RESEARCH

Smart way for managing patients' vital signs

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Abstract

Background: Health care is an integral part of human life, and due to the huge increase of people and the increase in diseases, especially cardiovascular diseases and chronic diseases, it has become difficult for hospitals to accommodate this huge number of people. The early detection of critical abnormal situations without the need for direct contact with the patient, so a remote health care system was proposed that relies on artificial intelligence and advanced computing. This system was designed to continuously monitor physiological processes such as heart rate and blood oxygen saturation level, and also detects abnormal conditions such as arrhythmia or cardiac arrest, and immediately alert the relevant organizations for the immediate intervention. In this paper, we review how to use wearable sensing devices for monitoring the physiological processes of an individual, detect the abnormal conditions such as arrhythmia and cardiac arrest, and immediately alert the relevant organizations.

Methods: This paper reviews the methods of estimating heart rate and blood oxygen saturation in different ways and the data structure, and then the system model developed to give the user the ability of storing and sharing the data, online database which allows all the users' data to be stored online safely and viewing the data changes in real time in case of real time data, and lastly cloud messaging provide the ability to send notifications from device to another in case of abnormal behavior detected in one of the users' vital signs, , and finally testing the performance and accuracy of the developed model.

Keywords: health care, early detection, vital signs monitoring, ML.

Keywords: sample; article; author

Introduction

Quality health care is a basic human right, and unfortunately it is not adequately provided as a result of the economic, social and environmental change and subsequent changes in lifestyle to a significant increase in chronic diseases such as heart disease, and this represents a major threat to human health and therefore every time an infectious disease spreads Hospitals are crowded and filled with people, sometimes diseases are linked to changes in some physiological rates in the human body, such as heart rate and blood oxygen saturation. Or the severe lack of normal rates is a strong sign of death for a large number of patients, and because some people cannot go to the hospital from time to time, they may not have enough time or they have a chronic disease or the specialist abroad.

In addition, health care may cost the hospital a lot for these people. Therefore, health devices are a reliable solution for monitoring, recording and tracking vital processes at home. We can also request medical help in case of emergency. Medical devices have a very great interest and have become very widespread and commercially available.

Remote health care monitoring has become a major concern in our time today, so specialists are looking for a system that monitors vital processes and provides accurate diagnoses and suggestions for user health, taking into account the patient's past and current health conditions.

With the many developments that have taken place in the Internet of Things and wireless sensor networks, many attempts have been made remotely without going to the hospital, and this helps specialists to determine appropriate procedures in advance or to send assistance in case of emergency, and the transfer of important data to the patient may affect his life using cloud computing, Which is a paradigm shift in computing and cloud storage is where patient data is stored and processed, allowing patient vital signs to be monitored and stored for historical reviews.

Storing patient data in the cloud provides low cost, convenience, and reliability, and we also need a way to deliver important patient data to healthcare providers while taking into account patient privacy.

The proposed system provides a very convenient and secure solution for recording health data stored in the cloud. Biometric sensors are used to remotely measure key biological markers such as heart rate and blood oxygen saturation for a person while they are resting at home.

This system targets patients with medical problems such as emergency diseases, accident patients, patients with movement disabilities and chronic diseases, as well as patients suffering from infectious diseases such as Covid 19 disease, patients who follow up with doctors abroad, as well as the elderly who need continuous care.

These devices send data wirelessly to the cloud via a mobile phone application, which makes it easier for doctors to monitor the condition of their patients, and this allows doctors to follow up on the condition of their patients and make suggestions accordingly.

Machine learning techniques allow a revolution in the digital healthcare sector, as well as artificial intelligence plays an important, essential and vital role in remote healthcare monitoring systems for patients based on the Internet of things to diagnose and prevent diseases in order to maintain the health of patients, especially cardiovascular patients.

Furthermore, sensors create a tremendous volume of data in the IoT environment. This data contains significant healthcare information; hence it is critical to study it in order to develop medical technology. AI and ML technology would be incredibly valuable in this area for doing data analytics, categorization, and forecasting healthcare issues based on this data.

We created and deployed a smart remote monitoring system based on IoT in response to the pressing requirement for remote patient monitoring and its benefits. The system records and sends data from several wearable sensors to the edge device, which leverages edge computing to make choices locally using ML approaches.

The suggested system is a device that uses a distant location to monitor a patient's vitals, such as oxygen saturation, body temperature, and heart rate.

Because the IoT node will create significant volumes of data on a regular basis from a variety of patients, AI and ML technologies are employed at the edge to do data analytics, categorization, and prediction of healthcare issues. ML algorithms

extract statistics from raw data to gain insights about the patient's health.
The system provides an application that allows to follow the status of the user. The application is small, simple, understandable, easy to handle and flexible. In order to know the health status of the patient or the user, the machine learning model is trained at the cloud level and then this model is implemented on the edge device, through which the patient's health status is predicted based on the readings.

Related Work

In Asia and Europe, cardiovascular diseases (CVD) are the leading causes of death; mortality rates are greater among women and patients with poor socioeconomic level. The system that will monitor patients' vital metrics on a regular basis and give treatment recommendations based on medical data and health state is urgently needed [1].
Different surveyed articles are examined in this part to evaluate the performance of digital healthcare systems that have previously been established and how they contribute to healthcare IoT. One study [2] highlights the necessity of healthcare monitoring systems for cardiovascular disease and the need for medical personnel to share data from patients living in remote locations. This is critical since inhabitants in rural locations are often cut off from the metropolitan population and have limited access to medical care.
The development and design of a wearable electrocardiogram (ECG) monitor using Arduino are discussed in this article. The system architecture consists of bio-sensing modules, a cloud (Google Firebase) for storing real-time patient data, and a web interface for medical experts to view the data and provide rapid diagnosis and treatment of any developing cardiovascular illness. The study's main result is the creation of a low-cost, portable, and full real-time ECG capture, transmission, storage, and display system based on the Internet of Things. Medical practitioners can use this real-time data to diagnose heart disorders by visualizing it. Furthermore, the information is sent into a diagnostic software with a graphical user interface (GUI). The biggest disadvantage of this technology is that it may have difficulties with latency and network access, particularly in remote locations. Our system includes an edge-based architecture that conducts local anomaly detection based on ML to deal with crises to handle this essential challenge.
The authors of [3] follow a similar approach, emphasising the relevance of ECG signals in cardiovascular patients. They offer an IoT-based health monitoring system that observes the underlying data using a statistical model called the Hidden Markov Model. ECG signal characteristics as collected by a sensor the aim of this program is to make it easier to get better results. Patients with CVD will benefit from better monitoring and faster intervention, which will improve medical care. in the case of such patients A patient path estimator, a patient path estimator, and a patient path estimator are all used in the system's implementation. Within the hospital, there are table and alert management schemes to help with localization and alarm management. Treatment of CVD patients should be started as soon as possible. The classification of an ECG signal is based on the time between each RR peak, as well as the amplitude R peaks. These are used combined to detect common

and significant rhythm problem peaks. The criteria of RR > 150 ms and t period >60 ms are determined based on comparative data of 50 normal patients and 50 CVD patients, resulting in a strong positive prediction of CVD. The disadvantage is that this article does not include the installation of smarter technologies based on AI and machine learning. As a result, additional modifications are still required to increase the diagnostic model's accuracy

The researchers in [4] believe that advances in machine learning technology have enabled early illness identification and diagnosis. This is especially beneficial in the case of chronic ailments, such as heart disease. A bespoke machine is proposed in this study. In the next ten years, a learning algorithm will be used to forecast the likelihood of cardiac disease. Hard Voting (HV) classifier is the name given to their algorithm. HV was created utilizing logistic Regression, Random Forest, Multilayer Perceptron, and other well-known classifiers Nave Bayes classifiers with Gaussian Multiple risk variables (e.g., age, gender) are taken into account by the meta-classifier. As inputs, sex, smoking, systolic blood pressure, and so on. Each of the four classifiers is employed, and a vote is taken to determine whose forecast is the best. The researchers utilized data from 3751 patients from a publicly available dataset on Kaggle. To eliminate any outliers, the authors utilized RobustScaler to scale the data. For training and testing purposes, the dataset was separated into two halves with an 80–20 percent split. The meta-classifier algorithm was successfully designed, with an accuracy of 88.42 percent and a precision value of 1.0 on the test. The construction of the ML model is the emphasis of this work, not any IoT-based ECG monitoring system. The authors did not test their model using real-time patient data. Not only are numerous vitals collected in our suggested architecture, but robust techniques are also applied to forecast the health status of real-time patients.

The researchers propose a method based on IoT and machine learning approaches to handle the issue of remote monitoring in [5]. It integrates an IoT-based sensor network with Arduino, namely a pulse sensor. On the data collected for heart ailment categorization, this system additionally incorporates ML classification algorithms. The Decision Tree method, Random Backwoods classifier, and Support Vector Machine were all put to the test in this study (SVM). The authors gathered data from 40 patients and used it to develop the aforementioned algorithms. It was discovered that SVM has a greater level of accuracy when it comes to accurately detecting a cardiac condition (an accuracy of 86 percent). Patients can use the suggested hardware and software system to forecast cardiac disease in its early stages. Although this technique aids CVD patients, a diagnosis based just on pulse data does not provide a complete picture of the patient's health. To increase the performance of the ML model, more sensors must be added. As a result, we incorporated many vital sign sensors in our suggested system to monitor the chronic patient's health.

Using federated learning on local Edge computing devices, Article [6] presents another another smart data analytics architecture for e-healthcare applications. The need of incorporating federated learning into the system architecture stems from the sensitive medical data obtained through wearable devices being kept private and secure. The article provides a detailed explanation of the proposed framework, which is divided into three modules: cloud, edge, and application. The authors, on the other hand, make no mention of the system's implementation. The study's major focus was on identifying federated learning on the edge for e-health system designs in order to provide service quality (quick reaction time) and security (data security).[7] proposes CAMISA, an AI-powered system for remote monitoring of COVID-19 patients. The authors created a Wireless Sensor Network (WSN) device in the form of a smart shirt and nebulizer that is equipped with several sensors for obtaining a patient's physiological information. A patient's pulse, SpO2 level, temperature, and breathing rate are all measured by the system. If any of these metrics surpass their threshold levels, notifications are sent to the hospital, including the patient's current location so that he or she can be sent to critical care as soon as possible. . In addition, the authors have used a neural network model to estimate the probability of a user contracting a coronavirus. The Artificial Neural Network (ANN) model takes 20 characteristics into account, such as the existence of a cold, fever, or cough, which are all indicators of coronavirus infection. The health monitoring app collects these parameters from the user via a questionnaire and determines whether or not the patient has COVID-19. Using the Thingspeak IoT platform, the app also visualises the sensor data from the system. This device may be used to remotely monitor COVID-19 patients in real time to help hospitals curb the virus's spread.

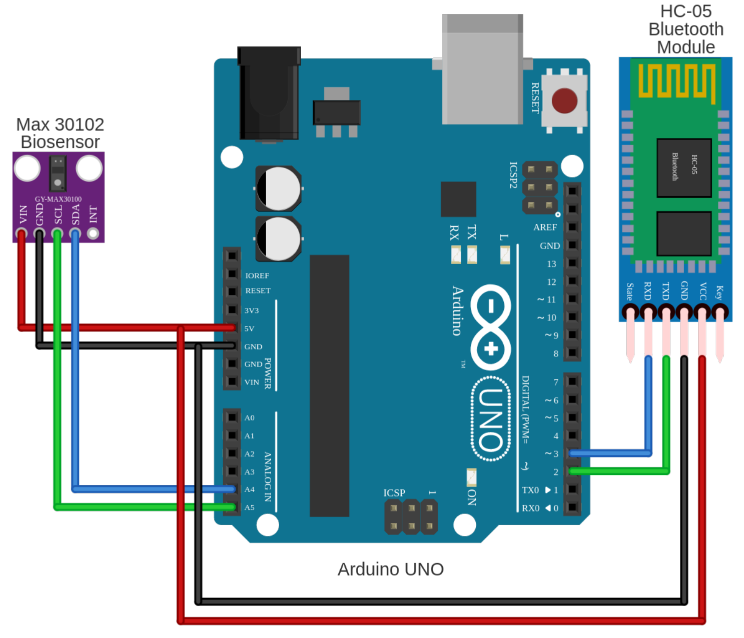
Methodology

The proposed method revolves around developing a system with the capability of monitoring patients' data using smart phone with the aid of either the phone camera and AI or a Bluetooth enabled oximeter and phone Bluetooth , then detecting abnormalities considering the processing ability of the modern smart phones combined with the cloud services to give each user the ability of storing and sharing the data, adding other users as connections and notifying other connections in the case of detecting abnormalities forming an IoT solution for remote patient health monitoring system that can be adopted as family-oriented or professional structure.
The mobile application developed to connect and receive the data from the Bluetooth enabled oximeter, making use of the phone camera and flash to estimate the heart rate and blood oxygen saturation, show the final result for the user. Besides, opening the gate to the web services giving the ability to connect to one of the web services SDKs for online collaborative and secure experience.
The Bluetooth enabled oximeter circuit consist of 3 main components, first the biosensor module MAX30102 for heart rate and blood oxygen saturation continues monitoring [A], second the Bluetooth interface HC-05 interface for data interfacing between the circuit and the smart phone, and the micro-controller Arduino UNO (REV3) for all the calculations and the other other components integration.
The mobile camera vital measurement can be divided into three operations, first getting the signal by recording a video of the users' fingertip when places on the camera and flash simultaneously for a period of time and converting the signal to a form can be used later, second the recoded signal passed to a ML model to estimate the blood oxygen saturation value and finally the same signal used again in different calculation discussed later to estimate the heart rate value.
The web services related to all the online features needed such as authentication to guarantee each user retain all the data in one single safe account, online database

which allows all the users' data to be stored online safely and sharing the data to the permitted users and viewing the data changes in real time in case of real time data, and lastly cloud messaging provide the ability to send notifications from device to another in case of abnormal behavior detected in one of the user's vital signs.

Circuit Design

The circuit design shown in Figure 1 illustrates the Bluetooth enables oximeter circuit used which consists of, Arduino Uno controller which responsible for all the calculations, decision making and the whole circuit integration, also acts as a power supply for the other components, MAX30102 sensor by MAXIM capable of taking reading of the vital signs with minimum margin of error with adequate size and power consumption, and HC-05 Bluetooth transceiver which allow delivery of vital signs to the mobile device.



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Signal Acquisition

A typical design will drive the red and IR and LEDs alternately to capture all the reflected light from the placed finger with the embedded photo-diode then sent to the controller for further processing.

Heart Rate Measurement

The process takes the advantage of the changing level of the light absorption of the skin associated with blood flow due to the increase of blood volume causing a brief expansion of the blood vessel as each heartbeat pushed through them leading to a noticeable peak in the photo-diode readings and by detecting the time for each peak the heart rate can be calculated according to Equation 1.

$$HeartRate = \frac{60,000}{CurrentPeakTimestamp - PreviousPeakTimestamp}$$

Blood Oxygen Measurement
The process also takes the advantage of the changing levels different light absorption of the blood, but unlike the heart rate the process depends on the different absorption of light found in the hemoglobin in the oxygenated and deoxygenated states as show in Fig 3.2, Deoxygenated hemoglobin (Hb) absorbs more light red than infrared light, while oxygenated hemoglobin (HbO2) absorbs more infrared light than red light by and with information in mind Eq.(2) is applied, since the final value requires empirical calibration between the ration and the final spo2 Eq.(3) is applied which proposed by MAXIM

$$Ratio = \frac{AC_r/DC_r}{AC_{ir}/DC_{ir}}$$

$$BloodOxygen = (-45.06 \times Ratio + 30.354) \times Ratio + 94.845$$

[1, 2, 3, 4, 5].

Model Training

Data Collection
Data have been collected using a Redmi Note 8 Pro phone consisting of 67 videos with 30fps captured by asking each patient for putting the index finger on the camera and the flash as shown in the figure 3.3 for at least 8 seconds, the labels for each video recorded using GRANZIA pulse-304.

Preprocessing
Each video divided into array of frames, each frame converted into a signal of the mean values of each RGB color channel, then the final arrays down-sampled to the middle 154 values as shown in Figure 3-4 as it's the most consistent using Equation. (4), then the data split to 8:2 ratio the 80the second part used for validation.

Training
The preprocessed data trained using deep learning algorithm specifically FCN as it performs tremendously with the time-series problems including the scaler as the first layer for normalized input and the global average pooling for estimating a single value as the final output the model consists of the constitutional layers show in Fig3.5 trained for 250 epochs with batch size of 32.

Mobile Application

The application developed to hub all the major functionality of the system e.g. collecting the data from the circuit deploying the ML model, calculating the heart rate using mobile camera, visualizing, storing and sharing users' personal and medical data through web services.

User Interface

The interface designed to include all the main system functions available to the user through the main pages (home – connections – profile) as shown in Figure 3-6, home page includes the ability to connect to the circuit using the upper plus button, also show all the vital signs measurement as time series chart to view the whole day data, connections page show all the connections and requests and the upper text field give the user the ability to send connection request using email, and profile page gives the user the ability to change all his data.

Model Deployment

After training the ML model using Tensorflow Keras the trained model converted to TfLite file format then the generated file included in the application assets ready for use, in order to apply the model the user asked to put the index finger on the main camera and flash as shown in Figure 3-7 for 8 seconds (280 frames) converted from YUV to RGB file format keeping only the mean value of each channel for each frame, then the 154 middle values of the values are used as it represent the most stable values for the signal and to mimic the training process for accurate results.

Heart Rate Camera Measurement

Taking into consideration the physical property of light absorption explained before the Algorithm. (1) is applied as the mobile camera work on a similar manner as photo-diode and the flash as the LED for detecting each peak appears in the heart beat utilizing the collected data in the process of applying the ML model, however the red channel only used to include the time stamp for each recorded value then applying Equation (1).

Handeling User's Data

After receiving the data from either the Bluetooth interface or internally the data shown in the screen combined with measurement time as shown in Figure 3-8 then stored in the Firebase real time database which allows near real-time experience for storing, fetching the data and listen to the data changes from other devices which allow each user to share his real time data alongside with other data as shown in Figure 3-8.

Cloud Functions

Data Storage

Due to the extensive amount of collected data from each user giving the importance for each piece of data, all the collected data stored in the cloud for backup and for further analysis; Users' non-sequential data e.g. name, birth date stored using Firebase's "Cloud Firestore Database" service as a key-value pairs as shown in Figure 3-9 and other users can access the data through email as key, furthermore the sequential data e.g. heart rate and blood oxygen stored using Firebase's "Cloud Real-time Database" for near real time experience for storing an accessing the data also as key-value pairs and using the measurement time as key after converting the value to Unix time as shown in Figure 3-10 and the connections can have a real time monitoring view of the data by starting a listener on the user's document.

Cloud Warnings
All the received vital signs values compared to the known normal value according to [b] and classified as normal or abnormal; in case of abnormality the users' phone automatically sends a notification warning to the users' phone with a message of the related abnormal reading as shown in Figure 3-11 and to each of the connection send a notification warning with the name of the connection and the related abnormal reading as shown in Figure 3-12.

External Gadget Support
Due to the increasing popularity of the fitness gadget e.g. smart bands and smart watches, and gadgets ability for making the same measurement with reasonable accuracy these gadgets can be integrated with the system, but the closed source nature of the APIs and SDKs with the variant brand makes it almost impossible to integrate all the marketed gadget, fortunately most of the gadgets integrated with Google Fit which provides API for accessing the required data and more. So, all the gadgets integrated with Google Fit API can be integrated with the system.

Results
The ML model has achieved an mea of $\pm$ 1.9461, using the FCN model on the spo2 signs and the algorithm used in the heart rate achieved unexpected result using a technique called photoplethysmography (PPG) - is an optically acquired plethysmogram that may be used to identify changes in blood volume in the tissue's microvascular bed. We can detect the variability of reflected light and extract the variation of blood flow by shining a light into a blood irrigated tissue. As we all know, blood flow is impacted by heart rate, thus we may use blood flow variability to measure heart rate. The application measures the blood flow volume variability and displays it in a chart. Now we only need to calculate the heart rate, which is the frequency of the plotted signal. In our application, we'll use the phone's camera to shine the camera's flash and measure the power reflected. More specifically, we'll calculate the average value of the camera image's pixel intensity. The intensity measured will differ with the blood flow if we cover the camera and flash with our finger. I used a simple algorithm that measures the average and the max along our window data, sets the threshold to the mean of those values, and detects the peaks above that threshold. It then updates the BPM value with' an attenuation coefficient so we don't have abrupt changes. The circuit is integrated with our mobile application and it measures the vital signs every two minutes. The normal ranges of these two vital signs: (a) Heart Rate: 60 to 100 beats per minute [c] (b) Blood Oxygen Saturation: 95These tables show the real data collected from the GRANZIA pulse oximeter and our application:

Conclusion
This article constructed an IoT-based prototype and applied ML and AI approaches to the system. The Internet of Things gadget allows for smart monitoring of human vitals such as oxygen saturation, heart rate, and body temperature. Real-time ML inference is enabled at the edge to offer essential notifications to patients as well as the relevant doctors or caregivers in the event that the patient's vitals show

an abnormality. Furthermore, the system is linked to a live online graphical user interface for both physicians and patients for management and monitoring. This user-friendly interface securely records and manages real-time patient data in a secure database. A doctor can simply view both recorded and live data (including ML inference results) and provide their analysis accordingly. The system has a number of hardware and software components. The system comprises of a versatile and user-friendly programme with a nice interface that can monitor a patient's vitals in real-time without causing discomfort to the patient. To make rapid and trustworthy judgments locally, the system employs edge computing techniques. This function reduces latency and identifies any abnormal situations. The best feature of this programme is that it can be used on any mobile device that has a camera and a flash. Even from a distance, the patient and guardian can watch the patient's vital signs. The established system may be proven to be a requirement in the medical sector, particularly in today's time when people rely heavily on technology and expect smart solutions to their day-to-day difficulties. The suggested method not only relieves people from their daily exams, but it also helps the medical personnel by decreasing their workload and allowing them to handle patients remotely. This prototype might be utilized at medical camps and places where established hospitals are scarce. In contrast to traditional healthcare, which is exclusively available in hospitals, the new paradigm of remotely monitoring patients using cutting-edge technologies like as IoT and AI is the future of health care and may assist us in leveraging these technologies and maximizing their advantages. More sensors, i.e., measured vitals, such as an electrocardiogram, blood pressure, or respiration rate, can be added as part of this project's future development. More decision-making elements can be introduced to the project to identify the likelihood of COVID, especially in the current condition of COVID. Because the model is simple, it may be used in conjunction with additional characteristics to develop for a specific illness. The AI component of the system may be enhanced to provide trend analysis on the user's data. Because medicine is such a wide subject and various disorders might have similar symptoms, a model with extremely high precision and accuracy would be necessary. In addition to the model and the site, the prototype may be utilized as a main registration step in hospitals, saving medical personnel time in gathering information and measuring vitals. As a result, it will be an excellent addition for automating the register system in hospitals. Furthermore, the concept may be expanded into a remote clinic where patients can select between continuous monitoring and consulting services. Furthermore, the project may be marketed by developing and deploying more units in a private or public hospital for initial testing, and if successful, more units can be created and deployed. As a result, the produced prototype is adaptable and may serve as a useful component in a variety of applications.

Competing interests
The authors declare that they have no competing interests.

Author's contributions
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Figures

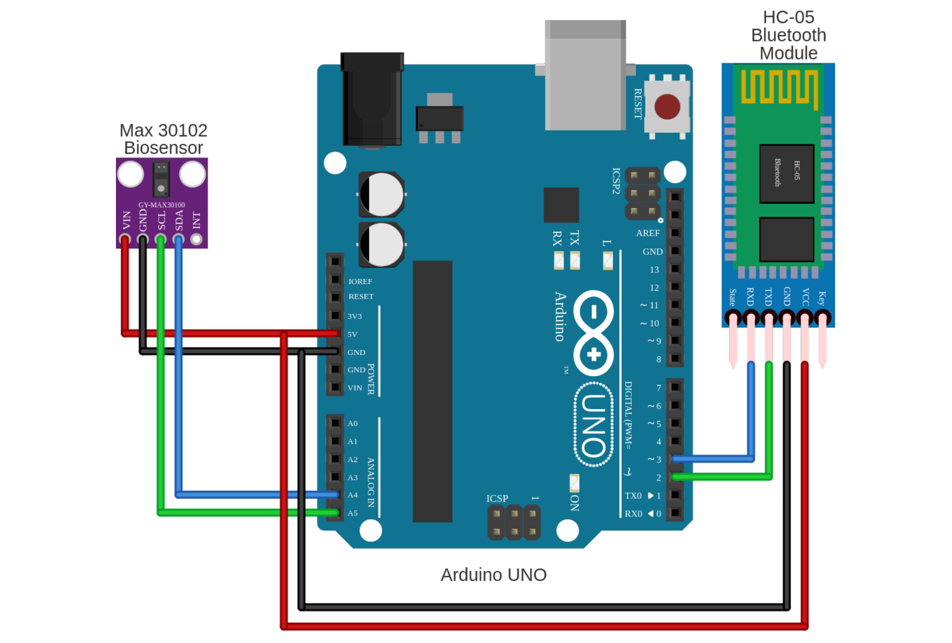

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Figure 3 Sample figure title. Figure legend text.

Tables

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Additional Files

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Additional file 2 — Sample additional file title
Additional file descriptions text.