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Implementation of Heart Rate System using AD8232 and Arduino Microcontrollers

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ABSTRACT

The human heart's pivotal role in maintaining overall health by ensuring oxygen and nutrient delivery to tissues and waste elimination highlights the global importance of cardiac health. Electrocardiography (ECG) is a fundamental tool for assessing cardiac conditions, capturing intricate electrical signals during each heartbeat. ECG sensors are instrumental in this process, finding extensive applications in personal health monitoring, disease management, and medical research. This article emphasizes the significance of ECG sensors, particularly the AD8232 ECG sensor paired with the Arduino Nano microcontroller. It outlines their operational principles, measurement methods, and signal-processing techniques. The research aims to enhance the accuracy and efficiency of ECG data capture, contributing to advanced cardiac monitoring systems. Intelligent systems employing biopotential sensors and electrocardiographs enhance diagnostic precision, minimizing interpretational errors. ECG sensors, which record and translate the heart's electrical activity into interpretable data, are integral to modern medicine. They are used in diverse settings, from clinical environments to personal health monitoring. Ensuring ECG sensor accuracy is critical, as the data directly impacts diagnosis and treatment. This article offers insights into fundamental principles, measurement procedures, and programming techniques for ECG sensors, facilitating efficient data capture and processing. These findings promise user-friendly cardiac monitoring systems advancements, significantly contributing to medical technology and healthcare.

1. Introduction

The prevalence of heart disease [1] as a leading global cause of mortality underscores the utmost importance of prioritizing cardiac health. Electrocardiography (ECG) stands as a cornerstone in evaluating cardiac conditions, capturing intricate electrical signals generated during each heartbeat and aiding in diagnosing irregularities [2]. ECG analysis encompasses determining heart rates and classifying signals as either normal or indicative of arrhythmias [3], [4], with noise reduction as a fundamental preprocessing step. The judicious selection of features further enhances signal classification accuracy while concurrently mitigating computational complexity [5]. Intelligent systems harness biopotential sensors and electrocardiographs to elevate diagnostic precision, thus minimizing the likelihood of interpretational errors. The ECG sensor, a linchpin in medicine, is a crucial instrument for recording the electrical activity of the human heart. These sensors can gauge the electrical signals emanating from the heart and translate them into interpretable data. ECG sensors have proliferated across diverse applications, spanning personal health monitoring [6], heart disease management[1], and cutting-edge medical research endeavors.

These sensors are applied in medical devices used outside clinical settings, such as heart monitoring during sleep [7], [8], sleep apnea [9], [10], heart monitoring during exercise [11], and even in portable devices [12], [13] that allow users to follow their heart health in real time. The accuracy and performance of ECG sensors are crucial in this aspect, as the information provided by these sensors can directly impact diagnosis and treatment.

Therefore, it is essential to discuss the ECG sensor to understand the basic principles of operation, appropriate measurement methods, and signal processing techniques needed to produce valuable data. One increasingly popular method is utilizing the AD8232 ECG sensor with a microcontroller like the Arduino Nano. This sensor has advantages in size, power and sufficient signal processing capabilities.

This paper outlines the theoretical basis, measurement methods and programming techniques for ECG sensors, especially using the AD8232 and Arduino Nano. We will explain the working principle of the ECG sensor, the steps to connect it to the Arduino Nano, and the programming techniques required to capture and process ECG data efficiently. The results of this research can significantly contribute to developing more sophisticated and easy-to-use cardiac monitoring systems.

2. Method

In this section, we embark on a comprehensive exposition encompassing the foundational principles of Electrocardiography (ECG), expounding upon the intricate facets of system design, which include the system block diagram and the flowchart system. Additionally, we delve into the intricacies of the wiring diagram system. This multifaceted exploration is the bedrock for understanding the ECG sensor's operation, the meticulous orchestration of system components, and the precise delineation of wiring connections. Such in-depth comprehension is pivotal for developing sophisticated and efficient cardiac monitoring systems, facilitating advancements in cardiovascular [14] health management.

2.1. ECG

The human heart, a vital organ responsible for blood circulation throughout the body, is essential for supplying oxygen and nutrients while removing waste products [15]. The global prevalence of heart diseases, a leading cause of mortality, underscores the critical importance of heart health maintenance. Electrocardiography (ECG) plays a pivotal role in assessing cardiac conditions by capturing electrical signals during heartbeats [16], [17], aiding in diagnosing abnormalities [18]. ECG analysis involves identifying heart rates and classifying signals [1], [19]-[21] as typical or indicative of arrhythmias. ECG signals provide graphical representations of the heart's electrical activity over time [22], characterized by distinctive waveforms and intervals, including the significant PQRST complex, contributing to a comprehensive understanding of cardiac health:

P-Wave: The P-wave is the first deflection seen in the ECG signal. It represents atrial depolarization, the electrical activation of the atria (the heart's upper chambers). The P-wave indicates the initiation of the heart's contraction process, where the atria contract to push blood into the ventricles [4].

QRS Complex: The QRS complex is a group of three waves (Q, R, and S) that follow the P-wave. It represents ventricular depolarization, the electrical activation of the ventricles (the heart's lower chambers). This depolarization leads to ventricular contraction, the main event of each heartbeat. The R-wave is typically the highest and most prominent wave in the QRS complex [12].

T-Wave: Following the QRS complex, the T-wave appears. It represents ventricular repolarization, which is the recovery of the ventricles after contraction. This phase prepares the heart for the next cycle of depolarization and contraction [12].

These components together form the PQRST complex, providing critical information about the heart's electrical activity and ability to contract effectively. Any abnormalities or deviations from the normal shape and timing of these waves can signal underlying heart issues and are carefully analyzed by medical professionals during ECG interpretation. Understanding the PQRST complex is essential for diagnosing arrhythmias, myocardial infarction, and other cardiac disorders. Fig. 1 shows the ideal ECG signal.

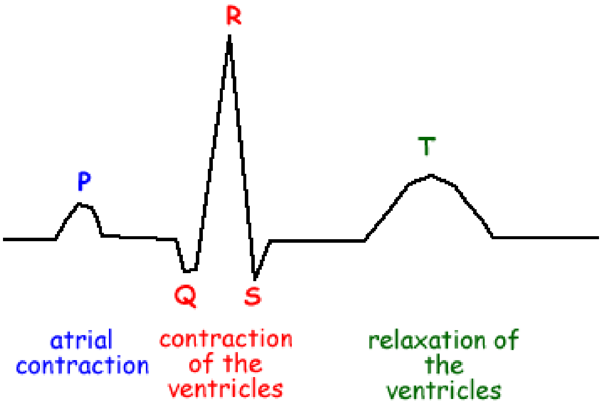

Fig. 1. ECG PQRST signals

A sampling approach is employed to ascertain the heart rate within a minute, wherein two or more Electrocardiography (ECG) signals are utilized. Heart rate calculation entails measuring time intervals between consecutive R-wave signals, which are then transformed into time units (in seconds). Equation 1 elucidates the methodology for computing the temporal gap between R-wave signals, while Equation 2 outlines the procedure for determining beats per minute (BPM).

$$diff\ R\ peaks\ (s) = \frac{diff\ R\ peaks}{sampling\ rate} \tag{1}$$

$$BPM = \frac{60}{diff\ R\ peaks\ (s)} \tag{2}$$

2.2. System Design

The system design in this research comprises various components, including the system block diagram, wiring diagram, and flowchart. Fig. 2 illustrates the system block diagram, visually representing the different elements and their interconnections.

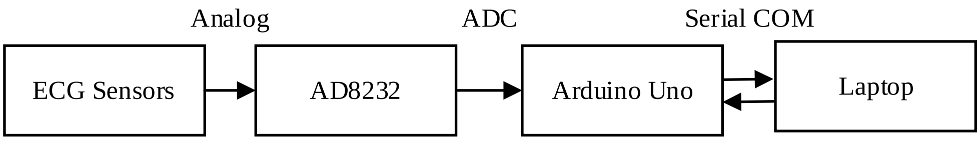

Fig. 2. System block diagram

In this research, Fig. 2 is a visual representation System Block Diagram where ECG signals transform from analog to digital form for comprehensive analysis. Three essential ECG sensors interface with the AD8232, facilitating the acquisition of valuable analog ECG data. The AD8232 sensor is pivotal in converting these analog signals into precise digital data. The Arduino Nano microcontroller then takes center stage, harnessing its computational capabilities to decode and interpret digital signals. This orchestrated process doesn't conclude with the Arduino Nano; instead, it extends to a digital dialogue via serial communication with a laptop. This interaction enables real-time display of ECG waveforms on the laptop screen and the systematic archival of recorded ECG data for future analysis. The intricate choreography illustrated in Fig. 2 signifies the seamless transition of ECG signals from analog origins to a digital legacy, ready for in-depth scientific exploration and insights. Fig. 3 shows the flowchart of the system.

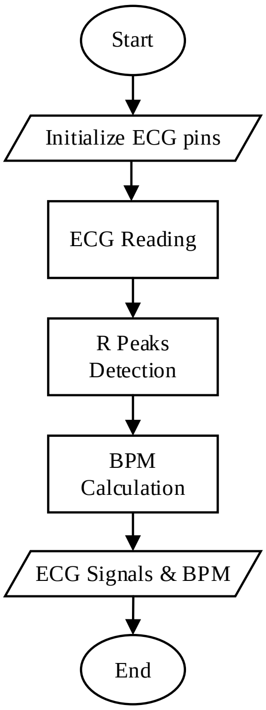

Fig. 3. Flowchart system

In this research, we introduce the system's workflow, succinctly depicted in Fig. 3, elucidating the comprehensive process of the Heart Rate Monitoring System. Commencing with the Initialization of ECG pins, this crucial phase involves precisely placing three ECG sensors on the body following established standards ECG placements. The subsequent ECG Reading block engages the Arduino's ADC in acquiring raw ECG data. Following the data acquisition, the BPM Calculation block takes center stage, diligently computing the heart rate by analyzing the temporal differences between R waves. The culmination of this intricate process yields two essential outputs: raw ECG signals and meticulously calculated BPM values. These outputs constitute the core outcomes of the Heart Rate Monitoring System, offering invaluable insights into cardiovascular health.

2.3. Wiring Diagram

Fig. 4 shows the system's wiring diagram, which involves connecting Analog Pin 0 to the output of the AD8232 sensor for ECG signal acquisition. The AD8232 sensor is powered through the 3.3V output provided by the Arduino Nano, and a solid grounding connection is established by linking the sensor's ground to the Arduino Nano's ground terminal [23].

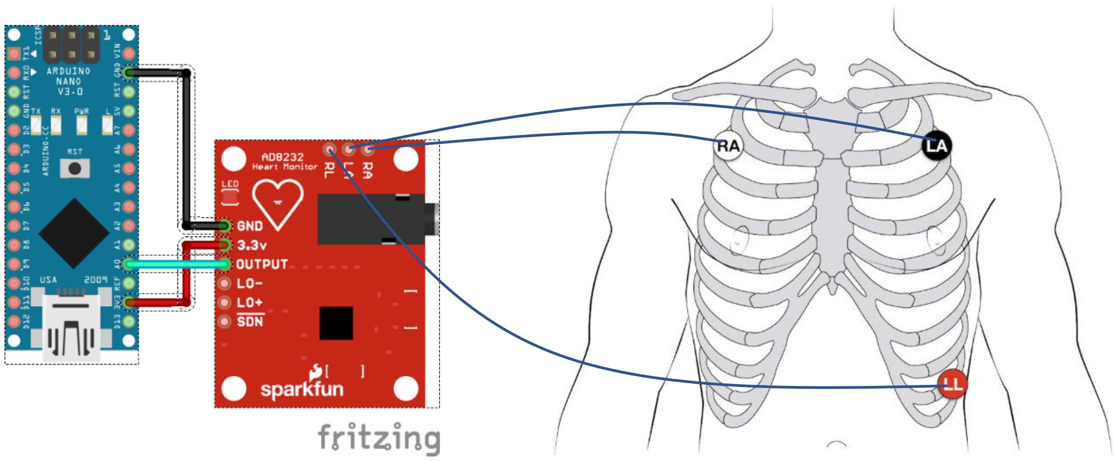

Fig. 4. Wiring diagram system

3. Results and Discussion

In this research, we delve into the intricate realm of electrocardiography (ECG) signal analysis, where the primary objectives encompass the precise calculation of heart rate measured in beats per minute (BPM) within a one-minute timeframe, alongside the sophisticated task of recognizing distinct ECG signal components, notably the PQRST waveforms. This investigation embarks on a journey that transcends the conventional boundaries of cardiovascular monitoring, aiming to unearth valuable insights and methodologies that hold significance in clinical practice for biomedical research.

3.1. ECG Analog Reading

In this section, we meticulously explore the intricate process of reading Electrocardiogram (ECG) signals through the harmonious integration of Arduino Nano and the ADC AD8232 sensor. The narrative unfolds against the backdrop of precision as we meticulously install three sensor leads at strategically chosen locations on the chest. Within this orchestrated endeavor, we engage the analog pins with dexterity to capture the subtle nuances of the ECG signals while maintaining a commendable sampling rate of 200 Hz. As we delve into the depths of this process, Fig. 5 emerges as an indispensable visual aid, offering a clear and insightful perspective on the interconnected facets of this complex operation.

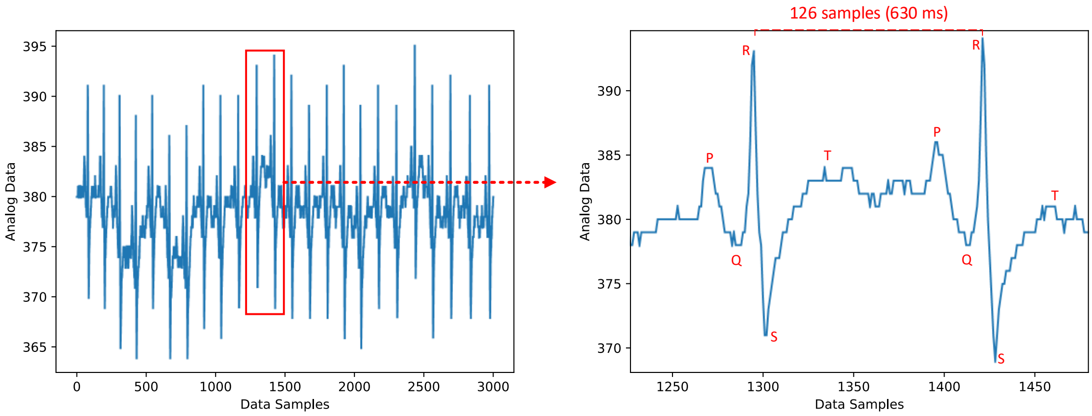

Fig. 5. ECG analog sample

Based on Fig. 5, the results of taking ECG data signals. Throughout 3000 samples, corresponding to a 15-second interval, our algorithm detected 25 discernible heartbeats, each prominently marked by a towering spike signal. However, it is crucial to acknowledge the prevailing challenge: the signal's persistence of noise. This pervasive element tends to obfuscate the clarity of ECG signal readings, rendering them less aesthetically presentable. This noise interference demands prudent consideration for further refinements in signal processing. Notably, a discerning eye may observe the inherent instability in the ECG signal readings. This manifests in the non-uniformity and fluctuations within the peak point of the R signal, a phenomenon particularly prominent within the sample 800-1100 on the dataset. Intriguingly, the ECG analog signal experiences a transient drop, followed by a return to normalcy. This intriguing behavior may be attributed to the absence of a reference electrode, which serves as a grounding point within the body, thereby exerting a discernible influence on ECG signal fidelity. While these findings underscore particular challenges, they also beckon opportunities for further research and refinement in the domain of ECG signal analysis. The code for reading the ECG signals with Arduino implementation is shown in Listing 1. The ECG reading was in analog that connected with AD8232 ADC with 12 bits calculation and had three lead placements.

```
int ecgValue = analogRead(SENSOR_ECG);
 Serial.println(ecgValue);
```

Listing 1 ECG signal analog code

3.2. Beats Detection on ECG

The code of detection R peaks and BPM calculation in ECG signals with Arduino Implementation is shown in Listing 2. The calculation of R waves peak detection was reading the maximum data, then calculate the differences of each R peaks for BPM calculation.

```
//RR peaks interval
   if (ecgValue > lastECGValue && ecgValue >threshold) {
       if (!peakDetected) {
         peakDetected = true;
         rrInterval = currentMillis - rrTimestamp;
         rrTimestamp = currentMillis;
         }
     } else {
       peakDetected = false;
       digitalWrite(LED_PIN, LOW); // Turn off LED when no R-peak
       }
//BPM calculation
   lastECGValue = ecgValue;
    // Calculate BPM and RR interval
   if (currentMillis - previousMillis >= SAMPLING_RATE) {
       previousMillis = currentMillis;
       if (rrInterval > 0) {
         float bpm = 60000.0 / rrInterval; // Calculate BPM (beats per minute)
         Serial.print("RR Interval (ms): ");
         Serial.println(rrInterval);
         Serial.print(",BPM: ");
         Serial.println(bpm);
         }
      }
```

Listing 2. R peaks detection and BPM calculation code

As shown by the algorithm in Listing 2, this research systematically identifies R peaks within the ECG signal using a predefined threshold value for robust peak detection in Fig. 5. These detected R peaks enable the meticulous computation of RR intervals, measured in milliseconds, while their respective timestamps are recorded. The core of our system lies in the real-time heart rate calculation, specifically Beats Per Minute (BPM), by leveraging these RR intervals. This calculation provides immediate insights into the user's heart rate, with shorter RR intervals indicating a higher BPM and vice versa. Consequently, our system seamlessly processes ECG data, continually determining these pivotal physiological parameters. Furthermore, we extend our analysis to elucidate the temporal distance between consecutive R peaks. In our ECG signal readings, this temporal distance measures 126 samples, equivalent to 630 milliseconds with a 200-sampling rate, then the R waves interval can calculate the BPM following equation (1):

$$diff\ R\ peaks\ (ms) = \frac{diff\ R\ peaks\ (sample)}{sampling\ rate} x1000$$

$$diff\ R\ peaks\ (ms) = \left(\frac{126}{200}\right) x1000$$

$$diff\ R\ peaks\ (ms) = 630\ ms$$

The obtained data shows that the temporal distance between the first and second R peaks is 675 milliseconds. This crucial temporal information serves as the foundation for calculating the BPM (Beats Per Minute) using the following equation (2):

$$BPM = \frac{60000\ ms}{diff\ R\ peaks\ (ms)}$$

$$BPM = \frac{60000\ ms}{630\ ms}$$

$$BPM = 95.24\ BPM$$

3.3. Implementation

In the implementation phase of our research, we meticulously recorded 125,000 data samples, encompassing a temporal span of 625 seconds for each ECG recording. These recordings were conducted on four voluntary respondents who participated in our research. Fig. 6 shows the BPM in 625 seconds for four respondents, and Table 1 shows the resume for the responding ECG recording.

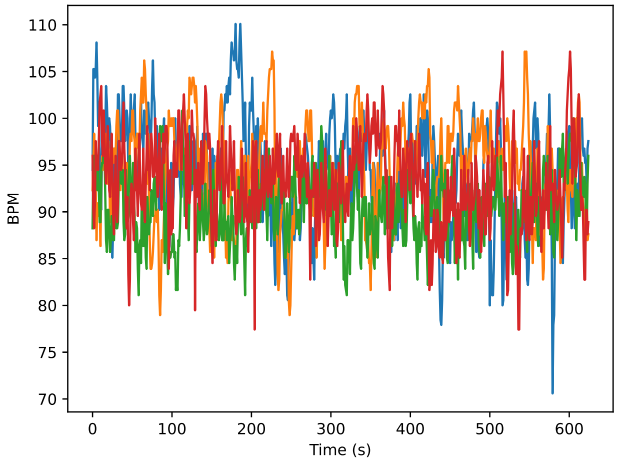

Fig. 6. BPM recordings of four respondents for 625 seconds

Table 1. BPM resume of four respondents

	Respondent 1	Respondent 2	Respondent 3	Respondent 4
Min	70.59	78.95	81.08	77.42
Max	110.09	107.14	100.84	107.14
Average	94.25	94.60	90.35	93.19
STD	5.67	5.19	3.55	4.66

Table 1 provides a comprehensive overview of four respondents' heart rate (measured in BPM) data. The minimum heart rate observed among the respondents ranges from 70.59 BPM to 81.08 BPM, indicating some variability in the lower range of heart rates. Conversely, the maximum heart rate varies from 100.84 BPM to 110.09 BPM, highlighting variations in the upper range of heart rates across the respondents. On average, the heart rates of these individuals fall within a relatively narrow range, with average BPM values ranging from 90.35 to 94.60 BPM. The standard deviation (STD) values, which provide insight into the dispersion of data points from the mean, range from 3.55 to 5.67 BPM. Lower standard deviation values suggest that the data points are closer to the mean, indicating less variability in heart rates within that group of respondents. Conversely, higher standard deviation values suggest more significant variability in heart rates. Overall, the data in Table 1 offers valuable insights into the range, average, and variability of heart rates among the studied respondents, contributing to our understanding of their cardiovascular health.

4. Conclusion

In conclusion, this research has significantly advanced our understanding and capabilities in electrocardiography (ECG) signal analysis. Through the seamless integration of the AD8232 ECG sensor with the Arduino Nano microcontroller, we have achieved precise and real-time heart rate calculations, measured in beats per minute (BPM), while also recognizing the distinctive components of ECG signals, notably the PQRST waveforms. These findings are significant for clinical practice and biomedical research, offering enhanced diagnostic tools and valuable insights into cardiovascular health. Our research has provided a comprehensive insight into the intricacies of ECG signals, including the P-wave, QRS complex, and T-wave, contributing to a holistic understanding of cardiac activity. By employing a meticulously designed algorithm, we have systematically identified R peaks and calculated RR intervals, allowing for the efficient determination of BPM. This methodology has enhanced our understanding of heart rate variability and provided a robust framework for assessing overall cardiac health. During the implementation phase, our analysis of ECG data from four voluntary respondents has shed light on the variability of heart rate parameters among individuals, offering valuable insights into resting and peak heart rates. These findings underscore the critical role of ECG sensors, particularly the AD8232 and Arduino Nano, in advancing cardiac health monitoring and diagnostic accuracy, paving the way for developing more sophisticated and user-friendly cardiac monitoring systems. This research is a foundational step toward further investigations and refinements in ECG signal analysis, ultimately benefiting clinical practice and ongoing biomedical research endeavors.

References

[1] K. C. Siontis, P. A. Noseworthy, Z. I. Attia, and P. A. Friedman, “Artificial intelligence-enhanced electrocardiography in cardiovascular disease management,” *Nature Reviews Cardiology*, vol. 18, no. 7. Nature Research, pp. 465–478, Jul. 01, 2021. doi: 10.1038/s41569-020-00503-2.

[2] V. Jahmunah *et al.*, “Computer-aided diagnosis of congestive heart failure using ECG signals – A review,” *Physica Medica*, vol. 62, pp. 95–104, Jun. 2019, doi: 10.1016/j.ejmp.2019.05.004.

[3] K. Surya, K. K. Abdul Majeed, and R. V. Ravi, “Diagnosis of Fetal Arrhythmia Using JADE Algorithm,” in *2020 7th International Conference on Smart Structures and Systems (ICSSS)*, IEEE, Jul. 2020, pp. 1–5. doi: 10.1109/ICSSS49621.2020.9202124.

[4] L. Maršánová, A. Němcová, R. Smíšek, M. Vítek, and L. Smital, “Advanced P Wave Detection in Ecg Signals During Pathology: Evaluation in Different Arrhythmia Contexts,” *Sci Rep*, vol. 9, no. 1, Dec. 2019, doi: 10.1038/s41598-019-55323-3.

[5] K. Friganovic, D. Kukolja, A. Jovic, M. Cifrek, and G. Krstacic, “Optimizing the Detection of Characteristic Waves in ECG Based on Processing Methods Combinations,” *IEEE Access*, vol. 6, pp. 50609–50626, Sep. 2018, doi: 10.1109/ACCESS.2018.2869943.

[6] E. Jovanov, “Wearables meet IoT: Synergistic personal area networks (SPANs),” *Sensors (Switzerland)*, vol. 19, no. 19. MDPI AG, Oct. 01, 2019. doi: 10.3390/s19194295.

[7] J. Schneider, M. Schroth, J. Ottenbacher, and W. Stork, “A Novel Wearable Sensor Device for Continuous Monitoring of Cardiac Activity During Sleep,” in *2018 IEEE Sensors Applications Symposium (SAS)*, IEEE, Mar. 2018, pp. 1–6. doi: 10.1109/SAS.2018.8336725.

[8] D. M. Roberts, M. M. Schade, G. M. Mathew, D. Gartenberg, and O. M. Buxton, “Detecting Sleep using Heart Rate and Motion Data from Multisensor Consumer-Grade Wearables, Relative to Wrist Actigraphy and Polysomnography,” *Sleep*, vol. 43, no. 7, pp. 1–19, Jan. 2020, doi: 10.1093/SLEEP/ZSAA045.

[9] G. B. Papini *et al.*, “On the generalizability of ECG-based obstructive sleep apnea monitoring: merits and limitations of the Apnea-ECG database,” in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, Jul. 2018, pp. 6022–6025. doi: 10.1109/EMBC.2018.8513660.

[10] H. Singh, R. K. Tripathy, and R. B. Pachori, “Detection of sleep apnea from heart beat interval and ECG derived respiration signals using sliding mode singular spectrum analysis,” *Digital Signal Processing: A Review Journal*, vol. 104, Sep. 2020, doi: 10.1016/j.dsp.2020.102796.

[11] R. Gilgen-Ammann, T. Schweizer, and T. Wyss, “RR interval signal quality of a heart rate monitor and an ECG Holter at rest and during exercise,” *Eur J Appl Physiol*, vol. 119, no. 7, pp. 1525–1532, Jul. 2019, doi: 10.1007/s00421-019-04142-5.

[12] S. Singh, U. Bhatt, D. Bisharad, D. Dey, and B. Bhowmik, “Portable System for Real Time Detection of P, QRS and T Waves from ECG Signals,” in *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, IEEE, Mar. 2019, pp. 1–5. doi: 10.1109/I2CT45611.2019.9033666.

[13] T. V. Tran and W. Y. Chung, “IEEE-802.15.4-based low-power body sensor node with RF energy harvester,” in *Bio-Medical Materials and Engineering*, IOS Press, 2014, pp. 3503–3510. doi: 10.3233/BME-141176.

[14] Z. Trzaska, “Study of mixed-mode oscillations in a nonlinear cardiovascular system,” *Nonlinear Dyn*, vol. 100, no. 3, pp. 2635–2656, May 2020, doi: 10.1007/s11071-020-05612-8.

[15] E. H. Van Iterson, C. H. Kim, K. Uithoven, and T. P. Olson, “Obesity and hemoglobin content impact peak oxygen uptake in human heart failure,” *Eur J Prev Cardiol*, vol. 25, no. 18, pp. 1937–1946, Dec. 2018, doi: 10.1177/2047487318802695.

[16] B. Furst, "Heartbeat and Respiration: Toward a Functional Chronobiology," in *The Heart and Circulation*, Cham: Springer International Publishing, 2020, pp. 287–317. doi: 10.1007/978-3-030-25062-1_23.

[17] S. Dhande, "LABVIEW BASED ECG SIGNAL ACQUISITION AND ANALYSIS," *International Journal of Engineering Applied Sciences and Technology*, vol. 5, no. 9, Jan. 2021, doi: 10.33564/IJEAST.2021.v05i09.046.

[18] C. Wijaya, Andrian, M. Harahap, Christnatalis, M. Turnip, and A. Turnip, "Abnormalities State Detection from P-Wave, QRS Complex, and T-Wave in Noisy ECG," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, Sep. 2019. doi: 10.1088/1742-6596/1230/1/012015.

[19] P. Lyakhov, M. Kiladze, and U. Lyakhova, "System for neural network determination of atrial fibrillation on ecg signals with wavelet-based preprocessing," *Applied Sciences (Switzerland)*, vol. 11, no. 16, Aug. 2021, doi: 10.3390/app11167213.

[20] R. M. Velazquez, R. Gamez, and A. El Saddik, "Cardio Twin: A Digital of the Human Heart Running on the Edge," in *Medical Measurements & Applications*, 2019. doi: https://doi.org/10.1109/MeMeA.2019.8802162.

[21] M. Rizwan, B. M. Whitaker, and D. V. Anderson, "AF detection from ECG recordings using feature selection, sparse coding, and ensemble learning," *Physiol Meas*, vol. 39, no. 12, Dec. 2018, doi: 10.1088/1361-6579/aaf35b.

[22] M. A. Serhani, H. T. El Kassabi, H. Ismail, and A. Nujum Navaz, "ECG Monitoring Systems: Review, Architecture, Processes, and Key Challenges," *Sensors*, vol. 20, no. 6, p. 1796, Mar. 2020, doi: 10.3390/s20061796.

[23] M. Wildan. Gifari, Hasballah. Zakaria, and Richard. Mengko, "Design of ECG Homecare: 12-Lead ECG Acquisition using Single Channel ECG Device Developed on AD8232 Analog Front End," in *Electrical Engineering and Informatics (ICEEI)*, 2015, pp. 371–376.