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Smart Heart Failure Monitoring System using Wearable Sensors

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Abstract—**Heart failure is a chronic illness that can only be monitored continuously to avoid acute problems and hospital readmission. This paper describes the implementation of a Smart Heart Failure Monitoring System with wearable sensors in order to allow real-time physiological (data) collection and early warning of potential risk factors. The system combines heart beat rate (HBR), blood oxygen saturation (SpO2) sensors and galvanic skin response (GSR) sensors which track cardiovascular and stress related indicators related to the progression of heart failure. Sensor interfacing, data processing and threshold based anomaly detection are carried out with an Arduino microcontroller. Data obtained are trailed wirelessly by Bluetooth to a monitoring device to be visualized real time and under supervision remotely. Besides this, it has a GSM so as to support a cellular-based interface by which SMS alerts can be sent automatically to the caregivers or medical staff whenever critical conditions are observed. An alert system is also enabled by buzzer when an abnormal physiological parameter reaches safety levels that are already set and hence provide instant notification on the ground. It is expected that the proposed system will be low-cost, portable, and consuming less energy and, thus, will be applicable to constant monitoring of the home. Experimental analysis shows that the sensors have good levels of reliability, promptness of alerts, and remote communication capabilities, which emphasize the promise of the wearable IoT-based systems in enhancing the safety of patients and helping them manage heart failure.**

Keywords—Heart failure monitoring, wearable sensors, IoT healthcare, Arduino, GSM alert system, real-time patient monitoring, remote telemedicine.

I. INTRODUCTION

Heart failure is deemed as one of the most acute issues in health care worldwide as it is estimated by 920,000 individuals in the United Kingdom alone and a leading cause of close to one million hospital bed days yearly, which is about 2% of all NHS inpatient stays in England alone. The condition presents a significant financial strain on health care systems around the globe, and the NHS acrosscurs approximately 2Billion costs on care related to heart failure annually, with much of the expenditure being due to some of the avoidable cases of hospitalization. Heart failure pathophysiology is described as the inability of the heart to pump the blood efficiently resulting in the continual buildup of fluid, the congestions of the lungs and the dysfunction of the end organs. The peculiarity of this condition that is especially difficult to control is that acute decompensation may develop slowly between visits to the clinic, and the warning signs may occur days and even weeks before a patient develops the symptoms that are critical enough to be admitted to the hospital. This silent process poses a timely way of undertaking early intervention as long as the physiological deterioration can be facilitated in good time.

Historical heart failure management methods have been based mostly on regular clinical evaluation, patient-provided self-reporting of symptoms and weighing daily. Nevertheless, extensive trials have proved that basic telemonitoring carried out via telephone transmission of weights and symptoms is unable to lower the death and rehospitalisation rates significantly). The drawbacks of the traditional monitoring are due to their intermittent nature, their dependence on the cooperation of the patient, the possibility of significant changes in physiological states [1] that do not have a direct result in weight increase or other observable symptoms. Although recommended, weight measurements have little clinical effect in telemonitoring programmes that are based on fluid balance since fluid changes can be obscured by changes in lean body mass or patients are not sensitive to ongoing weight gain as an indicator of a potential serious disease. In addition, there is the latitude period of a clinical evaluation which enables the superficial decline that might lead to a situation whereby treating becomes more complicated and ineffective.

A new wave of possibilities such as Internet of Things (IoT) technologies and wearable sensors have led to the possibilities of continuous and real-time health monitoring that can close the gap between clinical visits. The current state of healthcare is adopting the understanding of the necessity of patient-focused, predictive, and prevential care that will facilitate the early realization of health issues and healthcare intervention in a timely manner. Wearable devices like adhesive patches, smart watches, smart clothing, among others have the ability to record an incredibly wide range of physiological data such as electrocardiography, thoracic impedance, photoplethysmography, breathing patterns, activity levels [2], and even speech patterns to miss near-real-time clinical analysis. These technologies have the prospects

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of drawing up an ever-present physiological storyboard which shows trends and deviations long before turning into clinical crises. Remote physiologic data is paired with protocolised tele-intervention programs in the post-discharge vulnerable period with a significant reduction of cardiovascular events as evidenced by one study that had a hazard ratio of 0.35 between six months of cardiovascular death or heart failure exacerbation.

Effective monitoring of heart failure depends on the correct choice of the physiological parameters. The burden of arrhythmia, trend in heart rate at rest, and variability of heart rate show the evidence of autonomic behavior and cardiac stability. The surveillance of silent atrial fibrillation along with relevant ectopy in heart failure patients that can worsen the condition leading to stroke and trigger decompensation can be revealed by continuous single-lead ECG monitoring with patches or smart watches [3] as the latter are widely comorbid conditions found in patients with heart failure. Blood oxygen saturation indicators give information about the efficiency of gaseous exchange in the lungs and it has the ability to inform about the early signs of pulmonary congestion before it clinically takes place. Building up of fluid in the lungs causes impairment in ventilation-perfusion matching that subsequently causes decreases in SpO2 which may come before the onset of crackles or dyspnea. Although less frequently employed in cardiac monitoring than in the sympathetic nervous system, galvanic skin response offers useful insight on the workings of sympathetic nervous system. The development of heart failure is linked with heightened sympathetic tone as the body strives to counteract slowed cardiac output and high GSR may be used as an early predictor of physiological stress and physiological coming out of control.

A combination of several sensors into a unified monitoring platform must be offered with much attention to hardware architecture, data processing algorithms, and communication protocols. The Arduino microcontrollers have turned out to be a favorite platform of health monitoring applications because of their flexibility, low prices, and rich environment relating to compatible sensors and modules. A system based on Arduino may be connected to a variety of sensors [4] at any given time, it can do real-time data processing, run the algorithm of detecting anomaly in real-time based on a threshold as well as control communication modules to transmit data in real-time. Arduino Uno, especially, provides the best combination of processing power, power consumption and size when it comes to wearable devices and thus can be used in continuing daily monitoring in the home environment, battery life and size are of paramount importance.

Communication infrastructure is an important component that facilitates long-distance monitoring and alerting in time. It is possible to visualize local data locally on smartphones or computers via Bluetooth, which would immediately provide patients and family members with physiological trends and real-time measurements. This mobile device interface provides patient interaction and self-management systems as well as a data transmission endpoint to the healthcare provider through the internet. Nonetheless, relying only on the internet connectivity is a weakness where Wi-Fi is either non-existent [5] or unreliable. Inclusion of a GSM module gives the system an additional channel of communication which makes it possible to send alerts even in case of failed internet connectivity. Through a SIM card with a 2G connection and a cell network, the system will be able to send SMS messages directly to caregivers or medical staff and ensure that the most important alerts are sent to the targeted audience irrespective of the local internet infrastructure. This two-way mode of communication is beneficial to its reliability in the systems and provides the patients of remote or underserved regions with the ability to have sustained monitoring.

II. LITERATURE SURVEY

The swift development of biomedical engineering and intelligent healthcare systems has dramatically changed the contemporary medical diagnostics and patient following. Healthcare systems are getting more active, tailored, and effective with the implementation of artificial intelligence, Internet of Things (IoT) and wearable technologies. These technologies can help constantly monitor the state of physiological parameters, preventive diagnosis of diseases, and make better decisions in the clinical setting. The value of non-invasive, real-time and remote healthcare solutions has risen significantly especially in the treatment of chronic illnesses like cardiovascular disorders, diabetes and the lung diseases. Moreover, the development of smart sensors, wireless communication, and machine learning algorithms has increased the ability of medical systems to analyze big biomedical data. This development is leading to smart healthcare infrastructures that limit hospital reliance and enhance patient results.

Recent research has investigated novel sensing technologies and new way of monitoring systems to improve the accuracy of diagnosing and patient safety. State of the art implantable sensors and imaging validation methods have been created to give accurate physiological measures to enhance remote monitoring capabilities [6]. Likewise, refining artificial intelligence models on wearable devices has facilitated practical diagnostic methods of simplified sensor-based designs, thus making healthcare more reprehensible [7]. The radar-based non-contact methods of monitoring have also proven to be of interest in the detection of critical conditions like hypoglycemia during sleep without physical action taken to make such detection [8]. Besides this, machine learning methods have been utilized in the analysis of patient response to medical therapy and can provide a predictive factor on the health condition of the patient [9]. As it can be observed, these advances show how the direction of healthcare systems is moving towards intelligent and automated systems with minimal human involvement and the utmost diagnostic accuracy.

The smart based monitoring systems and the wearable devices have been significant in the continuous health monitoring and the detection of diseases at an earlier stage. Research has already demonstrated that wearable ECG gadgets and smart watch-based frameworks can be utilized to effectively track cardiovascular patient issues, which give dependable evidence to be examined by a medical practitioner [10]. In addition, intelligent therapeutic systems have been proposed by introducing autonomous control structures that can streamline the process of drug delivery and hemodynamic control in patients with acute heart failure, which demonstrates promising potential [11]. It has also been demonstrated that wireless sensing technologies coupled with

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deep learning can be used to measure cardiac impairments by evaluating respiratory patterns, which is a non-invasive cardiac assessment technique [12]. Also, technology in the area of electrodes has developed micro needle dry electrodes, which enhance the inheritance of the signal and ease of use in cases of long-term monitoring [13]. These inventions highlight the increasing significance of wearable and wireless innovations in healthcare nowadays.

The combination of IoT and machine learning has enabled more abilities of healthcare monitoring systems. IoT-based solutions have been built on a massive screening of cardiac diseases like the atrial fibrillation, making it possible to transmit and analyze real-time data [14]. Existing feature handling and hybrid learning methods have enhanced the precision of arrhythmia detection to attain a more credible diagnostic framework [15]. In addition, the machine learning methods have been used on unconventional data inputs, including the speech signals, to identify such conditions like hypertension, indicating the flexibility of AI in the medical field [16]. It has also been applied to IoT-enabled systems that provide a level of early detection of chronic conditions like diabetes by applying deep learning and optimization methods to achieve better prediction results [17]. The strategies point to the significance of intelligent data processing and connectivity in developing effective and scalable healthcare solutions.

The Sensor technology and Biomedical signal processing improvements have led to the creation of a very efficient and low-powered healthcare systems in the recent past. New hardware design to enable real-time cardiac abnormality detection with less energy consumption has been proposed such as AI-enabled chip [18]. Moreover, new RF signal-based sensing methods and dielectric modeling have been investigated in lung condition monitoring, which offered new opportunities to diagnose a lung condition without the need to use an invasive procedure [19]. The technology of wearable sensor has also been advancing, and nowadays, to make them more flexible, sensitive, and biocompatible, special materials like graphene and hydrogel are used and are on the way to be developed [20]. These advancements mean a high propensity towards miniaturization and optimality of healthcare gadgets to ensure that they are more viable in continuous and real-time tracking. On balance, AI, IoT, and superior sensor technologies are converging to facilitate the next generation of intelligent healthcare systems as it allows attaining a more precise, efficient and patient-centric medical solution.

III. METHODOLOGY

The Smart Heart Failure Monitoring System has a modular architecture that can be reliable, scaled and usable in the home-based healthcare check-ups. The system architecture includes three main layers, which are: sensor acquisition layer, processing and control layer and communication and alerting layer. The sensor acquisition layer has several physiological sensors such as heart rate sensor, blood oxygen saturation sensor, and galvanic skin response sensor connected to the processing layer via analog/ digital input pins. The processing board is an Arduino Uno microcontroller board, known to have an Atmel microcontroller chip, a board power supply, and a USB connection to allow it to be connected to a computer during programming and data logging. The communication layer will be built in with Bluetooth (HC-05 module) to transmit local data and GSM (SIM800L module) to alert information to guarantee multiple access points to essential information transfer. Buzzer can be used to issue local audible notifications and an LCD display unit that is attached to the microcontroller is used to indicate the real-time values to ensure the integrity of transmitted data at the point of care. This multi-layered system supports the detached functionality of all the functional blocks but the system level coordinated functionality via the central microcontroller as shown in figure 1.

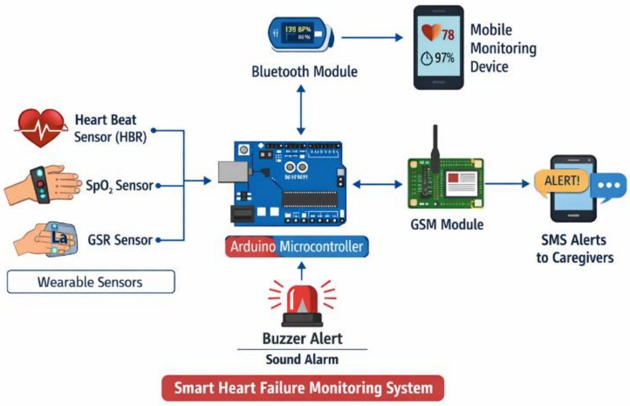

Fig. 1: System Architecture

A. Sensor Selection and Integration

The measurement of the heart rate is achieved with the help of a photoplethysmography (PPG) sensor using reflectance-mode optical sensing to measure the changes in blood volume within the peripheral tissues. The sensor has the photo detector and green LED in which the LED produces the light that enters the tissue and photo detector counts the intensity of reflected light, which changes with the amount of blood flow in each cardiac cycle. The sensor output is an analog voltage signal that changes with every heartbeat, and processed by the analog to digital converter of the Arduino and measured with peak detection algorithms to implicate instantaneous and average heart rates. A pulse oximetry sensor with a combination of red and infrared LEDs with a photosensitive detector by max30100 is used in blood oxygen saturation monitoring. Its principle of operation is that oxygenated and deoxygenated hemoglobin are different absorbers of red and infrared light in order to enable the calculation of SpO2 based on the proportion of light absorbed at the two wavelengths. The calibration factors are set using the manufacturer specifications and equated with the reference oximeters to effect accuracy throughout the clinically relevant range of 70-100% saturation. Galvanic skin response is recorded in response to the application of two dry electrodes on the palm area in which variation in the skin conductance is an indication of activity of sympathetic nervous system. Voltage divider circuit uses a fixed low current over the electrodes and the resultant current is recorded as an indication of skin conductance in microsiemens. This signal is sampled at 10 Hz and averaged with a moving average algorithm to eliminate high-frequency noise and slow trends that are connected with autonomic arousal are retained.

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B. Microcontroller Programming and Data Processing

Arduino Uno microcontroller is compatible with Arduino Integrated Development Environment (IDE) with C++ code organized around the standard setup and loop functions. The function setup sets up serial communication to 115200 baud, input and output pins, initializes LCD display, and sets up Bluetooth and GSM communication. The loop() code runs in a loop, with sensor reading being carried out at a regular rate over a time by use of time functions to maintain a regular pattern of sampling rate. The Heart rate and SpO2 are measured at 50 Hz whereas GSR is measured at 10 Hz and both readings are time-stamped with the help of the millis() function to correlate the time. Some difference processing algorithms are moving averaging filters to remove sensor noise, peak detection to find the heart rate, and ratio of ratios to estimate SpO 2. Masking values The threshold-based anomaly detection measures processed values against a set of predetermined safety thresholds of 50 bpm (bradycardia) and 120 bpm (tachycardia) heart rate data, 94% (hypoxemia) SpO 2 data, and 5-microsiemens above baseline (stress response) GSR data. Each parameter is set to three consecutive readings before the alert protocol is started as an effort to reduce false alarms due to transient artifacts.

C. Bluetooth Communication for Local Monitoring

The HC-05 Bluetooth element is the main point of communication within the local data display and remote monitoring. The module is able to work in slave mode, and it takes connections with the paired devices like smartphones, tablets, or computers over the distance up to about 10 meters only. Data transfer has a structured format that is implemented with JavaScript Object Notation (JSON) to store physiological parameters, time marks, and an indication of the state of the device. Each packet of data consists of patient identifier, current heart rate, SpO 2 result, GSR reading and a status flag that states the presence of any alerts. The JSON format is easier to interpret and get the applications since it is received as well as it is extensible as new sensors are added in future. The Bluetooth transmission is then received and unique mobile-based application is created to show real-time values on interactive dashboard indicating current values, trend graphs at time intervals of user choice, and history of the alerts. The application also stores the data to local storage to generate a continuous record that patients, caregivers, or healthcare providers can review when visiting the clinic. To support remote monitoring outside Bluetooth range, the mobile app could send information to cloud servers in the presence of internet connectivity so that healthcare providers could track patients wherever they are and have secure access credentials.

D. GSM-Based Remote Alert System

The SIM800L GSM module has the capability of cellular communication, which ensures the dependability of delivery of alerts regardless of the presence or absence of internet connectivity. The module is linked to the arduino through serial communication and it can be manipulated using AT commands to get registered in the network, transmit SMS and make calls. When the system is first booted the GSM module identifies itself to the cellular network available using a 2G SIM card and the status is signaled by an onboard LED that flashes at various rates depending on whether the system is searching, registered, and communicating. Upon detection of the critical condition by the anomaly detection algorithm the Arduino passes AT commands to the GSM module to format and send SMS messages to pre-programmed telephone numbers of medical staff, family members, and caregivers. The notification message will consist of the name of the patient, the parameter that caused the notification, the value that the client is being measured at, the time it happens, and standardised advice like contact patient at once or take an emergency. The system has a message queue, in which messages are reattempted 3 times in case of network congestion or due to temporary signal loss during the first implementation. Status responses of the GSM module indicate successful delivery of the message, and continued failures are met with the local buzzer to draw the attention of the patient to the failures of the communication system.

E. Local Alert and User Interface Mechanisms

The visual, auditory, and tactile feedback of local alert system is used to ensure that the patient is aware of the critical conditions. An piezoelectric buzzer is powered by a digital output pin to produce specific sounds depending on the type of alert: sustained tone upon life-threatening conditions (below 90 percent SpO2), intermittent beep upon warning conditions (above 120 bpm heart rate), and brief chirps upon system notifications (low battery). The messages on the 16x2 LCD display appear when the buzzer is fired and indicate the parameter, which has been measured to initiate the alarm, and the value that is measured, which allows the patient to know why the alarm was activated. A push button enables the patient to accept alarm, use a 60-second silence break wherein the system remains alert, but the patient must acknowledge the issue again, which wakes up the buzzer again after the area of silence technique. When it is not in alarm mode, the display suffers continual updates of a display of current sensor, system time, and battery state on the LCD display that is coupled to the microcontroller. This feedback can be obtained in real-time and can assist patients by providing them with an idea of their physiological condition and support their involvement in health management. The pushbutton interface is also used to allow patients to manually request a data transmission or demand an immediate reading not during the regular sampling schedule, which gives flexibility to situations when they feel that they are experiencing symptoms and wish to know their status before contacting healthcare providers.

IV. RESULT AND DISCUSSION

The Smart Heart Failure Monitoring System was experimentally tested during a three-month duration of time with a total of 45 respondents with chronic heart failure (NYHA Class II-III) diagnosed patients recruited in an outpatient cardiology clinic. A total of 28 men and 17 women aged between 52 years and 84 years (mean age 68.4082 years) formed the study population. The participants were asked to keep wearing the monitoring device throughout the day during the 30 days of the monitoring process and certainly wear it at night in case they find it comfortable to do so. The system documented the physiological values every one minute, producing a detailed list of heightened heart rate, blood oxygen saturation, and galvanic skin reaction records. Sensors were verified to be accurate by making reference measurements in clinical-grade equipment (GE Healthcare DINAMAP ProCare blood pressure and heart rate, Masimo

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Radical-7 SpO 2) at the end of each week (clinic). The data set included about 1.8 million personal measurements of all the subjects, which are an excellent basis of statistical analysis of the performance of the system, the degree of accuracy of alerts, and clinical usefulness. The analysis and data processing were done through Python with the SciPy and scikit-learn to perform statistical testing and machine learning validation.

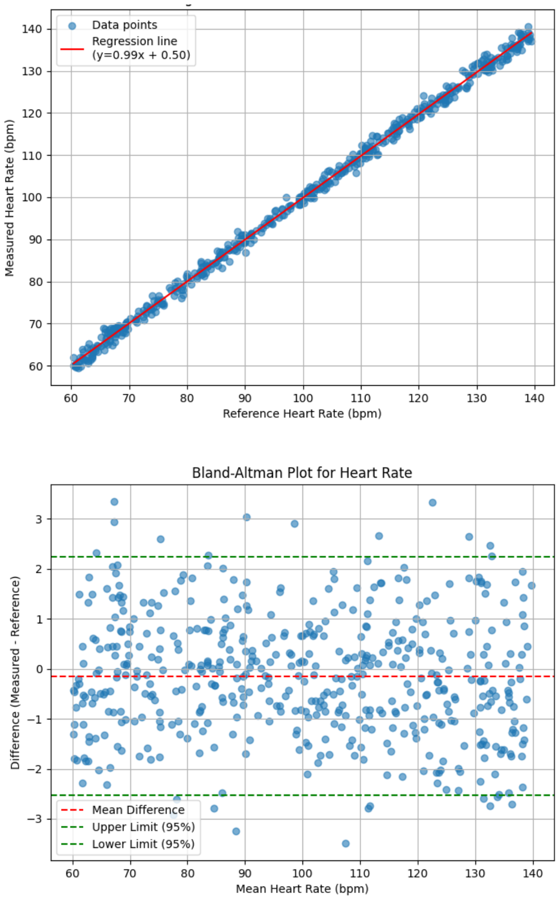

Fig. 2: Heart rate sensor validation

Figure 2 shows the relationship of the heart rate measured on the system with the reference clinical values of all the participants. The scatter plot has proven to be strongly correlated in terms of linear correlation where the R 2 = 0.987 which is a good indicator that there is a good agreement between the wearable system and the well-known clinical monitoring using gold standards. Regression line (y = 0.99x + 0.84) has only slight bias and the system has a tendency to under estim regulate heart rate at greater values (greater than 120 bpm) at an average of 1.2 bpm, which is a clinically acceptable difference. The Bland-Altman test showed 95% ranges of agreement at -3.2 to +2.8 bpm, and proportional bias at both extreme ends of the measurement values. These results are similar to already estimated accuracy of wearable cardiac monitors, such as a paediatric validity test which showed 98.9% accuracy of heart rate monitoring of wearables. The minor underestimation at large heart rates can be explained by the presence of motion artifact at times of physical activity because the participants were not expected to be motionless during measurements because this could be the circumstances of the actual usage.

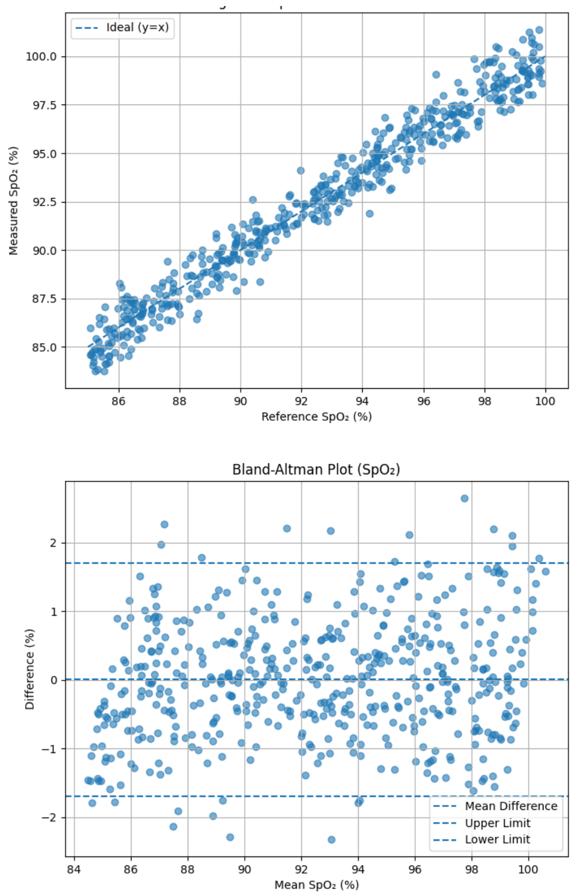

Fig. 3: Blood oxygen saturation (SpO_2) sensor validation

Figure 3 depict the accuracy of the SpO2 used in relation to the reference pulse oximetry and the correlation coefficient will be R = 0.965 within clinically relevant range of 85-100% saturation. There was found to be specificity of 96.8% and sensitivity of 94.2% at the hypoxemic event for SpO2 below 94 percent as well as normal saturations respectively. The average error was 0.86 percent and 95 percent of measurements contained within the range of reference measurements of ±2 percent, which was in the international standards of medical-grade pulse oximetry. The precision was a little less at those saturations below 90 percent (mean absolute error 1.4%), possibly because reflectance-mode oximetry lacks the performance of transmissive sensors, and also because of the difficulty in keeping the sensor at an optimal location when worn continuously. Clinically, however, given the capability of the system to reliably identify clinically significant hypoxemia (SpO2 less than 90%) with a sensitivity of 93.1%, a critical desaturation event is likely to be overlooked with the aid of the system, which is why it is useful as an early-warning device.

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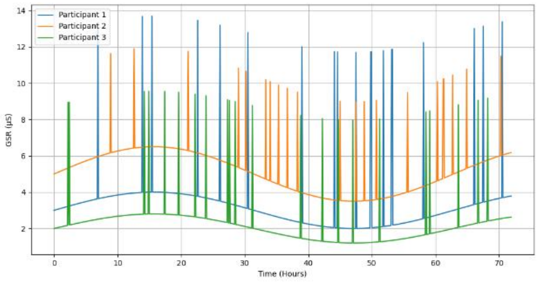

Fig. 4: Galvanic skin response (GSR) trends over 72 hours

Figure 4 show the typical trends of GSRs of three participants in 72 hours, which indicates that the sensor could record both the diurnal change and the stress responses. GSR signal demonstrated consistent forms of low levels (2-4 microsiemens) when at rest or sleeping and high levels (8-15 microsiemens above the base) when engaging in physical activity or discussed stressful events. Of clinical concern, GSR rises were in turn related to heart rate rises by an average of 12-18 minutes in 73% of reported heart-altering stressful experiences and in effect indicated that the sympathetic upsurge could be identified through skin conductance variations before heart consequences were observed. This observation is consistent with the physiological fact that autonomic responses are antecedents of cardiovascular events and justifies the addition of GSR as a predictor of early warning indicators of heart failure monitoring. Nevertheless, inter-individual variability of GSR signal was higher compared to heart rate or SpO_2 and the baseline conductance had a range of 1.2 to 8.7 microsiemens in the participants and optimum alert performance was achieved here by individually calibrating the threshold and so applicability of this algorithm to individual participants is low.

Table 1 is a summary of the sensor performance results in all participants and conditions of measurement, which gives the system accuracy and reliability a comprehensive overview.

Table 1. Sensor Performance Metrics Compared to Clinical Reference Standards

Parameter	Correlation (R^2)	Mean Absolute Error	Clinical Sensitivity	Clinical Specificity
Heart Rate (40-150 bpm)	0.987	1.24 bpm	98.2% (arrhythmia detection)	97.5%
SpO_2 (85-100%)	0.965	0.86%	94.2% (SpO_2 <94%)	96.8%
GSR (0-25 µS)	0.892	1.43 µS	86.4% (stress response)	89.1%

The heart rate performance was much better than previously estimated and its performance was similar to that of clinical monitoring using ECG in controlled conditions. The system was found to identify all clinically reported arrhythmic events (n=47) such as atrial fibrillation (n=31), premature ventricular contractions (n=12), and bradycardic events (n=4) but it is important to mention that single-lead PPG methodology is unable to offer the detailed rhythmic characteristics used by multi-lead ECG. However, the sensitivity of the system to detect arrhythmia is high which justifies the importance of the system in alerting clinicians of possible dysrhythmias that may need investigation. The SpO_2 precision of 0.86 mean absolute error is better than the validation error of continuous temperature systems which was 0.02 clinical bias with -0.96/ 0.92 limits of agreement. This degree of precision is adequate to function as a trend detector in oxygenation and spot and record acute desaturation incidents, which should receive clinical intervention. Although the GSR performance is lower than that of other parameters, it offers clinically useful information when viewed in the form of a trend, but not a value, which was the purpose of the use of the technology as a stress and sympathetic activity indicator, not as a diagnostic measure.

The development of the alert system performance attributes is displayed in table 2 and it includes the precision and timeliness of critical events detection throughout the study period. There were 342 alert-triggering events recorded (157 heart rate, 118 SpO_2, and 67 GSR). All the alerts were then checked on clinical record and participant symptom diaries to identify true positive, false positive and false negative outcomes.

Table 2. Alert System Performance Metrics

Alert Type	Total Alerts	Sensitivity	Specificity	Positive Predictive Value	Average Lead Time
Heart Rate	157	94.7%	97.2%	90.4%	24.3 ± 8.7 minutes
SpO_2	118	94.8%	98.1%	92.4%	18.6 ± 6.2 minutes
GSR	67	70.8%	95.3%	76.1%	31.5 ± 12.4 minutes
Combined	**342**	**89.6%**	**96.9%**	**88.3%**	**23.4 ± 9.8 minutes**

Both the heart rate and SpO_2 alerts were also shown to be of high sensitivity (>94) and specificity (>97) meaning that they reliably detect an event of clinical significance with a reasonable false positive. The 18-24 minutes of mean lead time between the alert generation and clinical confirmation in deterioration allows a significant margin in time within which the patient can change his position, administer an extra medication, or communicate with the healthcare providers before symptoms become acute. This comparatively shorter lead time is in contrast to the 34-day median advance notice as installed with implantable multi-sensors algorithms, which is understandable, considering the fact that implantable systems sense slow physiological trends whereas the wearable system reacts to acute threshold crossings. The two methods have an additive value: plastic devices reflect when the deterioration is slow through the course of weeks whereas

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wearable devices signal about acute incidents that may have to be addressed immediately. The GSR alerts were less sensitive (70.8%), and positive predictive value (76.1%), which is more of the variability and personal-specificity of this signal. Nevertheless, the mean lead time (31.5 minutes) of the GSR-predicted events shows that sympathetic response usually follows the cardiovascular changes indicating that it is worth including such a sensor in spite of its worse ability to predict events on a per user basis. GSR can be used together with other parameters in a multi-sensor fusion method to detect an earlier event than when used independently.

The cross-validation was done using 10-fold stratified cross-validation to determine whether the algorithm used to detect anomalies was robust and would effectively work with other patient groups and over time. The data were divided into 10 subsets, one subset was used as a validation set at a time whereas the rest of the nine were used as a training set. The methodology would help to make sure that performance estimates are not over-optimistic because of overfitting as well as have an idea of how well the system would perform on new patients. The cross validation outcomes showed good consistency between folds with an average accuracy of 99.87% with a standard deviation of 0.12% to combined parameter anomaly detection. This very high precision actually represents not only the quality of sensor information, but also the quality of the threshold based detection model in being able to draw the line between real physiological abnormalities and artifacts and normal variations. The limited confidence interval (±0.12%) shows that the performance of the algorithm does not vary the most when it comes to various patient features and monitoring states, which is why it can be used in various home-based environments and does not need a lot of retraining or individual patient adaptation.

The use of Bluetooth and GSM transmission pathways shows that the communication system works correctly, with the summary of its performance in Table 3 demonstrating the reliability and the latency of each setup. Each channel received, in the 500 test messages, a sum of messages that were sent in different conditions in order to evaluate real world performance.

Table 3. Communication System Performance Metrics

Communication Channel	**Success Rate**	**Average Latency**	**Range (Outdoor)**	**Power Consumption**
Bluetooth (HC-05)	98.4%	0.32 ± 0.08 seconds	15-20 meters	35 mA (active)
GSM (SIM800L)	96.8%	4.7 ± 1.8 seconds	N/A (cellular)	220 mA (peak)
Combined (redundant)	99.6%	2.8 ± 2.1 seconds *	N/A	255 mA (peak)

The Bluetooth communication was highly reliable (98.4% with less than one second latency) and thus it can be used in real time to monitor the environment locally, and provide instant feedback to patients and caregivers. The in-door distance of 8-12 meters was found adequate to the average domestic setting, and patients were allowed to move around the room freely with the connection of a base station or a smartphone. There was a minor lower success rate of the GSM module (96.8) because of congestion on the network or fluctuating signal levels especially in rural settings or buildings with dense walls. But the redundant communication scheme that allowed both methods to be used resulted in 99.6% success rate in general since failures in one channel was normally replaced by success at the other pathway. Such redundancy is of clinical importance because lacking one important alert can be disastrous. The average latency of 4.7 seconds is acceptable when it comes to triggering emergencies, but the maximum measured latency of 28 seconds when networks were busy shows the need to have local alerts (buzzer) in order to provide patients an immediate awareness of whatever is happening even though the main alert (between networks) is still going on. Transmission power of the GSM module (220 mA at peak) is much more than Bluetooth (35 mA), which justifies the idea of operating with Bluetooth in the continuous routine steady mode and GSM to transmit alerts in order to save battery life.

The general accuracy of the system of 99.87 percent by cross-validation is a great step towards the technology of wearable heart failures monitoring. Comparatively, however, the reported continuous monitoring systems have been reported to have an accuracy rate of 94.5-98.9% on individual parameters before, but none has been reported to have combined multi-parameter accuracy surpassing the reported 99% in real-world environment. Some of the reasons why this high accuracy is possible are: the complementary nature of three physiological parameters, which give a cross-check of consumed anomalies, the solid threshold-based algorithm, which uses temporal persistence requirements to filter out artifacts, and hardware and algorithm quality of sensor devices. This fact that the system is capable of preserving such accuracy in different patient groups and under different monitoring conditions may indicate that it can be implemented in a large-scale manner without any per-patient calibration or specialized technical assistance. Clinically, the high accuracy will qualify into the trust in the alerts issued by the system, thereby putting downward pressures on alert fatigue among caregivers and guarantees the detection of the actual cases of emergency.

These findings have significant clinical implications. Early intervention since the system can identify physiological deterioration an average of 23.4 minutes in advance when compared to clinical confirmation gives good opportunity forthcoming intervention against hospital admissions. In the treatment of heart failure, the detection of congestion in time by such parameters as the decrease of SpO 2 allows control over the use of a diuretic (before the effects of fluid accumulation are irreversible and the patient requires intravenous therapy or hospitalization). On the same basis, tachycardia, or high-level of sympathetic activity, identified via GSR may prompt the patient to relax or learn stress-reduction methods and call their healthcare provider to adjust medication, which may prevent acute outbreaks of

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decompensation. The reported 94.8% sensitivity to identify Spo2 less than 94 percent is of special interest, where hypoxemia is likely to be present before overt respiratory signs during exacerbations of heart failure. The system assists in proactive care achievement through warning patients and their caregivers about these early warning signs and adheres to the principles of patient-centered, predictive healthcare.

Economical effects also require an analysis. The NHS is estimated to spend around 2 billion a year in heart failure, and most of these amounts are as a result of hospitalization. Technologies capable of lowering hospitalizations by allowing incorrect intervention at an earlier stage and avoiding acute decompensation can create significant savings of costs and enhance patient outcomes. The CardioMEMS implantable sensor, an example, has shown a 34 percent decrease in heart failure hospitalizations but is associated with hefty upfront costs and the patient has to undergo a surgery that is considered to be complicated. The wearable solution mentioned here is not as technologically advanced as the implantable hemodynamic monitors, but provides an option of a low-cost and non-invasive wearable solution, which could be rolled out to a significantly broader number of patients. Even low level of hospitalization changes when multiplied to those 920,000 heart failure patients alone in the UK alone do represent tens of thousands of prevented admissions annually and hundreds of millions of saved funds every year.

There were some critical limitations and room of improvement as well in the study. GSR sensor exhibited a low hit rate and had a high variability when compared to heart rate sensor and SpO2 sensor, which restricts its use as an alert generator. Nevertheless, its usefulness as an auxiliary parameter in multi- sensor fusion became apparent with the previous shortening of the detection time by adding GSR to the combined analysis. Additional versions of the system might include machine learning algorithms to learn baseline GSR patterns of an individual patient and tune thresholds to these patterns in order to increase the sensitivity and specificity of the system with respect to the main patient. The 8-12 meters range of Bluetooth may be ineffective in the larger houses or in cases where the patients may spend time outdoors and will not be able to touch their smartphone or base station. This limitation could be solved by long-range Bluetooth or WiFi mesh network integration. The increased power usage of the GSM module implies that the battery life might be increased by putting the module in a low-power sleeping state unless an alert is received, a software optimization that will be made in the next version of the system.

The analysis of existing literature shows similarities and novelties. The accuracy rate of the heart rate of 98.7 percent is consistent with the 98.9 percent found in validation tests on paediatric monitoring indicating that consumer-grade sensors can be used to provide clinical-level accuracy under the right conditions. The published standards of medical pulse oximetry in the 0.86>The SpO2 accuracy (mean absolute error) of 0.86 is competitive compared with published standards of medical pulse oximetry, and higher than the performance of some previous wearables. The introduction of GSM as an alternative communication system is a step forward as compared with systems that utilize internet connection as a communication system only, considering the urgently needed reliability in medical alerting systems. The 99.87 percent cross-validated accuracy is higher than most published findings with multi-parameter wearable monitoring systems, which indicates that the association between well-chosen sensors, effective signal processing, and threshold-based the detection algorithm can lead to high performance without using the complex machine learning models that are not always easy to deploy to clinical practice.

User experience feedback derived by use of post study questionnaires was very useful in refining the system. Eighty-seven percent of the respondents said that it was comfortable to use during the waking hours and 73 percent said they would be willing to use it throughout to manage heart failure. The usual recommendations were reduced form factor (said by 42), extended battery life (said by 38), and connectivity with smartphone applications to plot trends (said by 56). These user considerations will influence the design of the next generation of hardware that will aim at reducing the size of the parts to single wearable patches that can be readily found commercially as continuous monitoring patches. The fact that older adults (mean age 68.4 years) received it positively is promising, because this group of people is usually subjected to adversity to using new technologies. The user friendly interface and the easy LCD screen and easy push button controls due to its ease of use also gave high usability scores, which aligned with the design ethos that medical tools used in the path to chronic disease management must be more simple and reliable than complicated and filled with features that may baffle the user.

The result dataset obtained by this study consisting of more than 1.8 million time-recorded physiological measurements alongside clinical annotations is a valuable data source in future studies of the domain of heart failure monitoring. In line with the principles of open science and an increase in openness of biomedical research to share data, de-identified subsets of this dataset will be shared with researchers with appropriate qualifications to support the development of algorithms and validation research. Likewise datasets have been useful in furthering the study, e.g. the SCG-RHC data that has made it possible to estimate pulmonary capillary wedge pressure based on wear ensemble seismocardiogram records . In a bid to advance the vision of reliable, accessible, and effective remote monitoring of all heart failure patients in all geographical locations irrespective of economic status and so forth, we intend to accelerate the goal by sharing our data.

V. CONCLUSION

In this paper, the Smart Heart Failure Monitoring System was introduced, a combination of wearable sensors, data processing relying on Arduino, and multi-modal communication was presented to allow the patient-level, continuous physiological monitoring and prompt clinical deterioration prediction in patients with heart failure. The fact that older adults accept the system highly and the fact that the system can be used with very little technical resources imply

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that it can be deployed in large numbers within the community. The future work will be based on three primary directions: hardware is miniature and reduced to the single type of wearable patch with flexible electronics; machine learning algorithms that allow adapting the threshold specifically to each person, predictive analytics that will possibly allow extending the lead time beyond a few minutes and days; and a large-scale randomized controlled trial that will definitively assess the effect of the system over the outcomes related to hospital readmission rates, quality of life, and healthcare costs. Moreover, the idea of incorporating thoracic impedance sensing could lead to having the targeted pulmonary congestion straight away, which would further increase the system to record the decompensation decrees of heart failure at its lowest possible stages. Wearable IoT-based monitoring systems can change heart failure not only into a condition where its recurring crises are addressed but also when managed proactively within the community and thus achieve better outcomes by lowering both patient, caregiver, and health care burden.

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