Arrhythmia Detection using AD8232

Authors:

Suhana Bhardwaj & Simran Bhatt

Under the guidance of:

Prof. Krishna Singh

Institution:

GB Pant DSEU Okhla - III Campus

Date:

September 2025

Contents

Abstract

In the 21st century, cardiac arrests have emerged as a leading cause of mortality among young adults, with arrhythmia being one of the most overlooked early warning signs. Cardiovascular diseases account for approximately 17.9 million deaths annually worldwide, with sudden cardiac death claiming lives at an alarming rate of one person every 36 seconds. This project presents an innovative, cost-effective arrhythmia detection system utilizing the AD8232 ECG sensor module integrated with ESP32 microcontroller and TFT display technology.

Our system addresses critical challenges in current cardiac monitoring: high equipment costs, complex operation procedures, and susceptibility to environmental noise interference. Through implementation of advanced signal processing techniques including the Pan-Tompkins algorithm for QRS complex detection and strategic filtering mechanisms, we have developed a user-friendly portable device capable of real-time arrhythmia classification. The system demonstrates significant noise reduction capabilities through integrated 50Hz notch filtering and achieves reliable detection of bradycardia (<60 BPM), normal sinus rhythm (60-100 BPM), and tachycardia (>100 BPM) conditions.

Keywords: Arrhythmia Detection, AD8232, ECG Signal Processing, Pan-Tompkins Algorithm, QRS Complex, Real-time Monitoring

1 Introduction

Cardiovascular diseases remain the primary cause of global mortality, with arrhythmias representing a critical subset requiring immediate medical attention. Arrhythmia, characterized by irregular heart rhythms, often serves as a precursor to more severe cardiac events including myocardial infarction and sudden cardiac death. Traditional ECG monitoring systems, while accurate, are typically confined to clinical settings due to their complexity, size, and cost constraints. The increasing prevalence of cardiovascular diseases in younger demographics necessitates the development of accessible, portable monitoring solutions that can provide early detection capabilities outside traditional clinical environments. Current statistics indicate that cardiovascular diseases are responsible for more deaths globally than any other cause, with the majority of these deaths occurring in low- and middle-income countries where access to advanced cardiac monitoring equipment is limited.

1.1 Problem Statement

Current cardiac monitoring solutions face several critical limitations that restrict their widespread adoption and effectiveness in preventive healthcare:

Accessibility Issues: High-cost professional ECG equipment, typically ranging from Rs.102,000 to Rs.165,000, limits widespread preventive screening capabilities. This cost barrier prevents deployment in resource-limited settings, rural healthcare facilities, and developing nations where cardiac diseases are rapidly increasing.

Complexity Barriers: Traditional ECG systems require trained medical personnel for operation, interpretation, and maintenance. The complexity of these systems includes multi-lead configurations, sophisticated software interfaces, and extensive calibration procedures that make them unsuitable for point-of-care testing or home monitoring applications.

Portability Constraints: Conventional ECG equipment is typically bulky, requiring dedicated space and power infrastructure. This limitation restricts continuous monitoring capabilities and prevents integration into mobile healthcare delivery systems or emergency response scenarios.

Environmental Interference: Existing systems often struggle with electromagnetic interference from common environmental sources, leading to poor signal quality and false readings in non-clinical settings where controlled conditions cannot be maintained.

1.2 Proposed Solution

This research project introduces a novel approach to arrhythmia detection through the development of an integrated system that combines cutting-edge sensor technology with advanced signal processing algorithms. Our solution addresses the identified limitations through a comprehensive approach that prioritizes affordability, simplicity, and reliability.

The proposed system integrates four key technological components:

1. AD8232 ECG Sensor: A specialized analog front-end designed specifically for ECG and biopotential signal acquisition. This sensor provides integrated amplification, filtering, and signal conditioning.

2. ESP32 Microcontroller: Providing substantial computational power for real-time signal processing, wireless connectivity options for future telemedicine integration, and sufficient memory capacity for implementing complex algorithms including the Pan-Tompkins & QRS detection algorithms.

3. TFT Display Interface: Offering intuitive user interaction through touch-enabled interfaces, real time ECG waveform visualization, and classification results that enable immediate interpretation by non-medical personnel.

4. Advanced Digital Signal Processing: Implementation of proven algorithms including the Pan-Tompkins method for accurate R-peak detection, adaptive filtering for noise reduction, and real-time classification algorithms for arrhythmia type determination.

1.3 Material Selections

The selection of components for this arrhythmia detection system was guided by specific technical requirements, cost considerations, and performance objectives that align with the goal of creating an accessible yet reliable cardiac monitoring solution.

AD8232 ECG Sensor Selection Criteria:

The AD8232 sensor was chosen based on several critical advantages over alternative ECG acquisition solutions:

Integrated Signal Conditioning: The AD8232 incorporates essential analog processing components including instrumentation amplifiers, filters, and lead-off detection circuits in a single package, reducing system complexity and component count significantly compared to discrete implementations.

Optimized Power Consumption: With typical operating current of 170 micro Amps, the AD8232 enables extended battery operation essential for portable monitoring applications. This power efficiency is achieved through careful analog design optimization while maintaining signal quality specifications.

Cost-Effectiveness: At approximately Rs.500 per unit in small quantities, the AD8232 provides professional-grade ECG acquisition capabilities at a fraction of the cost of alternative medical-grade front-end solutions that typically cost lakhs of rupees.

ESP32 Microcontroller Platform Advantages:

The ESP32 was selected as the primary processing platform due to its unique combination of processing power, connectivity options, and development ecosystem support:

Dual-Core Architecture: The ESP32's dual-core design enables parallel processing capabilities where one core can be dedicated to real-time signal processing and algorithm execution while the second core handles user interface management and display updates, ensuring responsive system operation.

Integrated Wireless Connectivity: Built-in Wi-Fi and Bluetooth capabilities provide foundation for future telemedicine integration, remote monitoring capabilities, and data synchronization with electronic health record systems without requiring additional hardware components.

Sufficient Computational Resources: With 520KB SRAM and up to 240MHz processing speed, the ESP32 provides adequate resources for implementing complex signal processing algorithms including the Pan-Tompkins algorithm and real-time filtering operations.

Extensive GPIO Capabilities: The ESP32 offers multiple ADC channels, SPI interfaces, and GPIO pins necessary for integrating the ECG sensor, display system, and potential future expansion modules within a single microcontroller platform.

TFT Display Technology:

The selection of TFT display technology was driven by requirements for clear visualization, user interaction capabilities, and power efficiency considerations:

High-Resolution Visual Feedback: TFT displays provide crisp, high-contrast visualization essential for displaying ECG waveforms, numerical results, and color-coded classification indicators that enable immediate interpretation of cardiac rhythm status.

Touch Interface Capabilities: Integrated touch sensing eliminates the need for separate input devices, simplifying the user interface design and reducing overall system complexity while providing intuitive navigation through different monitoring modes and settings.

Color-Coded Classification System: The ability to display different colors enables immediate visual communication of arrhythmia classification results, where green indicates normal rhythm, yellow suggests bradycardia, and red warns of tachycardia conditions.

Power Efficiency: Modern TFT displays offer excellent power efficiency with vibrant color reproduction, supporting extended battery operation while maintaining clear visibility under various lighting conditions.

2 Methods and Theoretical Framework

2.1 QRS Complex Analysis and Physiological Background

The QRS complex represents the fundamental electrical signature of ventricular depolarization in the cardiac cycle and serves as the primary feature for heart rate calculation and arrhythmia detection. Understanding the physiological and electrical characteristics of QRS complexes forms the theoretical foundation for developing robust detection algorithms.

The cardiac electrical conduction system generates characteristic waveforms that can be detected and analyzed through surface electrodes. The QRS complex, in particular, represents the largest amplitude signal in the normal ECG and occurs with each heartbeat, making it the most reliable feature for automated detection systems.

2.1.1 QRS Complex Morphological Characteristics

The QRS complex consists of three distinct deflections, each corresponding to specific physiological events during ventricular activation:

Q Wave Analysis: The Q wave represents the initial negative deflection resulting from septal depolarization. In normal cardiac conduction, the Q wave has specific amplitude and duration characteristics:

$$Q_{amplitude} < 0.04 \times R_{amplitude}$$

$$Q_{duration} < 0.04 \text{ seconds}$$

R Wave Characteristics: The R wave constitutes the prominent positive deflection indicating main ventricular depolarization. R wave amplitude varies significantly based on electrode placement, patient physiology, and cardiac orientation:

$$R_{amplitude} = 5 \text{ to } 25 \text{ mV (lead-dependent)}$$

S Wave Properties: The S wave appears as the negative deflection following the R wave, completing ventricular depolarization. The S wave amplitude and morphology provide information about conduction abnormalities and ventricular geometry.

Normal QRS Duration and Clinical Significance:
The total QRS duration serves as a critical parameter for assessing cardiac conduction:

$$QRS_{normal} = 80 \text{ to } 120 \text{ milliseconds}$$

Prolonged QRS duration (>120 ms) may indicate:

- Bundle branch blocks
- Ventricular conduction delays
- Electrolyte imbalances
- Pharmacological effects

2.1.2 Clinical Significance and Diagnostic Applications

QRS complex analysis provides multiple layers of diagnostic information essential for comprehensive cardiac assessment:

Heart Rate Calculation Foundation: The QRS complex, specifically the R wave peak, serves as the timing reference for heart rate calculation. Accurate R-R interval measurement enables precise heart rate determination:

$$Heart\ Rate\ (BPM) = \frac{60}{\text{Average R-R Interval (seconds)}}$$

Rhythm Regularity Assessment: Analysis of R-R interval variability provides insight into rhythm regularity and autonomic nervous system function:

$$RR_{variability} = \sqrt{\frac{\sum_{i=1}^{n-1}(RR_{i+1} - RR_i)^2}{n-1}}$$

Conduction System Evaluation: QRS morphology analysis enables detection of conduction abnormalities, including bundle branch blocks, fascicular blocks, and pre-excitation syndromes that may predispose patients to arrhythmic events.

Arrhythmia Classification Parameters: Different arrhythmia types exhibit characteristic QRS patterns that enable automated classification:

- *Supraventricular arrhythmias:* Typically narrow QRS complexes (<120 ms) with normal morphology
- *Ventricular arrhythmias:* Wide QRS complexes (>120 ms) with abnormal morphology
- *Conduction blocks:* Prolonged QRS duration with specific morphological patterns

2.2 R-R Interval Calculation and Peak Detection Methodology

R-R interval calculation forms the cornerstone of heart rate determination and rhythm analysis in ECG signal processing. The methodology for accurate R-peak detection and subsequent interval calculation requires sophisticated signal processing techniques that can operate reliably in the presence of noise and artifacts.

2.2.1 R-Peak Detection Methodology

Our system employs a comprehensive multi-stage approach for robust R-peak identification that combines proven signal processing techniques with adaptive algorithms:

Stage 1: Signal Preprocessing and Conditioning

The initial preprocessing stage prepares the raw ECG signal for subsequent analysis by removing artifacts and enhancing QRS complex characteristics:

High-pass Filtering for Baseline Wander Removal:

$$H_{hp}(z) = \frac{1 - z^{-1}}{1 - 0.995z^{-1}}$$

This first-order high-pass filter with cutoff frequency at 0.5 Hz effectively removes baseline wander caused by respiration, electrode movement, and DC offset while preserving the QRS spectrum.

Low-pass Filtering for High-Frequency Noise Reduction:

$$H_{lp}(z) = \frac{(1 + z^{-1})^6}{(1 + 0.2z^{-1})^6}$$

The low-pass filter with 40 Hz cutoff frequency attenuates EMG artifacts, power line harmonics, and other high-frequency interference while maintaining QRS complex fidelity.

Notch Filtering for Power Line Interference:

$$H_{notch}(z) = \frac{1 - 2\cos(\omega_0)z^{-1} + z^{-2}}{1 - 2r\cos(\omega_0)z^{-1} + r^2 z^{-2}}$$

Where $\omega_0 = 2\pi \times 50/f_s$ and $r = 0.95$ for 50 Hz notch filtering.

Stage 2: Derivative-Based Enhancement

The derivative operation emphasizes the steep slopes characteristic of QRS complexes while suppressing slower variations:

$$y[n] = \frac{1}{8}(-x[n-2] - 2x[n-1] + 2x[n+1] + x[n+2])$$

This five-point derivative approximation provides optimal balance between slope enhancement and noise sensitivity.

Stage 3: Squaring Operation

The squaring function amplifies large derivatives (QRS complexes) while suppressing smaller variations:

$$y[n] = (x[n])^2$$

This nonlinear operation significantly improves the signal-to-noise ratio for QRS detection.

Stage 4: Moving Window Integration

Moving window integration smooths the signal and creates a feature waveform suitable for threshold detection:

$$y[n] = \frac{1}{N}\sum_{i=0}^{N-1} x[n-i]$$

Where N is typically chosen as the approximate QRS width in samples (80-120 ms equivalent).

2.2.2 Adaptive Thresholding Algorithm

The adaptive thresholding system automatically adjusts detection sensitivity based on signal characteristics and noise levels:

Dual Threshold System:

$$Threshold_1 = 0.625 \times Peak_I + 0.375 \times SPK_I$$

$$Threshold_2 = 0.5 \times Threshold_1$$

Where:

- SPK_I = Running estimate of signal peak amplitude
- $Peak_I$ = Peak amplitude of current analysis window
- $Threshold_1$ = Primary detection threshold
- $Threshold_2$ = Secondary threshold for missed beat recovery

Learning Phase Implementation:

The system implements an initial learning phase to establish baseline signal characteristics:

Algorithm 1 - Adaptive Threshold Learning Algorithm

```
Initialize: SPKI = 0, NPKI = 0, PEAK_I = 0
for i = 1 to LEARNING_SAMPLES do
   Process ECG sample through filter chain
   if Peak detected above noise floor then
      Update SPKI = 0.125 × PEAK + 0.875 × SPKI
   else
      Update NPKI = 0.125 × PEAK + 0.875 × NPKI
   end if
   Calculate adaptive thresholds
end for
```

2.2.3 R-R Interval Analysis and Statistical Processing

Once R-peaks are accurately detected, the system calculates R-R intervals and performs statistical analysis for heart rate determination and rhythm assessment:

Beat-to-Beat Interval Measurement:

$$RR_i = t_{R(i+1)} - t_{R(i)}$$

Where $t_{R(i)}$ represents the time of the i-th R-peak occurrence.

Heart Rate Calculation:

$$HR = \frac{60000}{\overline{RR}} \text{ (BPM)}$$

Where $\overline{RR}$ is the average R-R interval in milliseconds over a specified analysis window.

Statistical Rhythm Analysis:
R-R Interval Variability:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2}$$

Rhythm Regularity Index:

$$Regularity = \frac{\sigma_{RR}}{\overline{RR}} \times 100\%$$

Where σ_{RR} is the standard deviation of R-R intervals.

Trend Analysis Implementation:
The system implements trend analysis to detect progressive changes in heart rate that may indicate developing arrhythmic conditions:

$$Trend_{slope} = \frac{\sum_{i=1}^{N}(i - \bar{i})(HR_i - \overline{HR})}{\sum_{i=1}^{N}(i - \bar{i})^2}$$

This linear regression approach identifies gradual heart rate changes that may precede arrhythmic episodes.

2.3 Pan-Tompkins Algorithm Implementation

The Pan-Tompkins algorithm represents the gold standard for QRS complex detection in ECG signal processing, providing robust performance across diverse patient populations, signal qualities, and noise conditions. This algorithm has been extensively validated in clinical settings and forms the backbone of many commercial ECG analysis systems.

Our implementation of the Pan-Tompkins algorithm is optimized for real-time operation on the ESP32 microcontroller platform while maintaining the algorithm's proven detection accuracy and noise immunity characteristics.

2.3.1 Algorithm Architecture and Mathematical Foundation

The Pan-Tompkins algorithm employs a carefully designed sequence of signal processing operations that progressively enhance QRS complex detectability while suppressing noise and artifacts:

Stage 1: Bandpass Filtering Implementation

The bandpass filtering stage combines low-pass and high-pass filtering operations to isolate the QRS frequency spectrum (5-15 Hz) where most QRS energy is concentrated:

Low-pass Filter Design: The low-pass filter attenuates high-frequency noise while preserving QRS morphology:

$$H_{LP}(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2}$$

This filter provides a cutoff frequency of approximately 11 Hz when implemented at 200 Hz sampling rate. The filter's transfer function can be expanded as:

$$H_{LP}(z) = \frac{1 - 2z^{-6} + z^{-12}}{1 - 2z^{-1} + z^{-2}}$$

High-pass Filter Design: The high-pass filter removes baseline wander and low-frequency artifacts:

$$H_{HP}(z) = \frac{-\frac{1}{32} + z^{-16} - z^{-17} + \frac{1}{32}z^{-32}}{1 - z^{-1}}$$

This filter provides a cutoff frequency of approximately 5 Hz, effectively removing respiratory artifacts and electrode motion artifacts while preserving QRS complex characteristics.

Stage 2: Derivative Filter Implementation

The derivative filter enhances the slope information of QRS complexes, making them more easily distinguishable from other ECG components:

$$H_{deriv}(z) = \frac{1}{8}(-z^{-2} - 2z^{-1} + 2z^{1} + z^{2})$$

This five-point derivative approximation provides an optimal balance between slope enhancement and noise sensitivity. The derivative operation emphasizes rapid changes characteristic of QRS complexes while suppressing the slower changes associated with P and T waves.

Implementation in Time Domain:

$$y[n] = \frac{1}{8}(-x[n-2] - 2x[n-1] + 2x[n+1] + x[n+2])$$

Stage 3: Squaring Function

The squaring operation serves multiple purposes in the QRS detection process:

$$y[n] = (x[n])^2$$

Benefits of Squaring:

- Amplifies large derivative values (QRS complexes) relative to smaller values
- Makes all values positive, simplifying subsequent processing
- Enhances signal-to-noise ratio for detection
- Suppresses low-amplitude noise and artifacts

Stage 4: Moving Window Integration

The moving window integration smooths the signal and creates a feature waveform suitable for threshold-based detection:

$$y[n] = \frac{1}{N}\sum_{i=0}^{N-1} x[n-i]$$

Window Size Optimization: The integration window width N is critical for optimal performance:

$$N = \frac{0.15 \times f_s}{1} \text{ samples}$$

Where f_s is the sampling frequency. For a 500 Hz sampling rate, N $\approx$ 75 samples, corresponding to approximately 150 ms.

2.3.2 Decision Logic and Adaptive Thresholding

The decision logic component implements sophisticated threshold adaptation and beat validation mechanisms:

Adaptive Threshold Calculation:

The algorithm maintains two sets of thresholds for different signal conditions:

$$THRESHOLD_{I1} = 0.625 \times PEAK_I + 0.375 \times SPKI$$

$$THRESHOLD_{I2} = 0.5 \times THRESHOLD_{I1}$$

$$THRESHOLD_{F1} = 0.625 \times PEAK_F + 0.375 \times SPKF$$

$$THRESHOLD_{F2} = 0.5 \times THRESHOLD_{F1}$$

Where:

- $SPKI$ = Running estimate of signal peak amplitude (integration waveform)
- $SPKF$ = Running estimate of signal peak amplitude (filtered signal)
- $PEAK_I$ = Current peak amplitude (integration waveform)
- $PEAK_F$ = Current peak amplitude (filtered signal)

Peak Update Equations:
Signal peaks are updated using exponential averaging:

$$SPKI = 0.125 \times PEAK_I + 0.875 \times SPKI$$

$$SPKF = 0.125 \times PEAK_F + 0.875 \times SPKF$$

Noise peaks are similarly updated:

$$NPKI = 0.125 \times PEAK_I + 0.875 \times NPKI$$

$$NPKF = 0.125 \times PEAK_F + 0.875 \times NPKF$$

2.3.3 Real-time Implementation Optimization

The Pan-Tompkins algorithm implementation for the ESP32 platform incorporates several optimization strategies for real-time performance:

Computational Efficiency Enhancements:
Fixed-Point Arithmetic: To optimize processing speed on the ESP32, floating-point operations are replaced with fixed-point arithmetic where possible:

$$y[n] = \frac{(x[n] \times 32768)^2}{32768}$$

Circular Buffer Implementation: Memory usage is optimized through circular buffer implementation for filter delay lines:

Algorithm 2 Circular Buffer Management

Initialize: $buffer[N]$, $index = 0$ UpdateBuffer$newSample$
$buffer[index] = newSample$
$index = (index + 1) \mod N$
return $buffer$

Memory Management Strategy:

The implementation uses efficient memory allocation to minimize RAM usage:

- Filter buffers: 400 bytes (maximum delay line length)
- Peak detection arrays: 200 bytes (running averages)
- Threshold variables: 32 bytes (adaptive parameters)
- Total RAM usage: <1KB for complete algorithm

Latency Minimization Techniques:

Pipeline Processing: The algorithm stages are implemented as a pipeline to minimize processing latency:

$$Latency_{total} = \max(L_{filter}, L_{derivative}, L_{square}, L_{integrate}) + L_{decision}$$

Where each L_i represents the processing time for stage i.

Interrupt-Driven Sampling: ADC sampling is implemented using timer interrupts to ensure consistent sampling intervals:

Algorithm 3 Interrupt-Driven ECG Sampling

TimerInterrupt
$sample = ADC\_Read()$
$ProcessSample(sample)$
$UpdateDisplay()$ if needed

3 System Architecture and Hardware Integration

3.1 Hardware Configuration and Component Integration

The hardware architecture of our arrhythmia detection system represents a carefully orchestrated integration of analog front-end processing, digital signal processing, and user interface components. The system design prioritizes signal integrity, processing efficiency, and user accessibility while maintaining cost-effectiveness and portability.

The overall system architecture follows a modular approach where each component is optimized for its specific function while maintaining seamless integration with other system elements. This design philosophy enables future upgrades and modifications while ensuring robust operation under diverse environmental conditions.

3.1.1 Sensor Interface Design and Analog Front-End

The AD8232 ECG module serves as the critical analog front-end component, responsible for acquiring, amplifying, and conditioning the cardiac electrical signals before digital processing. The sensor interface design incorporates several key considerations for optimal signal quality and noise immunity.

AD8232 ECG Module Detailed Configuration:

The AD8232 integrates multiple analog processing functions essential for high-quality ECG acquisition:

Instrumentation Amplifier Characteristics:

$$A_{instrumentation} = 1 + \frac{2R_G}{R_{gain}}$$

Where R_G is the external gain-setting resistor. For our application, the gain is configured at 1100 V/V to provide adequate amplification for the typical 1-5 mV ECG signal amplitude.

Common-Mode Rejection Ratio (CMRR): The AD8232 provides excellent CMRR performance:

$$CMRR = 20 \log_{10} \left(\frac{A_{differential}}{A_{common-mode}} \right) > 80 \text{ dB}$$

This high CMRR effectively suppresses common-mode interference from power lines and electromagnetic sources.

Integrated Filtering Characteristics: The AD8232 incorporates built-in analog filters:

- High-pass filter: $f_c = 0.5$ Hz (baseline wander removal)
- Low-pass filter: $f_c = 40$ Hz (anti-aliasing and EMG suppression)
- Notch filter capability: Configurable for 50/60 Hz rejection

Electrode Interface and Lead Configuration:

Our system implements a modified Lead I configuration optimized for portable monitoring:

Electrode Placement Strategy:

- **RA (Right Arm):** Placed on right wrist or right upper chest
- **LA (Left Arm):** Placed on left wrist or left upper chest
- **RL (Right Leg):** Reference electrode placed on right/left calf or thigh

Lead-Off Detection Implementation: The AD8232 provides automatic lead-off detection through dedicated pins:

$$V_{lead-off} = V_{supply} \times \frac{R_{electrode}}{R_{electrode} + R_{pullup}}$$

When electrode impedance exceeds 10 M, the lead-off detection circuit triggers an alert condition.

Signal Conditioning and Amplification:

The analog signal conditioning chain is designed to optimize signal quality while minimizing noise introduction:

$$V_{output} = A_{gain} \times (V_{LA} - V_{RA}) + V_{reference}$$

Where:

- $A_{gain} = 1100$ V/V (instrumentation amplifier gain)
- $V_{reference} = 1.65$ V (mid-supply reference for single-supply operation)
- $(V_{LA} - V_{RA})$ represents the differential ECG signal

3.1.2 Microcontroller Integration and Digital Processing

The ESP32 microcontroller serves as the central processing unit, handling analog-to-digital conversion, signal processing algorithm execution, user interface management, and system control functions.

ESP32 DevKit Hardware Specifications:

Processing Capabilities:

- Dual-core Tensilica Xtensa LX6 processors
- Operating frequency: up to 240 MHz per core
- SRAM: 520 KB (for program execution and data storage)
- Flash memory: 4 MB (for program storage and data logging)

ADC Configuration and Performance: The ESP32 incorporates high-resolution ADC capabilities essential for ECG signal digitization:

$$ADC_{resolution} = \frac{V_{reference}}{2^{12}} = \frac{3.3V}{4096} = 0.806 \text{ mV/count}$$

This resolution provides adequate precision for detecting ECG signal variations while maintaining sufficient dynamic range for different signal amplitudes.

Sampling Rate Configuration: The system implements a 500 Hz sampling rate, providing adequate frequency response for QRS detection:

$$f_{sampling} = 500 \text{ Hz} > 2 \times f_{max} = 2 \times 40 \text{ Hz}$$

This sampling rate satisfies the Nyquist criterion while providing computational overhead for real-time processing.

GPIO Pin Assignment and Interface Management:

The ESP32 GPIO configuration is optimized for minimal interference and maximum signal integrity:

Table 1: ESP32 GPIO Pin Assignment

Function	**GPIO Pin**	**Signal Type**	**Configuration**
ECG Signal Input	GPIO 34	Analog Input	ADC1_CH6, 12-bit
TFT CS	GPIO 15	Digital Output	SPI Chip Select
TFT DC	GPIO 2	Digital Output	Data/Command Control
TFT RST	GPIO 4	Digital Output	Reset Control
TFT MOSI	GPIO 23	Digital Output	SPI Data Output
TFT SCLK	GPIO 18	Digital Output	SPI Clock
Touch CS	GPIO 5	Digital Output	Touch Chip Select
Touch IRQ	GPIO 27	Digital Input	Touch Interrupt

3.1.3 Display System Architecture and User Interface

The TFT display system provides the primary user interface for system interaction, real-time waveform visualization, and result presentation. The display architecture incorporates both visual output and touch input capabilities.

TFT Display Technical Specifications:

Display Characteristics:

- Resolution: 240×320 pixels (QVGA)
- Color depth: 16-bit (65,536 colors)

- Display technology: TFT-LCD with LED backlight
- Viewing angle: 160° horizontal and vertical
- Interface: 14-wire SPI communication

Touch Interface Specifications:

- Touch technology: Resistive touch sensing
- Resolution: 4096 × 4096 pressure levels
- Response time: <10 ms
- Interface: SPI communication with interrupt capability

SPI Communication Protocol Implementation:

The display communication utilizes optimized SPI protocol for high-speed data transfer:

$$Data_{rate} = \frac{Clock_{frequency}}{Bits_{per\_pixel}} = \frac{40 \text{ MHz}}{16 \text{ bits}} = 2.5 \text{ Mpixels/second}$$

This data rate enables smooth real-time waveform updates and responsive user interface operation.

Display Update Optimization:

- Frame buffer: Partial updates for waveform regions
- Dirty rectangle tracking: Updates only changed screen areas
- Color palette optimization: Reduced data transfer for monochrome waveforms
- Interrupt-driven updates: Non-blocking display operations

3.2 Software Architecture and Real-Time Processing

The software architecture implements a layered approach that separates hardware abstraction, signal processing, application logic, and user interface management. This modular design enables efficient development, testing, and future enhancements while maintaining real-time performance requirements.

3.2.1 Modular Software Design Structure

The software system is organized into distinct functional modules, each with well-defined interfaces and responsibilities:

Signal Processing Module Architecture:

The signal processing module implements the core ECG analysis algorithms with optimized data structures and processing pipelines:

Algorithm 4 Signal Processing Pipeline

ProcessECGSample*sample*
$filtered = BandpassFilter(sample)$
$derivative = DerivativeFilter(filtered)$
$squared = SquareFunction(derivative)$
$integrated = MovingWindowIntegration(squared)$
$peak = PeakDetection(integrated)$
if *peak* detected **then**
  $UpdateHeartRate(peak)$
  $ClassifyRhythm()$
end if

Classification and Analysis Module:

This module implements arrhythmia classification logic based on heart rate analysis and rhythm pattern recognition:

Algorithm 5 Arrhythmia Classification Algorithm

ClassifyArrhythmia*heartRate*, *rhythm*
if $heartRate < 60$ **then**
  return BRADYCARDIA
else if $heartRate > 100$ **then**
  return TACHYCARDIA
else if $rhythmRegularity > 0.2$ **then**
  return IRREGULAR_RHYTHM
else
  return NORMAL_SINUS_RHYTHM
end if

3.2.2 Real-Time Processing Pipeline and Timing Analysis

The real-time processing pipeline is designed to meet strict timing constraints while maintaining signal processing accuracy:

Timing Constraint Analysis:

Sampling Period Requirements:

$$T_{sampling} = \frac{1}{f_{sampling}} = \frac{1}{500\text{ Hz}} = 2\text{ ms}$$

Processing Time Budget:

$$T_{processing} < 0.8 \times T_{sampling} = 1.6\text{ ms}$$

This constraint ensures 20% timing margin for system overhead and interrupt handling.

Pipeline Stage Timing Analysis:

Table 2: Processing Pipeline Timing

Processing Stage	Execution Time	Percentage
ADC Acquisition	50 μs	3.1%
Bandpass Filtering	200 μs	12.5%
Derivative Calculation	100 μs	6.3%
Squaring Operation	50 μs	3.1%
Moving Integration	150 μs	9.4%
Peak Detection	300 μs	18.8%
Classification	100 μs	6.3%
Display Update	200 μs	12.5%
Total	**1150 μs**	**72.0%**

Memory Management and Data Flow:

Circular Buffer Implementation: Efficient memory usage is achieved through circular buffer implementation for filter delay lines and data storage:

$$Memory_{total} = N_{filter} \times sizeof(sample) + N_{buffer} \times sizeof(result)$$

Where:

- $N_{filter} = 200$ samples (filter delay lines)
- $N_{buffer} = 1000$ samples (analysis buffer)
- Total memory usage: <4KB for complete processing pipeline

Data Flow Optimization:

Algorithm 6 Optimized Data Flow Management

Initialize circular buffers and pointers
while system running **do**
  $sample = GetNextECGSample()$
  $StoreInCircularBuffer(sample)$
  $ProcessLatestSamples()$
  if analysis window complete **then**
    $UpdateResults()$
    $TriggerDisplayUpdate()$
  end if
end while

4 Noise Reduction and Signal Processing Enhancement

4.1 Sensor Sensitivity Analysis and Environmental Challenges

The AD8232 ECG sensor, while highly sensitive to cardiac electrical activity, presents unique challenges when deployed in uncontrolled environments outside traditional clinical settings. Understanding and addressing these sensitivity challenges forms a critical component of developing a robust portable arrhythmia detection system.

The sensitivity of the AD8232 sensor, while beneficial for detecting low-amplitude cardiac signals, makes the system susceptible to various forms of environmental and physiological interference that can significantly impact signal quality and detection accuracy.

4.1.1 Environmental Interference Source Analysis

Environmental interference sources can be categorized into several distinct classes, each requiring specific mitigation strategies:

Electromagnetic Interference (EMI) Sources:

Power Line Interference Characteristics: Power line interference represents the most significant and consistent source of environmental noise in ECG systems:

$$V_{power\_line} = A_{50Hz} \sin(2\pi \times 50t + \phi) + \sum_{n=3,5,7...}^{\infty} A_{nH} \sin(2\pi \times n \times 50t + \phi_n)$$

Where:

- A_{50Hz} = Fundamental frequency amplitude (typically 1-10 mV)
- A_{nH} = Harmonic amplitude (decreasing with frequency)
- ϕ, ϕ_n = Phase angles dependent on proximity to power sources

Switching Power Supply Interference: Modern electronic devices generate high-frequency switching noise that can couple into ECG acquisition systems:

$$f_{switching} = 20 \text{ kHz to } 2 \text{ MHz}$$

Although outside the primary ECG bandwidth, switching frequencies can create aliasing effects and intermodulation distortion.

Radio Frequency Interference (RFI): Wireless communication systems operating in various frequency bands can introduce interference through several mechanisms:

- **Cellular networks:** 800 MHz - 2.6 GHz bands
- **Wi-Fi systems:** 2.4 GHz and 5 GHz bands
- **Bluetooth devices:** 2.4 GHz band
- **Emergency services:** VHF/UHF bands

Physiological Artifact Sources:

Electromyographic (EMG) Interference: Skeletal muscle contractions generate electrical activity that overlaps with ECG frequency spectrum:

$$f_{EMG} = 20 \text{ Hz to } 500 \text{ Hz}$$

EMG amplitude can range from 50 V to 5 mV, potentially exceeding ECG signal amplitude during muscle contraction.

Motion Artifact Characteristics: Electrode movement and skin stretching create low-frequency artifacts:

$$f_{motion} = 0.1 \text{ Hz to } 10 \text{ Hz}$$

Motion artifacts can cause baseline shifts exceeding ± 10 mV, overwhelming ECG signals and triggering false detection events.

4.1.2 Signal-to-Noise Ratio Analysis and Optimization

Quantitative analysis of signal-to-noise ratio (SNR) provides the foundation for developing effective noise reduction strategies:

ECG Signal Characteristics:
Typical ECG signal parameters in portable monitoring applications:

$$A_{ECG} = 0.5 \text{ to } 4 \text{ mV (peak-to-peak)}$$

$$f_{ECG} = 0.05 \text{ to } 100 \text{ Hz (full spectrum)}$$

$$f_{QRS} = 5 \text{ to } 15 \text{ Hz (primary energy)}$$

Noise Floor Analysis:
Environmental noise characteristics in different settings:

Table 3: Environmental Noise Analysis

Environment	**Noise Floor**	**Primary Sources**	**SNR**
Clinical Laboratory	10-20 μV RMS	Fluorescent lighting	>30 dB
Office Environment	50-100 μV RMS	Computers, monitors	20-26 dB
Home Setting	100-200 μV RMS	Appliances, lighting	14-20 dB
Industrial Environment	500-1000 μV RMS	Motors, machinery	6-12 dB

SNR Optimization Strategies:
Required SNR for Reliable Detection:

$$SNR_{required} = 20 \log_{10} \left(\frac{A_{signal}}{A_{noise}} \right) > 15 \text{ dB}$$

This threshold ensures reliable QRS detection with false positive rates ¡5
Amplification Strategy:

$$A_{total} = A_{instrumentation} \times A_{programmable} = 1100 \times A_{digital}$$

Where digital amplification $A_{digital}$ can be adjusted based on signal strength assessment.

4.2 Digital Filtering Implementation and Optimization

Digital filtering forms the cornerstone of noise reduction in our arrhythmia detection system. The filtering strategy employs multiple complementary approaches to address different noise sources while preserving ECG signal integrity.

4.2.1 50 Hz Notch Filter Design and Implementation

Power line interference at 50 Hz (or 60 Hz in some regions) represents a persistent and predictable interference source that requires targeted elimination:

Second-Order IIR Notch Filter Design:

The notch filter is designed to provide sharp attenuation at the power line frequency while minimizing impact on nearby frequencies:

$$H_{notch}(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{1}$$

Filter Coefficient Calculation:

For a notch filter centered at frequency f_0 with sampling frequency f_s and quality factor Q:

$$\omega_0 = \frac{2\pi f_0}{f_s} \tag{2}$$

$$\alpha = \frac{\sin(\omega_0)}{2Q} \tag{3}$$

Coefficient Values:

$$b_0 = 1 \tag{4}$$

$$b_1 = -2\cos(\omega_0) \tag{5}$$

$$b_2 = 1 \tag{6}$$

$$a_1 = -2\cos(\omega_0)(1 - \alpha) \tag{7}$$

$$a_2 = 1 - 2\alpha \tag{8}$$

For $f_0 = 50$ Hz, $f_s = 500$ Hz, and $Q = 25$:

$$\omega_0 = \frac{2\pi \times 50}{500} = 0.628 \text{ radians} \tag{9}$$

$$\alpha = \frac{\sin(0.628)}{2 \times 25} = 0.0118 \tag{10}$$

Filter Performance Characteristics:

Frequency Response Analysis:

$$|H_{notch}(\omega)|^2 = \frac{|b_0 + b_1 e^{-j\omega} + b_2 e^{-j2\omega}|^2}{|1 + a_1 e^{-j\omega} + a_2 e^{-j2\omega}|^2} \tag{11}$$

At the notch frequency ($\omega = \omega_0$):

$$|H_{notch}(\omega_0)| = \frac{|1 - 2\cos(\omega_0) + 1|}{|1 - 2\cos(\omega_0)(1-\alpha) + (1-2\alpha)|} \approx 0.01 \text{ (-40 dB)} \tag{12}$$

Phase Response Characteristics: The notch filter introduces minimal phase distortion away from the notch frequency:

$$\angle H_{notch}(\omega) = \arctan\left(\frac{\mathrm{Im}[H_{notch}(\omega)]}{\mathrm{Re}[H_{notch}(\omega)]}\right) \tag{13}$$

4.2.2 Cascaded Filter Architecture for Comprehensive Noise Reduction

A multi-stage filtering approach addresses different noise sources with optimized filter designs for each interference type:

Stage 1: High-Pass Filter for Baseline Wander Removal

Baseline wander caused by respiration, electrode movement, and DC offset requires removal while preserving low-frequency ECG components:

First-Order Butterworth High-Pass Filter:

$$H_{hp}(s) = \frac{s}{s + \omega_c} \tag{14}$$

Bilinear Transform for Digital Implementation:

$$s = \frac{2}{T}\frac{1 - z^{-1}}{1 + z^{-1}} \tag{15}$$

Where $T = 1/f_s$ is the sampling period.

Digital Filter Transfer Function:

$$H_{hp}(z) = \frac{1 - z^{-1}}{1 - \beta z^{-1}} \tag{16}$$

Where:

$$\beta = \frac{1 - \omega_c T/2}{1 + \omega_c T/2} \tag{17}$$

For $f_c = 0.5$ Hz and $f_s = 500$ Hz:

$$\beta = \frac{1 - \pi \times 0.5/500}{1 + \pi \times 0.5/500} = 0.9969 \tag{18}$$

Stage 2: Low-Pass Filter for High-Frequency Noise Reduction

High-frequency noise from EMG artifacts and electromagnetic interference requires attenuation while preserving QRS complex morphology:

Fourth-Order Butterworth Low-Pass Filter:

$$H_{lp}(s) = \frac{\omega_c^4}{(s^2 + \sqrt{2}\omega_c s + \omega_c^2)(s^2 + \sqrt{2}\omega_c s + \omega_c^2)} \tag{19}$$

Cascaded Biquad Implementation:

$$H_{lp}(z) = H_1(z) \times H_2(z) \tag{20}$$

Where each biquad section $H_i(z)$ implements a second-order Butterworth response.

For $f_c = 40$ Hz:

$$H_1(z) = H_2(z) = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}} \tag{21}$$

Stage 3: Adaptive Notch Filter for Power Line Interference

The notch filter implementation includes adaptive capabilities to handle frequency variations in power line interference:

Algorithm 7 Adaptive Notch Filter Implementation

AdaptiveNotchFilter$input$, $frequency$
Calculate filter coefficients for current frequency
Apply notch filter to input signal
Estimate residual power line interference
if interference level ¿ threshold **then**
  Adjust Q factor for deeper notch
else
  Reduce Q factor to minimize signal distortion
end if
return filtered signal

4.2.3 Advanced Noise Reduction Techniques

Beyond traditional filtering approaches, our system implements sophisticated noise reduction strategies tailored for portable ECG monitoring:

Adaptive Filtering and Noise Estimation:

Least Mean Squares (LMS) Adaptive Filter: The LMS algorithm adapts filter coefficients based on estimated noise characteristics:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}(n)e(n) \tag{22}$$

Where:

- $\mathbf{w}(n)$ = Filter coefficient vector at time n
- μ = Adaptation step size (0.001 to 0.01)
- $\mathbf{x}(n)$ = Input signal vector
- $e(n)$ = Error signal (desired - actual output)

Noise Level Estimation Algorithm:

$$\sigma^2_{noise}(n) = \alpha\sigma^2_{noise}(n-1) + (1-\alpha)|x(n) - \hat{x}(n)|^2 \tag{23}$$

Where $\hat{x}(n)$ is the predicted signal value and $\alpha = 0.99$ provides exponential averaging.

Statistical Signal Enhancement:

Ensemble Averaging for Periodic Noise Reduction: For signals with known periodicity, ensemble averaging effectively reduces random noise:

$$\bar{x}(n) = \frac{1}{K}\sum_{k=1}^{K} x(n+kT) \tag{24}$$

Where K is the number of averaged epochs and T is the signal period.

Median Filtering for Impulse Noise Removal: Median filtering preserves QRS sharp edges while removing impulse artifacts:

$$y(n) = \text{median}\{x(n-M), x(n-M+1), ..., x(n), ..., x(n+M)\} \tag{25}$$

Where the window size (2M+1) is typically 3-5 samples for ECG applications.