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Artificial intelligence in human activity recognition: a review

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Abstract: The various activities of human movements have been discussed for several years, such as sports activities, daily life activities, and so on. Their detection and classification have given crucial information about a person's behaviour and health status. So, there has always been a purpose for detecting and classifying these activities for real-life problems. Behavioural recognition, fall detection, intrusion detection, human health prediction model, ambulatory monitoring, smart access to electronic appliances, etc., are the main motives of the detection of physical activity in the context of daily life. Nowadays, various types of wearable sensors are available in tiny sizes due to the advancements in miniature technology in electronic devices, which proved very useful for detecting human motions. Here in this article, some important methodologies, physical activity basics, and their classification using machine learning and deep learning approaches are discussed in the context of wearable sensors. After reading this article, the researcher could summarise the whole theory and technical aspects of activity recognition. Wearable sensors have gained tremendous traction for sensing human motion due to their various advantages over other sensors.

Keywords: wearable sensors; deep learning models; machine learning models; accelerometer; gyroscope; activity recognition.

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1 Introduction

Any bodily movement resulting in energy expenditure is generally considered physical activity, and exercise is defined as the subset of physical activity (Hills et al., 2014). Physical activities like bathing, eating, walking, dressing, toileting, sitting, standing, lying, etc., are generally considered as an activity of daily living (ADLs) (Hall and Frcpc, 2012). The ADLs is further divided into two parts basic and instrumental ADLs (Koyano et al., 1988). Basic activities (BA) of daily living are required for personal care, such as bathing, eating, dressing, stair up and stair-down, etc. (Yang et al., 2011; Tolstikov et al., 2011; Van Kasteren et al., 2010; Hong and Ohtsuki, 2011) Instrumental activities or complex activities (CA) are the core activities of daily living for living independently, including preparing meals, doing household work, using the telephone, managing money, etc. (Hall and Frcpc, 2012). Physical activity assessment could be done in two ways one is a subjective assessment, and the other is an objective assessment. Subjective assessments such as surveys, questionnaires, and diaries are considered, but these methods have been followed inaccuracy in some extent due to human error involvement. In the objective assessment of physical activity, motion sensors, like accelerometers and gyroscopes, are considered for detecting human motion, posture orientation, and the intensity of movement (Yang and Hsu, 2010). Acceleration generated by human movement could be measured by the accelerometer along its reference axis for quantifying physical movement. Information about the intensity and frequency of movement are also obtained with the accelerometer (Chen and Bassett, 2005).

It is also evident that the assessment of various physical activities depends on the type of physical activity and duration of those activities. Pedometers are well suited as far as walking is concerned, where step counts are the measured quantity. Heart rate monitoring has been used for moderate activities. Triaxial accelerometers have been used for long-term and free-living types of physical activities (Freedson and Miller, 2000). The articles (Westerterp and Bouten, 1997; Eston et al., 1998; Welk and Corbin, 1995; Pereira and Freedson, 1997) described a better picture of how and why the selection of sensor completely depends on which type of activity is under consideration. Human activity recognition (AR) by capturing images and videos with the help of a video sensor has been studied in several studies (Cichy et al., 2016; Onofri et al., 2016). The wireless signal or Radio Frequency signal-based human AR utilises wireless signal distortion with the interaction of human beings for AR (Kianoush et al., 2017). The wearable sensors, smartphones, and inertial measurement units have been widely used for AR due to the advancement in the miniaturisation of electronic devices and their various advantages over other modes of sensing such as vision and wireless sensing. The vision-based AR systems require a clear line of sight, costly installation maintenance, high computation cost, static position, and illuminations. The wireless signal or radiation-based AR systems have various health-related issues (Nweke et al., 2018a). The Wearables sensors are characterised by their simple use, low power consumption, ease to wear, cheap installation, etc. Inertial sensors are defined as the force sensors that respond to linear acceleration (accelerometer) along with one or several axes and to angular motion (gyroscope) along with one or several directions (Yang and Hsu, 2010). The operating principle of an accelerometer is based on a mechanical sensing element called seismic mass or proof mass which is attached to mechanical suspension along the reference axis. Whenever the force is exerted on seismic mass, the mass is deflected along the reference axis which would be directly proportional to an applied acceleration. Further, this deflection is converted to the electrical quantity (Godfrey et al., 2008; Öberg et al., 2004). The importance of AR has been accepted by the research community due to its various real-time applications for the betterment of human life, such as elderly care, healthcare, fitness monitoring, sports analytics, security and surveillance, biometrics, etc. Wearable sensors-based AR is very useful in the case of getting rehabilitation of a patient after the attack of disease such as Parkinson's disease, sleep apnea, heart attack, and so on. Monitoring and care for these patients are required after major operations, but for that, the patient has to be present in the hospital compound for a long time. Today's technology-based wearable sensors can be able to send information about the patient's activities to a doctor or nurse who is far away from the patient (Mukhopadhyay, 2015). Falls are a very common problem in elderly people by which elderly populations have been facing dire consequences in their daily life due to various physical and mental problems after getting falls (Shany et al., 2012; Aziz and Robinovitch, 2011). Some of the applications of wearable sensor-based AR are given in Figure 1, such as e-health, e-emergency, e-factory, etc. E-health is the field where remote location health assistance is provided in the case of elderly care, patient monitoring, fall detection, rehabilitation, fitness monitoring, and so on. The emergency help in case of an earthquake, flood, cloud burst, riots, a stampede in public places, etc., is covered in the e-emergency domain. E-factory where workers' behaviour in a factory environment is monitored to protect them from any accident during working with heavy machines. The detection of human motions by analysing the data collected from sensors while the user is performing some actions is known as AR (Gupta, 2021). The wearable devices consist of different sensors like accelerometers, gyroscopes, and magnetometers that can be easily used for data collection related to human motions, and further, that data can be utilised for AR. Nowadays, the easy availability of different wearable devices with inbuilt sensors, such as smartwatches, smartphones, wrist bands, smart clothes, etc., makes them very useful for AR. The wearable sensors-based AR is focused in this paper due to its various advantages of it over other sensor modalities-based AR. The basic steps such as data acquisition, preprocessing, feature extraction and classification are shown in Figure 3 for AR. This comprehensive survey for wearable sensors-based AR includes the study of the importance of sensor locations, preprocessing of acquired data, feature extraction, conventional machine learning models, and deep learning models for classification.

To provide a comprehensive survey of wearable sensor-based AR, we have surveyed around 700 articles, including research as well as review by typing keywords in Google scholar like 'wearable sensor-based AR', 'smartphone-based AR methods', and 'filters used in data acquisition for AR', 'different machine learning techniques for AR', 'deep learning models for AR', 'wearable sensor-based datasets for AR' and others. The AR models based on vision sensors, wi-fi, and RADAR have been neglected from the study and the article mainly based on wearable sensors where data were taken locally are considered specifically. Therefore, in this way at last 257 articles are selected for writing this review paper. Some of the well-written review papers (Wang et al., 2019a; Nweke et al., 2018a; Wang et al., 2019; Ramanujam et al., 2021) are considered to define the structure of the paper.

Figure 1 Applications of human AR (see online version for colours)

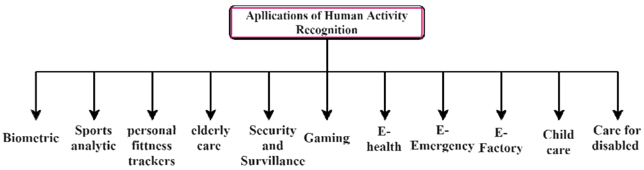
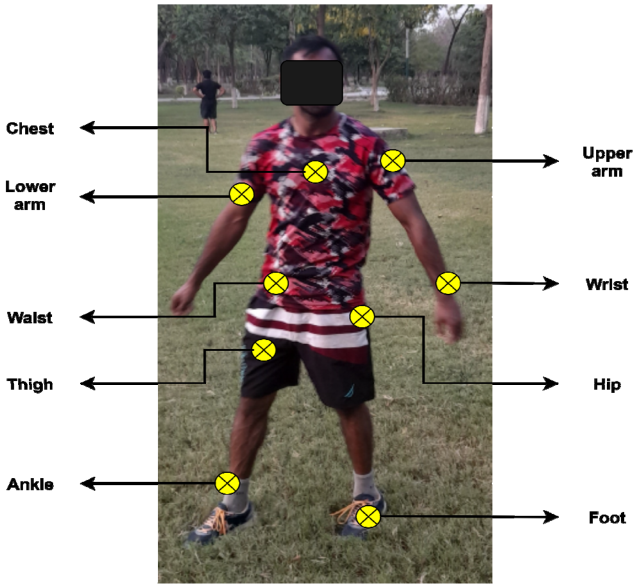


Figure 2 Some of the widely used sensor locations (see online version for colours)



The rest of the article is structured as follows. Section 1 describes sensor locations, the importance of location for particular activity and design issues related to wearable sensor for real time application of AR. Section 2 describes the preprocessing of acquired data in terms of filtration and segmentation. Section 3 has two subsections for manually extracted features and each subsection describes numerous techniques for feature extraction in time and frequency domains respectively. Section 4 presents the feature dimension and selection techniques. Section 5 describes the overview of traditional methods of classification. Section 6 presents the state-of-the-art methods of deep learning for AR. Section 7 discusses the theme of AR and Section 8 concludes the review and includes some widely accepted publicly available datasets.

2 Wearable sensor locations, their detected activities and design issues

Physical activity assessment methods vary according to the positioning of the sensor, the number of sensors, type of activity, statistical techniques, and signal processing methods (filtering, pattern recognition) (Foerster et al., 1999). In the late 1980 and 1990s, the devices and sensors which were used had massive structures, low storage and processing capabilities but nowadays the scenario has changed. These days the advancement in integrated technology has gained advantages in terms of oversize, speed, and processing capabilities compared to the previous one (Lee et al., 2010).

The growing advancements in electronics industries attract more researchers towards the designing of tiny devices with more features for fitness alert devices such as smartwatches, smart bands, heart rate monitors, fabric-based tracking devices, and so on. The wearable technology market for healthcare services is rapidly growing due to user comfort and easy-to-wear capabilities with a standard physiological data-taking capacity (Mukhopadhyay, 2015). Different kinds of sensors are available to measure human physiological parameters. Nowadays, it is possible to measure the physiological signals for very long durations with less power consumption and low-cost processing.

The body's temperature is a very common physiological parameter in wearable sensing technology. Medical stress, which creates various health-related consequences, can be detected with the help of the profile of temperature sensors. Body temperature is a very useful physiological parameter in activity classification (Parkka et al., 2006; Leonov, 2013; Winkley et al., 2012). The various methods are available for measuring the heart rate based on the brightness of a person's face, sound, etc.; further, it can be used to detect disease and activities (Zhang et al., 2010; Tamura et al., 2014; Poh et al., 2010; Inomata and Yaginuma, 2014). Accelerometers have been widely used sensors for the detection of physical activities such as the detection of falls (Shany et al., 2012; Kan and Chen, 2012; D'Angelo et al., 2014). Electrocardiograph sensors are very useful and widely used to assess the short-term cardiovascular disease. These sensors are very common for getting information on chronic heart patients. ECG signal provides crucial information regarding the regularity of heartbeats and R-R interval for knowing the heart's health. Nowadays, various wearable ECG sensors in different forms are available with low power and high resolution (Yan et al., 2011). The various wearable devices are in trend in these days due to their comfort to wear, smartness and specification of inbuilt sensors such as accelerometers, gyroscopes, magnetometers, light sensors, and so on (Zhuang et al., 2019). The location of the wearable devices is very important for getting the data quality because different activities impose different impacts on different body parts depending on the performed activities (Lawal and Bano, 2020). The Sensor placement was addressed in a study where different activities such as jogging, walking on a treadmill, stair ascent, stair descent, sitting, standing, and lying were detected with six sensors placed in different locations (left hip, left thigh, left wrist, chest, lower back, left foot) and it was observed that best activity signal obtained from the hip position (Cleland et al., 2013). The detail of some previous studies for AR with different locations, sensors and activities are given in Table 1.

Some of the widely used sensor locations on the human body are given in Figure 2. Sensor location selection is largely depends on the type of activities and for that some research papers have considered different location for their own selected activities such as wrist (Shoaib et al., 2016; Villar et al., 2015; Leutheuser et al., 2013), hip (Leutheuser et al., 2013; Banos et al., 2015; Shoaib et al., 2014; Liu et al., 2012; Debache et al., 2020), waist (Chung et al., Xie et al., 2018; Hossain Shuvo et al., 2020; Ahmed et al., 2020; Wang et al., 2016; Debache et al., 2020; Zebin et al., 2018; Ahmed et al., 2019) chest (Altun and Barshan, 2010; Zhuang et al., 2019; Chung et al., 2019; Attal et al., 2015), ankle (Chung et al., 2019; Attal et al., 2015; Wang et al., 2016; Debache et al., 2020), arms (Altun and Barshan, 2010; Chung et al., 2019; Shoaib et al., 2014; Wu et al., 2012), thigh (Attal et al., 2015; Trabelsi et al., 2012; Abhayasinghe and Murray, 2014; Hendry et al., 2020; Trabelsi et al., 2013) etc.

Table 1 Different body locations of wearable sensors and their detected activities

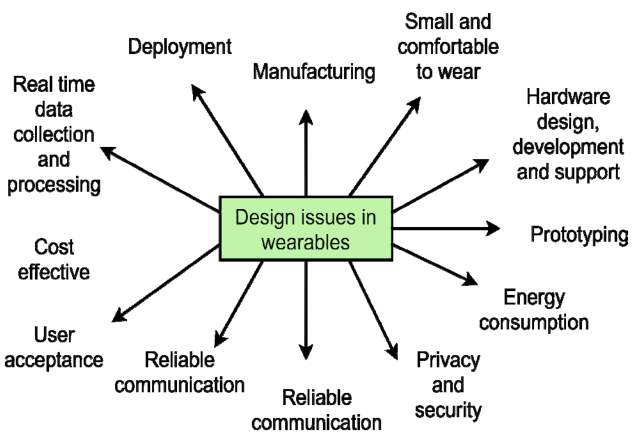
Ref.	*Sensor location*	*sensors*	*Detected activities*
Karantonis et al. (2006)	Waist	Accelerometer	Sit to stand, stand to sit, lie, lie to sit, sit to lie, walking, falls.
Pärkkä et al. (2006)	Wrist and chest	Heart rate, altitude, and acceleration	Lying, sitting, standing, Nordic walk, walking, rowing, cycling, running, etc.
Yang et al. (2008)	Left shin, right shin, left wrist, right wrist, waist, left thigh, right thigh, right bicep	Accelerometer and Gyroscope	Sit to stand, stand to sit, sit to lie, lie to sit, stand to kneel, kneel to stand, jump, rotate right, rotate left, bend upstairs and downstairs.
Chen et al. (2008)	wrist	Accelerometer	Standing, sitting, walking, running, vacuuming, scrubbing, brushing teeth, and working at the computer.
Yin et al. (2008)	Left shoulder, left ankle, waist	Light, temperature, accelerometer, magnetometer, and microphone	Slipping on the ground, falling backward, falling forwards, etc. (abnormal activities)
Atallah et al. (2009)	Ear	Accelerometer + ambient sensors	Preparing a meal, eating, physiological measurement, walking between rooms, getting dressed and washing, receiving visitors, etc.
Bächlin et al. (2010)	Shank, lower back, and thigh	Acceleration	Freezing of gait detection for Parkinson's disease patients.
Atallah et al. (2011)	Ankle, knee, waist, arm, chest, and ear	Accelerometer	Running in a corridor, wiping the table, walking, lying, drinking, eating, etc.
Bulling et al. (2012)	The opposite side of the eye, forehead, head	Skin electrodes and head-mounted accelerometer	Eye and head movements for recognition of reading
Cleland et al. (2013)	Left hip, left foot, left thigh, left wrist, chest, lower back	Accelerometer	Walking, jogging, sitting, lying, standing, upstairs and downstairs
Reyes-Ortiz et al. (2016)	Smartphone carrying with belt, chest, ankle, wrist, trunk, upper and lower extremities.	Accelerometer, Gyroscope, Magnetometer.	Sit to lie, sit to stand, stand to sit, lie to sit, stand to lie, lie to stand.
Gupta and Dallas (2014)	waist	Accelerometer	Stand to sit, sit to stand, stand to kneel, run, jump, walk and sit
Altini et al. (2015)	Wrist, ankle, thigh, right hip, and chest	ECG, accelerometer, calorimeter	Lying, sitting, standing, household activities, walking
Zhu et al. (2015)	Right thigh, waist, and right hand	Orientation, acceleration, angular rate, and magnetic field	Walking, lying, standing, sitting, sit to stand, stand to sit, sit to lie, lie to sit, and hand gestures
Wang et al. (2016)	Waist and ankle	Accelerometer	Sitting, lying, standing up from lying, standing, walking, running, bicycling, jumping
Moschetti et al. (2017)	Index finger and index	Acceleration	Eating with the hand, eating with a fork, drinking with a glass, eating with a spoon, drinking with a cup, drying the hair with a hair dryer, brushing the hair with a hair brush.

Table 1 Different body locations of wearable sensors and their detected activities (continued)

Ref.	*Sensor location*	*sensors*	*Detected activities*
Guo and Wang (2018)	Left thigh, right ankle, left arm, and right waist	Accelerometer	Going downstairs, climbing stairs, kicking left leg, pressing right and left leg, turning right waist, running, walking.
Insole-based et al. (2018)	Insole, wrist, thigh	Accelerometer, gyroscope, position	Lie, sit, stand, walk, descend stairs, ascend stairs, washing dishes, etc.
Guo et al. (2019)	Right wrist, left arm, waist, right ankle, and left thigh.	Accelerometer and gyroscope	Go downhill, running, walking, practice gymnastic, rope skipping, cycling
Quaid and Jalal (2020)	Wrist, knee, and back	Accelerometer	Basketball, badminton, skipping, football, cycling, and table tennis
Pham et al. (2020)	Sole of e-Shoe, wrist	Accelerometer and gyroscope	Brushing, washing hand, Slicing, Peeling, Up stair, downstair mixing, wiping, sweeping floor, cycling etc.
Randhawa et al. (2020)	Fabric sensor-based jacket	Stretch, pressure and accelerometer sensors	Still, standing up, twist jump-turn, dancing and violent actions
Cross et al. (2020)	Inertial sensor units on upper body chest, waist, right and left wrist,	Accelerometer and gyroscope	Filed hockey- passing, drive, drag flick, dribbling, receiving and tackling
Gao et al. (2021b)	iPhone7 in right trouser pocket	Accelerometer	Walking, jumping, jogging, going downstairs and upstairs
Fu et al. (2021)	Left thigh	Accelerometer, gyroscope, magnetometer and air pressure sensors	Sit, lie, walk, stand, running, go upstirs and downstairs
Khatun et al. (2022)	Smartphone in right trouser pocket	Accelerometer and gyroscope	Sitting/standing, walking, jogging and running
Link et al. (2022)	wrist	Accelerometer	Volleyball – underhand serve, block and dig, playing Frisbee

The manufacturing of small sizes wearable sensors with the specification of acquiring, processing, sending and receiving data is a challenging task and the research have been going on in that direction. The pervasive and ubiquitous computing technology largely depends on smart sensors. Some design issues in smart wearable sensors are shown in Figure 3.

Figure 3 Some challanging design issues in wearables (see online version for colours)



In the following headings the various steps in AR modelling are discussed as shown in Figure 4.

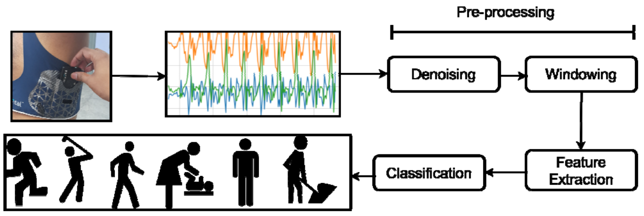
3 Pre-processing

Pre-processing step of AR is generally known for filtering and data segmentation and in this section, the various filtering and data segmentation techniques are discussed which have been used in previous state-of-the-art research.

3.1 Filtering

The acquired data from wearables require to be passed through a filtering step before feature extraction. Pre-processing is an important step in AR modelling due to its efficient impact on the model's overall performance. The data obtained from various wearables contains different types of noise due to mishandling of sensors, location displacement, loose tightening on body, etc., so appropriate filtering is required to denoising the data (Atallah et al., 2007; Fontana et al., 2015; Ordóñez et al., 2013). Most of the research work utilised filtration to remove the gravitational component from the acceleration data (Leutheuser et al., 2013; Anguita et al., 2013; Reyes-Ortiz et al., 2016; Karantonis et al., 2006). Some of the previously used filters in wearable sensor based AR modelling are moving average (span = 3,5,9) and Butterworth low pass filter (Nam and Park, 2013), mean filtering (sliding window of length 5) (Hu et al., 2014), moving average filter (span = 5) (Adaskevicius, 2014), median filter (size = 3) to remove the spikes and and 4th order infinite impulse response low pass elliptic filter (cut off frequency = 0.3 Hz) to remove the gravitational component of acceleration signal (Moncada-Torres et al., 2014) , digital low pass filter (cut off frequency = 0.25Hz) (Bayat et al., 2014), moving average low pass filter (span = 5) (Kalantarian et al., 2015), second order Butterworth high pass filter with cut off frequency of 0.25 Hz (Machado et al., 2015), 3rd order media filter, low pass Butterworth filter (cut off frequency of 20 Hz) and high pass filter with cut off frequency of 0.3Hz (Reyes-Ortiz et al., 2016), Kalman filter (Chen and Shen, 2017), Butterworth low pass filter (cut off frequency of 20 Hz) and Butterworth low pass filter (cut off frequency of 0.3Hz) (Hassan et al., 2018), Butterworth low pass filter (Gani et al., 2019), 2nd order low pass Butterworth filter (cut off frequency of 6Hz) (Hussain et al., 2019). It is also evident that sometimes filtering eliminates the required information therefore filtering may not always be required (Reyes-Ortiz et al., 2016).

Figure 4 Conventional method for AR (see online version for colours)



3.2 Data segmentation

The time duration of performed activity is larger than the sampling rate of sensors. Therefore, the sample extracted from sensors at a particular time cannot be able to represent a particular activity so that the extracted samples are segmented into different groups of the same length and sometimes in different lengths. This group of samples is known as the window and the samples contained in this window are more suitable for estimating an activity rather than the sample at any instant. Data segmentation is a process where the incoming data stream is partitioned into packets of samples by which activity can be recognised in a more sophisticated way (Triboan et al., 2019). The different methods for data segmentation have been used previously and most of them are divided into three parts, event-related, action-related and sliding window type. Separation of samples is carried out on the basis of events in event related window technique and in the same way action defines the window length in action related windowing. In the sliding window, the data streams are segmented into fixed length with overlapping and sometimes with no overlapping. The overlapping is required to retain the edge information in the corners of each window. The window size or length is an important factor in AR and its impact on classification performance was studied in Nurwulan and Jiang (2020). The segmentation of data obtained from basic repetitive activities like jogging, walking, sitting, and standing requires a small window size. The CA like eating, drinking, talking with someone, etc., cannot be estimated with a small size window due to their rare occurrence compared to BA (Shoaib et al., 2016). The window size of 0.08 to 30 sec has been widely used in past (Berchtold et al., 2010; Murao and Terada, 2014; Zhang and Sawchuk, 2012a; Chavarriaga et al., 2013; Suto et al., 2016; Laudanski et al., 2015; Hassan et al., 2018; Chernbumroong et al., 2014; Wang et al., 2013; Machado et al., 2015; Bao and Intille, 2004; Guo et al., 2012; Kalantarian et al., 2015; Catal et al., 2015; Wang et al., 2019a; Liu et al., 2011). The overlapping percentage of sliding window and size are also described in table 2 and it is evident that 50% overlapping is widely used.

4 Feature extraction

Features are useful information about the sensor's data within the defined length of window and the input to the machine learning algorithms. There are two feature extraction methods; the first is manually extracted by domain expertise (Morales and Akopian, 2017) and the other is automatically extracted by deep learning frameworks (Ronao and Cho, 2016). The manually extracted features are those which are extracted on the basis of human expertise in that application of interest. These features are extracted from the samples of a particular window in both the domain time and frequency. Those features that contain unique information about different activities and can differentiate them are considered useful or good features such as standard deviation variance, mean, and fundamental frequency (Hassan et al., 2018; Suto et al., 2016). Manually extracted features have gained much attention in AR (Hassan et al., 2018; Li et al., 2009). The low processing time and less computation requirement for extraction of these features make them capable of designing lightweight ubiquitous systems for AR (Morales and Akopian, 2017).

Nowadays, deep learning frameworks have been widely explored in AR for automatic feature extraction and classification (Hammerla et al., 2015; Sani et al., 2017a). The advantage of in-depth features is that they are automatically extracted by defined layers and do not require expert domain knowledge.

4.1 Manually extracted features

The raw time series data contains many samples for a concerning activity, but the reading of a sample at a particular time instant does not carry sufficient information to represent that activity. In the same way, the samples of different windows consist of different samples for the same activity. Therefore, some valuable and quantitative sets of variables are required to differentiate the different activities and that sets of variables are called as manually extracted features. A vast range of manually extracted features has been investigated to enhance the performance of AR architectures (Attal et al., 2015; Wang et al., 2016; Wang et al., 2019a; Wu et al., 2012). Broadly these features are divided into time and frequency space.

4.1.1 Time domain features

These features are calculated directly from sensor data inside a window and provide statistical information about the signal. Extracting these features requires a clear understanding of the quantitative information and related data statistics for concerned activities in a way that how and which sets of time-domain statistics are effective for better discrimination between different activities. For example, the signal magnitude area (SMA), the sum of acceleration in all the axes, provides useful information to discriminate activities like sitting and walking (Machado et al., 2015). SMA and other features are found effective in enhancing recognition performance (Hassan et al., 2018). The activities like staircase, walking and standing have been recognised effectively with standard deviation in Laudanski et al. (2015). Some of the widely applied features in time domain are peak to peak (Machado et al., 2015; Zheng et al., 2013), autoregressive coefficient (Hassan et al., 2018), skewness (Zhang and Sawchuk, 2011; Janidarmian et al., 2017), root mean square (RMS) (Maurer et al., 2006; Shoaib et al., 2014; Altun and Barshan, 2010; Zhuang et al., 2019), variance (Ahmed et al., 2019, 2020), mean (Xie et al., 2018; Attal et al., 2015; Reyes-Ortiz et al., 2016), median (Ahmed et al., 2020; Attal et al., 2015; Sztyler and Stuckenschmidt, 2016) and so on.

4.1.2 Frequency domain features

The periodicity of obtained signal in a window is described by the features in frequency domain. Firstly, the segmented data in a particular window is transformed with different frequency transformation methods such as discrete wavelet transform (DWT) sometimes it is also called as discrete cosine transform (DCT), fast Fourier transform (FFT). The coefficients of FFT are useful for evaluating the magnitude of frequency components and signal energy distribution. Power spectral density (PSD) is the most important feature in the frequency domain and is widely used for AR. PSD has been extracted in Attal et al. (2015) to recognise dynamic activities like driving, cycling and walking. The corresponding frequency of PSD is known as peak frequency which is used in several studies (Figo et al., 2010; Nham et al., 2008; Moncada-Torres et al., 2014). The different activities of the same PSD have been discriminated with the help of entropy in Bao and Intille (2004), Moncada-Torres et al. (2014), Reyes-Ortiz et al. (2016) and Suto et al. (2017). Some other widely used frequency domain features for AR are DC component (Attal et al., 2015; Sztyler et al., 2017), peak power (Ermes et al., 2008; Zebin et al., 2016; Zeng et al., 2014), spectral-energy (Suto et al., 2016; Sztyler et al., 2017), spectral-centroid (Leutheuser et al., 2013), FFT-coefficients (Dixon-Warren, 2010; Wu et al., 2012) and so on.

5 Dimension reduction and feature selection

Manually extracted features in time, frequency and hybrid domains are large in size and contain redundant information. More features can be helpful for enhancing the classification performance, but at the same time, when information becomes large the system becomes slow, computationally inefficient and overfitted. Therefore, to reduce these shortcomings some methods are required for selecting the subset of features from the original set and these techniques are called as feature selection techniques. In another way, when the features are reconstructed in low dimensions from the original high dimensions, these methods are called dimension reduction techniques.

Several dimension reduction techniques have been applied for AR in the recent past such as principal component analysis (PCA) (Suto et al., 2017; Hussain et al., 2019), linear discriminant analysis (LDA) (Wan et al., 2015), independent component analysis (ICA) (Attal et al., 2015), Kernel PCA (KPCA) (Hassan et al., 2018), Kernel LDA (KLDA) (Schölkopf et al., 1998), Autoencoder (Wang, 2016), sparse filtering (Ngiam et al., 2011) and so on. The PCA is most frequently used method for dimension reduction where linear transformation of original features is carried out to remap them into low dimension space according to variance (high to low). KPCA transformed the input features into a large dimension space by nonlinear transformation with kernel function and then dimension reduced by PCA (Wu et al., 2007). LDA is another linear transformation method where inter-class variability is maximised and intra-class separability minimised to transform the original high dimension features into low dimension features. Its nonlinear version is KLDA (Wang et al., 2019). The lower dimension representation is carried out by the autoencoder by reducing the error (mean square error) between input and output (Van Der Maaten et al., 2009). The performance of dimension reduction techniques like Fisher discriminant analysis (FDA), Kernel FDA (KFDA) and PCA were analysed in Tian et al. (2019).

Feature selection is different rather than feature reduction because in feature reduction, the features are reconstrued in a low dimension space from the original features and in the case of feature selection some valuable features are selected from the original feature set. These features are selected according to the domain knowledge and can discriminate the different classes efficiently. The effective feature selection technique can enhance the classification performance with low computational cost and faster response. Various feature selection methods have been utilised for AR in previous past studies and broadly, these methods are divided into three parts, filter, wrapper and embedded method.

In filter-based methods, some redundant features are thrown out by the relationship between input and output on the basis of statistical information, uniformity, similarity, correlation and distance (Dessi and Pes, 2015; Gheid and Challal, 2016). Some of the filter-based methods have been extensively explored in AR such as Mutual Information (MI) based (Cang and Yu, 2012), conditional mutual information maximum (CMIM) (Gao et al., 2016), double input symmetrical relevance (DISR) (Meyer and Bontempi, 2006), canonical correlation analysis (CCA) (Kaya et al., 2014), joint mutual information (JMI) (Bennasar et al., 2015), relief (Gupta and Dallas, 2014), sequential forward floating search (SFFS) (Ahmed et al., 2020) and so on.

In a wrapper-based method, the feature subset is selected on the basis of the predicted accuracy of a predefined classifier and the process is continued until any addition of a feature gives an accuracy less than the accuracy obtained from the preselected feature set. The wrapper-based method gives a better feature subset compared to filter method but overfitting is occurred due to the involvement of the classifier (Chong et al., 2021). In a wrapper-based method, the involvement of the classifier frequently occurs due to the inclusion of a new feature subset, so these methods are computationally expensive and time-consuming (Guyon and Elisseeff, 2003). Some of the researchers (Amezzane et al., 2017) have studied the impact of wrapper-based methods in different studies (Amezzane et al., 2017; Chen et al., 2020c; Bashar et al., 2020).

Embedded methods are based on the integration of filter and wrapper methods according to their merits (Li et al., 2017). The frequently used embedded methods are Ridge regression (Liu et al., 2015) and Lasso (Li et al., 2017).

The feature selection is used widely for the application of AR and readers can refer those for better understanding such as Gupta and Dallas (2014), Capela et al. (2015), Ahmed et al. (2020), Chong et al. (2021), Wang et al. (2016), Chetty et al. (2015), Chen et al. (2020a, 2020c), Fan et al. (2019), Amezzane et al. (2017), Bashar et al. (2020), Nweke et al. (2019), Zhang and Sawchuk (2011) and Helmi et al. (2021).

6 Traditional classification algorithms

In the classification phase, the features extracted from raw sensor data are mapped to different activity labels. Supervised and unsupervised learning are two approaches under traditional machine learning algorithms. The large labelled data is required for supervised learning and unsupervised learning works on unlabelled data. The model building is performed by training data and test data is used for validating the model in supervised learning. Supervised learning has been widely explored and proved efficient in many cases for AR. Some of the algorithms due to their performance has attracted more researchers in machine learning such as Multilayer Perceptron (MLP) (Bayat et al., 2014; Azmi and Sulaiman, 2017; Subasi et al., 2020), random forest (RF) (Pavey et al., 2017; Dang, 2017; Mehrang et al., 2018; Shoaib et al., 2017), support vector machine (SVM) (Mehrang et al., 2017; Davila et al., 2017; Mannini et al., 2013; Cleland et al., 2013; Ouchi and Doi, 2013), Naïve Bayes (NB) (Mortazavi et al., 2014; Azmi and Sulaiman, 2017; Yazdansepas et al., 2016; Subasi et al., 2020), k-Nearest Neighbour (kNN) (Adaskevicius, 2014; Sani et al., 2017bl Kaghyan and Sarukhanyan, 2012; Liu et al., 2021; Ignatov and Strijov, 2016), artificial neural network (ANN) (Khan et al., 2014; Rustam et al., 2020; Bangaru et al., 2021; Suto and Oniga, 2018), decision trees (DT) (De Leonardis et al., 2018; Lu et al., 2020; Nweke et al., 2018b; Wang et al., 2020), etc.

Artificial Hydrocarbon Network was proposed in Ponce et al. (2016) for recognition of physical activities and found immune to noisy and corrupt data. The voting rule-based ensemble learning algorithms were proposed in Nguyen et al. (2019), where several machine learning algorithms were used as the base learner for AR. It is evident that majority vote-based ensemble classifiers trained on randomly selected feature sets from the original feature set performed better than a single classifier (Subasi et al., 2018). The different machine learning algorithms such as DT, NB, kNN, SVM and Feedforward Neural Network were analysed on a reduced feature set and found that k-NN and DT performed well in De Leonardis et al. (2018)

There is no doubt that traditional supervised algorithms mentioned above proved very efficient in terms of accuracy but are not very efficient in terms of computational cost.

Unsupervised learning is another branch of traditional machine learning algorithms where labelled data does not require. It is difficult to acquire a large amount of labelled data, so unsupervised learning is helpful in the case of unlabelled input data. The most frequently and extensively used unsupervised learning approaches are cluster-based, where the hidden data patterns are identified and divided into clusters based on probabilistic and Euclidian distance, each cluster representing a particular class. The popular unsupervised learning algorithms are Hidden Markov Models (HMM) (Uslu et al., 2013; Cheng et al., 2017), Gaussian Mixture Model (GMM) (Kwon et al., 2014; Attal et al., 2015), k-Means (Kwon et al., 2014; Attal et al., 2015), etc.

Many challenges have been faced by conventional machine learning algorithms. These algorithms are basically based on data-driven modelling and require large labelled sensor data. Hand-crafted feature extraction is very tedious and complex task and also requires expert domain knowledge. These algorithms are application specific and do not perform well on new sensor data of the same task. Incremental learning cannot be successfully applied on these algorithms. To overcome these challenges nowadays, deep learning is widely accepted due to their automatic feature extraction and classification capability. Table 2 summarises a detailed information on some previous research in the conventional approach of AR.

Table 2 Summary of some research articles based on traditional methods

Ref.	*Sensors*	*Sampling frequency (Hz)*	*Segmentation (windowing)*	*Extracted features*	*Classifier*	*No. of activities*
Kwapisz et al. (2011)	Accelerometer (smartphone)	20	200 samples (10 sec)	Average, standard deviation, Average and absolute difference, Average resultant acceleration, Time between peaks, Binned distribution	Decision Tree (DT) (J48), Multi-layer perceptron (MLP) and logistic regression (LR)	6 (basic activities)
Nam and Park (2013)	Accelerometer and barometric pressure sensor	95	256 samples with 128 samples overlapping (50%)	Time domain: mean, standard deviation and slope Frequency domain: Energy, corelation coefficient and differential pressure	Naïve Bayes, Bayes Net (BN), K-Nearest Neighbour (k-NN), DT, J48, MPL,LR	11 (basic child activities)
Barshan and Yüksek (2013)	Accelerometer, Gyroscope and magnetometer	25	125 samples (5 sec)	Minimum, Maximum, mean, variance, skewness, kurtosis, autocorrelation sequence and peak of DFT	ANNs, NB, dissimilarity based, three types of DTs, GMM, SVM	19 (basic +complex activities)
Hu et al. (2014)	Accelerometer and gyroscope	100	256 samples (2.56 sec)	1st, 2nd and 3rd quartile, mean, standard deviation, energy, mean crossing rate, spectral peak position, spectrum peak value and 4 PSD statistical features	Constrained optimisation based extreme learning machine (COELM), add bias, b = 0 constrained optimisation extreme learning machine (b-COELM), 1-versus rest proximal support vector machine (PrSVM), Balanced and refined 1-versus rest proximal support machine (BR-PSVM)	6 (basic activities)
Adaskevicius (2014)	Accelerometer	20	100 samples (5 sec)	Average, standard deviation, maximum, minimum, frequency domain entropy, dominant frequency and average resultant acceleration (ARA)	K-NN	6 (walking and exercising)
Kwon et al. (2014)	Accelerometer and gyroscope (smartphone)	50	64 samples with 50% overlap	Average and standard deviation in both the domain time domain as well as in frequency domain	K-means, GMM, Average linking Hierarchical Agglomerative Clustering (HIER)	5 (basic activities)
Bayat et al. (2014)	Accelerometer (smartphone)	100	128 samples (1.28 sec) with 50% overlap	Average peak occurrence in each window (APF), Variance of APF, root mean square, standard deviation, minimum, maximum and corelation between different axes.	MLP, SVM, RF, simple logistic, logit boost	6 (basic activities)
Gupta and Dallas (2014)	Accelerometer	126	6 sec with 50% overlap	Spectral energy, spectral entropy, mean, variance, mean trend, windowed mean difference, variance trend, windowed variance difference, Detrended fluctuation analysis coefficients, X-2 energy uncorrelated (spectral), maximum difference acceleration	Naïve Bayes and K-NN	6 (basic activities)

Table 2 Summary of some research articles based on traditional methods (continued)

Ref.	*Sensors*	*Sampling frequency (Hz)*	*Segmentation (windowing)*	*Extracted features*	*Classifier*	*No. of activities*
Kalantarian et al. (2015)	Piezoelectric sensor and accelerometer	20	20 samples (1 sec) with maximum overlap	Harmonic mean, geometric mean, standard deviation, kurtosis, skewness, mean absolute deviation	Naïve bayes	4 (swallow, walking and head movement)
Machado et al. (2015)	Accelerometer	800	Minimum = 1,000 samples Maximum = 4,000 samples	Statistical domain: kurtosis, skewness, mean, standard deviation, interquartile range, histogram, root mean square, median absolute deviation Temporal: zero crossing rate, pairwise correlation, autocorrelation Spectral: maximum frequency, median frequency, cepstral coefficient, power spectrum, mel-frequency cepstral coefficients, fundamental frequency, power bandwidth	Clustering method: k-means, affinity propagation, mean shift and spectral clustering	7 (basic activities)
Attal et al. (2015)	Accelerometer, gyroscope and magnetometer	25	25 samples (1 sec) with 80 % overlap	Time domain: Mean, variance, median, interquartile range, skewness, kurtosis, root mean square, zero-crossing peak to peak etc. Frequency domain: DC component in FFT spectrum, energy spectrum, entropy spectrum, sum of wavelets coefficients, square sum of wavelet coefficients and energy of wavelet coefficients.	Supervised learning: K-NN, Random Forest (RF), SVM Unsupervised learning: Gaussian Mixture Model (GMM), Hidden Markov Model (HMM)	12 (basic activities)
Shoaib et al. (2016)	Accelerometer and gyroscope (smartphone)	50	2 to 30 sec with no overlap	Mean, standard deviation, minimum, maximum, semi quartile, sum of 10 FFT coefficients	NB, K-NN, DT	13 (basic complex activities)
Wang et al. (2016)	Accelerometer and (smartphone)	50	2.56 sec with 50% overlap	Time domain: Mean, standard deviation, maximum, minimum, median absolute deviation, signal magnitude area, energy measures, signal entropy, interquartile range, autoregression coefficients etc. Frequency domain: maximum magnitude, weighted average of frequency components, skewness, kurtosis, energy, entropy etc.	NB, K-NN	6 (basic activities)
Chen and Shen (2017)	Accelerometer, gyroscope and magnetometer	20	1 sec with 50% overlap	Mean, standard deviation, maximum, minimum, correlation, interquartile range, dynamic time warping distance, FFT coefficients, wavelet energy.	K-NN, RF, SVM	5 (basic activities)

Table 2 Summary of some research articles based on traditional methods (continued)

Ref.	*Sensors*	*Sampling frequency (Hz)*	*Segmentation (windowing)*	*Extracted features*	*Classifier*	*No. of activities*
Lu et al. (2017)	Accelerometer (smartphone)	30	Predefined with 75% overlap	Mean, standard deviation, variance, skewness, kurtosis, correlation, signal magnitude area	Molecular complex detection (MCODE) (unsupervised clustering mechanism)	3 (basic activities)
Hassan et al. (2018)	Accelerometer and gyroscope (smartphone)	50	2.56 sec with 50% overlap	Mean, standard deviation, mean absolute deviation, maximum, minimum, frequency skewness, maximum, frequency, average entropy, signal magnitude area, interquartile range, autoregression coefficient, spectral energy	Artificial Neural Network (ANN), SVM, Deep Belief Network (DBN)	12 (basic activities)

Table 3 Overview of advancement in human AR using deep learning

Ref.	*Model*	*Activities*	*Number of subjects*	*Sensor modality*	*Performance evaluation*
Tong et al. (2022)	Bi-GRU-Inception-	Command actions of traffic police	12	Wearable inertial sensor units	Accuracy, precision, recall, F1 score,
Tang et al. (2022)	Triplet cross dimension attention	Walking, going downstairs, going upstairs, jumping and jogging	10	Smartphone (iPhone 7)	F1 score
Gupta (2021)	Hybrid deep learning model CNN-GRU	Eating pasta, eating a sandwich, folding clothes, brushing teeth, walking, standing, kicking, clapping etc.	51	Smartphone	Precision, F1 score, recall and overall accuracy
Zhang et al. (2021)	Spatiotemporal multi-feature extraction with space and channel-based squeeze and excitation blocks (ScbSE-SMFE)	Handclap, running, sitting, walking, waving, punching and slapping	10	Smart wearable wrist band	F1 score and accuracy
Kim and Cho (2020)	LSTM	Construction worker's activities	3	Wearable motion sensors	Accuracy
Bi et al. (2020)	OcalDAL (dynamic active learning framework)	Walking forward, sleeping, walking upstairs, walking downstairs, etc.	14	Wearable sensors	Classification accuracy
Gholamiangonabadi et al. (2020)	CNN with Leave One Subject Out cross-validation (LOSOCV)	Sitting and relaxing, lying down, walking, etc.	10	Wearable sensors	Accuracy
Gjoreski et al. (2020)	Complex feature extraction and selection, methods, and deep multi-model Spectro-temporal fusion.	Locomotive activities (still, walk, run, bike, car, bus, train, subway)	3	Smartphone sensors	Accuracy
Lawal and Bano (2020)	Training of CNN with frequency domain images of time series data	Climbing up, climbing down, jumping, running, walking	15	Wearable sensor, accelerometer, and gyroscope	F1 score, precision, recall
Mukherjee (2020)	EnsemConvNet (CNN-Net+ Encoded – Net + CNN-LSTM)	Walking, Running, sitting, upstairs, downstairs	36	Wearable sensor data	Accuracy, precision, recall, F1-score

Table 3 Overview of advancement in human AR using deep learning (continued)

Ref.	*Model*	*Activities*	*Number of subjects*	*Sensor modality*	*Performance evaluation*
Zhou et al. (2020)	LSTM and auto labelling scheme based on Deep Q Network	Climbing down, climbing up, jumping, sitting, standing, cycling, walking, jogging	30	Wearable sensors	Precision, F1 score, Recall
Uddin et al. (2019)	Deep recurrent neural network (RNN) for behaviour recognition with body sensors	Sitting, sitting down, standing, standing up, walking	10	Wearable sensors (accelerometer, magnetometer, electrocardiography)	Precision, F1 score, recall, F1 score, support
Bianchi et al. (2019)	CNN	Walking, standing, sitting down, stay seated, standing up, etc.	15	Wearable sensors (accelerometer, gyroscope, magnetometer)	Accuracy
Chen et al. (2019)	Semis-supervised recurrent neural network	Sitting, standing, walking, ascending stairs, descending stairs	8	Wearable sensors	Classification accuracy
Gumaei et al. (2019)	Hybrid deep learning model Simple recurrent unit (SRU) with Gated recurrent unit (GRU)	Standing still, sitting and walking, lying down, walking, climbing, etc.	10	Wearable sensors	Accuracy, precision, recall, F1 score.
Kulchyk and Etemad (2019)	CNN	Sitting, sitting down, standing, standing up, walking	4	Wearable accelerometer unit	Accuracy, precision, recall, F1 score
Lv et al. (2019)	Hybridisation of convolutional neural network and recurrent neural network (HconvRNN)	Having dinner, doing exercise, queuing, shopping, watching movies.	9	Wearable sensor (accelerometer and gyroscope)	Recognition accuracy
Mohamad et al. (2020)	Conditional restricted Boltzmann machine (CRBMC) + Bayesian stream-based active learning (BSAL)+ semi-supervised classifier (OSC)	Stand, walk, lie, sit	3	Wearable sensors	Average accuracy, average class accuracy
Zhu et al. (2019b)	Novel ensemble model of CNN	Going upstairs, going downstairs, standing, running, walking, bicycling, swinging	100	Smartphone sensor	Classification accuracy
Hossain et al. (2019)	CNN	Speaking, eating, head shaking, head nodding	-	Wearable sensors (earable)	accuracy
Youssef et al. (2020)	K nearest neighbours – least square support vector machine (KNN-LS-SVM)	Walking, jogging, sitting, standing, walk-up, walk-down	10	Wearable sensors (accelerometer)	Recall, precision, F1 score
Zhu et al. (2019a)	Semi-supervised learning temporal ensembling of Deep Long Short-Term Memory (DLSTM)	Walking, walking upstairs, walking down-stairs, sitting, standing, lying down	30	Wearable sensors	Accuracy
He et al. (2018)	Recurrent attention learning	Go upstairs, go downstairs, jumping and jogging	10	Tri axial accelerometer (iPhone)	Accuracy and efficiency
Kim et al. (2018)	Deep gesture algorithm, deep convolutional and recurrent neural network	Arm gestures	10	Wearable sensors (accelerometer and gyroscope)	Accuracy and F1 score
Li and Trocan (2019)	Multi-layer sparse autoencoder for feature extraction and SoftMax for classification	Sitting, standing, walking, running	30	Smartphone sensors	Recall, precision

Table 3 Overview of advancement in human AR using deep learning (continued)

Ref.	*Model*	*Activities*	*Number of subjects*	*Sensor modality*	*Performance evaluation*
Xu et al. (2018)	Combination of Inception Neural Network and Recurrent Neural Network (InnoHAR)	Lie, sit, stand, run, cycling, vacuum cleaning, drive the car, play soccer etc.	12	Wearable sensors	F1 score
Xi et al. (2018)	Dilated convolutional neural network with novel recurrent model	Walking, running, cycling, spinning, drinking etc.	9	Wearable sensors	Weighted F1 score, precision, recall.
Uddin and Hassan (2019)	Gaussian kernel-based PCA, Z score Normalisation and deep convolutional neural network	jump front and back, running, jogging, cycling, knees bending, frontal evaluation of arms etc.	10	Wearable sensors (accelerometer, gyroscope, magnetometer, ECG)	Average accuracy
Hassan et al. (2018)	Kernel principal component analysis (KPCA) and Deep Belief Network (DBN	Standing, sitting, walking, talking	30	Smartphone inertial sensors (accelerometer and gyroscope)	Mean recognition rate
Münzner et al. (2017)	CNN-base sensor fusion techniques	Walking, stair climbing, cutting vegetables, writing a latter	31	Wearable sensor nodes(tri axial accelerometer and gyroscope)	F1 score
Sheng et al. (2016)	CNN	13 short time activities like stand, sit, lay, walk forward, walk left circle, walk right circle etc.	20	Wearable sensors (tri axial accelerometer and bi axial gyroscope)	Accuracy and time
Chen and Xue (2015)	CNN	Jumping, walking upstairs, walking quickly, falling running, step walking etc..	100	Smartphone (tri-axial accelerometer)	Accuracy

7 Deep learning approaches for AR

Deep learning, another branch of machine learning, has been widely accepted due to its outstanding performance in various fields like natural language processing, computer vision, face recognition, human AR, etc. The familiar deep learning algorithms for AR are long short-term memory (LSTM) (Barut et al., 2020; Boultache et al., 2022), convolutional neural networks (CNNs) (Tang et al., 2020) and recurrent neural networks (RNNs) (Javed et al., 2021). The multi-tasking deep model (AROMA) was designed for recognition of basic and CA in Peng et al. (2018) where CNN was used for complex and LSTM for BA. Smartphone based AR was designed where various features were extracted and processed with KPCA and LDA for AR with deep belief network (DBN) in Mehedi et al. (2018). It is difficult to acquire a strictly labelled data due to human interventions in data labelling therefore most of the acquired data are weakly labelled. An attention mechanism based CNN architecture was proposed to classify the weakly labelled data for AR (Wang et al., 2019b). The deep learning methods are well known for their capability of temporal and spatial feature extraction but these methods are not suitable for statistical features. A framework known as distribution-embedded neural network was proposed for extraction of statistical, temporal and spatial features in Qian et al. (2019). A lot of computation is required for deep learning models therefore it is difficult to use them for real time application through edge devices. A low weight and computationally efficient deep learning model was proposed in Agarwal and Alam (2019) for the deployment in edge devices It is seen that each feature layer in automatic feature extraction through deep learning methods use a same kernel size for receptive field but adaptable kernel size is possible according to data structure. The attention mechanism for selection of kernel size to obtain a different receptive field was proposed in Gao et al. (2021a) for AR The deep learning models based on CNN follows the short term temporal dependencies but to retain the long term temporal dependencies are also required for obtaining the more relevant deep features therefore some hybrid approaches by combining CNN and RNN have been proposed in Abbaspour et al. (2020) such as multibranch CNN-Bidirectional LSTM (BiLSTM), CNN-LSTM, CNN-Gated Recurrent Unit (GRU), CNN-Bidirectional GRU (BiGRU).The various other approaches and their descriptions are given in Table 3.

8 Discussion

A good amount of dataset with good quality is required for an accurate assessment of physical or daily living activities and this review indicates this. It means that the data-taking methods should be well defined and must have some credibility. Pre-processing of the available data is seen as removing unnecessary information for a particular application to enhance the assessment's accuracy. The selection of the feature extraction procedure is the most responsible step for the classification accuracy of human activities. Different classifiers provide different accuracy for different features, some are good for a particular activity, but others one is not. So, finding the corresponding classifier for the relevant features is required. The number of sensors and sensor locations are also important aspects of AR. A large number of sensor placements can improve the accuracy but it is difficult to wear while performing different activities.

Three-dimensional accelerometers, gyroscopes, and magnetometers can provide more information about physical activities than their one-dimensional counterparts. One or two sensor placements are sufficient for qualitative assessment if their placement location and feature extraction method are effective such as the hip position of the sensor giving good results. The revolution in machine learning such as deep learning algorithms can predict more accurate results with the low amount of information by which energy-efficient modelling could be done. Physical activity is shown as the classification problem in most cases.

9 Conclusions

It is observed that the accurate assessment of physical activity is required for various applications such as assistance in medical, intrusion detection, behavioural recognition, security issues, etc. This is also observed true that till now, a good amount of research has been conducted but there are also some areas where a lot of work is still required for improvement such as modifications in methods for feature extraction and searching the best classifier for corresponding features. Newly-developed feature extraction methods are considered as an area where researchers can add their efforts because classification accuracy largely depends on it. Publicly available datasets have various information in the form of rows and columns but it also consists of information that is not useful for a desired application. Finding undesirable information and removing that in pre-processing step can affect the accuracy of the assessment. So, in this regard, a new pre-processing method or searching redundant information and removal of it could be able to evaluate a more accurate assessment. How we can get an accurate assessment with less information on the input side would be a decisive factor regarding energy-efficient modelling, deep learning algorithms open the gate for it.

To set up an own dataset is a complex task and requires various types of resources such as the population of different age groups, keen observation, protocol set up, technical assistance, etc. there is a good contribution of universities and research projects in the development of some standard and quality datasets, and their availability in public domain gives more help in research for physical activity assessment. It is also noted that a smaller number of sensor placements in the subject's body gives more relevant information due to the comfort in movement. But complex nature of activities could not be detected with a smaller number of sensors. So, the quantity of sensors depends on selected activities. The most of the research in AR have been carried out by taking the publicly available dataset such as SBHAR (Chen et al., 2020b), UniMiB SHAR (Micucci et al., 2017), REALDISP (Aljarrah and Ali, 2021), USC-HAD (Zhang and Sawchuk, 2012b), UCI-HAR (Tang et al., 2020) OPPORTUNITY (Tang et al., 2020), PAMAP2 (Khan et al., 2016), WISDM (Ignatov, 2018), mHealth (Kumar and Suresh, 2022), FSP (Zdravevski et al., 2017), DaLiAc (Zdravevski et al., 2017) and so on.

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