EMPIRICAL STUDIES ON CHALLENGES OF HUMAN ACTIVITY RECOGNITION USING MACHINE LEARNING

Mohamed Elshafei

Department of Computer Science and Software Engineering

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Abstract

Human activity recognition (HAR) is one of the active research areas in pervasive computing where it's current interest focuses on identifying the specific movement or action of a person based on acquired data. The data may be remotely recorded, such as video, radar, or other wireless methods. Alternately, data may be recorded directly on the subject such as by carrying custom hardware or smart phones that have accelerometers and gyroscopes. The intent is to record sensor data and corresponding activities for specific subjects, fit a model from this data, and generalize the model to classify the activity of new unseen subjects from their sensor data.

This report surveys the literature for the state of the art in HAR to fulfill four objectives. First, look into the popularity of HAR systems and, for convenience, present summarizations of a few applications of wearable based HAR systems to show their impact in different aspects of medicine, sport, and lifestyle. Second, we look into the overview of HAR systems and, for convenience, present the characteristics and the general components of any HAR system where it describes the principal techniques applied in HAR, feature extraction, and learning methods. Third, we provide comprehensive summarizations of the recent related works to HAR systems where we look into the functionality of modern HAR systems and the motivations behind developing them. Finally, we introduce some of the open issues in the field to shed light on opportunities for future research.

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Chapter 1

Introduction

Human activity recognition (HAR) is one of the most important tasks in pervasive computing where systems provide accurate and opportune information on people's activities and behaviors. These systems have become a task of high interest within the data science field, where a physical activity can be defined as "*any bodily movement produced by skeletal muscles result in energy expenditure above resting level*" [11]. From a general point of view, a HAR system is a system that acquires data from the user/ environment by using sensors to fulfill a purpose related to human activities (e.g., activities classification, calories burn estimation, etc). For the past decade, HAR has utilized two types of sensors, namely using external and wearable sensors. External sensors are devices which fixed in predetermined points of interest (e.g., smart homes [48]), so the inference of activities entirely depends on the voluntary interaction of the users with the sensors. The use of external sensors allowed HAR systems to recognize fairly complex activities because they rely on data from a number of sensors placed in target objects which people are supposed to interact with, for example detecting cooking activity while using the stove as an external sensor. Unfortunately, there are two obvious limitations in using external sensors. First, it is impossible to detect any activities if the user is out of the reach of the sensors or the user performs activities that do not require interaction with them. Second, the installation and maintenance of the sensors usually entail high costs.

The aforementioned limitations motivate the use of wearable sensors in HAR systems. In the late 1990s, researchers performed the first feasibility studies on activity recognition using body-worn sensors, where the choice of activities seemed arbitrary and not always relevant to real-world applications. Most of the measured attributes are related to the users movement (e.g., using accelerometers or GPS), environmental variables (e.g., temperature and humidity), or physiological signals (e.g., heart rate or electrocardiogram). This led to acquiring a massive amount of data; therefore, there has been a remarkable involvement in data science and analytics in developing HAR systems [46]. Nowadays, wearable sensors are more popular than ever before through smart devices such as phones, watches, and eyeglasses. This led to developing more interactive and user-friendly wearable based HAR systems. Therefore, researchers start utilizing these systems recently in different aspects of medicine, sport, and lifestyle. For the remaining of chapter 1, we look into the popularity of HAR systems and, for convenience, present summarizations of a few applications of wearable based HAR systems to show their impact in different aspects of medicine, sport, and lifestyle.

HAR in Medical Applications

Nowadays, there is a rapid shift from a routine clinical system to home system by utilizing wireless sensor network systems to fill the gap in healthcare monitoring between clinical visits [45]. Such systems provide continuous physical and physiological monitoring in any environment would shorten hospital stay for patients, improve both recovery and reliability of diagnosis [50] and improve patients quality of life.

In the aspect of patients' monitoring and diagnostics, Jiang *et al.* [24] presented a remote health care service with movement and fall detection capabilities using body-worn accelerometers and gyroscopes. Also, Wu *et al.* [50] proposed a patient monitoring and medical diagnosis system by using ECG circuits, accelerometers, and gyroscopes. In the aspect of motions and emotions correlation, Picard *et al.* [40] presented a framework for emotion recognition by using EMG circuits to understand the correlation between peoples' intelligence and emotions. Also, Myrtek *et al.* [34] proposed a system detects the emotional activity by using ECG circuits and accelerometers to differentiate between metabolically and emotionally induced heart rate. According to the aforementioned works, it seems that HAR systems are popular in different aspects of medicine despite the similarity of sensors used in these systems.

HAR in Sports

In recent years, HAR has drawn much attention in the field of body-worn wireless sensor networks (WSNs). These sensors are commonly used in sports activities recognition in order to improve athletes' performance and metabolism. Such systems can even help integrating sports activities into people's daily lifestyle to improve their fitness and health.

In the aspect of performance, Heinz *et al.* [20] presented a system to improve reflexes and interactions in martial arts' video games by using body-worn accelerometers and gyroscopes. Also, Markus *et al.* [31] proposed a system to help children in their Kung-Fu education by using an interactive computerized toy ball embedded with an accelerometer. In the aspect of metabolism, Long *et al.* [30] presented a system for computing daily energy expenditure for daily and sport activities by using accelerometer. Also, Mortazavi *et al.* [32] presented a method for estimating the metabolic equivalent of task values achieved when users perform exergaming-specific movements by using body-worn accelerometer. According to the aforementioned works, it seems that HAR systems are popular in different aspects of sports despite the similarity of sensors used in these systems.

HAR in Modern Life

Nowadays, modern lifestyle requires smart systems to supervise or assist the residents to ensure their health, safety, and well-being. In order to accomplish this, assisted living systems provide services such as tracking, fall-detection, and security [21]. Some of these systems can be life saving during emergencies or caretaker for elders and patients during their daily lives.

In the aspect of life emergency, Hou *et al.* [21] presented an assisted living system providing services such as time-based reminder, vital sign measurement, and emergency help services using blood pressure and heart rating sensors. Also, Lee *et al.* [29] presented a remote patient monitoring to predict adverse events with sufficient accuracy in a cost-effective manner using blood pressure and heart rating sensors. In the aspect of caretaker, Osmani *et al.* [38] presented a scenario about activity recognition and reminding system composed of environmental and body-worn accelerometer and gyroscope for elders and dementia patients. Also, Kautz *et al.* [25] proposed an adaptive prompter system for Alzheimer patients by using various sensors such as accelerometers and gyroscopes and prompts appropriate messages verbally or visually. According to the aforementioned works, it seems that HAR systems are popular in different aspects of modern life despite the similarity of sensors used in these systems.

This report surveys the state of the art in HAR making use of wearable sensors where it's objectives spin around popularity, overview, functionality, and issues of these systems. In chapter 2, we look into the overview of HAR systems and, for convenience, present the characteristics and the general components of any HAR system where it describes the principal techniques applied in HAR, feature extraction, and learning methods. Chapter 3 provides comprehensive summarizations of the recent related works to HAR systems where we look into the functionality of modern HAR systems and the motivations behind developing them. Finally, chapter 4 introduces some of the open issues in the field to shed light on opportunities for future research.

Chapter 2

HAR Attributes & Overview

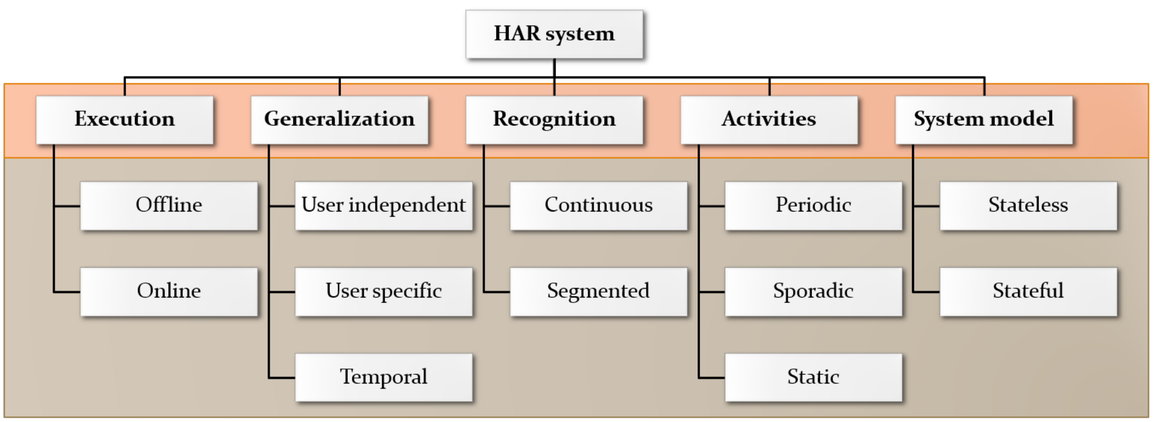

Figure 1: The five main attributes with their varieties in HAR systems

In this chapter, we present five main attributes with their varieties in HAR systems that were commonly reported in the literature, as shown in figure 1. Also, we describe the principal techniques applied in HAR, feature extraction, and learning methods. From figure 1, we can see that each attribute has at least two varieties, this led to higher degrees of freedom in terms of system design and implementation.

HAR Attributes

First attribute is execution which can be offline or online. In case of offline, the system records the sensor data first. The recognition is performed afterwards. Typically used for non-interactive applications such as health monitoring. On the other hand, the online system acquires sensor data and processes it in real time. Typically used for activity-based computing and interactive applications in human-computer interaction. Second attribute is generalization which can be user independent, specific, or temporal. In case of user independent, the system is optimised for working with a large number of users. On the other hand, the user specific system is tailored to a specific user. Performance is usually higher than in the user-independent case, but does not generalise as well to other users. Furthermore, the temporal system should be robust to temporal variations caused by external conditions including sensor displacement, drifting sensor response such as barometers or gyroscopes.

Third attribute is recognition which can be continuous or segmented. In case of continuous recognition, the system automatically spots the occurrence of activities or gestures in the streaming sensor data. On the other hand, the segmented system assumes that the sensor data stream is segmented at the start and end of a gesture by an oracle. It only classifies the sensor data in each segment into one of the activity classes. The oracle can be an external system (e.g. cross-modality segmentation) or the experimenter when assessing classification performance in the design phase. Fourth attribute is activities which can be periodic, sporadic, and static. Periodic activities have gestures exhibiting periodicity, such as walking, running, rowing, biking, etc. Sliding window segmentation and frequency-domain features are generally used for classification. Sporadic activities have gestures occur sporadically, interspersed with other activities or gestures. Segmentation plays a key role to isolate the subset of data containing the gesture. Static activities have static postures or static pointing gestures; thus, these activities may have the least amount of data so that continuous recognition is affordable. Fifth attribute is system model which can be stateless or stateful. In case of stateless model, the recognition system does not model the state of the world. Activities are recognized by spotting specific sensor signals. This is currently the dominant approach when dealing with the recognition of activity primitives (e.g. reach, grasp). On the other hand, stateful model uses a model of the environment, such as the user's context or an environment map with the location of objects. This enhances activity recognition performance, at the expense of more design-time knowledge and a more complex recognition system.

HAR Overview

Generally, a HAR system consists of microelectronics in form of wearable devices and a software which spins around data analysis and machine learning. Usually, the wearable devices in HAR systems are used for data acquisition while the software portion is used for applying data analysis and machine learning. Nowadays, wearables provide important features such as high computational power, small size, and low cost which promote people to interact with wearable devices as part of their daily lives. On the other hand, there has been an active research area within software engineering and data science with the main purpose of deriving the maximum knowledge from the data acquired by pervasive sensors [39]. This allowed a single HAR system to recognize several activities, for example, a system that consists of an accelerometer and a feedforward neural network can be used to detect walking and running [27].

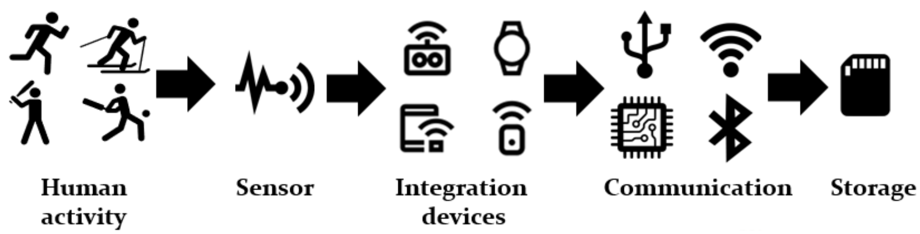

Figure 2: A generic diagram of data acquisition for HAR systems

In Figure 2, we present a generic diagram of data acquisition in HAR systems. It starts with a HAR system that aims to recognize a certain human activity; according to our literature survey, there are seven groups of activities that can be distinguished. These groups and the individual activities that belong to each group are summarized in Table 1. Then, we choose a certain type of wearable sensors to measure attributes of interest such as an accelerometer [22]. After that, we choose a suitable form of sensor integrated devices which suit the selected activity, for example, smart-phones [9, 37] for ambulation activities. Then, we select the means of communication to connect multiple sensors to each other or to the data storing device. Finally, we store all raw data in storage device for further preprocessing.

Once the data is acquired, the process of applying the machine learning starts as shown in Figure 3. In data preprocessing, the raw data is first preprocessed to filter out signal variability or artifacts then, segmented into sections of interest that are likely to contain an activity or gesture (see Section 2.1). In dimensionality reduction,

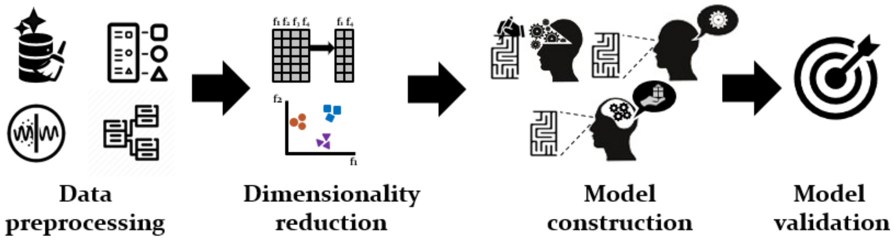

Figure 3: Generic diagram of applying machine learning in HAR systems

Table 1: Types of activities recognized by the state of the art HAR systems

Group	Activities
Ambulation	Walking, running, sitting, standing still, lying, climbing stairs, descending stairs, riding escalator, and riding elevator.
Transportation	Riding a bus, cycling, and driving.
Phone usage	Text messaging, making a call.
Daily activities	Eating, drinking, working at the PC, watching TV, reading, brushing teeth, stretching, scrubbing, and vacuuming.
Exercise/fitness	Rowing, lifting weights, spinning, Nordic walking, and doing push ups.
Military	Crawling, kneeling, situation assessment, and opening a door.
Upper body	Chewing, speaking, swallowing, sighing, and moving the head.

features that capture the activity characteristics are extracted from the processed data then, reduced to the most significant ones (see Section 2.3). In *model construction*, the reduced features are used as inputs for the machine learning models (see Section 2.3). In *model validation*, the models are tested/ evaluated using several validation techniques to assess the accuracy and performance (see Section 2.4).

2.1 Data Preprocessing

The first step to properly apply machine learning in HAR systems is to preprocess the acquired data to extract representative features. Generally, raw data acquired from the environment are often incomplete, inconsistent, lacking certain attributes of interest, containing errors or outliers. These impediments hinder the quality and quantity of knowledge extracted by machine learning models; therefore, data preprocessing techniques are used to refine raw data and solve these issues. Data preprocessing methods are divided into following categories [55]:

1. Data Cleaning: Data is cleansed through processes such as filling in missing values, smoothing the noisy data, or resolving the inconsistencies in the data.

2. Data Integration: Data with different representations are put together and conflicts within the data are resolved.

3. Data Transformation: Data is transformed into forms appropriate for machine learning applications by normalization, aggregation, and generalization.

4. Data Reduction: This step aims to present a reduced representation of the data in a data warehouse.

5. Data Discretization: Involves the reduction of a number of values of a continuous attribute by dividing the range of attribute intervals.

2.2 Dimensionality Reduction

The second step toward applying machine learning is to reduce the dimensions of representative features. Dimensionality Reduction involves reducing the number of features under consideration by obtaining a set of principal variables [42]. This process can be divided into feature selection and feature extraction [41].

Feature selection focuses on selecting a subset of variables from the input which can efficiently describe the input data while reducing effects from noise or irrelevant variables and still provide good prediction results [18]. This provides us a way of reducing computation time, improving prediction performance, and a better understanding of the data in machine learning or pattern recognition applications [12]. There are three main categories of feature selection which are filter, wrapper, and embedded methods.

The filter methods use features ranking techniques as the principle criteria for features selection by ordering. A suitable ranking criterion is used to score the features and a threshold is used to remove features below the threshold. Filter methods tend to select redundant features because they do not consider the relationships between features. Therefore, they are mainly used as a pre-process method.

The wrapper methods use a predictive model as a black box and its performance as the objective function to evaluate the features subset. Each new subset is used to train the model, which is tested on a hold-out set. Calculating the error rate of the model gives the score for that subset. The wrapper methods suffer from some sort of paradox represented by two main disadvantages which are: 1) The increasing of overfitting risk when the number of data observations are insufficient. 2) The significant computation time when the number of features is large.

The embedded methods main approach is to incorporate the feature selection as part of the training process. Embedded methods have been recently proposed that try to combine the advantages of both previous methods. A learning algorithm takes advantage of its own features selection process and performs selection and classification simultaneously. Embedded methods used to reduce the computation time taken up for reclassifying different features subsets which is done in wrapper methods.

2.3 Model Construction

In this section, we explore the third step toward applying machine learning in HAR systems which is to construct the machine learning model itself. This section provides a brief introduction to the most popular machine learning algorithms with a high-level understanding about the algorithms along with R & Python codes in appendix. Broadly, there are 3 types of machine learning algorithms which are, supervised, unsupervised, and reinforcement learnings.

In supervised learning, algorithms consist of a target / outcome variable (or dependent variable) which is to be predicted from a given set of predictors (independent variables). Using these set of variables, we generate a function that map inputs to desired outputs. The training process continues until the model achieves a desired level of accuracy on the training data. Examples of supervised learning: Regression, Decision Tree, Random Forest, k-nearest neighbors, Logistic Regression etc. In unsupervised learning, algorithm do not have any target or outcome variable to predict / estimate. It is used for clustering population in different groups, which is widely used for segmenting customers in different groups for specific intervention. Examples of unsupervised learning: Apriori algorithm, K-means. In reinforcement learning, algorithms are trained to make specific decisions. It is exposed to an environment where it trains itself continually using trial and error. This machine learns from past experience and tries to capture the best possible knowledge to make accurate business decisions. Example of reinforcement learning: Markov Decision Process. Here is the list of commonly used machine learning algorithms. These algorithms can be applied to almost any data problem:

Linear Regression

Linear regression is used to estimate real values (cost of houses, number of calls, total sales etc.) based on continuous variable(s). The objective is to establish relationship between independent and dependent variables by fitting a best line. This best fit line is known as regression line and represented by a linear equation $Y = a * X + b$, where Y is a dependent variable, a is the slope, X is an independent variable, and b is the intercept. Both a, b coefficients are derived based on minimizing the sum of squared difference of distance between data points and regression line.

Linear Regression is of mainly two types: Simple Linear Regression and Multiple Linear Regression. Simple Linear Regression is characterized by one independent variable. And, Multiple Linear Regression(as the name suggests) is characterized by multiple (more than 1) independent variables. While finding best fit line, it can fit a polynomial or curvilinear regression. And these are known as polynomial or curvilinear regression.

Logistic Regression

Logistic regression is a classification not a regression algorithm. It is used to estimate discrete values such as binary values, based on given set of independent variable(s). In other words, it predicts the probability of occurrence of an event by fitting data to a *logit* function. Since, it predicts the probability, its output values lies between 0 and 1 (as expected).

Logistic Regression is mainly used in for the binary problems where, for example, the log ONES of the outcome is modelled as a linear combination of the predictor variables $logit(ONES) = ln(p/(1 - p))$, where p is probability of event occurrence and $(1 - p)$ is probability of not event occurrence.

Decision Tree

Decision tree is a type of supervised learning algorithm (having a pre-defined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables. In this technique, we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter / differentiator in input variables.

Decision tree is of mainly two types: Categorical Variable Decision Tree which has categorical target variable i.e. 1 or 0. And, Continuous Variable Decision Tree which has continuous target variable i.e. real number values.

2.4 Model Validation

In this section, we explore the fourth step toward applying machine learning in HAR systems which is to validate the constructed machine learning model. Validation techniques in machine learning are used to get the error rate of the model, which can be considered as close to the true error rate of the population. Ultimately, If the dataset is large enough to be representative of the whole population, there will not a need for the validation techniques. However, in real-world scenarios, the majority of the datasets are samples of collected data that may not be a true representative of the whole population where validation techniques come into practice. In this section, we present six frequently-used validation techniques in machine learning.

Re-substitution

If all the data is used for training the model and the error rate is evaluated based on outcome vs. actual value from the same training data set, this error is called the re-substitution error. This technique is called the re-substitution validation technique.

Hold-out

To avoid the re-substitution error, the data is split into two different datasets labelled as a training and a testing dataset. This can be a 60/40 or 70/30 or 80/20 split. This technique is called the hold-out validation technique. In this case, there is a likelihood that uneven distribution of different classes of data is found in training and test dataset. To fix this, the training and test dataset is created with equal distribution of different classes of data. This process is called stratification.

K-fold cross-validation

In this technique, k-1 folds are used for training and the remaining one is used for testing as shown in Figure 4. The advantage is that entire data is used for training

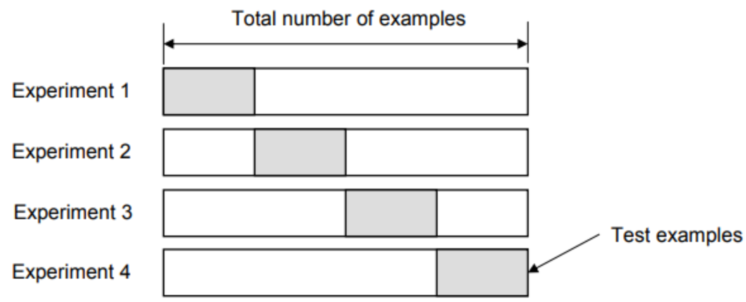

Figure 4: K-fold cross-validation

and testing. The error rate of the model is average of the error rate of each iteration. This technique can also be called a form the repeated hold-out method. The error rate could be improved by using stratification technique.

Leave-One-Out Cross-Validation (LOOCV)

In this technique, all of the data except one record is used for training and one record is used for testing. This process is repeated for N times if there are N records. The advantage is that entire data is used for training and testing. The error rate of the model is average of the error rate of each iteration. The following Figure 5 represents the LOOCV validation technique.

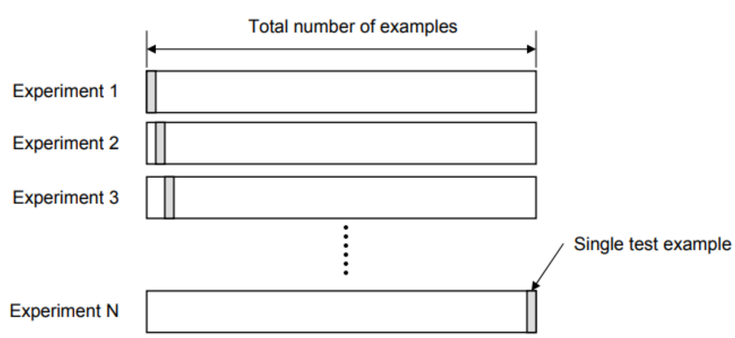

Figure 5: LOOCV validation technique

Random sub-sampling

In this technique, multiple sets of data are randomly chosen from the dataset and combined to form a test dataset. The remaining data forms the training dataset. The following Figure 6 represents the random sub-sampling validation technique. The error rate of the model is the average of the error rate of each iteration.

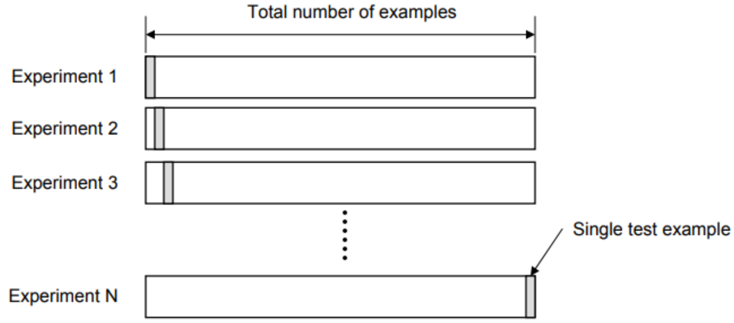

Figure 6: Random sub-sampling validation technique

Bootstrapping

In this technique, the training dataset is randomly selected with replacement. The remaining examples that were not selected for training are used for testing. Unlike K-fold cross-validation, the value is likely to change from fold-to-fold. The error rate of the model is average of the error rate of each iteration. The following Figure 7 represents the same.

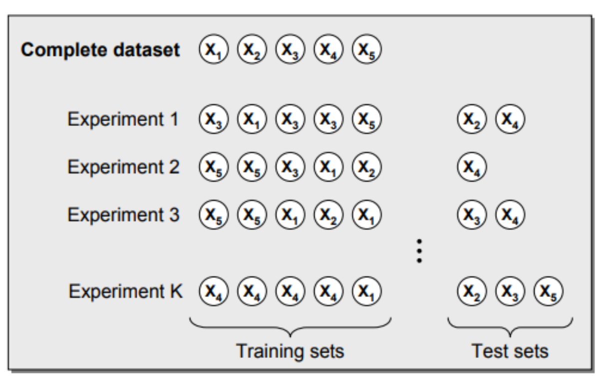

Figure 7: Bootstrapping validation technique

Chapter 3

Literature Survey

This chapter provides comprehensive summarizations of the recent related works to HAR systems where we look into the functionality of modern HAR systems and the motivations behind developing them. Table 4 summarizes and categorizes each work as constructive, evaluative, and optimization. A constructive work aims to build a new HAR systems from scratch without utilizing any existing systems including its dataset. An evaluative work aims to evaluate two or more HAR systems using new or existing dataset in order to determine which system is better to achieve certain performance. An optimization work aims to enhance an existing HAR system in order to improve its performance and under certain limits. Table 5 gives a brief description for the dataset used in each of the selected works. Every dataset is described in terms of data attributes and sensor type. The data attributes present the diversity of subjects who participated in data collection. These attributes include participant's age, gender, weight, hight, and activity duration. Sensor type presents the diversity of sensors used on the participant while collecting the data. Tables 4 and 5 show that although these works have different purposes, they still share several similarities in terms of data attributes and sensors.

For the remaining of this chapter, we summarize each related work in form of six points paragraph. first, we present its main purpose whether it constructs, evaluates, optimizes a HAR system, or publishes a new dataset. Second, we list the human activities targeted by the work. Third, we describe the used dataset in the work along with its properties. Fourth, we report the type of the sensors and in which form they were utilized. Fifth, we list the sensor placement used in the work, Sixth, we mention the used machine techniques for HAR in the work.

Anguita *et al.* [2] constructed and published a dataset, as well as, built a detection model using a M-SVM approach for HAR utilizing smart phones. This work targeted 6 activities which are walking, sitting, standing, laying, ascending, and descending stairs. The used dataset in this work consists of 30 subjects performing the activities without a specified gender, weight, height, but age ranges from 19 to 48 years and activity duration of 15 seconds. This work utilized the accelerometer and gyroscope sensors in Samsung Galaxy S II smart phone. The device was placed on subjects' waist while performing the activities. This work used a machine technique which is M-SVM, to recognize the preformed activities.

Kwapisz *et al.* [27] described and evaluated a system that used phone-based accelerometers to perform activity recognition, a task which involved identifying the physical activity a user is performing. This work targeted 6 activities which are walking, sitting, standing, jogging, ascending, and descending stairs. The used dataset in this work consists of 29 subjects performing the activities without a specified activity duration, gender, weight, height, and age. This work utilized the accelerometer sensor in Android smart phone. The device was placed in subjects' front pants leg pocket while performing the activities. This work used 3 machine techniques which are DT, LogR, and MP, to recognize the preformed activities.

Mortazavi *et al.* [33] focused minimizing computational load and power consumption in repetition counting by extracting the most informative activity-specific features to select only the best single axis for detecting each activity. This work targeted 3 activities with dumbbells which are biceps curls, shoulder lateral raises, crunches, and, 2 activities without dumbbells which are jumping jacks and push ups. The used dataset in this work consists of 12 subjects performing the activities without a specified activity duration, gender, weight, height, but age ranges from 23 to 38 years and activity duration of 10 time per activity. This work utilized the accelerometer and gyroscope sensors in Samsung Galaxy Gear smart watch. The device was placed in subjects' left wrist while performing the activities. This work used 3 machine techniques which are RF, DT, SVM, and NB, to recognize the preformed activities.

Shoaib *et al.* [44] constructed and published a dataset, as well as, built a detection model using 9 classifiers approaches for HAR utilizing smart phones. This work targeted 8 activities which are walking, running, sitting, standing, jogging, biking, ascending, and descending stairs. The used dataset in this work consists of 10 male subjects performing the activities without a specified weight, height, but age ranges from 25 to 30 years and activity duration of 4 minutes per activity. This work utilized the accelerometer, magnetometer, and gyroscope sensors in Samsung Galaxy S II smart phone. The device was placed on subjects' belt, right wrist, right upper arm, right and left jeans pocket while performing the activities. This work used 9 machine technique which are SVM, LogR, NB, k-NN, BN, two RBCs, and two DTs, to recognize the preformed activities.

Mortazavi *et al.* [32] estimated the MET values achieved when users perform exergaming. This work targeted exergames that focus on energy expenditure. The used dataset in this work consists of 6 male subjects performing soccer exergame play without a specified weight, height, but age ranges from 22 to 31 years and activity duration of 3 minutes per game movement. This work utilized an off shelves accelerometer sensor. The device was placed on subjects' foot, hip, and ankle while playing soccer. This work used a machine technique which is LinR, to estimate the MET when performing soccer exergame play.

Anguita *et al.* [3] presented a system for human physical activity recognition using smart phone inertial sensors and multi-class classification. This work targeted 6 activities which are standing, sitting, laying, walking, ascending, and descending stairs. The used dataset in this work consists of 30 subjects performing the activities without a specified activity duration, gender, weight, height, but age ranges from 19 to 48 years. This work utilized the accelerometer and gyroscope sensors in Samsung Galaxy S II smart phone. The device was placed on subjects' waist while while performing the activities. This work used a machine technique which is SVM, to recognize the preformed activities.

Ugulino *et al.* [47] constructed and published a dataset for HAR using an off shelves accelerometer sensor. This work targeted 5 activities which are sitting, sitting down, standing, standing up, and walking. The used dataset in this work consists of 2 males and 2 females subjects performing the activities without a specified weight, height, but age ranges from 28 to 75 years and activity duration of 12 minutes per activity. This work utilized an off shelves accelerometer sensor. The device was placed on subjects' waist, thigh, ankle, and arm while performing the activities. This work used 2 machine techniques which are AB with 10 DTs, to recognize the preformed activities.

Shoaib *et al.* [43] explored the role of gyroscope and magnetometer, as well as, combined with an accelerometer using smart phone. This work targeted 6 activities which are walking, sitting, standing, running, ascending, and descending stairs. The used dataset in this work consists of 4 males subjects performing the activities without a specified weight, height, but age ranges from 25 to 30 years and activity duration of 5 minutes per activity. This work utilized accelerometer, magnetometer, and gyroscope sensors in Samsung Galaxy S II smart phone. The device was placed on subjects' belt, wrist, arm, and jeans pocket while performing the activities. This work used 7 machine techniques which are NB, SVM, ANN, LogR, k-NN, RBC, DT, to recognize the preformed activities.

Cheng *et al.* [13] formulated HAR problem as a classification problem using data collected by wearable sensors and 3 different machine learning techniques. This work targeted 5 activities which are sitting, sitting down, standing up, standing, and walking. The used dataset in this work consists of 4 subjects performing the activities without a specified age, gender, weight, height, but a total activity duration of 2 hours. This work utilized off shelves accelerometer sensors. The devices were placed on subjects' left thigh, right arm, right ankle and abdomen while performing the activities. This work used 3 machine techniques which are SVM, HMM and ANN.

Baños *et al.* [5] investigated inertial sensor displacement effects, such as rotations (angular displacements) and translations (linear displacements), on HAR. This work targeted 33 activities which are listed in Table 2. The used dataset in this work consists of 17 subjects performing the activities without a specified weight, height, but age ranges from 22 to 37 years and activity durations listed in Table 2. This work utilized off shelves accelerometer, gyroscope, magnetometer sensors. The devices were placed on subjects' right and left calves, right and left thighs, right and left lower arms, right and left upper arms, back while performing the activities. This work used 3 machine techniques which are NCC, k-NN, and DT.

Zhang *et al.* [54] constructed and published a dataset of well-defined low-level daily activities intended as a benchmark for algorithm comparison particularly for healthcare scenarios. This work targeted 12 activities which are forward, left, right, upstairs, downstairs, running forward, jumping, sitting, standing, sleeping, elevator up, and down. The used dataset in this work consists of 7 males and 7 females

Table 2: Exercises considered for the activity set [5]. In brackets the number of repetitions (Nx) or duration of the exercises (in minutes)

E1: Walking (1 min)	E12: Waist rotation (20x)	E23: Shoulders high amplitude rotation (20x)
E2: Jogging (1 min)	E13: Waist bends (reach foot with opposite hand) (20x)	E24: Shoulders low amplitude rotation (20x)
E3: Running (1 min)	E14: Reach heels backwards (20x)	E25: Arms inner rotation (20x)
E4: Jump up (20x)	E15: Lateral bend (10x to the left + 10x to the right)	E26: Knees (alternatively) to the breast (20x)
E5: Jump front & back (20x)	E16: Lateral bend arm up (10x to the left + 10x to the right)	E27: Heels (alternatively) to the backside (20x)
E6: Jump sideways (20x)	E17: Repetitive forward stretching (20x)	E28: Knees bending (crouching) (20x)
E7: Jump leg/arms open/closed (20x)	E18: Upper trunk and lower body opposite twist (20x)	E29: Knees (alternatively) bend forward (20x)
E8: Jump rope (20x)	E19: Arms lateral elevation (20x)	E30: Rotation on the knees (20x)
E9: Trunk twist (arms outstretched) (20x)	E20: Arms frontal elevation (20x)	E31: Rowing (1 min)
E10: Trunk twist (elbows bended) (20x)	E21: Frontal hand claps (20x)	E32: Elliptic bike (1 min)
E11: Waist bends forward (20x)	E22: Arms frontal crossing (20x)	E33: Cycling (1 min)

subjects performing the activities with age from 21 to 49 year, height from 160 to 185 cm, weight from 43 to 80 kg, and 5 trials for each activity and each subject performed. This work utilized off shelves accelerometer, gyroscope, magnetometer sensors. The devices were placed on subjects' front right hip while performing the activities. This work used 2 machine techniques which are SVM and GMM.

Yang *et al.* [51] proposed a distributed recognition framework to classify continuous human actions using a low-bandwidth wearable motion sensor network, called DSC. This work targeted 13 activities which are stand, sit, lie down, walk for-ward, walk left-circle, walk right-circle, turn left, turn right, upstairs, downstairs, jog, jump, push wheelchair. The used dataset in this work consists of 13 males and 7 females without a specified activity duration, weight, height, but age ranges from 19 to 75 years. This work utilized off shelves accelerometer and gyroscope sensors. The devices were placed on subjects' waist, right and left wrists, right and left ankle while performing the activities. This work used a machine techniques which is DSC.

Frank *et al.* [16] compared the performance of inference in static and dynamic BN which have been learnt automatically from a recorded data set consisting of acceleration data observed from an inertial sensors. This work targeted 6 activities which are repetitive activities (walking and running) static activities standing (sitting and lying), short-time activities (falling and jumping) while performing the activities. The used dataset in this work consists of 10 males and 6 females without a specified age, weight, height, but a total activity duration more than 4.5 hours. This work utilized off shelves accelerometer, gyroscope, magnetometer sensors. The devices were placed on subjects' belt either on the right or the left part of the body while performing the activities. This work used 2 machine techniques which are BN and HMM.

Chetty *et al.* [14] applied body sensor networks for automatic and intelligent daily activity monitoring for elderly people by using wireless body sensors and smart phone inertial sensors. This work targeted 6 activities which are walking on flat ground, up and down stairs, sitting, standing, and lying down. The used dataset in this work consists of 30 subjects without a specified activity duration, gender, weight, height, but age ranges from 19 to 48 years. This work utilized the accelerometer and gyroscope sensors in Samsung Galaxy S2 smart phones. The devices were placed on subjects' waist while performing the activities. This work used 6 machine techniques which are NB, RF, DT, DCCA, k-MC, and RC.

Guo *et al.* [17] proposed a two-layer and multi-strategy HAR framework to overcome the major challenge of HAR using smart phone only, i.e., the variation in orientation and position of the device. This work targeted 6 activities which are sitting, standing, walking, running, ascending and descending stair. The used dataset in this work consists of 6 subjects without a specified activity duration, age, gender, weight, height. This work utilizes off shelves accelerometer, gyroscope, magnetic field sensors. The devices were placed on subjects' hand, coat pocket, trouser pocket and the rear pocket while performing the activities. This work used a machine technique which is RF.

Zebin *et al.* [52] used of CNN for HAR, in which inputs are multichannel time series signals acquired from a set of body-worn inertial sensors and outputs are predefined human activities. This work targeted 6 activities which are walking, sitting, standing, lying down, ascending and descending stair. The used dataset in this work consists of 12 subjects without a specified gender, but with an averages of ages: 24.6 $\pm$ 5.2 y, height: 1.63 $\pm$ 0.6 m, and weight: 64.7 $\pm$ 7.1 kg. This work utilized off shelves accelerometer and gyroscope sensors. The devices are placed on subjects' pelvis, left and right thigh, left and right shank while performing the activities. This work used 3 machine techniques which are SVM, CNN, and MP.

Davis *et al.* [15] used 3 machine learning techniques to detect activities that will later serve as inputs to a bidirectional activity awareness system for increasing social connectedness. This work targeted 6 activities which are walking, standing, sitting and laying, ascending and descending stair. The used dataset in this work consists of 31 subjects without a specified activity duration, gender, weight, height, but age ranges from 22 to 79 years. This work utilized the accelerometer and gyroscope sensors in Samsung Galaxy S2 smart phones. The devices were placed on subjects' waist using mounted smart phone belt on their left or right side while performing the activities. This work used 4 machine techniques which are SVM, HMM, SVM-HMM and ANN.

Zhang *et al.* [53] presented a statistical motion primitive-based framework for human activity representation and recognition. This work targeted 9 activities which are walk (forward, left, right), jump up, run forward, sit on chair, stand, ascending and descending stair. The used dataset in this work consists of 6 subjects without a specified age, activity duration, gender, weight, height. This work utilized off shelves accelerometer, gyroscope, and magnetometer sensors. The devices were placed on subjects' right front hip in mobile phone pouch while performing the activities. This work used 3 machine techniques which are SVM, K-MC, and GMM.

Nazabal *et al.* [35] proposed HAR systems with a very low number of wireless inertial sensors, each one providing an estimation of the performed daily activities. This work targeted 5 activities which are running, walking, standing, sitting, and lying. The used dataset in this work consists of 16 subjects without a specified activity duration, gender, weight, height, but age ranges from 24 to 33 years. This work utilized off shelves accelerometer, gyroscope, and magnetometer sensors. The devices were placed on subjects' waist, ankle, chest, and wrist while performing the activities. This work used 3 machine techniques which are PPC, SCC, MSCC.

Bruno *et al.* [10] assessed the level of independence of a person, based on the recognition of a set of activities of daily livings (ADLs) through a framework for the recognition of motion primitives based on GMM and GMR for creation of activity models. This work targeted 14 activities which are listed in Table 3. The used dataset in this work consists of 11 males and 5 females without a specified activity duration, weight, height, but age ranges from 19 to 83 years. This work utilized off shelves accelerometer sensors. The devices were placed on subjects' right wrist while performing the activities. This work used 2 machine techniques which are GMM, GMR.

Table 3: ADLs considered for the activity set [10].

ADL1: Personal hygiene	teeth brushing - hair combing
ADL2: Mobility	stairs climbing - stairs descending - walking
ADL3: Feeding	drinking from a glass - pouring water in a glass - eating with fork and knife - eating with spoon
ADL4: Communication	telephone
ADL5: Functional transfers	getting up from the bed - lying down on the bed - standing up from a chair - sitting down on a chair

Weiss *et al.* [49] compared between smart devices such as watch and phone in HAR where, smart watches show superiority in identifying specialized hand-based activities. This work targeted 18 activities which are walking, jogging, climbing stairs, sitting, standing, kicking soccer ball, dribbling basketball, playing catch with tennis ball, typing, handwriting, clapping, brushing teeth, folding clothes, eating pasta, eating soup, eating sandwich, eating chips, and drinking from a cup. The used dataset in this work consists of 17 subjects without a specified age, gender, activity duration, weight, height. This work utilized both accelerometer and gyroscope sensors in LG G Watch and Samsung Galaxy S4 phone. The smart watch was placed on subjects' dominant hand and a paired smart phone in the front-right pocket with the phone oriented upright with the screen facing outward while performing the activities. This work used 5 machine techniques which are RF, DT, NB, MP, and IBL.

Altun *et al.* [1] provided a comparative study on the different techniques of classifying human activities that are performed using body worn miniature inertial and magnetic sensors. This work targeted 19 activities which are sitting, standing, laying on back and on right side, ascending and descending stairs, standing in an elevator still and moving around, walking in a parking lot, walking and running on a treadmill, exercising on a stepper, exercising on a cross trainer, cycling on an exercise bike in horizontal and vertical positions, rowing, jumping, and playing basketball. The used dataset in this work consists of 4 males and 4 females without a specified activity duration, weight, height, but age ranges from 20 to 30 years. This work utilized off shelves accelerometer, gyroscope, and magnetometer sensors. The devices are placed on subjects' chest, right and left wrists, right side of the right knee, and left side of the left knee, while performing the activities. This work used 7 machine techniques which are BDM, DT, k-NN, SVM, ANN, DTW, and LSM.

Table 4: **C**: Constructive **E**: Evaluative **O**: Optimization

Paper	C	E	O	Purpose
Anguita	√	√	-	constructs and publishes a dataset, as well as, builds a detection model using a M-SVM approach for HAR utilizing smart phones.
Kwapisz	-	√	-	describes and evaluates a system that uses phone-based accelerometers to perform activity recognition, a task which involves identifying the physical activity a user is performing.
Mortazavi	-	-	√	aims to minimize computational load and power consumption in repetition counting by extracting the most informative activity-specific features to select only the best single axis for detecting each activity.
Shoaib	√	-	-	constructs and publishes a dataset, as well as, builds a detection model using 9 classifiers approaches for HAR utilizing smart phones.
Mortazavi	√	-	-	estimates the MET values achieved when users perform exergaming. This work targets exergames that focus on energy expenditure.
Anguita	√	-	-	presents a system for human physical activity recognition using smart phone inertial sensors and multi-class classification.
Ugulino	√	-	-	constructs and publishes a dataset for HAR using an off shelves accelerometer sensor.
Shoaib	-	√	-	explores the role of gyroscope and magnetometer, as well as, combined with an accelerometer using smart phone.
Cheng	√	√	-	formulates HAR problem as a classification problem using data collected by wearable sensors and 3 different machine learning techniques.
Ba	-	√	-	investigates inertial sensor displacement effects, such as rotations (angular displacements) and translations (linear displacements), on HAR.
Zhang	√	-	-	constructs and publishes a dataset of well-defined low-level daily activities intended as a benchmark for algorithm comparison particularly for healthcare scenarios

Yang	√	-	-	proposes a distributed recognition framework to classify continuous human actions using a low-bandwidth wearable motion sensor network, called DSC.
Frank	-	√	-	compares the performance of inference in static and dynamic BN which have been learnt automatically from a recorded data set consisting of acceleration data observed from an inertial sensors.
Chetty	√	-	-	applies body sensor networks for automatic and intelligent daily activity monitoring for elderly people by using wireless body sensors and smart phone inertial sensors.
Guo	√	-	-	proposes a two-layer and multi-strategy HAR framework to overcome the major challenge of HAR using smart phone only, i.e., the variation in orientation and position of the device.
Zebin	√	-	-	uses of CNN for HAR, in which inputs are multichannel time series signals acquired from a set of body-worn inertial sensors and outputs are predefined human activities.
Davis	√	-	-	uses 3 machine learning techniques to detect activities that will later serve as inputs to a bidirectional activity awareness system for increasing social connectedness.
Zhang	√	-	-	presents a statistical motion primitive-based framework for human activity representation and recognition.
Nazabal	√	-	√	proposes HAR systems with a very low number of wireless inertial sensors, each one providing an estimation of the performed daily activities.
Bruno	-	√	-	assesses the level of independence of a person, based on the recognition of a set of ADL through a framework for the recognition of motion primitives based on GMM and GMR for creation of activity models.
Weiss	-	√	-	compares between smart devices such as watch and phone in HAR where, smart watches show superiority in identifying specialized hand-based activities.
Altun	-	√	-	provides a comparative study on the different techniques of classifying human activities that are performed using body worn miniature inertial and magnetic sensors.
Total	**14**	**9**	**2**	

Table 5: **A**: Age **G**: Gender **W**: Weight **H**: Hight **D**: Duration

Paper	**Data Attributes**					**Sensor Type**		
	A	**G**	**W**	**H**	**D**	**Acc.**	**Gyro.**	**Mag.**
Anguita	√	-	-	-	-	√	√	-
Kwapisz	-	-	-	-	-	√	-	-
Mortazavi	√	-	-	-	√	√	√	-
Shoaib	√	-	-	-	√	√	√	√
Mortazavi	√	√	-	-	√	√	-	-
Anguita	√	-	-	-	-	√	√	-
Ugulino	√	√	-	-	√	√	-	-
Shoaib	√	-	-	-	√	√	√	√
Cheng	-	-	-	-	√	√	-	-
Ba	√	-	-	-	√	√	√	√
Zhang	√	√	√	√	√	√	√	√
Yang	√	-	-	-	-	√	√	-
Frank	-	-	-	-	√	√	√	√
Chetty	√	-	-	-	-	√	√	-
Guo	-	-	-	-	-	√	√	√
Zebin	√	-	√	√	-	√	√	-
Davis	√	-	-	-	-	√	√	-
Zhang	-	-	-	-	-	√	√	√
Nazabal	√	-	-	-	-	√	√	√
Bruno	√	√	-	-	-	√	-	-
Weiss	-	-	-	-	-	√	√	-
Altun	√	√	-	-	-	√	√	√
Total	**16**	**5**	**2**	**2**	**9**	**22**	**17**	**9**

Chapter 4

Challenges & Opportunities

This chapter introduces some of the open issues in the field to shed light on opportunities for future research. Despite considerable advances in inferring activities from wearables and activity recognition systems [19, 4], developing HAR systems that meet user requirements remains a daunting task. These systems can be severely impacted by some challenges such as sensor placement, activity's complexity, and performance retrogression. Sensor placement and activities complexity challenges occur frequently, unlike, performance retrogression challenge which occur rarely because it requires a long period of time to occur.

Sensor placement

Challenge: Placing a sensor incorrectly can negatively impact its performance, specially for accelerometer. Boerema [8] found that sensor location, type of activity, and their interaction-effect affect sensor output. Also, the loose fit results in lower sensor output, which cases inaccurate activity recognition. Boerema shows that the most lateral positions on the waist belt are the least sensitive for interference to accelerometer readings.
Solution: Such a solution [26] is adding another sensor to address the orientation sensitivity such as magnetometer. Another solution [7] presents a device pose classification method based on the regularized kernel algorithm. It provides a way of how to estimate the accelerometer pose before doing any motion data analysis.
Opportunity: Previous studies focused on accelerometer; therefore, there is an opportunity in facing a challenge of placing other sensors across subject's body such as

inertial sensors which combines gyroscope and accelerometer sensors inside it. Studying the impact of sensor placement on other sensors will guide us to find the sweet spots to get the best consistent readings for certain activities.

Activity's complexity

Challenge: The increasing complexity of subject's activities poses challenge to the recognition model. For example, a subject performing multiple stages activity [6] might confuse the classifier which is trained under one activity-per-segment assumption. In addition, individual difference might result in the variation in the way that subject performs such a complex activity, which in turn brings the difficulty in applying the activity recognition models globally.
Solution: Such a solution [36] is using a finite state based technique such as: HMM, to address the activity complexity by smoothing the error during the activity transition period.
Opportunity: Previous studies focused on either simple activities or used HMM; therefore, there is an opportunity in facing such a challenge by studying the impact of hybrid machine learning or ANN with moving windows on recognizing complex activities. This opportunity will help us to better detect multi-stages human activities.

Performance retrogression

Challenge: The performance of activity recognition models is heavily affected by the quality of the dataset. Optimally, we are looking to collect a data from healthy people, unfortunately, this is not the case in reality. A Subject who is performing an activity may suffer from exhaustion/ sickness leading to have "abnormal" data readings which leads to performance retrogression. Moreover, performing any activities for a long period of time may introduce fatigue which can hinder HAR based system because it can cause errors and false results.
Solution: Such a solution [28] is using psycho-physiological parameters as indicators of fatigue while driving. Another solution [23] investigates various physiological associations with fatigue to try to identify better fatigue indicators while driving to prevent accidents.
Opportunity: Previous studies focused on detecting fatigue as constant occupational

hazard for drivers. However, they did not consider fatigue as by product of long time activity which affect the performance of HAR system. For example, Gym applications which are mostly wearable based solutions may suffer from difficulties once the users perform their daily activities with a fatigue. The existence of fatigue may lead weaker performance for the daily activities that hinder wearables data readings; therefore, cause errors and false results. There is an opportunity in facing a challenge of exercise by products, through building a fatigue perception model to characterize fatigue in order to predict it during human activities. Moreover, there is an opportunity in facing such a challenge by studying the impact of different status of subject's physical capabilities. This opportunity will help us to efficiently and effectively build adaptive recognition models which can fit the physical status of a subject through series of activities.

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