

AI/ML-Enabled Internet of Medical Things (IoMT) for Personalized Cardiac Health Monitoring and Predictive Diagnostics [†]

Hira Mariam ^{*}, Anushay Khan, Humna Nadeem and Barirah Khan

Department of Telecommunications Engineering, NED University of Engineering and Technology, Karachi 72570, Pakistan; anushay.khan.tc@gmail.com (A.K.); humna7837@gmail.com (H.N.); kbarirah37@gmail.com (B.K.)

^{*} Correspondence: hiramariam@cloud.neduet.edu.pk

[†] Presented at the 12th International Electronic Conference on Sensors and Applications (ECSA-12), 12–14 November 2025; Available online: <https://sciforum.net/event/ECSA-12>.

Abstract

Cardiovascular diseases (CVDs) are a major cause of global mortality, underscoring the need for intelligent and accessible cardiac health monitoring. This paper proposes a non-wearable Internet-of-Medical-Things (IoMT) system combining real-time sensing, edge processing, and AI-driven diagnostics. Stationary sensors MAX30102 (heart rate, SpO₂) and AD8232 (ECG) interfaced with micro-controller (ESP8266), processes data locally and feeds into the machine learning models trained on UCI Cleveland dataset. Random Forest and XGBoost achieved over 80% accuracy in predicting early cardiac risk. A Flask-SQLite web application provides role-based doctor/patient access, and a Natural Language Processing (NLP) based interactive chatbot offers personalized guidance. The system delivers scalable, real-time, edge-enabled cardiac diagnostics without relying on wearable devices.

Keywords: IoMT; cardiac monitoring; machine learning; artificial intelligence; Max30102; AD8232; predictive diagnostics; web application; chatbot

1. Introduction

According to the World Health Organization, cardiovascular diseases (CVDs) are reportedly the major cause of global mortality, affecting more than half a billion people and approximately 19.8 millions deaths in 2022, with 85% due to heart attack and stroke. In low or middle income countries, barriers such as limited access to healthcare facilities, high costs of diagnosis, and shortage of specialists, make early diagnosis and treatment critical for the people with CVDs [1–3]. Traditional diagnosis methods involve either periodic in-clinic testings or Holter-based ECG monitoring that record continuous heart rhythms. The latter effectively diagnoses some CVDs that may be ignored in the absence of any symptoms [4]. However, increasing prevalence of chronic diseases and growing demand for personalized healthcare solutions requires innovative technologies that can provide real-time, accurate and user-friendly health monitoring. In this context, the Internet of Medical Things (IoMT) presents a promising opportunity to transform traditional healthcare into a more accessible, affordable, and proactive system [5,6].

IoMT enables a medical system to connect various smart devices, such as wearable sensors, medical examination instruments, and hospital assets, for establishing an

Academic Editor(s): Name

Published: date

Citation: Mariam, H.; Khan, A.; Nadeem, H.; Khan, B. AI/ML-Enabled Internet of Medical Things (IoMT) for Personalized Cardiac Health Monitoring and Predictive Diagnostics. *Eng. Proc.* **2025**, *5*, x. <https://doi.org/10.3390/xxxxx>

Copyright: © 2025 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

information platform. These smart devices act as basic nodes in an IoMT system, collecting health data and transmitting it to the server for further processing and analysis [7]. When combined with artificial intelligence (AI) and machine learning (ML) algorithms, it can benefit prospective clinical trials to compare state-of-the-art procedures for risk stratification, precision diagnostics, and personalized medicines. Mobile health technologies improve the live monitoring of patients and prediction of diseases without visiting health centers.

Several practical implementations demonstrating IoMT prototypes using connected and cost efficient microcontrollers (ESP32/ESP8266) with Electrocardiography (ECG) Sensor and Pulse/PPG (Photoplethysmography) have been widely reported in literature. These works establish feasibility of integrating real time cardiac activity monitoring with remote clinical access through sensors and cloud/server using Wi-Fi or Bluetooth [8–12]. The use of LoRA technology for data transmission of IoMT has proven to be both cost and power efficient [13]. Some IoMT architectures utilize fog computing to meet latency and real time requirements of CVD [14]. Recent research focuses on edge computing for cardiac monitoring and anomaly detection in a resource constrained environment [15]. Various literature have proposed different ML algorithms capable of determining if a person has a CVD [16,17]. Authors in [18,19] suggest different AI/ML models that predict or learn CVDs by analyzing the sensor data. Rani et al. [20] proposed a hybrid ML algorithm based on Support vector machine (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes (NB), and Adaboost. While, Amit and Wilson [21] applied different ML algorithms such as, Decision Tree (DT), k-nearest neighbor (KNN), multi-layer perceptron (MLP), RF, NB, and SVM, for early prediction of CVDs based on IoMT data. An interactive chatbot can also serve as an integral part of the IoMT-based cardiac health monitoring system. It engages users in a one-on-one discussion and questionnaire about their health issues. The system is given data about health symptoms and with the aid of NLP, the chatbot guides the user to provide self-care and disease diagnosis [22]. Despite these advancements in IoMT technologies, there remain several limitations and research gaps that require a comprehensive solution for integrating these technologies into a user-friendly and proactive diagnostic system with real time monitoring and predictive analytic using AI/ML models.

In this paper, we present a real time IoMT-enabled solution designed for cardiac monitoring and predictive diagnostics, continuous and personalized healthcare, especially in underserved and remote areas. In contrast to most of the ESP-based cardiac IoMT prototypes based on a single lead sensors that limit diagnostic variability, we employ multi-modal sensors that collects real time ECG, heart rate, blood oxygen saturation (SpO2) measurements that enhance diagnostic accuracy. These sensors work on photoplethysmography technology- an optical technique that monitors consistency in blood volume, thereby allowing to screen and detect the presence of CVDs. PPG measures oxygen saturation, blood pressure, and cardiac activity through a series of signals and peak detection to determine arterial irregularities [23,24]. The data streams are then wirelessly transmitted via an ESP8266 microcontroller to a web application for visualization and analysis. Furthermore, the system includes an ML pipeline trained on the Cleveland Heart Disease dataset [25] to assess heart disease risk. Further, an integrated AI-powered chatbot enhances patient engagement, providing recommendations based on symptoms and historical data. A comparative analysis of our proposed approach with existing IoMT solutions for CVD is presented in Table 1.

Table 1. Comparative analysis of the proposed system with existing state-of-the-art IoMT for CVD.

Literature	Sensors Module Features	Contribution	Limitations
Lee HY et al., [25]	ECG, heart rate and activity, respiratory, temperature	Portable ECG patch system, real-time detection of abnormal ECG events, Remote CVD monitoring during daily activity	Motion artifacts; single-lead
Georgieva-Tsaneva, G. et al., [26]	ECG, PPG/SpO ₂ , temperature, accelerometer, gyroscope with Wi-Fi	Wearable multi-sensor cardiac monitor (armband/vest), real-time (heart rate variability analysis and emergency alerts	Complex integration; increase power consumption
Rahman et al., [8]	ECG, heart rate using ESP32 and Wi-Fi	Real-time ECG and heart rate monitoring	Single lead heart rate sensor; no predictive analytics
Rincon et al., [14]	ECG monitoring using Fog computing and LoRA protocol	Fog-based ECG classification, real-time processing	High latency, lacks personalization
Hannan et al. [17],	ECG + SpO ₂ using Bluetooth	Cloud integrated portable system to continuously monitor and predict heart pattern abnormalities	Dependent on wearable only
Hizem et al., [15]	ECG using Edge AI	Real time ECG monitoring and edge-based anomaly detection	Limited interaction with patient-doctor platforms
Our Proposed System	MAX30102 (HR, SpO ₂), AD8232 (ECG), ESP8266 (Wi-Fi, local Flask server)	ML-enhanced real-time, edge enabled portable device, NLP chatbot, role-based dashboards	Integration of low-cost stationary sensors, predictive ML, and chatbot for continuous CVD monitoring, with scalable design with secure edge processing

The rest of the paper is organized as follows: Section 2, discusses the system design, elaborating the hardware implementation, data collection, web development, ML model and chatbot development. Section 3 elaborates main results and discussion. Finally, Section 4 concludes the paper.

2. System Design and Development

In this section, we present the components used to design and IoMT system and their interconnection for CVD monitoring.

The system design comprises of three main part:

- Microcontroller and sensors based IoMT prototype;
- A Flask-SQLite web application provides role-based doctor/patient access, and a chatbot offers personalized guidance;
- A machine learning pipeline trained on the Cleveland Heart Disease dataset.

Figure 1 represents the design of the proposed IoMT system.

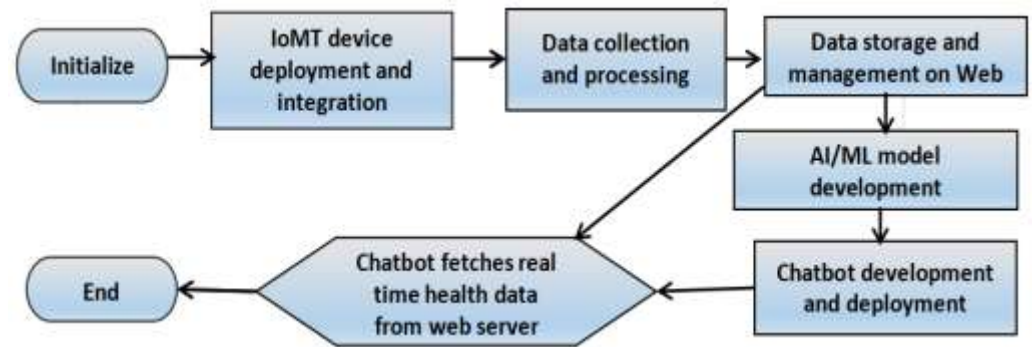


Figure 1. Methodology showing the process of system design.

In the subsequent subsections we discuss our system design in detail.

2.1. IoMT Prototype and System Design

The proposed system is a real-time, personalized cardiac health monitoring platform. It integrates biomedical sensors with a microcontroller, a lightweight backend, and a web-based user interface. The MAX30102 sensor is used for measuring heart rate and blood oxygen saturation (SpO₂), while the AD8232 sensor captures ECG signals. These sensors are connected to the ESP8266 microcontroller, which collects the data and transmits it to a local host based Flask server via HTTP requests over Wi-Fi. The system is designed to be compact and cost-effective, allowing patients to continuously monitor their cardiac activity. The collected data is stored in a SQLite database on the server machine, making it retrievable for visualization and analysis. This end-to-end system enables seamless communication between hardware and software components without requiring any third-party cloud integration.

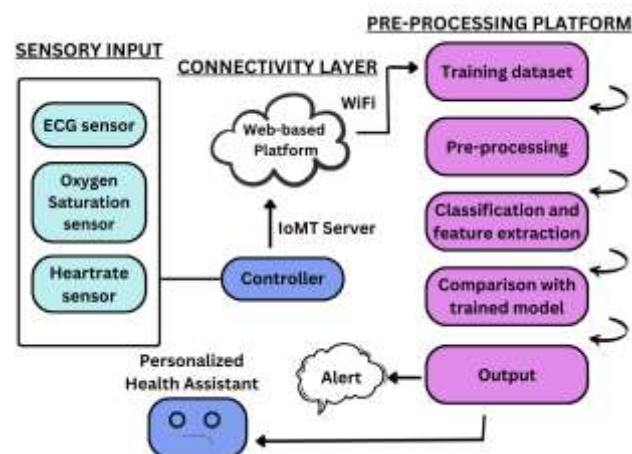


Figure 2. Block diagram of the Intelligent IoMT based Cardiovascular Disease Diagnosis System.

Data is acquired as physiological signals from the MAX30102 and AD8232 sensors through physical contact. The user touches their finger sensor, which measure fluctuations in blood volume, employing PPG for measurement of heart rate and SpO₂. For ECG monitoring, sticky electrodes attached to the AD8232 sensor are applied to the user's chest to capture the heart's electrical activity. The two sensors are connected to the ESP8266 microcontroller, and the readings are viewed in the serial monitor via the Arduino IDE. The system does not automatically sends data to the web interface; rather, the readings obtained are recorded and entered manually into the web dashboard for further visualization and storage in the local SQLite database. This half-automated solution enables system validation and functional testing prior to shifting to real-time transmission in subsequent

versions. It also provides users with full control over when and where data is stored and logged.

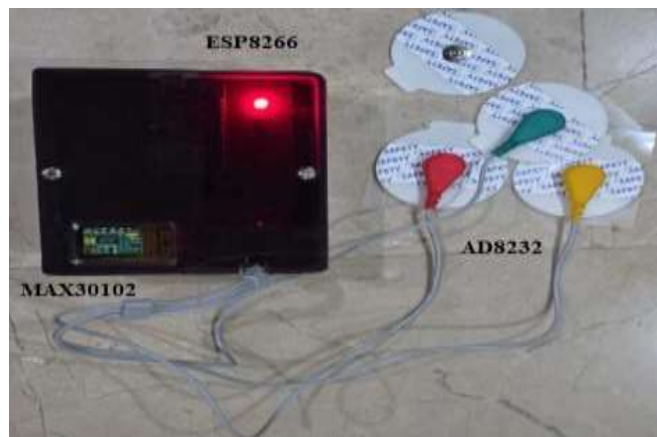


Figure 3. Prototype with MAX30102 and AD8232 sensors with ESP8266 on vero board for real-time health monitoring.

2.2. Backend and Web Interface

The backend system is developed using the Python Flask framework and functions as a REST API to manage cardiac health data. It is hosted on a local machine with Wi-Fi capability, enabling communication between the web interface and backend services. The physiological data including heart rate, SpO₂, and ECG values is captured using sensors and displayed on the Arduino IDE's serial monitor. This data is then manually entered into the system via a secure web interface. The backend stores all health data in a local SQLite database, which includes patient ID, timestamps, and corresponding health parameters. The frontend is built using HTML, CSS, and JavaScript and allows doctors and patients to log in. Doctors can add or delete patient records, while patients can view their individual health information. The system runs on Wi-Fi within a local network environment and is accessible via web browser, making it convenient for use in clinics, labs, or controlled setups without requiring internet-based cloud services. Figure 4a shows a form for adding new patient data. The form has fields like age, sex, cholesterol, chest pain type, heart rate, and SpO₂. Figure 4b shows the patient dashboard where the table is read-only with a search bar at the top. The patient enters their Patient ID and clicks search. If the ID matches a record in the database, that record is shown. If not, an error message is displayed.



(a) Doctor dashboard with patient records



(b) Patient dashboard

Figure 4. Dashboard access for doctor and patient roles.

2.3. Machine Learning Model Deployment

The machine learning based cardiac disease prediction system follows a structured workflow starting with the widely used UCI Cleveland Heart Disease dataset [27], for benchmarking in cardiovascular risk research. Data preprocessing involves handling missing values, encoding categorical attributes, and normalizing features with Standard-Scaler to improve model convergence and performance. Feature selection retains only the most informative attributes, reducing complexity while improving interoperability. The dataset is split into training and testing sets, and five algorithms—Logistic Regression, Random Forest, Support Vector Machine, k-Nearest Neighbors, and XGBoost—are evaluated using accuracy, precision, recall, and F1-score [29]. For performance optimization, we perform hyperparameter tuning via GridSearchCV and Bayesian Optimization, with 10-fold cross-validation [28]. For real-time deployment, the optimized model is integrated into an IoT-enabled healthcare framework using AD8232 and MAX30102 sensors connected via ESP8266, transmitting data to a backend system for analysis, with a chatbot delivering instant diagnostic insights to support continuous cardiac health monitoring. Following five supervised learning models are trained and evaluated [15]:

2.4. Chatbot Integration for Cardiovascular Diagnostic Support

This work combines a domain-specific chatbot with an AI/ML-powered IoMT system that deals specifically with cardiac diagnostics. It is developed with Python and the Falcon-7B-Instruct model through Hugging Face on Google Colab. The chatbot connects user inputs to relevant health information by examining real-time sensor data and answering in natural language. The chatbot is implemented with following technical stack:

- *Model:* Falcon-7B-Instruct (Hugging Face Transformer-based Large Language Model);
- *Frameworks:* PyTorch (model inference), Hugging Face Transformers;
- *Environment:* Google Colab with GPU acceleration;
- *APIs/Libraries:* Requests (HTTP), web-based API for real-time data integration.

Figure 5 demonstrates the procedure of user input and chatbot response to answer cardiac queries.

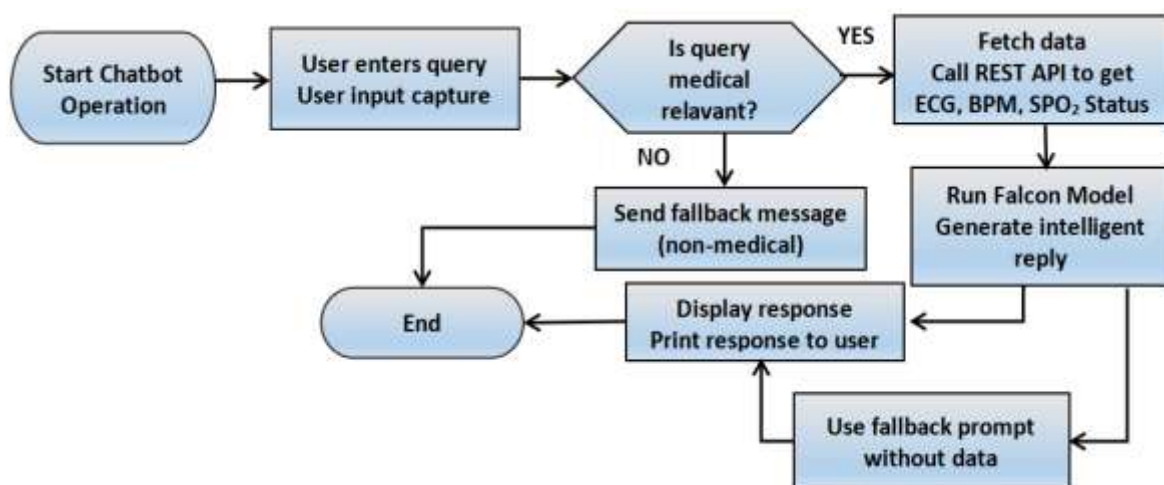


Figure 5. Chatbot flowchart with medical query handling and sensor-based response generation.

3. Results and Discussion

3.1. System Performance

The system prototype was tested in a controlled environment. ECG signals from the AD8232 were successfully captured and displayed in near-real time. Heart rate and SpO₂ data from the MAX30102 were recorded consistently, though with some sensitivity to finger placement. Web interface performance was smooth under local hosting conditions. Real-time updates were displayed on the dashboard with minimal latency. The database allowed efficient storage and retrieval of patient data. The chatbot accurately understood queries related to chest pain, fatigue, dizziness, and other heart-related symptoms. Responses were relevant, context-aware, and aligned with model predictions.

3.2. Evaluation of Machine Learning Models

After training, each ML model is evaluated on an 80:20 train-test split. The evaluation metrics for all models are summarized in Table 2. For each ML model, we evaluated performance using three main metrics: precision, recall, and F1-score. These are especially important in healthcare because wrong predictions, like missing a real case or giving a false alarm, can have serious effects on a patient's health. Precision measures how many of the cases predicted as heart disease were correct, helping reduce false positives. Recall tells us how many real heart disease cases the model was able to catch, which is very important to avoid missing patients who need help. The F1-score combines both precision and recall into one value and is useful when the dataset has uneven numbers of cases. In our results, the RF model showed the highest accuracy of around 83%, followed by XGBoost with about 82%. LR gave average performance. SVM had high recall, meaning it identified more real cases, but its precision was lower, which means it also had more false alarms. These evaluations helped us choose the best model for safer and more reliable heart disease prediction.

Table 2. Table comparing accuracy, precision, recall, and F1-score for the five ML models.

Model	Precision	Recall	F1-Score	Accuracy
Logistic regression	0.81	0.75	0.78	0.7683
Random forest	0.75	0.69	0.72	0.8293
Support vector machine	0.85	0.95	0.89	0.7439
K-Nearest Neighbours	0.81	0.79	0.80	0.7439
XGBoost	0.91	0.97	0.94	0.8170

Figure 6 reflects correlation heatmap that shows how different features in the dataset relate to each other and to the presence of heart disease (target). The values range from −1 to +1. A value close to +1 means a strong positive correlation, meaning both features increase together. A value close to −1 shows a strong negative correlation, meaning that as one feature increases, the other decreases. A value near 0 means little or no correlation. Important features identified by the models include: Chest pain type (cp), Age, Maximum heart rate achieved (thalach), Serum cholesterol (chol), depression induced by exercise (oldpeak). From the heatmap, we can see that features like cp, slope, ca, and thal have strong correlations with the target variable, meaning they are likely to be important in predicting heart disease. For example, cp has a positive correlation of 0.43 with heart disease, suggesting certain chest pain types are common in patients with CVD. On the other hand, maximum heart rate (max_hr) has a negative correlation of −0.42 with the target, meaning lower max heart rate is often linked to heart disease. This kind of heatmap is very helpful in identifying which features are most useful for model building. It also helps avoid multicollinearity, when two features are too similar, by showing which features are

highly correlated with each other. For example, slope and oldpeak or ca and thal show moderate-to-strong correlation, which is worth considering during feature selection.

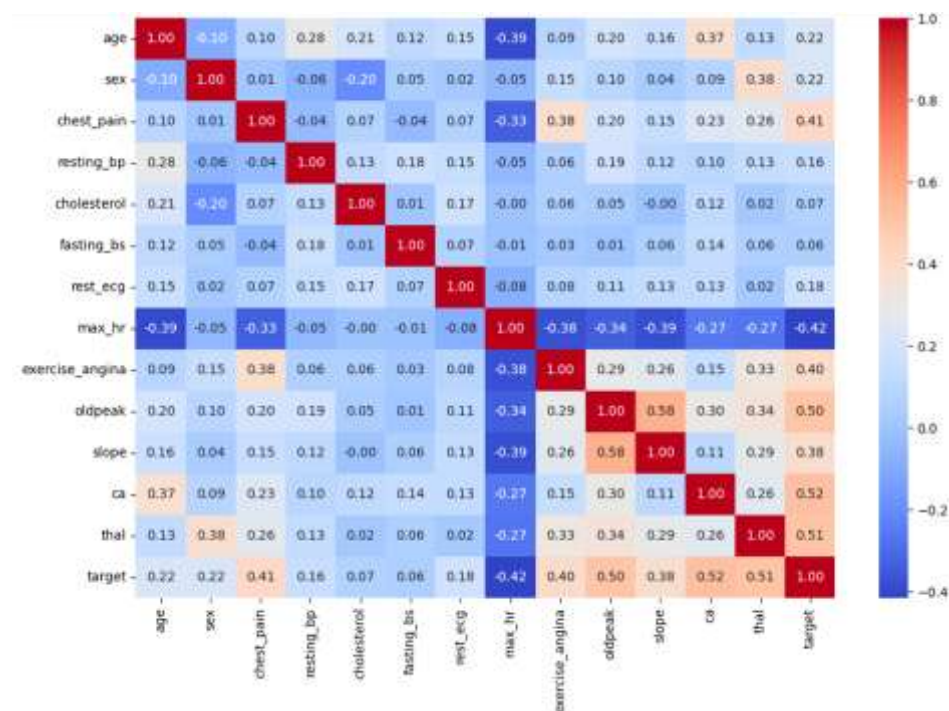


Figure 6. Heatmap of Feature Correlations and Target Relationships.

4. Conclusions

This paper presents an end-to-end, real-time cardiac health monitoring system that integrates wearable biomedical sensors, wireless data transmission, machine learning, and a chatbot interface. The proposed solution is low-cost, scalable, and suitable for deployment in remote or underserved regions. By leveraging machine learning algorithms, especially techniques like Random Forest and XGBoost, we achieved an accuracy of up to 85%, with further improvement through hyperparameter tuning and Bayesian optimization. The chatbot enhances usability, making the system patient-friendly. With future enhancements such as mobile application integration, cloud deployment, and stronger security protocols, this system has the potential to redefine how cardiac healthcare is delivered, making it smarter, faster, and more accessible.

Author Contributions: Conceptualization, H.M., A.K., H.N. and B.K.; methodology, H.M., A.K., H.N. and B.K.; software, A.K., H.N. and B.K.; validation, A.K., H.N. and B.K.; formal analysis, H.M., A.K., H.N. and B.K.; investigation, A.K., H.N. and B.K.; resources, A.K., H.N. and B.K.; writing—original draft preparation, H.M., A.K., H.N. and B.K.; writing—review and editing, H.M.; visualization, A.K., H.N. and B.K.; supervision, H.M.; project administration, H.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Dataset used is publicly available at: <https://archive.ics.uci.edu/ml/datasets/heart+Disease>.

Acknowledgments: The authors would like to express their sincere gratitude to Department of Telecommunications Engineering, NED University of Engineering and Technology, Karachi Pakistan for providing necessary facilities and support to carry out this work as Final Year Design Project.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Di Cesare, M.; Perel, P.; Taylor, S.; Kabudula, C.; Bixby, H.; Gaziano, T.A.; McGhie, D.V.; Mwangi, J.; Pervan, B.; Narula, J.; et al. The Heart of the World. *Glob. Heart* **2024**, *19*, 11. <https://doi.org/10.5334/gh.1288>.
2. Cardiovascular Diseases (CVDs). Available online: [https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-\(cvds\)](https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)) (accessed on 14 August 2025).
3. Mensah, G.A.; Fuster, V.; Murray, C.J.L.; Roth, G.A.; Global Burden of Cardiovascular Diseases and Risks Collaborators Global Burden of Cardiovascular Diseases and Risks, 1990–2022. *J. Am. Coll. Cardiol.* **2023**, *82*, 2350–2473. <https://doi.org/10.1016/j.jacc.2023.11.007>.
4. Ndreas, S.; Bothner, U.; De La Hoz; Kloer, I.; Trampisch, M.; Alter, P. Post Hoc Holter ECG Analysis Olodaterol Formoterol Moderate-to-Very-Severe COPD. *Int. J. Chronic Obstr. Pulm. Dis.* **1955**, 2020.
5. Aldahiri, A.; Alrashed, B.; Hussain, W. Trends in Using IoT with Machine Learning in Health Prediction System. *Forecasting* **2021**, *3*, 181–206. <https://doi.org/10.3390/forecast3010012>.
6. Rodríguez-Rodríguez, I.; Campo-Valera, M.; Rodríguez, J.-V.; Lok Woo, W. IoMT Innovations in Diabetes Management: Predictive Models Using Wearable Data. *Expert Syst. Appl.* **2024**, *238*, 121994. <https://doi.org/10.1016/j.eswa.2023.121994>.
7. Huang, C.; Wang, J.; Wang, S.; Zhang, Y. Internet of Medical Things: A Systematic Review. *Neurocomputing* **2023**, *557*, 126719. <https://doi.org/10.1016/j.neucom.2023.126719>.
8. Rahman, M.A.; Li, Y.; Nabeed, T.; Rahman, M.T. Remote Monitoring of Heart Rate and ECG Signal Using ESP32. In Proceedings of the 2021 4th International Conference on Advanced Electronic Materials, Computers and Software Engineering (AEMCSE), Changsha, China, 26–28 March 2021; IEEE: Piscataway, NJ, USA, 2021.
9. Palamar, A.; Palamar, M.; Osukhivska, H. Real-Time Health Monitoring Computer System Based on Internet of Medical Things. In Proceedings ITTAP'2023: 3rd International Workshop on Information Technologies: Theoretical and Applied Problems, 22–24 November 2023; pp. 106–115.
10. Pham, V.-N.; Coboi, A.; Nam, D.D.; Vien, L.G.; Thai, P.D. Design of ECG Circuit and Patient Remote Monitoring System Using MQTT Protocol for ECG Signals. *J. Basic Appl. Res. Int.* **2024**, *30*, 32–42. <https://doi.org/10.56557/jobari/2024/v30i48836>.
11. Le, D.-A.T.; Vo, B.-T.; Pham, V.-N.; Ba, Q.-H.D.; Nguyen, T.-N.; Ha, M.-H.; Kim, D.-T. Patient Remote Monitoring System Using MQTT Protocol for ECG Signals. In Proceedings of the 2024 9th International Conference on Integrated Circuits, Design, and Verification (ICDV), Hanoi, Vietnam, 6–7 June 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 114–118.
12. Wan, J.; A. A. H. Al-awlaqi, M.; Li, M.; O'Grady, M.; Gu, X.; Wang, J.; Cao, N. Wearable IoT Enabled Real-Time Health Monitoring System. *EURASIP J. Wirel. Commun. Netw.* **2018**, 2018. <https://doi.org/10.1186/s13638-018-1308-x>.
13. Li, C.; Hu, X.; Zhang, L. The IoT-Based Heart Disease Monitoring System for Pervasive Healthcare Service. *Procedia Comput. Sci.* **2017**, *112*, 2328–2334. <https://doi.org/10.1016/j.procs.2017.08.265>.
14. Rincon, J.A.; Guerra-Ojeda, S.; Carrascosa, C.; Julian, V. An IoT and Fog Computing-Based Monitoring System for Cardiovascular Patients with Automatic ECG Classification Using Deep Neural Networks. *Sensors* **2020**, *20*, 7353. <https://doi.org/10.3390/s20247353>.
15. Hizem, M.; Bousbia, L.; Ben Dhiab, Y.; Aoueleiyine, M.O.-E.; Bouallegue, R. Reliable ECG Anomaly Detection on Edge Devices for Internet of Medical Things Applications. *Sensors* **2025**, *25*, 2496. <https://doi.org/10.3390/s25082496>.
16. Bhirud, N.; Tataale, S.; Randive, S.; Nahar, S. A Literature Review Chatbots Healthcare Domain. *Int. J. Sci. Technol. Res.* **2019**, *8*, 225–231.
17. Hannan, A.; Cheema, S.M.; Pires, I.M. Machine Learning-Based Smart Wearable System for Cardiac Arrest Monitoring Using Hybrid Computing. *Biomed. Signal Process. Control* **2024**, *87*, 105519. <https://doi.org/10.1016/j.bspc.2023.105519>.
18. Yan, Y.; Zhang, J.-W.; Zang, G.-Y.; Pu, J. The Primary Use of Artificial Intelligence in Cardiovascular Diseases: What Kind of Potential Role Does Artificial Intelligence Play in Future Medicine? *J. Geriatr. Cardiol.* **2019**, *16*, 585–591. <https://doi.org/10.11909/j.issn.1671-5411.2019.08.010>.
19. Sun, X.; Yin, Y.; Yang, Q.; Huo, T. Artificial Intelligence in Cardiovascular Diseases: Diagnostic and Therapeutic Perspectives. *Eur. J. Med. Res.* **2023**, *28*, 242. <https://doi.org/10.1186/s40001-023-01065-y>.
20. Rani, P.; Kumar, R.; Ahmed, N.M.O.S.; Jain, A. A Decision Support System for Heart Disease Prediction Based upon Machine Learning. *J. Reliab. Intell. Environ.* **2021**, *7*, 263–275. <https://doi.org/10.1007/s40860-021-00133-6>.

21. Kishor, A.; Jeberson, W. Diagnosis of Heart Disease Using Internet of Things and Machine Learning Algorithms. In Proceedings of the Second International Conference on Computing, Communications, and Cyber-Security, Gujarat, India, 6–7 February 2021; Lecture Notes in Networks and Systems; Springer: Singapore, 2021; pp. 691–702, ISBN 9789811607325.
22. Habib, F.A.; Shakil, G.S.; Iqbal, S.S.M.; Sajid, S.T.A. Self-Diagnosis Medical Chatbot Using Artificial Intelligence. In *Algorithms for Intelligent Systems*; Springer: Singapore, 2021; pp. 587–593, ISBN 9789811567063.
23. Sadad, T.; Bukhari, S.A.C.; Munir, A.; Ghani, A.; El-Sherbeeney, A.M.; Rauf, H.T. Detection of Cardiovascular Disease Based on PPG Signals Using Machine Learning with Cloud Computing. *Comput. Intell. Neurosci.* **2022**, 2022, 1672677. <https://doi.org/10.1155/2022/1672677>.
24. Gaea Marelle Miranda, M.S. Photoplethysmography (PPG) for Heart Disease. Available online: [https://www.news-medical.net/health/Photoplethysmography-\(PPG\)-for-Heart-Disease.aspx](https://www.news-medical.net/health/Photoplethysmography-(PPG)-for-Heart-Disease.aspx) (accessed on 15 August 2025).
25. Lee, H.Y.; Kim, Y.J.; Lee, K.H.; Lee, J.H.; Cho, S.P.; Park, J.; Park, I.H.; Youk, H. Substantiation and Effectiveness of Remote Monitoring System Based on IoMT Using Portable ECG Device. *Bioengineering* **2024**, 11, 836. <https://doi.org/10.3390/bioengineering11080836>.
26. Georgieva-Tsaneva, G.; Cheshmedzhiev, K.; Tsanev, Y.-A.; Dechev, M.; Popovska, E. Healthcare Monitoring Using an Internet of Things-Based Cardio System. *IoT* **2025**, 6, 10. <https://doi.org/10.3390/iot6010010>.
27. UCI Machine Learning Repository. Available online: <https://archive.ics.uci.edu/dataset/45/heart+disease> (accessed on 15 August 2025).
28. Rohan, D.; Reddy, G.P.; Kumar, Y.V.P.; Prakash, K.P.; Reddy, C.P. An Extensive Experimental Analysis for Heart Disease Prediction Using Artificial Intelligence Techniques. *Sci. Rep.* **2025**, 15, 6132. <https://doi.org/10.1038/s41598-025-90530-1>.
29. Srinivasan, S.; Gunasekaran, S.; Mathivanan, S.K.; M. B, B.A.M.; Jayagopal, P.; Dalu, G.T. An Active Learning Machine Technique Based Prediction of Cardiovascular Heart Disease from UCI-Repository Database. *Sci. Rep.* **2023**, 13, 13588. <https://doi.org/10.1038/s41598-023-40717-1>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.