Design of a wearable analytic health monitoring system to assess COVID-19 risk

Author: Germán Sánchez,
Advisors: Johann Osma, Felipe Montes
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Universidad de los Andes

Resumen - COVID-19 has shown healthcare systems needs in order to better acquire, visualize and predict health care data. A system called Aly is proposed, an ally system that takes the form of a wristband that allow users to acquire temperature, oxygen saturation, heart rate and respiration rate data, in order to generate a system that alerts users by the use of a mobile application and a web platform. An analytical classification model is designed to assess the risk of a patient once symptoms and signs are reported and measured respectively.

Key words– wearable for covid 19, classification algorithm, mobile application for health care.

I. INTRODUCTION

This study aims to start the building process of a system for health care to better anticipate, prevent and monitor diseases using measurable markers in the human body. In particular, this research aims to generate a scalable system that continuously senses physiological variables of the body through invasive electronic techniques and non-invasive techniques such as infrared temperature measurement, photoplethysmography (PPG) embedded in wearables for daily use and user friendly hardwares and interfaces. These electronics communicate electric variables to a mobile phone app in charge of computing its value and correlating this signs with periodical self-reported symptoms and signs in order to generate early alarms for people, and help decisions making process for individuals, health care systems and governments. Once health reports are correlated to individuals profiles, this system to monitor should evolve to potentially control populations’ health system through electronic devices, computational tools and Big Data.

So far, latest advances in wearables technology and sociometric badges for medical applications consist on biophysical monitoring (heart rate, pulse, human motion, and temperature), biochemical tracking (biomolecule, blood glucose, and pH) and real-time environmental information detection (gas molecules and humidity) [1][2]. However, this wearable technology has several challenges to overcome such as processing unifying the measured quantities parameters and removing errors and statistical outliers from the data (processing), data transmission in terms of latency, energy consumption as complex operations are performed, and privacy aspects to secure the link between the phones and the wearables [3].

Besides, COVID-19 crisis, the pandemic that has worldwide infected up to 181 million people by june of 2021 [4], has shown the imperative need of alarms for preventing disease and even more the use of big data to predict and analyze contagions.

As health issues represent a demanding expense for governments in terms of public health, it will be important to understand diseases evolution and how they are correlated with populations environment at a granular level in order to generate ways to improve health care systems and human conditions in terms of environment and human behavior [5]. This is important not only in crisis moments, but also in developing a general understanding of contagion processes, diseases prevention, and its impact on every single country all over the world.

There have been studies aiming to explore wearables technologies, [1][5]–[10] and self-reporting techniques to prevent and diagnose diseases separately. These technologies commonly direct their applications to , but never before with the temporal and spatial granularity of our whole integrated electronics, communication and dataset analytics that we explore. This will allow us to look at a new wave of preventive medicine-oriented technology for populations and governments in more detail than previously possible (see figure 1).

Figure 1. Aly Overview
II. METHODS AND MATERIALS

The main purpose of the initial design that this paper presents, is to conceptualize the design of the products: A wearable able to measure temperature, heart rate, oxygen saturation and compute respiration rate. This wearable is designed to communicate the results by using low energy universally unique identifier (UUID) bluetooth public services oriented protocols to a mobile application designed for IOS and Android devices making sure the device presents a high compatibility with commercial devices. This mobile application lets the users register their profile, periodically report symptoms considered as risk factors of covid 19, and passively communicate with the wearable in the background to acquire wearable’s signals.

After this information is stored in the mobile application, the application makes use of API’s we designed to put, get and update data into a MongoDB database we store in the cloud as different web services after Keychain Services (IOS) and secure shared preferences (Android) are used to guarantee users’ privacy and the data is encrypted not only by these protocols but by SSL encryption [11]. The users not only can visualize de data in the mobile application, they can consult their risk level of COVID 19 contagion according to an asynchronous risk computation described in section D.

Finally, the latest product to develop is a web platform, that acts as a remote monitoring terminal to visualize the patients profile, the different signs and symptoms over time, visualize the assessed level of contagion, and finally incorporate a feedback that either patients’ families or doctors can fill to suggest behaviors the users can see by using the mobile application.

Following, there is a detailed description of the methods we used in designing each of the products:

A. Wearable design

Prototyping using arduino

Once the right sensors are found, there is a challenge to migrate the arduino nano approach to develop the final version of the board. There is first a modular design of 4 different components: The communication component, the power board, the temperature sensing, the pulsoximetry module that incorporates a brand new functionality for future work that is the electrocardiogram and electromyography capabilities. A description of each module is presented in order to guarantee readers can replicate the work. Finally, a description of the integrated board and its firmware is presented. Additionally, a protocol to load the firmware is presented.

Temperature sensing module

The temperature sensing is developed using the MAX30205 datasheet recommended schematic, which is simple [12]. The module has a I2C protocol that requires powering the module, setting a unique direction for the I2C channel, which is in this case 90h (by connecting A0, A1 and A2 terminals), an alarm control in the OS pin (included pull resistor of 4.7k Ohms) and the clock and data pins (4.7 Kohms pull resistors to guarantee a frequency of 100kbps). The schematic is generated and I2C pins, VCC, and GND pins are connected to a pin header. A 3D approach of this module is shown in figure 9C.

To write and configure the module, there is a protocol to be followed. First a start bit is sent by the master, which is the microcontroller described later. Then, the master must send an address byte, which sets the direction of the slave. After this, an acknowledgement signal is sent from the slave. After this, a register address is sent to the slave. In this case, the 30205 has three registers, a configuration one, a Thyst, and a OS register with the 0x01, 0x02 and 0x03 addresses. The thyst register is designed to establish a low threshold of temperature, and the OS to establish a high threshold. The configuration register is designed to establish a high threshold. The configuration register is designed to establish the mode in which the module operates. Once the registry address is sent, an acknowledge signal is sent by the slave. Finally, the data with either the limits or the mode of the module is sent. In case of the thyst register and and the OS register, which have 16 bits, the message is sent by separate, 8 bits, an acknowledge signal and then the less significant bits are sent. Finally, the slave sends an acknowledge signal and the slave sends and stop signal.

![Figure 1. Arduino nano connection](image1.png)

![Figure 2. I2C protocol used to write in slave sensors](image2.png)
In the case of reading the registries, there is a start signal followed by the same slave address and the first acknowledge signal. Then the registry address is set followed by its corresponding acknowledge. Then, a repeat start is sent by master, followed by the slave address with the difference that in this case the last bit is 1, to indicate the reading. After this signal, the slave sends an acknowledge and the first 8 bits. The master sends an acknowledge if more bits are allowed (In case of thyst, tos and temp) or a no ack signal followed by a stop signal.

**Figure 3. I2C protocol to read sensors.**

**Photoplethysmography sensing**

Photoplethysmography (PPG) is an optical non invasive technique to detect blood volume changes in microvascular tissues. It represents the pulsatile curve in an AC wave and respiration origin DC variations [13].

There is a measurement of absorbed, reflected, transmitted and fluorescence of light between a Light emitting diode (LED 50nm light) and a photodetectors working at red and infrared wavelengths (0.8 to 1um) affected by three light tissue interactions:

- **Water**: Water is the principal component of the tissues. It has a strong absorption of the ultraviolet and longer infrared wavelengths, but water allows light to pass and measure blood volumes. That is why red and infrared wavelengths are used.
- **Isobestic Wavelength**: Measurements performed at approximately 805nm don’t get affected by blood oxygen saturation.
- **Tissue penetration depth**: The depth of the penetration of the light depends on the probe wavelength design.

The photoplethysmography sensing using the max 86150 sensor allows to measure electrocardiogram, oxygen saturation and heart rate, with the optional computation of the respiration rate [14]. The used schematic is based on the evaluation kit schematic. The I2C protocol used to control and read this sensor is the same one used for the temperature sensor (see the datasheet for registry addresses). This system is powered with a 3.3V supply, has an Electrocardiogram measurement module, which allows dry electrodes connection, and a photoplethysmography sensor which can be positioned at the wrist and can obtain the heart rate and the oxygen saturation.

**Communication board**

The communication protocol uses a RN4871 low energy bluetooth module powered by 3.3V. It has a transmisión and a reception pin as the used HC05 had.

To configure this module, the module is connected to a YP05 serial converter module, which allows the users to get into the command mode. This command mode is designed to configure the module. Listed below are the principal configuration set for the module:

- Type $$$ to enter the command mode
- To perform a factory reset SF,2
- Set the name of the module: : S-, Aly
- Set the baud rate: SB,02 to 230400 baud

Once the module is configured, it can be connected directly to the microcontroller described in the firmware section.

**Power system**

The power system is in charge of delivering 3.3V to the output. In this case a switch is used to control the circuit powered by a CR2032 battery and managed by a TSP61 voltage regulator. In order to be able to reduce the size of this board, the battery holder is replaced by a battery holder of CR1220. No specifications on battery autonomy have been performed yet in this research.

**Firmware**

An assembler coded firmware is developed to use a PIC16F18345-I/P to control all the system. The firmware can be found here.

To interact with the mobile application, these are the main commands to interact with the module. These commands must be send in ASCII protocol to the BLE module, which transmits this data to the microcontroller and then the microcontroller generates the answer. Each command contains a starting symbol “{”, a two characters content that indicates which sensor to read, and a closing symbol “}”:

**Table 1. Communication protocol in ASCII**

<table>
<thead>
<tr>
<th>Description</th>
<th>Start Symbol</th>
<th>Content 1st character</th>
<th>Content 2nd character</th>
<th>Closing Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensors read</td>
<td>{</td>
<td>T (Temperature)</td>
<td>O (Oxygen)</td>
<td>}</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H (Heart rate)</td>
<td>E (Electrocardiogram)</td>
<td></td>
</tr>
<tr>
<td>Restart</td>
<td>{</td>
<td>R,</td>
<td>0 (Restart)</td>
<td>}</td>
</tr>
</tbody>
</table>
The specifications of the device are presented below:

<table>
<thead>
<tr>
<th>Variable</th>
<th>Features</th>
</tr>
</thead>
</table>
| **Temperature** [12] | • 0.1°C Accuracy (37°C to 39°C)  
• 16-Bit (0.00390625°C) Temperature Resolution  
• 2.7V to 3.3V Supply Voltage Range  
• 600μA (typ) Operating Supply Current  
• Comparator/Thermostat Output |
| **Heart rate**      | • Electrocardiogram (ECG) Optimized for Dry Electrode Operation  
• 3.3mm x 5.6mm x 1.3mm 22-pin Optical Module  
• High SNR and Robust Ambient Light Cancellation  
• -40°C to +85°C Operating Temperature Range  
• 18 bits ADC |
| **Oxygen saturation** [14] | • ISM Band 2.402 to 2.480 GHz Operation  
• RX Sensitivity: -90 dBm  
• ASCII Command Interface API Over UART  
• Qualified for Bluetooth SIG v5.0 Core Specification |
| **Powering system** | • 3.0 V 35 mAh 0.1mA CR1220 battery |
| **Communication protocol** [15] | • 44mm x 38mm  
• Thickness: 3mm  
• Flex PCB 0.005" |

Table 2. Aly hardware specifications

**Casing system**

The designers team presented different proposals for the casing of the final board. The first one is a classical wristband (see figure 9). This epoxy resin wristband is designed to be transparent and to incorporate conventional watch size with a 3D printed core of 38mmx 44mm and flexible adjustable bands of height of 38mm and with of 100mm and 120 mm with the adjustable holes on the right side. Additional research was performed by including a thermochromic pigment in the epoxy resin and including resistors inside the writband material and control the temperature and once risk of covid 19 the microcontroller shoots up the temperature and the wristband changed its color. Further research on this approach is under development.

**B. Mobile application design**

React Native is a JavaScript framework for writing natively rendering mobile applications for iOS and Android. It’s based on React, Facebook’s JavaScript library for building user interfaces, but instead of targeting the browser, it targets mobile platforms [16]. Most of the code written can be shared between platforms, React Native makes it easy to simultaneously develop for both Android and iOS. Figure 4 shows the internal architecture of react native.

Three threads run in parallel [17]:

- **Js Thread**: JS code is read and compiled for production. JavascriptCore runs the bundle when the app is started.
- **Native Thread**: Handle JS changes and update user interface in the native modules for either Android or iOS.
- **Shadow thread**: Layout is calculated and sent back to the native UI.

![Figure 4. React native architecture[17]](image)

To develop the mobile hybrid application to act as a bridge between the wearable, the back end risk calculation and the platform, first of all, it is needed to develop a database schema and create a single cluster for Aly on the cloud. MongoDB NoSQL database is selected due to its fast response and the no relational technology that allowed us to test different structures.

The set up configuration of the database is created in mongo atlas, allowing access from anywhere on the internet (Including authentication api keys included later). Once the cluster is defined, one collection is created named “pacientes”, that has a particular data scheme defined. Then, the second task is to develop the back end server, which is coded using a node and express architecture that is connected to the database when the server is running by using a mongoose connection.

Different APIs are defined for either POSTING, PUTTING, UPDATING or DELETING the database content filled by the application and queried by the web platform (CRUD operations support).

Once the APIs are generated and the server is running in a EC2 virtual machine in AWS, the building process of the mobile application is started after APIs url, headers and body content are defined in json format. At first, in collaboration with the designers team, a paper prototyping of the application is performed, defining users profile, demographical data to capture in the application, symptoms and signs stored by the app, and a visualization mockup is defined.
The first approach is implemented using MIT APP inventor, to acquire a pseudocode version of the data flow and test REST requests to retrieve data from the database. This first version is enough to get a functional version, but aiming to develop a industry level approach, a react native with ESLINT and prettier AIRBNB. This consists on drawing components using native resources, test a mobile compatible RN4871 low energy 5.0 bluetooth compatibility, and to test the component update due to rest requests.

C. Web platform design

Aly’s web platform has a simple structure that is common to most web applications. It has a client or front-end, and a server that are both hosted on AmazonWeb Services. The client, runs on the user’s browser on a computer or mobile device. The server, which in the case of Aly is hosted on Amazon WebServices, that retrieves data and sends it to the client, and it has a database where all the data used to make the visualisations is stored. This simple infras-structure is shown in greater detail in Figure 5.

![Figure 5. MERN application architecture. Client: ReactJS webapplication triggers REST APIs and retrieves server responses mapped to downloadable visualisations. Server: Back-end bridge for the client (APIs) and database. Database:MongoDB non relational database hosted in mongo Atlas [18].](image)

The web platform has a layout designed with react bootstrap and cascade style sheets (CSS). It is programmed in react JS, which is a frame work to create hot reloading web apps. Aly’s platform was developed by using reusable components: Home component, patients menu dashboard, monitoring dashboard in which all the signs and symptoms are plotted over time, and a simple box of recommendations that either doctors or families can feel to send a message to the application of the user.

In terms of the web services, a update of the state were performed when an asynchronous REST request with patient’s id and password was triggered, asking the backend to retrieve data from the mongodb and triggering the classification algorithm described later. Once this information is retrieved, it is sent back in JSON format and decoded by the JS Axios library. Same happens when functions of posting in data base are performed, and the mobile application performs the query of the database.

D. Classification model

Aiming to develop a first approach to a classifier of high risk-low risk patients, a first pilot test is performed, obtaining data from 60 people (40 non COVID patients – 20 COVID patients) in order to build an algorithm with input variables (level of symptoms from 0 to 10 and value of each sign we discuss during the paper) and as output variable the dicotomic variable meaning presence or absence of covid 19 (1 means current presence of covid 19 or the patient who had the virus maximum one week before the interview and 0 means no sign or symptom of covid is identified).

We measured the data of the 60 volunteers during idle and filled the format found in the figure 6. We asked them for their profile, their symptoms (0 meaning no symptom and 10 meaning high level), and finally we used the MAX30205 and max86150 sensors to measure their signs and manually register them as this interview was performed before having a functional version of the mobile application.

![Figure 6. Format of interview to build classification model](image)

To be able to train a logistic regression model to be triggered when health care providers or users look for their results in the platform, we used a logistic regression model. It’s an extension of linear regression where the dependent variable is categorical and not continuous. It predicts the probability of the outcome variable. Logistic Regression is in charge of developing a model of the probability of occurrence of a determined event (contagion of covid or not) once independent variables values are given for a training data set [19]. This estimated probability will predict the effect of a series of variables on a class response given a threshold of probability. The binomial logistic regression maps this probability to a dicotomic variable 1 or 0, such as the one mentioned before as a label for the trainig set acquired in the interview.
Equation (1) shows the purpose of finding the coefficients for the linear approach, which is then mapped by (2) to a logistic function centered at cero whose possible results are 0 or 1. We implemented an algorithm to find the coefficients in R and find what the significant variables were in this short sample of people.

III. RESULTS

A. Wearable design

Prototyping arduino nano

Two tests were performed. The first one was to determine the comparison between commercial sensors (Yonker YK-82C Pulsioximeter to measure heart rate and oxygen saturation and M5 Smart bracelet for temperature) and Aly’s sensors. We continuously measured the temperature of 5 people and randomly chose measurements of sensors at the same time (tables 1-3). In the case of the temperature, The max30205 presents an average accuracy of 96%, while in the case of heart rate measurement the accuracy tends to 98% of the MAX 30102 and the 86150 98.5%, which was the final sensor used into the microcontrollers approach. In terms of the Oxygen saturation both the max 30102 and the 86150 present a 98% accuracy, leaving the use of both for wearable applications.

Table 3. Temperature Measurements

<table>
<thead>
<tr>
<th>User</th>
<th>Average temperature (°C)</th>
<th>Deviation</th>
<th>Standard deviation</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mac30102</td>
<td>Commercial</td>
<td>Mac30102</td>
<td>Commercial</td>
</tr>
<tr>
<td>1</td>
<td>37.3</td>
<td>39.62</td>
<td>2.31</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>38.6</td>
<td>39.52</td>
<td>0.89</td>
<td>0.05</td>
</tr>
<tr>
<td>3</td>
<td>37.7</td>
<td>37.30</td>
<td>0.43</td>
<td>0.03</td>
</tr>
<tr>
<td>4</td>
<td>37.1</td>
<td>38.19</td>
<td>1.12</td>
<td>0.04</td>
</tr>
<tr>
<td>5</td>
<td>38.8</td>
<td>36.65</td>
<td>2.20</td>
<td>0.10</td>
</tr>
</tbody>
</table>

To test the first wearable (arduino approach) and determine a simple experiment was performed. One participant was asked to ride a bicycle at 3 different constant cadences within an hour. 20 minutes at 35rpm, 20 minutes at 50 rpm and 20 minutes at 70rpm, then the data was registered by using Aly’s arduino nano approach and two commercial sensors, the M5 pro and the M5 smart band. The average deviation from these sensors was 2% in terms of the heart rate measured once a minute. Oxygen saturation was not necessary to measure considering the fact that it is computed with the same IR information that the sensor provides. In terms of temperature, the same experiment was performed and the average deviation was about 3%. One can see in figures 7 and 8 how both measurements shoted up when the cadency changed.

Table 4. Heart rate measurements

<table>
<thead>
<tr>
<th>User</th>
<th>Average beats per minute (bpm)</th>
<th>Deviation</th>
<th>Standard deviation</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Max30102</td>
<td>Max 86150</td>
<td>Commercial</td>
<td>Max30102</td>
</tr>
<tr>
<td>1</td>
<td>81.5</td>
<td>80.9</td>
<td>82.2</td>
<td>0.7</td>
</tr>
<tr>
<td>2</td>
<td>76.5</td>
<td>75.9</td>
<td>76.2</td>
<td>0.3</td>
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<tr>
<td>3</td>
<td>65</td>
<td>65</td>
<td>63.8</td>
<td>1.2</td>
</tr>
<tr>
<td>4</td>
<td>74.6</td>
<td>73.8</td>
<td>75</td>
<td>0.4</td>
</tr>
<tr>
<td>5</td>
<td>79.2</td>
<td>80</td>
<td>79.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Table 5. Oxygen saturation measurements
Figure 7. Case study heart rate results. One patient cycling at three different rates.

Figure 8. Case study temperature results. One patient cycling at three different rates.

Aly device

As described in the methodology, there is first a modular design of the printed circuit boards (Figure 9), in which each functionality of the final board is tested. Figure 9A shows the modular board for communication, which has the power supply of 3.3V, GND, TX and RX terminals and P2_0 pin to program the BLE module. Figure 9B shows the Max86150 module. This one supports connection for ECG (electrocardiogram) dry electrodes (to be explored in further research), I2C data and clock entries with matching pull up resistors to work at 100kbps) [14], The 3.3V power supply and 2 pins for potential debugging and analog and digital ground separate pins. The temperature module (figure 9C) has the 3.3V input and GND, the I2C data and clock pins, and a temperature control PIN [12]. The power supply has a battery holder for de CR1220, a voltage regulator and an output of the regulated 3.3V. Finally, the module presented in figure 9E presents the integrated board, whose pin headers let electrodes connection and independent connections to program communication board and microcontroller by using a pic loader.

In terms of the casing, the figure 10 presents the iterative approaches the designers team did. At first, there is a common wristban approach as described in the methodology. Once the temperature control and the thermochromic pigment were not implemented, we decided to migrate to a simple core case (Figure 10C) where the final board fits. Renders of the latest version of the cas are presented in figure 10 d and e, which can use any commercial bracelet and can even be used in different places of the body where photoplethysmography presents a significant measurement.

E. Mobile application design

As described in the methodology, a hybrid functional prototype is under development. The figure 11 shows the different layouts that were generated. Figure 11A shows the authentication screen, where the users can type their id and their password. Once they log in, they can go to different tabs, the home screen (figure 11b) where users’ profile can be seen and updated through and API (profile post and update), a second tab where the signs and symptoms can be monitored when scrolling down (here an API to register new data is used. Then, the shown data is gotten by using another api to perform a get action contonously). A third screen reports and thanks the different participants in the development of the tool. A fourth and last screen lets the users periodically update the intensity level they feel of each of the symptoms from 0 to 10. Finally, it is important to describe the bluetooth low energy interaction was succesful and now the different services and public UUIDs services (49535343-1E4D-4BD9-BA61-23C647249616 and 49535343-8841-43F4-A8D4-ECBE34729BB3 for RN4871) are preconfigured to get notifications of RN4871 and write some services to indicate what variable the sensor should read.

F. Web platform design

The web platform is developed as stated in the methodology. It has a responsive design with a home screen in which patients, families, doctors and industries and governments can log in (industries and governments concepts are under development, to see aggregated information of patients and help decision making processes within a company or population). When logging in, the REST request is executed with patients’ id and password as parameters, retrieving the information from the database of the stored signs and symptoms. The users get access to a menu (figure 12 C) where they can choose to see their monitor, their personal calendar and suggested recommendations (currently under development), they can call a doctor (unavailable ) and trigger the algorithm that determines if the person has risk of covid 19 by using the different stored signs and symptoms as input and see their results.

Figure 10. a) Initial render of the wristband. b) Upper view of the initial design. c) Core case designed to incorporate hardware. d) Planes of latest core case. These include terminals to connect with any bracelet. e) Rendered wearable with two state switches. f) final PCB

Figure 11. React native prototype. a) Authentication screen. b) Patients profile. b) Monitoring Screen c) About Screen d) Symptoms periodical report. f) Application tabs menu
G. Classification model

As described in the methodology, an R code is developed and then migrated to node js to compute the dicotomic variable of risk as an output. We first used the 60 patients database to understand the different relations among the variables. Figure 13a shows the different relations among them. The strongest relations can be associated to Cough, Fatigue, Sputum, respiratory distress and muscle pain. That means that when a larger sample is used, these variables tend to reduce the dimension of the final regression model. Figure 13b shows a probability distributions for covid and non covid patients in red and blue color respectively.

This supports the idea of including some significant variables in the regression model. For instance, the symptoms that best correlate with others such as cough, fatigue and sputum show a different distribution of covid and non covid patients. The same happens with temperature and oxygen saturation. One can identify larger values in symptoms and signs, except oxygen saturation, are related with covid distribution. Taking that into account, we develop a regression algorithm considering only the significant variables.

The table 6 shows one of the reduced models. As one can see, when using significance level of 0.05, only temperature and oxygen saturation levels have an impact on the dicotomic variable. Then, a final test is used with additional 63 people we interviewed. We knew all the values of their symptoms and signs. We used the algorithm to classify if they had risk or not. Figure 7 shows the results, 24 patients had the virus. 22 of them were identified by the algorithm. 39 of them didn’t have the virus, and the algorithm wrongly said 10 of them had the virus. We keep working on the model and want to scale the size of the population to better anticipate and prevent contagion.
Wearable wireless devices and sensors for medical applications and monitoring have become an essential component in modern healthcare. These devices can track vital signs such as temperature, heart rate, and oxygen saturation, which are crucial for monitoring athletes' performance, diet management, and disease diagnosis issues including other variables in other to prevent other kind of health issues. In this study, a wearable system is designed and developed to fully deploy the web-platform presents responsive layouts, communication protocols and REST web services are terms of the application, there is a full designed architecture and its case must be tested before moving forward in the study. The final board and of the products: a wristband that performs temperature, heart rate and oxygen saturation measurement. The final board and of the products: a wristband that performs temperature, heart rate and oxygen saturation measurement. The final board and of the products: a wristband that performs temperature, heart rate and oxygen saturation measurement. The final board and of the products: a wristband that performs temperature, heart rate and oxygen saturation measurement. The final board and of the products: a wristband that performs temperature, heart rate and oxygen saturation measurement.

### Table 6. Reduced logistic regression model coefficients and significances.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>z value</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-107.4076</td>
<td>64.28145</td>
<td>-3.045</td>
<td>0.00217</td>
</tr>
<tr>
<td>Temperature</td>
<td>4.7712</td>
<td>1.57869</td>
<td>3.022</td>
<td>0.00251</td>
</tr>
<tr>
<td>Oxygen saturation</td>
<td>0.22487</td>
<td>0.19304</td>
<td>2.182</td>
<td>0.09988</td>
</tr>
<tr>
<td>Heart rate</td>
<td>0.05432</td>
<td>0.08318</td>
<td>0.654</td>
<td>0.10244</td>
</tr>
<tr>
<td>Respiratory cycle</td>
<td>-0.25787</td>
<td>0.18261</td>
<td>-1.389</td>
<td>0.16004</td>
</tr>
</tbody>
</table>

Table 6. Reduced logistic regression model coefficients and significances.

### Table 7. Evaluation of logistic regression algorithm for 6 new participants in the study

<table>
<thead>
<tr>
<th></th>
<th>True</th>
<th>False</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>22</td>
<td>10</td>
</tr>
<tr>
<td>Negative</td>
<td>2</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 7. Evaluation of logistic regression algorithm for 6 new participants in the study

### IV. CONCLUSION

A complete covid 19 scalable monitoring system is designed and currently under development. There are prototypes for each of the products: a wristband that performs temperature, heart rate and oxygen saturation measurement. The final board and its case must be tested before moving forward in the study. In terms of the application, there is a full designed architecture and layouts, communication protocols and REST web services are fully deployed. The web-platform presents responsive layouts for consulting signs and symptoms, and trigger an algorithm to assess COVID-19 risk. Further research on this field should be performed to guarantee accuracy and the whole integration of the different products.

### V. FUTURE WORK

Virus-driven diseases and physiological information on temperature and oxygen saturation are indicated to be the most useful pilot of this project. Further research is recommended on including other variables in other to prevent other kind of health issues [20] and impact other fields such as productivity and athletes performance, diet management, and disease diagnosis [21].

### VI. REFERENCES


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Felipe Montes. Associate professor at Los Andes University. He is a member of the research group of Theory Systems of Organizations (TESO) and of the Epidemiology Group of the Universidad de los Andes (EpiAndes), as well as of Onnela Lab of the Department of Biostatistics of the School of Public Health of Harvard University.