-pass filters are often applied to the acceleration signal to remove the gravitational and body motion components [79]. Median filters are good at removing the salt and pepper noise of images for vision-based activity recognition [11]. In Reference [237], the authors used a series of denoising methods (low-pass filtering, PCA, and median filtering) to deal with CSI-based activity recognition. In Reference [229], the authors compared the performance of different filters for accelerometer-based activity recognition, and concluded that the Kalman filter had the largest signal-to-noise ratio, followed by median filter, and low-pass filter. Apart from using filters, some studies reduce noise by applying a threshold to the data. In Reference [61], the authors first extracted histograms from accelerometer data for each activity, and then reduced noise by setting a threshold to the corresponding histograms.

4.8 Summary

Preprocessing is a crucial step of using deep learning for HAR, which may lead to low classification performance if it is not done properly. As for which preprocessing method should be used, it depends on the sensor data used, the selected deep model, as well as the activities of interest.

One important thing regarding preprocessing is that any preprocessing methods must only be conducted on the training data and then applied to the validation or test data [117]. For example, it would be a mistake to first compute the mean of input data across the entire dataset and then split the data into training and test data.

5 DEEP LEARNING MODELS

Recent years have witnessed the rapid development and advances of deep learning, and many deep models have been developed in the literature. In this section, we are interested in popular deep models that are constructed on some common building blocks including RBM, AE, CNN, RNN, and GAN, and some of their variants. The deep models based on these building blocks have been used or have the potential to be used for HAR.

5.1 RBM-based Models

RBM-based deep models are one of early successful deep models used for HAR, which are obtained by stacking multiple RBMs. The main intuition of applying RBM-based models for HAR is to reduce

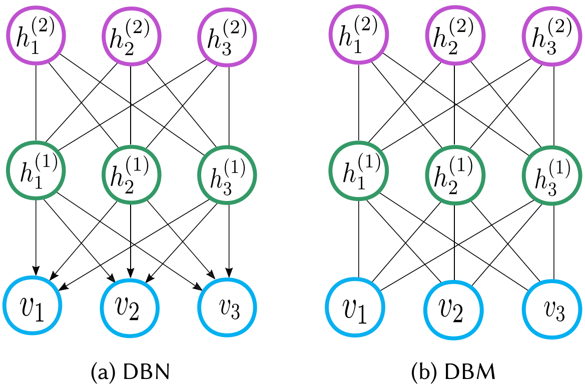


Fig. 3. (a) The structure of a DBN where there are multiple hidden layers and have both directed and undirected connections. Apart from the connections between visible units and hidden units, it has also connections between hidden units in different layers. (b) The structure of a DBM where there are undirected connections not only between visible units and hidden units but also among hidden units in different layers.

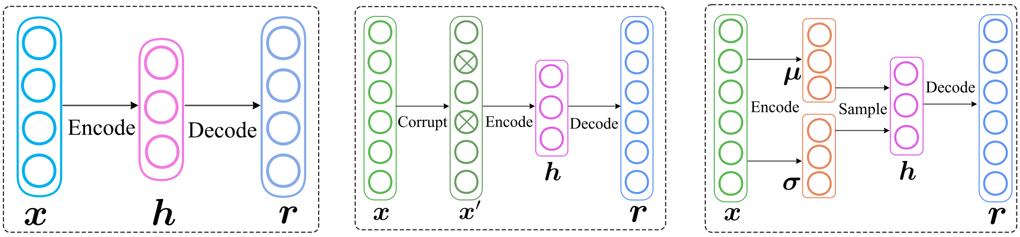
the dimensionality of sensor data and to extract useful features in an unsupervised way. Popular deep models based on RBMs include **Deep Belief Networks (DBNs)** [19, 84], **Deep Boltzmann Machines (DBMs)** [185], **Convolutional Boltzmann Machines (CBMs)** [115], and so on. We briefly introduce the DBN and DBM in the following.

A DBN has multiple hidden layers, as shown in Figure 3(a). The visible units in the DBN may be binary or real, while the hidden units are usually binary. Typically, the units in one layer are fully connected to the units in the neighboring layers except in a sparse DBN. The connections between the top two layers are undirected, while those between all the other layers are directed [64]. A DBN can be constructed by stacking multiple RBMs [84, 140].

DBNs are one of the first successful deep models for HAR. For instance, Zhang and Wu [252] presented a DBN-based method for activity detection based on voice signals. Fang and Hu [57] utilized a DBN of four hidden layers to recognize daily activities in a smart home. Uddin et al. [217] introduced a DBN method that consists of three hidden layers for recognizing facial expression. Zheng et al. [256] developed an EEG-based emotion method using a DBN. DBNs have a distinguishable property from other directed generative models that allow to infer the states of hidden units in a single forward pass [84]. The resulting weights can be used to initialize all the feature detecting layers of a classification network. However, DBNs are rarely used nowadays due to the problems associated with both directed models and undirected models such as intractable inference to marginalize out the hidden units, and intractable partition function of the top two layers [64].

Another popular deep model based on RBMs is DBM [185], which is also a generative model. Similar to DBNs, DBMs also consist of multiple RBM but all the connections in the DBMs are undirected, as shown in Figure 3(b). DBMs can be represented as a bipartite graph, which enables the conditional distribution over one DBM layer to be factorial. Compared to DBNs, DBMs are simpler, but allow richer approximations of the posterior [64]. In DBNs, there exist a series of variational bounds on the log probability of the training data [85], which cannot be explicitly optimized. By contrast, it is feasible to actually optimize the variational bounds in DBMs, since all the hidden units in one DBM layer are conditionally independent given the other layers.

So far, some works based on DBMs have been done for HAR. Bhattacharya and Lane [24] used a three-layer model consisting of RBMs to recognize gestures, transportation mode, and



(a) AE (b) DAE (c) VAE

Fig. 4. (a) The structure of an AE. It is trained to minimize the error to reconstruct the original input from the features (representations). (b) The structure of a DAE. It takes as input the corrupted version of input and is trained to reconstruct the original input. (c) The structure of a VAE with Gaussian probability distributions in its latent space. It is trained to learn the probability distribution of data, from which features are sampled and used to reconstruct its original inputs.

indoor/outdoor activities. Plötz et al. [162] presented a DBM-based method to learn features from data automatically for activity recognition. Lane et al. [109] proposed a deep model that is composed of three layers of RBMs for different audio sensing tasks (e.g., ambient scene analysis, stress detection, emotion recognition, and speaker identification). Radu et al. [172] presented a multimodal DBM learning method for HAR on mobile devices. Overall, RBM-based deep models are rarely utilized for HAR these days due to the difficulty to train them.

5.2 Autoencoders

AEs are another type of generative models, which are similar to RBM-based models. While both of them can learn useful representations of original data [21, 216], the AEs use deterministic units instead of stochastic units that are used in RBMs. An AE has two processes: encoding and decoding. In the encoding process, original inputs are transformed into features (representation of data). In the decoding process, the learned features are reconstructured to approximate the original inputs. By minimizing the reconstruction error between the input data and its reconstruction, the learning of an AE is trained. Figure 4(a) shows the encoding and decoding processes.

Like PCA, autoencoders were originally proposed for dimensionality reduction. An autoencoder with the input dimensionality larger than the feature dimensionality is called an undercomplete autoencoder [21]. The undercomplete autoencoder with linear decoder and the mean squared loss function learns the same subspace as PCA, but the autoencoder that has nonlinear encoder and decoder functions can learn a more powerful generalization than PCA. While undercomplete autoencoders are able to learn the most salient features of data, they may simply fail to learn useful information if the encoder and decoder have too much capacity [64]. Overcomplete autoencoders, where the feature dimensionality is greater than the input, also suffers a similar problem. To solve the problem, regularized autoencoders have been proposed in recent years, including **Sparse Autoencoder (SAE)** [148], **Denoising Autoencoder (DAE)** [219], **Variational Autoencoder (VAE)** [83, 103, 238], and so on [216].

Due to the excellent performance and representation ability, AE and its variants have been widely used for HAR. Gu et al. [70] designed a HAR method based on an stacked DAE based on data from four types of sensors built in a smartphone, including accelerometer, gyroscope, magnetometer, and barometer. Almaslukh et al. [5] developed a HAR method based on a SAE for recognizing locomotion activities. Wang [226] presented a HAR method based on a continuous AE, which uses data from accelerometer, gyroscope, and magnetometer. Li et al. [121] investigated the

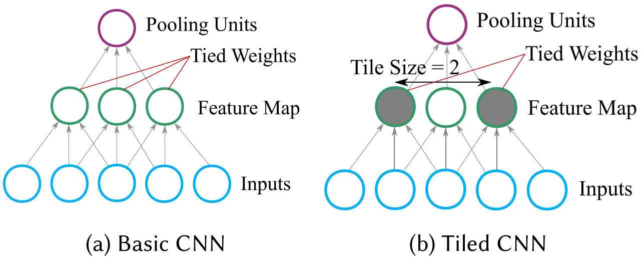


Fig. 5. (a) A basic CNN with local receptive fields and units in each feature map have the tied weights. (b) A tiled CNN with partially untied local receptive fields and units with the same texture in each feature map have tied weights. This figure is adapted from Reference [111].

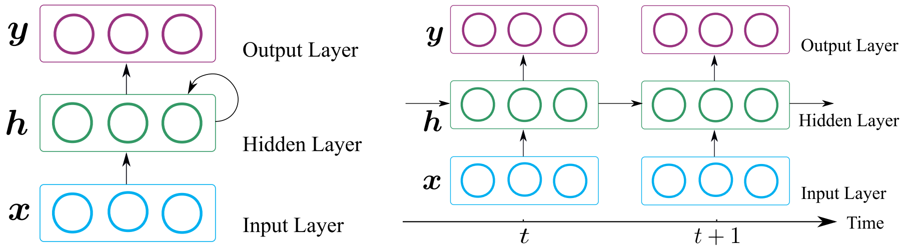
performance of SAE, DAE, and PCA in feature learning for activity recognition. Hasan and Roy-Chowdhury [78] introduced a framework based on stacked SAEs and active learning to recognize activities from streaming videos. Wang et al. [225] utilized a SAE to simultaneously recognize location, activity, and gesture from wireless signals. Wang et al. [230] presented a stacked AE for egocentric activity recognition from videos. Zhang et al. [251] utilized an AE to learn features from electroencephalographies to recognize brain activities. In HAR, AE and its variants are mainly used to reduce data dimensionality and learn features from data. Apart from achieving excellent performance, they can also make use of unlabeled data. They are often used for processing data from inertial sensors, WiFi, acoustic sensor, and so on. However, they are rarely used for dealing with images where CNNs methods perform the best.

5.3 Convolutional Neural Networks

Different from AEs and RBM-based methods, CNNs are discriminative models that use convolution operation to replace general matrix multiplication in at least one of their layers [80, 106, 113, 208]. CNNs include two operations: convolution and pooling. Convolution involves three key ideas: sparse connectivity, parameter sharing, and equivariant representations. Pooling uses a statistic of the inputs as the output. There are different pooling functions such as max pooling [106], average pooling [113], L^2-norm pooling [64], and tree pooling [114].

Basic CNNs usually have four types of layers: convolution layer, pooling layer, detector layer (e.g., ReLU layer), and fully connected layer (a layer in general neural networks). These layers can be stacked to form a deep CNN. Due to the excellent performance of CNNs in different domains especially image classification, many variants of CNNs have been proposed [72]. One of the popular variants is called tiled CNN [111]. While weight sharing mechanism in convolution can significantly reduce the number of parameters, it restricts the model from learning other invariant features (e.g., rotational invariant features). A solution to address this problem is the tiled CNN, which can learn diverse feature maps by constraining weights functions k steps away from each other to be equal. The parameter k here is called tile size, and the tiled CNN corresponds to the basic CNN when the tile size equals to 1. Compared to basic CNNs, tiled CNNs can not only reduce the number of parameters to be trained, but also allow to learn other invariances, as shown in Figure 5(a) and (b). It has been demonstrated that tiled CNNs outperform basic CNNs in References [111, 234]. Apart from tiled CNNs, there are many other variants of basic CNN. In Reference [72], the authors introduced many variants of CNN that are improved from different aspects including layer design, activation function, loss function, regularization, computation, and optimization.

As one of earliest successful deep learning methods, CNNs have also been widely used for HAR. Ronao and Cho [182] used a CNN to recognize six types of locomotion activities and demonstrated



(a) Folded RNN (b) Unfolded RNN

Fig. 6. Examples of folded RNN and unfolded RNN. (a) A simple folded RNN where there are loops in the hidden layers. (b) A simple unfolded RNN. The hidden units of the network at different times have connections.

that the CNN outperforms some conventional methods such as MLP, Naive Bayes, and SVM. Hughes and Correll [90] applied a distributed CNN to recognize some mid-level activities (e.g., opening a door, opening a drawer), and analyzed the effect of sensor location (e.g., body, arms, and legs) for recognizing these activities. Yang et al. [241] designed a CNN for recognizing hand gestures and daily activities. Ha and Choi [75] presented a CNN that employs both partial weight sharing and full weight sharing for HAR based on multimodal data (specifically, data from multiple accelerometer and gyroscope sensors). Zeng et al. [246] introduced a CNN for HAR using mobile sensor data. Zhou et al. [260] proposed a CNN-based locomotion activity recognition method using data from accelerometer, magnetometer, gyroscope, and barometer.

Overall, CNNs are suitable for dealing with data with a known, grid-like topology (e.g., images, time-series data that can be considered as one-dimensional (1D) grid sampling at regular time intervals). However, CNNs may not work well on processing sequential data.

5.4 Recurrent Neural Networks

RNNs are a family of neural networks that have recurrent connections [64, 183, 186]. While CNNs are specialized for processing matrix-like data (e.g., images, video streams), RNNs are favorable for dealing with sequential data (e.g., speech, accelerometer readings). Figure 6 shows the structure of a simple folded RNN and unfolded RNN.

The recurrent connections in RNNs enable them to outperform general neural networks in dealing with sequential problems, since they can learn the sequential dependencies. However, the memory produced from the recurrent connections is often limited by the algorithms used to train the RNN due to vanishing or exploding gradients issues. A popular way to reduce the effects of vanishing and exploding gradients is to use LSTM RNN [66]. Different from conventional RNNs, the LSTM RNN replaces hidden units with memory cells whose inputs and outputs are controlled by gates to store or forget information [186]. The LSTM was originally proposed in Reference [87] and modified in Reference [66] that has become popular later.

While the standard LSTM has demonstrated promising performance in a variety of tasks, it may fail to understand the input structures that are more complicated than a sequence. To address this challenge, a tree-structured LSTM network is proposed in Reference [263], which is called S-LSTM. The S-LSTM network consists of S-LSTM memory blocks, including an input gate, two forget gates, a cell gate, and an output gate. While the S-LSTM network can achieve better performance in complicated sequential modeling problems than the standard LSTM network, it has higher computational complexity. Another notable variant of the basic RNN is **Gated Recurrent Units (GRUs)** [40, 41], which can adaptively capture sequential dependencies. While it has a gated structure, which is similar to the LSTM, it is more computationally efficient than the LSTM. The GRU shares some common characteristics with the LSTM [45]. The most salient one is that both have the additive component in the update process from time t to $t + 1$, which distinguishes them from traditional recurrent units. This characteristic allows them to remember existing features and to bypass multiple temporal steps. However, they also have some differences. For example, the LSTM unit can control the exposure degree of the memory content by the output gate, while the GRU simply exposes the full content without any control. More specific similarities and differences between the LSTM and the GRU can be found in Reference [45]. In addition to the LSTM, GRU, and their variants, there are many other variants of RNN. Some of them are recurrent CNN [123], structurally constrained RNN [136], ubitary RNN [13], and gated orthogonal recurrent unit [96]. The advantages and disadvantages of these architectures are summarized in Reference [186].

RNNs have been widely used for HAR as activity recognition can be considered as a sequential problem. Usually, RNNs are considered as one kind of discriminative models though they can be used as generative models [206]. In the context of HAR, the discriminative RNNs are used. Its training is done in a supervised way, which minimizes the cost function of the network output and the corresponding label. Murad and Pyun [143] utilized a **deep RNN (DRNN)** consisting of LSTMs to recognize the activities from several open public datasets. They demonstrated that the unidirectional DRNN outperforms the bidirectional DRNN and the cascaded DRNN. Similarly, Inoue et al. [94] also used a DRNN composed of LSTMs to recognize human activities from acceleration signals. Guan and Plötz [73] developed a HAR method that ensembles multiple LSTMs, and showed that the ensembles of LSTM networks outperform individual LSTM networks. Qi et al. [166] proposed a structural-RNN method for recognizing group activities from videos, which are based on spatio-temporal attention and semantic graph. Edel and Köppe [54] developed a binarized BLSTM RNN for recognizing daily activities and locomotion activities. By replacing the arithmetic operations with bit-wise operations, the binarized BLSTM can significantly reduce memory size and accesses and is hence more computationally efficient than the standard LSTM. Overall, RNNs are perfect for processing sequential data due to its memory mechanism, but they consume larger energy to train.

5.5 Generative Adversarial Networks

GANs are a relatively new type of generative models [65], which have gained great popularity in image processing [126], classification [152], image generation [23], and so on. A GAN consists of a generator and a discriminator. The main task of the generator is to learn the data distribution so that it can generate samples to deceive the discriminator. By contrast, the discriminator examines samples to recognize whether they are from real data (training data) or fake data (produced by the generator). The training of the GAN is to let the generator and the discriminator to play a two-player zero-sum game until reaching a Nash equilibrium where the discriminator cannot tell whether the input sample is from the generated data [157]. Figure 7 shows the structure of a basic GAN that includes a generator and a discriminator.

GAN has achieved great success in different domains, but the original GAN also suffers from several problems such as gradient vanishing, poor diversity, and unstable training. Therefore, many variants of the original GAN [65] have been proposed. One of representative variant of the basic GAN is **Conditional GAN (CGAN)** [137], which controls the data generation process with auxiliary information (denoted by $\boldsymbol{c}$). Another representative variant of GAN is **Least Squares GAN (LSGAN)** [132], which uses the least squares loss function for the discriminator rather than the sigmoid cross entropy loss function used in the basic GAN. Compared to the basic GAN, the LSGAN can generate higher quality data and is more stable in the learning process. Apart from the CGAN and the LSGAN, there are other notable variants of GAN such as DCGAN [169], CycleGAN [262],

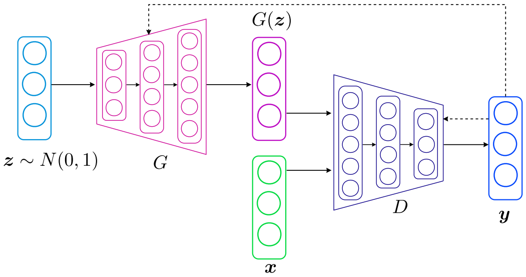


Fig. 7. The structure of a basic GAN, which contains a generator G and a discriminator D. The GAN is trained to update the parameters of G and D. The output $\boldsymbol{y}$ of the discriminator is a binary vector, indicating whether the input sample is real or fake.

InfoGAN [37], ProGAN [97], WGAN [12], SAGAN [247], EBGAN [253], BEGAN [23], and StyleGAN [98]. The key contributions, advantages, and disadvantages of GANs have been surveyed in References [47, 235].

To date, few works have used GANs and their variants for HAR, but they have great potential to be widely used in HAR as collecting labeled data in HAR is challenging and costly. The effort in collecting labeled data could be significantly reduced by making use of GANs. Li et al. [119] employed a CGAN to generate activity masks from video frames, which are then fed to a VGG-LSTM network [199] for activity recognition. Gammulle et al. [59] proposed a multi-level GAN architecture combining with LSTMs to recognize group activities from video sequences. Ahsan et al. [4] developed a HAR framework, which first trains a DCGAN on a large unlabeled video activity dataset and then fine-tunes the pretrained discriminator from the GAN model on a labeled dataset for activity recognition. Overall, GANs are suitable for the scenarios where labeled data are few. Existing GAN-based works for HAR use mostly videos or images. More studies are required to investigate the feasibility and performance of using GANs for HAR on other types of data (e.g., WiFi CSI, accelerometer readings).

5.6 Summary

Both generative deep models and discriminative deep models can be used for HAR. To date, there are many deep models available, it is natural to ask which model should one choose. While there is no consensus on this point, it might be useful to try different models that fit the problem domain. Discriminative deep models (CNNs, RNNs, and their variants) can be directly trained for HAR. CNNs are originally used for processing image and image-like data, and therefore they have excellent performance on HAR with images. Some recent works have also used CNNs on other sensor data (e.g., accelerometer data). RNNs are popular in dealing with sequential data, especially time-series data, and have been extensively used for HAR based on inertial sensor data.

Generative deep models (RBMs, AEs, and GANs) require to add a discriminative layer (e.g., softmax layer) on the top for HAR. They are often used to reduce the dimensionality of data or extract useful features in an unsupervised way. AEs are somehow similar to RBMs, but AEs are more straightforward and easy-to-understand than RBMs. Also, the optimization of AEs is much easier than that of RBMs. This makes AEs more popular than RBMs these days. GANs, which are another type of generative model, are often used to generate new images or other data. Although there are few works on using GANs for HAR, it is promising to apply GANs to reduce the number of labeled examples required to train a deep model.

Generative deep models and discriminative deep models can also be combined together to enjoy the benefits of both models. Such models are also called hybrid models. In Reference [192], an AE is combined with a CNN to classify human activities based on radar data. In Reference [264], an AE is fused with a CNN and a LSTM to achieve device-free HAR from WiFi CSI data.

Table 3 summarizes popular state-of-the-art HAR methods/systems with deep learning, including the model used, activity of interest, dataset, as well as their performance. From the table, one can see that varying deep models have been used for HAR. RBM and its variants (e.g., DBN, DBM) are widely used to recognize different activities in References [24, 57, 162, 172, 217, 256] and are gradually losing its popularity due to the difficulty in parameter optimization. AEs are also popular in HAR [5, 70, 78, 230, 251] and many variants have been developed. CNNs are becoming prevalent in HAR [75, 90, 182, 246, 260] nowadays though they are originally proposed for dealing with images. RNNs are more often used for modeling sequential data [73, 94, 143], which can capture the temporal dependencies of time-series data. GANs are less used in HAR so far, but they have great potential to be spread. Several works have integrated GANs with discriminative models (e.g., LSTM) [59, 119].

The most common activity type for which most deep models are trained is locomotion activity, followed by daily activity, gesture, and transport model. The may be because locomotion activity can be recognized by using both ambient sensors and mobile sensors. The ubiquity of sensor-rich mobile devices has made it easy to sense a variety of activity (not only locomotion activity, but also daily activity, gesture, and so on). Several studies have also investigated the use of deep models for recognizing emotion and health-related activity [109, 217, 256], which deserve more attention and efforts in the future. There is few work on investigating the applicability of deep models for recognizing activities such as phone usage, security, entertainment.

The commonly used datasets include Skoda [245], Opportunity [180], UCI-HAR [10], Ambient Kitchen [161], Daily Routines [91], PAMAP2 [177], USC-HAD [249], and USC-HAD [249]. More datasets that contain multimodal signals for more types of activity would be helpful in promoting the development and advances of HAR with deep learning.

Note that although deep learning networks have been widely used for HAR, there are scenarios that deep networks may not be the good choice. First, deep networks often require a large amount of training data to avoid over-fitting, which may be cost-prohibitive for some modalities (e.g., barometer data, and Zigbee data). Second, deep networks generally need to be run on high-performance servers or platforms, and therefore they are not suitable for resource-limited HAR (e.g., smartphone-based HAR tasks). Third, some types of data for HAR cannot be directly used by deep networks. For instance, the output of event cameras are discrete asynchronous events, and cannot be directly processed with state-of-the-art deep networks that usually run on fixed-size (e.g., grid-like) data.

6 EVALUATION

6.1 Evaluation Methods

There are mainly three methods used to evaluate the classification performance of a deep model, namely holdout, cross validation, and bootstrap [102].

6.1.1 Holdout. The holdout is a simple evaluation method, which randomly divides the dataset into training data, test data, and validation data (required by some modeling algorithms). The training data are used to fit the model. The validation data are utilized to assess the performance of the fit model to search for the optimal values of parameters. After that, the trained model is assessed on the test data to evaluate the generalization error of the model. The holdout method is

Table 3. State-of-the-art HAR Method/System with Deep Learning

Reference	Year	Deep Model	Activity	Dataset	Performance Metric	Performance
[24]	2016	DBM	Gesture, transport mode, indoor/outdoor detection	Private data collected by smart watch	Accuracy	About 73%, 93%, 94%, for respective activity
[162]	2011	DBN	Daily activity, factory maintenance	Ambient Kitchen [161], Daily Routines [91], Skoda [245], Opportunity [180]	Accuracy	88.7%, 86.8%, 75.8%, 74%, for respective dataset
[109]	2015	DBM	Daily activity, emotion	EmotionSense [168], StreeSense [129], SpeakerSense [128], JigSaw [130]	Accuracy	About 83%, 82%, 81%, 58% for respective dataset
[57]	2014	DBM	Daily activity	Private data collected by ambient sensors	Accuracy	About 87%
[217]	2017	DBN	Emotion	Private data collected by camera	Accuracy	96.67%
[256]	2014	DBN	Emotion	Private data collected by electroencephalography (EEG)	Accuracy	87.6%
[70]	2018	SDAE	Locomotion activity	Private data collected by smartphone	Precision, Recall F1 score	94% (F1 score)
[5]	2017	SAE	Locomotion activity	UCI HAR [10]	Accuracy	96.4%
[226]	2016	Continuous AE	Locomotion, transport mode	Altun et.al [7]	Accuracy	99.3%
[78]	2015	SAE	Locomotion, transport mode, daily activity	KTH [189], UCF50 [176], VIRAT [154], TRECVID [155]	Accuracy	98%, 53.8%, 62.6%, 6.7% for respective dataset
[225]	2017	SAE	Locomotion, gesture	Private data collected by WiFi nodes	Accuracy	85%
[230]	2018	AE	Locomotion, daily activity	UEC Park [104], LongEgo [163]	Accuracy, Recall	77.6% (Accuracy), 93% (Recall)
[182]	2016	CNN	Locomotion activity	Private data collected by smartphone	Accuracy	94.8%
[173]	2017	CNN	Locomotion activity, daily activity indoor/outdoor detection	STISEN [203], GAIT [149], Sleep-Stage [63], Indoor/Outdoor Detection [171]	F1 score	81.6%, 89.5%, 66.4%, 82.3% for respective dataset
[170]	2019	CNN	Locomotion activity	Private data collected by smartphone	Accuracy	92.38%
[241]	2015	CNN	Daily activity, gesture	Opportunity [180], Gesture [27]	F1 score, Accuracy	54.7% (F1), 89.6% (F1) for respective dataset
[260]	2019	CNN	Locomotion activity	Private data collected by smartphone	F1 score, Precision, Recall	97% (F1)
[221]	2019	CNN	Gesture	ARIL	F1 score, Precision, Recall	88% (F1)
[160]	2021	AE+CNN	Locomotion activity	Self-synthesized dataset	Accuracy	95.81%
[143]	2017	LSTM	Daily activity, locomotion, health-related activity, factory maintenance	UCI-HAR [10], USC-HAD [249], Opportunity [180], Daphnet FOG [14], Skoda [245]	Precision, Recall, Accuracy, F1 score	96.7%, 97.8%, 92%, 93%, 92.6% (Accuracy) for respective dataset
[94]	2018	LSTM	Locomotion activity	HASC [99]	Accuracy	95.4%
[244]	2017	LSTM	Locomotion activity	WiFi CSI	Precision	About 90.5%
[73]	2017	LSTM ensembles	Daily activity, factory maintenance	Opportunity [180], PAMAP2 [177], Skoda [245]	F1 score	About 72.6%, 85.4%, 92.4% for respective dataset
[166]	2018	Structural RNN	Daily activity, locomotion	Collective Activity [42], Volleyball [92]	Accuracy	89.1%, 89.3% for respective dataset
[145]	2020	GCN+MLP	Daily activity	EGTEA [120], EPIC-Kitchens [50]	Mean average precision	About 29.4%, 51.6%, respectively
[211]	2019	CNN	Daily activity	THU-READ [210], WCVS [139]	Accuracy	91.72%, 67.04%, respectively
[231]	2020	CNN	Daily activity	EGTEA [120], EPIC-Kitchens [50]	Accuracy	40.5% (Top-5), 62.7%, respectively
[56]	2019	CNN+LSTM	Locomotion activity	Self-collected dataset	Accuracy	94%
[54]	2016	Binarized BLSTM	Daily activity, locomotion	Opportunity [180], PAMAP2 [177]	F1 score	About 76%, 92% for respective dataset
[119]	2017	CGAN + VGG-LSTM	Locomotion, health-related activity	Private video data	Accuracy, Precision, Recall, F1 score	84.7%, 76.7% (F1) for respective data
[59]	2018	GAN + LSTM	Daily activity, locomotion	Collective Activity [42], Volleyball [92]	Accuracy	91.7%, 93% for respective dataset
[192]	2018	CNN + AE	Locomotion activity	Private data collected by Radar	Accuracy	94.2%
[264]	2018	AE + CNN + LSTM	Locomotion activity	Private CSI data	Accuracy, True Positive Rate, False Positive Rate	97.4% (Accuracy)
[131]	2019	CNN + GRU	Locomotion activity factory maintenance	STISEN [203], Skoda [245], PAMAP2 [177]	F1 score	About 96.5%, 93.1%, 89.3% for respective dataset
[33]	2019	LSTM + Attention Model	Locomotion activity	MHEALTH [16], PAMAP2 [177], UCI HAR [10]	Accuracy, Precision, Recall, F1 score	About 96.1%, 89.9%, 85.5% (F1) for respective dataset

advantageous of its simplicity and speed, and is often applied in the cases where there is a large dataset available or the training of the model is very slow. Nevertheless, it has high variability, since the difference in the training data and test data can lead to a significant difference in the classification accuracy [144].

Table 4. Confusion Matrix of a Binary Classification Task

	Actual Positive	**Actual Negative**
Predicted Positive	True positive (tp)	False positive (fp)
Predicted Negative	False negative (fn)	True negative (tn)

In practice, it is common to repeat the evaluation for multiple times (e.g., 30), since deep models are stochastic and involve different sources of randomness (e.g., random initial weights) [26]. In other words, the same model is evaluated on the same data for multiple times and only change the seed to generate random numbers. Then, the average performance can be taken as the performance of the model.

6.1.2 Cross Validation. Cross validation is a commonly used evaluation method. The most popular cross validation is k-fold cross validation, which divides the dataset into k sets where one set is used as test data and the remaining $k-1$ sets as training data. This process is repeated k times with each of these sets used exactly once as the test data. The value of k is usually 5 or 10. The average performance over all k trials is used as the performance of the model. In addition to k-fold cross validation, there are other cross validation methods such as leave-one-out, and shuffle-split. Compared to the holdout method, cross validation is more reliable and can use data more effectively [142]. The main disadvantage of cross validation is that it increases the computational cost. Cross validation is applicable for small datasets.

In the evaluation of deep models, it is also recommended to repeat the cross validation process for multiple times with only the change of random seed.

6.1.3 Bootstrap. Bootstrap is another method that can be used to evaluate a deep model, which involves resampling a dataset with replacement many times to obtain the statistical performance and corresponding confidence. It performs better for small datasets than cross validation [102]. It has been used in deep learning for different tasks [82, 174] though it is still not very popular.

6.2 Evaluation Metrics

There are many metrics that can be used to measure the classification performance of deep models [88, 165, 205], and the commonly used ones include *accuracy*, *error rate*, *precision*, *recall*, *F-measure*, **Receiver Operating Characteristic (ROC)** curve, and **Area Under the Curve (AOC)**. For clarification, we introduce these metrics using the confusion matrix of a binary classification task to predict the presence of human in an image (presence is encoded as 1, and non-presence as 0), but these metrics are also applicable for multi-class classification tasks. Table 4 shows the confusion matrix, which we will use to explain different metrics. The row of the table is the predicted label, and the column is the actual label. A true positive (denoted by tp) means that the predicted label is 1 and the actual label of the data example is 1, and a true negative (tn) means that the predicted label is 0, and the actual label is 0. A false positive (fp) represents that the predicted label is 1, but the actual label is 0. A false negative (fn) represents that the predicted label is 0, but the actual label is 0.

6.2.1 Accuracy and Error Rate. A commonly used classification performance metric is *accuracy*, which measures the proportion of correct predictions by the total number of data examples. It is written as follows:

$$accuracy = \frac{tp + tn}{tp + fp + tn + fn}. \quad (3)$$

Another metric related to *accuracy* is *error rate*, which measures the proportion of incorrect predictions by the total number of data examples. It is described as follows:

$$\begin{aligned} error\_rate &= \frac{fp + fn}{tp + fp + tn + fn} \\ &= 1 - accuracy. \end{aligned} \tag{4}$$

Note that *accuracy* and *error rate* are not suitable for the case where the data are very imbalanced.

6.2.2 Precision and Recall. *Precision* and *recall* are another two classification metrics that are usually used together. *Precision* measures the proportion of correctly predicted positive cases (human presence) by the total number of predicted positive cases, namely

$$precision = \frac{tp}{tp + fp}. \tag{5}$$

Recall measures the proportion of the correctly predicted positive cases by the total correct predicted cases, namely

$$recall = \frac{tp}{tp + tn}. \tag{6}$$

The *precision* provides information about the performance of a model regarding false positives, while the *recall* provides information about the performance regarding false negatives [205].

6.2.3 F-measure. Using both *precision* and *recall* metrics to evaluate the effect of each parameter of the model might be troublesome. One way to address this trouble is to use the harmonic mean of the two metrics, which is called *F-measure*. It is written as

$$F\text{-}measure = 2 \cdot \frac{precision \cdot recall}{precision + recall}. \tag{7}$$

6.2.4 True Positive Rate (Sensitivity). The true positive rate (tpr), also known as *sensitivity*, measures the proportion of correctly classified positive cases by the number of actual positive cases, namely

$$tpr = \frac{tp}{tp + fn}. \tag{8}$$

6.2.5 False Positive Rate. The false positive rate (fpr), also known as *fall-out*, measures the proportion of the number of negative cases that are wrongly classified as positive by the number of actual negative cases, namely

$$fpr = \frac{fp}{fp + tn}. \tag{9}$$

6.2.6 ROC. A ROC graph is used to visualize the performance of a classifier [58], which shows the relationship between true positive rate and false positive rate. It is believed to provide a richer information than scalar measures such as accuracy or error rate. Figure 8 shows a basic ROC graph with three classifiers. The closer a classifier plotted to the upper left corner, the better performance it has. In Figure 8, classifier 1 performs better than classifiers 2 and 3. Note that the performance of classifier 2 is actually equal to random guess (dashed line in Figure 8).

Fawcett [58] suggests that a classifier is more conservative if it is closer to the left-hand side of the graph; whereas it is more liberal if it is closer to the upper right corner. The concept is similar to the precision-recall tradeoff. Being conservative means minimizing false positives at a cost of missing some true positives; whereas being liberal means maximizing true positives at a cost of including more false positives.

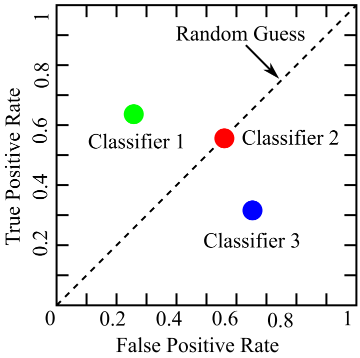


Fig. 8. A simple ROC graph with three binary classifiers.

6.2.7 AUC. AUC is another performance metric, which measures the area under the ROC curve. Compared to the ROC curve, which depicts the classification performance in 2D, AUC is a single scalar value [58]. The value of AUC ranges between 0 and 1, and random guessing has an area of 0.5. The greater the AUC value, the better the classification performance.

6.3 Datasets

There are a lot of public datasets available for HAR. We summarize the statistics of the common datasets in Table 5, including year of data collected, sensor used, activity type, number of activity, number of subject, number of instances, and download link. Most datasets are collected using inertial sensors and cameras, but there are some relatively new datasets that are collected using event cameras. More datasets that contain multi-modal signals for more types of activity would be helpful in promoting the development and advances of HAR with deep learning.

7 CONCLUSION AND OPEN CHALLENGES

In this article, we provide a comprehensive tutorial on deep learning methods for HAR. In particular, we introduce the related techniques in detail, ranging from preprocessing, model building, to evaluation. While this study is mainly developed in the context of HAR, the related techniques can be used for other tasks such as image processing, and speech recognition.

In the following, we provide open challenges that remain in deep learning or HAR.

- **Multimodal and universal activity recognition**. Activity has different levels. While it is easy to recognize simple activity (e.g., walking, running) using single sensor (e.g., accelerometer), complex activities (e.g., in a meeting) require to combine multiple sensors for accurate recognition. In recent years, some studies (e.g., References [70, 260]) have demonstrated that the combination of multiple sensors helps improve the classification accuracy of locomotion activities. However, most existing studies focus on recognizing few activities. Methods for recognizing more universal activities are required to be further explored based on multimodal signals from both ambient sensors and mobile sensors.

- **Developing new deep models that require less labeled data**. Collecting labeled data is usually expensive, which requires plenty of effort and time. Generative deep models (e.g., AEs and GANs) are able to make use of unsupervised data, but they are not directly applicable for HAR. New deep models that can be trained with few labeled data need to be developed. Hybrid models [192, 264], which combine generative models with discriminative models, are promising. Several

Table 5. Public Datasets for HAR

Dataset	Year	Sensor	Activity Type	#Activity	#Subject	#Instances	Download Link
Kasteren [218]	2008	Wireless sensor (RFM DM 1810)	Daily activity	8	1	245	Website
Skoda Mini Checkpoint [245]	2008	Inertial sensor	Factory maintenance	10	1	700	Website
UC Berkeley WARD [240]	2009	Inertial sensors	Locomotion acitivity	13	20	N/A	Website
Daphnet Freezing of Gait Syndrome [15]	2009	Inertial sensors	Health-related activity	3	10	237	Website
CMU-MMAC [51]	2009	Inertial sensors, camera, microphone, and so on	Daily activity (kitchen)	5	5	N/A	Website
Opportunity [180]	2010	Motion sensors	Daily activity	9	4	2,551	Website
HMDB-51 [107]	2011	Camera	Locomotion activity	51	N/A	6,849	Website
WISDM Actitracker Dataset [108]	2011	Accelerometer	Locomotion activity	6	29	5, 424	Website
ADL [10]	2012	Inertial sensors	Locomotion activity	6	30	10, 299	Website
UCF-101 [202]	2012	Camera	Locomotion activity	101	N/A	13,320	Website
USC-HAD [249]	2012	Inertial sensors	Locomotion activity	12	14	N/A	Website
PAMAP2 [177]	2012	Inertial sensors, heart rate monitor	Daily activity	18	9	N/A	Website
Berkeley MHAD [153]	2013	Camera, inertial sensors, microphone, and so on	Daily activity	11	12	660	Website
REALDISP [17]	2014	Inertial sensors	Locomotion, daily activity	33	17	1,419	Website
ActRecTut [28]	2014	Inertial sensors	Gesture	11	2	337	Website
HHAR [203]	2015	Inertial sensors	Locomotion activity	6	9	N/A	Website
ActivityNet-200 [29]	2016	Camera	Daily activity, entertainment, and so on	200	N/A	27, 801	Website
AReM [156]	2016	WiFi, accelerometer	Locomotion activity	6	N/A	42,240	Website
UniMiB SHAR [135]	2016	Accelerometer	Locomotion activity	9	30	11, 771	Website
UMAFall [32]	2016	Wearable sensors, inertial sensors	Daily activity	17	19	531	Website
UCF-50 DVS [89]	2016	Event camera	Daily activity	50	N/A	6,676	Website
DVS128 Gesture [8]	2017	Event camera	Gesture	11	29	1, 342	Website
Wifi-Activity-Recognition [244]	2017	WiFi (CSI)	Locomotion activity	6	N/A	720	Website
Orange4Home [48]	2017	236 heterogeneous sensors	Routine daily activity	20	1	493	Website
Kinetics-400 [100]	2017	Camera	daily activity, locomotion activity, entertainment, and so on	400	N/A	306,245	Website
Kinetics-700 [31]	2019	Camera	daily activity, locomotion activity, entertainment, and so on	700	N/A	650,317	Website
Epic Kitchen [50]	2018	Head-mounted camera	Kitchen activity	125	32	39,596	Website
LAR [70]	2018	Inertial sensors, barometer	Locomotion activity	8	12	12,822	Website
WESAD [187]	2018	ECG, EDA, EMG, respiration, body temperature, accelerometer	Emotion	15	N/A	63,000,000	Website
Multi-site Sensing [209]	2019	Accelerometer	Locomotion activity	22	42	6,674	Website
DVS Action [134]	2019	Event camera	Gesture	10	15	450	Website
DVS Fall [134]	2019	Event camera	Locomotion activity	4	15	180	Website

studies have been done though they are still in their infancy. It is also promising to develop new semi-supervised deep models [38] and active deep models [214] that require less labeled data.

• **Crowdsourcing quality data for deep models**. Deep models generally require to be trained on a large scale dataset; however, collecting such dataset can be cost prohibitive. A possible way to reduce the cost is to use crowdsourcing that allows each individual to contribute their own data. However, the challenge of crowdsourcing data is how to guarantee the quality of collected data. It worths to investigate or develop strategies to encourage individuals to share their data and to ensure the quality of data.

• **Efficient deep learning algorithms for resource limited devices (e.g., smartphones)**. Deep models are often computationally expensive, and most of them require to run on a server or PC with high configuration. Smart devices (e.g., smartphones, smart watches) have become prevalent in modern life these days, but their computing capability, though has been significantly improved, is still insufficient to run most deep models. More efficient deep models should be developed to be run on mobile devices [53], which will bring great convenience for people's life.

• **Stable and robust deep models**. While deep models have been shown effective and superior in many tasks, their performance may not be stable when the training data suffering small perturbations. This can reduce users' trust especially in health-related applications. Although some attempts have been done [76, 77], more works on developing stable and robust models are needed.

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Received June 2020; revised June 2021; accepted June 2021