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ECG Heartbeat Classification using Deep Learning

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1. Introduction

Automated heartbeat classification is essential for diagnosing cardiac conditions, overcoming the limitations of manual ECG analysis. Deep learning, particularly CNNs, has shown promise in this area by learning complex patterns from ECG data. However, challenges remain, including signal variability, noise, and data imbalance. This report proposes a CNN-based approach to enhance the accuracy and robustness of ECG heartbeat classification.

2. Background

2.1 ECG (Electrocardiogram)

The electrocardiogram (ECG) is a non-invasive test used to diagnose and monitor cardiovascular diseases by recording the heart's electrical activity. It provides key information about heart rate, rhythm, and conduction abnormalities. Heartbeat classification involves identifying and categorizing different types of heartbeats, which is crucial for ECG signal analysis. ECG signals, recorded via electrodes, consist of waves and intervals representing various parts of the cardiac cycle, with abnormalities in shape, amplitude, or duration indicating potential heart conditions.

2.2 CNN architecture

Convolutional Neural Networks (CNNs) are deep learning algorithms commonly used in image and signal processing. They are effective at extracting features from complex data, like ECG signals. CNNs consist of multiple layers—convolutional, pooling, and fully connected—that allow the network to learn hierarchical representations of the input data.

3. Dataset

The dataset used for this study is ECG Heartbeat Categorization Dataset It has been used in exploring heartbeat classification using deep neural network architectures, and observing some of the capabilities of transfer learning on it. The signals correspond to electrocardiogram (ECG) shapes of heartbeats for the normal case and the cases affected by different arrhythmias and myocardial infarction. These signals are preprocessed and segmented, with each segment corresponding to a heartbeat.

3.1 Data exploration

The dataset composed of two collections of heartbeat signals derived from two famous datasets in heartbeat classification, the MIT-BIH Arrhythmia Dataset

- Number of Samples: 109446
- Number of Categories: 5
- Sampling Frequency: 125Hz
- Data Source: Physionet's MIT-BIH Arrhythmia Dataset "cite"
- Classes: ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4]

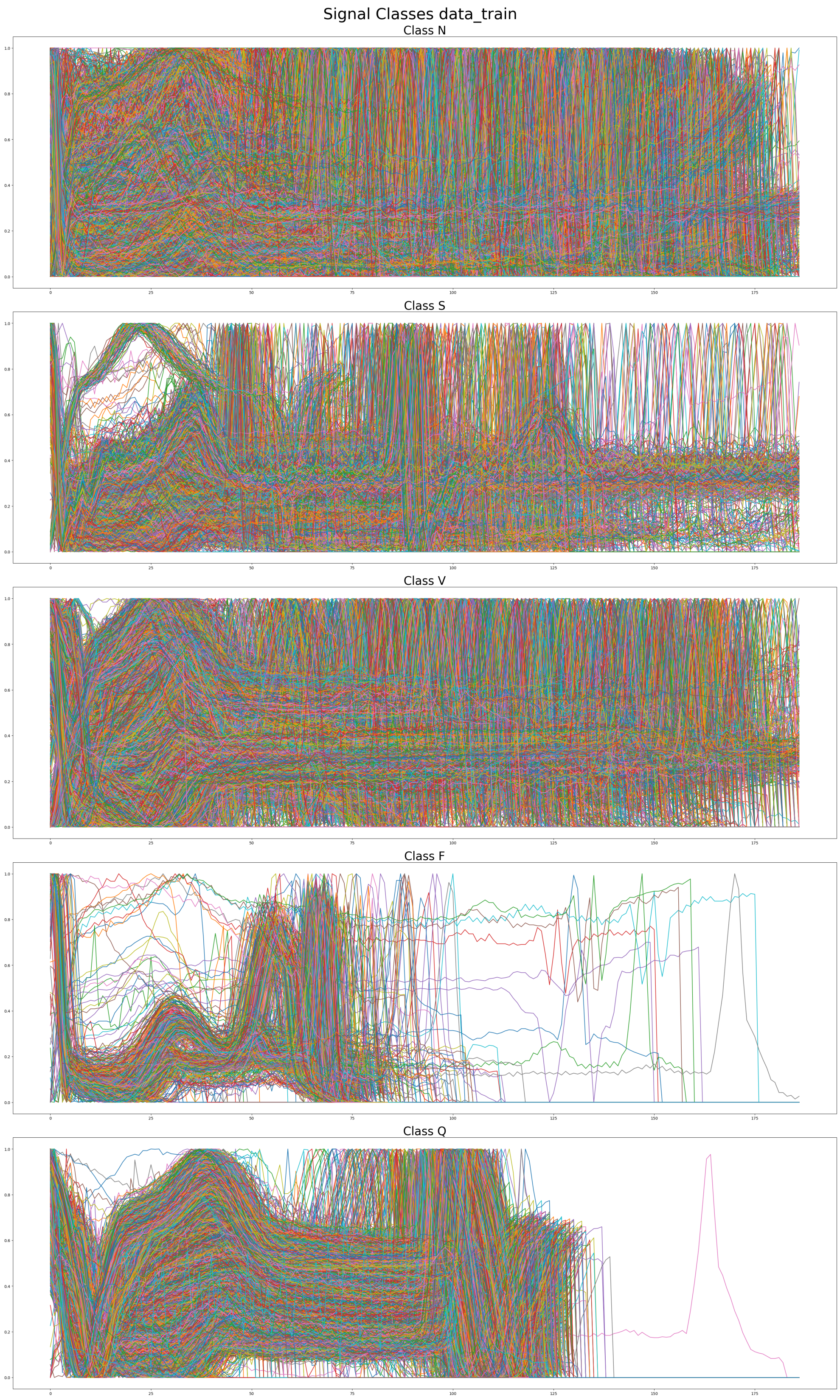

Figure 3.1: Sample ECG signal from the MIT-BIH Arrhythmia Dataset of all classes in train dataset

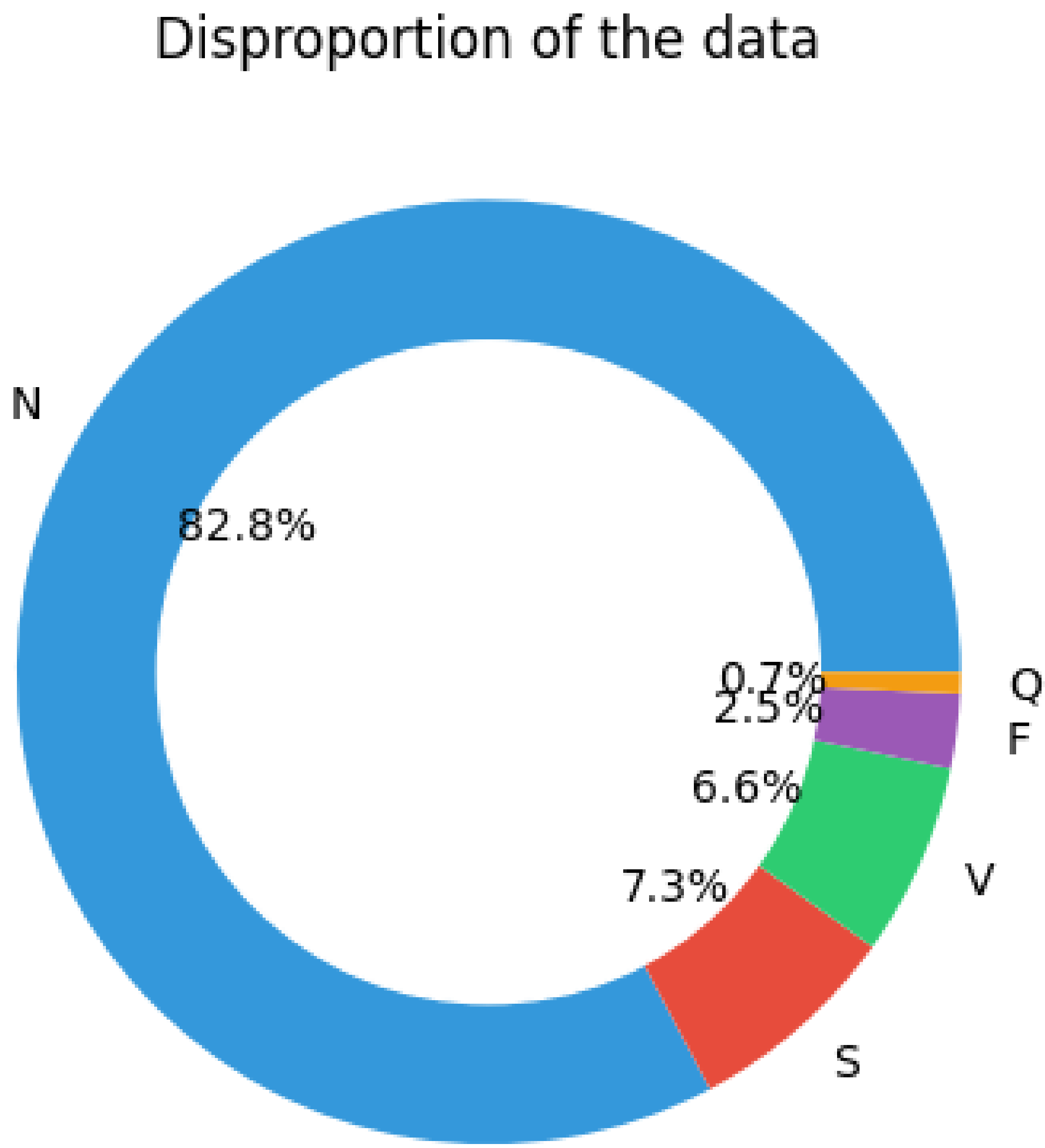

Figure 3.2: ECG class percentage in train dataset

The dataset is imbalanced, with most samples belonging to the 'N' class (normal heartbeats), which may bias the classification algorithm toward the majority class and hinder learning of minority class features. However, despite the lower quantity of 'F' and 'Q' class signals, their distinct shapes could lead to better classification performance.

3.2 Data processing

Due to the imbalance in the dataset, with the 'N' class (normal heartbeats) having significantly more samples, I applied under-sampling to balance the dataset. This process involves randomly selecting a subset of 'N' class signals, reducing their number to match the average number of signals in the other classes. Under-sampling helps prevent the model from becoming biased toward the majority class ('N') and ensures it can effectively learn the features of the minority classes.

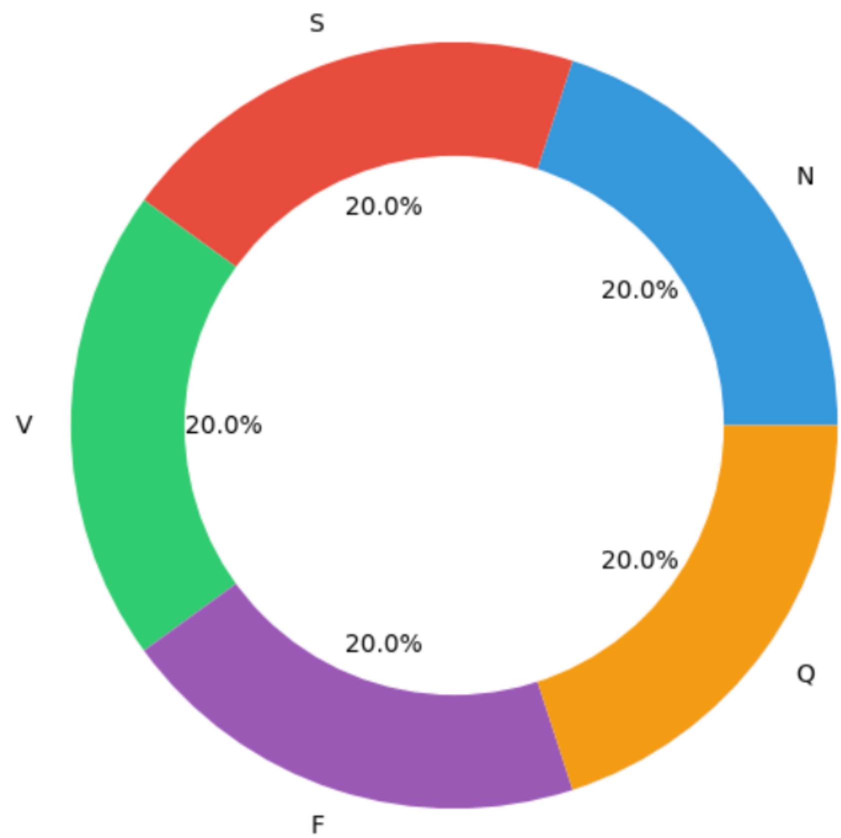

Figure 3.3: Dataset after Resampling

4. Method

4.1 Introduction to the Method

In this study, I use a **Convolutional Neural Network (CNN)** for ECG heartbeat classification, as CNNs automatically extract important features from raw ECG signals. The architecture includes convolutional, pooling, and fully connected layers for effective pattern recognition. Also CNNs are ideal for handling sequential data like ECG signals, automatically learning relevant features.

- **Convolutional Layers**:
  - 128 filters with a kernel size of 11
  - 64 filters with a kernel size of 3
  - ReLU activation
- **Pooling Layers**:
  - Max pooling with a pool size of 3 and strides of 2
- **Fully Connected Layers**:
  - 64 and 32 units in dense layers
- **Output Layer**:
  - Softmax activation with 5 units (classifies into 5 categories: N, S, V, F, Q)

5. Evaluation

To evaluate the performance of the model, I used the following metrics:

- **Accuracy**: The proportion of correctly classified samples to the total number of samples.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision**: The proportion of true positive samples to the total number of samples predicted as positive.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall**: The proportion of true positive samples to the total number of positive samples.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-score**: The harmonic mean of precision and recall, providing a balance between the two metrics.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- **Confusion matrix**: A table showing the number of true positive, true negative, false positive, and false negative samples for each class.
- **ROC curve**: A graphical representation of the true positive rate (sensitivity) versus the false positive rate (1-specificity) for different threshold values.
- **Precision-recall curve**: A graphical representation of precision versus recall for different threshold values.

Class	**Accuracy ↑**	**Precision ↑**	**Recall ↑**	**F1-score ↑**	**ROC AUC ↑**
N	**0.99**	0.98	0.99	0.99	0.99
S	**0.68**	0.84	0.75	0.85	0.97
V	**0.94**	0.96	0.95	0.98	1.00
F	**0.70**	0.84	0.76	0.84	0.99
Q	**0.99**	0.99	0.99	0.99	1.00

Table 5.1: Model performance metrics

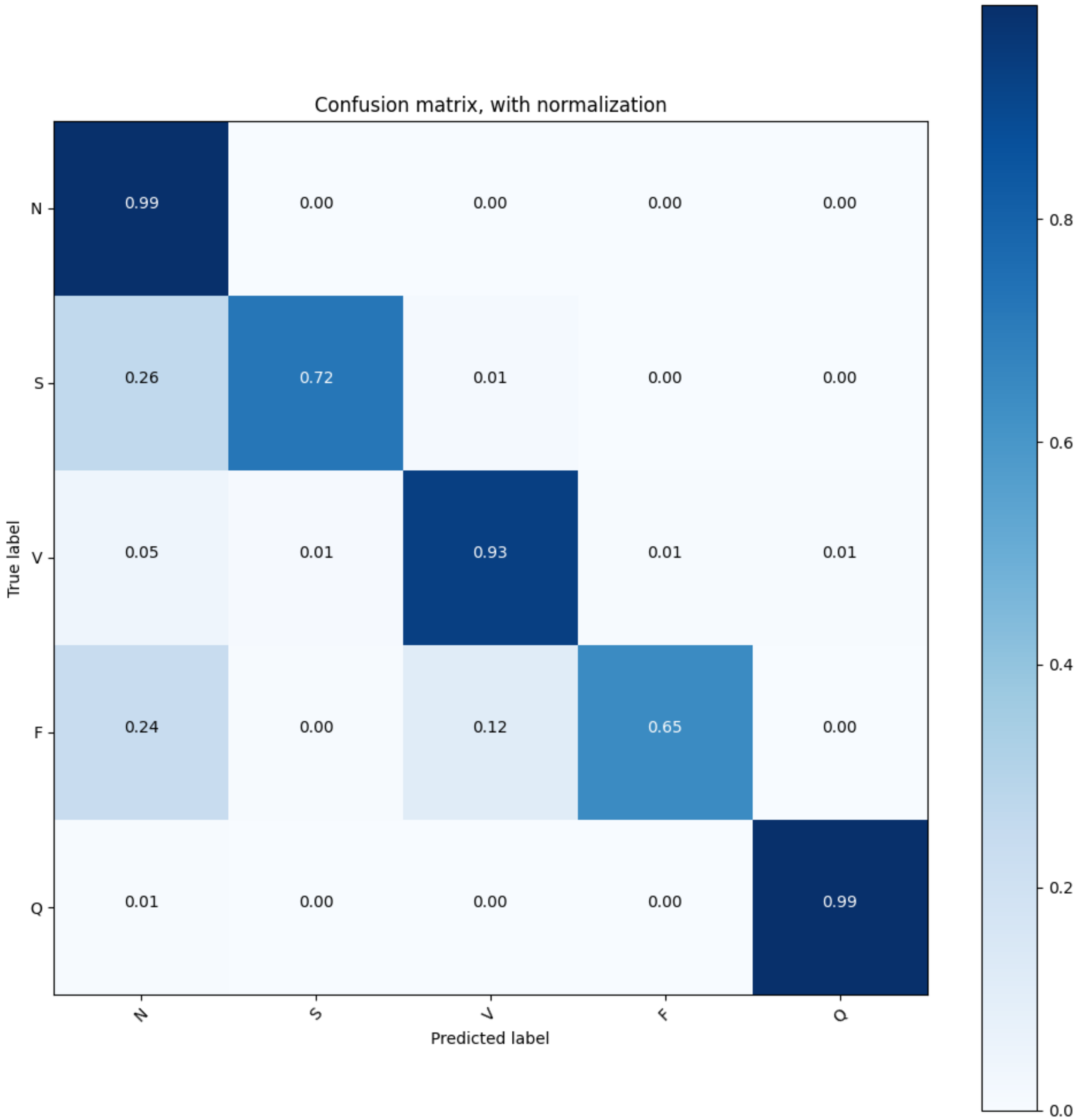

Figure 5.1: Confusion matrix

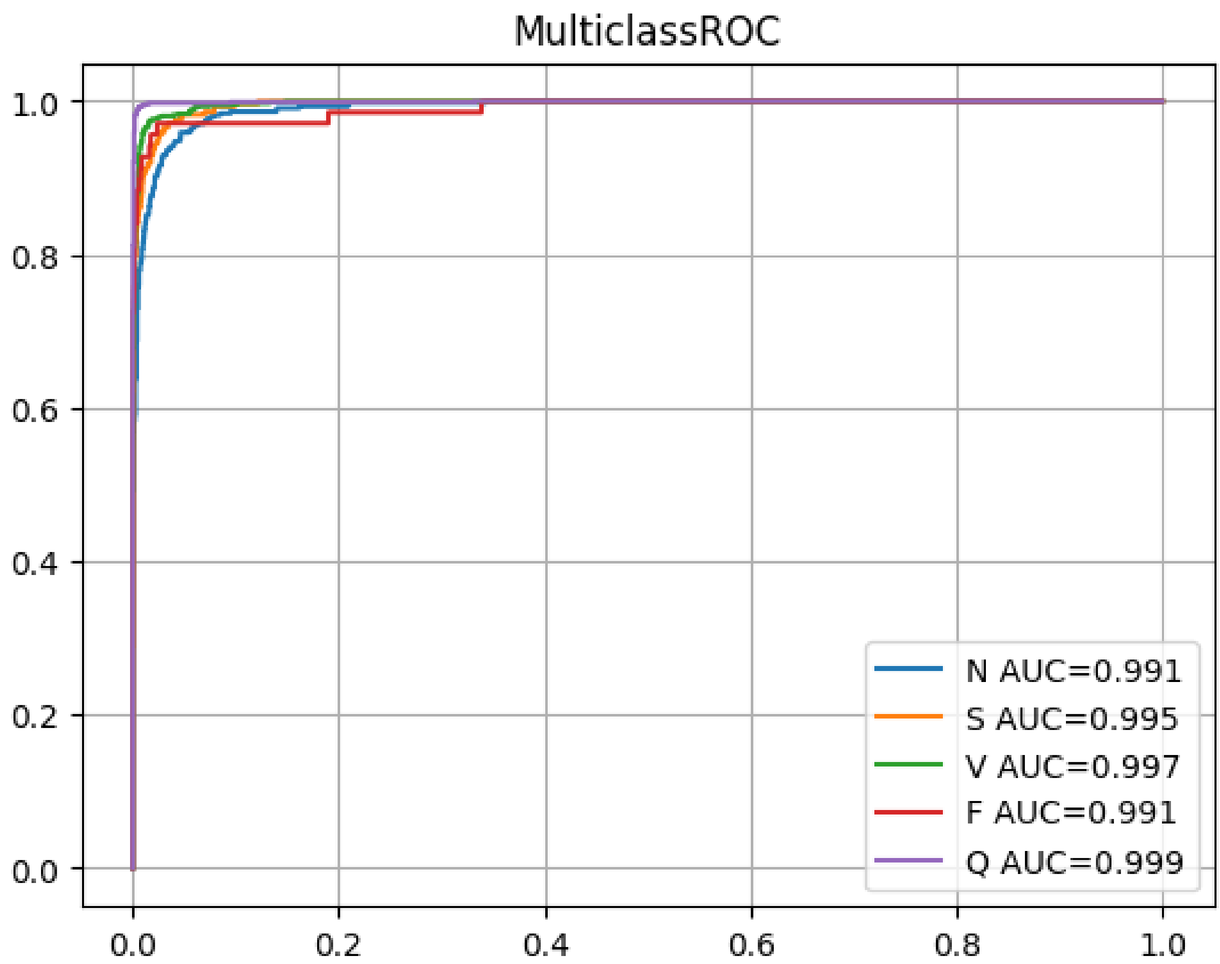

Figure 5.2: ROC curve

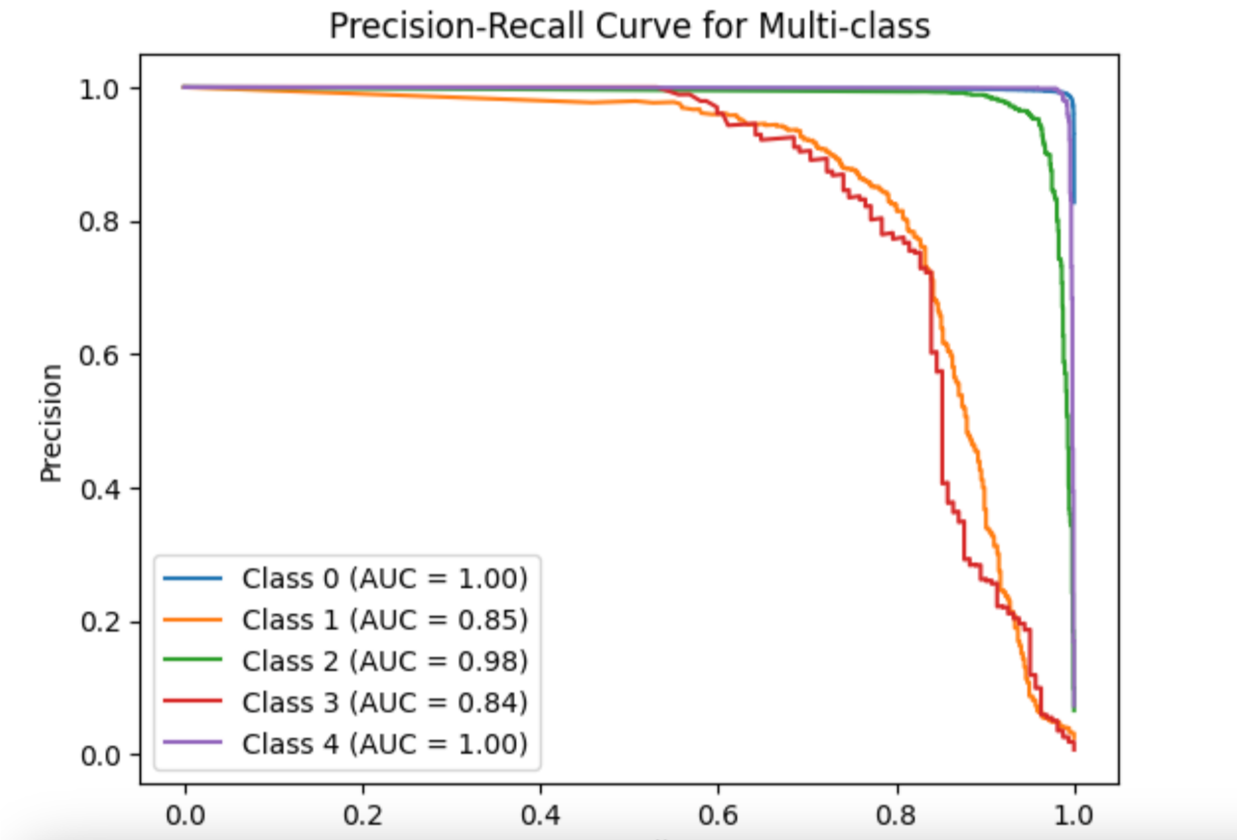

Figure 5.3: Precision-recall curve

6. Discussion

- **High Accuracy**: The model achieved high accuracy, especially for the minority classes ('F' and 'Q'). This is because the ECG signals for these classes have clear and distinct patterns, making it easier for the model to recognize them.

- **Class Imbalance Issue**: The dataset is imbalanced, with most samples belonging to the 'N' class (normal heartbeats). This could have made the model biased towards predicting 'N'. To address this, we used under-sampling to balance the classes, but this reduced the number of 'N' samples, potentially causing the model to miss some important details from normal heartbeats.

- **Simple Preprocessing**: The preprocessing steps were simple, such as normalizing and extracting R-peaks from the ECG signals. This worked well for the dataset because the signals were relatively clean and had clear patterns. However, in real-world data, ECG signals often have noise and more variation, which might affect the model's performance.

- **Distinct Signal Patterns**: Classes like 'Q' had high performance because their ECG signals have unique and recognizable shapes, which made them easier to classify. Other classes, like 'S' and 'V', might need more fine-tuning or more data to improve accuracy.

- **Future work**: - Test the model on more diverse and real-world ECG data to see how well it generalizes.

- Experiment with other techniques like over-sampling or more complex preprocessing methods to handle noisy signals and data imbalance better.

7. Conclusion

This study presents a deep learning-based ECG heartbeat classification approach using a Convolutional Neural Network (CNN). The model demonstrated high accuracy, precision, recall, and F1-score for all classes, along with strong performance in the ROC and precision-recall curves, showcasing its ability to distinguish between classes and balance precision and recall. These results suggest CNNs are effective for ECG classification, with future work focused on optimizing the model and exploring other deep learning techniques.

8. References

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