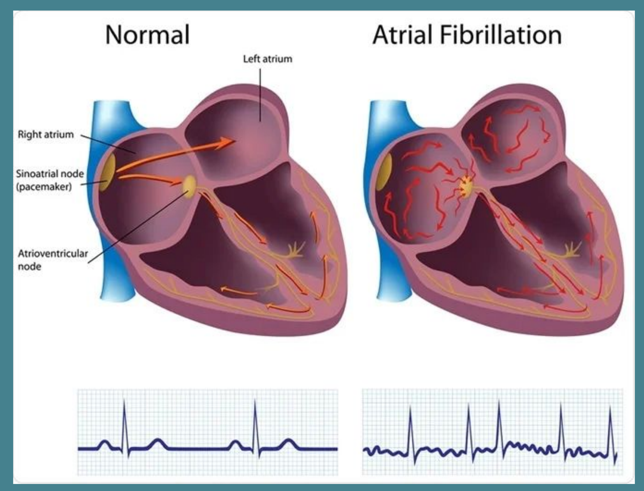

Obtained from SecondsCount.org

# Identifying Atrial Fibrillation with Stepping Windows


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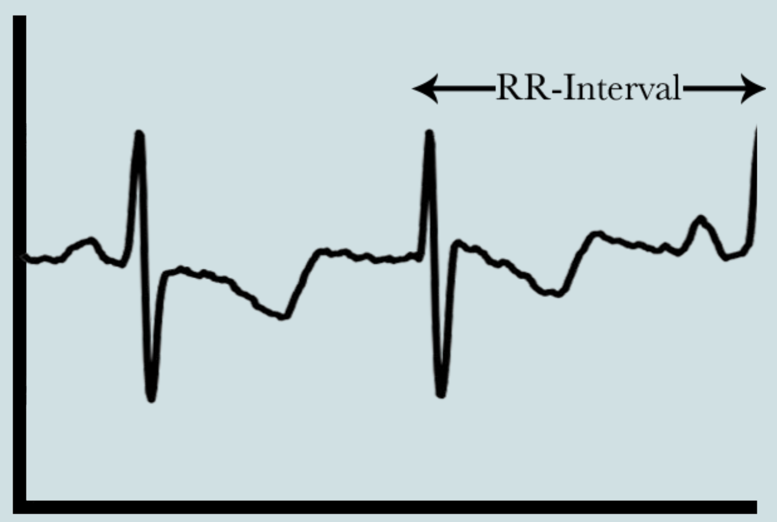
## Introduction

**Atrial fibrillation (Afib)** is a sudden and irregular heartbeat, or an arrhythmia, in the upper chamber of the heart. According to the CDC, this arrhythmia leads to over 158,000 deaths each year and can cause stroke, heart failure, and chronic fatigue[1]. This arrhythmia can only be detected when the heart is constantly being monitored, hence a real-time detector can be crucial in limiting the potential casualties and adverse effects.

## Data Overview

Utilizing the MIT-BIH Database comprised of 23 ECG records for 23 different Afib patients, we extracted the data for our project [2]:

- RR-Intervals
  - Lengths between consecutive R-Peaks
  - Primary focus of the machine learning classification
- Type of rhythm reported at the end of each interval
  - Normal, Afib, or other arrhythmia




## Features

- Interquartile Range
- Median Absolute Deviation
- Coefficient of Variance
- Range
- Standard Deviation
- Root Mean Square of Successive Differences
- Transition Proportions
- RR-Variance
- R-Mean Variance

$$rmean_i = 0.75 \times rmean_{i-1} + 0.25 \times RR_i$$

$$C_i = \left\{ \begin{array}{ll} short & RR_i < 0.85 \times rrmean_i \\ long & RR_i > 1.15 \times rrmean_i \\ normal & otherwise \end{array} \right\}$$

$$RMSSD = \sqrt{\frac{\sum_{i=1}^{N-1}(RR_i - RR_{i+1})^2}{N-1}}$$

## Acknowledgements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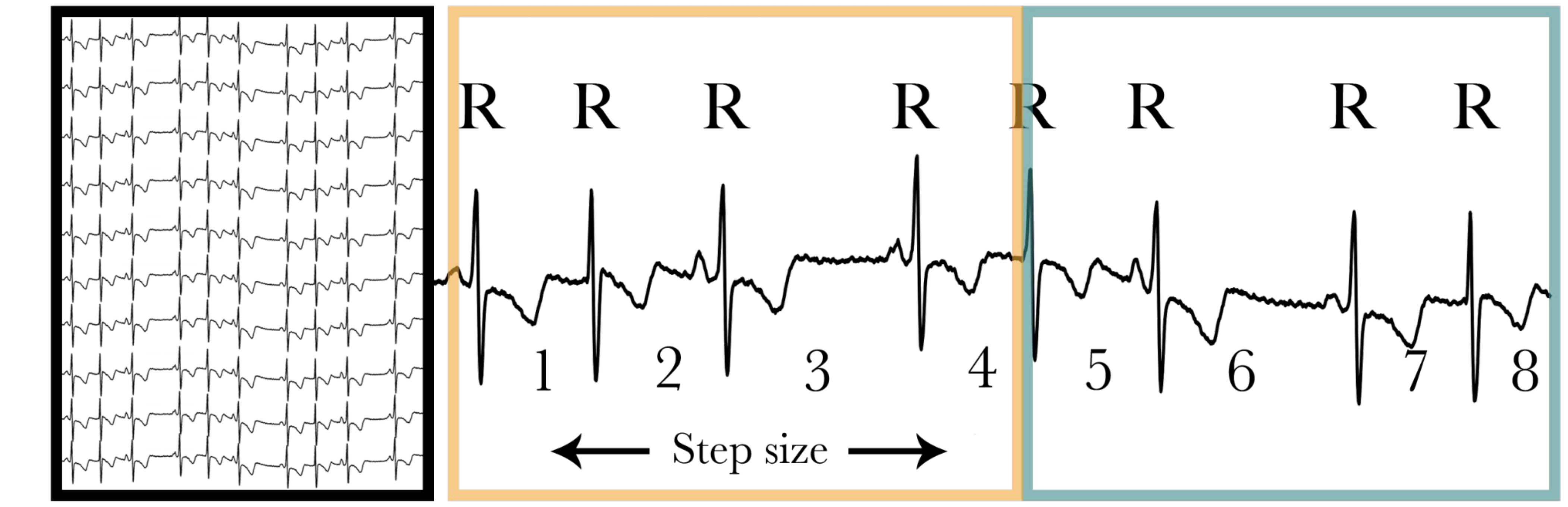
## Stepping Window

**Allows each segment of the data to be interpreted as Afib or normal using the RR-Intervals in near real-time**

**Splits the data into windows and calculates features for each while incorporating features from the previous window**

**100 RR-interval calibration period to stabilize features before continuing with near-real time classification**



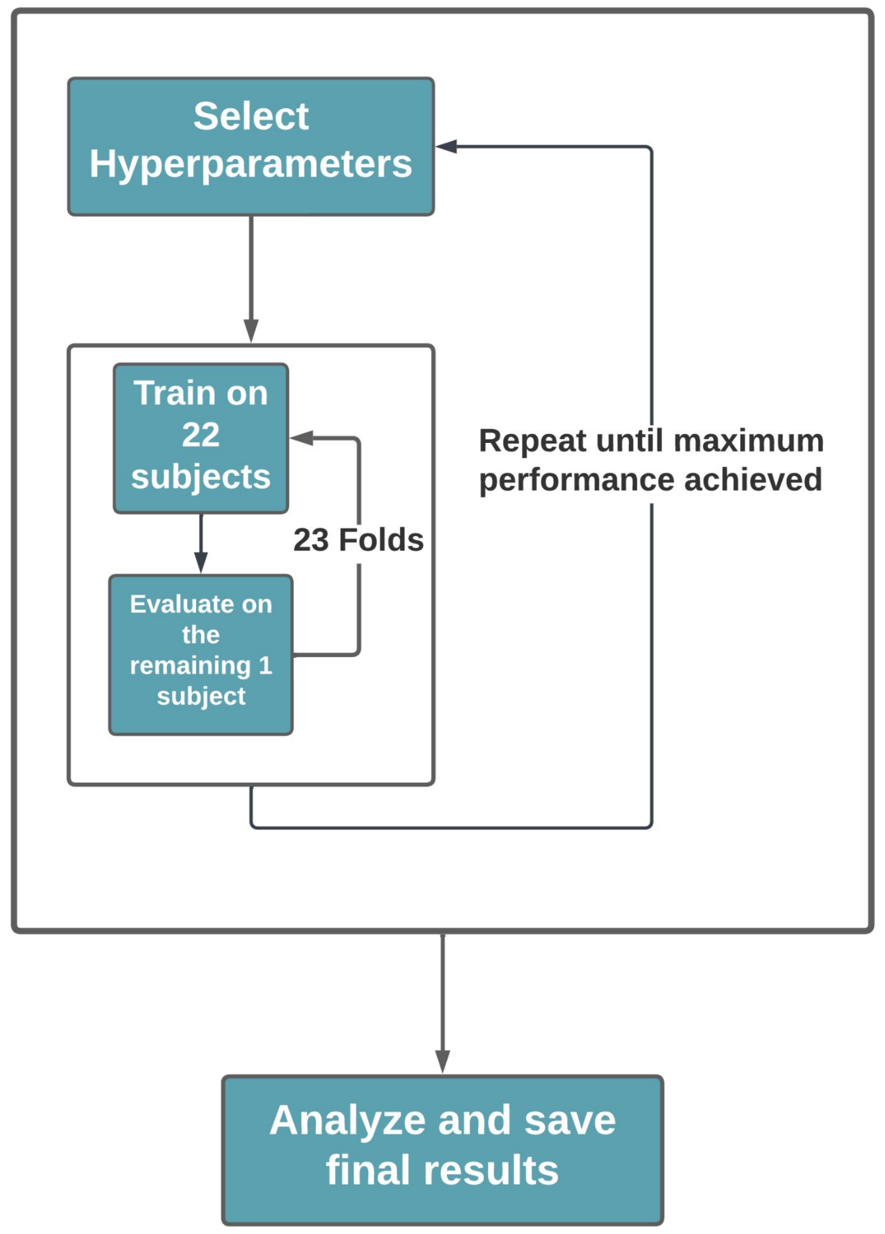

$$\mathbf{x}_{(i)} = a\mathbf{x}_{(i)} + b\mathbf{x}_{(i-1)}$$

**Each window includes four intervals without overlapping the previous intervals**

**Feature vector from previous window is used to aid in calculating features for current window.**

**Features that are fed to the model reflect current window as well as past trends**

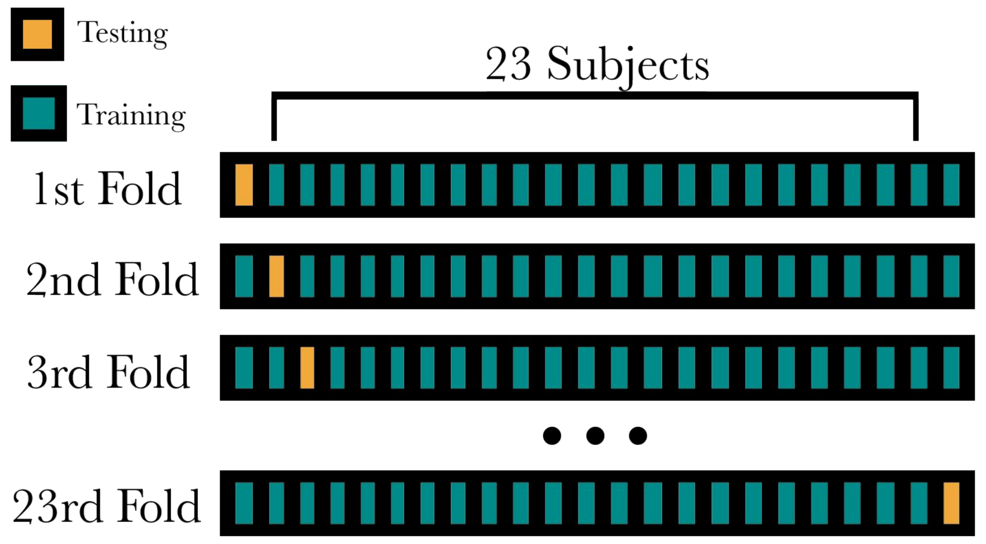
**Enables the model to draw more accurate conclusions using little data**



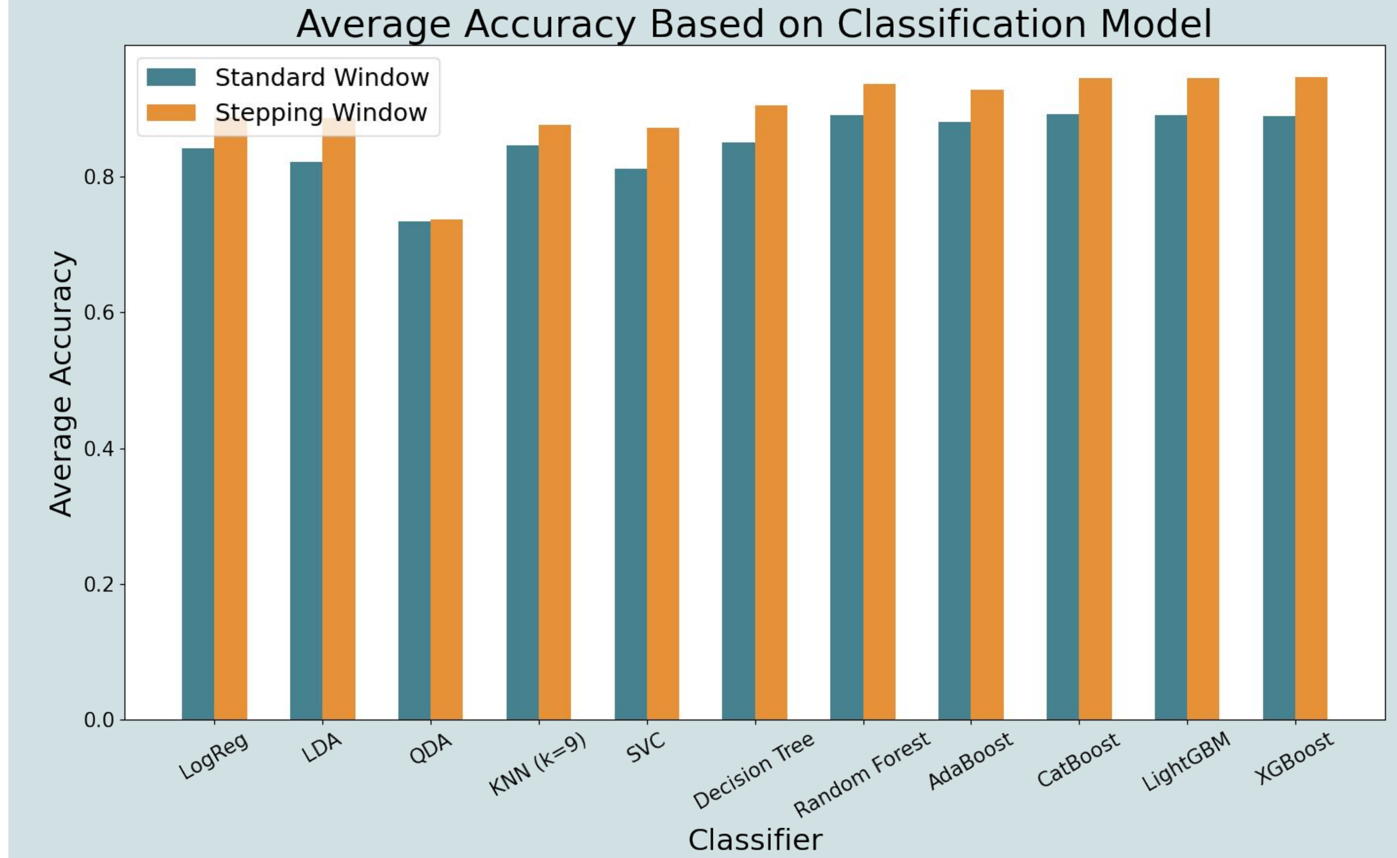

## Methods

**Leave-One-Person-Out (LOPO): 23 folds, one for each subject. 22 subjects are trained on, and the remaining subject is tested on**

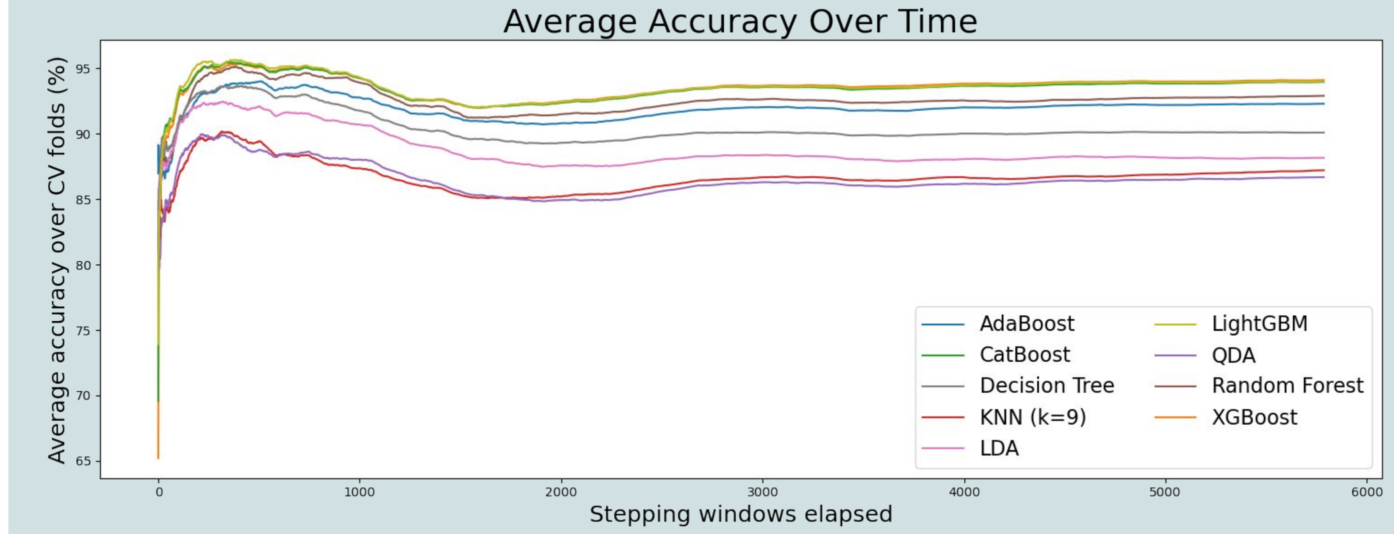
**Our model development pipeline also included hyperparameter tuning to maximize model performance.**




## Results




| Classifier | Avg Accuracy | Std Accuracy | Sensitivity | Specificity | Precision |
|---|---|---|---|---|---|
| LogReg | 88.73% | 11.50% | 89.16% | 89.19% | 82.61% |
| LDA | 88.64% | 11.79% | 90.03% | 86.85% | 81.70% |
| QDA | 73.69% | 22.13% | 88.78% | 42.14% | 65.56% |
| KNN (k=9) | 87.70% | 11.89% | 83.95% | 92.56% | 84.84% |
| SVC | 87.23% | 13.36% | 86.88% | 88.48% | 82.75% |
| Decision Tree | 90.44% | 8.35% | 90.55% | 85.06% | 80.85% |
| Random Forest | 93.64% | 7.17% | 91.93% | 89.45% | 87.17% |
| AdaBoost | 92.75% | 8.73% | 90.58% | 92.32% | 86.85% |
| XGBoost | 94.63% | 6.49% | 92.64% | 89.96% | 87.94% |
| CatBoost | 94.51% | 6.59% | 92.46% | 89.97% | 87.88% |
| LightGBM | 94.48% | 6.75% | 92.60% | 89.94% | 87.70% |




## Conclusions

The stepping window approach we explored proved able to classify Afib with shorter subsets than before, helping reduce the time necessary to detect Afib. We aim to do more research on feature calculation, classifier options, and optimal parameters for the stepping window. We can also explore signal processing, allowing us to feed raw ECG recordings into our model and move towards implementation into wearable technology to detect Afib in real time.

## References


[1]Atrial Fibrillation. url: https://www.cdc.gov/heartdisease/atrial_fibrillation.htm. (accessed:06.29.2022).

[2]A. L. Goldberger et al. "PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals". In: *Circulation* 101.23 (2000). Circulation Electronic Pages: http://circ.ahajournals.org/content/101/23/e215.full PMID:1085218; doi:10.1161/01.CIR.101.23.e215, e215–e220.


**All figures were created by our group unless otherwise specified***