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Real-Time Wearable Device for Predicting a Long Covid Patient's Condition

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Abstract— This paper aims to develop a wearable device that can be able to Predict the long covid-19 patients' conditions, to notify the doctors on a real-time basis. Long covid-19 patients suffer a lot during their daily activities especially if the lasting symptom is related to the respiratory system. By developing a system, that is easy and comfortable to wear during normal daily life, we believe that we will be able to predict the long covid-19 patients' condition. The system should first detect and analyze the patient's breathing pattern using artificial intelligence then store the patient's breathing pattern along with his status in an online database, then notify the doctors in case of a critical situation. To train the model the breathing pattern of current long covid patients and normal people was captured during doing daily activities such as walking, sitting, and climbing stairs. We hope that the developed system will help in easing the suffering of long covid patients by providing better monitoring of their health..

Keywords: *Long Covid-19, Post-Covid-19 Syndrome, Breathing Classification, Deep neural network.*

1. INTRODUCTION

Post-Covid-19 Syndrome or what is known as Long Covid can be defined as the chronic form of severe acute respiratory syndrome coronavirus (SARS-COV) where the patient keeps suffering from some of the SARS-COV symptoms after the recovery and is tested as negative. According to Dr. Janet Diaz, the team leader at World Health Organization (WHO), long Covid does not have a clear recovery duration as it might last for three months or even up to nine months. Long COVID makes the patient suffers a lot during his daily activities especially if the lasting symptom is related to the respiratory system [1]. Long COVID requires early detection to provide the necessary treatment before partially damaging the organ, that is why a system is needed to predict long COVID.

According to an online survey that was conducted by Helix DNA Discover Project and Healthy Nevada Project (April-October 2020), out of 21359 participants, 13838 participants suffered from one or more symptoms after the recovery. Another survey was conducted in Clichy, France, by contacting 120 patients by phone and it resulted in: a mean of 110.9 (±11.1) days following admission. The most frequently reported persistent symptoms were fatigue (55%), dyspnea (42%), loss of memory (34%), concentration (28%), and sleep disorders (30.8%) [2], [3]. Since covid-19 is a respiratory virus, we focused on predicting the patient's condition using the breathing pattern. Detection of breathing patterns using wearable devices can be done with the help of many sensors such as humidity sensors, oximeter sensors, and pressure sensors. We preferred to use a pressure sensor that can be mounted on the chest with the help of a belt as in Fig.1.

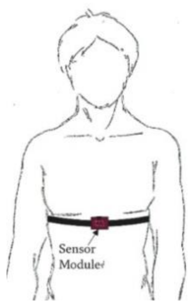


Fig. 1 Using Pressure Sensor to Detect Breathing Pattern

This paper aims to investigate parameters related to Long Covid, predict the patient's status based on AI using the data that will be stored online, develop an assistive wearable device that can detect the condition of Long Covid patients, and integrate the software with the wearable device and provide an immediate Alert to the authorized officer in case of any critical situation.

2. METHODOLOGY

The paper can be divided into four main parts, to start with, the system should first capture the patient's breathing pattern. The system should then store the data in a database to be classified and viewed in the future. The stored data will be analyzed and classified using Artificial Intelligence and store the pattern's type in the database. A mobile application should be developed to read the type of the patient's breathing pattern and to notify the users in case of any abnormal situation. The system flow graph can be shown in Fig. 2.

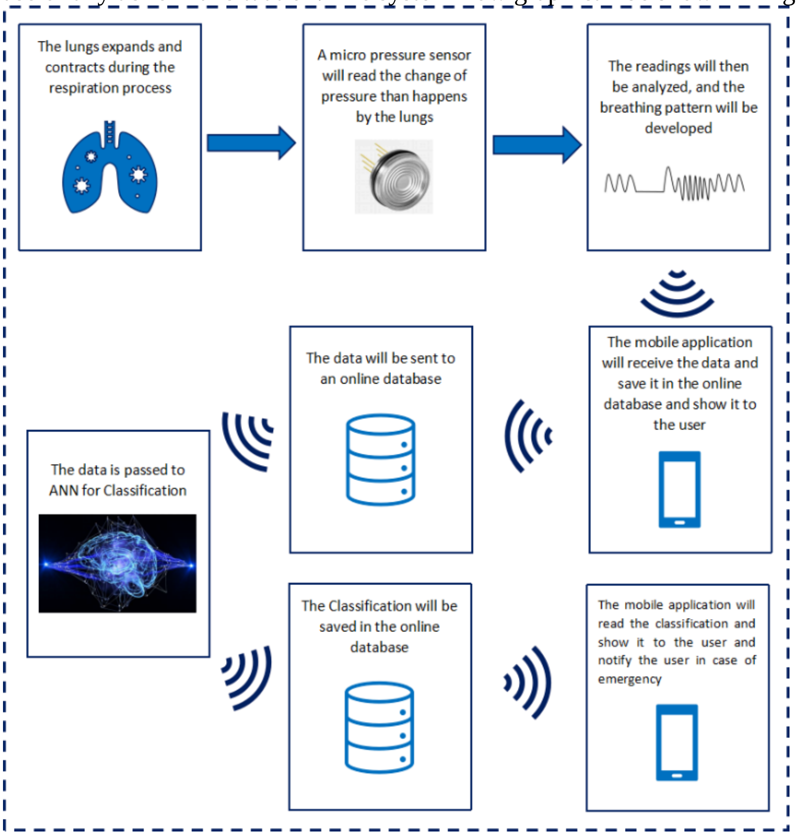


Fig. 2 System flow graph

2.1 Breathing Capturing

By taking advantage of the contraction and expansion of the lungs, a pressure sensor can be used to capture the change in pressure. The pressure sensor should be integrated with a micro-controller that is needed to process the breathing signal after being captured.

2.1.1. Pressure Sensor

To have accurate results, the pressure should have as low sensitivity as possible as the pressure exerted by the lungs is not large. And also, the pressure sensor should be small in size and light in weight as the whole system should be light in weight to provide more comfort to the patient while using it.
By referring to the datasheet of the force-sensing resistor [4], we can see that it is the best sensor that can meet our requirements as it has the following specifications:

a) Size:
FSRs come in different sizes starting from 5mm x 20 mm up to 13mm x 56mm.

b) Sensitivity:
The FSR can read from 0.2N up to 20N

c) Output:
By referring to Fig. 3, the output resistance of the sensor is inversely proportional to the applied force.

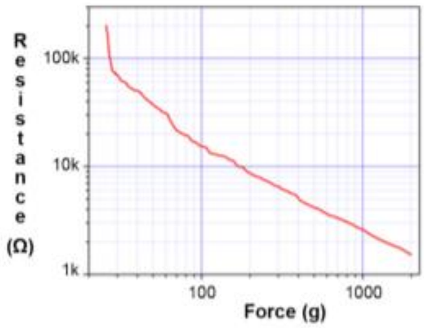


Fig. 3. Relation between the applied force and the output resistance

As discussed in the specifications, the output of the sensor is inversely proportional to the applied force, however, to convert the relation to be directly proportional we can use a voltage divider circuit as in Fig. 4 and change the output to be voltage where the microcontroller can measure it. By applying the voltage divider law the output voltage can be calculated using (1).

$$V_{out} = \frac{R_m V^+}{R_m + R_{FSR}} \tag{1}$$

Where V_{out} refers to the Voltage that will be read, R_{FSR} refers to the resistance value of the force sensor, V^+ is the source voltage which is 3.3V in our case, and the R_m is the used resistance to do voltage dividing which has a value of 1200 ohm in our paper.

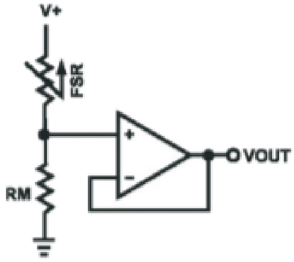


Fig. 4. Voltage divider circuit for FSR

2.1.2. Signal processing using a microcontroller

As the system needs to be small in size and at the same time provide a wireless communication protocol to reduce the total number of components, ESP32 will be the best microcontroller to be used as its chip supports both Bluetooth and Wi-Fi connection, which will ease the communication between the device and the database, and it relatively small in size as its board is 5.8 cm x 2.8 cm. The ESP32 Board will be used to read the value of FSR and to process the signal, where the system will have an automatic calibration by using the average of the previous readings as the zero axis for the next readings and then transferring it to the database.

The sampling rate of the signal will be 10 Hz. By referring to Nyquist's theory, the sampling rate should be at least twice the highest expected frequency. By referring to [5], we can see that the maximum expected number of breaths per min is 42 breaths which means the signal frequency is 0.7 Hz. Using 10 Hz as the sampling frequency will make sure that aliasing will not happen.

The ESP32 is programmed by Free RTOS to provide an accurate sampling rate of 10 Hz. The System first sets the patient ID, followed by getting the global timestamp to set the date and time accordingly to be easier to monitor. The ESP32 then reads the analog value of the FSR and maps it between 100 to -100, to have an accurate reading for the pressure applied by the lung's expansion and contraction. The ESP32 then stores the data in an online database using the JSON format shown in Fig. 5. The system will be updating the database every 1 second and will be able to save the readings of the past 30 minutes in case it was disconnected from the data and could not update it.

```
{
  "Global Timestamp": 1653124814217,
  "NewID": 105,
  "Patients": {
    "100": {
      "2022": { //Year
        "5": { //Month
          "10": { //Day
            "14": { //Hour
              "5": { //Minutes
                "6": {...}, //Seconds
                "7": {...}
              }
            }
          }
        }
      }
    },
    "102": {...},
    "103": {...},
    "104": {...}
  }
}
```


Fig. 5. Dummy Stored Data in the database

2.2 Saving the signal to the database

By using the Wi-Fi feature in ESP32, during the data collection the system updated the database directly. However, to ease the patient life, the system can send the data using Bluetooth to the mobile application that will update the database as we cannot guarantee that the system will always be able to connect to WiFi, unlike mobile phones which became a necessity for everyone nowadays.

The system will be using an online database to make it possible for the user to access it from different devices as long as the user is connected to the internet and also t be easier for the doctor to access it. Firebase is a free online database developed by Google and it can be integrated with various types of applications and software. The system will be using firebase to save captured data and also to save the type of the breathing pattern after passing the captured reading to the developed artificial intelligence model. One of the interesting features of firebase is that it supports adding a customized artificial intelligence model to the system, as it supports importing a pre-trained TensorFlow model.

2.3 Classification of the breathing signal

One of the most effective and popular ways for data classification is the deep neural network. The deep neural network is an artificial intelligence aspect that focuses on emulating the learning approach that humans use to gain certain types of knowledge. By referring to Fig. 6, we can see that Neural networks mainly consist of an input layer, which represents the data that it will be passed to the neural network, and hidden layers, which is can consist of many different layers where each layer is considered as an input of the previous layer, and a final output layer, which represents the final output of the neural network.

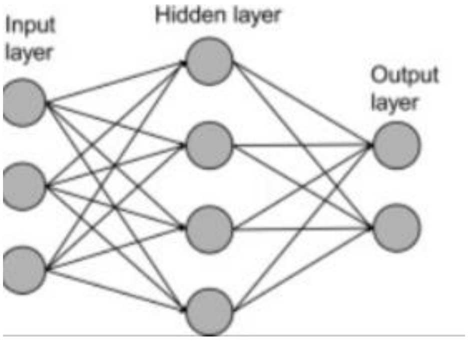


Fig. 6 Neural network Architecture

The trained model is developed to have an input of 300 nodes, which should correspond to the values captured every 0.1 seconds for a consecutive 30 seconds. The values then go throw several hidden layers until it reaches the output layer. The output layer is a dense layer that consists of 2 nodes, where each node represents a type (either normal or Long Covid). The value of each node represents the possibility of being under this particular type.

2.4 Mobile application

As was discussed, a mobile application was needed as it will be the gateway between the system and database, and also it is considered as the monitor where the patient and the doctor can check the breathing pattern history and its classification.

The mobile application is user-friendly and easy to understand the displayed information, to be suitable for any age use. The mobile application has two types of users with different permissions given to the doctors and patients as the doctor can add patients under his monitoring list. Another feature that is included in the mobile application, Alerting the patient and the doctor of any critical situation like the stop of breathing or having dysrhythmic breathing for a long time. One more feature is providing a communication platform between the patient and the doctor.

3. DISCUSSION AND RESULTS

This paper went through many phases, as in the beginning, an AI model was developed to classify the breathing pattern into seven types of breathing patterns. That had an accuracy of 98%. However, that model was trained using the data obtained from an experiment conducted using Doppler radar to capture the breathing pattern [5]. In that experiment, they were able to detect seven different breathing patterns, which are normal breathing, central sleep apnea breathing, ataxic breathing, biot's breathing, Cheyne-stokes and Cheyne-stokes variant breathing, and dysrhythmic breathing. But that model had a lot of limitations as all the data was captured from the graphs plotted by the output of the radar, and also that the breathing pattern was only captured from one patient at each type. To overcome these limitations, we decided to capture the data and modify the old model to classify it into normal or long covid only.

3.1 System Design

The system consisted of the capturing circuit and circuit holder. The circuit contained, an ESP32, force resistive sensor, 1200-ohm resistor, and 3V battery. To have a better connection between the circuit components, a PCB, as in Fig.7, was fabricated to connect all the components. A circuit holder, as in Fig.8, was needed to make it possible for the circuit to be placed on the patient's chest. The circuit holder was designed using SolidWorks and printed using 3D Printing.

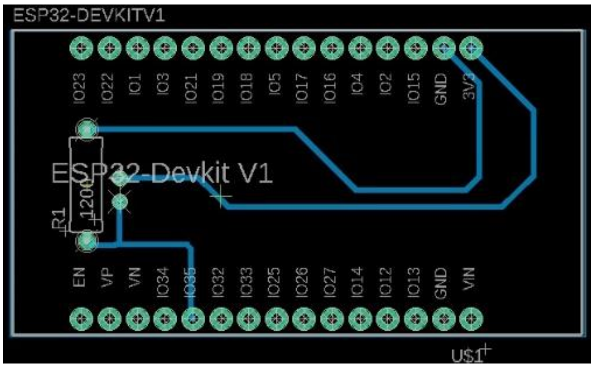


Fig. 7 System's PCB

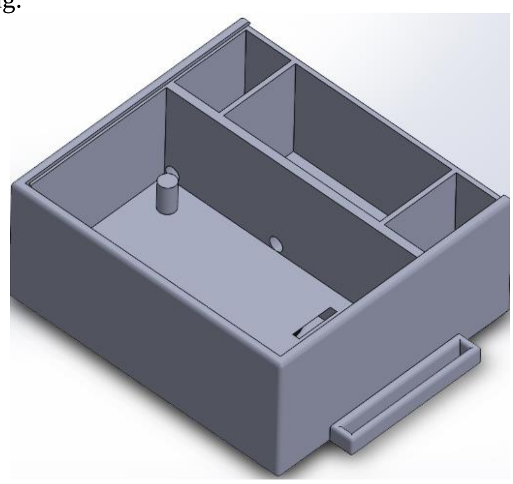


Fig. 8 3D model of The Circuit Holder

3.2 Data Collection

To collect data, we spread an online survey asking if the patient has been infected with covid or not, when was the last negative, and if what are the lasting symptoms after recovery. As a result of this survey, we got 23 responses however, only 8 showed up for the experiment, 1 female and 7 males, 50% of the participants are suffering from long covid while the other 50% either recovered from Covid-19 without any lasting symptoms or were not infected by Covid-19.

To cover most of the daily activities, the participants in the experiment were asked to rest for 1 minute at the beginning followed by walking 200 meters, then climbing upstairs consisting of 32 stairs, then having a walk of 150 meters, followed by going down the same stairs and walking 50 meters, and finally rest for another 1 minute. A demo video for the experiment can be checked either by Clicking on the following link https://bit.ly/3xy970M.

3.3 Dataset Preparation

The dataset was created inside the program used for model training. To begin with, the data was read from the database and mapped between 100 to -100, to avoid any data variance that might show up due to unequal tightness of the system on the patient's body, then stored in NumPy arrays. With the help of the preprocessing module from Keras, a sequence of length 300, which is equivalent to the reading of 30 seconds, and a sampling rate of 10, as the loaded presents the values every 0.01 second however the model should be trained to evaluate the values read every 0.1 seconds. All the obtained sequences should then be concatenated in one list as all the data will be fitted to the model in one dataset.

A corresponding dataset was created representing the actual output that the model should predict. As the developed model should classify the breathing pattern into normal or long covid breathing patterns, its output will be the probability of being under each class. Since the dataset has only two types, a list of two elements is developed, where each element represents the probability of each class so if the sequence belongs to that class its value should be one and the other elements are zeros. As a result of that, we had a dataset of 16861 sequences for both types. To provide a variety of breathing types in each batch of training, the dataset was shuffled twice before starting the training. During the training process, the dataset was split into 70% for training and 30% for validation, to have sufficient data for testing without affecting the training data. The whole dataset can be checked either by Clicking on the following link https://bit.ly/3xuBn4b.

3.4 Model Training

The model was set to be trained for 50 epochs, however, due to the early stop condition that was set to prevent overfitting, the training process stopped after 46 epochs. The trained model contained 15 hiding layers of different types as dense layers,1d convolution layers, and max padding layers. The model overall showed great results in terms of accuracy and loss, as it is shown in fig.9 the model accuracy is 99%.

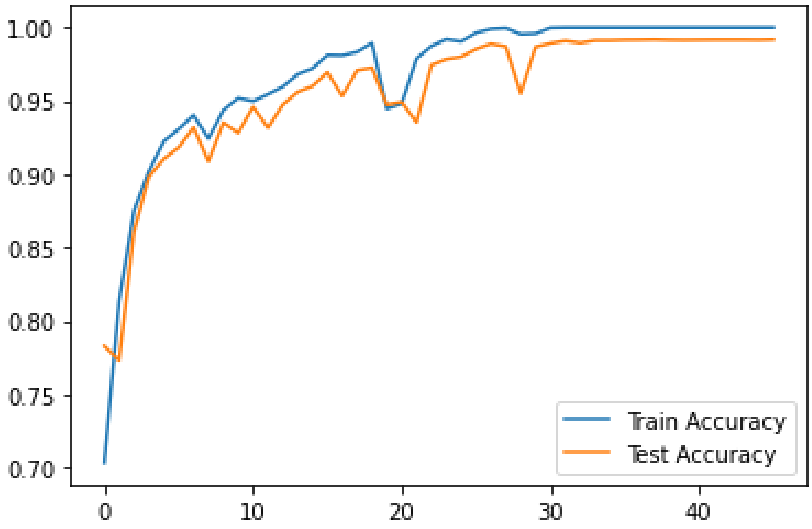
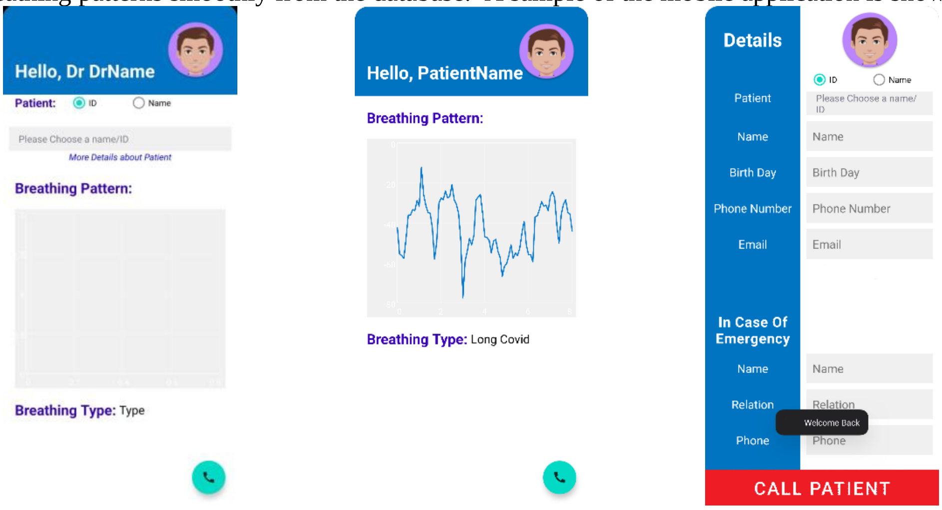


Fig. 9 The model accuracy over the training process

3.5 Mobile Application

The mobile application was developed using Java and successfully integrated with the Firebase server. As a result of that connection, the application has a great authentication system, also it can save the user's data and reads his breathing patterns smoothly from the database. A sample of the mobile application is shown in Fig.10.



a) b) c)

Fig. 10. a) Dr's home screen, b) Patient's home screen, c) Info Screen

4. CONCLUSION

In conclusion, the system will be very helpful as the doctors can monitor their patients anytime without being in danger of contacting them. At the end of this paper, the paper's objectives were satisfied as the patient's status can be monitored and predicted using a deep neural network using a wearable device. However, the system currently has some limitations due to the lack of data. To overcome that, a wider survey must be distributed to gather more data and have a better-trained model. Another limitation, the system works only if it is connected to Wi-Fi, however in the future, the system will be modified to give the user the choice of choosing his preferred type of communication, either Wi-Fi or Bluetooth, using a simple configuration page.

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