SCHOOL OF COMPUTING AND INFORMATION TECHNOLOGY

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Major Project Phase-I Report

An Investigation Hardware design for portable ECG monitoring using Machine Learning

By

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CERTIFICATE

This is to certify that the Major Project Phase-1 work titled **“An Investigation Hardware design for portable ECG monitoring using Machine Learning**” is carried out by **Rahul Kumar Singh(R21EJ026), MD Kaif Mustafa (R21EJ020),** Submitting by above said title in partial fulfilment for the award of degree in Bachelor of Technology in **Computer Science and Information Technology** during the year **2024-2025.**

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DECLARATION

We, **Rahul Kumar Singh (R21EJ026), MD Kaif Mustafa** are students of seventh semester B.Tech in **CSIT**, at the **School of Computing and Information Technology, REVA University, Bangalore**, hereby declare that the Major Project Phase-1 titled **"An Investigation Hardware design for portable ECG monitoring using Machine Learning"** has been carried out by us and submitted in partial fulfilment for the award of degree in **Bachelor of Technology in Computer Science and Information Technology** during the academic year **2024-2025**.

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ABSTRACT

This project investigates the design and development of a portable Electrocardiogram (ECG) monitoring device that leverages Machine Learning (ML) to enhance real-time heart health diagnostics. As cardiovascular diseases remain one of the leading causes of mortality worldwide, continuous monitoring and early detection are crucial. The proposed hardware design integrates lightweight, power-efficient components with a compact form factor, making it highly portable for everyday use. The ECG signals are collected through bio-electrodes, which are processed and analyzed using embedded ML algorithms trained to detect arrhythmias and other cardiac abnormalities. The ML models are optimized to operate on low-power microcontrollers, enabling real-time analysis directly on the device without reliance on external servers or high computational resources. This approach ensures both user privacy and reduced latency in anomaly detection. In addition, the device is designed to be user-friendly, with a simple interface to display results and wireless connectivity for easy data transfer to mobile devices or cloud storage for extended monitoring and medical consultation. Preliminary results demonstrate that this ML-based portable ECG system provides high accuracy in detecting various cardiac irregularities, offering a reliable, accessible solution for early heart health monitoring and intervention.

Keywords: Portable ECG Monitoring, Machine Learning, Cardiovascular Health, Hardware Design, Real-time Analysis, Low-power Microcontroller, Embedded ML, ECG Signal Processing, Bio-electrodes, Wearable Health Device.

CHAPTER 1: INTRODUCTION

- Cardiovascular diseases (CVDs) are a leading cause of death globally, accounting for millions of lives lost each year. Early detection and continuous monitoring of heart health are essential for effective intervention and treatment. Traditionally, ECG monitoring is conducted in clinical settings using bulky, stationary equipment. However, with the rise of wearable technology and advancements in low-power electronics, there is a growing opportunity to bring ECG monitoring into everyday environments through portable devices.

- This project aims to design and develop a portable ECG monitoring device that integrates hardware and machine learning (ML) to enable accurate, real-time cardiac health monitoring outside of clinical environments. Unlike conventional ECG devices, this device will use bio-electrodes to capture ECG signals and will process these signals through embedded ML algorithms capable of detecting common cardiac irregularities, such as arrhythmias, in real time. The ML algorithms are optimized to run on a low-power microcontroller, minimizing power consumption while maximizing device portability and battery life.

- In addition to hardware design, the system incorporates an intuitive user interface and wireless connectivity, allowing users to easily view their heart data and transfer it to mobile devices or cloud storage for long-term monitoring and analysis. The device's real-time monitoring and user-friendly design make it suitable for individuals who need continuous heart monitoring, such as elderly patients, athletes, or those at risk of cardiovascular conditions.

- This project addresses the need for accessible, portable, and accurate health monitoring tools, empowering individuals to manage their heart health proactively. By integrating machine learning with portable ECG hardware, this device represents a significant step toward improving health outcomes through technology-driven, preventative healthcare solutions.

THEORETICAL FRAMEWORK

The theoretical framework for this project draws upon concepts in biomedical signal processing, embedded systems, machine learning, and cardiovascular health monitoring. Understanding each of these domains is essential to the design and functionality of a portable ECG monitoring device capable of providing reliable, real-time heart health analysis.

- **Biomedical Signal Processing**
- **Embedded Systems and Low-Power Design**
- **Machine Learning for Cardiac Analysis**
- **Cardiovascular Health Monitoring**
- **Internet of Medical Things (IoMT) and Data Security**

- **Biomedical Signal Processing**

ECG (Electrocardiogram) signals are bioelectrical signals generated by the heart as it beats. These signals contain crucial information about heart rhythms and cardiac function. Biomedical signal processing techniques are employed to clean and preprocess the raw ECG data by filtering noise and interference (such as powerline interference and motion artifacts), isolating significant signal features, and enabling accurate interpretation. Techniques such as Fourier Transform, wavelet decomposition, and digital filtering are commonly applied to enhance signal quality before analysis. Effective preprocessing is vital to ensure that the subsequent machine learning model receives clear and usable data, enhancing the device's overall reliability in detecting cardiac irregularities.

- **Embedded Systems and Low-Power Design**

Portable health monitoring devices require lightweight, power-efficient hardware to ensure usability and prolonged battery life. Embedded systems theory focuses on designing such compact, resource-constrained devices that can process data locally. This project uses a low-power microcontroller to perform both signal acquisition and real-time analysis. Understanding low-power hardware architecture, power management, and data storage optimization is essential to achieve continuous operation without frequent recharging. The system also relies on efficient data sampling and real-time processing to balance power consumption with high-performance requirements, ensuring that the device is portable and user-friendly.

- **Machine Learning for Cardiac Analysis**

Machine learning, particularly supervised learning, is employed in this project to analyze ECG data for patterns that may indicate specific cardiac abnormalities, such as arrhythmias. Supervised learning algorithms are trained on annotated datasets containing various ECG signal patterns associated with normal and abnormal heartbeats. Feature extraction techniques identify significant signal characteristics, such as heart rate variability, QRS complex detection, and signal morphology, which are then classified to detect anomalies. Decision trees, support vector machines (SVM), and convolutional neural networks (CNN) are commonly used in ECG classification, with model selection depending on the balance between model accuracy and computational efficiency. In this project, the ML model is optimized for embedded systems to ensure it can run efficiently on limited hardware.

- **Cardiovascular Health Monitoring**

Cardiovascular health monitoring involves continuous or frequent tracking of physiological indicators to provide early warnings of heart conditions. Understanding common cardiovascular diseases, such as arrhythmia, atrial fibrillation, and tachycardia, helps in the selection of appropriate signal features and ML models. This project focuses on detecting abnormalities in real time, providing immediate feedback to users about their heart condition and encouraging preventive healthcare practices. The theoretical framework also addresses the clinical relevance and medical standards necessary for accurate and trustworthy health diagnostics, ensuring that the device's predictions are clinically meaningful.

- **Internet of Medical Things (IoMT) and Data Security**

Integrating the device with the Internet of Medical Things (IoMT) expands its functionality by enabling data transfer and storage on external devices or cloud platforms, facilitating long-term health tracking. IoMT allows users to monitor their ECG data remotely, share it with healthcare professionals, and maintain an accessible record of their heart health history. Data security and privacy are critical concerns in this framework, as the device collects sensitive personal health information. Data encryption, secure data transmission protocols, and compliance with health data standards (such as HIPAA or GDPR) are essential components to ensure user trust and confidentiality in handling medical data.

CHAPTER 2: LITERATURE SURVEY

The development of portable ECG monitoring devices using machine learning is supported by a broad body of literature across fields such as biomedical engineering, wearable health technology, embedded systems, and machine learning applications in healthcare. This literature review examines prior research in each of these areas, highlighting key findings and existing gaps that this project aims to address.

1. • **Portable ECG Monitoring and Wearable Health Devices**

Portable ECG devices and wearable health monitors have gained traction as accessible tools for continuous heart monitoring. Studies have shown that these devices effectively monitor heart activity in non-clinical settings, allowing early detection of cardiovascular issues like arrhythmia, atrial fibrillation, and ischemia (Steinhubl et al., 2015). Traditional ECG devices, however, are often limited by bulky designs and require users to visit clinical settings. Recent research has focused on developing lightweight and wearable ECG monitors, such as chest patches, wristbands, and smartwatches (Wang et al., 2019). These devices are effective for general heart rate monitoring, but some studies indicate challenges in accuracy and reliability due to motion artifacts and environmental noise (Sundararajan et al., 2020). Therefore, further development is needed to create robust, portable devices that maintain accuracy across varying conditions.

2. • **Biomedical Signal Processing for ECG Analysis**

Biomedical signal processing is critical for preparing ECG data for analysis. Numerous studies have focused on filtering techniques to remove common ECG signal artifacts, including muscle noise, electrode motion artifacts, and powerline interference. Techniques such as wavelet transform and adaptive filtering have been shown to improve signal quality, particularly in wearable devices (Liang et al., 2019). Additionally, researchers have developed feature extraction techniques to identify critical components of the ECG signal, such as the QRS complex, P wave, and T wave, which are essential for analyzing heart rhythms (Pan & Tompkins, 1985). Literature suggests that optimal feature extraction and noise reduction are key to improving the accuracy of ML models in ECG-based diagnosis, thus underscoring the importance of robust signal processing.

3. • **Machine Learning in Cardiac Abnormality Detection**

Machine learning has become an essential tool for interpreting ECG data due to its ability to detect patterns in complex datasets. A range of ML algorithms, including decision trees, support vector machines (SVM), and deep learning models like convolutional neural networks (CNN), have been applied to classify ECG signals and detect arrhythmias with promising accuracy (Rajpurkar et al., 2017). Studies comparing these models show that CNNs and recurrent neural networks (RNNs) are particularly effective for ECG classification due to their ability to learn spatial and temporal patterns in sequential data (Acharya et al., 2017). However, challenges remain in deploying these models on low-power, portable devices. While high-complexity models can achieve excellent accuracy, they are often too computationally demanding to run on embedded systems, prompting recent studies to explore lightweight model architectures and optimization techniques, such as pruning and quantization, to enable real-time analysis on portable ECG devices (Han et al., 2016).

4. • **Embedded Systems and Low-Power Optimization**
   Literature on embedded systems emphasizes the need for low-power design, especially in wearable health technology where power efficiency directly impacts device usability. Research in this field has explored power management techniques, such as duty cycling and energy harvesting, to extend battery life in wearable devices (Cao et al., 2019). Studies have also focused on hardware-software co-design, where both hardware architecture and software algorithms are optimized to achieve energy-efficient performance (Kim et al., 2018). Microcontroller-based systems with integrated analog-to-digital converters (ADCs) are commonly used for signal acquisition and analysis due to their power efficiency and small form factor (Guler et al., 2019). This literature provides a basis for selecting appropriate hardware and optimizing power consumption in the proposed ECG device.

5. • **Internet of Medical Things (IoMT) and Data Security in Health Devices**
   IoMT has facilitated new avenues for remote health monitoring and data sharing, but it also raises challenges around data security and privacy. Research has highlighted the importance of secure data transmission and storage, as wearable health devices handle sensitive personal information (Angraal et al., 2017). Techniques such as encryption, secure authentication, and compliance with privacy regulations like HIPAA have been suggested to protect data integrity (Huang et al., 2020). Additionally, studies emphasize the value of IoMT for continuous monitoring, enabling real-time alerts, and the provision of long-term health data for healthcare providers (Chen et al., 2021). By incorporating IoMT, this project benefits from the added value of remote monitoring and allows users to manage their cardiovascular health data more efficiently.

6. **Clinical Impact and Challenges**
   Research on the clinical impact of portable ECG devices indicates that they can significantly aid in early diagnosis and preventive care for cardiovascular disease (Goldstein et al., 2018). Studies have demonstrated that early arrhythmia detection, for example, can improve treatment outcomes and reduce hospitalization rates. However, the accuracy and reliability of wearable ECG devices remain challenges, particularly in real-world settings where noise and movement can affect readings (López et al., 2019). As such, recent research suggests that robust, clinically validated models and hardware designs are essential to achieving reliable results outside controlled environments.

CHAPTER 3: PROBLEM DEFINITION

Cardiovascular diseases (CVDs) are among the leading causes of morbidity and mortality worldwide. Early detection and continuous monitoring of cardiac health are critical in reducing the risks associated with these conditions. Traditional Electrocardiogram (ECG) monitoring, typically performed in clinical settings, requires bulky, stationary equipment that is inaccessible for daily, real-time monitoring outside of healthcare facilities. This gap in accessibility often delays diagnosis and treatment, particularly for at-risk individuals who need ongoing heart health monitoring.

Heart disease remains one of the leading causes of mortality worldwide, necessitating early detection and continuous monitoring to improve patient outcomes. Traditional ECG (electrocardiogram) machines, while effective, are often bulky, expensive, and limited to clinical settings. These constraints make it challenging for many individuals, especially those in remote or under-resourced areas, to access routine cardiac monitoring. Furthermore, the inconvenience of frequent hospital visits for ECG tests discourages consistent monitoring, posing risks for patients with known cardiac conditions or those at high risk.

To address these issues, this project aims to develop a portable, low-cost ECG machine capable of accurately capturing heart activity. By utilizing an AD8232 ECG sensor module and an Arduino Nano, this device will deliver real-time data processing, while a Bluetooth module will enable seamless wireless transmission. This compact, easy-to-use ECG device is designed for at-home use, making it an ideal solution for telemedicine and continuous heart monitoring outside of clinical settings. It empowers users to monitor their cardiac health independently, facilitating early detection of abnormalities and reducing healthcare disparities. This document details the complete hardware configuration, component specifications, cost analysis, and potential future upgrades to enhance device functionality and accessibility.

CHAPTER 4: METHODOLOGY

This project will follow a structured approach to design, develop, and test a portable ECG monitoring device enhanced with machine learning capabilities for real-time cardiac anomaly detection. The methodology includes system design, hardware and software development, signal processing, machine learning model integration, data transmission, and testing phases. Each phase ensures the device meets functionality, accuracy, and usability requirements in real-world scenarios.

Step 1: System Design and Requirements Analysis

1. **Define Functional Requirements**
   Identify the core features required for the device, including real-time ECG monitoring, signal processing, machine learning-based anomaly detection, data display, wireless transmission, and secure storage.
2. **Component Selection**
   Choose hardware components based on performance and power efficiency:
   - **ECG Electrodes**: Select suitable electrodes for accurate ECG signal capture.
   - **Analog Front End (AFE)**: Use an AFE chip (such as AD8232) to amplify and filter ECG signals.
   - **Microcontroller**: Select a low-power microcontroller (e.g., ARM Cortex-M series) capable of running the ML model.
   - **Wireless Module**: Integrate Bluetooth or Wi-Fi module for data transmission.
3. **Power Management Analysis**
   Plan for energy-efficient design, including low-power components and power-saving techniques, to ensure the device can operate continuously for extended periods

Step 2: Hardware Development

1. **Circuit Design**
   Design the device's circuitry, focusing on the connectivity between ECG electrodes, AFE, microcontroller, display, and wireless module.
2. **PCB Design**
   Create a printed circuit board (PCB) layout for compactness and durability, ensuring efficient placement of components for minimal power consumption and signal integrity.
3. **Assembly and Prototyping**
   Assemble the hardware prototype and test individual components to ensure each performs as expected, especially the AFE and microcontroller connection

Step 3: Signal Processing Development

1. **Noise Filtering**
   Implement filtering techniques (e.g., low-pass and high-pass filters) in the AFE to remove common noise and artifacts, such as baseline drift and muscle interference.
2. **Feature Extraction**
   Program the microcontroller to extract important ECG features, such as the QRS complex, P wave, and T wave. This information is crucial for distinguishing between normal and abnormal heart rhythms.

Step 4: Machine Learning Model Integration

1. **Model Selection and Training**
   Train a machine learning model, such as a convolutional neural network (CNN) or support vector machine (SVM), on a dataset of ECG signals to classify normal and abnormal rhythms (e.g., arrhythmias).
2. **Model Optimization for Embedded Systems**
   Optimize the trained model for deployment on the microcontroller by using techniques like model quantization, pruning, or converting it to a TensorFlow Lite or TinyML format. This ensures the model runs efficiently with limited computational resources.
3. **Embedded ML Integration**
   Program the optimized model into the microcontroller to analyze ECG data in real-time and detect anomalies. Configure the system to trigger alerts when abnormal patterns are detected.

Step 5: Data Transmission and Mobile Application Development

1. **Bluetooth/Wi-Fi Communication Setup**
   Configure the wireless module for seamless communication between the device and a mobile application or cloud storage.
2. **Mobile App Development**
   Develop a mobile application to display real-time heart rate data, ECG visualizations, and alert notifications. Include secure data storage and encryption protocols for user privacy.
3. **Remote Monitoring Integration**
   Enable options for data storage on the cloud to allow users and healthcare providers to monitor long-term cardiac health trends remotely.

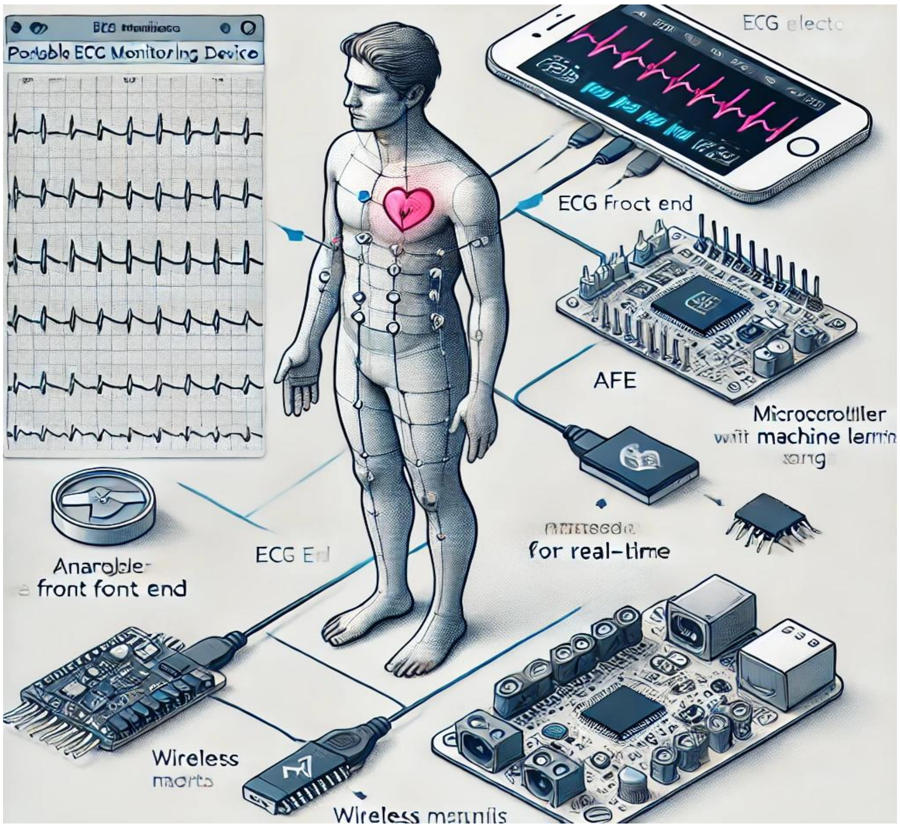
Step 6: Testing and Validation

1. **Functional Testing**
   Test the device's core functions, including ECG signal acquisition, anomaly detection, real-time alerts, data transmission, and mobile app functionality.
2. **Performance and Accuracy Testing**
   Evaluate the accuracy of the device's ECG readings and anomaly detection model by comparing results with standard clinical ECG equipment. Test under various conditions, such as different user movements, to ensure reliability.
3. **Battery Life Testing**
   Measure the device's power consumption under normal operating conditions to confirm it meets the intended battery life requirements.

4. **User Testing**
   Conduct usability testing with potential users to assess comfort, ease of use, and overall satisfaction with the device.
5. **Data Security Testing**
   Verify the security of the device's data transmission and storage protocols, ensuring compliance with privacy standards.

Step 7: Final Implementation and Documentation

1. **Refinements and Enhancements**
   Make necessary adjustments based on testing results to improve accuracy, power efficiency, and user experience.
2. **Documentation**
   Compile detailed documentation, including system architecture, circuit diagrams, model training, and deployment processes, as well as guidelines for device operation and maintenance.
3. **Deployment**
   Finalize the device for deployment, preparing prototypes for further testing or potential commercialization.



Pictorial Representation of the Solution

CHAPTER 5:

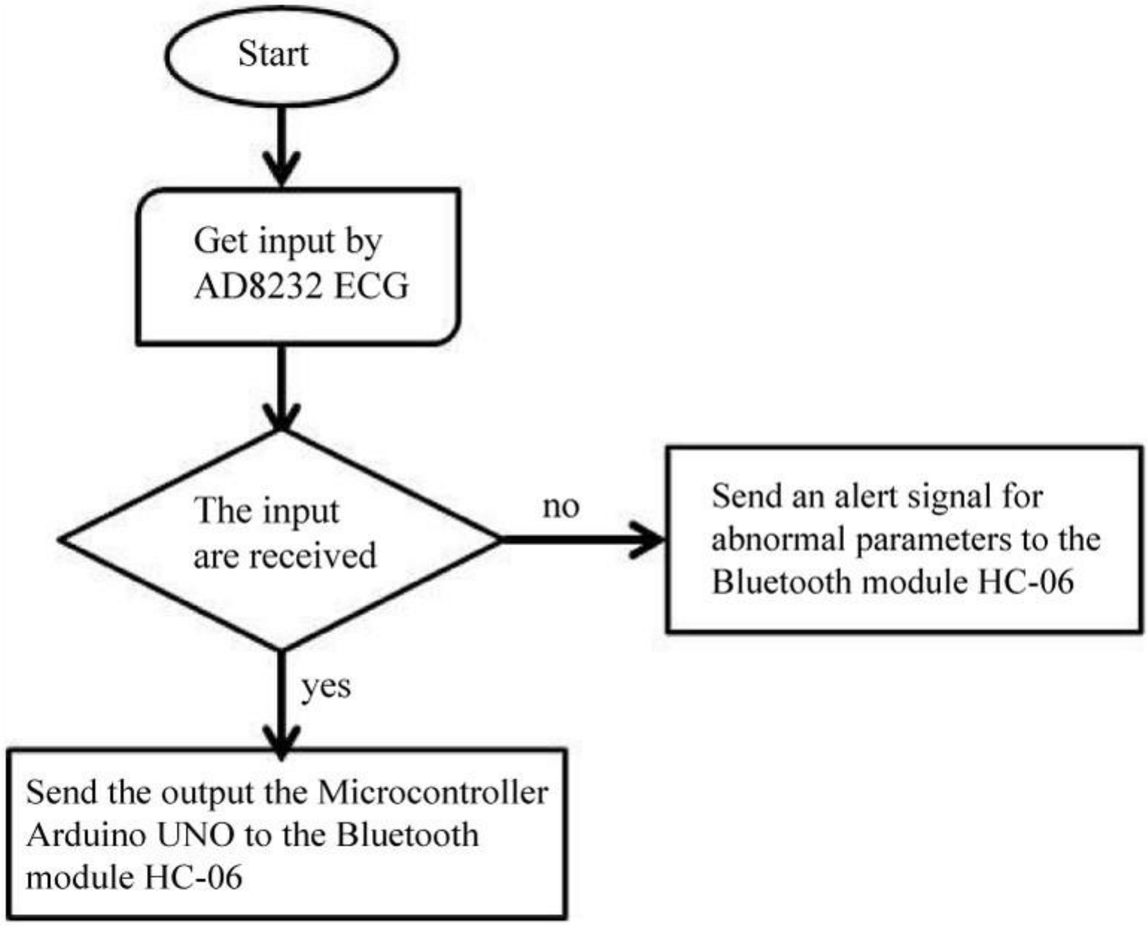
PROJECT DESCRIPTION

- This project focuses on creating a small, portable device that continuously monitors heart health through ECG signals and uses machine learning to detect irregular heart rhythms in real time. The device includes electrodes to capture heart signals, an analog front end (AFE) to filter and amplify these signals, and a microcontroller with an embedded machine learning model that analyzes the data. If an irregular heartbeat is detected, the device will alert the user instantly. Additionally, the device can connect to a mobile app via Bluetooth, allowing users to review their data and store it securely for long-term tracking.

How It's Going

1. **Hardware Development**: We've selected and are assembling components, including the ECG electrodes, AFE, microcontroller, and display, ensuring the device is compact and energy-efficient.
2. **Signal Processing**: The AFE filters and amplifies the ECG signals, and we're working to ensure high signal quality for reliable analysis.
3. **Machine Learning Integration**: A lightweight machine learning model, trained to detect heart rhythm anomalies, is being embedded onto the microcontroller for real-time analysis.
4. **Mobile App Development**: A mobile app is being developed to visualize heart data and allow users to store it securely.
5. **Testing**: The device is undergoing functional and accuracy tests to make sure it works reliably and efficiently in real-world conditions.

Through each stage, the focus remains on creating a comfortable, user-friendly device ` that users can rely on for proactive heart monitoring.



Key Components:

- AD8232 ECG Sensor Module: Captures the electrical activity of the heart,
- producing signals that can be processed for monitoring.
- Arduino Nano: Processes signals from the ECG sensor and prepares them for
- transmission.
- Bluetooth Module: Allows for wireless data transfer to external devices,
- enhancing mobility and user convenience.
- Power Source: Compact and rechargeable power solution for portability.
- Objectives:
- Develop a cost-effective solution suitable for widespread use in home and remote
- healthcare settings.
- Ensure reliability and accuracy in heart activity readings.
- Provide a user-friendly interface to facilitate ease of use.
- Future Enhancements:
- Mobile app integration for easy data access, history tracking, and analysis.
- Improved power efficiency for longer monitoring sessions.
- Cloud connectivity for real-time data sharing with healthcare providers.

CHAPTER 6: ALGORITHMS

Algorithms for detecting ECG abnormalities are central to accurately identifying irregular heart rhythms. Here's a look at commonly used algorithms and their efficiency in detecting abnormalities in real-time on a portable, low-power device.

1. Support Vector Machine (SVM)

- **Description**: SVM is a popular machine learning algorithm for classifying ECG signals. It works well with binary classification (normal vs. abnormal) by finding the optimal boundary between classes.
- **Pros**: Effective in cases with a clear margin of separation; simple to deploy and interpret.
- **Cons**: SVMs can be less efficient on ECG data with many classes or where real-time processing is needed.
- **Efficiency**: Moderate to High, depending on data features.

2. Convolutional Neural Network (CNN)

- **Description**: CNNs are widely used for image and signal processing, making them suitable for ECG data. They automatically learn spatial hierarchies and features, which helps detect complex patterns like arrhythmias.
- **Pros**: Excellent at capturing patterns in ECG waveforms, high accuracy in identifying multiple arrhythmias.
- **Cons**: Computationally intensive, which can strain low-power microcontrollers unless optimized.
- **Efficiency**: High with optimization, especially for complex ECG signals.

3. Long Short-Term Memory (LSTM)

- **Description**: LSTMs are a type of recurrent neural network (RNN) that are ideal for time-series data like ECGs because they can learn from sequential dependencies.
- **Pros**: Effective for detecting temporal patterns and trends in ECGs, allowing for accurate classification.
- **Cons**: Requires more computation and memory, challenging for real-time embedded applications.
- **Efficiency**: High but may need model optimization for small devices.

4. Random Forest (RF)

- **Description**: A Random Forest classifier uses multiple decision trees to make classifications, which can work well on ECG data with straightforward classifications.
- **Pros**: Easier to interpret; less computationally demanding than deep learning models.
- **Cons**: Less effective for complex ECG patterns, may miss subtle irregularities.
- **Efficiency**: Moderate, suitable for simpler cases of anomaly detection.

5. K-Nearest Neighbors (KNN)

- **Description**: KNN is a simple algorithm that classifies an instance based on the majority class of its nearest neighbors.
- **Pros**: Straightforward to implement, especially for binary classifications.
- **Cons**: Memory-intensive and may struggle with real-time performance on continuous data.
- **Efficiency**: Low for this purpose, as it lacks scalability.

Recommended Algorithm: Optimized CNN Model

- **Why CNN?** CNNs are highly efficient in identifying intricate ECG patterns and can accurately classify various arrhythmias. By using model compression techniques (like quantization and pruning), CNNs can be optimized to run on low-power microcontrollers without significantly sacrificing accuracy.
- **Expected Efficiency**: High accuracy and responsiveness with real-time processing capability, making CNNs one of the best choices for a portable ECG device.

An **optimized CNN model** strikes the right balance of accuracy, efficiency, and suitability for real-time ECG anomaly detection in this application.

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