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