A Machine Learning Approach for Human Activity Recognition: a Comprehensive Survey

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***Abstract*: Human Activity Recognition (HAR) has turn out to be a popular topic in the preceding period due to its standing in studying numerous ranges of extended electronic gadgets such as latest smartphones, recent smart-watches, modern smart homes and video-cameras present-day lives and also including interactive gaming, sports, health-care and intensive care systems. HAR goals to identify human activities is measured and unmeasured environments. Regardless of countless uses, HAR algorithms look a number of defies, plus the following intra subject and inter subject unevenness for the similar activity, complexity and variety of daily activities, computational efficiency in embedded and portable devices, tradeoff between performance and privacy and finally difficulty of data annotation. HAR has become a very important research area. In addition, the improvement of Deep Learning takes the scholars to habit HAR in various fields. It is one of the top favorable assistive information tools to care routine life. But, in this caring of algorithms wants bulky amounts of data. This paper work survey on focuses the critical uses of machine learning in the playing field of HAR, mostly concerned through Daily Life Activities.**

Keywords*: *Human Activity Recognition (HAR), smartphones, smart watches, video cameras, Deep Learning (DL), Machine Learning (ML).

I. INTRODUCTION

Human Activity Recognition (HAR) is the basic physical activities [1] such as standing, sitting, walking or running is a well-researched topic. Present-day research in the area of activity recognition focuses among other things on personalization, on increasing the number of activities to be recognized, HAR is the duty of categorizing human activities. Human activity approaches industrialized in uses such as smartphones, smart-homes, therapy, and health care support [2]. It is commonly processes signals from motion videos, Motion Capturing [Mo-Cap] schemes, and a number of on-body sensing devices or many other available data sources. Generally, the approaches of statistical pattern recognition utilized the human movements. These approaches mine valid handcrafted structures on or after pre-processed, segmented sequences, and also they train a classifier aimed at handover action labels to the sequences. A moment ago, deep learning methods are used for merging into its own method. HAR is to infer the present behavior and goals of the human body through a series of observations and analyses of human behavior and its environment. HAR [3] research has involved attention for its advantages of widespread application in healthcare systems, intelligent surveillance systems, smart homes, virtual reality interactions, abnormal behavior detection and other fields, as well as its ability to provide individualized support and interconnection for different fields. HAR [4] has been an imperative concern in the computer science community. With the in-depth development of machine learning and deep learning technologies and the release of complexity sensors, such as Microsoft Kinect, and NVIDIA’s GPUs, it has been possible to quickly identify human behavior using devices such as video and motion sensors. At present, HAR is mainly performed by external or internal sensing. In the former mode, devices such as cameras [5] are placed at certain fixed predetermined locations, and the inference of activities is entirely dependent on the user’s interaction with these devices. In the latter, a detailed device, such as an inertial sensor, is placed on a part of the user’s body to sense motion. In most cases, a camera is used as an external sensor for HAR. The implication of human activity comes from the camera recording a video sequence [6]. Human activity recognition is an important research field complete of challenges, most of which motivation on accuracy, robustness and real-time capability. It's too difficult for researchers to face all these challenges in the past. The excessive improvements made in sensor and processor technologies during the past decade, now acquire additional accurate sensors in a smaller size and faster processors with lower power consumption. In recent times, with a widely application requirements appearing in physical training, health care and military, HAR has involved additional and more attention from both academia and IT industry[7].

Human motions are cached by using sensor [8] devices. The sensor is divided into two sub systems that is optical and non-optical systems [9]. So, the optical systems relays on active or passive indicators that are involved to a person or they are

arranged markerless, using for example RGB (-D) cameras. Optical, marker-based Motion Capturing (OMMC) is considered more precise than markerless methods.
In HAR, recording, analyzing, and annotating measurements from IMUs is an expensive and time-demanding task. HAR faces challenges with regards to the settings of the recording environment, number of participants as well as sensors and their configuration.

The human activity recognition methods contain 4 main steps [10] as follow:
First one is Sensing: it is gather signal at an exact sampling rate and second one is preprocessing: it grouped signals and also using different approaches such as noise reduction and segmentation. Third one is feature extraction: its extracted many data feature form raw segmented data. Fourth one is training or classification: In training phase, it is led offline only, the model is constructed and adjusted with the optimal parameters. Future constructing the optimized model, it turn out to be ready to usage in classification stage. In current periods, several training and classification approaches for human activity recognition methods applied on the smart devices. These methods were employed using dissimilar. machine learning approaches such as decision tree, naive bayes, K-Nearest Neighbor (KNN), Boosting algorithm ,Support Vector Machine (SVM), Neural Network, ,etc. A deep belief network[28] model is proposed to predict the diabetes mellitus from electronic health records. Predictive Analytics Algorithms for Clinical Decision Making in Healthcare[]29 was analysed for its performance benchmark.

The rest of this paper is prearranged as follows. Section II literature review. Section III result and discussion. Section IV presents and future direction of the work. Finally section V conclude of this paper.

II. Literature Review

Smartphone based HAR

It is mainly based on dynamical schemes and chaos theory. A reconstructed stage space is formed from the accelerometer sensor, data using time-delay embedding. An axis of solitary accelerometer used to decrease memory and computational difficulty. A model of Gaussian mixture is well-read on the reconstructed stage [11] space. The Gaussian mixture model classify 10 different human activities. 1 public and 1 dataset were used to confirm this method. Data was collected from 10 different subjects. The public dataset covers data from thirty subjects. This method got 100% accuracy for individual models through all activities and datasets. The given figure shows the light weight smartphone based human activity recognizer.

The author discuss the system of smartphone based human activity recognition that uses one of the renowned deep learning styles called Stacked Auto Encoder (SAE) [12] to improve the recognition accuracy and decrease recognition time. Evaluate this method to applied public benchmark dataset and compared it to available methods. It found that the new-fangled method rise the overall classification accuracy.

A smartphone inertial sensors-based method for human activity recognition. First the raw data extracted form Well-organized structures. The structures take account of mean, median, autoregressive coefficients, etc. The structures are processed by a kernel principal component analysis and linear discriminant analysis to create them more robust. To sum up, the features are trained with a Deep Belief Network for positive activity recognition. Finally the approach was compared [13] with old-style expression recognition approaches such as typical multiclass Support Vector Machine and Artificial Neural Network.

Robust HAR Using Smartphone

In [14] this paper, a robust human activity recognition system in terms of orientation, placement and subject variations based on coordinate transformation and principal component analysis (CT-PCA) and online support vector machine (OSVM). The CT-PCA scheme is utilized to eradicate the effect of orientation differences, which proves the generalization ability of the scheme on the data from unseen orientations. It also show the effectiveness of this scheme on placement and subject variations. The inherent difference of signal properties for different placement and subject dramatically reduces the recognition accuracy, especially for different placement. An efficient OSVM algorithm, i.e. online independent support vector machine (OISVM), which utilizes a small portion of data from the unseen placement or subject to online update the parameters of the SVM algorithm.

Smartwatch based HAR

HAR System using wearable devices has been dynamically investigated in a varied range of applications. Maximum, either focus on simple activities wherein whole body movement is involved or require a variety of sensors to identify daily activities. In this study, [15] the HAR system gathers data from smartwatch and customs an artificial neural network for classification. So in this system is additionally enriched by using location information. It also consider eleven (11) activities, including both simple and everyday activities. The given figure shows the overall view of the smartwatch based human activity recognition system. Based on the experiment the results are show that various activities can be classified with an accuracy of 95%.

Smart city environment using HAR

Smart city environment [16] provides an accurate information about human activity. In this paper, the Adaboost ensemble classifier is used to classify human activity data taken from human body sensors. The classifiers are using a weighted mixture of a number of classifier models. To develop a robust human activity recognition system based on the wearable sensors data. In this framework, the Adaboost ensemble method is suggested to achieve high classification accuracy to know the human activity. The results demonstrated that the system has been checked for 7 different physical activities and 99.98% an overall accuracy has been achieved by using Adaboost with random forest.

Smart Healthcare

A new smart healthcare framework for AAL to screen the physical activities of elderly people using Internet of medical things (IoMT) and intelligent machine learning algorithms for quicker analysis, decision making and healthier treatment recommendations. Data is collected from numerous wearable sensors placed on subject's right arm, left ankle and chest, is transmitted through IoMT[17] devices to the integrated cloud and data analytics layer. To progression huge amounts of data in Hadoop MapReduce, parallel techniques are used. Multinomial Naïve Bayes classifier, which hysterics into the MapReduce paradigm, is utilized to recognize the signal experienced by different body parts and provides higher scalability and better performance with parallel processing when compared to serial processor. This framework foresees 12 physical activities with an overall accuracy of 97.1%.

UAV-captured video based HAR

The new approach for HAR from UAV-captured video sequences [18]. In this approach involves 2 phases: the first one is an offline phase and the second is an inference phase. A scene stabilization stage is performed together with these 2 phases. The offline phase intentions to generate the human/non-human model as well as a human activity model by means of a convolutional neural network. The inference phase use the previously generated models to detect human and recognize their activities. So this method adapting the convolutional neural networks, it dedicated the classification task, to detect human's activity. In addition to the classification of human activities, two scenarios are approved. An immediate classification of video frames and a whole classification of the video sequences. Be determined by on an experimental assessment of the methods for human detection and human activity classification on the UCF-ARG dataset, then it authenticated not only these contributions but also the performance of the methods compared to the existing ones.

HAR based on hybrid deep learning model

The author says [19] a novel approach for human action recognition based on hybrid deep learning model. It has significant challenge in a diversity of application including human-computer interaction and intelligent video surveillance to enhance security in different domains. The evaluation algorithm relies on the correct extraction and the learning data. The success of the deep learning led to many impressive results in several contexts that include neural network. The emergence of Gated Recurrent Neural Networks with increased computation powers is being adopted for sequential data and video classification. However, to have a well-organized classifier for assigning the class label, it is very necessary to have a strong features vector. Features are the furthermost important information in each data. This approach is evaluated on the challenging UCF Sports, UCF101 and KTH datasets.

Sensor-based movement recognition

Human activity recognition is a significant research topic in pattern recognition and pervasive computing. In this paper, the author [20] surveys the recent advance in deep learning approaches for sensor-based movement recognition. Associated to traditional pattern recognition methods, deep learning decreases the dependency on human-crafted feature extraction and attains better performance by automatically learning high-level representations of the sensor data. It highlight the recent progress in 3 important categories: sensor modality, deep model, and application. Next, summarize and discuss the surveyed research in detail. Finally, some outstanding challenges and feasible solutions are obtainable for future research.

MAchine Learning & Knowledge Extraction

The MAchine Learning & Knowledge Extraction [21] (MAKE). The area of Machine Learning is to develop software which can learn from previous experience. In due course, to reach a level of usable intelligence, need, to learn from prior data, to extract knowledge, to generalize, to fight the curse of dimensionality, and to disentangle underlying explanatory factors of the data. To talk these challenges and to guarantee successful machine learning applications in various domains an integrated machine learning approach is important.

Recent trends in ML for HAR

Activity Recognition (AR) is the new trend to addressing the boundaries of the traditional machine learning algorithms and uncommon classification design challenges. The deep learning architectures used mostly due to its advantage of hierarchically self-derived features, which help to represent the data better compared to the handcrafted structures. Hence, it is significant to design and raise robust data mining techniques to mine the knowledge and machine learning procedures to accomplish and authenticate that knowledge from data which will allow the AR [22] system to type intelligent results. This study presents the up-to-date trends and growths in machine learning techniques, to address the next-generation AR challenges over many devices, systems, persons and environments.

Sensor-based HAR

The deep learning approaches for sensor-based human activity recognition. 1st introduce the multimodality of the sensual data and provide information for public datasets that can be used for assessment in different challenge tasks, then a new taxonomy to structure the deep methods by challenges. Challenges and [23] it related deep methods are précised and analysed to form an imprint of the current research progress. At the conclusion deliberate the unspoilt issues and bring some visions for upcoming directions.

Deep Belief Network using HAR

The human activity recognition problem as a cataloguing problem by means of wearable body sensor data. In explicit, to utilize a Deep Belief Network faultless for successful human activity recognition. In this 1st mine the important early features from the raw body sensor data. Formerly, a kernel principal component analysis and linear discriminant analysis are complete to additional process and make them stronger to be useful for rough activity recognition. Finally, the DBN [24] is taught by these features. Several trials remained on an everyday wearable sensor dataset to settle the success of the deep learning algorithm. The results of the DBN algorithms produce the good accuracy level.

Transfer learning based on MMD

Unsupervised allocation learning from source dataset to target dataset, which are completely different in relations of number of users and samples. Used Maximum Mean Discrepancy (MMD) [25] based transfer learning model and compared with base Convolutional Neural Network (CNN) model. Used four datasets for experiment. Trained the model on a source dataset and then transferred the model to a target dataset, which has no labels to classify activities. Found that transfer learning model has attained better performance compared to the base model.

HAR via DL-based Domain Adaptation

A transudative transfer learning model that is exactly tuned to the properties of convolutional neural networks (CNNs). Heterogeneous Deep Convolutional Neural Network that is automatically adapts and learns the model across different domains. This model, called [26] HDCNN, assumes that the relative distribution of weights in the different CNN layers will keep on invariant, as long as the set of activities being monitored does not change. Assessment on real world data shows that HDCNN is able to achieve high accuracy even without any labelled training data in the target domain, and suggestions higher accuracy.

Asymmetric Residual NN for Accurate HAR

A novel ARN is asymmetric residual network. ARN [27] is employed by means of 2 identical path frameworks consisting of two methods, first a short time window and second a long time window. The first method of window is used to capture three-dimensional features, and a second method of window is used to capture fine sequential features. The second method of window (long time) path is through actually lightweight by reducing its channel capacity. The author mainly attention on a new model is to improve the accuracy of HAR. In way to show the competence of the ARN model, it accepted out extensive experiments on standard datasets and compared the results with some predictable methods. If shows that the results of the ARN is a real in recognizing human activities by wearable datasets.

III. Result and Discussion

Table 1: Related work classified by sensors

Ref.	Sensor Device	No of Activities	Accuracy
[11]	Smartphone	Body	100%
[13]	Smartphone	Twelve activities	95.85%
[14]	Smartphone	Bags and pants' pocket, shirt's pocket	--

[15]	Smart Watch	11 activities	95%
[16]	Smart City	Different activities	99.98%
[17]	Smart Health Care	12 physical Activities	97.1%
[18]	Video Camera	UAV	--
[19]	Video Camera	10 activities.	90.01%
[24]	Body	12 Exercise	97.5%
[25]	Body	“Jogging”, “Walking”, “Sitting	--
[26]	Smart watch, phone	Body	90%
[27]	Human body	set of active	98%

All the above **table1** methods conversed so far for HAR have its own merits and demerits. A review of HAR systems which uses signals generated from portable inertial sensors has been introduced. Kinds of HAR systems according to data acquisition paradigms, types of devices, number of activates and its accuracy have been presented. Furthermore, various machine learning algorithms which are used with human activity recognition systems have been stated. As a final point, some important related proposed systems are exemplified.

IV. DIRECTIONS OF FUTURE RESEARCH

To expand possible of machine learning in human activity recognition, positive future research guidelines are benign to additional analysis. Impending directions be inspired by the challenges summarized in this effort. In the look of the work keen to these challenges, some of them are quiet not fully discovered such as concurrent activities, class imbalance, composite activities, etc. Though, present research works still absence comprehensive and reliable solutions for the challenges and display guidance for future directions are essential for Identifying new activities, upcoming activity prediction, Self-determining unsupervised systems, etc. Also, Table 1 recaps all the aforementioned surveys on human activity recognition methods sorted. Furthermost of these HAR reviews focus on data management methods and activity recognition models.

V. CONCLUSION

The drive of this systematic literature review is to detention the Human Activity Recognition for several fields. To attain this goal, HAR systems which custom signals produced from convenient inertial sensors has been announced. Types of HAR structures giving to data acquisition models, types of attributes, and sensors, counts and locations have been presented. Similarly, several machine learning algorithms which are used with HAR systems have been stated and HAR applications in connected areas are taken into explanation. Future work should focus on the development of approaches with more advanced generalization capabilities and recognition of more complex activities.

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