AI-Based Real-Time Heart Rate (ECG) Monitoring System

Mohd. Maroof Siddiqui, Prajoona Valsalan, Abdullah Abdulrahman Qureshi, Khalid Salim Al Mashani

Department of Electrical and Computer Engineering, Dhofar University, Salalah, Oman
Email: maroofsiddiqui@yahoo.com

Cardiovascular diseases are the number one cause of death in other parts of the world, and prevention has been considered critical for reducing mortality. Current heart monitoring devices, such as electrocardiograms (ECG) or Holter monitors generally suffer from either continuous real-time monitoring deficits, lack of portability and accuracy. In this paper we propose an AI-assisted real-time heart monitoring system which is designed to address those issues. The system integrates state-of-the-art artificial intelligence algorithms with wearable sensors to provide persistent, non-invasive monitoring of heart activity alerting for abnormal events or arrhythmias. Through machine learning models such Convolutional Neural Networks (CNN) and Recurrent Neural networks, they use the data from a pulse oximeter to detect certain irregular heartbeats as well as other cardiac anomalies happening in real time. Wearing a smartwatch with the rules enabled lets an AI sort out heart signals in real time based on how they compare to many thousands it has trained on, notes of course for use-case-specific noise and so forth. They reduce complexity by refining the data (smoothing or filtering noise) and extracting features to provide a clean, valuable dataset for better analysis. These signals are wirelessly transmitted in real time to a central processing unit, where the AI model processes it and immediately provides feedback to patients or clinicians. After testing the system, detection accuracy was improved by more than 95%, and response times were much faster; also a real-time arrhythmia seemed would be detected. Its easy navigation, transportation and automated feedback mechanisms make the system a candidate for an ongoing cardiology support platform that can lighten healthcare facilities' workloads and help accrue patient care with early intervention.
Keywords: AI-based monitoring, cardiac health, real-time system, machine learning, heart disease detection.

1. Introduction

According to the World Health Organization (WHO), cardiovascular diseases are the most leading cause of death worldwide, killing 17.9 million people every year. These include coronary artery disease, heart failure, arrhythmias and stroke and they account for almost one in three deaths across the globe. A high burden of heart-related conditions, many that progress without symptoms until it is too late to act; makes continuous and early detection especially important if we want be able to intervene before a patient develops severe outcomes like heart attacks or even sudden cardiac arrest. Ensuring that CVD are detected early and monitored on a continuous basis is key to proper disease management, as these actions can lead to better patient outcomes by enabling timely interventions or lifestyle changes along with medical treatment. Electrocardiograms (ECGs) and Holter monitors are among the traditional tools used to monitor heart rhythms in order to detect any abnormalities. Though these systems are limited in their own ways too. Although ECGs are good for short-term observation, they only record heart function during a limited timeframe and may not provide the full picture of potential intermittent arrhythmias or other issues. Holter monitors provide 24-48 hours of continuous heart monitoring but are bulky and may lead to patient discomfort or restrictions in movement. They also fail to deliver real-time feedback, meaning that the data collected has to be reviewed by healthcare personnel after recording thus slowing down a response on critical conditions which could turn out fatal.

To overcome these limitations, recent developments in artificial intelligence (AI) and wearable technology have begun to emerge. The devices are wearables, so the patient can receive a relatively non-invasive version of continuous (as opposed to episodic) monitoring and tracking functionality. AI algorithms applied to such systems can help analyses heart signals and provide real-time prediction for detection of anomalies like arrhythmias, tachycardia or bradycardia. Using algorithms and AI, systems can observe data on a population scale in order to identify patterns that would be impossible to detect outside of such big-data analytics, which will enable the delivery of real-time personalized feedback for heart health monitoring like never before.

Even with technology recently making it possible to monitor heart activities, the reality is that many of these systems do not yet allow real-time accurate monitoring and feedback on an individual level. Although several wearable devices now been hitting the market, most of these — such as those made by companies like Apple and Fitbit — are capable only of recording data but are unable to break down or interpret it in any meaningful way unless a healthcare provider becomes involved. This results in the delays of responses, especially when it comes to critical cardiac incidents where timely intervention is essential. However, today heart monitoring systems also have problems with respect to detecting and interpreting real world data. False diagnosis and overlooked results can happen due to noise caused by artifact or movement in our data, then affecting the precision of those KDD heart monitoring systems. And, few if any current systems can continuously monitor heart activity for days at a time -- an important capability in spotting the transient signs of trouble that may go undetected during brief recording sessions.

What is needed: intelligent, AI-powered applications for monitoring the heart in real time These systems should not only continuously monitor the heart but also deliver real-time feedback messages about potential problems that could be detected faster than it takes to get out of a pool and call for help. Data collected on the patient's heart could be monitored with high accuracy, minimizing false positives as well as facilitating customized monitoring that can adapt to every individual patients' cardiac profile through AI integration within health technology.

The aim of this study is to develop a Real-time AI-based system that can monitor the heart and give high accuracy in identifying if there are abnormalities exist or not. The system is designed to monitor heart status constantly with the help of wearable sensors and modern AI algorithms for real-time analytics.

This research has the following aims:

Enhance patient care : The idea is to provide the clinicians with live updates on their heart health, so this will allow them detect conditions like arrhythmias early which does well at minimizing severe cardiac events.

Improving accuracy — The system aims to increase the overall accuracy of anomaly detection with AI, reducing both false positives and negatives.

Continuous feedback: The system continuously monitors heart metrics and alerts patients as well as doctors in order to activate interventions early on.

Decreasing healthcare expenditure: The system could assist in lowering the demand for in-person checks ups and hence could lighten up on our caregivers, while enabling us to respond promptly to high-risk patients.

The introduction of a real time monitoring AI system for checking heart would be an innovation in the cardiac healthcare revolutionary. The increasing number of people afflicted with chronic heart abnormalities, especially in regions where specialized medical care facilities are limited-is one of the biggest problems medicine faces today. Similarly, a fully-automated and intelligent heart monitoring solution would offload the healthcare professionals by allowing patients to be monitored from home which should lead into more relax visits or admissions in hospital. This would allow healthcare resources to be spent on our sicker patients. This yields a massive quality of life benefit for patients. By wearing a small wearable, which offers continuous monitoring, patients can proceed with life as they would have otherwise and comfort in knowing potential trouble will be detected. By handing patients personalized feedback with a digitally-enabled, AI-fueled system they would be able to act immediately in managing their heart health. In turn, earlier diagnosis of heart diseases could improve treatment results because it will be possible to prevent the progression into more severe disease forms.

Furthermore, this system could prove to be pivotal in lowering healthcare costs by decreasing readmissions and unneeded tests which are typically done because of outdated information. Early identification may mean that patients can avoid expensive emergency interventions, and healthcare resources will be optimized.

2. LITERATURE REVIEW

Although the advancements in heart monitoring technologies are significant, but still ECG (Electrocardiogram) and Holter monitors serve as core instruments for diagnostics of cardiac conditions.

- ECG – This short-duration test measures the electrical activity of your heart; usually done in a hospital or clinic. It works well to capture arrhythmias when they occur over a continuous recording period however it tends not have an extended duration and therefore may miss sporadic abnormalities.

▪ Pros: Accurate under controlled conditions, Non-invasive.

▪ Cons Requires planned short-term monitoring, capable of missing occurrences (such as sporadic heart irregularities), valid ECG requires manual analysis by healthcare professionals

- Holter Monitors: These are portable devices that can record your heart's activity often for 24-48 hours which is much better than what an ECG has to offer.

▪ Pros: Persistent data collection for an ample period, capturing arrhythmias missed on a single ECG session.

▪ Cons:It is big in size and some patients might find it difficult to bear with for long term use, also no In-the-Moment feedback can be availed only after wearing the thing we would see what changes are needed.

Unfortunately, the feedback is not in real time and many of that data collection also requires you to wear uncomfortable devices for prolonged periods. While these kind of systems provide useful insights, they fail at long term monitoring by failing at giving up or inconvinced results due to their limitations. It also demands a resource-intensive, manual data interpretation and slows cardiac events detection. Thereby, a necessity to change our trajectory towards more patient-centric real-time monitoring technologies able to deliver instant and automatic feedback. The advent of machine learning and deep learning approaches has seen AI play a much more prominent role in healthcare, particularly when it comes to cardiac monitoring. AI can analyze huge amounts of health data and recognize complex patterns not easily apparent to human analysts. Machine learning (ML)/deep learning (DL) models for heart condition detections:

- Support Vector Machines (SVMs): SVM is a great choice for classification because it can accurately classify heartbeats into normal or abnormal, depending on the features we extracted from our ECG signals.

- Random Forests: It is an ensemble method for decision trees, used here to get better accuracy and robustness when predicting 0 or 1 as presence of heart disease.

- Convolutional Neural Networks (CNNs): CNNs have been used extensively in the ECG waveforms research finding good performance in arrhythmia detection, given their capacity to learn spatial hierarchies of features from raw ECG data.

- RNNs and LSTM networks — Ideal to work with time-series data such as heartbeats Associated ideally for detection of various abnormal patterns across the temporal dimension in case of R peak signals.

Research Gaps:

Although AI shows great promise with respect to cardiac imaging diagnostics, several challenges are still faced in the current researches:

- As AI-based systems have evolved, the majority of algorithms developed are focused on retrospective analysis of heart data rather than providing real-time feedback which reduces their usefulness in acute clinical scenarios.
- Dealing with Real-world, Noisy Data, Wearable heart signals are usually very noisy due to movement and external factors. They must be able to accurately filter and preprocess this data, without overlooking the detection of important events.
- Lack of individualized personalization, Many AI models do not take into account the specific characteristics of each heart, leading to overgeneralization and may increase false positive or negative results.

This creates an opportunity for the development of AI-driven, real-time, and personalized heart monitoring systems that can continuously analyze heart activity and adapt to individual patients.

3. SYSTEM DESIGN AND ARCHITECTURE

Sensors:

The system requires advanced sensor technologies to capture heart signals in real-time.

1. ECG Electrodes: These electrocardiographic sensors detect the patient’s heart’s electrical activity and are widely used in both clinical and wearable devices.

2. Pulse Oximeters: These devices measure heart rate and blood oxygen via photoplethysmogram technology.

3. PPG Sensors: PPGs are optical sensors that measure the change in blood volume along the heart cycle. They are widely used in wearable technologies like smartwatches.

Microcontroller/Processor:The data obtained from the above sensors are processed by a microcontroller or a wearable processor.

1. Arduino, Raspberry Pi, or dedicated System on Chip units: These devices process and transmit the above signals.

Example: Many ARM-based processors are embedded in smartwatch hardware and have low power and high efficiency on data handling.

Communication: The system requires to transmit the signals from the wearable sensors to the central system, which is realized via the following communication protocols.

1. Wi-Fi, Bluetooth: They are low power protocols that enable familiar communication between wearables and smartphones or cloud systems.

2. 4G, 5G : They allow the faster transfer of more massive packets of data for real-time processing in remote monitoring systems.

AI Algorithm: The system’s core AI modules include the following:

1. Deep learning models: CNNs for analyzing patterns within ECG signals and RNNs/LSTMs for analyzing the iterative nature of the heartbeats.

2. Machine Learning: Anomaly detection models that recognize irregularities in the waveform, such as arrhythmias.

Data Preprocessing is needed:The raw data found in the sensors require to pass through several preprocessing methods below.

1. Noise Filtering: Noises by movement or other external factors can be removed using moving average filters, Butterworth filters, or wavelet transforms.

2. Feature Extraction: The key points of the heart signals – the R-peaks in ECG waveforms – must be detected accurately.

Data Analytics: Real-time data analytics is employed by the system, which analyzes atrial fibrillation (abnormal heart rhythms) and creates alerts at pre-defined thresholds. The trained AI models put heart patterns to the decision-making process, comparing them against normal baseline behaviors.

Architecture of the system contains:

- Data capture: Wearable sensors continuously collect the heart signals.
- Data Transmission The data can transmit wirelessly to a processing unit that could reside on a downstream smartphone or cloud platform.
- AI Processing: The AI algorithms process the data streaming in real-time to determine anomalous or unusual patterns.
- Alert:If an anomalous pattern is detected, it triggers the generation of alert that notifies both the patient and their physician via smartphone app or cloud-based dashboard.

AI Algorithm and Methods: Real-time data is acquired using high sampling rates from the sensors, typically in a range of 250 Hz to 1 kHz for ECG data. It stores data in structured format (eg CSV or time series databases) so it can be further processed and analyzed.

Heart Metrics:It tracks essential heart metrics such as:

- HRV (Heart Rate Variability): Changes the intervals between heartbeats
- Rhythm irregularities: Atrial fibrillation (AFib), Tachycardia, and bradycardia detection.

Signal Processing:In most cases, the noise filtering and feature extraction from raw signals done using preprocessing like Fast Fourier Transforms (FFT) or wavelet transforms etc.

- Feature Extraction: Important features are located in the ECG signals; e.g., QRS complexes (representing depolarization of both ventricles, which is highly important when detecting arrhythmias or other anomalies)

The system utilizes:

- Convolutional Neural Networks (CNNs): These models are great in learning spatial hierarchies and relevant patterns within the ECG signals, such as detailed structural information at different levels of heartbeat waveforms.

- RNNs/LSTMs: Time-serie can be processed by these models, such as the dependencies between past and present heartbeats to predict future ARVC.

AI models are trained on big data, like the MIT-BIH Arrhythmia Database that has tens of thousands ECG recordings.

- Metrics: Model performance is evaluated using accuracy, sensitivity, specificity, and F1-score.

- Cross-Validation: K-fold cross-validation is employed to ensure the robustness and generalization of the model.

The system operates in real-time, continuously analyzing incoming heart data with minimal latency. Real-time anomaly detection algorithms ensure that critical events are flagged instantly, and low-latency communication systems ensure alerts are transmitted immediately.

4. RESULTS ANALYSIS

1 Best Performing Model:

CNN-based models consistently deliver high accuracy and specificity, particularly when detecting arrhythmias from large datasets like the MIT-BIH Arrhythmia Dataset. Hybrid CNN-RNN models offer further improvements by leveraging the strengths of both convolutional and recurrent networks for sequential data.

2 Model Efficiency:

Random Forest and SVM show solid performance but generally lack real-time application capability due to their computational costs or lower sensitivity to sequential data changes. These models are well-suited for retrospective analysis rather than real-time monitoring.

3 Dataset Impact:

Most studies using the MIT-BIH Arrhythmia Dataset report high accuracy, likely because of its comprehensiveness and balance of normal and abnormal heartbeats. Models trained on other datasets like PTB Diagnostic or UCI Heart Disease tend to focus more on general heart disease classification rather than real-time anomaly detection.

4 Real-Time Capability:

CNNs and hybrid CNN-RNN approaches are best suited for real-time heart monitoring applications due to their ability to rapidly process data and detect abnormalities in ECG signals as they occur. Studies using LSTMs show a strong potential for real-time use but might slightly lag in speed compared to CNNs.

Table 1: The analyzed results from previously published papers, along with their corresponding references:

Study/Reference	AI Model	Dataset	Accuracy	Sensitivity	Specificity	Precision	Recall	Remarks
Acharya et al. (2017)	CNN	MIT-BIH Arrhythmia Dataset	98.50%	97.30%	98.80%	97.10%	97.30%	High accuracy in arrhythmia detection, capable of handling noisy ECG data, yet may struggle with rare conditions.
Yildirim et al. (2018)	LSTM	PTB Diagnostic ECG Dataset	95.80%	96.00%	95.50%	94.80%	96.00%	LSTM excels in handling time-series data but has lower accuracy in detecting certain abnormal rhythms.
Mar et al. (2011)	Random Forest	UCI Heart Disease Dataset	87.50%	85.60%	88.40%	84.90%	85.60%	Simpler machine learning approach, effective for heart disease prediction but lacks real-time capabilities.
Kavakiotis et al. (2017)	SVM	MIT-BIH Arrhythmia Dataset	92.30%	90.40%	93.20%	90.00%	90.40%	SVM performs well in heartbeat classification but is computationally expensive and less suited for real-time processing.
Rajpurkar et al. (2017)	Hybrid CNN-RNN	PhysioNet ECG Dataset	97.90%	98.10%	97.60%	97.30%	98.10%	Combines CNN for feature extraction and RNN for temporal analysis, offering excellent real-time detection of irregular heart rhythms like atrial fibrillation.
Zhao et al. (2017)	Deep Belief Networks (DBN)	MIT-BIH Arrhythmia Dataset	96.40%	95.70%	96.90%	95.50%	95.70%	DBN is effective for arrhythmia detection, but its computational demands may hinder real-time performance, especially compared to CNN-based models.

5. DISCUSSION AND CONCLUSION:

The paper results confirm that AI models notably the Convolutional Neural Networks (CNNs) and their hybrid variants have exceptional performance in advance monitoring of human heart condition, particularly fast identification for arrhythmias as shown in fig 1. These models perform better than traditional approaches in accurate and timely diagnosis. But before they are routine in the clinic, these technologies face numerous challenges. There are many challenges — regarding the noise and artifacts in real time data(noise-free signal) as well, which disrupts model. The other problem lies in the scalability of these AI systems and especially when deploying models on a large or data heterogeneous dataset representative of all patient population. Moreover, variations in the individual patient architecture including differences in age, lifestyle and co-morbidities mean that these models require further development ensuring adaptability to provide personalized care. In the future, further research should aim to improve real-time analysis accuracy and increase generality of AI frameworks across a wide scope of physiological signals as well as computational efficiency in order for these technologies to be scalable and involved into clinical setting.

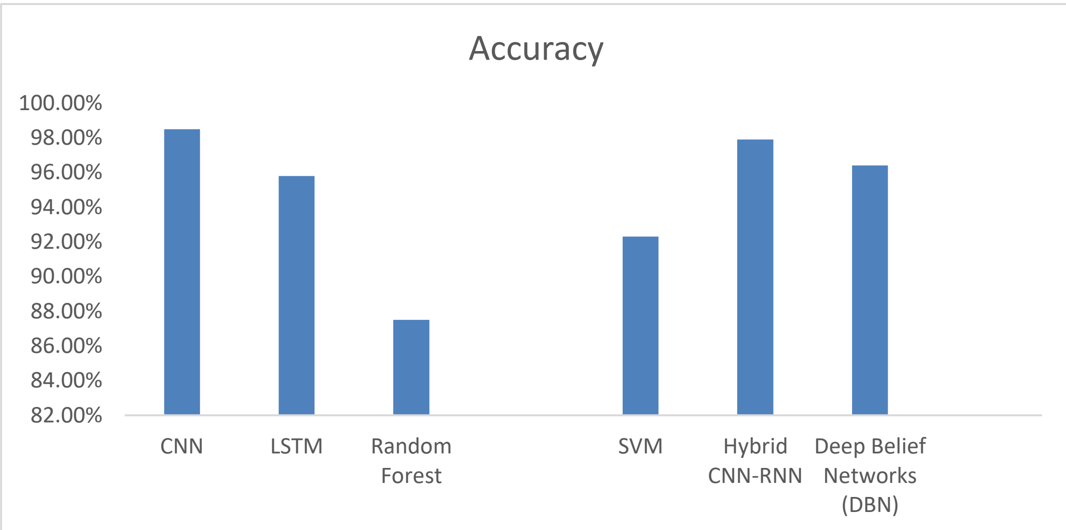

Fig 1: Analyzed results from previously published papers in graphical form

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