Approach for the Development of a System for COVID-19 Preliminary Test

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Abstract. Nowadays, Coronavirus is the biggest challenge of medicine. This problem is divided into two sectors: health and economy. In relation to health, there has been an alarming exponential rise in deaths, those who do not belong to the risk group are precisely those who contaminate and lead to disease. The economy also bleeds globally, and companies are failing. Thus, thousands of people are out of work. This paper is focused on predicting whether an individual is possible with symptoms of COVID-19 and proposing the use of technology. In a context of ambient assisted living, it can save thousands of lives and builds the world economy. Therefore, a preliminary mobile diagnosis may provide a reduction in government costs and a potential alternative to the existing tests. In view of all that has been mentioned, sensors are the best solution to detect the symptoms of the disease. This project will try to identify different symptoms, such as high body temperature, breathing difficulties, and cough. The sensors that may be used to identify these symptoms are a thermometer, an electroencephalogram (EEG) sensor, an electromyography (EMG) sensor and an electrodermal activity (EDA) sensor.

Keywords: Sensors · Mobile devices · Pandemic situation · COVID-19 · Algorithms

1 Introduction

Due to limited health infrastructure, the fast diagnosis of COVID-19 is a challenge in different countries, especially in emerging ones [13, 23]. Sensors retain immense perspectives to collect data, which, after being filtered and processed, can identify symptoms related to the disease [4, 14, 21, 33]. Therefore, a low-cost solution is to use BITalino devices (see Fig. 1) with mobile devices, which it is a medical sensor kit that allows the development of technology, algorithms and artificial intelligence methods for the differential diagnosis in medicine field [3, 27].

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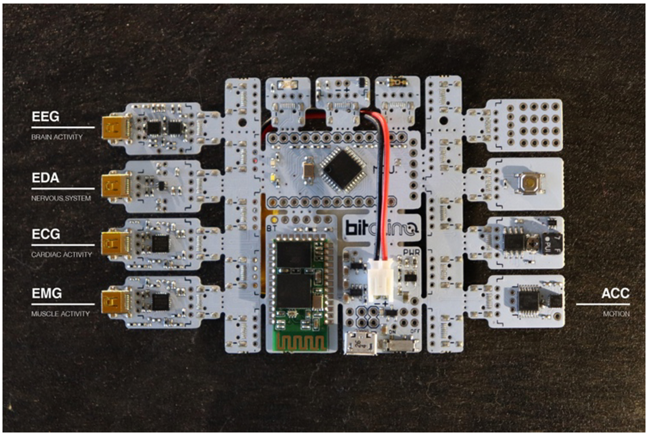

Fig. 1. BITalino device.

Coronavirus disease is a common virus that infects humans, and it is mainly related to an upper respiratory infection, commonly named as Severe Acute Respiratory Syndrome (SARS-CoV) [20]. Still, the Middle East Respiratory Syndrome (MERS-CoV) is another type of coronavirus [20]. The symptoms are like the flu, but it may cause a significant number of deaths than common flu. The air disseminates the coronavirus disease by coughing and sneezing, close personal contact, touching an object or surface contaminated with the virus and rarely, by faecal contamination [28]. The most common detailed symptoms are runny nose, sore throat, feeling unwell, cough, and fever [9].

Sensors allow the identification of different healthcare symptoms, such as high body temperature, breathing difficulties and cough [1, 2, 15, 18, 19]. The sensors that may be used are a thermometer, an electroencephalogram (EEG) sensor, an electromyography (EMG) sensor, and an electrodermal activity (EDA) sensor [10–12, 16, 24, 25, 30, 32].

The main objective of this paper is focused in the presentation of an approach for the development of a system that helps in the preliminar detection of COVID-19 with the use of different kinds of sensors embedded in the devices used daily. It was included in a summer course in 2020 that occurred in the Polytechnic of Viseu, Viseu, Portugal. The main contribution of this paper is the proposal of an architecture for a system that help in the detection of pandemic situations.

BITalino devices were created to solve a set of problems, with the premise of observing the need for medical solutions through technology [3]. It can be said that, due to this objective, results from these sensors are revolutionizing teaching, research and biomedical prototypes around the world [2, 6, 17, 26]. The success of this hardware is notorious since it has already been nominated for the Innovation Radar Prize 2017 [8]. This small hardware kit is essential for research and detecting possible patients with COVID-19, as it has the sensors previously mentioned. Therefore, it will collect the necessary data to recognize whether the person is sick or not [5, 15, 29, 31].

It is indisputable that artificial intelligence is currently the most explored concept in technology. Within this area, machine learning has been a concept with great potential being explored. Defining machine learning is essentially saying that a system can learn according to what has been trained, based on specific datasets and with minimal human interference. When establishing logical rules, the system itself can improve the performance of a task, that is, such practices are created based on the recognition of data patterns coming from the BITalino device, and it will be analyzed. The main objective here is to define the health standards of a particular individual and recommend, for example, that he check through a specific sensor to analyze any state of body imbalance.

As stated before, the goal is to get results that state changes in an individual's health. Thus, it is desired to obtain people's autonomy about their health, in other words, through the mobile application the user will have the ability to track some symptoms of COVID-19 and receive information about their status. Current health status. Furthermore, machine learning can be used to define health information more accurately.

The introductory section ends with this paragraph, and the remaining sections of this paper are structured as follows: Sect. 2 presents the description of the structure of the method implemented for the recognition of people with symptoms of COVID-19, including the sensors to be used with the proposed system. Section 3 presents the mobile application proposed. Finally, this article ends with the discussion and conclusions provided in Sect. 4.

2 Methods

The present methodology of this paper, presented in Fig. 2, can be elucidated mainly in three stages: data acquisition, processing and manipulation. Data acquisition will be made using BITalino sensors which are detailed in Sect. 3. After the data collection, possible noise filtering and data manipulation will be carried out. These procedures guarantee to eliminate false positives and through the algorithm exposed in Sect. 4. Thus, it is guaranteed that the systematic logic is obtained and therefore identify symptoms related to COVID-19.

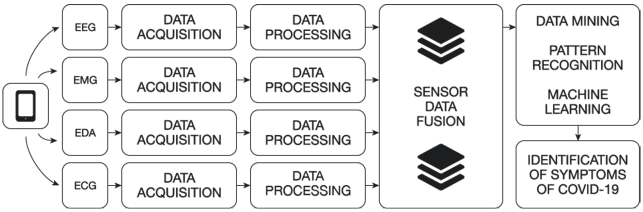

Fig. 2. Method for the identification of symptoms related to COVID-19.

There are several recent discussions about the concept of sensors and their importance for everyday life. Generally speaking, a sensor is a data monitoring device and is capable of verifying changes in a given environment. The use with an electronic system is efficient to measure various physical phenomena, such as heart rate and temperature. This device is intrinsically related to the internet of things (IoT), as they can detect conditions around which it is present. In summary, they are essential devices for IoT, in addition to measuring and indicating data related to light, heat, pressure, humidity and movement. Therefore, they will be used as the input data for analyzing the problem and baseline to identify patterns.

As far as BITalino device is concerned, mentioned in the introduction chapter, it is worth explaining that it is a low-cost, all-in-one hardware kit, an excellent development and research tool. Therefore, an inexpensive solution to measure the physiological signals evaluated to identify muscle contraction, temperature, electrical activity of the brain and measurement of skin activity. Given this training of BITalino device, it can verify common symptoms in people with COVID-19, which are: fever, dry cough, temperature, sweat and abnormal brain activity.

Additionally, discussions were performed about adequate measures to diagnose and detect severe cases of the disease. When using electroencephalogram (EEG), the studies reveal [22] that neurological abnormalities are being identified and that COVID-19 also involves brain investigation and nerves. Hence, the altered mental state is one of the symptoms that can manifest with those of fever, dry cough, tiredness and breathing difficulty.

When examining adult patients, the article published on NeurologyLive [33] experimented with 28 COVID-19 persons aged between 30 and 83 years old, of which 22 were positive for SARS-CoV-2 (63.6% men), and 6 were negative (33.3% men). Most were seriously ill, intubated due to acute respiratory failure (63.6% vs 100% in COVID-19 positive vs negative) and were already under sedatives or in anticonvulsant medications (86.4% vs 100% in COVID-19 affirmative vs negative). Because of the facts mentioned, it is clear that epileptiform abnormalities in the EEG of COVID-19 patients are relevant data that must be collected, thus seeking to prioritize possible severe cases of the disease.

For this reason, it stands out that processing and interpreting them is one more of the necessary filtering tools for possible symptom verification, so changes in mental status are an essential highlight to be measured. By observing the aspects mentioned, the predominance of frontal waves, bilateral symmetrical or asymmetrical, are the critical point and guide to the possibility of a frontal epileptiform focus and can be considered as evidence that this is the way that the virus the SARS- CoV-2 enters the CNS (via the nasopharyngeal mucosa or olfactory nerves).

EMG is the biggest sensor bet at the moment. Such a complementary exam consists of describing and evaluating muscle function, in an average session of 30 min. The preliminary exam designed for the mobile application, consists of using the sensor with Bluetooth connection to the cell phone and collects data from the electrodes, these non-invasively adhere to the skin to capture its ionic current.

The study of muscle activity can be applied to detect contractions in the chest and thus identify dry cough. Due to this aspect, when combining dry cough with other symptoms, it will be possible to alert the user of the mobile application that he has respiratory anomalies.

The electrothermal activity consists of verifying the peripheral response originated from the sympathetic nervous system [7]. Thus, an involuntary intervention moderated by the central nervous system. Given this activity, the sweat glands in the skin are activated, that is, sweat production. Such a method, being able to detect excessive sweating through empathic devices, soon detects one of the most common symptoms of coronavirus. The measurement is associated with two types, which are: phasic conductance response of the skin and tonic conductance level. The electrodes of the EDA sensor should be used on the palm, as the test will be done with the user awake and will result in a more significant signal. It should be noted that there is the advantage of doing a quick test, done several times over 24 h. EDA has data collected with greater efficiency in the long run, since it must be obtained through the average tonic level of an individual's skin.

3 Mobile Application

The algorithms will be essential to identify whether the individual is likely to be ill and suggest that he/she go to the doctor. As already explained briefly in Sect. 2, the algorithms are the sequence written logically, described in steps that will return an answer to the problem itself.

It was determined that applying algorithms is essential for the execution of what was proposed, *i.e.,* a COVID-19 symptom prediction tool. Given this proposal, the study (reference) that explored 2700 patients was examined, and many demographic and health parameters were collected associated with a higher risk of needing respiratory support. As a consequence of this, specific patterns were pointed out, namely: the body mass index in Kg/m^2 increased by 1.05 per unit, advanced age, fragility and possible relationship with the male sex. Such health parameters provide odds ratios and a 95% confidence interval.

By observing the overlooked aspects, an unsupervised time series was carried out in the group of patients, as well as being compared to 6 different groups of associated results. To visualize how the groups of infected people were distinguished, the authors used the reported average occurrence of a symptom each day and the Z-Score per event for each group concerning the presence of one of the 14 reported symptoms. Equivalent graphics for independent replication in the database are provided as supplementary material.

The data of the EMG activity should be analyzed and calculate the peaks and valleys to check if a patient has a dry cough. Therefore, the array is searched to search for all values, then the input value is checked against its predecessors and successors, that is, the next and the previous value. If this value is higher than both, then a local maximum is found, classified as a peak. Otherwise, a minimum is detected, this being the valley. However, to avoid false positives, the percentage difference between the absolute and a sample of possible false positives is then calculated. Another check to prevent false positives is to calculate the standard deviation, since this is a measure that expresses the degree of dispersion of a data set.

Consequently, with property to standardize data and make it more homogeneous. Taking advantage of this calculation, the percentage concept presented above applies for the same effect. Finally, this method allows you to increase the accuracy of the data and reduce noise.

4 Discussion and Conclusions

The proposed COVID-19 measurement system using sensors fulfils the requirement of being low-cost and allows the mobile application, through data processing and signalling of respiratory problems, COVID-19. In the face of such a typical scenario, the solution is efficient for non-invasive disease analysis and detection method is one of the most significant perspectives in modern medicine. Globally, such results mean preventing deaths, fast and cheap assistance. When individualizing data for a given user, it appears that the analysis will have higher precision and specific details, due to the identification of the daily data collected. Also, the relevant gain of what can be implemented allows for future improvements and to further increase the accuracy and to identify even more the rate of data acquisition is sufficient.

Through this paper, it was possible to demonstrate the usefulness of sensors associated with a mobile application, with the possibility of identifying respiratory problems, which in the current context are of high production and possibly effective in saving lives.

Also, using the algorithms and techniques outlined previously, to adapt to a set of usage scenarios and a class of mobile devices will make this methodology usable on most mobile platforms.

It is concluded that, given the methodology explained, it will be possible to present promising results with concrete numbers and corroborate the high relevance of the use of sensors in the health area. It is essential to use all technological resources and associate them with medicine, aiming at the evolution of human beings and enhancing their autonomy.

The proposed system has some limitations related to the use of sensors, because they are difficult to instrument in different people with different ages. In addition, it needs the constant Internet and Bluetooth connections in order to interconnect the different devices. The methods can be also developed with a large number of persons.

As future work, we intend to reduce the limitations of the system, creating machanisms to place the sensors in an easy manner, and the measurements should be improved and automated for the general people.

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