ECG Classification Report

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1 Introduction

1.1 Context

Electrocardiography (ECG) is a non-invasive diagnostic tool widely used to assess the electrical activity of the heart. Analyzing ECG signals plays a crucial role in detecting various cardiac abnormalities, such as arrhythmias, ischemia, and myocardial infarction. Traditionally, manual interpretation of ECGs is time-consuming and prone to human error.

1.2 Objectives

This report presents the results of my own study on ECG heartbeat categorization dataset taken from Kaggle. The report will demonstrates the dataset overview, then data analysis, then the model, lastly the result.

2 EDA

2.1 Dataset overview

The dataset I use is the Arrhymia Dataset, it contains 109.446 samples divided into 5 features. The ECG data are frequency of heartbeats, with the sampling frequency of 125Hz. The data source is: Physionet's MIT-BIH Arrhythmia Dataset, with 5 features named as follows: ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]. Remarks:

- This dataset consists of a series of CSV files.
- Each of these CSV files contain a matrix, with each row representing an example in that portion of the dataset.
- The final element of each row denotes the class to which that example belongs.
- All the samples are cropped, downsampled and padded with zeroes if necessary to the fixed dimension of 188.
- These signals are preprocessed and segmented, with each segment corresponding to a heartbeat.

2.2 Data analysis

The dataset is divided into train-test data (87.553-21.891). Here is a proportional visualization of the train data and test data: Figure 1 and figure 2 indicate that the training dataset in Kaggle is extremly bias to the Normal class ("N"), which is the most common type of heartbeat. This biasness can lead to the model being overfitted to the Normal class.

3 Model

I choose to use LSTM model, because when I look at the class frequency: Even if the Normal class has a lot of data, the temporal patterns within the class are still important for defining what "normal" looks like, and LSTM are specifically designed to learn these subtle, long-range dependencies.

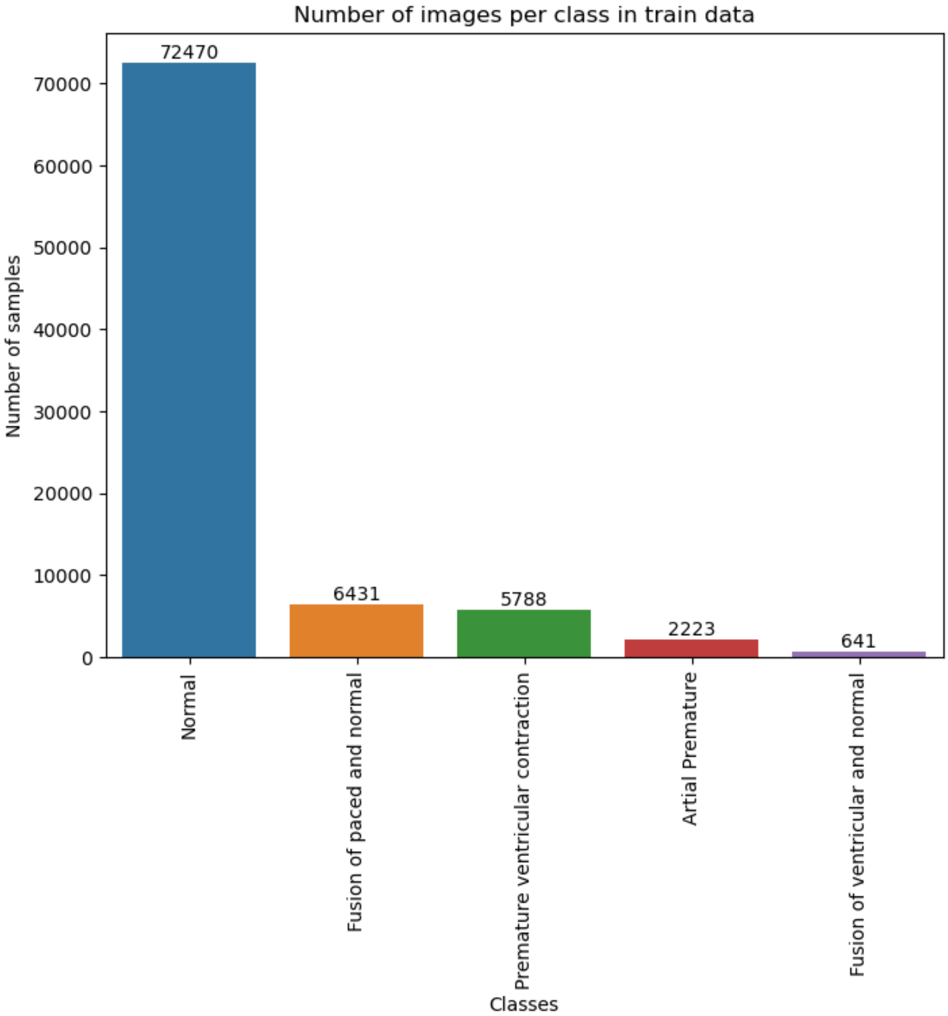
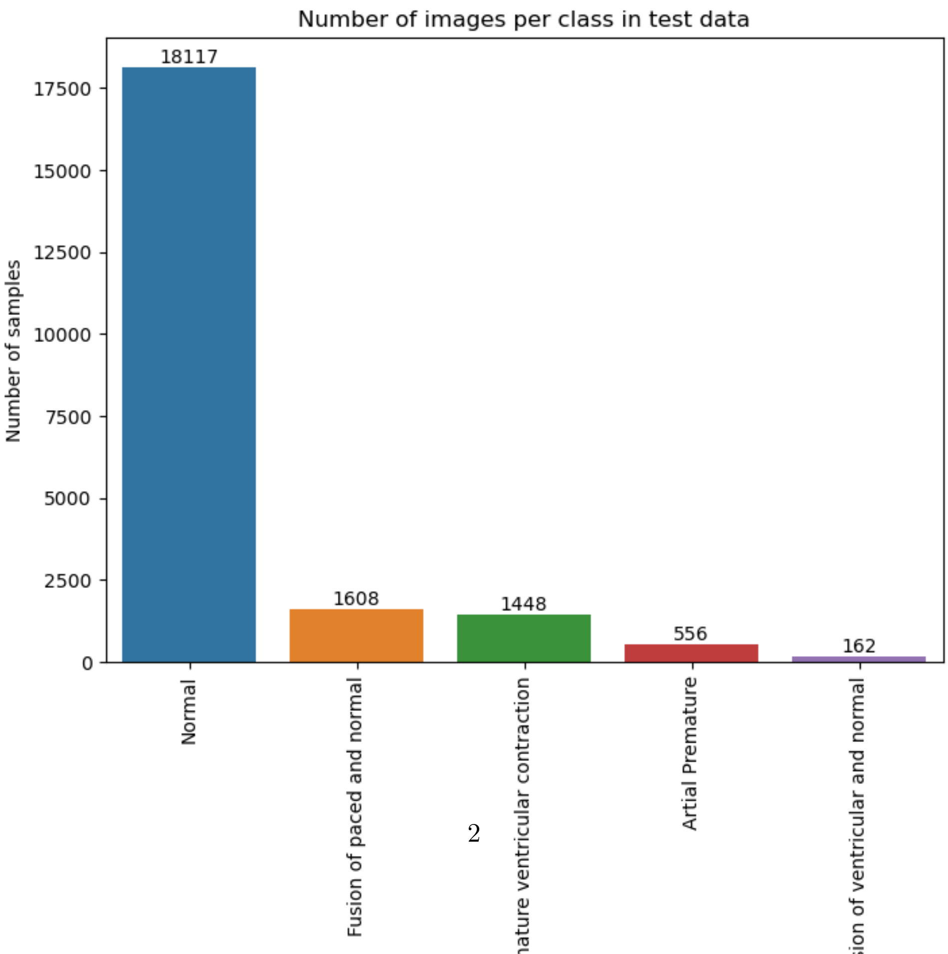


Figure 1: Figure 1: Number of images per class in train data



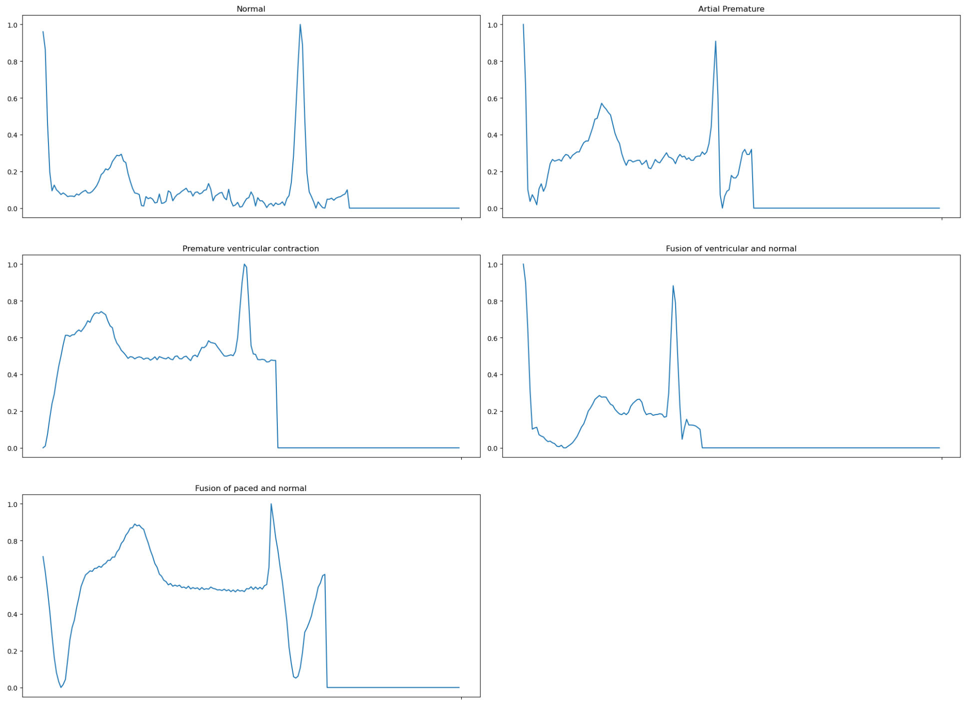


Figure 3: Figure 3: Each class' frequency

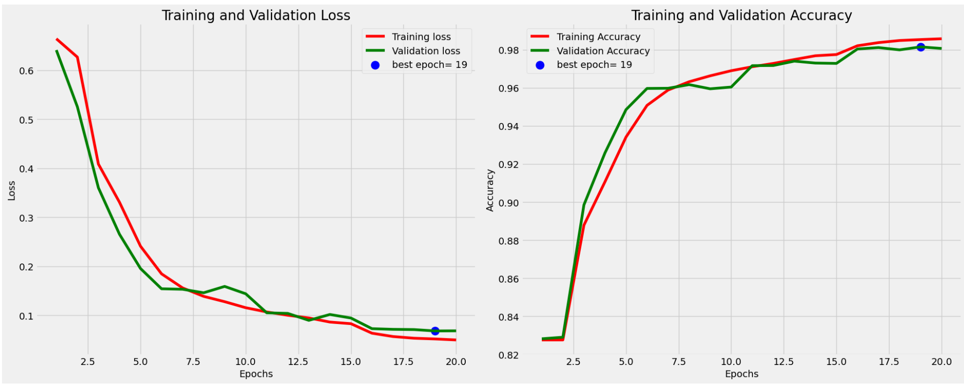


Figure 4: Figure 4: Training and validation loss/accuracy

4 Results

Here are the learning curve plots for training and validation loss/accuracy: The model learns effectively, minimal overfitting, and high performance. Here is the evaluation table of the model: The model achieves a great result.

Here is the model confusion matrix:

Table 1: LSTM Classification Report

	precision	recall	f1-score	support
0.0	0.99	1.00	0.99	9059
1.0	0.90	0.71	0.79	278
2.0	0.95	0.96	0.95	724
3.0	0.93	0.77	0.84	81
4.0	0.99	0.99	0.99	804
accuracy			0.98	10946
macro avg	0.95	0.88	0.91	10946
weighted avg	0.98	0.98	0.98	10946

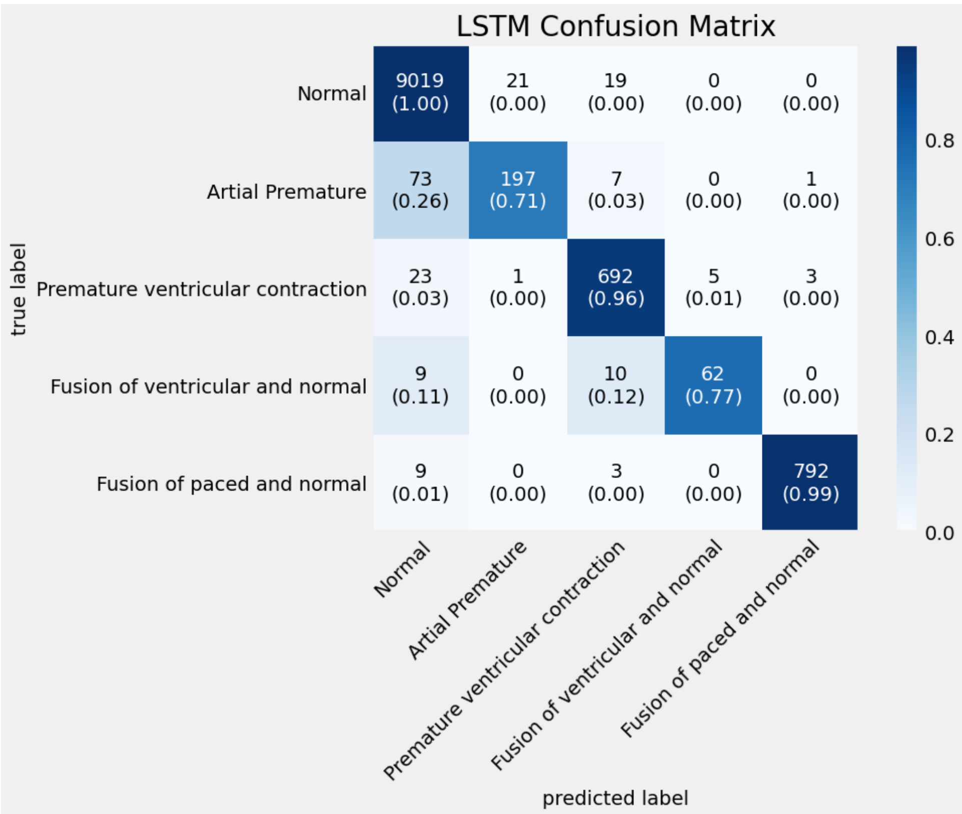


Figure 5: Figure 5: LSTM Confusion Matrix