Report: ECG Heartbeat Classification

Vu Hung Son

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1 Introduction

In the realm of healthcare, the importance of accurate and timely diagnosis cannot be overstated. Among the myriad of diagnostic tools available, Electrocardiogram (ECG) stands out as a non-invasive and cost-effective method for detecting heart abnormalities. However, the interpretation of ECG signals requires specialized knowledge and can be time-consuming, which is where machine learning comes into play.

This report presents my work on ECG Heartbeat Classification, a project aimed at automating the process of identifying different types of heartbeats from ECG signals. Leveraging the power of data science and machine learning, I have developed a model capable of classifying heartbeats into distinct classes, providing a valuable tool for rapid and efficient diagnosis.

This model was trained and evaluated on the widely recognized MIT-BIH Arrhythmia Database, a rich dataset consisting of two-channel ECG recordings from 47 subjects. Through rigorous pre-processing, feature extraction, and model training, I have achieved promising results, demonstrating the potential of machine learning in enhancing healthcare outcomes.

In the following sections, I will delve into the details of model architecture and performance evaluation.

2 Data Understanding

In this study, I utilized the PhysioNet MIT-BIH Arrhythmia and PTB Diagnostic ECG Databases as my sources for labeled ECG records. I showcased that the insights I gained from the MIT-BIH Arrhythmia database can be effectively applied to train inference models for the PTB Diagnostic ECG Database.

I used the second lead of the ECG, resampled to a sampling frequency of 125Hz, as my input. The MIT-BIH dataset, which is composed of ECG recordings from 47 unique subjects, was recorded at a sampling rate of 360Hz. Each heartbeat in this dataset has been annotated by a minimum of two cardiologists.

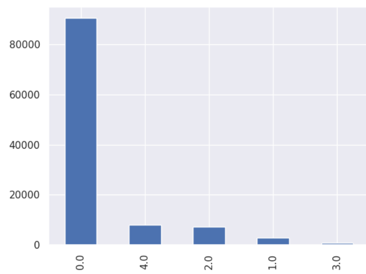

Figure 1: Bar Chart

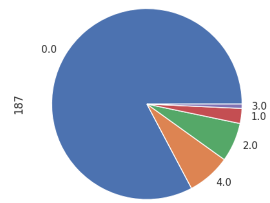

Figure 2: Pie Chart

3 Model

3.1 Model Architecture

The model used in this project is a feed-forward neural network, which is a type of artificial neural network wherein connections between the nodes do not form a cycle. This type of architecture is straightforward and widely used in many applications.

The model consists of three dense fully connected layers and an output layer:

1 **First Dense Layer:** This is the input layer of the model. It has 256 neurons and uses the Rectified Linear Unit (ReLU) activation function. The input shape for this layer is 187, which corresponds to the number of features in the dataset.

2 **Batch Normalization Layer:** This layer is used after the first dense layer. Batch normalization is a technique for improving the speed, performance, and stability of artificial neural networks. It normalizes the input for each mini-batch by both centering the inputs around zero and normalizing the input variance.

3 **Second Dense Layer:** This layer has 512 neurons and also uses the ReLU activation function.

4 **Batch Normalization Layer:** This layer is used after the second dense layer.

5 **Third Dense Layer:** This layer has 256 neurons and uses the ReLU activation function.

6 **Batch Normalization Layer:** This layer is used after the third dense layer.

7 **Output Layer:** This is the final layer of the model. It has 5 neurons, one for each class, and uses the softmax activation function. The softmax function outputs a vector that represents the probability distributions of a list of potential outcomes.

The model is compiled with the Adam optimizer and the sparse categorical cross-entropy loss function. The Adam optimizer is an extension of the stochastic gradient descent, which is known for its effectiveness. The sparse categorical cross-entropy loss function is used for multi-class classification problems where the classes are mutually exclusive.

In summary, the model architecture is well-suited for the task of classifying ECG signals into five distinct classes. The use of dense layers allows the model to learn complex patterns in the data, while the batch normalization layers help to speed up training and improve the model's performance. The softmax activation function in the output layer ensures that the output is a probability distribution, with each value representing the probability of a particular class.

3.2 Model Evaluation

3.2.1 Classification Report

Class	Precision	Recall	F1-Score	Support
0.0	0.99	1.00	0.99	9066
1.0	0.89	0.82	0.85	287
2.0	0.96	0.96	0.96	696
3.0	0.88	0.75	0.81	76
4.0	1.00	0.99	0.99	820
Accuracy			0.99	10945
Macro Avg	0.94	0.90	0.92	10945
Weighted Avg	0.99	0.99	0.99	10945

Table 1: Classification Report

This table provides a comprehensive view of the model's performance across different classes. The precision, recall, and F1-score for each class are listed, along with the number of samples of each class in the test set (support).

The model achieved an overall accuracy of 0.99, indicating that it correctly classified 99% of the total samples. The macro-average F1-score, which gives equal weight to each class, is 0.92, while the weighted-average F1-score, which gives more weight to the classes with more samples, is 0.99.

The model performed exceptionally well on classes 0.0 and 4.0, with high precision, recall, and F1-scores. For classes 1.0, 2.0, and 3.0, the model also performed well, although there is some room for improvement, especially in increasing the recall for class 3.0. Overall, the model demonstrated strong performance in classifying ECG signals.

3.2.2 Confusion Matrix

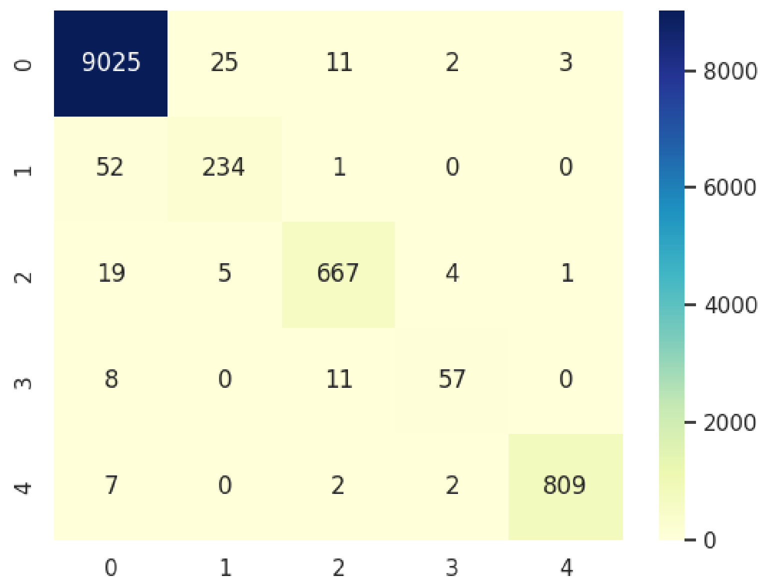

Figure 3: Confusion Matrix

4 Conclusion

The project demonstrates a successful application of a deep learning model for ECG signal classification. The model shows excellent performance across all classes. However, there is always room for improvement. Future work could explore the use of more complex models, hyperparameter tuning, advanced pre-processing techniques, and comprehensive model evaluation methods. This project serves as a solid foundation for such future explorations.