Development of a Cost-Effective Predictive Model for New-Onset Atrial Fibrillation using ECG-Derived Variables

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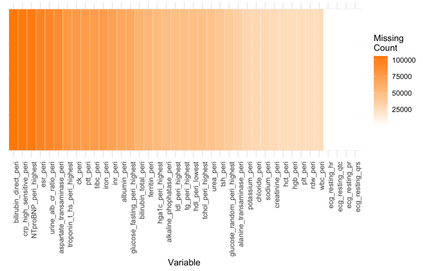
Introduction

- **Background**
  - Atrial fibrillation (AF) is a common heart rhythm disorder that affects more than 46 million people globally.[1]
  - AF increases the risk of stroke four- to fivefold, with risk markedly increasing with age.[2,3]
  - Existing machine learning (ML) approaches use uncommon blood biomarkers and expensive cardiac imaging.[4]
- **Study Focus**
  - To use ML models to analyze routinely collected electrocardiogram (ECG) data, an inexpensive and evidence-based alternative.
- **Objectives**
  - Use clinical and data-driven approaches to develop a risk prediction model to predict the future occurrence of new-onset AF.
  - Evaluate the importance of aggregate ECG variables in AF prediction.

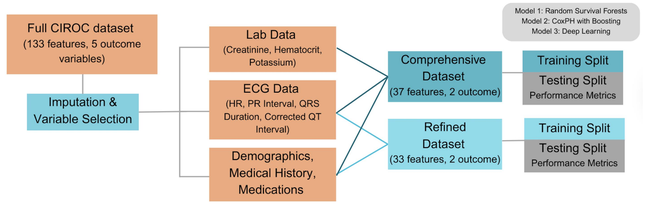
Data

- **CIROC Synthetic Dataset**
  - ~ 100,000 patients with no history of AF who had a baseline ECG performed between Jan 2010 and Jan 2023
  - Follow-up period of at least 12 months
- **Heatmap of Missingness:**

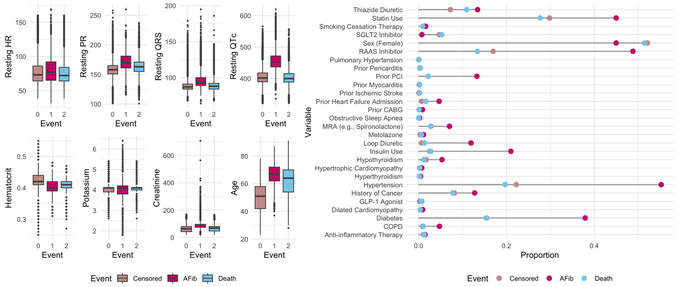


- **PTB-XL+ Publicly Available ECG Dataset[5]:**
  - 21799 ECGs from 18885 patients of 10-second length, with associated clinical data
  - 1874 patients with repeated ECG measurements free from AF at baseline

Methodology



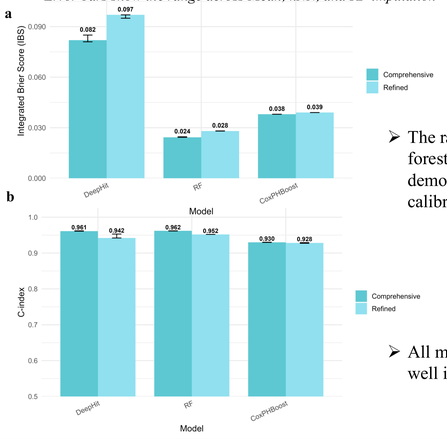
- **Variable Distribution of Clinical Measures Across Event Types**
  - Boxplots: ECG, lab, and age distributions; Dot plot: variable proportions



- **Imputation**
  - Random Forest (missranger); kNN and mean imputation for sensitivity analysis
- **Models**
  - CoxBoost (Cox Proportional Hazards with gradient boosting)
  - DeepHit (deep-learning survival model)[6]
  - Random Survival Forest (RSF)
- **Performance Metrics**
  - Harrell's C-index
  - Brier Score & Integrated Brier Score (IBS)
- **Variable Importance**
  - CoxBoost: Chooses variables which decrease the loss function the most in each boosting step
  - Random Survival Forest: Chooses variables with the greatest impact on the C-index (predictive performance)
  - DeepHit: Chooses variables that increase IBS when shuffled

Results

- **IBS (a) and C-index (b) across models for Comprehensive & Refined Data**
  - *Error bars show the range across Mean, kNN, and RF imputation*



- The random survival forest model demonstrated the best calibration.
- All models performed well in discrimination.

- **Top 5 Important Variables**

	DeepHit	Random Forest	CoxBoost
1	Corrected QT Interval	Corrected QT Interval	Corrected QT Interval
2	Age	Age	Age
3	Creatinine	Creatinine	Creatinine
4	Resting HR	Hematocrit	
5	Potassium	Potassium	

- **Results from logistic regression model predicting future AF in PTB-XL Dataset**
- $logit\big(Pr(AF = 1)\big) \sim Age + PR + HR + QRS + QTc + T$

	Coefficient	P-Value
Age (years)	0.00632	**0.0232**
Resting PR Interval (ms)	0.00580	**0.0033**
Resting Heart Rate	0.00843	**<0.0001**
QRS Duration (ms)	0.00689	0.2388
Corrected QT Interval (ms)	0.00574	0.2108
T Wave Duration	0.00851	**0.0232**

Conclusion

- **Summary of findings**
  - All models achieved strong performance (C-index > 0.92)
  - Age and corrected QT interval were the top predictors.
  - RSF performed best (C-index: 0.962, IBS: 0.024), followed by DeepHit and CoxBoost.
  - Removing lab values had minimal impact (C-index drop < 0.02).
- **Implications**
  - Results support low-cost, scalable AF risk prediction using routine ECGs and commonly collected clinical information.
  - These machine learning approaches show promise in early AF detection, highlighting their wide-spread potential.

Limitations

- Model performance may be inflated due to the synthetic dataset
- External validation with PTB-XL highlights the potential value of additional ECG features, like T-wave duration.

Next Steps

- Future work should expand ECG feature sets (e.g., T-wave) and validate models on real-world longitudinal data to enhance performance and generalizability.

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References

Our references can be found at this QR code: