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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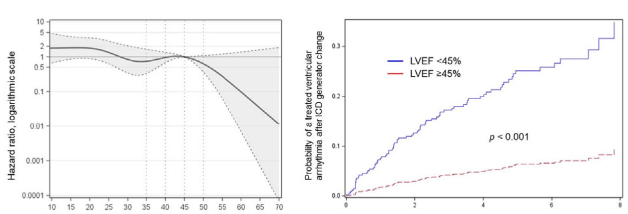
Background: Primary-prevention ICDs are indicated for most patients with LVEF ≤35%. Some patients improve their LVEF to >35% during the life of their first ICD. In present practice, when the battery is depleted, ICDs most often are replaced regardless of LVEF. In patients with recovered LVEF who have 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)

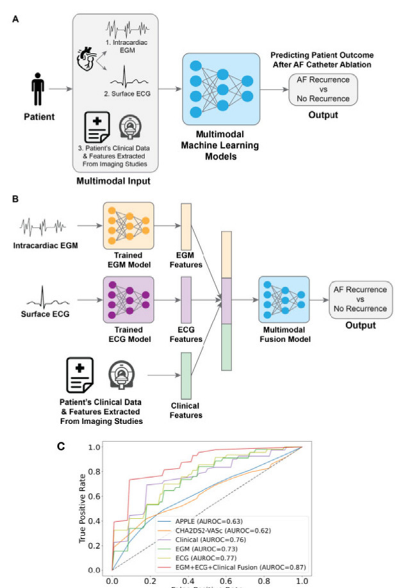

Figure 1. (A) Overview of our methods. The inputs come from three modalities: patient EGM signals, ECG signals, and clinical features. A multimodal machine learning model fuses the inputs from the three modalities and outputs prediction of AF recurrence. **(B) Details of our multimodal fusion framework**. 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).

and a fusion framework were developed for predicting 1-year AF recurrence after catheter ablation from EGM, ECG, and clinical features. The models were trained and validated using 10-fold cross-validation.
Results: 156 patients (64.5±10.5 years, 74% male, 42% paroxysmal) were analyzed. Using EGM alone, the CNN achieved an Area Under the Receiver Operating Characteristics Curve (AUC) of 0.73, outperforming existing APPLE (AUC=0.63) and CHA2DS2-VASc scores (AUC=0.62). Similarly using 12-lead ECG alone, the CNN achieved an AUC of 0.77. Combining EGM, ECG, and clinical features, the fusion model achieved an AUC of 0.87, outperforming single and dual modality models.
Conclusion: Deep neural networks trained on EGM or ECG greatly improved the prediction of catheter ablation outcome compared to existing clinical scores, and fusion of EGM, ECG, and clinical features further improved the prediction performance.

DH-575-02

IDENTIFICATION OF SUPRAVENTRICULAR TACHYCARDIA MECHANISMS WITH SURFACE ELECTROCARDIOGRAMS USING A DEEP NEURAL NETWORK

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Background: The current clinical paradigm to diagnose supraventricular tachycardias (SVTs) results in potential overlap between various ECG expressions. Machine learning may identify visually imperceptible ECG changes and augment the predictive accuracy of determining SVT mechanisms.
Objective: To compare a Convolutional Neural Network (CNN) with manual SVT identification among atrioventricular nodal re-entrant tachycardia (AVNRT), atrioventricular reciprocating tachycardia (AVRT), and atrial tachycardia (AT).
Methods: All patients with a 12-lead ECG of a diagnosed and successfully ablated SVT during an electrophysiology study from 2013-2020 were included. Digital ECG data ≥10 seconds were extracted from the recording system and split into training, validation, and test datasets in a ratio of approximately 7:1:2. The results were reported as the average across 10 random data splits and model initializations for robustness. We then compared the CNN performance with an independent adjudication by an experienced cardiac electrophysiologist.
Results: From 763 patients, 1524 ECGs (371 AVNRT, 312 AVRT, 95 AT, and 746 sinus rhythm) were used to develop the CNN. CNN identified 1) AVNRT with a higher sensitivity and similar specificity; 2) AVRT with a lower sensitivity but higher specificity; and 3) AT with a lower sensitivity and similar specificity compared to the adjudicator (Table). The CNN area under the receiver operating characteristic curve for AVNRT, AVRT, and AT was 0.855, 0.880, and 0.774 respectively.
Conclusion: In this primary model, CNN allowed differentiating SVT mechanisms characterized by a similar and variably higher or lower performance metrics compared with an experienced electrophysiologist.

	Convolutional Neural Network			Experienced Cardiac Electrophysiologist *	
	AUC	Sensitivity	Specificity	Sensitivity	Specificity
AVNRT	0.855	83.2%	77.1%	59.3%	78.7%
AVRT	0.880	40.7%	95.9%	73.9%	64.2%
AT	0.774	16.8%	95.1%	37.2%	94.2%

*Excluding 20 of 200 ECGs with "undetermined answers" from the analysis

DH-575-03

EXPLORING THE RELATIONSHIP BETWEEN LEFT VENTRICULAR WALL THINNING AND POST-INFARCTION VENTRICULAR ARRHYTHMIA USING EXPLAINABLE DEEP LEARNING ON COMPUTED TOMOGRAPHY IMAGES

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Background: Infarct heterogeneity plays a critical role in the development of scar-related ventricular arrhythmias (VA). Wall thickness (WT) from CT was shown to correlate with arrhythmogenic sites in the context of ablation.
Objective: To analyze the relationship between WT distribution and the presence VAs in patients with history of myocardial infarction (MI).
Methods: From 2010 to 2020, we retrospectively included consecutive patients who underwent CT more than 1 year after MI. Automated LV wall segmentation, reorientation, WT computation and flattening methods were applied to obtain 2D WT bullseye maps. The population was divided into a training set (3/4) and a testing set (1/4). On the training set, a conditional variational autoencoder (CVAE) model was trained to encode the WT map in its latent representation, which was then used by a classifier model to predict VA. For each prediction, a gradient back-projection method was used to generate attention maps highlighting the bullseye region most influential in the model's decision. The ability of the trained CVAE to identify patients with VA was then assessed on the test population, and compared to that of other clinical variables (age, gender, LVEF, scar size).
Results: 641 patients were included (age 73±7 years, 83% males, LVEF 46±10%), including 166 (26%) with history of VA. From original CT images, automated processing methods allowed for the obtention of a WT bullseye, a VA prediction and an attention map in less than 2 min. On the testing population, univariable correlates of VA were LVEF ($P<0.001$), scar size defined as WT area ($P<0.001$), CVAE prediction ($P<0.001$), and male gender ($P=0.007$). Multivariable analysis identified CVAE prediction and male gender as independent VA correlates ($P<0.001$ and $P=0.01$, $R^2=0.364$), while LVEF and scar size were not ($P=0.052$ and $P=0.60$). The CVAE model identified patients with VA with a sensitivity/specificity of 0.87/0.74. The