

ENCRYPTED MEDICAL IMAGE COMPRESSION USING HYBRID MODEL ANALYSIS

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Abstract: The exponential growth in medical image generation poses significant challenges for storage and management. Lossless compression of medical images is essential to reduce storage demands while ensuring image quality is preserved. Wavelet-based compression techniques, widely recognized in the literature, are commonly used to process and transmit medical images by isolating the Region of Interest (ROI) from other areas. Meanwhile, Convolutional Neural Networks (CNN) have shown promising results for medical image compression. In this study, we propose a hybrid model combining Discrete Wavelet Transforms (DWT) and CNN for medical image compression. DWT is applied to encode the ROI, while CNN is employed for non-ROI regions. Here, Singular Value Decomposition (SVD) is used to extract ROI features. We introduce the SDWTCNN framework, which integrates DWT and CNN to achieve scalable image compression with lower complexity compared to similar methods. The performance of SDWTCNN is evaluated using different performance metrics, demonstrating its effectiveness in maintaining image quality at various compression rates. Experimental results confirm the efficiency of our framework for storing and retrieving medical images in healthcare applications. Specifically, our SDWTCNN achieves 4.3 dB better performance on the BGPD dataset and 3.8 dB on the BraTS dataset than the existing best method in terms of the PSNR metric.

Keywords: Medical image compression, Scalable compression, Discrete wavelet transform, Convolutional neural networks, Hybrid compression model

I. INTRODUCTION

The rapid development of medical imaging technologies has led to an exponential increase in the volume of medical image data, often accumulating into petabytes, being generated daily. Managing and storing such large volumes of data presents significant challenges for healthcare providers, necessitating efficient storage and retrieval solutions, especially within Picture Archiving and Communication Systems (PACS). Medical images, essential for diagnosis, treatment planning, and patient monitoring, require considerable storage space, and preserving image quality is critical for accurate clinical assessment. Medical image compression techniques are typically classified into lossless and lossy methods. While lossless techniques preserve all image information, lossy methods may discard less significant data, leading to reduced file sizes at the cost of slight image quality loss. In this regard, wavelet-based techniques have gained recognition for their capability to compress images while effectively preserving the Region of Interest (ROI). Specifically, the innovative fusion of the Discrete Wavelet Transform (DWT) and Vector Quantization (VQ) has proven to be an effective approach in achieving high compression ratios with minimal loss of significant information. The encoder decoder structure in these algorithms further optimizes the compression process by systematically encoding and reconstructing images. With the growing demand for scalable solutions, deep learning-based methods have emerged as viable options for both lossless and lossy compression. These methods leverage Convolutional Neural Networks (CNNs) or other architectures to learn optimal compression strategies from large data sets, allowing for adaptable compression that balances quality and storage needs. Wavelet-based image coding algorithms exploit both inter-scale and intra-scale properties of the DWT, enhancing compression efficiency while preserving diagnostically important details. Medical image compression has been extensively studied using various methods, including lossless and lossy techniques, wavelet-based approaches, and deep learning models like CNNs. Wavelet-based compression methods are effective in isolating the ROI but often result in higher computational complexity. Existing hybrid models face challenges related to balancing compression efficiency, computational complexity, and image quality. Motivated by these challenges, our framework SDWTCNN framework aims to integrate DWT and CNN, leveraging Singular Value Decomposition (SVD) for efficient feature extraction in the ROI. This approach ensures high compression rates, reduced complexity, and maintains image quality, making it suitable for scalable medical image storage and retrieval in healthcare applications.

II. RELATED WORK

Existing solutions for scalable medical image compression often involve a combination of traditional techniques and modern deep learning approaches, aiming to balance compression efficiency and image quality. Techniques such as wavelet-based compression, CNNs, and fuzzy clustering have been explored to enhance the preservation of diagnostic information while achieving significant compression ratios. However, challenges remain, including the trade-off between lossless and lossy compression methods, the need for robust feature extraction from various image modalities, and the integration of different algorithms to optimize performance. Furthermore, there is a gap in addressing computational complexity and scalability issues, particularly when dealing with large datasets. In

the following, we will have an overview of the latest available methods for compressing medical images.

Introduced MedFormer, a transformer model for scalable 3D medical image segmentation. MedFormer included inductive bias, hierarchical modeling with linear-complexity attention, and multi-scale feature fusion. It learned across different scales of data without pre-training and outperformed CNNs and vision transformers on multiple datasets, covering CT (Computed Tomography), MRI (Magnetic Resonance Imaging), and various medical targets. The authors provided models and evaluation pipelines for future clinical applications. The model's reliance on inductive bias may limit its generalization capabilities across diverse medical imaging tasks. Roy et al. proposed MedNeXt, a Transformer-inspired segmentation network for data-scarce medical settings. MedNeXt featured a ConvNeXt 3D encoder-decoder network, residual up and down-sampling blocks, and a technique for iteratively increasing kernel sizes to prevent performance saturation. introduced a fast and scalable framework for medical image storage using a distributed (MISS-D) file system. The framework included an integrated indexing file model for efficient large-scale image storage and a virtual file pooling technology for efficient data reading via memory-mapped files. The MISS-D framework, demonstrated through an online web client, allowed rapid data access and offered features applicable to existing open-source and commercial solutions. The framework's dependency on a distributed file system may introduce latency and complexity in environments with limited network capabilities. Malayil and Vedhanayagam proposed a scheme for embedding authentication codes and Electronic Patient Record (EPR) data in scaled-up medical images. The method used a neighborhood pixel copying technique, with a fallback to least significant bit watermarking when neighborhood pixel values were identical. The OsiriX dataset was used for experimental validation.

Introduced a hybrid crypto-compression technique for securing healthcare image transfers. The approach combined Generative Adversarial Networks (GANs) with learned compression for lossy compression, followed by picture cryptography using a public key encoded with the DNA technique and a logistic chaotic map algorithm for generating pseudo-random bits. The method provided fault resilience, reliable encryption, and significant image size reduction, making it suitable for medical image encryption. The hybrid crypto-compression technique may compromise image quality due to lossy compression, which could hinder diagnostic accuracy. Reddy et al. proposed a data storage and protection system for the internet of medical things, using a modified lossless Lempel-Ziv-Welch (LZW) compression algorithm followed by encryption with elliptic curve Diffie-Hellman keys and the advanced encryption standard. The hybrid cryptography approach combined symmetric and asymmetric cryptography to enhance security. The solution was efficient and resource-friendly, making it suitable for edge devices in medical applications. The system's performance may vary based on the resource constraints of edge devices, impacting its efficiency in low-resource settings.

Yadav et al. proposed a Joint Compression and Encryption (JCE) method for images, utilizing Absolute Moment Block Truncation Coding (AMBTC) for compression and combining Arnold's Cat Map with Henon Map for encryption. The model provided enhanced security and faster computation, with results demonstrating its effectiveness against brute force, differential, and statistical attacks, ensuring robust image protection. The approach's security effectiveness could be compromised by potential vulnerabilities in the encryption methods used. Fred et al. proposed a hybrid block-based technique combining Hadamard

transform and Huffman encoder for compressing medical images during transmission to reduce bandwidth, storage, and power consumption. The Integer Wavelet Transform (IWT) initially decoded the input image, with the Loss-less Hadamard Transform (LHT) and Direct Current Prediction (DCP) applied to low-frequency sub-bands to remove correlations.

Subramani et al. introduced a fuzzy relaxation-based modified fuzzy c-means clustering algorithm for brain MRI segmentation. This approach incorporates an exposure-based sub-image fuzzy brightness adaptation algorithm to enhance brain tissues, followed by the clustering algorithm to segment white matter, gray matter, and cerebro-spinal fluid. The method was evaluated against existing techniques using metrics such as PSNR, discrete entropy, contrast improvement index, sensitivity, specificity, accuracy, Jaccard similarity, and dice similarity coefficient.

Kurmukov et al. evaluated the impact of lossy compression on medical image segmentation using Deep Neural Networks (DNN) as LCDNN. They demonstrated that lossy compression up to 20 times did not affect segmentation quality across three CT datasets and one MRI dataset. Furthermore, DNN models trained on compressed data were shown to predict on uncompressed data and vice versa, without quality loss. The results of the study may not be universally applicable, as the evaluation was limited to specific datasets and may overlook edge cases. Zhang et al. investigated the optimization and performance of deep learning algorithms in medical image processing.

III. METHODOLOGY

BLOCK DIAGRAM

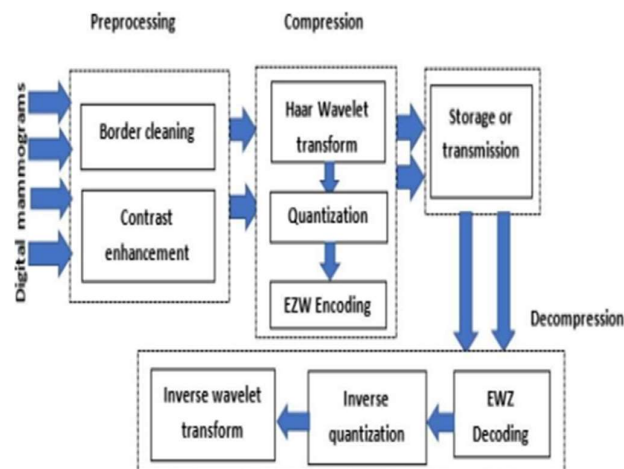


Fig 1: Block diagram

This block diagram outlines the image compression and decompression process for digital mammograms using Haar Wavelet Transform and Embedded Zero tree Wavelet (EZW) encoding. It includes three major stages: Preprocessing, Compression, and Decompression.

1. Preprocessing This stage prepares the mammogram image for compression by improving quality and removing unnecessary data:
 - Input: Digital mammograms
 - Steps: o Border Cleaning: Removes artifacts or noise at the image borders. o Contrast Enhancement: Improves the visibility of features by increasing the difference between light and dark areas.
2. Compression This stage reduces the image size for efficient storage or transmission.
 - Steps: o Haar Wavelet Transform: Decomposes the image into low- and high-frequency components. o Quantization: Reduces the precision of the wavelet coefficients to save space. o EZW Encoding (Embedded Zero tree Wavelet): Efficiently compresses the quantized data using a tree-based structure to exploit redundancy
 - Output: Compressed data suitable for storage or transmission
3. Decompression This stage reconstructs the original image (or an approximation) from the compressed data.
 - Steps: o EZW Decoding: Recovers the quantized wavelet coefficients. o Inverse Quantization: Reverses the quantization step to approximate the original values. o Inverse Wavelet Transform: Reconstructs the image from the wavelet coefficients.
 - Output: Decompressed image (close to the original)

FLOW CHART

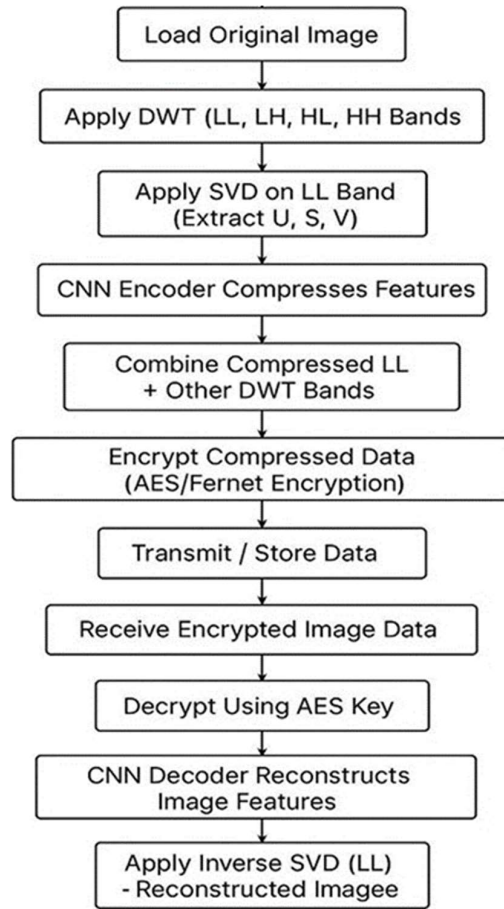


Fig 2: Flowchart

Proposed Methodology:

The proposed SDWTCNN framework combines SVD, DWT, and CNN to achieve efficient medical image compression. The initial preprocessing step entails filtering images to remove noise often present in ultrasonic imaging. Then, SVD is applied to the ROI to extract key features, optimizing the compression of this critical area. Next, the entire image undergoes DWT, which decomposes it into sub bands, with the low-frequency component of the image used to encode the ROI. The non-ROI areas are then processed through a CNN model to further reduce their size. Finally, the image is reconstructed by merging the compressed ROI and non-ROI regions. The final reconstructed image is derived from the reconstructed sub-bands using the IDWT. Specifically, the compressed non-ROI areas are combined with the lossless compressed ROI to form the final compressed image. This hybrid approach leverages the strengths of both DWT for the ROI and CNN for non-ROI, optimizing the overall image compression process. The result is an efficient, scalable compression method that balances storage needs with the preservation of critical medical information.

This flowchart represents a hybrid image compression architecture that intelligently compresses Region of Interest (ROI) and Non-ROI parts of an image differently to achieve efficient compression without compromising important visual details. Here's a step-by-step explanation:

1. Original Image
 - The process begins with an input image (e.g., medical scan, satellite image).
2. Image Preprocessing: Noise Removal (Using WF Technique)
 - WF stands for Wiener Filter or Wavelet Filtering (context-dependent).
 - Removes noise to improve clarity and feature extraction.
 - This step ensures better segmentation and compression accuracy.
3. SVD-Based ROI Feature Extraction
 - SVD = Singular Value Decomposition.
 - Used to extract significant features of the image to identify ROI (Region of Interest).
 - ROI could be a tumor in a medical image, or an object in surveillance footage.
4. Image Segmentation into ROI & Non-ROI Regions • Based on the extracted features, the image is split into:
 - a) ROI: Important areas needing high fidelity.
 - b) Non-ROI: Less critical areas where compression loss is acceptable.
5. ROI Region → Image Compression with DWT
 - DWT = Discrete Wavelet Transform.
 - A wavelet-based compression method that preserves details well in high-frequency components.
 - Used for ROI, as it retains essential visual data with minimal loss.
5. Non-ROI Region → Image Compression with CNN
 - CNN = Convolutional Neural Network.
 - A deep learning model trained to compress images in a lossy but efficient manner.
 - Suitable for non-ROI, where slight quality degradation is acceptable to save space.
7. Merge Compressed ROI and Non-ROI Regions
 - The compressed parts (ROI + non-ROI) are combined into a single format.
 - This hybrid output balances quality and compression ratio.
8. Image Reconstruction using IDWT
 - IDWT = Inverse Discrete Wavelet Transform.
 - Used to reconstruct the compressed image from the DWT-processed ROI.
 - Final step produces the compressed image, suitable for storage or transmission.

IV. Tools used (hardware/software) :MATLAB

MATLAB (with necessary toolboxes): 1. Image Processing Toolbox Purpose:

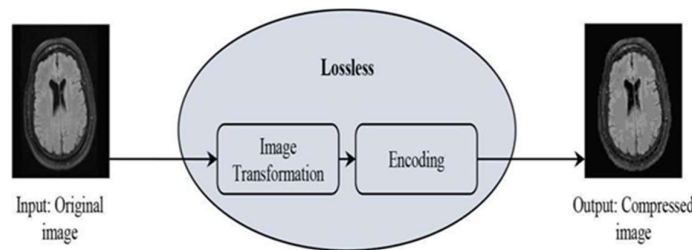
- Core toolbox for performing image preprocessing, enhancement, filtering, transformation, and analysis in MATLAB. Key Features: • Read/write images in various formats (BMP, JPEG, PNG, etc.) • Apply filters (e.g., Gaussian, median) • Perform edge detection, histogram

equalization, image segmentation • Support for image arithmetic, geometric transforms, color space conversion 2. Wavelet Toolbox Purpose: • Used for multi-resolution image analysis, compression, and denoising using wavelet

transforms. Key Features: • 1D, 2D wavelet transform functions (DWT, IDWT) • Wavelet packet decomposition • Image compression using wavelet-based coding (e.g., EZW, SPIHT) • Denoising with soft/hard thresholding. 3. Deep Learning Toolbox Purpose: • Enables design, training, and deployment of deep learning models like CNNs and autoencoders for image classification, object detection, etc. Key Features: • Define and train neural networks • Pretrained networks (e.g., AlexNet, ResNet, VGG) • Layer-wise customization and visualization tools • Integration with MATLAB Coder and GPU support 4. Neural Network Toolbox Purpose: • Focuses on building and simulating shallow neural networks (e.g., feedforward, recurrent, radial basis). Key Features: • GUI for designing, training networks • Support for backpropagation training • Simulate performance and generalization 5. HDL Coder Purpose: • Automatically generates synthesizable VHDL/Verilog code from MATLAB or Simulink models. Key Features: • Converts MATLAB algorithms or Simulink models into HDL • Supports floating-and fixed-point data types • Generates IP cores for Xilinx/Intel FPGAs 6. Fixed-Point Designer Purpose: • Allows simulation, design, and conversion of floating-point algorithms to fixed-point, which is essential for efficient hardware implementation. Key Features: • Analyze and simulate quantization effects • Optimize word lengths to minimize hardware resource usage • Integrated with HDL Coder for generating efficient hardware code.

V. IMPLIMENTATION

Expected Outcome: In this section, we present the results of our proposed framework and compare its performance with alternative approaches. The evaluation focuses on key metrics, including RMSE, PSNR, SSIM, WPSNR, and runtime efficiency. Here, SDWTCNN is evaluated against Med Former, Hybrid-Block, LCDNN, and Dense Net. The experiments were conducted using two publicly available datasets-BGPD for CT images and BraTS for MRI images—representing diverse medical imaging modalities. Through extensive testing, we demonstrate how proposed SDWTCNN framework contributes to the overall performance. ➤ Efficient Medical Image Compression – A hybrid model that significantly reduces medical image file sizes while maintaining essential diagnostic details, optimizing storage and transmission. ➤ Scalability Across Medical Imaging Modalities – The model will be adaptable to various medical imaging types (MRI, CT, ultrasound, etc.), making it applicable across different healthcare environments.



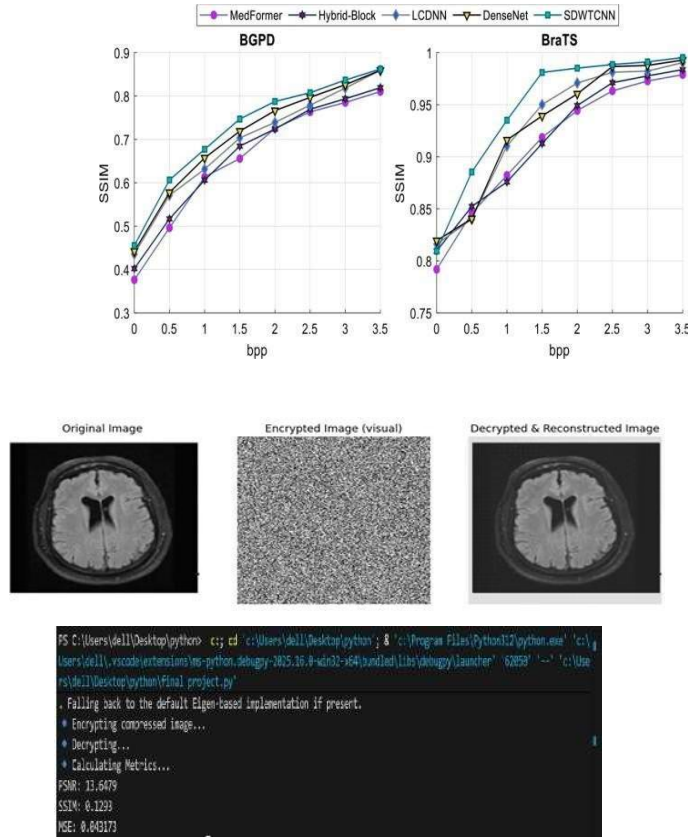


Fig. 3 The process of lossless compression in medical imaging

VI. CONCLUSION

The integration of hybrid compression models combining traditional transform techniques with modern machine learning approaches offers a promising solution for efficient medical image compression. Utilizing an FPGA platform for implementation leverages its inherent parallelism and reconfigurability, enabling real-time processing with low latency and power consumption—critical factors in medical applications. Through MATLAB-based algorithm development, simulation, and validation, the proposed hybrid model can be rigorously tested and optimized before hardware deployment, ensuring both high compression ratios and preservation of diagnostically relevant image quality. FPGA-specific optimizations further enhance performance by balancing resource utilization and throughput. Overall, this approach demonstrates a viable and scalable framework for compressing large medical imaging datasets, facilitating faster transmission, reduced storage requirements, and improved accessibility in telemedicine and clinical diagnostics.

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