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IOT-BASED HEART DEFECT MONITORING SYSTEM USING ECG

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***Abstract:** Cardiovascular diseases remain one of the leading causes of sudden mortality worldwide, highlighting the urgent need for early detection, continuous monitoring, and timely medical intervention. This project presents an AI-powered heart monitoring and disease prediction system that integrates IoT biomedical sensors with advanced machine learning and deep learning techniques on a Raspberry Pi platform. Real-time physiological signals—such as ECG readings, heart rate, body temperature, and humidity—are captured and processed locally on the device. ECG waveform images are analysed using a deep learning-based Convolutional Neural Network (CNN) to detect cardiac abnormalities and early risk indicators. For structured symptom datasets, traditional machine learning algorithms including Random Forest are used to classify potential heart diseases and assess user health risk levels. Processed data and real-time analytics are visualized and transmitted to cloud platforms such as ThingSpeak for remote monitoring by clinicians and caregivers. The system also provides instant alerts when abnormal cardiac activity is detected, helping users seek timely medical attention. Designed to be low-cost, portable, and intelligent, this embedded AI solution demonstrates how IoT sensing, deep learning-driven ECG analysis, and cloud-based health monitoring can collectively enhance preventive healthcare especially for home care, elderly patients, and rural or resource-constrained environments.*

***Keyword :** AI-powered Healthcare, Heart Disease Prediction, ECG Image Classification, Convolutional Neural Network (CNN), Deep Learning Algorithms, Raspberry Pi, IoT-based Health Monitoring, Biomedical Sensors, ThingSpeak Cloud, Heart Rate Sensor, ECG Sensor, Predictive Analytics, Remote Healthcare System. Etc.*

I. INTRODUCTION

Cardiovascular diseases (CVDs) continue to be one of the leading causes of death worldwide, emphasizing the critical importance of early diagnosis, continuous monitoring, and rapid medical response. With advancements in Artificial Intelligence (AI) and the Internet of Things (IoT), intelligent health-monitoring solutions can now be designed to operate in real time and at low cost, making them suitable for both clinical and remote environments.

This project proposes an AI-Powered Heart Monitoring and Disease Prediction System that integrates biomedical IoT sensors with Machine Learning (ML) and Deep Learning (DL) algorithms on a compact Raspberry Pi platform. The system collects real-time physiological data including ECG signals, heart rate, body temperature, and humidity. ECG waveform images are processed using a Convolutional Neural Network (CNN) to detect abnormalities such as arrhythmia or early indicators of cardiac risk. Meanwhile, structured patient symptoms are analysed using ML methods such as Random Forest to predict potential heart diseases.

The processed data and diagnostic results are visualized and transmitted to cloud platforms like ThingSpeak, enabling remote health monitoring by medical professionals. The system also triggers instant alerts when abnormal cardiac activity is detected, providing early warnings that can significantly reduce medical emergencies. Designed to be portable, low-cost, and highly intelligent, this solution demonstrates the potential of combining embedded computing, artificial intelligence, and IoT-based sensing for enhanced preventive healthcare—especially for elderly individuals, home-care patients, and people in rural or resource-limited settings.Cardiovascular diseases (CVDs) continue to be one of the leading causes of death worldwide, emphasizing the critical importance of early diagnosis, continuous monitoring, and rapid medical response. With advancements in Artificial Intelligence (AI) and the Internet of Things (IoT), intelligent health-monitoring solutions can now be designed to operate in real time and at low cost, making them suitable for both clinical and remote environments.This project proposes an AI-Powered Heart Monitoring and Disease Prediction System that integrates biomedical IoT sensors with Machine Learning (ML) and Deep Learning (DL) algorithms on a compact Raspberry Pi platform. The system collects real-time physiological data including ECG signals, heart rate, body temperature, and

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II.RELATED WORK

Recent advancements in machine learning (ML), deep learning (DL), and Internet of Things (IoT) technologies have significantly improved the early detection and monitoring of cardiovascular diseases (CVDs).Rudraksh Singh Bhaduaria, Iqra Javid, and Anirban Khara (2025) proposed an advanced heart attack risk prediction framework using stacked hybrid machine learning techniques. Their approach integrates multiple classification algorithms such as Random Forest, Support Vector Machine (SVM), XGBoost, and Logistic Regression to enhance predictive accuracy. Traditional models like K-Nearest Neighbors (KNN), Naive Bayes, and Decision Trees were used as baselines. The study highlights the importance of feature selection, particularly using Random Forest, to identify key predictors of heart disease.

Mohamed Aashiq Fakhrul Zaman Rokhani et al. (2025) introduced TFDGiniXML, an explainable machine learning framework for early detection of cardiac abnormalities. The model utilizes nonlinear time-frequency distribution features derived from ECG signals using the Choi-Williams method. The incorporation of Gini Index-based features improves interpretability and enables accurate detection of abnormalities from long-duration ECG recordings. B. Ramesh and Kuruva Lakshmanna (2024) developed a hybrid deep learning model combined with a Neural Fuzzy Inference System for early detection and prevention of coronary heart disease.
Their proposed O-SBGC-LSTM model leverages spatial and temporal relationships in medical data while optimizing hyperparameters using the Eurygaster Optimization Algorithm. This approach improves feature learning and reduces computational complexity.Anjan Gudigar et al. (2024) presented a systematic review of automated heart anomaly detection using phonocardiogram (PCG) signals. The study analyzed 103 research papers and compared various ML and DL techniques, highlighting their effectiveness, limitations, and challenges in clinical adoption.Umar Musa Huda et al. (2024) designed an IoT-based healthcare monitoring system incorporating active antennas. The system uses sensors such as pulse and temperature sensors, with data transmitted via NodeMCU ESP-32S to the ThingSpeak platform. The proposed antenna design supports dual-band operation for improved communication efficiency. Rachuri Harish Kumar and Bharghava Rajaram (2024) proposed an edge computing architecture for IoT-based Clinical Decision Support Systems (CDSS). Their work addresses the latency issues associated with cloud-based systems by processing real-time patient data locally, enabling faster and more reliable medical decision-making.Hira Khan et al. (2024) developed ensemble and blending-based deep learning models, namely EnsCVDD-Net and BlCVDD-Net, for cardiovascular disease detection. These models address challenges such as imbalanced datasets and complex feature extraction while achieving high prediction accuracy.Jhansi Bharathi Madavarapu et al. (2024) introduced HOT Watch, an IoT-based wearable device for continuous health monitoring. The system integrates sensors like ECG, temperature, and oximeter sensors and uses the Pan–Tompkins algorithm for accurate heart rate detection.Tahseen Ullah Ahmadkhan et al. (2024) proposed a machine learning-based framework with optimal feature selection for cardiovascular disease detection. Techniques such as FCBF, mRMR, Relief, and PSO were used to select the most relevant features, resulting in high classification accuracy using Extra Trees and Random Forest models. Sami Alrabie and Ahmed Barnawi (2023) introduced the HeartWave dataset, a comprehensive collection of heart sound recordings covering nine classes of cardiovascular conditions. The dataset includes 1353 annotated recordings and serves as a valuable resource for developing robust diagnostic models.Terumasa Kondo et al. (2023) proposed a method for predicting short-term mortality in cardiac care unit patients using image-transformed ECG signals. A convolutional neural network (CNN) was

employed, achieving an accuracy of 77.3%, with Grad-CAM visualization highlighting critical waveform features.Junhua Wong et al. (2023) developed an ultra-efficient edge-based deep learning model using knowledge distillation for real-time cardiac abnormality detection. The approach transfers knowledge from a complex teacher model to a lightweight student model, improving efficiency while maintaining accuracy. Parag Verma et al. (2022) introduced FETCH, a fog computing-based healthcare framework integrating IoT and deep learning for real-time monitoring and diagnosis. The system addresses latency and scalability challenges associated with traditional cloud-based solutions. Radek Martinek et al. (2019) proposed a low-cost system based on seismocardiography (SCG) for cardiac monitoring in MRI environments. The system demonstrated reliable performance compared to traditional ECG systems, with validation metrics including accuracy, sensitivity, and F1-score.

III.PROPOSED METHODOLOGY

The proposed system is designed to predict and monitor heart disease by integrating physiological sensor data, machine learning, deep learning, and cloud-based remote monitoring using Raspberry Pi as the central processing unit. The methodology combines real-time health parameter acquisition with intelligent analysis to improve early detection of possible cardiac abnormalities.

A. **System Overview:** The proposed methodology consists of three major stages: data acquisition, intelligent prediction, and remote monitoring. In the first stage, physiological data such as heart rate, ECG signal, temperature, and humidity are collected through sensors connected to the Raspberry Pi. In the second stage, the collected data and ECG images are analyzed using machine learning and deep learning models to identify possible heart-related abnormalities. In the third stage, the results and vital parameters are uploaded to the ThingSpeak cloud platform for visualization and remote observation by doctors, caregivers, or family members.

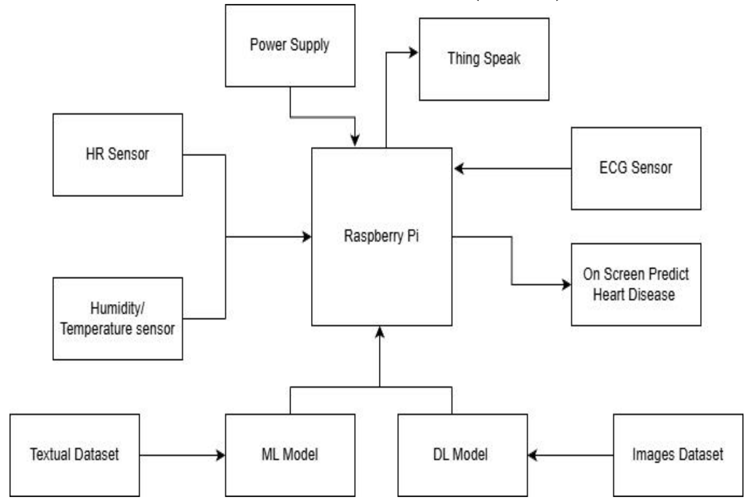

Figure-1. Block Diagram

B. **Data Acquisition and Sensor Integration:** The hardware section includes a Raspberry Pi, HR sensor, ECG sensor, humidity/temperature sensor, and regulated power supply. The Raspberry Pi acts as the central controller and manages communication with all connected sensors. The heart rate sensor measures the pulse rate in beats per minute, while the ECG sensor captures the electrical activity of the heart. The temperature and humidity sensor provides additional health and environmental information that may support patient monitoring.The Raspberry Pi continuously acquires sensor readings through suitable interfacing protocols such as GPIO, I2C, SPI, or UART. If the ECG sensor generates analog data, an ADC module is used to convert the analog signal into digital form before processing. These sensor readings are then preprocessed and stored temporarily for local analysis.

C. Dataset Preparation

Two different datasets are used in the proposed system. The first is a structured symptom-based heart disease dataset that contains patient-related attributes and symptoms such as chest pain, sweating, breathlessness, age, and other clinical parameters. This dataset is used for machine learning model training. The second is an ECG image dataset containing normal and abnormal ECG samples, which is used to train the deep learning model.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
2	52	1	0	125	212	0	1	168	0	1	2	2	3	0
3	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
4	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
5	61	1	0	148	203	0	1	161	0	0	2	1	3	0
6	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0
7	58	0	0	100	248	0	0	122	0	1	1	0	2	1
8	58	1	0	114	318	0	2	140	0	4.4	0	3	1	0
9	55	1	0	160	289	0	0	145	1	0.8	1	1	3	0
10	46	1	0	120	249	0	0	144	0	0.8	2	0	3	0
11	54	1	0	122	286	0	0	116	1	3.2	1	2	2	0
12	71	0	0	112	149	0	1	125	0	1.6	1	0	2	1
13	43	0	0	132	341	1	0	136	1	3	1	0	3	0
14	34	0	1	118	210	0	1	192	0	0.7	2	0	2	1
15	51	1	0	140	298	0	1	122	1	4.2	1	3	3	0
16	52	1	0	128	204	1	1	156	1	1	1	0	0	0
17	34	0	1	118	210	0	1	192	0	0.7	2	0	2	1
18	51	0	2	140	308	0	0	142	0	1.5	2	1	2	1
19	54	1	0	124	266	0	0	109	1	2.2	1	1	3	0
20	50	0	1	120	244	0	1	162	0	1.1	2	0	2	1
21	58	1	2	140	211	1	0	165	0	0	2	0	2	1

Figure-2. The dataset used in this study consists of clinical and demographic features commonly associated with cardiovascular disease. It is structured for binary classification, where the goal is to predict the presence of heart disease.

Feature	Description
age	Age of the patient (in years)
sex	Gender (1 = Male, 0 = Female)
cp	Chest pain type (0–3 categories)
trestbps	Resting blood pressure (mm Hg)
chol	Serum cholesterol (mg/dl)
fbs	Fasting blood sugar (>120 mg/dl: 1 = True, 0 = False)
restecg	Resting electrocardiographic results (0–2)
thalach	Maximum heart rate achieved
exang	Exercise-induced angina (1 = Yes, 0 = No)
oldpeak	ST depression induced by exercise
slope	Slope of peak exercise ST segment (0–2)
ca	Number of major vessels (0–3)
thal	Thalassemia (1 = Normal, 2 = Fixed defect, 3 = Reversible defect)
target	Diagnosis of heart disease (1 = Disease, 0 = No disease)

Table -1. Attributes Description

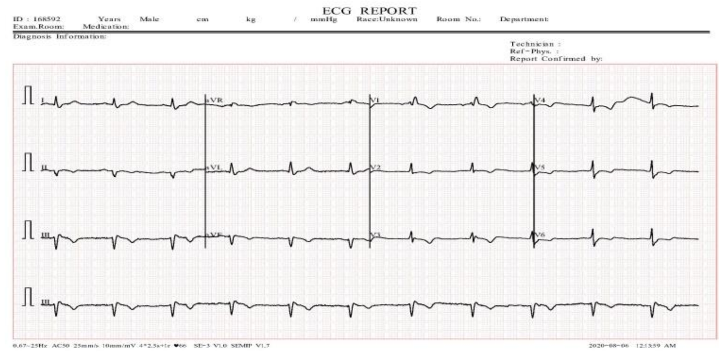

Figure-3 Dataset of ECG Images (Abnormal Heartbeat, History of Myocardial Infarction, Myocardial Infarction, Normal ECG etc)

D. Machine Learning-Based Heart Disease Prediction

For symptom-based heart disease prediction, a machine learning model such as Random Forest is employed. The symptom dataset is divided into training and testing sets. The Random Forest model learns the relationship between symptom attributes and heart disease outcomes during the training phase. After training, the model is evaluated using standard performance metrics such as accuracy, precision, recall, and F1-score. The best-performing model is then saved and deployed on the Raspberry Pi.In the real-time phase, when the user enters symptom-related information or when structured health features are formed from the available readings, these inputs are passed to the trained machine learning model. The model predicts whether the patient is likely to have heart disease or not.

E. Deep Learning-Based ECG Analysis

For ECG-based abnormality detection, a Convolutional Neural Network is used. The ECG image dataset is utilized to train the CNN model to classify ECG images into categories such as normal and abnormal. The CNN automatically extracts meaningful spatial features from the ECG waveform image and performs classification.Since training a CNN requires more computational resources, the training process is carried out on a PC or GPU-enabled system. After training, the model is saved in a deployable format such as .h5 and transferred to the Raspberry Pi. During the real-time monitoring phase, the user uploads an ECG image through the graphical interface. This image is preprocessed and given as input to the CNN model, which then predicts whether the ECG is normal or abnormal. This prediction helps in identifying potential heart risk.

F. Fusion of ML and DL Outputs

To increase the reliability of the system, the outputs of the machine learning model and deep learning model are combined using decision logic. The Raspberry Pi receives the prediction from the symptom-based ML model and the ECG-based DL model. If either one or both models indicate a high-risk or abnormal condition, the system generates a warning or alert. This combined decision-making process improves the robustness of heart disease detection by considering both clinical symptoms and ECG patterns.

G. Cloud Integration and Remote Monitoring

For remote healthcare monitoring, the Raspberry Pi uploads the processed health data and prediction results to the ThingSpeak cloud platform using HTTP or MQTT communication. Parameters such as heart rate, temperature, humidity, and ECG-based risk status are sent periodically to the cloud.

ThingSpeak stores this information and presents it in the form of graphs and visual dashboards. This allows doctors, caregivers, and family members to monitor the patient's condition remotely. In emergency situations, the system can also be extended to send alert notifications when abnormal conditions are detected.

H. Real-Time Working Procedure

The overall real-time working of the proposed system begins when the Raspberry Pi is powered on and connected to the sensors and internet. The sensors continuously collect physiological data from the patient. The heart rate sensor captures BPM values, the ECG sensor provides cardiac waveform data or images, and the humidity/temperature sensor records environmental or body-related values.

The symptom inputs and other structured data are passed to the trained Random Forest model for heart disease prediction. Simultaneously, the uploaded ECG image is analyzed using the trained CNN model. The outputs of both models are combined, and the final result is displayed on the local screen. Important readings and predictions are then sent to ThingSpeak for cloud-based storage and monitoring.

I. Advantages of the Proposed Methodology

The proposed methodology provides a low-cost and intelligent healthcare monitoring solution by combining IoT, machine learning, deep learning, and cloud technology. It supports continuous monitoring, early heart risk detection, remote observation, and portable deployment using Raspberry Pi. The dual-model approach increases prediction accuracy by analyzing both symptoms and ECG data, making the system suitable for smart healthcare applications.

IV.RESULT & DISCUSSION

The developed system was tested using both clinical heart disease parameters and ECG image analysis. The tabular heart disease prediction module accepts input features such as age, sex, chest pain type, resting blood pressure, cholesterol, fasting blood sugar, resting ECG, maximum heart rate achieved, exercise-induced angina, old peak, slope, number of major vessels (ca), and thalassemia type**.** These features are taken from the dataset and used by the trained model to classify the patient condition as either disease detected or no disease detected**.**

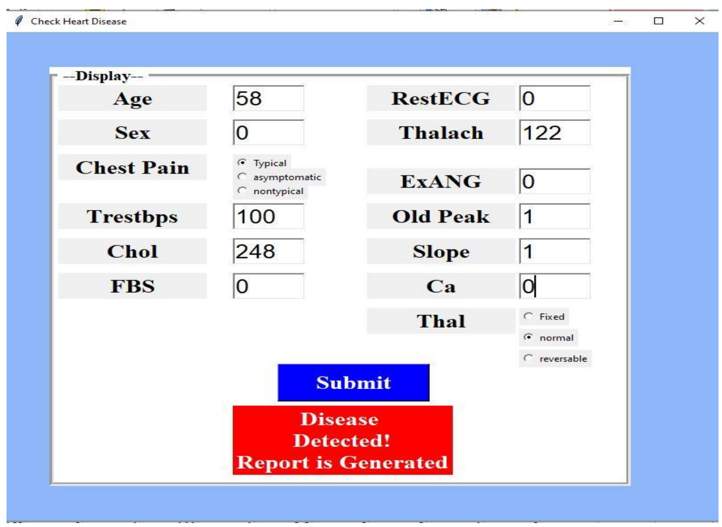

Figure – Heart Disease Detection Result

ECG Signal Analysis and Prediction System was also tested. The uploaded ECG image was processed through multiple steps: image loading, grayscale conversion, lead division, lead preprocessing, signal extraction, conversion to 1D signal, dimensionality reduction, and final prediction**.** The output shown in the system log indicates the final ECG prediction result as "History of Myocardial Infarction." This confirms that the ECG-based module successfully extracted meaningful signal information from the ECG image and classified the condition.

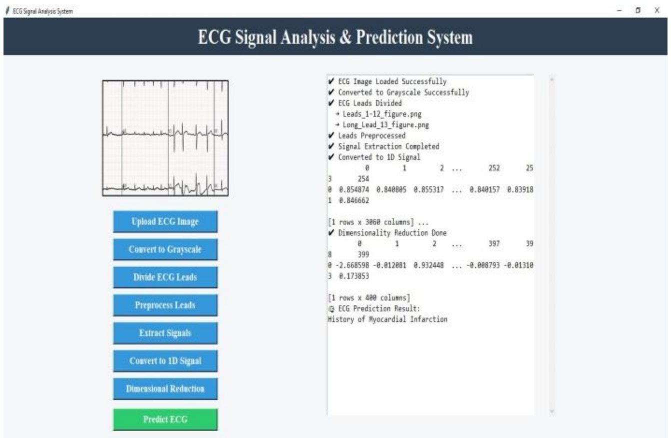

Figure – ECG Signal Analysis and Predict Result

V.CONCLUSION

The IoT-Based Heart Defect Monitoring System Using ECG and Machine Learning presents an efficient, cost-effective, and real-time solution for continuous cardiac health monitoring. By integrating ECG, heart rate, temperature, and humidity sensors with a Raspberry Pi microcontroller, the system enables continuous acquisition of vital physiological parameters and intelligent analysis using a trained Machine Learning model. This integrated approach supports early detection of cardiac abnormalities and accurate prediction of heart disease risk.

The incorporation of IoT connectivity through the ThingSpeak cloud platform allows patient health data to be stored, visualized, and accessed remotely by healthcare professionals or caregivers. This remote monitoring capability makes the system particularly suitable for home healthcare, rural and remote regions, and telemedicine applications, where access to medical facilities may be limited. The availability of real-time alerts and cloud-based visualization enhances timely decision-making and improves patient safety.Overall, this project demonstrates the effectiveness of combining IoT technology, biomedical sensors, and Machine Learning techniques to improve cardiac health monitoring and disease prediction. The proposed system offers a reliable tool for early diagnosis, preventive healthcare, and long-term patient management, thereby contributing to the advancement of smart healthcare solutions and improved quality of life.

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