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Phonocardiography for Early Detection of Arrhythmia Using Rule-Based Approach

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ABSTRACT Arrhythmia is a heart rhythm disorder that is often established through an electrocardiogram examination. This test is performed as part of a medical check-up, or used to determine the administration of medications or medical procedures on the heart. However, alternative methods such as Phonocardiography, which can record heart sounds produced by the opening and closing of heart valves, can provide information to diagnose heart disorders. The research seeks to estimate Heart Rate for early detection of Arrhythmia, and improve the implementation of real-time Arrhythmia detection with high efficiency. The use of Phonocardiography to detect Arrhythmia in real-time, and minimal human intervention for heart health monitoring. This research uses a rule-based method that utilises a combination of threshold-based and time-based for the detection of S1 and S2 peaks in Phonocardiography signals, testing is carried out on patients to evaluate system performance. The research shows that the designed Heart Rate module can detect Heart Rate in tachycardia, normal, and bradycardia conditions with a minimum error rate of 0% to 4.1%. The system is also able to show relatively small differences compared to the comparison standard. With high accuracy, the threshold-based and time-based rule-based system effectively identifies S1 and S2 heart sounds and calculates the intervals between sounds, allowing for early detection of Arrhythmia in real-time. In addition, the system also reduces the need for human intervention, speeds up response time, and supports simple and resource-efficient technology implemented.

INDEX TERMS Arrhythmia, Phonocardiography, Rule-based, Detection accuracy, Real-time monitoring

I. INTRODUCTION

Arrhythmia is a heart health disorder that refers to changes in the frequency, rhythm and strength of the pulse, either too fast/slow or irregular. Generally, the human heart under normal conditions beats at a regular rhythm rate of between 60-100 times per minute, while arrhythmia is a heart rhythm rate that is too fast (> 100 times per minute) or too slow (< 60 times per minute) [1]-[4]. Arrhythmia is a risky disease because it can cause complications such as fainting (syncope), hypertension, shortness of breath, sweat glands and others. The worst stage is thromboembolism which causes stroke, heart failure, sudden death and other blood vessel disorders [5]-[9]. To prevent serious complications and improve the quality of life of patients, diagnosis and prevention of this condition are essential [10].

So far, diagnosis Arrhythmia mainly enforced through examination Electrocardiogram (ECG). An ECG examination shows a graphic recording of the electrical activity that accompanies the contraction of the heart's atria and ventricles. The results of the ECG test are used by heart specialists to help in diagnosis and treatment determination. On the other hand, ECG has the disadvantage of being complex and expensive equipment which makes the technology limited, especially in patients undergoing long-term treatment and in remote areas [11].

Another common method for diagnosing heart defects is through heart sound analysis. PCG signal recording consists of four important elements of heart sounds, namely S1, S2, S3, and S4. Normal heart sounds will show a constant two-beat rhythm. The first sound is known as S1 or lub, while the second sound is called S2 or dub. S3 is known as another or abnormal heart sound and S4 is a murmur that appears when the heart is in an abnormal condition [12]-[15]. Both of these methods require the time and energy of a cardiologist to analyze the results of the signal readings that have been carried out. Therefore, there is an urgent need for accurate, automated arrhythmia classification using PCG to assist in the diagnosis of events of arrhythmia, but requires advanced designs such as more accurate signal processing algorithms, sensitive sensor designs, and is comfortable to use.

Several studies have been carried out to identify signals automatically. Research conducted for analysis of various methods used for classification, early diagnosis, and prevention of Cardiac Arrhythmias (AK) automatically

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using several methods such as IoT, approaches Machine Learning (ML), approach Deep Learning (DL), and so on for automatic detection of arrhythmia Kardia. However, fashion interpretability Deep Learning There is still a lack of data being built, there is a need for further analysis regarding how the classification decision making model works and this method has not been clinically tested on real patients, so its actual performance is not yet known. Clinical trials are needed to determine its real accuracy and performance [16].

Diagnostic research arrhythmia automatically using the method Convolutional Neural Network (CNN) and models Lateral Connetion Convolutional Autoencoder Neural Network (LCAN) to detect arrhythmia. This research found that the LCAN model was quite effective in detecting arrhythmia and has good interprability. The weakness of this research is that the classification process is still not good because the inequality between evaluation data can only be done on one row of data, and the performance is not yet known for larger data [17]. In a study that developed a hybrid approach that combines rule-based and anomaly-based detection to detect DDoS attacks, simulations showed that this scheme can effectively detect attack access traffic. Researchers realized real-time traffic detection in the upcoming fast network. The study argued that the combination of this hybrid, rule-based approach can work well with the right combination of thresholds [18]. Then in a study that discussed the Combined Belief Rule Based Expert System (CBRBS) clinical rule-based system to predict coronary artery disease (CAD), it was found that this system combines three Belief Rule Bases (BRB) based on pathological, demographic, and clinical factors. This system can predict coronary artery damage ranging from normal to blocked three-branch arteries. Based on the evaluation results, the proposed CBRBS system is able to predict CAD with an average success rate of 93.97%. The error and failure rates are relatively low for certain CAD classes. This paper proves that the combination of rule-based and trust-based approaches can work well to diagnose diseases if other features are added. This system is expected to help doctors in diagnosing and predicting the level of coronary artery damage [19].

Research describing the use of dual-diaphragm MEMS electronic stethoscopes (DMES) can improve sound sensitivity and medical diagnostic accuracy [20].Other studies have shown that the use of digital filters in electronic stethoscopes can improve the accuracy and diagnostic capabilities of cardiac auscultation [21], [22]. Then other research showed that heart sounds could be processed through signal processing real-time (RTST). Uses DSP (TMS320C6713) to detect signals Phonochardiography (PCG) human heart. Digital signal shooting techniques signal noise reduction Phonochardiography (PCG) and signal analysis Phonochardiography (PCG) used among others Noise Reduction, Windowing, Discrete Fourier Transform (TDF), Fast Fourier, Transform. However, this research only focuses on the signal windowing and filtering process without analyzing the results further [23]. Research that aims to classify heart sounds obtained from recording results Phonochardiography (PCG) uses artificial neural dimensions to determine the difference between normal and abnormal heart sounds. Can do signal analysis Phonochardiography (PCG) by extracting parameters such as S1-Systole and S2-Diastole signals to extract a single cardiac cycle. This method can be implemented independently real time for classification Phonochardiography (PCG) [24], [25], [26].

Based on several previous studies, one of the main challenges for cardiologists is to carry out early and accurate diagnosis and prognosis. Manual ECG analysis by a cardiologist is very time consuming and labor intensive. This method requires labeled data which is expensive and laborious to obtain. Thus, there is an urgent need for accurate automated arrhythmia classification using PCG to aid in the diagnosis of events of arrhythmia, but requires advanced designs such as more accurate signal processing algorithms, sensitive sensor designs, and is comfortable to use.

Based on this description, the author is interested in developing a PCG that can determine the interval between S1, S2, S3 (if any) and S4 (if any) as a basis for early diagnosis. Phonocardiography (PCG) can provide important information about the mechanical activity of the heart. The lack of research on S1 and S2 peak detection on PCG for heart rate estimation using rule-based methods is one of the challenges. This research aims to overcome the shortage by developing a rule-based method for real-time S1 and S2 peak detection on PCG, heart rate estimation, and cost-effective early arrhythmia detection for clinical applications. By adding a condenser microphone to record heart sounds which will then enter the pre-amplifier circuit and be further processed using ESP32 as its microcontroller and then will be analyzed using machine learning [28]-[30]. With machine learning, the classification process can become fully automatic after training[30], [31]. This can reduce human intervention and speed up response times. With a more accurate classification model, better and more precise decisions can be made. This can help with diagnosis of Arrhythmia.

II. MATERIALS AND METHODS

In this study, that combines S1 and S2 peak detection for heart rate estimation in the context of a rule-based method of PCG phonocardiography-based real-time detection system for heart rate estimation and early arrhythmia detection. After the module was designed, testing and analysis of the module results were carried out module reading against the advanced medical mannequin comparison device of reading results. Measurements are made at the Erb's point located in the third intercostal space (the space between the third and fourth ribs) on the left side of the sternum (breastbone) to get a complete picture of the acoustic signal produced by heart activity. In each rhythm, 5 measurements are made with a multiple of 10 heart rate setting on the comparison device, at

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each heart rate setting, measurements are made 5 times to ensure consistency and accuracy, the measurement duration is carried out for several heart cycles of 10-15 seconds to ensure all components of the heart sound are recorded.

A.The Diagram Block

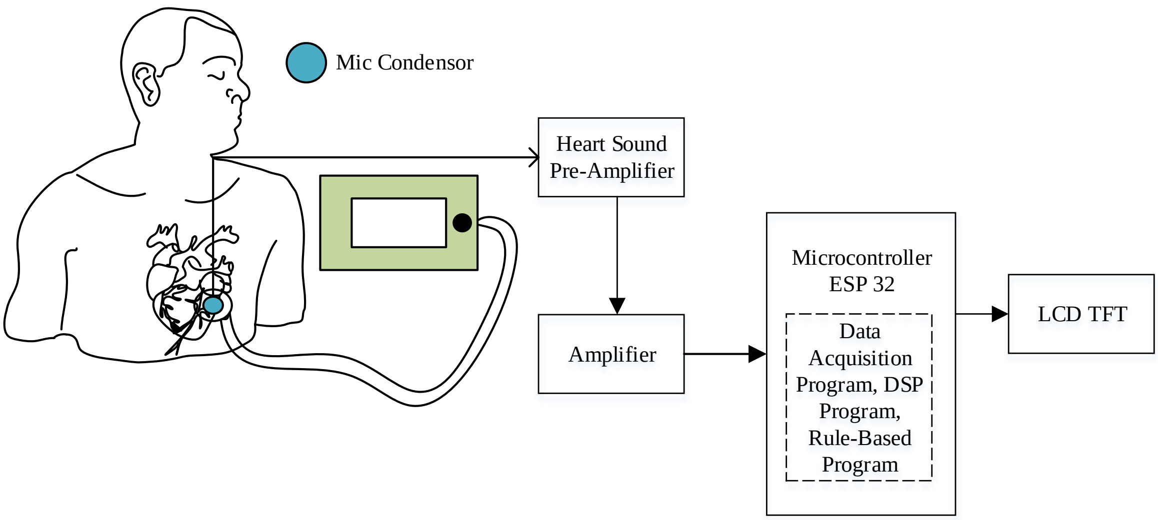

FIGURE 1 **Diagram Block of System**

Based on FIGURE 1 is a Phonocardiography for Early Detection of Arrhythmia by Referring to the system block diagram. Mechanical Stethoscope the initial component connected to the MIC (microphone) functions to capture the heart sounds from the patient. MIC (Microphone) converts heart sound vibrations into electrical signals, Pre-Amplifier amplifies the electrical signal from the microphone so that it can be processed further, then increases the signal level that has been amplified by the pre-amplifier to a level sufficient to be processed in the microcontroller using an amplifier, then the data acquisition process on the ESP32 Microcontroller to convert analog signals into digital signals then send digital data to a PC (Personal Computer) for Digital Signal Processing (DSP) filtering, for signal peak detection and time base determination, then TFT LCD to display the analysis results information

B. THE FLOWCHART

FIGURE 2 is shows the system flow diagram starting from Begin the process of detecting heart sound signals then the heart sound is amplified using a pre-amplifier so that it can be processed further, then the data acquisition process to convert analog signals into digital signals, then the Digital Signal Processing process for filtering signals so that heart sound signals can be determined peak to peak signal to determine t (time) between peaks using the Rule-Base System then processed and classified based on parameters and an evaluation is carried out whether these parameters are in accordance with normal limits or not. If "Y" Learning then the heart is classified Arritmya then the graph, BPM and diagnosis will appear on the LCD and if "N" then the heart is classified as normal then the graph, BPM and diagnosis will appear on the LCD.

FIGURE 3 is show flowchart of System Rule-Base Begin Start the process, input the PCG signal to be analyzed. Perform pre-processing such as noise filtering and signal normalization to ensure the signal is clean and ready to be analyzed. Set Threshold Level (Set Threshold Level) sets the threshold value for peak detection. This value is determined from the amplitude characteristics of the PCG signal relevant to S1 and S2. Identify peaks in the signal that exceed the set threshold. Peaks above this threshold are considered important peaks. Validate Detected Peaks Validate the detected peaks to ensure that they match the characteristics of S1 and S2 in the PCG signal. Peaks that do not match can be ignored. Calculate Peak-to-Peak Interval (Calculate Peak-to-Peak Interval) Calculate the time interval between two detected peaks (peak S1 to S2 or S2 to the next S1). Store Interval Data Store information about the time interval between detected peaks for further analysis. Analyzes the Peak Time Rule-Base Interval against the inter-peak interval to detect normal or abnormal patterns that indicate arrhythmia. Displays the results of the analysis, either as a graph or Heart Rate data, and indicates whether the pattern is normal or indicates arrhythmia. End process is complete.

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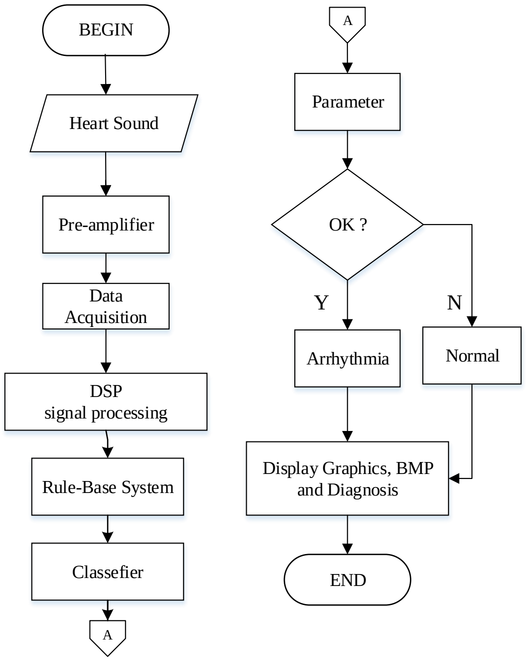

FIGURE 2 **Overall of System Flowchart**

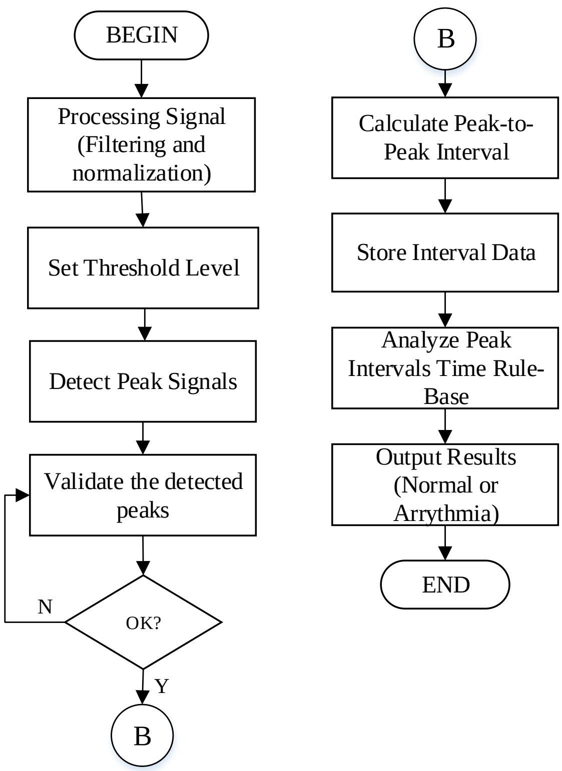

FIGURE 3 **Rule-Base System Flowchart**

Refer to FIGURE 4 is shows the flowchart of the Microcontroller Program BEGIN The process begins. Program Initialization: The initial stage of the program, where the system or **device** is initialized to start reading and processing the Phonocardiogram (PCG) signal. Read Signal the system starts reading the PCG signal from the connected electronic Stethoscope. OK (Signal Validation), If the signal is successfully read properly (Y), the process continues to the next stage (signal processing). If the signal is not read or an error occurs (N), the system displays the message "Leads Off" as an indication that the sensor connection is not properly connected or there is a problem in reading the signal. Signal Processing after the PCG signal is read, the signal is processed to the next stage. Mapping Signal Range 0-1023: The processed signal is then mapped in a digital value range from 0 to 1023 for further processing. Peak Detection: The stage where the peak of the PCG signal is detected. This peak is related to the heartbeat sound (S1 and S2) in the PCG signal. Heart Rate Calculation Based on the detected S1-S2 interval, the system calculates the heart rate. Once the heart rate calculation is complete, the results are displayed in real-time on the TFT display, which may be a small monitor screen attached to the device. END the process is complete.

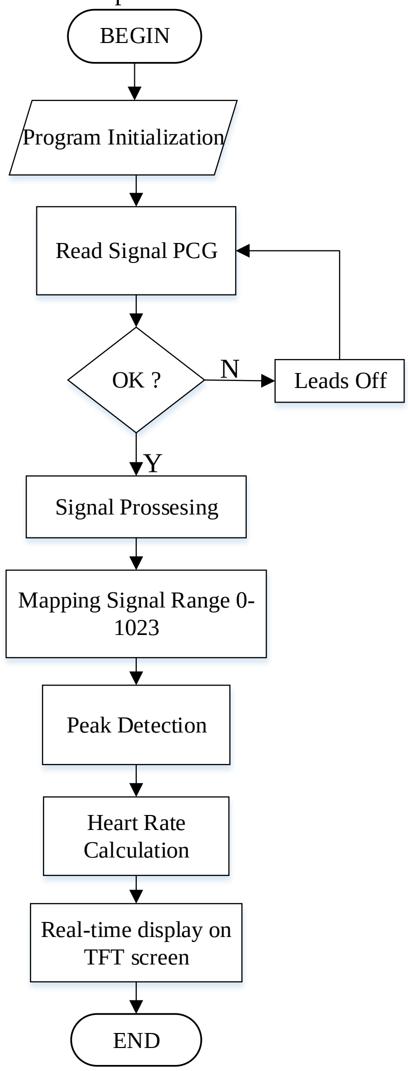

FIGURE 4 **Microcontroller Flowchart**

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C. DATA ANALYSIS

After obtaining data from respondents and mannequins, the relative error value can be calculated using equation (1):

$$\epsilon_e = \frac{x_n - \bar{x}}{x_n} \times 100\% \quad (1)$$

The relative error is used to determine the accuracy of the device reading against the actual value. Where x_n is the average BPM value on the PCG display. While $\bar{x}$ is the average value.

The calculation of the average value is carried out to determine the trend of the measurement value of the clean PPG signal and PPG with Motion by the tool module obtained by the author. The following equation shows the average formula that will be used in the data analysis process (2):

$$\bar{x} = \frac{\sum x_i}{n} \quad (2)$$

Where x¯is the average value, Σ is the sum of the data values and n is the number of data.

The value of the time interval between events (Δt) is the time difference between two events that occur in the signal. In PCG, the events analysed are the S1 and S2 peaks, which represent heartbeats. And is formulated in equation (3):

$$\Delta t_i = t_{i_{+1}} - t_i \quad (3)$$

Where t_i Is the first event time, t_{i+1} Is the second event time Δt_i,Is the time interval between events.

Normal time limit (*Tmin* and *Tmax*) is the range of time interval values And formulated in equation (4):

$$\Delta t_{min} \le t_i \le t_{max} \quad (4)$$

Where *Tmin* Is the lower limit that shows the shortest time interval that is still considered normal *Tmax* is the upper limit that shows the longest time interval that is still considered normal. Then, Errors in comparison to the standard may indicate issues with the model or design. Equation of error's formula (5):

$$\%\text{error} = \frac{\textit{Setting Data} - \textit{Average}}{\text{Setting Data}} \times 100\% \quad (5)$$

III. RESULT

In this study, arrhythmia detection will be performed using PCG to detect the patient's heart activity. Tests are carried out by measuring the comparison module and the patient to determine the heart rate frequency (BPM) in tachycardia, normal, and tachycardia heart rhythms. The form of phonocardiography module for early arrhythmia detection using machine learning is as follows:

TABLE 1
Results of Data Collection using PCG Module

No		Mean	SD	Error (%)
P1	Comparator	54,6	0,5	1,10%
	HR Module	55,2	2,5	
P2	Comparator	80,2	2	0,50%
	HR Module	80,6	0,5	
P3	Comparator	97,6	3,8	0,60%
	HR Module	97	1,6	
P4	Comparator	91,8	7,8	4,10%
	HR Module	88	7,6	
P5	Comparator	77,4	4,9	0,50%
	HR Module	77,8	8,4	

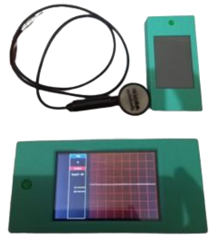

FIGURE 5 Phonocardiograph Module

FIGURE 5 is a picture of the module that has been made. At the top there is a stethoscope that has been integrated with a condenser microphone and a front view module. Then, in the bottom picture, there is a module and TFT LCD when the device is turned on. Data retrieval is done by placing the sensor at the ebr's point location of the third intercostal space on the left side of the chest stertum. Then the tapped heart signal will go to the pre-amplifier circuit and then be further processed on the ESP32 microcontroller, the results of which will then be processed by machine learning to be able to detect arrhythmia.

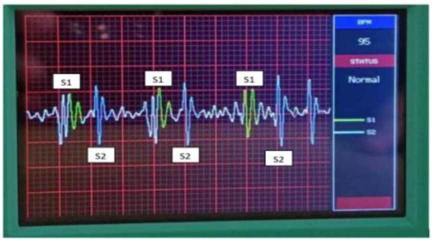

FIGURE 6 Display of signal peak detection result

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FIGURE 6 shows the results of signal peak detection the phonocardiography (PCG) signal detection process begins with the conversion of analogue signals into digital signals using ADC, followed by a filtering process to reduce noise. The filtered data is used to detect the main peaks, namely S1 and S2. using variable threshold values Lower Limit Peak BBP = 400, (Upper Limit) BA = 380, and (Lower Limit) BB = 250, and the peak S1 signal is coloured green and S2 signal is coloured blue.

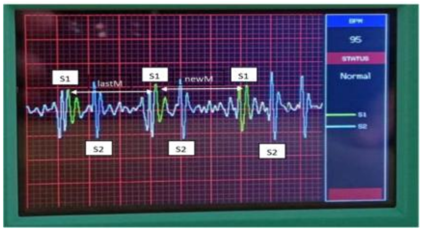

FIGURE 7 Defining the interval between peaks

FIGURE 7 is a process of calculating the time interval between two peaks of the S1 signal detected from the analysed results. Whenever an S1 peak is detected, the detection time is stored as 'lastM' as shown in Figure 7 for the first peak and 'newM' for the second peak. Determining the peak to peak interval. This interval is the time required for one heartbeat cycle, measured in milliseconds. By dividing 60,000 milliseconds (one minute) by the interval between peaks, the heart rate (BPM) can be determined. After the detection of the second peak, the value of 'newM' becomes 'lastM' for the next peak, and this process is repeated continuously to calculate the real-time Heart Rate (BPM).

FIGURE 8 ***Measuring Respondents***

FIGURE 8 is a picture of data collection on done by placing the module and oxymetry next to each other so that it can be seen how the results of the patient's heart rate are detected by the module and the comparison tool. Measurements were made of 5 respondents who were repeated 5 times for each measurement. TABLE 1 Based on the table of heart rate (HR) measurement results consisting of five respondents (P1 to P5), a comparison was made between two measurement methods, namely oximetry (comparative tool) and HR Module (tested tool). Data collection was carried out on 5 respondents with 5 repetitions of data collection per respondent. Of the data provided in Table 1, no significant difference was found between the average values generated by the Comparator and the HR Module. The results of the paired t-test showed a t-statistic value of 0.72 and a p-value of 0.51, meaning there was not enough statistical evidence to conclude a significant difference between the two devices. The error rate of the Comparator ranged from 0.5% to 4.1%, indicating good consistency in measurement. The average value of the HR Module is close to the results of the comparator, indicating similar performance.The measurement comparison shows fairly consistent results, especially in P2 and P3, where the average value is close to the HR Module result. However, in P1, there is a significant difference between the Comparator value and the HR Module, which indicates a Bradycardia condition. The error (Error%) varies between measurements, with the highest value in P4 (4.1%) and the lowest in P1 (-1.1%). P4 shows a large variation between the Comparator and HR Module results, which may indicate a problem in measurement accuracy. In P1, the analysis results show Bradycardia, which coincides with the Comparator result which is higher than the HR Module. However, in other measurements (P2 to P5), all show Normal conditions, although there is variation between the Comparator and HR Module results.

V. DISCUSSION

The analysis was conducted to determine the results of heart rate (HR) measurements consisting of five respondents (P1 to P5). The comparative measurement results for P1 showed an average of 54.6 and a standard deviation of 0.5. The percentage error was -1.1%, indicating that the HR Module results were slightly higher than the Comparator HR results. From the module measurement, the average value was 55.2 and SD 2.5. The analysis results indicated a Bradycardia condition. The comparative measurement results for P2 showed an average of 80.2 and SD 2.0. The measurement error was -0.5%, indicating that the HR Module gave slightly lower results. From the module measurement, the average value was 80.6 with SD 0.5. All measurements in P2 showed Normal conditions. The comparative measurement results for P3 had an average of 97.6 and SD 3.8. The measurement error was 0.6%, indicating that the HR Module results were slightly lower than the Comparator. From the module measurement, the average value was 97 with SD 1.6. Measurements at P3 also show Normal conditions. The comparative measurement results for P4 have an average measurement result of 91.8 and SD 7.8. The error is 4.1%, which shows quite a large variation. From the module measurement, the average value is 88 and SD 7.6. Measurements at P4 also show Normal conditions. The comparative measurement results for P5 have an average measurement result of 77.4 and SD 4.9. The error is -0.5%, indicating that the HR Module is slightly lower than the Comparator. From the module measurement, the average value is 77.8 and SD 8.4. Measurements at P5 show Normal conditions.

It can be concluded that the comparison of measurements shows fairly consistent results, especially at P2 and P3, where the average value is close to the HR Module results. However, at P1, there is a significant difference between the Comparator and HR Module values, indicating a

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Bradycardia condition. Error (Error %) varies between measurements, with the highest value at P4 (4.1%) and the lowest at P1 (-1.1%). P4 shows a large variation between the Comparator and Module HR results, which may indicate a problem in measurement accuracy. In P1, the analysis results showed Bradycardia, which coincided with the Comparator results being higher than the Module HR. However, in the other measurements (P2 to P5), all showed Normal conditions, although there was variation between the Comparator and Module HR results.

Several studies have been conducted to automatically identify signals. In a study conducted by Ahmed Faisal et al. (2020), they discussed the Combined Belief Rule Based Expert System (CBRBS) clinical rule-based system to predict coronary artery disease (CAD). This system combines three Belief Rule Bases (BRB) based on pathological, demographic, and clinical factors. This system can predict coronary artery damage ranging from normal to blocked three-branch arteries. Based on the evaluation results, the proposed CBRBS system was able to predict CAD with an average success rate of 93.97%. The error and failure rates were relatively low for certain CAD classes. This paper proves that the combination of rule-based and trust-based approaches can work well to diagnose diseases if other features are added. This system is expected to help doctors diagnose and predict the level of coronary artery damage [16]. In this study conducted by Chin-Ling Chen and Hsin-Chiao Chen, a hybrid approach was developed that combines rule-based and anomaly-based detection to detect DDoS attacks. Simulations show that this scheme can effectively detect attack access traffic. Researchers realize real-time traffic detection in upcoming fast networks. The study argues that this hybrid, rule-based approach can perform well with the right combination of thresholds[15].

The drawback of this research is that the dataset used in this study is still very limited, which may affect the ability of the model to be generalised to a wider population. The small dataset increases the risk of overfitting and decreases accuracy when applied to new data. Then the limitation on arrhythmia types although the model shows success in detecting several types of tachycardia, normal, and bradycardia wider testing for a wide variety of arrhythmias is needed to ensure accuracy in a wide variety of heart conditions.

This study has several advantages compared to previous studies. By using Phonocardiography (PCG) combined with machine learning algorithms, this study enables the detection of arrhythmia at an early stage, which is crucial for preventing serious complications such as stroke and heart attack. In addition, PCG is a non-invasive method, making it more convenient and safe for patients compared to invasive methods such as invasive electrocardiogram or heart monitor insertion. The developed system is also designed for real-time monitoring, enabling immediate detection of arrhythmia, which is beneficial for continuous monitoring of heart health conditions without requiring frequent medical intervention. The implication of this research is the potential to improve automatic diagnosis of arrhythmia with higher accuracy, speed up the diagnosis process, and increase convenience and safety for patients, so that this system can be an innovative solution in continuous monitoring of heart health.

Diagnostic research *arrhythmia* automatically using the method *Convolutional Neural Network* (CNN) and models *Lateral Connetion Convolutional Autoencoder Neural Network* (LCAN) to detect *arrhythmia*. This research found that the LCAN model was quite effective in detecting *arrhythmia* and has good interprability. The weakness of this research is that the classification process is still not good because the inequality between evaluation data can only be done on one row of data, and the performance is not yet known for larger data [17]. In a study that developed a hybrid approach that combines rule-based and anomaly-based detection to detect DDoS attacks, simulations showed that this scheme can effectively detect attack access traffic. Researchers realized real-time traffic detection in the upcoming fast network. The study argued that the combination of this hybrid, rule-based approach can work well with the right combination of thresholds [18].

V. CONCLUSION

This study aims to develop a Phonocardiography (PCG) system that can combine S1 and S2 peak detection for heart rate estimation in the context of rule-based methods. Real-time PCG-based detection systems for arrhythmia monitoring are still limited, and there is a need for efficient algorithms with low computational requirements. The availability of PCG data is also a challenge in evaluating existing methods. This system aims to improve the accuracy of arrhythmia classification, improve response time, and reduce human intervention in diagnosis, thereby supporting cardiologists in making more informed decisions. The HR module has demonstrated high accuracy in detecting heart rate in tachycardia, normal, and bradycardia conditions, with errors ranging from 0% to 4.1%. Measurement results on mannequins and patients show little difference between the HR module and the reference standard. The rule-based threshold system can identify S1 and S2 heart sounds and calculate their intervals, effective for early detection of arrhythmias in real time. The next work of this research is system needs to be developed for integration with remote monitoring, thus enabling real-time monitoring of patients and improving the quality of care.

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