Machine learning applied to energy waveform ECG for prediction of subclinical myocardial dysfunction

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Background

Energy waveform (ew) ECG uses continuous wavelet transforms (CWT) to deconstruct the ECG electrical signal in order to reveal abnormalities. The test is performed exactly like a standard 12-lead ECG .The visual result of this signal processing is an energy scalogram with a time x-axis correlated with the standard ECG recording. Multiple energy and frequency measures and indices can be generated for each ECG lead. Although ewECG changes have been shown to reflect myocardial disease, particularly abnormal relaxation in a symptomatic cohort, we feel this technology may have a role in population screening for Stage B heart failure (SBHF). However, the optimal measures for prediction of SBHF are unclear.

Aim: Using machine learning (ML), we investigated whether ewECG could predict SBHF in community with Stage A heart failure (SAHF).

Methods

254 asymptomatic community subjects aged ≥65 years HF risk factors (hypertension, type 2 diabetes or obesity but without known ischaemic heart disease) underwent clinical evaluation, ewECG (MyoVista, HeartSciences, Southlake, TX) and echocardiography. Global longitudinal strain (GLS) ≤ 16%, impaired relaxation (IR) or left atrial enlargement (LAE) with borderline GLS 16-18%, E/e' >10 + LAE, E/e' ≥ 15, or IR + LAE defined SBHF.

Supervised machine learning using a type of random forest classifier ('Extra Trees') was undertaken to create the final ML model using 33 of the 643 available CWT measures and indices. Algorithm training used 178 studies and performance was assessed by k-fold cross validation. 76 studies were used as a blind test. Improvements in sensitivity of the initial model (model1) were made by tuning the algorithm by increasing the probability threshold (models 2 and 3).

Table 1: Baseline characteristics

	Training data (n=178)	Test data (n=76)	P-value
Age (IQR)	70 (68-73)	72 (69-75)	0.05
Gender (% female)	94 (53)	52 (68)	0.03
Hypertension (%)	155 (88)	65 (86)	0.66
Diabetes Mellitus (%)	56 (32)	24 (32)	0.97
Atrial Fibrillation (%)	15 (8)	5 (7)	0.6
SBP, mmHg (IQR)	142 (133-152)	140 (130-149)	0.2
BMI, kg/m^2 (IQR)	31 (28-35)	31 (28-34)	0.6
6-min walk test, m (IQR)	442 (399-474)	447 (408-476)	0.7
NT-proBNP, pg/ml (IQR)	50 (26-101)	69 (38-125)	0.03
Echo variables			
LVEF, % (SD)	62 (8)	63 (5)	0.16
GLS, % (IQR)	18 (16-20)	19 (17-20)	0.02
LVMi, g/m^2 (IQR)	67 (54-78)	63 (52-80)	0.29
e', cm/s (IQR)	7 (6-9)	8 (6-9)	0.11
E/e' (IQR)	8 (7-11)	8 (7-10)	0.37
LAVi, ml/m^2 (IQR)	33 (28-39)	37 (32-45)	0.001
SBHF (%)	100 (56)	35 (46)	0.14
Systolic dysfunction (GLS ≤ 16%)	42 (23)	11 (14)	0.1
Diastolic dysfunction (%)	47 (26)	24 (32)	0.4
Borderline systolic and diastolic function (%)	32 (18)	9 (11)	0.2
LVH (%)	11 (6)	3 (4)	0.5

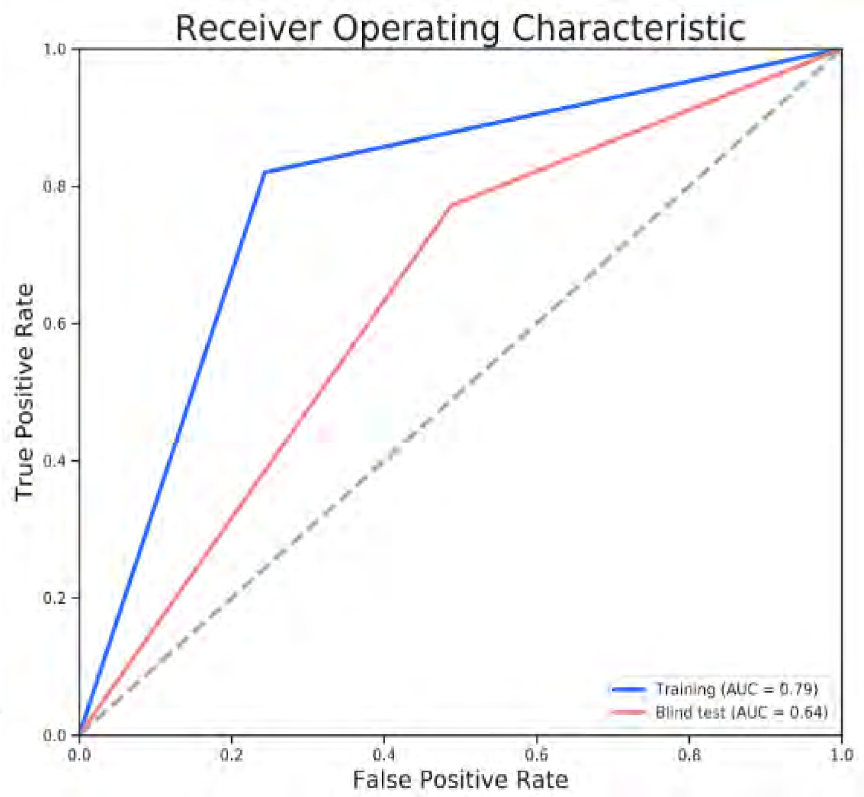
Results

- Of 178 subjects in the training dataset 100 (56%) had SBHF and there was a similar proportion (35 (46%)) in the test dataset (**Table 1**).
- The final ML model provided a reasonable sensitivity (82%) and specificity (76%) with AUC of 0.79 on cross validation. Sensitivity fell to 77% on the test data (Fig 1(a)).
- Sensitivity improved to 91% on the test data and 97%, with model tuning (increase in probability threshold from 0.5 to 0.55 for model 2 and 0.6 for model 3) (Fig1 b+c). This was at the cost of specificity.
- The tuned models, 2 and 3, could reduce the number of echocardiograms performed as part of a population screening program by 25% and 18% respectively, with the % of missed cases being 9% and 3% respectively.

Figure 1: Performance of the final ML model (a), with progressive increase in probability threshold (b+c)

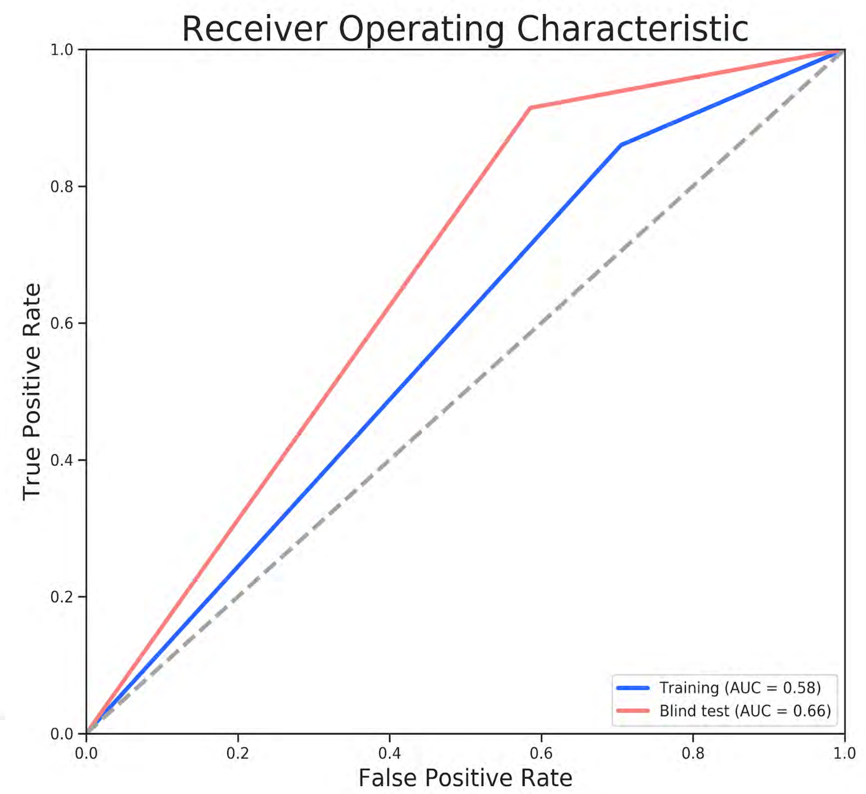
a) Model 1

	Training	Test
Sensitivity	82%	77%
Specificity	76%	51%
AUC	0.79	0.64



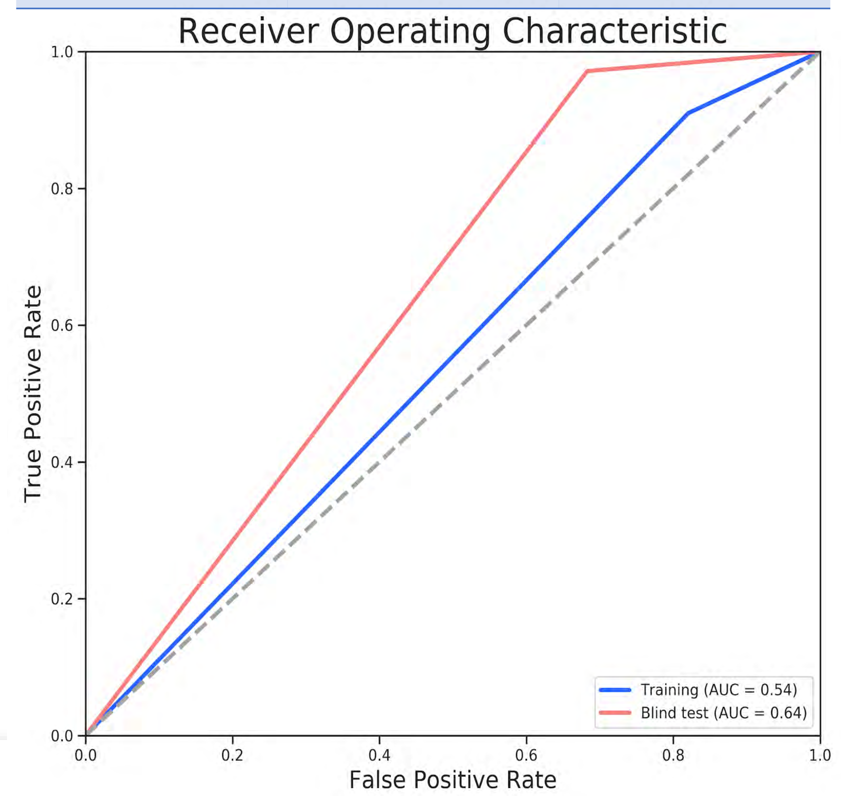
b) Model 2

	Training	Test
Sensitivity	86%	91%
Specificity	29%	41%
AUC	0.58	0.66

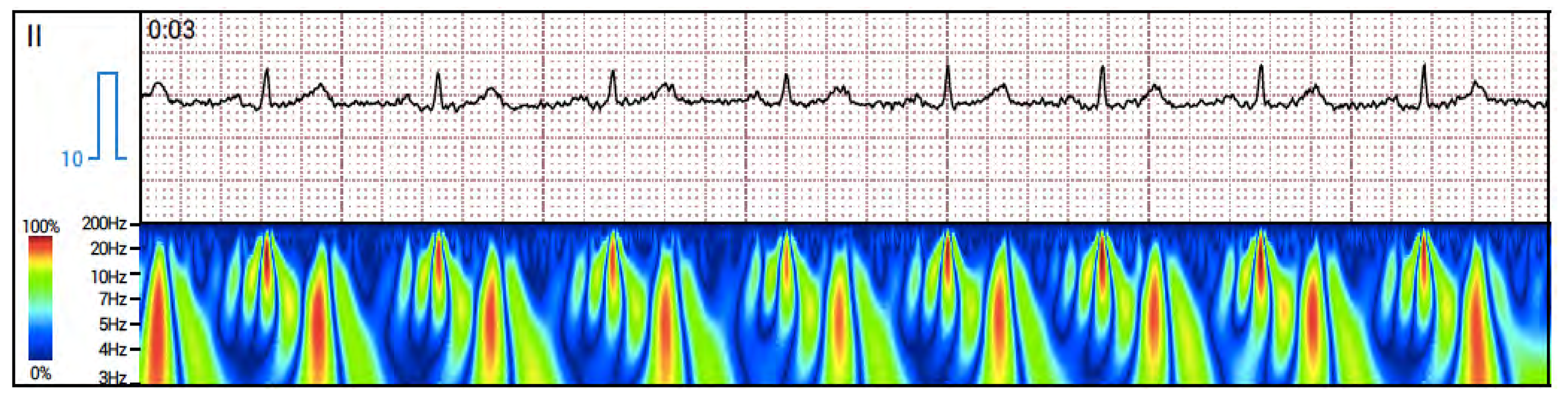


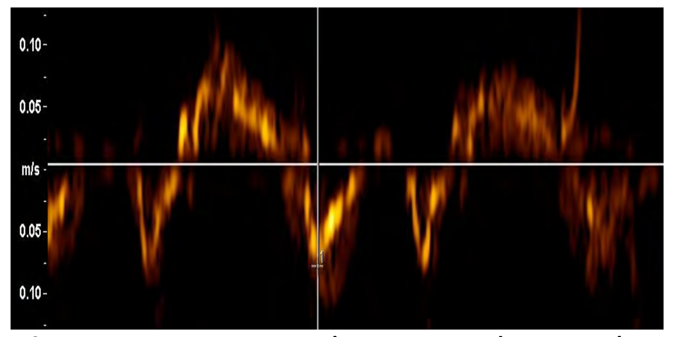
c) Model 3

	Training	Test
Sensitivity	91%	97%
Specificity	18%	32%
AUC	0.54	0.64



a)





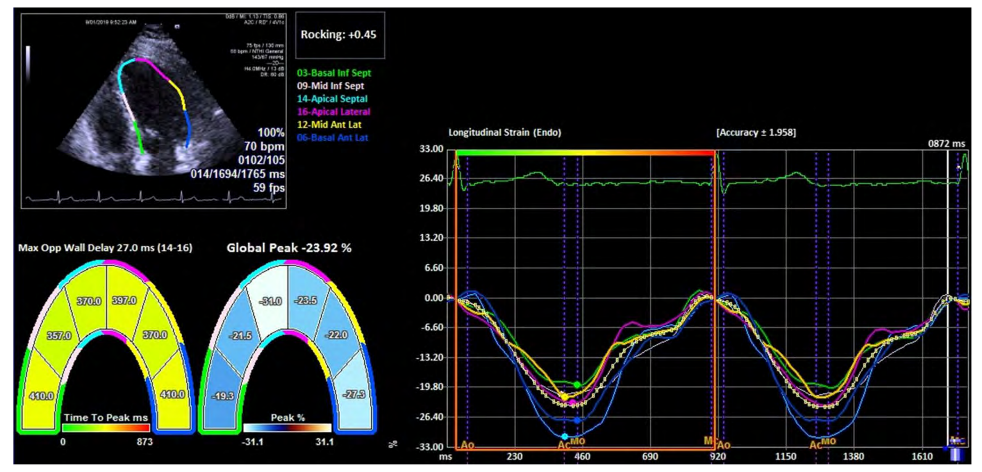


Figure 1: Patient with SAHF and normal energy waveform, note the yellow/red T-wave profile **(a)**. Patient with SBHF and abnormal energy waveform, note the light blue T-wave profile **(b)**. Normal septal e' and GLS **(a)** reduced septal e' and GLS **(b)**.

b)

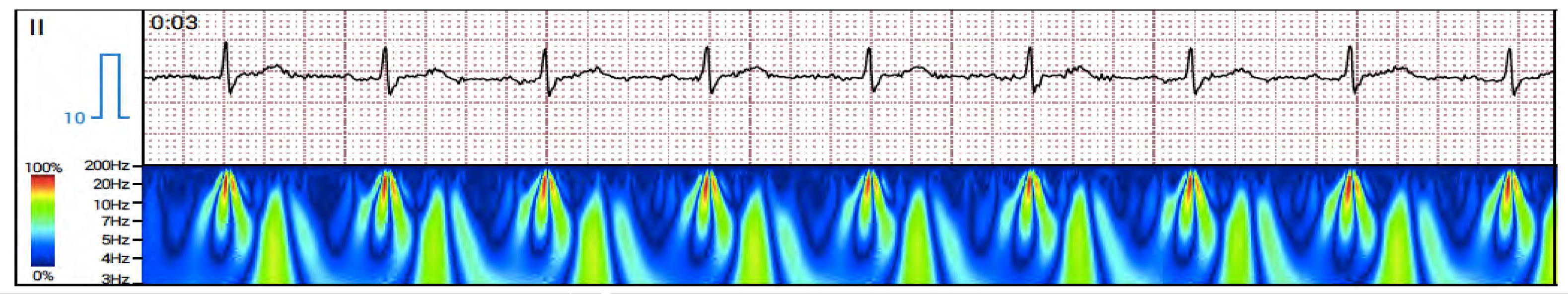


Table 2: Impact of ML model on ewECG-based population screening for SBHF in apparent SAHF (from test data performance)

	Reduction in screening echos ([True neg+false neg]/total)*100	Missed cases of SBHF
Model 1	37%	18%
Model 2	25%	9%
Model 3	18%	3%

Conclusion

Using ML algorithms, sensitivity of ewECG is suitable for application as a screening test for SBHF in apparent SAHF. Our data suggest ewECG could reduce the number of echocardiograms performed as part of a HF population screening program by 18-25%.

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Disclosures: None