IoT Based ECG Anomaly Detection Using Self Supervised Learning

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***Abstract*—Over the past few decades, heart disease has become one of the main causes of death worldwide. Timely diagnosis and prevention of life-threatening illnesses depend on early identification and ongoing heart activity monitoring. The goal of this project, "Anomaly Detection in Electrocardiograms: Advancing Clinical Diagnosis Through Self-Supervised Learning," is to create an intelligent ECG monitoring and analysis system that uses sensor-based data acquisition and self-supervised learning concepts to identify abnormal cardiac patterns. An Arduino microprocessor processes the electrical activity of the heart, which is recorded by an AD8232 ECG sensor. The ESP8266 Wi-Fi module transmits the analyzed ECG signals to the Thing Speak cloud for data storage and real-time monitoring. Without the need for large labeled datasets, a self-supervised learning model is intended to examine ECG patterns, spot abnormalities, and support clinical diagnosis. The device sounds a buzzer alert and shows the discovered condition on an LCD screen when it detects an aberrant ECG pattern. Through automated anomaly identification, this method not only guarantees ongoing, remote monitoring of cardiac health but also improves diagnostic precision and decision-making. For effective and intelligent cardiac care, the suggested solution shows a step forward in combining IoT, embedded technologies, and AI-driven learning.**

***Index Terms*—Multi-scale Cross-Attention, Trend Assisted Restoration, Attribute Prediction Module, Rare Cardiac Anomalies, Patient-specific attributes**

I. INTRODUCTION

One of the leading causes of death worldwide is heart disease, and early detection is essential to saving lives. An electrocardiogram (ECG) is a commonly used diagnostic technique that captures the electrical activity of the heart and aids in the early detection of abnormalities including arrhythmia, tachycardia, or cardiac arrest. Conventional ECG monitoring devices frequently depend on manual observation and recurring examinations, which could postpone prompt intervention. In order to automatically identify abnormalities in ECG data, this research presents an intelligent ECG monitoring system that combines embedded and Internet of Things-based hardware with self-supervised learning algorithms. The system records cardiac activity in real time using the AD8232 ECG sensor and transmits the information to the ThingSpeak cloud using an ESP8266 Wi-Fi module. A self-supervised learning algorithm finds aberrant ECG patterns without requiring a big labeled dataset, while the Arduino microcontroller processes and analyzes the information. When anomalies are discovered, the system sounds a buzzer alert and shows the status on an LCD screen. By making it possible to detect cardiac abnormalities in real time, remotely, and intelligently, this breakthrough improves cardiac health monitoring.

1.1 Problem Statement

Rare or unusual cardiac irregularities, which might be signs of serious, perhaps fatal illnesses, are frequently missed by conventional ECG diagnostic techniques. Current anomaly identification techniques ignore patient-specific information and minute signal variations since they mainly rely on labeled data and typical ECG patterns. This lowers clinical reliability by creating a diagnostic gap when important abnormalities go unnoticed. In order to overcome this difficulty, the research suggests a self-supervised learning framework that has only been trained on normal ECGs. The model greatly outperforms state-of-the-art methods in both detection and localization accuracy while autonomously detecting and localizing anomalies, including rare ones, through the use of masking and restoration techniques, multi-scale cross-attention, and integration of patient-specific features.

1.2 Objectives of the project

1. To create an ECG-based monitoring system that can automatically identify abnormalities in cardiac signals.
2. To measure heart signals accurately using the AD8232 ECG sensor.
3. To identify aberrant ECG patterns using self-supervised learning algorithms without the need for manual labeling.
4. To send real-time ECG data to the ThingSpeak cloud for online analysis and visualization.
5. To notify physicians and patients in the event of abnormal ECG activity via buzzer and LCD alerts.
6. To offer an affordable, ongoing, remote cardiac health monitoring system.

For effective cardiac monitoring, the suggested system integrates machine learning and embedded hardware. The patient's heart electrical signals are recorded by the AD8232 ECG sensor and sent to the Arduino microcontroller for signal processing. An ESP8266 Wi-Fi module is then used to upload the data to the Thing Speak cloud, allowing for the real-time remote display of ECG waveforms. This data is processed by a self-supervised learning algorithm to find abnormalities like irregular heartbeats or variations in rhythm. By reducing the reliance on manually labeled datasets, this method enables the model to extract patterns directly from the ECG signals. When an anomaly is found, the system shows the kind of abnormality on an LCD screen and sounds a buzzer to inform persons in the vicinity. Thus, an enhanced, automated, and intelligent cardiac detection system that facilitates prompt medical intervention is made possible by the combination of IoT with self-supervised learning.

II. LITERATURE SURVEY

[1] A new method for continuously monitoring vital indicators, such as the electrocardiogram (ECG), is wearable health monitoring. This signal is frequently used to identify and evaluate serious health hazards and long-term heart conditions. The review of wearable ECG monitoring systems for older persons that are wireless, mobile, and remote technologies is the main objective of this research. Along with a summary of the design and modeling, the effectiveness, user acceptability, tactics, and suggestions for enhancing the current ECG monitoring systems are also included. More than 120 ECG monitoring devices were examined and categorized into smart wearable, wireless, mobile ECG monitoring devices with associated signal processing methods in this work. According to the review's findings, the majority of wearable ECG monitoring system research focuses on senior citizens, and aged care facilities have embraced this technology. Furthermore, it is demonstrated how wearable wireless textile-based technology advancements and the evolution of mobile telemedicine systems could guarantee higher-quality healthcare delivery. The primary disadvantages of deployed ECG monitoring systems have also been explored, including restrictions placed on patients, a limited battery life, a lack of user acceptability and input from medical professionals, and a lack of confidentiality and privacy of critical data.

[2] Over the past ten years, deep supervised learning has seen tremendous success. However, its flaws such as its significant reliance on manual labels and susceptibility to attacks have prompted people to look for other paradigms. As an alternative, self-supervised learning (SSL) has garnered a lot of attention from researchers because to its exceptional performance in representation learning over the past few years. Nearly all kinds of downstream tasks benefit from self-supervised representation learning, which uses input data itself as supervision. In this overview, we examine novel self-supervised learning techniques for representation in graph learning, computer vision, and natural language processing. We thoroughly examine the current empirical approaches and classify them into three primary groups based on their goals: generative, contrastive, and generative-contrastive (adversarial). We thoroughly examine the current empirical approaches and classify them into three primary groups based on their goals: generative, contrastive, and generative-contrastive (adversarial). To offer more insight into the reasons for the effectiveness of self-supervised learning, we also gather relevant theoretical analysis. Lastly, we give a brief overview of open issues and potential future paths for self-supervised learning. There is a survey outline slide available.

[3] Signals from an electrocardiogram (ECG) are essential for monitoring and identifying individuals

with a variety of cardiovascular illnesses (CVDs). The goal of this research is to create a reliable algorithm that can correctly identify the ECG signal even when there is background noise. This paper proposes a one-dimensional convolutional neural network (CNN) comprising two convolutional layers, two down sampling layers, and a fully connected layer. To increase the model's classification accuracy, the identical 1D data was converted into two-dimensional (2D) images. Next, we used the 2D CNN model, which has three 2D convolutional layers, three down sampling layers, a fully connected layer, and input and output layers. When tested on the publicly accessible Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) arrhythmia database, the suggested 1D and 2D models achieve classification accuracy of 97.38% and 99.02%, respectively. For the same data, both the suggested 1D and 2D CNN models performed better than the comparable state-of-the-art classification methods, confirming the efficacy of the suggested models.

[4] The computers are able to observe behavior based on actual data thanks to machine learning techniques. Algorithms that enable computers to exhibit behavior acquired from prior experiences can be created based on prior experiences. The anomalous occurrences in a given network are examined using machine learning algorithms. The algorithms may monitor network exploitation and be taught for a variety of inputs. This concept is used to machine monitoring and fraud detection. In order to train and analyze anomalous behavior in a network, supervised learning is crucial. The supervised methods for identifying network anomalies are presented in this paper.

[5] One of the main illnesses that kills people, particularly the elderly, is cardiovascular disease. Early cardiovascular disease prevention and diagnosis depend on prompt and precise diagnosis of arrhythmia types. A method for classifying arrhythmias based on the multi-head self-attention mechanism (ACA-MA) was presented in this research. In order to improve the data quality of ECG signals and lower their noise, an ECG signal preprocessing algorithm based on wavelet transform is first proposed and put into practice using the db6 wavelet transform. Second, the matching relationship between segmented ECG signals and ECG tags is used to create a linear projection layer for obtaining semantic aspects of ECG signals. Third, time series data is integrated into a matrix operation using a position encoding-based spatiotemporal characterization approach of ECG signal sequences. Fourth, in order to extract relationships and semantic properties between ECG segments and accomplish semantic association and information stitching of nonadjacent ECG signals, a multi-head self-attentive mechanism that can capture global contextual information is presented. Lastly, ACA-MA exceeds other cutting-edge techniques with an overall classification accuracy of 99.4%, a specific rate of 99.41%, and a sensitivity of 97.36%, according to experimental results on the arrhythmia dataset MIT/BIH.

[6] One type of cardiac conduction issue that causes irregular heartbeats is called arrhythmia. Abnormalities in the conduction system may be detected by the electrocardiograph (ECG) signal. Its visual inspection is difficult and time-consuming, nevertheless. Early and accurate disease identification may be aided by an automated heart problem detection system. Prior to segmentation and normalization, the raw ECG signal in this study was pre-processed using the stationary wavelet transform (SWT). The classification of normal, left bundle branch block (L-BBB), right bundle branch block (R-BBB), premature atrial contraction (PAC), and premature ventricular contraction (PVC) beats has since been done using recurrent neural networks (RNN), gated recurrent units (GRU), and bi-directional long short-term memory (Bi-LSTM). Of the three implemented models, Bi-LSTM networks have demonstrated the highest accuracy of 99.72%. This indicates that this model is suitable for computer-aided heartbeat diagnostics.

[7] A collection of heart and blood vessel conditions known as cardiovascular diseases (CVDs) can result in breathing difficulties and chest pain, particularly during physical activity. Nonetheless, screening may be beneficial for some heart disease patients who do not exhibit any symptoms. An electrocardiogram (ECG) can be used to diagnose cardiovascular diseases (CVDs) in a timely manner by measuring the electrical activity of the heart using sensors placed on the skin over the chest. A method for categorizing deadly CVDs such as atrial fibrillation (Afib), ventricular

fibrillation (Vfib), ventricular tachycardia (Vtec), and normal (N) beats is presented in this work. The ECG signal was pre-processed using a new mix of stationary wavelet transformations (SWT) and a two-stage median filter with Savitzky–Golay (SG) filter, followed by segmentation and z-score normalization. Next, for automatic and dependable feature extraction, a 1-D six-layer convolutional neural network (1-D CNN) was employed. Following that, the back end employed bidirectional long short-term memory (Bi-LSTM) to classify arrhythmias. The use of 1-D CNN and Bi-LSTM architecture, followed by pertinent and efficient pre-processing of the ECG signal, is what makes the current study innovative and accurate. Using 10-fold cross validation, an accuracy of 99.41% was attained, which is better than the current state-of-the-art techniques. As a result, our approach offers a noble, precise, and trustworthy way to categorize cardiac arrhythmia beats.

III. PROPOSED SYSTEM

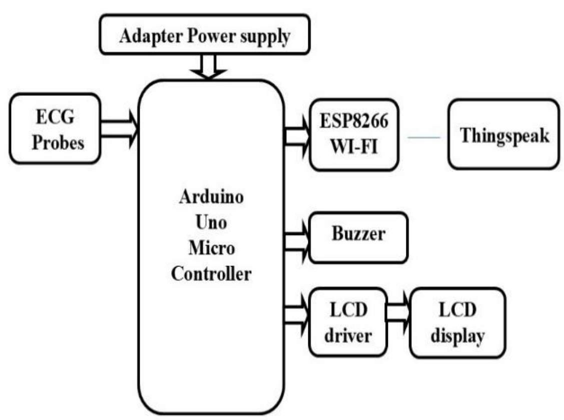


Figure 3.1 Block diagram of Anomaly Detection in Electrocardiograms: Advancing Clinical Diagnosis Through Self-Supervised Learning

The ECG monitoring system works by integrating several components to collect, process, display, and transmit heart activity data. The process begins with ECG probes attached to the patient, which detect the electrical signals generated by the heart. These signals are weak and require processing, so they are fed into the Arduino Uno microcontroller. The Arduino acts as the central unit, digitizing the signals and managing the flow of information to other modules. For local monitoring, the Arduino drives an LCD display through an LCD driver, allowing the patient or caregiver to view the ECG waveform or heart rate in real time. At the same time, the Arduino controls a buzzer that provides audible alerts if abnormal heart activity is detected, such as irregular beats or values crossing a set threshold. This ensures immediate feedback at the patient's location. To enable remote monitoring, the Arduino sends the processed ECG data to the ESP8266 Wi-Fi module. The ESP8266 transmits the data wirelessly to the Thingspeak cloud platform. Thingspeak stores, analyzes, and visualizes the ECG data, making it accessible to doctors or caregivers from anywhere. This dual pathway—local feedback through the LCD and buzzer, and remote monitoring through the cloud—ensures both immediate safety and long-term tracking of heart health. The entire system is powered by an adapter that supplies stable energy to the Arduino and connected modules, ensuring continuous operation. Overall, this setup provides a low-cost, scalable solution for real-time and remote ECG monitoring, combining IoT technology with healthcare needs.

IV. HARDWARE AND SOFTWARE REQUIREMENTS

The major building blocks of this project are:

- Power supply.
- Arduino UNO.
- AD8232 ECG module.
- ESP8266 WI-FI Module.
- ESP8266 WI-FI.
- LCD display.
- Buzzer.

4.1 Microcontroller

Figure: 4.1 Arduino uno atmega328p Microcontroller

The Arduino Uno is a microcontroller board which has ATmega328 from the AVR family. There are 14 digital input/output pins, 6 Analog pins and 16MHz ceramic resonator. USB connection, power jack and also a reset button is used. Its software is supported by a number of libraries that makes the programming easier.

4.2 Adapter Power Supply

The AC adapter, AC/DC adapter or AC/DC converter is a type of external power supply, often enclosed in a case similar to an AC plug. Other names include plug pack, plug-in adapter, adapter block, domestic mains adapter, line power adapter, wall wart, or power adapter. AC adapters are used with electrical devices that require power but do not contain internal components to derive the required voltage and power from mains power. The internal circuitry of an external power supply is very similar to the design that would be used for a built-in or internal supply.

Figure 4.2: Adapter Power Supply

External power supplies are used both with equipment with no other source of power and with battery-powered equipment, where the supply, when plugged in, can sometimes charge the battery in addition to powering the equipment.

4.3. LED

A light-emitting diode (LED) is a semiconductor light source. LEDs are used as indicator lamps in many devices, and are increasingly used for lighting. Introduced as a practical electronic component in 1962, early LEDs emitted low-intensity red light, but modern versions are available across the visible, ultraviolet and infrared wavelengths, with very high brightness.

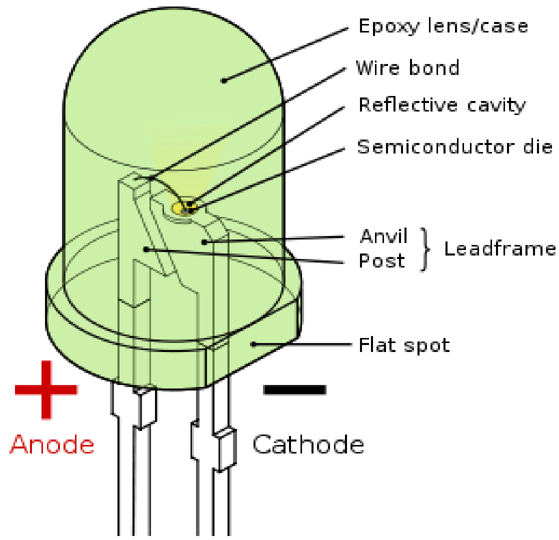


Figure 4.3: Parts of a LED

4.4 ECG

Electrocardiogram refers to the recording of electrical changes that occurs in heart during a cardiac cycle. It may be abbreviated as ECG or EKG. It works on the principle that a contracting muscle generates a small electric current that can be detected and measured through electrodes suitably placed on the body. An ECG is a paper or digital recording of the electrical signals in the heart. It is also called an electrocardiogram or an EKG. The ECG is used to determine heart rate, heart rhythm, and other information regarding the heart's condition. ECGs are used to help diagnose heart arrhythmias, heart attacks, pacemaker function, and heart failure.

Figure 4.4: ECG

ECG can be analyzed by studying components of the waveform. These waveform components indicate cardiac electrical activity. The first upward of the ECG tracing is the P wave. It indicates atrial contraction.

4.4.1 AD8232 ECG Sensor

This sensor is a cost-effective board used to measure the electrical activity of the heart. This electrical activity can be charted as an ECG or Electrocardiogram and output as an analog reading. ECGs can be extremely noisy, the AD8232 Single Lead Heart Rate Monitor acts as an op-amp to help obtain a clear signal from the PR and QT Intervals easily.

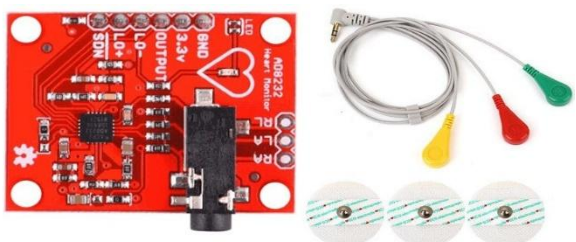


Figure 4.5 AD8232 Single Lead Heart Rate

The AD8232 is an integrated signal conditioning block for ECG and other biopotential measurement applications. It is designed to extract, amplify, and filter small biopotential signals in the presence of noisy conditions, such as those created by motion or remote electrode placement.

4.5 ESP8266 WI-FI Module

The ESP8266 Wi-Fi Module is a self-contained SOC with integrated TCP/IP protocol stack that can give any microcontroller access to your Wi-Fi network. The ESP8266 is capable of either hosting an application or offloading all Wi-Fi networking functions from another application processor. Each ESP8266 module comes pre-programmed with an AT command set firmware, meaning, you can simply hook this up to your Arduino device and get about as much Wi-Fi-ability as a Wi-Fi Shield offers (and that's just out of the box)! The ESP8266 module is an extremely cost-effective board with a huge, and ever growing, community.

Figure 4.6: Wi-Fi Module

4.6 Thing Speak

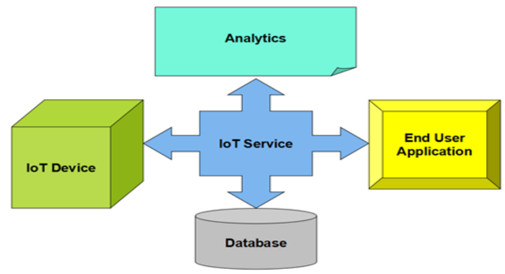


Figure 4.7: Structure of Thing Speak

One of the IoT application platform that offers a wide variety of analysis, monitoring and counter-action capabilities is 'Thing Speak'. Let us consider Thing Speak in detail.

What is Thing Speak

Thing Speak is a platform providing various services exclusively targeted for building IoT applications. It offers the capabilities of real-time data collection, visualizing the collected data in the form of charts, ability to create plugins and apps for collaborating with web services, social network and other APIs. We will consider each of these features in detail below. The core element of ThingSpeak is a 'ThingSpeak Channel'.

A channel stores the data that we send to ThingSpeak and comprises of the below elements:

8 fields for storing data of any type - These can be used to store the data from a sensor or from an embedded device.

3 location fields - Can be used to store the latitude, longitude and the elevation. These are very useful for tracking a moving device.

1 status field - A short message to describe the data stored in the channel.

To use ThingSpeak, we need to sign up and create a channel. Once we have a channel, we can send the data, allow ThingSpeak to process it and also retrieve the same. Let us start exploring ThingSpeak by signing up and setting up a channel.

4.7 LCD display

One of the most common devices attached to a micro controller is an LCD display. Some of the most common LCDs connected to the many microcontrollers are 16x2 and 20x2 displays. This means 16 characters per line by 2 lines and 20 characters per line by 2 lines, respectively.

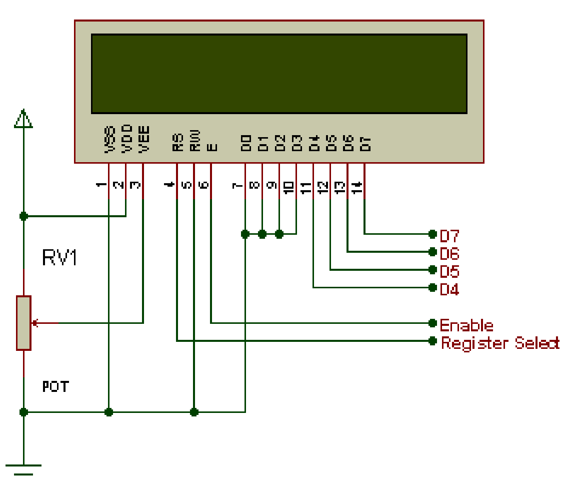


Figure 4.8: Character LCD pins with Microcontroller

The LCD requires 3 control lines as well as either 4 or 8 I/O lines for the data bus. The user may select whether the LCD is to operate with a 4-bit data bus or an 8-bit data bus. If a 4-bit data bus is used the LCD will require a total of 7 data lines (3 control lines plus the 4 lines for the data bus). If an 8-bit data bus is used the LCD will require a total of 11 data lines (3 control lines plus the 8 lines for the data bus). The three control lines are referred to as EN, RS, and RW.

4.8 Buzzer

Basically, the sound source of a piezoelectric sound component is a piezoelectric diaphragm. A piezoelectric diaphragm consists of a piezoelectric ceramic plate which has electrodes on both sides and a metal plate (brass or stainless steel, etc.). A piezoelectric ceramic plate is attached to a metal plate with adhesives. Applying D.C. voltage between electrodes of a piezoelectric diaphragm causes mechanical distortion due to the piezoelectric effect. For a misshaped piezoelectric element, the distortion of the piezoelectric element expands in a radial direction. And the piezoelectric diaphragm bends toward the direction. The metal plate bonded to the piezoelectric element does not expand. Conversely, when the piezoelectric element shrinks, the piezoelectric diaphragm bends in the direction Thus, when AC voltage is applied across electrodes, the bending is repeated, producing sound waves in the air.

Figure 4.9 Buzzer

V. ADVANTAGES, DISADVANTAGES AND APPLICATIONS

5.1 Advantages

- Enables early detection of heart-related abnormalities.
- Provides real-time and remote monitoring through cloud connectivity.
- Self-supervised learning reduces the need for manually labeled datasets.
- Low-cost and portable design suitable for continuous home monitoring.
- Alerts patients immediately in case of abnormal heart activity.
- Enhances accuracy and reliability of diagnosis compared to manual observation.

5.2 Disadvantages

- Accuracy depends on proper sensor placement and signal quality.
- Requires stable internet connection for real-time cloud updates.
- Power consumption may increase during continuous operation.
- Self-supervised models may need periodic retraining for new data patterns.

5.3 Applications

- Hospitals and healthcare centers for continuous ECG monitoring.
- Remote patient monitoring systems and telemedicine applications.
- Wearable or home-based cardiac health monitoring devices.
- Clinical research and medical data analysis.
- Early detection systems for arrhythmia and cardiac arrest.

VI. RESULTS AND ANALYSIS

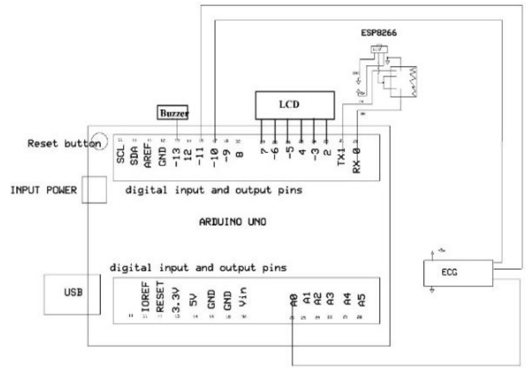


Fig 5.1: Schematic diagram of Anomaly Detection in Electrocardiograms: Advancing Clinical Diagnosis Through Self-Supervised Learning

The developed system successfully monitored and analyzed ECG signals using the AD8232 ECG sensor, with data processed by the Arduino microcontroller and transmitted to the Thing Speak cloud through the ESP8266 Wi-Fi module for real-time visualization. The self-supervised learning model effectively detected abnormal patterns in the ECG signals without requiring pre-labeled datasets, demonstrating accurate anomaly identification. When irregularities such as abnormal heart rhythms were detected, the system promptly activated the buzzer alert and displayed the corresponding condition on the LCD screen, ensuring quick notification to the user. The experimental results confirmed that the proposed model enables reliable, continuous, and intelligent heart monitoring, improving diagnostic accuracy and supporting timely clinical intervention.

- Continuous ECG data shows low frequency amplitude fluctuations
- There are occasional high amplitude spikes
- There is variability in the peak latency as well as individual timing and amplitude of ECG components from heart beat to heart beat
- There are occasional bursts of high frequency noise
- Adjusting for baseline drifts, aligning ECG peaks across heart beat segments, rejecting artifactual segments and scaling all heart beat segments to constant amplitude ensures that distance and similarity measures can be correctly computed for optimal classification
- Due to high class imbalance between normal and abnormal heart beats, modeling and model evaluation metrics have to take this class probability imbalance into account

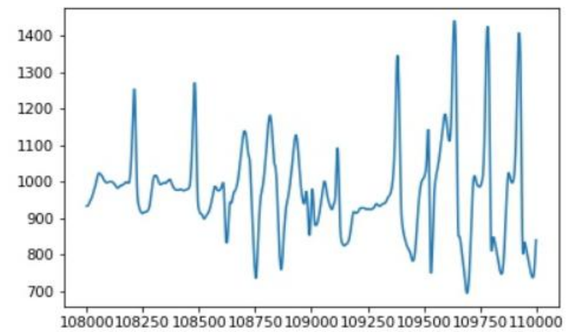
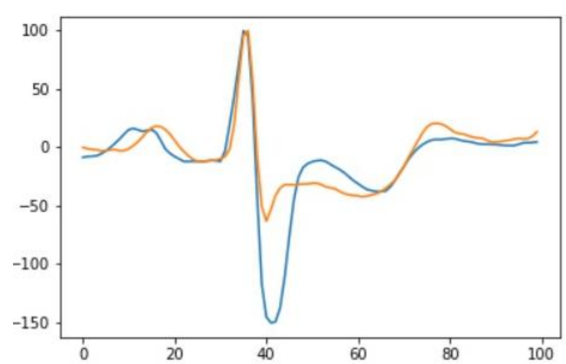


Figure 5.2: Continuous ECG

Continuous ECG time series (containing several normal heart beats) exhibiting slow baseline amplitude fluctuations, as well as differences in signal gain across time, causing heart beats in the latter half of the tine series to appear to have larger peak amplitudes. While a diagnostician who is visually monitoring for abnormal heart beats mentally takes variable in recording quality into account, an automated computer algorithm can mistake such changes due to the recording environment for genuine changes in heart activity, confounding similarity and distance computations when comparing single heart beats based on ECG signal amplitude at each time point. Also note that the time course of short ECG changes surrounding each ECG peak varies from beat to beat.

ECG segments corresponding to individual heart beats become better comparable for computational analysis, after baseline, signal gain and peak latency variability is controlled for. EDA showed that without such corrections, classification accuracy can be reduced by up to 20%.



VII. CONCLUSION AND FUTURE WORK

The project "Anomaly Detection in Electrocardiograms: Advancing Clinical Diagnosis Through Self-Supervised Learning" demonstrates a practical and intelligent solution for continuous heart monitoring. By combining AD8232 ECG sensing, IoT connectivity, and self-supervised learning, the system can detect cardiac anomalies in real-time and alert users immediately. This integration of hardware and AI ensures better clinical decision-making and reduces the delay in diagnosing heart diseases. The proposed model represents a significant step toward smart healthcare, enabling accessible, affordable, and intelligent cardiac monitoring for all.

VIII. FUTURE SCOPE

- Integration of advanced deep learning models for improved accuracy.
- Development of a mobile app for real-time ECG visualization and alerts.
- Implementation of wearable ECG patches with wireless power and communication.
- Cloud-based medical data analytics for long-term patient health trends.
- Integration with hospital databases and IoT healthcare platforms for centralized patient management.
- Use of edge computing for faster and more secure ECG data processing.

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