Generative AI Methods for Synthesizing Realistic ECG Data

UNIVERSITY OF ALBERTA

Pooja Premnath[1], Tayyib Ul Hassan[2], Weijie Sun[5], Md Saiful Islam[4], Sunil Kalmady[4,5], Russell Greiner[3,5], Padma Kaul[5]

[1]Sri Sivasubramaniya Nadar College of Engineering, Chennai, India, [2]National Institute of Sciences and Technology, Islamabad, Pakistan, [3]Alberta Machine Intelligence Institute (Amii), Edmonton, Canada, [4]Canadian Vigor Center, Edmonton, Canada, [5]University of Alberta, Edmonton, Canada

INTRODUCTION

Electrocardiograms (ECGs) are vital tools for diagnosing cardiovascular diseases. However, obtaining sufficient high-quality data, especially for anomalous cases, poses significant challenges due to the rarity of certain conditions.

OBJECTIVE: Use generative AI models to synthesize realistic 12-lead ECGs with a focus on generating anomalous cases, enhancing model training where real-world data is scarce.

MODELS: Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) can be utilized. Generated ECGs are evaluated by comparing the performance of downstream classifiers before and after data augmentation.

FEATURE REPRESENTATION: Provide models with spatiotemporal ECG features.

FEATURE REPRESENTATION

Vectorcardiography (VCG) is a technique that records the magnitude and direction of the heart's electrical activity in three dimensions.

Vectorcardiogram Feature Representation

Algorithm: Processing VCGs from Raw ECG Waveforms Using Dower's Transform

Given: Raw ECG waveforms: ECG_{12}={I, II, V1, V2, V3, V4, V5, V6, aVR, aVL, aVF}

Objective: Compute the VCG components X,Y, Z using Dower's transform

1.Lead Matrix Formation

$$M^T = (I \quad II \quad V1 \quad V2 \quad V3 \quad V4 \quad V5 \quad V6 \quad aVR \quad aVL \quad aVF)$$

2.Dower's Transform

$$(X \quad Y \quad Z) = M^T \times D^T$$

3. Baseline Correction

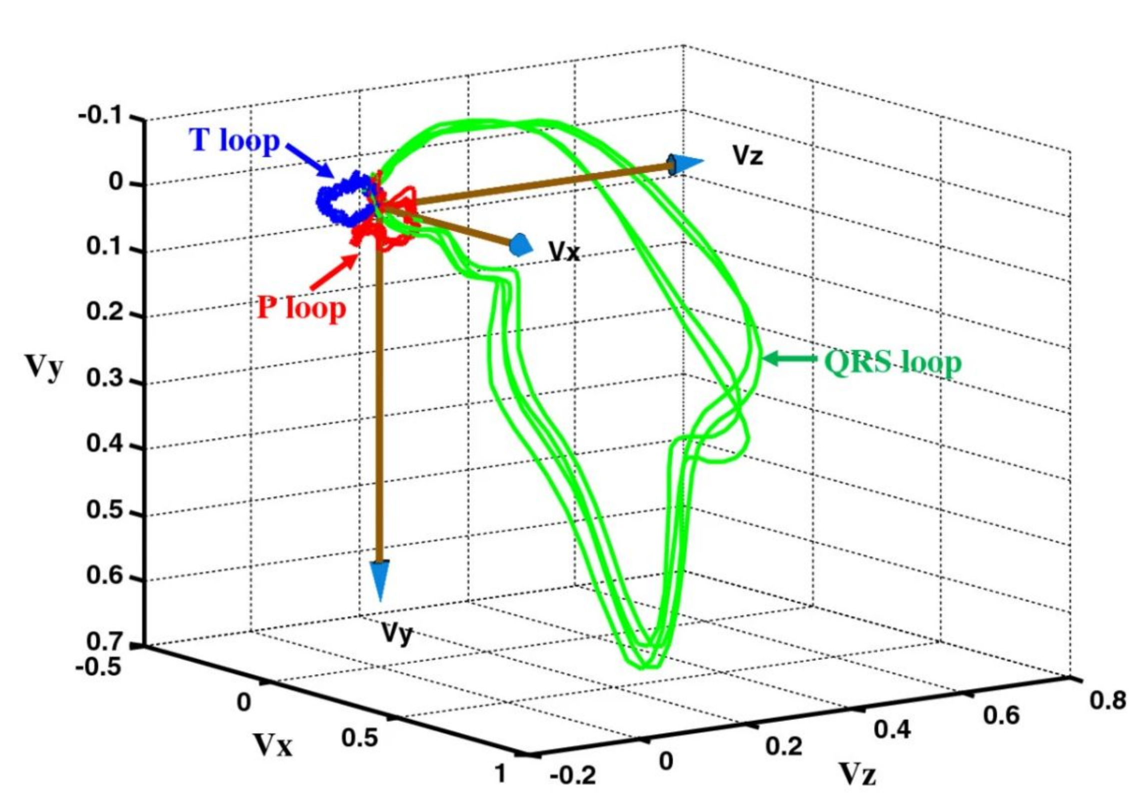
$$\hat{X} = H(X), \quad \hat{Y} = H(Y), \quad \hat{Z} = H(Z)$$

4. Signal Normalization

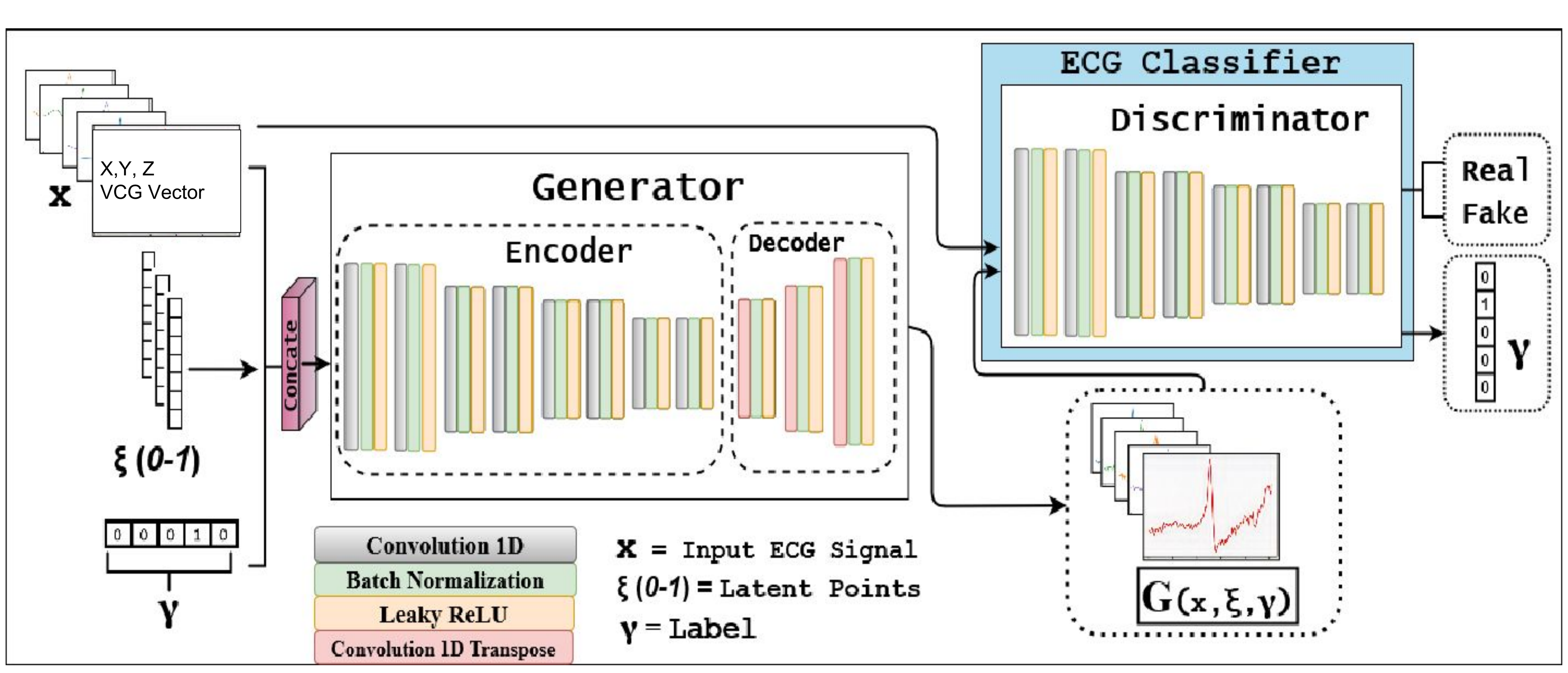
$$\tilde{X} = \frac{\hat{X} - \mu_X}{\sigma_X}, \quad \tilde{Y} = \frac{\hat{Y} - \mu_Y}{\sigma_Y}, \quad \tilde{Z} = \frac{\hat{Z} - \mu_Z}{\sigma_Z}$$

5. Processed VCG Components

$$\tilde{X}, \tilde{Y}, \tilde{Z}$$



MODEL FRAMEWORK



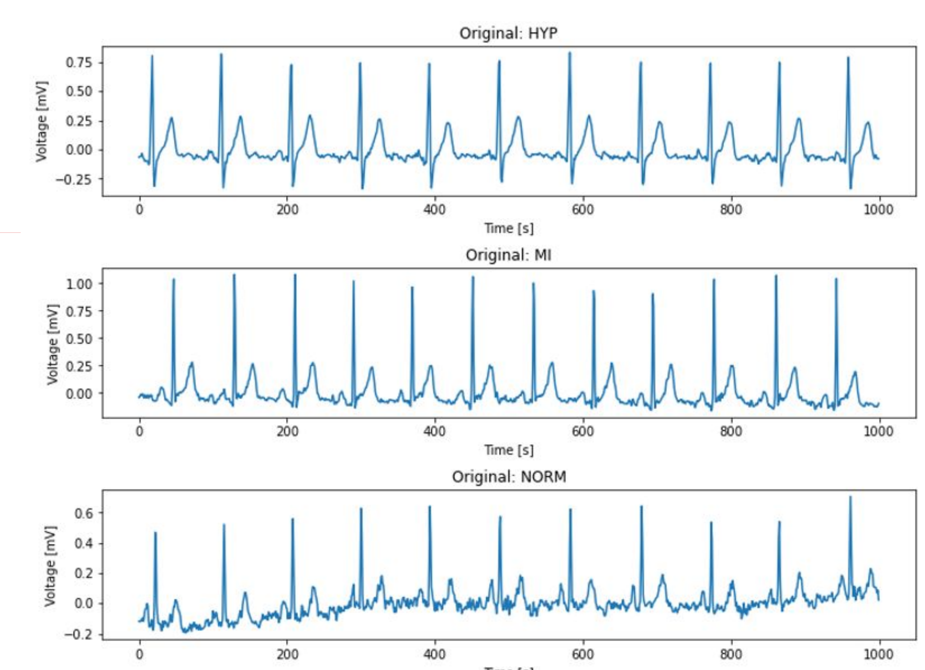
DATA

PTB-XL: Over 20,000 annotated 12-lead ECGs, with 73 different features, each pertaining to one of five super classes: Normal (NORM), ST-T Change (STTC), Myocardial Infarction (MI), Hypertrophy (HYP), and Conduction Disturbance (CD).

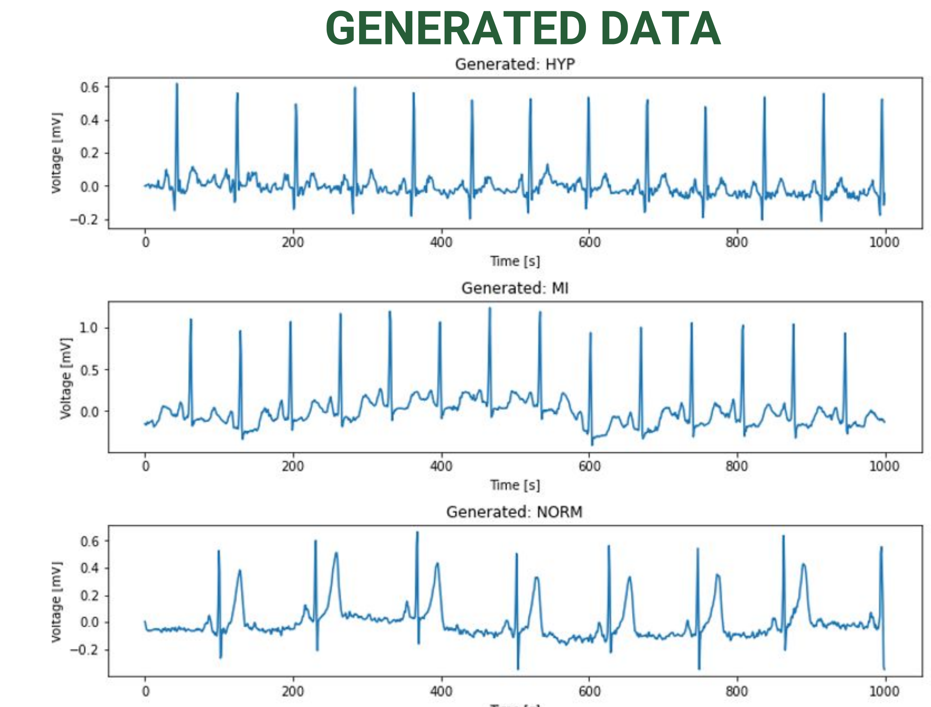
RESULTS

An 80-20 Train-Test split was utilized to generate samples for 5 super classes. 3000 samples from each class were added to augment the dataset.

ORIGINAL DATA



GENERATED DATA



Classifier	Baseline AUC	AUC with Augmented GAN Samples
Resnet_1d_wang	0.85	**0.87**
xresnet1d101	0.83	0.81
fcn_wang	0.82	0.79

FUTURE DIRECTIONS

Evaluate Generated Samples: Study the quality of the generated samples with quantitative metrics.

Enhance Model Robustness: Improve model to focus on specific statement codes, rather than super classes.

REFERENCES

1. Wagner, Patrick, et al. "PTB-XL, a large publicly available electrocardiography dataset." Scientific data 7.1 (2020): 1-15.
2. Wang, Huazhang, et al. "ECGGAN: A Framework for Effective and Interpretable Electrocardiogram Anomaly Detection." Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining. 2023.

Canadian VIGOUR Centre
Bridging Hearts and Minds
amii
SSN