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Solar powered internet of things-based heart rate monitoring system employing electrocardiogram signal analysis

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ABSTRACT

Electrocardiogram (ECG) test is used to record the electrical activity of a human heart for determining any problems with irregular heartbeat patterns and other cardiovascular conditions. This project deals with the implementation of an Internet of things (IoT) enabled ECG monitoring system with solar supply that can identify heart rate deviations from normal values (40 BPM, 80 BPM and 120 BMP) utilizing simulated ECG signals. The ECG data acquisition is done by using KL-76001 biomedical measurement training system, KL-75001 ECG module and multiparameter simulator MS400. The acquired ECG signals are processed through Python software to detect R-peaks and R-R interval. The counts of these R-R peaks are utilized in conjunction with the Blynk IoT platform, employing an ESP8266 module for monitoring via a mobile application and LCD display. The system was tested for detecting and monitoring three heart conditions which are bradycardia, normal, and tachycardia and successfully demonstrated alert capabilities for these conditions.

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1. INTRODUCTION

The heart functions as a continuous pump, generating electrical activity with each beat, which can be measured on the body's surface through an electrocardiogram (ECG) to monitor its rhythmic activity and overall function [1]. The device utilized for recording a patient's electrocardiogram is referred to as an electrocardiograph. ECG is a widely used medical test for detecting cardiac abnormalities caused by heart contractions, assessing the effects of cardiovascular medications, and evaluating the performance of pacemakers, making it a preferred tool for diagnosing heart-related conditions [2].

The ECG waveform consists of three key landmarks: the P-wave, QRS complex, and T-wave, each corresponding to specific phases of cardiac activity as in Figure 1. The P-wave reflects atrial contraction, the QRS complex signifies ventricular depolarization and serves as a crucial reference for signal analysis, while the T-wave represents ventricular repolarization [3], [4]. Due to its distinct nature, the R peak within the QRS complex, typically exhibiting the highest amplitude during depolarization, is highly effective for segment localization. The irregularity of the heartbeat and the number of beats per minute (BPM) can be determined using the R-R interval [5] to identify the abnormal heart rhythms.

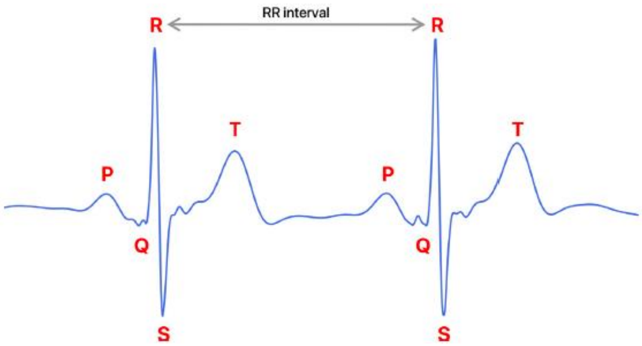

Figure 1. Rhythm heartbeat highlighting the P-QRS-T landmarks [4]

Irregular heartbeats, known as cardiac arrhythmias, result from abnormal electrical impulses in the heart, are classified into two main types: bradycardia, characterized by a heart rate below 60 BPM, and tachycardia, marked by a heart rate exceeding 100 BPM [6], [7] and normal ECG beats ranges from 60–100 BPM in rest [2]. Internet of things (IoT) monitoring widely used in the modern era. IoT monitoring allows for real-time tracking and management of connected devices, providing actionable insights and improving operational efficiency. IoT monitoring enables real-time data collection and analysis across various applications, such as healthcare [8], [9], smart homes [10], water quality monitoring [11]–[13], agriculture [14]–[16] and others for enhancing efficiency and decision-making.

IoT for ECG involves integrating electrocardiogram sensors with internet-connected devices to continuously track and transmit heart activity data [17], [18]. This technology enables real-time remote monitoring [9], [19], allowing healthcare providers to access and analyze ECG data from any location, enhancing early detection of potential cardiac issues [20]. Additionally, IoT-enabled ECG systems can facilitate timely intervention and personalized care by alerting patients and clinicians to significant changes in heart rhythm or abnormalities. Moreover, the combination of field programmable gate array (FPGA), Arduino, IoT technologies, advanced filtering techniques, and powerful software applications makes the portable ECG recorder a robust tool for continuous heart monitoring. This technology not only enhances patient care but also provides healthcare professionals with critical data for timely decision-making [21].

The detection of ECG signals can be achieved through various methods, including R-peak detection [9], R-R interval analysis [5], [17], machine learning techniques [22], [23], and others. Moreover, the research work on IoT based has been introduced in which the Node MCU ESP8266 Wi-Fi module was utilized to transmit ECG data to an IoT cloud, with Blynk 2.0 employed as the IoT platform for data visualization. The program code on this work was developed to capture ECG waveforms and extract key features, including R-R interval, QRS duration, PR interval, QT interval, heart rate variability (HRV), and heart rate [17].

The security of IoT devices is crucial due to their widespread connectivity and potential vulnerabilities, which can be exploited by attackers to gain unauthorized access to networks and sensitive data. Many researches have been done to analyse IoT technology, its components, security features, and the threats associated with each layer to help researchers address critical challenges [24]. Furthermore, the integration of machine learning (ML) and deep learning (DL) techniques into intrusion detection systems represents a transformative advancement in securing industrial internet of things (IIoT) environments. By enabling real-time anomaly detection and dynamic adaptation to cyber threats, these technologies bolster the security framework of industrial systems, addressing the unique challenges posed by the digital transformation in Industry 4.0 [25].

This research addresses the need for portable, sustainable, and real-time cardiac monitoring systems by introducing a solar-powered IoT-based ECG monitoring solution. Traditional ECG monitoring systems are bulky, expensive, and confined to clinical settings, limiting accessibility and continuous monitoring. IoT overcomes these challenges by enabling compact, wearable, and low-cost devices that transmit real-time data via Wi-Fi to cloud platforms, ensuring remote monitoring and enhancing healthcare accessibility and efficiency. Portability in ECG monitoring is essential for patient mobility and real-time health surveillance outside clinical settings. Solar power supports this by providing sustainable energy, reducing battery dependency, and ensuring uninterrupted operation, particularly in remote areas with limited electricity access [20], [26] The proposed system overcomes these limitations by utilizing solar energy to ensure uninterrupted functionality in remote or resource-constrained areas, and by integrating IoT technology for continuous, remote monitoring of heart conditions. Abnormal heart rates—such as bradycardia, normal, and tachycardia—are detected using R-peak and R-R interval analysis algorithms, which demonstrated high accuracy and clinically insignificant bias. Heart rates are classified into three categories (low, normal, high) based on voltage and peak data. Real-time data visualization is achieved through the Blynk IoT platform on both liquid crystal displays (LCDs) and smartphones. This system offers significant potential for early detection of cardiac anomalies, improved patient outcomes, and sustainable healthcare delivery in underserved regions.

2. METHOD

This research presents the implementation of a solar-powered IoT-based heart rate monitoring system employing ECG signal analysis, integrating three primary components: a solar photovoltaic (PV) charging system, ECG signal measurement and analysis, and an IoT monitoring system. The novelty lies in combining signal processing and IoT technology with renewable energy (solar power) to provide a portable, sustainable, and real-time health monitoring solution. ECG signals are acquired using specialized biomedical equipment (KL-76001 biomedical measurement training system, KL-75001 ECG module, and multiparameter simulator MS400) and processed using Python software to detect R-peaks and R-R intervals, which are essential indicators for identifying heart rate conditions such as bradycardia, normal rhythm, and tachycardia. Algorithms based on mathematical equations are developed to compute R-R intervals and detect R-peak amplitudes, demonstrating high accuracy and reliability with minor discrepancies that do not significantly affect clinical interpretation.

The system utilizes the Blynk IoT platform and ESP8266 microcontroller for real-time monitoring via mobile applications and LCD displays, facilitating remote observation of heart conditions and immediate alerts in the presence of abnormal rhythms. This theoretical contribution bridges the gap between conventional ECG analysis and IoT-enabled healthcare systems, with a central emphasis on sustainability through solar-powered operation. The proposed project integrates 3 main systems which are solar PV charging system, ECG signal as reference input and monitoring system with IoT as in Figure 2. Solar charging system as the main supply to the microcontroller ESP8266, therefore, the monitoring system can be used as a portable device. ESP8266 used the reference value from the ECG measurement data as the input, then processing the input condition to the monitoring system which are LCD display and either monitor or smart phone. The measurement system used to collect ECG signal for 40 BPM, 80 BPM and 120 BPM by using KL-76001 biomedical measurement training system, KL-75001 ECG module and multiparameter MS 400. The 3 categories of heart rate conditions were determined using the data acquired: bradycardia (40 BPM), normal (80 BPM), and tachycardia (120 BPM).

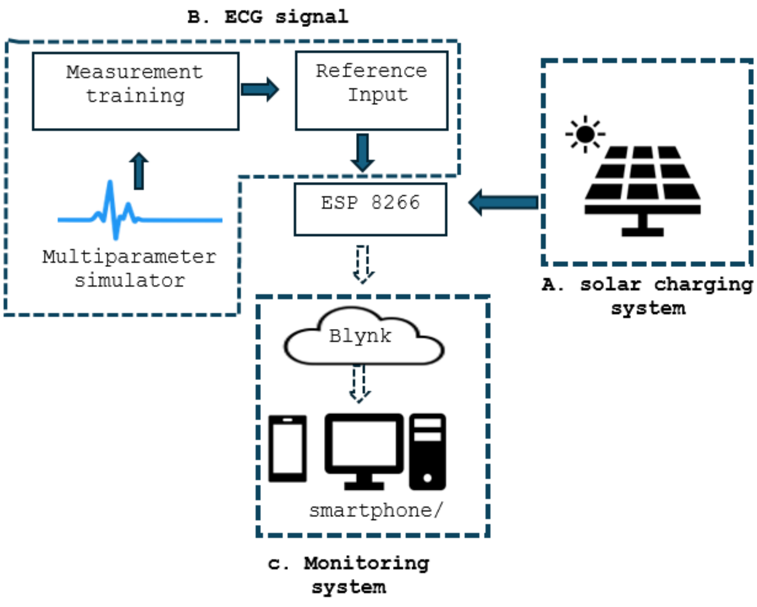

Figure 2. ECG monitoring system

The flow of the proposed project is in Figure 3 in which it illustrates ECG signals at 40 BPM, 80 BPM, and 120 BPM. These signals are analyzed using Python to detect R peak amplitudes, which are then categorized into low, normal, and high status conditions. The diagram illustrates a process for measuring ECG using a multiparameter simulator (MS400). It detects the R-R interval of the heartbeats, categorizing heart rate into three conditions: low (below 5 beats detected), normal (5 to 10 beats), and high (above 10 beats). LEDs indicate the heart rate status with yellow for low, green for normal, and red for high BPM.

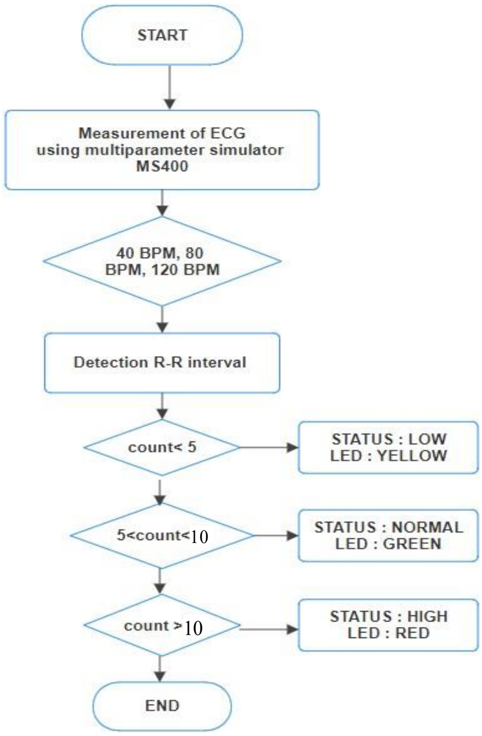

Figure 3. Flow of the project

2.1. Solar PV charging system

A solar PV charging system is one of the part in the proposed project as a main DC supply to the system. The PV charging system consists of photovoltaic cells that produce direct current (DC) upon exposure to sunlight. A solar charge controller manages the voltage and current produced by the solar panels before it reaches the battery bank, thereby preventing overcharging. The battery bank stores the electrical energy generated by the solar cells for utilization during periods when sunlight is not present. The solar charging system as in Figure 4.

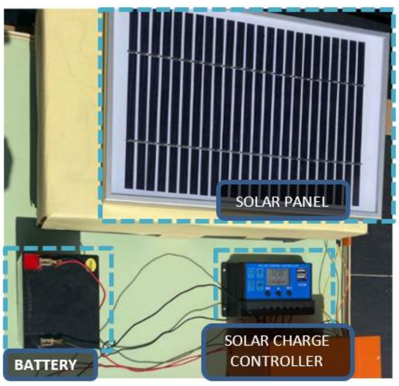

Figure 4. The solar charging system

2.2. ECG signal measurement and analysis

In the proposed project, data collection and evaluating the functionality of the system designed for biomedical measurements, specifically focusing on ECG signals. The laboratory setting, as in Figure 5, provided a controlled environment where instruments were employed to read and collect diverse ECG data. ECG signal is simulated by multiparameter S400, meanwhile ECG measurement set; KL-76001 biomedical measurement training system, KL-75001 ECG Module processes the ECG signal. The obtained ECH signal is displayed on the monitor This data collection process aims to obtain the ECG signal under different heart rate conditions (bradycardia, normal, and tachycardia), with the ECG signals expressed in beats per minute (40 BPM, 80 BPM and 120 BPM).

Figure 5. ECG signal measurement

The obtained ECG signal for 15 seconds are analyzed using Python by detecting the both number of the amplitute and R-R peak interval in seconds using the amplitude R peak detection algorithm and R-R interval time algorithm. The developed algotithms are based on (1)-(4).

$$BPM = \frac{60}{R\_R_{int}} \tag{1}$$

where R_R_{int} (in seconds) is the time between two successive R peaks which respond to one cardiac cycle. Thus,

$$R\_R_{int} = \frac{60}{BPM} \tag{2}$$

when measuring the ECG signal generated by the multiparameter S400, the biomedical measurement unit produces a sample count, N_{sample} .Using the sample rate over the duration of time, $T_{duration}$, the sampling rate, f_s is provided in Hz.

$$f_s = \frac{N_{sample}}{T_{duration}} \tag{3}$$

Thus, the equation to compute the R-R interval, $R\text{-}R_{intps}$, using Python software is derived from the provided ECG signal. The ECG signal measurement yields 799 samples for heart rates of 40 BPM, 80 BPM, and 120 BPM. Consequently, with 799 samples collected over 15 seconds, the sampling rate, fs is calculated to be 53.27 Hz.

$$R\_R_{intps} = \frac{N_{RR}}{f_s} \tag{4}$$

where N_{RR} is the detected difference between each consecutive pair of R peaks in which it is the number of samples between each pair of consecutive heartbeats. By dividing the differences in samples by the sampling rate, the differences convert from units of samples to units of time in seconds. This gives the time intervals between consecutive heartbeats, which are the R-R intervals.

The local maxima condition is applied to identify the R peak in signal analysis by checking if a point in a dataset or function exceeds its immediate neighbors. Equations (5)-(8) represent the criteria for determining the desired peaks. A sample $S(i)$ is considered a peak if it is greater than its neighboring samples $S(i-1)$ and $S(i+1)$, as in (5). Additionally, the peak must exceed a minimum height threshold, h_{min} and represent by (6).

$$S(i) > S(i-1) \; and \; S(i+1) \tag{5}$$

$$S(i) \geq h_{min} \tag{6}$$

If peaks are detected at indices $P = \{p_1, p_2, ..., p_n\}$, then must also satisfy a minimum distance constraint, d_{min} as in (7) where d_{min} depends on the sampling frequency, f_s and heart rate in BPM as in (8). Therefore, bradycardia, normal, and tachycardia were determined.

$$|p_i - p_{i-1}| \geq d_{min} \tag{7}$$

$$d_{min} = \frac{60}{BPM} x \, f_s \tag{8}$$

2.3. IoT monitoring system

Integrating NodeMCU ESP8266 with ECG data using the Arduino IDE involves reading ECG signals from sensors and transmitting the data to a remote server for monitoring. ECG signal from biomedical measurement set are analyzed and The count of amplitude R peaks are obtained to make it for the input reference to microcontroller ESP8266. ECG signal with 40 BPM, 80 BPM and 120 BPMs gives different number of the cound value. Thus, the conditions are set to categorize these value. Overall, The ESP8266 processes the ECG signal, monitors voltage levels, counts R-R intervals, and categorizes heart rate status based on the data. The connection between the ESP8266, voltage sensor and LCD as in Figure 6.

The NodeMCU ESP8266, an open-source IoT platform based on the ESP8266 Wi-Fi module, connects ECG sensors to the internet by reading analog voltage inputs from a sensor, pin A0. It scales and displays the amplitude on an LCD. If the voltage exceeds predefined thresholds, it increments a count displayed on the LCD. The system determines heart rate status (LOW, NORMAL, HIGH) based on BPM frequencies (40, 80, or 120 BPM). ESP8266 processes ECG signals using its ADC for R-peak detection and Wi-Fi for data transmission to the Blynk IoT platform. The application of IoT systems is implemented through the Blynk library, which enables effective communication between the ESP8266 and the Blynk server. Monitoring of the peak count and the status of the ECG signal is conducted using both an LCD display and a smartphone. This dual monitoring approach enhances the accessibility and usability of the data.

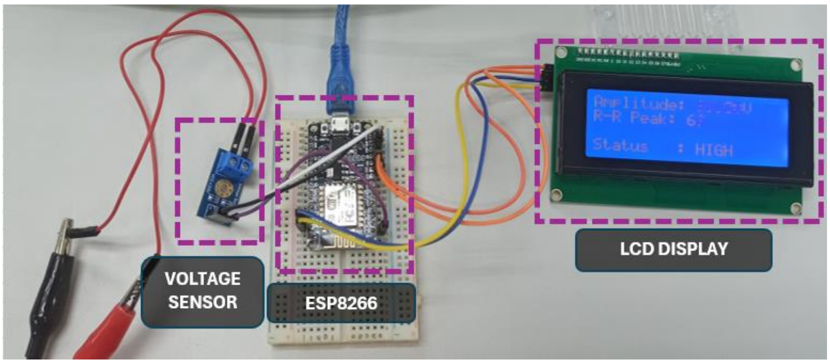

Figure 6. Monitoring system

3. RESULTS AND DISCUSSION

The IoT-based ECG monitoring system using ESP8266 for heart rate detection via R-R peak analysis has been successfully developed, adhering to the methodology outlined, and the proposed project has undergone measurement and analysis. The outcome is comprised of three primary components of the ECG monitoring system: a solar PV charging system, ECG measurement and analysis and an IoT Blynk monitoring system.

3.1. Solar PV charging system measurement

Data recording in solar PV systems involves capturing and analyzing various parameters related to system performance, energy production, and environmental factors. The data recorded from 8 am until 8 pm in a solar PV system provides a system's performance during daylight hours. Figure 7 illustrates the behaviour of voltage, current, and power in a solar system over the course of a day. Voltage exhibits a gradual increase starting from 8:00 am, peaking around midday, and then sharply decreasing towards 8:00 pm. Current remains relatively low and stable throughout the day, indicating minimal variation in amperage. Power, derived from the product of voltage and current, shows a similar trend to voltage but with a more moderate increase and decrease. The sharp drop in all measurements towards the end of the day likely corresponds to the reduction of sunlight as evening approaches. These trends highlight the typical performance of a solar system in response to changing solar irradiance throughout the day.

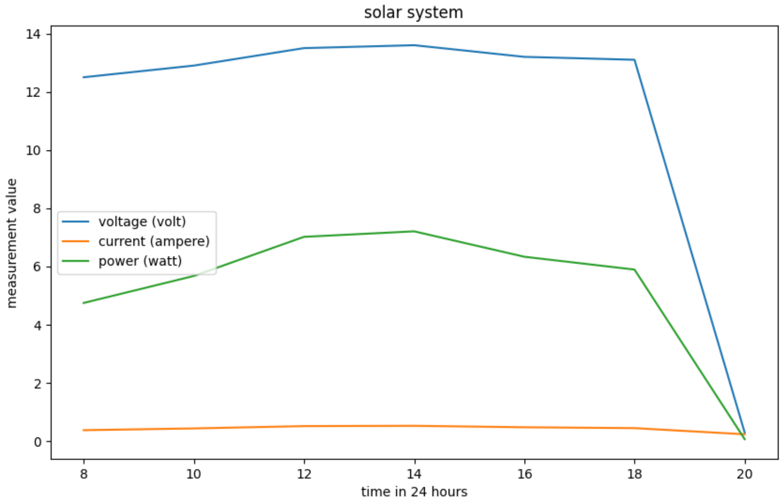

Figure 7. Monitoring system

3.2. ECG measurement and analysis

The measurement of electrocardiograms is a crucial part of this study effort since the three different types of heart rates; bradycardia, normal, and tachycardia in which it can only be identified by analyzing the ECG signal. The ECG monitors the time intervals between the electrical signals during each cardiac cycle, allowing for the precise calculation of the beats per minute. A normal resting heart rate typically falls within the range of 6 to 10 R-R peaks and more than 11 is 120 BPM for 5 seconds time frame. The ECG signal data from the biomedical measurement unit and multiparameter S400 is shown in Figure 8.

The obtained ECG measurement data then analyzed in Python software for the number counts on R peaks and R-R interval in seconds. Amplitude of the R peaks are obtained in Python software and presented in Figure 9. Based on data collection using ECG module, the collected data more than 7 peaks from ECG signal as refering to a normal functionality of heart rate at R-R interval signal. The output of the ECG signals of the three conditions heart rates (40 BPM, 80 BPM, and 120 BPM) was determined based on ECG module for 15 seconds. These ECG signals wre analyzed using Python software for the both amplitude R peak detection and R-R interval detection, the results as in as in Table 1 and Table 2 respectively.

The analysis of Table 1 shows that the amplitude R peak detection algorithm is generally accurate and reliable, with a high degree of agreement between the detected and calculated values. However, there are some discrepancies, particularly at the 5-second window for 40 BPM (20% error) and 120 BPM (10% error). The algorithm appears to be correctly identifying the R peaks, with a slight bias towards overestimation at higher heart rates. Further analysis and testing may be necessary to confirm these findings and to evaluate the algorithm's performance in different scenarios.

The analysis of Table 2 shows that the R-R interval detection algorithm is accurate and reliable, with a high degree of agreement between the detected and calculated values. The algorithm appears to be correctly identifying the R-R intervals, with a slight bias towards underestimation. Specifically, the percentage errors are 6% for 40 BPM, 5.33% for 80 BPM , and 6% for 120 BPM. However, this bias is small and may not be clinically significant. Further analysis and testing may be necessary to confirm these findings and to evaluate the algorithm's performance in different scenarios.

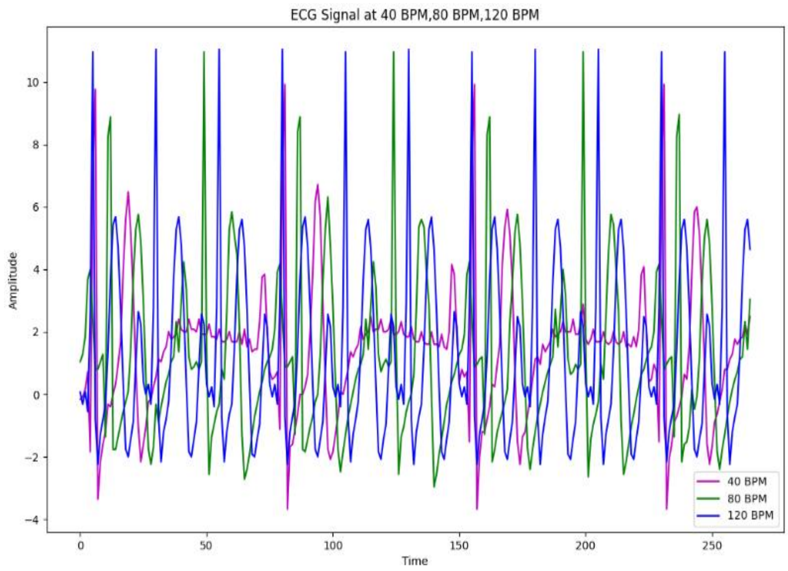

Figure 8. Combination ECG graph for 40 BPM, 80 BPM and 120 BPM for 5 seconds (measurement)

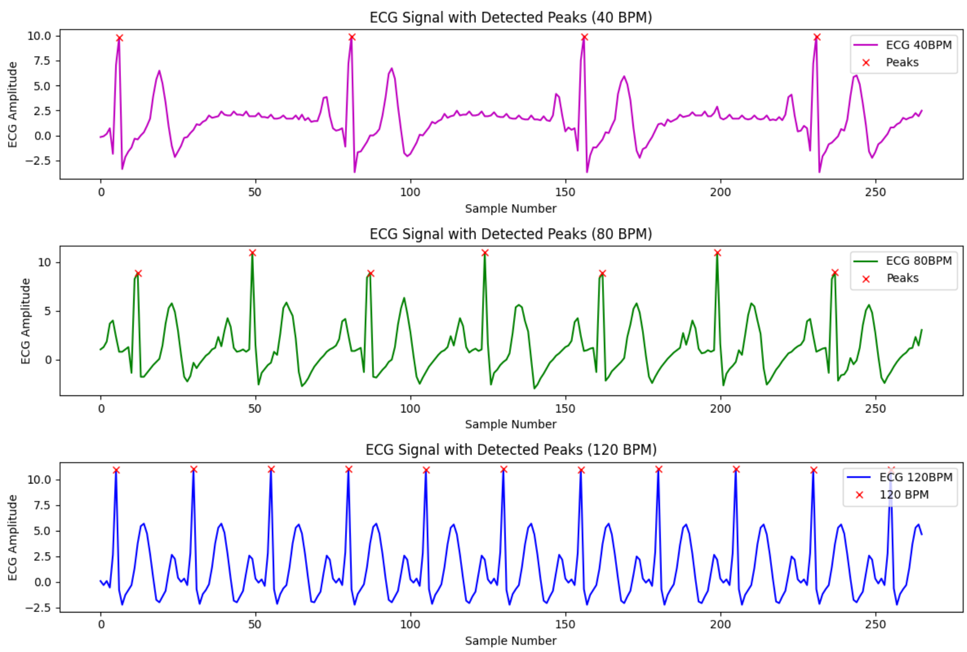

Figure 9. ECG graph for 40 BPM, 80 BPM and 120 BPM for 5 seconds (R peak detected)

Table 1. Number of the amplitude R peak

Parameter	5 seconds			10 seconds			15 seconds		
	Detect	Calculated	% error	Detect	Calculated	% error	Detect	Calculated	% error
40 BPM	4	5	20	7	7	0	11	10	10
80 BPM	7	7	0	14	13	7.7	21	20	5
120 BPM	11	10	10	21	20	5	32	30	6.67

Table 2. R-R interval detection in seconds

Parameters	15 seconds		
	Detect	Calculated	% error
40 BPM	1.41s	1.5s	6
80 BPM	0.71s	0.75s	5.3
120 BPM	0.47s	0.5s	6

Based on the data obtained, correlation coefficient is calculated to verify the algorithm’s accuracy by measuring how closely detected values match true values, ensuring reliable performance. Table 3 shows correlation coefficients for R-peak and R-R interval detection across heart rates (40, 80, 120 BPM). Amplitude R-peak detection achieves coefficients of 0.999, indicating excellent agreement between detected and calculated values. The R-R interval detection records a perfect 1.00 correlation, confirming its accuracy. The R-R interval values in Table 2 are presented as overall because the values represent average measurements over the 15-second window. This approach simplifies the data, reduces variability, and aligns with the study's focus on classifying heart rate conditions These near-perfect results demonstrate the algorithms' effectiveness in identifying R peaks and R-R intervals, validating the data in real-time monitoring. However, further testing with noisy or diverse datasets is needed to evaluate performance in challenging conditions.

This study has limitations, including the use of simulated ECG signals, which may not fully replicate real-world variability, and a limited sample size of 799 samples across three heart rates. Future research should focus on testing real-time ECG data from diverse populations to enhance accuracy and robustness. Additionally, incorporating advanced signal processing techniques and machine learning could improve detection under noisy conditions. Further validation in clinical settings is essential to ensure reliability for practical applications.

Table 3. Amplitude R and R-R detection correlation coefficient

Parameters	Amplitude R	R-R
40 BPM	0.999	
80 BPM	0.998	1.00 (overall)
120 BPM	0.997	

3.3. ECG monitoring with IoT

Based on the detected level in Table 4, the conditions are set for 5 seconds time frame for 40 BPM, 80 BPM and 120 BPM in which the counts are 4, 7 and 11 that converted to the voltage detection of 7 volts. The conditions are crucial for developing the IoT-based heart rate monitoring system. If the voltage exceeds 7 volts, the system increments a count and shows it on the LCD. The frequency of the counts is used to determine the system status (low, normal, high) for heart rates of 40 BPM, 80 BPM, and 120 BPM. This status is then displayed on the LCD and sent to the Blynk application for monitoring. Figure 10 shows a Blynk IoT system interface for heart rate detection, where the circular gauge displays the detected voltage level. The three different colors (yellow, green, and red) represent various heart rate zones: low, normal, and high, respectively. Additionally, an number of "R-R Interval Peak" is displayed at the bottom.

Table 4. Monitoring condition status

ECG signal	Parameters		
	Count	Conditions	Status
40 BPM	4	<5	Low
80 BPM	7	5<count<10	Normal
120 BPM	11	>10	High

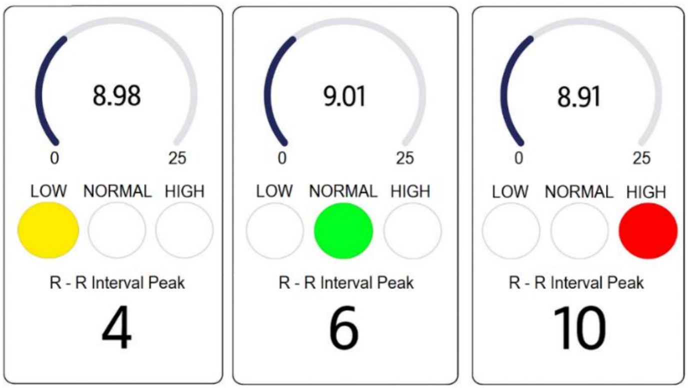

Figure 10. Interface Blynk IoT system

4. CONCLUSION

The proposed project has been done successfully focuses in three major part, solar charging system, EGG data measurement and analysis for 40 BPM , 80 BPM and 120 BPM and IoT monitoring system. The measurement signal has been done for 15 seconds times frame with 799 samples. The R-R interval detection algorithm and the amplitude R peak detection algorithm both demonstrate a high degree of accuracy and reliability, with some minor discrepancies and biases that may not be clinically significant. Overall, the results shows that the algorithms are effective in detecting R-R intervals and R peak amplitudes, but further analysis and testing may be necessary to confirm these findings and evaluate their performance in different scenarios. Future work could involve evaluating the performance of the R-R interval detection and amplitude R peak detection algorithms in more diverse and challenging datasets, such as those with noise to further assess their robustness and reliability. Leveraging the detection of R-peak occurrences, the IoT monitoring system has been successfully developed to identify and display the number of peaks on a smartphone interface. Future enhancements could focus on incorporating real-time measurement capabilities to improve the system's performance. Developed algorithms for R-peak detection and R-R interval analysis demonstrated high accuracy, enabling early detection of abnormal heart rhythms and improving patient outcomes. With its potential for global health impact, particularly in underserved and energy-limited regions, this system represents a novel, multidisciplinary approach to next-generation remote healthcare solutions.

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REFERENCES

[1] M. Sraitih, Y. Jabrane, and A. Atlas, "An overview on machine learning methods for ECG heartbeat arrhythmia classification," in *2021 International Conference on Digital Age & Technological Advances for Sustainable Development (ICDATA)*, Jun. 2021, pp. 8–14, doi: 10.1109/ICDATA52997.2021.00012.

[2] P. Lamba and K. Rawal, "A survey of algorithms for feature extraction and feature classification methods," in *2019 International Conference on Automation, Computational and Technology Management (ICACTM)*, Apr. 2019, pp. 338–341, doi: 10.1109/ICACTM.2019.8776804.

[3] B.-T. Pham, P. T. Le, T.-C. Tai, Y.-C. Hsu, Y.-H. Li, and J.-C. Wang, "Electrocardiogram heartbeat classification for arrhythmias and myocardial infarction," *Sensors*, vol. 23, no. 6, p. 2993, Mar. 2023, doi: 10.3390/s23062993.

[4] M. Kapsecker, N. Charushnikov, L. Nissen, and S. M. Jonas, "PeakSwift: mobile detection of R-peaks in single lead electrocardiograms," *SoftwareX*, vol. 25, p. 101608, Feb. 2024, doi: 10.1016/j.softx.2023.101608.

[5] T. Preethi, S. Shanmuga Priya, K. Arun Patrick, S. Sarkar, C. Jency, and N. Kumareshan, "ECG R-R interval automatic detection using IoT," in *2022 IEEE North Karnataka Subsection Flagship International Conference (NKCon)*, Nov. 2022, pp. 1–7, doi: 10.1109/NKCon56289.2022.10126731.

[6] M. Wasimuddin, K. Elleithy, A. S. Abuzneid, M. Faezipour, and O. Abuzaghleh, "Stages-based ECG signal analysis from traditional signal processing to machine learning approaches: A survey," *IEEE Access*, vol. 8, pp. 177782–177803, 2020, doi: 10.1109/ACCESS.2020.3026968.

[7] S. Naik, S. Debnath, and V. Justin, "A review of arrhythmia classification with artificial intelligence techniques: deep vs machine learning," in *2021 2nd International Conference for Emerging Technology (INCET)*, May 2021, pp. 1–14, doi: 10.1109/INCET51464.2021.9456394.

[8] C. R. Srinivasan, G. Charan, and P. C. Sai Babu, "An IoT based SMART patient health monitoring system," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 18, no. 3, pp. 1657–1664, Jun. 2020, doi: 10.11591/ijeecs.v18.i3.pp1657-1664.

[9] S. Rahman, C. Karmakar, J. Yearwood, and M. Palaniswami, "A real-time tunable ECG noise-aware system for IoT-enabled devices," *IEEE Sensors Journal*, vol. 22, no. 23, pp. 23277–23285, Dec. 2022, doi: 10.1109/JSEN.2022.3211318.

[10] C. Sisavath and L. Yu, "Design and implementation of security system for smart home based on IOT technology," *Procedia Computer Science*, vol. 183, pp. 4–13, 2021, doi: 10.1016/j.procs.2021.02.023.

[11] M. Singh, K. S. Sahoo, and A. H. Gandomi, "An intelligent-IoT-based data analytics for freshwater recirculating aquaculture system," *IEEE Internet of Things Journal*, vol. 11, no. 3, pp. 4206–4217, Feb. 2024, doi: 10.1109/JIOT.2023.3298844.

[12] A. C. D. S. Júnior, R. Munoz, M. D. L. Á. Quezada, A. V. L. Neto, M. M. Hassan, and V. H. C. De Albuquerque, "Internet of water things: a remote raw water monitoring and control system," *IEEE Access*, vol. 9, pp. 35790–35800, 2021, doi: 10.1109/ACCESS.2021.3062094.

[13] Y. Wang, I. W. H. Ho, Y. Chen, Y. Wang, and Y. Lin, "Real-Time water quality monitoring and estimation in AIoT for Freshwater biodiversity conservation," *IEEE Internet of Things Journal*, vol. 9, no. 16, pp. 14366–14374, Aug. 2022, doi: 10.1109/JIOT.2021.3078166.

[14] R. Perwiratama, Y. K. Setiadi, and Suyoto, "Smart hydroponic farming with IoT-based climate and nutrient manipulation system," in *2019 International Conference on Artificial Intelligence and Information Technology (ICAIIT)*, 2019, pp. 129–132, doi: 10.1109/ICAIIT.2019.8834533.

[15] A. F. Subahi and K. E. Bouazza, "An intelligent iot-based system design for controlling and monitoring greenhouse temperature," *IEEE Access*, vol. 8, pp. 125488–125500, 2020, doi: 10.1109/ACCESS.2020.3007955.

[16] A. A. Araby and others, "Smart IoT monitoring system for agriculture with predictive analysis," in *2019 8th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, 2019, pp. 20–23, doi: 10.1109/MOCAST.2019.8741794.

[17] M. Aqib, A. Alam, and A. Q. Ansari, "IoT based ECG system for arrhythmia detection using telemetry monitoring," in *2022 9th*

International Conference on Computing for Sustainable Global Development (INDIACom), 2022, pp. 437–442, doi: 10.23919/INDIACom54597.2022.9763246.
[18] A. Rahman, T. Rahman, N. H. Ghani, S. Hossain, and J. Uddin, "IoT based patient monitoring system using ECG sensor," in *2019 1st International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST)*, 2019, pp. 378–382, doi: 10.1109/ICREST.2019.8644065.
[19] A. F. Ghifari and R. S. Perdana, "Minimum system design of the IoT-based ECG monitoring," in *2020 7th International Conference on ICT for Smart Society (ICISS)*, 2020, pp. 2–7, doi: 10.1109/ICISS50791.2020.9307590.
[20] P. K. Vishwakarma and R. Singh, "A-review on IoT-assisted ECG monitoring framework for health care applications," in *2021 4th International Conference on Computer, Communication and Computational Technologies (CCICT)*, 2021, pp. 203–207, doi: 10.1109/CCICT53244.2021.00047.
[21] N. R. R. Raj, E. Priya, and G. F. Savari, "Design and implementation of portable electrocardiogram recorder with field programmable gate arrays and IoT interface," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 5, pp. 5176–5181, 2022, doi: 10.11591/ijece.v12i5.pp5176-5181.
[22] A. P. Shrestha and C. H. Yu, "ECG data analysis with iot and machine learning," in *2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC)*, 2022, pp. 323–327, doi: 10.1109/CCWC54503.2022.9720851.
[23] S. Satheeskumaran, K. Sasikala, K. Neeraj, A. Senthilkumar, and N. S. Babu, "IoT based ECG signal feature extraction and analysis for heart disease risk assessment," in *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, 2023, pp. 1060–1066, doi: 10.1109/ICSCSS57650.2023.10169414.
[24] A. A. Abbood, Q. M. Shallal, and M. A. Fadhel, "Internet of things (IoT): a technology review, security issues, threats, and open challenges," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 20, no. 3, pp. 1685–1692, 2020, doi: 10.11591/ijeecs.v20.i3.pp1685-1692.
[25] L. Idouglid, S. Tkatek, K. Elfayq, and A. Guezzaz, "Next-gen security in IIoT: integrating intrusion detection systems with machine learning for industry 4.0 resilience," *International Journal of Electrical and Computer Engineering*, vol. 14, no. 3, pp. 3512–3521, 2024, doi: 10.11591/ijece.v14i3.pp3512-3521.
[26] P. Kamble and A. Birajdar, "IoT based portable ECG monitoring device for smart healthcare," in *2019 5th International Conference on Science, Technology, Engineering and Mathematics (ICONSTEM)*, 2019, vol. 1, pp. 471–474, doi: 10.1109/ICONSTEM.2019.8918776.

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