

Biomedical ECG Signal Compression by Combining Wavelet Transform and Unsupervised Autoencoder Techniques

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Abstract: Storing biomedical signal data is a significant concern in the field of biomedical signal processing because it requires a substantial amount of storage space. These biomedical signals often contain hours of information, necessitating extensive storage capacity. Researchers employ Electrocardiogram (ECG) signal compression techniques to address this issue. However, compressing the ECG signal could potentially lead to the loss of important features or data. This loss may adversely impact the accurate analysis of heart patient conditions. This paper introduces a novel approach for compressing ECG signals by the combined power of Wavelet Transform (WT) and unsupervised Autoencoder (AE) techniques. ECG signal compression plays a crucial role in reducing data storage and transmission requirements without compromising diagnostic accuracy. The proposed methodology, termed WT-AutoEncoder, integrates Wavelet Transform for signal decomposition and feature extraction, followed by an Autoencoder for efficient encoding and reconstruction of the original signal. Unlike conventional methods, this approach utilizes the strengths of both WT and AE to achieve high compression ratios while preserving signal accuracy. The study conducts comprehensive experiments and evaluations using benchmark MIT-BIH datasets to assess the performance of the WT-AutoEncoder on specific records (101-109) in terms of compression ratio of 32.31, PRDN of 33.26, PRD of 3.06, and QS of 13.49. The final results demonstrate the effectiveness of the proposed model compared with existing methods in compressing ECG signals while maintaining high accuracy, suggesting its potential for secure transmission and storage in various healthcare applications.

Keywords: Electrocardiogram Signal, Signal Processing, Signal Compression, MIT-BIH Dataset, Wavelet Transform, Autoencoder

1. Introduction

The electrocardiogram (ECG) is an important tool in medicine for diagnosis. However, storing large amounts of clinical data can be costly if it isn't compressed, needing a lot of hard disk space. ECG data compression should be real-time, lossless, with high compression rates, and allow the use of compressed data without complete decompression. Automatic ECG recordings help diagnose cardiovascular diseases but take a long time to record. There's a need to analyze and store lots of

ECG data efficiently, preserving crucial features for diagnosis [1]. Hence, compression algorithms are necessary to improve storage and analysis efficiency.

Current ECG compression methods fall into three categories: direct processing, transformation, and neural networks. Direct processing methods like Evolutionary Computation [2], Turning Point Scan-Along Polygonal Approximation [3], and Differential-Pulse Coding Modulation like SVD [4], DPCM [5] algorithms eliminate redundant ECG information. Transformation methods, like Kanade Lucas Tomasi [6], Discrete Cosine Transform [10], and Fast Fourier Transform like KLT [7], DCT [8]-[9], FFT [10] algorithms, compress data using mathematical functions. Neural network-based methods [11]-[12] extract feature information from ECG through self-learning.

The methods that extract parameters are used to get important information from the signal. They use these details later to rebuild the signal [13]. In [14] one method called linear prediction coding (LPC) they proposed using a particular algorithm. Another approach combined finding the QRS in ECG and compressing data using an adaptive prediction technique [15]. In a different method, they suggested using Autoencoders for compression. These AEs were different from the regular ones and used a variation called denoising autoencoders (DAEs) [16].

Unlike these usual methods, DL has the potential to make algorithms based on signals. DL has been successful in many fields like recognizing images [17], objects [18], or speech [19]. Researchers also use DL for analyzing biomedical signals [20]-[21]. This research proposes the utilization of a specific DL model, the Autoencoder integrated with wavelet transform, for compressing ECG signals. This unique autoencoder model involves the tuning of hyperparameters and the introduction of a 'SparsityRegularization' function for the first time. While Autoencoder classifiers are commonly applied to 2-D images, this study stands out for focusing on compressing 1D ECG signals. The potential application of this model extends to securely transmitting biomedical ECG signals within the healthcare domain.

Neural network-based ECG compression is gaining attention due to its adaptability, parallel processing, waveform quality, and resistance to interference. Efficient ECG compression should achieve a high compression ratio without losing vital information. Designing a multi-objective function can optimize ECG compression, ensuring minimal loss of ECG data. Current neural networks focus on one objective, potentially reaching only optimal solutions or risking ECG data loss due to concentrating solely on improving data quality.

The main contribution of this paper is

- A Biomedical ECG signal compression unsupervised model is developed based on autoencoder and wavelet transform.
- Optimizes the autoencoder by tuning the hyperparameter to achieve the maximum compression ratio without noise in the ECG signal.
- The experimental study is conducted on the MIT-BIH dataset to validate the performance of the Proposed model. The final results are compared with the existing state-of-art methods.

The remaining sections of the paper are organized as follows: Section 2 presents previous research in the field of ECG signal compression. Section 3 discusses the proposed methodology in detail.

Section 4 presents the performance of the proposed model based on various evaluation parameters. Finally, the conclusion and future scope are discussed.

2. Proposed Methodology

In this part, we outline the mathematical expressions for the Wavelet Transform method and the unsupervised auto-encoder neural network. Figure 1 shows the block diagram of the proposed neural network for compressing the ECG signal based on the wavelet and autoencoder approach. Each block can be described in the following subsection.

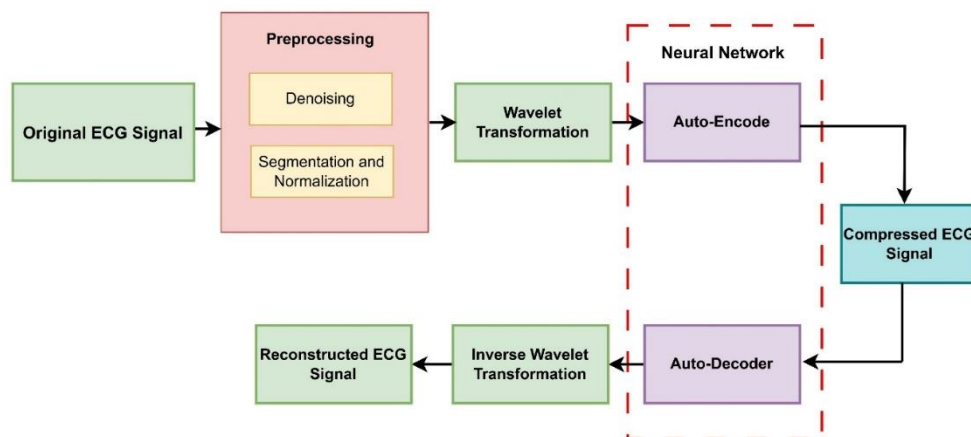


Figure 1: Architecture of Proposed ECG Signal Compression Model

Dataset Description: The MIT-BIH Arrhythmia Database comprises 48 half-hour segments of ECG recordings from 47 individuals studied between 1975 and 1979. The data was collected from the BIH Arrhythmia Laboratory. Among these, 23 recordings were randomly chosen from a collection of 4000 24-hour ambulatory ECG recordings, which included both inpatients (around 60%) and outpatients (around 40%) at Boston's Beth Israel Hospital. The remaining 25 recordings were specifically selected to include less common but medically significant arrhythmias that might not be found in a random sample. These recordings were digitally stored at 360 samples per second per channel with an 11-bit resolution within a range of 10 mV. Each record underwent independent annotations by two or more cardiologists [22]. Any discrepancies were resolved to generate computer-readable reference annotations for each heartbeat, resulting in approximately 110,000 annotations available in the database. Initially, only half of this database, including 25 complete records and reference annotation files for all 48 records, was accessible since September 1999. However, the other 23 signal files, previously exclusive to the MIT-BIH Arrhythmia Database CD-ROM, were made available in February 2005 on this platform.

3. Wavelet Transformation

Extracting features from ECG signals is essential [23]-[24] to eliminate noise interference from the environment. To achieve the best possible data compression while maintaining high quality, a Pareto-optimal solution is necessary. The Wavelet Transform is particularly useful for signals that change rapidly over time, instantly identifying and removing baseline drift noise. In the wavelet transform module, the input signal is made up of a smaller version of the main wavelet signal. In this paper illustrate the integral equations for wavelet functions:

$$WTf(t) = \frac{1}{s} \int_{-\infty}^{+\infty} f(\tau) s\left(\frac{t\tau}{s}\right) d\tau \tag{1}$$

Initially wavelet parameter chooses the value of 2 as an exponent that can be shows as $s = 2^j$, where $j = 1, 2, 3, \dots, n$. here, φ represents the parameter of basic wavelet transform as shown in equation 2.

$$\varphi_s(t) = \frac{1}{s} \varphi\left(\frac{t}{s}\right) \tag{2}$$

Based on the previous equation 1 and 2, the wavelet can be represented in equation 3

$$WT_2f(t) = \frac{1}{\sqrt{2^j}} \int_{-\infty}^{+\infty} f(\tau) \sqrt{2^j} \left(\frac{t\tau}{\sqrt{2^j}}\right) d\tau \tag{3}$$

The utilization of Wavelet Transform (WT) is essential for discrete signals. Subsequently, employing the WT algorithm enables the binarization of digital ECG signals using Equations 4 and 5.

$$WT_{2^j}f(t) = \sum_{i \in \mathbb{Z}} G_i S_{2^j-1}f(n - 2^{j-1}i) \tag{4}$$

$$S_{2^j}f(t) = \sum_{i \in \mathbb{Z}} H_i S_{2^j-1}f(n - 2^{j-1}i) \tag{5}$$

In this context, S_{2^j} represents a smooth function, $S_{2^j}f(t)$ stands for the original input ECG signal denoting low-frequency wavelet coefficients acting as the approximation function, and $S_{2^j}f(t)$ refers to the original signal signifying high-frequency coefficients. It's important to highlight that $H(i)$ and $G(i)$ correspond to coefficients of low-pass and high-pass filters respectively.

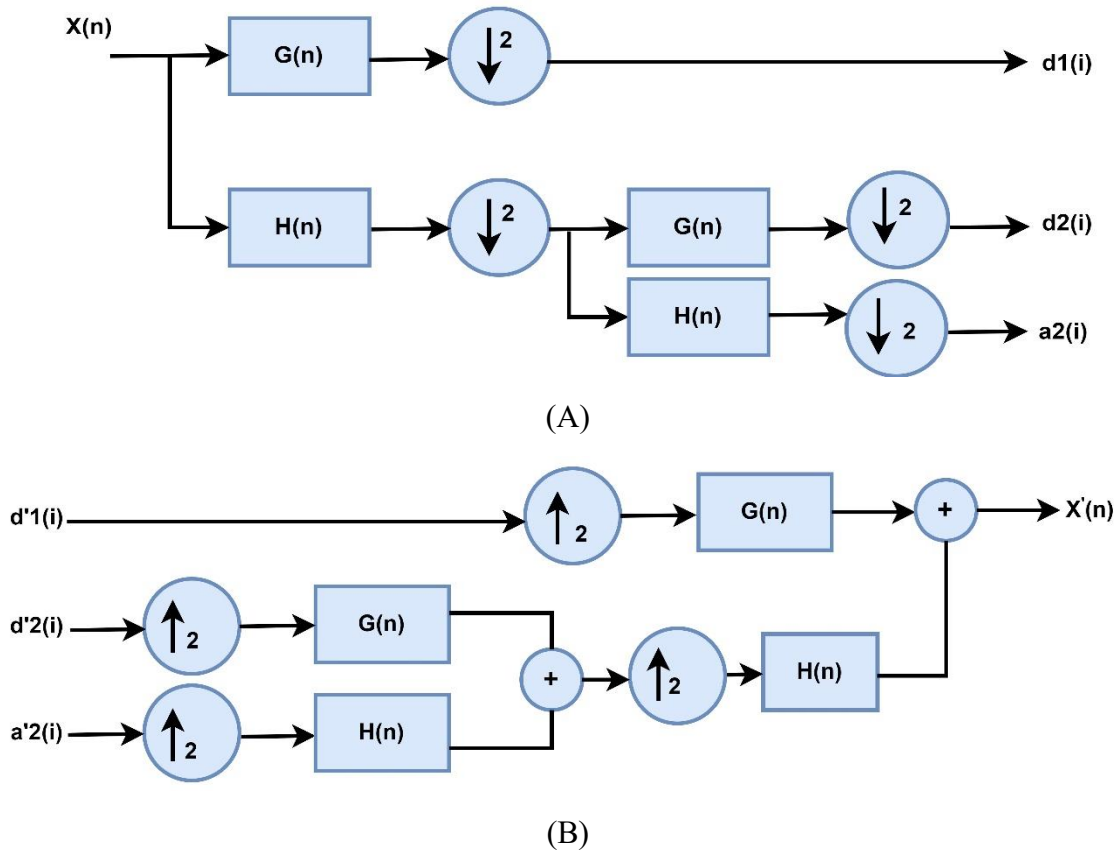


Figure 2: (A) Downsampling Decomposition of ECG Signal (B) Upsampling Decomposition of ECG Signal

The signal $x(n)$ in the observed signal $x'(n)$ can be transformed using the WT and inverse WT. Typically, the forward WT is as depicted in the equation:

$$W = Wx' \quad (6)$$

In this scenario, W stands for the forward transform matrix, and w represents the collection of wavelet coefficients including both detail and approximation components. However, the filter bank approach involves a step-by-step breakdown of the Low pass filter through an iterative process. During this decomposition phase, down-sampling and upsampling are implemented, illustrated in Figure 2 (A) and (B). Choosing the appropriate mother wavelet is crucial for accurately estimating the input ECG signal x . The subsequent action involves reducing the acquired coefficients. It's recommended to reduce the wavelet coefficients to generate favorable estimations [25]. These estimators using wavelets perform well across various loss functions and within a broad class of functions. They're straightforward, efficient, quick, and can adapt to variations in spatial and spectral aspects, and can easily scale to higher dimensions [26]. Reduction occurs by applying thresholds to the wavelet coefficients, transforming w into w'

When dealing with a wavelet coefficient w and a threshold $t > 0$, the outcome after hard thresholding is expressed as:

$$D(U, t) = U \quad \forall |U| > t$$

$$= 0 \quad \text{Otherwise} \quad (7)$$

And Soft thresholding is expressed as

$$D(U, t) = \text{sgn}(U)' \max(0, |U| - t) \quad (8)$$

Build Autoencoder Model with Hyperparameter

An autoencoder is a neural network designed for unsupervised learning that compresses data into a lower-dimensional representation and then reconstructs it. In the context of ECG signal compression, the specified hyperparameters govern the behavior of the autoencoder during training. The 'hiddenSize' parameter defines the size of the compressed representation layer, set at 30 nodes in this case. 'MaxEpochs' determines the number of epochs during training, with a value of 800 epochs. The 'EncoderTransferFunction' and 'DecoderTransferFunction' signify the activation functions used in the encoding and decoding layers, respectively, 'satlin' and 'purelin'. 'L2WeightRegularization' regulates the impact of large weight values in the network to prevent overfitting, set at 0.01. 'SparsityRegularization' controls the level of sparsity induced in the network, set at 4. 'SparsityProportion' sets the desired sparsity level to 0.10, which influences the activation of nodes to promote sparsity in the network representation. These hyperparameters were set to autoencoder's training process to efficiently compress ECG signals and effectively optimal reconstruction of ECG Signal.

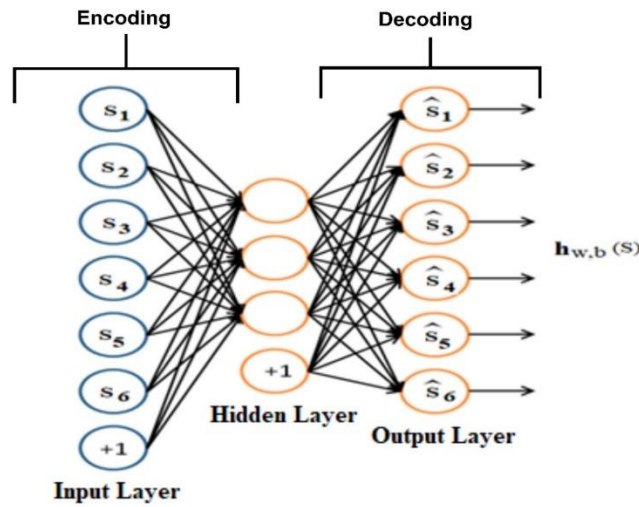


Figure 4: Structure of Autoencoder

Figure 4 shows the structure of autoencoder network based on backpropagation approach, to set the total targeted values is same as the inputs. $y(i) = s(i)$.

The autoencoder model is trained using the $hw, b(S) = s$ function. This function is used as an identity function so as output s' is same as the input s . Where, $a_j^{(2)}$ represents the activation of hidden layer j in model. The s is used to fed the input that activate the model, thus it can be write as $a_j^{(2)}(x)$ represents the activation of neurons of model when the model gives the specific input s .

$$\hat{p}_j = \frac{1}{n} \sum_{i=1}^n [a_j^{(2)}(s^{(i)})] \tag{1}$$

The equation 1 is average activation of j th neurons

$$\hat{p}_j = p' \tag{2}$$

Where p represents the sparsity value that is very small nearer to zero ($p=0.05$). This constrains shows the threshold is used to activate neuron must be nearer to zero.

To make the task simpler by adding a penalty to main goal. This penalty will punish a big difference between two values, p and p' . There are different penalties can use, but go with this one.

$$\sum_{j=1}^{s_2} p \log \frac{p}{\hat{p}_j} + (1 - p) \log \frac{1-p}{1-\hat{p}_j} \tag{3}$$

Where s_2 represents the total amount of neurons presents in hidden layer, and j is the index that adding over the hidden layer in model. This penalty is based on Kullback-Leibler (KL) divergence so it can be written as in equation 4.

$$\sum_{j=1}^{s_2} KL(p || \hat{p}_j) \tag{4}$$

it can be also written as

$$KL(p || \hat{p}_j) = p \log \frac{p}{\hat{p}_j} + (1 - p) \log \frac{1-p}{1-\hat{p}_j} \tag{5}$$

Where p and \hat{p}_j represents the divergence between a Bernoulli random variable with mean.

This penalty function has some conditions that

$$KL(p||\hat{p}_j) = 0$$

$$\text{If } \hat{p}_j = p$$

and otherwise it maximizes monotonically as \hat{p}_j diverges from p .

Overall cost function is

$$J_{sparse}(W, b) = J(W, b) + \beta \sum_{j=1}^{s2} KL(p||\hat{p}_j) \tag{6}$$

Where, β represents the control weight of sparsity penalty. \hat{p}_j is depend on the variable W, b because the average activation of neurons j and the activation of hidden layer is depending on the variables W, b .

The equation 6 represents a way to modify the original cost function $J(W, b)$ by adding a term β times the sum of KL divergences between two probability distributions: . Essentially, it enhances the cost function $J(W, b)$ by penalizing the divergence between the distributions p and \hat{p}_j where j varies from 1 to $s2$. The parameter β controls the impact of this penalty on the overall cost.

The autoencoder model is trained by n number of sample ECG inputs. The input function is as shown in equation 7.

$$a_j^{(2)} = f(\sum_{j=1}^n W_{ij}^{(1)} s_j + b_i^{(1)}) \tag{7}$$

$$s_j = \frac{W_{ij}^{(1)}}{\sqrt{\sum_{j=1}^n (W_{ij}^{(1)})^2}} \tag{8}$$

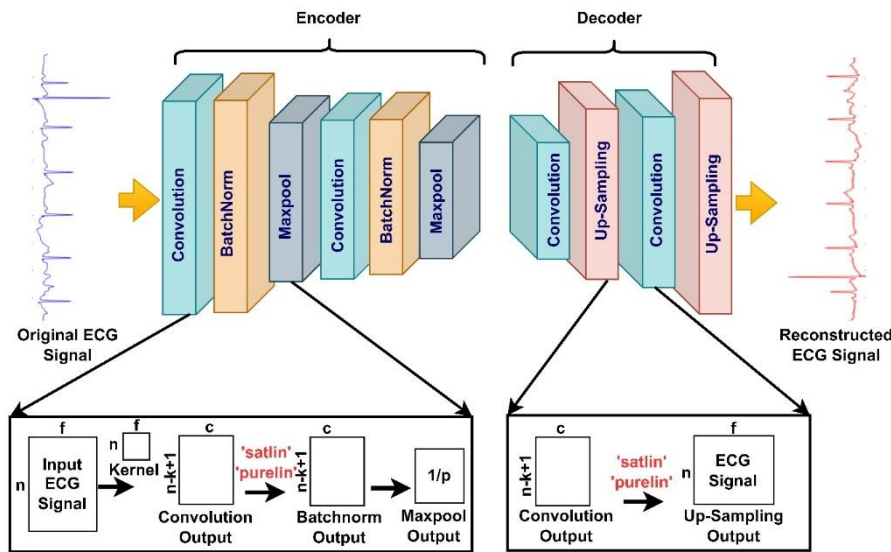


Figure 5: Architecture of Proposed Autoencoder Model

Figure 5 shows the complete architecture of autoencoder model.

Model Loss

The losses of the autoencoder model are measured during training to assess the quality of the training process. Minimal losses indicate accurate training of the model, indicating a minimal variance between the actual and predicted outputs. Conversely, higher losses suggest greater discrepancies between the actual and predicted outputs. The proposed experimental model addresses a regression problem and, therefore, utilizes Mean Squared Error (MSE) as the chosen loss function. The model's losses can be quantified using Equation 9.

$$MSE = \frac{1}{n} \sum_{j=1}^n (s_j - \hat{s}_j)^2 \quad (9)$$

Result Analysis

This section measures the performance of the proposed unsupervised autoencoder decoder model. The experimental results are carried out in MATLAB R2021b Software with Deep Learning Toolbox. The proposed model is trained on an Intel i5 processor, 16GB RAM, and 4GB Nvidia Graphics.

3.1 Performance Evaluation

The quality of the reconstructed signal should be clinically acceptable. The majority of ECG compression literature evaluates the global and local errors in the reconstructed signal using the following evaluation parameters. In the definitions symbols used are:

Compression Ratio (CR): CR in the context of ECG signal compression using unsupervised auto encoder decoder is a metric that quantifies the reduction in data size achieved through compression. The formula to calculate CR is straightforward:

$$Compression\ Ratio\ (CR) = \frac{Compressed\ Size\ of\ ECG\ Signal}{Original\ Size\ of\ ECG\ Signal} \quad (10)$$

Mean Square Error (MSE): The MSE is a metric utilized to measure the average of the squared differences between the initial uncompressed ECG signal and the reconstructed or compressed signal, achieved via unsupervised auto encoder decoder techniques. The computation for MSE is given by:

$$MSE = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2 \quad (11)$$

Where, n is the total number of data points in the ECG signal.

x_i represents the individual data point in the original uncompressed ECG signal.

\hat{x}_i represents the corresponding data point in the reconstructed/compressed signal obtained through unsupervised auto encoder decoder-based compression.

Normalized Mean Square Error (NMSE): NMSE is a statistical metric used to assess the accuracy and similarity between the original input ECG signal and the reconstructed signal. NMSE accounts for the scale of the signal and is particularly useful when comparing signals of varying magnitudes.

$$NMSE = \frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{\sum_{i=1}^n (x_i - \bar{x}_i)^2} \quad (12)$$

Root Mean Square Error (RMSE): RMSE is a commonly used metric to evaluate the accuracy of reconstructed signals in comparison to the original input ECG signal, particularly in cases involving unsupervised auto encoder decoder for compression. The formula to calculate RMSE is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{n}} \quad (13)$$

Percentage RMS Difference (PRD): The PRD is an evaluation used to assess the similarity between the original uncompressed ECG signal and the reconstructed signal obtained through unsupervised auto encoder decoder techniques.

$$PRD = \frac{\sqrt{\frac{\sum_{i=1}^n (x_i - \hat{x}_i)^2}{\sum_{i=1}^n x_i^2}}}{\sqrt{\frac{\sum_{i=1}^n x_i^2}{n}}} \quad (14)$$

PRD Normalized (PRDN): The PRDN is a variant of the Percentage RMS Difference (PRD) used to assess the similarity between the original input ECG signal and the reconstructed signal obtained through unsupervised auto encoder decoder techniques. The formula to calculate PRDN is:

$$PRDN = \frac{PRD \times Range_x}{100} \quad (15)$$

Signal to Noise Ratio (SNR): SNR calculates the proportion of the signal's useful power to the power of the background noise present in a signal. When assessing the quality of a reconstructed signal concerning the original signal and the noise added during compression, SNR is significant in ECG signal compression using unsupervised auto encoder decoder techniques. The equation 15 to compute SNR is:

$$SNR = 10 \cdot \log_{10} \left(\frac{Signal\ Power}{Noise\ Power} \right) \quad (16)$$

Peak Signal to Noise Ratio (PSNR): PSNR serves as a metric to assess the quality of a reconstructed signal by comparing it with the original signal. It determines the relationship between the highest potential power of a signal and the interference caused by noise, affecting its accuracy. In ECG signal compression using unsupervised auto encoder decoder, the PSNR is calculated using this equation 16:

$$PSNR = 10 \cdot \log_{10} \left(\frac{Max^2}{MSE} \right) \quad (17)$$

To assess the effectiveness of the proposed model, various test cases were conducted using the records available in the dataset. Figures 5 to 9 depict the original ECG signal alongside the reconstructed ECG signal. It is noteworthy that the reconstructed ECG signal closely resembles the original signal.

Table 1: Performance Analysis of Autoencoder Model

Records	CR	MSE	RMS	PRD	PRDN	SNR	QS
100	32.3	0.00006	0.008	1.67	45.57	15.85	19.31
101	32.5	0.00028	0.017	3.18	38.09	19.42	10.14

102	32.4	0.00010	0.009	1.50	32.89	18.76	26.87
103	32.2	0.00067	0.026	4.89	22.15	30.15	6.59
104	32.3	0.00012	0.011	2.16	37.30	19.83	14.93
105	32.2	0.00067	0.026	4.89	22.15	30.15	6.59
106	32.2	0.00010	0.010	1.85	51.22	13.53	17.43
107	32.6	0.00025	0.015	2.89	32.15	30.15	12.50
108	32.2	0.00078	0.028	5.39	31.40	23.43	5.98
109	32.2	0.00022	0.015	2.20	19.71	32.77	14.65
Average	32.31	0.00032	0.016	3.06	33.26	23.40	13.49

The table 1 represents the performance analysis of an Autoencoder model across multiple records (100 to 109). The CR measures the compression achieved by the autoencoder, with higher values indicating better compression. MSE and RMS evaluate reconstruction errors, with lower values indicating better performance. PSNR and PSNRN represent the quality of the reconstructed signal, with higher values indicating better quality. SNR measures signal quality, and QS is an overall quality score. The average values across these metrics for the records range from 32.2 to 32.6 for CR, 0.00006 to 0.00078 for MSE, 0.008 to 0.028 for RMS, 1.50 to 5.39 for PRD, 19.71 to 51.22 for PRDN, 13.53 to 32.77 for SNR, and 5.98 to 26.87 for QS, with average metrics summarized at the bottom of the table 1 for a holistic view of the model's performance.

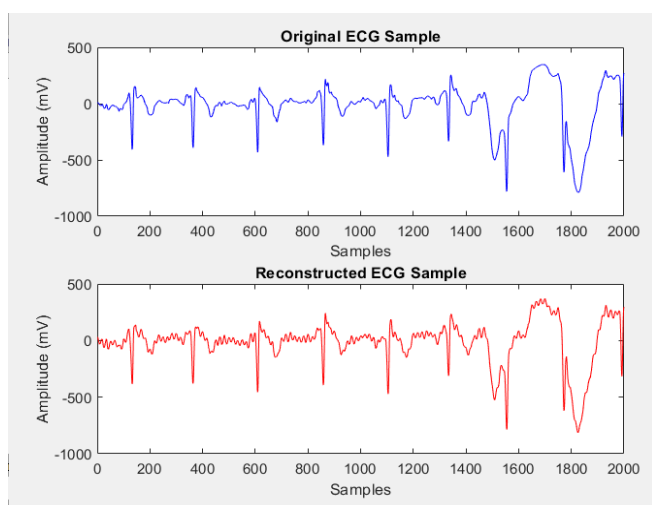


Figure 6: Original and Reconstructed ECG Signal over Record 100

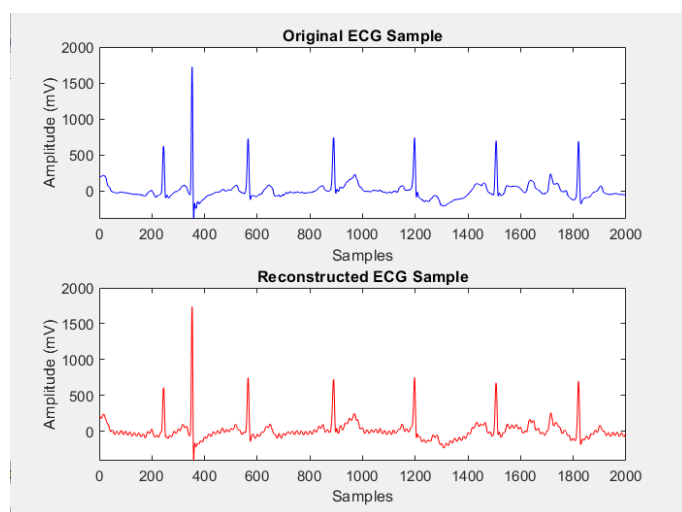


Figure 7: Original and Reconstructed ECG Signal over Record 101

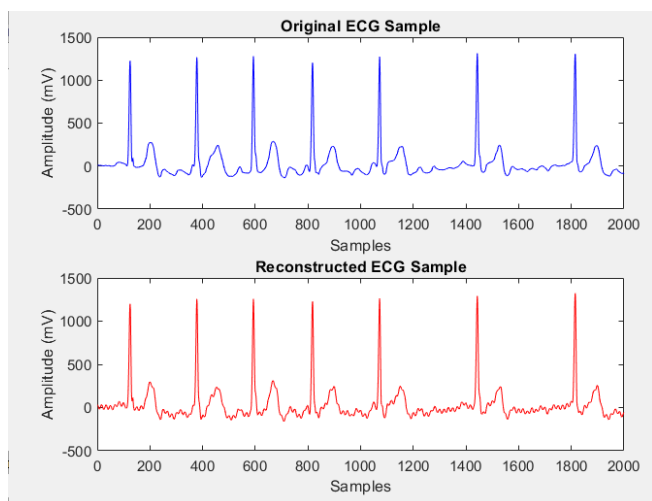


Figure 8: Original and Reconstructed ECG Signal over Record 102

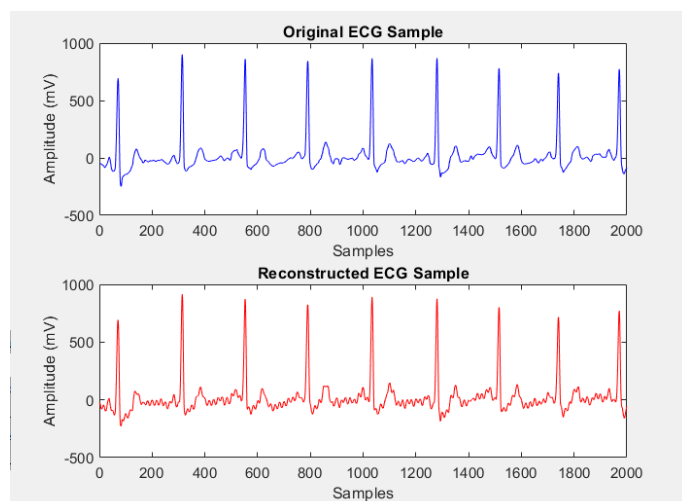


Figure 9: Original and Reconstructed ECG Signal over Record 103

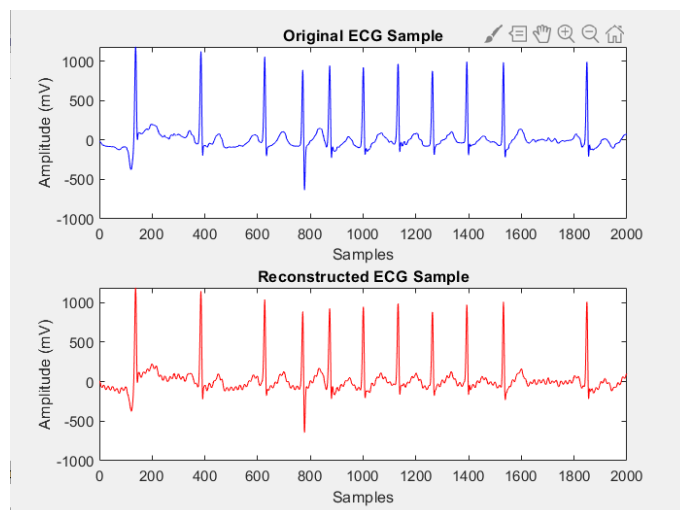


Figure 10: Original and Reconstructed ECG Signal over Record 104

Figures 6 to 10 display the original and reconstructed ECG signals from various records of the MIT-BIH dataset. The reconstructed ECG signals exhibit minor differences in amplitude and signal location. This clearly indicates that the quality of the reconstructed ECG signals approaches that of the original ECG signals. However, some distortion or noise is noticeable in the ECG signals.

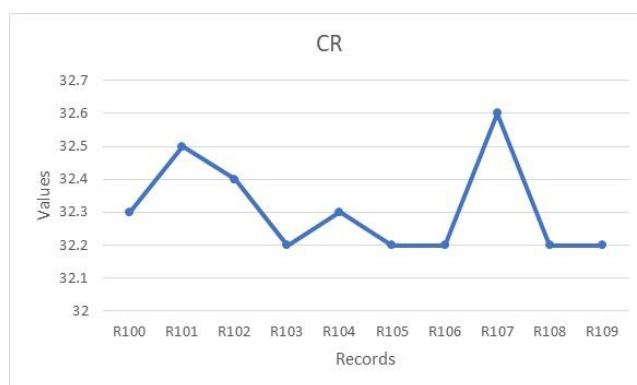


Figure 11: Compression Ratio of ECG Signal over 100 to 109 Records

The figure 11 depicts the Compression Ratio (CR) values of an ECG signal across records numbered from 100 to 109, with each record having its corresponding CR value. The Compression Ratio measures the extent of compression achieved by a data compression algorithm or model. In this specific case, the CR values range from 32.2 to 32.6 across the different records. The average CR value across these records is 32.31, which suggests that, on average, the compression technique applied to the ECG signal resulted in a compression ratio of approximately 32.31 times smaller than the original signal size. The graph provides a visual representation of how the CR varied across different instances of the ECG signal processing or compression, showcasing fluctuations and an overall average level of compression achieved.

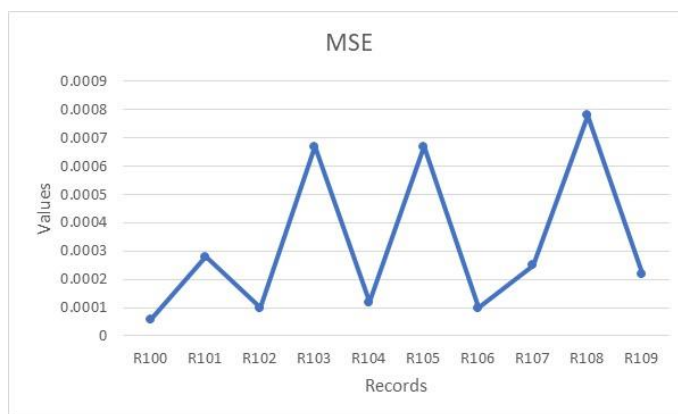


Figure 12: Mean Squared Error of ECG Signal over 100 to 109 Records

The figure 12 illustrates the Mean Squared Error (MSE) values associated with processing an ECG (Electrocardiogram) signal across records numbered from 100 to 109. MSE is a metric used to quantify the average squared difference between the original and reconstructed signals. In this context, the MSE values for the ECG signal vary across different records, ranging from 0.00006 to 0.00078. The graph visually represents how the MSE fluctuates across these records, indicating the level of fidelity or accuracy in signal reconstruction achieved by the processing or compression technique applied. The average MSE across these records is calculated as 0.00032, providing an overall measure of the typical squared error between the original and reconstructed ECG signal across multiple instances. A lower MSE value generally indicates better accuracy or similarity between the original and reconstructed signals.

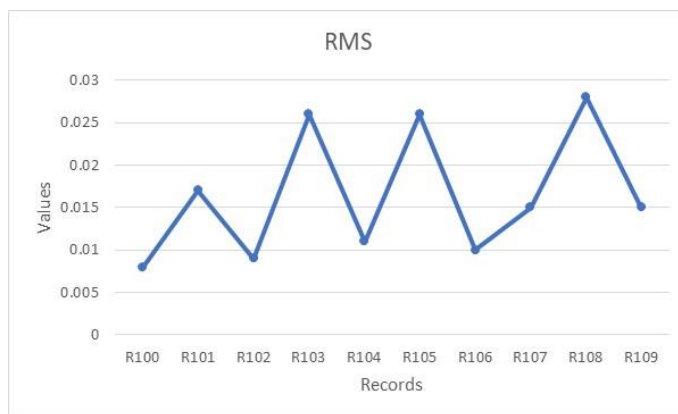


Figure 13: Root Mean Square of ECG Signal over 100 to 109 Records

The figure 13 visualizes the Root Mean Square (RMS) values associated with processing an ECG (Electrocardiogram) signal across records numbered from 100 to 109. The RMS values displayed in the figure 13 vary across different records, ranging from 0.008 to 0.028. These values reflect the magnitude of the deviation between the reconstructed and original ECG signals. Lower RMS values indicate less error in signal reconstruction, suggesting better accuracy of compression of proposed Model. The average RMS value across these records is calculated as 0.016, providing an overall measure of the typical root mean square error in the reconstructed ECG signal across multiple instances. The figure `13 visually shows how the RMS fluctuates across records, offering insights into the variation in the accuracy of the reconstructed ECG signals.

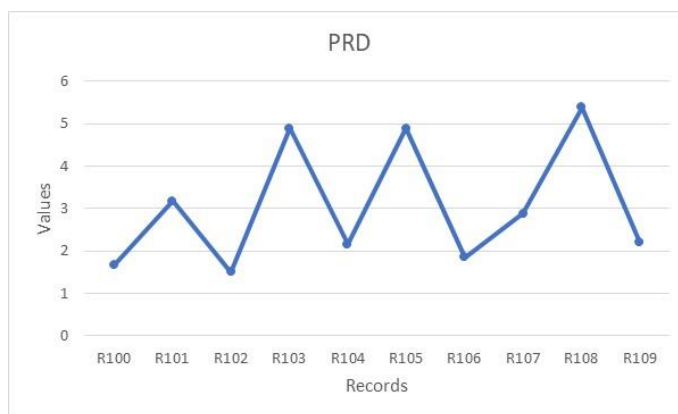


Figure 14: PRD of ECG Signal over 100 to 109 Records

The figure 14 illustrates the Peak Relative Difference (PRD) values associated with processing an ECG signal across records numbered from 100 to 109. the PRD values for the ECG signal vary across different records, ranging from 1.5 to 5.39. These values represent the maximum relative differences between the original and reconstructed ECG signals at their peak points. Higher PRD values indicate larger discrepancies or differences between the signals, suggesting lower similarity or accuracy in signal reconstruction. The average PRD value across these records is calculated as 3.06, providing an overall measure of the typical peak relative difference between the original and reconstructed ECG signals across multiple instances

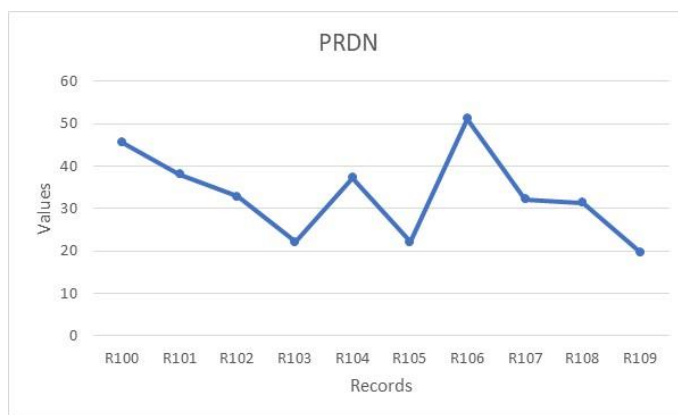


Figure 15: PRDN of ECG Signal over 100 to 109 Records

The figure 15 represents the Peak Signal-to-Noise Ratio Normalized (PRDN) values associated with processing an ECG signal across records numbered from 100 to 109. the PRDN values for the ECG

signal vary across different records, ranging from 19.71 to 51.22. These values represent the quality of the reconstructed signal, with higher PRDN values indicating better quality in terms of signal fidelity and lower noise in the reconstructed ECG signal compared to the original one. The average PRDN value across these records is calculated as 33.26, providing an overall measure of the typical quality, in terms of signal-to-noise ratio normalization, achieved in the reconstructed ECG signals across multiple instances.

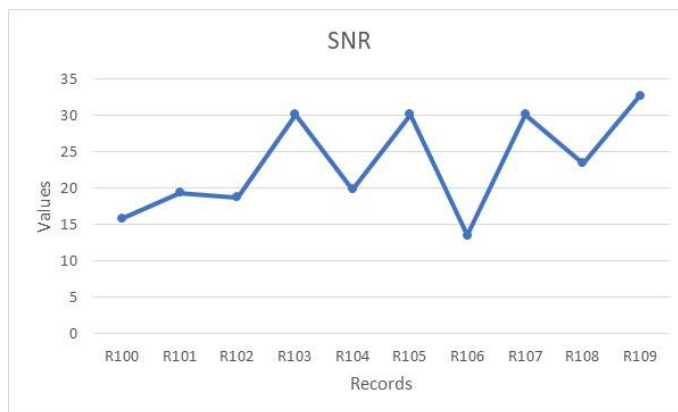


Figure 16: SNR of ECG Signal over 100 to 109 Records

The figure 16 displays the Signal-to-Noise Ratio (SNR) values associated with processing an ECG signal across records numbered from 100 to 109. SNR is a measure used to assess the quality of a signal by comparing the level of the desired signal. The SNR values for the ECG signal vary across different records, ranging from 13.53 to 32.77. These values represent the ratio between the strength of the ECG signal and the level of background noise. The average SNR value across these records is calculated as 23.4, providing an overall measure of the typical signal-to-noise ratio achieved in the reconstructed ECG signals across multiple instances.

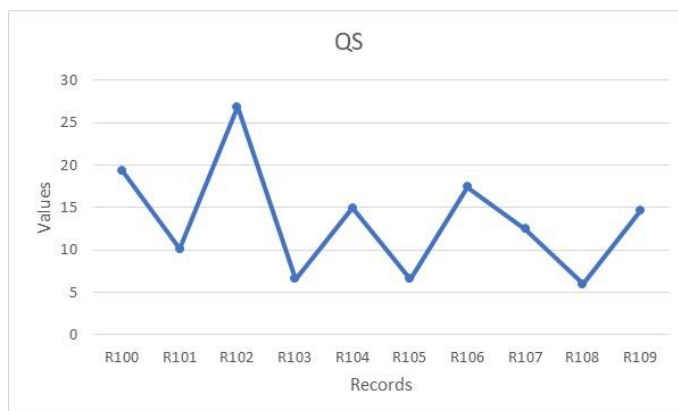


Figure 17: QS of ECG Signal over 100 to 109 Records

The Figure 17 shows the Quality Score (QS) values associated with processing an ECG signal across records numbered from 100 to 109. QS is a comprehensive metric used to evaluate the overall quality or performance of a reconstructed signal. the QS values for the ECG signal vary significantly across different records, ranging from 5.98 to 26.87. These values represent an overall assessment of the reconstructed signal quality, with higher QS values indicating better overall performance or quality in terms of fidelity, accuracy, and noise reduction in the reconstructed ECG signal. The

average QS value across these records is calculated as 13.49, providing an overall measure of the typical quality achieved in the reconstructed ECG signals.

Table 2: Comparative Result Analysis of Proposed Autoencoder with existing State-of-art Methods

Author	Method	CR	PRD	PRDN	QS
Oussama El B'charri et. al [27]	DWT	12.63	5.78	16.20	3.78
Peng Z. et. al. [28]	EZW	9.26	8.16	-	1.14
Chandan K.J. et. al. [29]	OCT	6.28	5.36	7.94	1.50
Mukhopadhyay et. al. [30]	ASCII character encoding	26.68	8.00	8.00	64.35
Ozal Yildirim et. al. [31]	Deep Convolutional Autoencoders	32.24	2.73	31.16	12.80
Thivaagar Thamil Selvan et. al. [32]	Non-linear Predictor and ASCII Character Encoding	2.37	0.0	-	-
Proposed	WT-AutoEncoder	32.31	3.06	23.40	13.49

The table 2 presents a comparative analysis of the proposed WT-AutoEncoder model against existing state-of-the-art methods for ECG signal compression. Various authors and their respective methods, including Discrete Wavelet Transform (DWT), Embedded Zero-tree Wavelet (EZW), Optimal Compression Trees (OCT), ASCII character encoding, Deep Convolutional Autoencoders, Non-linear Predictor, and ASCII Character Encoding, are evaluated based on different metrics. The proposed WT-AutoEncoder demonstrates results compared to these methods, this shows a Compression Ratio (CR) of 32.31, Peak Relative Difference (PRD) of 3.06, Peak Signal-to-Noise Ratio Normalized (PRDN) of 23.40, and a Quality Score (QS) of 13.49. It is clearly shows that WT-AutoEncoder achieves a high CR comparable to the best-performing Deep Convolutional Autoencoders by Ozal Yildirim et al. [31], while also maintaining favorable PRD, PRDN, and QS, indicating its potential as an efficient and accurate method for compressing ECG signals when compared to other existing techniques in the field of signal compression.

4. Discussion and Conclusion

Biomedical research's cornerstone resides in biomedical signal processing and analysis technology. Recent years have witnessed a surge in biomedical disciplines, such as signal compression for sensitive medical data transmission, significantly escalating the demand for extensive, multi-modal biomedical signal processing in this field. Relying solely on traditional signal compression methods by researchers has proven insufficient in meeting the requirements for a high compression ratio due to this rapid expansion. To effectively address the challenge of compressing and reconstructing biomedical ECG signals with a high compression ratio, this study integrates deep learning techniques into ECG signal processing. It introduces an ECG signal compression and reconstruction model employing autoencoders and wavelet transforms for enhanced performance. The model employs the encoder segment to eliminate redundant features and compress the waveform in layers. Subsequently, the decoder section rebuilds the ECG signal based on the minimally compressed features. This approach involves decomposing the ECG signal, implementing thresholding, and encoding the resulting data. The proposed model underwent testing on the publicly available MIT-BIH arrhythmia signals dataset obtained from the Physionet international database. The Autoencoder

with wavelet transform model automatically extracts relevant features from the ECG signal, efficiently encodes the signal, and effectively reconstructs the ECG signal through the decoding section. The model's performance is assessed using various evaluation parameters such as CR, PRD, PRDN, and QS. The proposed model's testing on specific records (100-109) demonstrated an average compression ratio of 32.31, PRDN of 33.26, PRD of 3.06, and QS of 13.49.

The future scope for ECG signal compression in deep learning encompasses the development of highly efficient and adaptable models tailored for real-time, resource-constrained environments like wearable devices and remote monitoring systems. Advancements will focus on creating deep neural network architectures specifically optimized for ECG signals, integrating novel techniques such as attention mechanisms, reinforcement learning, or spatiotemporal models to improve compression performance. Additionally, there will be a shift towards privacy-preserving techniques ensuring robust encryption during data transmission. Exploring multi-modal fusion with other physiological signals and standardizing compression techniques for interoperability across various healthcare systems will also be critical.

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