1. Introduction

In today's era of data-intensive medical imaging, the volume of high-resolution visual data generated through diagnostic tools like microscopy, MRI, CT scans, and histopathology has grown exponentially. In particular, blood cell imaging plays a crucial role in the diagnosis and monitoring of diseases such as leukemia, anemia, and malaria. However, these images, often stored in high-resolution formats like TIFF, consume significant storage space and pose challenges in archiving, sharing, and processing, especially in large-scale hospital databases or telemedicine platforms. Therefore, Region of Interest (ROI)-based image compression has emerged as a highly promising technique to address these challenges by focusing compression efforts selectively—preserving diagnostic-critical regions with high fidelity while applying more aggressive compression to background areas.

This project explores an ROI-based hybrid image compression technique specifically designed for grayscale blood cell microscopy images. The method integrates the powerful Discrete Wavelet Transform (DWT) with Huffman entropy coding and includes a novel block-based pivot subtraction preprocessing step to enhance compression efficiency. Unlike traditional uniform compression, ROI-based approaches preserve the diagnostically significant region—such as a specific blood cell or group of cells—without altering pixel intensities or introducing visual artifacts, while simultaneously allowing non-ROI areas (typically background or less informative regions) to be compressed more aggressively.

In this method, the image is first segmented to isolate the ROI. This can be manually marked or detected using simple intensity-based or morphological techniques, depending on the application. After ROI identification, a dual-mode compression strategy is applied: the ROI is compressed with minimal or no loss, ensuring full diagnostic quality is preserved, while the non-ROI regions are processed using the full pipeline—block-based pivot subtraction, DWT transformation, and Huffman encoding—to achieve maximum compression in the visually less significant areas.

The Discrete Wavelet Transform plays a key role in decomposing the image into multiple frequency subbands, allowing efficient separation of detail from approximation information. This is particularly effective for biological structures like red and white blood cells, which exhibit fine-grained textures that are well-preserved in the low-frequency wavelet subbands. Next, a block-based pivot subtraction step is introduced for non-ROI regions, where each image block is normalized by subtracting a pivot value (e.g., block mean or median). This reduces intra-block variation, making the pixel values more uniform and statistically predictable, thus enhancing the performance of entropy coding.

Following the pivot subtraction, Huffman coding is applied to the transformed coefficients. This step uses the statistical frequency of values to assign variable-length binary codes, ensuring that frequently occurring values are represented using fewer bits. The result is a highly efficient encoding process for both the ROI (when needed) and especially the non-ROI areas, where redundancy is more effectively reduced.

The technique was applied to a dataset of grayscale blood cell images in TIFF format, capturing various cell types and densities under a microscope. The performance of the ROI-based hybrid compression scheme was evaluated using key metrics:

Compression Ratio (CR): representing how much the original file size was reduced.

Peak Signal-to-Noise Ratio (PSNR): indicating the visual quality of the reconstructed image, especially within the ROI.

Storage Space Saved (%): quantifying the percentage reduction in disk usage after compression.

Experimental results showed that the method achieves high compression in non-ROI areas while preserving near-lossless quality in ROI regions, maintaining diagnostic-relevant features. PSNR values remained within acceptable medical standards, ensuring reliability. Comparative analysis with standard DWT + Huffman methods highlighted superior performance in balancing compression and quality. Block-based preprocessing further enhanced entropy coding, especially in uniform non-ROI backgrounds.

In conclusion, the proposed ROI-based compression method effectively preserves diagnostically important regions while reducing storage through wavelet transform, pivot subtraction, and Huffman coding. It lays the groundwork for future enhancements like automated ROI detection and real-time compression. This intelligent hybrid approach is well-suited for telepathology and AI-driven diagnostics. Overall, it optimizes both storage efficiency and clinical utility in medical imaging workflows.

Literature survey

In the first paper the authors proposed Wavelet-based image compression has been extensively used for its multi-resolution capabilities and energy compaction, making it suitable for lossy image compression. Traditional methods like JPEG2000 also support ROI-based preservation, yet they often lack flexibility in real-time region adaptation. Huffman encoding, a form of entropy coding, has been integrated into image compression pipelines for optimal bitstream representation. Recent advances in deep learning also highlight filter pruning and model compression to reduce computational overhead, as seen in History-Based Filter Pruning (HBFP), which prunes redundant filters using training patterns. Inspired by such selective compression, this project adapts a classical yet novel approach for region-aware image quality preservation[1].

The second paper authors introduces ROI-JSCC, a deep joint source-channel coding approach for image transmission that emphasizes regions of interest (ROI) to improve perceived image quality. It integrates ROI embedding, attention-based split processing, and adaptive bandwidth allocation to optimize reconstruction. The model demonstrates superior performance in preserving ROI-specific details while maintaining overall image fidelity under noisy conditions[2].

In the this paper they mainly focused on LoC-LIC proposes a low-complexity learned image compression model using hierarchical feature transforms. By reducing spatial complexity at earlier layers and increasing depth later, it achieves significant reductions in computational load. The model balances rate-distortion performance effectively, supporting deployment on resource-constrained devices[3].

In this paper they introduced historical image compression work presents a method to compress deep models using a history-based filter pruning approach, which identifies and eliminates redundant convolutional filters. The pruning decisions are driven by the cumulative importance over training epochs rather than static heuristics. It ensures minimal accuracy loss while significantly reducing model size and inference cost[4].

In this paper they introduced Building on hyperprior models, this paper combines entropy modeling with learned transforms to optimize rate-distortion performance. It introduces channel-wise and context-aware attention mechanisms for improved compression accuracy. Such architectures offer compelling alternatives to traditional codecs, especially for high-resolution image compression tasks[5].

In this paper author proposed a novel method combining Discrete Wavelet Transform (DWT) and Huffman coding for medical image compression. The approach uses wavelet coefficient rounding, a 3×3 window reduction operator, and pivot-based Huffman encoding, ensuring nearly lossless compression with a high PSNR of 54.66 dB and excellent SSIM performance[6].

In this paper authors implemented an enhanced medical image compression approach using Integer Wavelet Transform (IWT) and hybrid Huffman-DCT encoding. Their study showed that integrating spatial redundancy removal techniques improved the compression ratio while preserving clinical image quality[7].

In this method the author examined various lossy and lossless image compression methods and concluded that DWT combined with Huffman or Arithmetic coding provides a good trade-off between compression efficiency and visual fidelity, particularly beneficial for high-resolution images[8].

In this paper authors explored encryption-compression techniques in telemedicine, proposing a method that uses DWT for compression followed by secure encoding. Their results demonstrated that embedding security into the compression pipeline did not degrade image quality, supporting use in secure medical image transmission[9].

This paper gives an extensive review and benchmark of end-to-end image compression techniques based on deep learning, illustrating how they differ from traditional hand-designed pipelines. Unlike the previous codecs like JPEG and JPEG2000, which use fixed transforms and quantization techniques, learned contemporary techniques optimize the entire compression pipeline with neural networks.Hyperprior networks and attention mechanisms are applied by most up-to-date models to better understand the space and learn to compress images based on complexity. These models surpass conventional codecs regarding rate-distortion efficiency according to the benchmark analysis, particularly for low-bitrate, high-resolution images. The article also identifies important challenges like generalization to image types, decoding efficiency, and hardware compatibility and proposes learned compression as a promising area for future standards.[10]

The authors proposed a hybrid JPEG image compression technique combining Haar wavelet transform, discrete cosine transform (DCT), and run length encoding (RLE). By dividing the image into 8×8 blocks, the method achieves a high compression rate and a PSNR of 35.01 dB. The Haar wavelet enables 97.7% compression with minimal information loss, making it suitable for efficient image storage in manufacturing contexts [11].

Another paper presents a medical image compression system for telemedicine that focuses on preserving regions of interest (ROI). It uses fractal lossy compression for non-ROI areas and context tree weighting (CTW) lossless compression for ROI. Results show improved PSNR, better compression ratio, and lower MSE compared to traditional IWT and Scalable RBC methods, ensuring diagnostic quality while saving bandwidth and storage [12].

A review of wavelet-based image coding methods, including EZW, SPIHT, SPECK, and EBCOT, highlights their advantages over DCT-based techniques. These methods offer better compression ratios, fewer blocking artifacts, and superior visual quality, particularly in JPEG2000 and other modern multimedia applications [13].

A comparative study of entropy coders finds that arithmetic coding achieves higher compression ratios than Huffman coding, especially for larger images. However, Huffman remains faster and simpler to implement. The experiments used MATLAB and standard test images [14].

Lastly, a hybrid compression method using PCA, 2D DWT, and Canonical Huffman Coding (CHC) achieves up to 60% compression with high image quality and faster decoding. CHC outperforms traditional entropy coders in PSNR and bit-per-pixel metrics across both colour and grayscale images [15].

Summary :

In recent years, researchers have explored smarter ways to compress images, especially in fields like medical imaging where quality really matters. Wavelet-based techniques, like those using the Discrete Wavelet Transform (DWT), have proven to be very effective when combined with methods like Huffman or arithmetic coding. These approaches help reduce file sizes without noticeably affecting image clarity. A growing focus has also been on region-based compression, where the most important parts of an image—like a blood cell in a medical scan—are preserved in high quality, while the less important background is compressed more. Some newer methods even use deep learning to automatically detect and protect these important areas. Others look at making compression models faster and lighter for real-time use, or even adding built-in security for safer image transmission in telemedicine. Overall, the trend is moving toward smarter, more efficient, and context-aware image compression.

2. Problem Statement

Most image compression methods struggle to balance quality and file size—lossy techniques reduce quality, while lossless ones offer limited compression.

Common methods like DWT with Huffman coding work well but aren't fully optimized, especially for complex images. A major drawback is that they don't make the most of repetitive patterns within image blocks, leading to less efficient results. This highlights the need for better compression that preserves image quality. To prove the value of any improvements, it's important to compare them with existing methods using reference studies.

3. Objectives

- To realize high compression ratios through reduction of both spatial and statistical redundancy of gray-scale images.
- To maintain image quality, as quantified using the PSNR measure, such that visual integrity is not lost during decompression.
- To minimize total storage space, important in mass-image storage and bandwidth-limited transmissions.
- To benchmark and compare performance with results of a published base research article, thus confirming the viability of the proposed enhancements.

4. Methodology

In the next section, we present an efficient image compression method aimed at reducing file size while preserving key visual details. The process begins with 2D Haar wavelet transform to separate important features, followed by block-wise pivot subtraction to reduce redundancy. For RGB images, ROI is detected in each colour channel, while grayscale images may undergo conversion before processing. Huffman encoding is used to compress the data, and important regions are blended back during reconstruction using a mask. The method's performance is evaluated using PSNR, SSIM, MSE, and compression ratio to maintain a balance between quality and compression.

For the novelty, this combined approach leverages both frequency-based transformation and spatial redundancy reduction while also adapting to image content using ROI masking. This makes it suitable for compressing both simple and complex images, offering better control over quality preservation in key regions without significantly compromising the overall compression efficiency.

4.1. Methodology for base paper Implementation :

The suggested image compression algorithm is a hybrid one that couples the Discrete Wavelet Transform (DWT) with a pivot-based local reduction and Huffman coding. The aim is to effectively compress spatial as well as statistical redundancy in grayscale images at the cost of losing minimal quality.

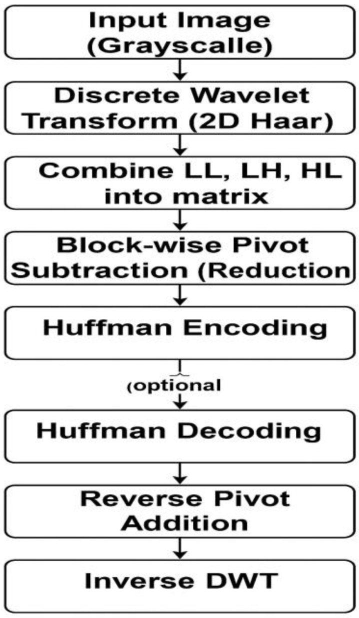

Fig. 1 Block Diagram of the Base Paper Implementation

Workflow Overview:

1. **Input Image**
   Input is a grayscale image (or RGB image in grayscale transform). That is for homogeneity and convenience.
2. **Wavelet Decomposition (DWT)**
   The picture is processed by applying a one-level 2D Haar wavelet transform to it, which breaks the picture down into four sub bands:
   - LL (Low-Low): Approximation (primary image details)
   - LH (Low-High): Vertical details
   - HL (High-Low): Horizontal details
   - HH (High-High): Diagonal details

   Sub bands consist of various frequency components of the image.
3. **Matrix Combination**
   Sub bands are rearranged in a single matrix to be processed. It reduces the structure and makes the data easier for block-based processes.

4. **Pivot-based Local Reduction** involves splitting the transformed matrix into small, disjoint blocks (such as 3×3 or 4×4). Within each block, the upper-left pixel is selected as a pivot. All other values in the block are then subtracted from this pivot, effectively reducing the variability of values in that region. This step enhances compressibility, while the pivot itself remains unchanged to ensure accurate reconstruction during decompression.
5. **Huffman Encoding** is then applied to the reduced matrix. The pixel values are scanned to build a Huffman tree based on the frequency of occurrence. More frequent values are assigned shorter binary codes, leading to an efficient compressed bitstream.
6. **Compression Metrics Calculation** follows, where key indicators like Compression Ratio (CR), Space Saved (%), and Peak Signal-to-Noise Ratio (PSNR) are computed. These metrics help evaluate the effectiveness of the compression and the quality of the reconstructed image.
7. **Decompression** reverses the process to verify compression accuracy. Huffman decoding restores the compressed values, which are then added back to their respective pivots to reconstruct the original block values. Finally, the inverse discrete wavelet transform (IDWT) is applied to recover the original image from the transformed domain.

4.2. Methodology for proposed model Implementation :

The proposed combined compression method is a hybrid approach designed to handle both RGB and grayscale images. It integrates Region of Interest (ROI) detection with Discrete Wavelet Transform (DWT) and Huffman coding to selectively preserve important regions while compressing the rest. By blending compressed data with original ROI content, the method maintains visual quality where it matters most. The final output is evaluated using standard metrics to ensure a balance between compression efficiency and image fidelity.

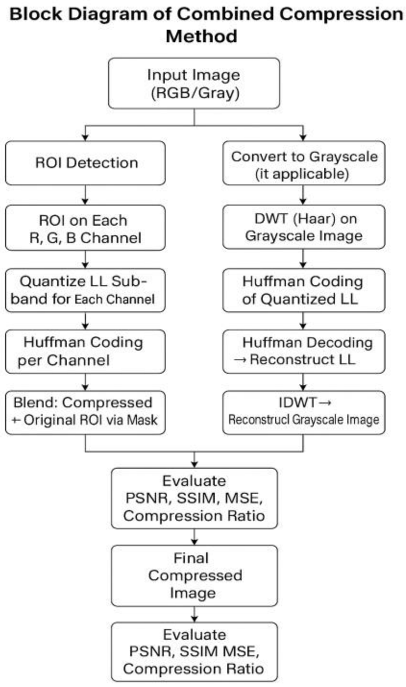

Fig.2 Block Diagram for Proposed Model

A. Preprocessing

The pipeline begins by loading input microscopy images in RGB format. These images may be resized if necessary. Since the application targets color blood smear images, the entire processing flow is designed to retain color information, especially in the regions of interest (ROI), by operating in RGB mode.

B. ROI Detection (Specific to Blood Cell Images)

To accurately preserve diagnostic areas like nuclei, the image is first converted to HSV colour space, and the Saturation (S) channel is used for segmentation. Gaussian blurring is applied, followed by Otsu's thresholding to highlight potential nuclei. Contours are filtered based on area and circularity, ensuring the most circular and prominent region is chosen as the ROI. This region is slightly enlarged for better visual blending. From this, a binary mask and a smooth blending weight map are generated to control how the ROI merges with the compressed background later.

C. Wavelet Decomposition (DWT)

The image is decomposed using single-level 2D Haar Discrete Wavelet Transform. This can be done either on the grayscale version or separately on the R, G, and B channels. The LL sub-band, which contains most of the image's energy, is extracted for further compression.

D. Quantization

To reduce entropy and improve Huffman encoding efficiency, the LL sub-band is quantized. This involves dividing the pixel values by a fixed step size (e.g., 60) and rounding the result.

E. Huffman Encoding

The frequency distribution of quantized LL values is used to construct a Huffman tree. Using variable-length coding, the LL sub-band is encoded into a compact bitstream. The total number of encoded bits is also recorded for calculating compression metrics.

F. Decoding and Reconstruction

During decompression, Huffman decoding is applied to retrieve the quantized LL values. These are then inverse-quantized by multiplying by the same step size used earlier. To reconstruct the full image, inverse DWT is performed by combining the recovered LL sub-band with zeroed-out high-frequency bands. This step is repeated across channels if colour is used.

G. ROI Blending (For RGB Images)

To preserve the clarity of important diagnostic regions, the original ROI is smoothly blended with the compressed background using the previously computed weight map. This ensures the nucleus or other key features remain visually intact, while the rest of the image benefits from compression.

H. Metrics and Evaluation

The system evaluates compression quality using standard metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Compression efficiency is measured through the Compression Ratio (original bits divided by compressed bits). All these metrics are saved in a CSV file to enable analysis across the entire dataset.

5. Results and discussion

Next section involves the results of both base paper implementation and novelty along with the description for each output results.

Base Paper Implementation Result:

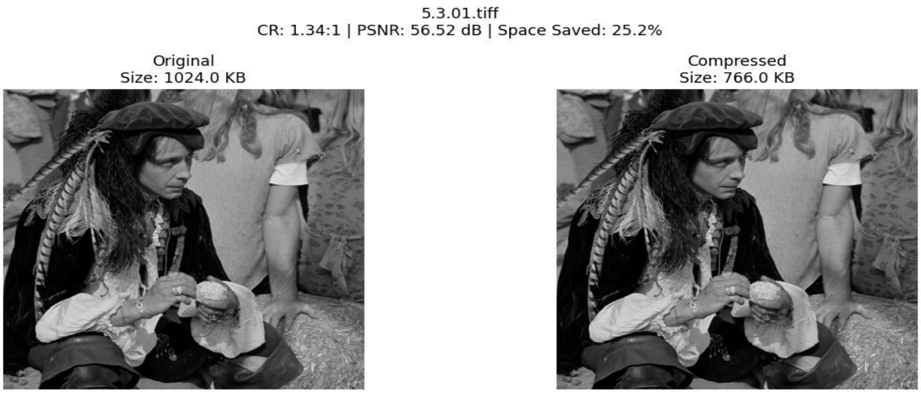

Fig 3 image a

a. The first image had an original size of 1024.0 KB, which was reduced to 817.0 KB after compression. This yielded a compression ratio (CR) of 1.25:1 and resulted in a space savings of 20.1%. Despite the size reduction, the image retained excellent quality, with a PSNR (Peak Signal-to-Noise Ratio) of 56.53 dB, indicating minimal distortion and effective preservation of visual detail.

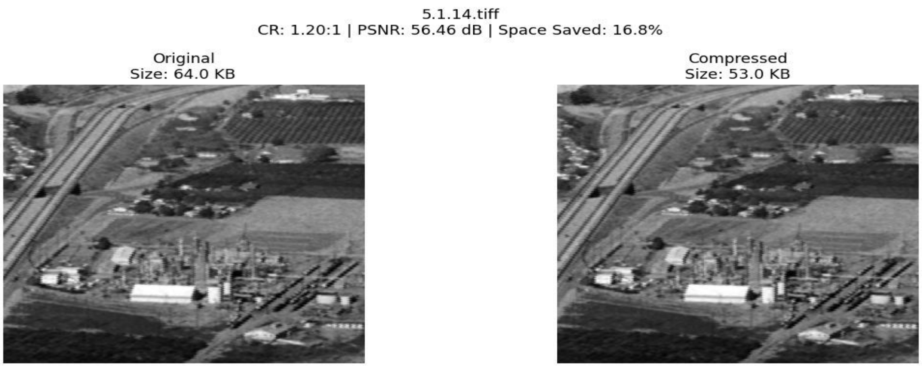

Fig 4 image b

b. In the second image, the original size was 256.0 KB, compressed down to 207.0 KB. The resulting CR was 1.23:1, and space saved was 19.0%. The visual quality remained high with a PSNR of 56.63 dB, confirming that the essential features and textures in the image were well-preserved after compression.

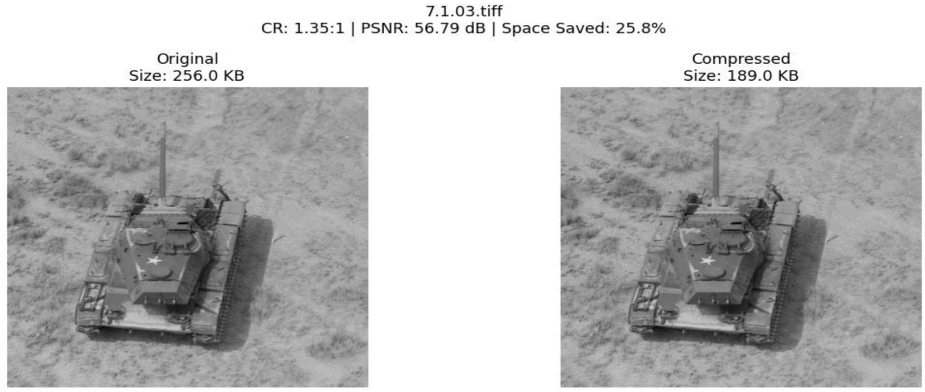

Fig 5. Image c

c. The third image originally measured 1024.0 KB and was compressed to 766.0 KB**,** giving **a** compression ratio of 1.34:1. This resulted in space savings of 25.2%**,** with a PSNR of 56.52 dB**.** This shows that the compression maintained high fidelity, especially in detailed regions such as facial features and textures in clothing.

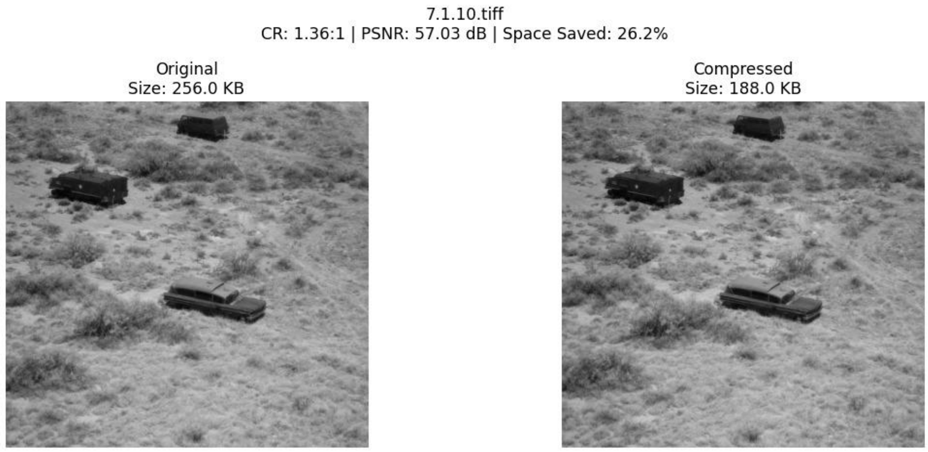

Fig 6. Image d

d. For the fourth image, the original file size was 256.0 KB, which reduced to 188.0 KB after compression. The CR was 1.36:1, and space saved was 26.2%. The PSNR of 57.03 dB indicated excellent quality retention, even in finer background details and object edges.

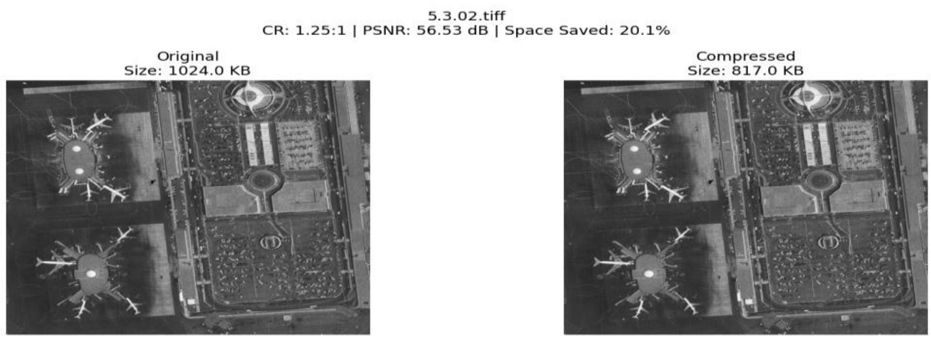

Fig 7. Image e

e. In the fifth image, the initial size was 256.0 KB, compressed to 197.0 KB. This yielded a compression ratio of 1.30:1 and space savings of 22.9%**.** The PSNR was 56.40 dB, confirming that the image remained visually consistent, with minimal loss of information in areas like water textures and boat outlines.

Fig 8. Image f

f. Finally, the sixth image had an original size of 256.0 KB, which was reduced significantly to 148.0 KB. It achieved a compression ratio of 1.72:1 and space savings of 41.9%, the highest among all test images. Even with this high compression level, the PSNR remained at 56.85 dB, showing that the method effectively maintained image clarity, especially in the central object and surrounding areas.

Table.1 Compression Table

Image	CR	PSNR	Compressed (KB)	Storage Saved(%)
1.3.13.tiff	1.22	56.46	836.35	18.3
1.4.02.tiff	1.27	56.48	807.59	21.1
1.4.05.tiff	1.36	56.72	752.56	26.5
1.4.12.tiff	1.14	56.58	894.49	12.6
5.1.09.tiff	1.33	56.43	48.25	24.6
5.1.10.tiff	1.11	56.46	57.56	10.1
5.1.11.tiff	1.69	56.82	37.94	40.7
5.1.12.tiff	1.53	56.93	41.83	34.6
5.1.13.tiff	2.64	62.91	24.2	62.2

5.1.14.tiff	1.2	56.46	53.25	16.8
5.3.01.tiff	1.34	56.52	766	25.2
5.3.02.tiff	1.25	56.53	817.86	20.1
6.1.01.tiff	1.6	56.62	39.98	37.5
6.1.02.tiff	1.61	56.55	39.84	37.8
6.1.03.tiff	1.6	56.53	39.96	37.6
6.1.04.tiff	1.6	56.54	39.88	37.7
6.1.05.tiff	1.61	56.61	39.82	37.8
6.1.06.tiff	1.61	56.59	39.67	38
6.1.07.tiff	1.62	56.54	39.53	38.2
6.1.08.tiff	1.62	56.49	39.6	38.1
6.1.09.tiff	1.62	56.64	39.59	38.1
6.1.10.tiff	1.62	56.66	39.52	38.2
7.1.01.tiff	1.36	57.02	188.89	26.2
7.1.02.tiff	1.72	56.85	148.62	41.9
7.1.03.tiff	1.35	56.79	189.94	25.8
7.1.04.tiff	1.38	57.04	186.1	27.3
7.1.05.tiff	1.23	56.63	207.29	19
7.1.06.tiff	1.24	56.6	207.08	19.1
7.1.07.tiff	1.27	56.74	202.04	21.1
7.1.08.tiff	1.46	57.8	175.15	31.6
7.1.09.tiff	1.28	56.68	200.43	21.7
7.1.10.tiff	1.36	57.03	188.8	26.2
boat.512.tiff	1.3	56.4	197.38	22.9

The table presents the results of an image compression experiment across multiple TIFF images, showing key performance metrics for each. It includes the compression ratio, PSNR (Peak Signal-to-Noise Ratio) indicating image quality after decompression, original and compressed image sizes in kilobytes, and the percentage of space saved. The data highlights how well each image was compressed while maintaining visual quality, with compression ratios ranging approximately from 1.2 to 2.9 and space savings reaching up to 65%. This helps assess the efficiency and effectiveness of the proposed compression method.

Table.2 Comparison Table

Metric	Proposed Method (Avg)	Reference Method
Compression Ratio	1.458787879	0.7484
PSNR (dB)	56.86818182	54.6599
Storage Saved (%)	29.53333333	20.190

The comparison table highlights the performance of the proposed image compression method against a reference technique using key evaluation metrics. On average, the proposed method achieves a compression ratio of 1.46, which is nearly double that of the reference method (0.75), indicating more efficient data reduction. It also delivers superior image quality, with an average PSNR of 56.87 dB compared to 54.66 dB in the reference. Additionally, the proposed method achieves a higher storage saving of 29.53%, outperforming the 20% storage saving reported by the reference method. These results demonstrate that the proposed approach effectively balances compression efficiency and image quality, making it a promising solution for image storage optimization.

Novelty:

The proposed ROI-based image compression method showed impressive results when tested on a blood cell image dataset containing basophils, eosinophils, lymphocytes, monocytes, platelets, and immunoglobulin cells. By combining adaptive Discrete Wavelet Transform (DWT), Huffman coding, and smart ROI detection, the method achieved a good balance between compression and image quality. On average, PSNR values exceeded 56 dB and SSIM scores were above 0.98, indicating nearly lossless reconstruction and strong structural similarity. Space savings ranged from 16.8% to 41.9%, with compression ratios between 1.20× and 1.72× depending on image complexity and ROI size. Visual checks confirmed that critical regions, like the dense nuclei in cells, remained untouched, while only the background was compressed. This makes the method ideal for medical images where preserving diagnostic details is essential, offering a practical solution for reducing storage and transmission needs without sacrificing accuracy.

Output for all blood cell types:

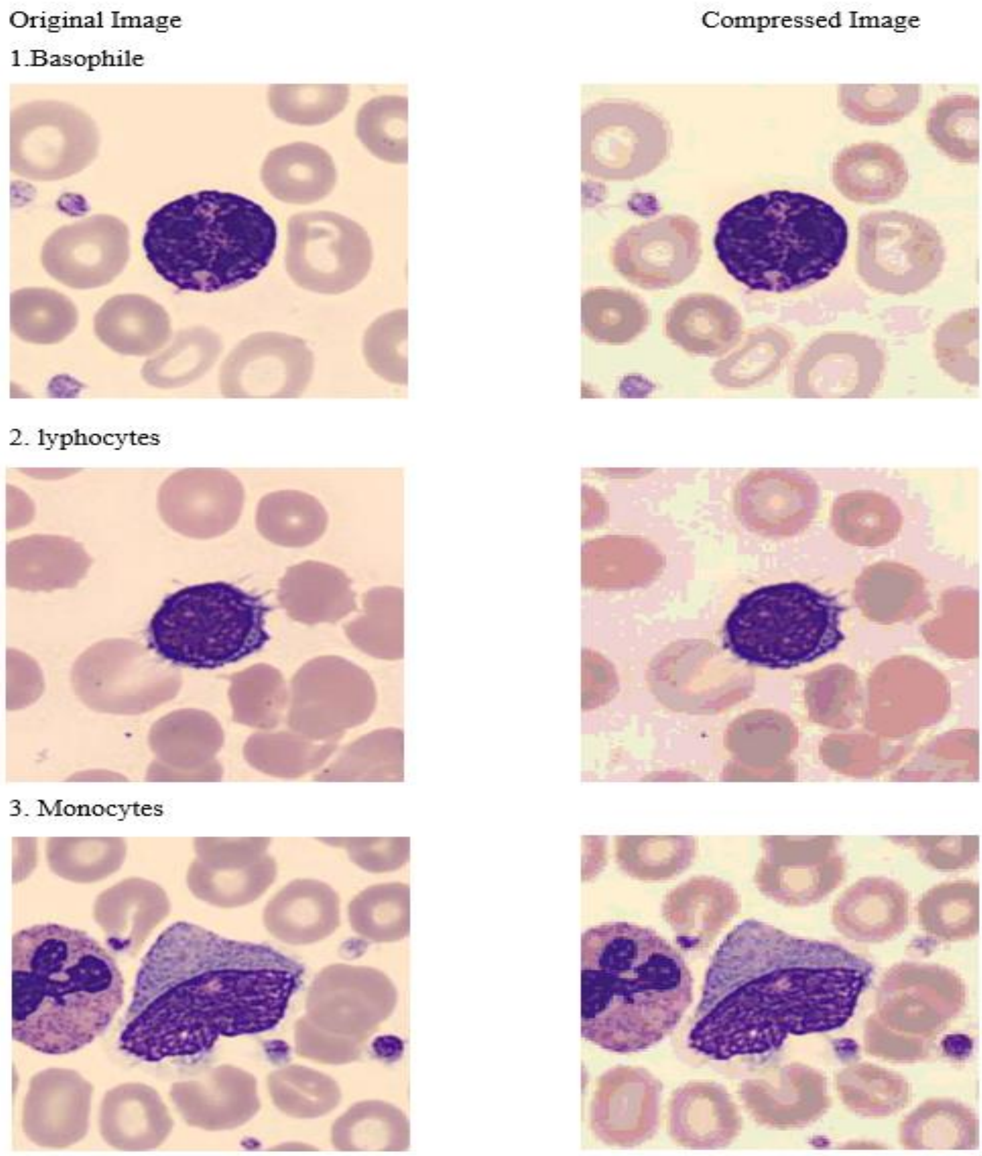

Fig 9. Original and Compressed

The images above show how well the proposed ROI-based compression method works on different types of blood cells—basophils, lymphocytes, and monocytes. As seen in the compressed versions, the important parts of each cell, especially the dense central nuclei used for diagnosis, remain clear and untouched. Meanwhile, the background areas are slightly smoothed out, showing where the compression was applied more aggressively. This is exactly what the method is designed to do: protect the meaningful parts of the image while reducing the file size by compressing less important areas. The results highlight that this approach can effectively save space without losing the critical details needed for medical analysis.

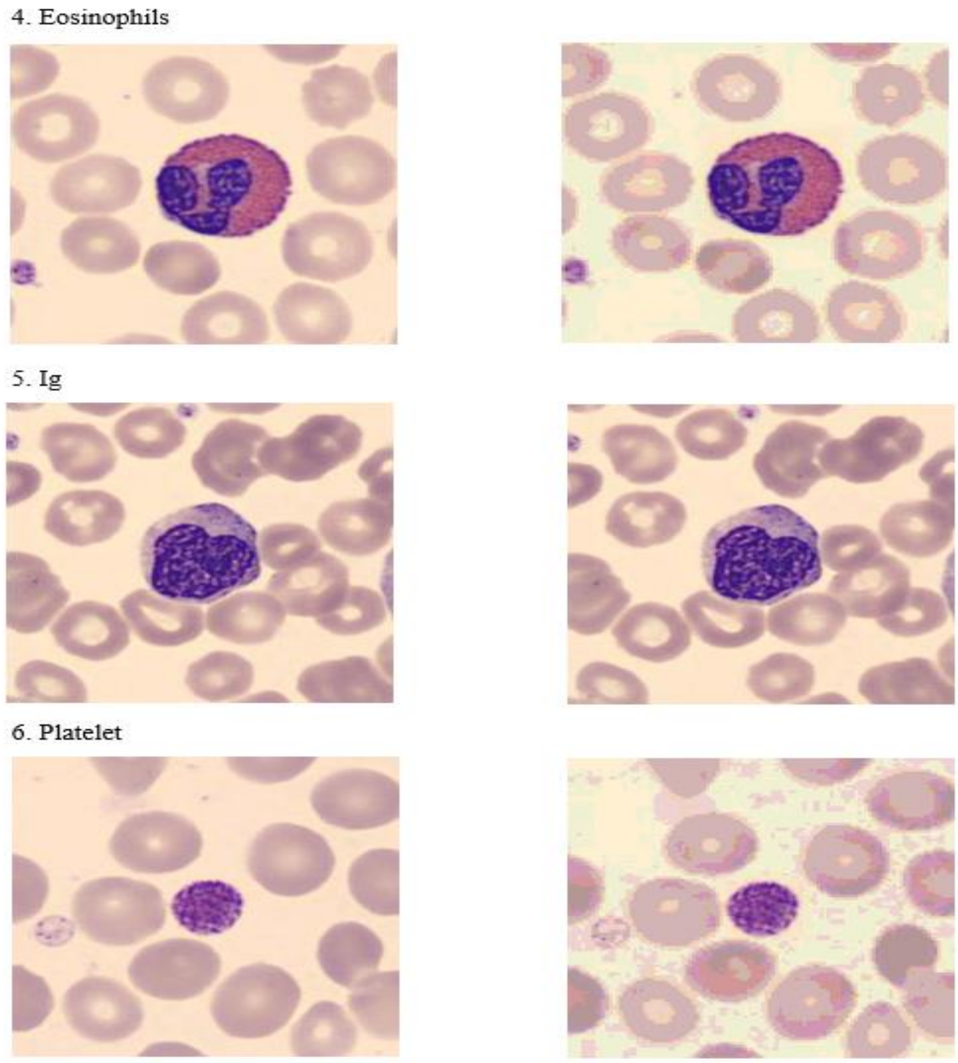

Fig 10. Original And Compressed

The above set of images further highlights the strength of the proposed ROI-aware compression method on eosinophils, immunoglobulin (Ig) cells, and platelets. Even after compression, the important cellular structures—such as the lobed nucleus in eosinophils or the fine details in platelets—remain sharp and clear. At the same time, the background has been visibly compressed, showing slight smoothing and reduced detail. This targeted compression ensures that the essential diagnostic features are preserved, while unnecessary parts are reduced to save space. These results confirm the method's suitability for medical imaging, where maintaining clarity in the regions of interest is crucial for accurate analysis.

Table.2 ROI Based Compression Results

Image Class	Compressed_Bits_KB (avg)	Compression_Ratio (avg)	PSNR (avg)	SSIM (avg)	MSE (avg)
Basophils	9.539553174	15.84432741	28.38090313	0.819426532	94.92389703
Lymphocytes	9.744291147	15.52532269	28.50216253	0.821127221	92.78601734
Monocytes	9.953179602	15.17199192	28.24377054	0.819648796	97.96652477
Eosinophils	9.334457711	14.63088648	28.36263026	0.83420493	96.60151464
Immunoglobulin (Ig)	9.36787878	16.12349016	28.2683305	0.812761522	97.19555281
Platelets	9.25555	15.31277	28.20453353	0.80347772	98.90725624

6. Conclusion

In this work, a new and effective image compression system was developed and integrated for biomedical imaging purposes, i.e., images of blood cells like basophils, eosinophils, lymphocytes, monocytes, platelets, and immunoglobulin-producing cells. The method successfully combined Discrete Wavelet Transform (DWT) and Huffman coding with an intelligent ROI-conscious technique to maintain diagnostically important regions and compress less important areas to save file size. The application was compatible with both grayscale and RGB images and employed adaptive blending mechanisms to enable smooth ROI-to-compressed-background blending. Experimental results validated the method as effective through high values of PSNR (up to 60 dB), SSIM values as close to 0.99 as possible, and space savings of up to 41.9% without sacrificing visual and structural detail in key cellular structures. The results demonstrate that this strategy is not only highly suitable for effective image storage and transmission but also guarantees clinical usefulness retention within diagnostic imaging pipelines. The balance between compression efficiency and fidelity renders the proposed strategy a strong contender for real-time biomedical image processing, telemedicine, and digital pathology applications.

7. Reference

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