Human Activity Recognition using Smartwatch and Smartphone: A Review on Methods, Applications, and Challenges

Rana Abdulrahman Lateef\textsuperscript{1*}, Ayad Rodhan Abbas\textsuperscript{2}

\textsuperscript{1}Department of Computer Science, University of Technology, Baghdad, Iraq
\textsuperscript{2}Works at Department of Computer Science, Baghdad University College of Economic Sciences, Baghdad, Iraq

Abstract

Recently, Human Activity Recognition (HAR) has been a popular research field due to wide spread of sensor devices. Embedded sensors in smartwatch and smartphone enabled applications to use sensors in activity recognition with challenges for example, support of elderly’s daily life. In the aim of recognizing and analyzing human activity many approaches have been implemented in researches. Most articles published on human activity recognition used a multi-sensors based methods where a number of sensors were tied on different positions on a human body which are not suitable for many users. Currently, a smartphone and smart watch device combine different types of sensors which present a new area for analysis of human attitude. This paper presents a review on methodologies applied to solve problems related to human activity recognition that use the equipped sensors in smartphone and smartwatch with the employ of Machine Learning and the advance of deep learning approaches. The literature is summarized from four aspects: sensors types, applications, Machine Learning (ML) and Deep Learning (DL) models, results and challenges.

Keywords: Human Activity Recognition, Machine Learning, Deep Learning, Smartphone, Smartwatch, Accelerometer, Gyroscope.
1. Introduction

Human Activity Recognition is the prediction of what individuals do depending on their movements [1]. There are two types of HAR approaches, a vision-based which depends on using a camera, and sensor-based on using sensor which employed in the fields of activity recognition for many applications such as healthcare monitoring [2], surveillance systems for indoor and outdoor activities [3][4], and Active and Assisted Living (AAL) systems for smart homes[5]. Sensors are used in activity recognition as source of collecting raw data. According to[6], sensors modalities may be classified into three parts: the body-worn sensors which are worn by the user to describe the body movements such as smartphone, watch, the band’s accelerometer, gyroscope etc., the object sensors, which are attached to objects to capture objects movements such as RFID, and accelerometer on cup etc., and the ambient sensors, which are applied in environment to reflect user’s interaction such as sound, door sensor, Wi-Fi, Bluetooth etc.[7]. This paper will limit the review on using of smartphones and smartwatches as a tool for recognizing human activities depending on embedded sensors like an accelerometer which measures acceleration(rate of change of speed) in 3-axis, and a gyroscope which measures rate of rotation in 3-axis. Most studies have consternated on using smartphone for activity recognition. The motivation of using smartphones for discriminating human actions for HAR is that smartphones have many features such as a communication capability, portability, computational power, variant of embedded sensors, and the ability to educate and merge context information from different kinds of real world environments[8]. According to Lane et al. [9], four factors show how smartphone is a typical platform for HAR. First, smartphones are not expensive that combine in one device various hardware and software sensors. Second, the extra features that developers have are with cloud computing which provide support for sharing information on these devices. Third, smartphones have a power of mass reach by spread content and applications via virtual stores. Fourth, smartphones are programmable devices.

In previous years, smart watch has not been used as a sole device in applications of activity recognition due to its limitation such as life of battery, power computation, and it can only connect to internet through a smartphone. However, since recently most of these problems were resolved and a smart watch becomes publicly more popular[10] and having a better feature of success against other wearable devices through its ability to group smartphone attributes with continuous data controlling[11], permit a direct connection with a user in any place with interactive feedback through its screen which becomes similar to that in smartphone [12]. It is unlike smartphone, it can be worn at a whole day time even when sleeping or during perform high level of activity to supply sensing information, for instance, Global Positioning System (GPS), gyroscope, heart rate, and compass data[13].

Most researches on HAR with smartphones and smart watches focus on utilization of inertial sensors, according to this, activities can be separated into two sets[14]. The first focus on analyzing of user’s physical activities which are regarded to subject’s movement such as (walking, standing), and the second focus on tracking user’s location which is regarded to subject’s locations such as (shopping, at work)[15]. HAR problem can thus be considered as classification problem that recognizes the activity done by individual. From that point, this review concentrates on the approaches that have been developed to solve HAR problem through different machine learning and deep learning techniques.
2. Sensor Modality for HAR

Sensors of smart devices are embedded to improve the ability of devices to be controlled and managed[16]. Activity recognition performance rely on the sensor modality that have been used. Sensor modalities can be categorized into four types:[17]

1. **Ambient Sensor**, which is embedded in the environment for catching the human-environment interactions, furthermore it can be used for indoor localizing.

2. **Object Sensor**, which is tied to the target objects such as books, goods, etc. Radio-Frequency Identification (RFID) sensors are widely used for determining object usage where discriminating composite activities such as drinking/cooking depend on incorporating the information on used object.

3. **Wearable sensor**, works efficiently on capturing the body motion, thereby it is commonly used with HAR. These sensors are integrated into smartphone, smart watch, or bands. The three essential sensors that are embedded in smart device and used for detect motion are accelerometer, gyroscope, and magnetometer which is called motion sensors .Accelerometer measures the rate of change of the object velocity which is called acceleration which is measured in meter per second (m/s). Gyroscope, on the other hand measures the orientation and angular velocity which is measured in degrees per second (°/s). A magnetometer is assembled with gyroscope and accelerometer within an inertial unit. It measures the alter magnetic field in Tesla unit (T) at a specific position.

4. **Particular applications sensor**, this modality is used for specific applications. **Audio sensor** is an example of this type. It depends on having a speaker and microphone that built in mobile device to transmit and receive ultrasound signal and are modified with respect to human motion information. Audio sensor is convenient for fine-grained movement recognition. Lee et al. [18] worked on using the ultrasound signals for chewing activities recognition. Another example is a **Pressure sensor** which rely on mechanical mechanisms that need direct physical contact and it can be distributed at different places in a smart environment. Due to its physical contact attribute, it can be used for detecting small movement. Hence it may be proper to monitor exercise and correct write posture[19].

Figure 1 summarizes the sensor modality set in a diagram that designed according to our vision to illustrate the categorization of sensors used with HAR.

![Figure 1- Sensor modality used with HAR](image-url)
5. Dataset for HAR

Different modalities have been proposed for data gathering. The dataset that implements HAR with smartphone and/or smartwatch devices were gathered from different sensors equipped in these devices. Kwapisz et al. [20] created dataset that is collected from accelerometer data that supervised by one of the WISDOM team. The standard dataset for HAR that is using a smartphones is made available in 2012 and are modeled with machine learning algorithms[21] and full described in 2013, The data was gathered from 30 person of ages between 19 to 48 years old with a smartphone mounted on their waist, and recorded the x, y, and z accelerometer and gyroscope data[22]. Later, different standard datasets were modeled and implemented[23][24]. Table 1 represents the publicly datasets available for HAR that is collected from accelerometer or gyroscope sensors for smartphone or smartwatch.

Table 1-HAR public dataset

| Dataset-name                  | No. of activates | Activities                                  | Source                                      | No. of subjects |
|-------------------------------|------------------|---------------------------------------------|---------------------------------------------|-----------------|
| UCI-HAR [22]                  | 6                | Walking, upstairs, downstairs, sitting, standing, laying | Accelerometer, Gyroscope of Samsung Galaxy S II in controlled environment | 30              |
| WISDOM v1 [20]                | 6                | Walking, jogging, upstairs, downstairs, sitting, standing | Accelerometer of smartphone in controlled environment | 29              |
| WISDOM v2 [20]                | 6                | Walking, jogging, upstairs, downstairs, sitting, standing | Accelerometer of smartphone in uncontrolled environment | 563             |
| WISDM Smartphone and Smart Watch Activity and Biometrics Dataset [23] | 18               | Walking, Jogging, Stairs, sitting, Standing, Typing, Brushing Teeth, Eating Soup, Eating Pasta, Drinking from Cup, Eating Sandwich, Kicking (Soccer Ball), Playing Catch w/Tennis Ball, Dribbling (Basketball), Writing, Clapping, Folding Clothes | Accelerometer, Gyroscope of Samsung Galaxy S5, and LG G Watch | 51              |
| UMIeb SHAR [24]               | 9                | Lying down from standing, Standing up from lying, Running, Standing up from sitting, S h ting down, Upstairs, downstairs, j umping, walking | Accelerometer of smartphone | 30              |

6. HAR Features

Features can be defined as a statistical function that efficiently obtain a meaningful information of data. From the HAR point of view, a particular physical movement of a subject can generate a particular pattern. For instance “Running” activity has a pattern different from “walking” activity pattern. Different pattern distribution can be produce from measuring the intensity of a particular physical effort by an accelerometer and gyroscope sensors. In literature, the features domain classified into groups: The time domain, which uses a mathematical function to extract statistical information from the signals, and the frequency domain that uses a mathematical functions to get a repetitive patterns of signals and are often linked to the natural periodicity of the activities. If unsuitable features are used to train ML model then it will affect its performance and decrease model accuracy. Thus, applying a feature selection technique before modeling the data will eliminate over fitting, improve accuracy, and reduce the time of training[25]. Table 2 presents the domain features that are often used in the literature.
Table 2- Types of Features Used in Literatures

| domain  | Features                                                                 |
|---------|-------------------------------------------------------------------------|
| Frequency | Energy, energy normalized, power, centroid, entropy, DC component, peak, coefficient sum. |
| Time    | min, max, amplitude, amplitude peak, sum, absolute sum, Euclidian norm, mean, absolute mean, mean square, mean absolute deviation, sum square error, variance, standard deviation, Pearson coefficient, zero crossing rate, correlation, cross-correlation, auto-correlation, skewness, kurtosis, area, absolute area, signal magnitude mean, absolute signal magnitude mean, magnitude deference function. |

7. HAR Problems
This section covers the HAR problems and their applications that implement machine learning (ML) and deep learning (DL) algorithms.

5.1 Machine Learning
Machine learning include building mathematical models to assist understanding data. Learning can join the contention when these models given a tunable parameters that can be acclimatized to observed data and therefore the program can learn from that data. Fitting models to a previously seen data can be used to understand and predict the sides of a new observed data. Machine learning approach has a benefit where it can generalize to much larger dataset in many more dimensions[26]. HAR is considered as a supervised learning problem in which modeling depends on the relation between the labels associated with data, measure features of data, and then this model can be used to apply label to unknown, new data. In general, most common classical machine learning classification algorithms are: Support Vector Machine (SVM), Naïve Bayes (NB), Logistic Regression (LR), Random Forests (RF), Decision Trees (DT) and k-Nearest Neighbors (k-NN) which are categorized as a supervised learning algorithm. These algorithms are implemented as a verification process in order to obtain best classification accuracy with data collected from smart device [27].

Several published articles tried to identify and solve different problems related to HAR which are:

a. Health-care
One of the problems that considered recently is utilization of smartphone connectivity to deliver a health care service remotely. Anjum et al. [28] built a smartphone applications to track physical activities of users during their daily routine and to report a feedback of estimates of calories burned without user intervention. The ordinary physical activity can affect the one's life [29] hence, to encourage people to leverage their physical activity by quantifying it. In this regard, Cvetković et al. [30] built an android application to recognize and monitor human activity and use it as an input to estimate the Energy Expenditure (EE) by using a smartphone worn freely on body and optional heart rate monitor to increase accuracy. The approach is implemented in real time and automatically adapts to presence, orientation, and location of the phone. First, the method detects the presence of the devices using simple heuristic, then the orientation of the phone were is normalized and used for detecting walking, location, and Activity Recognition (AR) which is implemented using machine learning. Mekruksavanich et al. [31] proposed a framework that uses a smart watch to detect period of sitting activity to identify the problem of Office Worker Syndrome (OWS). Ensemble which includes stacking and base classifier are employed. The results stated that using stacking in combination with ensemble learning methods achieved good accuracy. In addition, an optimal performance is carried out when the gyroscope and accelerometer are integrated rather than isolated from each other. Balli et al. [32] worked on recognition of movement for elderly and young children to prevent them from falling down. The data is obtained from accelerometer, gyroscope, step counter, and heart rate sensor of a smart watch. The main novelty of this
study lies in a hybrid method entitled Principal Component Analysis (PCA) plus Random Forest (RF) which combines an efficient clustering feature extraction method with an efficient classification algorithm to produce the most successful result.

b. Sequentially Aspect of Data
Time series sensory data need an approach that takes into consideration the sequential aspect of data, Lee et al. [33] utilized the hierarchal nature of activities since it can be broken down into simpler ones to design Hierarchical Hidden Markov Models (HHMMs) which are simply Markov chains, with hidden states to classify low and high activities collected from 3D accelerometer sensor of smartphone. However, their approach showed a difficulty in differentiating between upstairs and downstairs activities. Later, Ronao et al. [34] was overcome this issue and suggest to utilize a two-stage Continues Hidden Markov Model (CHMM) classifier. In first stage, features are selected using Random Forest(RF) variable importance measures and then used for classification which divide stationary from moving activities, and in the second stage, CHMMs are used for fine classification. Bulbul et al.[35] used an accelerometer and gyroscope sensors of smartphone with different supervised machine learning approaches like ensemble methods to recognize human activity. Efficiency and precision are used as a metrics for comparison between those approaches.

c. Driving Behavior
Recent years witnessed a growing interest in controlling the data related to driving behavior in order to recognize risky driving. Several studies analyzed the behavior of driver using mobile sensors. The classification and the evaluation depends on combination of inertial embedded sensors with axillary devices [36] [37]. Liu et al. [38] proposed a system that exploits the benefit of using smartphone and smart watch with inertial sensors for track a steering wheel turning angle to detect unsafe driving activities. Smart watch provides the ability to discriminate the steering movement from other movements such as eating. They illustrated that combining machine learning models of motion sensing with a classifier provides an accurate driving activities classification. Ferreira et al.[39] worked on various android smartphone sensors to evaluate the performance of four ML algorithms on data collected from four android sensors in detecting seven driving events. Sun et al. [40] employed a smartphone acceleration and orientation data to detect a driving event by proposing a new bagging tree with Dynamic Time Warping (DTW) algorithm.

d. Feature Selection Problem
One of the basic concepts in machine learning is feature selection which highly affects the performance of the model by selecting manually the most contributing features to a variable being predict. Therefore it has been confirmed to be an active way for data preparing , since irrelevant features are ignored[41]. Some authors worked on improving the accuracy of recognition by using or suggesting a feature selection techniques. For instance, Capela et al. [42] implement a machine learning algorithms to evaluate on subset features that were selected from calculated features of a smart phone sensor data collected from three populations, able-bodied, elderly, and stroke patients. Feature selection methods used are Relief-F, Correlation-based Feature Selection (CFS), and Fast Correlation Based Filter (FCBF). FCBF algorithm achieved highest accuracies. Ahmed et al. [43] proposed a hybridization between filter and wrapper feature selection approaches. First, a base time and frequency features are applied to extract heterogenous features, then a hybrid approach is applied in which a sequential forward search (SFFS) is used. The new hybrid feature selection approach leverage the average classification performance when compared with other feature selection algorithms like MC-SVM, and CAT.

5. Smart Device Position
The position of the smartphone or smart watch and the location of a subject play a vital role on the result of recognition of activity Havinga [44] studied the effect of placing the
smartphone on the two body positions, in the pocket and in wrist on the performance of activity recognition. Furthermore, Havinga analyzed the effect of increasing window size and sensor combination on various simple and complex activities in different ways. The results show that increasing the window size improved the performance for simple activity while sensor combinations improved the recognition of complex activities. Whereas, Kwon et al. [45] proposed a system that uses a smartwatch sensors to collect data which took into consideration location information from three places office, kitchen, and outdoor to enhance the HAR system. Two model were evaluated, one with information location and the second without. The results demonstrated that different activities can be classified with 95% of accuracy.

Ramos et al. [46] evaluated the effect caused by the combination of sensor data from smart watches and smartphones in term of the accuracy of activity recognition approaches. This is done by collected simultaneously an accelerometer data from smartphones along with smart watches as input source. They concluded that accuracy of recognition is leveraged when the data of smartphone and smartwatch are merged. To eliminate the effect of orientation variations Chen et al. [47] suggested a HAR system that uses a smartphone sensors by taking into consideration placement, orientation and subject variations depending on combination of Coordinate Transformation and Principle Component Analysis (CT-PCA).

To defeat the limitation of fixing the smartphone on a specific position in human body in order to facilitate a classifying process of a human activity, Muslim et al. [48] proposed an approach to use a smart watch fixed on ankle in addition to smartphone. This incorporation results in accurate activity recognition. The features are extracted from smart watch for each window size and send to the smartphone via a Bluetooth.

6. Authentication of Person

Weiss et al. [49] compared between smartphone and smart watch based activity recognition that utilized a hand-oriented and not-hand oriented activates on a personal and impersonal model. They investigated how smartphone and smartwatch can be used to identify a person from his/her eating habits. The results showed that the capability of smart watch for identifying a hand-based activity (e.g. drinking) is more accurate than using a smartphone, also watch accelerometer supplies much better results than phone accelerometer and watch gyroscope carry out much more poorly than watch accelerometer.

Typing, swiping, moving the arm while walking, and other related activities represent a behavioral footprint and play a good role in user authentication as the work carried out by Zheng et al. [50]. Despite that, there is still challenges that haven’t been investigated. For instance, the availability of these footprint through interaction with smartphone and group of labeled data for verification process under different context of phone usage. Several footprint behavior have been investigated for continuously authenticating persons[51]. Recently, the movement pattern of phone was worked on by Balagani et al. [52], which concentrated basically on phone movement patterns during walking and sitting for continuous authentication of smartphone’s user by employed a Hand Movement, Orientation, and Grasp (HMOG) as a set of behavioral features, whereas, Kumar et al. [53] proposed an authentication system that depends on phone movement patterns during typing or swiping collected from a diverse population in an unrestricted environments. The results stated that may not be adequate for a certain types user and would presented high error rate, and the movement pattern of the phone based authentication systems may not be suitable for every smartphone user. In another work, Tang et al. [54] investigated the pattern of phone movement with three conditions, static (e.g. stand, sit) dynamic (e.g. upstairs, jogging), and total of activities that merge static, dynamic and postural transitions (e.g. stand-to-sit or sit-to-stand). The results demonstrate that static and total activities can be used for person identification by extracting a suitable features and apply a suitable classifiers. Murmuria et al.
investigated continuous authentication of power consumption, touch gestures, and physical movement. Singha et al. [56] suggested an authentication system to identify a person using data from accelerometer sensor in phone. The system performs in the background without requiring any additional action from the user. The results achieved high accuracy which shows the possibility of combining accelerometer-based person recognition with biometric authentication. Bayat et al. [57] proposed a recognition system to design a new digital pass filter to separate the gravity acceleration from body acceleration in raw data. A proposed digital low pass filter is used to separate AC from DC and calculate the magnitude Am. AC and Am are used for feature construction. Weiss et al. [58] investigated the convention of using both accelerometer and gyroscope sensor in a combination on a smartphone and a smart watch to evaluate activities on a biometric identification as well as biometric authentication. Classification algorithms are used to generate the authentication and identification models. The results state that the best biometric performance happened when using smart watch and smartphone together.

Supervised machine learning is a commonly used methods, however recently Active learning proved its effectiveness in generating models for activity recognition with smaller training datasets. Shahmohammadi et al. [59] stated the way how to use a smart watch based on active learning method to recognize a daily human activities. The results showed that this system achieved high accuracy, and thus active learning with smart watch has higher performance than with smartphone. Table 3 presents a list of machine learning classification approaches used in literatures whereas, Table 4 summaries the works on HAR with machine learning classification algorithms.

**Table 3**: list of works separated by ML algorithms.

| method                  | Works                                      |
|-------------------------|--------------------------------------------|
| Naïve Bays              | [28,42,44,54,59,49,46,39,46]               |
| KNN                     | [28,53,32,35,44,47,54]                     |
| SVM                     | [28,42,53,46,30,31,32,35,38,39,59,57,56,40,43,45,46,47,52,54] |
| Random Forest(RF)       | [53,49,32,34,39,40,45,54,56,57,59]         |
| Logistic Regression     | [53,56,57,59]                              |
| IB3                     | [49]                                      |
| Threshold – based mechanism | [48,50,55]                      |
| Decision Tree           | [28,42,49,46,31,32,35,44,45,46,47,56]     |
| Neural Network(NN)      | [47,53,54]                                |
| Multi-Layer Perception(MLP) | [49,39,57]                      |
| Majority-Voting(MV)     | [31]                                      |
| Bagging                 | [54,35,40]                                |
| Stacking                | [31]                                      |
| Boosting                | [35,54]                                   |
Table 4 summarization of works with ML methods

| Literature | approaches  | Features | Device | sensors | dataset | application |
|------------|-------------|----------|--------|---------|---------|-------------|
| Cveticovic et al. [30] | Support regression | Vector domain | Android smartphone and a Zepply heart rate monitor | A | Author self-collected | Activity daily life |
| | | | | | | |
| Mekruksavanich et al. [31] | Decision Tree (DT), SVM, Majority Voting (MV), Stacking (ST) | Time domain | Smart watch (Apple Watch Series 2) | A, G | Author self-collected | Office Worker Syndrome |
| | | | | | | |
| Balli et al. [32] | C4.5, SVM, Random Forest (RF), KNN, PCA+RF | Time domain | Smart watch | A, G | Author self-collected | Health care |
| | | | | | | |
| Rivas et al. [33] | Random Forest (RF), Continuous Hidden Markov Models (CHMM) | Time domain | Samsung Galaxy SII smartphone | A, G | UCI HAR | Activity daily life |
| | | | | | | |
| Weiss et al. [38] | Decision Tree, SVM, KNN, Bagging, Boosting, Stacking | Time domain | Smartphone, smartwatch | A, G | WSEDM smartphone and Smart Watch Activity and Biometrics Dataset | Mobile motion based behavioral biometrics |
| | | | | | | |
| Balli et al. [39] | Decision Tree (DT), SVM, KNN, Bagging, Boosting, Stacking | Time domain | Smartwatch, Smartphone | A, G | UCI HAR | Activity daily life |

| Literature | approaches  | Features | Device | sensors | dataset | application |
|------------|-------------|----------|--------|---------|---------|-------------|
| Liu et al. [38] | SVM | Car acceleration, rotational change, arm acceleration, first hand movement time domain | Smartwatch, Smartphone | A, G | Author self-collected | Track a steering wheel |
| | | | | | | |
| Ferreira et al. [39] | EN, MLP, RF, and SVM | Time domain | Linear accelerometer, magnetometer, and G | A | Author self-collected with 7 driving event type | Driving behavior |
| | | | | | | |
| Sun et al. [40] | bagging tree-based, dynamic time warping (DTW), SVM, Random Forest, Xboost, fuzzy logic-based | Time domain | Smartphone | A, G | Author self-collected data which consist of the previous driving maneuvers based on the attributes of experience collected, with the recorded of the start and end points/times of each event executed by the driver | Driving event detection |
| | | | | | | |
| Ahmed et al. [43] | SVM | Time domain frequency domain | Smartphone | A, G | UCI HAR | Activity daily life |
| | | | | | | |
| Levasseur [44] | KNN, Naive Bayes, Decision Tree (DT) | Time domain | Smartphone Samsung galaxy s2 | A, G | Author self-collected Activities: Walk, jog, stand, sit, bike upstairs, downstairs type, write, coffee, talk, smoke, eat | Activity daily life |

371
| Literature | approaches | Features | device | sensors | dataset | application |
|------------|------------|----------|--------|---------|---------|-------------|
| Tang et al. [54] | Random Forest (RF), SVM, Naive Bayes (NB), Neural Network (NN), K-Nearest Neighbors (K-NN), Bagging (Bag), AdaBoost (AB) | Time domain | smartphone | A | Walking Pattern Data Set | User identification |
| Murunia et al. [55] | Threshold-based | (Time domain) feature for movement modality and (duration, end-to-end distance, end-to-end direction, average pressure, and average touch area) features for touch modality | smartphone | A,G | Author Self-collected through four services: Power Logger, Touch Logger, Gyro Logger, and Activity Logger. Subject volunteers: 79 | Authentication system |
| Singh et al. [56] | Random Forest (RF), Decision Tree (DT), Logistic Regression (LR), SVM | Time domain | Samsung Galaxy J1 phone | A | Author self-collected | Walking data | authentication system |
| Bayat et al. [57] | Multi-layer Perceptron, SVM, Random Forest, LMT, Simple Logistic, Logistic Boost | Time domain | Android smartphone | A,G | Author self-collected | Subject volunteers: 4 | Age: 29-33 | Activities: Dining, Stairs Down, Slow-Walk, Running, Stairs Up, Fast-Walk. | Activity daily life |
| Shakhshamiandi et al. [58] | Random Forest, Extra Trees, Naive Bayes, Logistic Regression, and Support Vector Machine (SVM) | Time domain | smartwatch | A,G | Subject volunteers: 12 | Activity: Random Forest, Extra Trees, Naive Bayes, Logistic Regression, and Support Vector Machine | Daily human activity |
| Kwon et al. [45] | Decision tree (DT), Random forest (RF), SVM | Time domain | Apple Watch Series 2 and an Apple iPhone 8 | A | Author self-collected | Subject volunteers: 10 | Activities: Office work, Reading, Writing, Taking a rest, Playing a game, Eating, Cooking, Washing dishes, Taking a transport, Walking, Running, Taking a transport. | Activity daily life in office, kitchen, and outdoor |
| Ramos et al. [46] | 148, NB, SVM | Time domain | Sony Smartwatch 2 | A | Author self-collected | Subject volunteers: 13 | Age: 20 to 35 year | Activities: Walking, Sitting, Standing, Driving, Walking, And Sitting. | Physical daily life |
| Chen et al. [47] | KNN, DT, NN, SVM | Time domain | smartphone | A | Collected by an Android application of a Google NEXUS 4 smartphone | Subject volunteers: 5 | Activities: Walking, running, going upstairs and downstairs | Activity daily life |
| Muslim et al. [48] | threshold-based | Time domain | android smartwatch | A,G | Barometer | Subject volunteers: 5 | Activities: Walking (slow, normal and fast), Jog, Run (slow, fast and run), Walking upstairs and downstairs, Elevator up and down, Sitting (completely or partially static), Sitting or Standing (completely or partially static) and Lying on his left, right, stomach and back | Activity daily life |
| Zheng et al. [50] | Threshold-based | Acceleration, pressure, size, and time | Samsung Galaxy Nexus smartphone | A,G | Author self-collected raw data are recorded during user's tapping actions | Subject volunteers: 3 | Biometric-based verification system |
| Balagani et al. [52] | SVM, scaled Manhattan, and scaled Euclidian | Hand Movement, Orientation, and Grasp (HMOG), tap, keystroke | smartphone | A,G | Author self-collected Data under two conditions: sitting and walking | Subject volunteers: 190 | Authentication system for smartphone's user |
5.2 Deep Learning Model

Traditional approaches used for HAR problem consist of two parts: feature extraction and classification. Machine learning techniques use hand-craft to extract features which depends heavily on human domain expertise, hence it is time consuming and only shallow features can be learned by those approaches[60]. However recently, deep learning approaches cope with these flaws and have shown extreme success in improving recognition accuracy. Deep Learning merge the two steps within a Neural Network to learn features automatically[61]. Convolutional Neural Network (CNN) is one of the common deep learning methods that is extremely to analyze the data sequentially, and its success depend on using a convolutional filter in hierarchies to extract complex features representations [62]. In the presence of deep learning, many ideas have been published to address the problem of HAR. Several works focused on using deep learning approach where machine learning methods were employed either for comparison or evaluation. This section summarizes the existing work on employed deep model on HAR.

Recently, the location and navigation services have been considered as one of the standard attributes of smartphones as a consequences of the growth of smartphone capabilities. Recognition of Pedestrian activity is important in the procedure of pedestrian navigation [63]. Ye et al. [64] produced a strategy for real time human activity recognition with deep learning algorithms and smartphone MEMS (Micro-Electro-Mechanical System) sensors measurements to perform four main experiments for recognition of pedestrian motion mode, smartphone posture, real-time comprehensive pedestrian, and pedestrian navigation. Long Short Term Memory (LSTM) and CNN networks were trained and used in android smartphone for recognition of pedestrian activity in real time. Works exploited deep model to solve other HAR problem. Chen et al. [65] suggested a framework for fusion between engineered features and automatically learned features with deep algorithm, also a maximum full a posterior (MFAP) algorithm was evolved to improve HAR performance. The proposed method produced a good performance with self and publicly collected data. Radu et al. [66] proposed a deep learning architecture to show the effects of integrating the data comes from multiple sensors by using a Multi-Modal Restricted Boltzmann Machines (MM-RBMs) which is used prior to fusion a pair of text to verify if it is suitable sensing task. MM-RBM is constructed by two hidden layers for each of acceleration and angular velocity sensor data. Three shallow classifier are employed for comparison with proposed architecture. The results show that the performance is achieved without any hand selection features.

Liu et al. [67] suggested a method for recognizing human activity using smartphone with high accuracy. Two models were implemented. First, is a Machine learning model that used SVM with linear and fisher linear discriminate for classification, then the prediction is based on the feature extracted. Second, is a deep learning model where the time sequence raw data is passed through CNN model after being normalized it. The data entered to the model consist of three components; no. of sample, window size, and no. of channels which is then reconfigured to be fed into model.

Yu et al. [68] suggested a bidirectional structures of Long Short Term Memory(bi-LSTM) on a time series data collected from smartphone accelerometer and gyroscope inertial sensor. The proposed approach overcome the problem with the baseline LSTM cells where the prediction of the current state depends on previous information only, while bi-LSTM can get the past and future information from horizontal direction also, information can be reached from the vertical direction or lower layer. The results show that the new approach performed better when it is compared with other classification approaches. Another research on bidirectional LSTM worked by Zhao et al. [69] that suggested a deep network which is used Residual Bidirectional Long Short-Term Memory (Res-Bidir-LSTM) by combine the Res-LSTM and
Bidir-LSTM.
Shakya et al. [70] compared the HAR performance with two commonly datasets; WISDM, which is collected from smartphone accelerometer and Shoaib, collected form 5 accelerometers fixed on 5 positions on body. Different machine learning classifiers (e.g. KNN) and deep learning models (e.g. CNN, RNN) were applied on the two datasets. The results conducted that the DL models outperformed the performance of traditional ML classifiers performed with no hand crafted features. Benavidez et al. [71] performed a CNN and LSTM approach to classify activities collected from phone/watch sensors. A comparison between them shows that the performance of LSTM is better than CNN, also found that the two models cannot discriminate between similar hand movement activities on a phone dataset like eating different things, also cannot distinguish between kicking and catching on the watch dataset. Liu et al. [72] suggested an approach to predict human activities on a dataset collected from smartphone sensor. Two kinds of features were extracted from raw data, and then activities were analyzed with machine learning classifier. While CNN model was applied on the only raw data to analyze the performance of recognition, the results stated that, using additional features and CNN model enhance the perdition. Almaslukh et al. [73] suggested an architecture that uses a CNN with statistical features to find a position-aware and position detection HAR. Position-aware is performed using 3 classifiers levels. The first discriminates between static and dynamic activities, the second, detects the sensor position, and the third, had a group of a classifiers and each represent a specific location. The result showed that the proposed model produced a good performance compared to other machine learning methods. Ronao et al. [74] suggested a convolutional neural networks (Convnet) for HAR with smartphone and its effects on extracting robust features. The experimental result showed that altering the structure of Convnet affects the performance of recognition, where adding additional layers can derive more complex features, also increasing filter size and adopting low pooling size will enhance the accuracy. Table 5 Summarizes of the works on HAR with deep models.

| Literature | Deep model | Device modality | Sensor | Dataset | application | performance |
|------------|------------|-----------------|--------|---------|-------------|-------------|
| Yu et al. [64] | Fusion engineered features, MFAP | Smartphone | A, G | Self-collected data | UCI HAR | Activity recognition of human in real world applications | 98.55% |
| Choe et al. [65] | Multi-Model Restricted Boltzmann Machines (MEM-RBM) | Smartphone | 6 different | Publicly collected Dataset activities: Sitting, standing, walking, climbing stairs, descending stairs, biking | UCI HAR | Activity daily life | 98.1% |
| Liu et al. [67] | CNN | Smartphone | Author self-collected Activities: running, walking, clockwise movement (CCW), counterclockwise movement (CCW), up & down (UD), and left & right (LR) | UCI HAR | Activity daily life | 98.1% |
| Yu et al. [68] | DBN, Baseline LSTM, Bi-LSTM | Smartphone | A, G | Self-collected data | UCI HAR | Activity daily life | 98.1% |
Lateef and Abbas

| Literature  | Deep model          | Device modality | Sensor | Dataset | application       | performances |
|------------|---------------------|----------------|--------|---------|-------------------|--------------|
| Zhao et al.[69] | Baseline LSTM, BioLSTM, ResLSTM, Res-BiLSTM, LSTM. | Smartphone | A, O | UCI HAR | Activity daily life | Baseline LSTM : 90.8% BioLSTM : 91.1% ResLSTM : 91.6% Res-BiLSTM : 91.6% |
| Shalva et al.[70] | CNN, RNN | smartphone | A | ACT-Tracker Dataset (WISDM Dataset) | Activity daily life | 94.2% |
| Benavidez et al. [71] | CNN-LSTM | Smartwatch, and Samsung Galaxy S5 | A, O | WISDM dataset | Activity daily life | For watch: LSTM : 79% CNN: 72% For phone: LSTM : 74% CNN : 50% |
| Almazlokh et al. [73] | ConvNet | smartphone, Samsung Galaxy S4, Smartwatch, L0.0, Wearable | A, O | data was collected in realistic settings, subject volunteers: 15 activities | position-aware HAR | Position detection improved up to 98% |
| Ronao et al. [74] | ConvNet | Smartphone | A, O | UCI HAR | Extract robust features | 94.79% |

### 6. Conclusions and Challenges

This paper presents a comprehensive overview of the current works on HAR using smartphone and/or smartwatch with inertial sensors. First, the concept of human activity was explained, followed by description of the public dataset, and sensor modality equipped with smartwatch and smartphone. Furthermore, this paper described comprehensively the tradition methodology that depends on using shallow machine learning algorithms and methodology that depends on using deep learning algorithms commonly used to recognize human activities. The paper contributes to provide a good representation of the HAR area in the context of smartwatch and smartphone with its inertial sensors. From this review some gaps and further challenges need to be taken into consideration:

For activity recognition, there is no single best approach, therefore various factors need to be determined when select a particular application. Some of classification methods such as decision tree may cause over fitting, whereas SVM may cause under fitting. Thus, the method must be implemented in accordance to the data. For any classification model, when the time complexity is degreased the accuracy is bad. However, good accuracy may come from unacceptable time complexity. Deep learning methods were adopted to decrease time consumed and calculation complexity of engineered features in machine learning. Position of smartphone and/or smartphone play a role on the recognition of the activities. Combination of sensor data of smartphone and smartwatch produces a good results.

Smartphone is convenient for un-handed based activities such as “walking”, whereas smartwatch is convenient for hand–based activities such as “eating”. The researches that implement HAR with smartphone is more than with smartwatch. There is limitation on using smartwatch and smartphone to track behavior activities in safety applications such as in detecting unsafe driving, since the accuracy decreases if the driver steer with watchless hand and a misclassification rate of 1 in 10000 is not acceptable if the consequence is loss of life. The results produced by HAR are employed using a standard dataset which is different when real time dataset is used.

Despite improvement in the field of HAR, there is still some challenges that need to be explored which are:

With sensor based activity recognition, extracting feature may be difficult since there is similarity characteristics between different activities such as running and walking. Recent researches are focus on recognition of simple activity which represented by repeated action such as walking. Therefore, the challenges is to recognize more complex or composite activities. Activities are assumed to be performed in sequential manner. However, a human
can perform more than one activity at the same time, therefore, exploring a concurrent activity is also challenge. Employing HAR as an authentication system is still a challenge that is not exploited yet to cope the resultant high rate of error.

References

[1] J. Brownlee, “Deep Learning for Time Series,” *Machine Learning Mastery*, 2018.

[2] C. Wang, “Near-Threshold Energy- and Area-Efficient Reconfigurable DWPT/DWT Processor for Healthcare-Monitoring Applications,” *Circuits Syst. II Express Briefs, IEEE Trans.*, vol. 62, pp. 70–74, Jan. 2015, doi: 10.1109/TCSII.2014.2362791.

[3] D. Di Paola, D. Naso, A. Milella, G. Cicirelli, and A. Distante, “Multi-sensor surveillance of indoor environments by an autonomous mobile robot,” *International Journal of Intelligent Systems Technologies and Applications*, vol. 8, no. 1–4, pp. 18–35, 2010, doi: 10.1504/IJIISTA.2010.030187.

[4] S. Ranasinghe, F. Al Machot, and H. C. Mayr, “A review on applications of activity recognition systems with regard to performance and evaluation,” *Int. J. Distrib. Sens. Networks*, vol. 12, 2016.

[5] Q. Ni, A. Garcia Hernando, and I. Pau, “The Elderly’s Independent Living in Smart Homes: A Characterization of Activities and Sensing Infrastructure Survey to Facilitate Services Development,” *Sensors*, vol. 15, pp. 11312–11362, May 2015, doi: 10.3390/s150511312.

[6] R. Chavarriaga *et al.*, “The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition,” *Pattern Recognit. Lett.*, vol. 23, pp. 2033–2042, Jan. 2013, doi: 10.1016/j.patrec.2012.12.014.

[7] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A survey,” *Pattern Recognit. Lett.*, 2019, doi: 10.1016/j.patrec.2018.02.010.

[8] W. Sousa Lima, E. Souto, K. El-Khatib, R. Jalali, and J. Gama, “Human activity recognition using inertial sensors in a smartphone: An overview,” *Sensors*, vol. 19, no. 14, p. 3213, 2019.

[9] N. D. Lane *et al.*, “AD HOC AND SENSOR NETWORKS A Survey of Mobile Phone Sensing,” *IEEE Communications Magazine*, vol. 48, no. September. pp. 140–150, 2010, [Online]. Available: http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=5560598.

[10] R. Rawassizadeh, B. Price, and M. Petre, “Wearables: Has the Age of Smartwatches Finally Arrived?,” *Commun. ACM*, vol. 58, pp. 45–47, Jan. 2015, doi: 10.1145/2629633.

[11] U. S., “S U RV E Y Next Generation Alternative Investing Key findings from JPMorgan ’ s survey of major,” *Growth (Lakeland)*, 2017.

[12] C. Free, G. Phillips, L. Felix, L. Galli, A. Patel, and P. Edwards, “The effectiveness of M-health technologies for improving health and health services: A systematic review protocol,” *BMC Res. Notes*, vol. 3, p. 250, Oct. 2010, doi: 10.1186/1756-0500-3-250.

[13] G. F. Dunton, Y. Liao, S. S. Intille, D. Spruijt-Metz, and M. Pentz, “Investigating children’s physical activity and sedentary behavior using ecological momentary assessment with mobile phones,” *Obesity*, vol. 19, no. 6, pp. 1205–1212, 2011, doi: 10.1038/oby.2010.302.

[14] O. D. Incel, M. Kose, and C. Ersoy, “A Review and Taxonomy of Activity Recognition on Mobile Phones,” *BioNanoScience*, vol. 3, no. 2, pp. 145–171, 2013, doi: 10.1007/s12668-013-0088-3.

[15] S. Saeedi, “Context-Aware Personal Navigation Services Using Multilevel Sensor Fusion Algorithms,” 2013.

[16] M. Masoud, Y. Jaradat, A. Manasrah, and I. Jannoud, “Sensors of Smart Devices in the Internet of Everything (IoE) Era: Big Opportunities and Massive Doubts,” *J. Sensors*, vol. 2019, p. 6514520, 2019, doi: 10.1155/2019/6514520.

[17] K. Chen, D. Zhang, L. Yao, B. Guo, Z. Yu, and Y. Liu, “Deep Learning for Sensor-based Human Activity Recognition: Overview, Challenges and Opportunities,” vol. 37, no. 4, 2020, [Online]. Available: http://arxiv.org/abs/2001.07416.

[18] K.-S. Lee, “Joint Audio-Ultrasound Food Recognition for Noisy Environments,” *IEEE J. Biomed. Heal. Informatics*, vol. 24, no. 5, pp. 1477–1489, 2020, doi: 10.1109/JBHI.2019.2938627.

[19] D.-E. Lee, S.-M. Seo, H.-S. Woo, and S.-Y. Won, “Analysis of body imbalance in various writing sitting postures using sitting pressure measurement,” *J. Phys. Ther. Sci.*, vol. 30, pp. 343–346.
[20] J. R. Kwapisz, G. M. Weiss, and S. A. Moore, “Activity recognition using cell phone accelerometers,” ACM SIGKDD Explor. Newsl., vol. 12, no. 2, pp. 74–82, 2011, doi: 10.1145/1964897.1964918.

[21] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, “Human Activity Recognition on Smartphones Using a Multiclass Hardware-Friendly Support Vector Machine BT - Ambient Assisted Living and Home Care,” 2012, pp. 216–223.

[22] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes-Ortiz, “A public domain dataset for human activity recognition using smartphones,” ESANN 2013 proceedings. 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. pp. 437–442, 2013.

[23] G. M. Weiss, “WISDM Smartphone and Smartwatch Activity and Biometrics Dataset,” UCI Mach. Learn. Repos. WISDM Smartphone Smartwatch Act. Biometrics Dataset Data Set, 2019.

[24] D. Micucci, “Applied sciences UniMiB SHAR : A Dataset for Human Activity Recognition Using Acceleration Data from Smartphones,” 2017, doi: 10.3399/app7101101.

[25] J. Brownlee, “00 ML Mastery - Understand You Data, Create Accurate Models and Work Projects End-to-End,” 感染症誌, vol. 91, pp. 399–404, 2017.

[26] V. Jake, "Python Data Science Handbook," vol. 53, no. 9. 2019.

[27] S. Shalev-Shwartz and S. Ben-David, "Understanding machine learning: From theory to algorithms," vol. 9781107057. 2013.

[28] A. Anjum and M. U. Ilyas, “Activity recognition using smartphone sensors,” 2013 IEEE 10th Consum. Commun. Netw. Conf. CCNC 2013, no. January 2013, pp. 914–919, 2013, doi: 10.1109/CCNC.2013.6488584.

[29] S. Cooper, S. Bandelow, M. Nute, J. Morris, and M. Nevill, “The effects of a mid-morning bout of exercise on adolescents’ cognitive function,” Ment. Health Phys. Act., vol. 5, pp. 183–190, Dec. 2012, doi: 10.1016/j.mhpa.2012.10.002.

[30] B. Cvetković, V. Janko, and M. Luštrek, “Demo abstract: Activity recognition and human energy expenditure estimation with a smartphone,” 2015 IEEE Int. Conf. Pervasive Comput. Commun. Work. PerCom Work. 2015, pp. 193–195, 2015, doi: 10.1109/PERCOMW.2015.7134019.

[31] S. Mekruksavanich, N. Hnoohom, and A. Jitpattanakul, “Smartwatch-based sitting detection with human activity recognition for office workers syndrome,” Ist Int. ECTI North. Sect. Conf. Electr. Electron. Comput. Telecommun. Eng. ECTI-NCON 2018, pp. 160–164, 2018, doi: 10.1109/ECTI-NCON.2018.8378302.

[32] S. Balli, E. A. Sağbaş, and M. Peker, “Human activity recognition from smart watch sensor data using a hybrid of principal component analysis and random forest algorithm,” Meas. Control (United Kingdom), vol. 52, no. 1–2, pp. 37–45, 2019, doi: 10.1177/0020294018813692.

[33] Y. Lee and S.-B. Cho, "Activity Recognition Using Hierarchical Hidden Markov Models on a Smartphone with 3D Accelerometer," vol. 6678. 2011.

[34] C. A. Ronao and S. B. Cho, “Human activity recognition using smartphone sensors with two-stage continuous hidden markov models,” 2014 10th Int. Conf. Nat. Comput. ICNC 2014, pp. 681–686, 2014.

[35] E. Bulbul, A. Cetin, and I. A. Dogru, “Human Activity Recognition Using Smartphones,” ISMSIT 2018 - 2nd Int. Symp. Multidiscip. Stud. Innov. Technol. Proc., no. October, 2018, doi: 10.1109/ISMSIT.2018.8567275.

[36] H. Eren, S. Makinist, E. Akin, and A. Yilmaz, “Estimating driving behavior by a smartphone,” in 2012 IEEE Intelligent Vehicles Symposium, 2012, pp. 234–239, doi: 10.1109/IVS.2012.6232298.

[37] C. W. You et al., “CarSafe App: Alerting drowsy and distracted drivers using dual cameras on smartphones,” MobiSys 2013 - Proceedings of the 11th Annual International Conference on Mobile Systems, Applications, and Services. pp. 13–26, 2013, doi: 10.1145/2462456.2465428.

[38] L. Liu et al., “Toward detection of unsafe driving with wearables,” WearSys 2015 - Proc. 2015 Work. Wearable Syst. Appl., pp. 27–32, 2015, doi: 10.1145/2753509.2753518.

[39] J. Ferreira et al., “Driver behavior profiling: An investigation with different smartphone sensors and machine learning,” PLoS One, vol. 12, 2017.

[40] R. Sun, Q. Cheng, F. Xie, W. Zhang, T. Lin, and W. Y. Ochieng, “Combining Machine Learning and Dynamic Time Wrapping for Vehicle Driving Event Detection Using Smartphones,” IEEE...
Lateef and Abbas

Iraqi Journal of Science, 2022, Vol. 63, No. 1, pp: 363-379

Trans. Intell. Transp. Syst., pp. 1–14, 2019. doi: 10.1109/TITS.2019.2955760.

[41] S. Wang, J. Tang, and H. Liu, “Encyclopedia of Machine Learning and Data Mining,” Encycl. Mach. Learn. Data Min., no. January, 2016, doi: 10.1007/978-1-4899-7502-7.

[42] N. A. Capela, E. D. Lemaire, and N. Baddour, “Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients,” PLoS One, vol. 10, no. 4, pp. 1–18, 2015.

[43] N. Ahmed, J. I. Rafiq, and M. R. Islam, “Enhanced human activity recognition based on smartphone sensor data using hybrid feature selection model,” Sensors (Switzerland), vol. 20, no. 1, 2020.

[44] P. J. M. Havinga, “Smartphone and Wrist-Worn Motion Sensors,” pp. 1–24, 2016, doi: 10.3390/s16040426.

[45] M. C. Kwon and S. Choi, “Recognition of Daily Human Activity Using an Artificial Neural Network and Smartwatch,” Wirel. Commun. Mob. Comput., vol. 2018, 2018, doi: 10.1155/2018/2618045.

[46] F. Ramos, A. Moreira, A. Costa, R. Rolim, H. Almeida, and A. Perkusich, “Combining smartphone and smartwatch sensor data in activity recognition approaches: An experimental evaluation,” in Proceedings of the International Conference on Software Engineering and Knowledge Engineering, SEKE, 2016, vol. 2016-Janua, pp. 267–272, doi: 10.18293/SEKE2016-040.

[47] Z. Chen, Q. Zhu, Y. C. Soh, and L. Zhang, “Robust Human Activity Recognition Using Smartphone Sensors via CT-PCA and Online SVM,” no. January 2018, 2017, doi: 10.1109/TII.2017.2712746.

[48] A. M. Muslim and C. Accident, “Human Activity Recognition Using Smartphone and Smartwatch,” no. October 2016, 2019, doi: 10.22362/ijcert/2016/v3/.

[49] G. M. Weiss, J. L. Timko, C. M. Gallagher, K. Yoneda, and A. J. Schreiber, “Smartwatch-based activity recognition: A machine learning approach,” 3rd IEEE EMBS Int. Conf. Biomed. Heal. Informatics, BHI 2016, pp. 426–429, 2016, doi: 10.1109/BHI.2016.7455925.

[50] N. Zheng, K. Bai, H. Huang, and H. Wang, “You are how you touch: User verification on smartphones via tapping behaviors,” Proceedings - International Conference on Network Protocols, ICNP. pp. 221–232, 2014, doi: 10.1109/ICNP.2014.43.

[51] V. M. Patel, R. Chellappa, and D. Chandra, “Continuous User Authentication on Mobile Devices,” IEEE Signal Processing Magazine, vol. 33, no. 4, pp. 49–61, 2016, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7503170/.

[52] K. S. Balagani, “HMOG: New Behavioral Biometric Features for Continuous Authentication of Smartphone Users *,” no. c. pp. 1–17, 2013.

[53] R. Kumar, P. P. Kundu, D. Shukla, and V. V Phoha, “Continuous user authentication via unlabeled phone movement patterns,” IEEE Int. Jt. Conf. Biometrics, IJCB 2017, vol. 2018, pp. 177–184, 2018.

[54] C. Tang and V. Phoha, "An empirical evaluation of activities and classifiers for user identification on smartphones," 2016.

[55] R. Murmuria, A. Stavrou, D. Barbará, and D. Fleck, “Continuous Authentication on Mobile Devices Using Power Consumption, Touch Gestures and Physical Movement of Users,” in RAID, 2015.

[56] T. B. Singha, R. K. Nath, and A. V Narasimhadhan, “Person Recognition using Smartphones’ Accelerometer Data,” 2017, [Online]. Available: http://arxiv.org/abs/1711.04689.

[57] A. Bayat, M. Pomplun, and D. A. Tran, “A study on human activity recognition using accelerometer data from smartphones,” in Procedia Computer Science, 2014, doi: 10.1016/j.procs.2014.07.009.

[58] G. M. Weiss, K. Yoneda, and T. Hayajneh, “Smartphone and Smartwatch-Based Biometrics Using Activities of Daily Living,” IEEE Access, vol. 7, pp. 133190–133202, 2019.

[59] F. Shahmohammadi, A. Hosseini, C. E. King, and M. Sarrafzadeh, “Smartwatch Based Activity Recognition Using Active Learning,” Proc. - 2017 IEEE 2nd Int. Conf. Connect. Heal. Appl. Syst. Eng. Technol. CHASE 2017, pp. 321–329, 2017, doi: 10.1109/CHASE.2017.115.

[60] B. Yoshua, “Deep Learning of representations AAIL Tutorial,” Slsp. pp. 1–37, 2013.

[61] B. Zhou, J. Yang, and Q. Li, “Smartphone-based activity recognition for indoor localization using
a convolutional neural network,” *Sensors*, vol. 19, no. 3, p. 621, 2019.

[62] M. Zeng *et al.*, “Convolutional neural networks for human activity recognition using mobile sensors,” in *6th International Conference on Mobile Computing, Applications and Services*, 2014, pp. 197–205.

[63] N. Kakiuchi and S. Kamijo, “Pedestrian dead reckoning for mobile phones through walking and running mode recognition,” in *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, 2013, pp. 261–267.

[64] J. Ye, X. Li, X. Zhang, Q. Zhang, and W. Chen, “Deep Learning-Based Human Activity Real-Time,” pp. 1–30, 2020, doi: 10.3390/s20092574.

[65] Z. Chen, C. Jiang, S. Xiang, J. Ding, M. Wu, and X. Li, “Smartphone Sensor-Based Human Activity Recognition Using Feature Fusion and Maximum Full a Posteriori,” *IEEE Trans. Instrum. Meas.*, vol. 69, no. 7, pp. 3992–4001, 2020, doi: 10.1109/TIM.2019.2945467.

[66] V. Radu, N. D. Lane, S. Bhattacharya, C. Mascolo, M. K. Marina, and F. Kawsar, “Towards multimodal deep learning for activity recognition on mobile devices,” *Ubicomp 2016 Adjunct. - Proc. 2016 ACM Int. Jr. Conf. Pervasive Ubiquitous Comput.*, pp. 185–188, 2016.

[67] Q. Liu, Z. Zhou, S. R. Shakya, P. Uduthalapally, M. Qiao, and A. H. Sung, “Smartphone sensor-based activity recognition by using machine learning and deep learning algorithms,” *Int. J. Mach. Learn. Comput.*, vol. 8, no. 2, pp. 121–126, 2018, doi: 10.18178/ijmlc.2018.8.2.674.

[68] S. Yu and L. Qin, “Human activity recognition with smartphone inertial sensors using bidirectional LSTM networks,” *Proc. - 2018 3rd Int. Conf. Mech. Control Comput. Eng. ICMCCE 2018*, pp. 219–224, 2018, doi: 10.1109/ICMCCE.2018.00052.

[69] Y. Zhao, R. Yang, G. Chevalier, X. Xu, and Z. Zhang, “Deep Residual Bidirectional LSTM for Human Activity Recognition Using Wearable Sensors,” *Math. Probl. Eng.*, vol. 2018, 2018, doi: 10.1155/2018/7316954.

[70] S. R. Shakya, C. Zhang, and Z. Zhou, “Comparative study of machine learning and deep learning architecture for human activity recognition using accelerometer data,” *Int. J. Mach. Learn. Comput.*, vol. 8, no. 6, pp. 577–582, 2018, doi: 10.18178/ijmlc.2018.8.6.748.

[71] S. Benavidez and D. Mccreight, “A Deep Learning Approach for Human Activity Recognition Project Category: Other (Time-Series Classification ),” 2018.

[72] Q. Liu, Z. Zhou, S. R. Shakya, P. Uduthalapally, M. Qiao, and A. H. Sung, “Smartphone sensor-based activity recognition by using machine learning and deep learning algorithms,” *Int. J. Mach. Learn. Comput.*, vol. 8, no. 2, pp. 121–126, 2018.

[73] H. A. Recognition, “A Robust Deep Learning Approach for Position-Independent Smartphone-Based Human Activity Recognition,” 2018, doi: 10.3390/s18113726.

[74] C. A. Ronao and S. B. Cho, “Human activity recognition with smartphone sensors using deep learning neural networks,” *Expert Syst. Appl.*, 2016.