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ECG Monitoring System Using Deep Learning

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Abstract - This study suggests employing deep learning methods to create a portable ECG monitoring device. A common diagnostic technique in cardiology is the electrocardiogram (ECG), which offers vital information about the electrical activity of the heart. However, manual ECG signal analysis can be laborious and error-prone. Current developments in deep learning present fresh possibilities for automated ECG signal interpretation and analysis.

Deep neural networks are used for categorization, feature extraction, and signal pre-processing in the proposed ECG monitoring system. To start, noise and artefacts are removed from the raw ECG signals through pre-processing. Using neural networks, which are intended to automatically learn pertinent features from the input signals, features are then extracted from the pre-processed data. The extracted features are then fed.

Key Words: ECG, Oximeter, Deep Learning, CNN, Peaks and troughs, Classification, smart monitoring system, cloud, sensors

1. INTRODUCTION

Monitoring of electrocardiograms (ECGs) is a crucial tool for identifying cardiovascular disorders. Traditional ECG monitoring techniques, however, frequently necessitate reducing patient comfort and movement. Remote ECG monitoring devices may now be developed thanks to recent developments in non-invasive wireless sensors and IoT technology. The detection of cardiac irregularities and arrhythmia patterns, which can be essential for precise diagnosis and treatment planning, has recently showed considerable promise thanks to deep learning approaches.

In order to automatically interpret ECG data, this study suggests an ECG monitoring system that uses deep learning algorithms. In particular, we investigate the incorporation of an oximeter sensor to offer extra data that can assist distinguish between various cardiac events and enhance the precision of the diagnosis of heart disorders. The design, execution, and assessment of the suggested proposed system using a publicly available dataset of ECG signals, demonstrating the effectiveness of deep learning techniques for automatic ECG analysis and monitoring.

2. METHODOLOGY

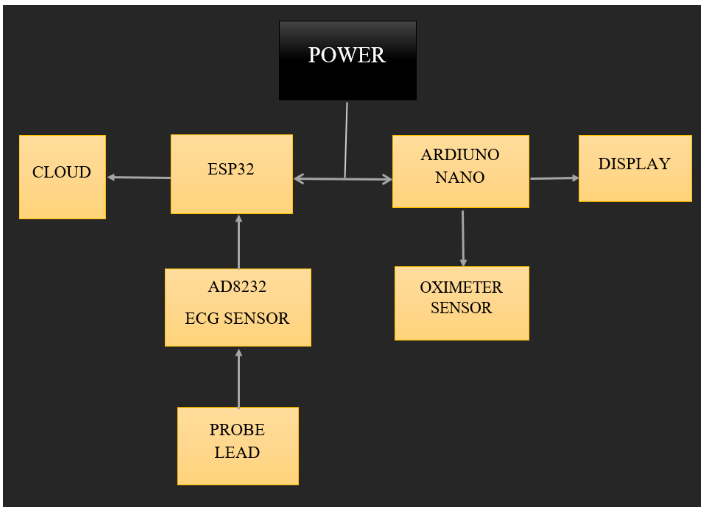
After carefully examining several ECG monitoring systems, we set out to design something that would be accessible to users of all ages, be portable, and be inexpensive. However, in doing so, we did not want to sacrifice precision; as a result, we developed this model.

Through looking at several projects and academic papers on related subjects, we integrated into a prototype that is market-ready. We made decisions on the services to offer and the metrics to use. After using the oximeter to our project, we discovered through our detailed research that it is rarely utilized in projects, and we obtained useful cardiac findings that would help medical professionals in more accurate results. Our project was kept small and compact. It has an adapter, can be plugged in, runs on batteries, and so on.

3. WORKING

A device that measures electric pulses through an ECG sensor, which is a differential amplifier. This sends analogue data to a microcontroller, which then processes it. Received analogue data is then sent to the cloud. Cloud data is first plotted into a graph, then displayed and mapped accordingly. The oxygen saturation levels are measured by the oximeter sensor along with heart rate to offer extra data for a precise diagnosis of heart disorders. This technology incorporates deep learning algorithms that enable the identification of arrhythmia patterns and other disorders connected to the heart. In the end, the fusion of deep learning with oximeter sensor technology offers a non-invasive and efficient method for enhanced heart illness detection and remote ECG monitoring.

3.1 Block Diagram



Block diagram: ECG Portable Monitoring system

3.2 Components used

A) ESP32

The ESP32 is conducted to capture and process the ECG signal from the sensor, transfer the information electronically to a distant monitoring system, and receive the signal from the sensor.

B) ECG Sensor

An ECG monitoring system's ECG sensor is an essential part that monitors and maintains heart health. The sensor is employed to obtain the electrical activity of the heart and produce an ECG signal, which is processed and analyzed to look for anomalies and identify cardiac problems.

C) Ardiuno Nano

The hardware's second stage is connected to the Arduino Nano. The oximeter sensor and display are both connected to the bluetooth module. The principal objective of incorporating an additional microcontroller is to alleviate the stress on the AD8232 and obtain more precise ECG readings.

D) OXIMETER AND Ssd1306 OLed display

The SSD 1306H Display and oximeter are utilized to improve accuracy and produce better cardiac results. The heart rate and SPO2 values are examined. Average levels are also shown on the display from the oximeter. Using a push-switch we operate the display.

3.3Modal architecture

The whole system can be segregated into two subsystems which are individually controlled by two microcontroller. Firstly, the esp32 module controls the ECG architecture. Esp32 is a 32bit microcontroller which is supplied by 5 volts through an external battery and equipped with an ECG sensor. The AD8232 sensor an integrated module which operated at nominal voltage of 2.0 V to 3.5V. Supply is given directly through Esp32's 3.3 volt output pin. This sensor is basically a differential amplifier with a very low supply current of 170uA and high signal gain (G=100). With further low pass filters and high pass filters are integrated too. It has three electrode probes which are attached to the body and the electrical pulses received from the probes are amplifies and the difference is calculated. This Analog data is transmitted to esp32 which plots a graph using the provided parameters and the obtained graph is then uploaded to the cloud.

The second subsystem is controlled by the Arduino nano microcontroller which is again supplied with 5 volts. Max30102 sensor is used to measure the Spo2 levels and heart rate. Max3010x library has an algorithm which measures and compares the red LED values and IR LED values and Spo2 value is calculated. These values are also averaged and displayed. Ssd1306 O Led display is used to display all the calculated values. The system has a standby mode to save power which disables the components and sensors until the switch button is pressed. The more stable finger placement on the sensor would result in more accurate values.

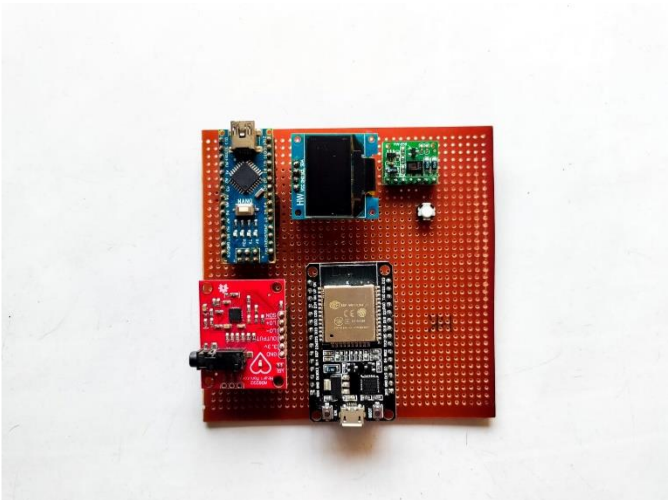


FIG 1: ECG Monitoring system with oximeter

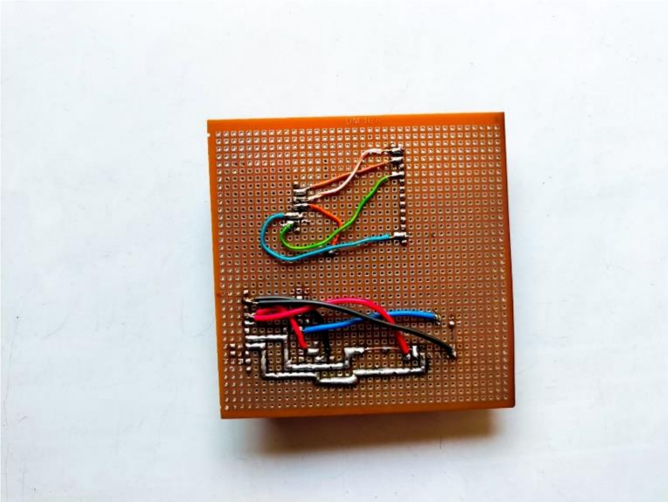


FIG 2: ECG Monitoring system with oximeter

3.4 Data Processing

Data processing utilizing deep learning methods can be effective for ECG monitoring systems. Large volumes of ECG data may be used to train deep learning systems to identify pertinent characteristics and spot anomalies. These algorithms can categorize ECG readings and find patterns that can point to particular heart diseases. Deep learning techniques may also be used to improve, compress, and denoise ECG signals. Health professionals may use the processed data to give them more precise and timely information about the heart health of their patients. We used the MIT-BIH database, which has 48 records of electrocardiogram (ECG) signals, for our experiment. For research purposes, we chose 1000 heartbeats at random from each record, totaling 48,000 beats. Then split the information into three sets: the training set, the test set, and the validation set. During 400 epochs with a batch size of 256 and training duration of around 10 s per epoch, the model was trained on 38,400 beats, which made up about 80% of the data. The remaining 2400 beat samples were utilized to assess performance during the testing phase after the optimization was completed on 7200 validation beats. The trained model was put to the test on all 48 records, and the effectiveness of compression was assessed both on the test set and on each individual record in the MIT-BIH database. EDA is a pre-processing component (electrical data analysis). With this information, we were able to identify the aberrant node. The acquired dataset is divided into training and testing groups. Valid datasets help us determine accuracy. The performance was assessed using many performance metrics, including the peak signal-to-noise ratio (PSNR), percentage residual difference (PRD), root mean square (RMS), signal-to-noise ratio (SNR), and quality score (QS). For the lost function when creating the neural network, an optimizer is employed. Each record has a 117.33 compression ratio (CR). The validation losses fell synchronously, and BCAE and RECN both converged to low losses in the training phase, demonstrating that the model is not over fit. In similar way we can hence, collect ECG signals store the data and integrate it in deep learning and get efficient results.

3.5 Deep Learning Model

Deep learning is a type of machine learning that uses artificial neural networks with multiple layers to analyze and process complex data. These networks can learn to recognize patterns, classify information, and make predictions based on large amounts of data. The key feature of deep learning is the ability to automatically extract relevant features from raw data without manual feature engineering. This has led to breakthroughs in many fields, including computer vision, natural language processing, and speech recognition. Deep learning has become increasingly popular due to its ability to improve accuracy and performance in tasks such as image and speech recognition, and natural language understanding.

3.6 Deep Learning Algorithm

A dense neural network, also known as a fully connected neural network, is a type of artificial neural network where all nodes in one layer are connected to all nodes in the next layer. In this type of network, each node in a layer receives input from all nodes in the previous layer, and passes its output to all nodes in the next layer. The layers in a dense neural network can have any number of nodes, and the network can have multiple hidden layers between the input and output layers. Dense neural networks are commonly used in deep learning and can be trained using back propagation to optimize their weights and biases.

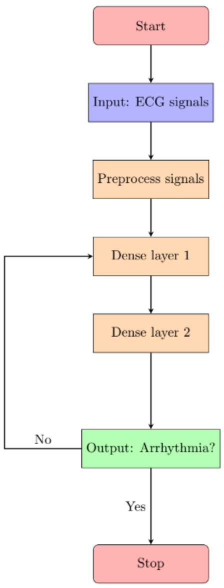


FIG 3: Flow Chart of Code Algorithm

4. RESULTS

In this project, we were capable of successfully extract ECG graphs from patients and upload them to the cloud, where they are then being maintained and stored. After incorporating this dataset via deep learning, we obtain precise ECG readings. Health experts can provide us with more accurate information on heart issues when using an oximeter which is also part of our project, since it provides heart rate, pulse, and the average of the two. Following are outputs from the MIT-BIH dataset as well as the graph and oximeter result of subject A:

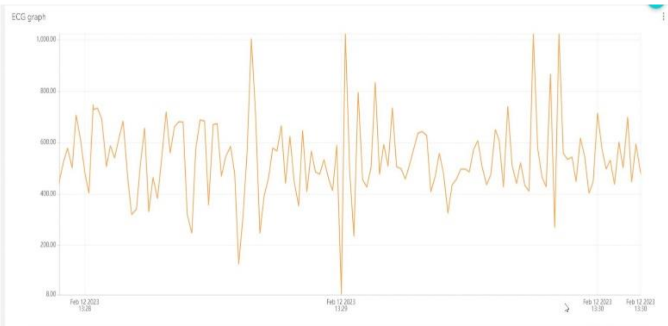
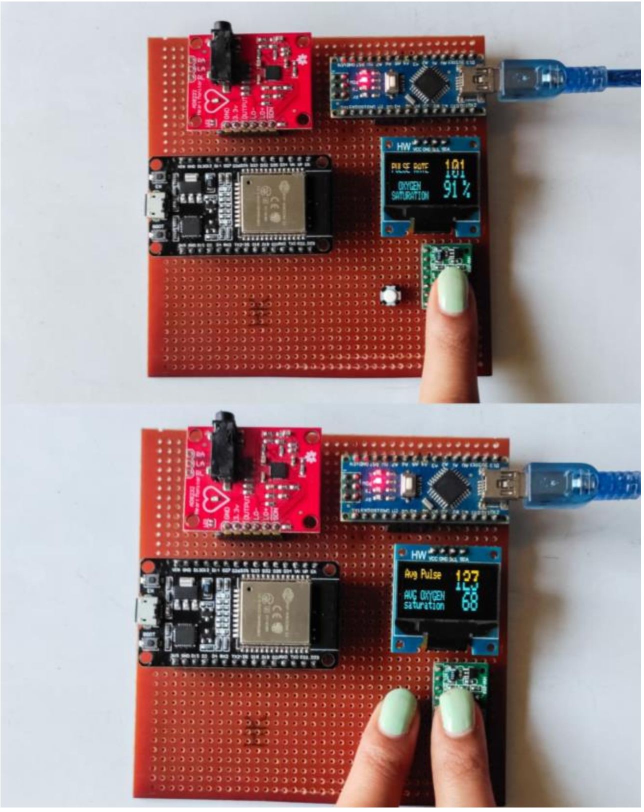
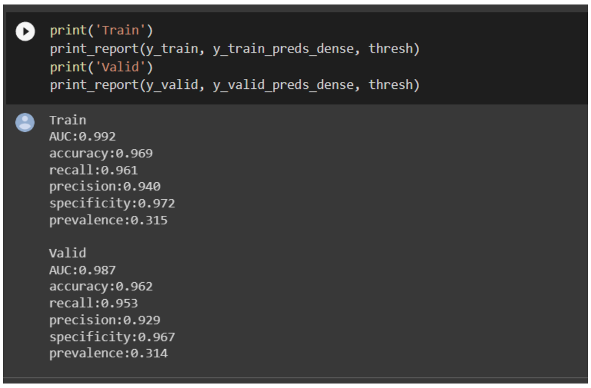


FIG 4: ECG Graph plotted and stored on cloud of Subject A





```
print('Train')
print_report(y_train, y_train_preds_dense, thresh)
print('Valid')
print_report(y_valid, y_valid_preds_dense, thresh)

Train
AUC:0.992
accuracy:0.969
recall:0.961
precision:0.940
specificity:0.972
prevalence:0.315

Valid
AUC:0.987
accuracy:0.962
recall:0.953
precision:0.929
specificity:0.967
prevalence:0.314
```

FIG 5: Output of dataset from MIT-BIH of deep learning

5. CONCLUSIONS

Based on our project, we've created a portable ECG monitoring device that includes an oximeter and analyses data using deep learning methods. Our device can give real-time monitoring of heart rate and blood oxygen levels and has shown to be highly accurate in identifying cardiac problems. By enabling early identification of key changes and timely action, this has the potential to enhance care of a variety of cardiac disorders, including arrhythmias and heart failure. The system's mobility also makes it perfect for usage in isolated and resource-constrained environments where access to specialized cardiac monitoring equipment may be restricted. Overall, our research demonstrates that incorporating deep learning algorithms into portable ECG monitoring systems can greatly increase the precision and usefulness of these systems and ultimately improving patient outcome and quality of life.

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