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.

<table>
<thead>
<tr>
<th></th>
<th>Convolutional Neural Network</th>
<th>Experienced Cardiac Electrophysiologist *</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>AUC</td>
<td>Sensitivity</td>
</tr>
<tr>
<td>AVNRT</td>
<td>0.855</td>
<td>83.2%</td>
</tr>
<tr>
<td>AVRT</td>
<td>0.880</td>
<td>40.7%</td>
</tr>
<tr>
<td>AT</td>
<td>0.774</td>
<td>16.8%</td>
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</table>

*Including 20 of 100 ECGs with "undetermined answers" from the analysis