Accurate detection of atrial fibrillation from 12-lead ECG using deep neural network

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Objective:-

In AF, the electrical impulses of the atria are disorganized and unsynchronized with the ventricles. A normal waveform is composed of the P wave, QRS complex, and T wave. However, in an AF waveform, the P wave is replaced by many inconsistent fibrillatory waves (F waves) and R–R irregularities.

The proposed method constructed a novel one-dimensional deep densely connected neural network (DDNN) to detect AF in ECG waveforms with a length of 10s.

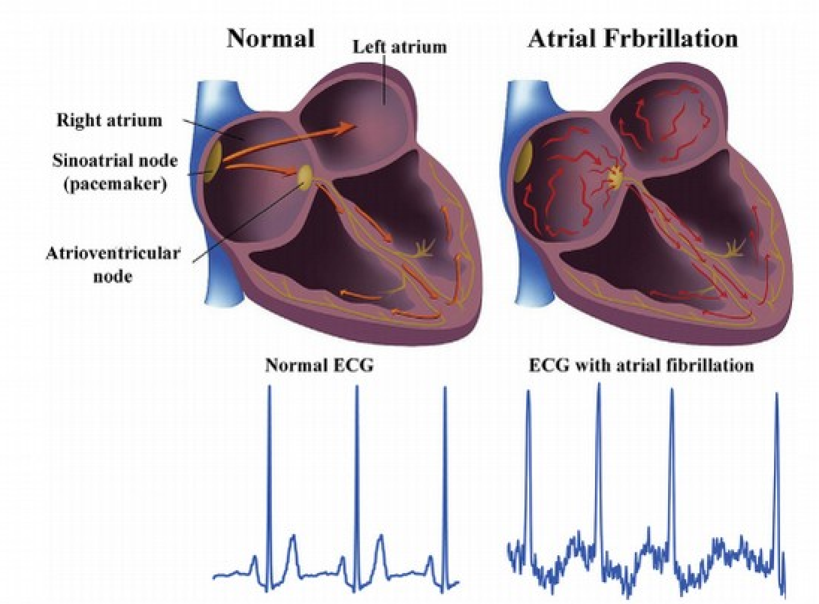


Fig. 1. Representations of a healthy heart and a heart with atrial fibrillation, a normal ECG waveform and an ECG waveform with atrial fibrillation (image adapted from Centers for Disease Control and Prevention) [22].

Table 1
Summary of the subjects and the ECG recordings.

Characteristics	n
Number of ECG recordings	16,557
Patient demographics	
Number of unique subjects	11,994
Age, mean ± SD	57.0 ± 18.7
Male, n_1/N_1 (%)	5620/11,856 (47.4%)
ECG rhythm diagnosis, n_2/N_2 (%)	
Normal	5650/16,557 (34.1%)
Atrial fibrillation	3353/16,557 (20.3%)
Other	7554/16,557 (45.6%)

n_1, number of males in total subject; N_1, total subject (loss of gender information in some subjects); n_2, number of subsamples; N_2, total sample.

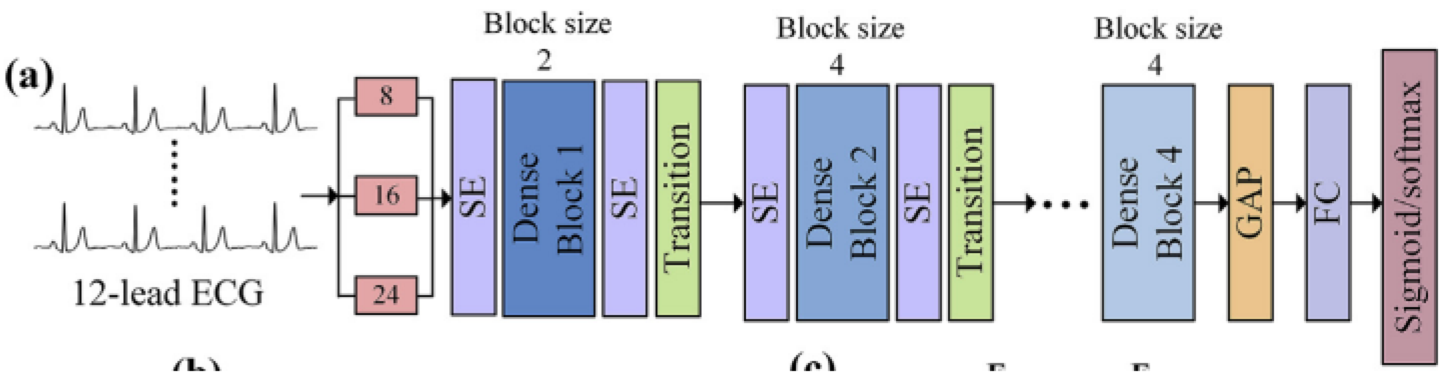
A large set of 16,557 12-lead ECG recordings collected from multiple hospitals and wearable ECG devices were used to evaluate the performance of the DDNN.

Preprocessing:-

1. All 12-lead ECG recordings were filtered by using a band-pass filter (0.5–35 Hz, an elliptical band-pass filter with filter order of 10) to remove baseline wander and high frequency components.
2. The ECG signal in each lead is normalized to address the problem of amplitude scaling and eliminate the offset effect.
3. All ECG recordings were divided into segments of 10 s.

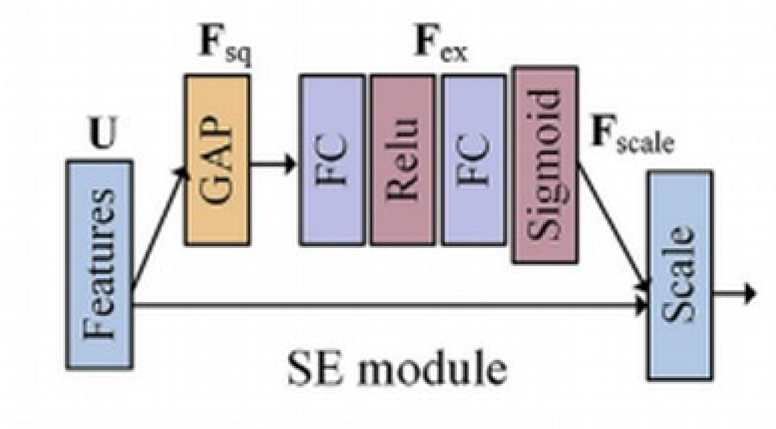
Neural network architecture:-

- The neural network takes as input a 12-lead ECG waveform of 10s long (12 × 10 s, the 12 channels are fed in parallel) and outputs a label prediction of two (AF and normal, AF and non-AF) or three (AF, normal, and other) classes.
- A densely connected DDNN architecture is designed with four dense blocks (a total of 36 layers) and a growth rate of 6.
- The block sizes (the numbers of convolutional layers) of the four dense blocks are 2, 4, 6, and 4, respectively.



- Inspired by inception module in the GoogLeNet, the network starts with the filter concatenation module, which uses convolutions of different sizes in parallel to capture details at varied scales (1×8, 1×16, 1×24), and the other convolutional layers all have a filter length of 16.

- To improve the computational efficiency and model compactness, bottleneck (1×1 convolution) and transition layers (convolution and pooling, placed between two adjacent dense blocks) in the DDNN.
- Before the fully connected layer they applied global average pooling (GAP).



- The squeeze-and-excitation (SE) module was employed to improve the representational power of a network by enabling it to perform dynamic channel-wise feature recalibration.
- In the DDNN, the SE module was placed before each dense block and each transition layer.

Results:-

- The DDNN model consists of a total of 69,087 trainable parameters and only requires 0.6 MB of storage space.
- After training model from scratch on the 12-lead ECG training subset by adopting weight initialization and using Adam optimizer with the default parameters for a total of 60 epochs, the performance of the model is in following table:

Performance of the DDNN for binary and three-class classifications on test subset (means ± SDs).

Classification		Accuracy (%)	Sensitivity (%)	Specificity (%)	F_1 score (%)
Binary	AF and Normal	99.35 ± 0.06	99.44 ± 0.06	99.19 ± 0.24	99.06 ± 00.09
	AF and Non-AF	98.21 ± 0.09	98.63 ± 0.28	97.04 ± 0.88	96.45 ± 00.12
Three-class	Normal	92.96 ± 0.28	93.18 ± 0.97	92.56 ± 1.05	90.86 ± 00.34
	AF	97.74 ± 0.30	98.38 ± 0.14	95.85 ± 0.89	95.36 ± 00.41
	Other	91.12 ± 0.18	94.12 ± 0.70	85.47 ± 2.13	85.90 ± 00.69

Non-AF, normal and other, the highest score is indicated in bold.

Conclusion:-

This method DDNN to detect AF from raw 12-lead ECG recordings can achieve promising performance. This new network is very suitable for automatic and accurate diagnosis of AF using 12-lead ECG.