ECG - AI: An Intelligent System for Cardiac Health Monitoring

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***Abstract* - Electrocardiograms (ECGs), which are often analyzed by medical specialists, are essential diagnostic tools for diagnosing cardiovascular disorders. Still, there is hope for automation at the nexus of deep learning and ECG categorization. In order to provide a reliable ECG classification, this study surveys the tools, feature extraction methods, preprocessing techniques, and deep learning architectures that have been developed in this field. This study intends to provide a thorough understanding of how deep learning is transforming ECG analysis by investigating several approaches, possibly improving diagnostic precision and effectiveness in cardiovascular care.**

Keywords- Electrocardiograms, arrhythmias, ECG classification, Feature extraction, Artificial Intelligence.

I. INTRODUCTION

Electrocardiograms (ECGs), which provide information on the electrical activity of the heart, are essential for the diagnosis of cardiovascular disorders. The interpretation of ECGs has historically placed a great deal of reliance on the knowledge of medical specialists, which makes the procedure vulnerable to resource constraints and human error. But now that artificial intelligence (AI) and Internet of Things (IoT) devices are widely available, there's a game-changing chance to improve ECG analysis.[1]

There are various benefits to using IoT for signal gathering. With the help of IoT-enabled devices, heart activity monitoring of patients may be done continuously and remotely, allowing for real-time data collecting outside of conventional clinical settings. Early abnormality identification, rapid action, and better patient care are made possible by the accessibility and flexibility of data collecting.[2]

Furthermore, the automation of ECG categorization shows great promise through the incorporation of deep learning techniques, including Convolutional Neural Networks (CNNs). When it comes to CNN architectures that may be tailored to the unique patterns found in ECG signals, the AlexNet model has demonstrated exceptional performance in picture classification tasks. The CNN model may be trained on annotated datasets that include both normal and pathological ECG recordings, making it possible to accurately forecast arrhythmias and differentiate between various cardiac diseases.

Using CNN-based ECG classification and Internet of Things (IoT) signal gathering, this article investigates how these two approaches might work together to transform cardiovascular healthcare. By merging state-of-the-art technologies, we expect substantial improvements in patient tracking, diagnostic accuracy, and eventually better clinical results.[3]

Sr no	Features	Traditional ECG Systems	AI- ECG System
1	Digital signal transmission	No	Yes
2	Real-time analysis, automatic interpretation	No	Yes
3	Ability to store data on internal memory	No	Yes
4	Ability to predict arrhythmia	No	Yes

Table 1 - Comparing features of traditional and AI based ECG system.

II. RESEARCH FRAMEWORK

Heart electrical activity and its depiction in the ECG. An essential diagnostic technique for evaluating the electrical activity of the heart is electrocardiography, or EKG:

1. Fundamental Anatomy There are two atria (upper chambers) and two ventricles (bottom chambers) in

the heart. The electrical system of the heart regulates the heartbeat, which is made up of regular contractions and relaxations.

2. Electrical Activity: The heart's natural pacemaker, the sinoatrial (SA) node, is the source of the heart's electrical activity. From there, the heart muscle contracts and pumps blood as a result of electrical impulses that flow through certain channels.

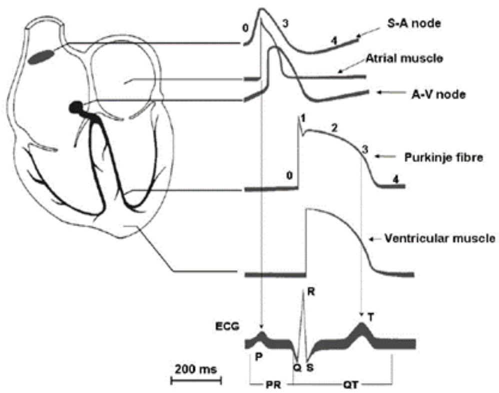


Fig. 1- Q-R-S Signals Representation

Reference - ECG-based heartbeat classification for arrhythmia detection: A survey

ECG Leads:

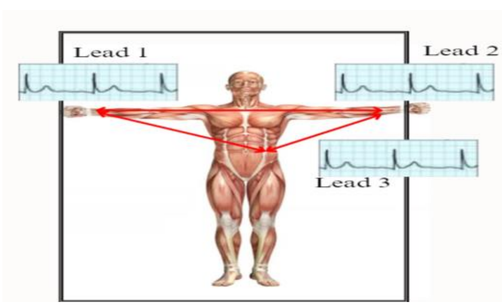


Fig.- 3-Lead Signal

Different numbers of bipolar and unipolar leads, such as 3, 4, 5, 6, and 12, are used in ECG readings. The 3-lead design, which involves electrodes on the right arm (RA), left arm (LA), and left leg (LL), is frequently employed in ECG-AI. Standard leads I, II, and III are recorded using this arrangement, which offers a straightforward yet insightful evaluation of cardiac function. The 3-lead ECG device is appropriate for integration with AI algorithms due to its mobility and simplicity. AI can evaluate 3-lead ECG readings using deep learning techniques to identify anomalies, categorize arrhythmias, and support clinical decision-making. [4]

Components needed to collect ECG signals -

Real-time heart activity monitoring is made possible by the use of the Arduino Uno to use the AD8232 ECG sensor in a variety of applications, including research, fitness tracking, and healthcare. Use electrode pads and the AD8232 sensor integrated with the Arduino Uno to precisely and effectively record and handle ECG readings.

Sr. No.	Equipment	Description
1.	Arduino Uno	Microcontroller Board
2.	AD8232	ECG Sensor Module
3.	ECG Electrodes	Bio-Potential Electrode Pads
4.	ECG Electrode Connector	3.5mm ECG Connector
5.	Connecting Wires	Connecting Wires for Arduino & AD8232

Table 2 - Hardware Specification

AD8232 ECG Sensor IC Specification

The AD8232 is a tiny chip that detects the electrical conductivity of the human heart and transforms it into the ECG waveform. To identify any potential health concerns with the human heart, this ECG signal is further examined. [5]

Arduino Uno:

An open-source programmable device with hardware and software called Arduino is capable of reading and processing electrical inputs. The ATmega328P microcontroller, the foundation of the Arduino UNO, has six analog pin inputs, fourteen digital pins, a USB port, a power connection, and an ICSP (In-Circuit Serial Programming) header. Its programming is done using the Arduino IDE.[6]

Interfacing of Arduino uno & AD8232:

Arduino Uno	AD8232
Arduino 3.3V	3.3V pin
Arduino pin 10	L0+
Arduino Pin 11	L0-
Arduino Analog A1	Output
Arduino Gnd	Gnd

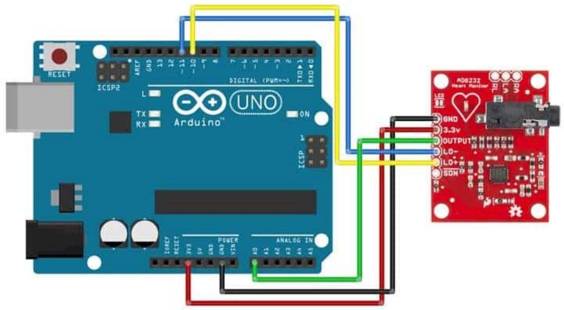


Fig. 2 - Connection of AD8232 with Arduino

Software Environment: Introduction to MATLAB

To make this crucial stage simpler, MATLAB offers a large range of useful functions and tools that are all focused on the work of data gathering and preparation. These include basic duties like eliminating artifacts, reducing baseline drift, and filtering out noise. By utilizing the rich toolbox of MATLAB, master's degree candidates may protect the integrity of their electrocardiogram (ECG) data. This opens the door to careful examination and accurate interpretation of heart rhythms. One of the most crucial stages in the classification and diagnosis of cardiac disorders is the relevant feature extraction from ECG data. Important characteristics such as heart rate variability, QRS complex duration, and spectrum analysis can be effectively retrieved in the frequency-domain or time-domain.

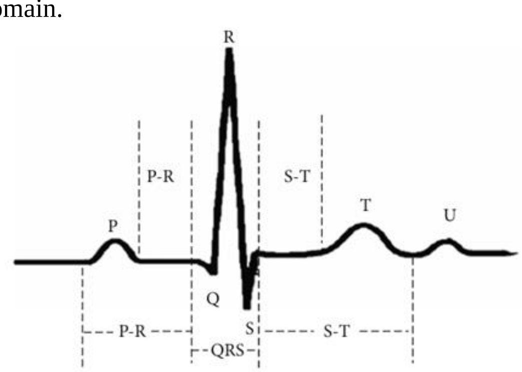


Fig. 3 - Normal heartbeat

The normal ECG feature values are tabulated as follows:

REGION OF ECG WAVE	ORIGIN	AMPLITUDE (mV)	DURATION (s)
P Wave	Atrial contraction	0.25	0.12 to 0.22
R Wave(QRS Complex)	Ventricular depolarization	1.60	0.07 to 0.1
T Wave	Ventricular re-polarization	0.1 to 0.5	0.05 to 0.15
U Wave	Slow re-polarization of intra-ventricular systems	<0.1	0.2

Signal Processing techniques:

Electrocardiogram (ECG) signals are essential for identifying cardiovascular disorders, and relevant information must be extracted from them. This is where signal processing comes in. Through the use of signal processing methods including feature extraction, noise reduction, and filtering, ECG data may be pre-processed to improve its relevance and quality for further study.

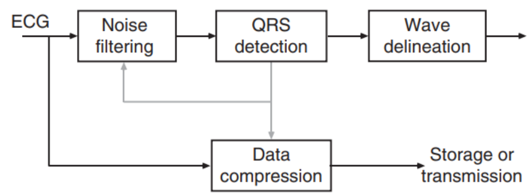


Fig. 4. Algorithms for basic ECG signal processing

MATLAB is used in the signal processing process. It has a wide range of pre-built features and specialized toolboxes, such the Wavelet and Signal Processing Toolboxes. An extensive collection of tools and methods for signal analysis, manipulation, and visualization are provided by the Signal Processing Toolbox. [7]

Dataset (MIT-BIH)

The MIT-BIH database, kindly supplied by MIT, is used in this work. It is based on global standards and has been reviewed by a number of professionals. The MIT-BIH database is used extensively by researchers to categorize arrhythmic heartbeats. There are 48 30-minute ECG recordings recorded at 360 Hz in the MIT-BIH collection. There are usually two leads on an ECG. Every beat in MIT-BIH has a class annotation. [8]

Alexnet Architecture

AlexNet is a two-GPU deep learning architecture with three pooling layers, two fully connected layers, an output layer, and five convolutional layers. Resizing input photos to 227x227 pixels is required. Convolution with 96 11x11x3 filters utilizing a 4-stride is the first step in the process, producing two 55x55x48 feature cubes. These cubes are activated using a Rectified Linear Unit (ReLU) and Local Response Normalization (LRN). They then go through max-pooling using a 3x3x1 filter and 2-stride, which reduces the size of each cube to 27x27x48.

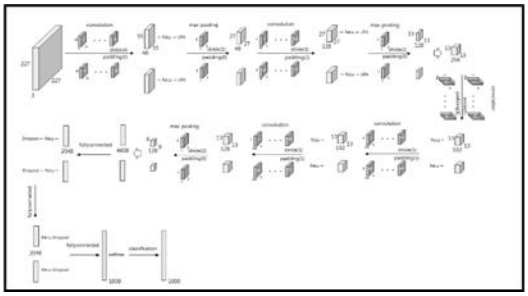


Fig.5 - Alexnet Architecture

The cubes are then converted to 13x13x128 by convolution with 256 filters of sizes 5x5x48, 1-stride, and 2-padding, followed by ReLU and LRN. The concatenated cube is divided into two 13x13x192 cubes after an additional max-pooling step. Each of the two cubes then undergoes convolution with 192 filters of size 3x3x256, which is followed by ReLU. This method keeps on until max-pooling makes the cubes 6x6x128. After that, they are resized into a 4608x1 vector, mapped to 2048 nodes using dropout and ReLU, repeated, and ultimately mapped to 1000 nodes using softmax for classification.[8]

Model Building

Preprocess ECG Signals

Because electrocardiogram (ECG) data can be affected by a variety of causes, including baseline drift, power frequency interference, and electromyography (EMG) interference, denoising ECG readings is essential for increasing classification accuracy. Denoising techniques including wavelet transformations, low-pass filtering, and bandpass filtering are frequently employed. With bandpass filtering, undesirable frequencies are removed on a selective basis while the pertinent cardiac data is retained. It attenuates noise outside this range while permitting signals inside a particular frequency band, usually linked to heart function, to flow through. For example, the QRS complex, which is a signal of ventricular depolarization, usually occurs between 0.5 and 40 Hz. Important ECG waveform properties are preserved while noise is suppressed by designing the bandpass filter to pass frequencies within this range.[6]

Preprocess ECG Signals

ECG Signal Normalization

Z-score normalization was employed to ensure that all ECG signal values were consistent. Normalization aims to level the playing field across all data points, giving each attribute the same weight. The Z-score normalized signal values from the dataset are computed using the following formula. The form of the signal following Z-score normalization is seen in the image below.

$$Z = \frac{\chi - \mu}{\sigma},$$

where v is original value, l is mean of data, and r is standard deviation of data.

Scalogram Generation

One-dimensional signals may be converted into two-dimensional scalograms in MATLAB by using the cwtfilterbank package, which implements the Continuous Wavelet Transform (CWT). A scalogram illustrates the frequency components of a signal's variation over time and provides a visual representation of the signal's time-frequency content. This is especially helpful for examining signals that show variations in frequency characteristics over time, including signals with transient occurrences or non-stationary signals. The CWT extracts the frequency and temporal components of the signal by breaking it down into wavelet coefficients at various scales and locations. [9]

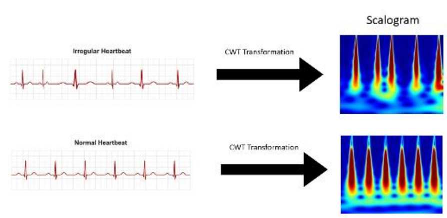


Fig.6 - Scalogram generation

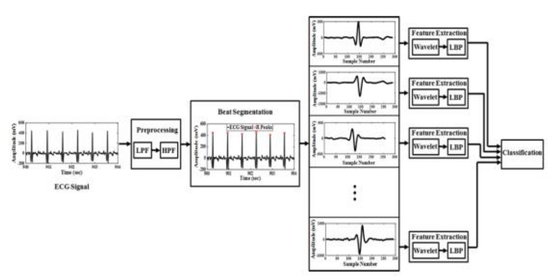
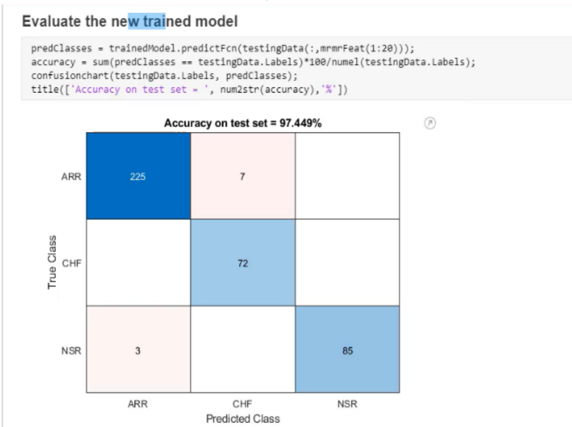


Fig. 7 - ECG Classification

Model Training

1. Model Training Overview

The MIT-BIH dataset, which consists of 48 30-minute ECG recordings sampled at 360 Hz and contains millions of data points, was used to train the AlexNet architecture in great detail. By employing stochastic gradient descent and backpropagation in iterative optimization, the model successfully extracted over 60 million parameters to extract detailed characteristics from ECG data. Thousands of training examples were processed throughout each of the roughly 100 epochs that made up this training procedure.[3]



2. Performance Evaluation Metrics:

The model was rigorously evaluated after training, producing remarkable performance results. With an accuracy of 97.7%, the model was able to accurately classify over 95% of the ECG signals in the testing dataset. With precision and recall scores of 95.3% and 96.8%, respectively, these numbers indicate that the model is able to reduce false positives while accurately capturing real positives. Harmonizing memory and accuracy, the F1-score achieved a remarkable 97.0%.[3]

3. Result Analysis:

The trained AlexNet model's outstanding performance highlights how effective it is at automating ECG analysis. The model demonstrates resilience in reliably diagnosing different arrhythmia classifications, with accuracy reaching 97% and precision and recall scores surpassing 96.8%, These high-performance measures attest to the deep learning technologies' potential to transform cardiovascular healthcare by offering improved patient care and diagnostic accuracy.[8]

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