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CardioHelp: A Smartphone Application for Beat-by-beat ECG Signal Analysis for Real-time Cardiac Disease Detection Using Edge-Computing AI Classifiers

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ABSTRACT

Cardiovascular diseases are a leading cause of morbidity and mortality worldwide. To diagnose cardiac diseases, physicians often utilize a combination of medical history, physical examination, and several diagnostic tests, such as electrocardiograms (ECG/EKG), echocardiograms, and stress tests. Early detection and effective management of cardiac diseases play a crucial role in improving patient outcomes and reducing healthcare burden. To address this concern, we introduce a novel edge-computing approach for cardiac healthcare using a smartphone application (CardioHelp) that combines heart rate monitoring with the detection of abnormal heartbeats in individuals. Our approach centers around a user-friendly smart-health application designed to visualize ECG signals, track and monitor heart rate continuously, and recognize and notify users of any anomalies through advanced beat-by-beat ECG analysis algorithms and artificial intelligence (AI) techniques including machine learning and deep learning. Our system includes a custom wearable ECG data collection system that can transfer data to CardioHelp in real-time. In this study, we have used the MIT-BIH Arrhythmia dataset to train deep learning models using intricate patterns and features representative of various heart conditions. Among the deep learning models, the Long Short-Term Memory (LSTM) demonstrated superior performance, obtaining an accuracy of 98.74% and precision and recall of 99.95% and 99.86%, respectively. By transferring the MIT-BIH Arrhythmia Database's test dataset through our application as mock real-time data, we assessed our CardioHelp application's accuracy in identifying and classifying various heart conditions. The LSTM model is found to be the most accurate model providing an accuracy of 95.94% for ECG beat classification. The results confirmed the effectiveness of our developed smartphone system, demonstrating its ability to accurately detect and classify cardiac conditions. As our novel approach presents a complimentary cardiac healthcare system using a smart health application, this CardioHelp has the potential to significantly enhance preventive care, enable early intervention, and improve overall cardiovascular health outcomes.

1. Introduction

Cardiac disease, also known as cardiovascular disease (CVD), refers to a group of conditions that affect the heart and blood arteries, such as coronary artery disease, stroke, heart failure, and peripheral artery disease. CVD is a global health burden, responsible for a significant number of deaths and disabilities each year (Glovaci et al. (2019)). Risk factors for CVD include modifiable factors such as an unhealthy diet, physical inactivity, tobacco use, and excessive alcohol consumption, as well as non-modifiable factors such as age, gender, and family history. Untreated

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heart disease has the potential to result in severe consequences such as heart attacks or strokes (Swanoski et al. (2012)). Detecting and managing CVD in its early stages is essential for preventing complications and improving outcomes. Delayed disease diagnosis results in complex treatments and reduced quality of life for patients, leading to increased healthcare burdens and costs.

Detecting diseases at earlier stages improves treatment outcomes. While modern technology has advanced clinical healthcare with precision diagnostics and remote consultations, early disease detection in pre-clinical living lab environments remains a challenge. Continuous analysis of vital signs (heart rate, respiratory rate, oxygen saturation, and blood pressure) can predict or detect neonatal pathophysiology, offering the potential to improve outcomes and mitigate neonatal diseases using big-data analytics (Kumar et al. (2020)). Several methods are commonly used for detecting heart problems, including electrocardiograms (ECG), echocardiograms, cardiac catheterization, nuclear imaging, and cardiac magnetic resonance imaging (MRI). One widely used method for detecting heart problems is analyzing electrocardiogram (ECG) signals. Wearable devices and smart health (sHealth) apps are becoming more popular as Internet-of-Things (IoT) technology is integrated into heart disease monitoring (Walker & Muhlestein (2018)). These devices can continuously monitor and record real-time data on an individual's physiological state and physical activities. Modern wearable sensors possess the remarkable ability to capture a variety of physiological indicators, including electrocardiogram (ECG), electromyogram (EMG), heart rate (HR), body temperature, respiration rate (RR), etc (Pantelopoulos & Bourbakis (2009)). Wearable sensors are connected to IoT devices via Bluetooth Low Energy (BLE), ZigBee, and ANT protocols for data transmission while BLE typically exhibits lower power consumption (Dementyev et al. (2013)).

Smart Health applications use advanced algorithms and machine learning to analyze ECG signals, monitor heart rate, enable early detection of heart diseases, and provide timely alerts for intervention. We found related articles on mobile apps for detecting CVDs using different technologies. Lee et. al developed a novel QRS detection algorithm and applied it to the analysis of heart rate variability (HRV) of patients with sleep apnea (Lee et al. (2005)). Galli et. al presented a Holter monitor as a portable device that records a person's heart activity continuously for 24 to 48 hours, allowing for the detection of abnormal heart rhythms and other cardiac abnormalities during daily activities (Galli et al. (2016)). Samuel et. al proposed a hybrid method for heart failure (HF) risk prediction based on ANN and Fuzzy analytic hierarchy process (AHP) techniques (Samuel et al. (2017)). KardiaMobile is a portable ECG device that can be attached to a smartphone, enabling individuals to record and monitor their heart activity anytime and anywhere, facilitating early detection of potential cardiac issues (Koltowski et al. (2021)). It has been demonstrated to be successful in diagnosing atrial fibrillation (AF) in clinical investigations, with a sensitivity of 96.6% and a specificity of 94.1% (William et al. (2018)). Mazaheri et. al also presented a computer-aided diagnosis (CAD) system for automated classification and accurate diagnosis of seven types of cardiac arrhythmias using ECG signals by combining morphological, frequency, and nonlinear feature extraction techniques (Mazaheri & Khodadadi (2020)). An electrocardiogram (ECG) check is a portable device, like KardiaMobile, that uses two or more electrodes to record the electrical activity of the heart (Haverkamp et al. (2019). With a high detection rate for AF, the ECG Check showed acceptable sensitivities and specificities in identifying several abnormal rhythms. Apple Watch records heart rate as photoplethysmography (PPG) waveforms during periods of minimal arm movement. If an irregular heart rate is detected, the algorithm triggers tachograms. After receiving 4 confirmatory tachograms, the participant is alerted via phone notification to connect with a Telehealth doctor for further evaluation (Raja et al. (2019)). iHealth Rhythm and QuardioCore are some other devices that offer convenient and accessible means for individuals to monitor their heart health through ECG measurements Ali et al. (2021); Kuzmin et al. (2017). Previously, a different smart health framework had been developed by our research team using body-worn flexible Inkjet-printed (IJP) sensors, commercial wearables like smart wristbands, a scanner on a printed circuit board, and specialized smartphone software (Rahman et al. (2022)).

In the field of healthcare, the integration of artificial intelligence (AI) has revolutionized the detection and diagnosis of abnormalities in various medical conditions, including cardiovascular health. Altan et. al proposed a model using a Deep Belief Network (DBN) classifier that classified the MIT-BIH Arrhythmia Database heartbeats into 5 main groups defined by ANSI/AAMI standards (Altan et al. (2016)). In our study, we have successfully integrated AI techniques, particularly in the form of deep learning models, to detect abnormalities in electrocardiogram (ECG) signals. Our CardioHelp application is based on *Smart Health Integrated Framework and Topology (SHIFT)* architecture that preserves Mobile Health (mHealth) for individuals to self-monitor their health and allows participants to share individual health severity data with doctors for further inspection (Morshed (2021)). This application has high scalability and low latency in addition to being low-cost and real-time.

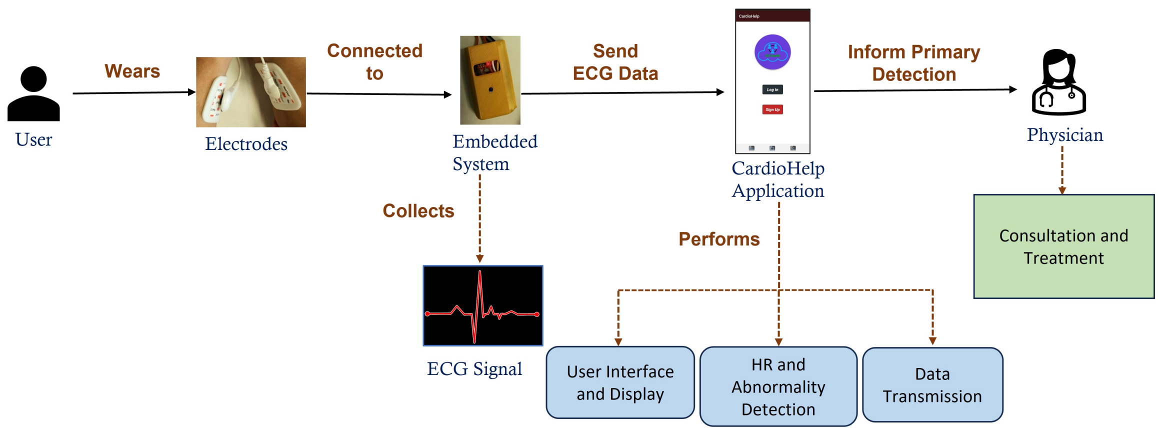


Fig. 1: Overall architecture of the system under development by our research team.

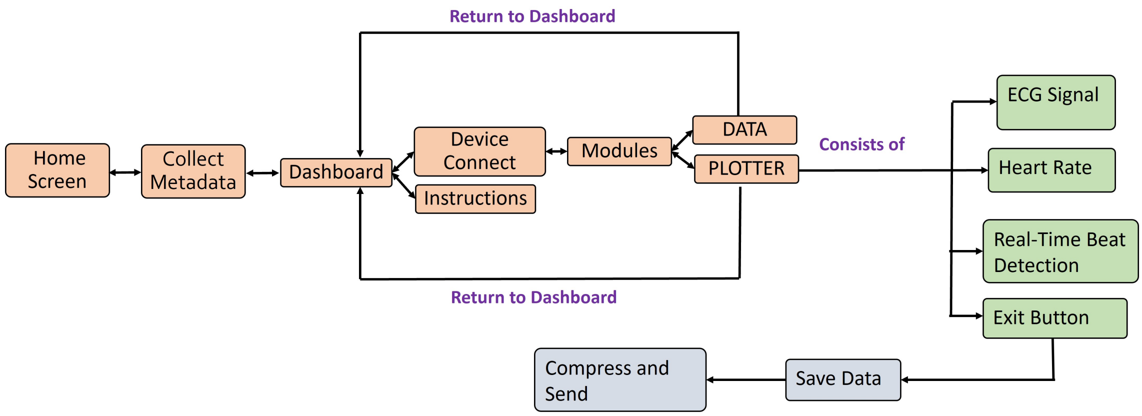


Fig. 2: Block diagram of main interactions of our CardioHelp smartphone application.

The main novelties of the proposed system include:

- CardioHelp provides a real-time graphical representation of the ECG signal, allowing users to visualize the collected signal and any issues (such as noisy data indicating issues with ECG electrodes) so that the issues can be resolved. This will increase the robustness of the system and the trust of the users.
- The application includes a heart rate monitoring feature that accurately measures and tracks the user's heart rate. It uses advanced algorithms to analyze the ECG signals and extract valuable insights that can detect irregularities or abnormal heartbeats.
- Users can store ECG data and share the information with stakeholders (such as healthcare professionals or cardiologists). This promotes seamless communication and collaboration between users and their healthcare providers, facilitating more informed decision-making and personalized care.

The remainder of this article is organized as follows: Section 2 describes the methodology used in this study, including application design, ECG data collection method, signal preprocessing, heart rate visualization, pre-trained model, and application validation. Section 3 focuses on the experimental details and presents the obtained results including heart rate comparison with KardiaMobile and detection of abnormalities. The experimental results are discussed in Section 4, while potential avenues for further research are highlighted in Section 5. Finally, the conclusions are drawn in Section 6.

2. Methodology

The entire setup of ECG monitoring and detecting diseases consists of some electrodes that are attached to the chests/wrists, a front-end ECG data collection device based on an AD8232 chip (Analog Devices, Wilmington, MA), and the CardioHelp application. Figure 1 shows the overall architecture of the entire system. The embedded system consists of Sparkfun nRF 52840 mini that is connected to the application via Bluetooth Low Energy (BLE) V5.3. Then the application collects ECG signals from users and provides a visual display on the screen. CardioHelp displays real-time heart rates and detects abnormal heartbeats, which are subsequently presented within the application's interface. These advanced features enable users to actively monitor their heart rate and promptly identify any irregularities or abnormal cardiac rhythms. The application provides users with immediate feedback and actionable insights regarding their cardiac health through a data-sharing feature that enables users to securely transmit their cardiac data to healthcare professionals. This feature promotes effective remote patient monitoring and allows for quick medical intervention.

2.1. Application Design

The CardioHelp application offers a seamless experience for users to access and monitor their ECG data, track their heart rate, detect any irregular cardiac rhythms over time, and share ECG recordings with their healthcare providers, enabling remote monitoring and diagnosis. Figure 2 displays the block diagram of the CarioHelp application.

For using the application, firstly, users are required to enter their metadata, with only the zip address being mandatory while others remain optional. Users can confidently use this application without providing any personal data. Then, users can proceed to the *Device Connect* and see the available devices to be connected via Bluetooth Low Energy (BLE) for data collection. The users can monitor real-time data on the ECG signal plotter, and then visualize their heart rate and track any abnormalities over an extended period. The ECG recordings and heart rates are stored in separate CSV files, which are located in a specific folder on the user's smartphone. In Android 10 (API level 29) and higher, applications are required to request the *MANAGE_EXTERNAL_STORAGE* permission to obtain write access to shared storage. Requesting the *WRITE_EXTERNAL_STORAGE* permission alone may not be sufficient to create files in specific directories.

The collected health data undergoes a secure process within the CardioHelp application. After the application is closed, all the data is automatically compressed into a ZIP archive to facilitate convenient transmission. Users have control over sharing, and initiating the process by selecting physicians' email addresses. The ZIP archive, containing metadata, ECG data, and heart rates, is then attached to an email and sent to the chosen physicians, ensuring that sensitive health information remains protected from unauthorized access. This method ensures that the data is securely transmitted to healthcare professionals for further analysis and evaluation. By following a user-friendly interface, CarioHelp empowers individuals to take control of their health and make informed decisions based on their ECG data.

2.2. ECG Data Collection

ECG data refers to the electrical activity of the heart recorded over time. It provides valuable information about the heart's rhythm, rate, and overall cardiac health. ECG data is obtained through the use of electrodes, which are small sensors that detect and transmit electrical signals generated by the heart. We collect ECG data through our custom ECG data collection device which contains a commercial nRF 52840 mini development board (Sparkfun, USA) and an AD8232 chip (Rahman et al. (2023)). The board is used in the processing unit that is paired with the application via Bluetooth. The device is equipped with a 3.7V nominal voltage Lipo battery (Pkcell LP552530), providing a capacity of 350 mAh. Despite using gel electrodes for collecting ECG data, the device is portable and can also employ other types of electrodes, such as metal and IJP electrodes. The most common placement involves attaching electrodes to the chest, wrists, and ankles. Wrist-worn devices offer the advantages of long-term monitoring during regular activities and a higher level of comfort compared to finger-worn acquisition methods (Nardelli et al. (2020)). The quality of the ECG signals acquired from the wrists can be influenced by various factors, such as the accuracy of the measuring device and its positioning relative to the heart. Generally, ECG signals obtained from the chest exhibit higher quality and greater reliability compared to signals obtained from the finger or wrist (Lourenço et al. (2011)). The Institutional Review Board (IRB) at Texas Tech University granted IRB approval for this study after a thorough consideration of the study protocol and risk factors (IRB2020-783).

2.3. Signal Pre-processing

Signal pre-processing of real-time ECG data is a crucial step in enhancing the quality and reliability of the acquired signals. It consists of a set of approaches focused on decreasing noise, eliminating artifacts, and increasing overall signal integrity for correct analysis and interpretation. In CardioHelp, the ECG signals that are collected from the embedded system are pre-processed where the frequency range of interest for ECG signals is between 0.5 Hz and 150 Hz (Golden et al. (1973)). The lower cutoff frequency of 0.5 Hz is chosen to remove any DC offset or drift in the signal and it captures the slow variations related to baseline wander. The upper cutoff frequency of 150 Hz is chosen to remove any high-frequency noise or artifacts in the signal and it captures the rapid changes associated with the electrical activity of the heart. The ECG signal is filtered on CardioHelp using bandpass filtering which allows for the selection of a specific frequency range of interest while attenuating frequencies outside this range. This targeted filtering approach helps to remove noise and artifacts that may be present in the ECG signal.

2.4. Heart Rate Visualization

The Pan-Tompkins algorithm is commonly used for QRS complex detection in ECG signals, which we use to calculate the heart rate on the CardioHelp application. Here are the necessary steps we followed to calculate the heart rate using the Pan-Tompkins algorithm:

1. **Pre-processing:** First, we applied a bandpass filter to the raw ECG signal to remove unwanted frequencies and retain the QRS complex.
2. **Differentiation:** Then, we differentiated the filtered signal to enhance the steepness of the QRS complex.
3. **Squaring:** After that, we squared the differentiated signal to emphasize the QRS complex peaks.
4. **Integration:** Then, we applied integration to smooth the squared signal and suppress noise. We used *Sliding Window Technique* to sum up the squared values over a specific window size.
5. **Peak Detection:** Then, we determined a suitable threshold level based on the signal characteristics and compared the integrated signal with the threshold to locate the QRS complex peaks, detecting local maxima as potential R-peaks.
6. **R-R Interval Calculation:** Lastly, we calculated the R-R intervals by determining the time intervals between successive R-peaks in the ECG signal. The average R-R interval is used to calculate the heart rate in beats per minute (BPM).

Also, we showed the Average Heart Rate on the application to get a better view of the heart conditions of the user. We used *Sliding Window* technique for that.

2.5. Deep Learning Models

In the CardioHelp application, we employed pre-trained models for real-time medical condition diagnosis. Figure 3 illustrates the training of the deep learning models and their subsequent utilization in the application for beat detection purposes. We used the MIT-BIH Arrhythmia Database for training the model, which contains ECG recordings of patients with different arrhythmias (Goldberger et al. (2000)).

We annotated the ECG recordings with corresponding labels from the five classes: N (normal heartbeats), SV (Supraventricular Ectopic beats), V (Ventricular Ectopic beats), F (Fusion beats), and Q (Unknown beats). After that, we normalized the ECG signal amplitudes to bring them to a common scale. We divided the records into training and testing datasets. The training dataset is used to train the models before using real-time data on the CardioHelp application. We trained three deep learning models, namely Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM) on a Python platform, resulting in impressive accuracies of 98.08%, 98.65%, and 98.74% respectively. Figure 4 represents the model architecture of all three models. The superior performance of the LSTM model can be due to its effective handling of the various temporal structures present in ECG signals. The LSTM excels at distinguishing tiny yet critical patterns required for precise beat detection by using its ability to successfully capture and utilize information over long sequences.

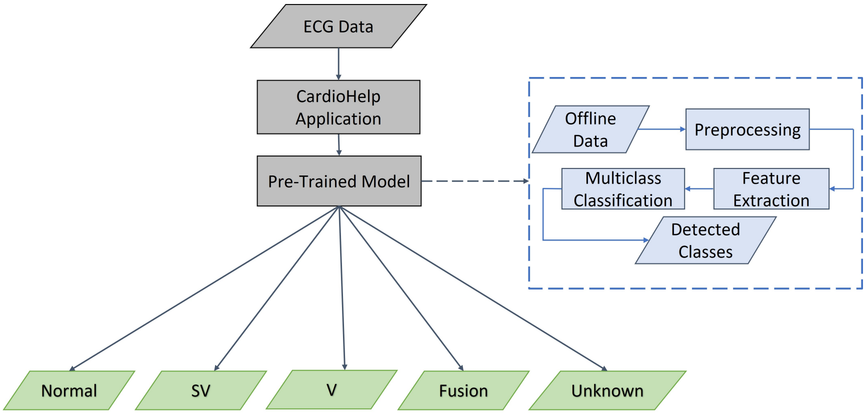


Fig. 3: A flowchart of our ECG signal classification approach.

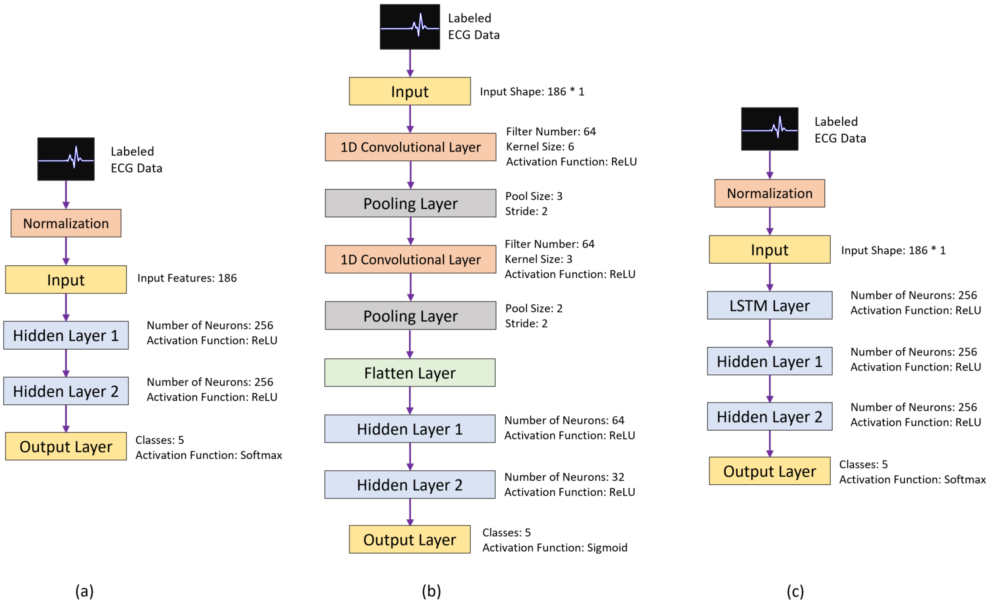


Fig. 4: Architectural representations of (a) Artificial Neural Network (ANN), (b) Convolutional Neural Network (CNN), and (c) Long Short-Term Memory (LSTM) models designed for real-time beat detection in the CardioHelp application.

2.6. Using Pre-Trained Models on the Application

Post-training, the pre-trained models were integrated into our *Android Studio Java application* for real-time utilization, for that, we followed these steps:

1. **Save and Convert the model to TensorFlow Lite format:** After training the model on *Python*, we saved it in a format that can be loaded by TensorFlow Lite on Android Studio.
   1..1 First, we saved the model as a *.h5* file using the Keras model.save() method.
   1..2 Then, we converted the pre-trained model to *.tflite* file using the TensorFlow Lite converter which is used as a pre-trained model on the CardioHelp application.
2. **Add the model in the android application:** After that, we loaded the *.tflite* file on Android Studio from *File*−*>Other*−*>Tensorflow Lite Model*. Android Studio will automatically add the file to the *ml* folder in the project structure.
3. **Add dependency:** Then, we added the TensorFlow Lite dependency to the project's build.gradle file: *implementation* '$org.tensorflow : tensorflow - lite - support : 0.1.0'$ and *implementation* '$org.tensorflow : tensorflow - lite - gpu : 2.3.0'$.
4. **Load the model:** After that, we loaded the model from the *ml* folder and created a *ByteBuffer* object to hold the input data.
5. **Get the predicted class:** Finally, we passed the ECG data through the TensorFlow Lite interpreter that performed the necessary calculations to get the predicted class.

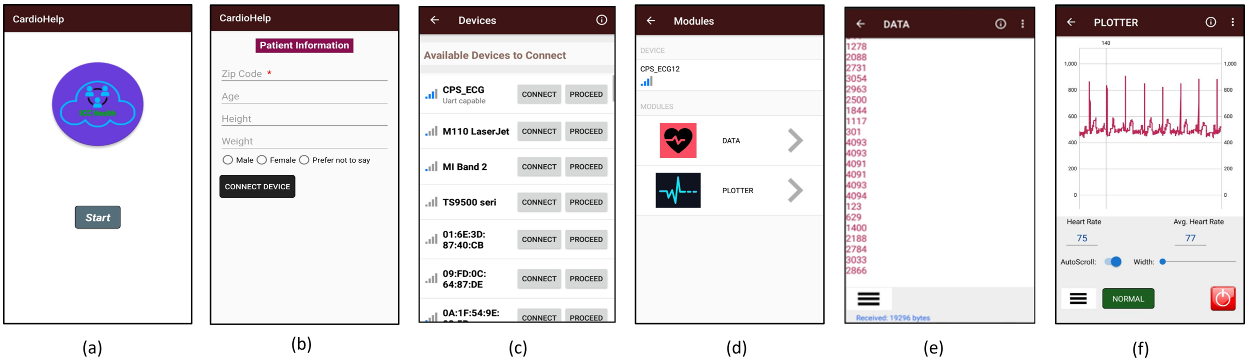


Fig. 5: Snapshots from CardioHelp smartphone application: (a) Home screen, (b) MetaData Collection, (c) Display of available devices, (d) Analysis modules, (e) Incoming streaming raw data, (f) Real-time plot of ECG trace, Heart Rate, and Cardiac Beat type (detected by AI algorithm).

2.7. Application Validation

To validate the performance of the pre-trained models, we utilized the remaining MIT-BIH Arrhythmia testing dataset. First, we selected one pre-trained model and then passed the testing samples through the model in the application and compared the predicted outputs with the corresponding ground truth labels. To incorporate the MIT-BIH testing dataset into the application, we first imported the dataset and substituted the real-time ECG data with the testing dataset's data. The ECG signals from the testing dataset were then passed as input to the pre-trained model. The model performed beat classification in the CardioHelp application, assigning each beat to a specific category. We did this with all three of the pre-trained models individually. The models' predictions were subsequently analyzed, and their performance was evaluated using confusion metrics. This process allowed us to utilize the pre-trained model effectively for accurate beat detection and classification within the context of the MIT-BIH testing dataset in the application.

Based on the successful validation of the pre-trained model with the MIT-BIH testing dataset, we can now proceed to conduct a pilot study on patients using real-time ECG data. With the availability of real-time data, the application can effectively detect abnormalities in the ECG signals, allowing for continuous monitoring and timely identification of any irregularities or cardiac issues. Figure 5 shows some snapshots of the CardioHelp application on real-time ECG data. In the *Plotter* screen of the application, real-time ECG signals, heart rates, and cardiac beats are displayed.

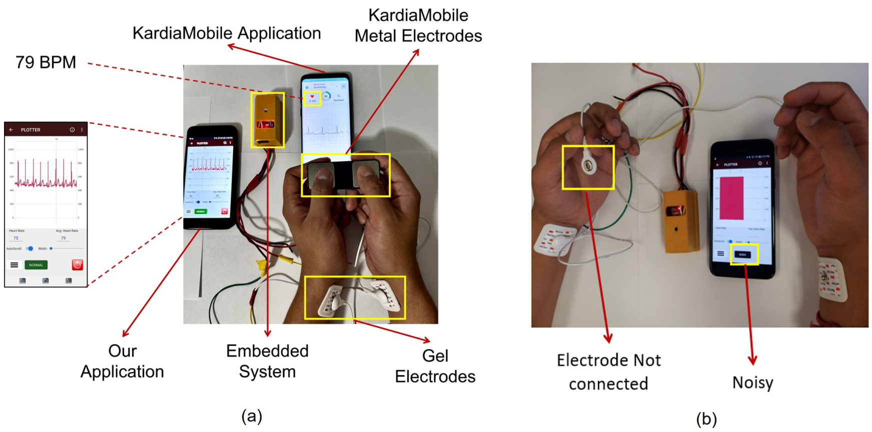


Fig. 6: Real-time data collection and analysis with concurrent data capture with CardioHelp and KardiaMobile Applications: (a) Proper ECG signals and (b) Noisy signals.

3. Results

3.1. Heart Rate Comparison with KardiaMobile

In our previous work, we evaluated the performance of the CardioHelp application in terms of heart rate measurements with the KardiaMobile device (Utsha & Morshed (2023)). The objective was to evaluate the accuracy and reliability of the application in heart rate measurement. At that time, we collected data from 10 participants for a duration of 5 minutes each and compared the heart rate obtained from our application with KardiaMobile. CardioHelp application achieved a heart rate detection accuracy rate of 95-99%. This comparison provides insights into the application's performance and its potential as a convenient tool for heart rate monitoring in real-world scenarios.

Figure 6 shows an illustration of the real-time data collection process. Figure 6(a) shows that the user's ECG signal is normal and that the average heart rate is 79 bpm on our application and KardiaMobile. The electrodes can be detached to produce fake noise, which leads to a Signal with noise (Figure 6(b)).

In this study, we collected data from three participants in a resting state for a duration of 30 minutes and conducted a simultaneous comparison with KardiaMobile. The comparison can be observed in Figure 7.

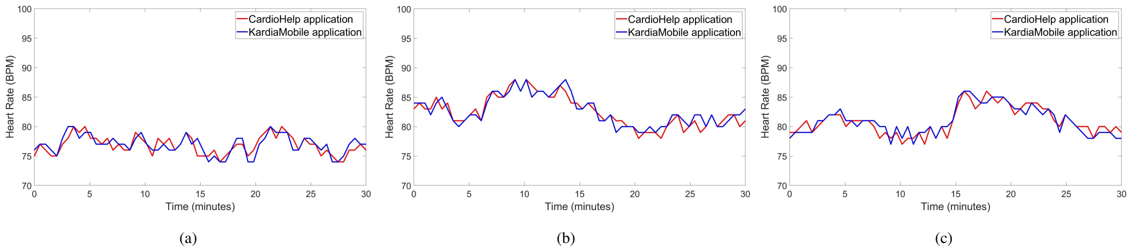


Fig. 7: Comparison of heart rate computation between CardioHelp application and KardiaMobile application on (a) Subject 1, (b) Subject 2, and (c) Subject 3.

We also calculated the average Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) value of three participants by comparing the heart rate data obtained from our application with the data obtained from KardiaMobile. In the following equations, y_i represents the truth values, $\hat{y}_i$ represents the predicted values, and $\bar{y}$ represents the mean of the truth values.

1. $$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

   MAE measures the average absolute difference between the truth value of Heart Rate which is from KardiaMobile and predicted values which is from the CardioHelp application. It provides a measure of the average magnitude of errors without considering their direction. The calculated MAE value is 0.75, indicating that the typical absolute deviation of the heart rates predicted by the CardioHelp application is closer to the heart rates from KardiaMobile.

2. $$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

   $$RMSE = \sqrt{MSE}$$

   The calculated RMSE value is 1.05 which indicates that the heart rate predictions closely match the actual values, reflecting high accuracy and minimal error.

3. $$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

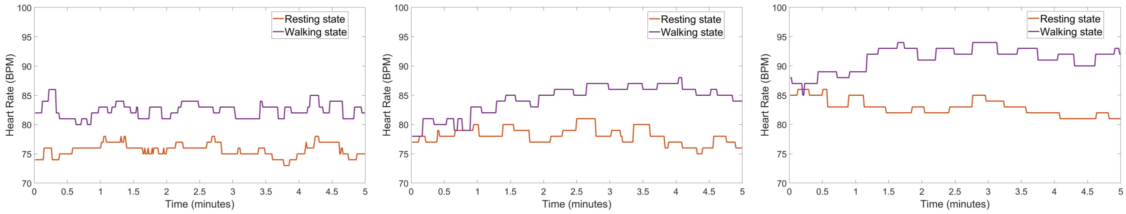
   Here, the R^2 value is 0.73 indicating that approximately 73% of the total variation in KardiaMobile's heart rate (dependent variable) can be explained by the heart rate predictions from CardioHelp (independent variable). This suggests a relatively good relationship between the predicted and actual heart rates, with the model accounting for a significant portion of the variability in KardiaMobile's heart rate data. However, it's important to note that the 73% R^2 value is partly due to the difference in data collection methodologies.

There is a significant distinction in data handling between the CardioHelp and the commercial KardiaMobile application. Our CardioHelp application collects real-time data and displays heart rates using a moving window average, while KardioHelp updates heart rates every 30 seconds, initiating a new calculation each time. This disparity in data handling may lead to a mismatch, and we posit that our application's approach, with continuous real-time updates, contributes to superior performance compared to KardioHelp.

During our study, we also gathered data from three participants under two different conditions: resting state and walking state, using our CardioHelp application. Each session lasted for 5 minutes. Figure 8 presents a comparison between the heart rates observed during these two states. It was observed that there was a difference of approximately 5-10 beats per minute (bpm) between the resting state and walking state heart rates. This finding highlights the impact of physical activity on heart rate and underscores the ability of our application to capture and analyze such variations effectively.

3.2. Detection of Abnormalities

The proposed abnormality detection algorithms achieved high accuracy in accurately identifying and classifying abnormal ECG patterns on the MIT-BIH dataset during training. Figure 9 presents a comparative analysis of the performance of various deep-learning techniques in detecting and classifying cardiac rhythms. First, we implemented the algorithm on a *Python* platform, ensuring its accuracy and reliability. The ANN algorithm achieved an accuracy of 98.08% in detecting abnormalities, while the CNN algorithm achieved 98.65% accuracy, and the LSTM algorithm outperformed them both with an accuracy of 98.74%. Then we integrated this pre-trained model as *.tflite* format on our application. To evaluate



(a) (b) (c)

Fig. 8: Comparison of heart rates using CardioHelp Application for resting state and walking state on (a) Participant 1, (b) Participant 2, and (c) Participant 3.

the performance of the pre-trained model, the MIT-BIH testing dataset was passed as input into the CardioHelp application. These predicted labels were then compared with the ground truth values of the dataset, allowing for an assessment of the model's accuracy and performance in correctly classifying different cardiac rhythms and abnormalities. We achieved remarkable accuracy rates of 90.74% on ANN, 93.91% on CNN, and an exceptional 95.94% on LSTM after passing the MIT-BIH testing dataset as input instead of real-time ECG data. This indicates the robustness and reliability of the models in accurately detecting and classifying various cardiac rhythms and abnormalities in real-time scenarios.

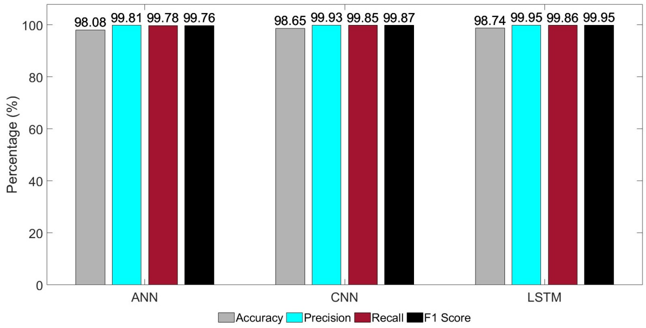


Fig. 9: Performance of deep learning classifier algorithms and their effectiveness on CardioHelp application.

The performance of the pre-trained models in classifying the MIT-BIH testing dataset was evaluated using confusion matrices, as depicted in table 1. The table is organized into distinct sections for each algorithm, with rows representing true classes (actual beats) and columns representing predicted classes by the respective models. The values in each cell denote the corresponding count of ECG beats falling into the specified category. For instance, in the ANN section, the top-left cell represents the count of true positives for normal beats (N), and the adjacent cells represent true positives for other beat types. The row and column headers indicate the true and predicted beat types, respectively. In our application, the LSTM model outperformed, successfully detecting 17,916 normal beats out of 18,118 data points, 388 SV (Supraventricular) beats out of 556 data points, 1,111 V (Ventricular) beats out of 1,448 data points, 75 F (Fusion) beats out of 162 data points, and 1,513 abnormal beats out of 1,608 data points.

Arrhythmia refers to an abnormal heart rhythm characterized by irregular or abnormal electrical activity in the heart. SV beats, V beats, and Fusion beats are the three types of arrhythmia that can occur in the heart. We classified a beat as Arrhythmic if any SV, V, or Fusion beats are detected. Figure 10 shows some snapshots of the CardioHelp application after the detection of Normal and Noisy beats. When arrhythmic beats occur, the application should display *Arrhythmic* instead of *Normal* or *Noisy* along with the corresponding timestamp.

	ANN					**CNN**					**LSTM**				
	N	**SV**	**V**	**F**	**Q**	**N**	**SV**	**V**	**F**	**Q**	**N**	**SV**	**V**	**F**	**Q**
N	**17067**	60	646	271	74	**17711**	53	216	72	66	**17916**	24	65	58	55
SV	139	**337**	77	3	0	141	**390**	22	2	1	146	**388**	17	3	2
V	88	74	**1160**	38	88	95	187	**995**	23	148	139	84	**1111**	27	87
F	75	24	23	**33**	7	70	19	5	**67**	1	60	12	14	**75**	1
Q	46	293	1	0	**1268**	126	68	18	0	**1396**	48	39	2	6	**1513**

Table 1: Comparison of performance metrics for ANN, CNN, and LSTM algorithms in various types of ECG beat classification.

4. Discussion

The model's performance heavily relies on the availability and diversity of training samples. Table 2 represents the performance evaluation of our pre-trained models on the CardioHelp application for various heartbeats. In the MIT-BIH dataset, the number of SV and F beats is relatively

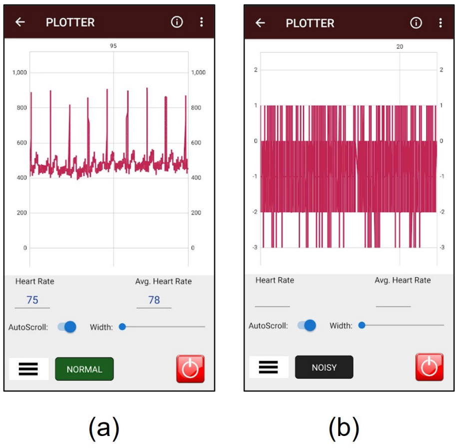


Fig. 10: Visualization of ECG data and beat types: (a) Normal signal, and (b) Noisy signal.

smaller compared to N, V, and Q beats, resulting in a limited representation of SV and F beats in the training phase. As a result, the model did not learn the distinct characteristics and patterns of SV and F beats as effectively as it did for N, V, and Q beats.

While achieving an impressive accuracy of 95.94% in detecting abnormalities using the LSTM algorithm on the application, it is important to note that a majority of the accurately predicted beats belong to the Normal category. This higher accuracy is mainly driven by the abundance of Normal beats in the training dataset, which allows the model to perform well in classifying them correctly. However, it is crucial to emphasize that the lack of SV and F beats compared to N, V, and Q beats during training led to lower accuracy in predicting these beat types in the CardioHelp application. A poor accuracy rate may fall short of the demanding standards required for effective arrhythmia identification and management in healthcare contexts, where precision and reliability are paramount. Furthermore, the accuracy for Fusion (F) beats is significantly lower than other beat types. This is because of the scarcity of F beats in the MIT-BIH dataset. Since the model had limited exposure to F beats during training, our application struggled to classify them in the application accurately. F beats are considered relatively rare compared to other cardiac beats (de Chazal & Reilly (2003)). F beats occur when electrical signals from both the atria and ventricles partially merge which results in a complex waveform that combines characteristics of both normal atrial and ventricular beats (Miller et al. (2006)). Their infrequency, relative to other beats, contributes to dataset imbalance, resulting in lower accuracy in detecting these specific arrhythmic beats. Dutta et. al proposed an efficient neural network with convolutional layers to classify significantly class-imbalanced clinical data curated from the National Health and Nutritional Examination Survey (NHANES), to predict the occurrence of Coronary Heart Disease (CHD). Still, they ended up getting a classification power of 77% for presence and 81.8% for the absence of CHD (Dutta et al. (2020)). This highlights the importance of having a balanced and diverse dataset of both abnormal and normal beats during the training phase to ensure better performance across all beat types.

Table 3 presents a comparative analysis of key features in smart health (sHealth) and mobile health (mHealth) applications. It aims to provide insights into different aspects such as data collection medium, connectivity, algorithms, functionalities, and future work of these applications. We compared the features of the other applications with our CardioHelp application. By juxtaposing CardioHelp with other applications, we gained a comprehensive understanding of its unique attributes and identified areas of potential improvement. This analysis enhances our understanding of CardioHelp's position in the broader landscape of sHealth/mHealth applications, enabling us to assess its strengths and identify opportunities for further development.

We used the Samsung Galaxy S10e as a test environment. We have carefully considered the power consumption, memory usage, and overall performance to ensure a seamless user experience. Based on our estimates, CardioHelp consumes minimal battery power, allowing for more than 60 hours of continuous operation on a single charge. It effectively manages memory usage, utilizing only 21.16 MB for active data processing and predictive computations. Even on devices with limited memory capacity, smooth performance is ensured by effective memory management. The application securely stores collected data in CSV format within a dedicated folder. To optimize storage space, the app automatically converts the data folder into a compressed .zip file that can be shared with the physician. Once the conversion is complete, the app automatically deletes the folder, ensuring efficient storage management without compromising data integrity. We conducted a thorough performance analysis using the Profiler tool in Android Studio. We found that CPU consumption continuously stayed below 20%, demonstrating effective use of the system's resources. Furthermore, the app's energy consumption was minimal, ensuring a light impact on the device's battery life.

Only a limited number of sHealth or mHealth applications offer the valuable functionality of ECG signal visualization, providing users with the ability to observe their heart rate. Furthermore, our application possesses the capability to detect abnormalities in the ECG signal. Users receive notifications and insights regarding any potential irregularities or anomalies. Moreover, CardioHelp offers the convenience of seamlessly sharing the captured ECG data with healthcare professionals. Users can easily transmit their ECG recordings to physicians or other medical experts for further analysis and evaluation. This functionality promotes effective remote monitoring and enables healthcare providers to review the data and offer appropriate medical guidance and interventions, ultimately facilitating improved patient care and outcomes.

Table 2: Performance evaluation of pre-trained models on CardioHelp application for each beat type.

ECG beat type	MIT-BIH test dataset samples	ANN algorithm			CNN algorithm			LSTM algorithm		
		Precision (%)	*Recall* (%)	F1 Score (%)	Precision (%)	*Recall* (%)	F1 Score (%)	Precision (%)	*Recall* (%)	F1 Score (%)
N (Normal)	18118	98.00	94.20	96.06	97.62	97.75	97.68	97.85	98.89	98.37
SV (Supraventricular Ectopic)	556	42.77	60.61	50.15	54.39	70.14	61.27	70.93	69.78	70.35
V (Ventricular Ectopic)	1448	60.83	80.11	69.15	79.22	68.72	73.60	91.89	76.73	83.63
F (Fusion)	162	9.57	20.37	13.02	40.85	41.36	41.10	44.38	46.30	45.32
Q (Unknown Beat)	1608	88.24	78.86	83.28	86.60	86.82	86.71	91.25	94.09	92.65
Overall	**21892**	Accuracy (%)			Accuracy (%)			Accuracy (%)		
		90.74%			93.91%			95.94%		

5. Limitations and Future Work

At present, the CardioHelp application can detect abnormal beats, including some types of Arrhythmia, monitor ECG signals and instantaneous Heart Rate, and store and send data to physicians. Our next goals are to conduct pilot studies to validate the effectiveness and reliability of the CardioHelp application in real-world scenarios and promote its adoption in healthcare contexts. Due to the complexity of our system's design, collecting data while jogging, walking, or performing any other activity is extremely difficult. Some wearable or IoT gadgets included in the package can be enhanced in the future. Our future development involves integrating an Inertial Measurement Unit (IMU) sensor into our embedded system to collect 3-axis accelerometer data, aiming to enhance our system's capabilities for respiration rate detection. We will add an additional plotter alongside ECG signal monitoring to facilitate respiratory signal monitoring. Using heart and respiration rates will enable us to develop more sophisticated and personalized healthcare interventions, contributing to improved monitoring, diagnostics, and overall well-being for individuals. We will also focus on minimizing the size and complexity of the developed wearable device, making it more compact, robust, and user-friendly.

Based on our observations, the pre-trained models, especially the LSTM model, have demonstrated effective performance in detecting normal and unknown beats, but the false-negative rate in detecting arrhythmias versus normal heart rhythms within the CardioHelp application raises concerns. Our CardioHelp application also couldn't perform very well in SV and F beats detection. Such a misdiagnosis rate, though seemingly small, can have significant implications for clinical applications. To address this concern, an in-depth examination of the algorithms and the characteristics of the data it processes is crucial. We will thoroughly analyze some factors such as the diversity of arrhythmias, the quality of input data, and the sensitivity of the detection model. The MIT-BIH Arrhythmia dataset exhibited imbalances among different arrhythmia classes, with some classes having significantly fewer instances than others. However, we firmly believe that it can be further improved by training the model on a broad dataset that includes a substantial amount of abnormal beats. Furthermore, the dataset's origin from a specific medical context and the manual annotations of ECG recordings introduce the potential for subjective interpretation. While some specific cardiac beats are rare, we address potential challenges by meticulously recording all ECG data in our application. Our system allows comprehensive data storage of all ECG data along with patients' metadata and heart rates. This extensive dataset facilitates cross-validation with medical experts and offers an avenue for precise labeling. Moreover, the labeled dataset serves as a valuable resource for continuous enhancements in our algorithms. This factor can influence the accuracy and reliability of the model during the training process. By providing more diverse abnormal beats while training, the model can learn their unique features more effectively. Then, the algorithm's integration into the application will undoubtedly result in improved accuracy in real-time beat detection. This will help mitigate the false-negative rate and enhance the overall performance of the CardioHelp application.

Also, we intend to implement the Hybrid (CNN+LSTM) and GAN (Generative Adversarial Network) algorithms. The Hybrid (CNN+LSTM) algorithm combines CNN and LSTM networks to leverage both spatial and temporal features in the data. CNN excels at capturing spatial patterns in ECG signals, while LSTM is effective in capturing temporal dependencies. By integrating these two architectures, the Hybrid model aims to enhance the overall accuracy of abnormal heartbeat detection by considering both local and sequential information. Combining CNN and LSTM architectures in a hybrid model often results in improved performance compared to using either model in isolation, making it well-suited for ECG analysis. Also, we can use the GAN algorithm which can be used to create artificial data that closely matches abnormal heartbeats. The GAN can learn to provide accurate representations of these beats by training the model on a wide variety of abnormal beats. Augmenting the dataset with more instances of under-represented beat types is a viable strategy to address the scarcity of rare arrhythmic beats. By incorporating synthetic data into the training dataset, we aim to improve the representation of abnormal arrhythmic beats. This augmentation strategy not only enriches the diversity of the dataset but also contributes to refining the performance of our detection algorithms. The utilization of this augmented dataset enhances the algorithms' ability to accurately identify and classify abnormal cardiac beats within the CardioHelp application.

Although validation of our CardioHelp application by an expert cardiologist is currently pending, we are dedicated to performing a subgroup analysis as we already have obtained IRB approval. We will also introduce a feature prompting new users for a review upon exiting, ensuring a one-time occurrence. These reviews will be showcased on the app store to enhance transparency and provide a platform for users to share their experiences. Prioritizing user experience, we will involve end-users in the design process to ensure seamless alignment with their needs. Concurrently, we will integrate a concurrent respiratory signal visualization alongside the ECG data. This dual-monitoring capability provides users with a more holistic view of their cardiovascular and respiratory health, offering a comprehensive understanding of physiological dynamics. Interactive educational content, including tutorials and quizzes, will be developed to educate and engage users. Such content not only educates users but also keeps them engaged and invested in their well-being. Concurrently, pilot studies with a user group will be conducted to gather empirical feedback. User feedback will serve as a valuable source for identifying specific areas for enhancement.

Table 3: Comparative Analysis of Key Features in Smart Health and Mobile Health Applications

Study reference	Data collection medium	Connectivity	Algorithms	Functionalities	Future work
KardiaMobile (Hickey et al. (2016))	AliveCor Kardia Mobile metal electrodes	Bluetooth	Supervised Machine Learning (classification)	Heart Rate (HR) monitoring, Atrial fibrillation (AF) detection and iHEART text messages	False Positive rate minimization
HR monitoring from in-ear pressure variance by wearable sensing (Park et al. (2015))	Piezoelectric film sensor and a hardware circuit module	Radio Frequency (RF) on the 2.4 GHz band	In-ear pulse waves (EPW) peak detection algorithm	HR monitoring from the ear canal surface, HR's sensitivity of 97.25% and a positive predictive value of 97.17% was found	Overcome sensitivity to the user's motion and monitor HR continuously
HeartMapp (Athilingam et al. (2016))	Chest-worn Bluetooth sensor with built-in algorithms from Zephyr BioHarness™ 3 and/or BioPatch	Bluetooth	Supervised Machine Learning	Chronic Heart Failure (CHF) symptom monitoring, improve self-care skills, adherence to medication, diet and physical activity	Replace chest-worn sensors with wrist-worn sensors, and test HeartMapp for its efficacy in a clinical trial
Seamless User-centred Proactive Provision Of Risk-stratified Treatment for Heart Failure (SUPPORT-HF) (Rahimi et al. (2015))	A blood pressure (BP), heart rate monitor and an electronic weighing scale	Bluetooth	Unsupervised Machine Learning	Heart failure home monitoring, alerts and medical recommendations	More user engagement needed for more accurate prediction of risks, increase wearable accuracy
TeleClinical Care (TCC) (Indraratna et al. (2022))	Bluetooth-enabled peripheral devices: sphygmomanometer, weighing scale and activity monitor	Bluetooth	Not Specified	Telemonitoring and education for patients with Acute Coronary Syndrome (ACS) or Heart Failure (HF)	Increase sample size and consider the inclusion of participants
Wearable Mobile Electrocardiogram Monitoring System (WMEMS) (Tseng et al. (2013))	Dry foam electrodes, an ECG acquisition module, and a wearable ECG vest	Bluetooth V2.0, and GSM	HR detection algorithm	Long-term ECG, HR monitoring	Detect and validate AF from R-wave
RITMIA™ (Reverberi et al. (2019))	Two electrodes integrated on the chest belt sensor	Bluetooth Low Energy (BLE)	Weighted combination assessment of RR interval variability and randomness/chaos algorithm (Supervised Machine Learning)	HR monitoring, diagnosis of AF recognized "probable AF" rhythm with 97% sensitivity and 95.2% specificity	Classify irregular rhythms, such as Atrial Flutter and presumably Atrial Tachycardias
HeartKeeper (de la Torre-Díez et al. (2016))	Personal health data by application	Not specified	Unsupervised Machine Learning	Medical recommendations, and alerts	Validate the app, fix errors and wrong behaviors, improve the usability of the mobile app
mHealth tool (Baek et al. (2018))	IoT device	Not specified	Not specified	Self-management (blood pressure, blood sugar test, body weight), Atrial Fibrillation (AF) and hypertension	Patient's diet inclusion, integrate app system with EMR (Electronic Medical Record) systems
HeartMan DSS (Bohanec et al. (2021))	Sensing wristband and other devices (bp monitor, environmental sensors)	Wireless Communication Protocol	Supervised Machine Learning, Classic Differential Evolution Algorithm	Physical exercise management, monitoring and Heart Failure risk detection	Enhanced patient lifestyle adaptation, activity recognition methods, and optimize module integration
CardioHelp (Proposed Work)	IoT device (consists of Sparkfun nRF 52840 min, AD8232 chip), Gel/Inject Printed(IJP) electrodes	Bluetooth Low Energy V5.3	Pan-Tompkins algorithm, Supervised Machine Learning (Classification)	Continuous ECG signal and HR monitor, detect abnormal heartbeats, alert patients, and store data for further inspection	Make embedded systems more user-friendly, improve algorithms for accurate abnormality detection

6. Conclusion

In this study, we presented a smartphone application that can continuously monitor ECG data, display Heart Rate, and detect cardiac abnormalities using edge-computing with a pre-trained deep-learning classifier. The CardioHelp application demonstrates promising capabilities in real-time ECG beat detection and classification, providing valuable insights into real-time and continuous cardiac health monitoring. We used the MIT-BIH test dataset to evaluate our AI model, and the findings suggest that our application can accurately detect various heart conditions. Along with the developed wearable device, this system holds great potential to be a valuable tool for the early detection and identification of cardiac problems in smart health applications. Further development, validation, and adoption of the application in clinical settings are necessary to unlock its full potential and contribute to improved cardiac health management.

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