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REAL TIME RISK PREDICTION OF HEART PATIENTS USING HRV AND IOT

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Abstract - Heart problems refer to any condition that affects the heart's ability to function properly, which can range from minor to severe. Common heart problems are : Coronary artery disease, Heart attack, Arrhythmia, Heart failure, Valvular heart disease, Congenital heart defects, Hypertension,etc. Heart Rate Variability (HRV) is a measure of the variation in time between successive heartbeats. HRV analysis can help to evaluate the balance between the sympathetic and parasympathetic nervous systems, which can give valuable insights into a person's overall health and their risk of developing heart problems. In this project, we have used components such as Temperature sensor, Pulse Oxi-meter sensor and ECG sensor to measure patients heart health. By leveraging the power of machine learning, the system predict risk of patients heart health. While HRV analysis can provide useful information, it should not be considered a solution or treatment for heart problems. Rather, HRV analysis can be used in conjunction with other diagnostic tools to assess a person's heart health and identify potential risk factors.

Key Words: Heart disease, Heart rate variability, Real time monitoring, Prediction, Machine learning, Internet of things.

1. INTRODUCTION

Heart problems are a leading cause of morbidity and mortality worldwide. According to the World Health Organization (WHO), heart disease is the leading cause of death globally, accounting for 17.9 million deaths in 2022, representing 31% of all global deaths. The prevalence of heart problems varies across different regions of the world. High-income countries tend to have higher rates of heart disease, while low-income and middle-income countries are also seeing increasing rates of heart disease as they undergo economic development and lifestyle changes. Some of the risk factors that contribute to heart problems include unhealthy diet, physical inactivity, smoking, excessive alcohol consumption, and chronic conditions such as hypertension, diabetes, and obesity. These risk factors are often influenced by social, economic, and environmental factors, highlighting the need for a comprehensive and integrated approach to address heart problems worldwide.

Internet of Things (IoT) and Machine Learning (ML) are two important technologies that can be used to enhance the accuracy and effectiveness of HRV monitoring and analysis. IoT devices such as wearables, smartwatches, and fitness trackers are commonly used for HRV monitoring. These devices can collect large amounts of ECG data and transmit it to cloud-based servers for processing and analysis. The use of IoT devices for HRV monitoring allows for continuous, real-time monitoring of HRV, which can be particularly useful for identifying early signs of heart problems. Machine Learning algorithms can be used to analyze the data collected by IoT devices and provide insights into the health of the cardiovascular system. ML algorithms can identify patterns in the ECG data that are indicative of high or low HRV. One of the main benefits of using ML algorithms for HRV analysis is that they can learn and adapt to new data, which can improve the accuracy of HRV predictions over time. ML algorithms can also be used to personalize HRV monitoring and analysis, by taking into account individual characteristics such as age, gender, and lifestyle factors.

Heart Rate Variability (HRV) analysis involves the measurement of the variation in time between successive heartbeats. HRV is commonly analyzed in two domains: time domain and frequency domain. Heart Rate Variability (HRV) time domain analysis involves the measurement of various statistical parameters from the time intervals between successive heartbeats. Some of the commonly used time domain parameters include:

Table -1: Time domain parameters

Parameter	Description
SDNN (Standard deviation of normal-to-normal intervals)	A measure of the overall variability of the HRV signal. It represents the standard deviation of all the NN intervals during a specific time period.
RMSSD (Root mean square of successive differences)	It measures the short-term variation in HRV by taking the square root of the mean of the sum of the squared differences between adjacent NN intervals.
pNN50 (Percentage of adjacent NN intervals differing by more than 50 ms)	the percentage of adjacent NN intervals that differ by more than 50 ms.
HRV Triangular Index	The HRV Triangular Index is calculated by dividing the height of the histogram of NN intervals by the width of the histogram at its base.

Time domain HRV analysis provides valuable information about the overall variability of the HRV signal and the short-term fluctuations in HRV, which are both important indicators of cardiovascular health. These time domain parameters can be calculated using ECG recordings collected over a specific time period and can be used to identify early signs of heart problems.

Heart Rate Variability (HRV) frequency domain analysis involves the measurement of the power spectral density of the HRV signal. The power spectral density is calculated using a mathematical technique called Fast Fourier Transform (FFT). The frequency domain analysis of HRV signal consists of three main frequency bands:

Table -2: Frequency domain parameters

Parameter	Description
Very low-frequency (VLF) band (0.0033 to 0.04 Hz)	VLF band represents the HRV signals with the slowest oscillations. The VLF band is associated with long-term regulatory mechanisms, such as hormonal and thermoregulatory mechanisms.
Low-frequency (LF) band (0.04 to 0.15 Hz)	LF band represents the HRV signals with intermediate oscillations. The LF band is associated with the activity of the sympathetic nervous system and reflects the combined activity of both sympathetic and parasympathetic nervous systems.
High-frequency (HF) band (0.15 to 0.4 Hz)	HF band represents the HRV signals with the fastest oscillations. The HF band is associated with the activity of the parasympathetic nervous system and reflects the respiratory sinus arrhythmia.
LF/HF ratio	The LF/HF ratio is thought to reflect the balance between the sympathetic and parasympathetic nervous systems, which play an important role in the regulation of the cardiovascular system.

Frequency domain HRV analysis provides valuable information about the underlying mechanisms that regulate the cardiovascular system. The LF and HF bands and their ratio can be used to identify changes in the autonomic nervous system activity, which may indicate early signs of heart problems. However, it is important to note that frequency domain analysis is limited to the analysis of stationary signals and may not be appropriate for the analysis of non-stationary signals.

Convolutional Neural Network (CNN) is used to predict Heart Rate Variability (HRV) by analyzing time-series electrocardiogram (ECG) data. CNN is trained to extract relevant features from the ECG data that are indicative of HRV. The CNN architecture typically includes multiple layers of convolutional and pooling layers, followed by fully connected layers. These layers are designed to identify and extract patterns from the ECG data. The CNN algorithm is trained on a large dataset of ECG recordings that have been labeled with their corresponding HRV values. During training, the CNN learns to identify the patterns in the ECG data that are associated with high or low HRV. Once the CNN has been trained, it is used to predict the HRV of new ECG recordings. The input data is fed into the trained CNN, which processes the data through the convolutional and pooling layers to extract relevant features. The fully connected layers then combine these features to make a prediction of the HRV value.

2. LITERATURE SURVEY

The current work is an attempt to identify heart-beat abnormalities, particularly PVCs, using HRV characteristics. For this investigation, time-domain metrics such as SDNN, mean HR, and RMSSD, as well as frequency domain parameters LFnu, HFnu, and the LF/HF ratio, were used. The presence of premature ventricular contraction (PVC) in the ECG signal causes a substantial variation in the time-domain and frequency-domain HRV parameters across individuals, according to the findings. Furthermore, for PVC validation, ECG signals were detected and categorised using BIOP AC MP45 student lab software. As a result, changes in HRV parameters can be readily interpreted for detecting the existence of PVCs.[1]

Individuals with stronger HRV are better able to exert control over their memories and suppress unpleasant recollections. Furthermore, some studies have connected decreased HRV to poorer language competence, poorer executive function, and slower processing speed. As a result, HRV can be useful in monitoring the diminishing functioning of various cognitive areas in dementia. Machine learning algorithms are used in this study to evaluate the association between HRV and cognitive performance across many cognitive domains. We investigated whether physiological factors derived from ultra-short-term (10s) HRV might predict cognitive performance across many cognitive domains. The results indicated that the support vector machine (SVM) classifier detected cognitive performance with 82% accuracy, while Linear Discriminant Analysis correctly classified data into high and poor performance across several tests with 90% accuracy.[4]

The basic signal utilised to detect any cardiovascular abnormalities is an electrocardiogram (ECG), although standard clinical ECG scans include limited time-duration ECG signals that lack the symptoms or fundamental characteristics of CVDs. The needed ECG data is collected using a wearable monitoring node comprised of an AD8232 ECG sensor with AgCl gel electrodes. Wi-Fi technology is used to send the conditioned ECG signal to the IoT cloud. We utilised the Node MCU ESP8266 Wi-Fi module to send the ECG data to the IoT cloud and the Blynk 2.0 IoT platform to show it. The software code was created to capture ECG waves as well as crucial parameters such as the R-R interval, QRS length, PR interval, QT interval, HRV, and heart rate. The Blynk IoT channel findings are compared to the clinical ECG of the same individual; the results are satisfactory, with an accuracy of more than 95% and conformity with the standard ECG. It can be used to detect arrhythmia problems.[7]

The P-QRS-T wave on an electrocardiogram (ECG) reflects the electrical activity of the heart. The cardiac anomaly is shown by minor variations in the amplitude and duration of the ECG signal. These minute alterations are extremely difficult to discern with the naked eye. As a result, a computer-aided diagnostic system will assist clinicians in monitoring heart health. In this research, we used higher order spectra (HOS) cumulants of wavelet packet decomposition to automatically classify normal and pathological beats (WPD). VPCs (ventricular premature contractions) and APCs (atrial premature contractions) are the aberrant beats (APC). Principal component analysis (PCA) is used to minimise the number of

HOS cumulant characteristics in the WPD to five. Finally, for automatic classification, these characteristics were loaded into a support vector machine (SVM) using kernel functions. With the radial basis function (RBF) kernel function and Meyer's wavelet (dmey) function, we achieved the maximum accuracy of 98.4%, sensitivity of 98.9%, and specificity of 98.0%.[17]

The heart is an important organ for the human body. Heart disease can be deadly for those who suffer from it. Arrhythmias (heart rhythm problems) are the fundamental cardiovascular illness, according to some conclusions. The resultant signal is conditioned and processed into an ECG signal comprised of PQRST parameters, which is then sent to a computer and recorded in a database. The R-R wave intervals and Heart Rate (HR) are considered in data processing, which is then categorised using Artificial Neural Networks to create conclusions regarding the findings of the diagnostic in the form of examination reports. The ADS 8232 and NI My-DAQ technology platforms were employed. The purpose of this work is to develop a cardiac record system that can read PQRST waves, which can identify a patient's heart status and distinguish arrhythmia from normal abnormalities. In terms of training results, the network recognises 100% of the data being learned.[22]

3. PROPOSED SYSTEM

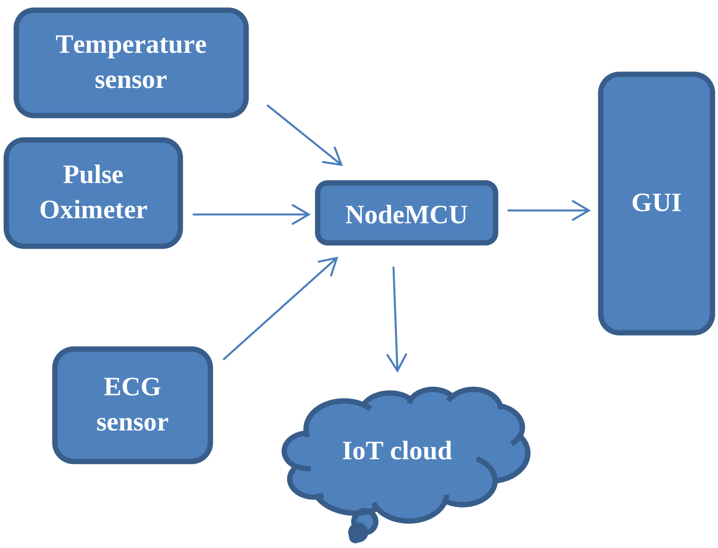

Fig -1: Block diagram of real time risk prediction of heart patients using HRV and IoT

According to the figure above, we are employing three sensors: temperature, pulse oximeter, and ECG. The temperature and pulse oximeter data are sent to NodeMCU and then to the ThingSpeak server, an IoT cloud platform. The NodeMCU is used to transport data to the IoT cloud. In the instance of an ECG sensor, because we require real-time monitoring and prediction of HRV, the ECG data is sent to NodeMCU and further sent to GUI for analysis. Finally, the findings from all of the sensors are shown in the system's graphical user interface.

Thingspeak server: Thingspeak server is a cloud based Internet of Things framework that enables users to collect, store, and analyse sensor data. It enables users to establish "channels" to represent various sensors or devices, and then use the ThingSpeak API to communicate data to those channels. The platform also provides visualisation tools such as graphs and maps to assist users in comprehending the data being collected. ThingSpeak also allows users to set up alerts and triggers depending on data, and it can interface with other apps and services via its API.

A Telegram bot is an automated program that interacts with users through the Telegram messaging app. Bots can perform various tasks such as providing information, answering questions, sending notifications, and more. Telegram bots can be helpful in IoT devices in various ways. Some examples of how Telegram bots can assist in IoT devices are: Remote Control, Monitoring, Data Analytics, and Automation. Overall, Telegram bots can be a useful tool for managing and controlling IoT devices, as well as for providing alerts, monitoring, and automation.

4. ALGORITHMS

CNN (Convolutional Neural Network) is a type of deep learning neural network that is primarily used for image processing, computer vision, and natural language processing tasks. The architecture of a CNN is designed to process and classify images by learning features from the raw pixel data.

Table -3: CNN Layers

Layers	Description
Input Layer	This layer takes in the raw pixel data of an image as input. The size of this layer depends on the size of the input image.
Convolutional Layer	This layer applies a set of filters or kernels to the input image. Each filter extracts specific features from the image, such as edges or textures. The output of this layer is a set of feature maps.
ReLU Layer	This layer applies an activation function called Rectified Linear Unit (ReLU) to each feature map. ReLU function introduces non-linearity into the network and helps in better feature learning.
Pooling Layer	This layer performs down-sampling on each feature map by selecting the maximum value within a specific region. This reduces the size of the feature

	maps and helps to avoid overfitting.
Fully Connected Layer	This layer flattens the feature maps and connects them to a fully connected neural network layer. This layer performs classification based on the learned features.
Output Layer	This layer gives the final output of the network. In a classification problem, the output layer contains the probability distribution of each class.

5. SYSTEM PROCESSING

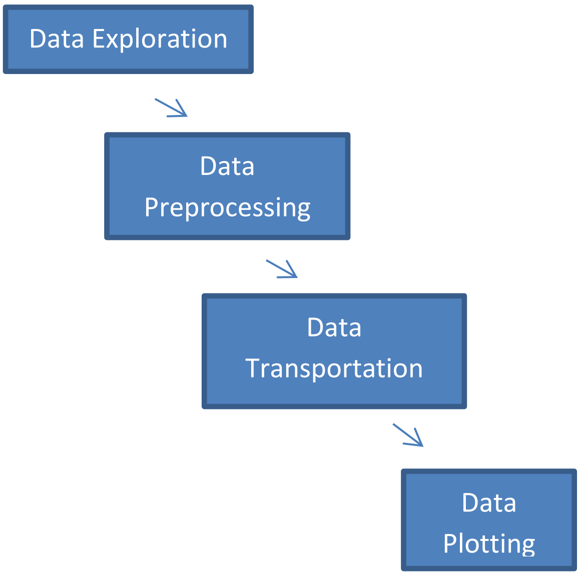

Fig -2: Python GUI Stages

Hardware and Software are the two parts of the system. The hardware part consists of the transmitter portion and the reception section, while the software package unit comprises of a software package language such as Python. Data exploration is the act of comprehending and studying a dataset in order to obtain insights and identify patterns. It can assist in identifying patterns, outliers, and possible data concerns. Real-time risk prediction of cardiac patients combining HRV and IoT entails monitoring a patient's heart activity using sensor data acquired through wearable devices. Data preparation is the process of cleaning and modifying data to prepare it for analysis. It has the potential to greatly enhance data quality and make it easier to evaluate. Data transportation refers to the process of transporting data from one location to another, whether inside an organisation or across organisations. Data plotting is the process of visualising data in the form of graphs or charts. It is a key stage in data exploration and analysis since it may aid in identifying patterns and trends in data and making it simpler to interpret.

6. DIFFERENT COMPONENTS FOR PROPOSED SYSTEM

DS18B20 Waterproof Temperature Sensor

Fig -3: DS18B20 Waterproof Temperature Sensor

Dallas semiconductor and maxim integrated produce a water resistant version of the DS18B20 water resistant temperature sensor, which is a pre-wired, 1metre-long, closed, water resistant digital temperature sensor probe. It is simple to use, well-designed, and convenient for measuring temperature in a variety of environments. The integrated digital-to-analog converter produces a 1-wire digital temperature sensor with a precision of 12 bits. It operates in parasitic power mode and is based on direct temperature transfer to digital format. This sensor contains a 64-bit unique serial code and transmits through a 1-wire serial interface. The data and GND pins are all that are required for this 1-wire digital temperature sensor to interact with the microcontroller. The detect temperature range between -55°C and +125°C with an precision of 5°C of the sensor. It is the suitable temperature sensor for multiple-location temperature monitoring, and data transmission only requires one data or digital pin on the microcontroller unit. It has a maximum current of 1mA and needs a positive power source between 3V and 5.5V. The alarm function of the DS18B20 is its primary benefit. When the temperature measurements exceed a user-specified high or low threshold value, the output signal can be configured to activate.

Pin 1 (Ground): This pin is used to attach to the circuit's GND terminal.
Pin2 (Vcc): This pin is used to supply the sensor with power, which might be in the range of 3.3V or 5V.
Pin 3 (Data): This pin provides the temperature value and is used for 1-wire communication.

Pulse Oximeter Sensor

Fig -4: Pulse Oximeter Sensor

To detect blood oxygen saturation, pulse oximeter sensor employs a light-emitting diode and a receptor. The fraction of oxygen bound to haemoglobin in the blood is referred to as oxygen saturation. The deciding principle is based on the fact that oxygenated blood absorbs more infrared light than deoxygenated blood. The pulse oximeter measures light absorption at various wavelengths and shows the pulse rate and percentage of oxygen in the blood.

Pin Configurations:
VIN: This pin delivers power to the sensor. The operating voltage for this sensor is 3.3 to 5V.
SCL: An I2C analog timer port.
SDA: A serial data pin on an I2C bus.
RD: Connection Point for Red LED Cathode and LED Driver
GND: This pin connects to the source ground pin and provides ground to this sensor.

AD8266 ECG Sensor

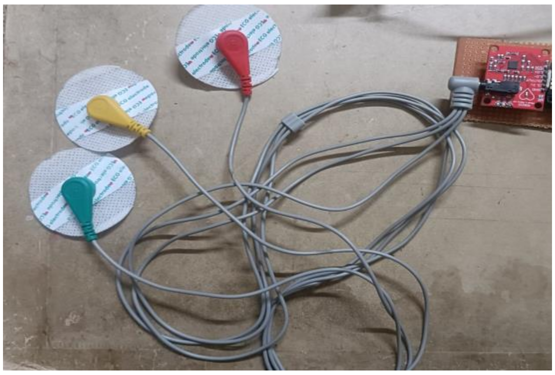

Fig -5: AD8266 ECG Sensor

The pulse rate of the person's heart is measured with the commercially available AD8232 ECG device. This activity may be charted in the same way that an electrocardiogram is, with the output being an analog readout. Because electrocardiograms may be highly loud, the AD8232 chip can be used to minimize the noise. To acquire a clear signal from the intervals, the ECG sensor works similarly to an operational amplifier. The AD8232 sensor is used in biopotential measurement and signal conditioning in ECG. This hardware's primary function is to enhance, recover from, and classify biopotential readings that are weak in loud places as a result of the removal of a distant electrode and mobility.

The pins SDN, LO+, LO-, OUTPUT, 3.3V, and GND are all part of a heart rate monitoring sensor like the AD8232. such that soldering pins will allow us to attach this IC to development boards like Node MCU. The right arm (RA), left arm (LA), and right leg (RL) are just a few of the unique devices that may be attached to this circuit using its ports (RL). This board displays the human heart rhythm using an LED indicator. The AD8232 sensor has a feature called rapid restoration, which is utilized to shorten the length of the HPFs' lengthy resolving tails. This sensor has a 20-lead LFCSP module and measures 4 mm by 4 mm. It performs between 40°C to +85°C, with performance stated between 0°C and 70°C.

NodeMCU

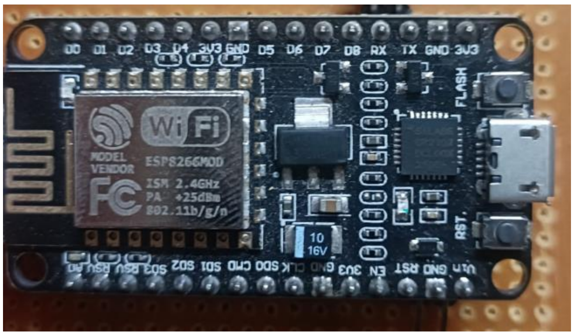

Fig -6: NodeMCU

The Node MCU is a system on chip micro chip that is primarily used in IoT implementations for constructing endpoint. It is known as a solo wireless receiver, and it is reasonably priced. A number of embedded device programs are linked to the internet using it.

Pin Configuration: The NodeMCU operates in two modes. These are their names:
The module executes the programme that was uploaded to it when the GPIO - 0 and GPIO - 1 pins are active high.
UART Mode: The device enters scripting mode when GPIO - 0 is lower and GPIO - 1 is strong.

7. RESULT

1) ECG & Sensor Data

This is the initial GUI displayed to users when sensors are attached to user's body, users get to know their Body temperature, BPM, Oxygen level and Status.

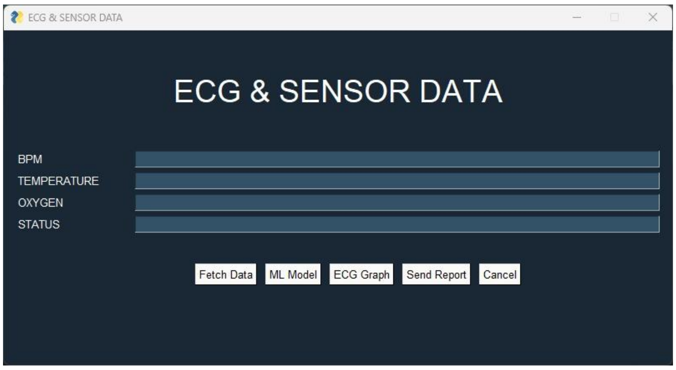

Fig -7: ECG & Sensor Data

2) ML Model Analysis

In this step, the ML model will analyze the risk of heart problems (high risk or low risk)

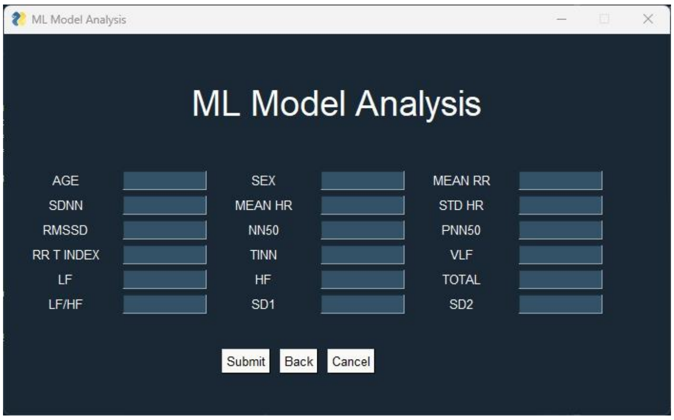

Fig -8: ML Model Analysis

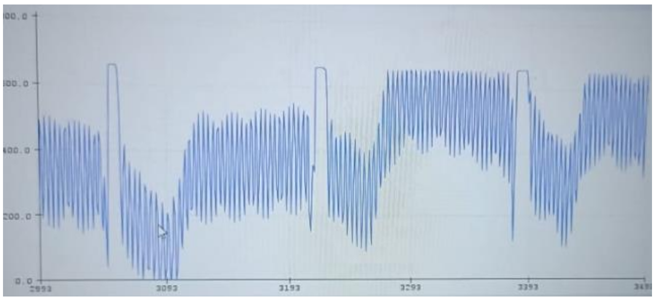

Fig -9: ECG waveform

8. CONCLUSION

There were preceding IOT-based projects for Heart Rate Variability (HRV) and some Machine Learning (ML)-based projects for HRV. However, we use and utilize the Internet Of Things (IoT) and ML for HRV to forecast the risk of heart patients in real time. Using machine learning and HRV potentialities, the project can estimate health status and anticipate patients' heart health (low-risk or high-risk) based on the ECG waveform and HRV characteristics such as time domain and frequency domain values. In Machine Learning, we employed the Convolutional Neural Network (CNN) approach to identify the stages of Hearth Risk. The use of IoT devices and machine learning algorithms for real-time risk prediction of heart patients using HRV provides a promising approach to improving the management of heart disease. By continuously monitoring the HRV data of heart patients, the proposed system can detect changes in HRV patterns that may indicate an increased risk of heart, and provide real-time feedback and guidance to both doctor and patients. The system can provide early identification of potential risks, allowing doctors to provide timely interventions to prevent adverse events and ultimately improve patient outcomes.

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