Conference on
Information Technology and
Data Science

Smartwatch Activity Recognition Using Ml.net Framework*

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Proceedings of the 1st Conference on Information Technology and Data Science
Debrecen, Hungary, November 6–8, 2020
published at http://ceur-ws.org

Abstract

Nowadays wearable devices are part of our everyday lives. More and more devices that we carry every day are becoming smart and gain more and more features. One of them is the humble watch, which has been telling the time and other useful basic information for ages. Since this inconspicuous device is worn almost all the time, it can be successfully used for activity recognition. We propose a system that uses a smartwatch as a primary movement data collection device that connects to a local data hub, which acts as a data gateway. The local hub's role is to upload the data into the cloud, a MongoDB database in realtime. To recognize activities, this system will process the obtained data offline, using the ML.net machine learning framework. This proposed activity recognition system can be easily expanded due to the local data hub and provides a non-intrusive method of collecting user's data with only a smartwatch. Combined with the machine learning data processing mechanism, this ensures a flexible activity recognition system that has a good recognition rate.

Keywords: Activity recognition, smartwatch, machine learning, ML.NET, IoT

*This work was supported by the Intelligent Embedded Systems research laboratories at the Technical University of Cluj-Napoca, North University Centre of Baia Mare.

1. Introduction

Wearable devices are becoming everyday objects, assisting us in many fields including healthcare [4]. One of the most popular wearable technology devices is the smartwatch, which replaced an every-day carry device with one capable of monitoring and assisting the wearer. This integrates very well with the smart house ideology [8], providing a device that can control any aspect of a smart House in an extremely small form factor. Although the initial reason for using a smartwatch[2] may not be health or IoT integration orientated, this small device can easily help in these areas and do much more. Even though these devices are not medical grade, they can help detect health problems [11] due to their multiple integrated sensor types and high wear time. Another area that can benefit from a small device that has movement sensors and is worn most of the time by the user is activity recognition. Activity recognition was extensively implemented using a smartphone [5], using one detection device that can record and process the user's movement data.

Our objective is to implement and test a data recognition system that uses a smartwatch as the main data source. The sensor data is then uploaded to the cloud so that the offline data processing phase can begin. The main difference between the proposed system and other similar systems is using the ML.NET framework for the processing phase to obtain a portable and low footprint activity recognition component that is .NET compatible.

2. Related Work

Activity recognition is done using various sensors [1] that can be roughly grouped into two main categories: ambient sensors [7] and wearable sensors [12]. Ambient sensors are comprised mainly of motion sensor like PIR, infrared, or ultrasonic. Vision based sensors are also part of this category and include video cameras and other detection modules that use vision based identification. Since these sensor types are part of the environment, they are fixed and cannot be used outside of the predefined perimeter. One advantage is that they don't have any kind of power or size restrictions and can easily provide wired and high power wireless capabilities. Wearable sensors are, as the name suggests, worn by the user and thus have size, power and connectivity restrictions. Examples of everyday objects that have activity recognition capable sensors build in are smartphones and smartwatches. Smartphones are being used extensively for activity recognition [10] and can yield good results. Smartwatches can be used for activity recognition and have an advantage over smartphones due to smaller size and, higher probable wear time, and similar characteristics. As shown in [6] activity detection is an important part of the data mining process as it classifies the data for further actions or processing. The accuracy of using a smartwatch for activity recognition is quite high, even reaching an accuracy of 99% as shown in [9].

3. Proposed System

Our proposed system consists in a smartwatch that is used for data acquisition and a couple of software applications that are used to retrieve, upload data into the cloud, and process the obtained data-set offline. Uploading data into the cloud is done using a middle-ware local data hub, that receives the data from the watch and uploads it directly to the cloud. The local data hub, a raspberry pi device, is used to overcome any networking issues and latency. The high level architecture of the proposed system, showing the main components and their interaction, is shown in Figure 1.

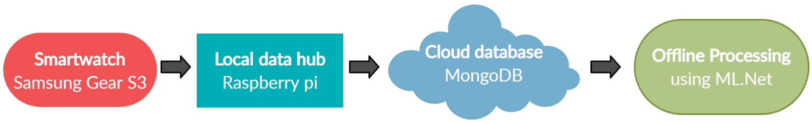

Figure 1. High level architecture.

The system can be used for activity recognition as a base system or can be part of a more complex activity recognition system, synchronizing and correlating data with other systems. Having another device, a smartwatch that is worn by the user on his wrist, helps significantly in providing correlation data and additional information regarding the user's current activity. The local data hub simplifies any future integration with other systems and allows for local data processing. It provides a simple method for the system to be expanded. Currently the proposed system is used standalone, without being integrated into a larger system, and only for testing.

3.1. Activity Detection Device

The chosen activity detection device is the Samsung Gear S3 smartwatch. This was chosen due to its low price, small form factor(46mm x 49mm), sensors, and additional features. Even though this is a commercially available product, due to its built-in sensors, it is capable of monitoring user activity [3]. It features a multitude of useful sensors: accelerometer, barometer, gyro sensor, heart rate monitor and ambient light sensor. Also, the provided connectivity is great, including Bluetooth and WiFi (802.11 b/g/n 2.4GHz). Its waterproof rating of IP68 ensures that the end-user can wear the watch all the time. Since it features a powerful processor, 1GHz, Dual Core (Exynos7270), it is capable of relaying data besides running the standard applications.

3.2. Data Gathering Application

The data from the chosen smartwatch, the Samsung Gear S3, was gathered using a custom Tizen app written in C#. This Tizen .NET application has access to the underlying sensor layer and its values and runs on the watch.There are multiple advantages of using the C# programming language, besides rapid application development, as we benefit from the Common Language Infrastructure standards and a managed runtime. This application handles the data gathering process from the smartwatch device and uses a WebSocket to transfer this data to the cloud. This process uses a middle-ware component, a simple local data hub, that handles the cloud uploading process.The obtained data is being also displayed on the watch face as shown in Figure 2 while the watch application is running.

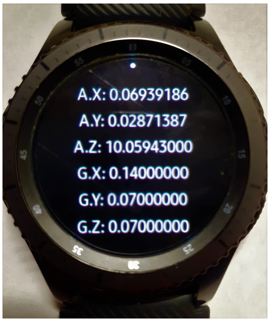

Figure 2. Sensor data displayed on the smart watch.

3.3. The Local Data Hub and Cloud

The local data hub is used as a temporary data storage and includes the cloud upload functionality. The data from the smartwatch is received using a WebSocket and then it is relayed to a cloud-based database. The cloud database we used for testing is a MongoDB database since it's document orientated and allows for rapid scaling. The local hub application runs on a Raspberry Pi computer and is comprised currently of a basic data routing logic, taking data from the WebSocket, storing the data in memory and uploading it immediately in the MongoDB database.

3.4. Data Processing

To identify the activity that the user was executing, based on the movement data collected from the smartwatch, we need to process this data. For the data processing flow, we choose a .net machine learning framework, ML.Net. With this framework, we have access to complex pipelines for machine learning processing. Due to the emergence of .net Core, which can run on multiple operating systems, this library can be used on a wide number of platforms. One of the most important aspects of choosing this framework was the fact that is open source, allowing the developer to see or even alter the source code.

The gathered and processed data is comprised of accelerometer and gyroscope data for the three axes: x, y and z. After the data is loaded into the cloud, it is currently offline processed using the ML.NET framework to analyze the activity types.

There are two major steps for the data processing phase: training the machine learning algorithm and using the algorithm to detect the activity type.

The machine learning training process was done using the ML.net framework, using a very small training time, 20 seconds. If required, this training time can be increased in order to allow more training time for each of the available algorithms that are used by the framework. After the training completes, we obtain a comparative list of algorithms used and their accuracy. The top five models are shown in Figure 3 alongside the validation error, loss for each algorithm.

Top 5 models explored

	Trainer	RSquared	Absolute-loss	Squared-loss	RMS-loss	Duration	#Iteration
1	FastTreeRegression	0.9392	0.12	0.16	0.40	2.7	1
2	FastTreeTweedieRegression	0.9370	0.13	0.17	0.41	3.1	2
3	LightGbmRegression	0.9368	0.15	0.17	0.41	3.3	3
4	FastForestRegression	0.8891	0.27	0.30	0.55	3.4	4
5	SdcaRegression	0.8203	0.39	0.50	0.70	1.8	5

Figure 3. Analyzed algorithms.

From the above-mentioned list, the best algorithm is selected to be used and the accuracy is displayed as the result alongside the actual training time used by this particular algorithm. The best algorithm, as shown in Figure 4, is FastTreeRegression with a coefficient of determination of 0.9392.

Training results

Best quality (RSquared):	0.9392
Best model:	FastTreeRegression
Training time:	18.10 seconds
Models explored (total):	1

Figure 4. Obtained results.

The chosen FastTreeRegression algorithm is an implementation of the MART gradient boosting algorithm and yielded good results on the used data-set. This machine learning algorithm was trained using a small data-set of about 9000 records and tested with an additional data-set of about 3000 records.

Once the training step is complete, the machine learning component can be used to detect the activity type for the received movement data.

4. Conclusions

This paper presents the implementation and testing of a smartwatch based activity detection system that process the data offline. The usage of a commercially available product proved to be a good choice, as it allows user activity monitoring without many additional body worn devices or sensors.

Using the ML.net framework provides a powerful sensor data analysis tool that can be rapidly trained and used in real-time applications. It can be greatly expanded with custom code and processing to further increase the data recognition rate. Also to increase the current recognition rate, a pre-processing step should be implemented as well.

Thus using a smartwatch based activity recognition system proved to be a great versatile and small footprint implementation that can easily be expanded or modified for various applications.

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