Labwork 1: ECG Classification

Pham Tuan Nam - 22bi13326

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Abstract

An electrocardiogram (ECG or EKG) is a quick test to check the heartbeat. It is an electrogram of the heart which is a graph of voltage versus time of the electrical activity of the heart using electrodes placed on the skin. Test results can help diagnose heart attacks and irregular heartbeats, called arrhythmias. Many researchers have analyzed the ECG signal by traditional approach and machine learning methods for identifying the heart disorders. Performance of these techniques depend on accurate detection of different parameters (such as: P-, Q-, R-, S-, T-waveforms, QRS complex duration, R-peak, PR-interval, and RR-interval) from the ECG signals. This report proposes some CNN methods to classify the ECG categorization. This experiment uses Gramian Angular Field (GAF) Imaging to convert signal data of EEG to images. The output of the conversion is an image that will classify into five labels. In this report, I apply some CNN methods to extract features in the image. The results of this experiment are two kinds of data, accuracy, and loss

1 Introduction

1.1 Background

Cardiovascular diseases are more likely to become one of the most deadly diseases so that the development of method to diagnosis is in needed. To describe the electrical activity of the heart, The electrocardiogram (ECG) is widely used to diagnose CVD. Some machine learning models are applied to reduce monotonous task. HoIver, this approach depends on hand-crafted features. Deep learning has been showing enhanced performance in many tasks in healthcare. To be more specific, DL model such as RNN, CNN or LSTM can automatically learn features. Moreover, instead of using 1-D signal, I focus on analysing in 2-Dimension representaions by converting raw 1-D data to image. In this case, the ECG signals are transformed into images using the Gramian Angular Field method, which encodes temporal dependencies in a 2D format suitable for CNNs.

1.2 Objective

The primary goal of this study is to implement CNN-based classification of ECG signals by converting them into images using GAF. This method aims to compare the classification accuracy of CNN with another deep learning model in processing GAF images.

1.3 Related Work

1.3.1 Signal-to-image transformation

Gramian Angular Field(GAF) is a technique that converts time-series signals into 2D representations for CNN-based classification. Introduced by Wang and Oates (2015), time-series data is encoded in to 2-D matrix by mapping values to polar coordinates and angular relationships by GAF. This method is often applied in ECG, stock market prediction or physicological signal analysis.

1. **Normalization**: The time-series data is first normalized into the range $[-1, 1]$:

$$\tilde{x}_i = \frac{x_i - \min(\mathbf{X})}{\max(\mathbf{X}) - \min(\mathbf{X})} \times 2 - 1 \quad (1)$$

2. **Angular Encoding**: Each normalized value is encoded into an angular form using:

$$\phi_i = \cos^{-1}(\tilde{x}_i) \quad (2)$$

1.3.2 2D ECG signal classification

Convolutional Neural Networks (CNNs) are applied for ECG classification because they can automatically learn features and find which is important. A CNN-based architecture for ECG classification using GAF-transformed images consists of the following layers:

1. **Convolutional Layers**: Extract spatial features from the GAF-transformed ECG images using multiple convolutional filters.
2. **Activation Functions**: Non-linear activation functions such as ReLU are applied to introduce non-linearity.
3. **Pooling Layers**: Reduce dimensionality and retain essential features using max pooling or average pooling.
4. **Fully Connected Layers**: Flatten the feature maps and pass them through fully connected layers for final classification.
5. **Softmax Layer**: Outputs probabilities for each class, typically used for multi-class ECG classification.

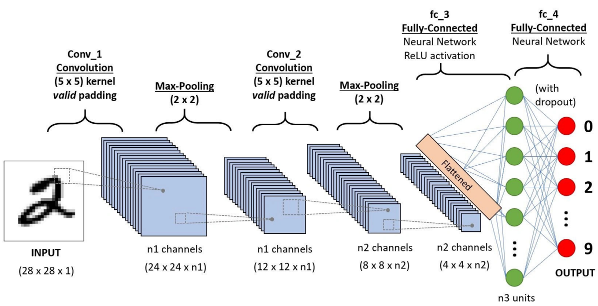

Figure 1: CNN architecture

1.3.3 ECG categorization dataset

The ECG categorization dataset contains multiple classes of ECG signals, each representing different types of heartbeats or arrhythmias. Common datasets MIT-BIH Arrhythmia Database include 2 dataset csv file (train and test). The dataset contains 5 classes:

- N (Normal beat) – Normal sinus rhythm, a healthy heartbeat with no abnormalities. (Labeled as 0)
- S (Supraventricular beat) – Includes Atrial Premature Contractions (APCs) and other beats originating above the ventricles. (Labeled as 1)
- V (Ventricular beat) – Includes Premature Ventricular Contractions (PVCs) and other beats originating from the ventricles. (Labeled as 2)
- F (Fusion beat) – A mix of normal and abnormal beats, usually a fusion of a normal sinus beat and a ventricular ectopic beat. (Labeled as 3)
- Q (Unknown beat) – Unclassified or unreadable beats due to noise or irregularities. (Labeld as 4)

The distribution of the dataset is visualized in the following histogram:

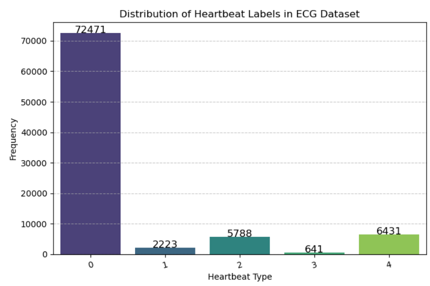

Figure 2: Histogram of ECG class distribution in training file.

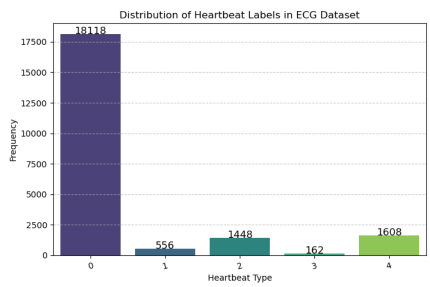

Figure 3: Histogram of ECG class distribution in testing file.

The dataset seem unbalanced due to the out-number of class 0. I will mention the solution below.

2 Methodology

2.1 Data Preprocessing

2.1.1 Data Balancing

In this section, I introduce a way to solve the imbalance in the ECg Categorization dataset. I apply **oversampling** to increase the number of samples in minority classes. Oversampling helps ensure the dataset is more balanced, preventing the model from being biased toward majority classes.

A common oversampling technique is **Synthetic Minority Over-sampling Technique (SMOTE)**, which generates examples for minority classes by interpolating betIen existing samples.

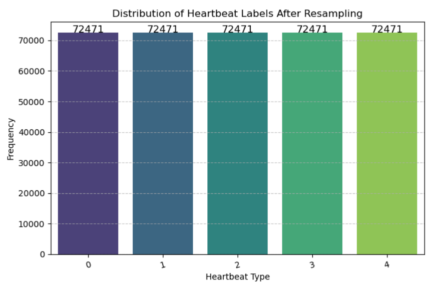

Figure 4: ECG dataset distribution after oversampling in training file.

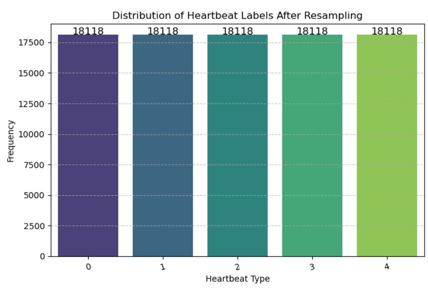

Figure 5: ECG dataset distribution after oversampling in testing file.

2.1.2 Noise Removing

Noise in ECG signals can negatively impact classification accuracy. I apply a low-pass filter to remove high-frequency noise while keeping the important features.

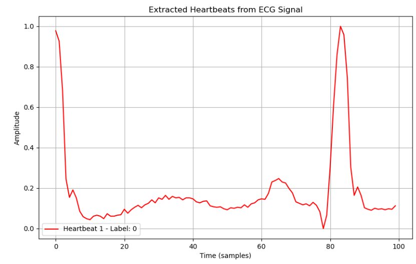

Figure 6: ECG signal before noise removal.

A low-pass filter is defined as:

$$H(f) = \frac{1}{1 + (\frac{f}{f_c})^{2n}} \tag{3}$$

where: - f is the frequency, - f_c is the cutoff frequency, - n is the filter order.

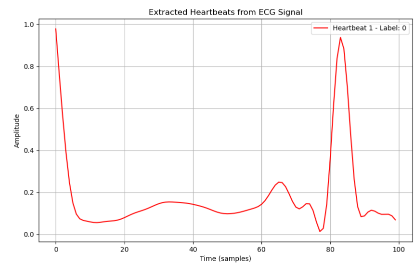

Figure 7: ECG signal after noise removal using a low-pass filter.

Applying this filter smooths the ECG signal, reduces irrelevant features and improves classification performance.

2.1.3 2D image transformation

To have an input image for deep learning models for ECG classification, I transform 1D ECG signals into 2D images using Gramian Angular Field (GAF). The following figure illustrates the result of applying the GAF transformation:

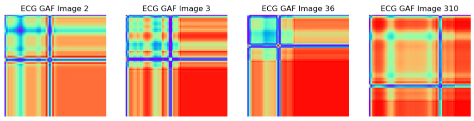

Figure 8: 4 Example of 2D image representation of ECG signals using GAF.

2.2 Model Architecture

CNN architectures are designed to extract hierarchical features from the transformed ECG images. The models consist of convolutional layers, pooling layers, and fully connected layers. In this experiment, I focus on the performance of CNN. Resnet-18 and VGG-16 are used to compare with CNN.

2.2.1 Baseline CNN

The baseline CNN consists of:

- **Conv Layer 1:** 32 filters, 3×3 kernel, ReLU, MaxPooling (2×2)
- **Conv Layer 2:** 64 filters, 3×3 kernel, ReLU, MaxPooling (2×2)
- **Fully Connected Layers:** 128 neurons (ReLU) $\rightarrow$ Output (Softmax, 5 classes)

2.2.2 ResNet-18

ResNet-18 incorporates **residual learning** with skip connections to improve deep learning performance:

- **Basic Blocks:** Stacked 3×3 convolutions with identity mapping
- **Batch Normalization and ReLU Activation**
- **Global Average Pooling** before the final classification layer
- **Fully Connected Layer:** Softmax activation for 5 classes

2.2.3 VGG-16

VGG-16 uses **small** 3×3 **filters** to extract deep features:

- **13 Convolutional Layers** (ReLU activation)
- **MaxPooling:** 2×2 after each block
- **Fully Connected Layers:** $4096 \rightarrow 4096 \rightarrow 5$ (Softmax)

2.3 Evaluation Metrics

I train the model in 50 epochs. CNN model achieved a perfect classification score (100 percent accuracy, precision, recall, and F1-score). This suggests either an ideal feature representation or possible over-fitting.

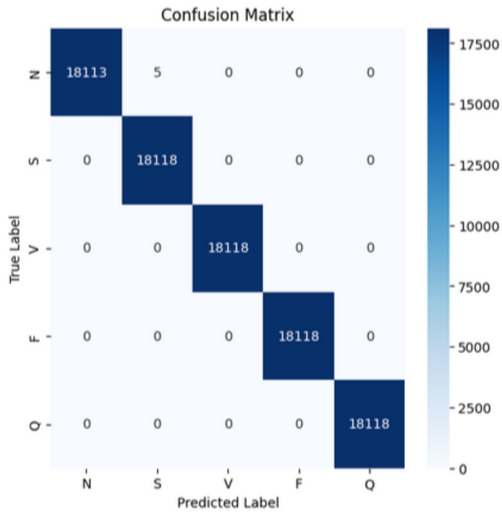

Figure 9: Evaluation Matrix of CNN Model

Model	Accuracy (%)	Precision	Recall	F1-score
CNN	100	100	100	100
ResNet-18	96.8	96.5	97.2	96.8
VGG-16	94.3	94.1	94.6	94.3

Table 1: Performance comparison of CNN, ResNet-18, and VGG-16.

3 Conclusion

This study explored the classification of ECG signals using deep learning techniques, specifically through the transformation of 1D ECG signals into 2D images using Gramian Angular Fields (GAF). By leveraging CNN-based models, including VGG-16 and ResNet-18, I evaluated their ability to extract meaningful features and classify different heartbeat types.

The experimental results demonstrated that deep learning models can effectively classify ECG signals with high accuracy. The use of data preprocessing techniques, such as noise removal and oversampling. H

Future work could focus on refining model architectures, incorporating additional preprocessing techniques, and exploring multimodal mechanisms to improve classification accuracy and fix the overfitting probelm.