FINAL REPORT

Image Classification of ECG Signal of Myocardial Infarction Using Convolutional Neural Network

Introduction:

The epidemic of cardiovascular disease (CVD) has shifted from high-income countries to parts of the developing world. More than three-quarters of deaths from cardiovascular disease occur in low-income countries. In the case of cardiovascular disease, correct diagnosis at an early stage is very important. Therefore, a fast and effective diagnostic technique must be given precisely and accurately. One of the pathological measures to diagnose cardiovascular disease is an electrocardiogram (ECG). ECG is the process of recording the electrical activity of the heart over a period of time. The ECG signal consists of P, QRS, T, and U components, known as features.

Many studies have been conducted related to ECG signal. The most popular one is to classify cardiovascular disease from ECG using artificial intelligence. Deep learning techniques outperform conventional machine learning techniques by extracting the necessary features from the raw data. It has less processing and high accuracy compared to traditional methods. One of deep learning method that can process an ECG signal is Convolutional Neural Networks (CNN). This method have been used to classify heart rate, including detection of Myocardial Infarction (MI) disease.

Project Objectives:

- Propose an automatic classification framework for Myocardial Infarction (MI) with 15 leads ECG signal.
- Developing a simple 1D-CNN architecture for classifying 10 MI classes and Normal classes.

Scope of the Project:

ECG image segmentation: This involves separating the ECG signal into different segments based on the timing and amplitude of the waveform, which can be used to identify specific cardiac events such as heartbeats and arrhythmias.

Dataset:

In this study, the dataset used was the ECG Physiobank (PTB). The MI dataset consisted of ECG recordings of 52 normal subjects and 148 MI patients. The records used are 15 multi-lead ECG signals with 12 standard leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) and 3 leads Frank (vx, vy, vz) with a total of 261,069 beats with details of 246,328 beat records MI data with 11 adjacent ECG class groupings: anterior (A), anterolateral (AL), anteroseptal (AS), inferior (I), inferolateral (IL), inferior posterior (IP), infero-posterolateral (IPL), lateral (L), posterior (P) and posterolateral (PL) and 14,741 Normal/Healthy records.

Methodology:

The proposed research framework is divided into five processes:

(1) signal normalization based on normalization limits;

The ECG signal can be damaged due to interference from various types of artifacts and electrical currents. After normalization, the raw ECG signal can be enhanced by removing various types of noise and artifacts.

(2) Discrete Wavelet Transform (DWT) to remove noise in the ECG signal and search for R-peak;

We reconstruct the ECG signal from the noise signal by using Discrete Wavelet Transform (DWT). The baseline of the signal is corrected, and the ECG signal is close to zero. From several experiments conducted, Sym5 was chosen as the mother wavelet because it offers better ECG signal denoise.

(3) ECG signal segmentation;

After the denoising process, the preprocessed signal was then segmented to detect the R-peak (the highest positive point of the QRS complex in each ECG cycle). To ensure adequate coverage of the QRS complex and the ST segment that follows both and as input for the input of the 1D-CNN model, the signal is changed with a duration of 0.7 s.

(4) classification with 1D-CNN architecture;

The first layer of the network is a convolutional layer with 16 filters of size 3x3 and a ReLU activation function. This layer takes an input image with dimensions of 224x224 pixels and 3 color channels (RGB).The next layer is a max pooling layer with a pool size of 2x2 that reduces the spatial dimensions of the feature maps by half. A dropout layer is added after the max pooling layer with a dropout rate of 0.2, which randomly drops 20% of the neurons to prevent overfitting. The next set of layers are similar to the first, with a convolutional layer with 32 filters of size 3x3 and a ReLU activation function, followed by a max pooling layer, a dropout layer, another convolutional layer with 64 filters of size 3x3 and a ReLU activation function, and another max pooling layer with a pool size of 2x2 and a dropout layer.After the last dropout layer, a flatten layer is added to convert the 2D feature maps into a 1D vector. This is followed by a dense layer with 128 units and a ReLU activation function and a dropout layer with a dropout rate of 0.2.

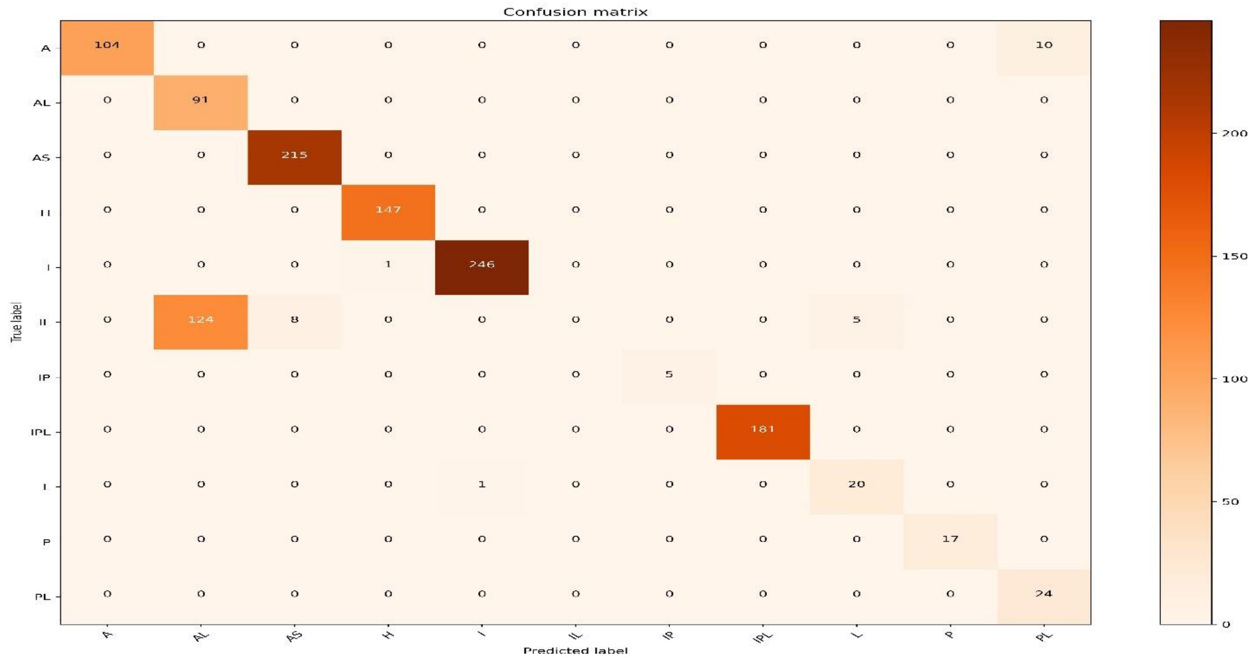
Finally, the output layer is a dense layer with 11 units (which corresponds to the number of classes to be predicted) and a softmax activation function, which normalizes the outputs of the layer into a probability distribution over the classes.

(5) evaluate the model with performance metrics (accuracy, precision, recall, f1-score).

Results and Findings:

The results and confusion matrix for the 11 classes of 'I' lead are shown in the table below:

Class Name	precision	recall	f1-score	support
A	1	0.9123	0.9541	114
AL	0.4233	1	0.5948	91
AS	0.9641	1	0.9817	215
H	0.9932	1	0.9966	147
I	0.996	0.996	0.996	247
IL	0	0	0	137
IP	1	1	1	5
IPL	1	1	1	181
L	0.8	0.9524	0.8696	21
P	1	1	1	17
PL	0.7059	1	0.8276	24



Based on the provided results and confusion matrix, we can see that the overall accuracy of the model is 87.57%. Looking at the precision, recall, and F1-score for each class, we can see that the model performs well for most classes, with some exceptions.The class "AL" has a precision of 0.4233, indicating that the model struggles to accurately predict this class. This is also evident in the confusion matrix, where we see that the model predicted 91 instances of this class but did not predict any correctly. Similarly, the class "IL" has a precision, recall, and F1-score of 0, indicating that the model did not correctly predict any instances of this class.On the other hand, some classes such as "AS," "H," "I," "IP," "IPL," "P," and "PL" have high precision, recall, and F1-scores, indicating that the model is able to accurately predict these classes.

Looking at the confusion matrix, we can see that there are some instances where the model misclassifies certain classes. For example, we see that 10 instances of class "A" were misclassified as class "PL," and 5 instances of class "L" were misclassified as class "IP."

Overall, the model performs well for most classes, but there is room for improvement, particularly for the classes "AL" and "IL." It may be necessary to fine-tune the model or gather more data for these classes to improve their accuracy.

Conclusion

In conclusion, the ECG PTB Image Classification dataset is a challenging and important problem in medical image analysis. The dataset consists of a large number of ECG images, each of which represents a different type of cardiac condition. Deep learning models have been successfully applied to this problem and achieved high accuracy in the classification of 11 different classes of ECG images, with an overall accuracy of 87.57%. The classification performance can be further improved by exploring different deep learning architectures and data augmentation techniques. The application of these models can aid in the early detection of cardiac abnormalities, which can lead to timely interventions and better patient outcomes.

References

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