Cardiac Arrhythmia Prediction from Pediatric ECGs: A Novel Machine Learning Risk Model

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Introduction

Machine Learning (ML) models are valuable tools in healthcare for early disease detection, risk stratification, and improved diagnostic accuracy, leading to more effective disease management. ML's application in cardiology is promising, as the early detection and/or prediction of cardiac events can significantly improve clinical outcomes through timely intervention.

However, the early detection of cardiovascular disease is limited in pediatric populations due to age-related physiological fluctuations in electrocardiogram (ECG) metrics, such as heart rate, wave durations, and amplitudes. Most existing ECG-based cardiac arrhythmia risk assessment tools were developed using adult populations, limiting their applicability in pediatric patients. Overcoming such limitations involves training ML and deep learning models with large, age-specific pediatric patient ECG datasets to improve early detection strategies and predict future risks of arrhythmia.

Objective

This in-progress study aims to build the comprehensive ECG database required to train a Pediatric Arrhythmia Risk Assessment Tool (PARAT), which leverages both traditional ML models and deep learning approaches to predict future arrhythmia onset in seemingly normal pediatric ECGs.

Methods

Data Collection

- ECGs were extracted from Children's National Hospital patient database.
- For each ECG, the following variables were acquired:
  - Patient DOB
  - Patient Age
  - Patient Sex
  - QT Length
  - QTcB Length
  - Heart Rate
  - Test Reason
  - Test Date
  - Test Location
- Two training datasets were created:
  A) Normal patients → never develop arrhythmia
  B) Normal patients → later develop arrhythmia

Patient Labeling for Dataset B

- Arrhythmic patients were added to patient lists on the PowerChart application.
- Patient medical history was collected to verify presence of arrhythmia, ensuring accurate labeling for ML and deep learning models.
- Raw ECG signals were downloaded for verified arrhythmic patients.

Preliminary Dataset

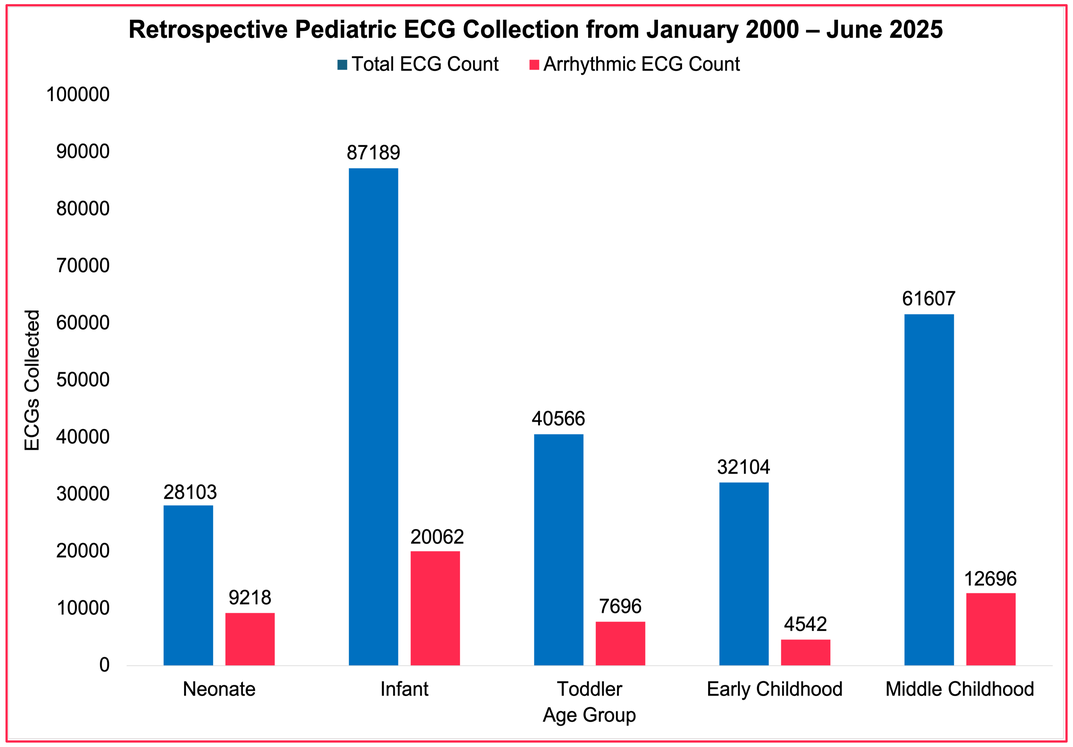

Fig 1. Graph displaying total ECGs and arrhythmic ECGs collected from pediatric patients across five developmental stages: neonate (1 day – 4 weeks), infant (1 month – 1 year), toddler (1 year – 3 years), early childhood (3 years – 6 years), and middle childhood (6 years – 12 years). ECG test dates range from January 2000 to June 2025.

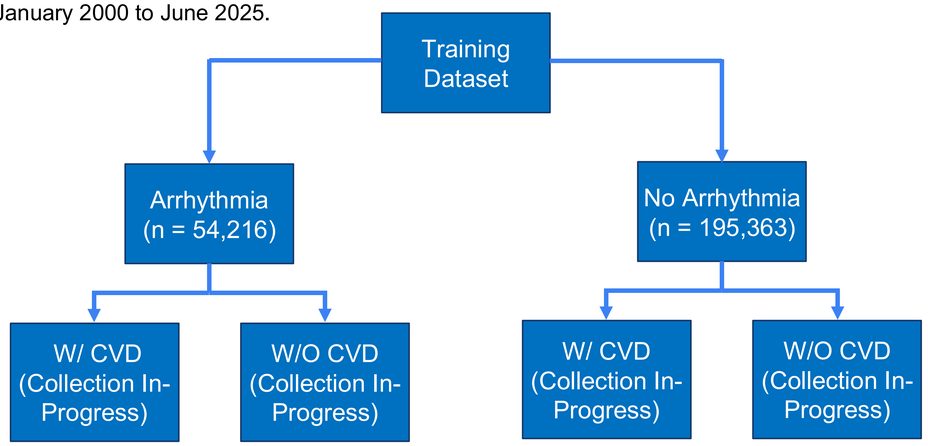

Fig 2. Flowchart illustrating composition of ECG training dataset, categorized into arrhythmia and no arrhythmia groups, each further classified by cardiovascular disease (CVD) status.

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Future Steps

- Train traditional ML models (Random Forest, Logistic Regression, etc.) with extracted ECG features.
- Train deep learning model (1D Convolutional Neural Network) with raw ECG waves.

1. **Arrhythmia Recognition:** Train models using datasets A & B to detect signs of arrhythmia in seemingly normal ECGs.
2. **Performance Evaluation:** Reserve 20% of the collected ECG data for model testing, where Area Under the Curve (AUC)–Receiver Operating Characteristic (ROC) curves will be plotted to evaluate the performance of the models.
3. **Clinical Case Testing:** Predict future arrhythmia risk in a) patients with Long QT Syndrome, b) preoperative patients with congenital heart disease (CHD), and c) postoperative patients with CHD receiving milrinone to improve low cardiac output.
4. **Model Selection:** Choose the optimal model after evaluating predictive performance.

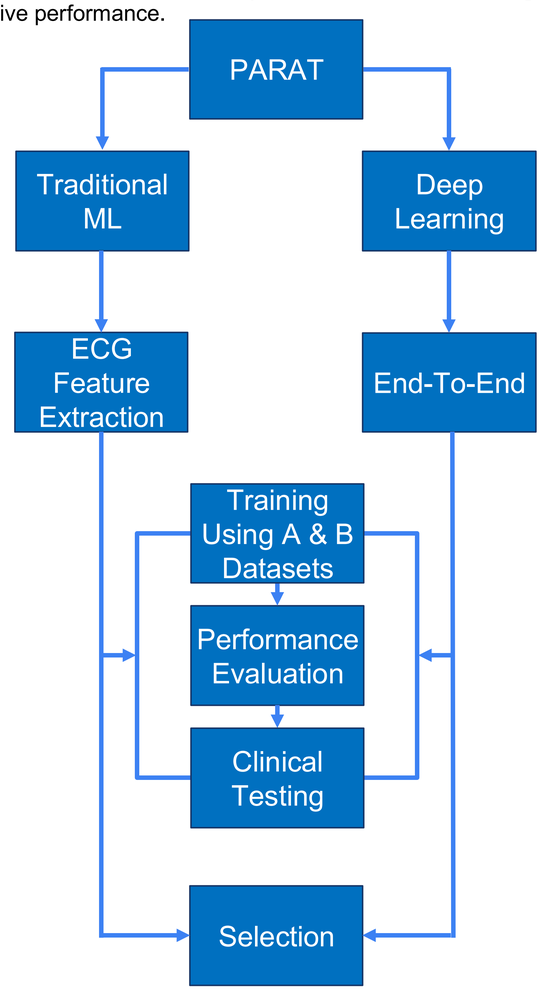

Fig 3. Future steps consist of training ML and deep learning models using ECG feature extraction and end-to-end learning, respectively, followed by performance evaluation in clinical cases.