CardioGAN: An Attention-based Generative Adversarial Network for Generation of Electrocardiograms

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PROBLEM

Here, we propose a deep generative architecture which can **generate synthetic electrocardiograms(ECGs)** that possess **human-like characteristics**.

ECGs convey important information regarding a patient's heart. As the demand for automatic diagnostic systems are increasing, so is the requirement of **large amounts** of **labelled training data**. This causes a data-imbalance problem. Additionally, the risk of **privacy breaches** increases too.

The drawback of previous approaches lies in the fact that:
- Lack of human-like characteristics
- Lack of consistent nature of the curves

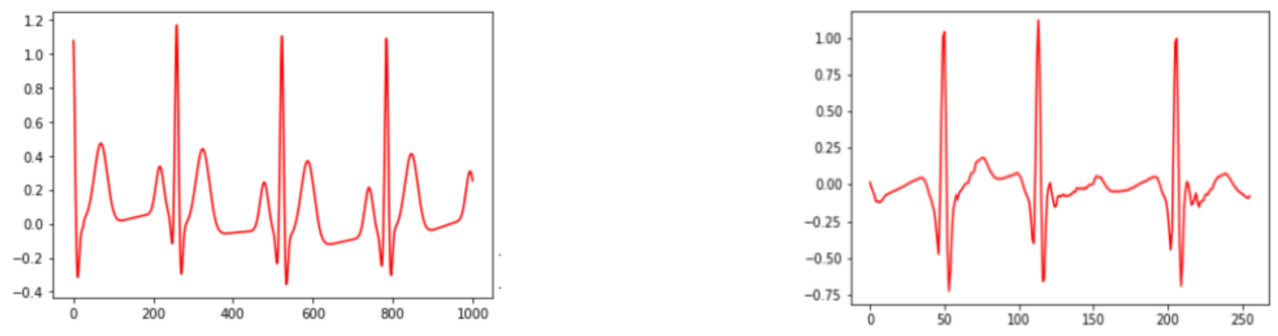

Fig - Results from existing approaches

APPROACH

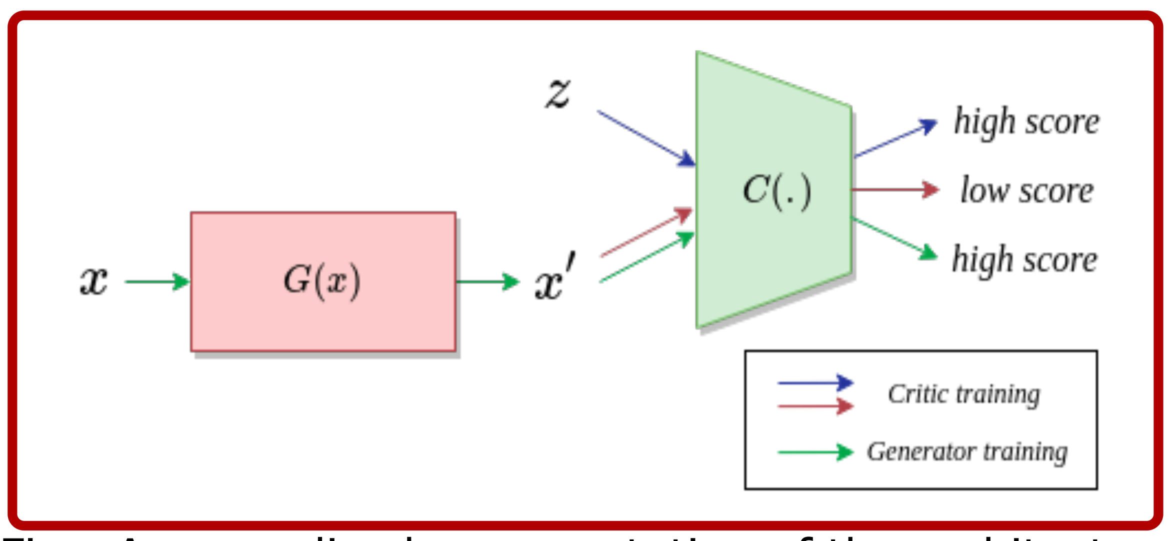

Fig - A generalized representation of the architecture

1 A generalized schematic representation of the architecture.

The archietcture follows a Wasserstein GAN-style training strategy. The Critic learns to generate high/low scores depending on the "realness" of the output ofthe Generator. This score helps the generator to learn to create better samples.

2 The Generator:

- Comprising the Pre-Attention Layers, the Attention Layer and the Post-Attention Layer

- Helps generate the synthetic ECGs from a given Gaussian noise.

1. Pre-Attnetion Layer comprises a stack of 2 bidirectional LSTM layers
2. Attention Layer is made of a dense feed-forward neural network to calculate the contexts
3. Post-Attention layer consists of a single LSTM layers to model the final ECGs depending upon the latent information and the contexts from previous layers.

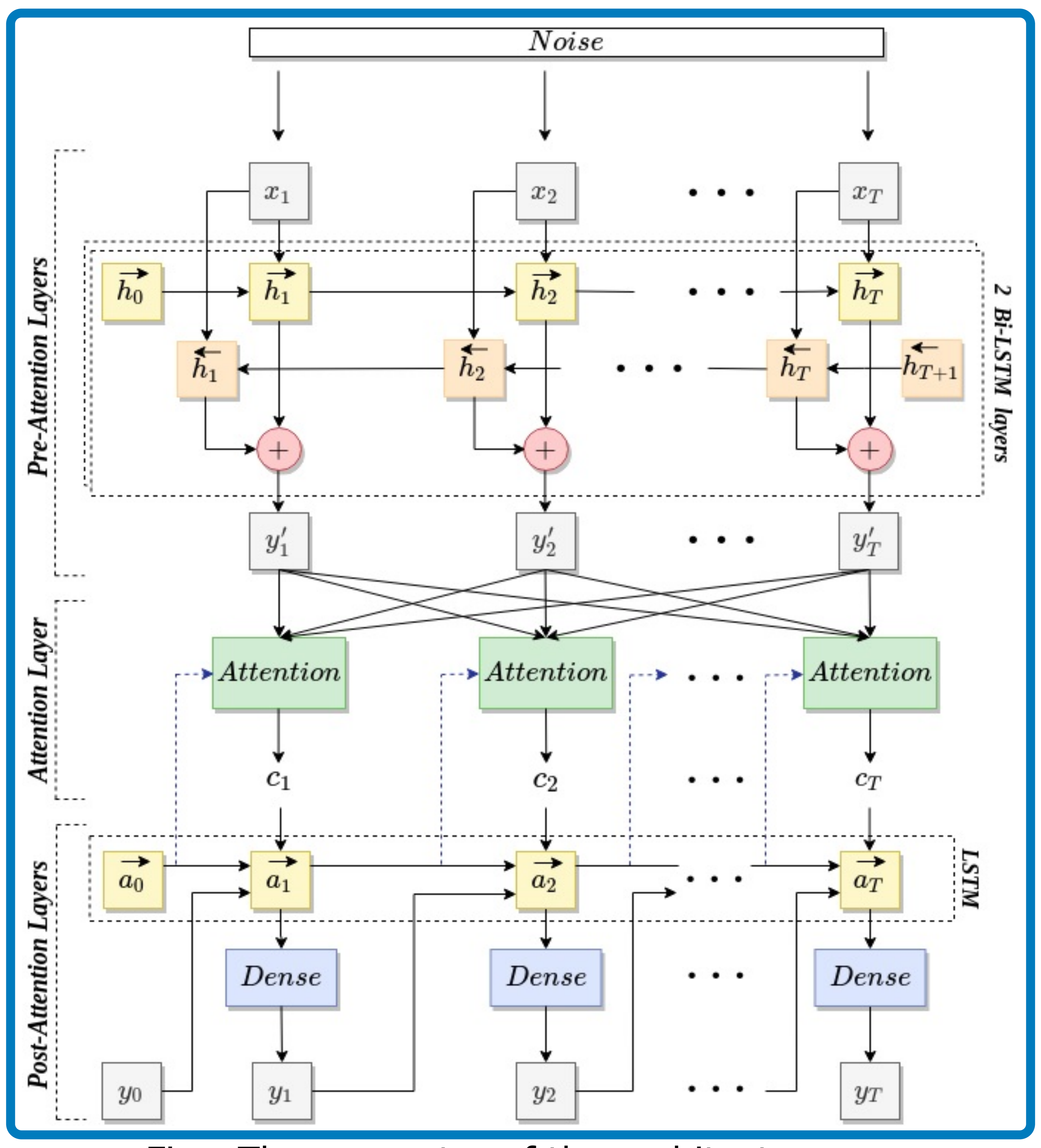

Fig - The generator of the architecture

3 The Attention module as a dense feedforward neural network. It helps understand the intricate inter-dependencies in the signals.

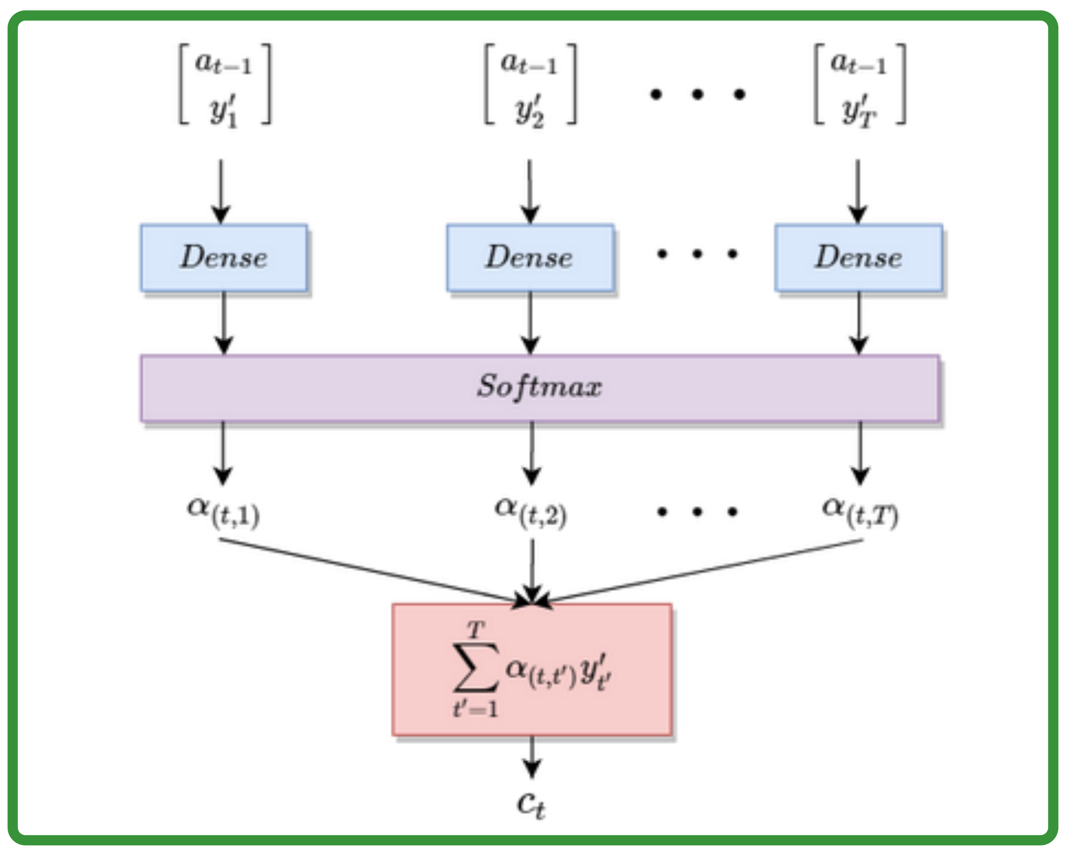

Fig - The Attention module

4 The Critic helps to assign a "realness" score to the samples generated by the Generator, that helps the generator to learn, in turn.

CONFIGURATION OF THE CRITIC WITH THE NUMBER OF PARAMETERS

LAYER	KERNEL SIZE/ STRIDE	OUTPUT SIZE	PARAMETERS
convolution(1D)	1×40 / 2	237×20	820
max-pooling(1D)	1×10 / 2	114×20	0
convolution(1D)	1×12 / 2	52×10	2410
max-pooling(1D)	1×5 / 2	24×10	0
convolution(1D)	1×6 / 2	10×5	305
max-pooling(1D)	1×2 / 1	9×5	0
linear	–	1×45	0
linear	–	1×1	46

5 Loss Function:

$$L = E_{x' \sim P_g}[D(x')] - E_{x \sim P_r}[D(x)] + \lambda E_{\hat{x} \sim P_{\hat{x}}}[(\|\Delta \hat{x} D(\hat{x})\|_2 - 1)^2]$$

(Wasserstein Loss)

RESULTS

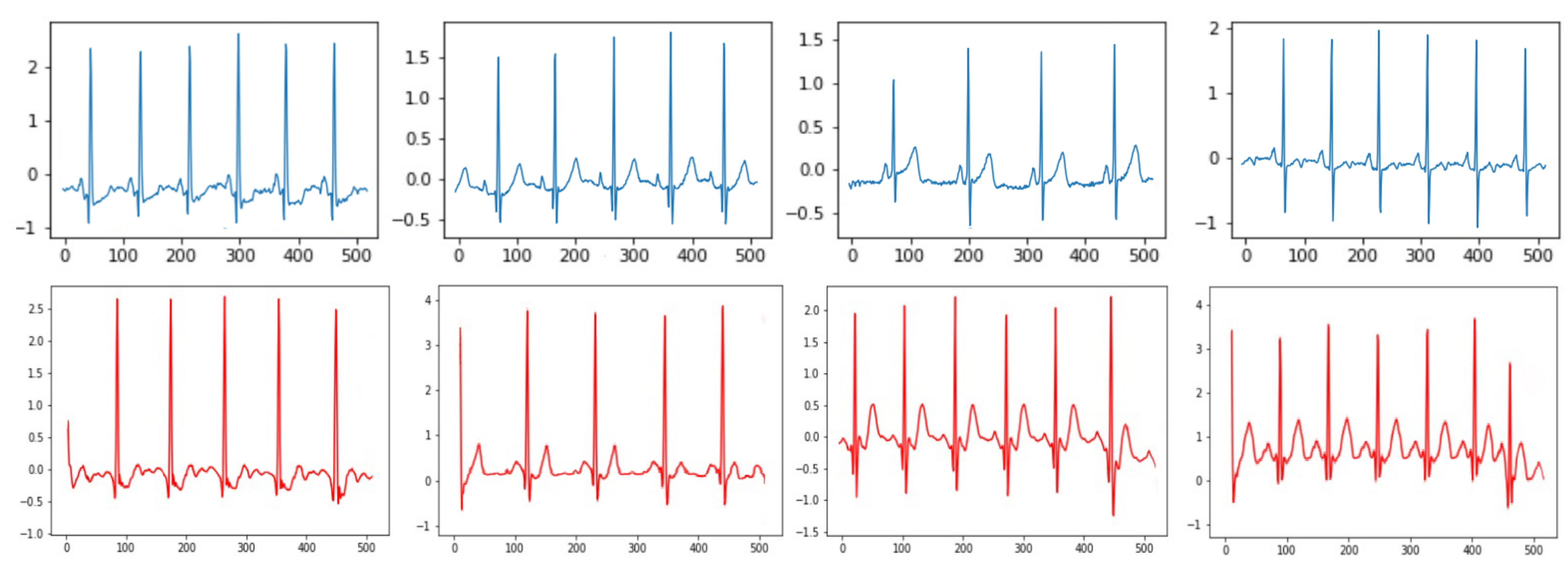

Fig - Visual representation of ECG signals. Blue - GT, Red - Generated.

QUANTITATIVE COMPARISON OF THE PERFORMANCE OF DIFFERENT ARCHITECTURES BASED ON DIFFERENT EVALUATION METRICS

ARCHITECTURE	PRD	RMSE	FD	DTW
CardioGAN [ours]	**38.566**	**0.157**	**0.606**	**4.146**
BiLSTM-GAN	66.408	0.276	0.756	9.375
ECGSYN	78.331	0.363	0.784	15.737
RNN-AE	121.877	0.506	0.969	–
LSTM-AE	148.650	0.618	0.996	–
RNN-VAE	146.656	0.609	0.982	–
LSTM-VAE	145.978	0.607	0.975	–

PERFORMANCE OF CARDIOGAN WITH DIFFERENT CRITIC ARCHITECTURES

ARCHITECTURE	PRD	RMSE	FD	DTW
CardioGAN(with 1D-CNN critic)	**38.566**	**0.157**	**0.606**	**4.146**
CardioGAN(with GRU critic)	59.674	0.294	0.762	9.604
CardioGAN(with LSTM critic)	65.101	0.327	0.781	11.871
CardioGAN(with RNN critic)	78.142	0.375	0.824	10.848