Supplementary Material

Semi-supervised learning for automatic atrial fibrillation detection in 24-hour Holter monitoring

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Supplementary Methods

1, The K-means method combined with supervised learning.

The details of the supervised learning method with K-means clustering are described below:

Step 1: Two centroids were obtained from the positive labeled samples and negative labeled samples, respectively.

Step 2: Measuring the Euclidean distance between the unlabeled sample and the two centroids, and the unlabeled sample was clustered to the centroid that had the shorter Euclidean distance.

Step 3: After all the unlabeled samples were clustered, two new centroids were obtained using the labeled data and the clustered data.

Step 4: Repeat Steps 2 and 3 until the clustering results did not change.

Step 5: The labeled data and the clustered data were used to train the model.

Step 6: Apply the trained model to the same testing data as in our semi-supervised learning method were used.

Supplementary Tables

Supplementary Table I. Overview of training and testing datasets in this study.

Dataset	The number of the patients	The number of AF episodes	AF duration/min	The number of positive samples	The number of negative samples
Labeled training set	10	145±74	4067±585	3815±450	7074±822
Unlabeled training set	790	8088±257	314 457±1777	314 090±2369	549 400±2322
Testing set	200	2058±311	79 631±1516	79 476±2228	139 118±2782

Supplementary Table II. Parameters of the CNN-LSTM model.

Layer Name	Input size	Output size	Number of parameters
Input	--	90, 1	0

Conv layer	90, 1	90, 64	384
Conv layer	90, 64	90, 32	6176
Bi-LSTM	90, 32	90, 200	106 400
Global max pooling	90, 200	200,	0
Dropout	200,	200,	0
FC layer	200,	32,	6432
Dropout	32,	32,	0
FC layer	32,	16,	528
Output	13,	2,	34

Supplementary Table III. The pseudocode of the mixed mean teacher algorithm.

Algorithm: Mixed mean teacher

1. **Input:** Labeled data and the corresponding labels $(X, Y) = \{(x_b, y_b); b \in (1, \cdots, B_1)\}$, unlabeled data $U = \{(u_b); b \in (1, \cdots, B_2)\}$, training epochs *es*, Initialize model S $S(\theta_s)$ and model T $T(\theta_t)$ with the same initial parameters.

2. **for** e = 1 **to** *es* **do**
   for u, x, y **in** U, X, Y **do**
   $u' = Noise(u)$ // Apply Gaussian noise as disturbance to u
   $l_u = T_{model}(u'; \theta_t)$ // "l_u" refers to guess labels
   $p_u = S_{model}(u; \theta_s)$
   $l_u = Update(l_u)$ // Modified guess labels (see *eq.4*)
   $l_u = Sharpen(l_u)$ // Reduce the entropy of guess labels (see *eq.5*)
   $loss_1 = w_1 * MSE(p_u, l_u)$ // Consistency loss (see *eq.2*), w_1 is the weight
   $loss_2 = w_2 * corssentropy(S_{model}(x; \theta_s), y)$//Classification loss (see *eq.1*), w_2 is the weight
   optimize $S\ using\ loss_1\ and\ loss_2$
   optimize $T\ using\ EMA$ // See *eq.3*
   end for
   end for

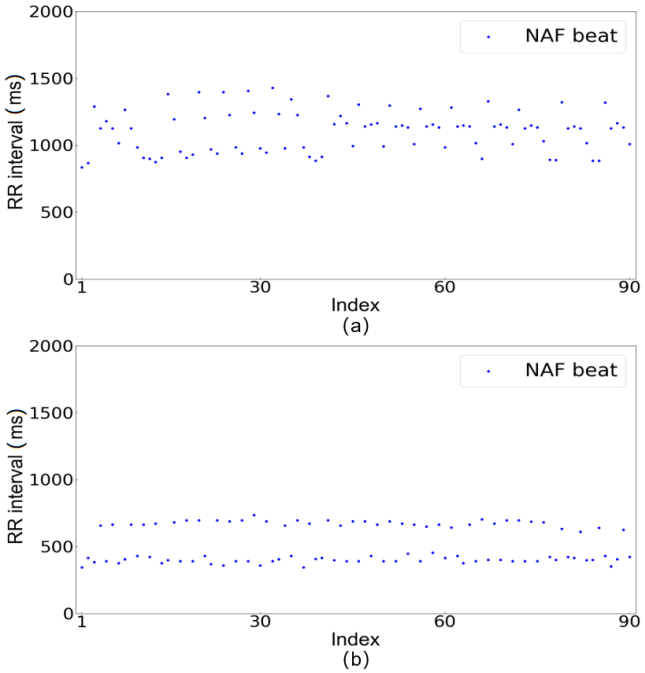
3. **Output:** well-trained model S.

Supplementary Table IV. Overview of the MIT-BIH AF database.

Dataset	The number of Recordings	The number of AF episodes	AF duration/min	The number of positive samples	The number of negative samples
AFDB	23	291	5492	5870	6655

*Recordings 00735 and 03665 were excluded.

Supplementary Figure



Supplementary Fig. 1. Two examples of the samples that were misclassified by our semi-supervised learning method but correctly detected by the "whole training" method. NAF = non-atrial fibrillation.