Classification of arrhythmias using an LSTM- and GAN-based approach to ECG signal augmentation

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Introduction: Automated classification of arrhythmias in ECGs is becoming increasingly important. Publicly available ECG datasets have been widely used by the research community to create novel artificial intelligence models that improve these detection rates. The development of these models requires access to large volume of labelled data. However, access to such databases is becoming increasingly limited. In addition, the datasets are often unbalanced because abnormal rhythms are far outweighed by normal samples. The unbalanced nature of the datasets can lead to less accurate models. Therefore, generating realistic synthetic signals can augment the real signals found in such databases and provide data that allows sophisticated model development.

Purpose: In this study, we propose a deep learning-based approach for synthetic ECG signal generation that uses long short-term memory (LSTM) autoencoder and generative adversarial networks (GAN) to generate signals that mimic the distribution of arrhythmia signals (Figure 1).

Methods: The LSTM autoencoder is composed of two parts: an encoder and a decoder (Figure 1b). The encoder takes original ECG signal as its input and uses LSTM layers to compress the signal into a set of features. The decoder is formed by reversing the encoding process, which uses the encoded features as its input and converts them back into the original signal.

To generate synthetic signals, we inserted GANs between the LSTM encoder and the decoder. GANs are composed of a generator and a discriminator (Figure 1c). The generator produces synthetic ECG features based on noise, whereas the discriminator tries to distinguish between real features and results received from the generator.

The pathological beats studies were: left bundle branch block (LBBB), right bundle branch block (RBBB), aberrated atrial premature (AA), and normal beats (N) from the MIT-BIH arrhythmia database, using lead II only.

To evaluate the quality of our synthetic signals, we trained an LSTM classifier on a combination of our real and synthetic data and compared the testing results with a model trained on real data alone.

Results: The LSTM encoder, decoder and GAN were trained individually for each beat type, and examples of generated signals are illustrated in Figure 2. The average accuracy of the classification for the original dataset was 90%, with a recall of 98% for N, 36% for AA, 39% for LBBB and 97% for RBBB. Once synthetic signals were added to the training set, the average testing classification accuracy increased to 98%, with a recall of 99% for N, 83% for AA, 99% for LBBB and 99% for RBBB.

For fair comparison, the testing set contained only real data and remained unchanged for both groups.

Conclusion: In this work, we proved the capability of GANs to generate realistic synthetic signals that helped to improve the detection rates of arrhythmias as measured by both increased overall accuracy and recall.

model

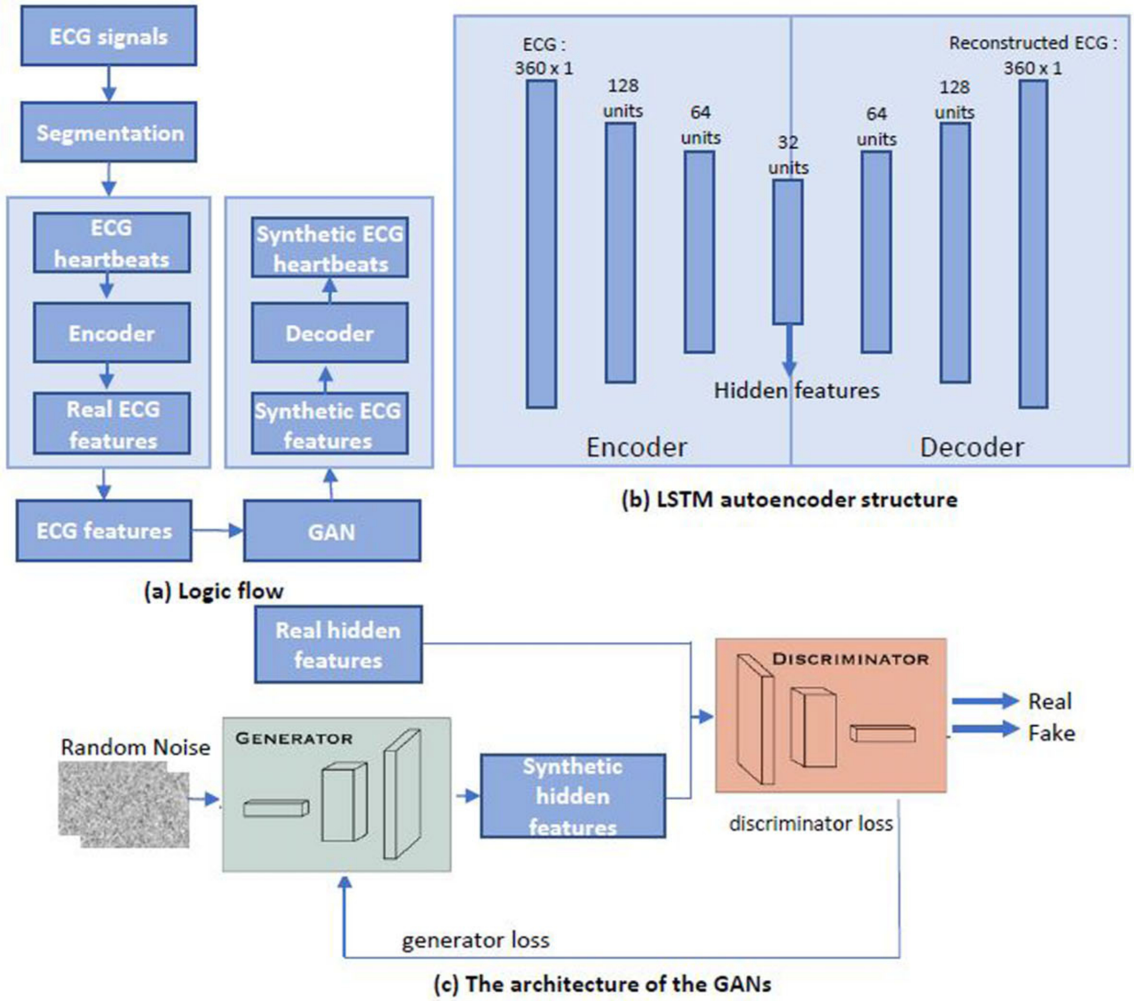

Figure 1. The proposed approach for synthetic ECG signal generation. **(a) The overall flow of the process:** the signals are segmented in heartbeats using the R peak annotations, reduced to a set of features using the LSTM encoder, and used to train the GAN. At the end of the training we use the GAN generator to create synthetic heartbeat features, and feed them to the LSTM decoder for reconstruction. **(b) LSTM encoder and decoder architecture**: The encoder takes as input ECG heartbeats of 360 data points each and compresses it into 32 representative features, while the decoder uses the resulting features to accurately reproduce the signal into its original form. **(c) GAN architecture and training process**: The discriminator is differentiating between real and synthetic heartbeats that it receives as input, whereas the generator receives as input Gaussian noise, and uses it to create synthetic signals in an attempt to fool the discriminator.

9.3.1 - Electrocardiography (ECG)

examples_signals

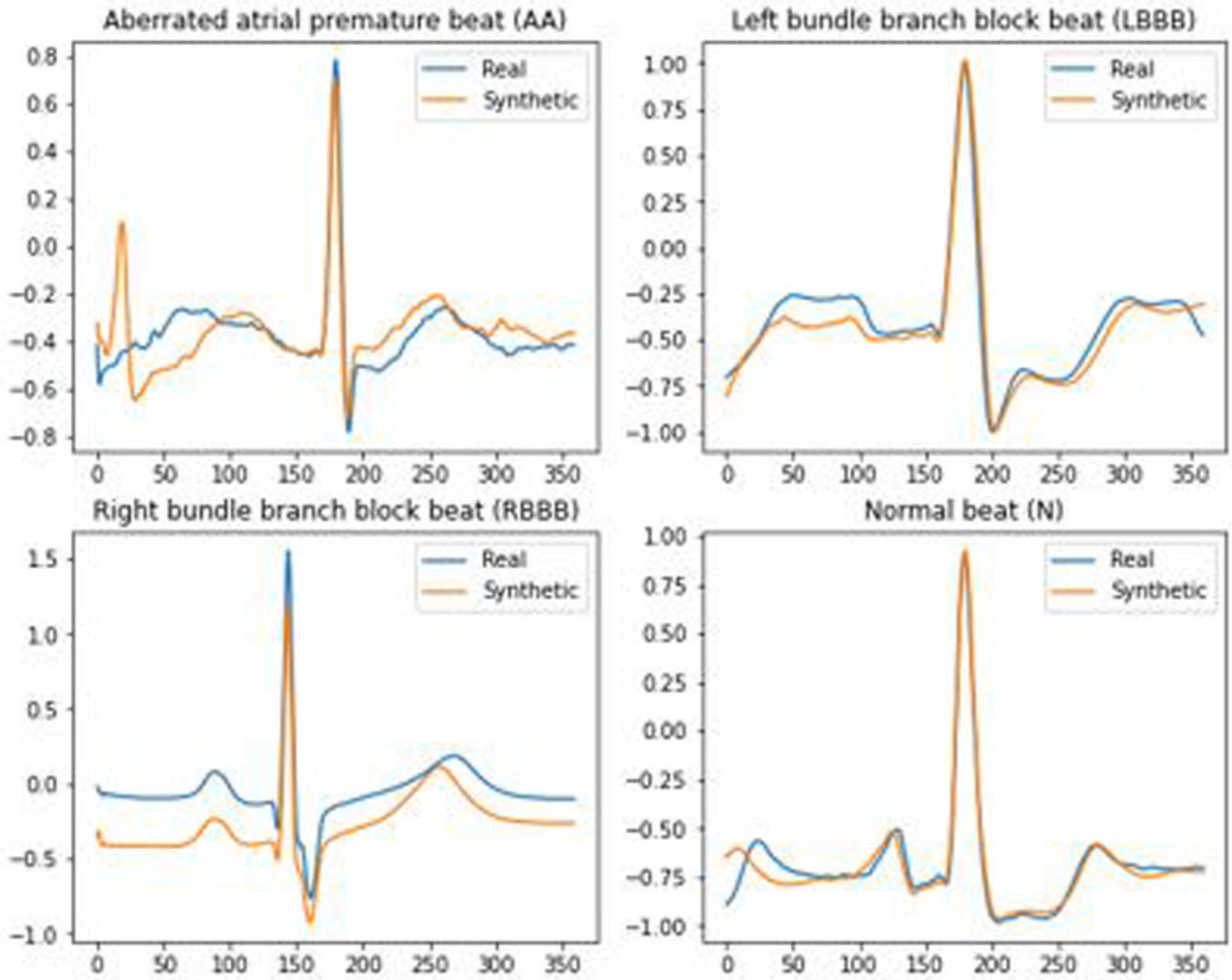

Figure 2. Examples of real ECG heartbeats (blue) and synthetic ECG heartbeats (orange) generated by our model.