# ECG Heartbeat Signals Classification

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***Abstract*—This project investigates the analysis and classification of ECG heartbeat signals using one dimension Res-Net. Several preprocessing and modeling approaches are evaluated, and experimental results are presented.**

## I. Introduction

Electrocardiogram (ECG) signals nowadays play a critical role in diagnosing heart diseases. With the growth of machine learning and especially deep learning, ECG analysis has gained significant benefit. This project focuses on exploring ECG heartbeat data and building models for classification.

## II. Dataset Description

The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database.

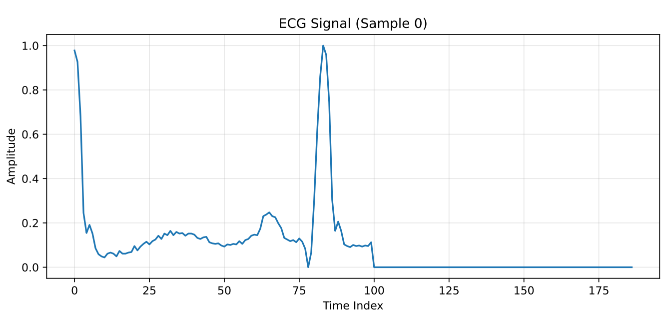


Fig. 1. Sample ECG Signal

### A. Label Distribution

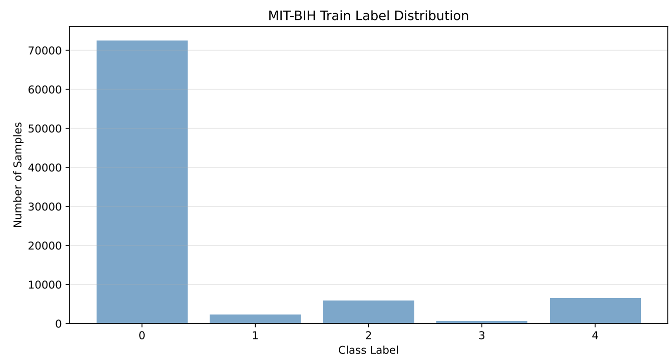


Fig. 2. Label Distribution

The figure shows a highly imbalanced class distribution in the training dataset.

TABLE I
Class Distribution in the MIT-BIH Train Dataset

| Class Label | Heartbeat Type | Number of Samples |
|---|---|---|
| 0 | Normal Beat (N) | 72,471 |
| 1 | Supraventricular Beat (S) | 2,223 |
| 2 | Ventricular Beat (V) | 5,788 |
| 3 | Fusion Beat (F) | 641 |
| 4 | Unknown / Paced Beat (Q) | 6,431 |

## III. Data Preprocessing

We applied several preprocessing such as label encoder and normalization of ECG signals

Due to uneven label distribution, we applied class weighting technique. The rare classes like class 3 will receive the higher weights, common classes like class 0 will receive the lower weights

## IV. Methodology

### A. 1D Res-Net

TABLE II
Res-Net 1D Architecture

| Stage | Layers | Output Shape |
|---|---|---|
| Input | ECG Signal (187 samples) | (187, 1) |
| Block 1 | Conv1D(64) + BN + ReLU + MaxPool | (62, 64) |
| Block 2 (Residual) | 2× Conv1D(64) + BN + Add + ReLU + MaxPool | (31, 64) |
| Block 3 (Residual) | Conv1D(128) + Conv1D(128) + BN + Add + ReLU + MaxPool | (15, 128) |
| Block 4 (Residual) | Conv1D(256) + Conv1D(256) + BN + Add + ReLU | (15, 256) |
| Pooling | Global Average Pooling | (256) |
| Classifier | Dense(128) + Dropout | (128) |
| Output | Dense(5) + Softmax | (5) |

## V. Results

We performed the predictions in test set and evaluated the results.

TABLE III
CLASSIFICATION PERFORMANCE ON THE MIT-BIH TEST DATASET

| Class | Precision | Recall | F1-score |
|---|---|---|---|
| Class 0 | 0.99 | 0.99 | 0.99 |
| Class 1 | 0.84 | 0.85 | 0.84 |
| Class 2 | 0.97 | 0.96 | 0.96 |
| Class 3 | 0.71 | 0.88 | 0.79 |
| Class 4 | 0.99 | 0.99 | 0.99 |

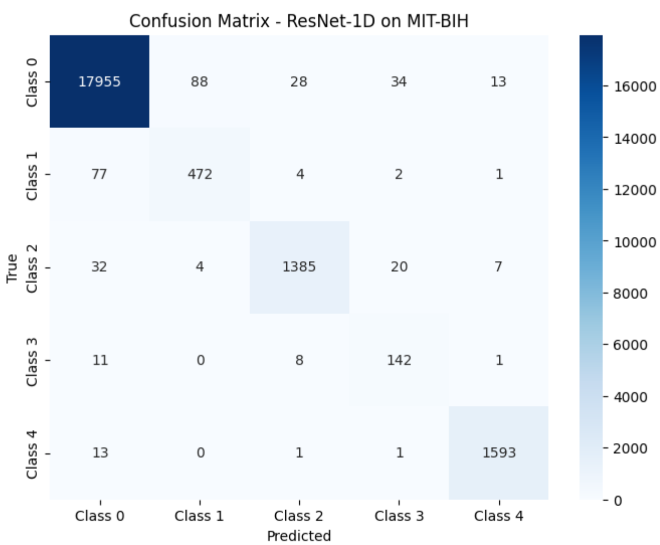


Fig. 3. Confusion matrix -ResNet-1D on MIT-BIH

## VI. Conclusion

This project demonstrates that deep learning(Res-Net-1D) can effectively classify ECG heartbeats.

## References


[1] Mohammad Kachuee, Shayan Fazeli, Majid Sarrafzadeh, "ECG Heartbeat Classification: A Deep Transferable Representation"

[2] Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng in Med and Biol 20(3):45-50 (May-June 2001). (PMID: 11446209)