Design and Implementation of PQRST ASIC for Energy-Efficient Cardiovascular Disease Diagnosis Using ECG Signal Feature Extraction

Sumit Kushwaha

Department of Computer Applications, Chandigarh University, Mohali, India

Email: sumit.kushwaha1@gmail.com

Abstract

Cardiovascular problems have become a major source of concern for people all over the world. The significance of disease necessitates proper diagnosis as well as right and early treatment. ECG is the most extensively utilized important signal nowadays, providing precise information regarding the function of the cardiovascular. A novel illness diagnostic algorithm created on the forward searching for ECG signal processing techniques is implemented in an Application Specific Integrated Circuit (ASIC) for the cardiovascular diagnosis of diseases on a feature extraction method. The CMOS small leakage research strategies are used to create an ASIC. The PQRST ASIC has a surface area of with a supply voltage of the PQRST ASIC dissipates of energy. ECGs can provide a great deal of information on the normal and anomalous functioning of the heartbeat. The form of the ECG is similar to the irregularities of a heart. One cardiovascular phase of an ECG signal is made up of the feature facts P-QRS-T. The magnitude and frequency principles of a P-QRS-T section define how a human's heart pumps. An anomaly in ECG signals occurs when the electrical impulses of a heart are unpredictable, quicker, or less than usual. The ASIC output has been sent to a feature extraction method to diagnose the ECG signal, which provides a show that the design can be emailed to a cardiologist. This research looks at numerous strategies provided by researchers for extracting features from ECG signals. Using the Manually curated PTB diagnostics ECG database, the ASIC and feature extraction are validated for the diagnosis of bundle branch blockage, hypertrophic, arrhythmias, and myocardial infarction. The proposed ASIC, in conjunction with the feature extraction method, is best suited for an energy-effective peripheral cardiovascular disease recognition technique.

Keywords

Cardiovascular Disease, ECG, Detection, Feature Extraction, PQRST Signal, SDG 3, SDG 7, SDG 9, SDG 12

1. Introduction

An electrocardiogram (ECG) is a comprehensive picture of such a heart's electrical movement upon that external of a human body, then it is widely employed in the medical judgement of cardiac problems. It may be used as an accurate indicator to evaluate the cardiovascular functional requirement. Because of their simple and non-invasive character, ECG signals have already been frequently employed for diagnosing heart problems. Several software's can analyze and identify ECG signal characteristics from the ECG data [1]. Thousands of people, for sample, suffering from heart difficulties, and it could be fatal in approximately situations. As a result, exact and low-cost cardiac arrhythmia heart rate detection is extremely necessary. Several research has been carried out to establish arrhythmia classification methods that rely on automated methods and diagnostic systems that are based using ECG data [2]. The most vital aspects in the assessment and diagnosis of cardiac problems appear to be the gathering of characteristics and the categorization of beats. The process of finding and categorizing arrhythmias can be extremely difficult for a human person since it is occasionally essential to assess each heartbeat of ECG readings obtained by a holter monitor over hours or days. Furthermore, due to weariness, there is a risk of human mistake during the processing of ECG records. Several techniques for categorizing ECG signals have been emerged in recent years, with notable improvements.

Many of the most critical steps in identifying cardiac diseases are the study of electrocardiographic signals (ECG). For centuries, researchers have been working on techniques of ECG signal diagnosis. An ECG is a non-invasive physiologic indicator that is extensively used during monitoring and detecting cardiovascular events. Furthermore, the signal is used to look for abnormal patterns that correlate to disorders. Understanding the position and structure of the multiple parts (P-QRS-T) in ECG recordings is required by ECG analysis programs [2]. The QRS complex and identification of R-waves are the most commonly used reference points for evaluating ECG signals. As an extra aspect of the signal, these trainings are supplemented by the R–R distance evaluation and pulse rate research. It should be emphasized that such approaches generally validate their performance using datasets including such Physio-net, Physio-Bank, and Physio-Toolkit datasets [3]. Their primary objective is to discover arrhythmia, which is an irregular heartbeat and a typical indication of cardiac illness.

The electrical development of the human heart is evaluated by applying the various suitable body environments, organized well over the body. The paper may construct a concept of heart limitation called an electrocardiogram based on estimation outcomes (ECG). In today's clinical contexts, the ECG is used to assess the cardiac disease. The heart flag concludes crucial biomedical indicators. To view cardiac rhythms, a device known as an ECG monitor is used. The beginning and development of electrical potential in the cardiovascular system are captured in the ECG banner. ECG banners and ventricular in one sequence of every heartbeat contribute to chambers deactivation. ECG exceptional is additional important than some other environmental indicators since it has unique morphological qualities. This shape appears to be common while investigating various cardiovascular diseases [4]. Banner preparation is familiar, as is the investigation and evaluation of ECG signals. The ECG flag is represented by six apexes and troughs. Figure 1 depicts the fundamental characteristics of a human ECG signal. As shown in Figure 1, the important waves P, Q, S, R, and T, among others, compose the important percentages of the ECG signals is known as the QRS compound, ST-segment, and PR interval. The ECG signals has indeed been varied to increase accuracy estimates and consistency [5]. The ECG signal is difficult to examine since it is hampered by clamor during acquisition. The collection of clinical factors to construct uproarious biological indicators is among the most challenging ECG signals.

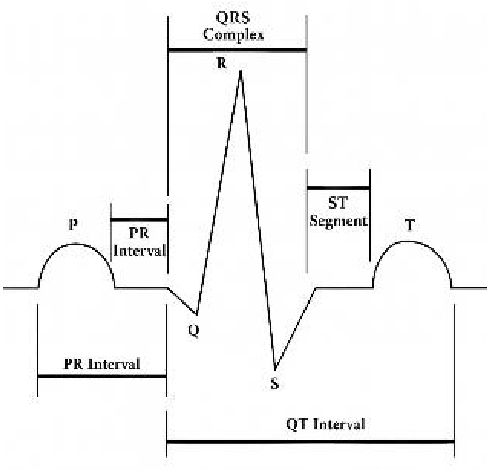

Figure 1. ECG signal characteristics

An ECG machine captures and progresses in different this activity via sensors on the skin. An ECG requires the attachment of ten power cables to a heart, one to every limb, and six from across the heart [6]. The ECG is a waveform which indicates an electrical activity in the heart, including left atrium depolarization, ventricle depolarization, right atrium repolarization, and ventricular repolarization. The signals are made up of a sequence of complicated repeated waveform signals with a speed of about . The P-QRS-T waves comprise one heartbeat in an ECG signal. The durations and pulse width determined by the ECG's characteristics generate the vast majority of medically valuable information.

The ECG feature selection technique generates fundamental characteristics (amplitudes and intervals) for further automated methods [7]. Several strategies for detecting these traits have been proposed in recent years. The previously proposed technique for analyzing ECG signals was defined as the time spectral domain. However, that's not always sufficient to investigate all of the properties of ECG signals. As a result, a frequency description of a signal is necessary. Deviations from normal electrical patterns suggest a variety of heart diseases. Cardiac batteries are usually polarized in their natural state [8]. The ECG is primarily in charge of patient diagnosis and monitoring. The characteristic retrieved from the ECG signal is critical in identifying heart illness. It is crucial to establish fast and accurate algorithms for automatic ECG feature extraction. As a result, the accuracy of the extraction of feature mechanism is serious. The objective of a feature is to locate as few qualities within an ECG signal as feasible that will enable good anomaly identification and efficient prediction.

A complete description of a PQRST ASIC design is included in this publication. Display the testing chip findings for ECG feature detection as well. PQRST ASIC was validated using the Physio-net QT database and the arrhythmia database, in addition to the PTB diagnosis ECG database. Previously, demonstrated ST segment, T wave, and QT length associated cardiovascular disease identification utilizing the Physio-net PTB diagnostic dataset predicated on post-layout calculations of a PQRST ASIC [9]. The outcomes of the PQRST ASIC test chip again for identification of cardiovascular events connected to i) The QRS sophisticated feature-based illnesses including such as ventricular tachycardia, arrhythmia, and bundle branch blockage, ii) ST-segment and T wave connected diseases including such ischemia and the major issues are arising of myocardial injury iii) QT duration disorders including such hypocalcemia and hypercalcemia; and iv) P wave disorders including such AV block and atrial hypertrophy are reported in this work. In this PQRST ASIC, ECG data across six leads are analyzed consecutively [10]. A simultaneous system can be achieved utilizing six PQRST ASICs to acquire R-R interval, P wave characteristics, QRS compound specifications, ST-segment voltages, and T-wave characteristics [11]. To an aimed to contribute, ASIC will be the first ECG signal processing that identifies different stages of myocardial injury and AV block, as well as bundle branch block, hypertrophic, and irregular heart rhythm, in conjunction. Previously, ASICs can only recognize the R-R interval and arrhythmia. Then, the feature extraction method is used to diagnose cardiac disease. In addition, PQRST ASIC and feature extraction identify the specified cardiovascular illnesses in existing industrial ECG diagnostic techniques.

2. Related Works

Cardiac disease is the main cause of death on a global scale. Cardiovascular illnesses can be avoided if an accurate diagnosis is obtained early on. The ECG trial is considered to be an analytical assistance device for heart disease screening. The research goals of a heart disease diagnosis system that relies on -lead ECG readings. The healthcare institutions employed a variety of ECG technology that produced results in non-uniform ECG file format. The paper presents a universal framework for processing all ECG forms. To diagnose cardiovascular disease, a Deep Neural Network structure centered on Single Shoot Detection (SSD) MobileNet v2 was utilized. The study concentrated on identifying the four primary cardiac anomalies, and the results were estimated with accuracy. Depending on their database, the research is relatively uncommon; a group of standardized -lead-based ECG pictures utilized in this research are physically gathered from universal healthcare institutions and evaluated by the subject specialists. The study produced high-accuracy findings in distinguishing and detecting four main heart anomalies. Numerous cardiologists personally validated the efficiency results for the proposed approach and advised that it be used to screen for a heart condition [12].

This research demonstrates how to use the discrete wavelet transform (DWT) to minimize drifting and disturbance in electrocardiographic (ECG) recordings. This describes a revolutionary one-step implementation that allows us to improve the entire denoising procedure. In addition, a thorough investigation is conducted to define threshold restrictions and thresholding procedures for optimum wavelet denoising utilizing the current method. The system was evaluated with synthetic ECG data, which allows for precise measurement of the effects of the planned processing. Furthermore, data from genuine abdominal of ECG signals obtained from pregnant women are shown to verify the provided technique [13].

Every year, millions of people die as a product of cardiovascular disorders, the majority of which are preventable if detected early. Inside this fight for cardiovascular illnesses, primary prevention plays a critical role. Initial, second, and third preventive each get their applications, as well as advantages and disadvantages. The purpose of this research is to increase the sensitivity of "prevention and treatment of cardiovascular diseases." To begin, it examines the most frequent kinds of cardiovascular disorders and their origins from around the world. Second, it examines various risk factors related to cardiac diseases, then mentions upcoming technology developments in cardiovascular disease forecasting, and at last, offers an understanding of the significance of supplementary cardio-vascular preventing disease and generally recommended initiatives for high-risk patients [14].

The automated detection and identification of life-threatening arrhythmias are critical in the treatment of many heart diseases. A unique strategy for classifying various categories of arrhythmias using the morphological and a dynamic data is provided in this research. To get the morphological information, the discrete wavelet transform (DWT) is performed on each heartbeat. It improves the temporal and frequencies precision of the electrocardiogram (ECG) signal, allowing significant data from a quasi-periodic ECG to be decoded utilizing various window widths. As a subsequently results, RR interval data is employed. The Teager energies operators capture the nonlinear effects of the RR interval, which enhances arrhythmia identification. Furthermore, to eliminate redundancy, DWT sub-bands were dimensionally reduced utilizing independent components analysis (PCA, as well as a total of values, are chosen as morphological characters. To identify arrhythmia, these hybrid characteristics are merged and supplied into a neural network. The suggested algorithm was tested utilizing beats from the MIT-BIH arrhythmia data collection and beats from the MIT-BIH supraventricular heart rhythm dataset. Utilizing three-fold cross verification, the suggested technique resulted in a better accuracy level of and for class- and topic schemes, respectively [15].

The electrocardiogram (ECG) is a normal for detection and diagnosis irregular cardiac rhythms and is among the most effective techniques being used in the hospitals to examine cardiovascular conditions and monitor health. In recent decades, cardiovascular health had already attracted considerable reflection. Traditional medical consultation, on the other hand, has drawbacks such as symptoms suggestive and a higher incidence of misdiagnosis, whereas cardiovascular disorders have the features of earlier detection, preventative care, and recovery process. As a result, it is critical to lower the rate of cardiovascular disease misdiagnosis. This research is based on five categories of ECG arrhythmias defined by the guidelines: non-ectopic, supraventricular abnormal, ventricle ectopic, fusing, and unidentified rhythm. This study suggested a convolutional neural network (CNN)-based high-accuracy ECG arrhythmia detection approach that could reliably classify ECG signals. Depending on the MIT-BIH arrhythmia dataset, assessed the categorization effectiveness of this technique on the supraventricular ectopic beat (SVEB) and ventricular ectopic beat (VEB). According to with findings, the suggested technique for identifying VEB obtained accuracy, sensitivity as , specificity as , and positive prediction frequency as . The identification of SVEB obtained accuracy as , sensitivities as , specificity as , and a positive prediction frequency of [16].

An electrocardiogram (ECG) monitors the electrical movement of the heart and provides valuable uncontrolled data about cardiovascular illnesses include arrhythmia. Nevertheless, because of their intricacy and nonlinearity, ECG signals are challenging to physically evaluate. Using a cascade of wavelet convolution operation with nonlinear threshold and average operations, the wavelet scattering transformation may construct translation-invariant and deformation-stable models of ECG signals. suggested a novel method for automatically identifying four types of arrhythmia ECG heartbeats, including supraventricular ectopic (S), fusion (F) nonectopic (N), and ventricular ectopic (V). The wavelet dispersion technique was used in this research to identify 8 durations from every ECG heartbeat. On the eight timeframes, two-dimensional reduction techniques, principal component analysis (PCA), and timeframe selecting, were used [17]. This research proposed a hierarchical ECG arrhythmia detection system based on a convolutional neural network (CNN) that could reliably classify ECG data. Depending on the MIT-BIH arrhythmia dataset, assessed the categorization efficacy of this technique on the supraventricular ectopic beat (SVEB) and ventricular ectopic beat (VEB). The suggested technique for detecting VEB attained accuracy as sensitivity as 99.9%, and specificity as positive prediction rate, according to data. SVEB identification reached accuracy as sensitivity as specificity as and successful predictive probability as 98.6% [18].

3. Materials and Methods

Because of the generally increasing computing overhead, the implementation period and the amount of power that a highly accurate approach uses is going to be longer. An ECG signal method with limited computational demand and optimum accuracy equivalent to that reached by high accuracy techniques is required for the design of an ASIC that is both efficient in terms of energy consumption and space use. Figure 1 depicts the execution steps of the illness diagnosing method. First, the 16-bit digital ECG signal is processed by a bandpass filter (bandwidth: $0.5-40Hz$). As seen in Figure 2, the production of the bandpass-filter is reflected by the ECG FILT signal. Previously, built a QRS ASIC in which the ECG signal is processed using a frequency range of to identify only QRS complex characteristics.

QRS identification is the greatest significant jobs in ECG signal treatment for ECG extraction of features is displayed in Figure 3. The detection of QRS complexes begins with the localization of the R peak. Using previously found R peak positions, further significant fiducial sites could be determined directly. Furthermore, attributed to the prevalence of disturbances, P wave, and T wave elements, the process of QRS recognition is challengin. Variations in heartbeat and QRS complex length caused by cardiac disorders need the adoption of adaptable approaches for QRS complex identification. In the research, a diversity of QRS detection solutions have been developed, including filter-based methods; QRS recognition algorithms depending on derivative wavelet transforms; neural network-based QRS diagnostic methods; and algorithms depending on hidden Markov models. QRS identification utilizing genetic algorithm; QRS identification utilizing phasor transformation; and QRS identification utilizing support vector machines.

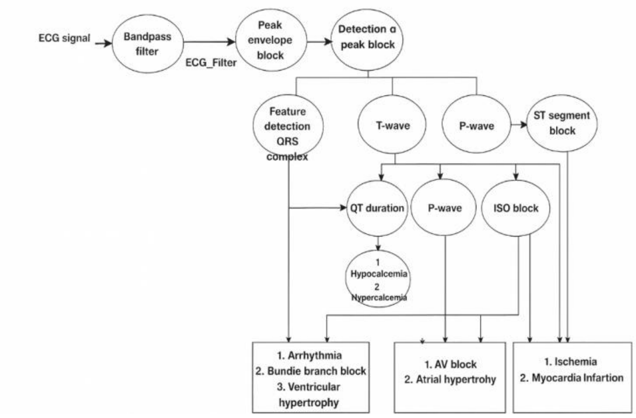

Figure 2. Detection of cardiovascular disease algorithm.

After determining the QRS complex characteristics, a J-point searching region (JPSR) is established within the point J blocks, as seen in Figure 2. This region lasts milliseconds from the peak position as S. If the gradient of the filtering ECG signal across three successive samplings becomes less than the only first position in the JPSR is used as the point J. If this criterion is not satisfied, the point J is away from the point S. point J block, as indicated in the Figure 2, triggers the computation in ST-segment blocks and T wave blocks at the same time.

To minimize baseline movement, the high pass filtering within the bandpass filter in Figure 2 has a cut-off value of For measures a ST-segment, worldwide guidelines for cardiac monitoring require a lower cut-off frequency of To determine the correct ST-segment assessment, cardiac monitoring employs a bandpass filter with such bandwidth of In cardiac monitoring, a supplementary high pass filter with a cut-off speed of is utilized to eliminate starting point wandering. This supplementary filter is constructed in such a way that it does not induce deformation into the ST-section. This modeled the output signals being used cardiac monitoring (bandpass filter having bandwidth supplemented by such a high pass filter having cut off frequencies) and the approach (bandpass filter having frequency) for the Physio net PTB database. In both situations, examined the segment strength ST. The median St-segment elevation voltage distance among different filter productions was with such a normal error of $5.5V$. In the Physio net PTB dataset, this degree of ST-segment variation has little effect on disease identification accuracy.

Figure 3. ECG Extraction of features.

Isoelectric searching regions (ISO) are produced in ISO block based on T wave terminal intelligence gathered from T wave blocking, as seen in Figure 2. As illustrated, the ISO zone extends from the conclusion of a T wave toward a start of the P wave (b). wave T end is defined as of T wave maximum point. The interval PR varies from to milliseconds. As a result, the start of the P wave was determined as $160ms$ even before the maximum of the QRS complex. This compute isoelectric potential within the ISO area when the slope of 8-consecutive values of processed ECG signal is much less than For a sampling rate of $250Hz$, the length of 8-consecutive observations is This creates a P wave search region (PPSR) from the end of the T wave to the starting of the Q wave. The wave P peak is acquired in this area on the zero crossing of a 3-point financial instrument of filtered ECG signal.

Table 1. T-wave thresholds.

ECG Lead(s)	T_threshold [mV]
Lead I, II, and VI	0.6
avL	0.256
V3	1
V6	0.752

After determine arrhythmia, ventricular tachycardia, and bundle branch blockage using data from the complex QRS feature-based blockage and the ISO blocked. The interval and QRS duration are used to identify arrhythmias. The grading parameters are used to identify ventricular hypertrophy. Two requirements are used to detect the left bundle branch blockage (LBBB). i) The amplitude QRS in a leads I, II, and must be equivalent to or better than and ii) the Q wave must be missing in leads and $V6$. Three criteria are used to detect the right bundle branch blockage (RBBB). i) The QRS frequency in leads I, II, and should be equivalent or better than ii) In lead V1, the inferior breadth of the wave will be more than or equivalent to the wave R; and iii) In lead lead or lead $V6$, the wavelength must be higher than the wave. If the QRS amplitude is more than and intraventricular transmission latency is found in Table 1.

After acquiring data from the P wave and ISO blocks, a diagnosis of atrial hypertrophy as well as AV blockage can be made. When the electrical signal that drives your heartbeat is blocked, either partially or entirely, you may experience heart block, which is also referred to as AV block. Your heartbeat will become irregular or slow as a result of this, and it will be unable to pump blood as efficiently. Atrial hypertrophy can be identified by looking for a peak in the P wave. There seem to be three main types of AV blocks, that are produced by abnormalities in the AV nodes, The bundle, or both of the right and left bundle branch blocks (RBBB and LBBB) (LBBB). As previously stated, either RBBB or LBBB occurs whenever the QRS duration exceeds $100ms$. Patients who have acquired full heart block or high-grade AV block, defined as having two or more non-conducted P waves in a row, are typically patients who exhibit symptoms. Children who are born with congenital total heart block typically do not exhibit any signs of the condition, but adults who have the condition typically do. It is essential to locate the location of an AV blockage within the cardiac electrical network in order to diagnose the problem. Table 2 shows the improvement of the AV blocking detection techniques. An R-R interval-based criterion has been devised to diagnose second-degree AV block. The second-order AV block is diagnosed if the present R-R timeframe is significantly greater than with the prior on R-R interval and the length is larger than $200ms$, as can be seen in Table 2. The placement of the AV block is determined by the QRS length values, which are provided in Table 2.

Table 2. AV block location detection criteria.

QRS Detection	P-R Interval	$(R - R_{cur})$	Position of Node	Degree
≤100 ms	>200 ms	NA	AV	1st
≤100 ms	>200 ms	$>1.5\times(R - R_{prev})$	AV	2nd
>100 ms	>200 ms	NA	AV	1st
>100 ms	>200 ms	$>1.5\times(R - R_{prev})$	Bundle branch block	2nd

4. Architecture Structure of PQRST ASIC

The PQRST ASIC implementations are built on top of the algorithm that was discussed in the preceding section. In order to do an analysis on the one lead serial data of the ECG (*ECG_DATA*) (*CLK*)., an external clock is required. The ASIC was developed for use with a single ECG lead and is clocked by an external source. It processes ECG data in serial form. This ASIC contains three units, as illustrated in Figure 4. Serial in the parallel output takes serial of ECG information and converts it to parallelism ECG data (*ECG_P*). At the internally generated clock the detecting block analyses the ECG P signal (16 bit). This time is produced inside the clock generator block and is divided by sixteen clocks out of an external clock. The detecting block is where the ECG signal is processed. QRS complex characteristics, T wave peak QT duration wave P peak PR duration as (PRD), ST-segment readings, and isoelectric voltages are also the detecting block's outputs (ISO). *ST_SEG*60, *ST_SEG*80, and denote the ST segment voltage at and respectively. QRS duration (QRSD), R-wave peak Q-wave duration (QWD), interval (*RR*), R-wave duration S-wave peak Q-wave peak and supplementary wave peak are among the observed QRS complex characteristics. In the event when the wavelength is greater than that of the wavelength, the strength of the logic behind the message *SGRTR*is increased. For the purpose of increasing the*ASIC*'s durability, it is possible to run this *ASIC*in diagnostic and scanning stages. If the PEAK signal has logic high, this means that the 16-bit parallel outputs can be converted into serial output by the PISO block at the negative edge of the PISO signal. The testing and scanning modes are activated by the test clock the TEST pin, and the sufficient current Aside from that, the internal sources clock waveforms are accessible for validation at the output pin as illustrated in Figure 4. The scanning flip-flops in the clock model is generated are activated at the rising advantage of the exterior clock under the mode of operation. All scanning flip flops that are generated at the positive edge of an external unit have a scanning route from to (clock generating blocks to detecting blocks). Likewise, all scanning flip flops that were activated at the positive control of the internal clock (*CLK_CHIP*) have a scanning route from signals ECG_SI to SOUT (SIPO blocks to detecting the block).

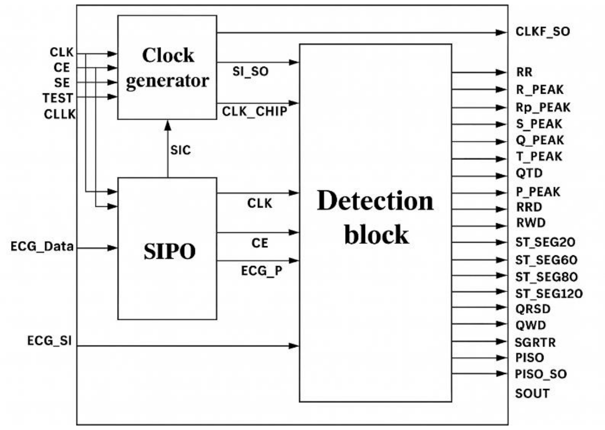

Figure 4. ASIC Architecture Model.

Algorithm 1. Wave Extraction from Pre-processed ECG Signal

Input: Pre-processed ECG signal

Output: QRS Complex, ST Wave

1: Begin

2: Let N ← length of P (signal length)

3: Normalize the ECG signal

4: Compute the average ECG signal

5: Calculate the mean of the averaged signal

6: Apply threshold to the averaged signal

7: Estimate the significant wave regions on both left and right sides

8: Extract R wave from the thresholded regions

9: Extract Q wave preceding R wave

10: Extract S wave following R wave

11: Extract T wave after QRS complex

12: Extract P wave before QRS complex

13: Form the QRS complex using Q, R, and S waves

14: Identify and isolate ST wave region

15: Return {QRS complex, ST wave}

16: End

When a QRS complex is identified, the signals QRS_END is sent to the point J detection block, and the QRS complexity variables are sent to the PISO block. This is also transmitting the position of the Q wave peak to the T wave detecting block to retrieve the QT delay In the J increases security block, a period of 68ms is created. This window begins at the transmitter positive edge, Just at the positive edge of the signal, the J increases security block changes The signal activates the T wave detecting and ST-segment blocks. The T wave detecting generator produces a window (signal TEW) that spans from to is displayed in Figure 5. Furthermore, the ST segment generator produces window signals and from an external clock generated inside the clock values generated. The detecting block is where the ECG signal is processed. QRS complex characteristics, QT duration (QTD), isoelectric potential, P wave peak T wave peak ST-segment values, and PR interval (PRD) are the detecting block's outputs (ISO). and denote the ST segment voltage at $J + 20ms$, $J + 60ms$, $J + 80ms$, and $J + 120ms$, correspondingly.

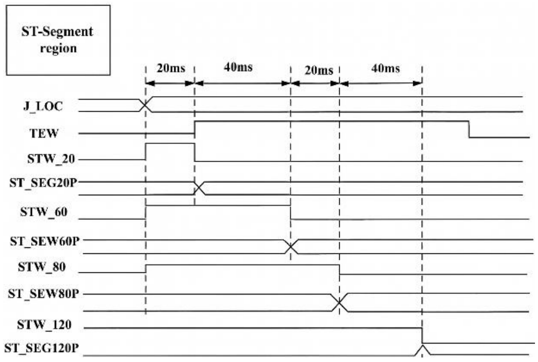

Figure 5. Waveform of timing block detection.

These interval signals begin at J END and end at $J + 60ms$, $J + 80ms$, and in that order. The ST segment values and are adjusted as per the filtering ECG signal values (ECG _FILT) at the zero-crossing of window signal and At the positive advantage of the signals, which signifies the conclusion of the T wave, the T peak value and the QT period values were changed. The signal QTEND activates an ISO and P wave detecting blocks. The ISO block generates a space signal ISOW that begins at the positive edge of QTEND and terminates at the starting of the wave P. The mean PR interval is used to determine the start of a P wave. At the transmitter end of a ISOW pulse, the isoelectric voltage (ISO_P) is adjusted. PW, a windows signal, is also generated at the positive superiority of the but stops at the SEL_PEAK positive control. At the transmitter end of the PW signal, the P wave peak (*P_PEAK_P*) and P-R period were changed.

If a maximum is identified in a filtering ECG signal (ECG_FILT) among consecutive SELECT signals (namely, inside a forward search zone), the peak detection block generates the SEL_PEAK signal. In the canny edge detection phase, a signal PEAK also was produced, indicating that a peak is a legitimate complex QRS peak. To preserve dynamic power, the timer of a ST-segment blocks, ISO block, wave P detecting blocks, and wave T detector block is controlled also with PEAK indication. As a result, it will not consume a correct complex peak as QRS, the computations in such blocks are suppressed in order can save voltage levels. At the primary side of VALID_PEAK signals, all the results of the ST segments block, block ISO, wave P detector block, wave T detector block, and QRS detection frame are transferred to the parallelism in series output (PISO) square. The VALID_PEAK signals are created only if the SELECT and PEAK signals are both set to logical strong. This is done to verify that outputs for a genuine complex QRS peak are accessible. The sequential output of PISO blocks was accurate as of the PISO signal's transmitter end.

For RTL development of the ASIC, used the Hardware description language system. The transistor-level configuration is generated using the Schematic capture designing generator. Cadence chip encounters are used for chip positioning and sequencing. Mentors Prototype was used to validate post-layout simulations. To do static performance analysis, the Schematic capture Primetime is still used. Utilizing Cadence chip encounters, build the designer netlist and GDSII files. Cadence virtuoso is used to build the ASIC schematics and arrangement view from the designer netlist and GDSII file. In the ASIC design, physically inserted outputs pads. The Mentor Caliber software is used to conduct the designing regulation checking (DRC) and layouts vs schematics (LVS) of ASIC architecture. The ASIC die photo is shown in Figure 6. This development's core area is $1.1 \times 1.1 mm^2$. The ASIC was verified using an exterior clock rate of the and an electricity usage of $96PJ$ at voltage source.

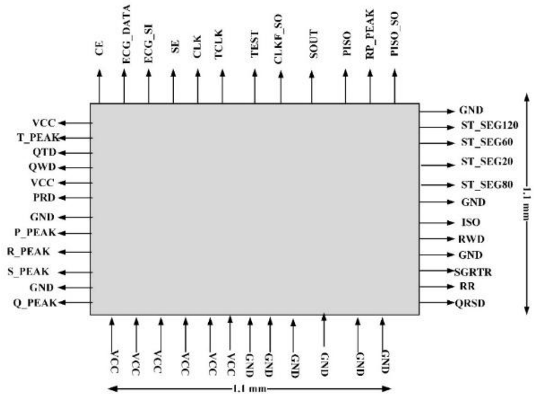

Figure 6. PQRST ASIC die picture.

5. Results and Discussion

In the previous work, validated leads II data from a MIT-BIH arrhythmia dataset to compare the technique to existing QRS complex peak detection techniques. This database collection has a lot of noise and artifacts. Such artifacts have a frequency range of less than The system's specificity and sensitivity for such a dataset are and respectively. In comparison to slope-built existing approaches, the technique of identifying complex QRS peak sites created on envelopes and dynamic threshold reduces noise. As a result, the MIT-BIH arrhythmia dataset has a very low failure detection accuracy of 0.23%.

The system's noise endurance was examined utilizing the gesture object dataset from a MIT-BIH noise strain dataset. This has stimulated the specificity, selectivity, and failure detection accuracy of the method in the MIT-BIH arrhythmia dataset with different signal-to-noise ratios (SNR) including using electrodes moving objects from the MIT-BIH noise stressing datasets. The median sensitivities, selectivity, and the failure detection accuracy with SNR for 48 recordings from the MIT-BIH arrhythmias dataset are displayed in Figure 7. As shown in Figure 7, the algorithm's noise sensitivity is equivalent to that of existing wavelet techniques with all SNR. During the recording process, motion artifacts in the ECG signal could be minimized. While capturing the ECG signal, an adaptive threshold method is used to eliminate ECG motion artifacts.

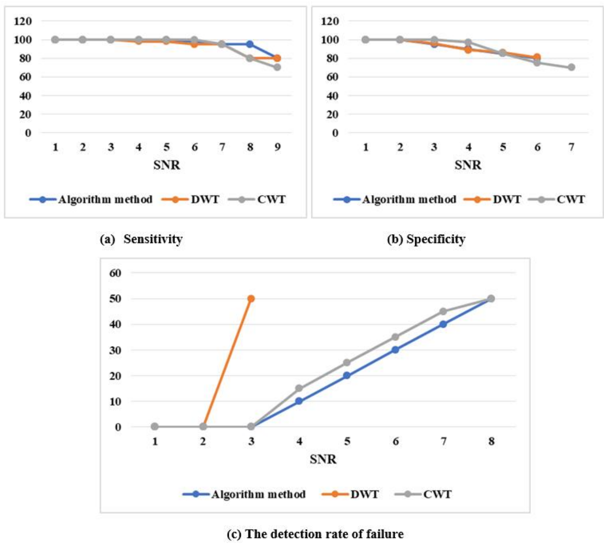

Figure 7. Test of noise stress.

Table 3 and Table 4 shows the sensitivities, specificities, and failure detection frequency of the QRS compound peak estimated with each lead. The object's unsuccessful detection rate for QRS complex peaks ranges from percent (lead to percent (lead II). This eliminated records patient (lead $V1$) and patient$s$ $285/s0544\_re$ (six leads) from this database due to lacking QRS complexes. Since of noise thereafter a recording discarded recorded patients for lead and lead avL. For lead and lead avL, the maximum noise amplitude is roughly Other connections, on either hand, show legitimate QRS complex peaking at these places. Considers each lead to have a legitimate QRS complex peak if the $\mathrm{R}-\mathrm{R}$ interval including all leads is less than $80ms$. When to add a qualified majority, rather than evaluating R-R interval with all leads, $\mathrm{R}-\mathrm{R}$ interval may be determined for the recording patient $141/s0307lre$ after the remaining four contacts, including I, $V1$, $V3$, and $V6$. In this manner, the occurrence of the noise in a two leads could avoided.

Table 3. Performance detection of Peak QRS complex.

Leads	T_{pos}	F_{neg}	F_{pos}	Sensitivity	Specificity	Detection rate of failure
Lead I	69136	70	56	99%	99.2%	0.16
Lead II	68767	66	119	99.9%	99.8%	0.25
Lead avL	69045	75	93	99.7%	99.7%	0.26
Lead $V1$	69052	36	49	99.8%	99.6%	0.11
Lead $V3$	69172	34	25	99.9%	99.9%	0.07
Lead $V6$	69175	28	20	99.9%	99.9%	0.08

Table 4. Comparison of the proposed method.

Techniques	P-wave Sensitivity	P-wave Specificity	T-wave Sensitivity	T-wave Specificity	QRS Sensitivity	QRS Specificity
Proposed method	98.90%	91.06%	99.96%	97.75%	100.00%	100.00%
DWT	98.88%	91.04%	99.78%	97.78%	99.98%	99.98%
CWT	97.72%	91.16%	99.90%	97.75%	99.93%	99.93%

6. Conclusion

This research presents a cheap computational cardiovascular disease diagnosis system based on a forward search. This method is talented of effectively recognizing QRS complex, P−wave, ST−section, and T wave properties. The method was tested utilizing the Physio net PTB ECG diagnosis dataset, with such a failure detection accuracy of percent for the QRS complicated peak. Utilizing the QT database, also evaluated the detection performance of P waves, QRS complexes, and T waves. P (T) wave identification with a sensitivity of percent percent) and a specificity of percent (97.76 percent). Based on the illness diagnostic algorithm, this demonstrated an area and efficient energy PQRST ASIC. PQRST ASIC has a surface area of 1.21 mm^2. With a power source, the power dissipation of such a device is For heart patients having bundles branch blockage and myocardial infarction, the QRS complex does have a small gradient. This results in a very lower power voltage following the discriminant and time series stages in the Pan-Tompkins method, and the QRS complex peak goes unreported. The forward-searching reduces the need for repeated overtime again for backward searching, which is utilized both in the wavelet and Pan-Tompkins's algorithms. For all three records in the dataset, efficiently determine the AV block and its placement. As a result, PQRST ASIC meets all of the requirements for portable ECG monitoring and diagnostics devices (compact space, lower power consumption, and high illness high detection). Using the obtained waveforms, QRS complex, and the ST−segments. The extraction of features method was used on obtained QRS complex as well as ST sections to reduce computing effort and increase accuracy. The proposed strategy outperforms previous methods by a wide margin. It is advised that other ECG cardiac datasets be used in future research.

References

[1] Ali, L., Rahman, A., Khan, A., Zhou, M., Javeed, A., & Khan, J. A. (2019). An automated diagnostic system for heart disease prediction based on χ^2 statistical model and optimally configured deep neural network. IEEE Access, 7, 34938–34945.

[2] World Health Organization. Cardiovascular diseases. https://www.who.int/health-topics/cardiovascular-diseases (Accessed April 19, 2025)

[3] Li, H., & Boulanger, P. (2020). A survey of heart anomaly detection using ambulatory electrocardiogram (ECG). Sensors, 20(5), 1461.

[4] Kushwaha, S. (2023). An effective adaptive fuzzy filter for speckle noise reduction. Multimedia Tools and Applications, 2023, 1-16. Springer.

[5] Isakadze, N., & Martin, S. S. (2020). How useful is the smartwatch ECG? Trends in Cardiovascular Medicine, 30(7), 442–448.

[6] A, S. B., S, S., S, R. S., Nair, A. R., & Raju, M. (2022). Scalogram based heart disease classification using hybrid CNN-naive Bayes classifier. In 2022 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET) (pp. 345–348). IEEE.

[7] Kushwaha, S., & Singh, R. K. (2019). Optimization of the proposed hybrid denoising technique to overcome over-filtering issue. Biomedical Engineering/Biomedizinische Technik, 64(5), 601–618.

[8] Sharma, P., & Gupta, D. V. (2018). Disease classification from ECG signal using R-peak analysis with artificial intelligence. International Journal of Signal Processing, Image Processing and Pattern Recognition, 11(3), 29–40.

[9] Ullah, A., Anwar, S. M., Bilal, M., & Mehmood, R. M. (2020). Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sensing, 12(10), 1685.

[10] Kushwaha, S., Kondaveeti, S., Vasanthi, S. M., W, T. M., Rani, D. L., & Megala, J. (2024). Graph-informed neural networks with green anaconda optimization algorithm based on automated classification of condition of mental health using alpha band EEG signal. 2024 4th International Conference on Sustainable Expert Systems (ICSES), 44–50.

[11] Mathunjwa, B. M., Lin, Y.-T., Lin, C.-H., Abbod, M. F., & Shieh, J.-S. (2021). ECG arrhythmia classification by using a recurrence plot and convolutional neural network. Biomedical Signal Processing and Control, 64, Article 102262.

[12] Rahuja, N., & Valluru, S. K. (2021). A deep neural network approach to automatic multi-class classification of electrocardiogram signals. In 2021 International Conference On Intelligent Technologies (CONIT) (pp. 1–4). IEEE.

[13] Malakouti, S. M. (2023). Heart disease classification based on ECG using machine learning models. Biomedical Signal Processing and Control, 84, Article 104796.

[14] Raviraja, S., Seethalakshmi, K., Kushwaha, S., Priya, V. P. M., Kumar, K. R., & Dhyani, B. (2023). Optimization of the ART tomographic reconstruction algorithm - Monte Carlo simulation. In Proceedings of the 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC) (pp. 984-988). Salem, India.

[15] Duong, L. T., Doan, T. T. H., Chu, C. Q., & Nguyen, P. T. (2023). Fusion of edge detection and graph neural networks to classifying electrocardiogram signals. Expert Systems with Applications, 225, Article 120107.

[16] Akcin, E., Isleyen, K. S., Ozcan, E., Hameed, A. A., Alimovski, E., & Jamil, A. (2021). A hybrid feature extraction method for heart disease classification using ECG signals. In 2021 Innovations in Intelligent Systems and Applications Conference (ASYU). IEEE.

[17] Gulati, S., Guleria, K., & Goyal, N. (2022). Classification and detection of coronary heart disease using machine learning. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1728–1732). IEEE.

[18] Nagavelli, U., Samanta, D., & Chakraborty, P. (2022). Machine learning technology-based heart disease detection models. Journal of Healthcare Engineering, 2022, 1–9.