ECG Heartbeat Categorization Using a CNN–LSTM Model

I. Introduction

Electrocardiogram (ECG) signals are widely used to monitor cardiac activity and to detect various heart abnormalities. In recent years, ECG heartbeat classification using deep learning techniques has attracted significant attention due to their ability to automatically learn informative features directly from raw signals.

In this project, we propose a deep learning architecture that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) layers to classify ECG heartbeats into multiple arrhythmia categories. CNN layers are employed to extract local morphological features from ECG waveforms, while LSTM layers are used to capture long-term temporal dependencies within the signal.

The objective of this work is to design, train, and evaluate a CNN–LSTM model for multi-class ECG heartbeat classification and to analyze its performance on an imbalanced dataset.

II. Dataset and Preprocessing

This project utilizes a preprocessed ECG heartbeat dataset obtained from Kaggle [**?**]. The dataset is organized in a tabular format, where each row corresponds to a single heartbeat sample and each column represents a signal amplitude value. Each heartbeat consists of 187 time steps.

The target labels are divided into five classes:

- Normal (N): Normal sinus rhythm
- Atrial Premature Beat (APB): Early atrial depolarization
- Premature Ventricular Contraction (PVC): Abnormal early ventricular contraction
- Fusion of Ventricular and Normal Beat (FVN): Fusion between normal and ventricular beats
- Fusion of Paced and Normal Beat (FPN): Fusion between paced and normal beats

The original categorical labels were converted into integer values and subsequently transformed using one-hot encoding, which is required for multi-class classification tasks. The dataset was then split into training, validation, and testing subsets. The training set was further divided to obtain a validation set for hyperparameter tuning.

Figure 1 illustrates the original class distribution. The dataset exhibits a significant class imbalance, with the Normal class dominating the dataset (72,471 samples) compared to the minority classes (2,223, 5,788, 641, and 6,431 samples, respectively). Moreover, certain arrhythmia classes share similar waveform morphologies, increasing the difficulty of accurate classification.

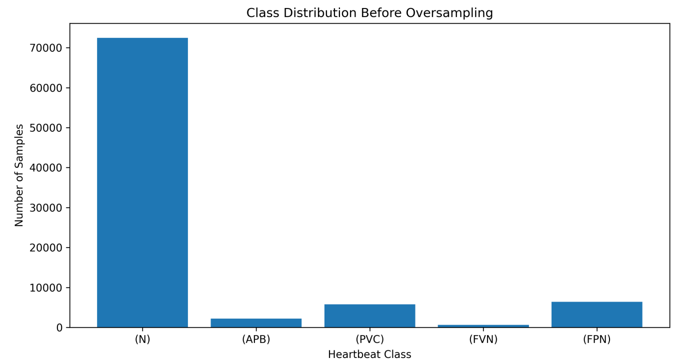

Fig. 1. Class distribution before oversampling

To address this issue, random oversampling was applied to the minority classes in the training set. After oversampling, the class distribution becomes more balanced, as shown in Figure 2. This preprocessing step helps mitigate the impact of class imbalance and improves the model's ability to learn representative features for all classes.

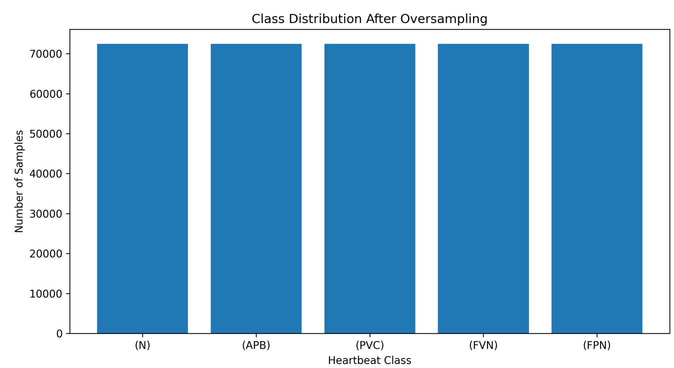

Fig. 2. Class distribution after oversampling

III. Model Architecture

The proposed model is a hybrid CNN–LSTM architecture designed for one-dimensional ECG signal classification. The input to the model is a one-dimensional ECG signal with a fixed length of 187 time steps and a single channel.

Multiple Conv1D layers are employed to automatically extract local morphological features from the ECG waveforms. Each convolutional layer is followed by batch normalization and a MaxPooling1D layer. This combination stabilizes the training process, reduces overfitting, and lowers computational complexity.

The extracted feature sequences are then passed to an LSTM layer, which is capable of modeling long-term temporal dependencies in sequential data. This allows the model to learn relationships between different components of the ECG waveform over time.

Finally, the output of the LSTM layer is fed into fully connected layers. The output layer consists of five neurons corresponding to the five heartbeat classes, with a softmax activation function to produce class probability distributions.

IV. Experimental Results

To evaluate the performance of the proposed model, several standard classification metrics were employed, including accuracy, precision, recall, and F1-score. In addition, a confusion matrix was used to visualize the classification results across different classes.

Figure 3 presents the confusion matrix obtained on the test set.

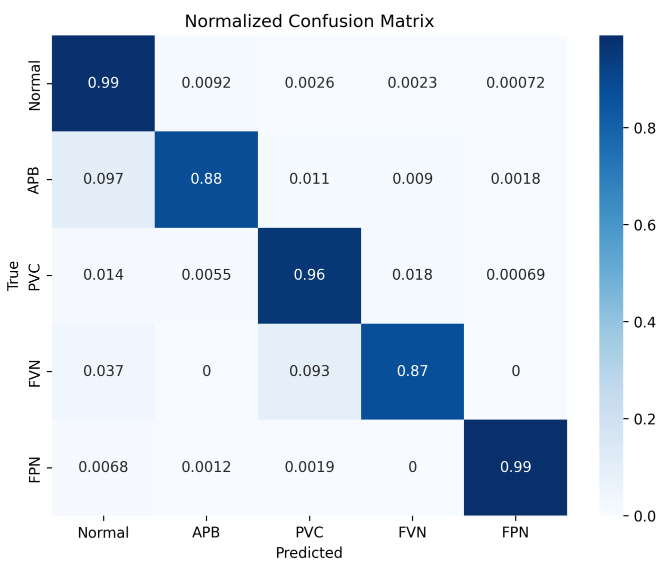

Fig. 3. Confusion matrix of the CNN–LSTM model

The experimental results indicate that the model achieves high precision and recall for the majority class, while the minority classes also obtain competitive F1-scores. These results demonstrate that the oversampling strategy effectively reduces the impact of class imbalance and enables the model to learn meaningful representations for underrepresented heartbeat types.