Lab 1 - Biomedical Signals

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I. Introduction

Electrocardiography (ECG) is a critical tool for monitoring heart activity and diagnosing cardiac conditions such as arrhythmias. Traditional methods for analyzing ECG signals rely on manual interpretation by healthcare professionals, which can be time-consuming and prone to errors. To address this challenge, deep learning techniques, particularly Convolutional Neural Networks (CNNs), are applied as a powerful approach for automated ECG classification.

II. Dataset

A. Dataset Information

This dataset is the combination of two collections of heartbeat signal obtained from two well-known datasets, the MIT-BIH Ahrrhythmia Dataset and the PTB Diagnostic ECG Database[2]. The Arrhythmia Dataset contains **109446** samples categorized into five classes ('N', 'S', 'V', 'F', and 'Q') with a sampling frequency of 125Hz. It is sourced from Physionet and is widely used for arrhythmia classification tasks. The PTB Diagnostic ECG Database contains **14,552** samples divided into two categories ('normal', 'abnormal'), also recorded at 125Hz. It is derived from Physionet's PTB Diagnostic Database and is primarily used for diagnostic ECG analysis.

B. Exploratory Data Analysis

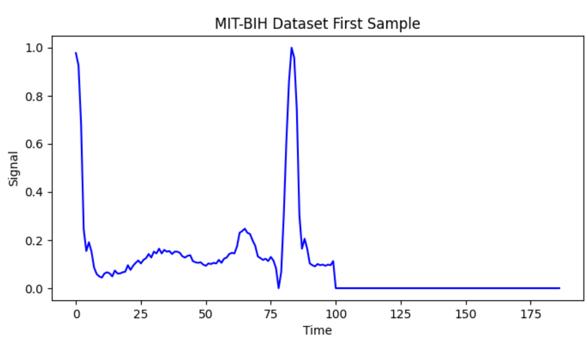

Fig. 1: One sample in MIT-BIH Dataset

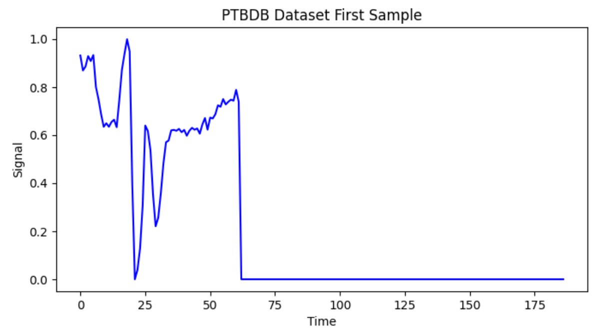

Fig. 2: One sample in PTB Diagnostic ECG Dataset

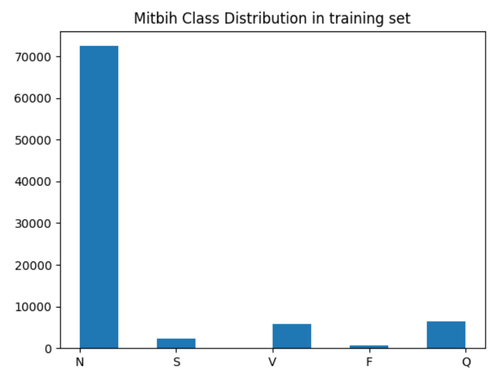

Fig. 3: Class Distribution in MIT-BIH Training Dataset

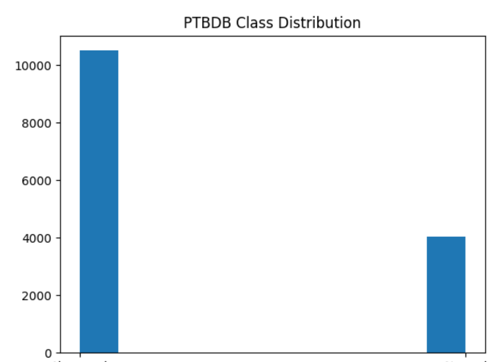

Fig. 4: Class Distribution in PTB Diagnostic ECG Dataset

Figures 1 and 2 illustrate a heartbeat sample at a frequency of 125Hz. Figures 3 and 4 present the class distribution of the two datasets. The histogram of the MIT-BIH training dataset reveals a significant class imbalance, with the 'N' (Normal Beat) class containing over 70,000 samples, whereas all other classes have fewer than 10,000. In contrast, the class distribution in the PTB Diagnostic ECG dataset shows a smaller imbalance, where the 'Abnormal' class has more than twice as many samples as the 'Normal' class.

III. Method

A. Preprocessing

A **StandardScaler** is applied to normalize the input features, ensuring they have a mean of 0 and a standard deviation of 1. The scaler is trained on train dataset and then applied to test dataset for consistency.

The preprocessed feature matrices are converted into PyTorch tensors with an additional dimension to match model input requirements. Labels are converted into torch.long tensors for classification tasks. The preprocessed data is loaded into **DataLoader**, enabling efficient batch processing.

B. Model

The **CNN (Convolutional Neural Network)** was chosen for the ECG heartbeat classification task due to its strong ability to automatically extract hierarchical features from raw 1D signals. Unlike traditional machine learning methods that rely on handcrafted features, CNNs learn spatial and temporal patterns directly from the data, making them suitable for ECG signal analysis.

As can be seen in Figure 5, the designed CNN consists of three convolutional layers with ReLU activation, each followed by max pooling to progressively reduce the feature map size while preserving essential features. The first convolutional layer has 32 filters, the second has 64 filters, and the third has 128 filters, all using a kernel size of 5 with padding to maintain input dimensions. After convolutional processing, the feature maps are flattened and passed through a fully connected layer with 64 neurons, followed by a dropout layer (0.3 probability) to reduce overfitting. The final output layer predicts class labels for heartbeat classification.

This architecture efficiently extracts both low- and high-level ECG features, enabling accurate classification of heartbeat types while being computationally efficient for real-world applications.

C. Experiment

The MIT-BIH dataset was trained using a Convolutional Neural Network (CNN) with **cross-entropy loss** as the objective function. The **Adam optimizer** with a learning rate of 0.001 was employed to optimize the model's parameters. Training was conducted for **30 epochs** to ensure convergence while preventing overfitting.

To assess the generalization ability of the trained model, we applied the model trained on the MIT-BIH dataset to the PTB Diagnostic ECG dataset using the same preprocessing and evaluation methods. The PTB Diagnostic ECG dataset was normalized using **StandardScale**, and the trained CNN was directly used for classification without additional fine-tuning. The same training procedure, including mini-batch processing and accuracy evaluation, was followed to ensure consistency in performance assessment.

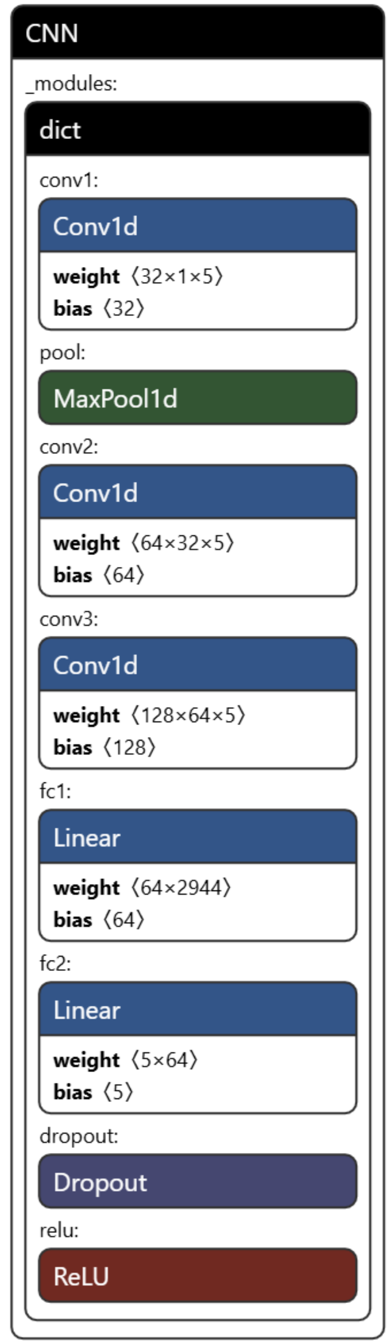

Fig. 5: CNN model visualization

IV. Evaluation

A. MIT-BIH Dataset

Class	Precision	Recall	F1-Score	Support
Normal Beats	0.99	0.99	0.99	18,118
Supraventricular Ectopy Beats	0.87	0.82	0.84	556
Ventricular Ectopy Beats	0.96	0.96	0.96	1,448
Fusion Beats	0.83	0.77	0.80	162
Unclassifiable Beats	0.99	0.99	0.99	1,608
Accuracy	-	-	0.99	21,892
Macro Avg	0.93	0.91	0.92	21,892
Weighted Avg	0.99	0.99	0.99	21,892

TABLE I: Classification Report for MIT-BIH

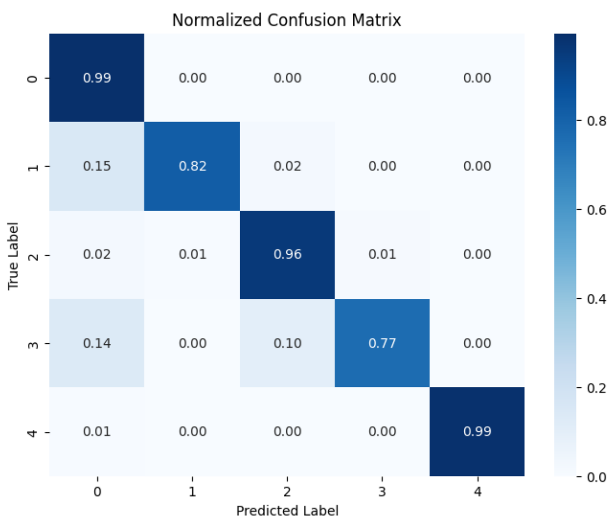

Fig. 6: MIT-BIH's Normalized Confusion Matrix

B. PTB Diagnostic ECG Dataset

Class	Precision	Recall	F1-Score	Support
Normal	0.96	0.98	0.97	809
Abnormal	0.99	0.98	0.99	2102
Accuracy	-	-	0.98	2911
Macro Avg	0.98	0.98	0.98	2911
Weighted Avg	0.98	0.98	0.98	2911

TABLE II: Classification Report for PTB Diagnostic ECG

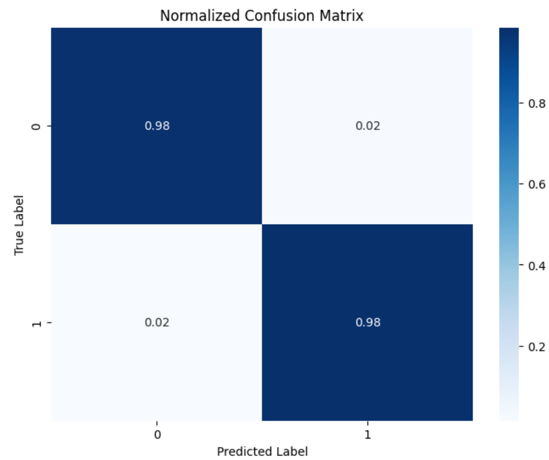

Fig. 7: PTB Diagnostic ECG's Normalized Confusion Matrix

V. Comparison

In this section, I will compare my result with the result in paper **'ECG Heartbeat Classifi- cation: A Deep Transferable Representation'**[1], which proposed a Residual Convolutional Neural Network to classify heartbeat signals.

Work	Approach	Average Accuracy (%)
This Report	**CNN**	**98.6**
M.Kachuee *et al.* [1]	Residual CNN	93.4

TABLE III: Comparison of classification approaches and their accuracy.

Table III indicates that my approach achieves a higher accuracy by roughly 5%. Despite such high accuracy, the precision and recall shown in Table I observes lower results, especially in 'Supraventricular Ectopy Beats' and 'Fusion Beat' classes. This suggests model might be overfitting to the dominant classes while failing to generalize well for minority classes.

Predicted Label / True Label	N	S	V	F	Q
N (Normal Beats)	**0.97**	0.01	0.00	0.00	0.00
S (Supraventricular Ectopy Beats)	0.08	**0.89**	0.00	0.00	0.00
V (Ventricular Ectopy Beats)	0.02	0.00	**0.96**	0.00	0.00
F (Fusion Beats)	0.08	0.00	0.05	**0.86**	0.00
Q (Unclassifiable Beats)	0.00	0.00	0.00	0.00	**0.98**

TABLE IV: Deep Residual CNN Approach

Predicted Label / True Label	N	S	V	F	Q
N (Normal Beats)	**0.99**	0.01	0.00	0.00	0.00
S (Supraventricular Ectopy Beats)	0.15	**0.82**	0.02	0.00	0.00
V (Ventricular Ectopy Beats)	0.02	0.01	**0.96**	0.01	0.00
F (Fusion Beats)	0.14	0.00	0.10	**0.77**	0.00
Q (Unclassifiable Beats)	0.01	0.00	0.00	0.00	**0.99**

TABLE V: My CNN Approach

The two Tables IV and V present the normalized confusion matrices for The Paper's Deep Residual CNN Approach and

My CNN Approach, respectively. Both models demonstrate high true positive rates in classifying 'Normal Beats' (N), 'Unclassifiable Beats' (Q), and 'Ventricular Ectopy Beats' (V), with values close to 1.00 in both matrices. However, there are some notable differences. The Deep Residual CNN performs slightly better in classifying 'Supraventricular Ectopy Beats' (S) (0.89 vs 0.82) and in Fusion Beats (F), the Deep Residual CNN achieves 0.86, while the CNN approach was only 0.77. This outcome suggests that the approach presented in the paper handles class imbalance more effectively than mine, as it demonstrates superior performance in classifying low-sample classes.

VI. Conclusion

To conclude, regardless of the high accuracy that my CNN approach achieves, it is less effective in handling class imbalance, as it struggles to detect minority classes as well as the paper's approach. For future work, I plan to explore techniques such as data augmentation or class weighting to improve the model's performance on underrepresented classes.

References

[1] M. Kachuee, S. Fazeli and M. Sarrafzadeh, "ECG Heartbeat Classification: A Deep Transferable Representation," 2018 IEEE International Conference on Healthcare Informatics (ICHI), New York, NY, USA, 2018, pp. 443-444, doi: 10.1109/ICHI.2018.00092.

[2] Kaggle, "ECG Heartbeat Categorization Dataset