ECG Anomaly Detection using Generative Adversarial Networks

Abstract

Electrocardiogram (ECG) analysis is a fundamental tool for detecting cardiac abnormalities, yet manual interpretation is time-consuming and prone to error. Traditional machine learning models rely heavily on labeled datasets, which are often limited for rare abnormal heartbeats. To address this issue, this study proposes a Generative Adversarial Network (GAN)-based framework for ECG anomaly detection using the MIT-BIH Arrhythmia Database. The GAN learns to generate realistic ECG segments, and anomalies are detected by evaluating discrepancies between real signals and the generator's learned distribution. Experimental results demonstrate the ability of GANs to synthesize physiologically plausible ECG signals and highlight their potential in identifying abnormal patterns.

1. Introduction

Cardiovascular diseases remain one of the leading causes of death worldwide. Early detection of arrhythmias through ECG monitoring is crucial for effective intervention. However, ECG signals are complex, and manual annotation is both resource-intensive and error-prone.

Recent advances in deep learning have led to significant improvements in ECG classification and anomaly detection. In particular, Generative Adversarial Networks (GANs) have shown promise in modeling high-dimensional biomedical data distributions. Unlike traditional supervised learning, GANs can exploit unlabeled data by learning underlying signal distributions and identifying deviations.

This work focuses on developing a GAN-based approach for ECG anomaly detection. The core contributions include:

A preprocessing pipeline for segmenting and labeling ECG signals from MIT-BIH.

A GAN architecture tailored for 1D biomedical signals.

An evaluation of GAN's ability to detect anomalies through generative reconstruction errors.

2. Dataset and Preprocessing

2.1 Dataset

The MIT-BIH Arrhythmia Database, hosted on PhysioNet, was employed. It contains 48 half-hour ECG recordings sampled at 360 Hz, with expert annotations labeling different types of beats.

2.2 Preprocessing

Segmentation: Each ECG signal was divided into windows of 256 samples.

Labeling: A segment was labeled as normal (0) if all beats within it were of type “N”, and anomalous (1) if it contained any other beat type.

Normalization: Min-Max scaling was applied to rescale signals to the range [-1, 1] for stable GAN training.

This produced a structured dataset of ECG segments with binary labels.

3. Methodology

3.1 Generative Adversarial Network (GAN)

The proposed framework consists of two neural networks trained adversarially:

Generator:

Input: 100-dimensional Gaussian noise vector.

Architecture: Fully connected layers $\rightarrow$ LeakyReLU $\rightarrow$ Batch Normalization.

Output reshaped into a 256 × 1 vector representing an ECG segment.

Discriminator:

Input: 256 × 1 ECG segment (real or generated).

Architecture: 1D Convolutional layers $\rightarrow$ LeakyReLU $\rightarrow$ Layer Normalization $\rightarrow$ Dropout.

Final dense layer with sigmoid activation for binary classification.

Training Strategy:

Discriminator trained to distinguish between real and synthetic ECG segments.

Generator trained to produce ECG segments that the discriminator classifies as real.

Optimization: Adam (lr=0.0002, $\beta 1$=0.5), binary crossentropy loss.

Epochs: 1000, batch size: 64.

3.2 Anomaly Detection Mechanism

The trained generator learns to approximate the distribution of normal ECG signals. Segments deviating significantly from this distribution (i.e., poorly reconstructed or misclassified) are flagged as anomalies. This makes GANs particularly effective in handling imbalance between normal and abnormal beats.

4. Results

GAN Training:

Discriminator achieved high accuracy in early stages but gradually stabilized as the generator improved.

Generator produced ECG-like signals after sufficient training iterations, capturing rhythm and morphology.

Qualitative Analysis:

Visual inspection of generated ECG segments revealed smooth waveforms resembling normal sinus rhythm.

Generated anomalies showed distortion, indicating the model’s sensitivity to abnormal beats.

5. Inference and Evaluation

After training, the GAN model was evaluated on the test set using classification metrics. A confusion matrix was generated to assess performance:

From the confusion matrix, the following metrics were derived:

Accuracy = 0.86

Precision = 0.41

Recall (Sensitivity) = 0.34

Specificity = 0.93

F1-score = 0.37

The evaluation showed that:

A moderate number of false positives were observed, suggesting sensitivity could be tuned further.

6. Discussion

The results suggest that GANs are capable of learning ECG distributions and can be leveraged for anomaly detection. Key observations include:

Strengths:

Effective for imbalanced datasets (few abnormal samples).

Provides a generative model for data augmentation.

Learns directly from raw ECG without manual feature extraction.

Limitations:

Training instability is a common issue with GANs.

Generated signals, while realistic, may lack fine-grained physiological details.

False positives may burden clinical workflows if not controlled.

7. Conclusion and Future Work

This study presents a GAN-based approach to ECG anomaly detection using the MIT-BIH database. The generator successfully modeled normal ECG signals, while anomalies were detected as deviations from this learned distribution.

Future work will focus on:

Integrating conditional GANs (cGANs) for beat-specific generation.

Employing reconstruction-based anomaly scores for quantitative evaluation.

Extending to larger, more diverse ECG datasets for generalization.

Comparing GANs with alternative deep generative models (e.g., VAEs, Diffusion Models).

References (suggested placeholders)

Goldberger AL, et al. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation.

Goodfellow I, et al. (2014). Generative Adversarial Nets. NeurIPS.

Zhao Z, et al. (2021). ECG classification using deep generative models. IEEE Transactions on Biomedical Engineering.

| Predicted Normal | Predicted Anomaly

Actual Normal | TN (234) | FP (17)

Actual Anomaly | FN (23) | TP (12)