Comparative Research on ECG Image Compression: Assessing Diagnostic Integrity

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**Abstract.** Electrocardiogram images have been widely used in the medical field in recent years, but their high sampling rate and long recording time require a lot of resources to transmit and store, so their popularity is still limited. This study aims to compress the file size of electrocardiogram images while maintaining complete diagnostic. In this study, lossy and lossless compression methods and hybrid methods based on bilateral and entropy coding are compared to obtain the most ideal method to reduce the burden of using electrocardiogram images. This study will evaluate the effectiveness of each method based on compression ratio (CR), peak signal-to-noise ratio (PSNR), structural similarity index metric (SSIM) and percentage root mean square difference (PRD) and processing time.

# INTRODUCTION

Electrocardiogram images, also known as ECG images, are recorded by recording the electrical activity of the heart. They are often used to detect and diagnose cardiovascular diseases. ECG images usually contain waveforms such as P waves, QRS complexes, and T waves. Because recording ECG images requires extremely high sampling rates and long-term monitoring, ECG recordings generate a large amount of data, which means that a lot of resources are required for storage and transmission. In order to alleviate this problem, different compression methods are usually used to compress it to reduce the size of the data. Compression methods are divided into two categories: lossy compression and lossless compression. The former retains the original data and can ensure complete diagnostic but has a lower compression rate. The latter removes minor information to achieve a high compression rate but may cause the loss of information and lose complete diagnostic. This project aims to apply and evaluate multiple ECG image compression methods, including single and hybrid methods, to identify the optimization technique that achieves the best balance between compression efficiency and diagnostic relevance.

# LITERATURE REVIEW

Lossless compression works by identifying redundant data in a file and removing it without deleting any important information in the process. Secondly, it also rearranges the data well to better reduce the space required. While this can maintain good integrity and reconstruct the original file, since only redundant data is identified, removed, and rearranged during the compression process, the file size does not change much after compression, which means that the compression ratio is lower than lossy compression [1]. However, since it guarantees the integrity of the data, it is often used for more important files, software, or images, such as Zip Archive File (ZIP), Portable Network Graphic (PNG) (for images), Free Lossless Audio Codec (FLAC) (for audio). The more common lossless compression method is predictive coding and Context Adaptive Lossless Image Compression (CALIC).

Compared to lossless compression, lossy compression can achieve a very high compression ratio, which means that the compressed file size is smaller. This is because lossy compression reduces the file size by discarding some unimportant data. It identifies some data that is not easily perceived by humans, such as colour changes, high and low frequencies of audio, and then permanently deletes these imperceptible data [2]. This will cause the quality of the file to deteriorate after compression. Therefore, lossless compression is generally applied to some image, audio, or video files whose file quality degradation is within an acceptable range, to reduce the space required for storage and the bandwidth required for transmission by reducing the file size. Its common method is Wavelet Transform (WT) [3].

In terms of principle and effect, entropy coding is one of the lossless data compression technologies. Its basic principle is to greatly improve the coding efficiency of data by assigning shorter codes to symbols with higher frequency, and vice versa, assigning longer codes to symbols with lower frequency. Thanks to the fact that entropy coding does not compress by deleting some unimportant data, there will be no information or data loss in the compressed file [4]. In the early stage of work, it will determine the probability distribution of each symbol by analysing the data. Then in the encoding stage, the distribution of the code will be used to divide the binary code. For example, Huffman coding or arithmetic coding. For Huffman coding, it will construct binary numbers according to the frequency of occurrence. Those symbols with higher frequency will be placed near the root and can be assigned shorter binary codes [5]. Arithmetic coding is to encode the entire message as a single number from 0 to 1 and then divide the range according to the probability iteration of the symbol [6]. But it also has some limitations. For example, its overall effect depends on the uniformity of symbol distribution. When the symbol distribution is more uniform or unpredictable, it will affect the overall performance and decrease. Secondly, although the performance of arithmetic coding is better than that of Huffman coding, it also means that its computational complexity is relatively higher, which means that more computing resources are required to use this arithmetic coding.

## Related Work

Bekiryazıcı et al [7]proposed a deep learning-based convolutional autoencoder (CAE) model for ECG compression. The goal is to achieve a high compression rate while ensuring a fixed error rate for accurate diagnosis. An encoder in the CAE compresses the data and multiple decoders reconstruct the signal at different compression rates. This model also uses a series of processes such as quantization and Huffman Coding to improve the compression rate. When training the model, a large dataset is used for training and then a small dataset is used for overall fine-tuning. After evaluation using the MIT-BIH Arrhythmia Database and the PTB-XL dataset, this model achieved an average compression rate of 13.02:1 at a normalized root mean square difference (PRDN) error rate of 10%. However, its high computational complexity may be limiting when used on devices with limited processing power.

Cao and Yi [8] used discrete wavelet transform (DWT) and transform run length encoding (VL-RLE) to compress ECG. To reduce storage requirements and improve the transmission efficiency of wearable ECG monitoring systems. They used DWT to decompose the original ECG signal to obtain transform coefficients and then quantized the decomposed change coefficients by using dead quantization. The overall threshold was determined based on energy packaging efficiency. Then, VL-RLE was used to dequantize the non-quantized coefficients. In terms of performance, a compression ratio (CR) of 20.48 and a root mean square error percentage (PRD) of 0.47% were obtained after evaluating the ECG using the MIT-BIH arrhythmia database. Therefore, it is known that this method achieves a good compression ratio while maintaining signal quality.

Sharma et al [2] effectively reduce the storage space required by the remote ECG system for cardiac diagnosis and analysis, they evaluate and compare different ECG compression techniques. The techniques used in this paper include discrete cosine transform (DCT), DCT2, DCT3, fast Fourier transform (FFT), FFT2, Chirp Z Transform (CZT) and Complex Cepstral Analysis. To be fair, the ECG signals in the MIT-BIH arrhythmia database were used in this test for overall testing, and then the Compression Ratio (CR), Percent Root Mean Square Difference (PRD), Quality Score (QS), Root Mean Square Error (RMS), and Signal to Noise Ratio (SNR) were used for overall performance evaluation. After further experiments, a higher compression ratio is obtained in FFT. The compression ratio of 98.16 in 205 of the databases means that it can retain basic diagnostic information while compressing the ECG signal.

Kaushal et al [9]proposed a performance analysis of four different transforms (Fast Fourier Transform (FFT), Discrete Hartree Transform (DHT), Discrete Cosine Transform (DCT) and Discrete Sine Transform (DST)) applied to ECG compression. First, they obtained ECG data from the MIT-BIH Arrhythmia Database. After preprocessing the collected data using Python in Visual Studio, the processed signal was used as the input signal to calculate its N-point transform. The N outputs will be truncated to a compression ratio (CR) of length L. The low-order harmonics are retained, and the high-order harmonics are discarded. Then reconstruction and inverse transformation calculations are performed to obtain the reconstructed signal. After testing, it can be found that among the four transforms, the discrete cosine transform (DCT) has the best performance, PRD: 4.8, CR: 5.14 and SNR: 26.36. Although it is known that DCT has the best effect, considering the high computational complexity of the transform, it may limit the use of some devices with limited processing power.

# Methodology

This study investigates and compares multiple ECG image compression methods, both lossy and lossless, to assess their performance in preserving diagnostic quality while optimizing data size. The compression techniques applied include Discrete Wavelet Transform (DWT), Convolutional Autoencoder (CAE), Context-Based Adaptive Lossless Image Compression (CALIC), Huffman Coding (HC), and Arithmetic Coding (AC). Each method is implemented independently using a standardized ECG image dataset to ensure consistency in evaluation.

Discrete Wavelet Transform (DWT) is a lossy compression method based on multi-resolution decomposition. The ECG image is decomposed into six levels of approximation and detail coefficients using the Daubechies-4 wavelet. A dynamic threshold is applied to retain only the top 20% of coefficients, effectively discarding the remaining coefficients to reduce redundancy. During reconstruction, adaptive adjustments are made to accommodate varying ECG image resolutions. The final output is saved in PNG format to preserve clinical readability.

Convolutional Autoencoder (CAE) employs a neural network with an encoder-decoder architecture for lossy compression. The encoder consists of three convolutional layers that progressively reduce the spatial dimensions of the ECG image. The decoder uses transposed convolution layers to reconstruct the image. The model is trained for 40 epochs using the Mean Squared Error (MSE) loss function and the Adam optimizer. Input images are normalized to the range [-1, 1], and the Tanh activation function is applied to the output. The trained model weights are saved in a .pth file to enable efficient inference during testing.

Context-Based Adaptive Lossless Image Compression (CALIC) is a lossless compression algorithm that uses Gradient-Adjusted Prediction (GAP). It predicts pixel values based on local gradients and neighboring pixel relationships. Prediction errors are quantized into 256 adaptive contexts based on a custom threshold array (thre = [5, 15, ..., 140]) tailored for ECG waveform characteristics. Context counters maintain error statistics and perform normalization to prevent overflow, ensuring accurate image reconstruction and sensitivity to subtle waveform variations.

Huffman Coding (HC) is a lossless entropy coding technique that assigns variable-length prefix codes to symbols based on frequency. A priority queue is used to construct a Huffman tree, which merges nodes with the lowest frequencies. The 8-bit gray pixel values from flattened ECG images are mapped to their frequencies to generate efficient codes, particularly effective for repetitive waveform patterns. Decompression is performed by reversing the encoded bitstream using the constructed Huffman tree.

Arithmetic Coding (AC) is another entropy-based lossless compression method that encodes data as intervals on the number line based on symbol probabilities. ECG images are divided into 32 × 32 pixel blocks to balance memory efficiency and computation accuracy. Laplace smoothing is applied to avoid zero-probability issues, and a 200-bit precision arithmetic model is used to prevent underflow. The resulting compressed data, including code blocks and metadata, are serialized using Python’s pickle module to ensure accurate reconstruction.

Each method is applied to the same ECG dataset, called MIT-BIH Arrhythmia. This database is usually used for research and development on arrhythmias or testing a series of electrocardiogram analysis algorithms. This database contains normal and arrhythmic heartbeats, totalling 48 and a half hours of two-lead electrocardiogram records. The data comes from 47 patients examined at Boston Beth Israel Hospital between 1875 and 1979. Each data set has an annotation of the beat and heart rate by an expert. This allows the identification of arrhythmias, beat types, and signal characteristics through expert annotations. The signal sampling frequency collected in the data set is 360 Hz. And within the range of 10 mV, so the sampling frequency is 11 bits each time13.

Performance is evaluated based on compression ratio, reconstruction quality (e.g., PSNR and SSIM), and preservation of diagnostic features. To evaluate the effectiveness of each compression method, several performance metrics are used to assess both compression efficiency and the preservation of diagnostic image quality (refer to Table 1). Each method is evaluated using these metrics to provide a comprehensive assessment of its ability to compress ECG images effectively while preserving the critical information necessary for clinical interpretation.

**TABLE 1.** Performance metrics

|  |  |
| --- | --- |
| **Performance Metric** | **Description** |
| Compression Ratio (CR) | Compression Ratio is calculated as the ratio of the size of the original image to the size of the compressed image. A higher CR indicates more efficient compression. This metric is essential for understanding how well the method reduces storage and transmission demands [10]. |
| Peak Signal-to-Noise Ratio (PSNR) | PSNR can measure the error between the original image and the compressed image. It will quantify the overall compression performance with a numerical value and is measured in decibels (dB). The PSNR judgment method is that when the decibel value is higher, the quality of the reconstruction is better, which means the distortion is lower [11]. |
| Percentage Root Mean Square Difference (PRD) | The role of PRD is to calculate the difference between the original image and the compressed image, that is, the distortion value. The smaller the percentage of PRD, the higher the fidelity, which can ensure the overall good diagnostic performance [12]. |
| Structural Similarity Index Measure (SSIM) | The use of SSIM is based on the observation method close to that of humans and can be well applied to evaluate the visual integrity of the compressed ECG images. It will be based on the similarity between the brightness, contrast and structure of the compressed image and the original image. This can ensure the complete diagnostic of the compressed ECG image [11]. |

# Performance AND DISCUSSION

## Performance

In all tests, 48 different ECGs from MIT-BIH were used [13]. All images were captured within the first ten seconds. CR, PSNR, SSIM, PRD, and duration for the highest, lowest, and overall average values from the 48 results are tabulated in Tables 2, 3, 4, 5, and 6, respectively.

|  |  |  |  |
| --- | --- | --- | --- |
| **TABLE 2.** Compression Ratio (CR) for highest, lowest, average from 48 results from each 9 compression methods | | | |
| **Method** | **Highest** | **Lowest** | **Average** |
| DWT | 2.229407995 | 1.885843466 | 2.051875846 |
| DWT + HC | 2.550480428 | 2.223116267 | 2.410194468 |
| DWT + AC | 2.550480428 | 2.223116267 | 2.410194468 |
| CAE | 1.880390874 | 1.51660603 | 1.674583014 |
| CAE + HC | 1.880825028 | 1.516315678 | 1.674637072 |
| CAE + AC | 1.880390874 | 1.51660603 | 1.674583014 |
| CALIC | 1.972688999 | 1.728677095 | 1.843308237 |
| CALIC + HC | 2.253961926 | 1.912275995 | 2.056919063 |
| CALIC + AC | 2.253961926 | 1.912275995 | 2.056919063 |
| **TABLE 3.** Peak Signal-to-Noise Ratio (PSNR) for highest, lowest, average from 48 results from each 9 compression methods | | | |
| **Method** | **Highest (dB)** | **Lowest (dB)** | **Average (dB)** |
| DWT | 76.86145995 | 72.48567241 | 74.59360093 |
| DWT + HC | 52.28189562 | 46.97930925 | 49.44729472 |
| DWT + AC | 52.28189562 | 46.97930925 | 49.44729472 |
| CAE | 35.66705063 | 31.74453509 | 34.08279602 |
| CAE + HC | 35.6677031 | 31.74488579 | 34.08285297 |
| CAE + AC | 35.66705063 | 31.74453509 | 34.08279602 |
| CALIC | 27.40025594 | 23.62384888 | 25.08729597 |
| CALIC + HC | infinity | infinity | infinity |
| CALIC + AC | infinity | infinity | infinity |
| **TABLE 4.** Structural Similarity Index Measure (SSIM) for highest, lowest, average from 48 results from each 9 compressions method | | | |
| **Method** | **Highest** | **Lowest** | **Average** |
| DWT | 0.999997451 | 0.999992384 | 0.999995697 |
| DWT + HC | 0.999455434 | 0.998580357 | 0.999112607 |
| DWT + AC | 0.999455434 | 0.998580357 | 0.999108934 |
| CAE | 0.996283799 | 0.991588871 | 0.994924162 |
| CAE + HC | 0.996284709 | 0.991589874 | 0.99492418 |
| CAE + AC | 0.996283799 | 0.991588871 | 0.994924162 |
| CALIC | 0.985062953 | 0.970376611 | 0.97899445 |
| CALIC + HC | 1 | 1 | 1 |
| CALIC + AC | 1 | 1 | 1 |
| **TABLE 5.** Percentage Root Mean Square Different (PRD) for highest, lowest, average from 48 results from each 9 compression methods | | | |
| **Method** | **Highest (%)** | **Lowest (%)** | **Average (%)** |
| DWT | 0.02503505 | 0.014638318 | 0.019365613 |
| DWT + HC | 0.471918078 | 0.248856036 | 0.351531203 |
| DWT + AC | 0.471918078 | 0.248856036 | 0.351531203 |
| CAE | 2.726498873 | 1.681093582 | 2.048052779 |
| CAE + HC | 2.726388792 | 1.680967304 | 2.048040464 |
| CAE + AC | 2.726498873 | 1.681093582 | 2.048052779 |
| CALIC | 6.803990781 | 4.393758011 | 5.757306998 |
| CALIC + HC | 0 | 0 | 0 |
| CALIC + AC | 0 | 0 | 0 |

|  |  |  |  |
| --- | --- | --- | --- |
| **TABLE 6.** Duration for highest, lowest, average from 48 results from each 9 compressions methods | | | |
| **Method** | **Highest (sec)** | **Lowest (sec)** | **Average (sec)** |
| DWT | 0.06990242 | 0.037111521 | 0.04824168 |
| DWT + HC | 2.097971678 | 1.602782488 | 1.727038369 |
| DWT + AC | 327.0455456 | 223.8088398 | 258.4581777 |
| CAE | 0.021710157 | 0.007456064 | 0.01208367 |
| CAE + HC | 0.50706172 | 0.343387365 | 0.374580353 |
| CAE + AC | 0.151028156 | 0.077765226 | 0.091409052 |
| CALIC | 4.196611881 | 3.915789366 | 4.023735151 |
| CALIC + HC | 2.733147383 | 2.684987068 | 2.707456142 |
| CALIC + AC | 11.7858088 | 10.95532084 | 11.24748172 |

## Discussion

After testing and evaluating all compression methods and combinations, it can be found that the performance indicators of each method are very different. The hybrid method of discrete wavelet transforms (DWT), and entropy coding (Huffman coding or arithmetic coding) can obtain the highest compression ratio (CR: 2.41) among all, which means that the overall integrity is preserved while the overall redundancy is well reduced. However, the single DWT also shows the best signal fidelity, with the highest peak signal-to-noise ratio (PSNR: 74.59 dB) and structural similarity index (SSIM: 0.9999), as well as the lowest root mean square difference percentage (PRD: 0.019%). This shows that DWT can well balance compression efficiency and minimal distortion.

In comparison, it can be found that the overall processing time of Convolutional Autoencoder (CAE) is the fastest (average 0.012 seconds) but its CR is lower (average 1.67), but it also has a higher PRD (average 2.05%), which shows that it is a trade-off between speed and reconstruction quality. CAE, a deep learning method, can achieve fast compression but the lower fidelity may affect clinical applications.

CALIC is the only lossless compression method in the basic compression in this study, which achieves perfect reconstruction (PRD: 0%, SSIM: 1, PSNR: infinity) when used in combination with entropy coding. However, when CALIC is run independently, its CR value (average: 1.84) and long calculation time (average: 4.02 seconds) indicate that although it has more integrity than other lossy compression methods, it is slightly inferior in efficiency and compression ratio.

In this study, it can be found that entropy coding can greatly improve the compression ratio of lossy compression. For example, the overall CR of DWT + HC/AC increased by 17%, but it was also found that PRD increased and SSIM values decreased. Compared with Huffman coding, arithmetic coding (AC) takes longer processing time. For example, DWT + AC takes 258.46 seconds, but DWT + HC only takes 1.73 seconds. It also shows that arithmetic coding requires a higher computational cost to use it.

# CONCLUSION

This study evaluated eight ECG compression methods. In terms of balancing diagnostic completeness and efficiency, discrete wavelet transforms (DWT) and Huffman Coding and hybrid were found to be the best lossy methods, achieving a high compression ratio (CR: 2.41) while also obtaining minimal distortion (PRD: 0.35%, SSIM: 0.9991). Although CALIC and entropy coding hybrid methods can achieve perfect reconstruction, the compression ratio is not as good as other hybrid methods. In addition, although CAE has a faster processing speed, it still needs to be improved to improve completeness. In summary, the choice between different methods should depend on clinical considerations: lossy compression technology can be preferred for efficient transmission and storage, and lossless compression technology is recommended for critical diagnosis. In future work, the use of hybrid models should be explored in depth, which may be able to get just the right compression, accuracy and overall speed.

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