CardioVision : Early Cardiac Arrest Risk Prevention App - Summary Report

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Lukhsaan Elankumaran, Nirjhar Dey, Varun Gande

I. Introduction

A. Main Theme & Problem

CardioVision is a machine learning powered system designed to predict cardiac arrest risk in real-time using ECG waveforms and HealthKit metrics (Heart Rate, Resting Heart Rate, Heart Rate Variability, High Heart Rate Events) from wearable devices like the Apple Watch. Current methods for detecting cardiac risk are reactive, often relying on manual interpretation of ECGs after symptoms occur. This results in missed early warning signs and delayed interventions for high-risk individuals. Our solution aims to proactively monitor cardiac health, providing timely risk predictions and enabling preventive care.

B. What we intend to do

The main objective of CardioVision is to develop an accurate, real-time cardiac risk prediction system capable of processing ECG data and physiological metrics directly from wearable devices. This system will provide users with a dynamic risk score (Low, Medium, High) and notify them to seek medical assistance if necessary. By leveraging a lightweight fine-tuned deep learning model, CardioVision aims to deliver accurate predictions while maintaining compatibility with edge devices like Apple Watch.

II. Dataset

CardioVision was trained on various datasets which include the MIT-BIH Arrhythmia Database (48 half-hour ECG recordings with multi-class arrhythmia labels), INCART 12-Lead Database (Multilead ECG signals for diverse arrhythmias), Out-of-Hospital Cardiac Arrest Database (Real-world cardiac arrest ECGs), MIMIC-III Waveform Database (Real-time ICU physiological signals), Sudden Cardiac Death Holter Database (ECG recordings of patients with sudden cardiac death), simulated Healthkit Metrics based on established ranges from health institutions. These datasets provided a wide range of cardiac conditions, allowing the model to learn both normal and abnormal heart rhythms.

III. Related Work

Existing cardiac risk prediction methods are either manual (ECG interpretation) or limited to post-event analysis (ICU monitoring). Notable related works include LSTM and CNN models for arrhythmia detection (MIT-BIH Arrhythmia Database), transfer learning in ECG classification for improved generalization, real-time health monitoring using wearable devices (Apple Watch ECG). CardioVision builds on these by integrating multiple signal types (ECG, HR, HRV, RHR, HHR) into a unified prediction model.

IV. Methods

CardioVision utilizes a Bidirectional LSTM (BiLSTM) as the primary model for sequential ECG analysis, classifying cardiac risk into three categories: low, medium, and high. In addition to the BiLSTM, the system employs a range of specialized submodels for different physiological metrics. These include a Random Forest model for the initial metrics model and high heart rate events (HHR), an ensemble of gradient boosting models (XGBoost, CatBoost, and LightGBM) for heart rate variability (HRV), a rule-based threshold model for heart rate (HR), and a Logistic Regression model for resting heart rate (RHR). Furthermore, a fine-tuned BiLSTM with an adaptive metalearner acts as an ensemble model, integrating predictions from these submodels for enhanced accuracy for final prediction. To enhance generalization, ECG waveforms were augmented using techniques such as noise addition, scaling, and shifting. The BiLSTM model was optimized with static quantization for efficient deployment. Fine-tuning used CrossEntropyLoss with Focal Loss for class imbalance, leveraging feedback samples from MIT-BIH, Holter, and INCART. SMOTE balanced classes, while the Adam optimizer with a learning rate scheduler (ReduceLROnPlateau) ensured stable training.

V. Conclusion and Future Work

CardioVision achieved real-time cardiac risk prediction by effectively leveraging ECG waveforms and physiological metrics from Apple HealthKit. It demonstrated robust performance across multiple datasets, including MIT-BIH and OHCA, providing accurate classification of cardiac risk. Future work will focus on enhancing the submodels for HealthKit metrics to improve overall prediction accuracy, deploying the system as a native watchOS app with on-device inference, and expanding its adaptability through continual learning, enabling personalized predictions for users.