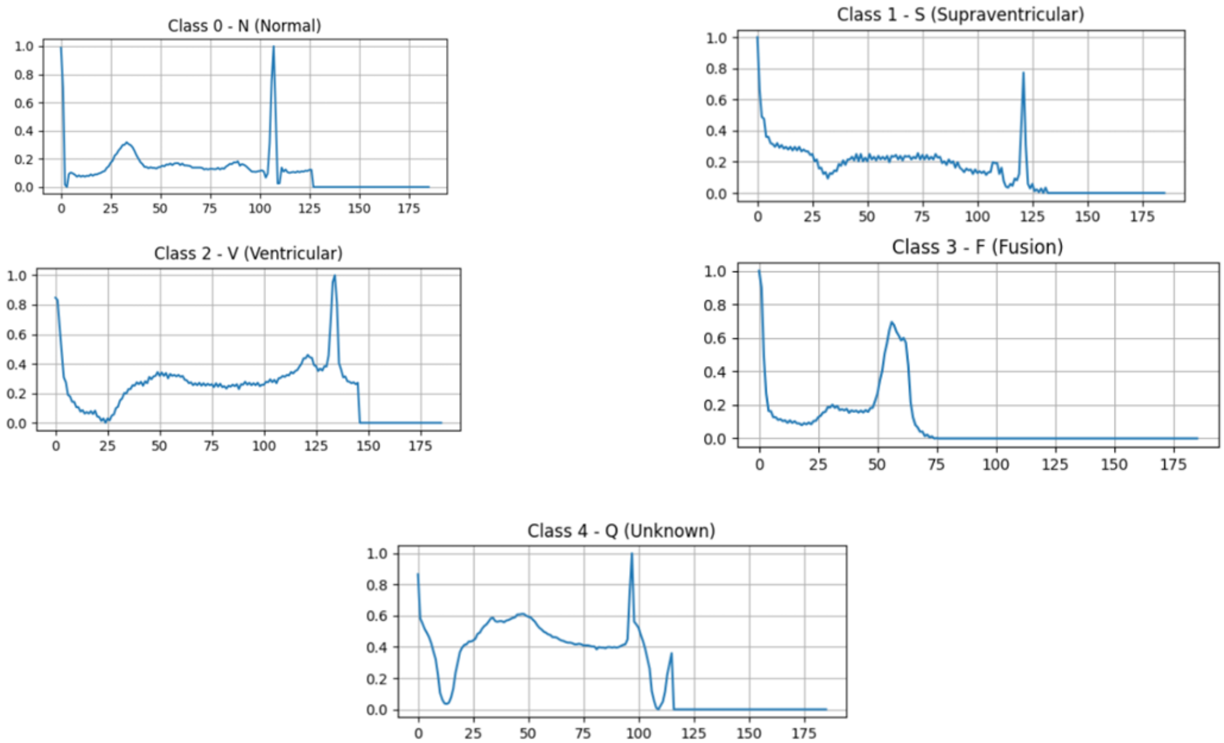
Arrhythmia on ECG Classification

By Mahshad Mohit

Electrocardiogram (ECG) signals, which represent the electrical activity of the heart, are stored in these files such that each row corresponds to a single extracted heartbeat. The upward and downward fluctuations of the signal indicate the contraction and relaxation of the heart chambers.

In cases of arrhythmia, the shape of these waveforms changes; for example, the distance between peaks or the width of the waves may vary. These variations must be learned by the model.

This function is designed to illustrate the differences among the various classes. There are five classes in total, including normal, supraventricular, ventricular, fusion, and unknown, representing four types of arrhythmia and one normal class.



To make the right decision, we first need to examine the distribution of samples across the classes:

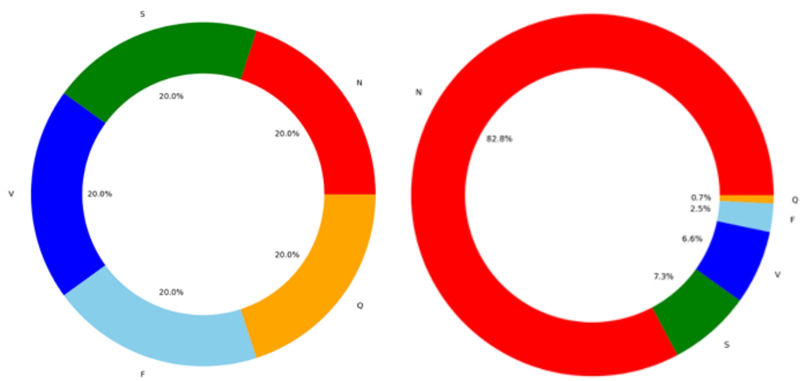
As can be seen, there is a severe imbalance, which causes the model to learn only the majority class.

187	
0	72471
4	6431
2	5788
1	2223
3	641

Before paying attention to this issue, I trained the model and reached 99% accuracy, which indicated a strong bias toward the majority class. To better understand this issue, a chart of each class was created (Figure 1).

To address this imbalance, we use the Upsampling method, increasing the size of the training data from around 70,000 samples to 290,000 samples.

Also, before feeding this data into the model, it must be converted from 2D to 3D so that it can be understood by the convolutional layers. Additionally, some categorical labels need to be converted into vectors using One-Hot Encoding.



The final distribution of the data, which has been balanced fairly, is shown in (Figure 2).

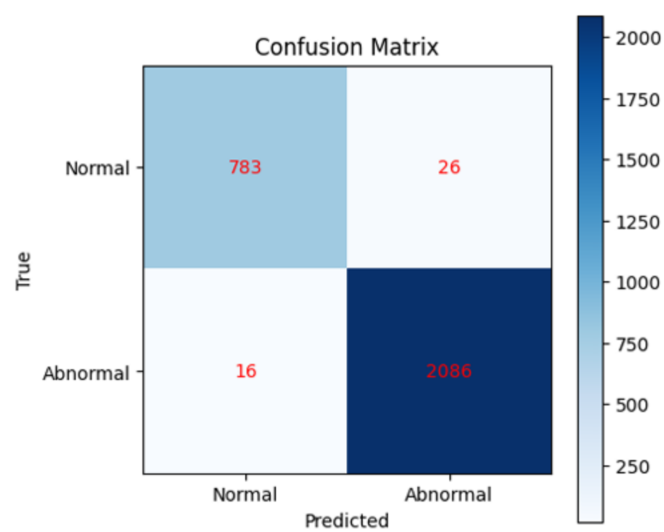
Finally, we use a simple one-dimensional CNN model. Only two important techniques were applied: first, we used EarlyStopping so that if the validation data error does not improve, training stops to prevent overfitting. Then, we used ModelCheckpoint to save the best version of the model based on the lowest validation error.

In the end, the results show that the model achieved 97.94% accuracy, and the classification report indicates that the accuracy for classes N and Q is very high. The model performed very well in detecting most classes, although the Fusion class partially overlapped with other classes (Figure 3).

Of course, I examined this issue scientifically because this signal is a combination of two types of heartbeats and visually resembles the other classes closely.

Finally, to validate the model, we show a few sample results to demonstrate whether the model performed correctly or not.

The model was trained for 20 epochs and, based on the final results, achieved an accuracy of 98.55%. Additionally, only a very small number of abnormal samples were misclassified as normal, which is critical in medical applications.



Normal vs Abnormal Predictions

To analyze model behavior, accuracy and error plots were drawn for both the training and validation sets. As the number of epochs increased, accuracy improved and error decreased. The closeness of the validation and training curves indicates that the model generalized well and did not suffer from overfitting.