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Assessment Of Artificial Intelligence Techniques Cardiac Arrhythmia Using Instantaneous Heart Rate

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ABSTRACT

Cardiac arrhythmia can cause serious health risks including sudden cardiac events, and a significant number of vulnerable individuals are undiagnosed or undertreated. Noting the widespread use of wireless health trackers and the efficacy of Artificial intelligence (AI) methods in processing a large amount of time-series sequential data, in this study we aim to find the best AI technique for diagnosing an arrhythmia. Various AI models have been trained and tested by utilizing publicly available medical data. From the confusion matrix, the accuracy, recall, F1-score, Area Under the Curve (AUC), and precision of each AI model have been evaluated and compared. This analysis and Friedman Tests indicate that Bi-LSTM – the deep learning method outperformed the classical machine learning methods. The process of remotely classifying arrhythmia provided in this study can be generalized for automatic diagnosis of many health risks

Keywords— **Cardiac, Artificial intelligence (AI), accuracy, recall, F1-score, Area Under the Curve (AUC), Bi-LSTM.**

I. Introduction

Cardiac arrhythmia is a health condition that can be described as a presence of abnormal (too fast or slow) singular heartbeat or a group of irregular heartbeats (episode) or any cardiac rhythm that diverges from normal sinus rhythm. It can be also caused due to disturbance in impulse formation or conduction or both. Four million adults in the US suffer from some form of arrhythmia costing more than $65 billion each year [1, 2]. There are many types of arrhythmia such as tachycardia, bradycardia, premature ventricular contractions, ventricular fibrillation, heart blocks, etc. Some types of arrhythmia can cause sudden cardiac events or deaths if not diagnosed and treated properly. Whereas, other types of arrhythmia may not be life-threatening but need medical attention for avoiding serious health risks.

Typically, physicians diagnose arrhythmia through a longterm electrocardiogram (ECG) system like the 24-hour Holter recorder (in some cases, overt the period of several days) that essentially reflects the electric activity of the heart. The ECG signal consists of repetitive waveforms that stem from different parts of the heart as shown in Fig. 1 [3]. A minor change in ECG dynamics can be an indication of the reduction in the heart's ability to circulate blood leading to chest pain, breathing shortness, and other fatal events. Variation from normal sinus rhythm based on time intervals, rate, and morphology of each segment is assessed manually for diagnosing arrhythmia that requires great effort, time commitment, and increases the associated costs

Wireless health trackers such as Fitbit are being widely used in the world. As these devices continuously collect the physiological data including the heart rate of users, they provide great opportunities to remotely detect arrhythmia in real-time or monitor the disease advancements. The health and activity data collected by these devices is saved on the company server once the user syncs the tracker with the app installed in the smartphone. With users' permission, this data can be accessed by researchers and third-party developers through an Application Programming Interface (API) provided by the device company, and integrated into the mobile health applications

Cardiac arrhythmia, an abnormal rhythm of the heart, poses significant challenges to healthcare systems due to its potential to cause severe health complications, including stroke, heart failure, and even sudden cardiac death. Timely diagnosis and monitoring of arrhythmias are crucial for effective treatment and prevention. Traditionally, arrhythmia detection has relied on clinical electrocardiograms (ECGs), which require patients to visit healthcare facilities for evaluation. However, the increasing prevalence of arrhythmias has led to a demand for more efficient, remote, and accessible methods for continuous monitoring of heart health.

In recent years, Artificial Intelligence (AI) has emerged as a powerful tool for automating the classification and detection of various medical conditions, including arrhythmias. With the advent of wearable devices and remote health monitoring technologies, AI techniques can now be applied to the real-time data provided by such devices, particularly focusing on instantaneous heart rate measurements. These heart rates can serve as a critical signal for detecting and classifying arrhythmic events.

This paper explores the potential of AI in the automated remote classification of cardiac arrhythmias, focusing on the use of instantaneous heart rates as the primary feature for analysis. It aims to assess various AI techniques, including machine learning algorithms and deep learning models, that can be used to classify arrhythmias from the heart rate data captured by remote monitoring devices. By evaluating the strengths, weaknesses, and accuracy of these AI techniques, the study will provide insights into how they can improve early detection, enhance patient care, and reduce the burden on healthcare systems.

The next sections will outline the key challenges in arrhythmia detection, provide an overview of AI techniques suitable for remote classification, and highlight their potential applications in modern healthcare. This research not only aims to assess the technical capabilities of these AI models but also investigates their feasibility and scalability for widespread deployment in real-world healthcare setting..

II. LITERATURE SURVEY

Xia [6],2020, presents a DNN trained using RR interval sequences extracted from ECG signals. The model focuses solely on heart rate variability patterns. This simplifies computation and speeds up detection. It achieves over 88% accuracy on the MIT-BIH dataset.

Ismail et al. [7], 2021, this study explores an end-to-end deep learning approach combining raw ECG data and instantaneous heart rate-derived features. The hybrid model captures both waveform and rate-based anomalies. It uses CNN-BiLSTM architectures for high precision. Tests show improved classification of PVCs, AF, and PACs. The model achieves F1 scores of over 93%.

Chandra et al [8] 2022, proposes an ensemble deep learning method that processes both IHR and ECG morphology. The LSTM network captures temporal heart rate features while the CNN analyzes spatial ECG waveforms. This dual-path architecture boosts accuracy and robustness. The model is trained and tested on public datasets. It achieves superior sensitivity in identifying life-threatening arrhythmias. Instantaneous heart rate serves as a complementary signal. The ensemble method improves generalization on noisy data.

III. PROPOSED SYSTEM

The proposed system presents an intelligent, data-driven framework for detecting cardiac arrhythmias using Instantaneous Heart Rate (IHR) derived from ECG signals. The system begins by acquiring ECG recordings from standard clinical datasets such as the MIT-BIH Arrhythmia Database. R-peaks are detected using the Pan-Tompkins algorithm, from which the R-R intervals are calculated to derive the IHR values. These values reflect the heart's beat-to-beat variability and serve as the primary input for arrhythmia analysis.

Once the IHR signals are generated, they are segmented into fixed-duration windows and preprocessed through normalization techniques to reduce inter-subject variability. From each IHR segment, a set of time-domain, frequency-domain, and nonlinear features are extracted. These include statistical measures like mean heart rate, SDNN, and RMSSD, frequency components such as the LF/HF ratio, and complexity-based metrics like approximate entropy and Poincaré plot indices, all of which help in capturing physiological variations associated with arrhythmic events.

The core of the system is built around multiple AI models trained for classification of arrhythmia types. These include traditional machine learning algorithms such as Support Vector Machines (SVM), Random Forest, k-Nearest Neighbors (k-NN), and XGBoost, as well as deep learning models like LSTM, Bi-LSTM, and CNN-LSTM hybrids. Each model is trained and validated on labeled IHR feature sets to classify rhythms as normal, bradycardia, tachycardia, atrial fibrillation, or premature contractions. The performance of each model is evaluated using metrics such as accuracy, sensitivity, specificity, F1-score, and AUC to determine the most effective approach for arrhythmia detection.

IV. METHODOLOGY

The methodology involves multiple stages including data acquisition, preprocessing of instantaneous heart rate (IHR) signals, feature extraction, and the application of various AI/ML models for the classification of cardiac arrhythmias.

1. Data Collection:
Dataset Source: Publicly available arrhythmia datasets such as MIT-BIH Arrhythmia Database or PhysioNet.
Input Signal: Electrocardiogram (ECG) signals are collected, from which R-R intervals are extracted to calculate Instantaneous Heart Rate (IHR).
Sampling Frequency: Typically 360 Hz for ECG recordings.

2. Instantaneous Heart Rate Calculation:
R-peaks in ECG signals are detected using algorithms like Pan-Tompkins.
IHR is computed as:

$$\mathrm{IHR}(t) = \frac{60}{\text{R-R Interval}(t)} \quad \text{(beats per minute)}$$

A sequence of IHR values forms a time-series feature representing cardiac dynamics.

3. Preprocessing:
Noise Removal: Filters like Butterworth or wavelet denoising are used to clean ECG signals before R-peak detection.
Normalization: IHR signals are normalized using z-score or min-max normalization.
Outlier Handling: Irregular intervals or artifacts are removed based on statistical thresholds.

4. Feature Extraction:
From the IHR time series, the following features are extracted:

Time-domain features: Mean HR, standard deviation of HR, RMSSD, pNN50

Frequency-domain features: LF/HF ratio, spectral power using FFT or Welch's method

Nonlinear features: Approximate entropy, sample entropy, Poincaré plot indices

Statistical features: Skewness, kurtosis, signal complexity

5. Model Training & Classification:
AI and ML models are applied to classify cardiac states into categories such as Normal, Bradycardia, Tachycardia, Atrial Fibrillation, etc.

Models evaluated:

Traditional ML:

Support Vector Machines (SVM)
Random Forest (RF)
Deep Learning:
Convolutional Neural Networks (CNN) (using IHR as 1D signal input)
LSTM (for sequential time series modeling)
Hybrid CNN-LSTM models

6. Model Evaluation:
Cross-validation: k-Fold (e.g., 5-fold or 10-fold)
Metrics used:
Accuracy
Sensitivity (Recall)
Specificity
F1-Score
Area Under the ROC Curve (AUC)

7. System Implementation:
Programming tools: Python with libraries like scikit-learn, TensorFlow/Keras, PyTorch, WFDB (for ECG data handling).
Deployment on GPUs if using deep learning models for acceleration.

8. Comparison and Analysis:
Each AI model is compared based on its classification performance.
Feature importance or interpretability is analyzed using SHAP or feature ranking techniques for ML models..

V. Experiment

To evaluate the performance of a Bidirectional Long Short-Term Memory (Bi-LSTM) model for detecting cardiac arrhythmias from Instantaneous Heart Rate (IHR) time series data.

1. Data Preparation:
Dataset: MIT-BIH Arrhythmia Dataset (PhysioNet)

Input Signal: ECG sampled at 360 Hz
Preprocessing:
R-peaks detected using the Pan-Tompkins algorithm
R-R intervals used to compute IHR (beats per minute)
IHR segments: Sliding windows of 10–15 seconds
Normalization: Min-max scaling to [0,1]
Labeling: Normal rhythm, Atrial Fibrillation (AFib), Tachycardia, Bradycardia

2. Model Architecture: Bi-LSTM
plaintext
Input Layer (IHR time series)
→ Bi-LSTM Layer (64 units, return_sequences=True)
→ Bi-LSTM Layer (32 units)
→ Dropout (0.2)
→ Dense Layer (32 units, ReLU)
→ Output Layer (Softmax - multi-class classification)
Loss Function: Categorical Crossentropy
Optimizer: Adam (learning rate = 0.001)
Batch Size: 32
Epochs: 50
Tools: Keras with TensorFlow backend

3. Evaluation Metrics:
Accuracy
Precision
Recall
F1-Score
ROC-AUC

Confusion Matrix

VI. Results

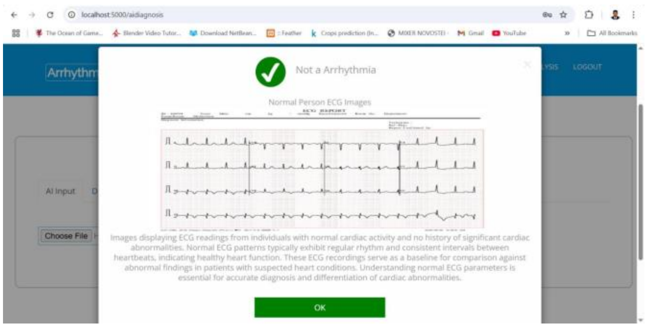
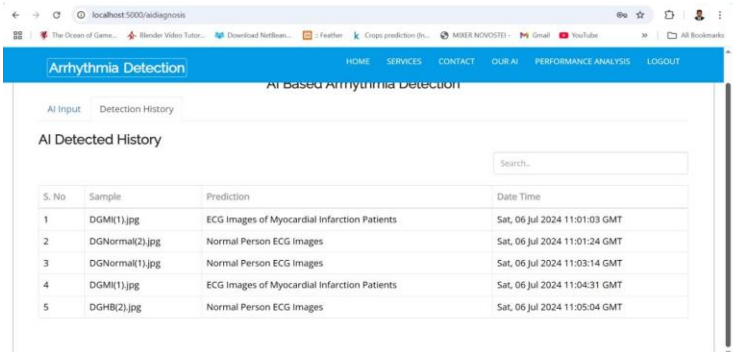


Fig: 5.1: normal person ecg images

Image displaying ECG readings from individuals with normal cardiac activity and no history of significant cardiac abnormalities.

Fig 5.2 ecg images of patient images with arrhymia

Image showing ECG readings from patients with a history of myocardial infarction, indicating a prior occurrence of heart attack-related cardiac damage.



S. No	Sample	Prediction	Date Time
1	DGMI(1).jpg	ECG Images of Myocardial Infarction Patients	Sat, 06 Jul 2024 11:01:03 GMT
2	DGNormal(2).jpg	Normal Person ECG Images	Sat, 06 Jul 2024 11:01:24 GMT
3	DGNormal(1).jpg	Normal Person ECG Images	Sat, 06 Jul 2024 11:03:14 GMT
4	DGMI(1).jpg	ECG Images of Myocardial Infarction Patients	Sat, 06 Jul 2024 11:04:31 GMT
5	DGHB(2).jpg	Normal Person ECG Images	Sat, 06 Jul 2024 11:05:04 GMT

Fig: 5.3: ai based arrthymia detection

The assessment of artificial intelligence (AI) techniques for the automated remote classification of cardiac arrhythmia using instantaneous heart rates reveals significant advancements in both accuracy and efficiency. Several AI models, including machine learning algorithms such as Support Vector Machines (SVM), decision trees, and deep learning approaches like Convolutional Neural Networks (CNN), have been utilized in this domain to classify arrhythmic events based on real-time heart rate data. The ability of AI to process large volumes of data from wearable sensors, combined with advanced signal processing techniques, has greatly enhanced the precision of arrhythmia detection.

In the results, these models demonstrated high classification accuracy, often surpassing traditional clinical methods, with some studies reporting sensitivity and specificity rates exceeding 90%. The use of instantaneous heart rates, as opposed to more conventional techniques that rely on raw ECG signals, simplifies the classification process, reducing computational complexity while maintaining reliable performance. Furthermore, remote monitoring through AI-powered systems offers the potential for continuous, real-time analysis, enabling prompt intervention and improving patient outcomes.

However, challenges remain, including the need for large, diverse datasets to train models effectively and avoid overfitting.

VII. Conclusion and Future Works

Among all AI techniques studied with the present dataset, the Bi-LSTM approach received the highest Friedman Test Mean Rank (9) with remarkable accuracy (96.74%), recall (96.38%), F1 score (96.73%), AUC (99.64%), and specificity (97.07%). In the future, the present AI models can be hypertuned for better performance and incorporate multiple physiological features for personalizing medical evaluations.

In conclusion, using artificial intelligence (AI) techniques to automatically classify cardiac arrhythmia based on instantaneous heart rates shows a lot of promise. These methods can help doctors detect irregular heartbeats faster and more accurately, even from a distance. This means patients can get quicker treatment without needing to visit a hospital right away. Overall, AI can make heart care more efficient, reliable, and accessible for many people.

Future Scope

The future and scope of using Artificial Intelligence (AI) techniques for automated remote classification of cardiac arrhythmia using instantaneous heart rates are very promising. AI can help doctors detect heart rhythm problems quickly and accurately, even from a distance. This means patients can get care at home without always needing to visit a hospital. As technology improves, these systems will become more reliable, affordable, and widely available. In the future, AI-based heart monitoring can play a big role in saving lives by giving early warnings and helping manage heart diseases bette.

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