

Research Article

An IoT-Based Vital Signs System for Early Heart Attack Detection**NigaAmanj Hussain^{1,*} and Aree Ali Mohammed²**¹ Student, Department of Computer Science, University of Sulaimani, Sulaimaniyah, 46001, Iraq.² Professor, Department of Computer Science, University of Sulaimani, Sulaimaniyah, 46001, Iraq.

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Abstract: Heart disease, particularly heart attack, remains a leading cause of mortality worldwide, necessitating the development of accurate, real-time early detection systems. This study proposes a real-time heart attack monitoring and prediction system that integrates the Internet of Things (IoT) and advanced Deep Learning (DL) techniques—two powerful and trending technologies, especially in the field of healthcare. Critical physiological data, including Systolic Blood Pressure (SysBP), Diastolic Blood Pressure (DBP) and Heart Rate (HR), are collected continuously in real time using wearable IoT sensors that provide immediate data transmission to the ThingSpeak cloud for timely monitoring of vital signs, while also locally processing the data to trigger immediate alerts. Immediate alerts are triggered by the system when abnormal signs are detected. The system concurrently transmits notifications to the patient's family or care providers in case of heart attack or fall detection, and a buzzer with an accelerometer sensor is activated in the event of a fall. The trained model and incoming patient data from the cloud are continuously loaded into the customized prediction script for real-time analysis and heart attack prediction. In real-time testing involving 373 data entries, the model maintained a prediction accuracy of 93.55%, showcasing its stability and scalability for continuous data streams. The overall IoT system's average response time was approximately 3.889 seconds, reflecting efficient data processing and timely alert generation. These results validate the proposed IoT-enabled DL system as an effective and efficient solution for continuous heart attack monitoring and early warning. The proposed system's real-time predictive capability and rapid alert mechanism represent a significant advancement in remote cardiovascular monitoring, offering a practical solution for early intervention and potentially reducing heart attack-related mortality.

Keywords: Real-Time Monitoring, IoT-Enabled Healthcare Systems, Deep Learning Algorithms, Wearable Sensors, Real-Time Alert Systems.

1. Introduction

The growing aging population will increasingly strain healthcare systems and lead to a higher prevalence of non-communicable diseases, especially cardiovascular disorders. Currently, the field of medicine stands on the brink of a revolution, with cutting-edge technologies enabling the development of highly targeted therapies. Precision medicine is emerging with advanced digital diagnostic tools and companion devices that support early detection and help direct patients to the most appropriate healthcare providers in their communities. In addition, breakthroughs in robotics have introduced a wide range of medical applications that not only improve treatment effectiveness but also have the potential to significantly reduce healthcare costs [1].



Cardiovascular diseases (CVDs) are the leading cause of illness and death worldwide, accounting for over 70% of global fatalities. A 2017 study on the Global Burden of Disease found that CVD was responsible for more than 43% of all deaths. [2]. Studies show that 2.8 billion people die from heart complications associated with being overweight, which affect blood pressure, cholesterol, and—most importantly—the influence of stress hormones on the heart [3]. Approximately 26 million adults worldwide are currently living with heart failure. In the United States alone, there were 5.8 million cases reported in 2012, a number projected to increase to 8.5 million by 2030. Globally, 17% to 45% of patients hospitalized for heart failure die within the first year of admission, and most succumb within five years. The prevalence of heart failure is expected to rise further, particularly in countries with ageing populations [4]. A myocardial infarction, commonly known as a heart attack, is the loss of a portion of the heart muscle. This occurs when blood flow to the heart is interrupted or completely stopped. The heart's main function in both humans and animals is to pump blood into the circulatory system. If one of the heart's ventricles malfunctions, it can lead to severe damage and, if not treated promptly, can result in death [5]. In healthcare, IoT plays a crucial role in continuously monitoring health parameters and assisting in the diagnosis of related conditions [6]. By enabling more personalized treatment, reducing costs, and minimizing errors, IoT technologies are transforming how care is delivered. They also enhance patient safety and allow faster responses in emergencies [7]. With IoT devices, vital signs can be monitored continuously, no matter where a patient is. This data can be transmitted cost-effectively to remote healthcare providers, who can track a patient's condition in real time without interruption [8]. For patients with heart conditions, this real-time monitoring can be especially valuable, as it helps detect irregularities early and lessens the effects of cardiovascular disease [9].

Different studies and works in this field used various IoT architectures [10–13].

This study's implementation of IoT for real-time heart attack detection represents a major contribution and advancement in the medical field.

- The integration of IoT-enabled wearable devices for continuous remote health monitoring, allowing Automatic transmission of data to healthcare providers and ensuring timely intervention, particularly for patients in rural or remote areas.
- The design of an efficient and scalable architecture using low-cost, energy-efficient components such as Arduino Uno, ESP-01, and lightweight physiological sensors, making the system affordable and deployable in resource-constrained settings.
- The implementation of a hybrid edge–cloud architecture, where immediate local alerts (buzzer, smartphone notifications) are triggered on the device while data is simultaneously transmitted to the cloud for monitoring and analysis, ensuring fast and reliable response during critical cardiac events.

The remaining of this paper is organized into four sections. Section 2 reviews the relevant studies in the field. Section 3 outlines the methodology, including the design and implementation of the proposed IoT system. In Section 4, a real-time assessment of the system's performance is provided, followed by an analysis of the evaluation metrics and results. The paper concludes in Section 5 with a discussion of future research directions.

2. Related Works

Many IoT-based systems are designed to collect patient data continuously in real time and send instant alerts—such as notifications—to help detect cardiac issues early. Recently, various researches have been conducted as presented below:

Zahra et al. [14] implemented an early heart attack detection device to help monitor patients with heart disease and lower the risk of death from sudden cardiac events. The system continuously tracked Electrocardiogram (ECG) and Peripheral Capillary Oxygen Saturation (SPO2), along with key vital signs such as heart rate, Respiratory Rate (RR), and body temperature. It combined several sensors, including a DS18B20 temperature sensor, a piezoelectric sensor, a pulse oximeter, and the AD8232 ECG module. Real-time wireless monitoring was achieved through the integration of a radio frequency module for data transmission and an alert system for potential emergencies. Timely notifications were successfully delivered upon the detection of heart attack symptoms.

Fitria et al. [15] proposed a heart attack alert system with the objective of assisting patients with heart disease in the rapid notification of family and access to medical services during a sudden cardiac event. The system was implemented on IoT technology, with components including an AD8232 ECG sensor, an ESP32 microcontroller, a buzzer, and a push-button. A single patient press activated an alert to emergency contacts. It also facilitated the automatic sharing of the user's real-time location. This enabled a fast emergency response and subsequent transport to a hospital.

Muthusundari et al. [16] presented a smartwatch which was equipped with integrated sensors for the purpose of facilitating the early detection of heart attacks and the automatic activation of emergency alerts. Continuous monitoring of cardiac metrics, including heart rate, rhythm, and vital signs, was performed through the utilization of various sensors such as ECG, accelerometer, gyroscope, and Photoplethysmography (PPG). A Machine Learning (ML) time series analysis algorithm was employed to process the acquired data in real time. Upon the identification of abnormal heart activity, the smartwatch would immediately connect to a dedicated mobile application to activate emergency assistance.

Khamitkar and Rafi [17] developed an IoT-based system to monitor heart rate. This system had two main goals: to enable routine health tracking and to assist in heart attack risk assessment. The project used an affordable, fingertip-based device that detected a user's heartbeat with Bluetooth. The signals were captured by sensors, processed by a microcontroller, and then sent to an IoT platform for real-time analysis. In addition, data was sent via Bluetooth to an Android app called Blynk, which provided users with a visual alert. The project demonstrated a method for heart rate monitoring that was flexible, reliable, and secure.

In Kalyan and Sharma [18] a web-based ECG monitoring system was introduced to provide real-time ECG signals and a patient's Global Positioning System (GPS) location, which served to minimize the need for expensive equipment and hospital visits. The system's operational methodology utilized an AD8232 ECG sensor, processed data via an Arduino, and subsequently transmitted it to a Raspberry Pi. The resulting data was presented on a web interface, which enabled real-time monitoring of ECG data and concurrent location tracking.

Majumder et al. [19] employed an embedded IoT system to remotely track heart health and physical activity right from a person's smartphone. The system integrated a wearable ECG sensor to track cardiovascular activity. Concurrently, the smartphone's accelerometer and GPS sensors enabled the monitoring of body movements and location. This setup allows for the continuous tracking of cardiac irregularities and physical activity metrics via a smartphone platform.

Wan et al. [20] presented the Wearable IoT-Cloud-Based Health Monitoring System (WISE), a wearable health monitoring system based on IoT and cloud technology, designed for real-time patient tracking, particularly suited for elderly users. The system used a Body Area

Sensor Network (BASN) to integrate sensors for heart rate, body temperature, and blood pressure. Unlike typical systems that rely on smartphones, WISE transmitted data directly to the cloud and features a lightweight wearable Liquid Crystal Display (LCD) for quick and convenient health updates.

Armand et al. [21] designed a cost-effective, wireless system to remotely monitor cardiovascular patients in Cameroon. The device measured SysBP, DBP, and HR, showing the results on an LCD screen. Patients could start a measurement with a mobile app or by pressing a button. The system then sent the data in JavaScript Object Notation (JSON) format, checking it against normal values based on the patient's age and sex. If the data was abnormal, the system automatically sent a Short Message Service (SMS) alert via Global System for Mobile Communications (GSM) (for areas with poor internet), transmitted the data via Bluetooth, and triggered app notifications for doctors and family members.

Abdulrahman et al. [22] proposed an enhanced ECG heartbeat classification model based on a one-dimensional Convolutional Neural Network (1D-CNN) algorithm. The system was developed for efficient binary classification of ECG signals to distinguish between normal and abnormal heartbeat patterns. The model was trained and tested using the MIT-BIH dataset and demonstrated improved classification accuracy through the use of various activation functions and multiple training epochs.

Sneha[23] proposed an Automated Machine Learning Model for Heart Disease Prediction using IoT. The system continuously collected vital signs such as heart rate, blood pressure, and ECG from IoT sensors and processed the data with an automated ML model for early detection of heart disease. By combining real-time monitoring with predictive analytics, the system provides timely alerts and enables remote patient management for improved cardiovascular care.

Dami et al. [24] presented an IoT-Based Health Monitoring System for Early Detection of Cardiovascular Events. The system integrated multiple sensors to monitor vital signs and applied deep learning for prediction. Data were transmitted over IoT networks for real-time remote monitoring and timely alerts for abnormal cardiovascular events.

Among the approaches reported in the literature, our prior study [25] proposed a hybrid CNN with an attention mechanism using sequential data for heart attack detection. The current work builds on this model by integrating an IoT-based system for real-time data collection and alert notifications. In addition, a customized script is implemented to enable real-time prediction.

Even with recent advancements, hybrid DL and IoT heart attack detection systems have critical gaps. Their effectiveness, adaptability, and real-world deployment remain limited. The following outlines the main challenges with current approaches:

- Lack of end-to-end IoT-integrated deep learning pipelines.
- Low-cost, scalable deployments in resource-constrained settings.
- Lack of context-aware systems.
- User compliance and wearability issues.
- Need for immediate alerts and cloud sync.

Employing IoT technologies for real-time prediction of heart attacks constitutes a significant advancement in healthcare, strengthening diagnostic precision and improving patient outcomes.

A comparison of related works in heart disease detection, techniques/tools used, data source, input parameters, approach type (ML/DL and IoT), year, strengths and performance metrics is presented in Table 1.

Table 1: Comparison of related works

Paper	Year	Approach Type	Techniques/ Tools	Data Source	Input Parameters	Performance	Strengths
[18]	2017	IoT + ML	Arduino, Raspberry Pi, ECG Sensor, GPS	ECG clinical data	ECG intervals, GPS location, HR	Real-time detection	ECG + GPS + disease prediction
[20]	2018	IoT	Arduino, WiFi, Cloud, Web GUI, ML	Wearable sensors (Heartbeat, Temp, BP)	Heartbeat, Body Temperature, BP, Radio Frequency Identification(RFID)	Not reported	Real-time, direct cloud, LCD, alerts, historical data
[19]	2019	IoT + ML	Embedded sensors, smartphone, Arduino, ECG sensor, Bluetooth	ECG and body accelerations	ECG patterns, body acceleration	Accurate classification and prediction of heart rate quality, high prediction accuracy	Real-time monitoring and prediction of cardiac abnormality
[17]	2020	IoT System	PPG, Bluetooth, HR module, Android	Fingertips	Heart Rate	Not reported	Low cost, real-time, data save, telemedicine, 15-20m range
[14]	2021	Monitoring Device	Piezo sensor, DS18B20, ESP32, HC-12	Respiration, Body Temp	Piezoelectric sensor, DS18B20 temperature sensor	Respiration error 4%, Temp. error 0.55%	Real-time, Wireless, Alerts, Monitors patient
[15]	2022	IoT Monitoring & Alert	AD8232, ESP32, Wi-Fi, Web App, Buzzer	Heartbeat	Heartbeat	1.96% sensor error	Wearable, real-time, hospital alerts, family web access
[21]	2023	IoT Patient Monitor	Lean UX, Sensors, IoT App	Vital signs	Systolic, Diastolic, HR	High accuracy and practical effectiveness	Low-cost, Wireless, Accessible, Alerts, User-friendly
[16]	2024	Smart	ECG, PPG,	Physiologic	ECG and	Not	Early detect,

		Watch, IoT	ML (Time Series), Mobile App	al signals (from the heart)	PPG sensors, Rhythm, Physiology	reported	Auto emergency, Alerts contacts, Provides vital info
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3. Proposed Methodology

The proposed IoT-based wearable devices for heart attack detection, developed using Arduino and biomedical sensors, enable continuous monitoring of critical health parameters. The system diagram is presented in Figure 1.

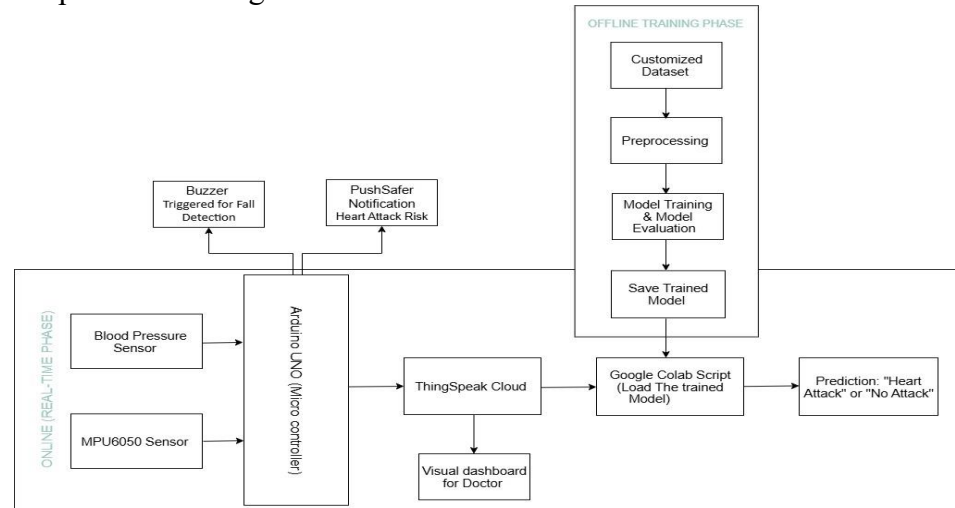


Figure1: The general diagram of the proposed system

3.1 Proposed deep learning techniques

Data preprocessing involved refining the original Kaggle dataset of 71,760 records to keep only three essential features—SysBP, DBP, and HR—along with a binary label indicating normal (0) or abnormal (1). Abnormal cases were defined using the condition $\text{SysBP} \geq 130$, $\text{DBP} \geq 60$, and $\text{HR} \geq 70$, ensuring a clear distinction between normal and high-risk records.

The proposed model is a hybrid Convolutional Neural Network (CNN) with an attention mechanism as described in our earlier work [25] and illustrated in Figure 2.

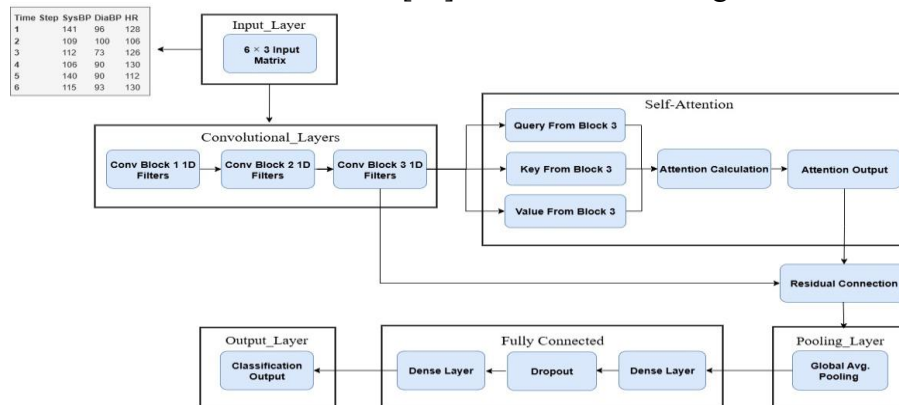


Figure2: General diagram of the proposed hybrid CNN with attention mechanism

The model has been enhanced with several modifications for heart attack detection. Data are processed as sequences with six-time steps and three features, allowing the system to analyze

patterns over time. This sequential approach enables the model to anticipate future outcomes rather than classify a single snapshot. Since the risk of a heart attack depends on how vital signs change over time, the use of time steps improves both accuracy and reliability.

3.2 IoT-based healthcare proposed model

This section presents the system's IoT hardware setup, highlighting how each component contributes to real-time data collection, emergency alerting, and heart attack prediction through an integrated, automated script as presented in Figure3.

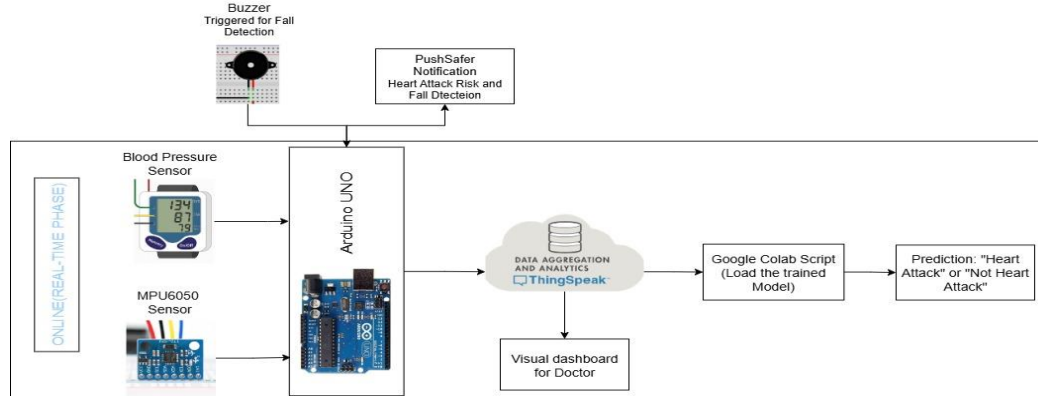


Figure 3: Proposed IoT system for real-time heart attack detection and alerting

3.2.1 System setup: Sensor integration and cloud communication

The primary objective of this system is to collect real-time blood pressure and heart rate data from patients using non-invasive sensors. These readings are crucial for monitoring health conditions such as hypertension and detecting potential heart-related issues or emergency events like falls.

Sensors and Hardware Components: The core sensors and components integrated into the system are as follows:

1. Blood pressure sensor:

This sensor provides real-time readings of SysBP, DBP, and HR. The blood pressure sensor is connected to the Arduino board using three pins: TX, RX, and GND.

2. Arduino Uno
3. MPU6050 (accelerometer + gyroscope)

Figure4 shows the detailed circuitry and wiring of the proposed IoT-based heart attack monitoring system.

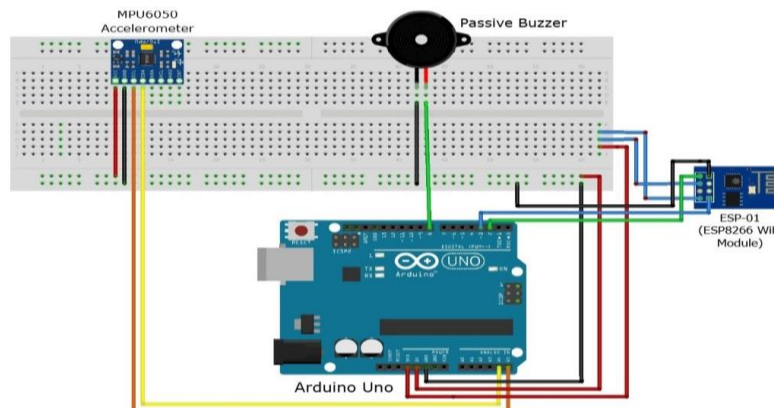


Figure 4: Circuit diagram of the proposed IoT-based heart attack detection and alert system

Alert and Notification System: Push notifications via Pushsafer: The system includes a real-time notification feature powered by Pushsafer, a cloud-based service that enables sending and receiving alerts on various devices, notifying doctors or family members instantly.

- High blood pressure alerts:

A notification is triggered when the following condition is met:

$\text{SysBP} \geq 130$ AND $\text{DBP} \geq 60$ AND $\text{HR} \geq 70$

- Fall Detection Alert.

Data Transmission and Cloud Integration: All sensor data are transmitted and managed using the following components:

Wi-Fi module (ESP8266-01). ESP8266-01 Wi-Fi module is used to:

- Transmit sensor data in real time
- Enable remote communication (including notification delivery)

ThingSpeak cloud platform. All sensor data sent to ThingSpeak, a cloud-based IoT analytics platform used for:

- Real-time data collection
- Data visualisation and monitoring
- Historical data access in Comma-Separated Values (CSV) format

3.3 Customized script for real-time prediction

This system uses a customized Python script for real-time heart attack prediction using IoT sensor data. The script is designed to continuously load new data from the cloud and use the DL model to make predictions.

Figure 5 presents the flowchart of the proposed IoT system.

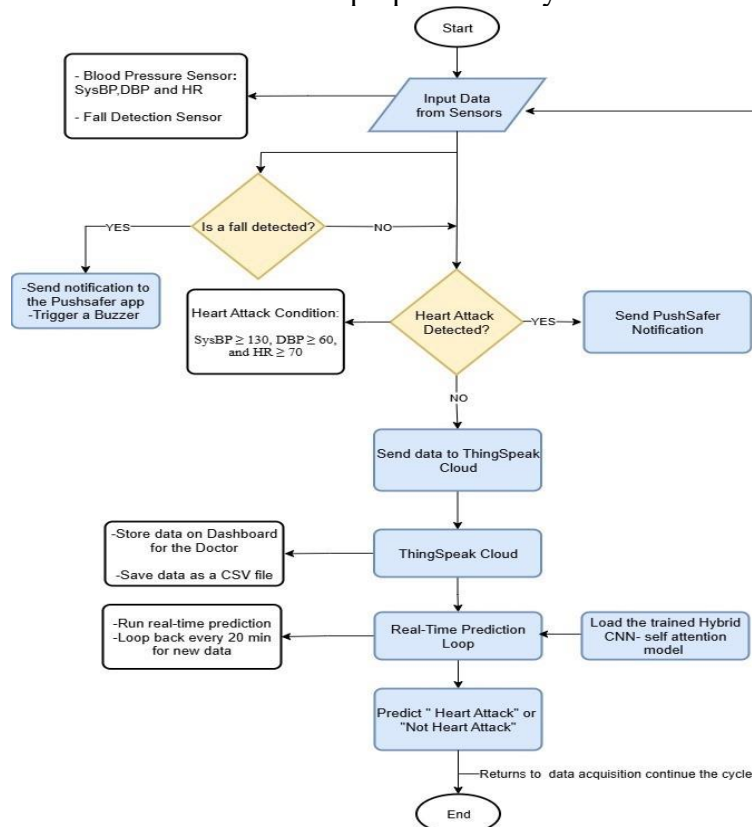


Figure 5: Flowchart of the proposed IoT system

4 Results and Discussions

The system's average response time is 3,889 ms (approximately 3.889) seconds that reflects the overall time to process data uploads and send notifications. A performance is well-suited for early heart attack detection, as it provides rapid alerts that can significantly enhance timely intervention and improve patient outcomes.

4.1 Performance results of the proposed IoT healthcare model

The IoT system begins by collecting patient data, transmitting it to the cloud, and triggering notifications and alerts as needed.

An example of the system implementation is shown in Figure 6, illustrating the cloud updates. Table 2 provides an example of real-time data, demonstrating how the IoT system stores this data in the ThingSpeak cloud and allows CSV export for analysis.

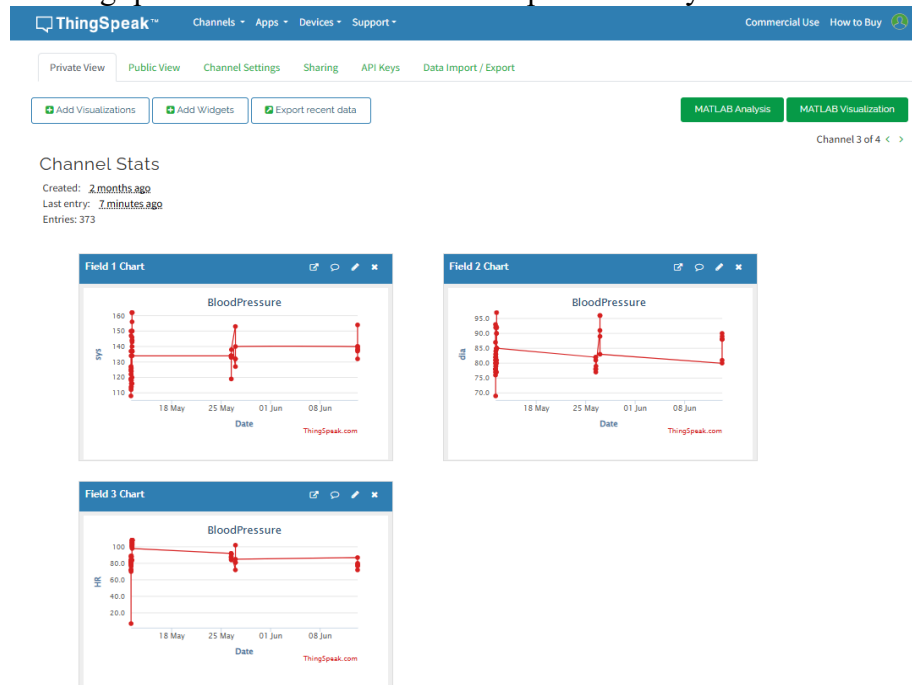


Figure 6: Corresponding cloud updates

Table 2: Example of a CSV file from the ThingSpeak cloud displaying real-time sensor data

created_at	entry_id	SysBP	DBP	HR
2025-05-27T08:44:44+00:00	366	140	83	85
2025-06-13T15:19:58+00:00	367	140	80	87
2025-06-13T15:21:39+00:00	368	137	90	72
2025-06-13T15:26:32+00:00	369	154	88	78
2025-06-13T15:27:45+00:00	370	132	81	79
2025-06-13T15:30:49+00:00	371	138	88	77
2025-06-13T15:33:39+00:00	372	138	88	77

2025-06-13T15:35:39+00:00	373	140	89	80
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4.1.1 System performance evaluation

This evaluation analyzes the system's response time in ms, based on data collected from 17 distinct test events. It focuses on measuring response times for health notifications and data uploads to the ThingSpeak platform. Both ThingSpeak and Pushsafer notifications are configured to attempt up to three retries in case of Wi-Fi connection failures.

Table 3 includes ThingSpeak send times, Pushsafer notification times for heart attack and fall detection, and notes on notification status or failures. All time measurements are recorded in ms.

Table 3: Sample-wise response times for notifications and ThingSpeak uploads

Patient	ThingSpeak Send Time (ms)	Pushsafer Heart Attack Notification Time (ms)	Pushsafer Fall Detection Notification Time (ms)	Notes
1	N/A	N/A	3525	Fall detected, no Heartattack
2	3525	3528	N/A	Heart attack notif.
3	3525	3527	N/A	Heart attack notif.
4	3526	3527	N/A	Heart attack notif.
5	3526	N/A	N/A	No notif sent
6	3525	3528	N/A	Heart attack notif.
7	3706	10025 (failed)	N/A	Heart attack notif failed
8	6530	3528	N/A	Heart attack notif.
9	3525	3528	N/A	Heart attack notif.
10	N/A	N/A	3525	Fall detected
11	Failed (9527 ms)	10024 (failed)	N/A	Heart attack notif failed
12	3525	3528	N/A	Heart attack notif.
13	3524	N/A	N/A	No notif sent
14	3524	N/A	N/A	No notif sent
15	3525	N/A	N/A	No notif sent
16	N/A	N/A	3525	Fall detected
17	N/A	N/A	3526	Fall detected

Table 4 presents the classification of patient test results, excluding fall detections and failed transmissions. Out of 17 total tests, excluding 4 fall detection cases, 13 tests remained for heart attack analysis. Among these, 7 patients were classified as heart attack cases with successful notifications sent, and 4 patients were classified as normal cases with no heart attack detected.

Table 4: Classification of patient test results and notification times

Classification	Count (patients)	AvgThingSpeak Send Time (ms)	AvgPushsafer Notification Time (ms)
Heart attack cases (successful notification)	7	3454 ms	3485 ms
Normal cases (no heart attack notification)	4	3524 ms	N/A

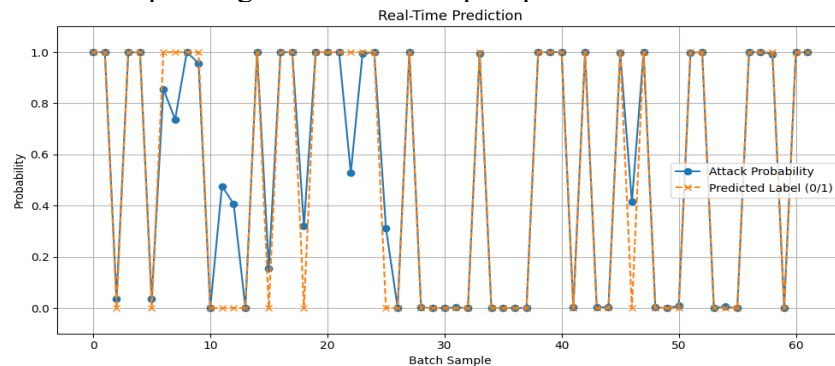
Table 5 includes both usual and worst-case response times for Pushsafer notifications and ThingSpeak transmissions.

Table 5:Summary of response time ranges and worst cases

Action	Usual time (ms)	Worst case (ms)	Notes
Pushsafer (success)	~3525–3528	~10025	2 failed cases, both took ~10s
ThingSpeak (success)	~3524–3706	~6530	Most are fast, one with retry
ThingSpeak (failure)	N/A	9527	One failure after 3 retries

4.2 Real-time prediction from customized script

Using 362 live data entries, the system successfully mounted the drive, loaded the model, downloaded and sorted the CSV file, detected new rows, and achieved a prediction accuracy of 93.33%. When the number of input entries was increased to 373, the script continued to perform well, achieving a slightly improved prediction accuracy of 93.55%. The results include in Figure 7, illustrating real-time predictions. The blue line shows the model's confidence (as a probability) that each data point is an attack. The orange line shows the final decision the model makes — labeling it as either an attack (1) or normal (0) based on that confidence. illustrating real-time predictions. And the corresponding classification report presented in Table 6.

**Figure 7:**Real-time prediction**Table 6:**Results of real-time classification

Classification Report:			
	Precision	Recall	F1-Score
No Heart Attack	1.0000	0.8824	0.9375
Heart Attack	0.8750	1.0000	0.9333
Accuracy			0.9355
Macro avg	0.9375	0.9412	0.9354
Weighted avg	0.9435	0.9355	0.9356

The results show that the model performs reliably in real-time, maintaining high accuracy as new data is continuously received. When the input increased from 362 to 373 entries, the prediction accuracy slightly improved to 93.55%.

Table 7 provides a detailed comparison of the various hardware configurations.

Table 7:Comparison of hardware implementations across previous studies

Study	Microcontroller / Platform	Sensors used	Communication	Cloud used	Cost & complexity	Notes
[26]	Embedded system +	ECG, BP, SpO ₂	Bluetooth / Zigbee	Local only	Moderate	Neural network-

	ANN					based offline prediction
[27]	General IoT + Cloud platform	ECG, BP, Temperature, Glucose	Wi-Fi / Custom server	Web-based cloud	Higher setup cost	Uses DL, multi-sensor framework
[28]	IoMT + ML integration	Multiple wearable health sensors	Wi-Fi / IoMT protocols	Custom cloud	Moderate to high	AI-based classification & monitoring
The Proposed Study (2025)	Arduino Uno + ESP-01	BP sensor, MPU6050 (fall), Buzzer	Wi-Fi	ThingSpeak	Low-cost, simple	Real-time monitoring with affordable setup

5 Conclusions and Future Directions

This study proposed a real-time, wearable IoT-based system that integrates DL techniques for continuous monitoring and early detection of abnormal cardiac conditions. A fully automated Python-based deployment pipeline was developed to handle data acquisition from the cloud, pre-process it into a structured time-series format, and perform inference every 20 minutes. This end-to-end integration ensures that the system remains efficient, autonomous, and suitable for continuous real-time operation with minimal human intervention. During real-time deployment, the model maintained an accuracy of 93.55%, based on 373 live entries collected from wearable devices. The system demonstrated a low average response time of 3.889 seconds, indicating its suitability for continuous real-time monitoring. The work highlights the development of an automated, real-time monitoring framework that efficiently analyzes physiological data and triggers immediate alerts, enhancing the effectiveness of remote cardiovascular monitoring.

Despite the promising findings of this study, future research could build on the current system in several ways. Using more powerful microcontrollers would allow for advanced features and greater flexibility. Connectivity could be improved by adopting Wi-Fi modules with extended range and stability, ensuring reliable operation across different environments. Finally, refining the fall detection algorithm to better distinguish true falls from normal movements would reduce false positives and increase user confidence in the system.

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