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DIGITAL SIGNAL PROCESSING

Improving and Classification ECG Signal Using CNN by Comparison Signal Processing Techniques

Zohra Bshara Blal [1], Rasim Amer Ali [1,*], Salam Neamah Yasser [2]

[1] Electrical and Electronic Engineering Department, Wadi Alshatti University, Brack-Libya
[2] Electrical and Computer Engineering Department, University of Altinbas, Istabul-Turkey

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ABSTRACT

Detecting health issues is critical for saving patients' lives, especially when they are far from medical professionals, highlighting the importance of building highly accurate classification models. In this paper, a Convolutional Neural Network (CNN) model was designed and tested for analyzing and classifying electrocardiogram (ECG) signals. The main objective of this paper is to classify five types of heartbeats using a CNN model trained on the MIT-BIH Arrhythmia Database. Preprocessing techniques such as Butterworth band-pass filtering and Discrete Wavelet Transform (DWT) were applied to enhance the signals. The comparison between the two methods showed that the wavelet transform was more effective in denoising and preserving the essential signal components. A classification accuracy of 89.82%, recall of 69.61%, and an F1 score of 77.66% were achieved using wavelet-transformed pre-processed data, compared to an accuracy of 83.30% for the band-pass filtered data.

تحسين وتصنيف إشارة تخطيط القلب باستخدام CNN عن طريق مقارنة تقنيات معالجة الإشارات

الزهراء بشارة بلال [1]، راسم عامر على [1,*]، سلام نعمة ياسر [3]

الكلمات المفتاحية

الشبكات العصبية التلافيفية
تحويل المويجات المنفصلة
مخطط كهربية القلب
مرشح تمرير النطاق
التعلم العميق
تحليل التردد الزمني

الملخص

يعد الكشف عن المشكلات الصحية أمرًا بالغ الأهمية لإنقاذ حياة المرضى، خاصة عندما يكونون بعيدين عن المهنيين الطبيين، مما يسلط الضوء على أهمية بناء نماذج تصنيف دقيقة للغاية. في هذا البحث، تم تصميم واختبار نموذج الشبكة العصبية التلافيفية (CNN) لتحليل وتصنيف إشارات مخطط كهربية القلب (ECG). الهدف الرئيسي للورقة هو تصنيف خمسة أنواع من نبضات القلب باستخدام نموذج CNN الذي تم تدريبه على قاعدة بيانات عدم انتظام ضربات القلب في معهد ماساتشوستس للتكنولوجيا (MIT-BIH).، حيث تم تطبيق تقنيات المعالجة المسبقة مثل ترشيح تمرير النطاق بتروورث وتحويل المويجات المنفصلة (DWT) لتعزيز الإشارات، وأظهرت المقارنة بين الطريقتين أن تحويل المويجات كان أكثر فعالية في تقليل الضوضاء والحفاظ على مكونات الإشارة الأساسية.، حيث تم تحقيق دقة تصنيف قدرها 89.82%، واستدعاء 69.61%، ودرجة F1 قدرها 77.66% باستخدام البيانات المعالجة مسبقًا والمحولة بالمويجات، مقارنة بدقة 83.30% للبيانات التي تمت تصفيتها بتمرير النطاق.

Introduction

Cardiovascular diseases are the leading cause of death worldwide, with an estimated 17.9 million people having died from cardiovascular diseases in 2019, representing 32% of all global deaths [1]. One of the main manifestations of cardiovascular disease is arrhythmia, primarily due to abnormal electrical activity in the heart. The electrocardiogram (ECG) is an effective tool physicians use to detect heart diseases [2]. An ECG is a method of recording the heart's electrical activity over time. It captures changes in electrical voltage during the depolarization and repolarization of heart muscle fibers using electrodes placed on the chest and limbs. Contracting heart muscle cells are the source of these electrical potentials. The ECG waveform is either printed on graph paper at a fixed speed or displayed on a computer screen. This method is cost-effective, widely available, and non-invasive [3]. Figure 1. shows a normal electrocardiogram signal.

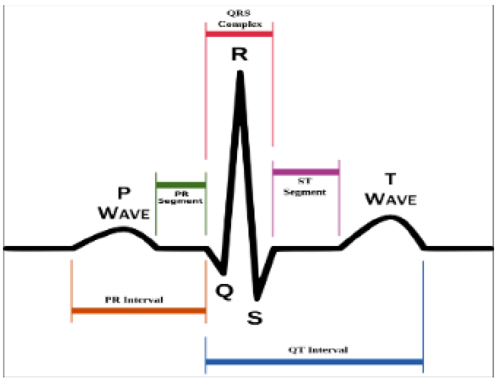

Figure 1: Electrocardiogram Signal

The P wave represents atrial activation, the QRS complex represents ventricular activation, and the T wave represents

*Corresponding author: ras.ali@wau.edu.ly
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recovery. Manual analysis of ECG signals is prone to human error in detecting the various waveforms of the signal because it is nonlinear time-series data, making classification challenging and requiring significant expertise. Furthermore, the analysis may vary from one physician to another, and manual analysis is time-consuming, leading to delays in diagnosis and treatment [4], [5].

With the advancement of artificial intelligence technologies, various machine learning techniques are now being used to analyze the specific features of ECG signals (ECG) to address the challenges doctors face in manually analyzing ECG signals [6]. Today, deep learning techniques have proven to be effective tools in assisting physicians in patient evaluation and risk classification. Moreover, some studies highlight the strength of deep learning when applied to ECG analysis, leveraging large datasets, with convolutional neural networks being one of the enhanced techniques for effectively handling this data [7].

The use of CNNs is widespread, typically trained using gradient-based optimization algorithms. A CNN generally consists of several sequential layers connected in a feedforward manner, including convolutional layers, normalization layers, pooling layers, and fully connected layers. The first three layers are responsible for feature extraction, while the fully connected layers handle classification [8]. CNNs can automatically extract features from signals. Therefore, pre-processing and initial filtering of the signal can be beneficial for improving the network's accuracy in pattern recognition and reducing signal distortion, thereby enhancing the network's generalization capability [9].

Before feeding ECG signals into a CNN model, it is essential to preprocess the signals to remove noise and enhance the model's performance [10]. Numerous studies have been conducted on the classification of ECG signals using artificial intelligence techniques. For instance, Wu et al. (2021) presented a deep convolutional neural network model consisting of 12 layers, achieving excellent performance in classifying ECG signals using the MIT-BIH dataset. However, the model's complexity requires substantial computational resources, which may limit its application in clinical settings with constraints [11]. In a more recent study, Kazemi et al. (2024) employed advanced techniques based on autoencoder models, convolutional neural networks, and transfer learning, achieving an accuracy of 99.53%. Nevertheless, these approaches demand massive computational resources and accurately labeled data, which may hinder their implementation in medical institutions with limited resources [12].

Signal processing techniques such as bandpass filtering (Butterworth filter) and discrete wavelet transform (DWT) are widely utilized. This study compares the performance of these two preprocessing techniques in the classification of electrocardiogram signals. We aim in this study to explore how artificial intelligence techniques can be used in the analysis of ECG signals and the extent to which data preprocessing impacts the classification process and its evaluation, intending to improve the accuracy and quality of early diagnosis of various heart conditions with high precision.

Methodology

The ECG data used in this study were obtained from the MIT-BIH Arrhythmia Database, which is one of the most commonly used databases among researchers. It comprises 48 sets of two-channel ECG data collected from 47 individuals at a sampling rate of 360 Hz. Each dataset lasts approximately 30 minutes and includes recordings from two leads: one from MLII and the other from either V1, V2, V4, or V5 [13].

A bandpass filter was applied to remove high and low-frequency noise. The lower cutoff frequency was set at 0.5 Hz and the upper cutoff frequency at 45 Hz, based on the sampling frequency of the used signal and according to previous studies that support these choices to ensure accurate and effective filtering. The digital filter was designed using the "butter" function to create the filter coefficients, and then it was applied to the signal using the "filtfilt" function in MATLAB. This function provides zero-phase filtering, preserving the true shape of the signal without altering its phase.

The Discrete Wavelet Transform (DWT) was applied to analyze the ECG signal using the "wavedec" function, which decomposed the signal into multiple levels according to its different frequencies. In this analysis, the number of levels was set to five, based on previous studies that demonstrated the effectiveness of this number for accurate signal analysis. Each level reflects a different component of the signal at a specific frequency. The Sym4 wavelet, a type of Symlet, was chosen due to its similar properties to Daubechies wavelets and to enhance consistency in the analysis. The signal is divided into detail coefficients representing high frequencies and approximation coefficients representing low frequencies, aiming for a precise analysis of the signal and all its components.

This technique is effective due to its ability to handle noise in both the time and frequency domains. The wavelet transform allows for the identification of noise present at specific frequencies at specific time locations, facilitating its removal without affecting the main signal.

After noise removal using one of the preprocessing techniques, the signal was reconstructed using the waverec function, which reconstructs the filtered signal after noise removal. The filtered signal was then normalized to the range (-1, 1) using a simple normalization equation. This step aims to facilitate signal processing in subsequent steps, especially in peak detection and feature analysis. The next step involves applying the Pan-Tompkins algorithm to detect QRS peaks. This algorithm is used to identify points indicating the presence of heartbeats (the characteristic peaks in ECG signals). After detecting QRS peaks, the nearest annotation associated with each QRS peak from the original data is identified by calculating the time difference between the detected peak and available annotations, and selecting the nearest annotation for each peak using the min function, after detecting and annotating the peaks, the ECG signal is divided into fixed-length segments of 10 seconds each. The number of segments is determined based on the total length of the signal and the sampling frequency, and the signal is cut into equal-length segments. Each segment is stored in a list X, with the associated labels stored in a list y.

The model used is a Convolutional Neural Network (CNN) designed to analyze ECG signals. The model consists of four convolutional layers followed by ReLU activation layers and MaxPooling layers to reduce the size of the extracted features. After the convolutional layers, the data is flattened and fully connected layers are used to aggregate the discovered patterns. Finally, a SoftMax layer is employed to convert the outputs into classification probabilities, with the model classifying the signals into several categories, the data is divided into a training set (80%) and a testing set (20%). The Adam optimizer with a small initial learning rate of 0.0001 is used to train the model for 50 epochs using the training data. The model's performance is then evaluated on the test set, and accuracy is computed. Additionally, a Confusion Matrix is used to illustrate the model’s performance in classifying each category, the metrics calculated include Precision, Recall, F1-Score, Classification Accuracy, and Error Rate, where Accuracy (Acc) represents the ability to detect the true state of the sample:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Precision represents the ratio of correctly classified samples for each category:

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (2)$$

Recall represents the ability to distinguish different conditions:

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3)$$

The F1-Score is the harmonic mean of Precision and Recall, reflecting the balance between the ability to detect positive cases and reducing false positives:

$$F_1 = \left(\frac{recall^{-1} + precision^{-1}}{2}\right)^{-1} = 2 \cdot \frac{precision\,.recall}{precision\, +\, recall} \qquad (4)$$

Results and Discussion

The proposed convolutional neural network (CNN) algorithm was trained on a computer equipped with Intel i5-7300HQ processors, 512 GB of RAM, and an Intel graphics card. The training took approximately 1903 minutes to complete, and the algorithm was implemented using the MATLAB Deep Learning Toolbox and the MATLAB Neural Network Toolbox, Figures 1 and 2 illustrate the frequency spectrum of the signal before and after filtering. Figure 1 displays the frequency spectrum of the original signal before filtering for record 109, while Figure 2 represents the frequency spectrum of the signal after filtering. In Figure 1, the signal was filtered using the Butterworth filter, whereas in Figure 2, the signal was filtered using the Discrete Wavelet Transform.

The frequency spectrum from the pre-processing using the Discrete Wavelet Transform (DWT) demonstrates the effectiveness of the filtering process. It successfully removed noise, particularly the 60 Hz AC noise, while better preserving the essential components of the ECG signal in the most critical frequency bands compared to filtering with the Butterworth filter, additionally, the results of training and testing the model on ECG data show that the DWT method achieved better performance in data classification. Table 1 provides a comparison of the model's performance on ECG data processed using the two different techniques.

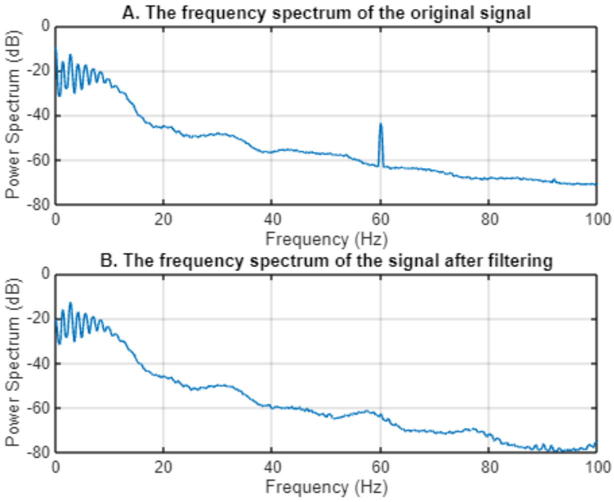

Figure 2: Frequency spectrum of the signal after processing using a Butterworth filter

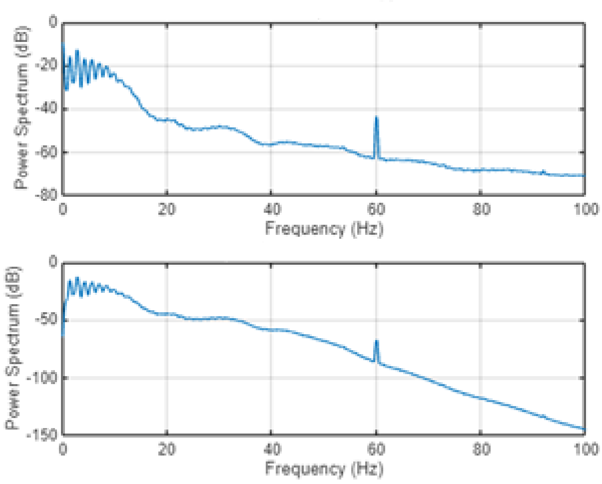

Figure 3: Frequency spectrum of the signal after processing using the Discrete Wavelet Transform

Table 1: Comparison of the model's performance on data processed with different techniques

	Butterworth filter	DWT
Precision	82.17%	93.20%
Recall	58.33%	69.61%
F1 Score	65.93%	77.66%
Accuracy	83.30%	89.82%
Error Rate	16.7%	10.18%

Table 1, demonstrates the clear improvement in the model's performance after using the data processed with DWT. The confusion matrix also showed the difference in signal classification, Figure 4 presents Confusion Matrix 1 using data processed with the Butterworth filter.

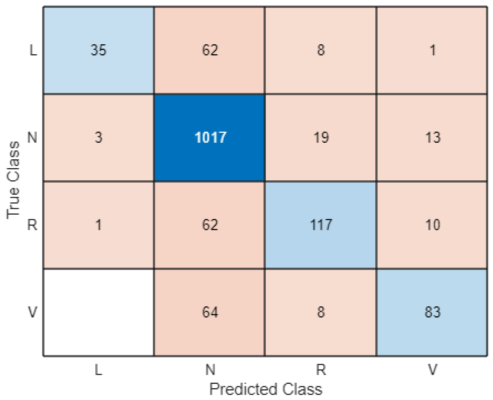

Figure 4: Confusion Matrix 1

only four classes (L, N, R, V) were classified, which indicates that some samples from category (F) were lost during processing and were not preserved. Meanwhile, Confusion Matrix 2 in Figure 5, shows that five classes (F, L, N, R, V) were classified, and with better performance compared to Confusion Matrix 1. This confusion matrix was obtained from training and testing the model using data processed with DWT, this indicates that using DWT for pre-processing is better than the Butterworth filter in terms of preserving samples and improving classification accuracy.

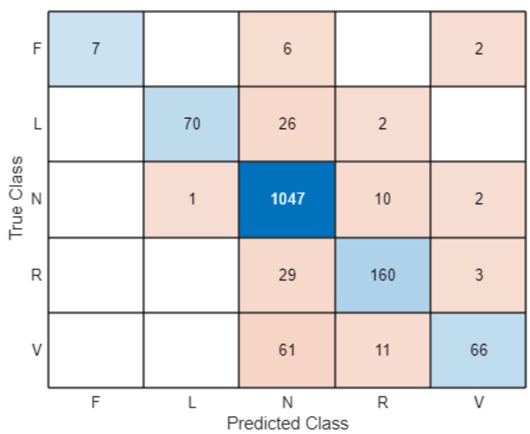

Figure 5: Confusion Matrix 2

Conclusion

The results demonstrated that using the Discrete Wavelet Transform (DWT) as a preprocessing procedure for ECG signals provides superior performance compared to the Butterworth filter. The DWT method significantly excelled in removing noise while preserving the essential components of the signal, leading to improved classification accuracy in the convolutional neural network (CNN) model. The metrics indicated that the classification accuracy using DWT reached 89.82%, while the Butterworth filter accuracy was 83.30%. Additionally, the error rate was lower with DWT (10.18%) compared to 16.7% when using the Butterworth filter. Despite the high accuracy demonstrated by some studies, employing the DWT technique in preprocessing offers a more efficient and suitable model for real-world applications, making this work distinctive in terms of generalization capabilities and usability in resource-constrained environments. These results reflect the importance of selecting appropriate preprocessing techniques in analyzing ECG signals, as the use of DWT contributes to enhancing the model's performance and its classification of different heartbeats more accurately. Future research can build on this study by expanding the database used and incorporating other techniques, such as combining convolutional neural networks with Long Short-Term Memory (LSTM) networks to enhance the understanding of temporal patterns and improve classification outcomes. Additionally, utilizing devices with NVIDIA graphics cards can speed up the training of models using MATLAB.

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