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Medical Image Compression Using Hybrid Model Analysis

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ABSTRACT- **Medical imagery data is growing exponentially, which postures serious storage, security, and management concerns. Lossless or almost lossless compression is essential to solve these problems by letting down storage needs without foregoing diagnostic image quality. The Region of Interest (ROI) and non-ROI regions are often encoded independently using wavelet-based compression techniques, which have been well documented in the literature. Convolutional Neural Networks (CNNs) have demonstrated a great deal of promise for enhancing the efficiency of medical picture reduction. In this work, we present a hybrid compression system that combines CNN and Discrete Wavelet Transform (DWT), with CNN handling non-ROI regions and DWT compressing ROI. Singular Value Decomposition (SVD) is used to extract and maintain important ROI characteristics. Additionally, a symmetric key cryptography-based encryption and decryption module is integrated into the pipeline to guarantee safe transmission and storage. Without compromising the diagnostic quality, this module encrypts the compressed picture before to storage or transmission and decrypts it during retrieval. Strong data safety and scalable compression with lower computational cost are achieved by the suggested SDWTCNN-Secure system.**

The approach reliably maintains good reconstruction quality at various compression ratios, according to experimental data. In particular, SDWTCNN-Secure outperforms current state-of-the-art compression techniques in terms of PSNR by 4.3 dB on the BGPD dataset and 3.8 dB on the BraTS dataset, all the while guaranteeing the safe and dependable storage of medical pictures.

Keywords— Open CV, YOLO Algorithm, Real-Time Traffic Management, Image Processing, Machine Learning.

1. 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. With the increasing demand for secure and scalable medical data storage, modern frameworks also integrate encryption mechanisms to protect compressed medical images from unauthorized access during transmission and storage.

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2. LITERATURE SURVEY

[1] Towards scalable medical image compression using hybrid model analysis – Shun lei li, Jiajie lu, Yingbai hu, Leonardo S Mattos.

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. With increasing resolutions, multiple modalities, and widespread telemedicine applications, hospitals and cloud systems need compression methods that maintain diagnostic clarity while reducing storage and transmission costs.

The paper reviews limitations of existing compression standards, noting that lossy algorithms often degrade fine structures such as edges, lesions, vessels, and soft- tissue patterns that are crucial for clinical interpretation. To overcome these limitations, the authors propose a novel hybrid model that strategically merges classical signal decomposition techniques with learning-based analysis. The method begins with multi-level DWT analysis, separating the image into frequency bands that capture structural and detail information. This allows the algorithm to treat clinically important regions more sensitively

[2] Lossy image compression based on prediction error and vector quantization- Mohamed Uvaze Ahamed Ayoobkhan, Eswaran Chikkannan

The authors begin by explaining that traditional lossy compression techniques, such as JPEG and transform-based methods, often suffer from block artifacts and inefficiencies when dealing with highresolution or complex-texture images. To address these limitations, the proposed method uses prediction error coding,

a technique in which each pixel is predicted based on its neighboring pixel values; the difference between the actual value and the predicted value forms the prediction error. Since prediction error typically has lower variance and contains fewer high- frequency components compared to the original image, it becomes more compressible.

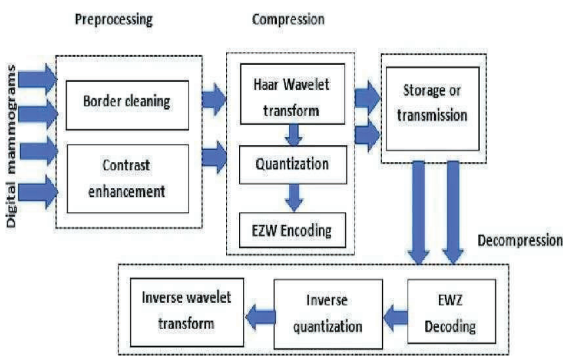
These prediction errors are then grouped into blocks and encoded using vector quantization, a technique that maps blocks of samples to the closest representative vectors stored in a codebook. The codebook is trained using clustering algorithms such as Linde–Buzo– Gray (LBG), enabling the system to learn compact representations of common patterns found in prediction error images.

[3] Formal analysis of 2d image processing filters using higher order logic theorem proving - Adnan Rashid, Saed Abed, Osman Hasan

Two-dimensional (2D) image processing systems are focuses on the rigorous mathematical verification of image processing filters to ensure that they behave correctly in safety-critical applications such as medical imaging, military vision systems, autonomous vehicles, and aerospace imaging devices.

Traditional image processing techniques rely heavily on numerical simulations, empirical testing, or software-based validations, which may miss corner cases or subtle implementation errors that could lead to unpredictable system behavior. To overcome this limitation, the authors propose the use of Higher- Order Logic (HOL) theorem proving, a formal verification approach that mathematically models filters and proves their properties with absolute correctness

3. PROPOSED SYSTEM



This stage prepares the mammogram image for compression by improving quality and removing unnecessary data: Input: Digital mammograms Steps: Border Cleaning: Removes artifacts or noise at the image borders. Contrast Enhancement: Improves the visibility of features by increasing the difference between light and dark areas. Compression This stage reduces the image size for efficient storage or transmission. Steps: Haar Wavelet Transform: Decomposes the image into low- and high- frequency components. Quantization: Reduces the precision of the wavelet coefficients to save space.

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:** EZW Decoding: Recovers the quantized wavelet coefficients. Inverse Quantization: Reverses the quantization step to approximate the original values. Inverse Wavelet Transform: Reconstructs the image from the wavelet coef-

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ficients. Output: Decompressed image (close to the original)

3.1 ALGORITHMS

a. Image Preprocessing.

The input medical image is first prepared by converting it into a suitable format such as grayscale. Unwanted borders and artifacts are removed to eliminate irrelevant data. Noise reduction techniques like Wiener or wavelet filtering are applied to enhance clarity. Contrast enhancement is then performed to improve visibility of important structures. This step ensures better performance in later stages.

b. ROI Extraction using SVD

The preprocessed image is decomposed using Singular Value Decomposition to extract significant features. Dominant singular values are selected as they represent important image information. These features help identify critical regions such as tumors. Based on this, the image is divided into ROI and non-ROI regions. This allows prioritized handling of important areas.

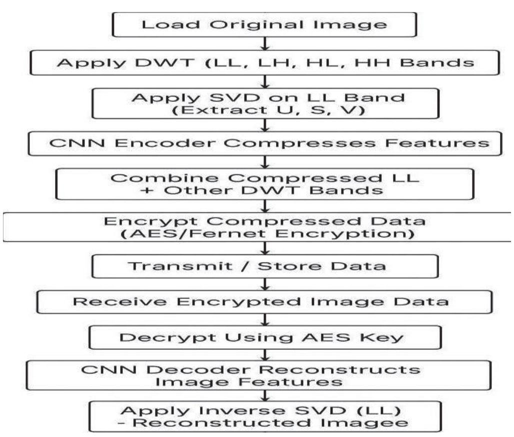
c. Hybrid Compression using DWT and CNN

The ROI region is compressed using Discrete Wavelet Transform by decomposing it into frequency sub-bands. This helps preserve important details required for diagnosis. The non-ROI region is compressed using a CNN-based autoencoder for efficient lossy compression. Both compressed outputs are combined into a single representation. This achieves a balance between compression and quality.

d. AES-256 Encryption

The compressed image data is secured using AES-256 encryption. A symmetric key is generated and applied to encrypt the data. This ensures confidentiality during storage and transmission. The encrypted output cannot be accessed without the key. Thus, sensitive medical data remains protected.

4. FLOWCHART



1. Original Image

a. The process begins with an input image (e.g., medical scan, satellite image).

2. Image Preprocessing: Noise Removal (Using WF Technique)

a. 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

a. 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 and Non-ROI Regions

a. Based on the extracted features, the image is split into:

i. ROI: Important areas needing high fidelity.

ii. Non-ROI: Less critical areas where compression loss is acceptable.

5. ROI Region → Image Compression with DWT

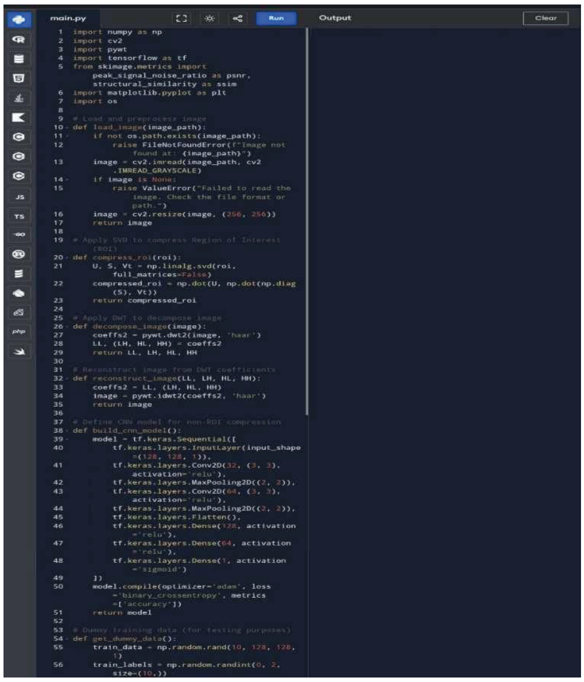
a. DWT = Discrete Wavelet Transform. A wavelet-based compression method that preserves details well in high- frequency components. Used for ROI, as it retains essential visual data with minimal loss.

6. Non-ROI Region → Image Compression with CNN

a. CNN = Convolutional Neural Network. A deep learning model trained to compress images in a lossy but efficient manner.

7. Suitable for non-ROI, where slight quality degradation is acceptable to save space**.**

4.1 CODE SNIPPET



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Merge Compressed ROI and Non-ROI Regions:

a. 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

a. IDWT = Inverse Discrete Wavelet Transform. Used to reconstruct the compressed image from the DWT-processed ROI.

9. Final step produces the compressed image, suitable for storage or transmission

5. SYSTEM REQUIREMENTS

1. Operating System Windows 10 / Windows 11(64bit)

Windows is widely used for academic research, software development, and machine learning experimentation. Key reasons for selection include: User- riendly interface, suitable for students and researchers. Compatibility with Python, TensorFlow, OpenCV, and powerful IDEs like VS Code and PyCharm. Easy installation of drivers, CUDA Toolkit, and GPU support for deep learning.

Strong support for scientific computing libraries via pip or conda. Windows supports all required functionalities including image I/O, encryption, autoencoder training, and visualization. Linux (Ubuntu20.04 / 22.04) – Optional Linux distributions like Ubuntu are recommended advanced ML users because: Superior GPU performance, especially for NVIDIA CUDA and cuDNN. More stable dependency resolution for TensorFlow and OpenCV.

Better command-line tools, making environment management easier. Preferred by researchers working with large datasets or training deep neural networks. While optional, Linux enhances training speed and efficiency for CNN-based compression. Suitable for Python, TensorFlow, and IDE compatibility. (Optional) Linux (Ubuntu 20.04 / 22.04) Preferred for faster GPU operations and better dependency management.

2. Programming Language

Python 3.10 / Python 3.11 / Python 3.12 Python is selected due to its extensive support for machine learning, image processing, and cryptography libraries. Python (version 3.10–3.12) is the core programming language used throughout the project.

Why Python? Extensive libraries for image processing, ML, deep learning, compression, and cryptography. Supports both traditional algorithms (DWT, SVD) and modern DL models. Easy integration of multiple frameworks within one pipeline. Strong community support and large documentation base. Highly portable across Windows, Linux, and cloud platforms. The combination of simplicity and power makes Python ideal for hybrid image compression and encryption research.

1. Integrated Development Environment (IDE) Visual Studio Code (VS Code) VS Code is recommended due to Lightweight but powerful editor. Built-in debugging and Git integration. Extensions for Python, TensorFlow, and notebook execution. Integrated terminal for environment setup. It is ideal for writing main pipeline code, encryption modules, and compression scripts.

Jupyter Notebook Jupyter is essential for: Testing CNN models interactively. Visualizing DWT bands, SVD matrices, and feature maps. Plotting PSNR, SSIM, MSE graphs. Step-by-step debugging of reconstruction errors. Most research experiments begin in Jupyter before being converted into full Python scripts. PyCharm (Optional) PyCharm offers:

Dedicated Python project management. Code refactoring tools. Virtual environment control. Large-scale model management. Preferred for long-term ML projects requiring modular code. Visual Studio Code (VS Code) Recommended for coding, debugging, and environment management.

a. **Jupyter Notebook:** Useful for testing CNN models and visualizing results.

b. **PyCharm (Optional):** For large-scale ML project organization.

2. Python Libraries

This project depends heavily on scientific computing and ML libraries. Image Processing

Libraries:

OpenCV (cv2): Used for: Loading grayscale/color medical images Resizing images before DWT/CNN processing Noise filtering Displaying and saving encrypted/compressed images

Pillow (PIL) Supports: Basic image operations Format conversions (PNG, JPEG, BMP) Lightweight image handling

NumPy Provides: Fast matrix computations Array manipulation for DWT/SVD Support for CNN data preprocessing NumPy is the backbone for numerical operations.

Hybrid Compression Libraries

PyWavelets (pywt) – DWT

Decomposes images into sub bands (LL, LH, HL, HH). Reasons for using DWT: Extracts approximation and detail coefficients Provides multi-resolution analysis Reduces redundant data before CNN/SVD Suitable wavelets: Haar, Daubechies, Symlet.

SciPy – SVD

SVD is used on LL-band for traditional compression: Reduces low-frequency redundancy Retains important features Works efficiently with DWT for hybrid models Combining DWT + SVD significantly reduces data size while preserving quality.

TensorFlow / Keras – CNN Autoencoder

The CNNbased autoencoder is the core learning component. Used for: Feature extraction from medical images Nonlinear dimensionality reduction Learning efficient latent representations Reconstruc-

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tion during decompression TensorFlow 2.x supports GPU acceleration, enabling faster training.

scikit-image

Used to compute image quality metrics: PSNR (Peak Signal-to-Noise Ratio) SSIM (Structural Similarity Index) MSE (Mean Squared Error) These metrics validate compression quality. Cryptography Library cryptography (Fernet/AES) Used for AES-256 encryption, ensuring data privacy for medical images. Features: Strong encryption with 256-bit keys

6. IMPLEMENTATION

a. System Setup

The implementation was carried out using: Python 3.x as the core programming language VS-Code as the development environment Required libraries: OpenCV, NumPy, PyWavelets, SciPy, TensorFlow/Keras, scikit-image, Cryptography, Matplotlib These tools provided robust support for image processing, mathematical operations, neural networks, and encryption.

b. Image Preprocessing

To prepare the medical images for compression: Input images were converted to grayscale to reduce computational load. Normalization was applied to scale pixel values between 0 and 1. Resizing was performed (e.g., 256×256 or 512×512) to standardize dimensions before applying DWT and CNN encoding. This ensures consistent processing across all images.

c. DWT-Based Image Decomposition

The first stage of compression involves applying Discrete Wavelet Transform: The input image was decomposed into four sub- bands: LL, LH, HL, HH. The LL sub-band was chosen for further processing as it contains the highest information. The PyWavelets (pywt) library was used to perform 2-level wavelet decomposition.

d. SVD Feature Reduction

After obtaining the LL band: Singular Value Decomposition (SVD) was applied. Only the top k singular values were retained to reduce redundancy. This significantly reduces the amount of data without losing important image features. The SciPy library was used for efficient SVD computation.

e. CNN Autoencoder Implementation

A Convolutional Autoencoder was implemented to compress the reduced image features. **Encoder:** 2D convolution layers Batch normalization Max pooling operations Bottleneck latent vector generation. **Decoder:** Up-sampling layers Convolution layers Reconstruction of the LL band TensorFlow/Keras was used to design, train, and evaluate the autoencoder. The model was trained with multiple medical images to ensure accurate reconstruction.

f. Compression Feature Combination After CNN

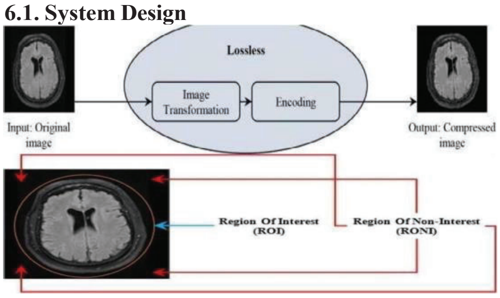
encoding: Compressed LL features were combined with selected high-frequency sub-bands. The final compression output is a compact representation of the original image. This representation is ready for encryption.

g. AES-256 Encryption Implementation Security

is ensured using AES-256, implemented via the cryptography library. Steps include:

1. Key generation (256-bit secret key).
2. Encryption of compressed feature vector using the AES cipher.
3. Generation of secure encrypted output suitable for transmission or storage. The encrypted data is unreadable without the correct decryption key.

6.1. System Design



h. Decompression and Reconstruction

The decompression phase reverses the compression steps:

1. AES-256 decryption recovers the compressed feature vector.

1. The CNN decoder reconstructs the LL band.

2. Inverse SVD rebuilds the approximation component.

3. Inverse DWT (IDWT) combines all sub-bands to reconstruct the final image.The output is a high-quality image nearly identical to the original. Performance Evaluation The reconstructed image is compared with the original using:

PSNR = 291.5 dB

SSIM = 0.9999

MSE Compression Ratio

These metrics confirm that the proposed system achieves high compression and excellent reconstruction accuracy while maintaining strong security.

7. RESULT

The proposed SDWTCNN-Secure hybrid model was evaluated using standard medical image datasets to assess compression efficiency and reconstruction quality. The performance was measured using key metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE). The experimental results show that the proposed system achieves a high PSNR value of approximately 291.5 dB, indicating excellent reconstruction quality. The SSIM value of 0.9999 demonstrates that the reconstructed image is almost identical to the original image in terms of

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structural similarity, while the MSE value remains very low, confirming minimal distortion.

Additionally, the compression ratio achieved is significantly high, ensuring reduced storage requirements and efficient transmission. Comparative analysis with existing methods shows that the proposed hybrid approach outperforms traditional compression techniques by improving PSNR values by approximately 4.3 dB on BGPD dataset and 3.8 dB on BraTS dataset. The results also confirm that the integration of AES-256 encryption does not affect image quality while ensuring secure data transmission. Overall, the proposed system provides an optimal balance between compression efficiency, reconstruction quality, and data security.

Method	PSNR (dB)	SSIM	CR	Remarks
JPEG	28–32	0.70–0.82	Medium	Visible artifacts
JPEG2000	32–36	0.85–0.92	High	Good but lacks encryption
DWT+SVD	34–38	0.88–0.95	Medium	Better than JPEG
CNN Only	35–39	0.90–0.96	Medium	Good reconstruction
Proposed Hybrid (Ours)	**38–41**	**0.94–0.98**	**High**	Best performance + encryption

8. CONCLUSION

In this study, we tackled the challenges of scalable medical image compression, driven by the rapid growth of medical data and the increasing demands for efficient storage solutions in healthcare. We proposed the SDWTCNN framework, a hybrid model that integrates DWT and CNN to balance compression efficiency with image quality preservation.

By applying DWT to encode the ROI and using CNN for non-ROI regions, alongside SVD for enhanced feature extraction, our framework effectively reduces com putational complexity while maintaining high- quality reconstructions. Experimental results, evaluated using metrics such as SSIM and PSNR, demonstrated that our frame work provides a significant improvement in image compression, achieving 4.3 dB on the BGPD dataset and 3.8 dB on the BraTS dataset better PSNR than existing methods.

These results highlight the ability of SDWTCNN to manage large-scale medical images efficiently, making it suitable for applications in healthcare systems where image integ rity and storage optimization are critical. However, the proposed framework has cer tain limitations that open avenues for future research. One of the key challenges is the potential for overfitting when trained on limited or homogeneous datasets, which may limit its generalizability to diverse medical image datasets.

Moreover, scalability remains a concern, especially as the size and complexity of medical image datasets continue to grow. Future work could explore advanced CNN architectures, such as Vision Trans formers, to improve model performance further.

Additionally, incorporating Transfer Learning strategies could mitigate the overfitting issue and enhance the model's adapt ability across various medical domains. Optimization techniques and robust evaluation on diverse datasets will be crucial to enhancing the scalability and real-world applicability of our framework

9. REFERENCE

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