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Machine learning-based smart wearable system for cardiac arrest monitoring using hybrid computing

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ABSTRACT

Every year, the percentage of people affected by cardiovascular diseases increases drastically. Out of them, a heart attack is the most prominent and painful disease. According to the World Health Organization, approximately 17.5 million people lose their lives yearly due to this disease, which is alarming. The remarkable advancement in wearable technology has opened doors to propose many effective smart solutions to tackle this disease efficiently. Furthermore, early diagnosis of heart attack proliferates the compatibility of meditation and expedites the diagnostic recommendation by clinical experts. Considering this problem's sensitivity, we proposed a wearable smart and early Heart Attack diagnosis system and adopted a decentralized computational phenomenon using hybrid computing architecture. It reflects better response time and minimal latency to detect a heart attack in its preliminary stage for homage patients. The proposed system can monitor and trigger the patient current heart status classified on required heart diagnosis parametric sensors assembled on the patient's body with the help of an android application. In this study, three models are developed using the Support Vector Machine (SVM), Adaptive Boosting (AdaBoost), and Random Forest (RF) algorithms for the classification. Performance measures: accuracy, error rate, and response time are used to evaluate the proposed system. Our research findings promise that it can be implemented on patients diagnosed with the risk of a heart attack to monitor their heart health remotely and prevent sudden heart failure without impeding a person's everyday life.

1. Introduction

Cardiovascular diseases (CVDs) are the leading cause of death globally [1–3]. CVDs are disorders in blood vessels and the heart causing coronary heart disease, rheumatic heart disease, cerebrovascular disease, congenital heart disease, and other conditions [4]. According to a world health organization survey, 17.5 million people die due to cardiovascular diseases, approximately 32% of all deaths worldwide. Every year about 85% of all CVD deaths occur just because of heart attacks and strokes [5]. Most CVD diseases can be prevented by addressing behavioral risk factors like physical inactivity, tobacco usage, unhealthy diet, usage of alcohol, obesity, and many others. But it is essential to monitor and detect CVD diseases at their early stage so that proper medication and counseling can begin [6,7]. For this, it is imperative to take protective measures for a person who is supposed to be at high risk of disease [8].

A heart attack and stroke are often the first signs of underlying disease. Vital signs of heart attack and stroke are shortness of breath, a cold sweat, nausea, faintness, numbness or pain of the left arm, face, and leg, especially on one side of the body, back or jaw pain, discomfort or pain in the center of the chest and severe headache [9]. This work concentrates on monitoring and predicting heart attack, a leading cause of global death. In addition, studies revealed that the life expectancy for people with cardiac vascular diseases might get curtailed by as much as 15 years.

Policy-makers and technology companies are enthusiastic about the potential of digital technologies to transform healthcare and bring expertise to the patient rather than the other way around. It allows for earlier identification of de-compensation and better adherence to lifestyle changes, medication, and interventions [10].

Monitoring health parameters using the Internet of Things (IoT) is a trend for future well-being. Sensors are used to collect and monitor the

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real-time health parameters of individuals [11]. Collecting, processing, and analyzing health parameters help to predict the risk factors and tackle the diseases at an early stage [12,13]. In correlation to the above, advancements in IoT wearable devices help patients monitor and control their health metrics. Their availability aids the patients in continually checking their health parameters. With the help of these devices, patients can be notified about the reputation of their health condition at any time. Wearable IoT technology is increasing day by day. It provides many solutions in healthcare, decreases the disease rate, and improves the quality of life [14].

Mobile health technologies collect real-time data of patients and embed decision support systems with mobile devices to provide health services remotely. Mobile health technologies improve the live monitoring of patients and prediction of diseases without visiting the health centers [15–20]. Machine learning algorithms can benefit prospective clinical trials to compare state-of-the-art procedures for risk stratification, precision diagnostics, and personalized medicines [21–23]. Researchers proposed various machine learning models capable of determining if a person has coronary heart disease (CVD), but still implementation in some systems is missing, and higher accuracy can be achieved [24–27].

This research aims to find early risk prediction of cardiac arrest based on real-time data collected from an individual using sensors and equipment. We designed and developed an Internet of Things (IoT) based smart wearable system that can monitor the heart health status of a person at low or high risk of cardiac arrest or stroke. The proposed system enables a person to monitor, predict and control a heart attack at its early level remotely. Furthermore, it can save them from any unpleasant situation to occur. Our significant contributions (key objectives) are summarized as follows:

1. To monitor and collect an individual's vital signs of CVD in real-time using wearable multisensory and Internet of Things (IoT) based smart equipment.
2. Early predict cardiac arrest by applying relevant machine learning algorithms.
3. To classify any individual's cardiac arrest risk among three categories: less critical, more critical, and normal.
4. Designing and developing an Android application for remote supervision, heart health monitoring, and observation purposes.

2. Literature review

This section discusses the existing approaches and systems to predict and diagnose heart diseases using several techniques and datasets with various features and classification techniques.

The expansion in commonness for wearable advancements has exposed the hinged door for an Internet of Things (IoT) answer for medical administrations [28–31]. Perhaps one of the most transcendent considerations that are clinical today could be the vulnerable perseverance motion of out-of-crisis facility sudden cardiovascular breakdowns [32]. Authors in [33] present a multisensory framework, embedded product structure, and a Low Energy (LE) Bluetooth correspondence module to build up ECG and inward warmth level data employing wireless within a familiar atmosphere. Their evaluations present using signs working with AI techniques for sensor data examination for unexpected cardiovascular breakdown and scene prediction that can also be coronary. The researchers explain the progression of a framework subject to demand that is familiar with the heart dataset for the very early study of heart-based afflictions. The different attributes related to the explanation behind heart problems are via sexual direction, age, chest torture kind, circulatory stress, glucose, etc., which can anticipate early indications of disease that is coronary [34]. Authors designed an intelligent and smart stethoscope to collect heart beat rate remotely and predict common cardiac diseases with trained machine learning models [35].

In [36], authors developed a system to diagnose coronary heart disease (CVD) by applying Adaboost, ANN, and Decision Tree. A hybrid model was proposed to find the risk of cardiac events in hypertension patients employed with a convolutional neural network (CNN) and a long short-term network. The model took ECG signals as input [37]. Tama et al. [38] designed a model to diagnose heart disease using random forest (RF), extreme gradient boosting, and gradient boosting. Mienye et al. [39] designed a model to diagnose coronary heart disease (CVD) by using an artificial neural network (ANN). Performance was optimized using a sparse auto-encoder. Rani et al. [40] developed a hybrid model for a decision support system to assist in the detection of coronary heart disease (CVD) by using Support vector machine (SVM), Naïve Bayes, Random forest (RF), logistic regression (LR) and Adaboost. Genetic algorithm (GA) and recursive feature elimination methods were used for feature extraction from the patient's clinical parameters dataset available at the UCI ML repository. Amit and Wilson [41] applied various machine learning methods: k-nearest neighbor (KNN), Decision Tree (DT), random forest (RF), multilayer perceptron (MLP), Naïve Bayes (NB), and Linear-Support vector machine (L-SVM) to produce data. They designed IoT based framework to predict coronary heart disease early. Zahra et al. [42] contributed by designing a device to detect indicators or vital human signs for heart attack. The system captured real-time parameters such as respiratory rate, ECG, and body temperature. If an indication of a heart attack is detected in the parameters, the system generates notifications and alerts. The approach reflects higher performance.

"PatientsLikeMe" [43] did introduce the very first community online in 2018, and also, the absolute goal of the community was to tune in to clients to recognize the measures of outcomes, treatments, and symptoms. "DailyStrength" [44] is just a platform where social clients discuss the battles and successes they face while working with heart diseases. Limitations of "PatientsLikeMe" and "DailyStrength" are that "DailyStrength" does not involve research institutes nor provides a mobile application, and, in "PatientsLikeMe", clients share their experiences only. In [45], authors highlighted a neuro-fuzzy system to disappoint acknowledgment that is coronary. The neuro-feathery structure was arranged with eight data industries plus one yield industry. The information and knowledge factors are beaten; exercise, circulatory stress, age, cholesterol, chest torture type, glucose, and sex. The yield acknowledges the number of risks of patients, which are requested into four fields interesting low, low, high, and high.

Nausea is coronary functions as the fundamental wellspring of death around the globe. The prosperity area contains covered information that can be huge in selecting today. Data mining figures, for instance, J48, Naïve Bayes, REPTREE, CART, and Bayes web, are applied in this evaluation for predicting disappointments that can be coronary. The evaluation outcome shows a precision of 99%. Data mining engages the success zone to envision plans into the dataset [14]. The summary of related research efforts shown in Table 1.

3. Proposed methodology

The dominance of the proposed system depends on portable devices to design low-power modules with utmost liberty for users to provide them ease. In our proposed system, we have used multiple lightweight sensors, i.e., Electrocardiogram (ECG), Pulse oximeter, Galvanic skin response (GSR), and Infrared (IR) Temperature sensor. By adopting the architecture of the Internet of Things (IoT) domain, we developed a sensory-embedded module to perform a large set of experiments to evaluate and distinguish between normal and abnormal cardiac arrest patterns. Testimonials wear the sensory-embedded module, which continuously monitors the user's ECG, Pulse oximeter, GSR, and IR temperature sensor readings.

The proposed system is divided into three major layers, i.e., the sensory input, connectivity, and processing platform layers, as shown in Fig. 1.

Table 1
Summary of related research efforts 1A.

Study	Objective	Algorithm	Parameters	Accuracy	Dataset	Limitations
[11]	Measures ECG and pulse rate to monitor patients' health	KNN, Naïve Bayes	N/A	80%	UCI repository database	High power consumption, High latency, Not portable, app not developed
[46]	To early diagnose the risk of cardiovascular disease	KNN, Naïve Bayes, AdaBoost, RF, LR	Age, Weight, height, gender, cholesterol level, hypertension, alcohol, diabetes, family history of CVD, stress, exercise, smoking, healthy diet	93.8%	Collected dataset from a tertiary hospital in south India	Did not implement any system or app.
[42]	To develop a device to monitor and detect early detection of heart attack	If-then-else manner	Heart Rate (BPM), Oxygen Saturation (SpO2), Body Temperature, Respiration Rate-RR (BrPM)	N/A	N/A	System performance is not evaluated. Furthermore, the system is not trained on any dataset.
[14]	Main idea is to monitor the patient's health using IoT devices	Naïve Bayes, SVM, KNN	N/A	78.5%	Heart Disease UCI	High power consumption, not portable, high latency, app not developed
[47]	Measures ECG and pulse rate to monitor patients' health	SVM, Naïve Bayes	N/A	72%	UCI- ML repository	High power consumption, high latency, Not portable, System not developed
[48]	To predict CVD quickly and accurately	NB, DT, KNN, XGB, RF, SVM, Stacked Ensemble	Age, Gender, Cholesterol, Blood Pressure	88%	Kaggle and UCI Machine learning Repository	Neither implemented nor developed any system
[49]	To detect and recognize cardiac arrest in patients at early using ML model.	ANN, RF, XGBoost, SVM, Naïve Bayes, Decision Tree	Age, Gender, Weight, Height, BMI, SBP, DBP, Oxygen Level (SPO2%), HR (beats per minute)	98%	Real-time dataset by using sensors	Only detect survival probability with gender-based and age-based factors.
[22]	To classify and compare the performances of ML methods for predictive classification of coronary heart disease	SVM, LR, RF	Age, gender, chest pain type, BP, serum cholesterol, fasting blood sugar, max heart rate, resting ECG results, exercise-induced angina, ST slope	92%	IEEEDataPort database [50]	Neither implemented nor developed any system, hardware or app
[51]	To monitor a patient's heart status	SVM, LR, RF, MLP, KNN, DT, Naïve Bayes	ECG, EEG, EMG, BPv	96%	Hungarian Heart Disease Dataset [52]	Processing Delay
[53]	To diagnose a person has cardiac disease	Naïve Bayes, DT, RF, AdaBoost	Age, Gender, FBS, Chol, Exang, BP, Chest pain, Slope, Ca, Max Heart Rate, Defect Type, ECG	95.47%	UCI Repository	Not implemented any system

3.1. Sensory input

In the sensory input layer, the sensory data is gathered from the sensors like ECG, Pulse oximeter, IR temperature sensor, and GSR. Moreover, the IR temperature sensor provides two types of readings, i.e., ambient and object temperature values. The pulse oximeter provides the heart rate and oxygen saturation (SPO2) parameters.

3.2. Connectivity layer

In this layer, the data collected from the embedded sensory module is received as input to the controller, which will be sent to the IoT analytics platform (ThingsSpeak) via the IEEE 802.11 WiFi connectivity module. The Thing-Speak gathers the data in the form of '.Jason' or '.csv' file format. It further sent the dataset file to the processing platform layer for the implementation of pre-processing and Artificial Intelligence approaches.

3.3. Processing platform

The collected data set goes through multiple stages in the processing platform layer, i.e., pre-processing, feature extraction, classification, comparison with the trained model, and output platform.

3.3.1. Pre-processing

In this section, gathered data is pre-processed for the removal of data anomalies like data redundancy, data cleaning, data transforming, and data quality assessment.

3.3.2. Features extraction and classification

The processed data is further classified through multiple supervised machine learning models, *i.e.*, Support vector machine (SVM), Random Forest tree, and AdaBoost. Out of them, our data set best performs with the Random Forest classification model. Finally, Google colab platform is used for the utilization of Free GPU and TPU.

3.3.3. Comparison with trained model

The test data is received from the sensors via ThingSpeak through a real-time WiFi connectivity medium. It further compares the test data with the trained model to get the appropriate cardiac arrest health, whether it is a normal, less critical, or more critical stage. Finally, the recommended output is shown on the Android application via IEEE 802.11 WiFi connectivity standard to alert the patient members.

The ultimate purpose of the proposed system is only to trigger an alert if some irregular patterns in the heart rate occur, which affect the temperature, pulse rate, and sweating level to reach a determined

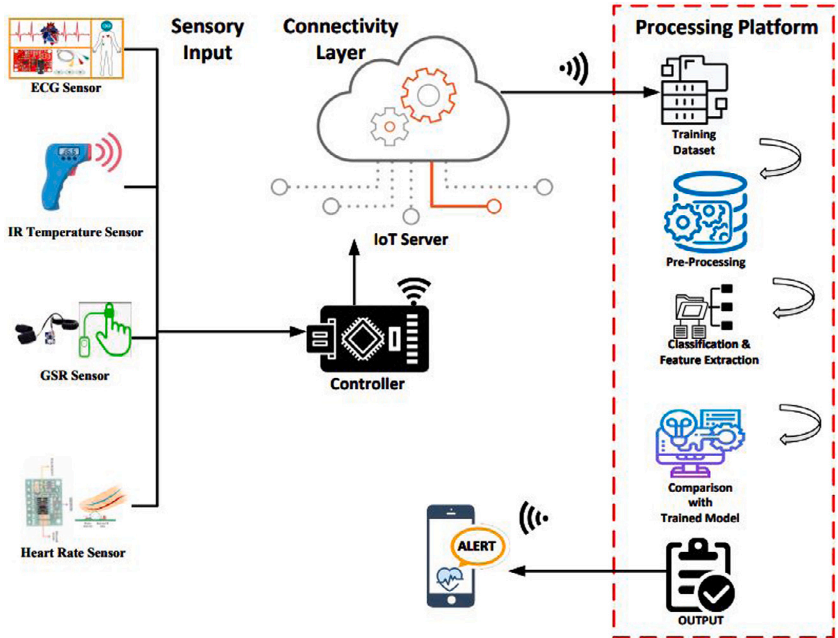

Fig. 1. Block diagram of SEHAD-HC.

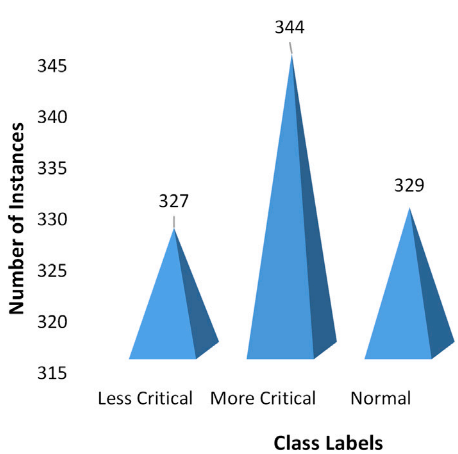

Fig. 2. Dataset distribution in terms of instances.

threshold. The warning is transmitted to the doctor monitoring the patients and the patient's acquaintance as an alert message, as shown in Fig. 1.

3.4. Dataset Acquisition (DAQ)

By random selection, anonymized medical records of heart patients and healthy persons were collected from a tertiary hospital in East Pakistan. Personal details were not collected to ensure the data privacy of participants. The dataset used in our research [54] spans 1000 instances belonging to the participants between the ages of 22 to 87 years. In this study, the ethnicity of the data is observed to be Asian. The dataset spans three labels for the target class: less critical patient '1', more critical patient '2', and healthy person '3'. The persons who visited the hospital for medical checkups and were not diagnosed with any heart disease but had diabetes and high blood pressure are referred to as less critical patients. Out of 1000 records, 327 instances belong to class 1, 344 to class 2, and 329 records to class 3, shown in Fig. 2, ensuring a balanced dataset and not skewed to the favor of any specific class. The average age of less critical patients is 60 years, the average age of more critical patients is 49, and the average age of healthy persons is 40. The dataset's attributes are Age, ECG, Pulse Rate, Peripheral Capillary Oxygen Saturation (SpO2), Galvanic Skin Response (GSR), Diabetic/Non-Diabetic, Body Temperature, and surrounding temperature. We split the dataset into two subsets, i.e., training subset and test subset, as per the 80-20 rule, as shown in Table 2. Fig. 3 reflects the sample distribution regarding attributes.

3.5. Algorithmic analysis

Algorithm 1, represents the pseudo-code of the proposed methodology for cardiac arrest monitoring in real time. Initially, all sensors embedded in the cardiac monitoring belt acquire real-time patient data. The sensory information is passed to Thing Speak for real-time data storage and fetching if the sensory values are greater than '0'. Afterward, the data is passed to the cloud processing platform for implementation of artificial intelligence (AI) algorithms. Then, the most appropriate ML classifier is trained on the acquired sensory data set, i.e., in our Random Forest, to alert the patient acquaintances in real time. We have used five sensors, i.e., ECG (ES), IR Temperature (IS), Galvanic Skin Response (GS), Pulse Sensor (PS), and SPO2 (SP), for patient heart health monitoring. Based on them, we have classified Cardiac health into three classes, i.e., Less Critical, More Critical, and Normal. It ultimately sent the patient's heart health status to their registered acquaintances through an Android application.

Moreover, each cardiac health status class computes based on five sensor values. Each sensor has threshold values under specified stages, as shown in Table 3. Furthermore 'Less Critical' cardiac health stage depicts the proposed system seeing some abnormalities in the patient's heart but still not on a serious note. Prompt action can cure a patient from danger. Similarly, the 'More Critical' stage requires a more rapid response else the patient can lose their life. Finally, we do not have to worry about the 'Normal' stage. In this stage, a person's heart is healthy without any anomalies.

3.6. Experimentation

The experimental setup shown in Fig. 4 consists of three major components: Arduino, Thingspeak, and Google Cloud Platform, where

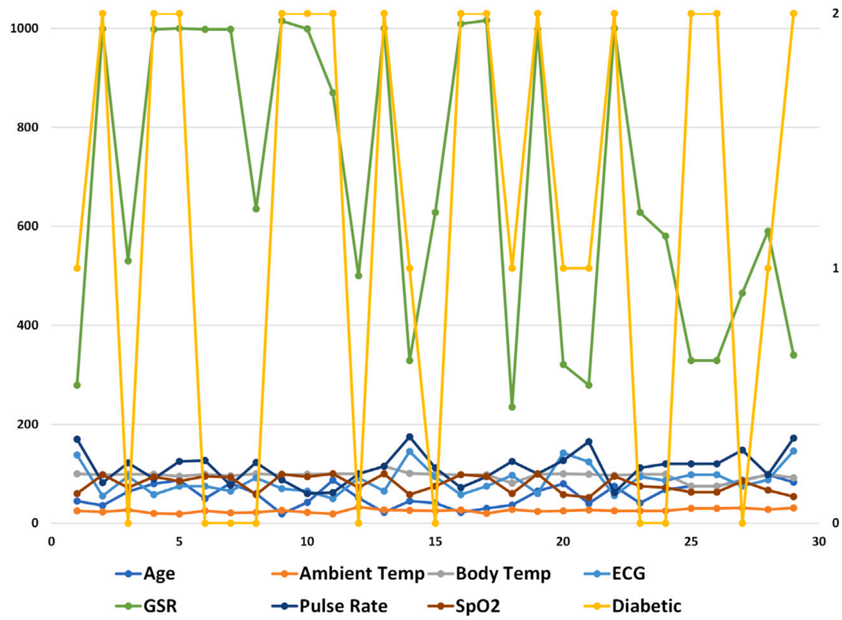

Fig. 3. Dataset distribution concerning parameters.

Table 2
Details of training and test subsets.

Class	Training subset	Test subset	Total records
Less critical patients	261	66	327
More critical patients	275	69	344
Normal persons	263	66	329
Total records	799	201	1000

Thingspeak is an aggregation and analytics platform that allows aggregate analysis of the live data stream. At the same time, Google Cloud is a cloud platform, and Arduino is an open-source major hardware and software platform. These platforms complement a heart attack prediction system. In this work, we have developed a method for testing purposes. We have used 5 biomedical sensors ECG, Spo2, Pulse rate, Galvanic skin response sensor, and IR temperature sensor, to monitor heart status. The dataset was collected manually from the hospital patients. The functional details of these components are given in Table 3 with their normal and abnormal range. In the case of ECG, the normal range should be between 55–75 ms, whereas the abnormal range should be between 80–145 ms. The Spo2 normal range is between 90%–100%, whereas the abnormal range is below 80%. In the case of pulse rate, the normal range should be between 60–100 bpm, whereas abnormal ranges from 100–180 bpm. The normal range of GSR is 980 μS, and the abnormal range is above 240–350 micro-Siemens (μS).

3.6.1. Hardware components

Table 3 shows the sensors used in our system, and their ranges show the condition of the patients. For example, in the table below, the values range from less critical to more critical for patients and normal persons. The dataset was collected manually by visiting the hospital. The components used for experimentation include Arduino, Thingspeak, and Google Cloud platform. We used 4 IoT sensors (ECG, IR temperature sensor, heart rate sensor, GSR) placed in a wearable jacket. The data from sensors is collected through an Arduino controller and sent to Thingspeak for aggregation and analytics. The Google Cloud platform is used for training, and the model is saved for prediction. After the prediction is made, a push notification will be generated on the Android application. The push notification will notify about the patient's heart health status, whether the condition is less critical, more critical, or normal, as shown in Fig. 5.

Algorithm 1 Algorithmic View of the Proposed System

Input: ECG Sensor (ES), IR Temperature Sensor (IS), GSR Sensor (GS), Pulse Sensor (PS), and SPO2 (SP)
Output: Alert message on Android Application

Initialize All sensors value set to zero
if $Check\_sensors\_value > 0$ **then**
    Input passed to Real-Time IoT Thing-Speak Cloud Analytics Platform
end if
repeat
    Data passed from Thing-Speak to Google Cloud Processing Platform for Artificial Intelligence (AI) implementation
    Data passed to AI Platform through cloud functions
    Classification Algorithm = Random Forest
    Prediction forwarded to Android through the cloud via Real-Time Database
    if $(ES \geq 80 \wedge ES \leq 100) \wedge (IS \geq 99) \wedge (GS \geq 450 \wedge GS \leq 650) \wedge (PS \geq 100 \wedge PS \leq 130) \wedge (SP < 80)$ **then**
        Less Critical
    else if $(ES \geq 100 \wedge ES \leq 145) \wedge (IS \geq 99) \wedge (GS \geq 240 \wedge GS \leq 350) \wedge (PS \geq 130 \wedge PS \leq 180) \wedge (SP < 60)$ **then**
        More Critical
    else if $(ES \geq 55 \wedge ES \leq 75) \wedge (IS \geq 95 \wedge IS \leq 98) \wedge (GS > 980) \wedge (PS \geq 60 \wedge PS \leq 100) \wedge (SP \geq 60 \wedge SP \leq 100)$ **then**
        Normal
    else
        Junk values
    end if
    Android receives Alert Message based on Prediction
until $Cardiac\_Health\_Status \neq Normal$

4. Performance metrics

Performance metrics are part of every machine learning pipeline. Statistical validation of our proposed system and evaluation parameters used for the proposed waste classification architecture are as follows:

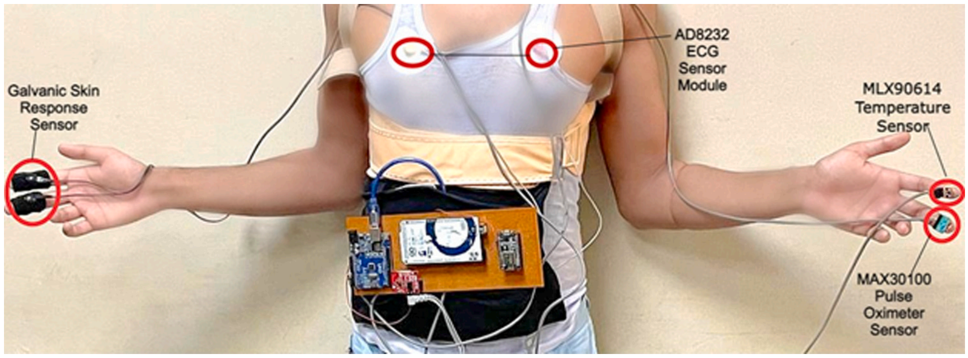

Fig. 4. Experimental setup.

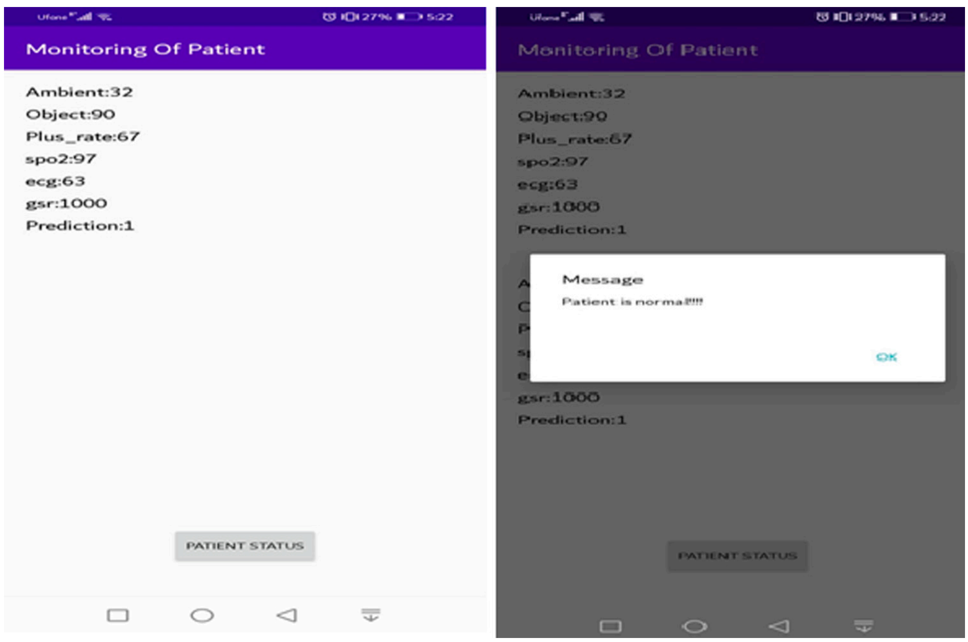

Fig. 5. Patient's heart health status.

Table 3
Sensors ranges.

Sensor	Less critical	More critical	Normal	Description
Electrocardiogram (ECG)	80–100 ms	100–145 ms	55–75 ms	ECG is used to generate an electrocardiogram of heart activity during a particular time interval.
Pulse sensor Max30100	100–130 bpm	130–180 bpm	60–100 bpm	Pulse sensor calculates the total number of heartbeats per uni time.
Spo2	<80%	<60%	80%–100%	Spo2 measures the oxygen saturation (SO2) in blood.
MLX 90614	99 °F and above	99 °F and above	95–98 °F	This IR temperature sensor measures the body and its surrounding temperature.
Galvanic Skin Response (GSR)	450–650 μS	240–350 μS	Above 980 μS	GSR is used to check the body sweating level.

4.1. Percentage system accuracy

The system's performance can be measured by calculating the accuracy parameter of the system. The system accuracy (AC) is the ratio of true positive predictions for the complete dataset. Mathematically it is represented in Eq. (1)

$$AC = \frac{(TP + TN)}{(TP + FN + TN + FP)} * 100 \tag{1}$$

Here TP is true positive, TN is true negative, FN is false negative, and FP is false positive.

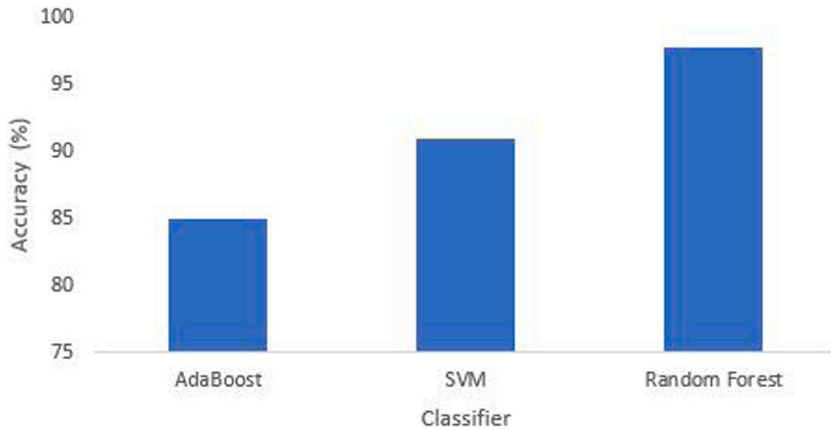

Fig. 6. Accuracy comparison b/w machine learning classifiers.

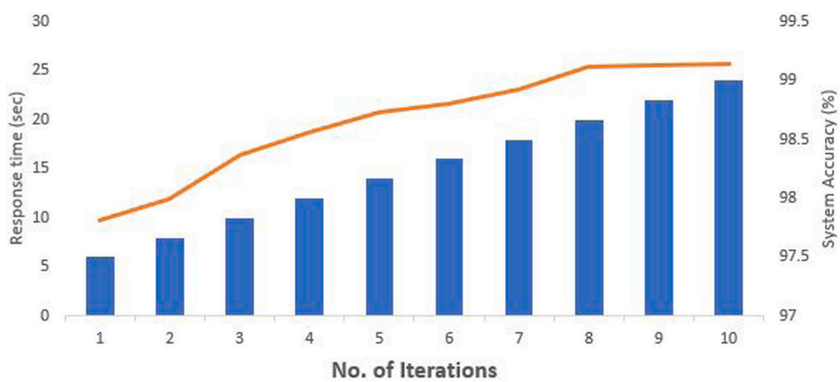

Fig. 7. Average system response w.r.t no. of trained model iterations.

4.2. System response time

It is a sum of transmission time, propagation delay, and overhead time. However, the overhead time is the overhead latency factor based on the total number of attempts for prediction. Mathematically, it is represented in Eq. (2):

$$SRT = TD + PD + OT \tag{2}$$

Here TD is the transmission time, i.e., 1.5 s, PD is the propagation delay, i.e., 2.5 s, and OT is overhead time, i.e., ‘X’ sec. However, ‘X’ is 2, 4, 6, 8, 10, …, sec.

4.3. Percentage system error rate

This evaluation parameter shows the percentage error rate in the proposed system SEHAD-HC concerning multiple ML classification models. It is calculated by taking a difference in the system accuracy parameter from the maximum value, *i.e.*, ‘1’. The resulting value is multiplied by 100 to get the final result in the desired format. Mathematically, it is represented in Eq. (3):

$$SER = (1 - AC) * 100 \tag{3}$$

4.4. Performance evaluation

The performance system analysis parameters are thoroughly analyzed and illustrated in this section.

4.4.1. Accuracy comparison

Fig. 6 depicted the accuracy of the proposed system concerning multiple ML classifiers. We have tested multiple ML classification models on the proposed (SEHAD-HC) cardiac arrest monitoring system. On the top of the three, we have Random Forest, SVM, and AdaBoost, respectively, reporting the maximum accuracy with a Random Forest classifier, i.e., 97.81%. Afterward, we have SVM and AdaBoost, which are 91% and 85%, respectively. The overall accuracy results are phenomenal as tested in a real-time environment.

4.5. System response time

The overall response time of the proposed system mainly depends on the total no. of iterations used for the ML training model. However, it ultimately affects the whole system’s performance. As shown in Fig. 7, system response time increases with the increase in the no. of iterations which ultimately enhances the proposed system accuracy. In the first iteration, the overall system response time is $\tilde{6}$ s, i.e., 1.5+2.5+2. Here, the transmission delay is 1.5 s, propagation delay is 2.5 s, and overhead is equal to 2 s, respectively. In the second iteration, the system response time is 10 s, i.e., (1.5+2.5+4). As the number of iterations increases, the overhead increases with the factor of 2 s It is the time required to complete one iteration to train the ML model.

Similarly, the system’s accuracy increases as we increase the number of iterations. At iteration 1, system accuracy is 97.81%, system accuracy is slightly at iteration 2, i.e., 98%, and the phenomenon continues with the iterations increment unless iteration 8. At this point, the system accuracy almost becomes static, i.e., 99%. Irrespective of the benefit we got in system accuracy, we have to pay the overhead response time price with the number of iterations increasing.

Table 4
Tabular analysis of the proposed w.r.t existing approaches.

Ref.	Objective	Cloud Supp.	APP. Supp.	IoT Supp.	Portable	Accuracy	Limitations
[11]	Monitor Heart status by ECG and pulse rate	✗	✗	✗	✗	80%	High power consumption, High latency
[14]	Heart check monitoring using E shield	✗	✓	✓	✓	78.5%	High power consumption, high latency
[51]	Monitor Heart health by ECG, EMG BPv, EEG	✗	✗	✗	✗	96%	High Processing Delay, High resource utilization
Proposed	Monitor Cardiac Arrest by ECG, GSR, SPO2, pulse rate, and IR sensors	✓	✓	✓	✓	97%	–

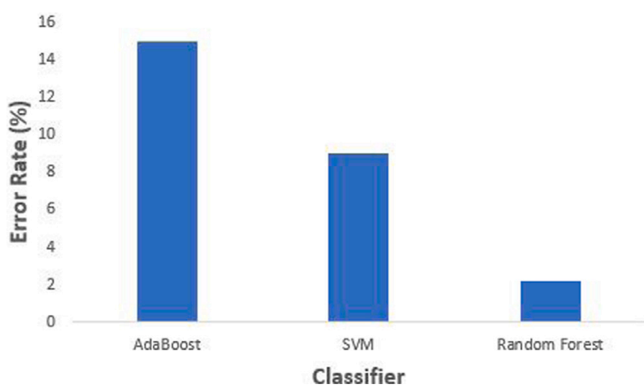

Fig. 8. Error rate in-accuracy w.r.t ML classifiers.

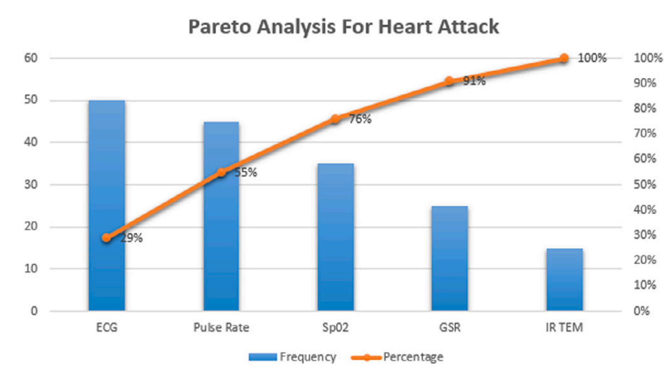

Fig. 9. Pareto analysis concerning sensors.

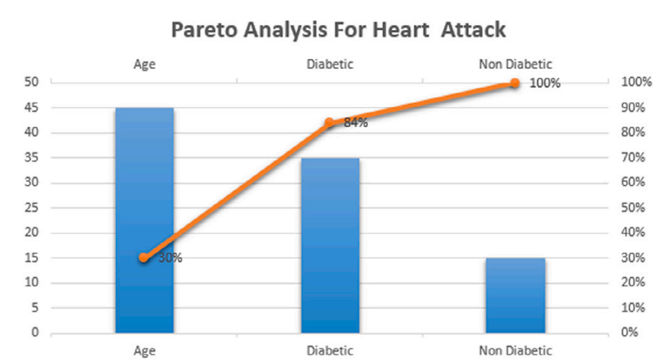

Fig. 10. Pareto analysis concerning parameters.

Moreover, our proposed smart system also tackles a time-critical problem. We cannot afford the response time overhead penalty as it drastically affects the overall system performance. So, considering the real-time environmental fact, we trained the ML model in our proposed (SEHAD-HC) system on a single iteration respectively.

4.6. Percentage system error rate

Fig. 8 shows the proposed system inaccuracy concerning multiple ML classifiers. As discussed in Section 4.4.1, the minimal error rate factor is achieved through the random forest classification model, i.e., 2.19%. Afterward, we have an SVM classifier through which we got an error rate of 9%, and the maximum error rate is calculated by the AdaBoost classifier, i.e., 15%, respectively. So, the most realistic and reliable classification model in our proposed smart cardiac arrest monitoring system is considered a random forest.

5. Pareto analysis

Fig. 9 and Fig. 10 show the Pareto analysis done concerning sensors used and dataset attributes, respectively. This statistical technique shows which input factor has the most significant impact on an outcome. Five sensors have been used as input. Among these sensors, ECG has the highest impact on results generated, which is 29% as in Fig. 9. The bar at ECG shows the frequency that 50 persons having abnormal ECG have more chances of heart attack than other parameters. After ECG, pulse rate reasonably impacts results, i.e., 26%. The percentages of ECG and pulse rate collectively make a 55% impact on results. Then Spo2 has an impact on the outcome in 21%. Then, the GSR has an impact of 15%. Finally, according to an analysis done and the graph shown below, it is seen that the IR temperature sensor has the most negligible impact on results. All these sensor impact percentages collectively make a 100% chance of heart attack.

Fig. 10 shows the impact on outcomes w.r.t attributes like Age factor, diabetic and non-diabetic patients. The graph shows that Age factor and diabetic attributes have the highest impact on an outcome, i.e., 84%. The more the age, the more the chance of a heart attack, and if the patient has diabetes, they are more likely to have the possibility of a heart attack. At the same time, the non-diabetic attribute has the most negligible impact on results, i.e., 16%. The bars show the frequency of the attributes that what people think of and which attribute the highest impact has on an outcome.

6. Conclusion

In this study, we proposed and implemented IoT-based, portable, wearable, and smart system for cardiac arrest monitoring using hybrid computing. Moreover, the immediate response to cardiac arrest monitoring can save valuable lives and consult physicians before time. We created an integrated IoT-based smart and cardiac arrest monitoring system to monitor and continuously predict heart pattern abnormalities. We developed a low-power communication channel between IoT sensors and the Android Application. This research provides users with a portable device they may carry anywhere and know about their heart patterns continuously. The results from the data collected from the hospital patients visited to create a dataset show the correctness of the classification algorithm used in distinguishing between normal and abnormal heart patterns. We also tested our system on different persons to get the results. We have achieved 97% accuracy through our proposed SEHAD-HC system, which highlights the effectiveness and reliability of our system. Table 4, shows the analytical comparison of the proposed system concerning the existing approaches. Our proposed system SEHAD outperforms resource utilization, transition and propagation delay, portability, and accuracy. Moreover, we have computed the major processing modules on the cloud platform, one of our major objectives in implementing the IoT-based smart system in a real-time environment. The system could contribute to excellent heart health monitoring and improve alerting services to patients and their emergency medical caregivers.

CRediT authorship contribution statement

Abdul Hannan: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Sehrish Munawar Cheema:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Ivan Miguel Pires:** Conceptualization, Validation, Writing – original draft, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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