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Predicting atrial fibrillation recurrence after pulmonary vein isolation from ECG data

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Abstract: Catheter-based pulmonary vein isolation (PVI) is widely used to treat atrial fibrillation (AF). The procedure isolates the pulmonary vein from the left atrium to suppress irregular heartbeats. If AF recurs, further interventions may be required. This study investigates model-based prediction of AF recurrence using only electrocardiogram (ECG) data. We benchmarked two neural networks for the prediction task. The task-specific convolutional neural network achieved an AUROC of 0.755, slightly exceeding the foundation model (AUROC 0.742). These results confirm earlier findings that ECGs contain predictive information about AF recurrence and they can be extracted by foundation models.

I. Introduction

Atrial fibrillation (AF) is one of the most predominant cardiovascular diseases with an estimated global prevalence up to 59.7 million cases when combined with atrial flutter in 2019 [1]. High-income countries have particularly high prevalence. While symptoms include palpitations, fatigue and fainting, reducing the quality of life, AF also contributes to increased risk of stroke and heart failure [2]. Treatment aims to restore sinus rhythm by interrupting irregular atrial activity. In addition to antiarrhythmics and cardioversion, catheter ablation is the main treatment option. Pulmonary vein isolation (PVI) can be performed using different technologies, such as radiofrequency, cryoenergy and pulsed field ablation. Despite their widespread use in clinical practice, all methods have a high rate of AF recurrence. Some studies report recurrence rates over 40% [3]. Identifying patients at risk of developing AF recurrence could improve their follow-up, with more flexible post-procedure examinations and individualized care plans. In the past clinical scores like APPLE, ATLAS, and CHA_2DS_2-VASc have been evaluated for predicting the recurrence of AF after PVI, but their predictive values were poor [4]. Recent methods used machine learning and multimodal data for predictions leading to improved performances [5, 6]. Tang et al. showed that the electrocardiogram (ECG) contains valuable information for the prediction of AF recurrences [7]. As ECG is routinely used in follow-up examinations, it may be a cost-effective marker for AF recurrence, however evidence on diverse dataset remains limited. Further, the impact of foundation models is not yet investigated for AF recurrence prediction. In this work, we (1) solely use ECG data for the prediction of AF recurrence after PVI and compare our results to previous findings, and (2) compare an ECG foundation model against a task specific neural network for AF recurrence prediction.

II. Material and methods

Two neural networks were used as ECG-based predictors for AF. First, we reimplemented the convolutional neural network (CNN) described in [7], originally proposed for this task. It comprises six bottleneck blocks with residual connections. Each block consists of two convolutional layer, ReLU activations and batch normalization. The same preprocessing (bandpass filtering of 0.05 to 100 Hz and resampling to 200 Hz), hyperparameters and training augmentations were used. Second, we employed a pretrained foundational model (ECG-FM) as feature extractor [8]. This transformer-based model is pretrained via contrastive learning on large public datasets. Three linear layers with nonlinear activation and batch normalization in between were used in finetuning as classification head. The ECG-FM expects inputs of 500 Hz and z-normalization is the single preprocessing step.

For this study, data from publicly available MIMIC datasets are used as they contain all relevant variables [9]. We used MIMIC-IV [10] for patient identification, demographic statistics, and recurrence/mortality evaluation. For every patient we collected their latest ECG per hospital visit from MIMIC-IV-ECG [11]. Only patients with ICD diagnosis of AF, PVI and ECG data are included. PVI procedures were confirmed by inspection of discharge notes [12]. Just the first intervention is included per patient. Recurrence of AF is defined as true if patients were treated again for AF in a

time span of one year. Patients who died in this time window, were excluded from the evaluation. A total of 189 individual patients were included with 45 positive cases of recurrence (see Fig. 1). Patients had an average age of 65.1 (± 9.8) years and of whom 67% were male. The data was split on patient-level into training and testing datasets according to the splits reported in the ECG-FM repository, resulting in 148 and 41 patients for training and testing respectively. Each ECG was segmented into samples of 5s with an overlap of 80%. This increased the training data and matched the input length to both models as required. In testing, the maximum of the six resulting predictions (one per segment) is taken as the output for the whole ECG. Both models were trained for 50 epochs, using the AdamW optimizer and the binary cross entropy loss function.

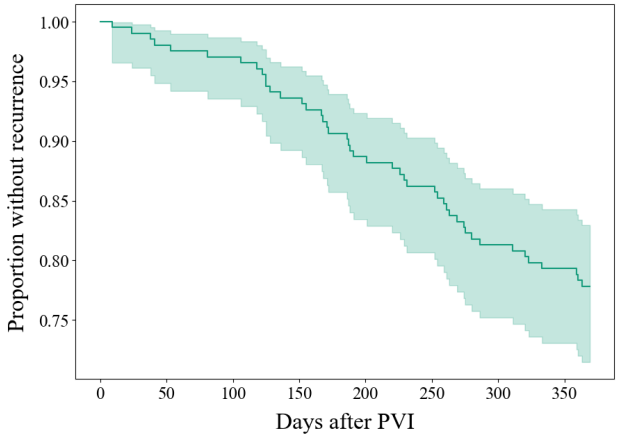

Figure 1: Kaplan-Meier plot of the complete dataset.

III. Results and discussion

Both the task-specific neural network and the ECG foundation model successfully predicted AF recurrence, yielding similar performances (see Fig. 2). Absolute AUROC was minimally higher for the CNN model (0.755 compared to 0.742), but the difference is not significant. Both scores are slightly lower than the results of Tang et al. who reported an AUROC of 0.767 on a different dataset [7]. Although their study design and cohort characteristics differ from this study, the results are comparable.

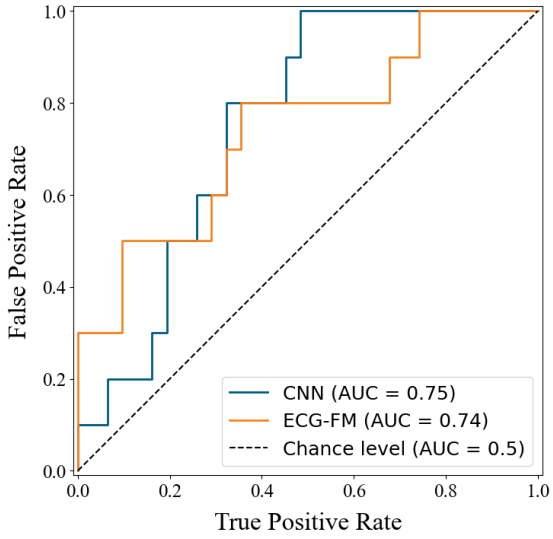

Figure 2: ROC curve of both neural network-based predictors.

IV. Conclusions

Our findings confirm previous results that ECG data are informative for predicting AF recurrence after PVI and should be collected in future studies. No definite statement can be made about the best model choice, as both approaches scored equally well. Given the retrospective, single-center nature of this analysis, limited sample size and potential biases introduced by the cohort definition, generalizability is constrained and conclusions should be interpreted cautiously. Future work should validate these results in larger, multi-center cohorts to evaluate generalizability across hospitals and identify which models' predictive performance scales best with dataset size. Another approach would be the combination of ECG data with laboratory values, demographics, vital signs, and procedural data.

Author's statement

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