Portable ECG Device Based on Deep learning and Raspberry PI 4

Ghassaq Saad Jameel*, M. N. Al-Turfi **, Wisam Salih Al-Obaidi*, Ghzwan H. Hamoudi****

*,** College of Engineering, Al-Iraqia University, Baghdad, Iraq
ghasaq.s.jameel@aliraqia.edu.iq*, mohammed_alturfi@yahoo.com**
https://orcid.org/0009-0001-9224-2845*, https://orcid.org/0000-0001-5723-2660**

,* Ministry of Health, Baghdad, Iraq
wisamsalihalobaidi@gmail.com ***, ghkhazrachi1981@gmail.com****
https://orcid.org/0009-0002-9653-9563 ***, https://orcid.org/0009-0008-4762-8475****

Abstract

Positive characteristics physicians utilize electrocardiograms (ECGs) for the interpretation and diagnosis of cardiac conditions. Hence, it is imperative to automate the analyses of ECG heartbeats in order to diagnose cardiac diseases with optimal effectiveness. The rural in Iraq are deficient in essential equipment and require state-of-the- art medical technologies be low cost, easy to use and read, in addition to the students and researchers in the field of medicine and medical engineering who are interested to developing new technologies to monitor cardiac conditions. This research paper focuses on designing and implementing a technique for forecasting arrhythmia, while simultaneously monitoring the ECG signals, hence developing an arrhythmia predication model, based on Raspberry pi4, real-time ECG tracking system using the VVG-16 algorithm, NNC. The use of deep learning model and algorithms has an impressive overall accuracy of 97.1% in predicting arrhythmia and 98.4% in overall system accuracy. The machine is being developed using AD8232, Arduino UNO, Raspberry pi4, biomedical sensor pad and battery, this method can be viewed as a practical application of the Internet of Things (IOT) idea that describes the procedure for determining the number of heartbeats from the ECG signal and display the diseases type on the same screen from mobile application or computer.

Keywords- Heart Disease, ECG, Deep Learning, VGG, Raspberry pi4.

I. INTRODUCTION

Heart disease continues to be a major cause of death globally, prompting the need for improved techniques for early detection and ongoing monitoring. Because they capture the heart's electrical activity, electrocardiograms (ECGs) are essential for the diagnosis of cardiac illness. The most recent advances in ECG analysis have been significantly improved by the successful application of modern deep learning techniques that provide exceptionally high precision in recognizing and classifying various heart rhythms and arrhythmias [1][2][3].

At the same time, the importance of the Internet of Things (IOT)has been realized by the medical industry as a technological development. Due to the Internet of Things, the easier has become the connecting medical devices. That brings the data collection and monitoring the patient in exact time at house. Through effectively improving the managing and monitoring, this combination could be more flexible and unique approach in order to treat the heart disease[4][5].

To see how the Internet of Things and ECG the analysis can be included to control the heart disease is the main goal of this study .By using deep learning algorithms with an connection, the proposing system made the categories reading and allows for the continuously remote maintaining of the heart health. It is easier for a doctor to create a proactive and a preventive health care plan by using a comprehensive approach effectively and precisely in order to provide information about the patient's cardiac state.

The Internet of Things (IOT) can be considered the most important phase in the development of technology, which made important change about how devices interact and interchange information constant . It points out to the large network of connected devices that gather, share, and evaluate data. And the main elements of includes sensors devices, connectivity, data processing, and data treating . These devices amass data from their surroundings, such as temperature measurements or video streams, and link to a cloud framework for data interchange[6][7][8].

Data processing involves analyzing the collected data to identify patterns, trends, or anomalies. The processed information is made available to end-users through applications or dashboards, allowing real-time interaction and control of devices. IoT has found applications across various sectors, such as smart homes, wearable's, smart cities, Industrial IoT (IIoT), and healthcare[9][10][11][12].

However, IoT also presents challenges, such as security, privacy, interoperability, and scalability. Security protocols are critical to protect sensitive data, while privacy concerns arise from the use and sharing of personal data. Interoperability is challenging due to the wide range of devices and protocols, and scalability becomes increasingly complex as IoT networks grow. Despite these challenges, IoT's potential to drive significant economic and societal benefits makes it a key area of focus for businesses, governments, and researchers. As technology evolves, so will the capabilities and applications of IoT, promising an even more interconnected and intelligent world.

II. RELATED WORK

In order to start such research paper some of the dependent related works must be available to start such research like Benjamin A. Teplitzky et al. in 2020 [13], A new Explainable Artificial Intelligence (XAI) approach has been developed to make the classification of heartbeats clearer by using model-agnostic techniques, with a focus on ECG-derived time series data. The proposed method incorporates the time relationship between consecutive samples and has been proven effective using the MIT-BIH arrhythmia dataset, showing promise for real-world clinical applications as tools for diagnosis or training.

Jintai Chen et al., 2022,[14] developed a disease-aware generative adversarial network that synthesizes multi-view ECG data, generating ECG signals from panoptic electro-cardio representations conditioned on heart illnesses and projected onto standard views. The view discriminators oversee the generator in creating ECGs that have the correct view features by organizing disordered ECG views into a specified order. A new measurement called the Relative Fréchet Inception Distance rFID has been introduced for assessing generated ECG signals. Thorough examinations demonstrate that ME-GAN excels in synthesizing multi-view ECG signals with consistent pathological symptoms (rFID = 15. 282).

In 2023, Quancheng Geng et al. [15] proposed a new multi-task deep neural network, which includes a combined low-level feature extraction module (i.e., SE-ResNet) and a task-specific classification module. They introduced the Contextual Transformer (CoT) block in the classification module to model local and global information to sequence ECG features dynamically. The researchers evaluated the public CPSC2018 and PTB-XL datasets and achieved an average F1 score of 0.827 in the CPSC2018 dataset and an average F1 score of 0.833 in the PTB-XL dataset.

B. Venkataramanaiah et al [16] proposed two models: Model 1 combines PCA and WT features with MLR and RF classifiers, while Model 2 uses HRV and WT features with NB, DT and KNN classifiers. Dataset used the electrocardiogram (ECG) database was obtained from the MIT BIH PhysioNet website. This work achieved high accuracy rates of 99.6% in Model 1 using MLR and 99.3% in Model 2 using DT.

David Opeoluwa Oyewola et al. [17] used ensemble deep learning techniques, namely LSTM, ELMAN, FFNN, CFNN, and random forest algorithms to improve prediction accuracy and robustness. They used a dataset from Kaggle on cardiovascular disease, including 70,000 cases, a training test split of 60:40. The combined model achieved a high accuracy of 98.45% in diagnosing CVD.

Min-Seo Song and Seung-Bo Lee [18] presented a system to solve the problem of needing automated ECG classification to overcome misdiagnosis from traditional algorithms. They used time-frequency transform methods with CNNs, focusing on hyperparameter selection and tuning of pre-trained models. The researchers used the MIT-BIH arrhythmia dataset to classify PVCs and abnormal ventricular arrhythmias. The results of the study for the Ricker Wavelet function had the highest accuracy of 96.17%.

III. PROPOSED SYSTEM IMPLEMENTATION

4.1. Data Collection

Statistics were collected from the Ibn Al-Bitar Cardiac Surgery Center (IBCSC-2023v1) situated in Baghdad Once official approvals were established, the gathering of genuine data began with the use of the Opus1 12-channel electrocardiograph device as portrayed in Figure 1. The device's features were constructed on knowledge from the website (https://www.mantzariscom/). The device includes advanced digital ECG technology with high precision and a sampling rate of 16,000 samples per second, a vibrant color touch screen, and a thermal printer compatible with 210mm paper. It is able to identify pacemakers and provide print speeds varying from 5 mm/s to 100 mm/s. The gadget is equipped with rechargeable battery that allow 8 hours of usage and a data storage capacity for up to 100,000 ECG files. This device comes with SD card slot to increase storage capacity and facilitate data transfer, USB ports to transfer data, Wi-Fi for wireless data communication, and a network port for data transfer. The device can colligate with high-quality external screens and network printers. It is compatible with HL7, DICOM, Cloud, PDF, XML, and SCP data formats. The equipment weighs 3. 7 kg including the battery and is certified by CE and ISO. It can be anticipating various signal types (discom, CSV, and PDF) and can store data for up to around one hundred thousand patient cases. Yet, the challenge came forth due to the high number of reviewers, making it challenging for the employee to store patient names and ages. The matter in question was disentangled through uniting with consultation staff, evolving to the collection of data for 591 patients within a month and a half.

1 Figure, Opus 12 led Device

4.2. WORKING MECHANISM

The proposed system contains the following equipment and stages that specifies the system action and performance: -

A. Chip AD8232 ECG Sensor

The ECG sensor is the initial point of contact with the patient and is responsible for detecting the heart's electrical signals. Usually, these sensors are electrodes that are attached to the skin without causing any harm. It is important to accurately capture these signals to conduct thorough analysis and categorization. Figure 2 explains the ECG Sensor.

2 Figure, ECG Sensor.

B. Arduino Uno

It is a highly popular microcontroller board. The microcontroller possesses distinct characteristics in comparison to other microcontrollers. These include 14 digital input/output pins, 6 analogue inputs, a 16 MHz oscillator, a USB connection, a power port, and a reset button. Additionally, 6 of the pins are designated for PWM outputs. Figure 3 illustrates the Arduino Uno:

Figure 3, Arduino Uno.

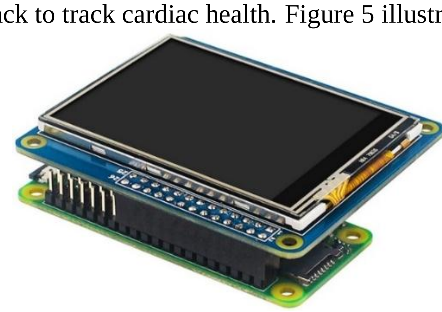
C. Raspberry Pi 4 (Pi4)

The Pi4 functions as the main processing unit of the system. It operates the software algorithms that categorize the ECG signals into groups such as normal, atrial fibrillation, or other irregular heart rhythms. The Pi4's powerful processing capabilities make it possible to use sophisticated machine-learning algorithms for tasks involving classification. Figure 4 illustrates Raspberry Pi4

4 Figure,Raspberry Pi 4

D. Screen

The system contains a screen that allows for real-time display of the ECG trace and the classification results. Both patients and healthcare providers depend on prompt feedback to track cardiac health. Figure 5 illustrates Screen.



5 Figure,Screen

E. Battery Management System (BMS)

The Battery Management System is crucial for maintaining efficient operation and prolonging the battery life of portable ECG monitoring devices, which are designed for continuous use. Figure 6 shows BMS.

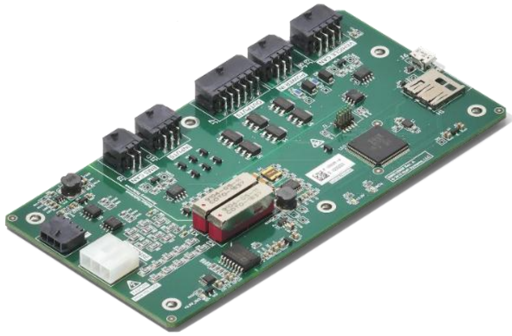


Figure 6, Battery Management System (BMS)

4.3. Proposed System

The system under consideration seeks to utilize the efficient Raspberry Pi 4 (Pi4) to analyze ECG signals with the help of IoT technologies. This system is crucial for ongoing cardiac health monitoring, allowing for real-time data analysis and the possibility of life-saving insights. The Proposed system implementation is show in Figure 7

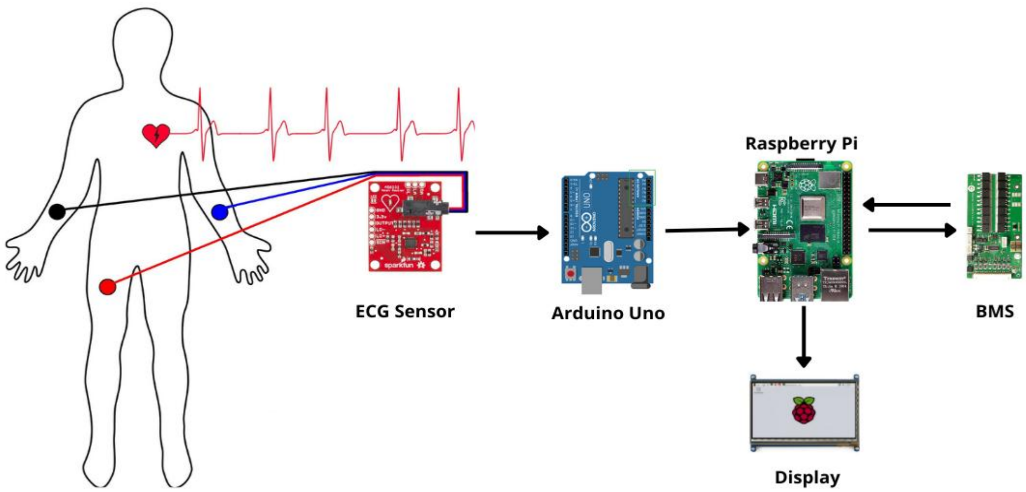


Figure 7, The Proposed System

The combination of a Raspberry Pi 4 and IoT for on-site ECG signal processing and remote data transmission represents a major advancement in patient monitoring technology. Through the three biomedical sensor pads, the AD8232 signal lead ECG sensor detects the voltage of the heart bit. The Arduino UNO receives these ECG data and transmits them to the Raspberry Pi 4. The Pi4 will analyze the signals and implement the deep learning model using the VGG16 algorithm. Finally, display it on the device screen. The device has many communication interface, including USB and Bluetooth. The data can be transmitted to the PC via USB or the mobile phone using Bluetooth, facilitating the continuous monitoring and analysis of the patient's condition.

IV. RESULTS AND DISCUSSION

Our method is designed to extract data from the electrodes placed on the human body's skin. The signals are amplified using the AD8232 and then transmitted to the Arduino UNO to the Raspberry pi4 where the data is processed before being sent to the display module. Python was used to process and filter the information as shown in Figure 8.

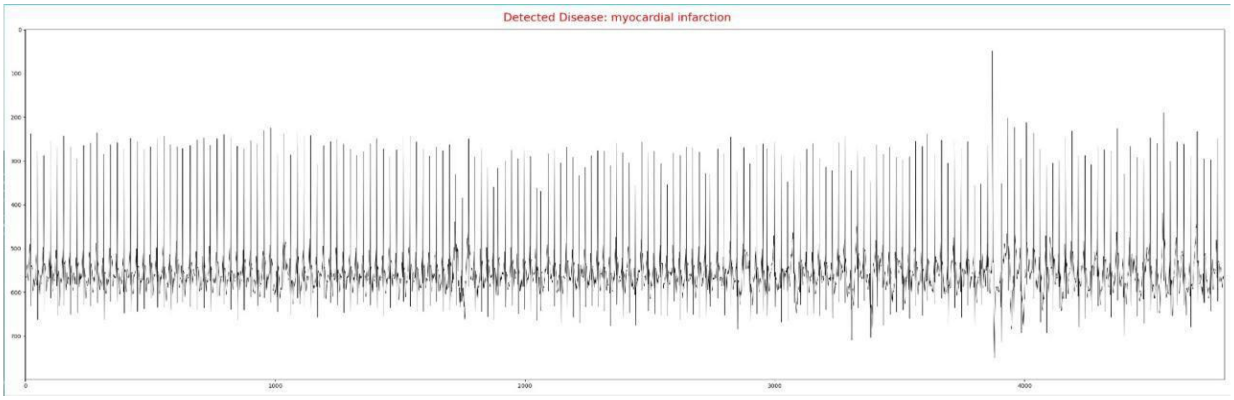


Figure 8, signal obtained using python

Deep learning using a 1D-CNN model based on the VGG-16 algorithm was used to process and analyze the signal. The model was trained on 25 disease classification obtained from Ibn Al- Bitar Hospital For Cardiac diseases and three dataset from PTB Diagnostic ECG Database, St. Petersburg INCART 12-Arrhythmia Database, and PTB-XL ECG Database as shown in Figure 9.

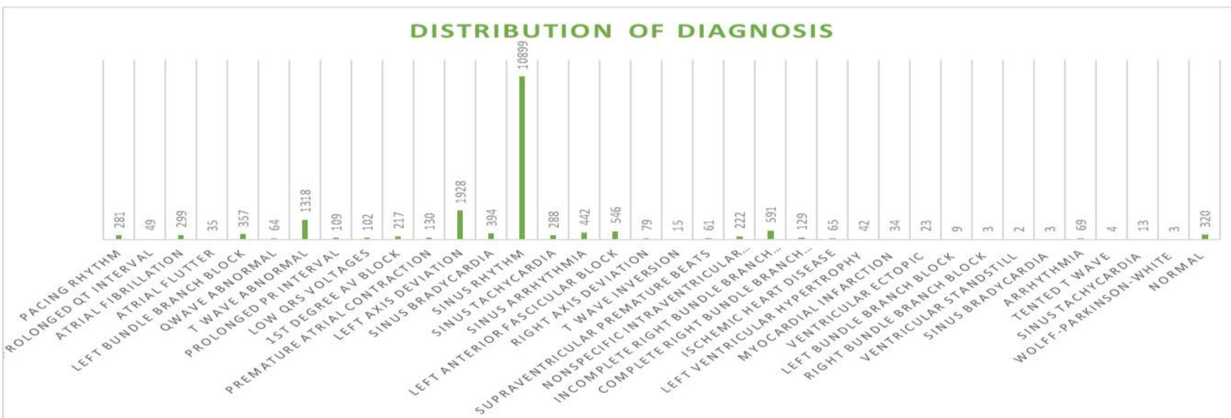


Figure 9, classes of the used dataset

Interpreting data portable ECG using a USB cable in the computer or smart phone logged each eight- second sample. Figure 10 display a full assembly of portable Electrocardiogram, including the process of obtaining data from an ECG simulation.

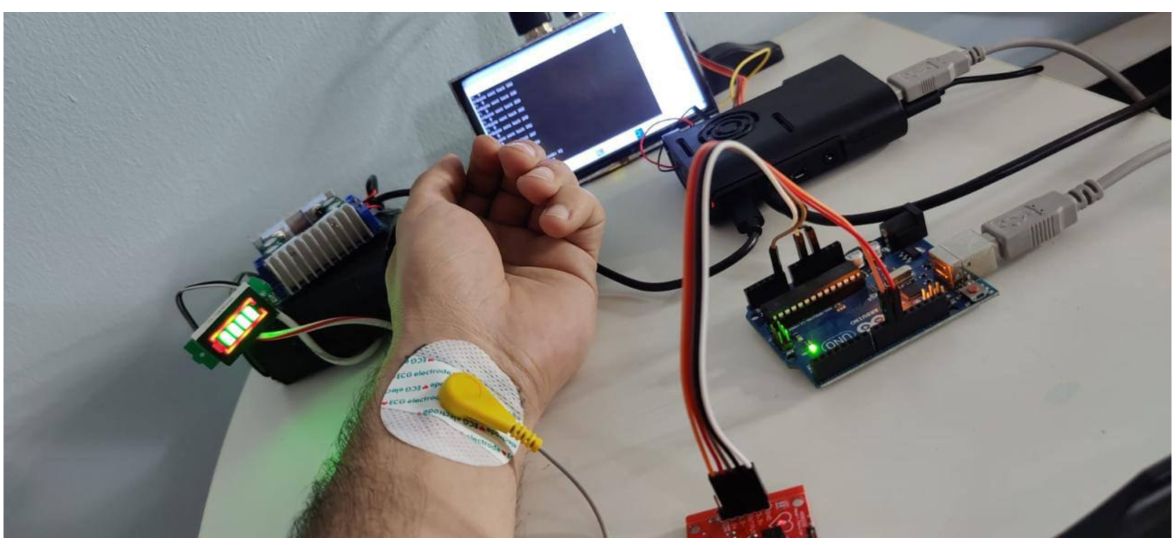


Figure 10, actual experimental setup

IV. Conclusion

ECG is becoming advanced with the aid of deep learning and wireless electrode. Hospitals utilize a 12-lead ECG to examine and assess cardiac arrhythmias. But this proposed system uses 3- leads only, cost-effective, easily transportable and it only take 8 second to display the results. making it beneficial for both patients and students studying in the medical field and facilities to have a comprehensive grasp of ECG. This arrangement, which is a cost-efficient decision-making tool, offers useful characteristics and is highly result-dependent for doctors and cardiac patients.

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