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Human Activity Recognition using Deep Learning

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Abstract

Machine learning research is heavily focused on human activity detection since it has various applications in a variety of fields, including security, entertainment, ambient supported living, and health management and monitoring. Researchers' interest in human daily activities is seen from studies on human activity recognition (HAR). As a result, the general architecture of the HAR system and a description of its key elements are described in this work. Review of the state-of-the-art in accelerometer-based human activity recognition According to this survey, the majority of recent research that employed CNN for HAR identification relied on it even though other deep learning models also showed acceptable accuracy. The paper suggests a 2 different classification depending on the kind of machine learning (conventional or deep learning) and the manner of execution (online or offline). Comparing 48 studies prediction performance, algorithms, activity categories, and used equipment. The study concludes by contrasting the difficulties and problems associated with identifying human movement based on accelerometer sensors utilizing deep learning versus conventional machine learning, as well as online versus offline.
Keywords—Human activity recognition; accelerometer; online system; offline system; traditional machine learning; deep learning

1. Introduction

Technologies that engage with one's own biological identity, improved technology, health and wellness tracking, social support, etc. are all built on the foundation of human activity recognition (HAR). The input of HAR models is raw data stream measurements, and their estimation of the person's mobility activities is their result.

A. Sensors Approaches

Wearable sensors and external sensors are the two sensors available to monitor human activities. User interaction with the sensors serves as the main basis for activity detection because the detectors were previously positioned in predetermined areas of interest. One use for external sensors is the intelligent home [2,3], which uses information taken from several sensors placed in particular products to recognize complicated behaviors like feeding, showering, cleaning dishes, etc. People's interactions with those objects, such as the stove, faucet, washing machine, etc., sustain them [4-6].
Additionally, some of the in-depth studies [7-9] have concentrated on the identification of actions and gestures from video clips. However, various problems can be seen in HAR's video sequences, such [10]:

- Everyone values their privacy and doesn't want to constantly be watched and filmed by cameras.
- Techniques for processing videos take time and are relatively expensive

B. Challenges Face HAR System Designers

The ability to identify activities is a must for every HAR system design. The types and complexity of actions have the potential to influence the recognition's quality. Some of the difficulties that researchers must face are listed below: (1) how to select the characteristics to be evaluated; (2) how to design a system with compact, inconspicuous, and affordable information processing; (3) how to extract designs and construction prediction methods; (4) how to get information in a genuine environment; (5) how to recognize new users' activities without the system needing to be retrained; and (6) how to implement in mobile devices that meet energy and manufacturing drawbacks [11].

C. Offline Versus Online HAR Systems

Both offline and internet methods could be used to detect human activities. The offline processing can always be employed when the Programme does not require internet processing. For instance, if the goal is to record a person's usual schedule, as in [12], information was collected all day long using the sensors and now can be sent to a database at night.

D. Machine Learning Techniques

The machine learning method that is most appropriate in the given problem instance determines whether the HAR process is successful. There are two distinct approaches: one uses traditional machine learning methods such as KNN, Naive Bayes, Bayes Net, IBK, J48, Random Forest, SVM, and DTW, while the other utilizes deep learning methods such as CNN model, recurrent neural networks, vanilla RNN forward, and Gated Recurrent Unit RNNs among others. Realize that human effort has a purpose. The

article discusses the most recent deep learning and conventional machine learning techniques for HAR.
In Section 2, the basic HAR system components are illustrated. In Section 3, the contrast between online and offline systems is explored. In Section 4, conventional and machine learning methodologies are contrasted.

2. General Structure of HAR Systems

The Four key phases of the Human Activity Recognition process are Data Acquisition, Pre-Processing, Object Recognition and Classification. Data acquisition: It is the initial stage of wearable sensors, which entails collecting sensor data. Pre-processing: After the data is gathered, it is the next phase. When processing the received data, it performs essential tasks including removing noise from the original data and using virtualization or separation techniques. The raw information needs several transitions, such as separating the constant input signals into periods of a certain duration, since utilizing the collected data straight in the classification process may not have been the best course of action.

Table 1. Categorization of activities

Activity	**Category**	**Related Ref.**
Moving up and Lying quietly, heading up and reclining, down stairs and climbing up	Transitional Activities	[15]
teeth-brushing, using the restroom, cleaning the toilet, Putting on clothes, putting on makeup, washing your hands, face, and clothing hair drying, hair brushing, grooming and using pills	Self-care Activities	[16,17]
Jogging on a treadmill, hopping, playing football, basketball, jogging, aerobic dance, strolling on a treadmill, and rowing	Exercise/fitness	[18-20]
Fill the cup with piping hot water, put sugar in ,put milk in , take out the teabag, pour milk outside of the mug, brewing coffee brewing tea properly fry eggs, add one teabag, Creating a beverage, a sandwich, boiling rice, pasta, Fill the kettle. Cooking, Outside of the mug, pour the boiling water, preparing oatmeal , Feed the fish. checking the kitchen's appliances and utensils.	Kitchen Activities	[21,22]
seated, upright, and lying climbing stairs, going up an escalator using an elevator, slipping, pausing, flexible motion, Running, climbing stairs and the escalator.	Ambulation	[23,24]
Driving, Riding a bus, Cycling.	Transportation	[25-27]
cleaning tables, Hoovering, Keeping a dining table clean ,using a broom to sweep, tidying up, sorting documents on paper, removing rubbish, doing the dishes.	Household Activities	[28,29]
using a phone, drinking, viewing TV, using a computer, reading a book or magazine, out of bed, napping, a computer, lugging a box, Standing up, Sorting, Eating, hearing music or the radio, Participating in dialogue	Daily Activities	[30,31]

Feature extraction: Three 3D acceleration readings are collected from the segmented data in a pattern. It changes the information into the essential components unique to the activity. Extracting characteristics from data that is based on a spatial frame is superior to utilizing raw data, which relies on categorizing every single observation. By utilizing the features rather than the raw data, classification algorithms' computing requirements are reduced as well as the impacts of noise. The two domains of standard characteristics are time and frequency. Janidarmian et al. claim that the time or frequency domain and intuitive features are best for recognizing human action. [14]. Classification: The process of recognizing human activity has reached its conclusion.
The various actions are classified using the trained classifiers. Either offline or online methods of classification are available.

3. Online Vs. Offline Har Systems

The classifiers are trained using the classification model in the initial step [15-18]. There are online and offline options for both the classification process itself and training the human induced analyzer. Semi or offline categorization is sufficient if there is no immediate requirement on the part of the user. However, online real-time categorization enables consumers to receive immediate feedback. A method for gesture recognition was developed by Liang et al. employing offline pre-processing steps and online categorization. [19,20].

A. Online vs. Offline Training Phase

On the enabling device, including a smartphone, cloud, or Raspberry Pi, the classifiers are trained in real-time. However, the models are typically created beforehand for offline training on a computer. In addition, the sensor-gathered activity raw data is saved and utilized later to train the classification model. To save time, the raw data are processed for training right away during the online training phase rather than being retained for later use. [21, 22]

B. Online vs. Offline Classification

According to the training data, there are two approaches to classify an action for a given label in the final step of classification: online or offline. Offline implementation and evaluation of semi supervised classification have been done most frequently. [23, 24]

4. Traditional and Deep Learning Techniques

Wearable sensors, smartwatches, and other intelligent machine technologies have improved significantly in recent years. Based on the initial altimeter sensor data, these devices might now predict human behavior using artificial intelligence-powered applications. Using machine learning techniques, HAR's main objective is to predict human behavior properly. Numerous conventional learning methods, including Decision Tree, Random Forest, AdaBoost, Support Vector Machine, K-nearest Neighbor, and Naive Bayes, among others, produced accurate results. However, HAR makes extensive use of deep learning. [25, 26] after reviewing numerous studies, we discovered three distinct methods from fig. 1.

A. Traditional model flow

Sensors collect the data, characteristics are retrieved, a conventional technique is utilized, and then the task indicator is produced. [27, 28]

B. Deep learning model flow

Data collection, feature extraction, application of a deep learning technique, and label extraction are all steps in a deep learning model, as shown in [29].
After gathering the data and using deep learning to automatically extract the features, a SoftMax layer that is comparable to those shown in [30,31] is used to forecast the category of the event.

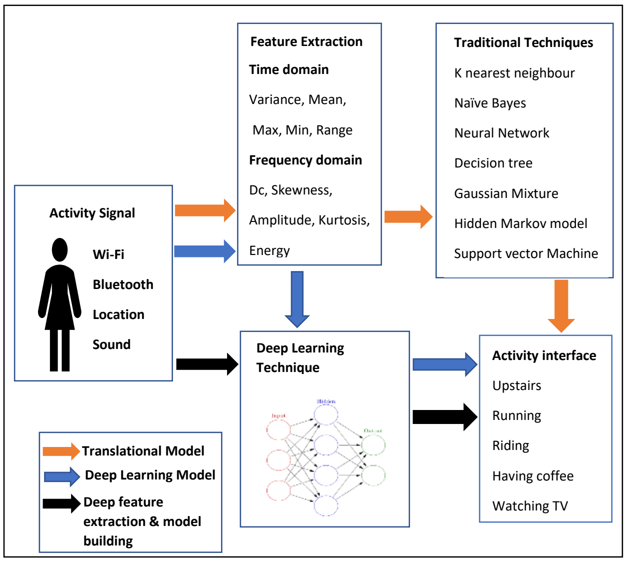

Figure 1. Basic Components of Conventional and Deep Learning Models

5. Conclusion

This study examines the current state of human activity recognition using velocity measurements. We described the fundamental framework of classic and deep learning machine learning algorithms, as well as online and offline activity identification systems. These researches also focus on classifying the multiple tasks and classification methods used during the analysis procedure. 48 research are qualitatively evaluated with regard to the tasks, tools used, learning models, database, and detection rate. Finally, we talk about the various problems and difficulties with these investigations. Even though RNN and AE both achieved an acceptable level of precision that is more than 96%, this survey showed that deep learning has recently been employed as much as traditional machine learning. But it also demonstrated how regularly CNN deep learning is employed.

6. References

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