



Deep Learning-Based Classification of Paroxysmal Supraventricular Tachycardia Types Using Sinus Rhythm Electrocardiograms



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COI Disclosure

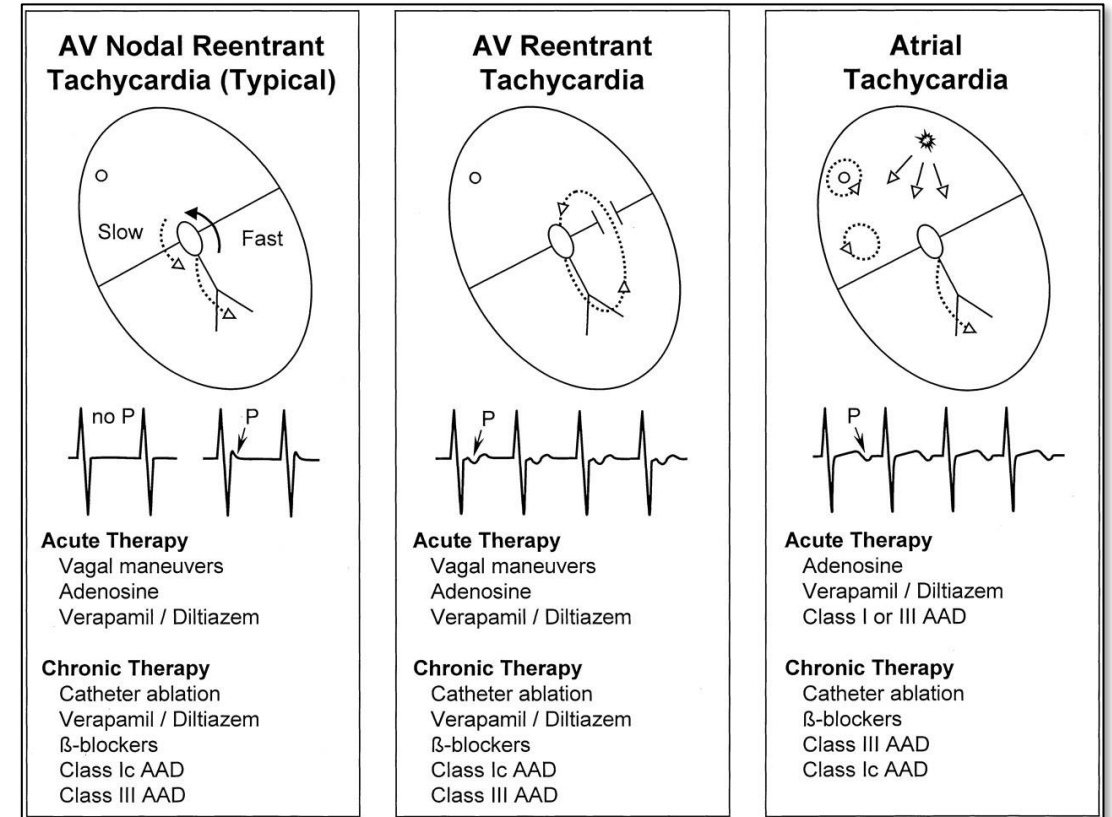
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The authors have no financial conflicts of interest
to disclose concerning the presentation



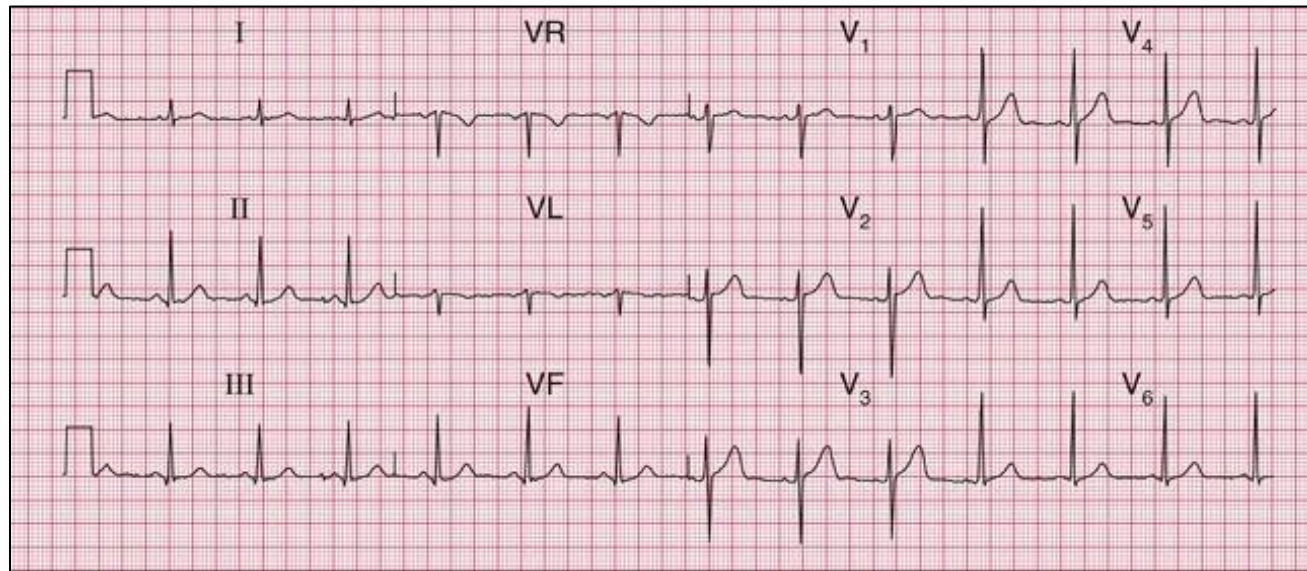
Introduction: PSVT

- Prevalence: 0.2~0.3%
- Incidence: 35/100,000 PY
- Most common PSVT types: AVNRT, AVRT
- Success rate of RFCA for PSVT: $\geq 90\%$
- Orthodromic AVRT with concealed AP:
 - 30% of PSVT without preexcitation
- To confirm the diagnosis of PSVT types
 - Requires EP study



Difficulties in identifying PSVT types

- For patients without preexcitation,
 - AVNRT vs. concealed AVRT
 - Tachycardia ECGs are often unavailable
 - Oftenly normal echocardiography and ECGs



- DDX of PSVT types require invasive tests (EP study)
- What if deep learning can predict PSVT types by analyzing ECGs?

Study aims

- Investigate deep learning-based classification of AVNRT and concealed AVRT using sinus rhythm ECGs

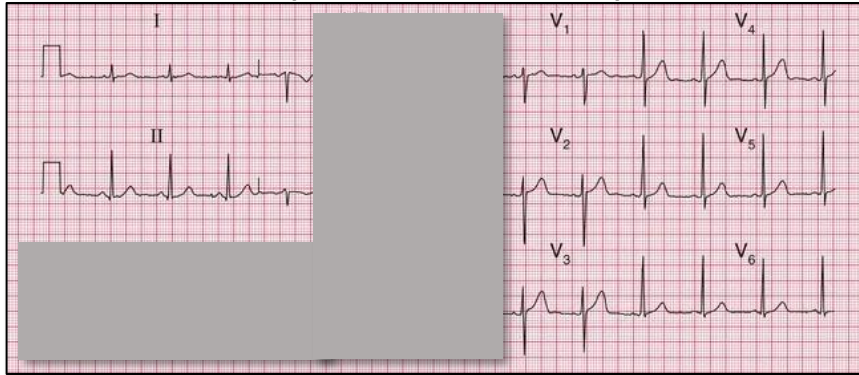
Methods

- Design Retrospective single-center cohort study
- Recruiting Cardiology clinics in 2001-2021
- Eligibility Patients with AVNRT or AVRT
 - *confirmed by EP study and*
 - *with normal ECG available prior to ablation*
- Study N 1001 pts
 - AVNRT : 696 pts
 - cAVRT : 305 pts
- DL architecture ResNet-34, pre-trained with open-source DB*
- Analysis 10-fold cross validation
SN, SP, AUROC
Grad-CAM

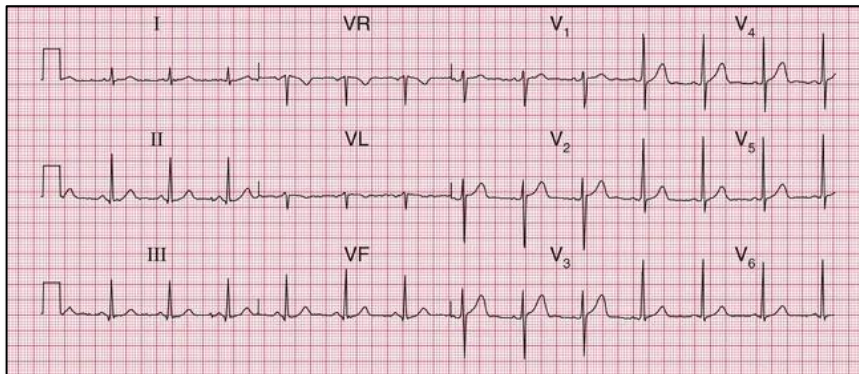
* PhysioNet/CinC Challenge 2021 dataset

Training dataset construction

Raw data (500 Hz, 10 s)

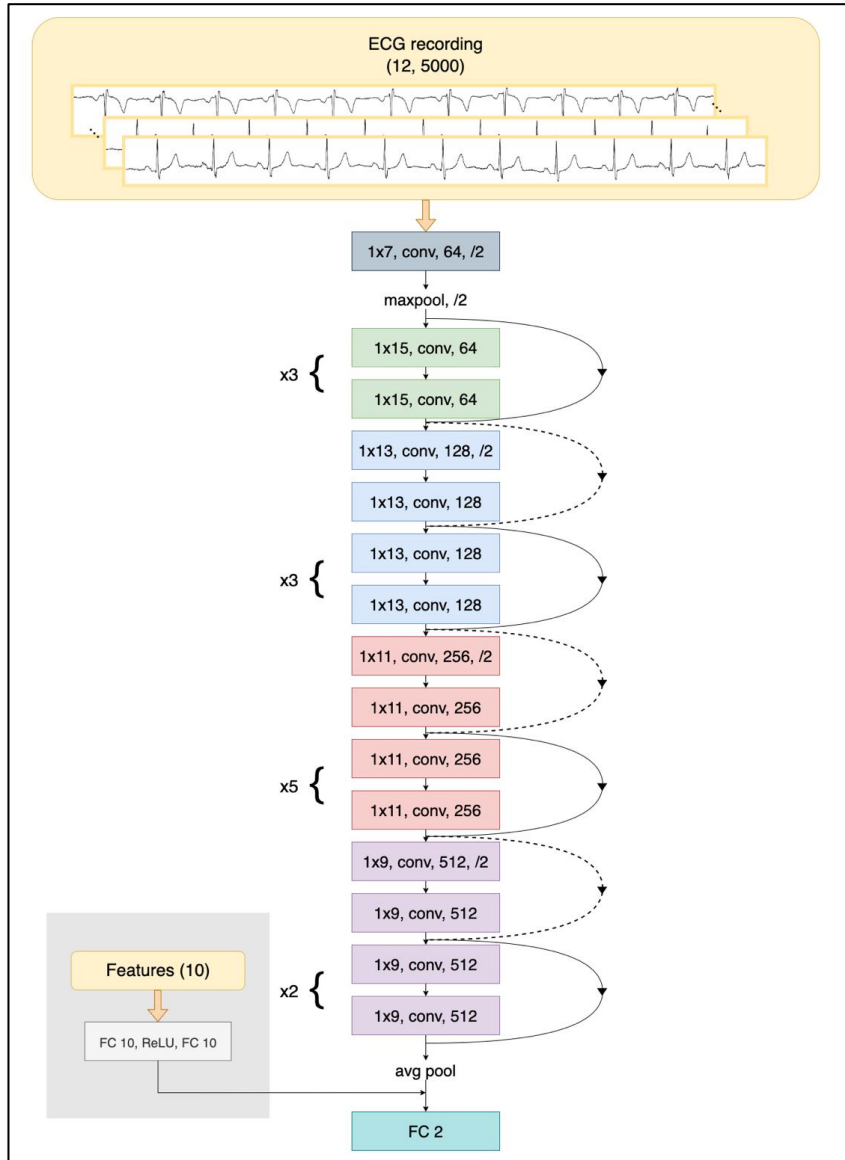


12-lead reconstruction



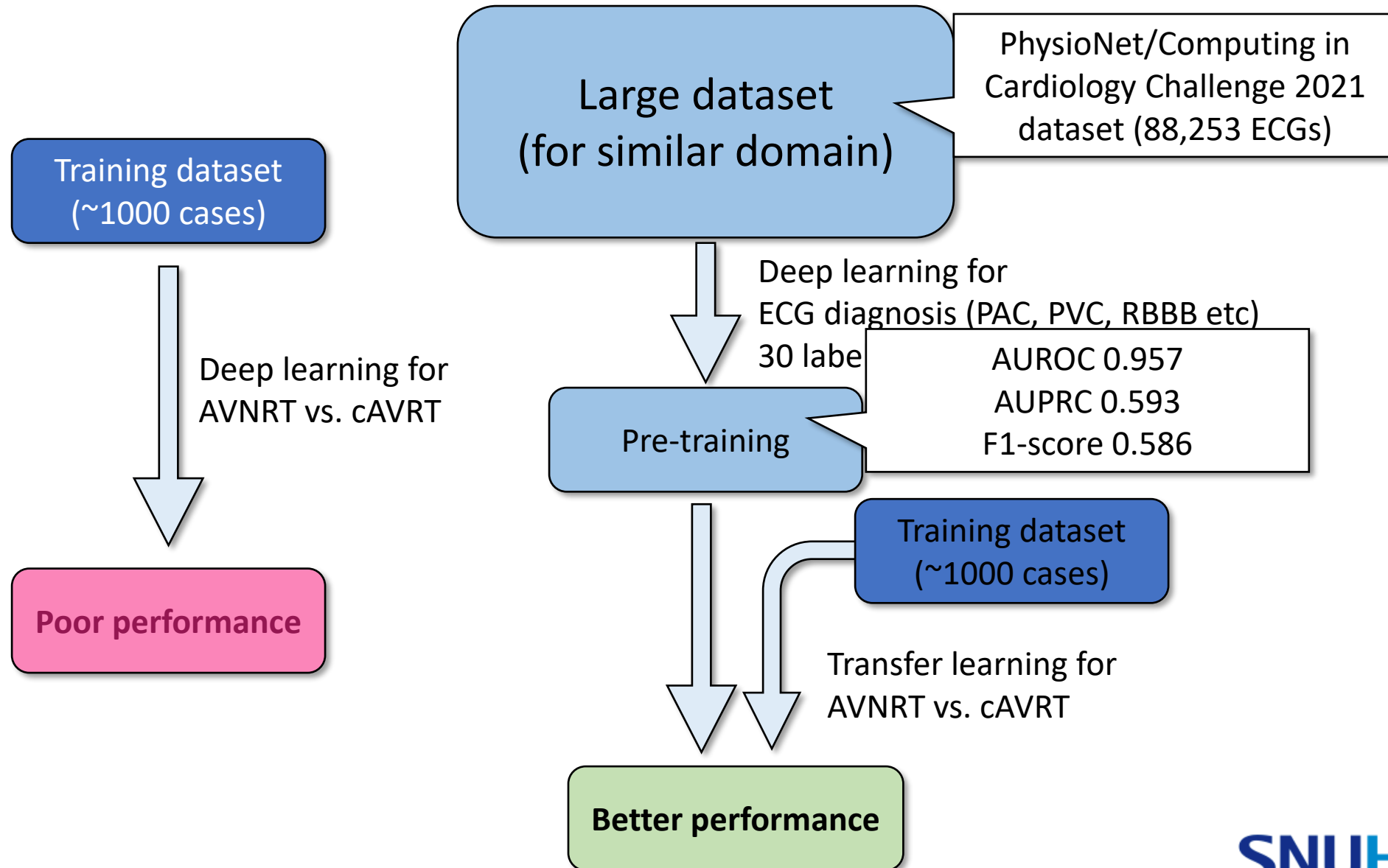
- Baseline model
 - ECG raw data only
- Experimental model
 - ECG raw data and
 - ECG features
 - Heart rate
 - PR interval
 - QRS duration
 - QT interval
 - P axis
 - R axis
 - T axis

Deep learning architecture



- ResNet-34
- With kernel size modification (12x5,000)
- Python 3.8, PyTorch 1.8.1

Transfer learning



Hyperparameters

	For pre-training	For transfer-learning
Batch size	32	32
Learning rate	5.00E-04	1.00E-04
Epochs	30	15
Optimizer	Adam	Adam
Beta1	0.9	0.9
Beta2	0.999	0.999
Weight decay	No weight decay	1.00E-04
Scheduler	Cosine annealing learning rate scheduler	Cosine annealing learning rate scheduler
Loss	Binary cross-entropy	Cross-entropy

Performance evaluation

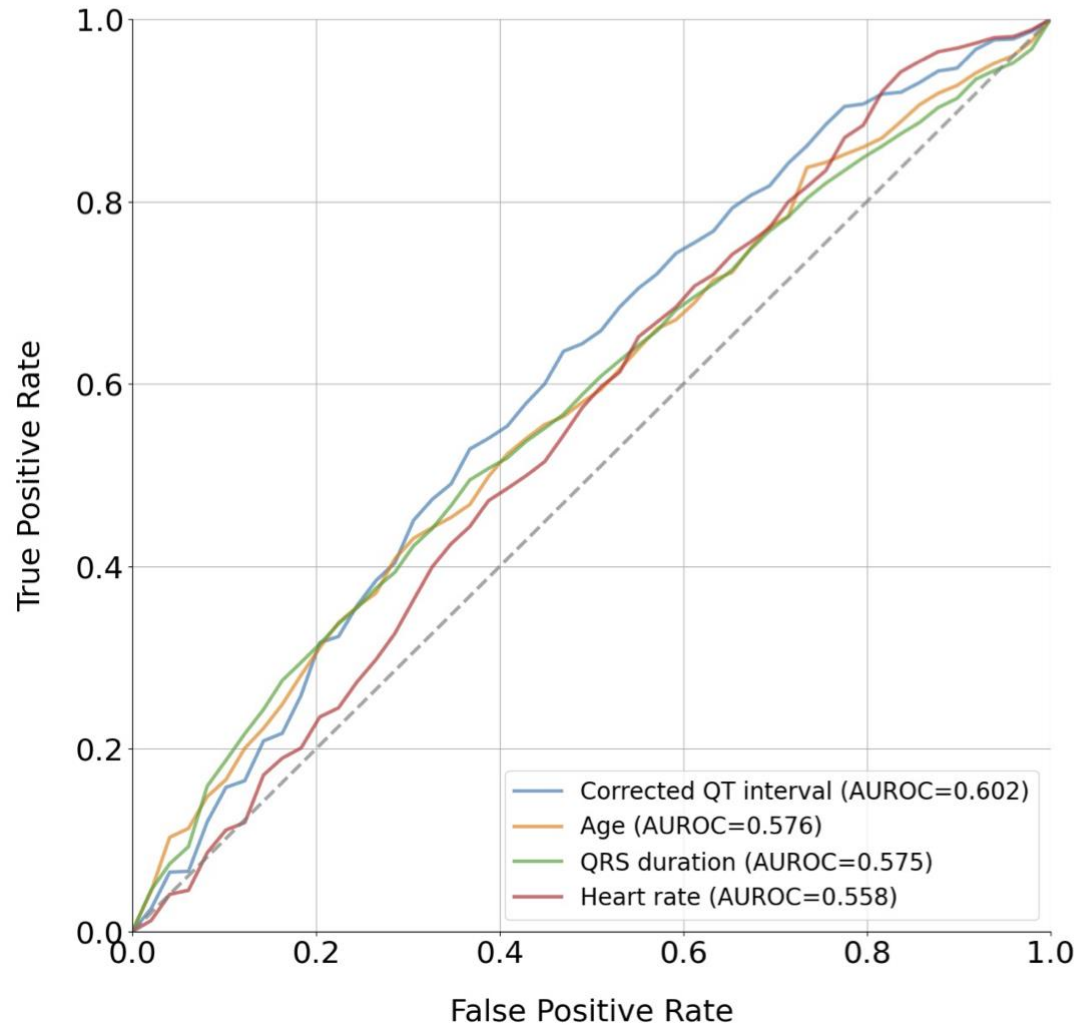
- DTraining : Validation = 9 : 1
- 10-fold cross validation
- Repeat over 10 times for each fold
- Performance metrics: SN, SP, PPV, NPV, Accuracy, AUROC
- Calibration plots

Result: *baseline characteristics*

	AVNRT (N=696)	Concealed AVRT (N=305)	P-value
Age (yr)	51 (36–60)	48 (28–57)	<0.001
Men	239 (34.3)	193 (63.3)	<0.001
Heart rate (per min)	69 (65–77)	68 (62–76)	0.007
PR interval (ms)	152 (138–166)	152 (138–164)	0.96
QRS duration (ms)	90 (84–98)	94 (86–100)	<0.001
Corrected QT interval (ms)	428 (412–441)	418 (401–435)	<0.001
P axis (degree)	55 (40–65)	54 (36–65)	0.546
R axis (degree)	55 (31–73)	59 (32–76)	0.072
T axis (degree)	44 (30–56)	47 (30–58)	0.263
Premature atrial complex	11 (1.6)	5 (1.6)	0.946
Premature ventricular complex	8 (1.1)	8 (2.6)	0.087
Left ventricular hypertrophy	11 (1.6)	8 (2.6)	0.266
Low voltage	7 (1.0)	1 (0.3)	0.268
Early repolarization	16 (2.3)	13 (4.3)	0.088
Right atrial enlargement	6 (0.9)	6 (2.0)	0.139
Left atrial enlargement	12 (1.7)	8 (2.6)	0.35
1st degree atrioventricular block	16 (2.3)	4 (1.3)	0.304
Right bundle branch block	33 (4.7)	5 (1.6)	0.018
Left bundle branch block	0 (0)	0 (0)	>0.999
Left anterior fascicular block	7 (1.0)	1 (0.3)	0.268
Left posterior fascicular block	1 (0.1)	0 (0)	0.508
Bifascicular block	2 (0.3)	0 (0)	0.349
Any infarct	26 (3.7)	11 (3.6)	0.921
Any ischemia	18 (2.6)	10 (3.3)	0.541

Result: C-statistics

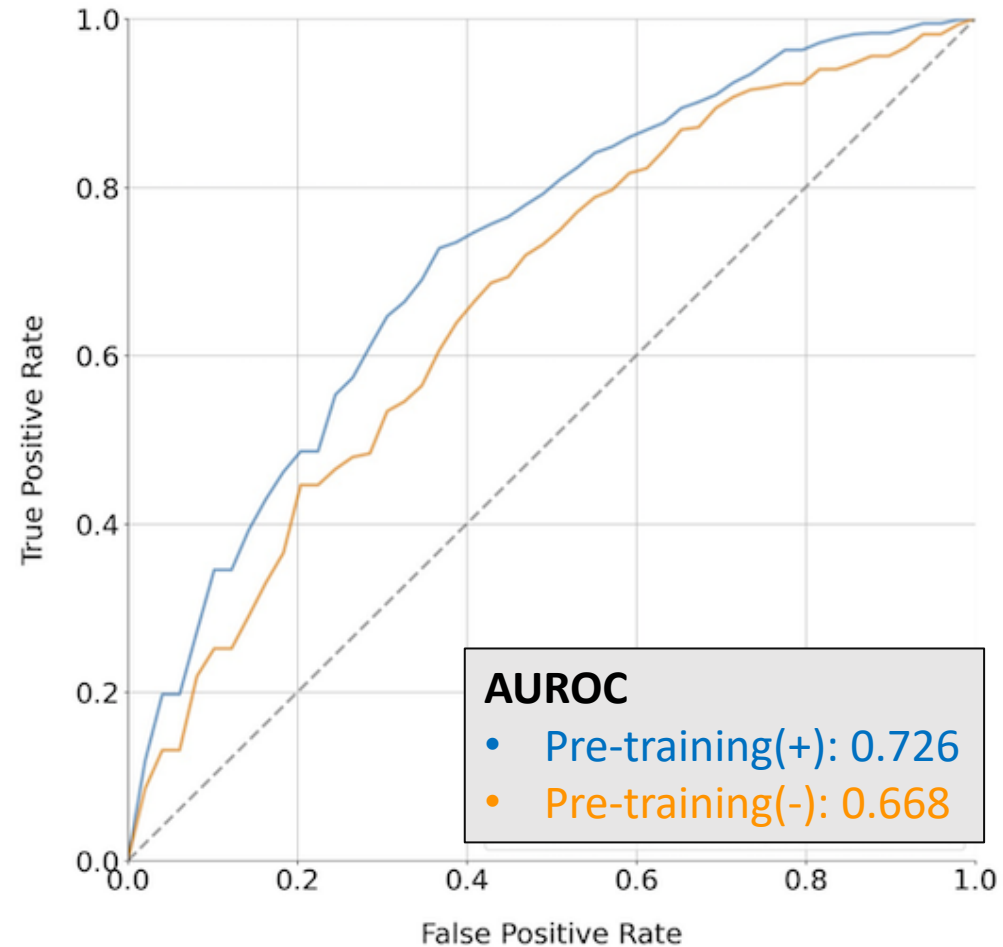
Diagnostic performance of ECG features



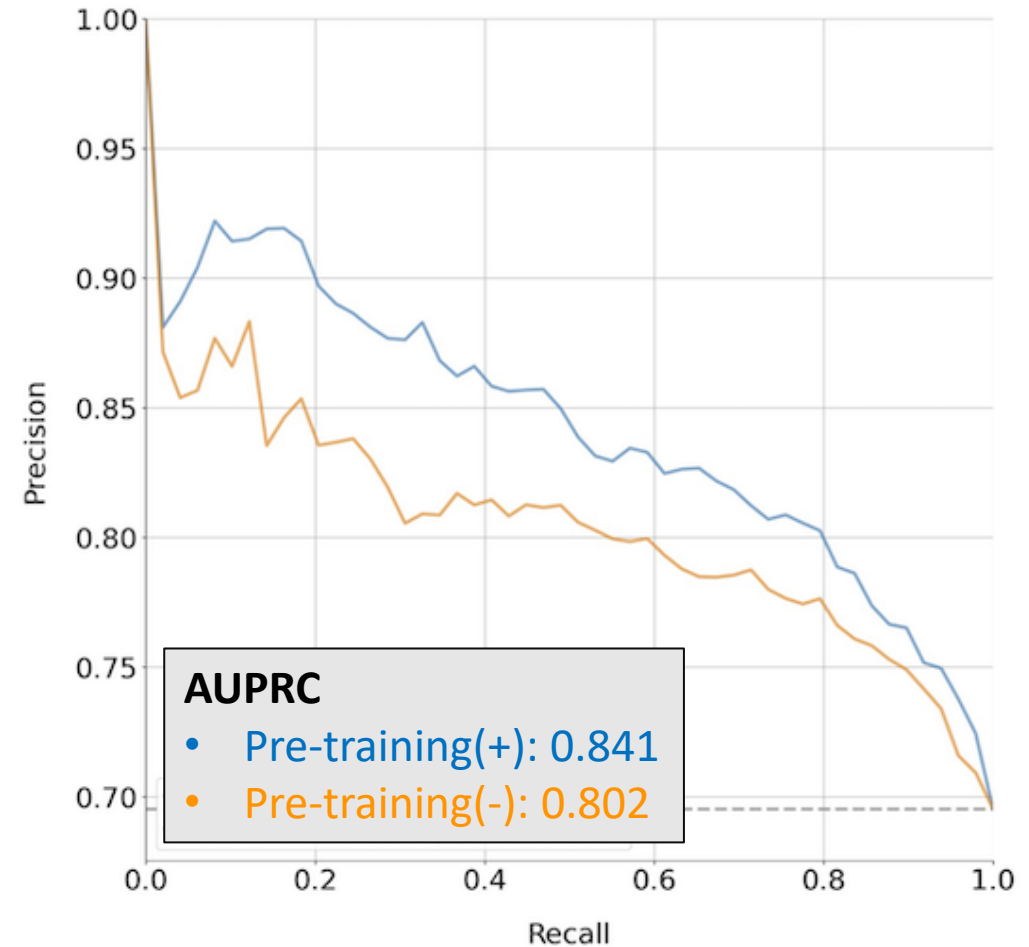
Feature	AUROC
QTc interval	0.602
Age	0.576
QRS duration	0.575
Heart rate	0.558

Result: *deep learning performance*

Mean ROC curves of 10-fold cross validation



Mean PR curves of 10-fold cross validation



Result: *deep learning performance*

	AUROC (95% CI)	AUPRC (95% CI)	F1-score (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)	PPV (95% CI)	NPV (95% CI)
Pre-training (-)	0.67 (0.62-0.72)	0.80 (0.76-0.84)	0.73 (0.67-0.79)	0.68 (0.58-0.79)	0.63 (0.52-0.73)	0.81 (0.78-0.85)	0.49 (0.43-0.56)
Pre-training (+)	0.73 (0.69-0.76)	0.84 (0.81-0.87)	0.74 (0.70-0.80)	0.68 (0.61-0.75)	0.71 (0.65-0.77)	0.85 (0.82-0.87)	0.51 (0.47-0.55)

➤ Improved performance with transfer learning

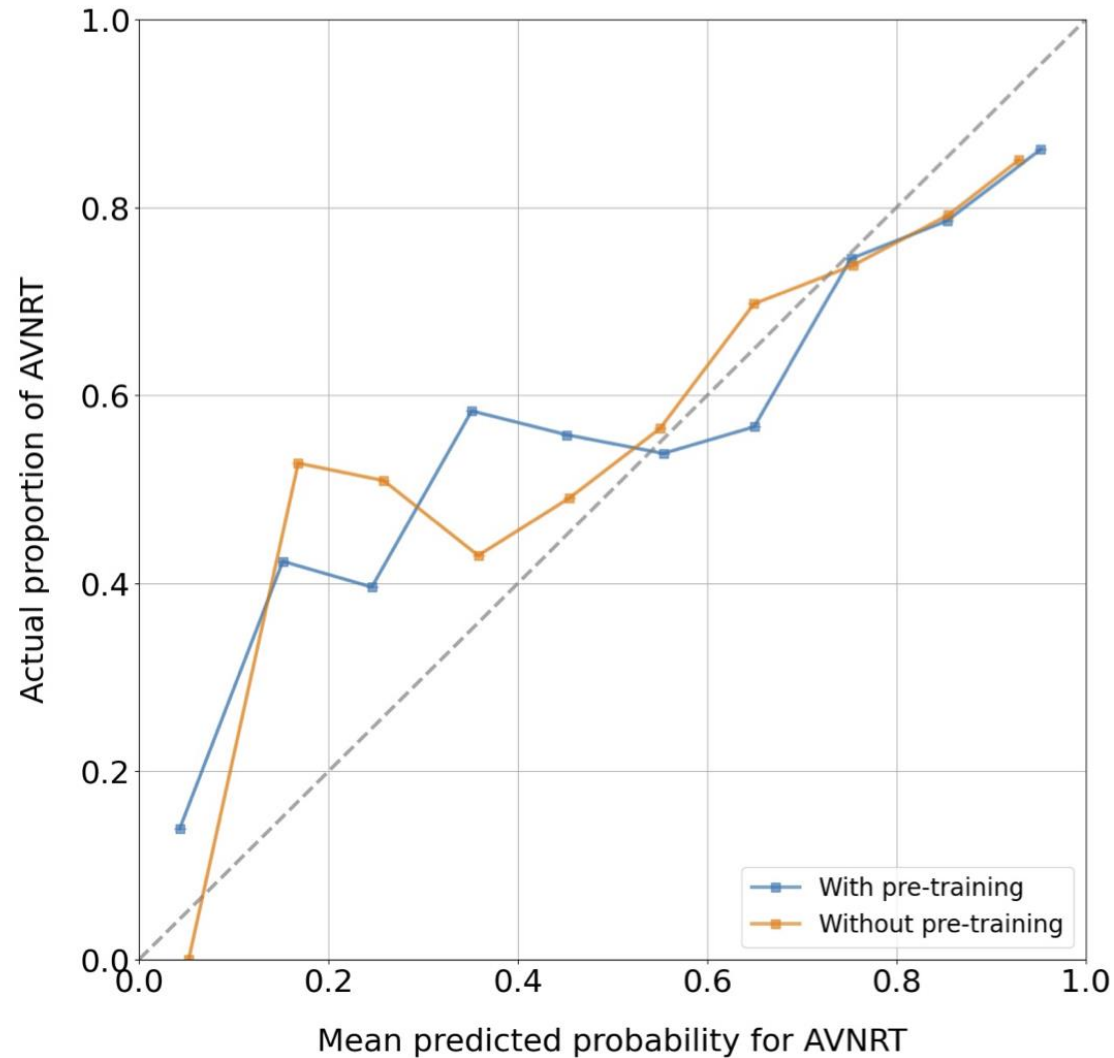
Result: *impact of additional ECG feature learning*

	AUROC (95% CI)	AUPRC (95% CI)	F1-score (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)	PPV (95% CI)	NPV (95% CI)
ECG raw data learning only	0.73 (0.69-0.76)	0.84 (0.81-0.87)	0.75 (0.70-0.80)	0.68 (0.61-0.75)	0.71 (0.65-0.77)	0.85 (0.82-0.87)	0.51 (0.47-0.55)
+ECG feature learning	0.71 (0.66-0.75)	0.83 (0.80-0.86)	0.74 (0.69-0.79)	0.69 (0.61-0.77)	0.66 (0.56-0.76)	0.83 (0.80-0.87)	0.50 (0.45-0.55)

➤ No improvement by additional feature learning

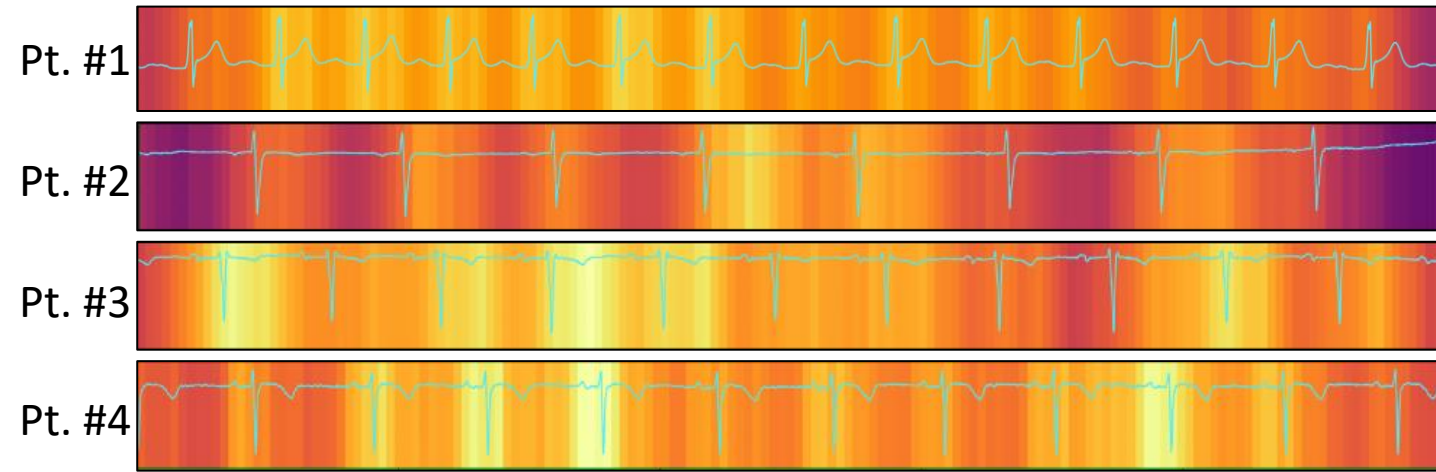
Result: *model's calibration*

Calibration plots of 10-fold cross validation

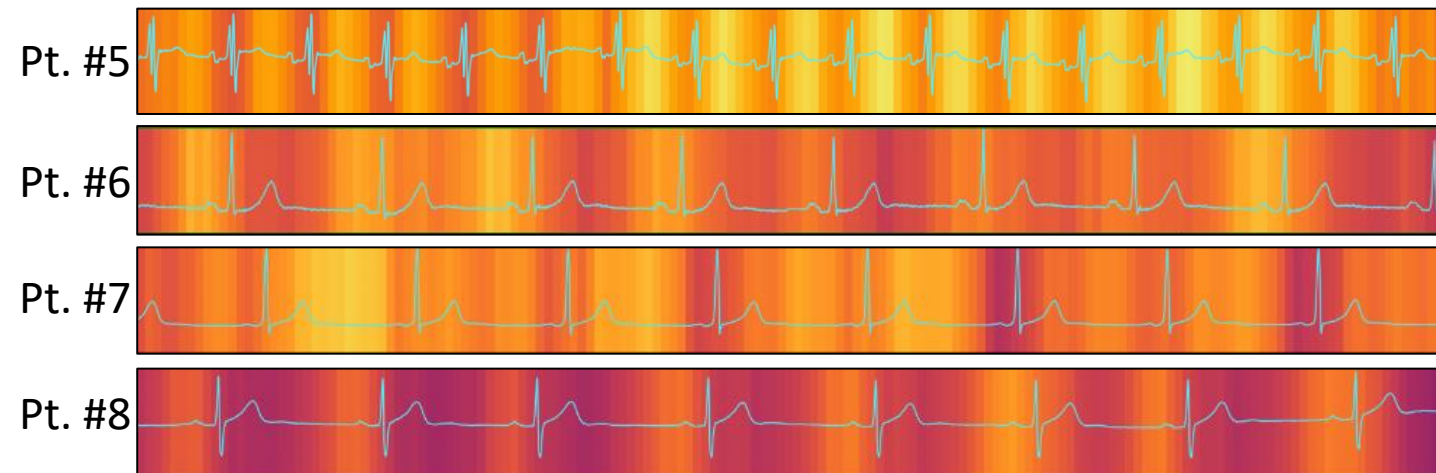


Result: *feature attribution by ECG segments*

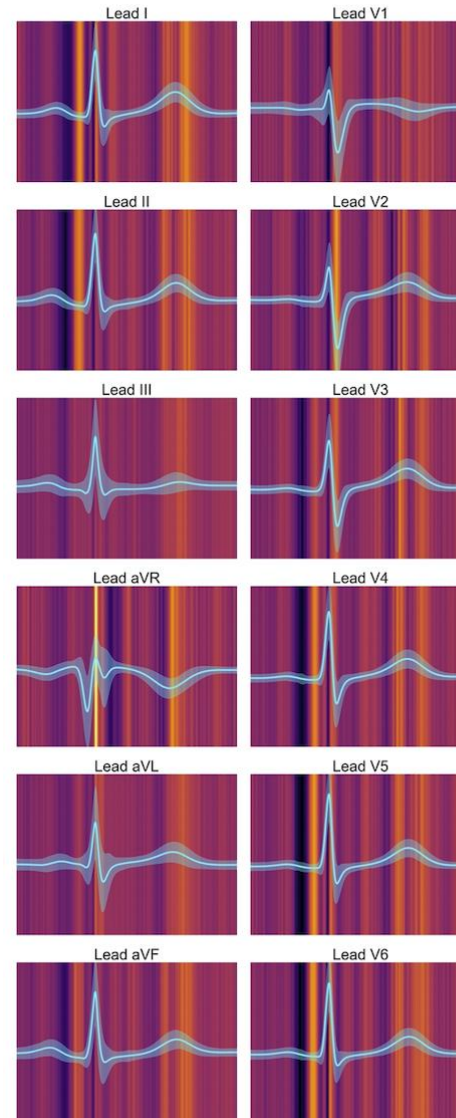
AVNRT



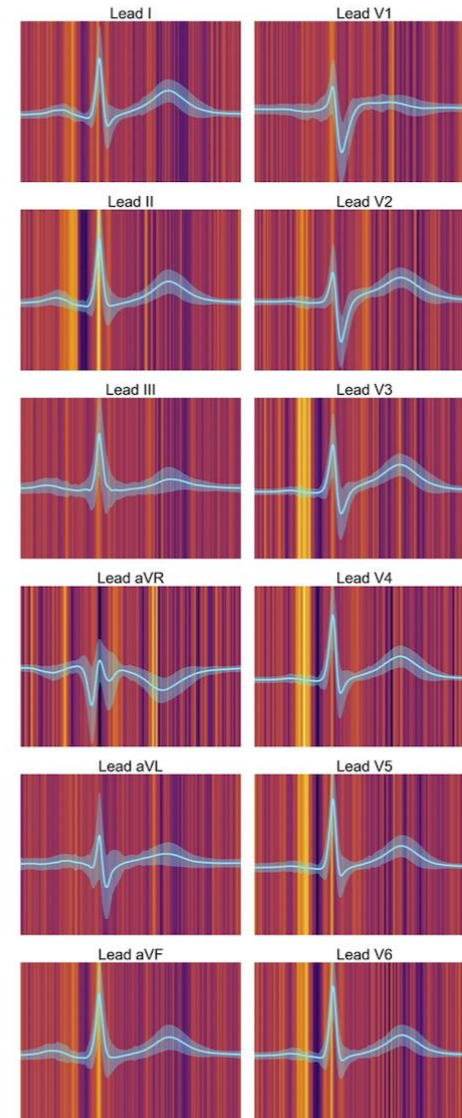
Concealed AVRT



AVNRT



Concealed AVRT



Summary and conclusions

- Deep learning classification of AVNRT and concealed AVRT using sinus rhythm ECG is feasible
- Transfer learning of general structure of ECG improved model's performance
- External validation and investigation of other types of arrhythmias are warranted in future studies



Thank you for your attention