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ECG Signal Denoising Using 1D Convolutional Neural Network

Ahmad Rifai[1], Muhammad Naufal Rachmatullah[2], Winda Kurnia Sari[1]

[1]*Department of Information System, Faculty of Computer Science, Universitas Sriwijaya*
[2]*Department of Informatics, Faculty of Computer Science, Universitas Sriwijaya*
**naufalrachmatullah@unsri.ac.id*

ABSTRACT

Electrocardiogram (ECG) signals are crucial for monitoring cardiac activity and diagnosing various cardiovascular conditions. However, these signals are often contaminated by different types of noise, such as baseline wander, muscle artifacts, and power line interference, which can obscure critical information and hinder accurate diagnosis. This study used a 1-Dimensional Convolutional Neural Network (1D CNN) architecture with seven convolutional layers for denoising ECG signals. The model utilizes a fully convolutional autoencoder approach, comprising an encoder that transforms noisy input signals into compact feature representations and a decoder that reconstructs the cleaned signals. The proposed architecture was tested using the MIT-BIH Noise Stress Test Database, which includes ECG recordings with simulated noise conditions. Performance evaluation metrics such as Mean Squared Error (MSE), Signal-to-Noise Ratio (SNR), and Mean Absolute Deviation (MAD) were used to assess the model's effectiveness. Results showed a low MSE of 0.034, a high SNR of 15.8 dB, and a MAD of 0.754, indicating significant noise reduction and high-quality signal reconstruction. These findings demonstrate that the 1D CNN architecture effectively reduces various types of noise in ECG signals, thereby enhancing signal quality and facilitating more accurate analysis and diagnosis. The model's ability to maintain the integrity of crucial ECG features while removing noise suggests its potential utility in clinical applications for improving cardiovascular disease diagnosis.

Keywords: ECG, Denoising, Convolutional Neural Network.

1. INTRODUCTION

An electrocardiogram (ECG) is a crucial diagnostic tool in the medical field for monitoring the electrical activity of the heart. ECG results are used to detect a variety of heart conditions, ranging from arrhythmias to ischemic heart disease [1], [2], [3]. However, ECG data often get contaminated by various types of noise, such as muscle noise, respiratory noise, and power line interference, which can obscure the original signal and complicate interpretation.

Traditionally, noise removal methods for ECG signals have relied on conventional signal processing techniques such as digital filtering [4], Fourier transform [5], [6], [7], [8], wavelet transformation [9], [10], [11], savitzky-golay filter [12], [13], and moving average filter [14], [15]. Although these methods are effective in certain cases, they have limitations, especially when dealing with complex and non-stationary noise, adaptability and learning from data. Therefore,

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more advanced approaches are needed to improve the accuracy and efficiency of noise removal in ECG signals.

In recent years, advancements in deep learning technology have led to significant breakthroughs in various fields, including biomedical signal processing. Deep learning, with its ability to learn from large datasets and capture complex patterns, offers great potential for noise removal in ECG signals. Deep learning algorithms, such as Convolutional Neural Networks (CNN)[16], Denoising Autoencoder [17] and Recurrent Neural Networks (RNN)[18], [19], have demonstrated superior performance in various signal processing tasks, including ECG signal denoising.

CNNs, 1-Dimensional (1D) have demonstrated significant potential in biomedical signal processing. 1D CNNs are designed to capture temporal patterns in time-series data, such as ECG signals, making them highly suitable for denoising tasks. 1D CNNs consist of multiple convolutional layers that effectively extract important features from ECG signals while reducing noise. Each convolutional layer applies filters to the input signal, resulting in increasingly complex feature representations at each subsequent layer. By utilizing techniques such as pooling and up sampling, the 1D CNN architecture can retain crucial information from the original signal while removing noise.

By leveraging the power of CNNs, noise removal algorithms for ECG signals can be trained to recognize and eliminate various types of noise while preserving essential information from the original signal. This process involves training the model with a dataset of noisy ECG signals and corresponding clean ECG signals as targets. The model then learns to map the contaminated signals to clean signals, resulting in more accurate and reliable ECG signals for medical analysis.

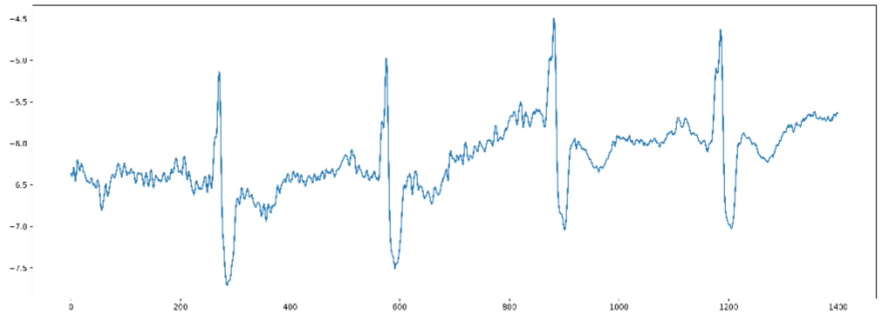
This paper discusses various deep learning approaches and methods that have been applied to noise removal in ECG signals, as well as an evaluation of their performance in enhancing ECG signal quality. The aim of this research is to provide insights into the potential of deep learning in advancing heart diagnostic technology through more sophisticated and efficient signal processing.

2. MATERIAL AND METHODS

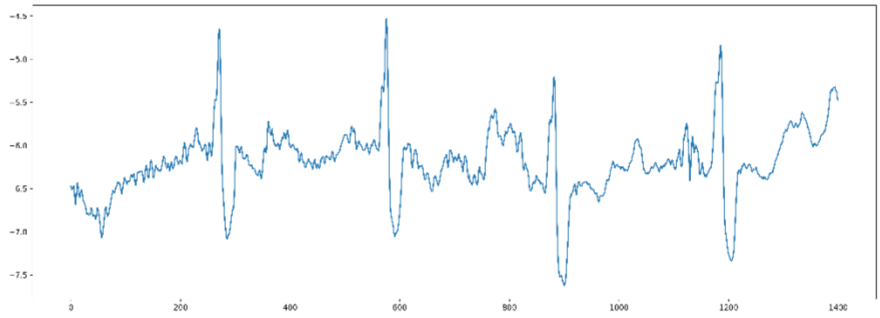
2.1 Dataset

This study utilizes the MIT-BIH Noise Stress Test Database [20]. This dataset is one of the widely used datasets in biomedical signal processing research, particularly in the development and evaluation of noise removal techniques for electrocardiogram (ECG) signals. The dataset was developed by the MIT Laboratory for Computational Physiology and serves as a standard data source for testing noise removal algorithms.

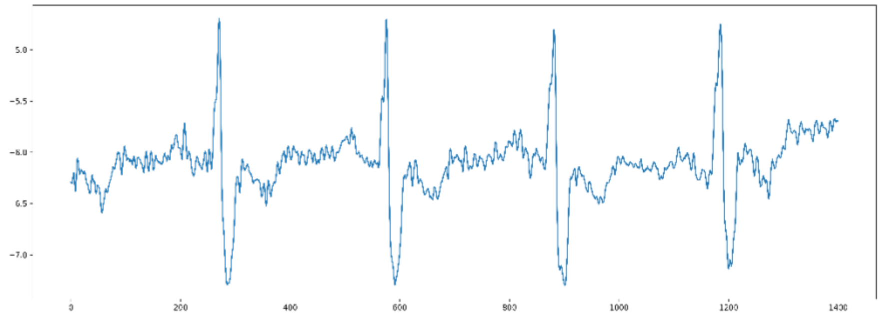
The three main types of noise used in this dataset are; Baseline Wander (BW): Noise resulting from body movement or respiration, Muscle Artifact (MA): Noise generated by muscle activity, Electrode Motion Artifact (EM): Noise caused by electrode movement. The dataset consists of recordings of 12 ECG signals from two individuals, taken from the MIT-BIH Arrhythmia Database. Each recording has a duration of 30 minutes and a sampling frequency of 360 Hz. Figure 1 illustrate the BW, EM and MA noise respectively



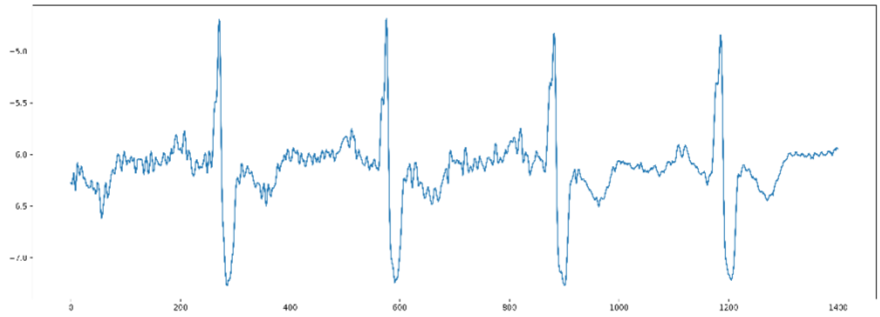
(a)



(b)



(c)



(d)

Figure 1. Example of (a) BW, (b) MA, (c) EM and (d) Clean Signal Noise

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2.2 CNN Architecture

The CNN architecture used in this study is based on [16], utilizing a fully convolutional autoencoder approach to reduce noise in ECG signals. The convolutional autoencoder consists of two main components: the encoder and the decoder. The encoder transforms the input signal, which is contaminated with noise, into a more compact feature representation, while the decoder reconstructs the cleaned signal from this feature representation.

The encoder consists of three consecutive convolutional layers that gradually reduce the temporal dimension of the input signal and extract important features. Each convolutional layer is followed by an activation layer (ReLU) and a pooling layer for dimensionality reduction. The middle part of the autoencoder, where the signal dimension is significantly reduced but the main features have been extracted, this part consist of one convolutional layer without pooling. The decoder performs the inverse operation of the encoder, restoring the signal to its original temporal dimension. Transposed convolutional layers (deconvolutions) and up sampling are used in this part.

This architecture consists only of convolutional and transposed convolutional layers, allowing the model to learn from the overall temporal context of the ECG signal without losing important information. By gradually extracting and reconstructing features, this architecture can effectively remove various types of noise from the ECG signal. Furthermore, the bottleneck layer provides a very compact representation of the ECG signal, which not only aids in denoising but also in data compression for efficient storage and transmission. The detailed information about CNN architecture is illustrated in figure 2.

Layer (type)	Output Shape	Param #
input_layer_15 (InputLayer)	(None, 512, 1)	0
conv1d_54 (Conv1D)	(None, 512, 32)	128
Pool1 (MaxPooling1D)	(None, 256, 32)	0
conv1d_55 (Conv1D)	(None, 256, 64)	6,208
Pool2 (MaxPooling1D)	(None, 128, 64)	0
conv1d_56 (Conv1D)	(None, 128, 128)	24,704
Pool3 (MaxPooling1D)	(None, 64, 128)	0
conv1d_57 (Conv1D)	(None, 64, 256)	98,560
Upsample1 (UpSampling1D)	(None, 128, 256)	0
conv1d_transpose_25 (Conv1DTranspose)	(None, 128, 128)	98,432
Upsample2 (UpSampling1D)	(None, 256, 128)	0
conv1d_transpose_26 (Conv1DTranspose)	(None, 256, 64)	24,640
Upsample3 (UpSampling1D)	(None, 512, 64)	0
conv1d_transpose_27 (Conv1DTranspose)	(None, 512, 32)	6,176
conv1d_transpose_28 (Conv1DTranspose)	(None, 512, 1)	33

s

Figure 2. CNN Denoising Architecture

2.3 Evaluation Metrics

Evaluating the performance of an ECG signal denoising model involves using several metrics that provide an overview of how well the model removes noise while preserving important features of the original signal. The following are some of the evaluation metrics used in this research

Mean Squared Error (MSE) measures the average squared difference between the actual values and the predicted values. MSE provides an assessment of how much the signal predicted by the model differs from the clean original signal. The smaller the MSE value, the better the model's performance in denoising the ECG signal.

$$MSE = \frac{1}{N}\sum_{i-1}^{N}(y_i - \hat{y}_i)^2 \quad (1)$$

Where y_i is the actual of the clean signal $\hat{y}_i$ is the value predicted by the model.

The next metric is the Signal-to-Noise Ratio (SNR), which measures the strength of the original signal relative to the strength of the existing noise. This metric is crucial in the context of denoising because it indicates how well the model preserves the original signal compared to the noise. A higher SNR indicates better denoising performance.

$$SNR = 10\, log_{10}\left(\frac{\sum_{i=1}^{N} y_i^2}{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}\right) \quad (2)$$

Mean Absolute Deviation (MAD) is a statistical measure that evaluates the average absolute differences between observed values and their mean or median. In the context of ECG denoising, MAD can be used to assess the performance of denoising algorithms by quantifying how much the denoised signal deviates from the original clean signal.

$$MAD = \frac{1}{N}\sum_{i-1}^{N}|y_i - \hat{y}_i| \quad (3)$$

3. RESULT AND DICUSSION

After developing a CNN architecture with seven convolutional layers for ECG signal denoising, testing was conducted using data from the MIT-BIH Noise Stress Test Database. This database provides ECG recordings with various types of added noise to simulate common clinical conditions. The input for CNN architecture is noisy ECG, interfere with BW, EM and MA noise while the output is the clean signal. We train the model using 10.160 signal which segmented into 512 nodes. In order to evaluate the learning process, a test data consist of 5.076 signals is used. This study used 500 epoch, 10^{-3} learning rate and 512 batch size. To prevent overfitting, we performed early stopping mechanism with patience of 25 epochs. The train ad validation loss is illustrated in figure 3.

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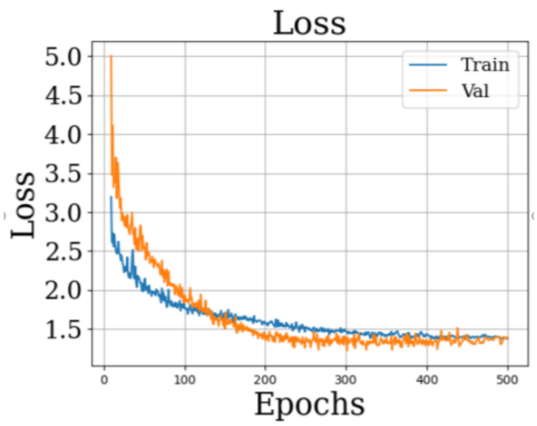

Figure 3. Loss graphics during training and validation model.

The evaluation process on testing data resulted 15.8 dB for SNR, 0.034 for MSE, and 0.754 for MAD. The low MSE value indicates that the average squared difference between the original and denoised signals is small, demonstrating good performance in noise reduction. Moreover, the low MAD value indicates that the average absolute deviation between the original and denoised signals is small, reflecting high accuracy in noise removal. In addition, SNR value of 15.8 dB indicated that the signal is approximately 36 times stronger than the noise which is reasonably good, as the signal is significantly stronger than the noise. Even though the acceptable SNR level can vary depending on the application and the specific requirements for signal clarity, this level of SNR is typically considered acceptable for many clinical applications. Figure 4 shows the cleaned, noised, and predicted signals.

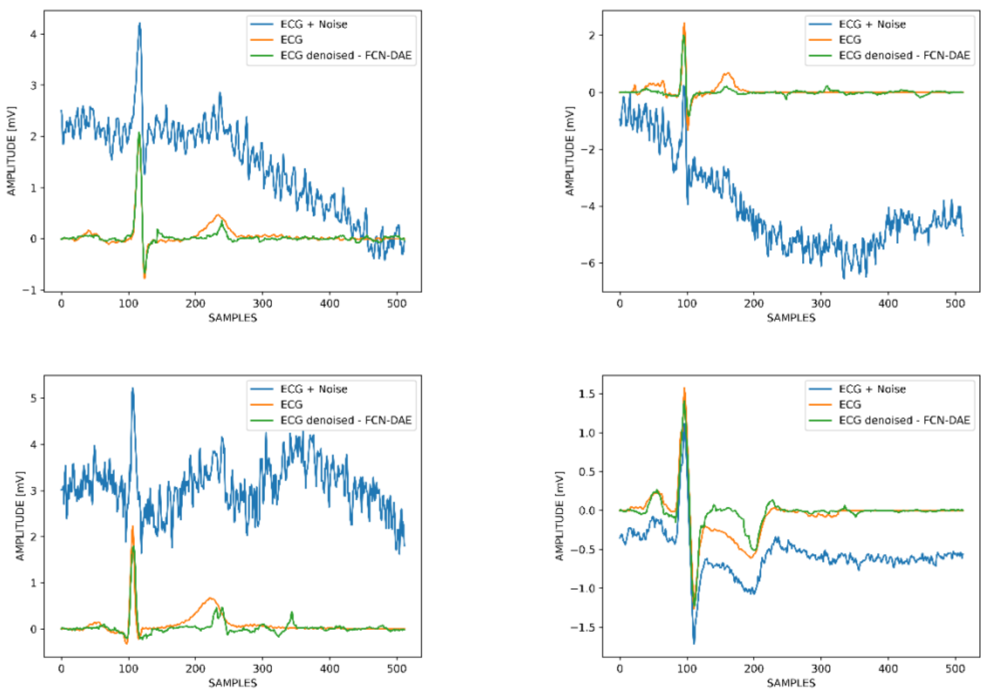

Figure 4. A Collection of Cleaned, Noised, and Predicted signals

4. CONCLUSION

The test results show that the CNN architecture with seven convolutional layers developed for ECG signal denoising performs excellently in reducing noise in ECG signals from the MIT-BIH Noise Stress Test Database. With MSE, SNR, and MAD values indicating high denoising quality, this model effectively enhances the quality of ECG signals, facilitating further analysis and diagnosis. This model can be a useful tool in clinical applications to improve the accuracy of ECG signal interpretation and assist in the more precise diagnosis of cardiovascular conditions.

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