ECG Heartbeat Classification Using 1D Convolutional Neural Networks

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***Abstract*—Electrocardiogram (ECG) signal classification is a fundamental task in automated cardiac disease diagnosis. This report presents a deep learning approach based on a one-dimensional Convolutional Neural Network (1D-CNN) for heartbeat classification using the MIT-BIH Arrhythmia dataset. The proposed model employs convolutional layers, batch normalization, global average pooling, and adaptive learning rate scheduling to achieve high classification accuracy with a relatively small number of parameters. Experimental results demonstrate that the model achieves a validation accuracy of 97.67%.**

***Index Terms*—ECG Classification, Convolutional Neural Network, Deep Learning, MIT-BIH Dataset, TensorFlow**

I. Introduction

Cardiovascular diseases are among the leading causes of mortality worldwide. Electrocardiogram (ECG) signals provide critical information about the electrical activity of the heart and are widely used for diagnosing cardiac arrhythmias.

Traditional machine learning approaches often rely on handcrafted features and domain expertise, which may limit their generalization capability. Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), enable automatic feature extraction directly from raw signals and have shown superior performance in ECG classification tasks.

This report presents the design, implementation, and evaluation of a 1D-CNN model for ECG heartbeat classification using the MIT-BIH Arrhythmia dataset.

II. Dataset Description

The experiments are conducted on the MIT-BIH Arrhythmia dataset, obtained from PhysioNet. The dataset contains segmented ECG heartbeat signals, where each sample consists of 187 signal values followed by a class label.

The dataset is divided into two subsets:

- Training set: `mitbih_train.csv`
- Testing set: `mitbih_test.csv`

A total of five heartbeat classes are considered in this study.

III. Data Preprocessing

Several preprocessing steps are applied before training the model.

A. Normalization

All ECG samples are normalized using the StandardScaler to ensure zero mean and unit variance:

$$X' = \frac{X - \mu}{\sigma}$$

B. Reshaping

The normalized data is reshaped into a three-dimensional format compatible with Conv1D layers:

$$(N, 187, 1)$$

where N denotes the number of samples.

C. Class Imbalance Handling

The MIT-BIH dataset exhibits class imbalance. To mitigate this issue, class weights are computed using a balanced strategy and incorporated into the loss function during training, ensuring fair contribution from minority classes.

IV. Model Architecture

The proposed model is a one-dimensional Convolutional Neural Network consisting of three convolutional blocks, followed by global average pooling and fully connected layers.

Each convolutional block includes:

- A Conv1D layer with ReLU activation
- Batch Normalization to stabilize training
- Max Pooling for temporal downsampling

Global Average Pooling significantly reduces the number of parameters and improves generalization performance. A Dropout layer is applied before the final classification layer to reduce overfitting.

A. Detailed Model Summary

Table I presents the detailed architecture of the proposed 1D-CNN model.

V. Training Strategy

The model is trained using the Adam optimizer with an initial learning rate of 10^{-3}. Sparse Categorical Crossentropy is used as the loss function, and accuracy is employed as the evaluation metric.

Training is conducted for 30 epochs with a batch size of 64. A ReduceLROnPlateau callback is applied to dynamically adjust the learning rate when validation performance stagnates.

VI. Experimental Results

A. Training Accuracy

Fig. 1 illustrates the training and validation accuracy over 30 epochs. The model converges rapidly and maintains stable performance after learning rate adjustments.

TABLE I
DETAILED CNN MODEL ARCHITECTURE

Layer	Output Shape	Parameters
Conv1D (64 filters, kernel size 5)	(None, 187, 64)	384
Batch Normalization	(None, 187, 64)	256
MaxPooling1D	(None, 93, 64)	0
Conv1D (128 filters, kernel size 5)	(None, 93, 128)	41,088
Batch Normalization	(None, 93, 128)	512
MaxPooling1D	(None, 46, 128)	0
Conv1D (256 filters, kernel size 3)	(None, 46, 256)	98,560
Batch Normalization	(None, 46, 256)	1,024
Global Average Pooling	(None, 256)	0
Dense (128 neurons)	(None, 128)	32,896
Dropout (0.3)	(None, 128)	0
Dense (5 classes)	(None, 5)	645
Total Parameters		**175,365**

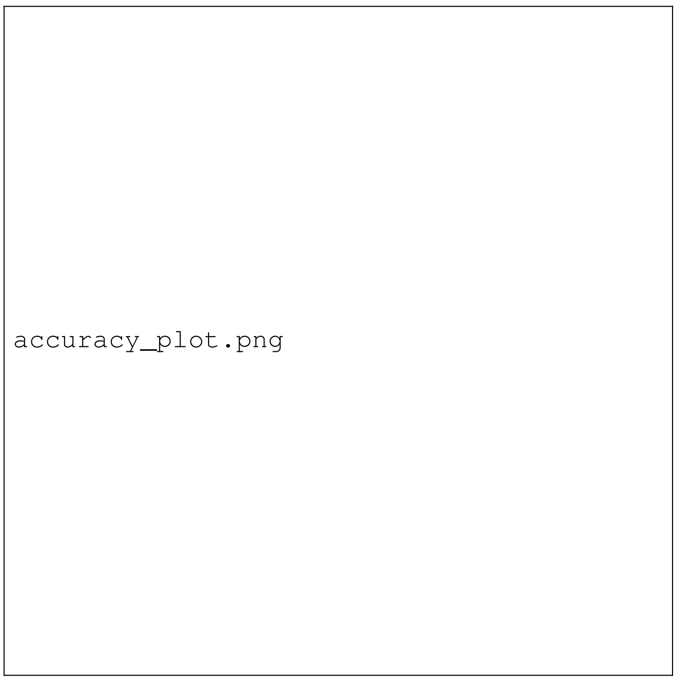

Fig. 1. Training and Validation Accuracy over Epochs

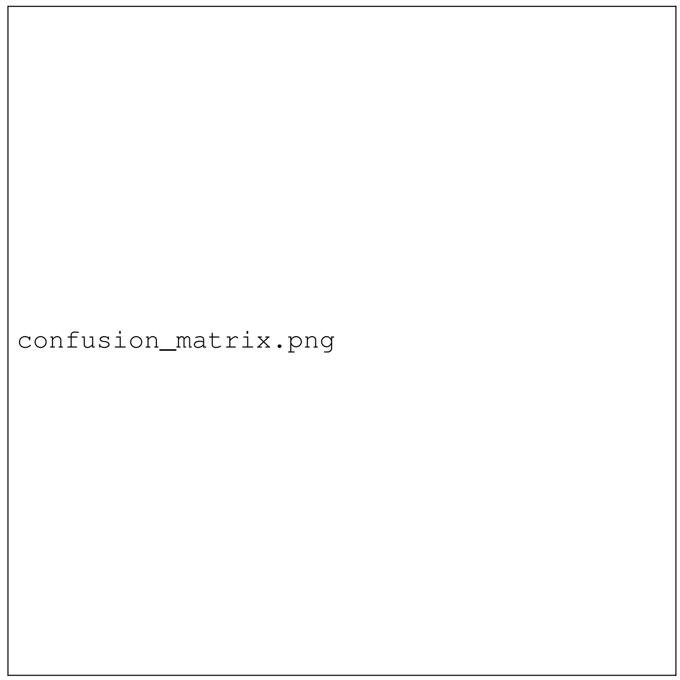

Fig. 2. Confusion Matrix on Test Dataset

B. Confusion Matrix Analysis

Fig. 2 presents the confusion matrix on the test dataset. Most heartbeat classes are classified correctly, with minimal confusion between categories.

C. Classification Performance

The proposed model achieves a training accuracy of 98.23% and a validation accuracy of 97.67%. High precision and recall across all five classes indicate strong discriminative capability and robustness of the learned features.

VII. CONCLUSION AND FUTURE WORK

This study demonstrates the effectiveness of a 1D-CNN architecture for ECG heartbeat classification using the MIT-BIH Arrhythmia dataset. The combination of convolutional feature extraction, batch normalization, and adaptive learning rate scheduling enables high accuracy and stable convergence.

Future work will focus on extending the model with residual connections, exploring attention mechanisms, and evaluating performance using additional metrics such as sensitivity and specificity for clinical relevance.

REFERENCES

[1] MIT-BIH Arrhythmia Database, PhysioNet.

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