

# ECG Data Augmentation for Atrial Fibrillation Detection

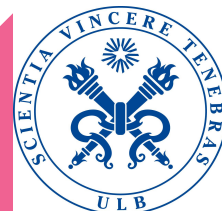
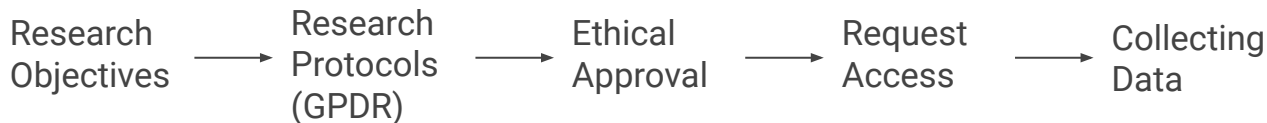
## Authors :

Edoardo Luziatelli, Tobia Bacchiddu, Matteo Silvestri



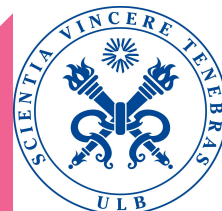
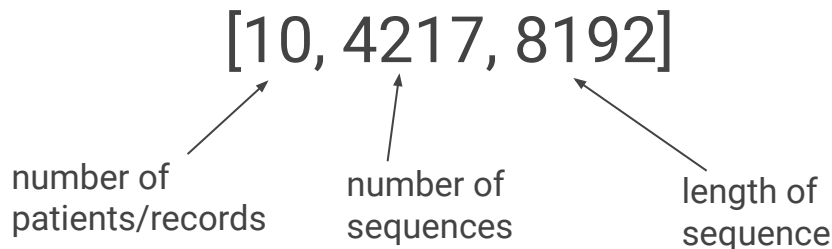
# Definition and motivations

- **Data Augmentation** comprises several techniques used in Data Science to increase the diversity of a training dataset without actually collecting new data  
→ robustness of models by enabling them to generalize better to new data.
- Our **motivations** come from the difficulty of collecting data, especially in the medical field, and our interests in generative models

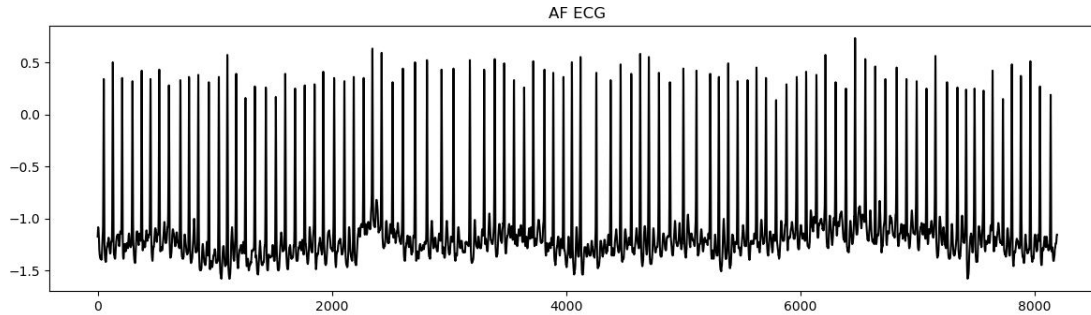


# Dataset

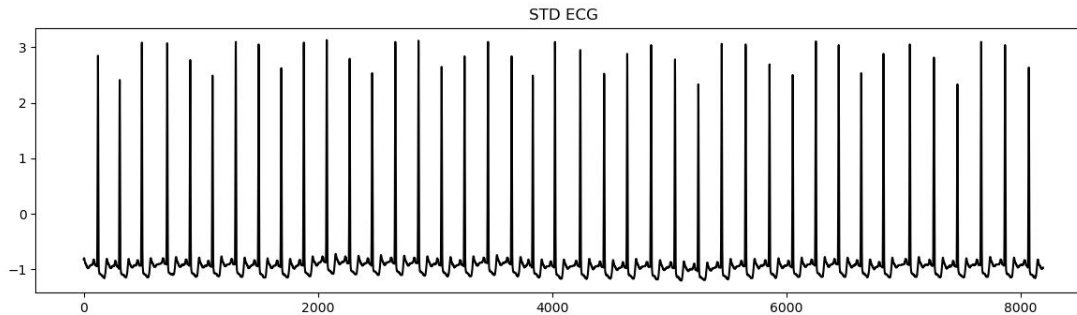
- IRIDIA-AF v1 : Holter monitoring database from patients with paroxysmal AF with 167 records from 152 patients, acquired from 2006 to 2017 in Belgium. Records last from 19 hours up to 95 hours, divided into 24-hour files.
- We focus on the AF detection task, thus working with fragments of ECG sequences (~ 20 sec) manually annotated by experts. In particular, we work with a **reduced dataset** of size



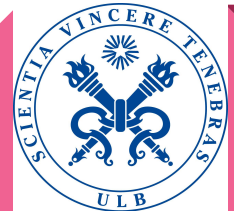
# Task: Atrial fibrillation detection



→ label 1

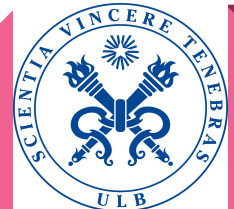
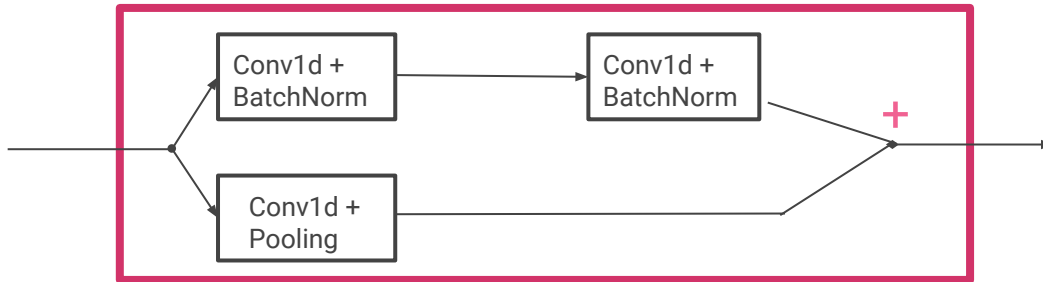
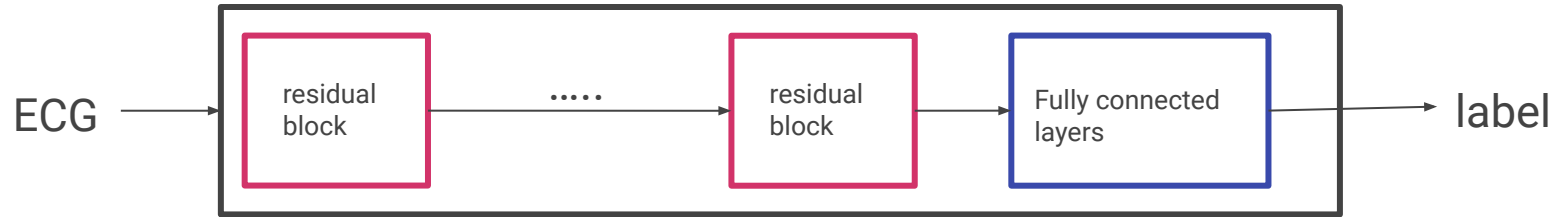


→ label 0



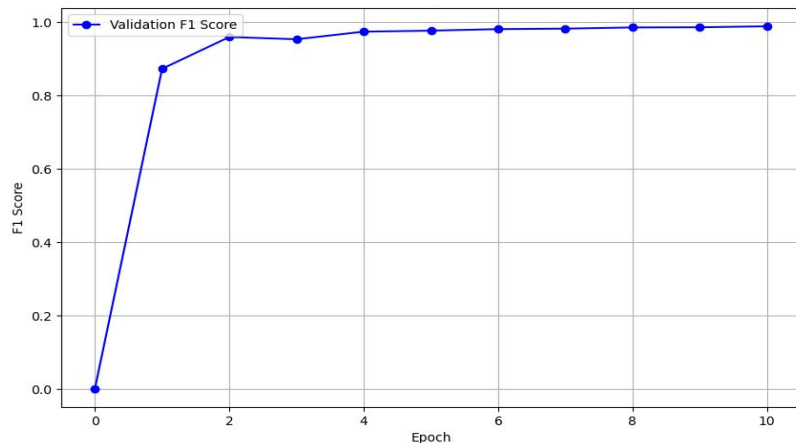
# Detection model

- We implement in [PyTorch Lightning](#) a **Residual-CNN** model.

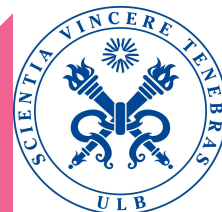


# Training and test results

- We train the model using 8 patients for the training set and 2 patients for test set.
- We get 0.97 test accuracy



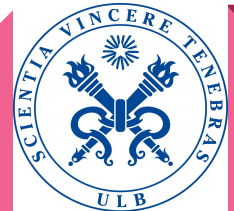
Patient number	Prediction Accuracy
15	0.99
20	1.0
25	0.93
30	0.98
35	0.7954
40	0.96



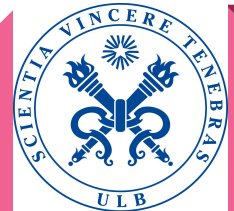
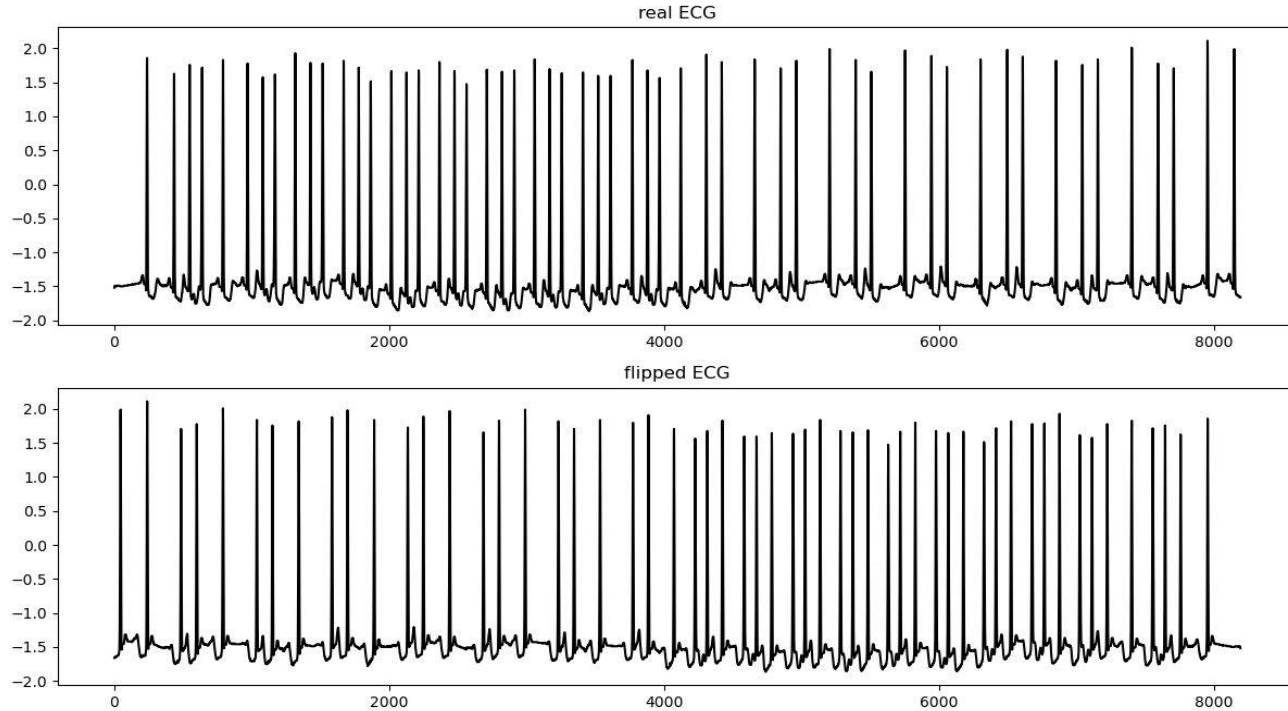
# Augmentation techniques

We experiment two simple techniques to augment an ECG sequence:

- **Flipping**, calling the function `.flip(0)`
- **Permutation**, we split the ECG sequence into blocks of length 128 and then we permute them



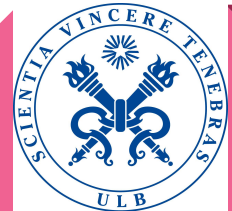
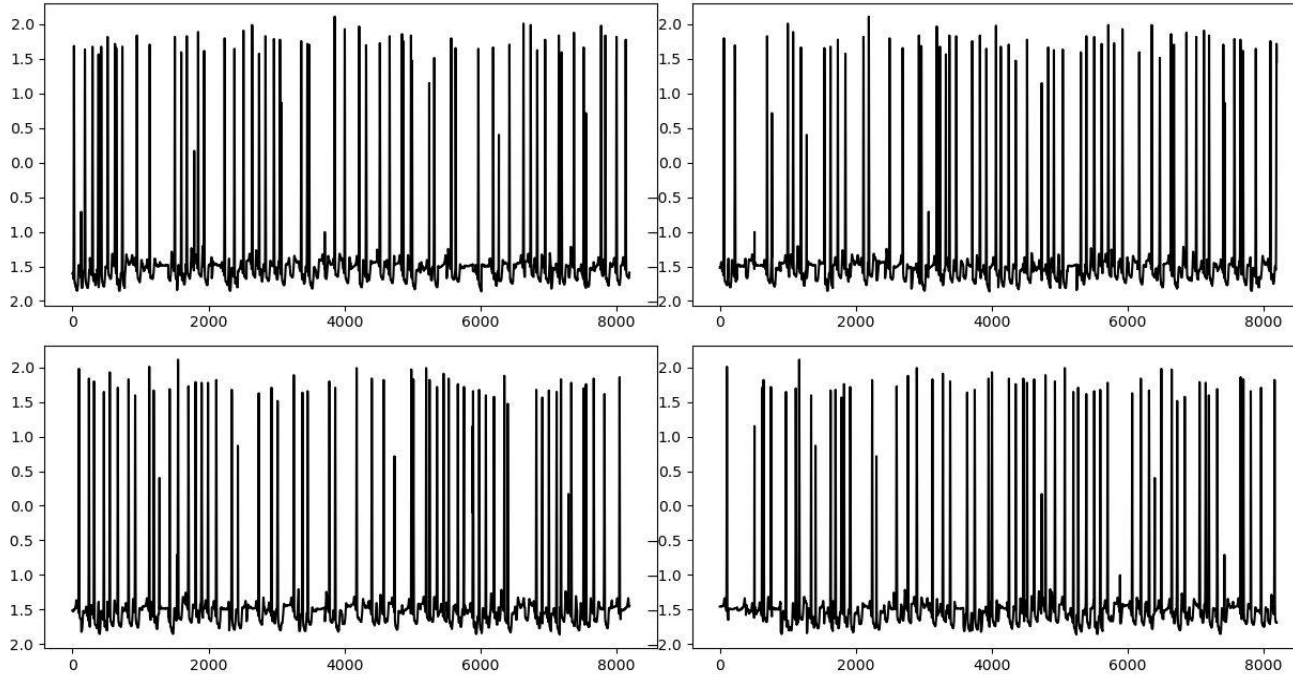
# Augmentation by Flipping





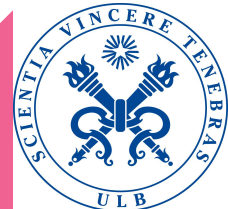
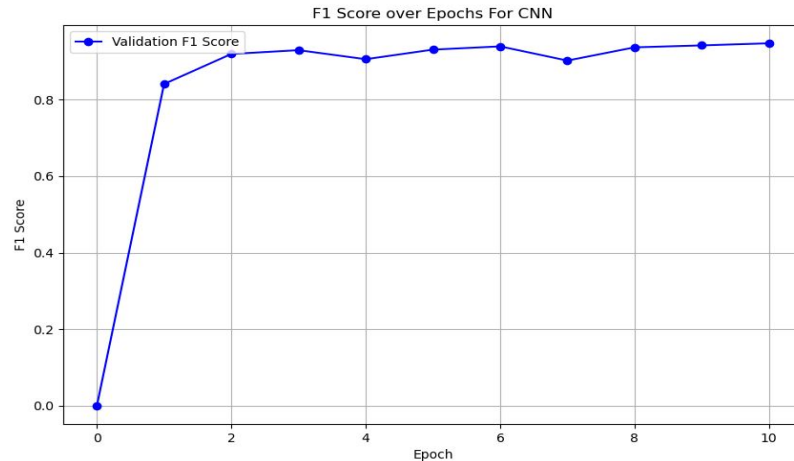
# Augmentation by Permutation

Permuted ECG

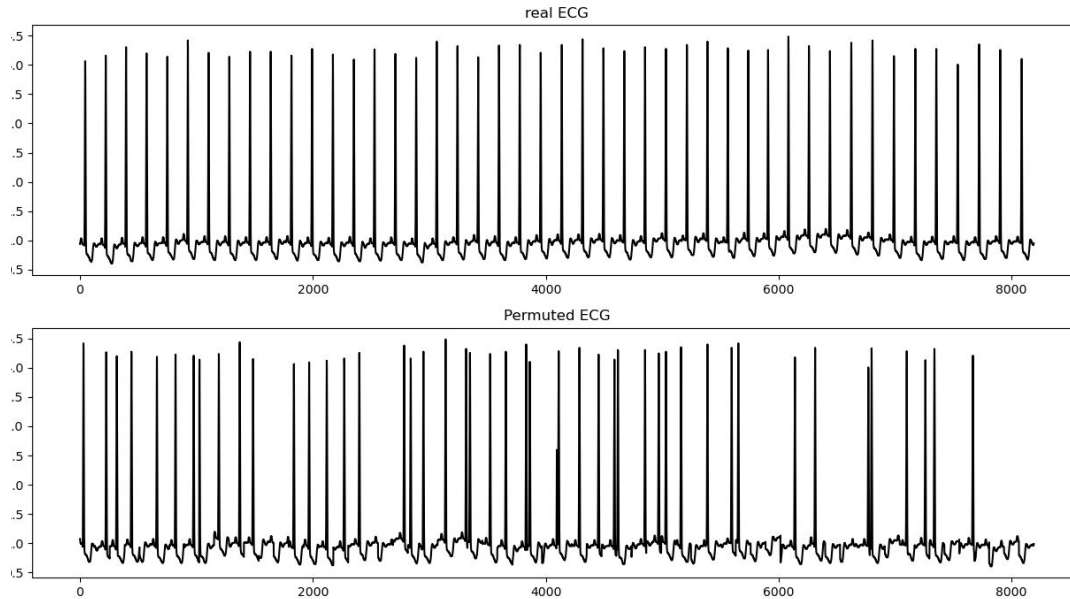


# Results of coarse Augmentation

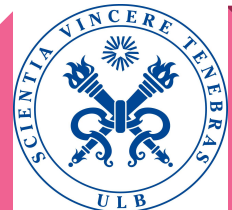
- We analyse the reliability of the fake data. Starting with a small number of ECGs (about 1000 for AF-ECG and 3000 for STD-ECG), we increase the dataset to obtain a training set of the same proportions as in the previous experiment (the test set remains unchanged). We get 0.9 test accuracy.



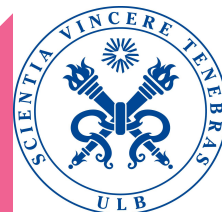
# Limits of coarse Augmentation



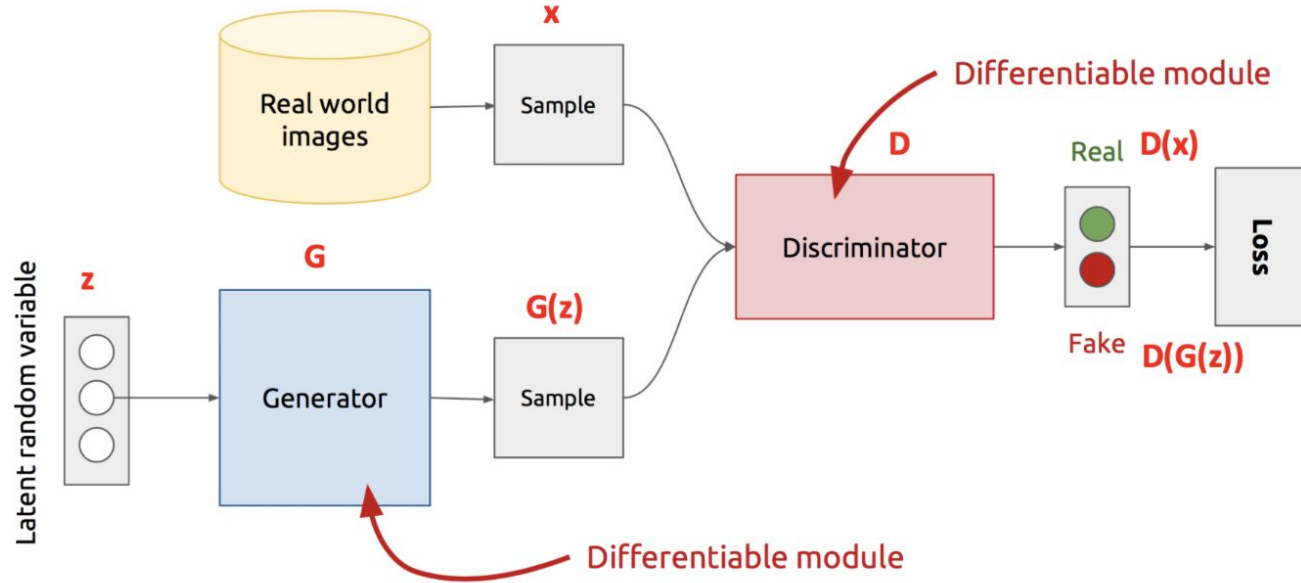
Patient number	Prediction Accuracy
15	0.85
20	1.0
25	0.95
30	0.94
35	0.49
40	0.5



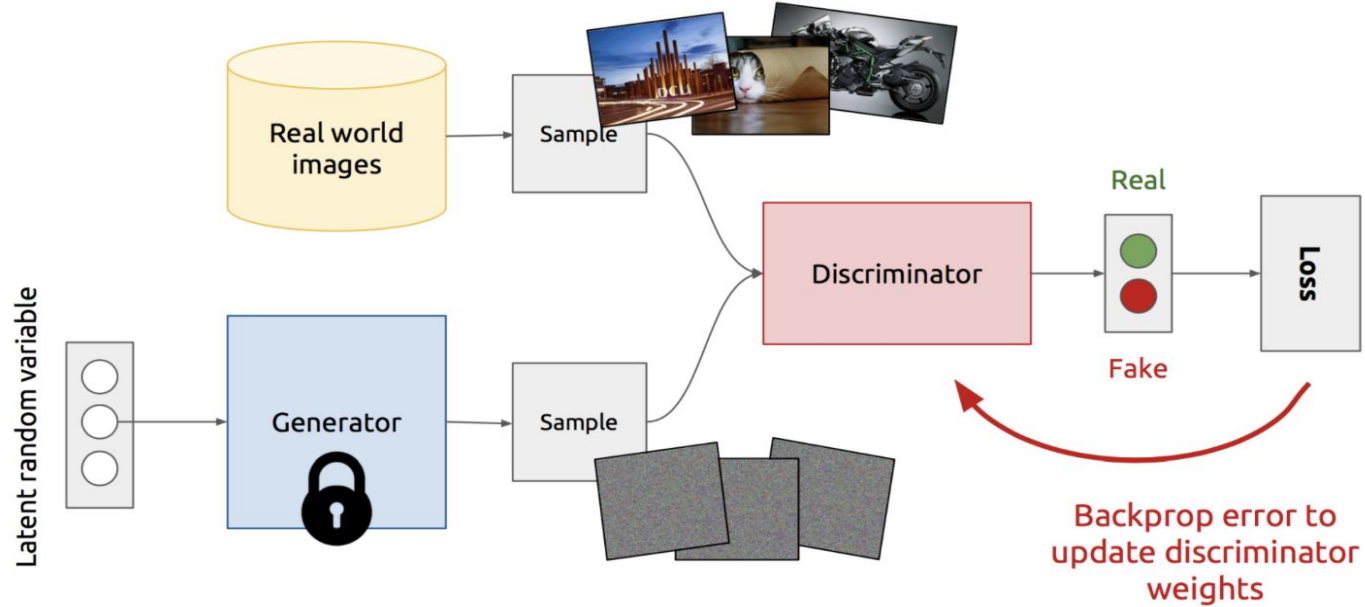
# Generative Adversarial Networks



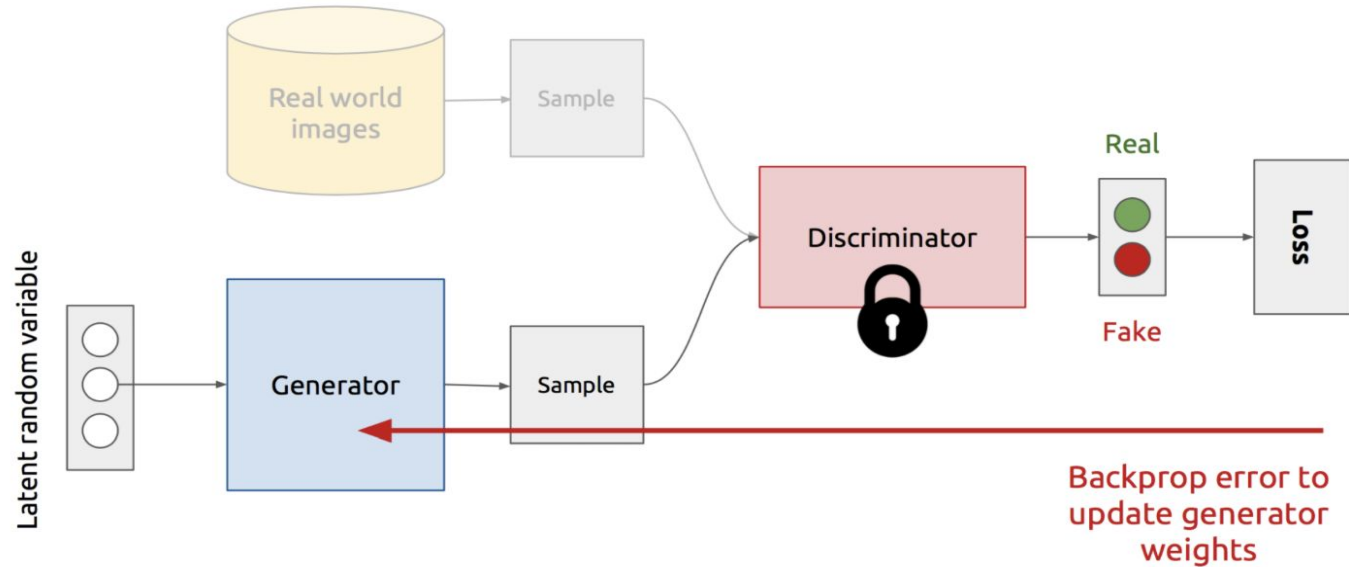
# GAN Architecture



# Training Discriminator

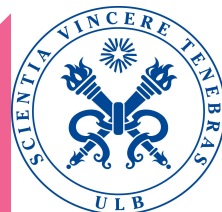


# Training Generator



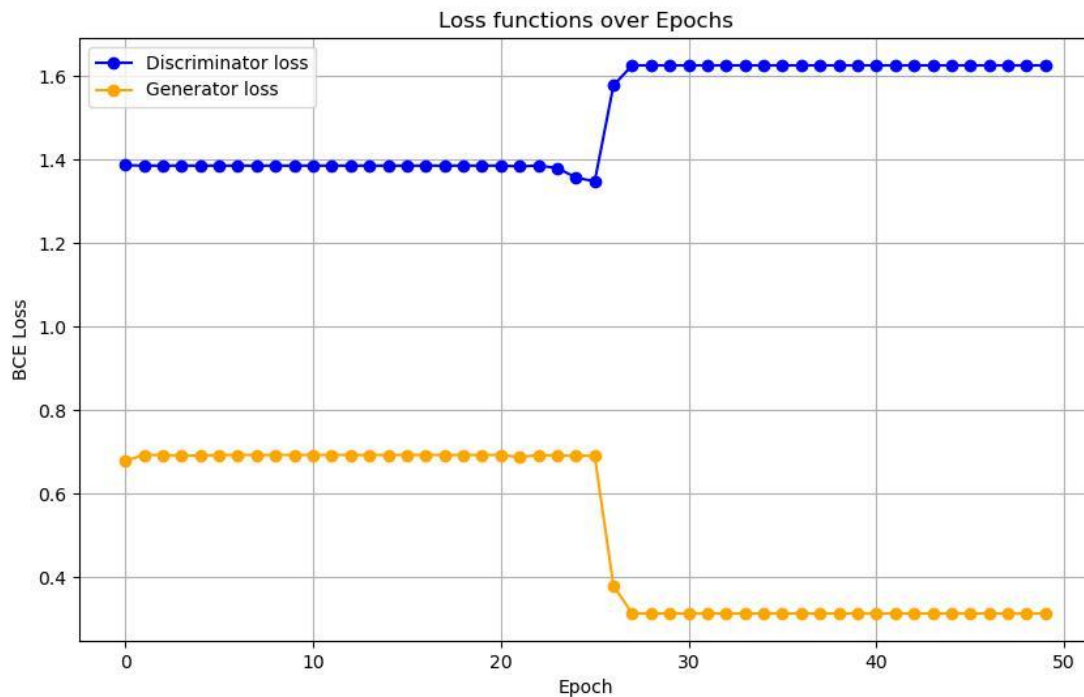
# GAN implementations

- We implement a GAN using several architectures for the generator and discriminator :
  - **CNN** generator - **CNN** discriminator
  - **BiLSTM** generator - **CNN** discriminator with **Softmax** activation function in last MLP of discriminator (v1)
  - **BiLSTM** generator - **CNN** discriminator with **Sigmoid** activation function in last MLP of discriminator (v2)

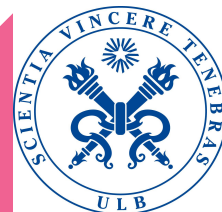




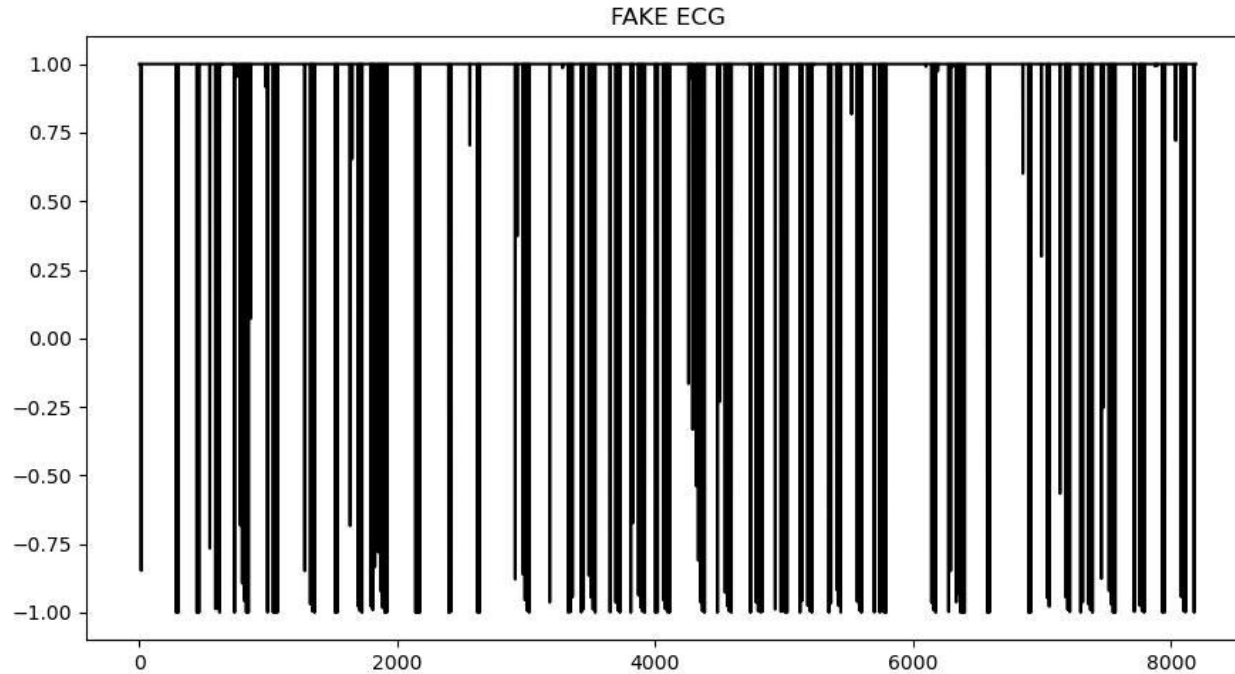
# CNN - CNN GAN : training losses



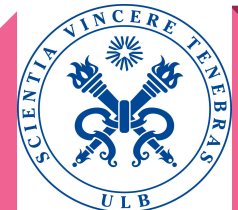
Discriminator is too weak!



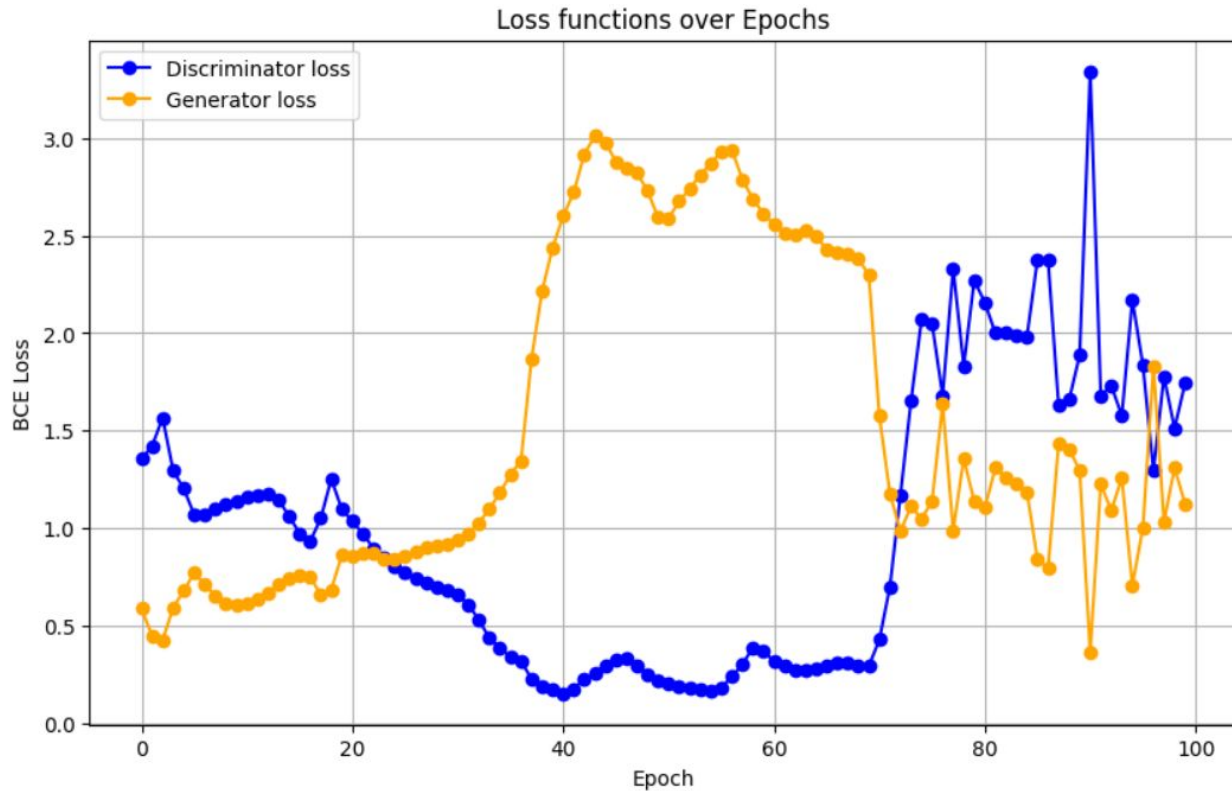
# CNN - CNN GAN : generator output



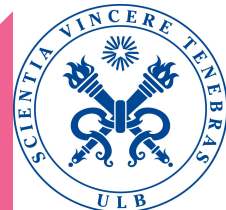
It really does not resemble a time series...



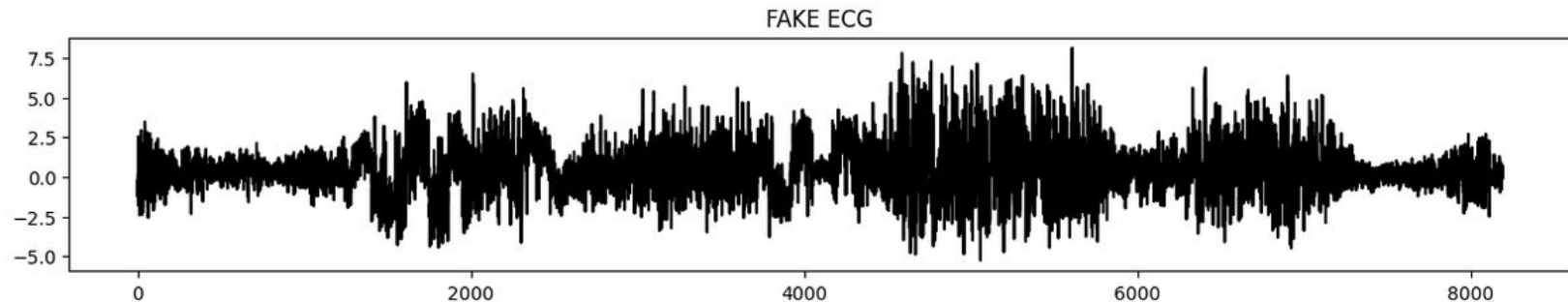
# BiLSTM - CNN GAN v1 : training losses



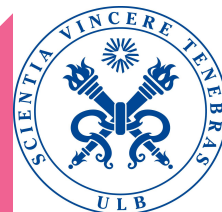
Now there is an adversarial game!



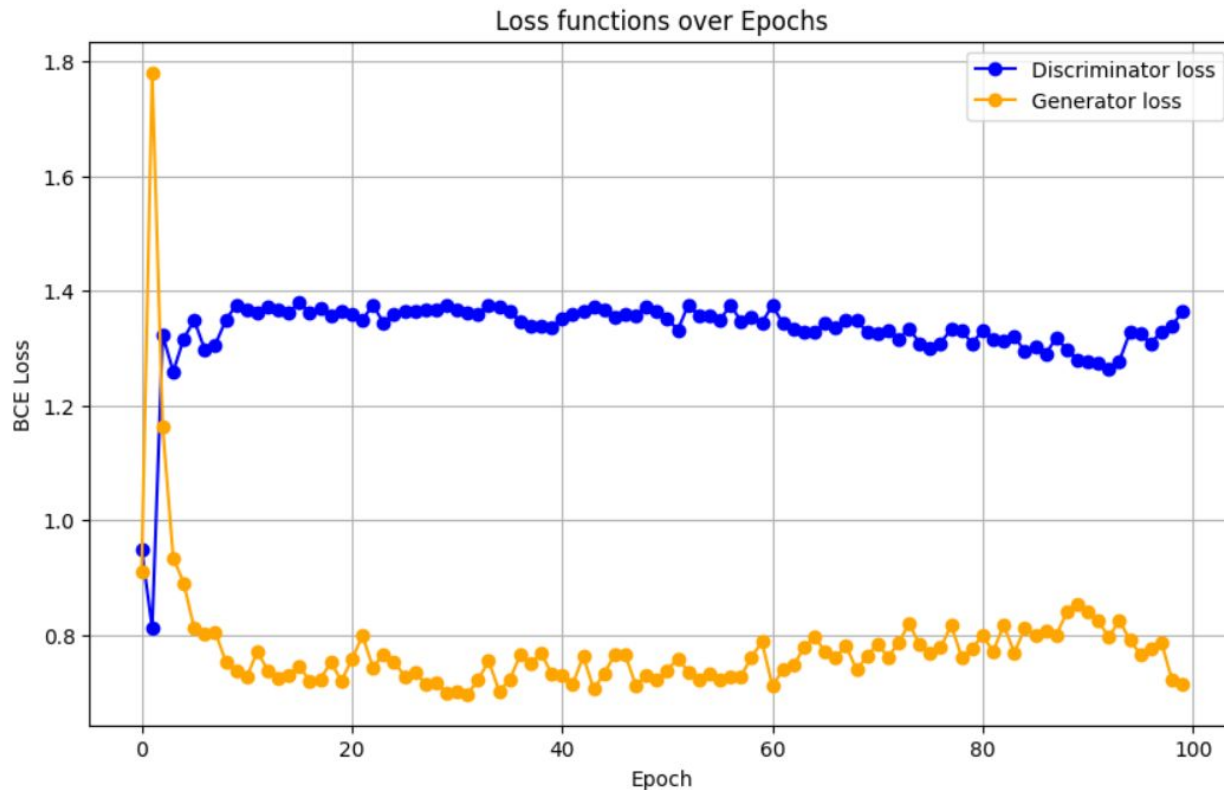
# BiLSTM - CNN GAN v1: generator output



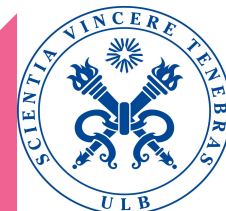
More like a time series...



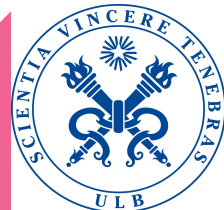
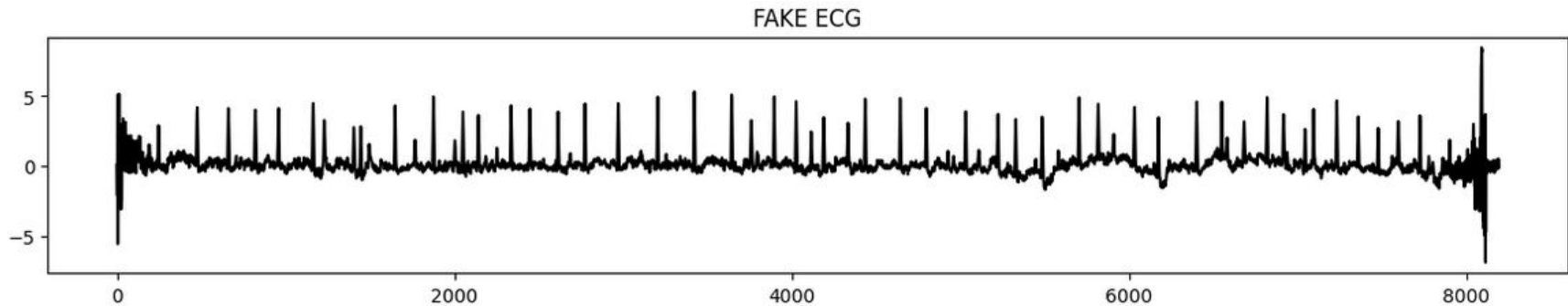
# BiLSTM - CNN GAN v2 : training losses



- Discriminator weak
- Mode collapse effect

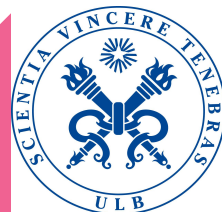


# BiLSTM - CNN GAN v2: generator output



# Conclusions

- Simple yet effective data Augmentation techniques
- More time and study is needed to find the right architecture
- Future research needs for generative time series models requiring affordable computational resources



# References

- [1]** Delaney et al. Synthesis of Realistic ECG Using Generative Adversarial Networks. 2019.
- [2]** Jang et al. Unsupervised feature learning for electrocardiogram data using the convolutional variational autoencoder. PLoS ONE, 2021.
- [3]** Rahman et al. A Systematic Survey of Data Augmentation of ECG Signals for AI Applications. Sensors, 2023.
- [4]** Thambawita et al. DeepFake electrocardiograms using generative adversarial networks are the beginning of the end for privacy issues in medicine. Scientific Reports, 2021.
- [5]** Zhu et al. Electrocardiogram generation with a bidirectional LSTM-CNN generative adversarial network. Scientific Reports, 2019.

Github repository: [https://github.com/msilver22/ECG\\_augmentation](https://github.com/msilver22/ECG_augmentation)

