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ECG AND PULSE OXYGEN LEVEL MONITORING AND ARRHYTHMIA CLASSIFICATION USING CNN

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Abstract— **Early Diagnosis of disease has always been a boon for the treatment of any disease. However, for people living in remote areas, health facilities have not been easily accessible. A few of the critical parameters for determining whether the person is healthy or not depend on a few health parameters such as Heart Rate, electrocardiogram (ECG), oxygen saturation (SpO_2), and Body Temperature. To avoid overcrowding hospitals, we have developed a remote monitoring and prediction system. We have developed Arduino-based low-cost hardware that can be used for telemedicine service and remote monitoring of patients in India directly from expert doctors in the field. The system was successfully tested and got around 97 percent successful transmission of data without latency. The model includes a web app that directly reports the data to the doctors and has been trained with many machine learning models to predict abnormal patterns. Ultimately the web app gives a composite score based on heart rate and arrhythmia to facilitate subjects for heart health. Created a system, which is the dynamic web app to display real-time data and plot the graph of the variation dynamically. Using this system to check our health periodically makes it possible to reduce the chances of deteriorating health conditions**

Keywords- **D8232, Arduino, MAX30102, Python, Rasp berry Pi, Streamlit**

I. INTRODUCTION

Nowadays the Indian population rises exponentially, new diseases are rising – which leads to insufficient hospital personnel. For reducing this main problem this paper proposes a model. In 2019, Coronavirus (COVID -19) shatters the world. It is a kind of RNA virus – that comes under the difficult category. Many people have suffered due to insufficient beds in hospitals, this model gives a solution to that. In hospitals, doctors mostly monitor some basic parameters like body temperature, pulse oxygen level, heart rate, ECG and many more. This system (WebApp) provides a solution to the doctors to monitor the basic vitals of patients from their homes. Once the setup is complete, the doctors can monitor SpO2, ECG from patients' homes [3]. It may help to reduce overcrowding at hospitals, travel avoidance for senior citizens and rural peoples. In addition to that, the developed system that can predict cardiovascular disease (CVDs). According to the World Health Organisation (WHO), cardiovascular diseases (CVDs) are the leading cause of death globally, over 17.9 million people died from cardiovascular disease (CVDs), which is about 32% of deaths worldwide. Arrhythmia is a kind of classification of cardiovascular disease (CVDs), there are several types of Arrhythmias, which can be classified by cardiologists (Doctors) with the help of an Electrocardiogram (ECG) -PQRST wave[7]. Generally, a normal person can classify the heartbeat with the help of an ECG signal as normal, abnormal – but, cardiologists define it with special terms called Arrhythmia. In this paper, the developed system classified the arrhythmia into 6 types on the basis of a 2D Convolutional Neural Network (CNN)[8]. The system proposed a method of classifying ECG arrhythmias by using a two-dimensional depth CNN with grayscale ECG imaging. By converting the one-dimensional ECG signal into a two-dimensional ECG image, the noise filtering and extraction features are no longer required. This is important because some of the ECG beats are missed during noise filtering and feature extraction. In addition, the training data can be enlarged by enlarging the electrocardiogram (ECG) image, resulting in higher classification accuracy. Data augmentation is difficult to apply in the previous literature[6] because distortion of the one-dimensional ECG signal can degrade the classifier's performance. However, enhancing the two-dimensional electrocardiogram images with different cropping methods helps the CNN model to form different views of the single electrocardiogram images. The use of ECG images as input for the classification of ECG arrhythmias is also beneficial in terms of robustness. Current ECG arrhythmia detection methods are sensitive to noise because each ECG signal value on a one-dimensional image is processed to have an equal degree of classification. However, when the ECG signal is converted into a two-dimensional image, the proposed CNN model can automatically ignore the noise data when extracting relevant feature maps in any convolution and pooling layers. Therefore, the proposed CNN model can be applied to ECG signals from different ECG devices with different sample rates and amplitudes, while previous literature[6] requires a different model for different ECG devices. In addition, they detect ECG arrhythmias with ECG images the same way medical professionals diagnose arrhythmias when they view a patient's electrocardiogram on the screen, which shows a series of electrocardiograms. ECG signals help experts more accurately identify ECG arrhythmias. Our developed system will do these all functions.

II. STRUCTURE AND HARDWARE DESIGN OF SIGNAL ACQUISITION AND PROCESSING SYSTEM

A. PULSE–OXYGEN LEVEL MONITORING

The principle of pulse oximetry is based on the differential absorption characteristics of oxygenated and deoxygenated haemoglobin. Oxygenated hemoglobin absorbs more infrared light and allows more red light to pass through. Whereas Deoxygenated haemoglobin absorbs more red light and allows more infrared light to pass through. Pulse Oximeter sensor uses an IR Transmitter, red LED & a Light Dependent Resistor (LDR), Which then can be connected to a microcontroller and the ratio of red light absorbed vs Infrared light absorbed can then be calculated and from that SPO2[1] value can be calculated. Two transmitting LEDs, a Red led of approximately 650 nm and infrared led which has a wavelength of 950 nm.

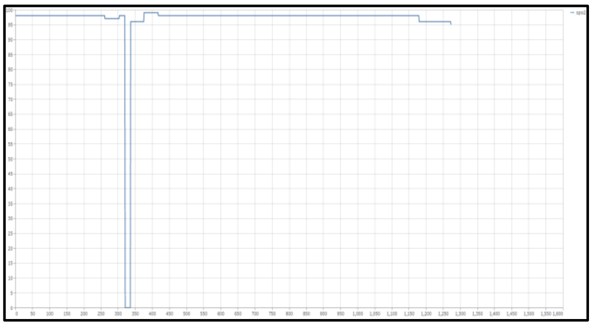

Fig.1 Constant SpO2 (pulse-oxy level)

Depending on the amount of Oxygenated hemoglobin or Deoxygenated hemoglobin the ratio of red light absorbed vs Infrared light (R/IR)[4] absorbed will change. Typically R/IR ratio of 0.5 equates to approximately 100% SpO2, a ratio of 1.0 to approximately 82% SpO2, while a ratio of 2.0 equates to 0% SpO2[2].

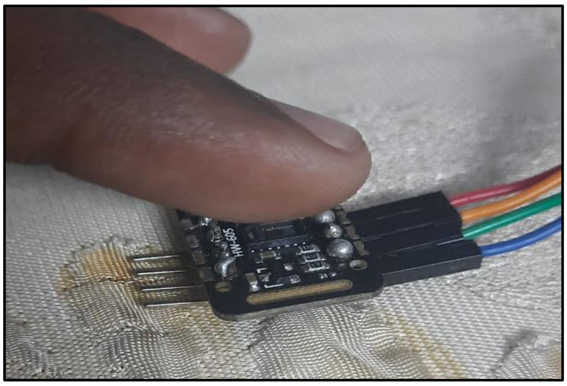

Fig.2 SpO2 Sensor setup with human interface

With the help of this portable device, patients are able to monitor themselves even in rare situations like the COVID Isolation periods.

B. Ecg Monitoring –

Using the AD8232 sensor, the electrical activity of the heart[5] is then measured, interpreted, and printed out. No electricity is sent into the body. But the electrical reading from the heart is amplified using an operational amplifier to get clear signal/ amplified signal at the intervals specified by the user. The P wave is produced by the sinoatrial node (SN), which is the heart's pacemaker.The atrioventricular node generates the QRS wave (AV). Atrial depolarization is shown by the P wave in an ECG complex. Ventricular depolarization is caused by the QRS, and ventricular repolarization is caused by the T wave. There is no atrial depolarization if there is no P wave. Atrial standstill is another name for this condition. Combination of P waves. The QRS complexes in the QRS are symptomatic of ventricular or junctional tachycardia. P waves that are not present at the moment

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Black Electrode	Left forelimb
Green Electrode	Right hind limb
Red Electrode	Left hind limb

Table.1 Electrode placement in human body pose

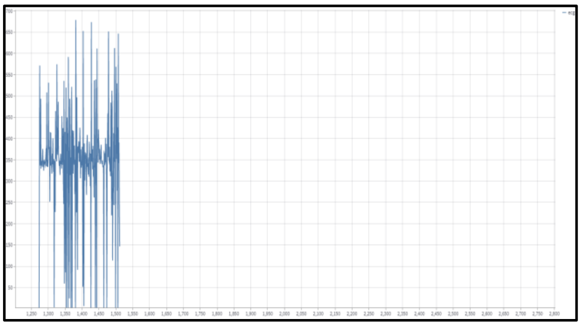

Fig.3. Dynamic ECG from webApp

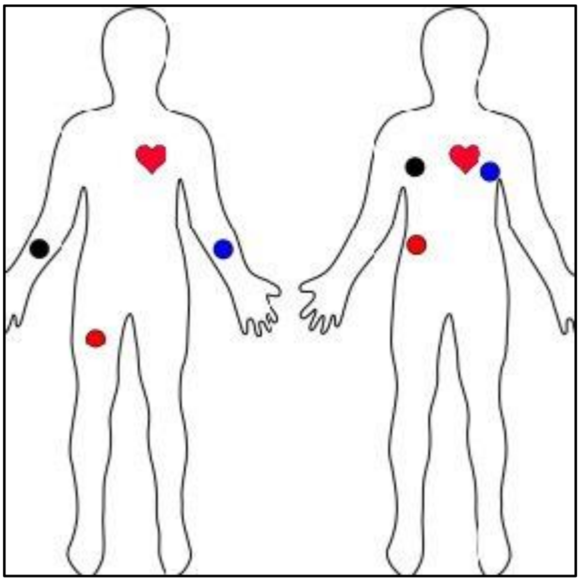

Fig.4.AD8232 Electrode Placement

A QRS indicates that an atrial depolarization has occurred without passing via the AV node. Without a QRS complex,

C. Arrhythmia Prediction Model

Developed a system to predict heart disease. The system uses Spo2 and calculates heart rate. Here, Dataset is taken from the internet, which is classified into the patients having heart disease or not according to its features. This data will be used to create a model which will try to predict if a patient has heart disease or not. This will require three Python libraries: streamlit, pandas, and scikit-learn. Classification is a technique that categorises data into a given number of classes. The main goal is to identify the category/class to which new data will fall. A random forest[10] is a meta estimator that fits several decision tree classifiers on various sub-samples of the Dataset and uses averaging to improve the predictive accuracy and control over-fitting. Input datas was gathered from the user Table.2. with the help of a panda's data frame.

Name of the Data	Parameters
Name	"Patient Name"
Age	46
Gender	Male
Chest pain type	Non-anginal Pain
Blood Pressure	156
Cholesterol	459 mg/dl
Thalach	177
Induced Angina	yes
Old peak	7
Slope of ST segment	1
Vessel of fluoroscopy	3
Thalassemia	Reversible defect (7.6)

Table.2 Experimental Input for heart rhythmic/unrhythmic predictor

Once the data frame gets ready, which passes through the fitted random forest classifier model to predict whether the person has heart disease or not, the modelled web app shows the probability of heart disease. The parameters are the input to the model, such as age and chest pain type classified into four types: Typical Angina, Atypical Angina, Non-anginal Pain, and Asymptotic. Other important parameters are also important, such as blood pressure, serum cholesterol, thalach (maximum heart rate achieved), induced angina, ST peak, the slope of PQRST waves's ST segment (where the P wave in an ECG complex indicates **atrial depolarization**. The QRS is responsible for ventricular depolarization and the T wave is ventricular repolarization.), vessels fluoroscopy, and thalassemia. Once every data is received, the web app shows the results.

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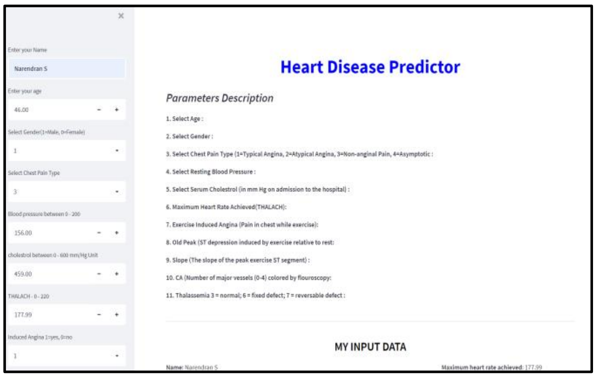

Fig.5. Heart Disease Predictor (unrhythmic/rhythmic)

Random Forest algorithm is a powerful yet simple algorithm that is especially useful when classifying different features, and even this model accuracy is also acceptable. with the help of experimental input, In Fig.6. The model predicts that the probability of heart disease coming is 29 percent, and by 71 percent, not possible.

Prediction :

	0	Chances of Heart Disease
0	0	No

Prediction Probability in % :

	0	1
0	71.0000	29.0000

Fig.6. Experimental result for heart rhythmic/unrhythmic predictor

This developed model also predicts the type of arrhythmia. Arrhythmia is a condition in which the heart beats with an irregular or abnormal rhythm[9]. Atrial fibrillation is the most prevalent type of arrhythmia, which causes an irregular and rapid heartbeat. A heart attack, smoking, congenital heart problems, and stress are all variables that might disrupt your heart's rhythm. Certain chemicals or medicines can also cause arrhythmias. The MIT-BIH arrhythmia database provided the ECG arrhythmia recordings used in this study. Between 1975 and 1979, 48 half-hour ECG recordings were gathered from 47 people and stored in the database. At 360 samples per second, the ECG recording is sampled. There are roughly 110,000 ECG beats in the MIT-BIH database[14] with 15 different forms of arrhythmia, including normal. The goal of this paper's experiment is to evaluate the performance of our proposed CNN to that of well-known CNN models and earlier ECG arrhythmia classification studies. This system included with normal beat (NOR) and seven forms of ECG arrhythmias from the MIT-BIH[15] database, including premature ventricular

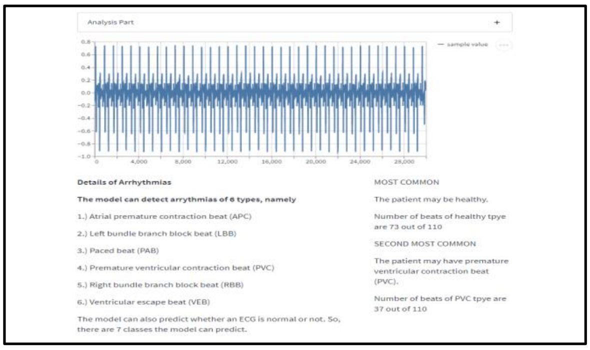

Fig.7. Arrhythmia Classified Output

contraction (PVC), paced beat (PAB), right bundle branch block beat (RBB), left bundle branch block beat (LBB), and premature atrial contraction (APC), ventricular escape beat (VEB) and ventricular flutter wave (VFW). While sensing data from the AD8232 sensor, that ECG data directly feeds into the pre-trained model to validate and classify the type of arrhythmia only if the arrhythmia exists[11].

III. OVERALL SETUP

The complete setup is easy to handle by patients. The completed setup has been divided into two phases: sensing and analysing. The sensing phase consists of sensors such as MAX30102 and AD8232, which sense the human vitals as physical parameters to analyse their health behaviour[12]. The system will power ON only if the patient presents in the place, or else the microcontroller called ESP32 goes to deep sleep mode for power consumption. Once every data is gathered,

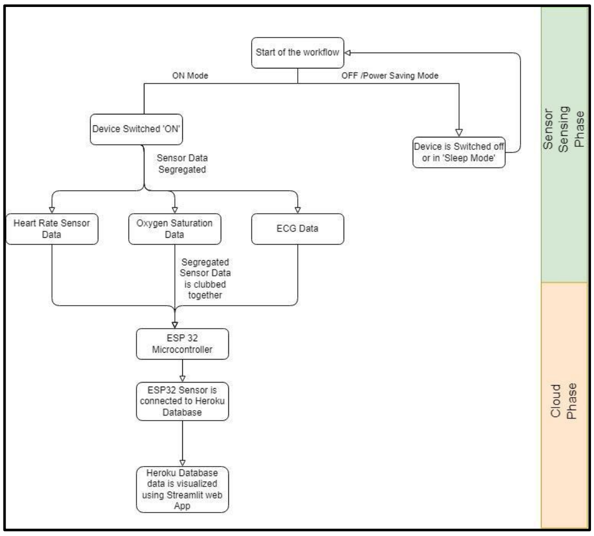

Fig.8. Complete system Flow chart

Then clubbed together as a single list of sets, while dynamic sensing, the database will include enlarger. The system will push their complete dataset into a cloud, which is a Heroku database. Heroku[13] is an integrated cloud platform, which is easy to pull and push our required data whenever a user wants. Here, streamlit is a visualisation and monitoring platform for doctors. Complete patient vitals dataset fetched from the Heroku database and feeds into the streamlit visualisation web app with the help of pyserial, which is one of the libraries in python.

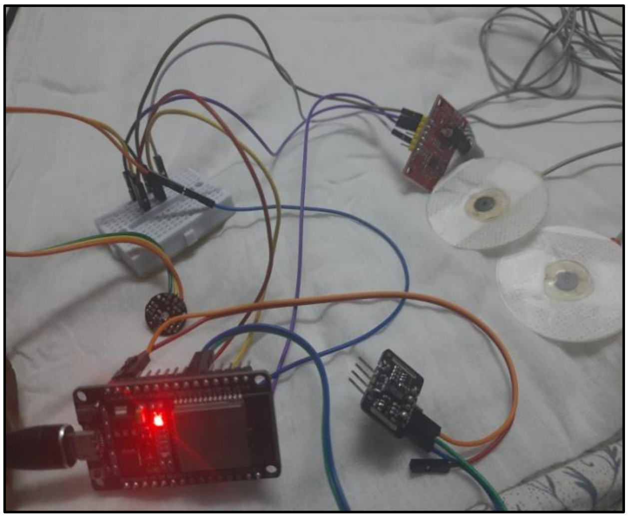

Fig.9. Complete Prototype setup

In a streamlit web app - doctors have their individual login credentials to monitor the allocated patients to themselves completely. The web app consists of three modules: dynamic vitals monitoring, heart disease predictor, and arrhythmia classifier. Doctors can get alert only if the patient's conditions go to a dangerous state, which the system can generate a trigger message to a doctor with the help of a predefined saturated value of each vital parameter.

IV. CONCLUSION

In the future, this system will help a lot because of the viral spreading of new viruses and diseases; doctors can easily monitor the patient's health conditions remotely. It is a virtual semi cardiologist that remotely monitors the patient's pulse oxygen level, heart rate, and dynamic ECG monitoring. If there are any abnormal heart beats or unconditional rhythm, the system will immediately push notification to the doctor with patient ID. This system approach is easy to set up and understand by patients who do not have readable knowledge.

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