Heart health prediction and classification: an IoMT and AI collaborative model

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Abstract. Internet of Things (IoT) technology has been used in medical care as the Internet of Medical Things (IoMT) to gather sensor data for diagnosing and predicting cardiac disease. IoMT allows users to access real-time tracking information and manually estimate the person's health using Machine Learning (ML) algorithms. The primary goal of the study proposal is to categorize data and forecast heart illness using health information and medical imagery. The suggested IoMT-based Heart Health Prediction and Classification (IoMT-HHPC) model is a medical data categorization and forecasting framework in two phases. If the first stage's outcome effectively predicts heart disease, the second step is image classification. Data collected from medical equipment attached to the person's body were initially categorized. Echocardiography (ECG) images were analyzed to forecast cardiac problems. This article used many ML techniques to forecast cardiac disease. An IoMT-HHPC model with ANN achieved an accuracy of 99.02%, surpassing the performance of other ML algorithms.

1 Introduction to heart health prediction and IoMT

The IoMT is a connected system with medical sensors and equipment that revolutionizes healthcare by enabling instant data gathering, remote surveillance, and seamless interaction between gadgets and medical providers. The primary goal of the proposed framework is to enhance the accuracy and efficiency of predicting heart diseases by combining DL techniques with the IoMT platform [1]. The structure aims to provide early detection of

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risk factors for cardiovascular disease and support healthcare practitioners in making educated choices by analyzing intricate patterns in health information. The IoMT's continuous monitoring capabilities allow immediate intervention and personalized therapeutic strategies.

Cloud Computing (CC) provides adaptable, on-demand services with almost unlimited processing and storage capabilities simultaneously [2]. CC and the Internet of Things (IoT) synergize while following distinct developmental trajectories. The CC-IoT paradigm, formed by integrating these technologies, has exceptional potential for advanced application and service development. IoT-driven solutions have revolutionized the medical field by gathering, monitoring, and managing patients' vital signs via sensor networks and wearable devices. CC and IoT enable the storage and analysis of large volumes of medical and sensor information for medical analytics.

Medical analytics utilizes systematic qualitative and quantitative analyses to facilitate informed choices. Prediction analytics is a complex field that uses historical data to forecast future occurrences. Various methodologies, ranging from traditional linear models to advanced AI and ML algorithms, assist with statistical analysis for medical purposes [3]. Deep learning (DL), a subset of ML, is proficient at processing complex medical information and generating practical ideas and solutions.

The Recurrent Neural Network (RNN) is notable in time-sequential applications for its ability to capture temporal relationships [4]. Chronic cardiac diseases are becoming more common due to the increasing number of elderly individuals worldwide. Constant, real-time tracking of patients is essential to deal with this issue. The growing use of the IoT has led to the development of wearables and linked devices equipped with medical sensors, allowing for distant surveillance of cardiac disease in patients. The IoT sensors collect important data sent to the CC for in-depth analysis and storage with previous healthcare records [5].

In conclusion, integrating CC-IoT technologies provides a groundbreaking approach to patient care. Healthcare professionals may use IoT devices and wearables to continuously monitor patients and get data for prompt decision-making, personalized treatment, and risk evaluation. IoT, CC, and predictive analytics provide efficient, proactive, patient-centered medical services [6].

Heart attacks and strokes are responsible for 85% of deaths related to cardiovascular disease, occurring prematurely [7]. Timely actions may prevent premature deaths by recognizing those at risk. Here is where the IoT, AI, and ML-powered prediction algorithms demonstrate their effectiveness in handling large amounts of diverse information. In the medical industry, identifying and grouping sickness patterns relies on categorizing patterns, a crucial aspect of supervised learning. Researchers developing algorithms to identify cardiac disease aim for the highest possible accuracy due to its significant impact on patient's well-being.

2 Related works on heart disease prediction, AI, and IoMT

Forecasting and categorizing heart health is essential for proactive healthcare management, especially with the rise of IoMT and AI technology. This literature review examines the latest developments in this field, investigating several strategies suggested by researchers to use IoMT and AI for predicting and categorizing heart-related ailments. This survey offers insights into various methodologies and innovations that are advancing heart health prediction and classification, such as federated learning in health service providers, IoT-based remote monitoring systems for heart failure patients, deep learning models integrated with IoMT for disease prognosis, and secure IoMT frameworks for disease prediction.

Yaqoob et al. (2023) suggested a hybrid classifier-based federated learning method for predicting cardiovascular disease in healthcare professionals [8]. They obtained favorable outcomes with a 91% accuracy rate, showcasing the efficacy of federated learning in maintaining data privacy during collaborative model training in dispersed healthcare systems.

Umer et al. (2023) created an IoT-enabled remote monitoring system for individuals with heart failure. Their technology enabled the immediate monitoring of vital signs and early identification of abnormalities, leading to prompt treatments and enhanced patient results [9]. The system's scalability and interoperability might provide issues when implementing it on a big scale. Singh et al. (2024) used DL and the IoMT to predict cardiac illness. Their model demonstrated a 92% accuracy, highlighting the promise of using sophisticated technology for precise and early detection of cardiovascular problems [10].

Abbas et al. (2023) suggested a safe IoMT architecture for illness prediction by incorporating transfer learning into healthcare 5.0. Although their method improves security and model strength, the capacity to transfer learned characteristics across various healthcare environments may need further research [11]. Talha and colleagues (2022) investigated the monitoring of cardiovascular health using IoMT and Edge-Artificial Intelligence (AI). The research emphasized the significance of edge computing for processing medical data in real time, decreasing latency, and facilitating prompt treatments [12]. However, difficulties concerning edge infrastructure and dependability may need attention.

Petreska and colleagues (2023) examined machine learning methods for predicting heart disease outcomes using IoMT devices [13]. The comparison showed that ensemble learning approaches performed better than individual classifiers, highlighting the need to use various algorithms for precise illness forecasting. Adewole et al. (2021) introduced a cloud-based IoMT architecture for predicting and diagnosing cardiovascular illness in tailored E-healthcare. Although the architecture provides scalability and accessibility benefits, it is crucial to address concerns about data privacy and security in cloud contexts [14].

Baseer et al. (2024) suggested an adaptable deep learning model combined with IoMT for healthcare diagnostics [15]. Their model demonstrated the potential of DL in using diverse medical data from IoMT devices for accurate illness prediction and diagnosis, achieving a high accuracy of 94%. Ultimately, this literature review highlights the substantial progress in predicting and categorizing heart health by combining IoMT and AI technology. The evaluated research has shown the effectiveness of many methods, including federated learning, remote monitoring systems, DL models, and secure IoMT frameworks.

3 Proposed IoMT-based heart health prediction and classification (IoMT-HHPC)

The model created for health information categorization and forecasting utilizes AI and ML methods. Fig. 1 depicts the architecture of the proposed IoMT-based Heart Health Prediction and Classification.

Sensors (wearables) and databases are crucial elements of the proposed study—the suggested model functions in two phases. Healthcare sensors attached to a patient's body create information from the sensors in the initial phase, followed by the subsequent step where ECG images are classified. Once each categorization process is completed, the results are combined and verified to predict heart disease. The categorization model is binary, with results indicating the existence or absence of ailments.

The research collected and recorded sensor data, with the ECG sensor signals sampled at 50 Hz. Information has been sent to the network via Bluetooth and saved as .csv files. The personalized echocardiography image data collected in a private setting under medical supervision has been utilized for the image categorization study. The files have been saved in a cloud repository. Feature selection was performed using ResNet-101, and several ML classifiers have been employed for classification. A specialist has verified the categorized data and images to ascertain whether the patient had heart disease. In wearable form, medical data has been gathered using ECG, pulse oximeter, temperature, and blood pressure sensors. The sensors collected ECG, pulse, arterial pressure, and temperature data when attached to the human body. The data was collected and stored in the cloud via IoT technologies.

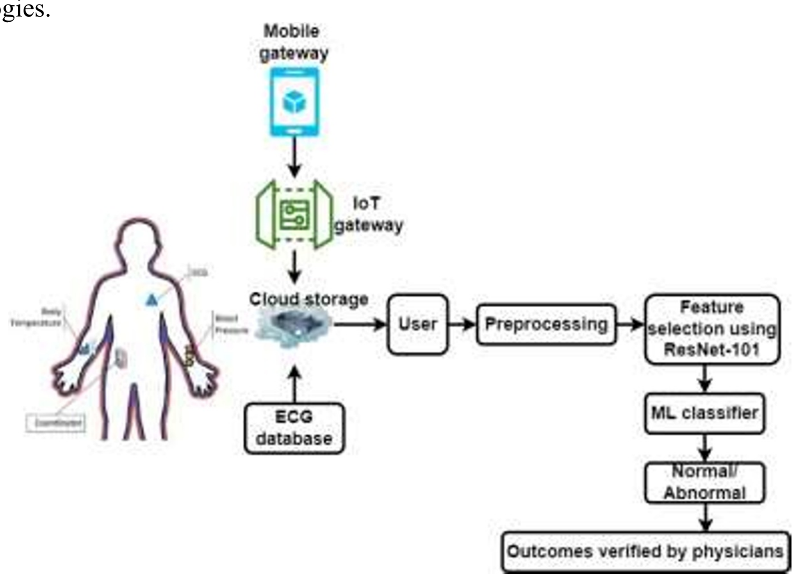


Fig. 1. Architecture of the proposed IoMT-based heart health prediction and classification

3.1 Preprocessing

The first phase of the classification model involves preprocessing, which consists of three steps: replacing missing characteristics, eliminating redundant information, and separating. After evaluating the patient's age, heart rate, and cholesterol levels, any missing data for these parameters was included. The value was adjusted if most of a patient's characteristic values aligned.

3.2 Feature selection using ResNet-101

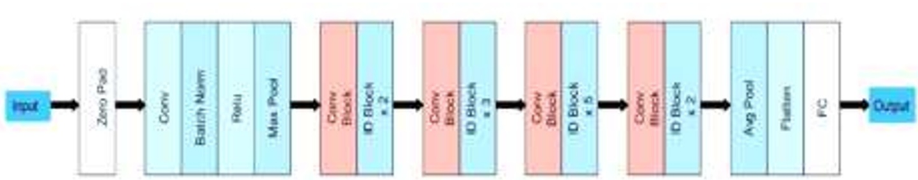


Fig. 2. Architecture of ResNet-101

ResNet-101 is a Convolutional Neural Network (CNN) architecture part of the ResNet (Residual Network) model group. Kaiming He et al. presented it in their 2015 publication "Deep Residual Learning for Image Recognition." ResNet-101 is an enhanced version of the original ResNet structure, created to tackle the disappearing gradient issue that arises when training deep neural networks.

Input Layer: The block diagram commences with the input layer, symbolizing the incoming picture or data. Each block in the diagram represents a layer or a collection of layers inside the ResNet-101 architecture.

Convolutional layers (CL): The essence of ResNet-101 is a series of CLs organized in a hierarchical structure. These layers extract characteristics from the supplied data. Each CL in the block diagram is shown as a rectangular block labeled with the kernel size and the number of filters.

Residual Blocks: Residual blocks (RB) are the fundamental components of ResNet-101. The RB has many CL, Batch Normalization (BN), and ReLU activation algorithms. The skip connection is a straight line that skips one or more CLs, adding the input of the block to the output of the block.

Bottleneck design: ResNet-101 utilizes a bottleneck design in its RB to enhance computational efficiency. The bottleneck blocks include 1x1, 3x3, and 1x1 convolutions and BN and ReLU activation algorithms. This architectural component may be a distinct RB, including supplementary 1x1 convolutions.

Layer stacking: The block diagram illustrates the stacking of RB to create the deep layers of ResNet-101. The network's stages consist of varying numbers of RB, with the number of blocks rising as the network becomes more complex.

Global Average Pooling: This layer is often seen in ResNet-101 after the convolutional layers. Its purpose is to decrease the spatial dimensionality of the feature maps. This layer is shown as an individual block in the block diagram.

Fully connected (FC) layer: ResNet-101 usually incorporates one or more FC layers for classification after the global average pooling layer. The layers are rectangular blocks identified as completely linked or dense.

Softmax activation: The last layer of ResNet-101 often uses a softmax activation function to provide probability ratings for various classifications. This layer is shown as an extra block after the FC layers.

3.3 ML classifiers

ML classifiers are essential in categorizing cardiac illnesses by examining different aspects derived from medical data [16]. Common ML classifiers used in this scenario include:

Logistic Regression (LR) is a linear classification technique that predicts the likelihood of an event happening by considering one or more independent variables. LR may be used in heart disease categorization to forecast the probability of a patient having a certain kind of heart disease using factors like age, gender, cholesterol levels, and blood pressure.

Support Vector Machine (SVM) is a potent supervised learning technique that excels in linear and non-linear classification applications. SVM operates by identifying the hyperplane that most effectively divides distinct classes within the feature space. SVM may be used in heart disease classification to differentiate between distinct heart disorders using a range of clinical and diagnostic factors.

Random Forest (RF) is an ensemble learning technique that creates many decision trees during training and provides the most frequent class (classification) or the average prediction (regression) of the individual trees as the output. RF efficiently classifies heart illness because it can manage data with many dimensions and understand intricate connections between different characteristics.

Gradient Boosting Machines (GBM) is an ensemble learning method that constructs a series of decision trees, with each tree aimed at rectifying the mistakes made by the preceding one. Gradient Boosting Machine enhances the model's accuracy by reducing a loss function during iterations. GBM in heart disease classification may improve prediction accuracy by learning from errors made by earlier trees and using a mix of variables.

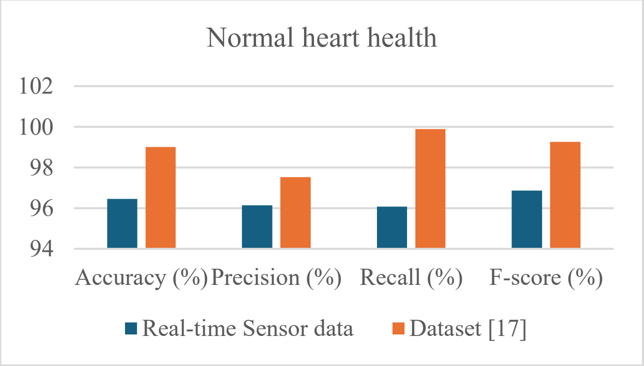
Artificial Neural Networks (ANNs) are machine learning models that draw inspiration from the structure and function of the human brain. ANNs are composed of linked neurons that are structured in layers, including input, hidden, and output layers. Artificial neural networks (ANNs) can effectively identify intricate patterns and connections within data, making them well-suited for classifying cardiac diseases with interrelated input characteristics.

K-Nearest Neighbors (KNN) is a classification technique that assigns a class label to a new data point by considering the majority class of its k closest neighbors in the feature space. KNN is appropriate for heart disease classification jobs with limited or changing datasets due to its ability to adapt to new data quickly without the need for training.

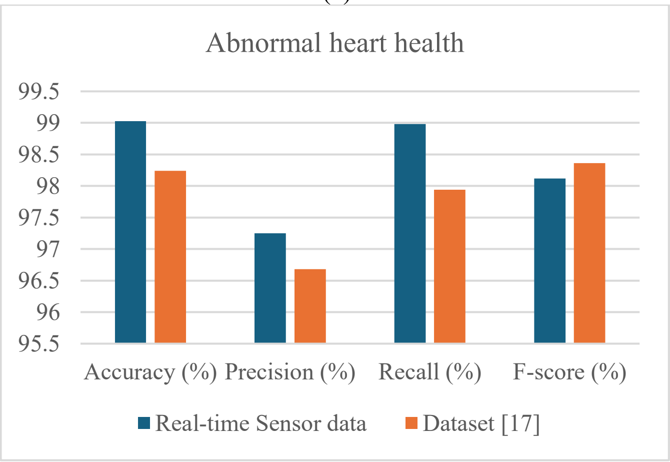
ML classifiers may be trained on labeled datasets, including patients' medical history, diagnostic tests, and other relevant aspects, to effectively predict the presence or absence of different cardiac conditions. The selection of a classifier relies on several elements, including the data's characteristics, the required interpretability level, and the computing resources at hand.

4 Results and discussion

The simulation has been evaluated using the MATLAB Simulink tool, version 2019a. The studies have been conducted on a PC equipped with an Intel Core i5-CPU operating at speeds ranging from 2.5 to 4.8 GHz, 4 GB of RAM, and running a 64-bit Windows 10 operating system. The proposed model has been evaluated using the Cleveland database from the UCI repository [17].



(a)



(b)

Fig. 3. Normal and abnormal heart health conditions compared by utilizing the proposed IoMT-HHPC approach

Fig. 3 compares normal and abnormal heart health states using the proposed IoMT-HHPC technique. During normal data collection, real-time sensor data and the dataset from reference [17] both demonstrate great accuracy, with values of 96.46% and 99.01%, respectively. The precision, recall and F-score measures demonstrate high performance for both datasets. The real-time sensor data reaches an accuracy of 99.03% for aberrant data collection, compared to 98.24% achieved by the dataset from reference [17]. The study demonstrates that the IoMT-HHPC technique successfully distinguishes between normal and abnormal heart health situations, indicating its potential for reliable monitoring and diagnosis.

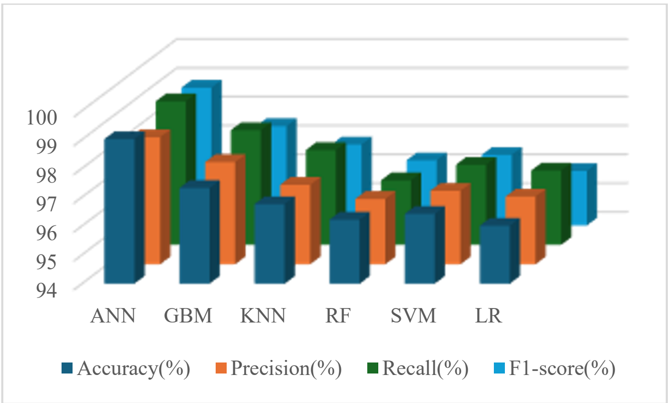


Fig. 4. Performance analysis of various ML algorithms in the proposed IoMT-HHPC framework

Fig. 4 displays the performance study of several ML algorithms in the IoMT-HHPC framework. ANN had the greatest accuracy of 99.02% among the examined methods, along with outstanding precision, recall, and F1-score metrics. GBM has a somewhat reduced accuracy compared to other methods but still maintains competitive precision and recall levels. KNN, RF, SVM, and LR perform well, achieving 96.01% and 96.76% accuracy. The findings highlight the efficiency of ML algorithms in precisely predicting and categorizing heart health issues in the IoMT-HHPC framework, providing significant information for medical professionals and patients.

5 Conclusion

The IoMT-HHPC model is a two-stage medical data classification and forecasting methodology. If the first phase's result accurately forecasts cardiac disease, the subsequent step involves image categorization. The data from medical equipment connected to the person's body has been classified. ECG images and sensor data were examined to predict heart issues. The personalized echocardiography image data collected in a private setting under medical supervision has been utilized for the image categorization study. The files have been saved in a cloud repository. Feature selection was performed using ResNet-101, and several ML classifiers have been employed for classification. The paper used several ML algorithms to predict heart illness. The proposed IoMT-HHPC model using ANN had an accuracy of 99.02%, outperforming other ML techniques.

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