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Remote Health Monitoring System for the Estimation of Blood Pressure, Heart Rate, and Blood Oxygen Saturation Level

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***Abstract*—This article presents the design and implementation of an Internet of Things (IoT)-based remote health monitoring system for the estimation of blood pressure (BP), heart rate (HR), and blood oxygen saturation levels (S_pO_2). Our designed sensor can remotely monitor BP, HR, and S_pO_2. Our device collects, evaluates, predicts, and reads health data and then stores it on a remote platform named "ThinkSpeak," which forms an IoT platform, with a 0.91 organic light-emitting diodes (OLEDs) screen display for viewing numerical health readings locally. We used a biomedical sensor device with an embedded signal condition unit, and a single photoplethysmography (PPG) signal was employed to derive and measure the PPG signal. A computer-based algorithm was generated, which factored in selected beneficial parameters measured from a single bio-inspired PPG signal. The measured PPG signal was used to estimate the individual user's BP (both systolic and diastolic values), HR, and S_pO_2. An automatic multiscale-based peak (AMBP) detection algorithm was developed to obtain the maximum peak of the PPG signal. Furthermore, the developed sensor was benchmarked against two standard commercially available measurement devices: a Contec ambulatory BP sensor and a Braun pulse oximeter monitor. Our developed sensor is worn as a ring sensor and is interfaced with an Arduino 1010 WIFI MKR for remote health monitoring. Our estimated BP, HR, and S_pO_2 values were remotely monitored and a graphical representation was constructed.**

***Index Terms*—Blood pressure (BP) monitoring, heart rate (HR), medical devices, oxygen saturation level, remote monitoring, wearable body ring sensor.**

I. Introduction

THE COVID-19 pandemic has raised awareness of the importance and benefits of health monitoring. There is a growing demand across primary and secondary healthcare for accurate measurement of key vital health parameters to enable earlier detection of the potential clinical deterioration of a patient. The ability to provide a sensor system that would enable accurate and continuous remote monitoring of blood pressure (BP), heart rate (HR), and blood oxygen saturation levels (S_pO_2), which would be of immense value as it could potentially enable earlier detection of clinical deterioration and thereby offer an opportunity for timely medical intervention. The facilitation of health monitoring through the application of technology is fundamental for the remote monitoring of health parameters [1], [2], [3]. The usual practice for an individual who has a health concern is to book an appointment with their general practitioner (GP) to discuss their concern and understand what relevant tests and measurements are needed for diagnosis. A variety of health parameter measurements may be carried out to establish a baseline. These may include

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BP, HR, body temperature (BT), and S_pO_2 measurements. It is understood that there is a shortage of GPs in the U.K. NHS system [4] and data show that the number of fully qualified GPs has fallen by 416 since 2016 [5]. In addition, high workloads and COVID-19 pandemic pressures are causing GPs to be increasingly reliant on ancillary assistant staff to conduct and enable the continuous 24-h monitoring of a specific health parameter, while the patient may be remote.

BP is a measure of the amount of force that the human heart uses to supply blood to organs of the body. When BP is measured, the reading consists of two numerical figures. The systolic BP (SBP) is written as the upper number and the diastolic BP (DBP) is written as the lower number, with both recorded in millimeters of mercury (mmHg). The SBP value is the numerator of the measured BP value resulting from the contraction of the heart muscle to pump blood into the arteries. DBP is the denominator of the measured BP value resulting from the relaxation of the heart muscle when blood flows back in to fill the chambers of the heart [6]. An individual is considered to have Stage 1 high BP (HBP) if the SBP value is continuously over 130 mmHg when measured over 24 h. HBP has been identified as a risk factor for stroke and cardiovascular disease (CVD) [6]. The normal BP for adults is usually considered to be an SBP of less than 120 and a DBP of less than 80 [7], [8], [9] It is known that several variables influence BP throughout the lifetime of individuals: biological sex, age, and body weight. Traditionally, a sphygmomanometer has been used for the measurement of BP [9]. This device comprises an inflatable rubber cuff, which is applied to the upper arm close to the elbow or wrist dependent on the type of exact, device, and is attached to a measurement system. When switched ON, the cuff is inflated to exert pressure on an artery and through timing and gradual release of pressure; a clinical reading of BP can be obtained [10]. This process involves the application and use of controlled pressure onto part of the upper limb, and the pressure itself may cause temporary discomfort to the individual patient. In addition, when a healthcare professional measures BP with traditional measurement systems in a clinical setting, this can cause an element of anxiety, which can cause an increase in the measurement obtained, a phenomenon known as "white-coat hypertension [11]." Hence, the opportunity to gain accurate BP information over 24 h via a less invasive system, such as this comfortable sensor worn on the finger, would be a superior strategy to enable safer and more effective delivery of care [11], [12].

The ability to continuously monitor and accurately measure BP over 24 h would offer a more effective and reliable identification of a key cardiovascular risk factor and enable more rapid prevention.

S_pO_2 relates to the amount of hemoglobin in the blood that is carrying oxygen with the total amount of hemoglobin in the blood and is expressed as a percentage.

To sustain human life, oxygen is a fundamental requirement. The normal range for S_pO_2 in humans is from 95% up to 100% [13]. Normally, the brain monitors and controls these health parameters via homeostatic mechanisms at a subconscious level. During serious, e.g., COVID Pneumonia or Heart Failure, it is critically important that the S_pO_2 level is accurately measured to guide any treatment decision. If the S_pO_2 level drops to 92% or lower, this is known as "Hypoxemia." Hypoxemia is also frequently referred to as and manifests as a variety of symptoms, including shortness of breath and increased HR. Without prompt medical intervention, a person is likely to die. Therefore, accurate measurement and timely intervention are of critical importance.

Traditionally, S_pO_2 is measured through the use of a pulse oximeter by placing the middle or index finger into the sensor [14]. With the emergence of the Internet of Things (IoT), the connection of different objects and sensors has been made possible. IoT is the network capability that provides enablement for real-time decision-making and analysis of specified data categories. Generally, it provides the platform for the interconnection of different devices to Internet infrastructure and data flow. IoT has improved remote health vital monitoring. The employment of IoT in the healthcare sector has provided a high quality of care delivery, low cost of treatment, and continuous monitoring of health parameters [15]. In the event of an abnormal reading in health parameters, prompt action can be taken, hence forestalling the negative prognosis of delayed medical care [16].

In our previously published research [13], we demonstrated an IoT-based low-cost pulse oximeter, where the prototype was capable of continuously monitoring the HR, SPO2, and temperature. It uploads the data on ThinkSpeak platform networks [17] accessible to professionals without the need for the patient physically present.

This article presents a novel low-cost remote health monitoring system for monitoring BP, HR, and S_pO_2. The sensors are embedded within a 3-D finger case and fit with a microcontroller (Arduino board) to estimate the BP, HR, and Spo2 levels simultaneously. The collated data are transmitted remotely through the ThinkSpeak cloud platform for remote data collation and graphical representation from the embedded sensor. In addition, this article proposes a continuous BP estimation aimed at providing a method of estimating BP through the obtained photoplethysmography (PPG) signal from the finger. A few parameters were selected from the obtained PPG signal waveform from the finger. This article implemented an automatic multiscale-based peak (AMBP) detection algorithm to obtain the maximum peak of the PPG signal, which corresponds to the BP values [18], [19], and a bandpass filter was used to filter out quasi and noisy periodic peaks and amplify the obtained PPG signal. We developed a machine-learning algorithm for our regression model to be applied the processed PPG signal and filter was applied to our time-varying regression model for stability. The developed wearable finger sensor demonstrated high computational power with low power consumption and user comfort in design.

II. Related Work

Das et al. [16] proposed an IoT-enabled health monitor using noninvasive health parameters. Their system used several health monitoring sensors, Raspberry Pi, and the ThinkSpeak platform. They monitored HR, electrocardiogram (ECG), BT, body movement, and S_pO_2 of five individuals. They executed their design on a breadboard using Arduino Uno and Raspberry Pi. They employed an Arduino pulse sensor for measuring HR, Lm35 BT, AD8232 ECG sensor for evaluating ECG, and ADXSL345 sensor for motion detection and their obtained results were uploaded to the ThinkSpeak platform [16]. The use of an ECG probe for the measurement of ECG through the attachment of the probe to the wearer's body makes the system invasive.

Nookhao et al. [18] proposed a method of remotely monitoring BT and HR. They monitored the HR of their volunteers using an Easy pulse V1.1 sensor, LCD for showing measured readings, and ThinkSpeak for the IoT platform. In the event of a discrepancy in reading, the developed system would remotely send an alert to the line application. Their developed android application was integrated using the firebase database. The BT and HR readings were stored in specified intervals [18]. Their solution showed user satisfaction in the usage of the sensor although their developed sensor is invasive and might limit continuous measurement of the sensor.

Reddy et al. [19] proposed a health monitoring system that is IoT based, and they developed a sensor to evaluate HR and BT. They employed DS18B20 and SEN-11574 sensors and interfaced to IoT using Raspberry Pi. They stored and visualized their data remotely using the ThinkSpeak platform. In addition, they furnished their sensor with an android application for emergency communication [19].

Liang et al. [20] proposed the detection of BP and CVD through the use of PPG signals obtained from the fingertip. They acquired data from 219 volunteers within the age range of 20–89 years, thereby acquiring 657 data segments. Their experimental result revealed that PPG features can be used for the prior detection of hypertension and diabetes [20].

Xie et al. [21] proposed real-time continuous BP measurement based on PPG and machine learning. They employed different machine-learning estimation algorithms on distinct PPG signals. Their method showed a promising 3.24 ± 5.39 mmHg SBP and DBP, respectively [21].

Cohen et al. [12] proposed a ring approach to obtaining and measuring HR through PPG. They additionally proposed that BP can be measured based on their cuffless noninvasive technique [12].

The highlighted papers employed multiple sensors to collate health monitoring parameters and are invasive in the everyday life of the user. The papers mostly measured one or two health parameters: BT, HR, S_pO_2, ECG, and BP, and they uploaded their results on IoT for graphical representation only. Our proposed design proffers a solution to measure vital health parameters HR, BP, and S_pO_2, the measurements of S_pO_2 would aid in the early detection of hypoxia, and BP measurement would aid in the early detection of CVD and prevent the bad prognosis associated with it. Dashboards were created to represent alerts for easy monitoring.

III. System Design and Implementation

The primary objective of our proposed system is to enable remote communication and observation between patients and medical practitioners. With the emergency of COVID-19, there is a rising demand for patients, medical practitioners, and the general public to continuously know their health parameters. In this section, we show how the hardware component was integrated with the IoT for the implementation of our remote health monitoring system.

Our developed sensor was designed and implemented as an optical-based finger sensor device. The sensor was housed on a 3-D printed casing with a 0.91 in screen attached at the top along with a micro universal serial port.

A. Trial of Developed Sensor With Healthy Volunteers

A multidisciplinary team was formed comprising an Electronic Engineering Team from a U.K. university and a healthcare team from a large university teaching hospital in U.K. The lead researcher obtained ethics approval and IRB authorization for conducting this study on neurotypical healthy volunteer students.Reference of the ethics code: REC Project ID: 1501. The study was performed in the Laboratory of Microwave Photonics and Sensors at the Department of Electronic Engineering, School of Engineering, Physical and Mathematical Sciences, Royal Holloway, University of London. The Consultant Physician doctor took the BP of the volunteers himself using the conventional traditional method of sphygmomanometer and stethoscope. This physician doctor also trained the researchers on how to measure BP and confirmed the competency of that training. In the trial, the subjects had their BP measured by both the traditional method and our developed BP estimate sensor method.

B. Data Acquisition

We obtained our PPG signal from ProtoCentral Electronics ProtoCentral Pulse Express optical PPsensor with MAX30102 and MAX32664D [22]. The sensor was worn on the right index finger. The sensor has an inbuilt signal conditioning circuit, which consists of high- and low-pass filters for noise.

Variations in amplitude and corresponding position in the PPG curve show variations in vascular status. Our interest is from points A to C from Fig. 1, as it shows the systolic waveform.

1) Point A shows the contraction of the ventricular state.
2) Point B shows the rising point of the ventricles.
3) Point C shows the peak systolic value, which shows the maximum blood flow in the vascular [23].

C. Processing Stage

The obtained analog signal from the Arduino is processed by the microcontroller for peak value detection. The AMBP algorithm for peak detection according to Marek et al. can operate on noisy quasi-periodic and periodic signals. The AMBP algorithm requires the input signal from the sensor to be detrended linearly through the use of filter characteristics as described in the previous section. The key part of the AMBP algorithm is the local maxima scalogram (LMS) matrix M calculation [24]. The obtained signal from the ring finger of the pulse sensor $x = [x_1, x_2, \ldots, x_n]$ is discretely uniformly sampled in window length w_k. From the signal x, the LMS is calculated. The least-square fit of the straight line to x is

Fig. 1. Developed BP, HR, and S_pO_2 monitor, enclosed in a 3-D case with a 0.91″ OLED display to be worn on the finger of the user.

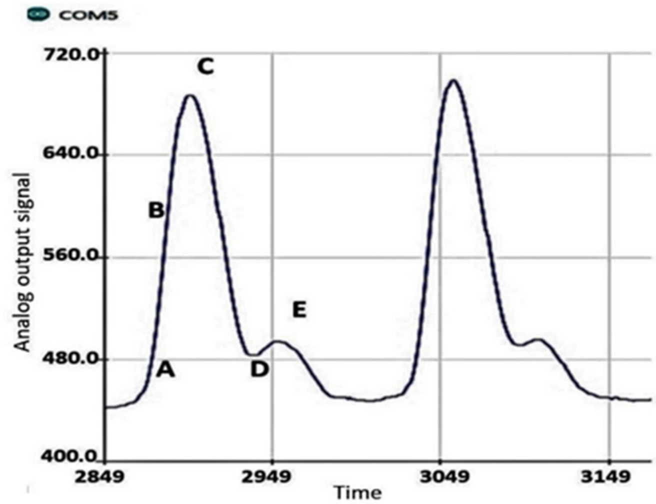

Fig. 2. Single PPG signal waveform was obtained from the sensor with a few extracted PPG features from one of our volunteers.

calculated. To evaluate the maxima of x, the moving window approach is applied [24]

$$m_{i,k} = \begin{cases} 0, & x_{i-1} > x_{i-k-1} > x_{i+k+1} \\ r+\beta, & \text{otherwise} \end{cases} \quad (1)$$

where $m_{i,k}$ denotes the LMS matrix M and r denotes the randomly uniform distribution of numbers [0, 1]. β represents a constant ($\beta = 1$). k denotes the kth term of signal ($k = 1, 2, 3, \ldots, L$. window length $L = \text{ceil}(N/2) - 1$ and $i = k+2, k+3, \ldots, N - K + 1$ [24], [25], [26].

The AMPD algorithm showed the optimum performance for the filtered PPG signal obtained from the ring sensor. Unfortunately, AMBP is not suitable for wearable sensors as its computation is expensive. Our proposed method used a modified form of the AMBP algorithm for peak detection. We detected our peak through a written code developed in Arduino integrated development environment. Through the implementation of the code, the maximum and minimum peaks from Fig. 2 were detected, which correlates with the SBP and DBP, respectively, as earlier started in the preceding sections. The extracted peak data were processed using Arduino and uploaded to IoT through MATLAB ThinkSpeak. The extracted data were further processed using MATLAB software for the development of our regression model.

1) BP Estimate: For our BP, the peak detection signal obtained from the PPG signal is employed to estimate the BP values for our BP estimation, and the mathematical regression model was generated to determine the estimation and accuracy of the estimated BP values calculated from the peak PPG signal measured from the finger. A commercial BP monitor was used to measure the actual BP. The corresponding regression equation was obtained using a machine-learning algorithm. The goodness of fit between the predicted and the measured BP was defined by the coefficient of determination (R^2), which reveals the degree of closeness between the actual and predicted BP values. We calculated that the standard deviation for our proposed estimated BP sensor and commercial BP monitor values was calculated. The R^2 value was calculated using the following equation [25]:

$$R^2 = \frac{A}{B} \quad (2)$$

where A is the standard deviation square of estimated BP and B denotes the standard deviation square of the commercial BP monitor.

2) Spo2 and HR Estimation: The sensor consists of a light-emitting diode LED (wavelength of 660 nm) and an infrared LED (880 nm). The LEDs are switched ON and OFF rapidly. The LED was operated in the reflective mode, i.e., LED and photodiode are mounted in the same position. Blood absorbed by the pulsatile arteries is modulated by the reflected light from the body tissues to form a PPG. The PPG signal consists of an ac and dc components. The light absorbed by the blood arteries is synchronous to the ac component of the PPG. The ac component is the light absorbed by human tissue and blood. The Arduino evaluated the average value of the dc and ac components through a collection of multiple samples of the ac and dc components. The averaging aided in making our sensor with increased accuracy [27].

For our S_pO_2 estimation, we took a ratio of light absorbed by the red LED and infrared light [13]

$$R = \frac{(\text{ac}/\text{dc})_{\text{RED}}}{(\text{ac}/\text{dc})_{\text{IR}}} \quad (3)$$

where R is our oxygen saturation level, ac and dc represent the ac and dc voltage of red LED, respectively, and ac and dc voltage IR is the ac and dc voltage of IR LED, respectively.

In the determination of the percentage of oxygen saturation level in the blood, the R ratio was used for evaluation.

D. IoT

Our remote health monitoring principle is the collection of patient health data in real time by a health professional or users. The data were collected through our biomedical sensor and interfaced with the ThinkSpeak platform for IoT and cloud storage. Arduino MKR WIFI 1010 [28] was configured to

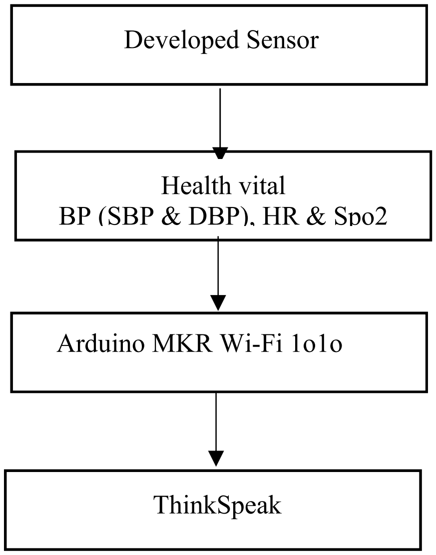

Fig. 3. IoT platform design flowchart for interfacing ThinkSpeak with our developed remote monitoring system for BP, HR, and S_pO_2.

connect to ThinkSpeak. The collated data on ThinkSpeak can be viewed by users and medical professionals.

E. Hardware Connection

Remote health monitoring was developed on a PCB board for connections. The PCB board was housed in a 3-D case for housing the PCB board, biomedical sensor, Arduino MKR Wi-Fi 1010 and 0.91 organic light-emitting diode (OLED) screen. The Arduino was interfaced with the PC through a USB type-B cable. The biomedical sensor pins SDA and SCL were connected to the SDA and SCL pins of the Arduino, MFI0 and Reset pins were connected to digital pins 2 and 4, respectively, the VCC pin was connected to 3.3 V, and the GND pin was connected to the PCB ground pin. The 0.91″ OLED screen pins SDA and SCL were connected to the Arduino pin SDA and SCL, respectively, for serial clock communication.

F. Software Integration

We developed our sensor for connection to the IoT platform in steps, as shown in Fig. 3.

The Arduino MKR WIFI 1010 is fit with an embedded WIFI module. The Arduino used a secured WIFI connection to connect to the Internet for transmitting the estimated sensor data to the MATLAB ThinkSpeak platform. ThinkSpeak was used to graphically represent the collated data from the Arduino microcontroller. The estimated health parameter was visualized graphically in real time. ThinkSpeak has a security layer that requires a unique username and password to access the data.

G. Measurement Process for Benchmarking

For our clinical study, we obtained data from a group of volunteers. First, we measured the BP of the volunteers using a commercially available BP monitor Contec ambulatory BP monitor and compared with our sensor. Consequently, we then measured the BP of our volunteers using our developed BP monitor. We measured the HR and S_pO_2 of our volunteers for benchmarking with a commercially available Braun monitor. In addition, we considered other variables, which could influence the BP value of individuals. British heart foundation [28] highlighted some of these variables. Some of the variables affecting SBP that we took into consideration are body mass index (BMI), height (cm), weight (kg), ethnicity, handedness, medical condition, gender [29], and measurement position that was sitting in a relaxed position with our volunteer's arm placed in the right atrium [30].

We maintained a constant posture for measuring all our volunteers, and the volunteers were sat in a relaxed upright position, sitting on a chair with both feet fixed on the floor and arms supported in a position in which the elbow is slightly above the heart level.

IV. Results and Discussion

From our obtained results from 20 volunteers of our pilot study, we took measurements from the right index finger. The demographic characteristics of our enrolled volunteers are shown in Table I. We measured the HR, S_pO_2, and BP from our developed sensor and commercial sensor.

A. BP Estimation

Of our 20 volunteers, 13 agreed to have their BP checked while seven declined, we had ten male and three female volunteers with normal BP and no known medical history.

1) Measurement Techniques for BP: We employed two (2) measurement techniques for measuring and benchmarking our developed sensor with commercially available Contec Ambulatory BP monitor.

a) Instantaneous measurement: The 13 volunteers were employed for benchmarking our developed sensor with an already existing Contec commercial sensor. The data collection time was approximately 30 min.

We first measured the instantaneous SBP using the commercial BP monitor three times with a brief break between each measurement and the same technique using our developed BP estimation monitor. The measurement was conducted in a controlled environment, where the volunteers were allowed to relax and stay still for 30 min before the measurement was carried out. The volunteers were male (He) and female (She) without medical conditions within the age range of 25–45 years old. The benchmarking of the SBP with the commercial sensor and developed sensor was carried out within a constant time interval on the same arm. The readings were collected simultaneously.

We noted that our sensor performed equally well and within the minimum error with the commercial sensor in some of our volunteer readings. From the obtained result in Table II, our developed estimation monitor follows the trend with the commercial sensor, as shown in Fig. 4.

The accuracy between our developed monitor and commercial was calculated using (5) [16]

$$A = \frac{1}{n}\sum_{1}^{n}\frac{BP_c}{BP_d} \times 100\% \tag{4}$$

TABLE I
SELECTED VARIABLES AFFECTING BP OF VOLUNTEERS

Volunteer	Age	Color	Gender	Ethnicity	Handedness	Medical condition
1	28	Black	F	African	Right	No
2	32	Black	F	African	Right	No
3	45	Black	M	African	Right	No
4	38	Black	M	African	Right	No
5	23	Brown	M	Asian	Right	No
6	27	Brown	M	Asian	Right	No
7	28	Brown	M	Asian	Right	No
8	25	White	M	Asian	Right	No
9	28	Brown	M	Asian	Right	No
10	29	Brown	M	Asian	Right	No
11	37	White	M	Asian	Right	No
12	25	Brown	M	Asian	Right	No
13	25	White	F	Asian	Right	No
14	59	White	F	British	Right	HBP
15	20	White	F	British	Right	No
16	29	White	M	British	Right	No
17	39	White	M	British	Right	No
18	37	White	M	British	Right	No
19	34	Brown	M	European	Left	No
20	30	Brown	M	European	Left	No

TABLE II
BENCHMARK OF DEVELOPED SENSOR AND COMMERCIAL SENSOR

Volunteers	Gender	Commercial (mmHg)		Developed (mmHg)	
		SBP	DBP	SBP	DBP
1	M	109	77	106	74
2	M	111	74	116	78
3	M	110	72	109	77
4	M	105	73	101	70
5	M	109	65	111	64
6	M	92	59	92	58
7	M	114	51	112	60
8	M	116	71	118	72
9	M	133	51	130	53
10	M	131	65	129	68
11	F	96	89	97	80
12	F	114	70	113	73
13	F	112	85	115	84

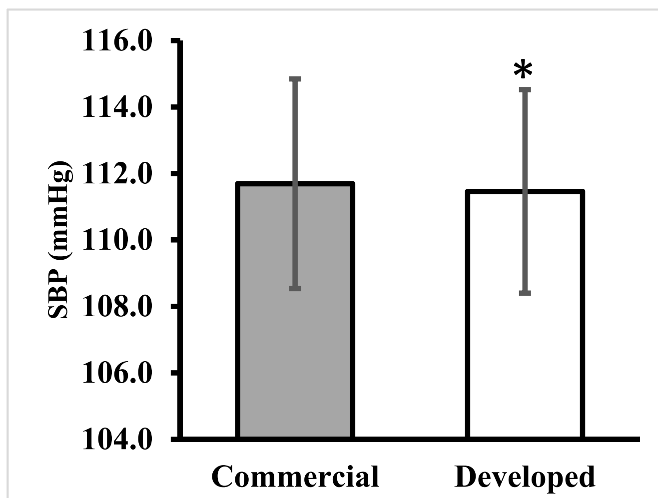

Fig. 4. Benchmark of commercial BP reading with our developed BP monitor for our volunteers.

where A denotes the accuracy in %, BP_c is the commercial BP, and BP_d is the developed sensor BP.

The accuracy of our developed monitor was calculated to be using (3).

For our statistical analysis, we employed the Pearson correlation test and single-factor analysis of variance (ANOVA) test we used for comparing the commercial and our developed sensor estimate for SBP. In our comparative analysis and correlation of commercial BP monitor for measuring SBP and our developed BP estimate, we observed that there is a strong correlation between them, correlation coefficient $r = 0.97$ using the Pearson correlation. The Pearson coefficient shows that the commercial sensor measurement and our developed sensor estimate result are close in comparison. In addition, we performed a single-factor ANOVA test on the commercial and developed an estimate of SBP and set the alpha $p = 0.05$; we developed two null hypotheses, which reflect the acceptability and accuracy of the sensors. We also performed a T-test to show whether there is a difference between commercial SBP and our developed SBP reading.

We classified the data into two groups of variations, the mean square identified the average variation between the two groups $ms = 0.34$; the test statistic for single ANOVA F stat $= 0.0028$, probability value; and p-value $= 0.96$. From our analysis, we identified that the p-value is greater than our alpha value (0.005), and hence, there is a relationship between the commercial sensor and our estimated SBP sensor.

b) Continuous measurement: We carried out continuous SBP measurements for 3 min on one volunteer. We used the ADLX335 accelerometer [31] in our design to mitigate the problem of user movement. This movement comes in form of noise and adversely affects the accuracy of measurement. With the accelerometer, we were able to carry out measurements without affecting the movement of the user.

Table III shows the benchmark between our continuous SBP and commercial instantaneous SBP monitor for one volunteer.

Variations in measured SBP and predicted sensor were maximum at 3 mmHg. The calculated mean difference between our continuous SBP monitor and commercial monitor was within the acceptable of SBP as standardized by the America National Standard for electronics or automated. Our employed Contec commercial ambulatory BP monitor could not obtain the continuous BP readings when applied for daily activity such as running in a controlled environment as it displayed different errors: time-out, excessive movement, and saturation errors. Hence, we could not benchmark our estimated BP obtained from running with the commercial sensor. The errors emerged from the continuous movement of the commercial sensor as it was obtrusive.

TABLE III
CONTINUOUS SBP FROM DEVELOPED SENSOR AND INSTANTANEOUS MEASUREMENT FROM COMMERCIAL BP FROM ONE VOLUNTEER

Developed Sensor			Commercial Sensor		
Time (sec)	SBP (mmHg)	Average SBP(mmHg)	Time (Mins)	SBP (mmHg)	Error Margin
0.0	111	113	1.0	114	1
15.0	114				
30.0	113				
45.0	113				
60.0	114				
75.0	112	113.8	2.0	115	1.2
90.0	115				
105.0	112				
120.0	114				
135.0	113				
150.0	110	111	3.0	114	3
165.0	110				
180.0	112				
195.0	113				
210.0	110				

B. S_pO_2 and HR Estimation

1) S_pO_2 Estimation: From our developed sensor, we took the highest stable reading from our developed sensor estimate level of S_pO_2 and compared it with the highest stable reading from the commercial Braun pulse oximeter monitor simultaneously. Braun is widely used in the NHS U.K. by physicians and healthcare professionals for measuring S_pO_2 and HR, respectively [32].

Our S_pO_2 Table IV shows the benchmark for estimating S_pO_2 with our developed sensor and measuring S_pO_2 from the commercial sensor. The accuracy between our developed monitor and commercial was calculated using the following equation [16]:

$$A = \frac{1}{n}\sum_{1}^{n}\frac{Sc}{Sd} \times 100 \quad (5)$$

where $\boldsymbol{A}$ denotes accuracy in %, Sc is the commercial S_pO_2, and Sd is the developed sensor S_pO_2.

Our experiment trial was not tested against low oxygen levels (hypoxemia) as our recruited volunteers all had normal S_pO_2 readings of $\geq$95%. Conducting experiments on volunteers with hypoxemia would require urgent medical intervention in order to mitigate the bad prognosis associated with low oxygen levels. In addition, it should be stated that at a low saturation level, different factors play a significant influence such as skin color and the type of measuring technique used such as arterial blood gas.

The accuracy of our developed monitor was calculated to be 99.5% with a commercial monitor. Using Microsoft excel, we found that our mean standard deviation between our developed sensor and commercial is $\pm$3.45. We used the Pearson correlation test from Microsoft excel to evaluate the correlation r between commercial and developed HR estimates, the evaluated correlation $r = 0.83\%$ or 83%

The maximum marginal deviation between our developed sensor and the commercially available sensor is within the acceptable error margin of S_pO_2 value of 85%. From our S_pO_2 result, we discovered that none of our volunteers was hypoxemia, i.e., S_pO_2 reading of less than 85%. We also performed a T-test to show whether there is a difference between commercial S_pO_2 and our developed S_pO_2 reading, illustrated in Fig. 5.

2) HR Estimation: We took the most stable HR reading from our developed sensor and compared it with the reading from a commercial pulse oximeter.

Our HR Table V shows the benchmark for estimating HR with our developed sensor and measuring HR from the commercial sensor. The accuracy between our developed monitor and commercial was calculated using the following equation [16]:

$$A = \frac{1}{n}\sum_{1}^{n}\frac{Hc}{Hd} \times 100 \quad (6)$$

where A denotes the accuracy in %, Hc is the commercial HR, and Hd is the developed sensor HR.

TABLE IV
BENCHMARK OF COMMERCIAL AND OUR DEVELOPED S_PO_2

Volunteer	Commercial sensor SpO2 (%)	Developed Sensor SpO2 (%)	Marginal deviation (±)
1	99	99	0
2	98	98	0
3	99	97	2
4	99	99	0
5	99	98	1
6	99	99	0
7	95	90	5
8	92	96	4
9	92	92	0
10	90	86	4
11	94	96	2
12	98	96	2
13	93	92	1
14	97	98	1
15	98	98	0
16	94	95	1
17	92	95	3
18	99	97	2
19	90	88	2
20	97	97	0

TABLE V
BENCHMARK OF COMMERCIAL AND OUR DEVELOPED HR

Volunteer	Commercial sensor HR(bpm)	Developed Sensor HR (bpm)	Marginal deviation (±)
1	70	71	1
2	87	88	1
3	66	63	3
4	64	66	2
5	82	88	6
6	85	86	1
7	89	90	1
8	83	79	4
9	77	76	1
10	73	77	4
11	87	82	5
12	66	63	3
13	67	65	2
14	85	79	6
15	69	65	1
16	52	55	3
17	65	63	2
18	51	54	3
19	90	84	6
20	65	75	20

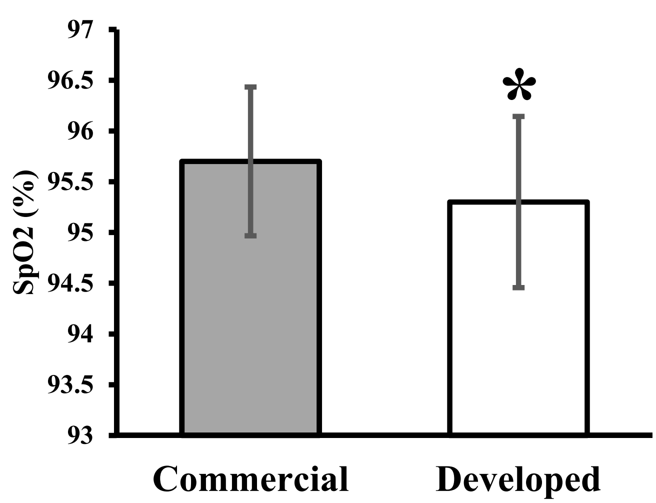

Fig. 5. Benchmark of commercial S_pO_2 reading with our developed S_pO_2 monitor from our volunteers.

The accuracy of our developed monitor was calculated to be 98.7% with a commercial monitor.

We used the Pearson correlation test from Microsoft excel to evaluate the correlation r between commercial and developed HR estimate, the evaluated correlation $r = 0.94\%$ or 94%. Through the correlation, we can conclude that there is a very close relationship between our developed HR and commercial HR.

C. Remote Monitoring Data From ThinkSpeak

Our obtained results were uploaded to the ThinkSpeak Internet server through our Arduino using a Wi-Fi connection. ThinkSpeak was used to remotely monitor the obtained BP, HR, and S_pO_2 data. On the Internet, we obtained real-time graphical readings of a single volunteer as shown in Figs. 6–9, and each health vital was represented in a different graphical field. It should be emphasized that the readings of 0 s from Figs. 6–9 reflect the start and end time of placing and removing the measuring probe on the finger while

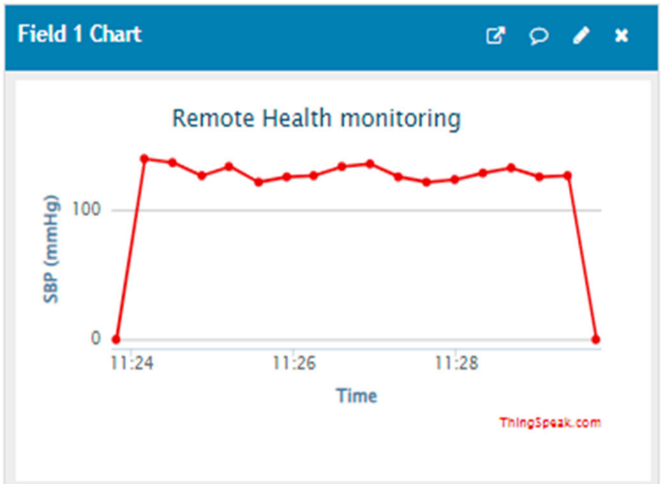

Fig. 6. Our SBP estimation remote monitor.

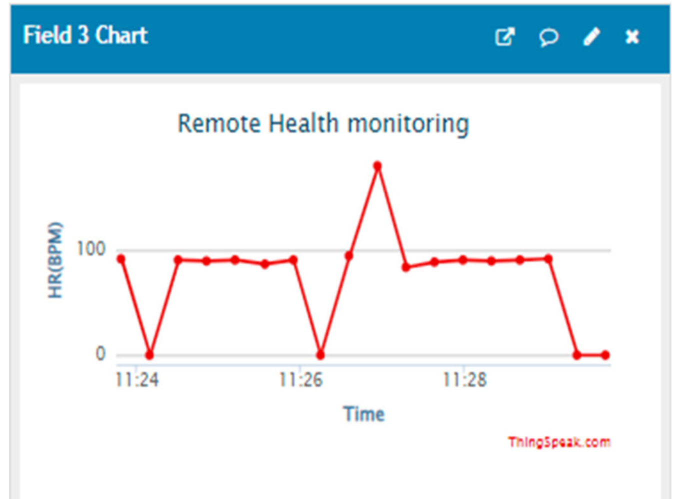

Fig. 8. Represent the Heart Rate.

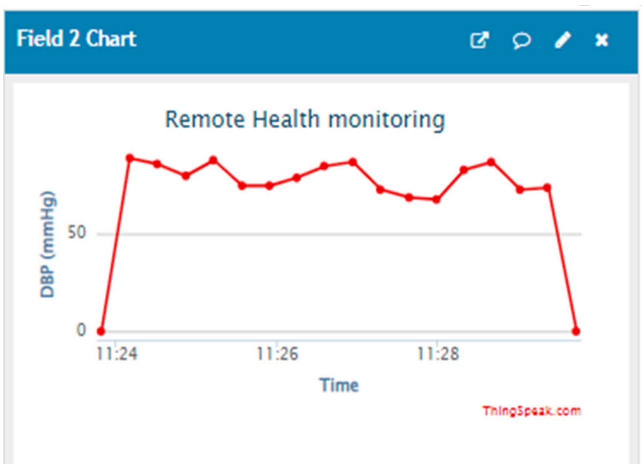

Fig. 7. Our DBP estimation remote monitor.

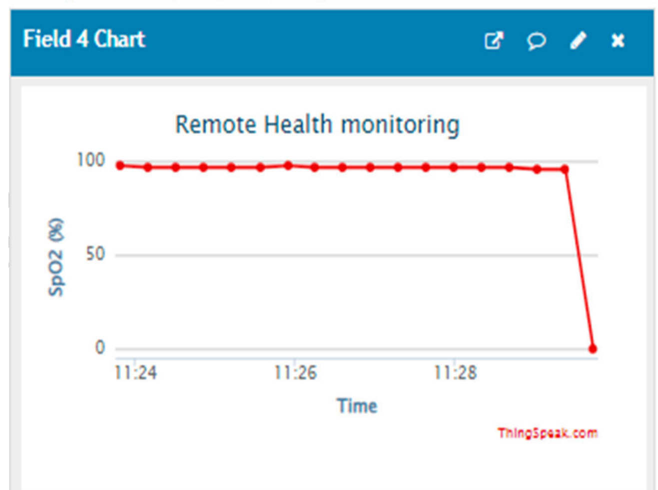

Fig. 9. Represent the S_pO_2.

remotely monitoring the BP, HR, and S_pO_2 data. ThinkSpeak enabled our proposed system to an IoT platform for remote monitoring of our system. We configured a local Internet network and interface it with Arduino MKR Wifi 1010, and we uploaded our health data every 20 s.

Our remote monitoring system graphically represents the health parameters SBP, DBP, HR, and S_pO_2:

1) SBP remote monitoring;
2) DBP remote monitoring;
3) S_pO_2 remote monitoring;
4) S_pO_2 remote monitoring.

V. Conclusion

We present the design of an IoT-based remote health monitoring system for BP, HR, and S_pO_2 estimation and describe its implementation of it with an Arduino MKR WIFI 1010 board all housed in a 3-D case with a 0.91 OLED screen display. The system used a single PPG feature and machine-learning algorithm to achieve continuous health vital monitoring. Our proposed system was designed to operate in a reflective mode and housed a 3-D finger-styled printed case for the firm position of the sensor to avoid movement of the finger, which could result in an erroneous reading. The accuracy of the sensor was also tested against a commercially obtainable sensor and reading accuracy was found to be within acceptable comparative limits. We employed a Contec ambulatory BP monitor to benchmark our developed BP monitor. In addition, we used a Braun pulse oximeter to benchmark our developed HR and S_pO_2 with our developed sensor. The Arduino MKR Wi-Fi 1010 provided the platform for us to interface our developed sensor with the ThinkSpeak platform for visualization and remote monitoring. Our developed sensor was embedded with a 0.91 OLED screen for visualization. Further research on gaining individual patient and clinician user experience perspectives would be helpful to understand whether the system is considered user-friendly by patients and physicians and the various potential clinical applications. In addition, the research could also explore if such an unobtrusive measurement system could also be validated for patients who are on antihypertensive medications.

Future research could explore the design of a sensor capable of predicting and forecasting BP, HR, and S_pO_2 rise or decline in a given period. In our next research, we are conducting pilot research to highlight the influence of daily activities, such as walking, resting, and running on volunteers. Some daily activities have been highlighted as contributing factors to HBP.

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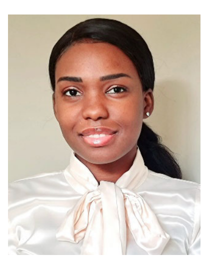

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