University of Science and Technology of Hanoi

Machine learning in medicine

ECG HEARTBEAT CLASSIFICATION USING DEEP LEARNING

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Contents

1. Introduction

An electrocardiogram, or ECG, is a testing tool that captures the electrical activity of the heart. This helps identify cardiovascular conditions such as myocardial infarction and arrhythmia.

LSTM (Long Short-Term Memory) was created especially to handle time-series data. LSTM may learn complex correlations in ECG signals that are challenging to identify using conventional techniques due to its ability to "remember" information over extended periods of time.

In this report, I propose the LSTM approach in ECG analysis, covering data preprocessing, feature extraction, model training, and evaluation, comparing it with original papers using CNNs.

2. LSTM

The primary parts of LSTM are as follows:

- Cell state: The main information path through the network
- Input gate: Decides which new values should be stored in the cell state
- Output gate: Decides which parts of the cell state should be output

The sigmoid and tanh functions are used by each gate in the LSTM to regulate the information flow, functioning as an information filter. The tanh function normalizes the input value between -1 and 1, while the sigmoid function determines how much information is let through by producing a number between 0 and 1.

3. Dataset

3.1 Data overview

The dataset is divided into two primary files for training and testing, which contain 21,892 and 87,554 entries, respectively. Each file has 188 columns reflecting characteristics derived from ECG signals, along with one target column that stores the class designation.

The target column contains five classes of heartbeat signals, each represented by a numerical label:

- 0: "N" for normal heartbeats
- 1: "S" for supra-ventricular premature beats
- 2: "V" for ventricular escape beats
- 3: "F" for fusion of ventricular and normal beats
- 4: "Q" for unclassified heartbeats

Here are a few samples of this dataset.

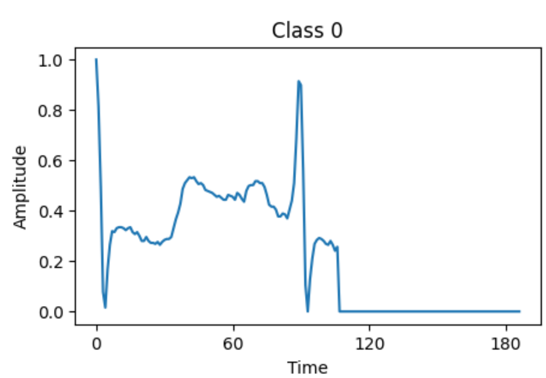

Figure 3.1: Sample ECG signal

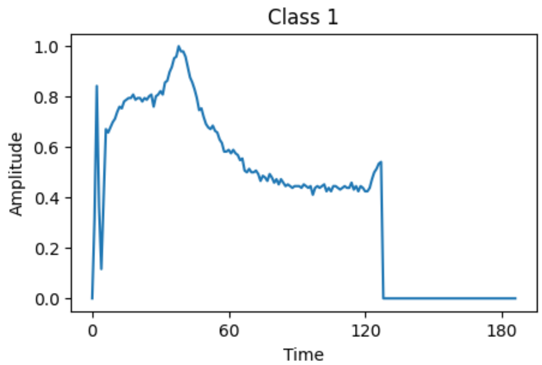

Figure 3.2: Sample ECG signal

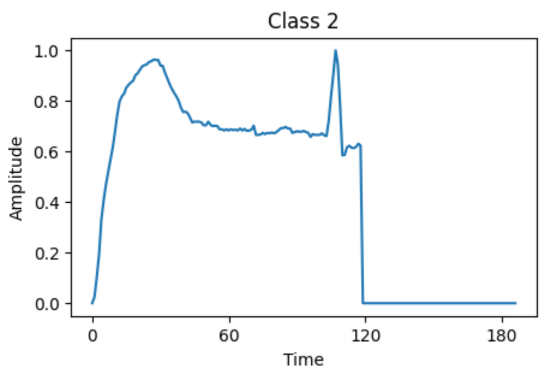

Figure 3.3: Sample ECG signal

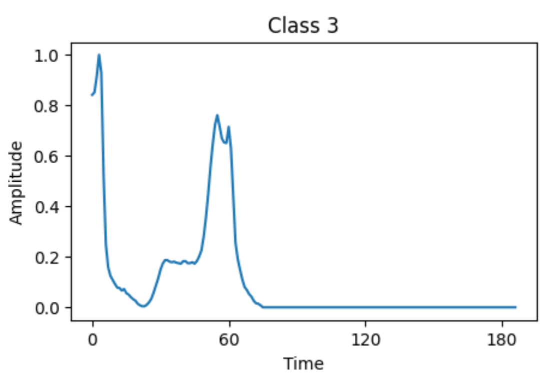

Figure 3.4: Sample ECG signal

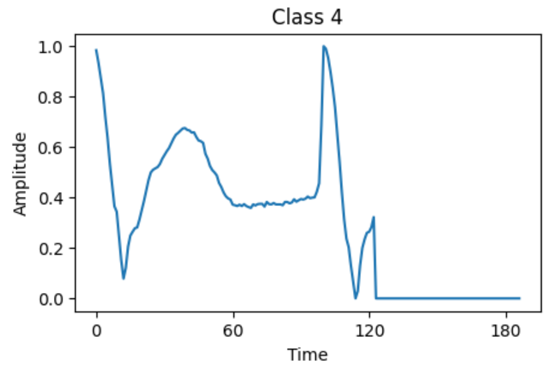

Figure 3.5: Sample ECG signal

Checking the class distribution in the target variable is an important step in the process of data analysis and machine learning model building.

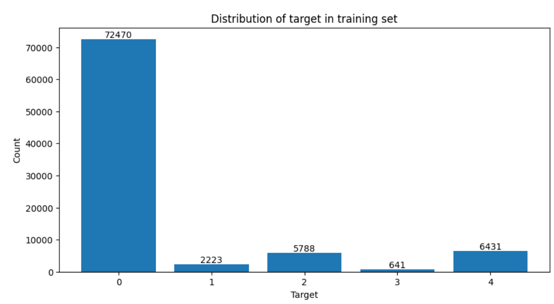

Figure 3.6: ECG class distribution in train dataset

As seen in Figure 3.6, the dataset is imbalanced, with the majority of samples belonging to the 'N' class, representing normal heartbeats. This imbalance can affect the performance of the classification algorithm, as the network may be biased towards the majority class and struggle to learn the features of the minority classes.

3.2 Preprocessing data

To deal with the imbalance problem, I applied the undersampling method to ensure each class has 4000 samples, keeping the most meaningful data. The minority classes were oversampled to meet this threshold. The under- and oversampling processes resulted in a balanced dataset ready for training.

4. Training

The model consists of two LSTM layers with 128 and 64 units, each with L2 regularization and a dropout rate of 0.5 applied to avoid overfitting. To categorize into one of the five heartbeat classes, I employed a Dense layer with 64 neurons and a ReLU activation function, followed by a final Dense layer with 5 neurons and a softmax activation function.

It uses a categorical cross-entropy loss function and is trained with the Adam optimizer, starting with a learning rate of 0.0001. Early stopping and a learning rate reduction to at least 1e-6 were also applied to optimize training.

The training ran for 200 epochs with a batch size of 32.

5. Evaluation

To evaluate the model's performance, I used the following metrics:

Class	Accuracy	Precision	Recall	F1-score
0	0.7691	0.6965	0.8642	0.7711
1	0.7358	0.8682	0.6914	0.7699
2	0.8580	0.9048	0.8210	0.8608
3	0.8691	0.8448	0.9074	0.8750
4	0.9564	0.9686	0.9506	0.9595
Overall	**0.8469**	**0.8565**	**0.8469**	**0.8472**

Table 5.1: Model performance metrics

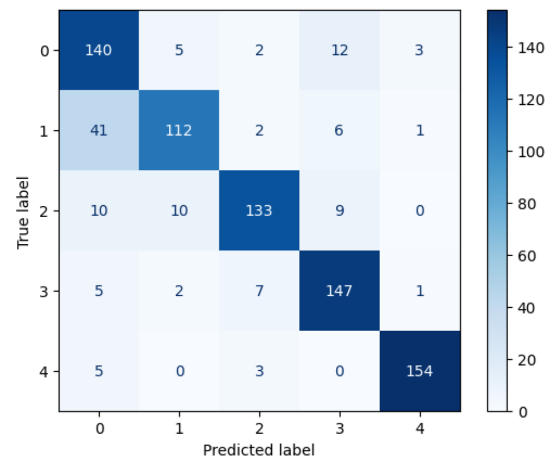

Figure 5.1: Confusion matrix

Additionally, the ROC curve is shown, a graphical representation of the true positive rate (sensitivity) versus the false positive rate (1-specificity) for different threshold values.

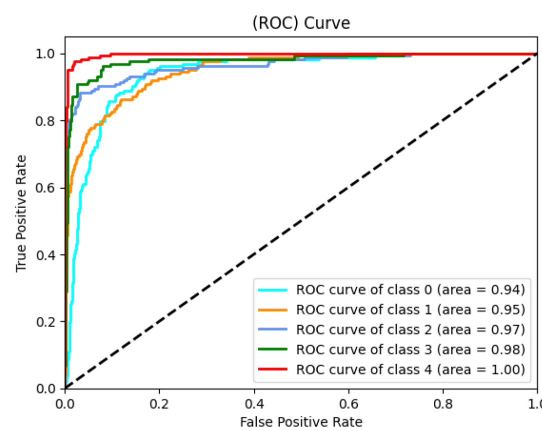

Figure 5.2: ROC curve

Observing these figures, we can see that the model achieved good performance with high accuracy, precision and recall with balanced results (85.66% and 84.69% respectively) showing that the ability to classify data is quite accurate. The ROC curves for each class are good, approaching 1.0. However, the model seems to have more difficulty in classifying class 0 and 1, in the future it is necessary to improve the two classes, possibly collecting more data or adjusting the appropriate threshold.

6. Conclusion

In this study, I proposed a deep learning-based approach for ECG heartbeat classification using a Long Short-Term Memory (LSTM) network. The model achieved high accuracy, precision, recall, and F1-score for all classes, indicating its effectiveness in classifying ECG heartbeats. While it didn't outperform CNN, the model performed well in terms of the area under the ROC curve, which demonstrates its ability to balance precision and recall.

The results suggest that recurrent neural networks, specifically LSTMs, are well-suited for capturing temporal dependencies within ECG data and achieving effective heartbeat classification. Future work could involve further optimizing the model architecture and hyperparameters, as well as exploring other deep learning algorithms and techniques, including hybrid approaches combining LSTMs with other architectures.

7. References

[1] Mohammad Kachuee, Shayan Fazeli, and Majid Sarrafzadeh. "ECG Heartbeat Classification: A Deep Transferable Representation." arXiv preprint arXiv:1805.00794 (2018).