

CI-524-04

RISK OF VENTRICULAR ARRHYTHMIAS FOLLOWING IMPLANTABLE CARDIOVERTER DEFIBRILLATOR GENERATOR CHANGE IN PATIENTS WITH RECOVERED EJECTION FRACTION: IMPLICATIONS FOR SHARED DECISION MAKING

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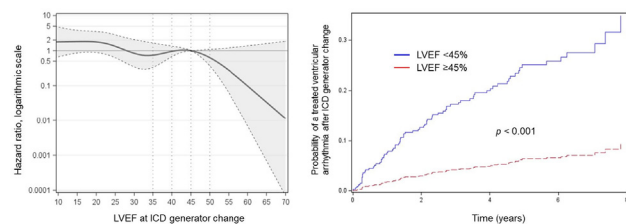
Background: Primary-prevention ICDs are indicated for most patients with LVEF <35%. Some patients improve their LVEF to >35% during the life of their first ICD. In present practice, when the battery is depleted, ICDs most often are replaced regardless of LVEF. In patients with recovered LVEF who have never received appropriate ICD therapy, the utility of ICD generator replacement remains unclear.

Objective: To evaluate rates of appropriate ICD therapy based on LVEF at the time of generator change, in order to educate shared decision making.

Methods: We enrolled patients with a primary-prevention ICD originally implanted for LVEF <35%, who underwent ICD generator change within our state's largest multihospital health system. Patients who required appropriate ICD therapy for VT/VF prior to generator change were excluded. Cumulative incidence curves were Fine-Gray adjusted for the competing risk of death.

Results: Among 951 generator changes, 423 patients (69±12 y, 65% men, 29% Black, LVEF 34±15%, 222 [52%] ischemic) met inclusion criteria. Over 3.4±2.2 years after generator change, 78 (18%) received appropriate therapy for VT/VF. Compared to patients with recovered EF>35% (n=161 [38%]), those with LVEF persistently <35% (n=262 [62%]) more likely required ICD therapy (p=0.005; 5-year rates: 13% vs. 25%). ROC analysis (AUC 0.66, p<0.001) revealed the optimal cutoff for VT/VF prediction was LVEF 45%, which was supported by the plot of hazard vs. EF as a continuous variable, modeled by restricted cubic splines. There was much lower VT/VF incidence among those with LVEF ≥45% vs. <45% (p<0.001); 5-year rates: 6% vs. 25%. These findings were similar for patients with either ischemic or nonischemic cardiomyopathy (HR 3.9, p<0.01; and HR 8.5, p=0.035).

Conclusion: At the time of ICD generator change, patients with primary-prevention ICDs and LVEF ≥45% with no prior ICD therapy have a significantly lower rate of subsequent ventricular arrhythmias compared to those with LVEF<45%. These data may be useful during shared decision-making at the time of ICD generator battery depletion.



ABSTRACT DH-575:

Deep Learning and AI for Heart Rhythm Disorders

Friday, April 29, 2022

1:00 PM - 2:00 PM

DH-575-01

MACHINE LEARNING-ENABLED MULTIMODAL FUSION OF INTRA-ATRIAL AND BODY SURFACE SIGNALS IN PREDICTION OF ATRIAL FIBRILLATION ABLATION OUTCOMES

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Background: Machine learning (ML) is a promising approach to personalize atrial fibrillation (AF) management strategies for patients after catheter ablation. Prior studies applied classical ML methods to clinical scores, and none have leveraged intracardiac electrograms (EGM) or 12-lead electrocardiograms (ECG) for outcome prediction.

Objective: We aimed to show that (a) ML models trained on EGM or ECG can better predict patient outcomes after AF ablation than existing clinical scores and (b) fusion of EGM, ECG, and clinical features can further improve the prediction performance.

Methods: Consecutive patients who underwent catheter ablation between 2015-2017 with panoramic left atrial EGM prior to ablation and clinical follow-up for at least one year following ablation were included. A convolutional neural network (CNN)

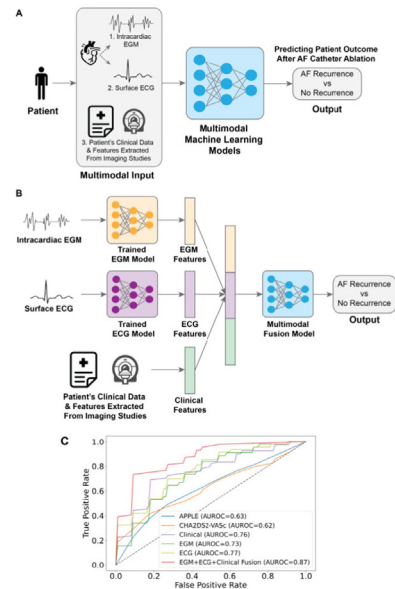


Figure 1. (A) Overview of our methods. The inputs come from three modalities: patient EGM signals, ECG signals, and clinical features. A multimodal machine learning model fuses the inputs from the three modalities and outputs prediction of AF recurrence. **(B) Details of our multimodal fusion framework.** We first trained a model on EGM signals only for AF recurrence prediction, and a separate model on ECG signals only for AF recurrence prediction. We then extracted EGM and ECG features from the respective trained models. Finally, the EGM and ECG features were concatenated with the clinical features, and were subsequently passed to a multimodal fusion model to predict AF recurrence. **(C)** Receiver operating characteristics (ROC) curves of clinical feature-based models, signal-based models, and fusion model (averaged across 10 folds).