Practical 1 Report

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I. Introduction

Electrocardiogram (ECG) signals record the electrical activity of the heart and are widely used to detect heart rhythm problems. Automatic ECG classification can help doctors by reducing manual workload and improving diagnosis speed. In this project, a deep learning model based on Convolutional Neural Network (CNN) was trained to classify ECG heartbeats into different categories using a public dataset from Kaggle.

II. Dataset Description

The dataset used in this project is the MIT-BIH Arrhythmia Dataset, available on Kaggle under the name Heartbeat. It contains ECG heartbeat signals that were extracted from long ECG recordings.

The dataset is divided into two files:

- mitbih$_train.csv$
- mitbih$_test.csv$

Each row in the dataset represents one ECG heartbeat. The first 187 columns are numerical values that describe the ECG signal shape over time. These values are sampled from the original ECG signal and represent amplitude changes. The last column (column 187) is the class label.

There are 5 heartbeat classes:

- Class 0: N
- Class 1: S
- Class 2: V
- Class 3: F
- Class 4: Q

The dataset is imbalanced by default: normal beats appear much more often than abnormal beats. To solve this problem, oversampling was applied to the minority classes so that each class contains the same number of samples. This helps the model learn all classes equally.

III. Data Preprocessing

Before training the model, several preprocessing steps were applied. First, the dataset was balanced using random resampling so that each class had 20,000 samples. Next, the ECG signal values were normalized using StandardScaler. This step ensures that each feature has zero mean and unit variance, which helps the neural network train more effectively.

The input data was then reshaped to match the CNN input format, where each ECG signal is treated as a one-dimensional sequence with one channel.

IV. Model Architecture

The model used in this project is a one-dimensional Convolutional Neural Network (CNN). CNNs are well suited for ECG signals because they can learn local patterns such as peaks and waves.

The model architecture consists of:

- An input layer with shape (187, 1)
- Three Conv1D layers with ReLU activation
- MaxPooling layers after each convolution to reduce dimensionality
- A Flatten layer to convert feature maps into a vector
- Two fully connected (Dense) layers
- An output layer with 5 neurons (one for each class)

A. *CNN Architecture Summary*

Table I summarizes the architecture of the proposed CNN model, including output shapes and number of parameters for each layer.

TABLE I
CNN Model Architecture

Layer	**Output Shape**	**Parameters**
Conv1D (128 filters, kernel=11)	(187, 128)	1,536
MaxPooling1D	(94, 128)	0
Conv1D (64 filters, kernel=3)	(94, 64)	24,640
MaxPooling1D	(47, 64)	0
Conv1D (64 filters, kernel=3)	(47, 64)	12,352
MaxPooling1D	(24, 64)	0
Flatten	(1536)	0
Dense (64 units)	(64)	98,368
Dense (32 units)	(32)	2,080
Dense (Output)	(10)	330
Total Parameters		**139,306**

The model uses the Nadam optimizer with a learning rate of 0.001. The loss function is Sparse Categorical Crossentropy, which is suitable for multi-class classification with integer labels.

V. Training Process

The model was trained for 16 epochs with a batch size of 32. During training, the model learned to minimize the classification loss by adjusting its weights. The training was performed using the balanced dataset to avoid bias toward the majority class.

After training, the model was evaluated on both the training set and the test set to measure its performance and generalization ability.

VI. Evaluation Metrics

The model performance was evaluated using accuracy, confusion matrices, and classification metrics including precision, recall, and F1-score.

A. Confusion Matrix

Figures 1 and 2 show the confusion matrices for the test set and training set, respectively. The matrices visualize the number of correct and incorrect predictions for each heartbeat class.

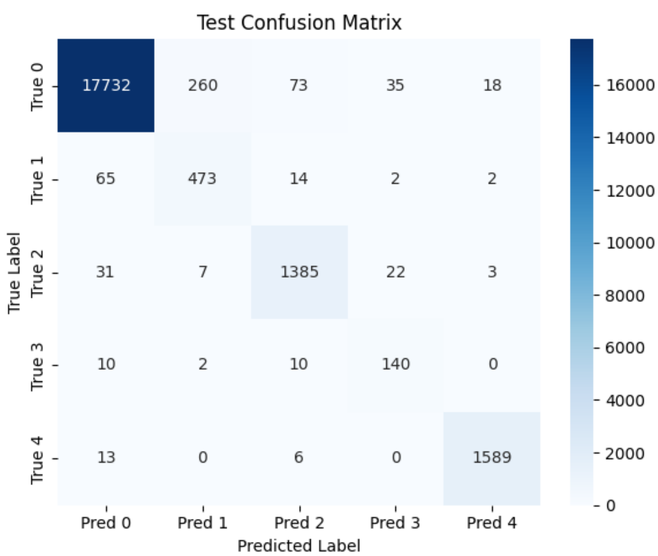

Fig. 1. Confusion Matrix on Test Set

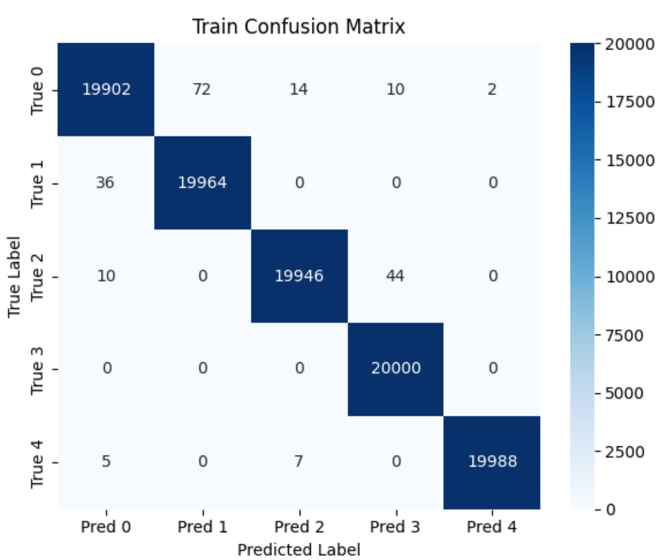

Fig. 2. Confusion Matrix on Training Set

B. Classification Report

Table II presents the classification performance on the test dataset. The model achieves high overall accuracy, with strong performance on the normal heartbeat class and good recall for abnormal classes.

TABLE II
Test Classification Report

Class	**Precision**	**Recall**	**F1-score**	**Support**
Class 0 (N)	0.9933	0.9787	0.9860	18,118
Class 1 (S)	0.6375	0.8507	0.7288	556
Class 2 (V)	0.9308	0.9565	0.9435	1,448
Class 3 (F)	0.7035	0.8642	0.7756	162
Class 4 (Q)	0.9857	0.9882	0.9870	1,608
Accuracy		0.9738		
Macro Avg	0.8502	0.9277	0.8842	21,892
Weighted Avg	0.9775	0.9738	0.9751	21,892

The confusion matrix shows that the model performs well on the normal heartbeat class and reasonably well on abnormal classes. Some confusion exists between similar abnormal beat types, which is expected due to their similar ECG patterns.

VII. Results and Discussion

The trained CNN achieved high accuracy on both the training and test sets, showing that it learned meaningful ECG features. The balanced dataset helped improve classification of minority classes. The classification report shows strong precision and recall for most classes, although some rare classes remain challenging.

VIII. Conclusion

In this project, a CNN-based model was successfully implemented to classify ECG heartbeats. The use of data balancing, normalization, and a carefully designed CNN architecture resulted a decent classification performance. Future work could include using deeper networks and more advanced techniques to further improve results.