ECG Heartbeat Categorization Classification

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1. INTRODUCTION

An electrocardiogram (*ECG*) is a simple and non-invasive test used to monitor the heart's rhythm and electrical activity.

Sensors attached to the skin detect the electrical signals generated by the heart with each heartbeat. These signals are recorded by a machine and analyzed by medical professionals to identify any abnormalities.

An ECG may be requested by a heart specialist (*cardiologist*) or any doctor who suspects a potential heart condition, including a general practitioner (GP).

In this report, I apply Keras to develop a deep learning model for classifying ECG signals from the MIT-BIH Arrhythmia Dataset, leveraging convolutional neural networks to accurately distinguish between different heartbeat categories.

2. DATASET

This dataset consists of two well-known collections of heartbeat signals used in heartbeat classification: the **MIT-BIH Arrhythmia Database** and the **PTB Diagnostic Database**. These datasets provide ECG waveform data for normal and abnormal heartbeats, making them valuable for deep-learning applications in medical diagnostics.

The MIT-BIH Database is a widely used collection of EGG signals recorded from patients with various cardiac arrhythmias. It contains 109,446 samples classified into 5 classes:

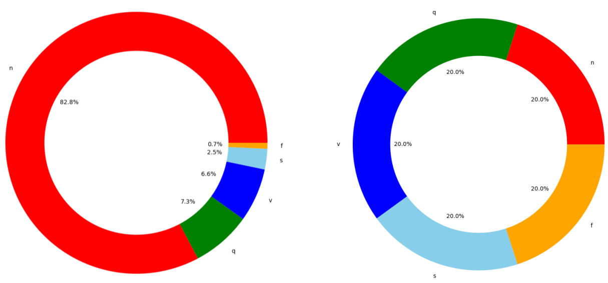
- **Normal:** N, labeled as 0
- **Supraventricular ectopic:** S, labeled as 1
- **Ventricular ectopic:** V, labeled as 2
- **Fusion beat:** F, labeled as 3
- **Unknown beat :** (Q, labeled as 4)

The dataset is stored in CSV files, each row represents an individual heartbeat sample. Each row contains numerical values representing the ECG waveform. And the final column indicates the class label of the heartbeat.

This dataset is referenced in the following research paper: *Mohammad Kachuee, Shayan Fazeli, and Majid Sarrafzadeh. "ECG Heartbeat Classification: A Deep Transferable Representation." arXiv preprint arXiv:1805.00794 (2018).*

3. DATA PREPROCESSING

Before training the model, it is essential to ensure that all ECG signals are scaled consistently. This normalization process helps stabilize training by reducing numerical variations.



(a) Original dataset (b) Balancing dataset

Figure 1: Scaled dataset

After normalization, the dataset is split into training and testing sets to allow the model to learn patterns from one subset and be evaluated on another.

Since the target labels were categorical (0 to 4, representing five different heartbeat types), they were one-hot encoded to make them compatible with the softmax activation function used in the output layer.

Finally, the input data is reshaped to match the required format for deep learning models, particularly 1D CNNs.

4. MODEL ARCHITECTURE

The model implemented is a Convolutional Neural Network (CNN) designed using Keras for the classification of ECG signals into five distinct heartbeat categories. The model includes convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for final classification.

The input layer takes the preprocessed ECG signals as input. Since the data consists of time-series signals, a 1D CNN was employed instead of a 2D CNN. Each sample have a shape of (186,1). The input is processed through a series of convolutional layers to extract meaningful features.

Three convolutional layers, each followed by batch normalization and max pooling: each convolutional block have 64 filters of size 6 with ReLU activation, followed by batch normalization and max pooling (3, stride 2).

These convolutional layers help the model extract spatial and temporal features from ECG waveforms.

After feature extraction, the output from the last pooling layer is flattened and passed through 2 fully connected (dense) layers (64 neurons and 32 neurons) to process the extracted features further. Finally, a softmax output layer with 5 neurons (one for each heartbeat category) is used for classification.

5. RESULTS

The trained model demonstrated classification accuracy, making it effective for automated heartbeat classification:

Confusion Matrix Analysis: Most heartbeat categories were correctly classified, with minimal misclassification in rarer classes.

Class	Precision	Recall	F1-Score
N	0.94	0.81	0.87
S	0.19	0.52	0.28
V	0.46	0.52	0.49
F	0.09	0.81	0.16
Q	0.79	0.84	0.81
Overall Accuracy	0.78		

The normalized confusion matrix helps analyze misclassifications and class separability.

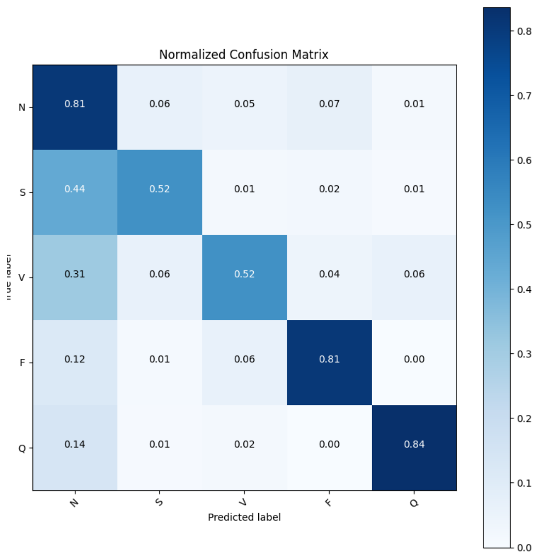


Figure 2: Confusion matrix

These results highlight the potential of deep learning for real-world automated cardiac arrhythmia detection, reducing reliance on manual ECG interpretation.

The CNN model successfully classifies ECG signals with an overall test accuracy of 78.32%, showing strong performance for normal and unknown beats but struggling with supraventricular and ventricular ectopic beats.