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Research Article

Enhancement of Discrete Wavelet Transform Algorithm Applied in Medical Image Compression

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ABSTRACT

The Discrete Wavelet Transform (DWT) is a widely adopted technique in medical image compression for its ability to capture spatial and frequency characteristics. Clinical diagnosis may be impacted by distortions and the loss of important details caused by DWT's inability to preserve phase information, which is crucial for keeping the alignment of edges and textures in images. By incorporating a trained Autoencoder to learn and preserve essential image features for improved reconstruction, this limitation is addressed effectively. The Autoencoder comprises an encoder with convolutional layers using non-separable filters to enforce orthogonality, and a decoder with trans-posed convolutions for image reconstruction. JPEG2000 was employed as the compression technique, with the proposed method achieving a similar compression ratio to traditional DWT, indicating no compromise in efficiency. The results show that the enhanced DWT with autoencoder significantly out-performs the traditional DWT method, achieving up to 61.90% improvement in Peak Signal-to-Noise Ratio (PSNR), thereby reducing distortions and preserving critical image details more effectively. This improvement is crucial for maintaining the integrity and diagnostic quality of medical images, ensuring that essential features are accurately represented.

Keywords: Autoencoder, Discrete Wavelet Transform, Image Compression, Medical Images, Wavelets.

INTRODUCTION

The advancement of digital imaging technology has significantly increased the demand for efficient image compression methods, as digitized images, videos, and audios have led to a substantial rise in data storage requirements. With the rapid advancement of digital image processing technologies and the widespread adoption of the Internet, digital images are now utilized in numerous applications, including medical imaging. [1]. Representing even one digital image often requires a large number of bits, and as sensor and digital technology advances, this requirement increases with each new product generation. Furthermore, the number of digital images created each day increases as more applications are developed. To efficiently utilize digital images, specialized techniques are required to minimize the number of bits needed for their representation. The branch of digital image processing that deals with this problem is called image compression.

Among the various techniques, wavelet transform has emerged as a highly effective method for image compression because it enables the representation of data at different levels of detail. The wavelet transform (WT) relies on wavelets to decompose a signal (or image) into various frequency components across multiple resolution scales, enabling the simultaneous analysis of the image's spatial and frequency characteristics.

Discrete wavelet transform algorithms have become widely used in discrete-time signal and image processing across various research fields and industries [2]. It transforms data into different frequency components, allowing each component to be analyzed with a resolution that matches its scale. It is widely used in image compression techniques, such as JPEG2000. JPEG2000 utilizes DWT to achieve superior compression ratios compared to its predecessor, JPEG, while maintaining high image quality. Despite its advantages, DWT presents certain drawbacks when utilized in image compression. DWT lacks phase information, which is crucial for accurately representing fine details and textures in images. The absence of phase information in DWT means that while it effectively captures the magnitude of signal components, it fails to preserve the relative alignment and orientation of features within an image. This can lead to distortions and misalignment in reconstructed images, particularly affecting areas with fine textures or intricate details.

Medical Imaging

One industry that produces enormous amounts of digital images every day is the medical industry. According to [3], medical imaging encompasses various techniques used to visualize the human body for diagnosing, treating, and monitoring medical conditions. Medical imaging has a critical role in contemporary clinical diagnosis, as previous research has linked imaging technology to longer life expectancy, declines in mortality and hospital admissions, as well as shorter hospital stays [4]. Hospitals and clinics utilize advanced medical imaging technologies, such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and traditional radiography—conducted through computed radiography (CR) and digital radiography (DR)—to capture digital images of the human body for medical diagnostics and services. These images are typically very large in size, and it leads to an increasingly heavy burden for data storage and transmission via the Internet. Considering the substantial volume of data produced by imaging systems, implementing effective compression techniques becomes essential, and would greatly reduce the data storage and transmission requirements. In medical imaging where any loss in data may lead to incorrect prediction or diagnosis, lossless compression methods are used.

Every image contains redundancy, meaning there is a repetition of data within the image [5]. This could involve recurring pixels or patterns that appear frequently throughout the image. Image compression algorithms exploit these redundancies to compress images, and they usually have two main parts, the encoding and decoding process. As mentioned in [6], the encoding process transforms the source image data file into a compressed format and is structured into three fundamental steps: transformation, quantization, and entropy coding. Conversely, the decoding process reconstructs the compressed image data back into its original form, essentially reversing the steps of the encoding process.

Wavelet-based compression

Wavelet-based compression is extensively utilized in medical imaging due to its capacity to manage large image sizes while preserving essential diagnostic details. It is stated in [7] that modern compression techniques utilizing wavelet transforms have the potential to revolutionize the medical field. Furthermore, [8] highlights that lossless wavelet-based image compression enhances accuracy and lowers bit rates, thereby improving compression efficiency for storing and transmitting medical images. This approach ensures that the image quality remains suitable for diagnostic use.

One widely used wavelet-based compression technique in medical imaging is JPEG2000, due to its superior compression efficiency and flexibility. The adoption of JPEG2000 in the Digital Imaging and Communications in Medicine (DICOM) standard underscores its significance in healthcare. DICOM incorporated JPEG2000 as an encapsulation format in 2002, facilitating efficient storage and transmission of medical images. This integration allows for seamless interoperability among medical imaging devices and systems, enhancing the efficiency of medical data management [6]. JPEG2000 employs discrete wavelet transform, enabling both lossless and lossy compression. This dual capability ensures that critical diagnostic details are preserved, which is essential for accurate medical analysis.

Discrete Wavelet Transform

Discrete wavelet transform algorithms have emerged as essential tools in various research and industrial applications for processing discrete-time signals and images [2]. It transforms data into various frequency components, enabling each component to be examined with a resolution appropriate to its scale. It is a step-by-step computational procedure used to transform a signal from the time (or spatial) domain into the wavelet domain. DWT is an outstanding tool for multi-resolution analysis, allowing signals to be decomposed into various sub bands that contain both time and frequency information [9].

The standard 1D DWT operates by analyzing the signal at multiple levels of detail, enabling efficient representation of both high and low-frequency components. The process begins with the input signal being passed through a series of filters to separate the signal into two distinct parts: low-frequency (approximation) components and high-frequency (detail) components. Figure 1 illustrates the process of 1D Discrete Wavelet Transform [10].

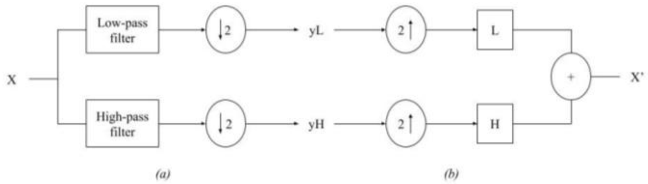


Figure 1. 1D Discrete Wavelet Transform. (a) Decomposition. (b) Reconstruction.

In the decomposition stage, Figure 1 (a), the input signal X is filtered into low-frequency (approximation) and high-frequency (detail) components using low-pass and high-pass filters, respectively. These components are then down sampled by a factor of 2 to reduce data size. Approximation coefficients capture the signal's general structure, while detail coefficients highlight fine features. In the reconstruction stage, Figure 1 (b), the original signal is reconstructed by up sampling and filtering these components using synthesis filters.

Images are considered two-dimensional signals, varying both horizontally and vertically. As a result, 2D wavelet transform is necessary for processing images. The JPEG2000 standard and other image coding techniques make use of the separable 2D DWT, which is only an extension of the 1D DWT applied independently to an image's rows and columns.

According to [10], the method for applying 2D Discrete Wavelet Transform (DWT) on images is to first apply DWT in the row direction, then another DWT in the column direction. This is illustrated in Figure 2.

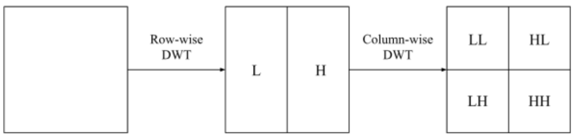


Figure 2. Two-dimensional row and column computation of DWT

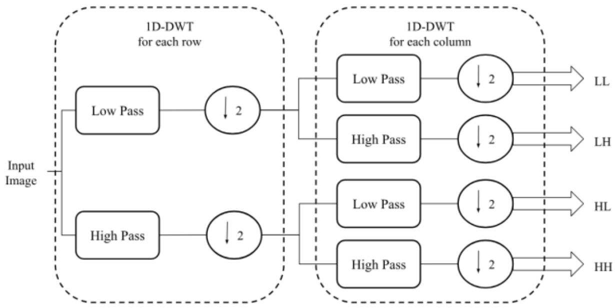


Figure 3. The two-dimensional DWT analysis filter bank

Figure 3 illustrates the process of two-dimensional row and column computation using the Discrete Wavelet Transform (DWT). The LL subband in the figure provides a simplified version of the original image, containing low-frequency approximation details. Meanwhile, the LH, HL, and HH subbands capture high-frequency components, representing the image's detailed information [10]. According to [11], the 2D DWT can be expressed mathematically by

$$a^j(n) = \sum_{i=0}^{L-1} l(i) * a^{j-1}(2n-i), \ 0 \le n < N_j \quad (1)$$

$$d^j(n) = \sum_{i=0}^{L-1} h(i) * d^{j-1}(2n-i), \ 0 \le n < N_j \quad (2)$$

The approximation and detailed components of the signal at decomposition level j are denoted by the coefficients $a^j(n)$ and $d^j(n)$. The coefficients $l(i)$ and $h(i)$ represent the coefficients of low-pass and high-pass filters, respectively.

Phase Information

Phase information (PI) in images refers to the relative alignment and orientation of features, which is essential for accurately representing textures, edges, and fine details. As stated in [12], PI can provide not only phase angles but also frequency as well as ridge and skeleton curves, offering a comprehensive understanding of an image's structural characteristics. In image processing, PI is crucial because it preserves the structural integrity of visual data, ensuring that features such as edges and textures are accurately represented. This preservation is vital for tasks like edge detection and image segmentation, where precise delineation of structures is required.

In medical imaging, the importance of PI is further amplified. Accurate representation of anatomical structures is essential for diagnosis and treatment planning. For instance, phase-contrast X-ray imaging leverages PI to enhance the visibility of soft tissues, which are often difficult to distinguish using traditional absorption-based X-ray techniques. This method provides higher contrast and spatial resolution, allowing for better visualization of fine anatomical details without the need for contrast agents [13].

Autoencoder

Autoencoders have emerged as a powerful tool for anomaly detection in various domains, including medical imaging, fault detection and traffic system control. These neural network architectures are particularly well-suited for unsupervised learning tasks, where labeled data is scarce. The idea behind autoencoders is to learn a compressed representation of the input data and use this representation to reconstruct the original input. By training the autoencoder on normal data, it learns to capture the underlying patterns and structures of data, allowing for an accurate reconstruction of normal instances. However, when presented with anomalous data, the autoencoder may struggle to reconstruct it accurately, resulting in higher reconstruction errors. This discrepancy in reconstruction error can be used to identify anomalies [14].

In the context of DWT for image compression, autoencoders enable the design of data-independent wavelets, ensuring desirable properties like orthogonality, smoothness, compact support, and vanishing moments through architectural constraints and regularization [15]. This allows for improved directionality and phase preservation, addressing some of the limitations of conventional DWT in applications like medical image compression. By learning wavelet filters from Gaussian training data, the method ensures near-perfect reconstruction, making it suitable for adaptive and efficient image compression algorithms like JPEG2000.

PROPOSED FRAMEWORK

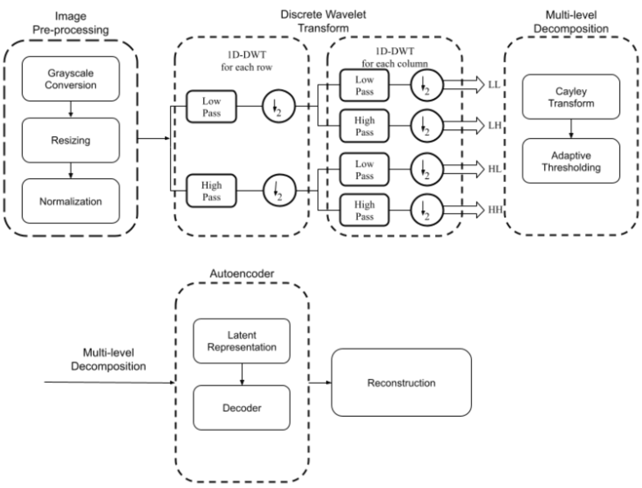


Figure 4. Proposed Architecture

Figure 4 shows the proposed framework which uses a novel approach to medical image compression by enhancing the Discrete Wavelet Transform (DWT) with a trained autoencoder and adaptive thresholding. This combination addresses the limitations of DWT in preserving image details [15]. By incorporating Cayley transform into DWT filters, the framework ensures orthogonality and symmetry, thereby improving the retention of phase information which is critical for maintaining the alignment of edges and textures in images. This enhancement directly tackles a key weakness of standard DWT, where the loss of phase information can lead to distortions and loss of fine details, potentially affecting clinical diagnosis.

The use of a trained autoencoder further strengthens the framework's ability to preserve essential image features. The autoencoder, with its encoder-decoder structure, learns to efficiently compress and reconstruct the image data, specifically the LL sub-band which contains the most crucial low-frequency information. This learning process allows the autoencoder to identify and retain key features, leading to improved reconstruction quality. Additionally, the application of adaptive thresholding to the wavelet coefficients reduces redundancy and further enhances the compression efficiency.

Data Collection

The first step involves obtaining medical image datasets from public available sources which includes modalities such as MRI, CT scans, and X-rays. X-ray images are retrieved from [16]. To ensure comprehensive analysis and applicability, the framework considers diverse medical imaging modalities. The collected images are then preprocessed by converting them to grayscale or the YCbCr color space to reduce color redundancy. Subsequently, to ensure computational consistency, all photos are then downsized to a consistent 256x256 pixel size. Pixel values are standardized to a range of [0,1] to boost the model's learning capabilities and efficiency during the compression procedure.

Let $I(x, y)$ represent the image intensity at pixel (x, y). The preprocessing steps can be expressed as:

Conversion to grayscale or YCbCr color space:

$$I_{greyscale}\,(\mathrm{x,y}) = 0.2989 * R + 0.5870 * G + 0.1140 * B$$

Resizing images to $M \, x \, N$:

$$I_{resized}(\mathrm{x,y}) = \mathrm{Rescale}\ \{\mathrm{I(x,y), M, N)} \tag{3}$$

Normalization:

$$I_{normalized}\,(\mathrm{x,y}) = Iresized\,\frac{(\mathrm{x,y})}{255} \tag{4}$$

Discrete Wavelet Transform (DWT) Enhancement

The preprocessed images undergo a multi-level Discrete Wavelet Transform (DWT) to decompose them into sub-bands: *LL, LH, HL, HH*. This decomposition is expressed as:

$$LL(x,y) = \sum_{i=1}^{M} \sum_{j=1}^{N} I\,(x+i, y\ +\ j) * h(i) * h(j) \tag{5}$$

$$LH(x,y) = \sum_{i=1}^{M} \sum_{j=1}^{N} I\,(x+i, y\ +\ j) * h(i) * g(j) \tag{6}$$

$$HL(x,y) = \sum_{i=1}^{M} \sum_{j=1}^{N} I\,(x+i, y\ +\ j) * g(i) * h(j) \tag{7}$$

$$HH(x,y) = \sum_{i=1}^{M} \sum_{j=1}^{N} I\,(x+i, y\ +\ j) * g(i) * g(j) \tag{8}$$

Where $h(i)$ and $g(i)$ represent the low-pass and high-pass filters, respectively.

The proposed enhancement improves the DWT filters using the Cayley Transform for orthogonality and symmetry, addressing phase information issues [17]. The enhanced wavelet filter is expressed as:

$$W_{enh} = (I - A)(1 + A)^{-1} \tag{9}$$

Where A is the matrix of initial filter coefficients and I is the identity matrix.

To reduce redundancy, adaptive thresholding is applied to wavelet coefficients using:

$$T = \alpha * \sigma + \mu \tag{10}$$

Autoencoder-Based Compression

The enhanced DWT sub-band LL is passed as input to the autoencoder, which compresses and reconstructs the image. The encoder compresses the input into a latent representation Z, defined as:

$$Z = E(LL) = \sigma(W_e * LL + b_e) \tag{11}$$

The decoder reconstructs the sub-band as:

$$LL = D(Z) = \sigma(W_d * Z + b_d) \tag{12}$$

Here, W_e and W_d are weight matrices, b_e and b_d are biases, and σ is the activation function.

The reconstructed image is obtained by applying the inverse DWT:

$$\hat{I}(x, y) = IDWT\ (LL, LH, HL, HH) \tag{13}$$

The loss function for training the autoencoder is the Mean Squared Error (MSE):

$$\mathcal{L} = \frac{1}{MN} = \sum_{x=1}^{M} \sum_{y=1}^{N} \{I(x, y) - \hat{I}(x, y)\}^2 \tag{14}$$

Evaluation Metrics

The suggested system was assessed using three important parameters to ensure improved image quality and the retention of critical qualities. Peak Signal-to-Noise Ratio (PSNR) was used to assess the quality of reconstructed images, revealing the framework's capacity to reduce distortions while maintaining clarity. Heatmap Detection provided a visual study of differences between original and reconstructed images, with a focus on preserving structural details and reducing phase distortions. Furthermore, the Mean Reconstruction Error (Mean Difference) measured reconstruction accuracy, emphasizing the retention of important image information. These metrics collectively demonstrate the framework's capacity to improve image compression and fidelity for medical applications.

RESULTS AND DISCUSSION

This section evaluates the performance of the enhanced Discrete Wavelet Transform (DWT) framework with an integrated autoencoder, specifically addressing the preservation of phase information and improvement in medical image compression. Results are presented using metrics such as mean reconstruction error (mean difference), Peak Signal-to-Noise Ratio (PSNR), and comparative improvement percentages over the traditional DWT method. These findings demonstrate the proposed framework's potential for reducing distortions and improving image quality.

Quantitative Results

1. Mean Difference Analysis

The mean difference quantifies the reconstruction error, where lower values indicate better image detail preservation. Table 1 illustrates the comparative results between the traditional DWT-only method and the enhanced DWT with Autoencoder across five test images.

Table 1: Mean Difference Analysis Result

Test Image	**DWT with Autoencoder**	**DWT Only**	**Percentage Improvement**
1	0.2075	0.3378	38.59%
2	0.2765	0.3220	14.13%
3	0.2512	0.2942	14.61%
4	0.3494	0.3571	2.15%
5	0.2890	0.3598	19.68%

The results shown in Table 1 indicate that the enhanced DWT framework consistently outperforms the traditional method, achieving up to 38.59% reduction in reconstruction error for Test Image 1. This demonstrates the framework's capability to address phase distortion and retain critical image details.

2. Peak Signal-to-Noise Ratio (PSNR) Analysis

PSNR measures the quality of reconstructed images, with higher values reflecting reduced distortions and improved clarity. Table 2 summarizes the PSNR comparison.

Table 2: PSNR Analysis Result

Test Image	DWT with Autoencoder	DWT Only	Percentage Improvement
1	10.29	6.65	54.74%
2	9.68	6.99	35.48%
3	10.03	6.29	59.46%
4	10.41	6.43	61.90%
5	10.93	10.65	2.63%

Table 2 shows that the enhanced DWT with Autoencoder achieves significant improvements in PSNR, with a maximum percentage improvement of 61.90% for Test Image 4. Even the lowest improvement of 2.63% for Test Image 5 highlights the robustness of the proposed method across diverse image sets.

Visual Comparisons

Visual comparisons between the original, DWT-only, and enhanced DWT-autoencoder reconstructed images, as depicted in Figure 5, reveal noticeable improvements in structural detail preservation and reduction of phase distortions. Artifacts and edge misalignments in DWT-only reconstructions are mitigated in the proposed method, emphasizing its effectiveness for medical imaging applications.

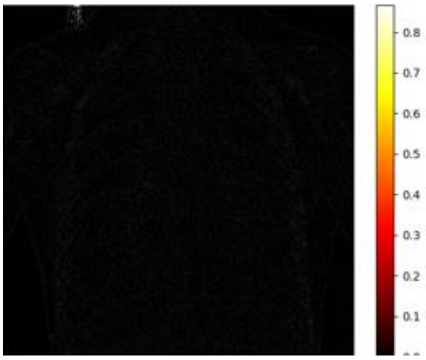
(a)

(b)

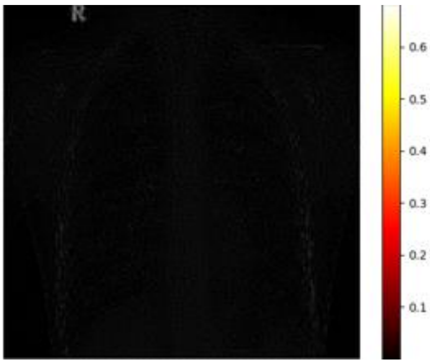
(c)

Figure 5. Comparison of the Proposed and Current Framework. (a) Original Image. (b) Proposed Framework. (c) DWT Reconstrructed

To further analyze the differences, heatmaps were generated to visualize discrepancies between the original image and the reconstructed outputs. Figure 6 shows the heatmaps which highlight areas with significant changes in wavelet coefficients, emphasizing the differences in reconstruction fidelity. Comparisons between the original image and the traditional DWT-only reconstruction reveal pronounced artifacts, particularly along edges and regions with high-frequency details. Conversely, heatmaps comparing the original image with the enhanced DWT-autoencoder reconstruction show substantially lower intensity differences, indicating superior preservation of structural features and reduced phase distortions.



(a)



(b)

Figure 6. Heatmap Comparison. (a) Original vs. Proposed Framework. (b) Original vs. DWT Reconstructed

CONCLUSION

The proposed enhancement of the Discrete Wavelet Transform (DWT) algorithm addresses its critical limitation in preserving phase information, which is essential for maintaining the alignment of edges and textures in images. By integrating a trained Autoencoder, the method effectively learns and retains essential image features, ensuring improved reconstruction quality. The results show that the enhanced DWT with Autoencoder significantly outperforms the traditional DWT method, achieving up to 61.90% improvement in Peak Signal-to-Noise Ratio (PSNR), thereby reducing distortions and preserving critical image details more effectively. This advancement is particularly vital in medical image compression, where maintaining the diagnostic integrity of images is paramount. The integration of the enhanced DWT with the JPEG2000 compression framework achieves a balance between compression efficiency and image quality, providing a robust solution for modern medical imaging needs. These findings highlight the potential for further applications and refinements in the use of wavelet-based algorithms in critical domains.

Recommendations

Future research could optimize the Autoencoder to reduce complexity and improve speed for resource-limited hardware. Incorporating multi-scale phase preservation and adaptive wavelet bases tailored to specific medical modalities, such as MRI or CT, could enhance performance. Testing on real-world datasets and clinical evaluations would validate its practical applicability and diagnostic impact.

REFERENCES

[1] Lu, Z., & Guo, S. (2017). Wavelet-based methods in image compression: A survey. In Handbook of Image and Video Processing. https://doi.org/10.1016/B978-0-12-812006-4.00001-2.

[2] Olkkonen, J. T. (Ed.). (2011). Discrete wavelet transforms: Theory and applications. IntechOpen. https://www.intechopen.com/books/121.

[3] Liu, F., et al. (2017). Evaluation of wavelet-based compression techniques in telemedicine applications. Information, 8(4), 131. https://doi.org/10.3390/info8040131.

[4] Cazañas-Gordon, A., et al. (2022). Applications of wavelet transform in image compression for medical imaging. Amelica Portal. https://doi.org/10.5281/zenodo.5816321.

[5] Vijayvargiya, G., et al. (2013). Wavelet transforms in image processing: State-of-the-art techniques. Retrieved from https://doi.org/10.48550/arXiv.1311.6877.

[6] Foos, D., et al. (2000). Compression of digital medical images using JPEG2000. SPIE Medical Imaging, 3980, 328–336. https://doi.org/10.1117/12.386390.

[7] Agarwal, R., et al. (2019). Multiple image compression in medical imaging techniques using wavelets for speedy transmission and optimal storage. Biomedical and Pharmacology Journal, 12(1). https://dx.doi.org/10.13005/bpj/1627.

[8] Streenivasulu, P., & Varadarajan, S. (2018). Wavelet-based compression techniques: A comprehensive analysis. Journal of Intelligent Systems, 27(1), 35–46. https://doi.org/10.1515/jisys-2018-0180.

[9] Zhang, Y., et al. (2016). A study on wavelet-based image compression techniques. Journal of Visual Communication and Image Representation, 38, 437–445. https://doi.org/10.1016/j.jvcir.2016.03.014.

[10] Al-Shereefi, A. A. (2013). Image compression using wavelet transform. Retrieved from https://www.researchgate.net/publication/309592100_Image_compression_using_wavelet_transform.

[11] AlZubi, S. (2011). Analysis of the performance of wavelet-based image compression techniques. Advances in Multimedia, 2011, Article ID 136034. https://doi.org/10.1155/2011/136034.

[12] Chen, N. X. (2008). Real Wavelet Transform-Based Phase Information Extraction Method: Theory and Demonstrations. IEEE Transactions on Industrial Electronics, 56(3), 891–899. https://doi.org/10.1109/tie.2008.2004389.

[13] Zhou, S. (2008). Application of wavelet transforms in medical imaging. European Journal of Medical Physics, 35(5), 248–256. https://doi.org/10.1016/j.ejmp.2008.05.006.

[14] Yao, Y., Ma, J., & Ye, Y. (2022). Regularizing autoencoders with wavelet transform for sequence anomaly detection. Pattern Recognition, 134, 109084. https://doi.org/10.1016/j.patcog.2022.109084.

[15] Jawali, D., Kumar, A., & Seelamantula, C. S. (2021). Wavelet Design in a learning Framework. arXiv (Cornell University). https://doi.org/10.48550/arxiv.2107.11225.

[16] Yao, Y., Ma, J., & Ye, Y. (2022). Regularizing autoencoders with wavelet transform for sequence anomaly detection. Pattern Recognition, 134, 109084. https://doi.org/10.1016/j.patcog.2022.109084

[17] Mooney, P. T. (n.d.). Chest X-Ray Images (Pneumonia) [Data set]. Kaggle. Retrieved from https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

[18] Cayley's Parameterization of orthogonal matrices. (n.d.). https://planetmath.org/cayleysparameterizationoforthogonalmatrices