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Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions

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ABSTRACT

Activity detection and classification using different sensor modalities have emerged as revolutionary technology for real-time and autonomous monitoring in behaviour analysis, ambient assisted living, activity of daily living (ADL), elderly care, rehabilitations, entertainments and surveillance in smart home environments. Wearable devices, smart-phones and ambient environments devices are equipped with variety of sensors such as accelerometers, gyroscopes, magnetometer, heart rate, pressure and wearable camera for activity detection and monitoring. These sensors are pre-processed and different feature sets such as time domain, frequency domain, wavelet transform are extracted and transform using machine learning algorithm for human activity classification and monitoring. Recently, deep learning algorithms for automatic feature representation have also been proposed to lessen the burden of reliance on handcrafted features and to increase performance accuracy. Initially, one set of sensor data, features or classifiers were used for activity recognition applications. However, there are new trends on the implementation of fusion strategies to combine sensors data, features and classifiers to provide diversity, offer higher generalization, and tackle challenging issues. For instances, combination of inertial sensors provide mechanism to differentiate activity of similar patterns and accurate posture identification while other multimodal sensor data are used for energy expenditure estimations, object localizations in smart homes and health status monitoring. Hence, the focus of this review is to provide in-depth and comprehensive analysis of data fusion and multiple classifier systems techniques for human activity recognition with emphasis on mobile and wearable devices. First, data fusion methods and modalities were presented and also feature fusion, including deep learning fusion for human activity recognition were critically analysed, and their applications, strengths and issues were identified. Furthermore, the review presents different multiple classifier system design and fusion methods that were recently proposed in literature. Finally, open research problems that require further research and improvements are identified and discussed.

1. Introduction

The recent development in sensor technologies and decrease in the cost of sensor based devices have driven the implementation of health monitoring and human activity detection using mobile and wearable sensors. The implementation is vital to understand people's interaction with their environments which has become driving force for smart home and other cyber-physical applications [1,2]. Human activity recognition has become significant in wide areas of researches and applications that include ubiquitous computing, military, health monitoring and elderly assisted living, life logging, computer interaction, surveillance and sports activity to mention but a few. Activity data collected with varieties of sensors in these areas are analysed to recognize simple and complex activities such as walking, sitting, running and other activities of daily living [3,4]. These activities are very important to provide real time feedback for medical rehabilitations and to caregivers about patients' behaviour especially for elderly and those with special needs [5]. Other crucial applications are in the areas of fall detection and postural recognition [6,7], where there are high risks of fall among the elderly populations and recognition of what constitute actual fall can help to prevent them with their negative health cost tendencies.

Based on devices and sensor types, human activity recognition can be classified into wearable, video, ambient and smartphone based

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approaches [1,8]. Wearable devices are worn by the users for unobtrusive monitoring of body physiological signals such as accelerometers, gyroscopes and magnetometers. Video based approaches [9,10] deploy video based sensors that capture images or surveillance camera features to recognize daily activities. Alternatively, ambient devices [8] capture the interaction between human and their environments and are attached to smart environment objects. Ambient sensors include sound, pressure, temperature and other sensors that are vital for effective monitoring for the elderly [11]. In recent years, the use of smartphone based sensors for human activity recognition has also attracted enormous researches [12,13]. Smartphones are ubiquitous devices with rich sets of sensors embedded in them such as accelerometer, GPS, gyroscope, microphone etc. for comprehensive health monitoring, indoor localization and pedestrian navigation [14,15]. In addition, other studies using social network [16] and wireless network signals [17] have also gained considerable attentions in human activity monitoring.

However, these approaches come with different issues that are still active researches [18]. Effective activity recognition with wearable devices require the users to wear high number of devices on different part of the body such as chest, ankle, leg and other parts of the body which can be uncomfortable to wear and also suffer from low battery life [19]. Video and ambient sensor approaches operates in fixed environments and not suitable for normal activities [1]. Furthermore, video sensors based approaches have been found to intrude on user privacy, confine user to particular location and capture non-target information [20], while ambient sensor performance is affected by environmental noise. Even though smartphones are widely accepted and have become part of our daily life, their applications for human activity recognition are affected by placement and orientation issues. There are high numbers of researches in solving issue related to placement and orientation in smartphone based human activity recognition [3,21]. Orientation of smartphones during activity has been found to lower accuracy [22].

Existing works in human activity recognition defined the procedures for development and implementation of activity monitoring systems [23] termed the activity recognition pipeline. These include data collection, pre-processing and segmentation, feature extraction and dimensionality reduction, classification and evaluation of learning algorithms. This is illustrated in Fig. 1. As shown in the Fig. 1, human activity recognition begins with data collection using variety of sensors. Sensors are hardware components that have the capability to capture different type of signals and are embedded in daily devices such as smartphones, smartwatches and other wearable medical devices [24]. These devices come with rich resources of sensors such as motion sensor (accelerometers, gyroscopes, magnetometer, and motion video), environment and ambient sensors (pressure, oximeter, temperatures, oxygen saturation, heart band, microphone, etc.) and location based sensor (GPS) that are collected and exploited to infer users' contexts and activities [24]. These Sensor data are collected at varying sampling rates ranging from 20 to 50 Hz depending on the type of activities. Another important step is data pre-processing that involve the removal and representation of the raw signal [25]. Generally, sensor data are affected by noise and spike that lead to measurement inaccuracies. Different methods such as nonlinear, low pass and high pass filter, Laplacian and Gaussian filter, Kalman filtering [26] and spectrogram representation [27] have been proposed for sensor data pre-processing in human activity recognition. Part of data pre-processing that is vital for increased performance accuracy is data imputation. Data imputation is necessary when data collection fails resulting to missing values. Several methods have also been developed and evaluated to minimize effect of missing values. These include Imputation Tree (ITree), Multi-matrices factorization model for missing sensor data estimation, k-Nearest Neighbor (k-NN) imputation methods and discarding of some instances [24].

Segmentation procedure divide the signal into manageable frames using fixed or overlap window sizes to extract useful features. Segmentation and window sizes play vital role in recognition of specific activities and minimizing computation time in mobile based implementation. The approach involves the use of sliding window, events or energy based methods [4,28]. Feature extraction and dimensionality reduction identify lower set of features to reduce classification error, increase accuracy and minimize computation time. Feature extraction can be subdivided into shallow features and deep features. Shallow feature involve the extraction of handcrafted feature such as time domain, frequency domain, Hilbert–Huang and ensemble empirical mode decomposition features [23,29]. The high dimension features are reduced using principal component (PCA) or Empirical cumulative distribution functions to enhance computation time. However, shallow features rely heavily on human experts, learned with heuristic means and require large number of labelled data that are quite difficult to collect [8]. Recently, automatic feature extraction through deep learning [30] were also proposed for human activity detection approaches. Deep learning methods apply high level data representation to extract salient features from sensor data with multiple layers of neural networks and represent features from low level to high levels hierarchy. Deep learning methods such as Autoencoder, convolution neural network and recurrent neural network are very popular methods in object recognition, machine translation [30] and now in mobile based human activity recognition [31]. These methods are explained in details in Section 2. The extracted features are combined with machine learning algorithms that include support vector machine (SVM), Decision Tree, k-Nearest Neighbor, Hidden Markov model and SoftMax for activity classification [4]. For deep learning, both feature extraction and activity classification are trained as part of model building [27]. Finally, the human activity recognition system is evaluated for performances using various metrics such as accuracy, precision and recall.

However, major studies in human activity recognition focus on use of single sensor modality [32,33], features [27,34,35] and classifiers [36,37]that are sometimes ineffective to discriminate complex activity details. To fully exploit data, features and classifiers for effective health and activity monitoring require fusion strategies.

Data fusion involves integration of data collected by multiple mobile and wearable sensor devices to increase reliabilities, robustness and generalization ability of recognition system. The aim is to decrease uncertainty and the effect of indirect capture which is quite difficult to eliminate with single sensor data [38].

Feature fusion is commonly applied to data measuring separate signal properties. In this case, features extracted from heterogeneous sensors or homogeneous sensor at different placement positions are combined using machine learning algorithms such as support vector machine, decision tree and Hidden Markov model to discriminate the data into higher level of abstraction [39]. Furthermore, automatic feature representation using deep learning to solve the issues of spatial and temporal dependencies have become progressive research areas in sensor based human activity recognition [31]. Moreover, time and frequency domain features are inherently linear but in real life, human activity recognition systems are nonlinear [40]. Deep learning automatically extracts translational invariant and robust features in sensor data to minimize application dependencies and time spent on extensive feature extraction and selection processes.

Classifier fusions are implemented to handle complex systems, high dimensional and uncertainty in sensor data. This involves combination of individual weak classifiers which maybe homogenous or heterogeneous to increase robustness, accuracy and generalization [41]. The aim of multiple classifiers is to reduce uncertainty and ambiguity by fusion of outputs generated by different classification models to achieve higher performance that are unlikely when the classifiers are used in isolation [42]. Data manipulation, input feature manipulation and model diversification are commonly used to build multiple classifier systems [43]. However, other methods have also been proposed such as random initializations that were recently implemented [44, 45] for

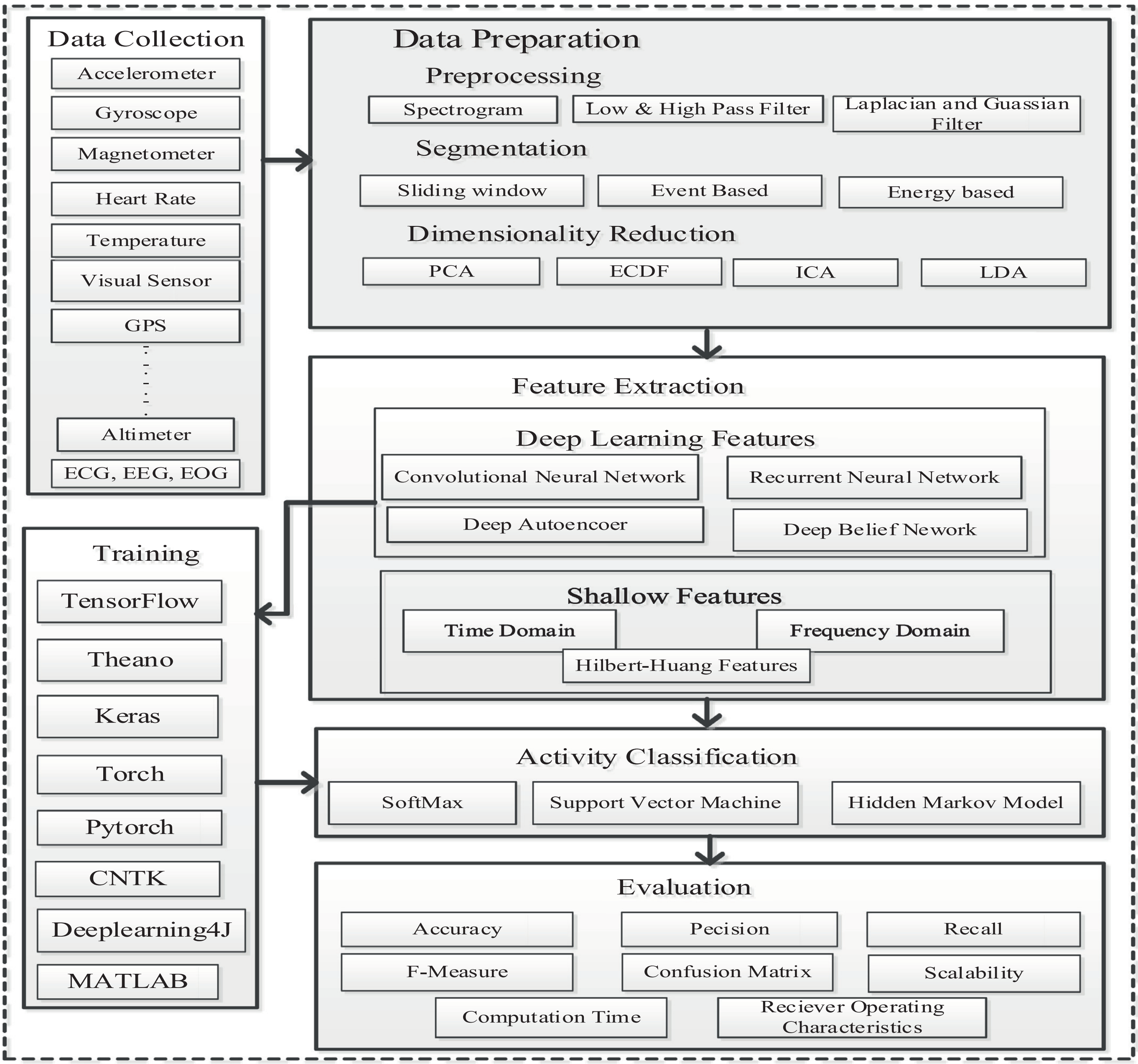

Fig. 1. Typical human activity recognition process using both handcrafted and deep learning feature representations.

human activity detection using mobile and wearable sensor data.

Generally, data fusion and multiple classifier systems have been proposed and evaluated in human activity recognition in recent years. It is imperative to review and characterize these studies for in-depth analysis. The aim of this study is to review different data fusion and multiple classifier system in human activity recognition, focusing on studies that utilize different sensor modalities for health monitoring, energy expenditure, health status reports and activity of daily living (ADL). We provide an extensive review of recent development in the data fusion and multiple classifier system for activity detection and classification. Specifically, we offer a comprehensive review of data fusion methods, fusion of different sensor modalities such as inertial and multimodal sensors, feature fusion with handcrafted features and deep learning fusion for automatic feature representation. Furthermore, we review different base classifiers for building multiple classifier systems, design approaches and fusion strategies for human activity recognition. The review taxonomy is presented in Fig. 2, and list of used abbreviations with their descriptions and full form are shown in Table 1 Furthermore, we systematically categorized the methods, algorithms, feature selection and inference algorithm building process for activity detection and health monitoring. Based on the reviewed papers, open research issues were derived and future research directions suggested.

Quite numbers of interesting surveys have been published in human activity recognition in recent years [3,23,46–48]. Conversely, these studies focus on the activity recognition process and classification of activity based on global and location interaction in mobile, wearable and video sensors. However, in the present review, we focus on data fusion, feature fusion and multiple classifiers system method for human activity recognition. Recently, reviews on data fusion were presented by [18,24]. Chen et al. [18] surveyed fusion of video and inertial sensor for human activity recognition which only comprises of basically two modalities (visual and Inertial sensors). However, our review extends beyond two data modalities to include studies with more

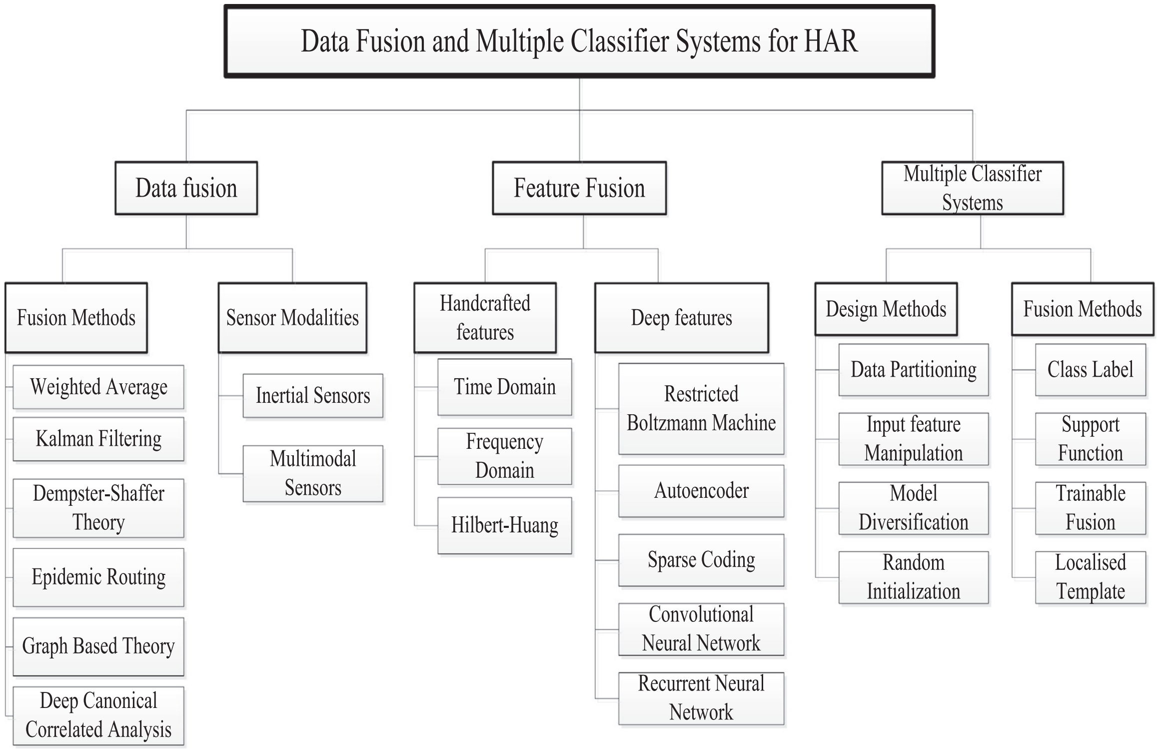

Fig. 2. Taxonomy of data fusion and multiple classifier systems for human activity recognition.

Table 1
List of abbreviations with their full forms.

Abbreviations	Definitions	Abbreviations	Definitions
ADL	Activity of Daily Living	HMM	Hidden Markov Model
CNN	Convolutional Neural Networks	ICA	Independent Component Analysis
DBM	Deep Boltzmann Machine	IoT	Internet of Things
DTC	Decision Tree Classifier	IMU	Inertial Measurement Unit
ECDF	Empirical Cumulative Distribution Function	k-NN	K-Nearest Neighbors
ECG	Electrocardiography	LDA	Linear Discriminant Analysis
EEG	Electroencephalogram	LDC	Linear Discriminant Analysis
EMD	Empirical Mode Decomposition	LSTM	Long Short-Term Memory
EEMD	Ensemble Empirical Mode Decomposition	MSDF	Multisensory Data Fusion
EMG	Electromyography	PCA	Principal Component Analysis
EOG	Electrooculography	RBM	Restricted Boltzmann Machine
FFT	Fast Fourier Transform	RNN	Recurrent Neural Network
GRU	Gated Recurrent Unit	SpO2	Capillary Oxygen Saturations
GPS	Global Positioning System	SVM	Support Vector Machine
GPU	Graphic Processing Unit	WISDM	Wireless Sensor Data Mining

comprehensive sensors to enable health monitoring and activity of daily living. Similarly, Pires et al. [24] discuss data acquisition and data fusion methods that focused basically on mobile phone implementation of activity of daily living (ADL). Finally, review that look at data, feature and decision fusions were presented by [39,49] for wireless and body sensor network. The studies focused on the general applications, architecture and implementation methods in varieties of areas such as emotion recognition, activity recognition and general health. The reviews failed to cover substantial new researches proposed in recent years in activity detection and health monitoring. A closely related survey to our study is the one done by [50] that review application of data fusion in human activity recognition using wearable sensors.

The current review differs with their study in many ways. *First,* while their review discussed data fusion techniques, the current not only discuss the methods but also categorize the sensor modalities as yards stick for measuring activity types. *Second,* with the current wave of deep learning for automatic feature extraction, we discuss deep learning fusion for feature extraction for human activity recognition. *Finally,* the current review also discusses multiple classifiers system design and fusion strategies for human activity recognition. From available studies in literature, there are no comprehensive reviews or surveys that explicitly discuss data fusion and multiple classifier systems for human activity recognition in multimodal sensor scenario. To fill this gap, this review is a timely exploration of data fusion and multiple classifier systems in this significant area.

The contributions of this paper are as follows:

- To summarize recent advances in data fusion, feature fusion and multiple classifiers system.
- To provide analysis on methods, modalities, strengths and weaknesses of these methods
- To point out research gaps and future directions in the developments of data fusion, feature fusion and multiple classifiers system in activity detection and classification.

The remainder of this paper is organized as follows: Section 2 discusses data fusion methods and sensor modalities for human activity recognition. Section 3 explores handcrafted feature fusion and deep learning feature representations, characteristics, strengths and weaknesses of each deep learning method. Section 4 reviews multiple classifier systems in mobile and wearable sensor based human activity recognition, base classifiers, design methods and fusion approaches. Section 5 provides brief open research directions that require further improvement and Section 6 concludes the review.

2. Data fusion for human activity recognition

Multi-sensor data fusion in human activity recognition using mobile and wearable sensor data is the integration of multiple sensor modalities in order to increase reliabilities and reduce uncertainty in health monitoring, activities of daily living and human activities identification. With combination of different sensor modalities, sensor effects such as rotational and additive noise can be reduced thereby increasing the robustness and minimize the effects of incorrect data capture [38]. Different data fusion strategies have been proposed over the years for mobile and wearable sensor to reduce the effect of displacement and increase human activity recognition performance accuracies. Generally, these approaches can be broadly categorized into probabilistic methods, statistical approaches, evidential theory, knowledge based method or concatenation of different sensor modalities using machine learning algorithms [24,51]. In these methods, data fusion provide likely estimation process to combine data from diverse sources to ensure data reliability [52]. In this section, data fusion and sensor modalities fusion for human activity detection and health monitoring is analysed. In addition, possible applications, strength and weakness of these sensor modalities for human activity are presented Table 2.

2.1. Data fusion methods

In human activity recognition system, the main critical issues that constantly appear in literature are how to provide robustness, generalization and reliability, reduce uncertainty and increase performance accuracy [18,31,49,53]. Multiple sensor modalities are combined to minimize these issues and achieve implementation objectives. The essence is to combine heterogeneous sensor data to enable implementation of complementary information processes. A number of techniques have been developed over the years to fuse different data modalities for human activity recognition. Methods for real-time heterogeneous or homogeneous sensor fusion are can be classified into recursive or non-recursive methods [52]. Recursive methods include weighted average and least square while non-recursive methods are Kalman filter and extended Kalman filter. In addition, methods using probability estimation techniques [50] that employ probability density estimation to fuse heterogeneous sensors from different modalities have also been proposed. In this section, we briefly discuss some of these data fusion techniques for human activity recognition found in literatures. Fig. 3 depicts different data fusion and sensor modalities fusion in human activity detection discussed in this section.

2.1.1. Weighted average and least square method

During data collection processes, number of errors and noise maybe introduced due to time lag, incorrectly placed sensors, orientation and sensor malfunctions. Weighted average and least square methods provide techniques to merge sensor data or take average of erroneous sensor reading placed at different sensor positions [54,55]. Taking magnitude of the sensor reading in different dimensions (x, y and z) is very popular method in human activity recognition [46,56] to reduce error due to rotation components.

2.1.2. Kalman filtering

Kalman filtering was proposed by Kalman Rudolph in 1960 [52,57] as predict update fusion and efficient method for processing sequence of signals at time interval. Given a sequence of observations from different sensors, the method computes the estimated covariance and relative confidence between the estimated past observation and current observation of the sensor reading in order to minimize posteriori estimate covariance [52]. Kalman filtering with relaxed zero velocity update provide important platform to solve the challenges of sensor placement and data collection errors. The method has been extensively used for data fusion in human activity recognition systems [14,58–60]. Tunca et al. [58] propose mobile based Pathological gait analysis by combining accelerometer and gyroscope sensor mounted on the foot using Kalman filtering algorithm. The approach is computationally efficient and can provide techniques to fuse accelerometer and gyroscope data to provide better estimate for linear filtering system [52] and static posture analysis [61].

However, Kalman filtering is restricted to linear and Gaussian values that is sometimes impractical in real-time applications such mobile and wearable based human activity recognitions. Therefore, other modified approaches such as Extended Kalman filtering, Quaternion based extended Kalman filtering and Rao–Blackwellization unscented Kalman filtering [52,61,62] to deal with issue ranging from sensor orientation, postural instability to sensor placements were recently developed. Particularly, extended filtering method is adaptive and easy to use with stable practical estimation as well as computationally efficient model [63].

Table 2
Sensor modalities, applications, strengths and weaknesses.

Sensors	Applications	Strengths	Weaknesses
Accelerometer, gyroscopes	Differentiate between activity of similar patterns, recognize concurrent activities	Reduce the effects of noise, offer complementary information and ensure quick response rate	Unable to detect posture in real time and correlation between posture and actions
Accelerometers, gyroscopes, magnetometer	Helps to correct sensor drift, recognize transitional activity and accurate posture identification	Remove the effects of gravity and enable independent orientation with clean output rotations	High energy consumption and lead to performance degradation
Accelerometer, gyroscope, magnetometer, blood pressure, Electrocardiography (ECG), oxygen, temperatures, state change sensors, pulse rate, pulse oximeter, microphone, pressure insole, infrared, door contact sensor, vital sign, heart rate	Context-aware localizations, energy expenditure estimations, health status reporting and monitoring, strength estimation during intensive exercise, location intention prediction and transportation mode analysis	The fusions of several sensors enhance the system reliabilities and provide comprehensive health status monitoring for the elderly.	The ambient sensors are location dependent and also, it is challenging to fuse high number of sensors to provide real time monitoring. This result to computation complexity and large computation burden
Wearable camera, eye-glass mounted systems, accelerometer, gyroscopes, infrared, GPS, acoustic sensor, pressure	Behaviour tracking and emotion detection, identification of mobility changes between static and dynamic activities	Resolve issues of intrinsic ambiguities between certain types of activities such as reading, watching TV, cleaning, drinking etc.	Lack of scene semantic, temporal dynamics and hierarchical activities representation. Issues bothering on privacy and location dependencies

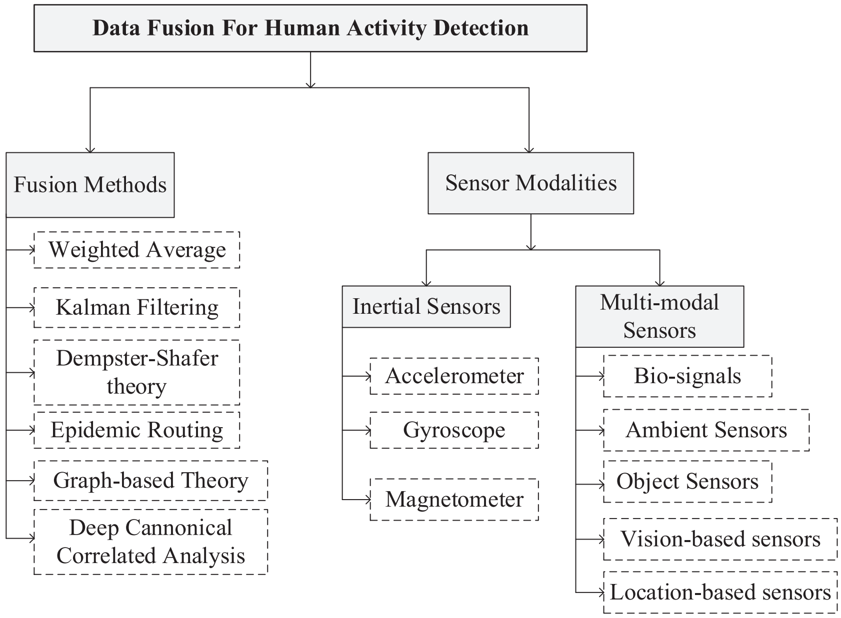

Fig. 3. Data fusion methods.

2.1.3. Dempster–Shafer theory

Dempster–Shafer theory of evidence [64] is a data fusion method that computes the sensor reliabilities before combining them with alternative combination rule. It represents uncertainties and impression in sensor reading such as calibration drifts, sensor orientation, missing values, intra and inter temporal constraints and best sensor distribution to increase robustness and reliability of human activity detection systems [34,65–67]. To correct uncertainty in multi-sensor measurement in human activity recognition, Sebak and Benhammadi [68] proposed combination alternative rules called Majority consensus combination rule, an evidence theory based method that were merged into two combination rule. The proposed method was combined with Shafer theory of evidence to produce more intuitive results. While Tsai et al. [69] utilize statistical detection and estimation theory to combine physical and human sensor data with value fusion for human activity detection.

2.1.4. Epidemic routing and binary spray and wait with fusion

Epidemic routing with fusion and binary sparsity is novel cooperative data sensing frameworks that help to reduce energy consumption and delay in data transmission. Energy conservation is critical in context-aware frameworks in order to provide effective activity detection [70].

2.1.5. Graph-based theory

The proposed system called crowdsourcing system for disaster surveillance combine smart phone and social network sensor for the purpose of effective monitoring and increased decision making process. Graph theory for socialsense integrates social sensors and physical sensor for context-aware activity. In addition, the method helps to reduce computation complexity and allow modular implementation of rule based technique for fusion of different data level in human activity recognition [71].

2.1.6. Deep canonical correlated analysis

Deep canonical correlated analysis learns complex non-linear transformation of heterogeneous data modalities and produce output representations that have high linear correlation by minimizing the total correlation effects. The method allows representation of data with different modalities and fused these modalities to enhance human activity recognition. Recently, deep canonical correlated analysis was developed to fuse accelerometer and gyroscope data for human activity recognition [72].

2.2. Fusion based on sensor modalities

Various research efforts have been conducted on activity detection and classification, either with inertial or multimodal sensors [3,12]. Inertial sensors are self-contained devices that provide dynamic information through direct measurement and include accelerometer, gyroscope and magnetometer. Accelerometer measure acceleration force and dynamically sense movements and vibrations. Similarly, gyroscope sensor provides angular rate information through direct measurement while magnetometers ascertain the relative change or variation in magnetic field in particular directions. The decrease in size, cost and miniaturization of these sensors have made them more pervasive, unobtrusive, viable and are now embedded into smartphones, smartwatches or other wearable devices termed the inertial measurement unit(IMU) [58,73]. Inertial measurement unit sensors provide information to assess individual activity patterns either separately or when fused together [4,73]. Accelerometer-based system have been extensively researched in literature, especially in the area of sports, workout and ambulatory activities [74–77], fall detection [78–82], posture recognition and movement pattern [7]. Recently, with the increase processing power of mobile phones coupled with varieties of sensors that enable collection and transmission of sensor data via Wi-Fi or Bluetooth interface, activity recognition has also been modelled and implemented on-board mobile devices to ensure effective and real-time monitoring [76,83-85]. However, single accelerometer is ineffective to recognize or discriminate dynamic and similar motion such as descending or ascending stair [35,65,77]. Furthermore, accelerometer based sensors are sensitive to sensor locations, sensor drift and power consumption for sensors on-board battery [18]. To achieve higher recognition rate, other studies have proposed the use of gyroscope that measure angular velocity and orientation [86,87] or multiple accelerometer placed on different parts of the body [32,35,88,89]. Janidarmian et al. [90] conducted comprehensive human activity recognition using 293 classifiers on accelerometer placed on ten (10) major part of the body such as upper arm, ankle, chest etc. Other studies have also been proposed on placement of multiple accelerometers [91–93] to distinguish between walking, sittings down, standing, standing up, walking down and up stair, lying on the bed, sitting down on the chair, walking forward, right cycle, jogging and jumping. The accelerometers were placed on positions ranging from waist, left thigh, right thigh, ankle, right arm, left wrist and left ankles achieving relative performance improvements. However, this entails wearing high number of sensors that add extra burden and intrusive on the elderly patients and even the use of smartphones have introduce other challenging issues [85].

The trend now, is the development of sensor fusion techniques that combine multiple inertial (accelerometer, gyroscope and magnetometer) and multimodal sensors for human activity recognition, elderly care and patient monitoring [65,94]. The fusion of these sensors has some complementary advantages inform of orientation detection and reduce low response rate. For instance, accelerometer-based sensors are noisy with low response rate while magnetometers produce inaccurate results from magnetic field. Therefore, fusions of these sensors with gyroscope enhance the response rate and provide smooth output. Nevertheless, gyroscope sensors suffer from drifting overtime, but gyroscopes fusions provide rotation speed relative to the body coordinate system that helps to correct error caused by accelerometer and magnetic field sensors [95]. On the other hand, magnetic field helps to generate the acceleration output independent of orientation of the smartphone devices for instance during motion. Therefore, the effect of gravity in accelerometer reading can be remove to enable independent orientation of the sensors and produce clean output rotation [95,96]. Here, we categorize data fusion for human activity recognition into studies that utilize inertial sensor unit which include accelerometers, gyroscope and magnetometer or multimodal sensor that include those that combine inertial sensor with other modalities [97]. The representations of these sensors are depicted in Fig. 3.

2.2.1. Inertial measurement unit (IMU) sensor fusion

In general, accelerometer sensor data are noisy and greatly affect the performance of machine learning classifiers for human activity recognition [96], discriminating similar activities like downstairs and upstairs [35] are quite challenging. Therefore, tri-axial gyroscope provide angular acceleration information from three different view, estimate orientation and rotation of movement pattern with the help of pitch, roll and yaw angle(X, Y, Z) dimensions [98]. Combination of accelerometer and gyroscopes provide mechanism to differentiate activities of similar patterns. Studies such as [99] and [100] proposed mobile phone based simple and complex human activity recognition by fusing accelerometer and gyroscope sensor data. In addition, integration of accelerometer and gyroscope helps to convert motion into transcript of smaller activities [97], classify human activities into zero displacement activities, transitional activities, strong displacement activities [101] or solve the problem of temporal activities using Continuous Hidden Markov Model [37]. Spinsante el al. [102] present model for monitoring of physical activities in the workplace to prevent sedentary lifestyle using decision tree using accelerometer and gyroscope data fusion. They categorized activities into active or non-active and develop mechanism for feedback update achieving 99% accuracy. One major challenge in human activity recognition is how to recognize concurrent activities. These types of activities occur simultaneously and include walking while brushing teeth, lying down and talking on the phone. In this, the activities to be recognized are segmented into lower and higher activities with hierarchical algorithms [103]. To achieve this, multiple accelerometer sensors are attached to the chest, left forearm; right thigh, left ankle and right wrist to enable whole body movement monitoring. However, the use of multiple sensors will greatly affect movement. Nonetheless, accelerometer and gyroscope sensor fusion provide effective means to solve the problem. In [58], media-lateral foot angular change detection method was proposed to solve the problem sensor placement for gait analysis of Parkinson disease patient by fusion of accelerometer and gyroscope using Kalman filtering algorithm. They extracted sample set of features such as stride length, cadence, cycle time, stance time, swing time, stance ratio, speed and turning rate with higher spatio-temporal accuracy when compared with IR-depth camera based gait analysis. With recent innovation toward automatic feature extraction for human activity recognition, fusion of accelerometer and gyroscope provide rich set of sensor data to avoid algorithms overfitting with deep learning implementation. Deep learning techniques enable automatic feature extraction and real time human activity recognition without relying on handcrafted features [20,53,104,105].

Furthermore, with the increase in processing power of smartphones, numbers of studies have proposed on-board implementation of smartphone based human activity recognition with fusion of inertial sensors [106–108]. Bahrepour et al. [109] propose data fusion strategies utilizing distributed algorithm that allow implementation on resource constraint wireless node for real time activity detection in patient with Parkinson disease. The combinations of sensors ensure reliability and robustness in recognition of activity such as sitting, walking and standing still using patient mobile phone. Bahrepour et al. [109] present power aware feature selection system that minimizes energy consumption using efficient classification algorithms based on Graph theory model. The proposed methods represent set of features as correlation and compute the complexity of these features for real time implementation. Being part of daily life, smartphone implementation of human activity recognition can also provide automatic intelligent monitoring and fall detection for the elderly and provide contextual information to the caregiver and medical practitioners for prompt medical care.

Despite the tremendous achievement of accelerometer and gyroscope fusion in human activity recognition, there are still issues yet unresolved. It is quite difficult to detect posture in real-time and detect the correlations between posture and actions being performed overtime [110] or correctly recognize transitional activities [111]. Furthermore, fusion of accelerometer and gyroscope cannot correct activity drift that is prevalent in gyroscope sensor data. Early correction of sensor drift is important in tilt orientation by calculating both the vertical acceleration and velocity accuracy and such method is vital for pre-impact fall detection [112].

These issues can be resolved by the inclusion of magnetic sensor (magnetometer) that helps to remove the effect of gravity and provide orientation independent or problem of sensor position [59]. Recently, comparative study by [65] showed the importance of magnetometer in recognition of transitional activities and postures in activity of daily living. The incorporation of magnetometer and gyroscope sensor in human activity recognition enable accurate posture identification in elderly, automatic monitoring, human motion tracking and detection of abnormal events especially in remote e-Health application [42,60,105,113–115]. The fusion of inertial measurement unit sensors (accelerometer, gyroscope, magnetometer) have also been extensively deployed for real time context-aware navigation in smartphones, where the aim is for pedestrian navigation system and uncertainty modelling of users [116,117]. Other areas in which the fusion are important are in recognition and classification of activity into sporadic and static activities, and recognition of hand gestures such as smoking, eating, drinking coffee and giving talks [31,118]. This is done toward detection of bad habit, modelling temporal and local correlation features in human motion modelling, and classification of daily activities [4,118,119]. To ensure accurate patient monitoring, rehabilitations, emergency and safety, orientation and position estimate of the patient posture is important. Qiu et al. [14] Proposed fusion of inertial sensors to accurately estimate pedestrian location and position called the pedestrian dead reckoning. They developed Kalman filtering approach to fuse the inertial sensor and reduce errors caused by sensor installation path integration.

2.2.2. Multi-modal sensors fusion

Major studies in multi-modal sensor fusion are implemented for health monitoring, energy expenditure estimation, health status delivery, identification of stress and mental loads, object interaction in smart environment, indoor localization and chronic disease management. Bio-signals, electrocardiography (ECG), electromyography (EMG), ambient sensors, object and visual sensors are combined with inertial sensor to provide complementary information and increase accuracy of activity detection systems [94,120,121]. Inertial measurement unit sensors (IMU) such as gyroscope or magnetometer are power hungry and may result to degradation and fault during activity detection. Therefore, instead studies combine accelerometer and physiological signal for human activity recognition and health status monitoring [122].

For instance, electrocardiography (ECG) and accelerometer are fused for the purpose of monitoring activity of stroke patient, energy expenditure calculation and lifelogging [121,123–125]. The fusion of accelerometer and electrocardiography provide functional means to estimate strength during extraneous exercises, keep track of health management issues, prevent disease and enable lifestyle improvement [125]. To fully exploit data fusion for daily activity pattern, Zdravevski et al. [126] propose real time smartphone multimodal activity recognition and inference using Logistic regression with fusion of inertial sensors and physiological signals. While Jia and Liu [127] achieved 99.57% accuracy in recognition of relevant activities by fusion of multi-lead ECG and accelerometer sensors, they noted that the combinations prevent the attachment of multiple accelerometer sensors on different body parts and ECG serves as both motion sensors and vital sign physiological signal for human activity monitoring.

In some cases, the fusion of physiological signals such as bio-sensor signal and heart rate can help to reduce noise in accelerometer data, computation complexity and increase recognition accuracy for certain types of activities [128]. Lara et al. [129] investigated combination of sensor modalities for human activity recognition under different feature set strategies and noted that the fusion of vital signs and accelerometer and this aided recognition of descending stairs by 100% accuracy. Also physical activities have high correlation between heart rate and breath amplitudes. Martin et al. [130] propose to enhance real time mobile phone based activity detection by combining barometric sensors and accelerometers. Furthermore, fusion of barometric sensor can also play vital role in detection and prevention of child related unintentional injuries at home [131]. The collected data from children between the ages of 6 and 12 months were utilized to recognize activities such as wiggling, rolling, toddling, crawling, sitting which were classified as safe or dangerous activities with 98.4% accuracy. Activity localization and estimation of energy level can be achieved by integration of Global positioning systems (GPS) and inertial measurement unit [132]. Accordingly, the fusions enable location inference in activity details, context-aware monitoring [21,133], and individual energy level calculation for health notification and transportation mode analysis and detections [134] in real time using smartphones.

Previously, studies have also proposed techniques for fusion of inertial sensors and medical application sensors for comprehensive human activity recognition and alternative health applications. These include important health applications such as health status monitoring, mental load identification and chronic disease management [58,135]. The sensors deployed in these scenarios are mostly all-inclusive to achieve robust recognition systems. Majority of these sensors include inertial measurement unit (accelerometer, gyroscope, magnetometer), electrocardiograph (ECG), physiological sensor, state change sensors, blood oxygen saturation, temperature, respiration rate, pulse oximeters, microphone (audio), humidity, physical images, pathological parameters of human body, vital signs, SpO2 sensors, altimeter, pressure insole, heart rate monitor, barometers, light sensors, photocell, digital sensor, infrared receivers, GPS and door contact sensors. Some of these sensors are attached to objects in the environment for continuous and real time event monitoring [136], comprehensive monitoring of activity of daily living(ADL) for the elderly [58,137,138] or detection of abnormal behavioural changes [135,139] and have contributed to improve the performance of human activity recognition system.

Bellos et al. [140] and Gong et al. [141] combined combine physiological signals, ECG, humidity, pulse rate, temperature and pathological parameters for disease management and health status monitoring for elderly population in ambient environment and smart homes [142]. These systems were developed as mobile based system for real time recognition of physical fitness and total well-being [82,143–145]. Chen et al. [82,146] propose inertial sensor and pressure insole fusion to recognize locomotion mode and detect locomotion transition in advance using Linear Discriminant Analysis (LDA). In related study, Sebestyen et al. [51] present human behaviour assessment with fusion of inertia sensor, temperature, pressure and contact sensor using Hidden Markov model from data collected in internet of things (IoT) environment. The essence was to categorize the activity changes overtime and recognize complex activities as means of behavioural changes.

In addition to the fusion of the sensors listed above, there are recent works that focus on fusion of vision-based sensor with other sensor modalities for activity recognition and health monitoring [18] especially with the advent of wearable camera and eye glass-mounted system that remove the need to install camera in particular locations [147,148]. Fusion of accelerometer and wearable vision-based sensor provide complementary information to increase performance and robustness of human activity detection systems, identify mobility changes between static and dynamic activities. Wearable sensors have intrinsic ambiguities that prevent certain activities such as eating, reading, cleaning and drinking to be accurately recognized using inertial or vision sensors alone. However, with robust framework that integrates 3-axis accelerometer and wearable camera, such activities can be categorized [131,149–151]. Witchit [152] proposed multisensory data fusion (MSDF) architecture that combine video camera, infrared, acoustic and pressures sensor using fuzzy inference engine. The integration of the sensor enable improved accuracy and robustness to recognize difficult activities such as bending, lying while reading, sitting and eating with these sensors attached to environmental objects. The fusion of vision based sensor and number of environmental or wearable sensor have also played vital role in behaviour tracking and analysis that encompasses emotional, social and physical aspect [153]. In this scenario, the activities gathered with vision-based, accelerometers and geo-position sensors can be divided into low level and high level representation and then use machine learning or ontological mechanisms to categorize the activity details. Nevertheless, the fusion of wearable inertial sensor and vision-based sensor are not trivial due to the inherent disparity between the two sensor modalities. Whereas wearable inertial provide rich representation of body dynamics, they are subject to motion noise, inter sensor calibrations and high number of sensor to recognize complex activity details. In case of vision based sensor, issues such as lack of scene semantic, temporal dynamic and hierarchical structures of complex event are still challenging and unresolved problems [154]. To resolve the problem of heterogeneity and uncertainty in sensor fusion, Crispim-Junior et al. [67] propose probabilistic framework based on Dempster–Shafer theory of evidence that resolve the above mentioned issues for event description and detections.

Another important area of applications of inertial based and vision based sensor are in temporal segmentations of activities, reduction of false positive rate and to provide orientation based human activity recognition systems [147,155,156]. Feature vectors extracted from accelerometer, gyroscopes and wearable camera were combined with machine learning algorithms such as support vector machine (SVM), Hidden Markov Model (HMM) and k-Nearest Neighbour (k-NN) to segment complex activities along temporal patterns in order to resolve the issues bothering on large variability and complexity in representing human motion for daily event segmentation [155]. Despite the inherent advantages of camera providing complementary information for human activity recognition, issue bothering on privacy is still a challenge that limits their application [18].

Furthermore, comprehensive health monitoring requires effective recognition of individual emotion state, monitoring and detection of stress and quality of sleep patterns for overall quality of life. Different physiological signal such as ECG, EMG EOG, EEG are analysed in this regards for emotion detection, sleep stage detection and stress monitoring [157,158]. Physiological signals are excellent means to model temporal dependencies and observable posterior distribution in sensor data for diagnosis and recognition of emotions state in elderly using wearable sensor worn on the patients' scalp [159,160]. In addition, fusion of physiological signals such as ECG, EMG, EEG were recently proposed for comprehensive health monitoring and health status report information [161–163]. Furthermore, Cinaz et al. [164] investigated the use of mobile-based ECG for detection and monitoring of workload related stress using Linear discriminative analysis (LDA), support vector machine (SVM) and k-Nearest Neighbours (kNN). Other classification algorithms that have played prominent role in health monitoring using multi-modal physiological signals are Random forest, Neural Networks and ensemble-based learning algorithms [164–167]. Physiological signal classification for health monitoring are broad research areas and recent reviews provide important information on data collection, feature extraction and classification approaches [158,168].

Some of the applications, advantages and issues inherent in these sensor modalities are presented in Table 2.

3. Feature fusion for human activity recognition

Feature fusions provide excellent means to combine heterogeneous sensor data. In this case, features extracted from sensor data are combined using machine learning algorithms and this can be categorized into handcrafted features that involve carefully engineered feature by human experts [169] or Deep features that automatically extract feature representation with deep learning algorithms [30]. In this section, different features sets and features extraction commonly used in activity detection and health monitoring are critically discussed and their combination mechanism using machine learning algorithms. Furthermore, deep learning fusion for automatic feature representation that enables hierarchical and translational invariant feature extraction is also presented.

3.1. Handcrafted feature fusion

In human activity recognition and time series data analysis, feature extraction is one the most studied area and play important role to reduce computation time and complexity especially for mobile and wearable based implementation [12,23,30]. Feature extraction and dimensionality reduction identify set of feature vectors that minimize classification errors, and to select the most discriminative features for the recognition tasks. Human activity recognition based handcrafted feature fusions can be discussed under three themes. These include types of features, feature selection and machine learning algorithms.

3.1.1. Feature types

Different feature vectors can be extracted from sensor signals over fixed or varied window lengths [169]. Majority of the studies considered in this review extract time domain, frequency domain or time-frequency such as wavelet [32,113,170] or Hilbert–Huang Transform [29,171]. Time domain show how signal changes with time. Time domain feature provide better computation time and efficient for real-time implementation of human activity detection system [4]. The most outstanding time domain features in literatures are mean, median, standard deviation, percentile, signal magnitude, root mean square, correlation between sensor axes, entropy, variance, kurtosis, interquartile range, skew, cumulative histograms [34,37,154,172–174]. On the other hand, frequency domain features show the distribution of signal energy and predominantly used to capture repetitive nature of sensor signals [175]. The frequency domain features are extracted from sensor data with consideration on frequency band and include Fast Fourier transform (FFT), discrete cosine transform, spectral energy, entropy, power spectral density, Fourier coefficient and wavelet features [32,113,119,126]. Studies by Refs. [49,176] and [50] provide excellent description on some of these features sets. In addition, Fong et al. [177] proposed shadow feature for human activity detection and health monitoring. The proposed feature vectors are derived from dynamic nature of human body motion and efficient to infer dynamic body movement and underlying momentum of activity details. The main advantages of shadow feature are the incremental nature, simplicity and low computation time and efficient for mobile phone and wearable devices implementation.

Recently, Hilbert–Huang and ensemble empirical mode decomposition mode features were proposed as important feature vectors for human activity recognition [29,40]. Time domain and frequency domain features are good for linear signals; however activity data are nonlinear and non-stationary in nature [29,171] and Hilbert–Huang provide attractive nonlinear feature vectors. Hilbert–Huang features include instantaneous amplitude, frequency using empirical decomposition (EMD), density and marginal spectrum from Hilbert spectral analysis. Feature extraction stage may extract high number of irrelevant features that may increase computation time and reduce classifiers performance. Dimensionality reduction reduces the feature vectors using methods such as Principal component analysis, Empirical cumulative distribution functions and Linear discriminative analysis [178,179].

3.1.2. Feature selection methods

Feature selection strategies help to select optimal feature vectors with filter, wrapper or embedded feature selection methods. Filter based use data characteristics for feature selection, wrapper based method consider inference algorithms' performance such as classification accuracy and error rate as evaluation criteria and search for feature subset that fit the classifier. Therefore, wrapper based is classifier dependent. Conversely, embedded methods incorporate feature selection as part of classifier training procedure [32,50,180,181]. Some of the feature selection methods recently investigated for human activity detections are kernel and fisher based discriminant ratio criterion [34,113], Minimal Redundancy Maximal Relevance [32,139,182], correlation based features selection method [116,139,183] and RELIEF F [32,183]. Recently other feature selection techniques have also been proposed to increase performance and reduce computation time. Zdravevski et al. [126] propose wrapper based feature selection called *diversified forward-backward feature selection* that uses greedy heuristic method to estimate feature importance and relevance with logistic regression. Ghasemzadeh et al. [184] develop power-aware feature selection method for mobile based human activity recognition. The method utilizes integer programming and greedy approximation approaches to combine and select relevant feature vectors to reduce computation complexity. Recently, Wei et al. [185] investigated the fusion of feature selection approach and selective ensemble algorithm for multi-class classification problem. The method uses sum of relevance maximization, and novel parallel optimization and hierarchical selection approach to reduce high dimensional prediction instances to minimize computation time. The main advantage of the proposed approach is the ability to solve high dimensional data problem and improve the generalization performances of multi-class classification. Furthermore, Li et al. [186] proposed Elitist Binary Wolf Search Algorithm (EBWSA) to select efficient feature vectors in order to reduce computation time. In recent publication, Wang et al. [40] investigated the use of game-based theory for feature selection. Game based theory is mathematical method that defines rational decision making process based on entropy and mutual information theory.

3.1.3. Machine learning algorithms for feature fusion

Then, the extracted or reduce feature vectors are combined by exploiting different machine learning algorithms. Different classification algorithms have been proposed to build effective multi-features based human activity detection and classification. These include Support vector Machine [36,107,126,139,140,145,173,187,188], k-Nearest Neighbor [32,117,118,174,188,189], Artificial Neural Network [103,116,120,129,135,139,188], Decision Tree [116,120,122,129,140,189,190], Random forest [119,126,188,191], Hidden Markov Model [107,190,192,193], Naïve Bayes [116,122,126,129,140,189,194], Multiple Kernel Learning [187], Gaussian kernel [195,196], Linear Discriminant classifier [115] and k-mean clustering [33,97,197,198].

Some of the studies [73,116,188] compare different machine learning algorithms for feature vectors fusion and provide means for effective performance evaluations. From the reviewed works, we observed that Hidden Markov model and Decision tree are mostly deployed for hierarchical activity recognition, whereby activities are subdivided into lower and high activities. These include partitioning of concurrent, overlap and continuous activities [37,190] and the algorithm considers the hierarchical structure of human activity details. Furthermore, k-mean clustering is utilized for grouping similar activity before integration into higher activity details to reduce computation complexity especially for mobile based implementation [33]. Also, k-mean clustering provides semi-automatic training examples from motion sensor data that is feed into supervised algorithms for human activity recognition [199].

3.2. Deep learning fusion for automatic feature representation and extraction

Recently, automatic feature extraction and representation have become an emerging area of research in human activity recognition. To reduce reliance on hand engineered features and time spent on selecting appropriate features for particular application and task, Deep learning have become sought after in this regard [30]. Deep learning use appropriate machine learning techniques to present and model high level representational features in sensor data by deploying multiple layers of neural network that represent features from low level to high level hierarchically. It has become influential in research areas such as image and object recognition, natural language processing, machine translation, environmental monitoring [200] and in mobile and wearable sensor based human activity recognition [201,202]. Since improved implementation of deep learning in 2006 [203], different methods have been develop and modified to solve varieties of challenging problems. These include Restricted Boltzmann machine, Autoencoder, Sparse Coding, Convolutional Neural Network and Recurrent Neural Network. Generally, deep learning provide flexibility, robustness, and improved performance by utilizing the power of several layers of neural networks. In addition, deep learning resolves the issue of domain knowledge dependencies by automatically modelling the structures of the sensor data and extract salient and discriminative features. Previous studies in deep leaning based feature representation for human activity recognition can be largely categorized into generative and discriminative models [204]. The generative models are graphical models that model independent or dependent distributions in sensor data where graphs node represent the random variable of the given sensors data and arc represent the relationship between variables. Generative model capture higher order correlation by identifying joint statistical distribution with associated classes. Typical examples are the Restricted Boltzmann Machine, Autoencoder and Sparse Coding. The models are trained with unlabelled datasets that are pre-trained with greedy layer by layer approach in the case of Restricted Boltzmann machine, and then fined tuned with labelled data to be classified with classical machine learning. Discriminative model on the other hand, provides posterior distribution and discriminative power to classify label sensor data. Deep learning methods in these categories are Convolutional Neural network and Recurrent Neural Network. It is imperative to briefly explain these deep learning methods, look at their characteristics, strength and weakness. Furthermore, various fusion strategies that been adopted to represent higher features for performance enhancement will be presented in the next subsection.

3.2.1. Restricted Boltzmann machine

Restricted Boltzmann machine [205,206] provides building block in greedy layer by layer of deep neural network trained with contrastive divergence to provide unbiased estimate of maximum likelihood learning. Conversely, restricted Boltzmann machine methods during training are challenging to converge to local minimum and various data representation, parameter setting definition to achieve best performance improvements [207]. Techniques such as regularization using noisy rectified linear unit and temperature based Restricted Boltzmann machine [208,209] were recently proposed as solutions. A number of variant of Boltzmann Machine has been proposed. These include the *Deep Belief Network* and *Deep Boltzmann machine*. Deep Belief network [203] is restricted Boltzmann machine methods that enable greedy-wise layer learning of feature representation by fusion of several Restricted Boltzmann Machine to extract hierarchical features from data. In Deep Belief Network, there are directed connections between lower layer and undirected connection between layers at the top to handle sensor streams distribution between vectors space and hidden layers. It estimates the conditional probabilities of each sensor distribution to learn robust features invariant to change in distribution, noise and sensor locations [203]. Similarly, Deep Boltzmann machine [210] model several hidden layers of deep neural networks in undirected connection in the entire layers of the deep network. In this way, the algorithm exploits hierarchical framework to automatically model feature representation from data in which features learnt in the first layer are used as latent variables in the next layers. Specifically, DBM are trained using stochastic maximum likelihood algorithms with intent to minimize lower bound likelihood, determine appropriate training statistics, weight initialization terms and how to update the training minibatch [211]. Restricted Boltzmann machine have become best alternative to solve the issues of unlabelled data in human activity recognition [212] and also provide robust feature vectors for implementation human motion analysis [213,214].

3.2.2. Autoencoder

Autoencoders are deep learning methods that reproduce the copies of the input values to produce output values. Autoencoder is divided into two main parts vis a viz: encoder and decoder units. The *encoder* unit transforms the input data into hidden features while the decoder parts reconstruct the hidden features into approximate representation to reduce likelihood of error rate [215]. Autoencoder algorithm are stacked into multilayers to convert the high dimensional data into lower dimensional code vectors and then pre-trained using Restricted Boltzmann machine to automatically obtain discriminative features representation from raw sensor data [216]. Generally, diverse methods of autoencoder have been proposed recently for feature representation. Methods such as *denoising autoencoder, sparse autoencoder* and *contractive* autoencoder have wide spread applications in human activity detection for feature fusion [179,215]. *Denoising autoencoder* [217] use partial destruction of the input samples to reconstruct the original input data trained in unsupervised layer by layer initialization to capture the robust data invariants to changes. Likewise, *sparse autoencoder* [218] learn sparse and over-complete data representation to solve the problem of high dimension feature vectors and make it linearly separable by introducing sparsity term loss function. On the other hand, *contractive autoencoder* [219] uses penalty term of partial derivatives to extract features to reduce sizes of data and feature spaces. This help to reduce the dimensional feature space with the training datasets and make them invariant to changes and distortions. In [220,221] deep autoencoder methods were developed for feature representation in smartphone and health monitoring applications.

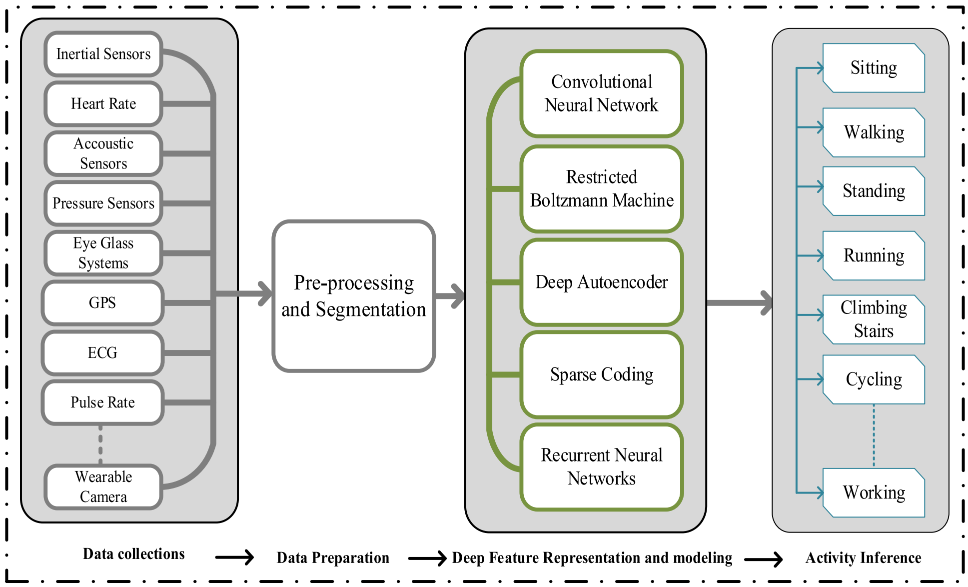

Fig. 4. Deep learning based human activity recognition process.

3.2.3. Sparse coding

Sparse Coding [222] was developed as dimensionality reduction algorithms and represent the data as linear combination of linear basis vectors. The major advantages of sparse coding are the ability to learn over complete basis vectors and ensure efficient data representation. Therefore, sparse coding accurately model the data structure and estimate the input vectors [223]. Although sparse coding is not popular for time series data analysis due to its lack of deep architecture, few works have attempted its implementation for human activity recognition and monitoring to enable compact and sparse representation from unlabelled data [224,225].

3.2.4. Convolutional neural networks

Convolutional Neural network and Recurrent Neural Network are the most widely used deep learning for feature representation method as they provide automatic, salient and translational invariant features for different application areas [30]. Convolutional neural network [226] uses deep interconnected structure to perform convolutional operation on sensor data using several hidden layers. Convolutional Neural Networks are subdivided into different components that include convolutional layer, pooling layer and fully connected layers fused together to form deep architectures for locally correlated feature extraction from data [227]. The convolutional layers capture the feature map using various kernel sizes and strides and then pooled to minimize the number of connection between the convolutional layer and pooling layer. Likewise, pooling layer component reduces the feature map, the number of parameters and makes the network translational invariance to changes and distortion. Numerous pooling strategies have been proposed by different studies. Some of the most widely used pooling strategies are max pooling, average pooling, stochastic pooling or spatial pooling strategies [200]. The fully connected layers is fussed with the inference engine such as Multinomial regression (SoftMax), Support vector machine or Hidden Markov Model that discriminate the feature vectors into activity details [228,229]. Another vital component of Convolutional Neural Network is the activation unit values, derived at each region to learn patterns from data using the bias terms and feature maps [30]. Some of the studies treat sensor data as time series 1D channel with single dimensional image vector that are flatten after convolution and pooling operation [230,231] or combine all the sensor axes to for 2D convolutional for modality transformation [8,201,232].

3.2.5. Recurrent neural networks

Recurrent Neural Network (RNN) was developed for sequential data modelling and analysis and integrate temporal layer to learn intricate variation in sensor data with time. Recurrent Neural Network estimate the variation in sequential data using the hidden unit cell with the activation units of the previous hidden state. Nevertheless, training Recurrent Neural Network is challenging due to exploding or vanishing gradients. Recently, Long Short Term Memory was developed by [233], integrates memory cells to store contextual information and control the flow of information into the network. Therefore, LSTM integrate memory cell such as input gate, output gate, function gate with learnable weight. In [234], observed that the use Long Short Term Memory enable the Recurrent Neural Network to model long range structures in data and capture long term dependencies and increase performances of the network. But, recent experimental analysis of Long short term memory, Cho et al. [235] noted that, the algorithm require huge number of parameter definition and update. These parameter definition makes the network complex with higher computation time specifically with the current wave of mobile based data analysis. The authors propose Gated Recurrent Units (GRU) with less parameters definition and update, faster and less complex to implement. Moreover, LSTM and GRU vary based on hidden states update and content exposure techniques. Long short term memory update by summation operation but Gated Recurrent Unit update by taking the correlation based on the amount of time needed to keep such information in the memory [236]. Furthermore, comparative study [237] has shown the superior performance of Gated recurrent units over Long Short term memory in terms of performance and computation time analysis. Recently, numbers of studies have proposed Recurrent Neural Network for feature representation in human activity recognition [238–240] and Ensemble based approach to enhance robustness and generalization [241]. The process for developing human activity recognition using various deep learning [8] discussed in this section is presented in Fig. 4

However, numbers of issues have been observed on the training and implementation of deep learning methods for human activity recognition using mobile and wearable sensor data and other application areas (Table 3). These include extensive initialization, difficult optimization, high computation time and overfitting.

3.3. Deep learning fusion for feature representation

To increase robustness and generalization of deep learning based

Table 3
Strength and weaknesses of deep learning algorithms.

Methods	Strengths	Weaknesses
Deep Boltzmann Machine [203,206,212,213]	Unsupervised deep learning algorithms trained with unlabelled and provide iterative for robust feature representation	Computationally complex training processes that is challenging to attain enhanced optimization as a result of large-scale initialization operation during implementation
Deep Autoencoder [218,219,245–248]	Produce robust and reduced dimensional feature vectors invariant to changes in data distributions	Inadequate scalability mechanism, and require long training time
		Require numerous forward passes for data samples Difficult optimization procedure and not suitable for nonlinear feature vectors
Sparse Coding [222,224,225,249,250]	Provide efficient means to reduce feature vectors and extract robust features from raw sensor data	It is highly challenging to implement deep architecture for efficient feature extraction
Convolutional Neural Network [201,202]	Provide numerous resources and enhancement for deep architecture implementation for robust feature extraction	Require high hyper-parameters tuning and huge amount of training examples to minimize overfitting the algorithm
Recurrent Neural Network [238,241]	Important deep learning methods for modelling temporal variations and sequences in sensor data.	Training the network is challenging and may require too many large prameter update such as LSTM. Moreover, RNN peformance deteriorate due to vanishing or exploding gradients

feature representation, different works have proposed fusion strategies to different deep learning methods discussed Section 3.2. The individual methods play vital role to extract hierarchical and translation invariant features from sensor data, reduce source of instability, and provide sparse representation and temporal dependencies in data. Convolutional neural network and recurrent neural network are fused together to model spatial and temporal dependencies in data especially in multimodal and multisensory human activity recognition applications. The most common fusion of deep learning methods for human activity recognition is *Convolutional Neural Network* with other methods discussed earlier. Li et al. [242] propose convolutional neural network and long Short term memory for concurrent human activity recognition. The proposed algorithm model and determine if activity is in progress or not in progress with different sensor modalities. In [243] convolutional neural network and long short term memory was proposed to automatically learn translational invariant features and model temporal dependencies in data by integrating the pooling layer in Convolutional neural network with Long short term memory. the evaluation of the proposed algorithms on publicly available data indicates improved performance over single architectures. Fusion of convolutional neural network and bidirectional long short term memory was reported by [244] for health monitoring using various sensor modalities in order to model temporal and sequential structure of the data.

Similarly, fusion of convolutional neural network and autoencoder have also been proposed for extraction of robust features vectors [251] and increase performance by varying the input values and weight initialization to develop channel wise ensemble algorithm for unseen fall detection using wearable sensor devices [252–254]. Furthermore, ensemble of long short term memory [241] was proposed by varying the subset of the training data and epoch bagging mechanism to obtain improve robustness and generalization of deep learning algorithm.

To minimize instability and extract translational invariant features, Gao et al. [255] investigated convolutional Restricted Boltzmann machine while [256] propose fusion of Deep Belief Network and Convolutional neural network for activity recognition in prognostic and health monitoring. The algorithm was evaluated using electroencephalogram sensor data. However, the result deteriorated due limited amount of training and testing data. Recently, fusion techniques that combine multi-sensor and multimodal methods have also been proposed by various studies. In [258], develop recurrent neural network and convolutional neural network to extract shift invariant features for mobile sensor tracking of body movement while [259] propose multi-modal sensor fusion for human activity recognition in order to reduced computation time for mobile based implementation. The performance evaluation of different deep learning algorithm for human activity recognition was proposed by [231] for human activity recognition and show the impact of varying the hyper-parameters values on performance of the deep learning. Furthermore, Morales and Akopian [260] examine the effects of transfer learning in deep learning for human activity recognition. They noted that transfer learning help to reduce training time and sensitivity to sensor placement. Yao et al. [261] propose fusion of convolutional neural network and Gated recurrent neural network for mobile data sensor analysis and activity tracking. Similarly, Sathyanarayana et al. [262] propose deep learning method to evaluate the impact of sleep in human activity using Long short term memory and convolutional neural network.

Other deep learning fusion methods were recently developed and implemented by various studies by integrating deep learning algorithm and handcrafted features techniques due to high computation complexity and memory requirement of deep learning. Handcrafted feature and convolutional neural network fusion was developed in [229] for human activity recognition on-board mobile and wearable sensor implementation. Alzantot et al. [263] propose fusion of long short term memory and mixture density network for generation of sensor data for human activity recognition in order to solve the problem of limited number of training data. These studies provide optimal decomposition of complex activity into individual components, recognize concurrent activity that occur at the same time and achieve high model diversity and generalization of performance accuracy. In addition, Bhattacharya and Lane [213] propose sparse coding based convolutional neural network for human activity recognition by introducing *sparsification* of fully connected layer and separation of the convolutional kernel to reduce computation time and memory usage. Some of the fusion methods include sparse deep belief network by combination of deep belief network and sparse coding [257] for analysis of health and brain activities for the elderly.

The characteristics of these fusion strategies, strengths and weakness are shown in Table 4 below.

4. Multiple classifier systems for human activity recognition

A combination of multiple classifiers implemented to handle complex systems, high dimensional and uncertainty in data have been active research areas in pattern recognition and supervised learning for decades [41,265,266]. This involves systematic fusion of individual classifier decision to arrive at consensus in order to increase accuracy, robustness and generalization. Multiple classifier systems or classifier ensembles combine heterogeneous or homogenous classifiers to arrive at final decisions. The aim is to reduce uncertainty and ambiguity by fusion of outputs generated by different classification models to achieve higher performance that is unlikely when such classifier is used in isolation [42]. With classifier fusion, issue such as diagnostic errors can be reduced by combining the output of individual classifiers where the diversity of each algorithm is taken into consideration [128,185].

Table 4
Deep learning fusion for feature representation in human activity detection.

References	Methods	Strengths	Weaknesses
[157,213]	Convolutional Neural Networks, Deep Belief Networks and Sparse coding	The fusion exploit sparsification methods at the fully connected layer and separation of convolutional kernel to minimize memory usage	Maybe difficult to develop efficient and deep feature representation using sparse coding
[255,256]	Convolutional Neural Networks, Restricted Boltzmann Machine	Extract translation invariant features and reduce instability during training	Use of few data set and single sensor modality (e.g. ECG) results to lack of generalizations to new applications. Also, RBM with high initialization procedure tends to increase the computation time
[241,252,253]	Deep learning ensemble algorithm	Fusion of various deep learning allow high model diversification and performance generalization	Ensemble algorithms implementation requires high parameter tuning and computation time to achieve maximum performance enhancement and accuracy
[242–244,258]	Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM)	The fusion of the two discriminative model are applicable for multimodal and multi-sensor based human activity identification. Furthermore, the algorithms are essential for detection of complex and concurrent activities and learn spatial-temporal features from raw sensor data	The fusions of the two architectures increased the computation time and complexity, making them difficult for real time mobile implementation
[261,263]	Convolutional Neural Network, Gated Recurrent Unit (GRU)	Gated recurrent unit has compact parameters and simple terms with reduce network complexity for efficient development on mobile devices	The high number of parameters optimization of Convolutional neural networks may increase the computation cost for real-time mobile sensing implementation. The energy cost of implementing the algorithm on wearable or mobile devices is challenging
[264]	LSTM, Mixture Density Network	Generation of synthetic sensor dataset to improve privacy in data collection and consistency in recognition output. The algorithm was trained to differentiate synthetic and real datasets using generator and discriminator modules	It is difficult to evaluate the model performances using baseline metrics. The study use heuristic means to distinguish between real dataset and synthetic data
[27]	Deep Learning and Handcrafted features	Ensure automatic feature extraction with reduced dimension and less computation complexity	The fusion techniques are inefficient to extract temporal features for high feature representation and ability to model concurrent activities

Furthermore, multiple classifier systems have been proposed to resolve the issues of bias and variance were weak learners are systematically combine through weighted or unweighted majority voting to produce stronger classifier where the error rate is better than random guessing [265–267].

According to Kuncheva [41], the architecture of multiple classifier system can be informs of parallel or sequential methods. In parallel architectures, each classifier is given the same training samples and the final decision is a combined classifiers output based on independent output of the individual classifier. While in sequential architecture, classifier is trained with data point sampled from the training examples and the classifiers are arranged in their ability to estimate certainty of classification. Sequential architectures is applied in area where computation cost is utmost important and especial case is the Adaptive boosting [41,266,268].

In recent comparative analysis, Dietterich [265] outlined reasons driving the implementation of multiple classifier systems. These include insufficient training data, how to reduce computation complexity and the need to find better algorithm representation. In mobile and wearable sensor based human activity recognition, these issues are still challenging researches due to data collection and implementation techniques. Issues of insufficient training data can be resolved through bootstrapping ensemble methods where the subsets of the data are randomly drawn with replacement and the output of the individual classifiers are combined with plurality voting [41]. Moreover, combining classifier trained with different subset of the training data helps to overcome the problem of overfitting, increase the probability of finding optimal solutions and enable efficient implementation learning algorithms [266]. Therefore, issues such as pattern variations and insufficient computation resources [128], signal degradation, sensor failure, environmental fluctuation [269], spatial variability of data sample and selecting appropriate classifier combinations [270] and best form of data representation for ensemble methods are still challenging research areas in human activity detection and health monitoring.

Therefore, lots of research efforts have been geared toward the development of multiple classifier algorithms for human activity detection and classification to solve the above stated issues. For instance, Jurek et al. [42] propose cluster based ensemble learning algorithm to group activity into cluster of activities with similar features. In [271], ensemble of fuzzy rule based one class classifier was developed for human activity recognition using sample data collected from public parks. The aim was to prevent littering of Public Park by identification of outlier objects within the park area.

The main challenging tasks in multiple classifier system for human activity and pattern recognition are how to choose the base classifiers, ensemble design techniques and fusion strategies to ensure high performance accuracy and reduce computation complexity [266,272]. Fig. 5 depicts major design and fusion strategies depicted implemented for human activity detection and health monitoring. From available literatures on ensemble algorithm for human activity recognition, decision tree is the most widely implemented base classifier. Other classifiers are Support Vector machine, artificial neural network and deep learning, linear discriminant analysis and Hidden Markov model. Ensemble design methods provide increase diversity and reduce correlation following different modelling and learning approaches [266]. There are a variety of approaches used to ensure output variance. These include input data manipulation, use of different feature sets, model variation and injection of noise or randomness in the data [41,265]. In fusion strategies, methods such simple voting, majority voting, weighted majority, fusion score and posterior probability methods have been proposed in recent literatures [128,272,273]. In the following subsections, overviews of the above issues are presented in the context of human activity recognition with typical examples from literatures (Fig. 6).

4.1. Base classifiers

4.1.1. Decision tree

Decision Tree Classifier (DTC) is classification algorithm that recursively partition training data into node segments composed of the root node, internal split and the leaves [274]. Data splitting is performed at each node based on simple feature with certain stopping criteria [50]. Decision tree is non-parametric and does not require assumption on the distribution of the training data and can model nonlinear relations between features and classes [275]. A good number of decision tree algorithm have been proposed and utilized in human

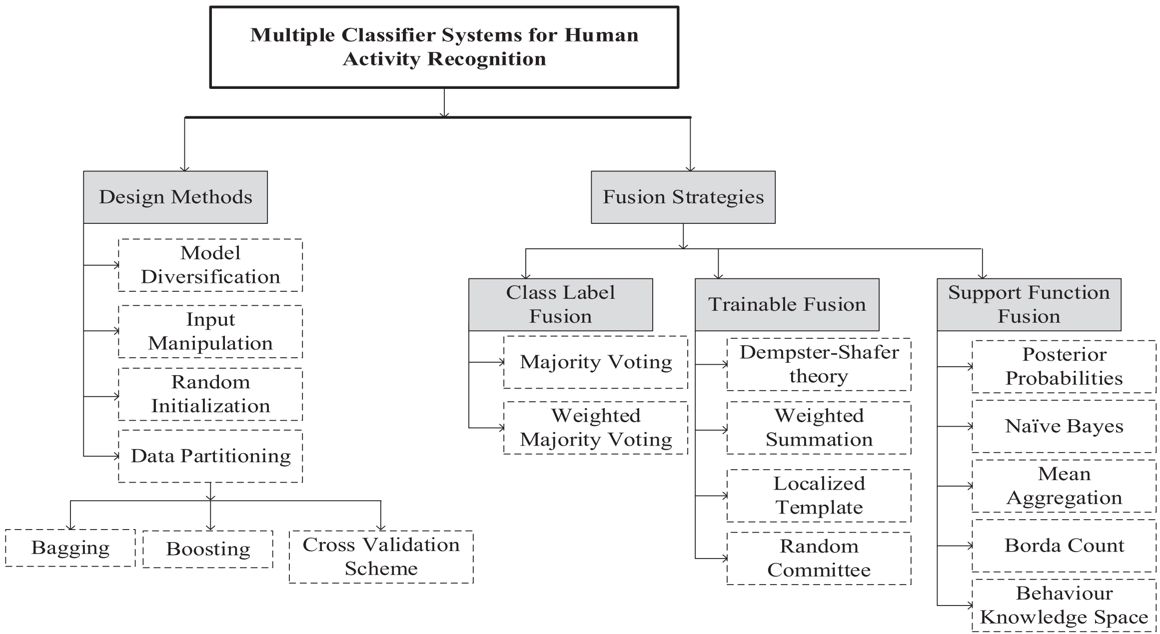

Fig. 5. Multiple classifier system development for human activity recognition.

activity recognition such as ID3, C4.5, Random forest and J48 [116,190,272,276–279]. Azhar and Li [190] examined decision tree based hierarchical partition algorithm to recognize similar activities with overlaps. Feng et al. [279] propose multiple sensor based ensemble of random forest classifier trained separately on different sensor feature sets with weighted majority voting fusion strategies for human activity recognition. The algorithm evaluated with Physical monitoring for aging people (PAMAP2) dataset successfully recognize 19 physical activities with accuracy of 93.44%. In [278], feature motion primitive forest with ensemble decision tree based classifier was developed to cluster and group activities with similar motion patterns.

4.1.2. Support vector machine

SVM provide linear and nonlinear classification methods for mapping data into high dimensional space using different kernel fusion methods. Support vector machine was first developed by Cortes and Vapnik [280] and uses optimal hyperplane that maximize the decision boundary between the class labels [107]. Support vector machine is a powerful classifier for pattern recognition but with high computation time and complexity [126]. SVM have been extensively utilized as base classifier for building multiple classifier systems in human activity classification and motion analysis [128,269,270,281,282]. Sagha et al. [269] proposed one class support vector machine based ensemble for detection of abnormal sensors in human activity recognition. The major contribution was the development of method based on Mohalanobis distance and information theory to compare classifier decision before fusion and remove faulty classifiers based on behaviours and sensors that can be removed to improve classification accuracy.

4.1.3. Hidden Markov Model

HMM is statistical and embedded stochastic process for modelling time series and signal data in human activity recognition due to its ability to capture temporal correlation in observed data distributions [37,193]. The model is made up of observable and hidden states that represent sample data and class label in this case human activity details. The connection between the states form joint probability distribution over the observable state [193]. Building multiple classifier system for human activity recognition using Hidden Markov model were recently proposed [270,273,283]. Kim et al. [283] evaluated Hidden Markov model ensemble (HMME) that combine multiple decisions of Hidden Markov model classifiers using Decision template for human activity recognition. The ensemble algorithms help to solve the problem of intra-class variability and inter-class similarity by integrating probability of multiple decisions with respect to an observation sequence. The multiple templates were developed by grouping the training sample and the final result as the average of all the decision templates.

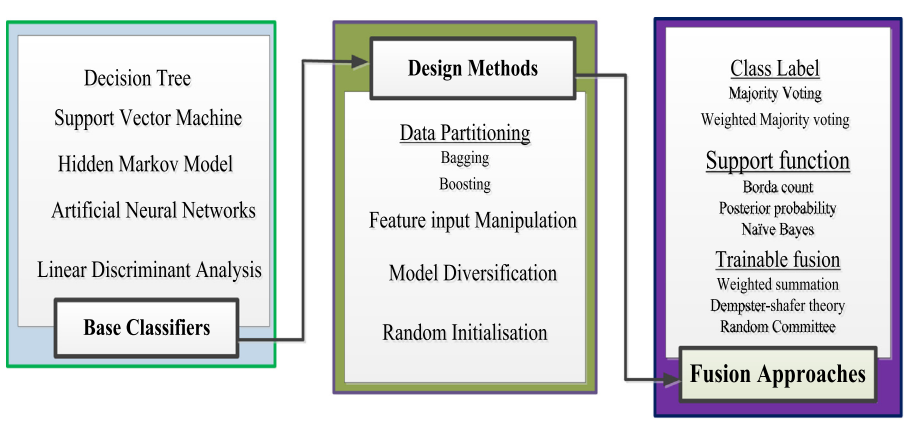

Fig. 6. Multiple classifier system building process for human activity recognition.

4.1.4. Artificial neural network

The biologically inspired information processing network of artificial neuron composed of collection of interconnected neurons grouped in layers, which are capable of automatic learning based on experience and approximating non-linear combinations of features for pattern recognition [107]. Artificial Neural network inputs are propagated through multiple layers to compute the output of the neuron using activation function and weights and then adjusted through back-propagation to minimize error rate [50]. Artificial neural network can be combined with other classifiers to build heterogeneous ensemble algorithm for human activity recognition [270,284]. The classifier provides efficient and robust methods to automatically learn feature representation from complex and uncertain sensor data [107]. However, artificial network require large training examples, difficult to derive explicit model and can stuck at local optima [44]. Recently, ensemble learning algorithms based on deep learning algorithm [44,241,252,285] were recently proposed for human activity recognition and elderly health monitoring with robust performance accuracy.

4.1.5. Linear Discriminant classifier

LDC is a robust supervised classification algorithm that project high dimensional data into one dimensional space to minimize the distance between two classes [286]. Linear Discriminant classifier is combined with other heterogeneous classifier through stacking to form multiple classifier system for human activity recognition [277,287].

4.2. Multiple classifier systems design methods

The main theme of multiple classifier system is how to ensure diversity of opinion of different classifiers and increase robustness and accuracy of the recognition system [43,288]. Diversity of opinions of heterogeneous or homogenous classifiers can be achieved through output variance, pairwise measure entropy, manipulation of individual classifier input data, output or feature vectors differences [266], where base classifiers are trained on different partition of the training sample input space, feature set or individual classifier [288]. Many methods have been proposed to design classifier systems. These include data partitioning, input feature manipulation, model diversification and injecting randomness into the training data [265,288]. There methods have been implemented in the context of human activity recognition to increase performance and reduce uncertainty. Here, we reviewed these methods and some of the important techniques proposed in literatures for human activity recognition with their strengths and weaknesses presented in Table 5.

4.2.1. Data partitioning

In data partitioning, multiple classifiers systems is constructed by training the classifiers with different subsets of the training samples for several times to generate classifier with output variance and diversity. With data partitioning, multiple hypotheses can be generated with the base classifiers and only appropriate for unstable learning algorithms such as Decision trees, Neural Network and rule based learning [265]. Input data partitioning to generate ensemble algorithms can be classified into cross validated committee, bagging and boosting.

- *Cross validation scheme* is used to assess how the recognition system generalize to new and unseen situations. Cross validation typically leave one disjointed subset of the training sample. The training sample maybe divided into different fold cross validation schemes. In human activity recognition, an number of such scheme have been proposed in literatures ranging from leave one out cross validation, 10-fold cross validation, leave one subject out cross validation and leave one sensor out cross validation [12,31,293] for testing the performance of particular user activity details. These cross-validation methods allow the training data to be repeated number of times to ensure generalization across datasets.
- *Bagging* [294], each classifier is trained with randomly selected number of subset of the training sample without replacement. Bagging, also called *bootstrap replicate* of the original training set and contain more than average percentage of the training examples with some examples appearing many times [288]. Ensemble bagging are applied in human activity recognition to generate diverse decision that are combined with weighted voting [128,277,281,283,289]. Guan and Ploetz [241] proposed epoch bagging method that uses probabilistic selection of the subset of the original data for mini-batch based training of Long Short Term Memory Network(LSTM) with stochastic gradient descent learning. They noted that the techniques will enhance generalization and robustness of LSTM for human activity recognition. Jurek et al. [42] examined the cluster based ensemble methods for recognition of concurrent and interleaved activities whereby activities are modelled as cluster built on the training set with different subset of the original dataset. Presentation of new instance is based on the closest cluster from each collection and final prediction is based on the class label instances that belong to the selected clusters. However, the algorithm has high computation complexity and can only work in the presence of small instance or training samples.
- *Boosting* is another alternative method for constructing multiple classifier with data partitioning [295]. Boosting generate classifier diversity through targeted reweighting of training sample data to be considered into the ensemble training [241]. The data distribution dynamically changed the training sample based on the classifier performance. Through iterative approach, Boosting focus on the training with higher error rate or hard to classify [41]. Recently,

Table 5
Multiple classifier system design methods.

References	Methods	Strengths	Weaknesses
[31,102,241,287,289,290]	Data partitioning	Build multiple hypotheses to achieve high output diversity and robustness. Also, data partitioning helps to reduce data uncertainty and sensitivity	Difficult to generate fully independent individual base classifiers or to be applied in high dimensional datasets
[108,272,278]	Input feature manipulation.	Ensure high dependences of base classifiers and faster due to reduced size of the input space	Input feature manipulation increases the chances of including irrelevant and redundant feature sets thereby increasing the computation time. Furthermore, the method suffers from fragmentation problem especially with fewer instances (decision tree method) leading to poor performance
[195,270,291,292]	Model Diversifications	Achieve high diversity, increase reliabilities of predictions and output generalization using biases and variance of each base classifier. The methods enable accurate detection of fine and coarse grain activities	It is challenging to choose the base classifier to form the multiple classifier system
[44,45]	Random initialization	Ability to provide diversity for nonlinear space distribution in activity recognition dataset	Increased computation complexity of the network due to high parameters updates

boosting methods have been proposed to construct ensemble algorithms for physical health monitoring [19,38,102,269,287,290]. Other boosting algorithm such as Adaboost [287] and Gradient Boosting [290] were evaluated in human activity recognition in the context of their ability to solve the problem of redundant feature vectors, low variability, biases and gait style differences by iterative fusion of weak learner to construct strong model. Adaboost construct number of hypotheses and assign weights based on error rates, assigning higher weights to hypothesis with low error rate and vice versa. Then, the final prediction is based on weighted summation of all the hypotheses. Alternatively, Gradient boosting build ensemble of decision tree based on optimization of loss functions and it is effective for feature selection [290].

4.2.2. Input feature manipulation

Input feature manipulation is one of the most widely deployed methods of constructing ensemble algorithm where input features extracted from sensor data are trained with multiple classifiers. Random forest [296] is very prominent method for input feature manipulation for multiple classifier system design. Random forest is a classifier consisting of collection of tree-structured classifier where the independent and identically distributed random vectors, and each tree casts a unit vote for the most popular class at training examples [296]. Recent years have seen researches demonstrating the implementation of random forest based ensemble learning by manipulating the input feature for human activity recognition [272,273,278,279,282,289,290]. Mo et al. [281] proposed multiple classifiers based ensemble by combining number of weak learners trained on feature extracted from sensor placed on different part of the body. The decisions of each sensor were combined with weighted majority voting. To effectively maximize information gain, training feature are randomly sampled with uniform sampling of the feature threshold at each split node. Then, each splitting node store decision function associated with the probability of predicting the classes. The final decision is made as aggregation of all the decision of the weak learners. One important advantage of random forest is its high generalization ability using randomization of the feature vector at the splitting nodes [108,272]. In similar research, Diep et al. [278] developed feature motion primitive forest that utilize visual code book to implement randomized decision tree on local feature vectors. Then cluster based techniques is utilized to group similar feature vector belonging to the same decision tree leaf with higher probability. However, ensemble design using feature manipulation only perform effectively with highly redundant features leading to high computation time [265] and sometimes used for feature selection process .

4.2.3. Model diversification

This involve construction of multiple classifiers using heterogeneous individual classifier by taking advantages of the biases of each classifier model [266]. Model diversification also called *stacking* is a Meta learning approach and generally fuse models that were built using different algorithms on same training sample [42]. The first step at building successful classifier with model diversification is the selection of the base classifiers. The decision of the meta-learning algorithms is collection of the all the decision made by each based classifier on the training sample [42]. The use of multiple classifier systems facilitate the implementation of unified model for multiple tasks from multimodal data, capture uncertainty and model temporal dependencies for complex activities [292]. Moreover, combination of multiple classifier offer complementary information that can be exploited through majority voting or average probabilities fusion to improve accuracy, robustness and efficiency of physical activity monitoring algorithm [88,103,195,291,297] and further detect coarse grain and fine grain activities [298]. In recent studies, Fatima et al. [270,284] noted that combination of multiple classifier provide effective methods to enhance the reliabilities of the prediction of each classifier due to variations in activities, sensors, environmental setting and habitants characteristics. They propose Genetic algorithm (GA) to optimize the measurement level outputs of each classifier in terms of weighted feature vectors before final decision of activity labels. The underlying objectives of the method are to reduce computation complexity and high dimensional variances that increase the algorithm search space [270].

4.2.4. Random initializations

Multiple classifiers can also be designed by injecting randomness into the training samples to achieve diversity [45,265] which is popular with ensemble of neural network models. The techniques involve varying the initialization weights of the networks and biases of the hidden and output layers during training [44]. Zappi et al. [299] observed that using separate initialization parameters combined with majority voting help to solve the problem of sensor degradation, interconnection failure and jitter in senor placement and orientation in activity detection and classification.

4.3. Fusion strategies

Fusion strategies is essential part of building successful multiple classifier systems. Fusers combine the various output generated by the base classifiers from the ensemble algorithms to give final decision. As noted by Ijjina and Krishna Mohan [45], fusion could be based on maximum values across the classifier output or posterior probability of individual classifier. There are different methods to fuse classifier ensemble and can be considered in terms of whether it is fused at the class label, combine using decision scores or part of the algorithms learning process [41,45]. These methods strengths and limitations are presented in Table 6 below.

4.3.1. Class label

Class label fusion method use classifiers votes and agree to certain degrees to make final decision. The popular fusion strategies include majority voting and weighted majority voting. In *majority voting*, the classifiers' unanimous, simple or majority votes are used to decide the final prediction [42,277,283,299,300]. Bahrepour et al. [109] proposed reputation voting that use consensus to decide the final prediction. Alternatively, *weighted majority* voting assign positive weights to the classifier in the ensemble algorithms based on performances and the

Table 6
Multiple classifier system combination methods.

References	Fusion methods	Strengths	Weaknesses
[42,109,283,301]	Class label	Very popular method for multiple classifier combination and provide accurate representation of label outputs	May not be suitable for practical applications and does not guarantee to do better than single classifier
[74,241,271,276]	Supported function fusion	Efficient and accurate method for multiple classifiers combination	Impose hard condition on base classifiers for combination which is difficult to implement for practical applications. May only be applied to mutually independent classifiers
[44,67,282,289]	Trainable fusion	The use of optimization methods improve accuracy and reduce decisions uncertainties	Trainable fusion may produce outputs that are not entirely distinguishable and cannot represent correct outputs combinations

Table 7
Comparative analysis of recent works that implement data fusion, feature fusion and multiple classifier systems.

Study	Data fusion								Feature fusion			Multiple classifier systems						
	Fusion methods						Modalities		Handcrafted features		Deep learning	Design methods				Fusion methods		
	Weighted Average	Kalman Filtering	Dempster–Shafer	Graph based	Epidemic Routing	Deep Canonical correlated	Inertial Sensors	Multimodal Sensors	Time and Frequency domain	Hilbert Huang features	Deep learning fusion	Data partitioning	Input feature manipulations	Model Diversification	Random Initialization	Class Label	Support function	Trainable Fusion
[56]	✓	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
[46]	✓	–	–	–	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–
[14]	–	✓-		–	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
[68]	–	–	✓	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–
[70]	–	–	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–	–	–
[71]	–	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
[72]	–	–	–	–	–	✓	–	–	–	–	–	✓	✓	–	–	–	–	✓
[37]	–	–	–	–	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–
[58]	–	✓	–	–	–	–	✓	✓	✓	–	–	–	–	–	–	–	–	–
[297]	–	–	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–
[104]	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
[112]	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
[111]	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–	–
[4]	–	–	–	–	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–
[31]	–	–	–	–	–	–	✓	–	–	–	✓	✓	–	–	–	–	–	–
[119]	–	–	–	–	–	–	✓	–	✓	–	–	–	–	–	–	–	–	–
[126]	–	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–
[29]	–	–	–	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
[40]	–	–	–	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–
[261]	–	–	–	–	–	–	✓	–	–	–	✓	–	–	–	–	–	–	–
[242]	–	–	–	–	–	–	✓	–	–	–	✓	–	–	–	–	–	–	–
[252]	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	✓	–	–	✓
[241]	–	–	–	–	–	–	✓	–	–		✓	✓					✓	
[308]	–	–	–	–	–	–	✓	–	–	–	✓	–	–	–	–	–	–	–
[21]	–	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–
[309]	–	–	–	–	–	–	✓	✓	–	–	–	–	–	–	–	–	–	–
[67]	–	–	✓	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	✓
[147]	–	–	–	–	–	–	–	✓	–	–	–	–	–	–	–	–	–	–
[277]	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	✓	–	–
[290]	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–	✓	–
[278]	–	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–	–
[282]	–	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–	✓
[103]	–	–	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–
[279]	–	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	✓	–	–
[276]	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	✓	–
[74]	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	✓	✓
[153]	–	–	–	–	–	–	–	✓	✓	–	–	–	–	–	–	–	–	–
[118]	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	–	–	–	–
[44]	–	–	–	–	–	–	–	–	–	–	–	✓	–	–	✓	–	–	✓

classifier with the highest weight is taken as the final prediction [19,270,273,279,281,284,301]. Chowdhury et al. [302] proposed posterior adapted class label fusion strategy to combine accelerometer sensor data attached at different positions of the body. The propose method calculate class weights for each models and then adjust these weight based on score functions using posterior probability of the predicted class label. The class label with the highest score is selected as final prediction.

4.3.2. Support function fusion

Support function fusion strategies provide scores for the decision taken by individual classifier computed as the estimated likelihood, posterior probabilities or neural network outputs [266]. The method include *Borda count* that use scores and ranking of each base classifier [195] or *posterior probabilities* produced through probabilistic model within the classifiers [34,74,88,108,276,290]. There are many other works that use *mean aggregation* [241], *Naïve Bayes and Behaviour Knowledge space* as combination approaches [291,299,303]. In a related method, Tripathi et al. [271] evaluated fuzzy decision rule ensemble algorithm that use simple combination rule for adaptive based human activity recognition where new classifier is generated as batch of new activities.

4.3.3. Trainable fusion method

Trainable fusion strategies consider the weights used for fusion as part of the learning process [45] and use optimization strategies to reduce computation cost and improve activity detection accuracy [270,304]. Trainable fusion includes *weighted summation* of all the hypotheses where hypothesis with least error rate is given higher weight [44,74,102,272,287] and *Dempster–Shafer theory* to solve the problem of uncertainty in decision making [67,282].

Recently, methods using *localized template* with decision profile [128,283] and *Random committee* [289] were proposed to combine multiple classifiers in human activity recognition.

5. Open research directions

Integration of multiple heterogeneous and homogeneous data modalities, features and classifier systems to increase reliabilities, robustness and performance accuracy of human activity recognition have dominated research landscape in recent years. Quite a number of studies, techniques, approaches and sensor modalities have been implemented. In data fusion, strategies such as weighted average and least square method, Kalman filtering and its variants, epidemic routing, graph based theory and deep canonical correlated analysis were proposed to fuse heterogeneous sensor. Combinations of sensor modalities enable different activity recognition scenario such as health status monitoring, fall detection, stress identification, energy expenditure estimation, objects interaction in smart environments and chronic disease management. Feature fusions provide means to combine multiple features vectors of different types to achieve spatial-temporal association which is very important in human activity recognition due to their hierarchical natures. In feature fusion, machine learning algorithms play important roles, combining heterogeneous features extracted from sensor data into multidimensional feature vectors. Furthermore, achieving diversity and robust features for human activity recognition performance generalization across heterogeneous domains require fusion of multiple features either in manually engineered domains or deep learning feature representation [49,305,306]. Another way of increasing robustness and generalization of human activity recognition systems is through multiple classifier system methods that combine opinion diversity of heterogeneous or homogeneous classifiers training through model diversity, different weight initializations and data partitioning. Then, the classifiers are combined through fusion strategies to increase performance accuracy. Different ensemble classifier design and fusion methods have been proposed in literature for human activity recognition. The prominent ensemble design methods are bagging, boosting, input feature manipulations and random initializations. After the design of the ensemble classifiers, they are combined through majority voting, weighted majority voting, Dempster–Shafer algorithms and posterior probabilities [266]. In Table 7, comparative analysis of recent works that implement data fusion, feature fusion and multiple classifier systems for human activity detection and monitoring are analysed. Due to high volume of studies reviewed, only recent implementations were presented in the table, to visualize the importance of each discussed methods.

However, the current research activities in data fusion and multiple classifier system have led to more challenging research directions that can be further pursued. These include:

- *Collection of Large Multimodal Datasets for Algorithm Evaluation:* The use of mobile and wearable devices to collect large dataset of multiple modalities for human activity recognition is challenging. The collection and annotation process are tedious to scanning through the raw data to manually label the datasets. In most cases, the experiments to collect large datasets require extensive infrastructural setups that are time consuming and high number of subjects to perform. Many researchers rely on collection of their own datasets that cannot be generalized to new applications and few benchmark datasets such as MHEALTH, PAMAP2, OPPORTUNITY AND WSDM data are not large enough to develop effective human activity detection and health monitoring systems. Furthermore, these data contain limited number of multimodal and multiview instances to accurately and comprehensively model effective human activity detection and health monitoring. Therefore, there is a need for collection of large sensor data of multiple modalities for human activity detection. Moreover, collection of large multimodal dataset will enable shift from atomic activities to interaction activities and increase the generalization of the learning algorithms. Collection of large multimodal datasets can be collected leverage either Internet of Things (IoT) in the smart homes or crowdsourcing. With crowdsourcing, large datasets can be collected through smart home for elderly care and monitoring, transportation mode based location information and other Internet of things or context-aware applications.
- *Mobile Cloud and Cyber physical system Implementation:* Development of cloud based activity as a service and cyber-physical to support multiple and community based human activity recognition and health status monitoring. The current human activity detection and health monitoring provide less interoperability, scalability and difficult to sustain for comprehensive assisted living and health monitoring. Therefore, Implementation of cyber-physical and cloud based activity recognition will enable integration of wide range of multimodal sensors for automatic data collections, processing and development of community based applications for human activity recognition. Furthermore, integration of human activity recognition with IoT-based healthcare will support decentralization and provide heterogeneous and efficient health monitoring [2]. Despite the research going on in this area, we envized higher improvement to ensure efficient health monitoring by fusion of diverse multimodal sensor data.
- *Computationally efficient development of deep learning fusion for human activity recognition on-board smartphones and wearable devices:* Deep learning implementation on-board smartphone and wearable devices is challenging due to memory constraint and high number of parameters update in deep learning. Hyper-parameter update leads to increase in computation time and this is not suitable for less computationally intensive devices such as mobile phone or other wearable sensors. On-board developments of deep learning algorithms will remove the need for server based data transmission and therefore reduce computational time and ensure efficient real time prediction of activity details. This makes the development scalable,

and ensure users' privacy, since the sensors data would be stored and analysed locally on the device. Although, there are recent attempt to implement on-board smartphone and watches [213,232] for single deep learning model using Convolutional Neural Networks and Restricted Boltzmann machine, the training was done offline using CPU and then exported to mobile or wearable devices for activity classification. However, the approach could be improved and extended to fusion strategies using data compression, GPU-based smartphone implementation or wearable devices and mobile cloud computing platforms to reduce training time and memory usage.

- *Improved decision fusions for human activity recognition:* In human activity detection health monitoring, decision fusion strategies are important to improve generalization and diversities. Fusion of different features and opinion made by different classifiers further enable wider applications and understanding of performed activities. In case of deep learning algorithms, fusion can be conducted through combination of heterogeneous, homogeneous architectures or fusion with handcrafted features. However, providing effective fusion strategies with reduced computation complexity is still challenging. Therefore, important research direction include design and evaluation of hyper-parameters tuning and fusion of classifiers opinion through boosting approaches such as extremely gradient boosting and evidential reasoning classifier combination.
- *Fusion of multiple sensors for context-aware activity recommendation*: Comprehensive and accurate activity detection and health monitoring require holistic sensor fusion and integration with context-aware frameworks for detection of complex and higher activity details. This is possible through leveraging different multimodal sensors such as mobile and wearable sensors, ambient sensors and mobile social network data. However, challenging issues such as, dealing with uncertainties in different data modalities, appropriate fusion methods, leading sensor modalities to provide both activity detection and context of user environments are still very challenging area to tackle [117]. Thus, major researches are required to provide context-aware activity detection and appropriate fusion approaches to ensure real-time activity detection and health monitoring.
- *Privacy and security*: Multimodal data fusion involves seamless collection of data from heterogeneous sources and subjects using different approaches for accurate activity detection. Then, these data are transmitted over cyber-physical systems and mobile cloud for analysis. However, information collected maybe targets of unauthorized persons especially for health data that require maximum levels of security and privacy. Criminal elements (such as, hacker) may cause harm to the systems by jamming the wireless signals exchange between medical devices resulting to unavailability of the devices or failure to deliver expected information for efficient data analysis, activity detection and health monitoring [307]. Therefore, encryption and authentication approaches to protect the sensors data from being transmitted to unauthorized users are required especially for data transmitted over cyber-physical systems.

6. Conclusion

Data fusion and multiple classifier systems are increasingly being implemented in health monitoring and human activity recognition to boost robustness and performance accuracy. In this review paper, comprehensive state of the art data fusion, feature fusion and decision fusion approaches are presented. Data fusion method such as weighted average, Kalman Filtering, Dempster–Shafer theory, Epidemic routing and Binary and Wait fusion, Graph based theory and Deep Canonical correlated fusions were identified as essential strategies that provide generalization, reliabilities and reduce uncertainty. Similarly, we outline data fusion along inertial sensor fusion and multimodal fusion. Inertial sensor fusion (accelerometer, gyroscopes and magnetometer) provide mechanism to estimate orientation and rotation of movement patterns, distinguish activity of similar pattern for inter-group activities and accurate posture identification to prevent falls in elderly citizens. On the other hand, multimodal data fusions are implemented for health monitoring, energy expenditure estimation, object interaction in smart environments and indoor localization.

Feature fusion strategies provide excellent means to combine heterogeneous sensor data using machine learning algorithms. The features extracted from different sensor modalities are combined using machine learning algorithms such as Support Vector Machine, Artificial Neural Networks, Decision Trees, and Hidden Markov Model etc. In addition, to reduce computation time and select optimal feature vectors, different feature selection methods have been proposed. These feature selections such as filter, wrapper and embedded base approaches were critically analysed. However, handcrafted features are time consuming and application dependents. Recently, deep learning algorithms such as Deep Boltzmann Machine, Autoencoder, Convolutional Neural Networks and Recurrent Neural Networks were proposed for automatic feature representation to reduce reliance on hand engineered features and the time spent in selecting appropriate feature sets. We reviewed different deep learning algorithm for human activity recognition, identified strength and weaknesses of these methods. Also, we present deep learning fusion algorithms recently presented in literature to increase robustness and generalization. Deep learning fusion facilitates hierarchical, translational invariant and temporal dependent features feature extraction from sensor data and reduce the source of instability.

Furthermore, multiple classifier systems are implemented in human activity recognition to reduce uncertainty and ambiguity by fusion of outputs generated by different classification models to achieve higher performance that is unlikely when such classifier is used in isolation. A number of design and fusion approaches have been proposed and, we provide these design methods and their implementation techniques.

To point out unresolved issues and directions of the research progress, we presented the open research challenges that require the attention of researchers. These include in area such as large data collection through crowdsourcing, cloud and cyber-physical support implementation to improve integration of multimodal sensor data require further considerations. In addition, computationally efficient deep learning development on mobile and wearable devices, decision fusion of heterogeneous architecture and classifier opinion, multimodal data fusion for context-aware detection, privacy and data security are other important areas that need further exploration.

References

[1] L. Cao, Y. Wang, B. Zhang, Q. Jin, A.V. Vasilakos, GCHAR: an efficient Group-based Context–aware human activity recognition on smartphone, J. Parallel Distrib. Comput. 118 (Part 1) (2017) 67–80.

[2] R. Gravina, C. Ma, P. Pace, G. Aloi, W. Russo, W. Li, G. Fortino, Cloud-based Activity-Service cyber–physical framework for human activity monitoring in mobility, Fut. Gen. Comput. Syst. 75 (2017) 158–171.

[3] M. Cornacchia, K. Ozcan, Y. Zheng, S. Velipasalar, A survey on activity detection and classification using wearable sensors, IEEE Sens. J. 17 (2017) 386–403.

[4] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J. Havinga, Complex human activity recognition using smartphone and wrist-worn motion sensors, Sens. (Basel, Switzerland) 16 (2016) 426.

[5] S. Mendes, J. Queiroz, P. Leitão, Data driven multi-agent m-health system to characterize the daily activities of elderly people, Proceedings of the Twelfth Iberian Conference on Information Systems and Technologies (CISTI), 2017, pp. 1–6.

[6] M. Ponti, P. Bet, C.L. Oliveira, P.C. Castro, Better than counting seconds: identifying fallers among healthy elderly using fusion of accelerometer features and dual-task Timed Up and Go, PLoS One 12 (2017) e0175559.

[7] M. Yu, A. Rhuma, S.M. Naqvi, L. Wang, J. Chambers, A posture recognition-based fall detection system for monitoring an elderly person in a smart home environment, IEEE Trans. Inf. Technol. Biomed. 16 (2012) 1274–1286.

[8] J. Wang, Y. Chen, S. Hao, X. Peng, L. Hu, Deep learning for sensor-based activity recognition: a survey, arXiv:1707.03502, (2017).

[9] E.P. Ijjina, K.M. Chalavadi, Human action recognition using genetic algorithms and convolutional neural networks, Pattern Recognit. 59 (2016) 199–212.

[10] R.M. Cichy, A. Khosla, D. Pantazis, A. Torralba, A. Oliva, Deep neural networks predict hierarchical spatio-temporal cortical dynamics of human visual object

recognition, arXiv:1601.02970, (2016).
[11] M.S. Hossain, Cloud-supported cyber–physical localization framework for patients monitoring, IEEE Syst. J. 11 (2017) 118–127.
[12] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J.M. Havinga, A survey of online activity recognition using mobile phones, Sensors 15 (2015) 2059–2085.
[13] D. Tao, Y. Wen, R. Hong, Multicolumn bidirectional long short-term memory for mobile devices-based human activity recognition, IEEE Internet Things J. 3 (2016) 1124–1134.
[14] S. Qiu, Z. Wang, H. Zhao, K. Qin, Z. Li, H. Hu, Inertial/magnetic sensors based pedestrian dead reckoning by means of multi-sensor fusion, Inf. Fusion 39 (2018) 108–119.
[15] Y. Sun, B. Wang, Indoor corner recognition from crowdsourced trajectories using smartphone sensors, Expert Syst. Appl. 82 (2017) 266–277.
[16] Y. Jia, X. Song, J. Zhou, L. Liu, L. Nie, D.S. Rosenblum, Fusing social networks with deep learning for volunteerism tendency prediction, Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, 2016.
[17] S. Savazzi, V. Rampa, F. Vicentini, M. Giussani, Device-free human sensing and localization in collaborative human–robot workspaces: a case study, IEEE Sens. J. 16 (2016) 1253–1264.
[18] C. Chen, R. Jafari, N. Kehtarnavaz, A survey of depth and inertial sensor fusion for human action recognition, Multimed. Tools Appl. 76 (2017) 4405–4425.
[19] O. Banos, M. Damas, H. Pomares, I. Rojas, Activity Recognition based on a multi-sensor meta-classifier, in: I. Rojas, G. Joya, J. Cabestany (Eds.), Advances in Computational Intelligence, 2013, pp. 208–215 Pt Ii.
[20] J. Yang, M.N. Nguyen, P.P. San, X. Li, S. Krishnaswamy, Deep convolutional neural networks on multichannel time series for human activity recognition, Proceedings of the IJCAI, 2015, pp. 3995–4001.
[21] T. Hur, J. Bang, D. Kim, O. Banos, S. Lee, Smartphone Location-independent physical activity recognition based on transportation natural vibration analysis, Sensors 17 (2017) 931.
[22] J. Morales, D. Akopian, Physical activity recognition by smartphones, a survey, Biocybernet. Biomed. Eng. 37 (3) (2017) 388–400.
[23] A. Bulling, U. Blanke, B. Schiele, A tutorial on human activity recognition using body-worn inertial sensors, ACM Computing Surveys (CSUR) 46 (2014) 33.
[24] I.M. Pires, N.M. Garcia, N. Pombo, F. Florez-Revuelta, From data acquisition to data fusion: a comprehensive review and a roadmap for the identification of activities of daily living using mobile devices, Sensors 16 (2016).
[25] G. Zhang, Z. Wang, L. Zhao, Y. Qi, J. Wang, Coal-rock recognition in top coal caving using bimodal deep learning and hilbert-huang transform, Shock Vib. 2017 (2017).
[26] S.-M. Lee, S.M. Yoon, H. Cho, Human activity recognition from accelerometer data using Convolutional Neural Network, in, Proceedings of the IEEE, pp. 131–134.
[27] D. Ravì, C. Wong, B. Lo, G.-Z. Yang, A deep learning approach to on-node sensor data analytics for mobile or wearable devices, IEEE J. Biomed. Health Inform. 21 (2017) 56–64.
[28] O. Banos, J.-M. Galvez, M. Damas, H. Pomares, I. Rojas, Window size impact in human activity recognition, Sensors 14 (2014) 6474.
[29] H.L. Xu, J.Y. Liu, H.B. Hu, Y. Zhang, Wearable sensor-based human activity recognition method with multi-features extracted from hilbert-huang transform, Sensors 16 (2016).
[30] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (2015) 436–444.
[31] F.J. Ordonez, D. Roggen, Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition, Sensors (Basel, Switzerland) 16 (2016).
[32] L. Atallah, B. Lo, R. King, G.Z. Yang, Sensor Positioning for activity recognition using wearable accelerometers, IEEE Trans. Biomed. Circuits Syst. 5 (2011) 320–329.
[33] I.P. Machado, A.L. Gomes, H. Gamboa, V. Paixdo, R.M. Costa, Human activity data discovery from triaxial accelerometer sensor: non-supervised learning sensitivity to feature extraction parametrization, Inf. Process. Manag. 51 (2015) 204–214.
[34] L. Gao, A.K. Bourke, J. Nelson, A system for activity recognition using multi-sensor fusion, Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011 2011, pp. 7869–7872.
[35] U. Maurer, A. Smailagic, D.P. Siewiorek, M. Deisher, Activity recognition and monitoring using multiple sensors on different body positions, Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks (BSN'06), 2006, pp. 4–116.
[36] Z. Chen, Q. Zhu, C.S. Yeng, L. Zhang, Robust human activity recognition using smartphone sensors via CT-PCA and online SVM, IEEE Trans. Ind. Inf. 13 (6) (2017) 3070–3080.
[37] C.A. Ronao, S.B. Cho, Recognizing human activities from smartphone sensors using hierarchical continuous hidden Markov models, Int. J. Distrib. Sens. Netw. 13 (2017).
[38] O. Banos, M. Damas, H. Pomares, I. Rojas, On the use of sensor fusion to reduce the impact of rotational and additive noise in human activity recognition, Sensors 12 (2012) 8039–8054.
[39] A. Abdelgawad, M. Bayoumi, Data Fusion in WSN, Resource-Aware Data Fusion Algorithms for Wireless Sensor Networks, Springer, 2012, pp. 17–35.
[40] Z.L. Wang, D.H. Wu, J.M. Chen, A. Ghoneim, M.A. Hossain, A Triaxial Accelerometer-based human activity recognition via EEMD-based features and game-theory-based feature selection, IEEE Sens. J. 16 (2016) 3198–3207.
[41] L.I. Kuncheva, Combining Pattern Classifiers: Methods and Algorithms, John Wiley & Sons, 2004.
[42] A. Jurek, C. Nugent, Y. Bi, S. Wu, Clustering-based ensemble learning for activity recognition in smart homes, Sensors (Basel, Switzerland) 14 (2014) 12285–12304.
[43] L.I. Kuncheva, C.J. Whitaker, Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy, Mach. Learn. 51 (2003) 181–207.
[44] I. Hwang, H.-M. Park, J.-H. Chang, Ensemble of deep neural networks using acoustic environment classification for statistical model-based voice activity detection, Comput. Speech Lang. 38 (2016) 1–12.
[45] E.P. Ijjina, C. Krishna Mohan, Hybrid deep neural network model for human action recognition, Appl. Soft. Comput. 46 (2016) 936–952.
[46] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, Y. Amirat, Physical human activity recognition using wearable sensors, Sensors 15 (2015) 31314–31338.
[47] L. Onofri, P. Soda, M. Pechenizkiy, G. Iannello, A survey on using domain and contextual knowledge for human activity recognition in video streams, Expert Syst. Appl. 63 (2016) 97–111.
[48] P. Turaga, R. Chellappa, V.S. Subrahmanian, O. Udrea, Machine recognition of human activities: a survey, IEEE Trans. Circuits Syst. Video Technol. 18 (2008) 1473–1488.
[49] R. Gravina, P. Alinia, H. Ghasemzadeh, G. Fortino, Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges, Inf. Fus. 35 (2017) 68–80.
[50] R.C. King, E. Villeneuve, R.J. White, R.S. Sherratt, W. Holderbaum, W.S. Harwin, Application of data fusion techniques and technologies for wearable health monitoring, Med. Eng. Phys. 42 (2017) 1–12.
[51] G. Sebestyen, I. Stoica, A. Hangan, Human activity recognition and monitoring for elderly people, Proceedings of the IEEE Twelfth International Conference on Intelligent Computer Communication and Processing (ICCP), 2016, pp. 341–347.
[52] R.C. Luo, C.C. Chang, C.C. Lai, Multisensor Fusion and integration: theories, applications, and its perspectives, IEEE Sens. J. 11 (2011) 3122–3138.
[53] S. Yao, S. Hu, Y. Zhao, A. Zhang, T. Abdelzaher, DeepSense: a unified deep learning framework for time-series mobile sensing data processing, Proceedings of the Twenty-Sixth International Conference on World Wide Web, International World Wide Web Conferences Steering Committee, Perth, Australia, 2017, pp. 351–360.
[54] R.C. Luo, M.G. Kay, A tutorial on multisensor integration and fusion, Proceedings of the IEEE, 1990, pp. 707–722.
[55] H. Lee, K. Park, B. Lee, J. Choi, R. Elmasri, Issues in data fusion for healthcare monitoring, ACM, 2008, p. 3.
[56] L. Song-Mi, Y. Sang Min, C. Heeryon, Human activity recognition from accelerometer data using Convolutional Neural Network, Proceedings of the IEEE International Conference on Big Data and Smart Computing (BigComp), 2017, pp. 131–134.
[57] R.E. Kalman, A new approach to linear filtering and prediction problems, J. Basic Eng. 82 (1960) 35–45.
[58] C. Tunca, N. Pehlivan, N. Ak, B. Arnrich, G. Salur, C. Ersoy, Inertial sensor-based robust gait analysis in non-hospital settings for neurological disorders, Sensors 17 (2017) 825.
[59] D. Roetenberg, P.J. Slycke, P.H. Veltink, Ambulatory position and orientation tracking fusing magnetic and inertial sensing, IEEE Trans. Biomed. Eng. 54 (2007) 883–890.
[60] R. Zhu, Z. Zhou, A real-time articulated human motion tracking using tri-axis inertial/magnetic sensors package, IEEE Trans. Neural Syst. Rehabil. Eng. 12 (2004) 295–302.
[61] A. Al-Jawad, A. Barlit, M. Romanovas, M. Traechtler, Y. Manoli, The use of an orientation Kalman filter for the static postural sway analysis, APCBEE Proc. 7 (2013) 93–102.
[62] J.I.Z. Chen, An algorithm of mobile sensors data fusion tracking for wireless sensor networks, Wirel. Person. Commun. 58 (2011) 197–214.
[63] V. Fox, J. Hightower, L. Liao, D. Schulz, G. Borriello, Bayesian filtering for location estimation, IEEE Perv. Comput 2 (2003) 24–33.
[64] W. Huadong, M. Siegel, R. Stiefelhagen, Y. Jie, Sensor fusion using Dempster–Shafer theory [for context-aware HCI], Proceedings of the Nineteenth IEEE Instrumentation and Measurement Technology Conference (IEEE Cat. No.00CH37276), 11 2002, pp. 7–12.
[65] K. Altun, B. Barshan, Human Activity recognition using inertial/magnetic sensor units, in: A.A. Salah, T. Gevers, N. Sebe, A. Vinciarelli (Eds.), Proceedings of the Human Behavior Understanding: First International Workshop, HBU 2010, Istanbul, Turkey, Springer, Berlin Heidelberg, 2010, pp. 38–51. August 22, 2010.
[66] C. Zhu, Q. Cheng, W. Sheng, Human activity recognition via motion and vision data fusion, Proceedings of the Conference Record of the Forty-Fourth Asilomar Conference on Signals, Systems and Computers, 2010, pp. 332–336.
[67] C.F. Crispim-Junior, Q. Ma, B. Fosty, R. Romdhane, F. Bremond, M. Thonnat, Combining multiple sensors for event detection of older people, Health Monitoring and Personalized Feedback Using Multimedia Data, Springer, 2015, pp. 179–194.
[68] F. Sebbak, F. Benhammadi, Majority-consensus fusion approach for elderly IoT-based healthcare applications, Ann. Telecommun. 72 (2017) 157–171.
[69] P.H. Tsai, Y.J. Lin, Y.Z. Ou, E.T.H. Chu, J.W.S. Liu, A framework for fusion of human sensor and physical sensor data, IEEE Trans. Syst. Man. Cybernet. 44 (2014) 1248–1261.
[70] D. Zhao, H.D. Ma, S.J. Tang, X.Y. Li, COUPON: a cooperative framework for building sensing maps in mobile opportunistic networks, IEEE Trans. Parallel Distrib. Syst. 26 (2015) 392–402.
[71] T. Phan, S. Kalasapur, A. Kunjithapatham, Sensor fusion of physical and social data using Web SocialSense on smartphone mobile browsers, Proceedings of the Eleventh IEEE Consumer Communications and Networking Conference (CCNC), IEEE, 2014, pp. 98–104.
[72] G. Chetty, M. White, Body sensor networks for human activity recognition, Proceedings of the Third International Conference on Signal Processing and Integrated Networks (SPIN), 2016, pp. 660–665.

[73] A.G. Wang, G.L. Chen, J. Yang, S.H. Zhao, C.Y. Chang, A comparative study on human activity recognition using inertial sensors in a smartphone, IEEE Sens. J. 16 (2016) 4566–4578.
[74] M.S. Zainudin, M.N. Sulaiman, N. Mustapha, T. Perumal, Activity recognition based on accelerometer sensor using combinational classifiers, Proceedings of the IEEE Conference on Open Systems (ICOS), IEEE, 2015, pp. 68–73.
[75] T. Tamura, Wearable accelerometer in clinical use, Proceedings of the IEEE-EMBS Twenty-Seventh Annual International Conference of the Engineering in Medicine and Biology Society, IEEE, 2006, pp. 7165–7166.
[76] M. Ermes, J. Pärkkä, J. Mäntyjärvi, I. Korhonen, Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions, IEEE Trans. Inf. Technol. Biomed. 12 (2008) 20–26.
[77] O. Banos, M.A. Toth, M. Damas, H. Pomares, I. Rojas, Dealing with the effects of sensor displacement in wearable activity recognition, Sensors 14 (2014) 9995–10023.
[78] Y. Cao, Y. Yang, W. Liu, E-FallD: a fall detection system using android-based smartphone, Proceedings of the Ninth International Conference on Fuzzy Systems and Knowledge Discovery, 2012, pp. 1509–1513.
[79] J. Mantyjarvi, J. Himberg, T. Seppanen, Recognizing human motion with multiple acceleration sensors, Proceedings of the IEEE International Conference on Systems, Man and Cybernetics. e-Systems and e-Man for Cybernetics in Cyberspace (Cat.No.01CH37236), 742 2001, pp. 747–752.
[80] D.M. Karantonis, M.R. Narayanan, M. Mathie, N.H. Lovell, B.G. Celler, Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring, IEEE Trans. Inf. Technol. Biomed. 10 (2006) 156–167.
[81] J. Surana, C.S. Hemalatha, V. Vaidehi, S.A. Palavesam, M.J.A. Khan, Adaptive learning based human activity and fall detection using fuzzy frequent pattern mining, Proceedings of the International Conference on Recent Trends in Information Technology (ICRTIT), 2013, pp. 744–749.
[82] W.-J. Yi, O. Sarkar, S. Mathavan, J. Saniie, Wearable sensor data fusion for remote health assessment and fall detection, Proceedings of the IEEE International Conference on Electro/Information Technology (EIT), 2014, pp. 303–307.
[83] K. Taylor, U.A. Abdulla, R.J.N. Helmer, J. Lee, I. Blanchonette, Activity classification with smart phones for sports activities, Proc. Eng. 13 (2011) 428–433.
[84] G.A. Koshmak, M. Linden, A. Loutfi, Evaluation of the android-based fall detection system with physiological data monitoring, Proceedings of the Thirty-Fifth Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 1164–1168.
[85] I. You, K.-K.R. Choo, C.-L. Ho, A smartphone-based wearable sensors for monitoring real-time physiological data, Comput. Electr. Eng. 65 (2017) 376–392.
[86] K.-C. Lan, W.-Y. Shih, An intelligent driver location system for smart parking, Expert Syst. Appl. 41 (2014) 2443–2456.
[87] Y. Chen, M. Guo, Z.L. Wang, IEEE, an improved algorithm for human activity recognition using wearable sensors, Proceedings of the Eighth International Conference on Advanced Computational Intelligence (ICACI), 2016, pp. 248–252.
[88] A. Bayat, M. Pomplun, D.A. Tran, A study on human activity recognition using accelerometer data from smartphones, in: E.M. Shakshuki (Ed.), Proceedings of the Ninth International Conference on Future Networks and Communications, Elsevier Science BV, Amsterdam, 2014, pp. 450–457.
[89] O. Banos, M. Damas, A. Guillen, L.J. Herrera, H. Pomares, I. Rojas, C. Villalonga, Multi-sensor fusion based on asymmetric decision weighting for robust activity recognition, Neural Process. Lett. 42 (2015) 5–26.
[90] M. Janidarmian, A.R. Fekr, K. Radecka, Z. Zilic, A Comprehensive analysis on wearable acceleration sensors in human activity recognition, Sensors 17 (2017) 26.
[91] W. Ugulino, D. Cardador, K. Vega, E. Velloso, R. Milidiú, H. Fuks, Wearable computing: accelerometers' data classification of body postures and movements, Adv. Artif. Intell. SBIA 2012 (2012) 52–61.
[92] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza, R. Zaccaria, Analysis of human behavior recognition algorithms based on acceleration data, Proceedings of the IEEE International Conference on Robotics and Automation, 2013, pp. 1602–1607.
[93] P. Casale, O. Pujol, P. Radeva, Personalization and user verification in wearable systems using biometric walking patterns, Pers. Ubiquit. Comput. 16 (2012) 563–580.
[94] L. Atallah, B. Lo, R. Ali, R. King, G.Z. Yang, Real-time activity classification using ambient and wearable sensors, IEEE T. Inf. Technol. Biomed. 13 (2009) 1031–1039.
[95] Y.E. Ustev, O.D. Incel, C. Ersoy, User, device and orientation independent human activity recognition on mobile phones: challenges and a proposal, Proceedings of the ACM conference on Pervasive and ubiquitous computing adjunct publication, ACM, Zurich, Switzerland, 2013, pp. 1427–1436.
[96] I. Mishkhal, Human activity recognition based on accelerometer and gyroscope sensors, Master's theses submitted to the Graduate School by Ball State University master's degree candidates in partial fulfillment of degree requirements, 2017, Page 52.
[97] H. Ghassemzadeh, E. Guenterberg, S. Ostadabbas, R. Jafari, A motion sequence fusion technique based on PCA for activity analysis in body sensor networks, Proceedings of the IEEE Annual International Conference of the Engineering in Medicine and Biology Society EMBC 2009, IEEE, 2009, pp. 3146–3149.
[98] Y. Kwon, K. Kang, C. Bae, Unsupervised learning for human activity recognition using smartphone sensors, Expert Syst. Appl. 41 (2014) 6067–6074.
[99] S. Dernbach, B. Das, N.C. Krishnan, B.L. Thomas, D.J. Cook, Simple and complex activity recognition through smart phones, Proceedings of the Eighth International Conference on Intelligent Environments, 2012, pp. 214–221.
[100] J.-H. Chiang, P.-C. Yang, H. Tu, Pattern analysis in daily physical activity data for personal health management, Pervas. Mob. Comput. 13 (2014) 13–25.
[101] C. Zhu, W. Sheng, Multi-sensor fusion for human daily activity recognition in robot-assisted living, Proceedings of the Fourth ACM/IEEE International Conference on Human-Robot Interaction (HRI), 2009, pp. 303–304.
[102] S. Spinsante, A. Angelici, J. Lundstrom, M. Espinilla, I. Cleland, C. Nugent, a mobile application for easy design and testing of algorithms to monitor physical activity in the workplace, Mob. Inf. Syst. 2016 (2016) 1–17.
[103] Y. Chen, Z.L. Wang, A hierarchical method for human concurrent activity recognition using miniature inertial sensors, Sens. Rev. 37 (2017) 101–109.
[104] B. Almaslukh, J. AlMuhtadi, A. Artoli, An effective deep autoencoder approach for online smartphone-based human activity recognition, Int. J. Comput. Sci. Netw. Secur. (IJCSNS) 17 (2017) 160.
[105] W. Jiang, Z. Yin, Human activity recognition using wearable sensors by deep convolutional neural networks, Proceedings of the Twenty-Third ACM international conference on Multimedia, ACM, Brisbane, Australia, 2015, pp. 1307–1310.
[106] C. Brüser, J.M. Kortelainen, S. Winter, M. Tenhunen, J. Pärkkä, S. Leonhardt, Improvement of force-sensor-based heart rate estimation using multichannel data fusion, IEEE J. Biomed. Health Inf. 19 (2015) 227–235.
[107] K. Davis, E. Owusu, V. Bastani, L. Marcenaro, J. Hu, C. Regazzoni, L. Feijs, Activity recognition based on inertial sensors for ambient assisted living, Proceedings of the Nineteenth International Conference on Information Fusion (FUSION), 2016, pp. 371–378.
[108] S. Ghose, J. Mitra, M. Karunanithi, J. Dowling, Human activity recognition from smart-phone sensor data using a multi-class ensemble learning in home monitoring, Stud. Health Technol. Inform. 214 (2015) 62–67.
[109] M. Bahrepour, N. Meratnia, Z. Taghikhaki, P.J. Havinga, Sensor fusion-based activity recognition for Parkinson patients, InTech (2011).
[110] M. Berenguer, M.-J. Bouzid, A. Makni, G. Lefebvre, N. Noury, Evolution of activities of daily living using inertia measurements: the lunch and dinner activities, J. Int. Soc. Telemed. eHealth 5 (2017) 10–11.
[111] L. Schwickert, R. Boos, J. Klenk, A. Bourke, C. Becker, W. Zijlstra, Inertial sensor based analysis of lie-to-stand transfers in younger and older adults, Sensors 16 (2016) 1277.
[112] J.K. Lee, S.N. Robinovitch, E.J. Park, Inertial sensing-based pre-impact detection of falls involving near-fall scenarios, IEEE Trans. Neural Syst. Rehabil. Eng. 23 (2015) 258–266.
[113] Y. He, Y. Li, Physical activity recognition utilizing the built-in kinematic sensors of a smartphone, Int. J. Distrib. Sens. Netw. 9 (2013) 481580.
[114] O. Salah, A.A. Ramadan, S. Sessa, A.A. Ismail, M. Fujie, A. Takanishi, Anfis-based sensor fusion system of sit-to-stand for elderly people assistive device protocols, Int. J. Autom. Comput. 10 (2013) 405–413.
[115] G. Chetty, M. White, M. Singh, A. Mishra, IEEE, multimodal activity recognition based on automatic feature discovery, Proceedings of the International Conference on Computing for Sustainable Global Development (Indiacom), 2014, pp. 632–637.
[116] S. Saeedi, N. El-Sheimy, Activity recognition using fusion of low-cost sensors on a smartphone for mobile navigation application, Micromachines 6 (2015) 1100–1134.
[117] S. Saeedi, A. Moussa, N. El-Sheimy, Context-aware personal navigation using embedded sensor fusion in smartphones, Sensors 14 (2014) 5742–5767.
[118] M. Shoaib, S. Bosch, H. Scholten, P.J. Havinga, O.D. Incel, Towards detection of bad habits by fusing smartphone and smartwatch sensors, Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), IEEE, 2015, pp. 591–596.
[119] J. Zhu, R. San-Segundo, J.M. Pardo, Feature extraction for robust physical activity recognition, Hum. Centric Comput. Inf. Sci. 7 (2017) 16.
[120] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, I. Korhonen, Activity classification using realistic data from wearable sensors, IEEE T. Inf. Technol. Biomed. 10 (2006) 119–128.
[121] M. Li, V. Rozgica, G. Thatte, S. Lee, A. Emken, M. Annavaram, U. Mitra, D. Spruijt-Metz, S. Narayanan, Multimodal physical activity recognition by fusing temporal and cepstral information, IEEE Trans. Neural Syst. Rehabil. Eng. 18 (2010) 369–380.
[122] E.M. Tapia, S.S. Intille, W. Haskell, K. Larson, J. Wright, A. King, R. Friedman, Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor, Proceedings of the Eleventh IEEE International Symposium on Wearable Computers, 2007, pp. 37–40.
[123] S.H. Roy, M.S. Cheng, S.S. Chang, J. Moore, G. De Luca, S.H. Nawab, C.J. De Luca, A combined sEMG and accelerometer system for monitoring functional activity in stroke, IEEE Trans. Neural Syst. and Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc. 17 (2009) 585–594.
[124] C.-W. Lin, Y.-T.C. Yang, J.-S. Wang, Y.-C. Yang, A wearable sensor module with a neural-network-based activity classification algorithm for daily energy expenditure estimation, IEEE T. Inf. Technol. Biomed. 16 (2012) 991–998.
[125] T. Fujimoto, H. Nakajima, N. Tsuchiya, H. Marukawa, K. Kuramoto, S. Kobashi, Y. Hata, Wearable human activity recognition by electrocardiograph and accelerometer, Proceedings of the IEEE Forty-Third International Symposium on Multiple-Valued Logic, 2013, pp. 12–17.
[126] E. Zdravevski, P. Lameski, V. Trajkovik, A. Kulakov, I. Chorbev, R. Goleva, N. Pombo, N. Garcia, Improving activity recognition accuracy in ambient-assisted living systems by automated feature engineering, IEEE Access 5 (2017) 5262–5280.
[127] R. Jia, B. Liu, Human daily activity recognition by fusing accelerometer and multi-lead ECG data, Proceedings of the IEEE International Conference on Signal Processing, Communication and Computing (ICSPCC 2013), 2013, pp. 1–4.

[128] J.-K. Min, S.-B. Cho, Activity recognition based on wearable sensors using selection/fusion hybrid ensemble, Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC), IEEE, 2011, pp. 1319–1324.
[129] Ó.D. Lara, A.J. Pérez, M.A. Labrador, J.D. Posada, Centinela: a human activity recognition system based on acceleration and vital sign data, Pervas. Mob. Comput. 8 (2012) 717–729.
[130] H. Martín, A.M. Bernardos, P. Tarrío, J.R. Casar, Enhancing activity recognition by fusing inertial and biometric information, Proceedings of the IEEE, 2011, pp. 1–8.
[131] Y. Nam, J.W. Park, Child activity recognition based on cooperative fusion model of a triaxial accelerometer and a barometric pressure sensor, IEEE J. Biomed. Health Inf. 17 (2013) 420–426.
[132] J. Iglesias, J. Cano, A.M. Bernardos, J.R. Casar, A ubiquitous activity-monitor to prevent sedentariness, Proceedings of the IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), IEEE, 2011, pp. 319–321.
[133] D. Riboni, C. Bettini, COSAR: hybrid reasoning for context-aware activity recognition, Pers. Ubiquit. Comput. 15 (2011) 271–289.
[134] Z.B. Xiao, Y. Wang, K. Fu, F. Wu, Identifying Different transportation modes from trajectory data using tree-based ensemble classifiers, ISPRS Int. J. Geo Inf. (2017) 6.
[135] S. Chernbumroong, S. Cang, H. Yu, A practical multi-sensor activity recognition system for home-based care, Decis. Support Syst. 66 (2014) 61–70.
[136] A. Fleury, M. Vacher, N. Noury, SVM-based multimodal classification of activities of daily living in health smart homes: sensors, algorithms, and first experimental results, IEEE Trans. Inf. Technol. Biomed. 14 (2010) 274–283.
[137] C. Tunca, H. Alemdar, H. Ertan, O.D. Incel, C. Ersoy, Multimodal wireless sensor network-based ambient assisted living in real homes with multiple residents, Sensors 14 (2014) 9692–9719.
[138] D. De, P. Bharti, S.K. Das, S. Chellappan, Multimodal wearable sensing for fine-grained activity recognition in healthcare, IEEE Internet Comput. 19 (2015) 26–35.
[139] S. Chernbumroong, S. Cang, A. Atkins, H. Yu, Elderly activities recognition and classification for applications in assisted living, Expert Syst. Appl. 40 (2013) 1662–1674.
[140] C. Bellos, A. Papadopoulos, R. Rosso, D.I. Fotiadis, Heterogeneous data fusion and intelligent techniques embedded in a mobile application for real-time chronic disease management, Proceedings of the IEEE, 2011, pp. 8303–8306.
[141] J. Gong, L. Cui, K. Xiao, R. Wang, MPD-Model: a distributed multipreference-driven data fusion model and its application in a WSNs-based healthcare monitoring system, Int. J. Distrib. Sens. Netw. 8 (2012) 602358.
[142] P. van de Ven, A. Bourke, C. Tavares, R. Feld, J. Nelson, A. Rocha, G.O. Laighin, Integration of a suite of sensors in a wireless health sensor platform, Proceedings of the IEEE, 2009, pp. 1678–1683.
[143] A.M. Khattak, Z. Pervez, S. Lee, Y.K. Lee, Intelligent Healthcare service provisioning using ontology with low-level sensory data, KSII Trans. Internet Inf. Syst. 5 (2011) 2016–2034.
[144] B.C. Yuan, J. Herbert, Fuzzy CARA – a fuzzy-based context reasoning system for pervasive healthcare, Proc. Comput. Sci. 10 (2012) 357–365.
[145] A.M. Khan, A. Tufail, A.M. Khattak, T.H. Laine, Activity recognition on smartphones via sensor-fusion and KDA-based SVMs, Int. J. Distrib. Sens. Netw. (2014) 14.
[146] B.J. Chen, E.H. Zheng, Q.N. Wang, A locomotion intent prediction system based on multi-sensor fusion, Sensors 14 (2014) 12349–12369.
[147] K. Ozcan, S. Velipasalar, Wearable camera- and accelerometer-based fall detection on portable devices, IEEE Embedded Syst. Lett. 8 (2016) 6–9.
[148] K. Zhan, S. Faux, F. Ramos, Multi-scale conditional random fields for first-person activity recognition on elders and disabled patients, Pervas. Mob. Comput. 16 (2015) 251–267.
[149] H.H. Wu, E.D. Lemaire, N. Baddour, Change-of-state determination to recognize mobility activities using a BlackBerry smartphone, Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2011, pp. 5252–5255.
[150] A.R. Doherty, P. Kelly, J. Kerr, S. Marshall, M. Oliver, H. Badland, A. Hamilton, C. Foster, Using wearable cameras to categorise type and context of accelerometer-identified episodes of physical activity, Int. J. Behav. Nutr. Phys. Act. 10 (2013) 22.
[151] B. Delachaux, J. Rebetez, A. Perez-Uribe, H.F.S. Mejia, Indoor activity recognition by combining one-vs.-all neural network classifiers exploiting wearable and depth sensors, in: I. Rojas, G. Joya, J. Cabestany (Eds.), Advances in Computational Intelligence, Springer-Verlag, Berlin, 2013, pp. 216–223 Pt Ii.
[152] N. Wichit, Multisensor data fusion model for activity detection, Proceedings of the Twelfth International Conference on ICT and Knowledge Engineering (ICT and Knowledge Engineering), IEEE, 2014, pp. 54–59.
[153] O. Banos, C. Villalonga, J. Bang, T. Hur, D. Kang, S. Park, T. Huynh-The, V. Le-Ba, M.B. Amin, M.A. Razzaq, W.A. Khan, C.S. Hong, S. Lee, Human behavior analysis by means of multimodal context mining, Sensors (2016) 16.
[154] C. Chen, R. Jafari, N. Kehtarnavaz, Improving Human Action recognition using fusion of depth camera and inertial sensors, IEEE Trans. Hum. Mach. Syst. 45 (2015) 51–61.
[155] Z. Li, Z. Wei, W. Jia, M. Sun, Daily life event segmentation for lifestyle evaluation based on multi-sensor data recorded by a wearable device, Proceedings of the Thirty-Fifth Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 2858–2861.
[156] E.H. Spriggs, F.D.L. Torre, M. Hebert, Temporal segmentation and activity classification from first-person sensing, Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, 2009, pp. 17–24.
[157] J. Zhang, Y. Wu, Automatic sleep stage classification of single-channel EEG by using complex-valued convolutional neural network, Biomed. Eng. Biomed. Tech. (2017).
[158] A. Alberdi, A. Aztiria, A. Basarab, Towards an automatic early stress recognition system for office environments based on multimodal measurements: a review, J. Biomed. Inf. 59 (2016) 49–75.
[159] L. Zhang, X. Wu, D. Luo, Improving activity recognition with context information, Proceedings of the IEEE International Conference on Mechatronics and Automation (ICMA), 2015, pp. 1241–1246.
[160] X. Jia, K. Li, X. Li, A. Zhang, A novel semi-supervised deep learning framework for affective state recognition on eeg signals, Proceedings of the IEEE International Conference on Bioinformatics and Bioengineering (BIBE), IEEE, 2014, pp. 30–37.
[161] H. Xu, K.N. Plataniotis, EEG-based affect states classification using Deep Belief Networks, Proceedings of the IEEE Digital Media Industry and Academic Forum (DMIAF), 2016, pp. 148–153.
[162] Z.Y. Wu, X.Q. Ding, G.R. Zhang, A novel method for classification of ecg arrhythmias using deep belief networks, Int. J. Comput. Intell. Appl. (2016) 15.
[163] M. Längkvist, L. Karlsson, A. Loutfi, Sleep stage classification using unsupervised feature learning, Adv. Artif. Neural Syst. 2012 (2012) 5.
[164] B. Cinaz, B. Arnrich, R. La Marca, G. Tröster, Monitoring of mental workload levels during an everyday life office-work scenario, Pers. Ubiquit. Comput. 17 (2013) 229–239.
[165] K.N.V.P.S. Rajesh, R. Dhuli, Classification of imbalanced ECG beats using re-sampling techniques and AdaBoost ensemble classifier, Biomed. Signal Process. Control 41 (2018) 242–254.
[166] W. Lu, H. Hou, J. Chu, Feature fusion for imbalanced ECG data analysis, Biomed. Signal Process. Control 41 (2018) 152–160.
[167] T. Li, M. Zhou, Ecg classification using wavelet packet entropy and random forests, Entropy 18 (2016) 285.
[168] G.K. Verma, U.S. Tiwary, Multimodal fusion framework: a multiresolution approach for emotion classification and recognition from physiological signals, Neuroimage 102 (2014) 162–172.
[169] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J. Havinga, Complex human activity recognition using smartphone and wrist-worn motion sensors, Sensors 16 (2016) 426.
[170] H.L. Xu, Y. Chai, W.L. Lin, F. Jiang, S.H. Qi, An Activity recognition algorithm based on multi-feature fuzzy cluster, in: Y. Jia, J. Du, H. Li, W. Zhang (Eds.), Proceedings of the Chinese Intelligent Systems Conference, 2 2016, pp. 363–375.
[171] F.S. Ayachi, H.P. Nguyen, E.G.d. Brugiere, P. Boissy, C. Duval, The use of empirical mode decomposition-based algorithm and inertial measurement units to auto-detect daily living activities of healthy adults, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (2016) 1060–1070.
[172] O. Banos, J.M. Galvez, M. Damas, A. Guillen, L.J. Herrera, H. Pomares, I. Rojas, C. Villalonga, C.S. Hong, S. Lee, Multiwindow fusion for wearable activity recognition, in: I. Rojas, G. Joya, A. Catala (Eds.), Advances in Computational Intelligence, 2015, pp. 290–297 Pt Ii.
[173] H. Aly, M.A. Ismail, ubiMonitor: intelligent fusion of body-worn sensors for real-time human activity recognition, Proceedings of the Thirtieth Annual ACM Symposium on Applied Computing, I and II 2015, pp. 563–568.
[174] Y. Gu, F.J. Ren, J. Li, PAWS: passive human activity recognition based on wifi ambient signals, IEEE Internet Things J. 3 (2016) 796–805.
[175] C. Dobbins, R. Rawassizadeh, E. Momeni, Detecting physical activity within lifelogs towards preventing obesity and aiding ambient assisted living, Neurocomputing 230 (2017) 110–132.
[176] G. Chandrashekar, F. Sahin, A survey on feature selection methods, Comput. Electr. Eng. 40 (2014) 16–28.
[177] S. Fong, W. Song, K. Cho, R. Wong, K.K.L. Wong, Training classifiers with shadow features for sensor-based human activity recognition, Sensors (2017) 17.
[178] B.M.h. Abidine, L. Fergani, B. Fergani, M. Oussalah, The joint use of sequence features combination and modified weighted SVM for improving daily activity recognition, Pattern Anal. Appl. 21 (1) (2016) 119–138.
[179] T. Plötz, N.Y. Hammerla, P. Olivier, Feature learning for activity recognition in ubiquitous computing, Proceedings of the IJCAI Proceedings-International Joint Conference on Artificial Intelligence, 2011, p. 1729.
[180] I. Guyon, A. Elisseeff, An introduction to variable and feature selection, J. Mach. Learn. Res. 3 (2003) 1157–1182.
[181] A. Wang, N. An, J. Yang, G. Chen, L. Li, G. Alterovitz, Wrapper-based gene selection with Markov blanket, Comput. Biol. Med. 81 (2017) 11–23.
[182] S. Liu, R.X. Gao, D. John, J. Staudenmayer, P.S. Freedson, SVM-based multi-sensor fusion for free-living physical activity assessment, Proceedings of the Conference Proceedings on Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society, 2011 2011, pp. 3188–3191.
[183] N.A. Capela, E.D. Lemaire, N. Baddour, Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients, PLoS ONE 10 (2015) e0124414.
[184] H. Ghasemzadeh, N. Amini, R. Saeedi, M. Sarrafzadeh, Power-aware computing in wearable sensor networks: an optimal feature selection, IEEE Trans. Mob. Comput. 14 (2015) 800–812.
[185] L. Wei, S. Wan, J. Guo, K.K. Wong, A novel hierarchical selective ensemble classifier with bioinformatics application, Artif. Intell. Med. 83 (2017) 82–90.
[186] J. Li, S. Fong, R.K. Wong, R. Millham, K.K. Wong, Elitist binary wolf search algorithm for heuristic feature selection in high-dimensional bioinformatics datasets, Sci. Rep. 7 (2017) 4354.
[187] S. Althloothi, M.H. Mahoor, X. Zhang, R.M. Voyles, Human activity recognition

using multi-features and multiple kernel learning, Pattern Recognit. 47 (2014) 1800–1812.
[188] C. Shen, Y. Chen, G. Yang, On motion-sensor behavior analysis for human-activity recognition via smartphones, Proceedings of the IEEE International Conference on Identity, Security and Behavior Analysis (ISBA), 2016, pp. 1–6.
[189] Y. Nam, S. Rho, C. Lee, Physical activity recognition using multiple sensors embedded in a wearable device, ACM Trans. Embed. Comput. Syst. (TECS) 12 (2013) 26.
[190] F. Azhar, C.T. Li, Hierarchical relaxed partitioning system for activity recognition, IEEE Trans. Cybernet. 47 (2017) 784–795.
[191] M.T. Uddin, M.A. Uddiny, A guided random forest based feature selection approach for activity recognition, Proceedings of the International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), 2015, pp. 1–6.
[192] N. Najjar, S. Gupta, Better-than-the-best fusion algorithm with application in human activity recognition, SPIE Sensing Technology + Applications, International Society for Optics and Photonics, 2015, pp. 949805–949810.
[193] W. Li, Y. Xu, B. Tan, R.J. Piechocki, Passive wireless sensing for unsupervised human activity recognition in healthcare, Proceedings of the Thirteenth International Wireless Communications and Mobile Computing Conference (IWCMC), 2017, pp. 1528–1533.
[194] A. Grunerbl, A. Muaremi, V. Osmani, G. Bahle, S. Ohler, G. Troster, O. Mayora, C. Haring, P. Lukowicz, Smartphone-based recognition of states and state changes in bipolar disorder patients, IEEE J. Biomed. Health Inf. 19 (2015) 140–148.
[195] J.A. Ward, P. Lukowicz, G. Troster, T.E. Starner, Activity recognition of assembly tasks using body-worn microphones and accelerometers, IEEE Trans. Pattern Anal. Mach. Intell. 28 (2006) 1553–1567.
[196] Z. Wang, D. Wu, R. Gravina, G. Fortino, Y. Jiang, K. Tang, Kernel fusion based extreme learning machine for cross-location activity recognition, Inf. Fusion 37 (2017) 1–9.
[197] F. Sikder, D. Sarkar, Log-sum distance measures and its application to human-activity monitoring and recognition using data from motion sensors, IEEE Sens. J. 17 (2017) 4520–4533.
[198] L. Peng, L. Chen, X. Wu, H. Guo, G. Chen, Hierarchical complex activity representation and recognition using topic model and classifier level fusion, IEEE Trans. Biomed. Eng. (2016).
[199] S.W. Abeyruwan, D. Sarkar, F. Sikder, U. Visser, Semi-automatic extraction of training examples from sensor readings for fall detection and posture monitoring, IEEE Sens. J. 16 (2016) 5406–5415.
[200] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, M.S. Lew, Deep learning for visual understanding: a review, Neurocomputing 187 (2016) 27–48.
[201] D. Ravi, C. Wong, B. Lo, G.-Z. Yang, A deep learning approach to on-node sensor data analytics for mobile or wearable devices, IEEE J. Biomed. Health Inf. (2016).
[202] C.A. Ronao, S.-B. Cho, Human activity recognition with smartphone sensors using deep learning neural networks, Expert Syst. Appl. 59 (2016) 235–244.
[203] G.E. Hinton, S. Osindero, Y.-W. Teh, A fast learning algorithm for deep belief nets, Neural Comput. 18 (2006) 1527–1554.
[204] L. Deng, A tutorial survey of architectures, algorithms, and applications for deep learning, APSIPA Trans. Signal Inf. Process. 3 (2014) e2.
[205] G.E. Hinton, T.J. Sejnowski, Learning and releaming in Boltzmann machines, Parallel Distril. Process. (1986) 1.
[206] A. Fischer, C. Igel, Training restricted Boltzmann machines: An introduction, Pattern Recognit. 47 (2014) 25–39.
[207] K. Cho, T. Raiko, A.T. Ihler, Enhanced gradient and adaptive learning rate for training restricted Boltzmann machines, Proceedings of the Twenty-Eight International Conference on Machine Learning (ICML-11), 2011, pp. 105–112.
[208] V. Nair, G.E. Hinton, Rectified linear units improve restricted Boltzmann machines, Proceedings of the Twenty-Seventh International Conference on Machine Learning (ICML-10), 2010, pp. 807–814.
[209] G. Li, L. Deng, Y. Xu, C. Wen, W. Wang, J. Pei, L. Shi, Temperature based restricted Boltzmann machines, Sci. Rep. 6 (2016) 1–12.
[210] R. Salakhutdinov, H. Larochelle, Efficient learning of deep Boltzmann machines, Proceedings of the International Conference on Artificial Intelligence and Statistics, AISTATs, 2010, pp. 693–700.
[211] L. Younes, On the convergence of Markovian stochastic algorithms with rapidly decreasing ergodicity rates, Stochast. Int. J. Prob. Stochast. Process. 65 (1999) 177–228.
[212] M.A. Alsheikh, A. Selim, D. Niyato, L. Doyle, S. Lin, H.-P. Tan, Deep Activity Recognition Models with Triaxial Accelerometers, arXiv:1511.04664, (2015).
[213] S. Bhattacharya, N.D. Lane, From smart to deep: Robust activity recognition on smartwatches using deep learning, Proceedings of the IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), 2016, pp. 1–6.
[214] N.D. Lane, S. Bhattacharya, P. Georgiev, C. Forlivesi, F. Kawsar, Accelerating embedded deep learning using DeepX: demonstration abstract, Proceedings of the Fifteenth International Conference on Information Processing in Sensor Networks, IEEE Press, 2016, p. 61.
[215] L. Wang, Recognition of human activities using continuous autoencoders with wearable sensors, Sensors 16 (2016) 189.
[216] J. Zhang, S. Shan, M. Kan, X. Chen, Coarse-to-fine auto-encoder networks (CFAN) for real-time face alignment, Proceedings of the European Conference on Computer Vision, Springer, 2014, pp. 1–16.
[217] P. Vincent, H. Larochelle, Y. Bengio, P.-A. Manzagol, Extracting and composing robust features with denoising autoencoders, Proceedings of the Twenty-Fifth International Conference on Machine learning, ACM, 2008, pp. 1096–1103.
[218] C.P. Marc'Aurelio Ranzato, S. Chopra, Y. LeCun, Efficient learning of sparse representations with an energy-based model, Proceedings of NIPS, 2007.
[219] S. Rifai, P. Vincent, X. Muller, X. Glorot, Y. Bengio, Contractive auto-encoders: Explicit invariance during feature extraction, Proceedings of the Twenty-Eight International Conference on Machine Learning (ICML-11), 2011, pp. 833–840.
[220] Q. Song, Y.J. Zheng, Y. Xue, W.G. Sheng, M.R. Zhao, An evolutionary deep neural network for predicting morbidity of gastrointestinal infections by food contamination, Neurocomputing 226 (2017) 16–22.
[221] X. Zhou, J. Guo, S. Wang, Motion recognition by using a stacked autoencoder-based deep learning algorithm with smart phones, Proceedings of the International Conference on Wireless Algorithms, Systems, and Applications, Springer, 2015, pp. 778–787.
[222] B.A. Olshausen, D.J. Field, Sparse coding with an overcomplete basis set: a strategy employed by V1? Vis. Res. 37 (1997) 3311–3325.
[223] X. Ding, H. Lei, Y. Rao, Sparse codes fusion for context enhancement of night video surveillance, Multimed. Tools Appl. 75 (2016) 11221–11239.
[224] S. Bhattacharya, P. Nurmi, N. Hammerla, T. Plötz, Using unlabeled data in a sparse-coding framework for human activity recognition, Pervas. Mob. Comput. 15 (2014) 242–262.
[225] J. Guo, X. Xie, R. Bie, L. Sun, Structural health monitoring by using a sparse coding-based deep learning algorithm with wireless sensor networks, Pers. Ubiquit. Comput. 18 (2014) 1977–1987.
[226] Y. LeCun, F.J. Huang, L. Bottou, Learning methods for generic object recognition with invariance to pose and lighting, Proceedings of the Conference on Computer Vision and Pattern Recognition, CVPR and IEEE Computer Society, IEEE, 2004, pp. II–104.
[227] L. Wang, L. Ge, R. Li, Y. Fang, Three-stream CNNs for action recognition, Pattern Recognit. Lett. 92 (2017) 33–40.
[228] S.M. Erfani, S. Rajasegarar, S. Karunasekera, C. Leckie, High-dimensional and large-scale anomaly detection using a linear one-class SVM with deep learning, Pattern Recognit. 58 (2016) 121–134.
[229] D. Ravì, C. Wong, B. Lo, G.Z. Yang, A deep learning approach to on-node sensor data analytics for mobile or wearable devices, IEEE J. Biomed. Health Inf. 21 (2017) 56–64.
[230] A. Sathyanarayana, S. Joty, L. Fernandez-Luque, F. Ofli, J. Srivastava, A. Elmagarmid, S. Taheri, T. Arora, Impact of physical activity on sleep: a deep learning based exploration, arXiv:1607.07034, (2016).
[231] N.Y. Hammerla, S. Halloran, T. Ploetz, Deep, convolutional, and recurrent models for human activity recognition using wearables, arXiv:1604.08880, (2016).
[232] D. Ravi, C. Wong, B. Lo, G.Z. Yang, Deep learning for human activity recognition: a resource efficient implementation on low-power devices, Proceedings of the Thirteenth IEEE International Conference on Wearable and Implantable Body Sensor Networks (BSN), 2016, pp. 71–76.
[233] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (1997) 1735–1780.
[234] A. Graves, Generating sequences with recurrent neural networks, 16 (1) (2013) 115.
[235] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio, Learning phrase representations using RNN encoder-decoder for statistical machine translation, arXiv:1406.1078, (2014).
[236] S. Valipour, M. Siam, M. Jagersand, N. Ray, Recurrent fully convolutional networks for video segmentation, arXiv:1606.00487, (2016).
[237] J. Chung, C. Gulcehre, K. Cho, Y. Bengio, Empirical evaluation of gated recurrent neural networks on sequence modeling, arXiv:1412.3555, (2014).
[238] Y. Chen, K. Zhong, J. Zhang, Q. Sun, X. Zhao, LSTM networks for mobile human activity recognition, Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1 New York, USA, 2017, pp. 152–155.
[239] M. Edel, E. Köppe, Binarized-BLSTM-RNN based human activity recognition, Proceedings of the International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2016, pp. 1–7.
[240] M. Inoue, S. Inoue, T. Nishida, Deep recurrent neural network for mobile human activity recognition with high throughput, arXiv:1611.03607, (2016).
[241] Y. Guan, T. Ploetz, Ensembles of Deep LSTM learners for activity recognition using wearables, arXiv:1703.09370, (2017).
[242] X. Li, Y. Zhang, J. Zhang, S. Chen, I. Marsic, R.A. Farneth, R.S. Burd, Concurrent activity recognition with multimodal CNN-LSTM structure, arXiv:1702.01638, (2017).
[243] F.J. Ordóñez, D. Roggen, Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition, Sensors 16 (2016) 115.
[244] R. Zhao, R. Yan, J. Wang, K. Mao, Learning to monitor machine health with convolutional bi-directional LSTM networks, Sensors 17 (2017) 273.
[245] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, P.-A. Manzagol, Stacked denoising autoencoders: learning useful representations in a deep network with a local denoising criterion, J. Mach. Learn. Res. 11 (2010) 3371–3408.
[246] M. Chen, Z. Xu, K. Weinberger, F. Sha, Marginalized denoising autoencoders for domain adaptation, arXiv:1206.4683, (2012).
[247] A. Ng, Sparse autoencoder, CS294A Lecture Notes 72 Andrew Ng, 2011, pp. 1–19.
[248] H. Schulz, K. Cho, T. Raiko, S. Behnke, Two-layer contractive encodings for learning stable nonlinear features, Neural Netw. 64 (2015) 4–11.
[249] M.T. Harandi, C. Sanderson, R. Hartley, B.C. Lovell, Sparse coding and dictionary learning for symmetric positive definite matrices: a kernel approach, Proceedings of the Computer Vision, ECCV 2012, Springer, 2012, pp. 216–229.
[250] Y. He, K. Kavukcuoglu, Y. Wang, A. Szlam, Y. Qi, Unsupervised feature learning by deep sparse coding, Proceedings of the SIAM International Conference on Data Mining, SIAM, 2014, pp. 902–910.
[251] C.-Y. Ma, M.-H. Chen, Z. Kira, G. AlRegib, TS-LSTM and temporal-inception: exploiting spatiotemporal dynamics for activity recognition, arXiv:1703.10667,

(2017).
[252] E.P. Ijjina, C.K. Mohan, Hybrid deep neural network model for human action recognition, Appl. Soft Comput. 46 (2016) 936–952.
[253] S.S. Khan, B. Taati, Detecting unseen falls from wearable devices using channel-wise ensemble of autoencoders, arXiv:1610.03761, (2016).
[254] S.S. Khan, B. Taati, Detecting unseen falls from wearable devices using channel-wise ensemble of autoencoders, Expert Syst. Appl. 87 (2017) 280–290.
[255] J. Gao, J. Yang, G. Wang, M. Li, A novel feature extraction method for scene recognition based on Centered Convolutional Restricted Boltzmann Machines, Neurocomputing 214 (2016) 708–717.
[256] S. Sarkar, K. Reddy, A. Dorgan, C. Fidopiastis, M. Giering, Wearable EEG-based activity recognition in PHM-related service environment via deep learning, Int. J. Prognost. Health Manag. 7 (2016) 10.
[257] J. Zhang, Y. Wu, J. Bai, F. Chen, Automatic sleep stage classification based on sparse deep belief net and combination of multiple classifiers, Trans. Inst. Meas. Control 38 (2016) 435–451.
[258] N. Neverova, C. Wolf, G. Lacey, L. Fridman, D. Chandra, B. Barbello, G. Taylor, Learning human identity from motion patterns, IEEE Access 4 (2016) 1810–1820.
[259] S. Song, V. Chandrasekhar, B. Mandal, L. Li, J.-H. Lim, G. Sateesh Babu, P. Phyo San, N.-M. Cheung, Multimodal multi-stream deep learning for egocentric activity recognition, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2016, pp. 24–31.
[260] J. Morales, D. Akopian, Physical activity recognition by smartphones, a survey, Biocybernet. Biomed. Eng. 37 (2017) 388–400.
[261] S. Yao, S. Hu, Y. Zhao, A. Zhang, T. Abdelzaher, DeepSense: a unified deep learning framework for time-series mobile sensing data processing, arXiv:1611.01942, (2016).
[262] A. Sathyanarayana, S. Joty, L. Fernandez-Luque, F. Ofli, J. Srivastava, A. Elmagarmid, T. Arora, S. Taheri, Sleep quality prediction from wearable data using deep learning, JMIR mHealth uHealth 4 (2016) 1–22.
[263] M. Alzantot, S. Chakraborty, M.B. Srivastava, SenseGen: a deep learning architecture for synthetic sensor data generation, arXiv:1701.08886, (2017).
[264] M. Alzantot, S. Chakraborty, M. Srivastava, SenseGen: a deep learning architecture for synthetic sensor data generation, Proceedings of the IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), 2017, pp. 188–193.
[265] T.G. Dietterich, Ensemble methods in machine learning, in: J. Kittler, F. Roli (Eds.), Multiple Classifier Systems, 2000, pp. 1–15.
[266] M. Woźniak, M. Graña, E. Corchado, A survey of multiple classifier systems as hybrid systems, Inf. Fusion 16 (2014) 3–17.
[267] K. Tumer, J. Ghosh, Analysis of decision boundaries in linearly combined neural classifiers, Pattern Recognit 29 (1996) 341–348.
[268] Y. Freund, R.E. Schapire, A decision-theoretic generalization of on-line learning and an application to boosting, J. Comput. System Sci. 55 (1997) 119–139.
[269] H. Sagha, H. Bayati, J.D. Millan, R. Chavarriaga, On-line anomaly detection and resilience in classifier ensembles, Pattern Recognit. Lett. 34 (2013) 1916–1927.
[270] I. Fatima, M. Fahim, Y.-K. Lee, S. Lee, A genetic algorithm-based classifier ensemble optimization for activity recognition in smart homes, TIIS 7 (2013) 2853–2873.
[271] A.M. Tripathi, D. Baruah, R.D. Baruah, Acoustic sensor based activity recognition using ensemble of one-class classifiers, Proceedings of the IEEE International Conference on Evolving and Adaptive Intelligent Systems (EAIS), 2015, p. 7.
[272] R. Kumar, I. Qamar, J.S. Virdi, N.C. Krishnan, Multi-label learning for activity recognition, Proceedings of the International Conference on Intelligent Environments, IE, 2015 2015, pp. 152–155.
[273] J.A. Stork, L. Spinello, J. Silva, K.O. Arras, Audio-based human activity recognition using non-Markovian ensemble voting, Proceedings of the IEEE RO-MAN: The Twenty-First IEEE International Symposium on Robot and Human Interactive Communication, 2012, pp. 509–514.
[274] J.R. Quinlan, Induction of decision trees, Mach. Learn. 1 (1986) 81–106.
[275] M.A. Friedl, C.E. Brodley, Decision tree classification of land cover from remotely sensed data, Remote Sens. Environ. 61 (1997) 399–409.
[276] J. Rodriguez, A.Y. Barrera-Animas, L.A. Trejo, M.A. Medina-Perez, R. Monroy, Ensemble of One-Class Classifiers for personal risk detection based on wearable sensor data, Sensors (Basel, Switzerland) 16 (2016).
[277] M. Farooq, E. Sazonov, Detection of chewing from piezoelectric film sensor signals using ensemble classifiers, Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2016, pp. 4929–4932.
[278] N.N. Diep, C. Pham, T.M. Phuong, Motion primitive forests for human activity recognition using wearable sensors, in: R. Booth, M.L. Zhang (Eds.), PRICAI 2016: Trends in Artificial Intelligence, Springer International Publishing AG, Cham, 2016, pp. 340–353.
[279] Z. Feng, L. Mo, M. Li, A random forest-based ensemble method for activity recognition, Proceedings of the Thirty-Seventh Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2015, pp. 5074–5077.
[280] C. Cortes, V. Vapnik, Support-vector networks, Mach. Learn. 20 (1995) 273–297.
[281] L. Mo, S. Liu, R.X. Gao, P.S. Freedson, Multi-sensor ensemble classifier for activity recognition, J. Softw. Eng. Appl. 5 (2012) 113.
[282] E. Mohammadi, Q.M.J. Wu, M. Saif, Human activity recognition using an ensemble of support vector machines, Proceedings of the International Conference on High Performance Computing and Simulation (HPCS 2016), 2016, pp. 549–554.
[283] Y.J. Kim, B.N. Kang, D. Kim, Hidden Markov model ensemble for activity recognition using tri-axis accelerometer, Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, 2015, pp. 3036–3041.
[284] I. Fatima, M. Fahim, Y.-K. Lee, S. Lee, Classifier ensemble optimization for human activity recognition in smart homes, Proceedings of the Seventh International Conference on Ubiquitous Information Management and Communication, ACM, 2013, p. 83.
[285] A. Ortiz, J. Munilla, J.M. Gorriz, J. Ramirez, Ensembles of deep learning architectures for the early diagnosis of the Alzheimer's disease, Int. J. Neural Syst. (2016) 26.
[286] I. Arora, A. Dadu, M. Verma, K.K. Shukla, Random projections of Fischer Linear Discriminant classifier for multi-class classification, Proceedings of the Fourth International Symposium on Computational and Business Intelligence (ISCBI), 2016, pp. 165–169.
[287] H.S. AlZubi, S. Gerrard-Longworth, W. Al-Nuaimy, Y. Goulermas, S. Preece, Human activity classification using a single accelerometer, Proceedings of the Fourteenth UK Workshop on Computational Intelligence (UKCI), 2014, pp. 273–278.
[288] P. Melville, R.J. Mooney, Creating diversity in ensembles using artificial data, Inf. Fusion 6 (2005) 99–111.
[289] G. Chetty, M. White, F. Akther, Smart phone based data mining for human activity recognition, in: P. Samuel (Ed.), Proceedings of the International Conference on Information and Communication Technologies, ICICT 2014, Elsevier Science BV, Amsterdam, 2015, pp. 1181–1187.
[290] H. Mazaar, E. Emary, H. Onsi, ACM, Ensemble based-feature selection on human activity recognition, Proceedings of the International Conference on Informatics and Systems (INFOS 2016), 2016, pp. 81–87.
[291] L. Rong, L. Ming, IEEE, recognizing human activities based on multi- sensors fusion, Proceedings of the Fourth International Conference on Bioinformatics and Biomedical Engineering, IEEE, New York, 2010.
[292] L. Liu, S. Wang, Y.X. Peng, Z.G. Huang, M. Liu, B. Hu, Mining intricate temporal rules for recognizing complex activities of daily living under uncertainty, Pattern Recognit 60 (2016) 1015–1028.
[293] A. Bulling, U. Blanke, B. Schiele, A tutorial on human activity recognition using body-worn inertial sensors, ACM Comput. Surv. 46 (2014) 1–33.
[294] L. Breiman, Bagging predictors, Mach. Learn. 24 (1996) 123–140.
[295] Y. Freund, R. Schapire, N. Abe, A short introduction to boosting, J. Jpn. Soc. Artif. Intell. 14 (1999) 1612.
[296] L. Breiman, Random forests, Mach. Learn. 45 (2001) 5–32.
[297] Y. Chen, C. Shen, Performance analysis of smartphone-sensor behavior for human activity recognition, IEEE Access 5 (2017) 3095–3110.
[298] W.H. Sheng, J.H. Du, Q. Cheng, G. Li, C. Zhu, M.Q. Liu, G.Q. Xu, Robot semantic mapping through human activity recognition: a wearable sensing and computing approach, Robot, Auton. Syst. 68 (2015) 47–58.
[299] P. Zappi, T. Stiefmeier, E. Farella, D. Roggen, L. Benini, G. Troster, Activity recognition from on-body sensors by classifier fusion: sensor scalability and robustness, Proceedings of the Thirrd International Conference on Intelligent Sensors, Sensor Networks and Information, 2007, pp. 281–286.
[300] A. Jurek, Y. Bi, C.D. Nugent, S. Wu, Application of a Cluster-Based Classifier Ensemble to Activity Recognition in Smart Homes, Springer, 2013, pp. 88–95.
[301] O. Banos, M. Damas, H. Pomares, F. Rojas, B. Delgado-Marquez, O. Valenzuela, Human activity recognition based on a sensor weighting hierarchical classifier, Soft Comput 17 (2013) 333–343.
[302] A. Chowdhury, D. Tjondronegoro, V. Chandran, S. Trost, Physical activity recognition using posterior-adapted class-based fusion of multi-accelerometers data, IEEE J. Biomed. Health Inf. (2017) 1.
[303] A.K. Chowdhury, D. Tjondronegoro, V. Chandran, S.G. Trost, Ensemble methods for classification of physical activities from wrist accelerometry, Med. Sci. Sports Exerc. 49 (2017) 1965.
[304] H. Inoue, H. Narihisa, Optimizing a multiple classifier system, Pacific Rim International Conference on Artificial Intelligence PRICAI 2002: PRICAI 2002: Trends in Artificial Intelligence pp. 285–294.
[305] M. Shoaib, S. Bosch, O.D. Incel, H. Scholten, P.J.M. Havinga, Complex human activity recognition using smartphone and wrist-worn motion sensors, Sensors (2016) 16.
[306] R.F. Alvear-Sandoval, A.R. Figueiras-Vidal, On building ensembles of stacked denoising auto-encoding classifiers and their further improvement, Inf. Fusion 39 (2018) 41–52.
[307] A. Humayed, J. Lin, F. Li, B. Luo, Cyber-physical systems security—A survey, IEEE Internet Things J. 4 (2017) 1802–1831.
[308] X. Gao, W. Li, M. Loomes, L. Wang, A fused deep learning architecture for viewpoint classification of echocardiography, Inf. Fusion 36 (2017) 103–113.
[309] Y. Xia, C. Liu, Y. Li, N. Liu, A boosted decision tree approach using Bayesian hyper-parameter optimization for credit scoring, Expert Syst. Appl. 78 (2017) 225–241.