

# Accessible, AI-enabled TeleMedicine Solution for Multi-organ Dysfunction Caused by SARS Infections

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## Abstract:

SARS patients have common symptoms of Multi-Organ Dysfunction (MOD), including fatigue, difficulty breathing, and fever. Delays in the detection, diagnosis, and treatment of MOD indicators can lead to the inability to manage severe symptoms, conditions worsening, and even deaths that can be prevented. The spirometer, oximeter, and thermal camera are the devices that measure these defined symptoms and were utilized in this solution to output correlative analysis. Code developed in C with the Arduino IDE is used to develop the correlation algorithm to output an "Overall Health" reading for the user to interpret. Integration of these vital elements led to a contactless telemedicine device that can display comprehensive data/results along with the use of IoT and Machine Learning. Lung Capacity, Oxygen Saturation, and temperature reading had an inaccuracy of approximately 1-5%. The correlative analysis provides a precise overall health reading for users to utilize. With the affordable design, we can leverage this to be accessible to low-income and underserved communities. A more sustainable flow of ICU admissions can be achieved because users will have real-time data on their state of being.

## Keywords:

Machine Learning; SARS; Multi-Organ Dysfunction; Overall Health Indicator; TeleMedicine; Internet of Things; Oximeter; Thermal Camera; Spirometer; Regression analysis.

## Introduction:

Coronavirus is a common, diverse family of viruses. They can cause upper respiratory tract infections. COVID-19 is the name of the infectious disease caused by SARS-CoV-2, a strain of coronavirus. SARS-CoV-2 can cause multi-organ injury via direct infection or through cytokine storms as shown in Figure 1.<sup>1</sup> These injuries entail cardiovascular/respiratory damage, high blood pressure, acute kidney injury (AKI), liver injury, and damage to the central nervous system.<sup>2</sup> The problem in the status quo is that monitoring is often qualitative, so there is no direct measures to evaluate overall health of the patient during quarantine.

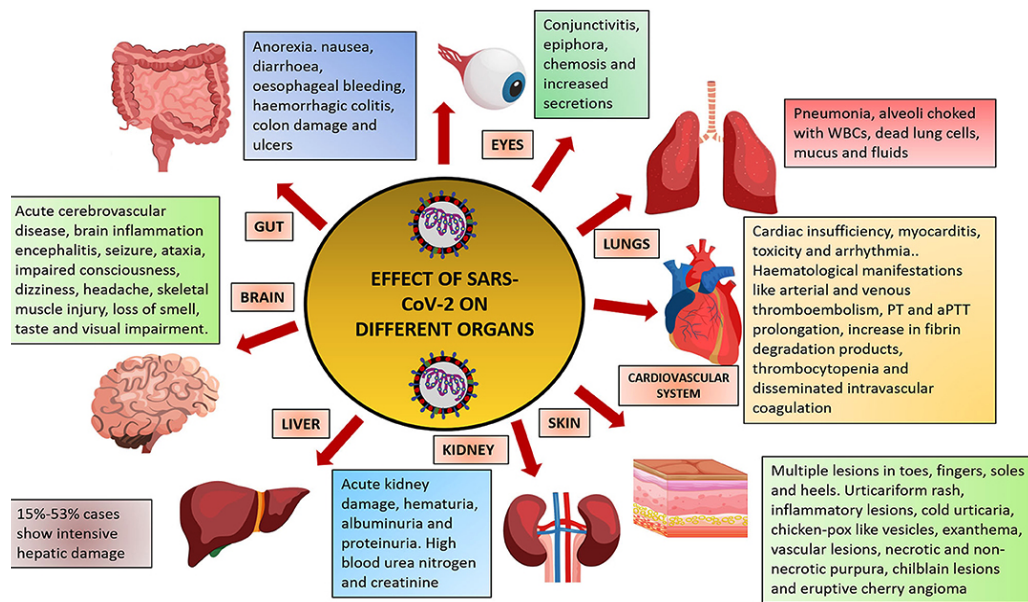


Figure 1: Organs impacted by SARS-CoV-2<sup>1</sup>






Symptoms of COVID-19		Percentage of Patients	Monitorable?	Organs Impacted	Measurement Device
Area of Focus	Fever 	78%	Yes	Central and Peripheral Nervous Systems	Thermometer / Thermal Sensor
	Cough 	57%	Yes	Heart Disease	Self Assessment / Clinical Evaluation
	Fatigue 	31%	Yes	Central nervous and immune system,	Patient Wellness and Oximeter
	Loss of smell 	25%	No	Tongue and nervous system	Self Assessment / Clinical Evaluation
	Difficulty Breathing 	23%	Yes	Lungs	Spirometer and Oximeter

Table 1 (prepared by student researcher): Key indicators of SARS infections and their impact on organs

## Methods:

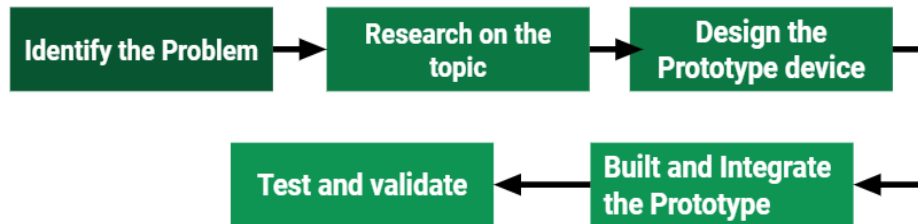


Figure 2 (prepared by student researcher): Development of the Solution

SARS-CoV-2 can be monitored in many ways. My methodology takes it to a MOD (multi-Organ Dysfunction) perspective. First, the trend of body temperature, oxygen levels, and lung capacity was researched, as shown in Figure 1. Then, knowing these common symptoms, the oximeter, spirometer, and thermal sensor were implemented to monitor most of these trends as depicted in Figure 2. The reason why both the spirometer and the oximeter was used is due to the inaccuracy of the individual sensors due to cheap materials. Hence, taking a multiple biosensor approach was best for overall accuracy. Finally, with the three measurement data points, a correlational algorithm was executed that can be used to monitor and track the progress of a person's condition for SARS-related infections. The measurement data points were taken once per patient for each trial (2 trials). There is also an inclusion of potential SARS patients in the testing with randomly generated readings to demonstrate how the device would work on unwell patients.

### A. Solution Components

#### Pulse Oximeter

A Pulse Oximeter measures oxygen saturation in the blood (non-contact). It consists of 2 LEDs that shine red and infrared light through the skin. The Photodetector collects reflected light off the tissues and returns corresponding values. Refer to Figure 4.

#### Thermal Camera

A Thermal Camera, also known as an "infrared thermometer," measures the temperature. An array of infrared detectors detect the radiation given off by objects. The ESP32 maps the values onto a comprehensive grid. Refer to Figure 5.

#### Spirometer

A Spirometer measures lung capacity which the user exhales into a sterile tube. The exhaled pressure is sensed by a pressure sensor in the venturi tube and forced vital capacity (FVC) is calculated. Refer to Figure 6.<sup>3</sup>

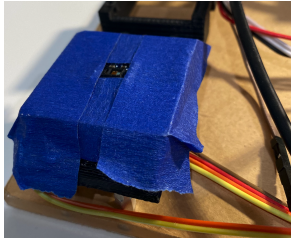


Figure 3 (prepared by student researcher):  
MAX30102 pulse oximeter

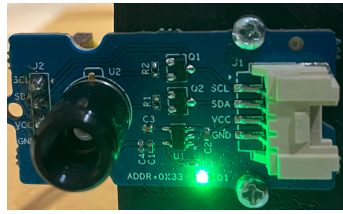


Figure 4 (prepared by student researcher):  
MLX90640 thermal sensor

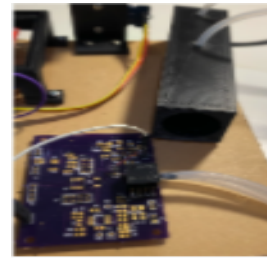


Figure 5 (prepared by student researcher):  
MPXV7025 spirometer

Building the telemedicine device with these three biotechnologies integrated on a single board with ESP 32 microprocessor and a TFT LCD touchscreen display makes the diagnostic solution both self-contained and accessible for the user's health monitoring purposes. To ensure the precision of readings taken, optimal distances between the patient and the device are suggested as illustrated in Figure 7.

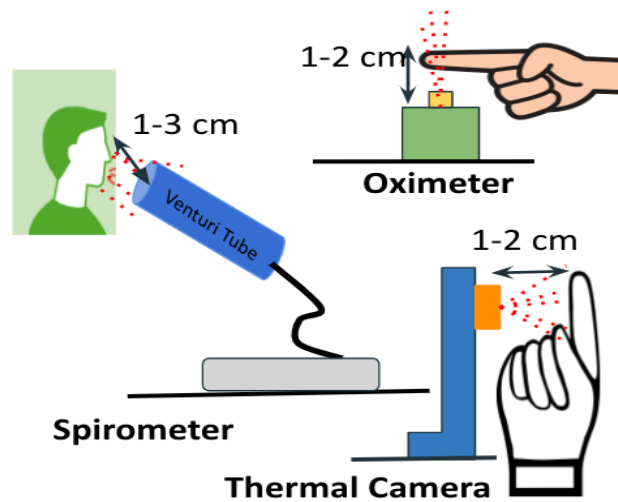


Figure 6 (prepared by student researcher): Optimal distance to obtain precise readings.

## B. Correlational Algorithm Theory:

To properly assess a user's well-being through their self-isolation, this device must also calculate overall health. To measure overall health, a weighted average is taken based on a points system out of 100 of the 3 data points that come from the user. These 3 data points come from the Oximeter, Spirometer, and Thermal Sensor. Correlation equation -  $(2a + 2b + c)/(a+b+c)$ , where a and b are the oximeter and spirometer points, respectively, and where c is the temperature value (as illustrated in Figure 8 and Figure 9). Lung capacity (spirometer) and Fatigue (oximeter) data points are the same weight because they

directly correlate with each other since the oxygen levels in our blood are proportional to the lungs' capacity to circulate oxygen properly. The thermal temperature is weighed less since viral infections can cause fever.

<b>Readings</b>	<b>Normal</b>	<b>Slightly Abnormal</b>	<b>Abnormal</b>	<b>Severely Abnormal</b>
Temperature	97-99°F	100-101.4°	95.6-96°, 102-104°	Less than 95.5°, Greater than 104°
SpO2	95-100%	Not Applicable	90% - 94%	Less than 90%
Lung capacity (FVC)	80%-120%	70%-79%	60%-69%	35%-59%

Table 2 (prepared by student researcher): Table showing the three categories of readings from the three individual biotechnologies.

<b>Readings</b>	<b>Oxygen Levels (SpO<sub>2</sub>)</b>	<b>Lung Capacity (FVC)</b>	<b>Thermal Measurement (°F)</b>	<b>Overall health</b>
Scenario 1	97.5%	98%	97.8	Normal
Scenario 2	89%	68%	97.3	Needs medical attention

Table 3 (prepared by student researcher): Example readings with an overall health indicator

Using the Correlational algorithm, the measured values of oxygen levels (SPO2), lung capacity (FVC), and Thermal measurement (degree Fahrenheit) are used, with different weights, to calculate the overall health indicator of the patient. Based on the derived health indicator value, normal (green), slightly abnormal (yellow), and Abnormal/Severely Abnormal (Red) are displayed on the TFT screen as illustrated in Figure 10.

## Results:

	Readings	Oxygen Levels (SpO <sub>2</sub> )	Lung Capacity (FVC)	Thermal Measurement (°F)	Indicator results on TFT Screen
Real People	Person 1, Trial 1	97.5%	98%	97.8	Normal
	Person 1, Trial 2	98.3%	96%	97.3	Normal
	Person 2, Trial 1	97.8%	101%	96.7	Normal
	Person 2, Trial 2	96.7%	100%	96.5	Normal
	Person 3, Trial 1	95.3%	91%	98.6	Normal
	Person 3, Trial 2	96.9%	94%	98.2	Normal
	Person 4, Trial 1	98.2%	104%	97.4	Normal
	Person 4, Trial 2	98.7%	103%	97.1	Normal
Hypothetical patients	COVID patient 1	91%	79%	100.4	Slightly Abnormal
	COVID patient 2	92.5%	68%	98.5	Abnormal
	COVID patient 3	87% <sup>o</sup>	63.7%	101.1	Severely Abnormal

	Fatigue (Oximeter Reading)	Difficulty Breathing (Spirometer)	Fever (Thermal Camera)	Overall Health Indicator
Person 1	Green	Green	Green	Green
Person 2	Green	Green	Green	Green
Person 3	Green	Green	Green	Green
Person 4	Green	Green	Green	Green
COVID patient 1	Yellow	Grey	Grey	Grey
COVID patient 2	Yellow	Yellow	Green	Yellow
COVID patient 3	Red	Yellow	Grey	Red

Table 3 (prepared by student researcher): Real and Hypothetical readings with color categories for the corresponding user's overall Health Indication

## A. Statistical Model Leveraged in AI/ML Approach

The device utilized the Non-linear regression analysis to show predictive analytics of the trend of increasing or decreasing readings depending on the model parameters chosen and the measured variables. Due to the nonlinear nature of the readings taken for a given SARS patient, the nonlinear regression supervised learning algorithm was used which gave me the best curve-fitting results.

General Formula:  $f(x) = A + B \ln(x)$

The general formula is derived from a testing of 50 individual patients. A combination of statistics and ML approaches was used to conclude this general formula that could be applied to all patients. Further testing for how accurate this model is on a large scale is needed.

The A value is changed based on the vertical translation of the values. The value  $B > 0$  indicates a growth model versus  $B < 0$  indicates a decay model

Specifics: Based on the given values for a hypothetical patient monitoring their symptoms, the following best-fit curves were determined using the optimal readings (reflected on the graphs below in Figure 11, Figure 12 and Figure 13):

Spirometer -  $[103 + [-13.6 \ln x]]$

Oximeter -  $[98 + [-2.62 \ln x]]$

Thermal Camera -  $[99.1 + [1.62 \ln x]]$

\*\* When actual normal distribution patient data is publicly available, incorporation of 2 standard deviation percentile curves will be leveraged further to validate the accuracy of the current statistical model. All the statistical analysis was performed using Python SciKit learn libraries, and plotted the results in Excel to evaluate best-fit curves.

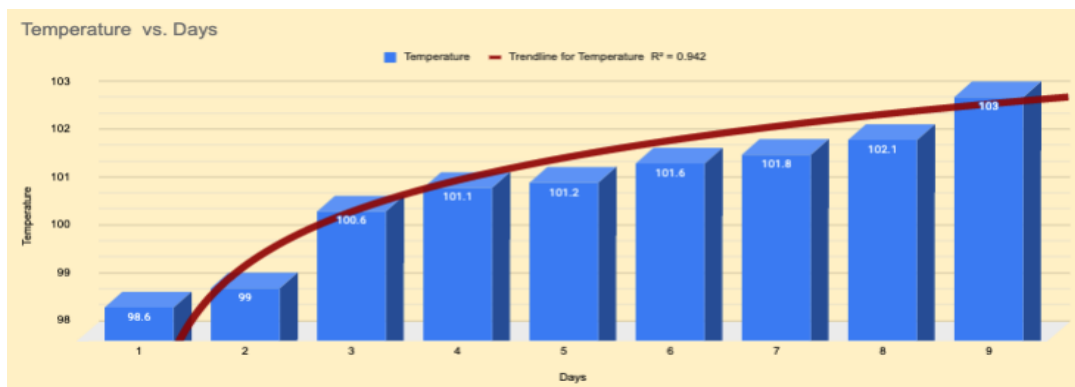


Figure 7 (prepared by student researcher): Temperature simulated reading curve

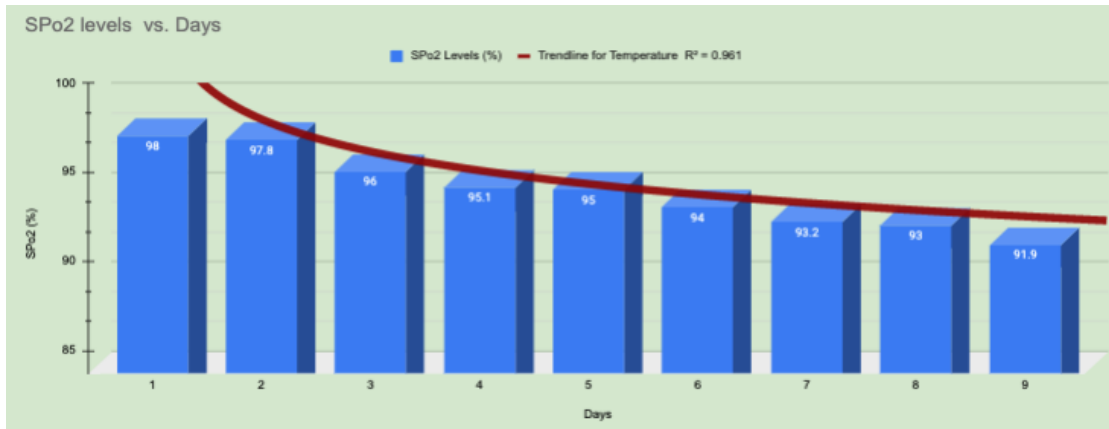


Figure 8 (prepared by student researcher): Oxygen saturation simulated reading graph

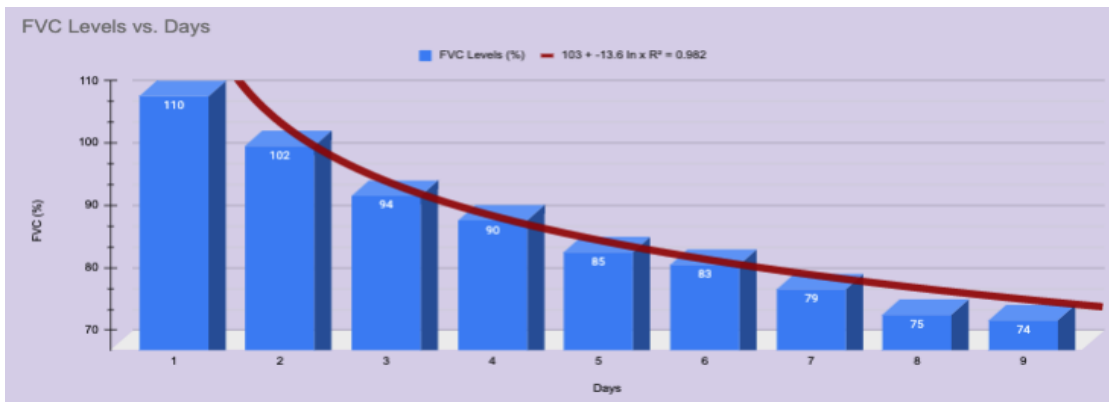


Figure 9 (prepared by student researcher): Lung capacity simulated reading graph

## Discussion:

Below is the comparison of the triage process as prescribed by the World Health Organization Model and the solution that is being proposed as an outcome of my research:

World Health Organization Model<sup>4</sup> -

1. The patient has imposed an onset of 14 days in strict home quarantine without any insight into the ongoing deterioration of the body organs.
2. All the monitoring must be done at the hospital after a patient is forced out of the home due to extreme circumstances and advanced symptoms of SARS-CoV-2.



## My Solution -

1. Constant monitoring provides capabilities to record oxygen levels, lung capacity, and body temperature from a single, home-based diagnostic unit. In addition, patients can now get a rough understanding of what their overall condition can become.
2. We are reducing the burden in hospitals by providing at-home diagnostic needs for a more organized triage process.

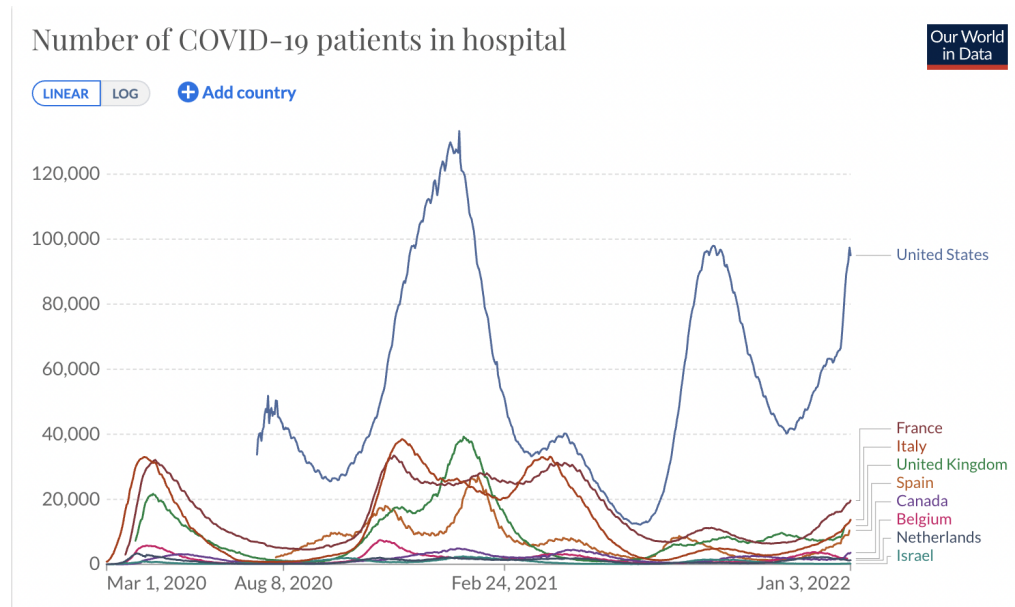


Figure 10: Number of SARS patients admitted to ICUs<sup>5</sup>

The benefits of my solution are:

- ❑ 1. Promote psychological well-being in patients
- ❑ 2. Avoid influxes of SARS cases in ICUs. Refer to Figure 14.
- ❑ 3. Improve patient outcomes resulting in decreased mortality through telemedicine

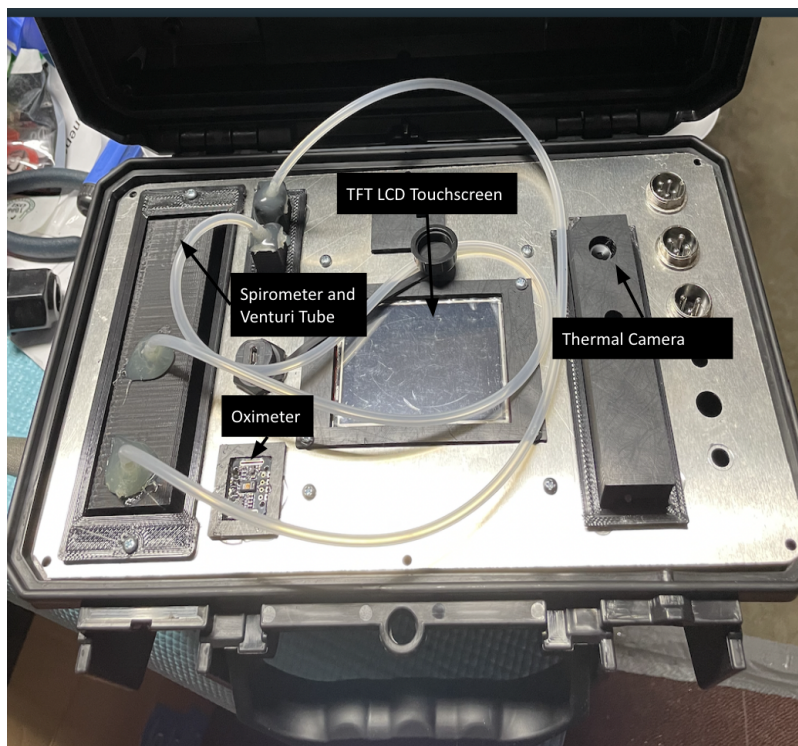
## The Future Growth of Telemedicine Powered by Emerging Technologies

So far, one of the main hurdles to adopting emerging technologies in the healthcare field has been due to strict government restrictions and guidelines. But recently, the US Food and Drug Administration announced the “Artificial Intelligence/Machine Learning as a Medical Device Action Plan” which provides a framework for all healthcare providers to encourage the development of intelligent telemedicine applications.

This framework is essential for AI in telemedicine to grow and evolve. Another aspect is the behavioral change for adopting IoT in Healthcare, securing patient data, and developing trust for the new interface between doctors and patients, which are all significant steps. But due to the advancements in the standards and frameworks set by both federal and industry-level participation, the adoption of new technologies like IoT and AI/ML looks promising as the telemedicine industry continues to grow and enable a better patient experience with their healthcare providers.<sup>6</sup> With all the opportunities that exist and the progress that we have made in modern technologies that can help us make healthcare provisions more efficient, effective, and enjoyable, telemedicine is clearly becoming a leading modality between patients and doctors.

### **Visual Model of working prototype product:**

Below is the visual representation of the final working prototype (Refer to Figure 15) that shows integrated biotechnologies necessary to remotely monitor and diagnose progressing health conditions of patients while quarantined at home or to enable continuous health data sharing mechanisms with their healthcare providers via Mobile Apps (Refer to Figure 16).



*Figure 11 (prepared by student researcher): Prototype Design*

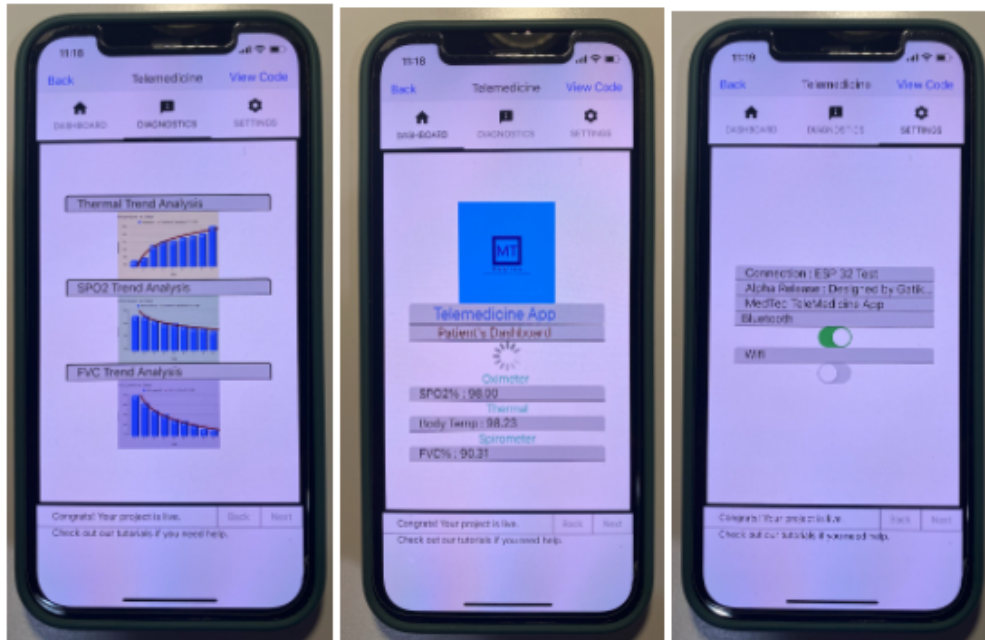


Figure 12 (prepared by student researcher): Mobile app readings

## Conclusions:

Successfully developed a novel telehealth solution that incorporates three biosensors onto a single platform for accurate and continuous self-monitoring of patient symptoms. An algorithm using C programming to correlate the data collected was executed as an indicator of overall patient health - critical for timely medical intervention and patient recovery. In addition, preliminary results using a limited number of individuals demonstrated the efficacy of the built solution - further testing of the device on actual patients is needed to corroborate this work's findings further. We successfully integrated machine learning statistical analysis using hypothetical patient data to evaluate predictive trends. To increase user accessibility, a prototype mobile app (alpha release) was developed that leverages patient data and statistical analysis to track health-related trends. Ultimately, a contactless product (with a disposable venturi tube) was achieved to eliminate the risk factors of accidental spread while taking readings.

## The Roadmap:

The future area of focus is to explore additional machine learning models further and integrate AI directly into the telemedicine device to help improve the performance and accuracy of the predictive models that could help accurately predict the health progression of patients. It is also imperative to continue improving the device's sensitivity and specificity to enable accurate and rapid diagnosis - which is critical to patient recovery and limiting contagion spread. In the long term, IoT and mobile applications can be utilized to send patient data to doctor's offices for immediate intervention and hospitalization if needed.

## Future Telehealth Application:

The current pandemic situation has forced all of us to take a pause and realize the importance of self-management of health and more importantly, being able to monitor and track the current situation of vital health statistics like blood oxygen levels, lung capacity, and body vitals through remote analysis and monitoring services. Being able to transmit this data via electronic data storage of their healthcare providers can not only ensure timely action can be taken with professional medical advice and intention but also significantly reduce healthcare service costs and potentially eliminate risks of exposure and spreading of viruses due to multiple in-person hospital visits for triage purposes. Telehealth also reduces unnecessary non-urgent ER visits and eliminates transportation expenses for regular checkups.

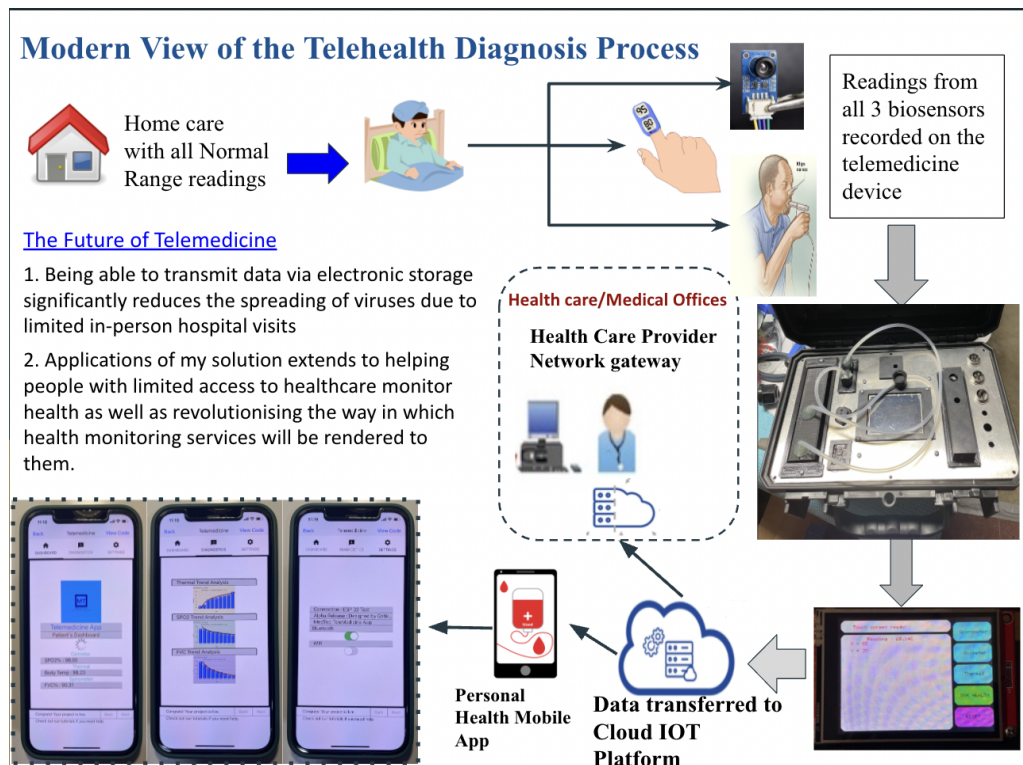


Figure 13 (prepared by student researcher): Future view of Telemedicine based triage process based on IoT capabilities

The evolving IoT capabilities would catalyze the design and deployment of remote diagnostic-based solutions that are both accessible and affordable for use in all parts of society as illustrated in Figure 17. These technologies could become a significant factor in public health mitigation strategies as the Centers for Disease Control and Prevention outlined. In addition, they can help shape future policies in this evolving landscape of medical practice. Regardless of the pandemic situation, the area of telemedicine is being well received by primary healthcare providers due to several factors like health care and insurance costs, timely insights and alerts for the doctor to diagnose a patient, timely intervention for potential life-threatening considerations, and improving overall patient and healthcare provider satisfaction.

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## Biography:

Gatik is a Junior at Dougherty Valley High School with a passion for BioMedical and BioTechnology Engineering. He is an aspiring technologist with a deep interest in bio-instrumentation, tissue engineering, biomedical science, and Bioinformatics