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Tracking individuals' health using mobile applications and Machine Learning

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***Abstract*—The widespread availability of smartphones and their high processing power have made them powerful mobile tools able to host and run various apps. In addition, wearable devices with low cost and accurate sensors gathering various physiological data and information are now available. Meanwhile, automated activity recognition is a rapidly evolving research area directly related to the mobile Health (mHealth) field. Rapid advancements in the Human Activity Recognition (HAR) field are mainly based on combining smartphones and wearable devices to succeed in advancing health tracking. This paper presents a mobile app designed and developed for monitoring changes in variables related to the physiological health status of an individual when he is moving around. The app tracks the physiological status of a human along with machine learning algorithms able to recognize and identify human activity and produce automatic alerts warning of dangerous health situations.**

Keywords—Mobile app, Wearables, Machine Learning, Human activity recognition, mHealth

I. Introduction

The automated Human Activity Recognition (HAR) field is rapidly developing and has attracted scientists' attention. HAR is a study field that aims to identify the activities performed by an individual. In other words, HAR is the modelling of human behaviour [1], [2] so that the automatic detection of different activities an individual performs can be realized. The field has experienced significant growth over the past few years due to its many applications, such as in health services, smart homes, autonomous living assisted by the environment, monitoring, construction, etc. [3], [4]. Monitoring and analyzing human behavior can help promote healthier lifestyles (e.g., by encouraging physical activity), avoid stressful activities, and detect dangerous situations (e.g., falls) [5]. In the field of health care, HAR includes a significant number of applications, such as falls detection in patients with mobility disorders, information collection regarding gait and posture, metabolic energy consumption, and the monitoring of physical activity [3].

Today, with the technological development and the new generations of sensors, it is a straightforward task to record bio-signals, and it is possible to design advanced machine learning models that use sensor data as input and then recognize the human activity while assessing the state of human health and drawing automated conclusions and warnings [6].

As the machine learning models concern, different approaches are used, and each one of them presents advantages and disadvantages, depending on the problem's nature and restrictions. Thus, it is the engineer's choice to implement and design the most effective model based on the needs and requirements imposed. Indeed, deep learning approaches [4] dominate the HAR field due to the vast amounts of data now available (big data, IoT, 5G) [7], the high computational power, and the impressive prediction levels they report. Nevertheless, conventional machine learning techniques [4] have not yet become obsolete but are still in use, exhibiting remarkable results and are the first choice in case deep learning models cannot be applied (restrictions in computational cost, limited dataset) [8]. In the last years, another classification method -ensemble machine learning- has attracted scientists' interest that leverages the assets of different approaches [9]–[11]. Moreover, some interesting machine learning approaches taking advantage of the symbolic space traits [12] have been applied to HAR problems lately [13]–[15], thus, avoiding the need for hand-crafted feature extraction.

At the same time, the rapid development of technology and computer science has brought impressive technological results in the capabilities of smartphones and wearable devices. Today, smartphones' improved processing power and enrichment with a wide range of sensors, such as position (GPS), connectivity (Bluetooth and WiFi), light intensity, etc. [16], have made them valuable and powerful tools in the hands of the individual user. Furthermore, various wearable devices such as healthcare devices and activity trackers are equipped with multiple precision sensors, providing sensing capabilities at motion and direction (accelerometer and gyroscope), heart rate, etc. [17]. Also, wearable devices can connect to smartphones, which can be used to gather and analyze data [18], [19]. One of the significant advantages of smartphones and wearable technologies is their ability to collect passive data streams. The concept of passive data refers to information gathered automatically without the participant's involvement [20].

Also, the technology improvement has led to the development of specific applications that offer the possibility of monitoring the health of the individual. A large number of medical and health-related apps are available on the market today and have made health care more affordable and accessible to all [21], [22]. Most of these applications are used by health professionals and patients and operate as medical education and teaching, physical and mental health improvement, telemedicine, telehealthcare, etc. [21], [23].

Today, the widespread availability of smartphones (almost 6.7 billion worldwide [24], and the high accuracy of the sensors of wearable devices [25] have attracted the interest of the scientific community, with researchers using them for data acquisition in several studies such as social, and mobile health (mHealth). In particular, the use of mHealth for in situ tracking and direct interventions has shown growing interest on both a scientific and commercial level. Lastly, it is common for researchers to conduct these mHealth studies by designing and developing their own applications, data storage and data analysis systems [18]. In this way, researchers gain more freedom to customize their research (e.g., collecting data at different sampling frequencies from sensors of wearable devices).

Throughout this paper, we will follow the following structure. The mobile application that was designed and implemented is detailed in Section II. Specifically, in Section II.A we present the wearable and sensors that were utilized. In Section II.B there is an analysis of the subsystem that implements the physiological condition tracking, while in Section II.C, we describe an implementation of the HAR model using machine learning. In Section II.D the embedded GPS tracking system is presented and in Section II.E we refer to the various alerts the system may send under conditions. The current section is completed with Section II.F with a brief description of the web server. Finally, in Section III, we conclude the work have been done.

II. Mobile Application

Within the framework of the TrackMyHealth project [26], we developed a system that integrates wearables and machine learning algorithms to monitor and support individuals (elderly and lonely workers). The diagram of the proposed system is shown in Fig. 1.

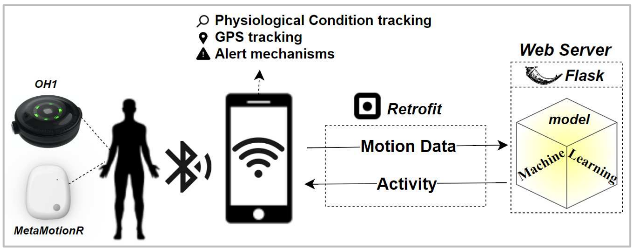

Fig. 1. Overview of the TrackMyHealth System.

This system consists of a mobile application that works with wearable devices to acquire heart rate and motion data via Bluetooth communication protocol. The motion data is transferred to a Web server via Retrofit. Retrofit is a type-safe library for accessing the Representational state transfer (REST) Web APIs [27]. On the Web server, has been developed a Flask Web Framework [28] for hosting the machine learning model, which implements the HAR. After that, the outcome of the model is forwarded to the application, which compares the instant heart rate data with the model's result and makes the decision for further actions (e.g., stop activity alert). Next, we describe in more detail each one of these components.

A. *Wearables and Sensors*

The proposed system uses wearable devices to collect motion and heart rate data. The choice of wearable devices was based on the characteristics of the sensors, the connectivity and battery features of the device, user-friendliness, and the availability of open-source code. For the collection of motion data, the MetaMotionR (MMR) device was used [29], and for the collection of heart rate data, the OH1 Polar was used [30].

MMR consists of built-in Inertial Measurement Unit (IMU) sensors that provide continuous real-time motion monitoring with an accelerometer and a gyroscope. IMU sensors can collect acceleration and angular velocity data. Their low purchase cost, the multiple integration possibilities, and the simplicity of their implementation have made them widely known in various scientific fields (e.g., HAR). [31], [32]. Also, it includes sensor fusion that combines the measurements of the two sensors. On the other hand, OH1 is an optical sensor that monitors heart rate through photoplethysmography (PPG) technology. PPG is a low-cost technology that makes an optical assessment of blood volume changes in the microvasculature with a Light-Emitting Diode (LED) and a photodetector (photodiode) [33], [34]. An overview of key features of MMR and OH1 devices is presented in TABLE I.

Fig. 2. Boards view of MMR and OH1 wearable devices.

TABLE I. Characteristics of MMR and OH1 wearable devices.

Characteristics		**Wearables devices**	
		MMR	***OH1***
Sensors	Type	3-axis gyroscope & accelerometer	optical
	Sampling rate	0.001Hz – 100 Hz	1Hz
Board	Connectivity	Bluetooth LE	Bluetooth
	Rechargeable battery	70-100 mAH	45 mAh
User-friendly	Weight	5.67g	5g
	Body position	wrist	arm
API		Open-source	

B. *Physiological Condition Tracking*

As part of the proposed system, a subsystem was implemented for tracking the physiological status of the participant utilizing the interaction with the mobile application. This system is based on wearable devices MMR and OH1, the extracted results of the machine learning model, and the user's personal information. In addition, to ensure the secure interaction of the user with the application, required the completion of the Physical Activity Readiness Questionnaire for Everyone (PAR-Q+). This system aims to maximize the benefits and safety of the participant during the use of the mobile application.

Initially, the participant, after logging in to the application, is asked to add personal information about their gender and age. This information is important for the extraction of the user's maximum Heart Rate (HRmax). HRmax is the maximum heart rate achieved by an individual who is exercising to exhaustion, despite the increasing workload and heart rate plateauing [35] and is measured using the following equations [36], as is shown in Fig. 3:

Men:

$$HRmax = 203.7/(1 + \exp(0.033 \times (age - 104.3))) \quad (1)$$

Women:

$$HRmax = 190.2/(1 + \exp(0.0453 \times (age - 107.5))) \quad (2)$$

Fig. 3. The first stage of the physiological condition tracking system.

In the next stage, the user fills the PAR-Q+. The PAR-Q+ consists of general and specific questions concerning both the general health of the individual and various medical conditions. Its use is intended to maximize the participant's safety before starting any kind of physical activity [37]. Upon failure of the PAR-Q+, the participant is referred to a qualified physician or is asked to fill out the electronic Physical Activity Readiness Medical Examination (ePARmed-X+) [38] for further evaluation as it is shown in the Fig. 4.

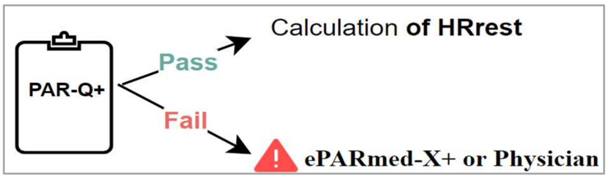

Fig. 4. The second stage of the physiological condition tracking system.

Next, the app asks the participant to record the resting Heart Rate (HRrest) using the OH1 wearable device. In the general population (non-athlete), where the range of normal values is between 60 and 100 bpm (or under 60bpm for athletes), an increased heart rate may indicate problematic conditions [39], [40]. Therefore, if the participant's HRrest is reported above a threshold (100 bpm), the participant is asked to visit a specialist for further elaboration as it is shown in the Fig. 5.

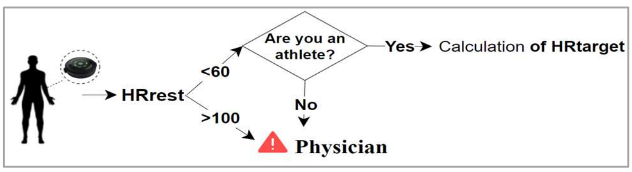

Fig. 5. The third stage of the physiological condition tracking system.

After the successful completion of the previous steps, the application records the activity and the instant Heart Rate (HRinstant) of the user in real-time using wearable devices. The app uses the HRinstant to extract the average Heart Rate (HRavg) per minute. HRavg aims to track the physiological status of the person concerned. Also, depending on the type of activity extracted from the machine learning model, an intensity range is defined that will be used to calculate the target Heart Rate (HRtarget). HRtarget is widely used as a tool for individualized exercise and is measured using the Karvonen formula [41]:

$$HRtarget = ((HRmax - HRrest) \times \%intensity) + HRrest \quad (3)$$

where the intensity is in the range of [42]:

- <30% for very light activity.
- 30% - 49% for light activity.
- 50% - 69% for moderate activity.
- 70% - 89% for vigorous activity.

Finally, useful conclusions can be extracted about the current status that a user experiences during their interaction with the application. The conclusions are exported by comparing each time the HRavg with the HRtarget. In case the HRavg value is bigger of the max HRtarget value, the application alerts the user to stop the activity. In this way, the application can record at any time the normal or abnormal state of the participant as the figure below displays.

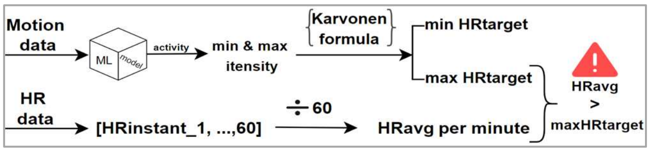

Fig. 6. The final stage of the physiological condition tracking system.

C. Machine Learning model

The activity recognition system bears at its core a Machine Learning (ML) model. Machine learning is the study of computational algorithms that can improve themselves through experience [43], [44]. Implementing a machine learning model aims to predict the status/activity in which a person finds himself at a particular time. The ML model aims to predict the following six activities:

- Downstairs
- Upstairs
- Sitting
- Standing
- Walking
- Jogging

The building of a machine learning model entails specific steps depending on the approach the engineer chooses to apply. In a nutshell, here, we implemented a supervised machine learning model, which means that the exploited data are labelled (bear a label that indicates the class/category in which an instance belongs) and compose the dataset of the problem. Supervised learning is the machine learning process where the model "learns" (through training) a function that is based on input-output pairs [45]. Supervised learning refers to learning a function appropriate to the problem under examination. This function receives input variables (X) and assigns them to an output variable (Y):

$$Y = f(X).$$

Generally, the used dataset can be divided into training and testing datasets. The ratio of the above varies, but it is usually tuned to 2:8 (i.e., 20% testing and 80% training datasets, respectively) [46].

Fig. 7 depicts the steps we followed for constructing our model. First, we obtain our data from the application. In fact, our data are signals that are received from the accelerometer and gyroscope embedded into the MMR device. We note, that our signals are three-dimensional signals (x-axis, y-axis, z-axis) of acceleration and angular velocity, respectively. In the next step, we preprocess our data; e.g., we remove void records, synchronize the data, apply signal filtering, and finally, we standardize them. The data segmentation step follows. Here, we use the overlapping sliding windows approach to prepare our data for processing by the classifier. Afterward, the so-called feature extraction step takes place. By this, we manually extract features from the time and frequency domain to best describe the nature and behaviour of the signals (data) utilized [47]–[53]. In the final stage, we apply a classification algorithm. To this end, we applied two different algorithms: k-Nearest Neighbours and Random Forests and evaluated the results using some common metrics (accuracy, sensitivity).

Via the adjustment of the values of the parameters of the model and via a trial-and-error process, we achieved the optimal predictive ability of the model. The model then was tested in real-time streams of data, and again new adjustments were realized to optimise the results.

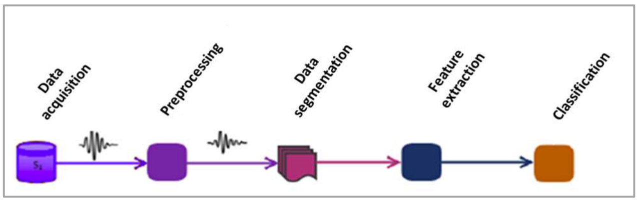

Fig. 7. The stages of building the machine learning model.

D. GPS tracking

In the case of the TrackMyHealth project, geolocation plays a crucial role as it is utilized to ceaselessly monitor the supervised person's exact position. This is the case for both the elderly and the ailing people, as well as for the lone workers. The logic behind geolocation in the proposed system is real-time locating, especially in the case of fall detection. In this case, the supervisor will be able to obtain information about the exact location of the user when he/she receives an S.O.S alert message from the supervised person's device.

There are several technologies that can help determine the real geographical location of items of interest, such as GPS (Global Positioning System), Bluetooth, WiFi and network-based tracking. In our system, we leveraged the GPS technology, as it is the one that is mostly used in general. The tracking system in the TrackMyHealth project is not just a way to track the location of each user but is an essential tool in the direction of fully staying informed and consequently managing all the situations that the integrated system is about to deal with. The proper design and the correct and complete development of the system are the basis of success in terms of meeting the requirements set.

The GPS tracking system in the TrackMyHealth system includes the involvement of the system clients (web & mobile applications), as well as the API (Application Programming Interface) server. In this system, users (patients and lonely employees) provide information about their location in the system and this, in turn, undertakes the task of regularly informing the supervisors about their location.

However, there is a limitation that acts as a safety valve; that is, the supervised person should have accepted that a supervisor has access to his/her location data. In order to do this, a connection must have been established between the two; to this end, the user should have accepted the request for supervision from the supervisor. In any other case, the supervisor will not be able to have any authorization from the system to access the user's data and, consequently, the location-related data.

The system uses tokens (special identifiers that give access to data) that can identify whether the specific token corresponds to a user who is connected (supervisor) with another user (patient, elderly, lonely worker) or if not. Fig. 8 illustrates this process that is integrated into the TrackMyHealth system.

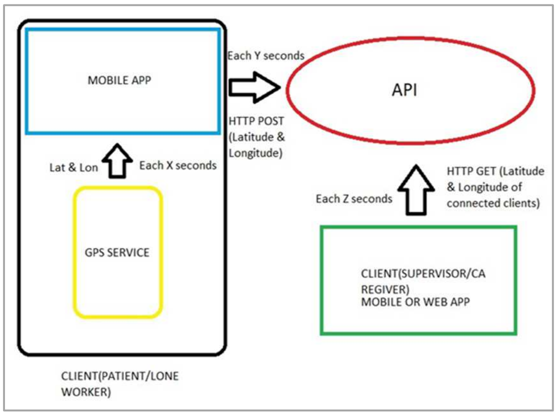

Fig. 8. GPS tracking system on the TrackMyHealth system.

In more detail, the client (supervised person's mobile app) has an uninterrupted GPS tracking service. GPS locations are not constantly sent but rather at regular intervals, which prevents the API server from operating on the edge by managing many simultaneous clients. In the case of all the clients continuously sending their location-related data, there would be a strong possibility of having a slow service from the server and consequently poor user experience or even non-detection of critical data. In addition, such an approach has a positive impact in the direction of battery saving; battery consumption is lower compared to uninterrupted sending. As API regards, when it receives the coordinates from the users, it saves them in appropriate fields of the corresponding table of the database.

In turn, clients (supervisors and caregivers) request from the system the most recent location of the people they supervise at regular intervals (for smaller battery consumption reasons).

The logic behind making "calls" at regular intervals is that in this way, we ensure the server's smooth operation, congestion avoidance, latency spikes & throughput drops that consequently lead to a bad user experience. In other words, the supervisor's concern is not knowing the supervised person's location every time but at regular intervals so that he/she can intervene if something beyond the ordinary occurs.

GPS data (latitude & longitude) is accompanied by the time and date the location was received. In the database behind the API, the data are accessible only to authorized users. That is, the user requesting access to another user's location data must have a valid token (ID via which the API comprehends if the request comes from someone who has access to the system and not from someone else who just somehow is aware of the endpoint and may have malicious intent).

In addition, the system gains knowledge of whether the authorized user has obtained the consent of a supervisor, i.e. let him have the token. In case he is not connected to a supervisor, the system refuses to provide data of the specific user and, consequently, location data. As a result, the integrity and security of the users and the system are guaranteed.

E. Alerts

To ensure the participant's safety, the proposed system includes automated alert mechanisms. These mechanisms include a text and an audio message and are displayed on the mobile phone as push notifications. Such notifications are used to provide timely updates to smartphone applications and typically assume the role of event reminder, user prompting, situation prevention, etc. [54].

In our case, push notifications hold the role of situation prevention and are activated whenever the application perceives some kind of abnormal state. Specifically, the application displays alert messages to the participants in the following situations:

- When they fail to complete the PAR-Q+ questionnaire, suggest visiting a physician or continuing by completing the ePARmed-X+ online test.
- When the heart rate at rest exceeds 100bpm or is less than 60bpm (if he is not an athlete in the latter case), suggest visiting a physician.
- When the average heart rate exceeds the upper limit of the target heart rate, suggest stopping any activity.

F. Web Server

In order for the exported model to be tested in real-time with data taken in situ, it was necessary to develop a web server. The purpose of this server was to host the machine learning model. In practice, this means that the server is responsible for receiving the motion data sent from the mobile application, importing this data into the model and finally sending the extracted status back to the application.

The development of the server was carried out via Flask. Flask is a very simple yet highly extensible Web Framework written in Python, with multiple libraries, packages and modules for machine learning actions. Lastly, for the communication between mobile smartphone and server was to use the Retrofit technology.

III. Conclusions

In this study, we described the overall architecture and the proposed methodology for tracking human activity and identifying the health situation of the monitoring subject. There are designed and developed state-of-art machine learning methods to realize the HAR based on the data gathered by sensors embedded in two wearable devices. We have developed and presented a user-friendly mobile app functioning as the intermediate agent for exchanging information between the sensors and the web server that hosts and run the machine learning model. The individual's health status during daily activity is monitored in real-time. At the same time, notifications and alerts are sent and illustrated to the app on the user's smartphone and his/her supervisor's monitoring device in case of exceeding some physiological health values, which means that the human is in a possible critical health situation. To this end, the developed system's ultimate goal is to promote individuals' health and well-being via the ceaseless tracking of their physical condition while performing various daily activities.

Our future work will include many health physiological variables gathered by wearable sensors and to investigate and propose advanced learning algorithms with outstanding performance on identifying human activity and health status. In addition, we plan to develop an integrated system that will be embedded and run locally on the smartphone that will transmit only warning and diagnostic reports.

Acknowledgment

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