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Content-Based Image Compression Using Hybrid Discrete Wavelet Transform with Block Vector Quantization

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Abstract: Image compression is necessary for the conveyance of information in the form of images. Images that have been compressed are fewer in size and sent over networks more quickly. Many algorithms focus on compressing images without prior knowledge on the image content type. But certain applications require content-based compression where degree of compression is controlled based on the image content type and should be able recover completely without loss of information. The proposed work aims at compressing the images based on the contrast variations and hybridizing discrete wavelet transform (DWT) and block vector quantization (BVQ) techniques. Two level DWT is applied on the image, then each sub-band is divided into non-overlapping blocks and a decision is made for each block based on the block variance before going for quantization. The proposed work calculates variance at the local regions to make decision as lower and higher contrast blocks, this helps to control degree of compression as only redundant/repeated blocks are allowed for quantization by preserving the edge information. Considering the entire image at once for vector quantization (VQ) diminishes the images' quality of compression. The VQ compression method often makes use of codebooks which possess lack of optimization. The proposed work implements BVQ technique, where only minimal pixels in a block are considered for quantization at once. This technique greatly reduces the computation time and also increases compression ratio. At last, huffman encoding is applied to the quantized coefficients. Following that, the bits that constitute the compressed image are saved and later restored. The suggested approach compresses and reconstructs images with adequate quality, on number of standard images as implemented. The effectiveness of the suggested work is also assessed by testing with custom real time images. When compared to current approaches, the findings suggest that the proposed work outperforms.

Keywords: *BVQ, Block Variance, Quantization, Compression ratio*

1. Introduction

Image compression is important for the transmission and storage of images. Compression makes it simple to produce images with a reasonable size and store, transmit, and save them [5]. Resolution and quantization of the grey level determine how many pixels are utilised to create an image. In order to store and transmit images more efficiently, image compression aims to eliminate redundancy and pointlessness in the image. Less bits that are similar to the original image make up the compressed image [7]. JPEG was the main image compression method [14], which was created by a group known as the Joint Photographic Expert Group (JPEG). Large bandwidth is needed on computer networks in order to send data through them. Therefore, data compression is crucial in a variety of industries, including entertainment, medicine, military and others. For the reconstructed pictures to have strong peak signal-to-noise ratio (PSNR) and compression ratio (CR), image compression is necessary to provide optimal performance with high quality [2].

The ability to interpret the compressed picture and achieving high compression ratios are the two main issues that image compression systems must deal with. In this study, both specifications were taken into account in order to preserve the image's important details [4]. The lossy image compression consists of three main steps as shown:

- Transformation: there is a linear transformation of the original picture from one domain to another.
- Quantization: where the quantization matrix is used to quantize the modified picture coefficients.

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- Encoding: after the quantization stage, the encoding is done to give the compressed image. The compressed picture is decoded, then dequantized, and lastly an inverse transformation operation is carried out to produce the rebuilt image as part of the reconstruction process.

Transform coding, continues to be the most effective coding method especially at low bit rates. The two primary transformation techniques utilised are DWT and DCT [6]. The most popular method for compressing images is called DWT. In essence, wavelets are just brief waveforms with finite durations and zero average values. The range of the wavelets is between -∞ to +∞ comparison with the sine function. In DWT, the wavelets are discretely sampled. Wavelets are a mathematical tool for breaking down pictures or mathematical calculations. The crucial characteristic of a wavelet is how it connects to other objects via scaling, shifting, and translation [19].

For image compression, there are several lossless and lossy compression methods [9]. The different sorts of quantization are scalar and vector quantization. Vector quantization is typically used to carry out lossy picture compression. However, vector quantization is a non-transformed compression method, it is a strong and effective technique for lossy picture compression. [11]. One of the most effective methods for producing acceptable codebooks has been demonstrated to be vector quantization. Vector quantization is used to separate the picture into a series of rectangular squares. The training data vector is created when such squares are added together. To create a codebook, each training vector is divided into a number of clusters [32]. Similar to this, a picture is reconstructed by substituting the closest codebook vector for each training vector. The fast compression process is a benefit of the VQ approach [27].

1.1 Need of image compression

Compression is a process where a certain piece of information is described by fewer data points. A compression algorithm's job is to turn a source of data into a compressed version that can then be uncompressed to reveal the original material [12]. Raw images take harder to upload and demand more bandwidth. Before compressing the pictures, a lot of redundant information must first be eliminated. In most instances, there are three primary redundancies in digital images, and they are listed below:

- **Spatial Redundancy (Interpixel Redundancy):** Typically, the values of nearby pixels are tightly connected in all images. Using the values of nearby pixels, it is possible to practically predict the value of any given pixel. Using this prediction, redundancy can be removed [19]. A variety of sizes can be successfully detected by the wavelet's modification. Therefore, these wavelets are ideal for this use.
- **Coding Redundancy:** The values in a matrix representation of an image vary from 0 to 255; this normal probability plot of pixel values is known as a histogram. It is simple to find instances of each number that appear repeatedly across the image using this storage structure. Certain pixel values tend to appear more commonly than others in ordinary photographs [6]. When all of the pixels are assigned the same code word size, coding redundancy is produced. Huffman coding can be used to lessen duplication. This is accomplished by using fewer bits for the extra grey scale values for the less useful bits.
- **Psycho visual Redundancy:** Psychovisual redundancy is dependent on aspects of human nature vision. All optical input cannot be processed by human eyes with the same intensity [20]. The term psycho visual redundancy describes how certain information is perceived as being less important than other information.

The suggested method involves

1. A considerable rise in quality measure values such as PSNR and CR.
2. High SSIM values suggest that the original and restored images are very equivalent to one another.
3. Low RMSE results demonstrate that block distortions have been completely eliminated.
4. According to space-saving (SS) and compression tests, the suggested approach accomplishes bulk image compression at a high rate.

The operational upgrades comprise

1. Use of multi-level DWT increases the number of discarded coefficients in high frequency bands resulting higher compression ratio.
2. Usage of content-based compression, saves execution time for bulk images.
3. Usage of block-based variance technique controls degree of compression depending on the image content.
4. Usage of non-overlapping block division for vector quantization greatly reduces execution time.

This suggested paper includes six sections which includes an introduction. Second section covers the literature survey. The third section clarifies content-based compression. The fourth section elaborates on the suggested technique and algorithm. Section five contains the results and discussion. The last section contains the conclusion.

2. Literature Survey

[1] Mohammed F. Radad et.al. [2022] suggested an approach that combines vector quantization and the wavelet transform technique (DWT). A technique for compressing medical pictures that keeps the image's diagnostic information while yet achieving a high compression ratio. The pictures were further reduced by applying DWT to the wavelet coefficients in the low

frequency sub-band. However, as the thresholding strategy was the most efficient, it was employed to produce coefficients for the sub-bands of high frequency. The use of the BPNN approach provided the result with a vector quantization. The utilisation of an artificial neural network design results in a very efficient method for CR, PSNR, and MSE image compression. The suggested approach can improve compression efficiency while striking a reasonable balance between compression ratio and picture visual quality.

[2] Javad Rahebi [2022] proposed a method, which utilise the whale optimization technique to find the best codebook in image compression. Several standard images using the suggested approach for compression demonstrate that the approach preserves image quality. In comparison to algorithms like bat, particle swarm optimization and firefly algorithms, the suggested technique achieves compression more effectively. Compression quality is improved through codebook optimization. The whale algorithm optimises the code with the spiral, rotational, and random motions. The suggested approach also performs better at storing pictures more efficiently in memory types and has a detrimental impact on cost-cutting.

[3] Muhammad bilal et.al [2021] offers a histogram-oriented pattern-based masking (PBM) approach to compress images that uses less iterations and more computational efficiency. This algorithm uses the histogram's peak values to forecast picture patterns for codebook creation by applying them to specified pattern masks. Processing time is reduced by decreasing the amount of nearest similarities between both training vector with codewords in the codebook. By requiring only two iterations, the proposed algorithm is shown to be more advantageous for SSIM and PSNR while maintaining high bitrates and minimal computational time.

[4] Shuying Xu et. al. [2021] proposes, a revolutionary picture compression technique based on VQ compresses called a pixel prediction-based picture compression method. This compresses the picture in accordance with the outcome of the prediction using linear regression, wherein may greatly improve the CR. A simple picture compression technique that may reduce images to 1/16th of their original size is vector quantisation (VQ) compression. It integrates linear regression prediction with VQ compression. Here, first train a codebook which contains the codewords using a few photos after that use linear regression, followed by pixel prediction. Then, choose whether to employ pixel prediction compression or VQ compression by evaluating the gap among both the source and predicted pixel block. The suggested approach can therefore greatly increase the ratio of image compression.

[5] U. Naveenakumara et.al. [2021] proposes a technique where, image compression using the block truncation coding (BTC) technique is used to create an ideal DWT with singular value thresholding for compressed JPEG and PNG images. The cover picture is divided at one level into sub-bands of various frequencies using a DWT technique. Singular value decomposition was used to break up a low frequency subband. As the thresholding of singular values continues, adaptively change the low-rank approximation precision threshold. The IDWT is employed in the reconstruction the approximation matrix after the high-frequency components below a specific threshold are removed. The suggested enhanced BTC image compression method displays anticipated average PSNR values.

[6] Gaurav Kumar et. al. [2021], suggested a hybrid DWT-DCT combined arithmetic and huffman compression algorithm. In order to obtain high CR and high PSNR values, the input image would be first decomposed until it reaches the third level using the DWT and followed by arithmetic & huffman coding is done individually on quantized sub-bands on the second and third approximated level coefficients from sub-bands. The DCT approach is used for the third level approximation sub-band to lessen the blocking impact. According to the results, arithmetic coding and huffman coding both accomplish extremely high compression ratios utilising the haar and db9 filters, respectively. DWT-DCT systems used encoding and decoding techniques to obtain greater PSNR and CR values.

[7] Taiwo Samuel Aina et.al. [2021] proposes an effective image compression approach, wavelet transformations and image approximation with a modified wavelet coefficient were developed. The DWT really does have the benefit of providing a high compression ratio with minimum information loss and shown how to split an image into four sub-band images, such as the approximation image and detailed image. They are divided into four additional sub-band images using the wavelet coefficients. The 2D-DWT multi-resolution decomposition was used to achieve the image approximation. The three-level decomposition result was used to recover the lowest frequency sub-band image (LL), which was then used to rebuild the basic picture. Using just the approximate image to rebuild the source image allowed for the alteration of the wavelet coefficients and results shows a minimal error. Consequently, the two-dimension DWT method is quite good in creating an estimated picture of high quality.

[8] S. Boopathiraja et.al. [2021] proposed a nearly lossless method of compressing three-dimensional medical images utilizing the 3D-discrete wavelet transform. This method may be used right away with 3D photos. The encoding is Huffman encoding and the decomposition algorithm is 3D-DWT. The almost lossless quality is maintained via Huffman encoding and thresholding with mean value. Results of suggested method demonstrate this; it averagely saves 0.45 bit-rate for provided 3D volumetric photos with minimal

MSE. Threshold technique improves compression while simultaneously maintaining picture quality.

[9] Rajaa khalaf gaber et al. [2020] suggested compression method that uses high-level DWT to separate the image into smaller images. The huffman algorithm with non-uniform quantizer was implemented in order to lower the compression data rate with great picture reconstruction. Initial RGB picture conversion to luminesces and chrominances (YCbCr), partitioning the image into sub-images by three-level harr transform decomposition. Next filtered by variable threshold values, one threshold for LL3 sub bands and another threshold for other sub bands. To reduce the pace of compression data rate with excellent reconstruction images, the non-uniform quantizer for the huffman code was additionally utilised. Two Huffman coder dictionaries have been built for each group in order to get the compressed image. Rebuild the three components by regrouping the reconstructed sub-image by the full unselected subband by zeros, then decode the compressed data utilizing the first and second Huffman coder dictionaries. Finally, convert the Y,Cb,Cr colour module to RGB. With an increase in threshold, the PSNR has decreased. Using a collection of genuine photographs has helped to illustrate the efficiency of this technique.

[10] Saradha Rani Sabbavarapu et al. [2020] proposed an algorithm for a greater compression rate with fewer loss, brain pictures are utilised in conjunction with DWT and RNN. To differentiate between the ROI picture and the non-ROI image, region growth and otsu thresholding were applied. The medical image is analyzed using DWT and RNN, respectively, for the ROI and non-ROI areas. Comparing the suggested approach to current ones, the PSNR is high. The important medical picture information is preserved during compression and restoration using the lossless DWT based ROI compression. The medical pictures ROI and non-ROI areas were subjected to a combination of lossless and lossy compression. Higher compression ratio is attained while still preserving the required PSNR.

[11] Pratibha Pramod Chavan et. al., [2020] proposes a work that has made use of the VQ idea and the LBG model for picture compression. The image was first divided into blocks, and an appropriate codeword was determined for each vector which represented the nearest equivalent of that input vector. A codebook is created by the encoder by mapping vectors based on code words, and vector compression happens as a result. After that, the encoder transmits a compressed stream of such vectors to the decoder, which detects and inserts the compressed vector on the picture. The updated rider optimization algorithm is employed to optimize the codebook. Codebooks typically optimised so that the sum of the compression ratio and the quality difference between the source and decompressed pictures is as low as feasible.

[12] Paul Nii Tackie Ammah et.al. [2019] developed a DWT-VQ approach to scale back the size of pictures yet keeping overall visual efficiency at a level that is tolerable for medical use. Speckle and salt and pepper sounds in ultrasound images are greatly minimized by this hybrid method. After that, DWT is used to filter the photos. To efficiently create coefficients, a threshold technique is used. After that, the result is vector quantized. Finally, Huffman encoding is applied to the quantized coefficients. The bits that make up the compressed image are then saved and then recovered. The outcome of the suggested approach is encouraging because it performs better than other recent strategies.

[13] Marcos Roberto e Souza et. al. [2020] proposed a technique, to improve the capacity of the k-means method to discover a suitable cluster centre initialization, examined the enhancement of picture colour quantization approaches utilising genetic algorithms. This shows that using the MSE measure as a fitness function or to assess the accuracy of the picture colour quantization is not recommended. The ideal parameter values for the picture clustering issue were determined using a novel fitness function based on image similarity. In comparison to the results produced using the k-means method, the experiment outcomes on several photos showed that there is a constant increase towards SSIM. Furthermore, both the image's information and the number of colours it will be quantized rely greatly on the level of improvement attained.

[14] Karri Chiranjeevi et. al. [2018] shown a vector quantization for picture compression based on the cuckoo search (CS) technique. The method creates training vectors and an effective codebook. It has been found that the PSNR and reconstructed picture quality achieved with the CS method are greater to those achieved with the LBG, PSO-LBG, QPSOLBG, HBMO-LBG, and FA-LBG algorithms. According to the results, CS-LBG converges approximately 1.425 times more slowly than HBMO-LBG and FA-LBG. The main flaw in the suggested approach is slower convergence, which will be remedied by changes to the algorithm in the future. But compared to other algorithms, the CS-LBG method needs less parameters.

[15] Ms. D. Preethi et.al. [2020] proposes an algorithm on VQ with comparison of the firefly by tumbling effect (FF-T) and firefly with teaching and learning based optimization (FF-TLBO). Both of these techniques try to solve the best fit value to each block, which is called as local best. The best value for the entire image is known as global best. Results of the tests show that the given FF-LBG approaches are faster than the other algorithms.
Images are reconstructed with better quality. This method is tested for some standard group of images. This achieves a good result with respect to RMSE, MSE, PSNR and SNR.

[16] Srijati Agrawal [2020] presented side-match vector quantization and conventional vector quantization as two Finite-State Vector Quantization (FSVQ) concepts. In this paper, side-match vector quantization (SMVQ) method is implemented to create high-quality compressed images. The codebook is generated using rapid generation of state codebook method. This approach is significantly more computationally demanding, quicker, and produces greater visual quality without sacrificing quality.

[17] H. B. Kekre et.al. [2016] proposes, a straightforward wavelet-based vector quantization method for compressing images proposed. The Kronecker product of two distinct transforms is used to create a hybrid wavelet transform. In order to achieve excellent compression, the picture is changed into the transform domain using a hybrid wavelet transform and only a small number of low frequency coefficients are kept. These coefficients are subjected to vector quantization in order to considerably improve compression ratio. After applying VQ algorithms to the altered picture, codebooks of the smallest 16 and 32 feasible sizes are produced. KFCG and KMCG operate more quickly and outperform the LBG algorithm. At compression ratio 192, KFCG in combination with a hybrid wavelet transform provides the least distortion and acceptable image quality.

Despite the fact that image compression has been researched for over two decades, there continues to be opportunity to improve its efficiency and practicality in real-world applications. According to the aforesaid research, previous studies focused mostly on compressing images without prior knowledge of the image content type. But certain applications require content-based compression where degree of compression is controlled based on the image content type and should be able recover completely without loss of information. The suggested image compression model works by reducing redundancy in local areas based on variance. The model manages spatial redundancy in the image by removing the duplication in the DWT's high-frequency coefficients via block variance, whereas the redundancy inside the low-frequency (high energy) coefficients are reduced through block vector quantization (BVQ) techniques. Further, the aforementioned works considers the entire image at once for vector quantization (VQ) results in diminishing the images' quality of compression. The proposed work implements block vector quantization (BVQ) technique, where only minimal pixels in a block are considered for quantization at once. This technique greatly reduces the computation time and also increases compression ratio with quality reconstruction.

3. Content Based Compression

The proposed algorithm aims at compressing the images based on the contrast variations and by combining discrete wavelet transform and vector quantization techniques. With the nature of image content, lower contrast blocks contain more change in pixels basically the edge information (Foreground; Region of Interest (ROI)) while higher contrast blocks contain less change in pixels basically plain information (Background) [16]. Therefore, the higher contrast blocks are need to be compressed as these blocks carries lesser information and can be recovered successfully from minimal data (compressed bits). The lower contrast and higher contrast regions in the image can be easily detected by calculating variance at the local regions [30].

3.1 Variance Calculation

A collection of pixels' width is measured by an image's variance. A lower variance shows that the group of pixels values are close to the average value, while a higher variance suggests that the group of pixels are spread out over a large range of values. High variance indicates complex component composition of the image block and vice versa [30]. The mean of the pixels in a block is used to compute the variance of that block.
The variance equation can be given as

$$V(x) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu(x))^2 \qquad (1)$$

$\mu(x)$ is the mean of that block.

$$\mu(x) = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (2)$$

The figure 1 displays the variance value for the standard Lena image for four 32x32 blocks.

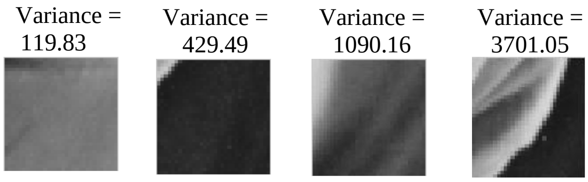

Fig. 1: Variance of Lena for four blocks

4. Proposed Methodology

In this work content-based image compression technique based on DWT and BVQ is implemented. The source image has been decomposed at multiple discrete wavelet levels. The resulting sub-bands are divided into non overlapping blocks and a decision is made before applying lossy compression VQ technique. The decision on image content evaluation is made by analyzing low and high frequency sub-bands and also by calculating the variance of each block. The appropriate blocks are subjected to vector quantization in order to considerably improve compression ratio. VQ algorithms are applied on blocks having higher variance and variable sized codebooks are generated between the sub-bands for better compression. Following that, a compressed image is produced by encoding the quantized coefficient (symbols) in a bit stream using huffman encoding. Figure 2 displays the suggested block diagram for compression technique.

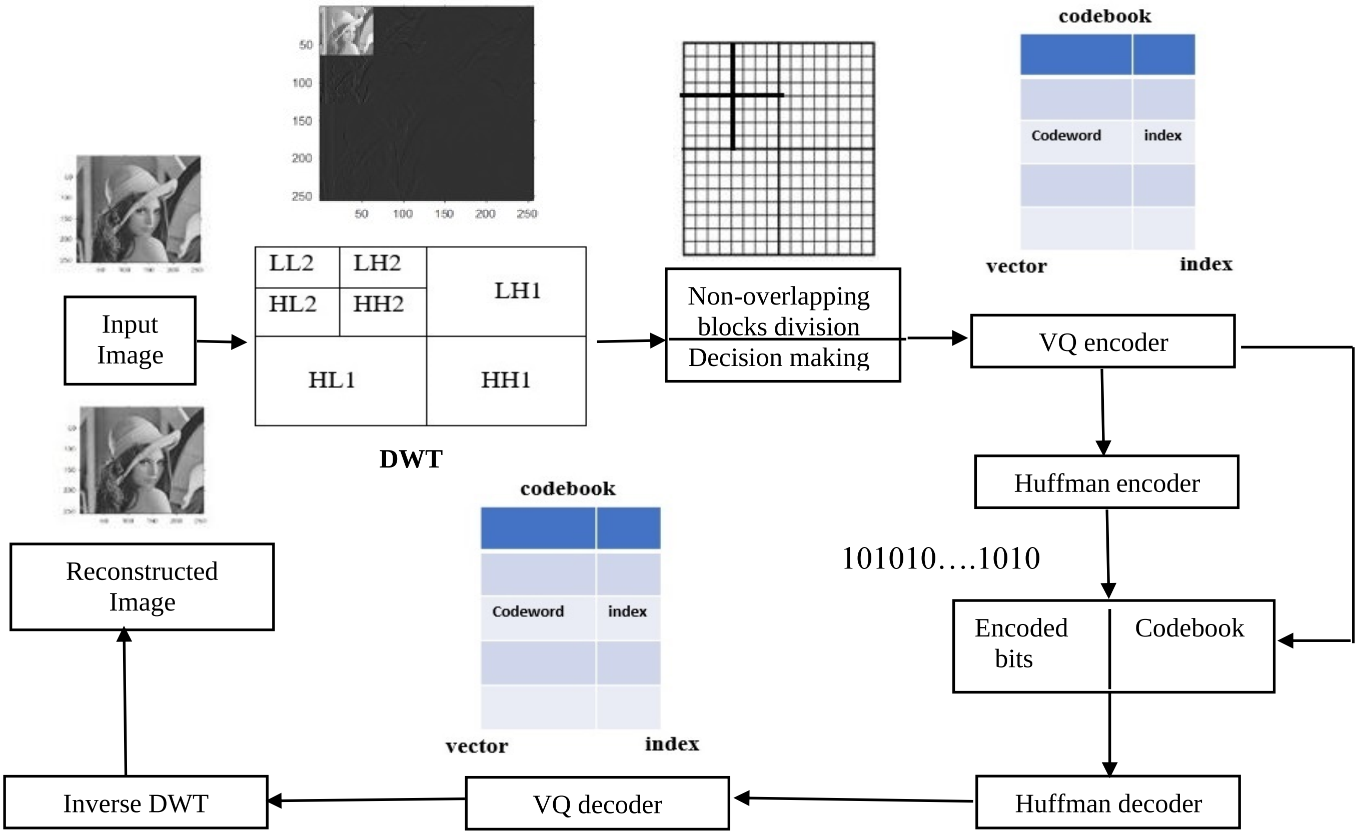

Fig. 2: Proposed Block diagram using Hybrid DWT and BVQ

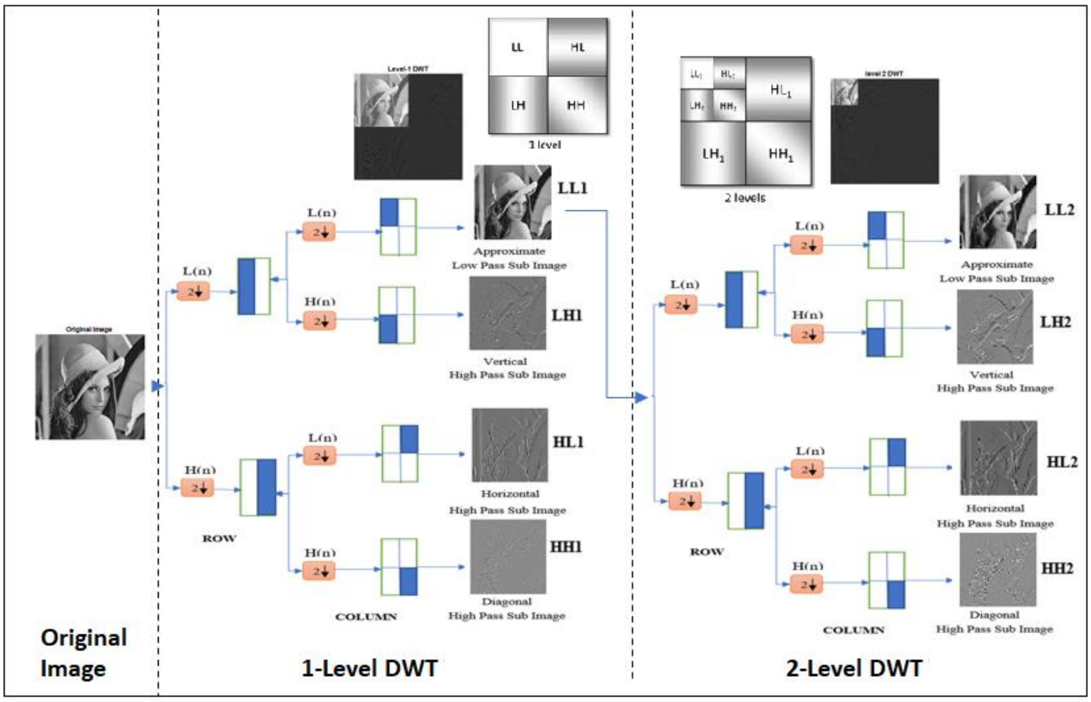

Fig. 3: 2-Level DWT decomposition using row and column procedure with low and high sub-bands

4.1 Discrete Wavelet Transform

A discrete wavelet decomposition is performed on the input image at multiple levels. The information about frequency modules is presented using multilevel wavelet
decomposition, which also improves the information about the image for subsequent use. Additionally, because the subsequent levels include less noise and more usable information, it gives the ability to perform better reconstruction following compression. Figure 3 displays the in-detail view of 2-Level DWT decomposition using row and column transformation procedure with low and high frequency sub-bands.

Since it is quicker and more effective, a one-dimensional technique is employed to transform an image using rows and the columns. By applying filters to the image's rows and columns, the transformation is accomplished. Because Daubechies filter can generate a large number of zeroes or vanishing moments, it is used here [19].

The following two conditions are tested as:

TEST CONDITION 1: Single-Level Image Decomposition.

- STEP 1: DWT transform is applied on the input image to generate four sub-bands: LL, LH, HL, and HH. The approximation sub-band is the LL sub-band.

TEST CONDITION 2: Two-Level Image Decomposition.

- STEP 1: DWT transform is applied on the input image to generate four sub-bands; LL, LH, HL, and HH. The approximation sub-band is the LL sub-band [10].
- STEP 2: Transform the LL block from the first operation to obtain the sub-bands for the second level.

At the end of this process, 4 sub-bands are obtained (LL1, LH1, HL1 and HH1) for the first condition and 7 different sub-bands for the second condition (LH1, HL1, and HH1 of first level of decomposition and LL2, LH2, HL2 and HH2 of second level of decomposition). The several coefficients from high frequency sub-bands are discarded by replacing them with zero values [4].

4.1.1 Co-efficient rejection

1. High frequency sub-bands (3 from single level and 6 from two level) are considered for co-efficient rejection.
2. Calculate the sub-band variance for all high frequency sub-bands.
3. Each sub-bands are divided into $N \times N$ non-overlapping blocks.
4. Calculate the block variance of each block in a sub-band.
5. The block variance that falls below sub-band variance (calculated from step 2) are discarded by replacing them with zero values.

4.2 Block division and Decision making

The proposed work performs image compression based on the nature of content. The wavelet results in two different frequency components namely low and high frequency sub-bands. The level of compression and the accuracy of the reconstructed image are primarily determined by two parameters.

1. The degree of compression applied between the bands (Low and High frequency).
2. Removing the redundant and less priority information within the band.

4.2.1 Block division and Decision making for Low Frequency band

1. Calculate the low frequency sub-band variance.
2. The low frequency sub-band is divided into $N \times N$ non-overlapping blocks.
3. Calculate the block variance for all the blocks.
4. Blocks whose block variance is lesser than sub-band variance (calculated from step 1) are undergoes VQ compression, considering that blocks contain redundant information.
5. Blocks whose block variance is greater than sub-band variance (calculated from step 1) are undergoes no compression, considering that blocks contain edge information and needs to be preserved for better reconstruction.

4.2.2 Block division and Decision making for High Frequency bands

1. Calculate the sub-band variance for all high frequency sub-bands.
2. Each sub-bands are divided into $N \times N$ non-overlapping blocks.
3. Calculate the block variance of each block in a sub-band.
4. Blocks whose block variance is greater than sub-band variance (calculated from step 1) are undergoes VQ compression, considering that blocks contain edge information and requires minimal data (since these are high frequency bands) for better reconstruction.
5. Blocks whose block variance is lesser than sub-band variance (calculated from step 1) is discarded or made zero, considering that blocks contain less priority information.

Algorithm for *Block division and Decision making for Low Frequency band*

Input : *low_frequency_block (N,N)*
Output : *low_frequency_block (N,N)*
Or
compressed_block (N, N/2)

Calculate *sub_band_variance (X, Y)*
Begin:
Calculate *low_frequency_block_variance (N,N)*
If (*low_frequency_block_variance (N,N) < sub_band_variance (X, Y)***)**
// Undergoes VQ
compressed_block (N, N/2)
Else
// Retain block
low_frequency_block (N,N)
end if
end

Algorithm for *Block division and Decision making for High Frequency bands*

Input : *high_frequency_block (N,N)*
Output : *compressed_block (N, N/2)*
Or
block_rejected (N, N) = 0

Calculate *sub_band_variance (X, Y)*
Begin:
Calculate *high _frequency_block_variance (N,N)*
If (*high _frequency_block_variance (N,N) > sub_band_variance (X, Y)***)**
// Undergoes VQ
compressed_block (N, N/2)
Else
// Reject block
block_rejected (N, N) = 0
end if
end

Figure 4 displays the detailed explanation about the block division which uses non-overlapping blocks. Consider 4x4 blocks for both low frequency and high frequency band. Finally, decision making is made based on the block variance and sub-band variance as explained in the algorithm1 and algorithm 2.

4.3 Block Vector Quantization (BVQ)

The concept of vector quantization is based on LBG (Linde-Buzo-Gray) model, a state of art technique mostly used in image compression [32]. In the area of image and video processing, vector quantization is a straightforward approach for compression. It combines together a huge number of data points known as vectors. The vectors of an image are used to create a set of vectors known as a "training set". The code vectors must lessen the distortion [20]. This is a common code generation approach that creates a codebook with the least amount of error from a training set. The suggested block-based approach optimises code word generation in LBG-based VQ for enhanced image compression [16].

In this method, the blocks obtained from decision making phase are subjected to modified LBG VQ which alternatively resolves optimality criteria, with the minimal codebook dimension. Each block is having $N \times N$ dimension [29]. In this work, codebook of minimal size 2 is used to compress each 4x4 block. The k-means technique was used, and a power of two is thought to be the ideal codebook size.

The algorithm is progressed in the following ways:

1. Load the wavelet sub-band blocks to be quantized. From the previous phase, for condition 1: where single level decomposition is conducted followed by block division and decision making for all four (LL, LH, HL and HH) sub-bands.
   For condition 2: where two-level decomposition is conducted followed by block division and decision making for all seven (LL2, LH2, HL2 and HH2; LH1, HL1 and HH1) sub-bands.
2. Divide the block into the required number of non-overlapping vectors. Select the codebook size and should be 2 (since minimum block size considered is 4x4). This is done to test how well compression, while simultaneously examining quality, performs when block sizes are changed.
3. For the complete collection of vectors produced by the previous step, find their centroid.
4. Divide each centroid into two centroids, x and y, and permit a little offset to have a small normal and random direction.
5. Assign each piece of information to a centroid to create distinct groupings. From here onwards, the groups are treated separately.
6. Find the centroids of the clusters produced.
7. Use the Euclidean distance formula to get the total distance and compare it to the required distortion value. If the number of centroids is less than the necessary number, proceed to STEP 4,
8. If the distortion is more than the maximum allowable, go to STEP 5.
9. The final codebook generated are saved and end.

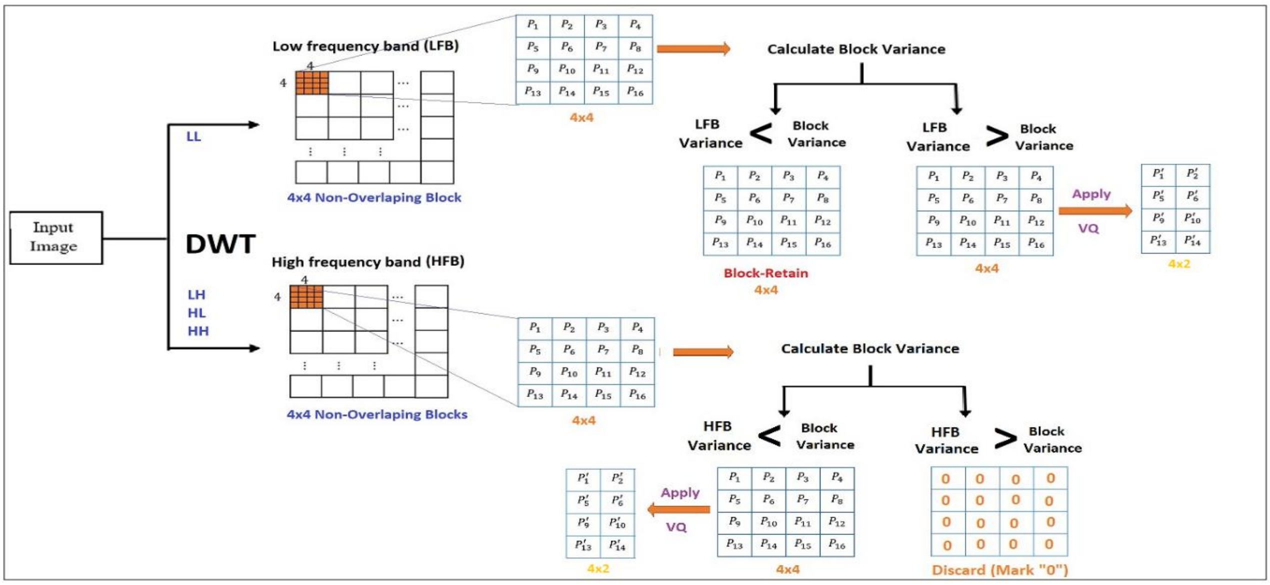

Fig. 4: Block division and decision making before lossy compression

The approach is quick since calculations are performed on block level which is a minimal data, while ensuring that each group's vectors have a deep relationship to the produced centroids [31].

The DWT block coefficients are encoded by the VQ encoder using the codebook. The encoder substitutes each valid non-overlapping block with an index of the codeword from the codebook with the lowest distortion rate. Only after calculating the Euclidean distance between each codeword and the block to be quantized is this achievable [15]. The DWT's original coefficients are compressed in the final data, which consists of sets of indices. The figure 5 displays the flowchart of the proposed BVQ algorithm. Moreover, quantization is only applied to blocks with proper criteria, which significantly reduces execution time and facilitates effective reconstruction.

4.4 Huffman Encoding

This is the most efficient coding scheme and is typically used to create the lowest extra codes when compared to other computations [17]. Huffman coding is determined by the rate with which a data pixel is associated with images. The objective is to encrypt data that is more often occurring with less bits [8]. To reduce the bit length of the compressed image, the huffman coding technique is applied. In the huffman coding method, attempt to locate the codes without any of them serving as prefixes to any other codes. [4]. The length of the code is decided according to the probability that the character will appear. The most probable character has the shortest length code to get the best outcome [19].

The decoder effectively restores the original data using the encoded sequence. The compressed image undergoes the de-compression process backwards in order to restore the image. The huffman-encoded data must first be decoded in order to extract the indices. Following that, the codebook and collection of indexes are passed to the VQ decoder in order to successfully reconstruct the data [6]. The decoder presently employs the indices to look up the code-word in the codebook to rebuild the wavelet coefficients at the block level. After reconstructing co-efficient from each sub-band at different levels, the image is recovered using an inverted DWT. The size of the reconstructed image matches that of the original.

4.5 Performance Parameters

The performance of compression algorithms may be assessed using the metrics listed down.

4.5.1 CR (Compression Ratio):

The ratio of the size of the original image to the size of the compressed image [8], is called compression ratio (CR) which is given by

$$CR = \frac{\text{Original image size}}{\text{Compressed image size}} \quad (3)$$

The percentage of compression of the original image is evaluated using CR.

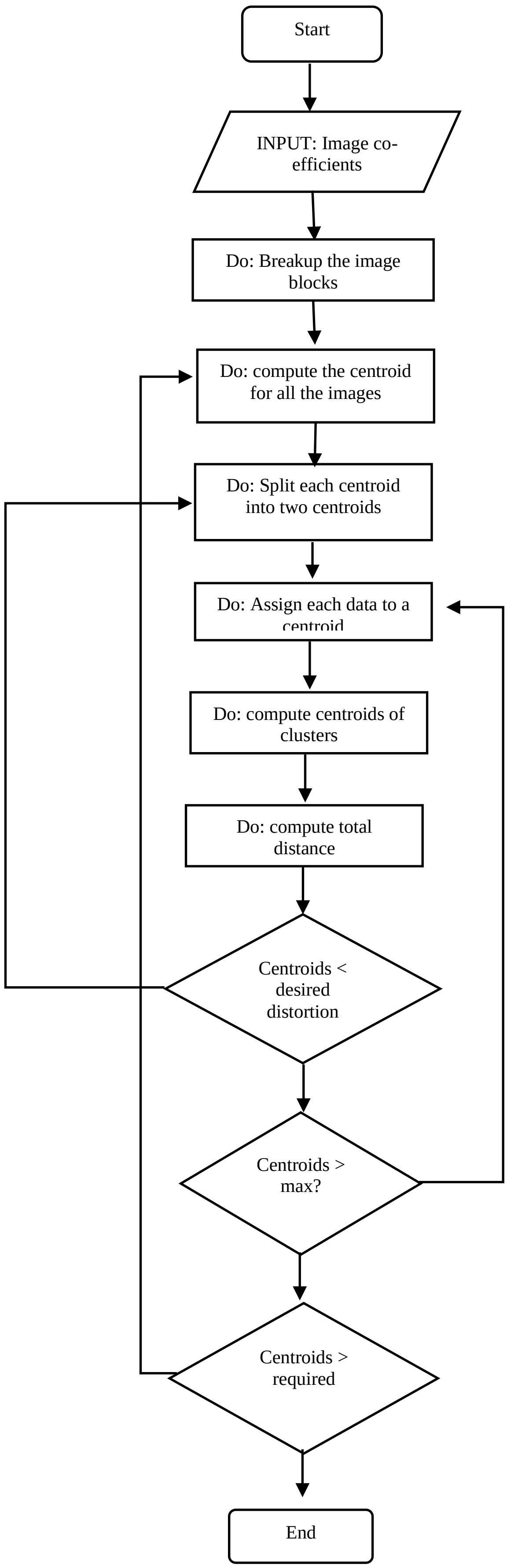

Fig. 5: Flowchart of block vector quantization (BVQ)

4.5.2 PSNR (Peak Signal to Noise Ratio):

It is an assessment metric to measure the visual degradation in image. The PSNR reflects the reconstructed image's quality [10]. PSNR must be high for an image reconstruction to be of noticeably high quality. Mathematically it can be given as

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}}\right) \qquad (4)$$

With the value 255 denotes 8-bit grayscale images and MSE is the Mean Squared Error.

4.5.3 MSE (Mean Square Error):

The most popular estimate of the metric used to measure image quality is MSE. The values that are nearer to zero are preferable since it is a full reference measure [2]. MSE between two images is given as

$$\mathrm{MSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[\mathrm{original}(i,j) - \mathrm{reconstructed}(i,j)]^2}{M * N} \qquad (5)$$

. Where M and N are dimensions of the image.

4.5.4 RMSE (Root Mean Square Error):

Another typical method of assessing error is the root mean square error, which is employed to determine how much the actual result deviates from the prediction. It calculates the size of the inaccuracy. It is a superb indicator of precision [7].

The square root of the Mean Square Error is the Root Mean Square Error.

$$\mathrm{RMSE}(\theta) = \sqrt{\mathrm{MSE}(\theta)} \qquad (6)$$

4.5.5 SSIM (Structural Similarity Index Measure):

The SSIM is a visual measurement that evaluates image quality reduction because of compression or transmission losses. It is designed to improve on standard measurements that have shown to be incompatible with vision perception in humans [27]. It is calculated on various image windows. Mathematically it can be given as

$$\mathrm{SSIM} = \frac{(2 * \bar{x} * \bar{y} + c1) * (2\sigma_{x,y} + c2)}{(\bar{x}^2 + \bar{y}^2 + c1) * (\sigma_x^2 + \sigma_y^2 + c2)} \qquad (7)$$

Where

$$\bar{x} = \frac{1}{M*N}\sum_{i=1}^{M*N} x_i \quad \text{and} \quad \bar{y} = \frac{1}{M*N}\sum_{i=1}^{M*N} y_i$$

$$\sigma_x^2 = \frac{1}{M*N}\sum_{i=1}^{M*N}(x_i - \bar{x})^2 \quad \text{and}$$

$$\sigma_y^2 = \frac{1}{M*N}\sum_{i=1}^{M*N}(y_i - \bar{y})^2$$

$$\sigma_{x,y} = \frac{1}{M*N}\sum_{i=1}^{M*N}(x_i - \bar{x}) * (y_i - \bar{y})$$

$c1$ and $c2$ are constants.

s

4.5.6 BPP (Bits per Pixel):

For visual display, grayscale pictures are typically stored with 8 bits per sampled pixel. There are 256 distinct intensities possible with this pixel depth. The BPP or bits per pixel denotes the number of bits per pixel [29]. The BPP is known as the ratio between the sizes of the reconstructed image to the size of the original image.

$$BPP = \frac{\textit{size of the reconstructed image}}{\textit{size of the original image}} \quad (8)$$

4.5.7 Space Saving):

The reduced in size compared to the original image size is referred to as space saving.

$$\text{Space Saving} = 1 - \frac{\text{Compressed original image size}}{\text{Original image size}} \quad (9)$$

4.6 Algorithm

4.6.1 Encoding

Input: Natural image.
Output: Compressed bits.
Step 1: Input any natural or real-time image has been selected for reading.
Step 2: Color space conversion is applied if the input image is color image and resized to 256 × 256 dimensions.
Step 3: Condition 1: Single level DWT is performed over the image resulting 4 sub-bands LL, LH, HL and HH.

Condition 2: Two level DWT is performed over the image resulting 7 sub-bands (three from the first level of decomposition and four from the second level of decomposition).

Step 4: Each sub-band is divided into non-overlapping blocks and a decision is made for block quantization-based block variance.
Step 5: BVQ is applied on blocks with minimal code book size of 2 for all sub-bands.
Step 6: The compressed coefficients are binary encoded using Huffman encoding technique.

4.6.2 Decoding

Input: Compressed bits.
Output: Reconstructed image.
Step 1: Input the compressed binary obtained after compression.
Step 2: Apply Huffman decoding technique to obtain the coefficients.
Step 3: Apply BVQ decoder for sub-bands with code book size of 2.
Step 4: Rebuild the wavelet coefficients at the block level using the codebook.
Step 5: After reconstructing co-efficient from each sub-band at different levels, a perfect reconstructed image is obtained by applying IDWT.
Step 6: Different assessment parameters like CR, PSNR, RMSE and SSIM are evaluated for performance analysis.

5. Results and Discussion

5.1 DWT operation

At this stage, the work is assessed for the impact of compression by taking into account two distinct situations; a single level decomposition and two-level decomposition. After the transformation, block variance condition is applied for low (only LL) and high frequency (include LH, HL and HH) sub-bands [17]. For low frequency band; compress the blocks only, if their variance falls below the sub band variance otherwise retain the block as it is. For high frequency bands; compress the blocks only, if their variance greater than the sub band variance otherwise discard the block. Table 1 shows the original image size and the number of discarded coefficients for different levels of wavelets [23]. Daubechies wavelet families are used for experimentation as theses filters creates a large number of zeros or vanishing points.

The results conclude that, the discarded coefficients likewise increase with an increase in the number of levels. Further the, Table 1.0 also shows image quality parameter SSIM obtained after image reconstruction. It is discovered that there was not too much distortion in the recovered images even after some coefficients were discarded. Consequently, the image's quality continues to remain maintained. The high SSIM values shows effect of quality reconstruction even after discarding more coefficients for higher levels. The overall samples used for experimentation consist of more than 100 images of both standard images and real-time images. Figure 6 shows the sample standard test images used for experimentation. Further, the experiment is also conducted for custom real time images captured using high resolution camera. Figure 7 displays the sample high resolution test images used for experimentation.

Table 1: DWT of sample standard images for two different situations**.**

Image	Single level decomposition (Situation 1)			Two level decomposition (Situation 2)	
	Size in bytes	Discarded Coefficients	SSIM	Discarded Coefficients	SSIM
Foreman	65536	30928	0.998599	34368	0.996591
Pepper	65536	28288	0.997381	30976	0.990417
Lena	65536	29024	0.994325	32160	0.98207
Butterfly	65536	15408	0.995517	16864	0.976427
Barbara	65536	23536	0.993778	24816	0.981365
Cameraman	65536	28016	0.994845	33616	0.980048
Boat	65536	19824	0.994623	22320	0.976033

Fig.. 6- Sample standard test images used for experimentation

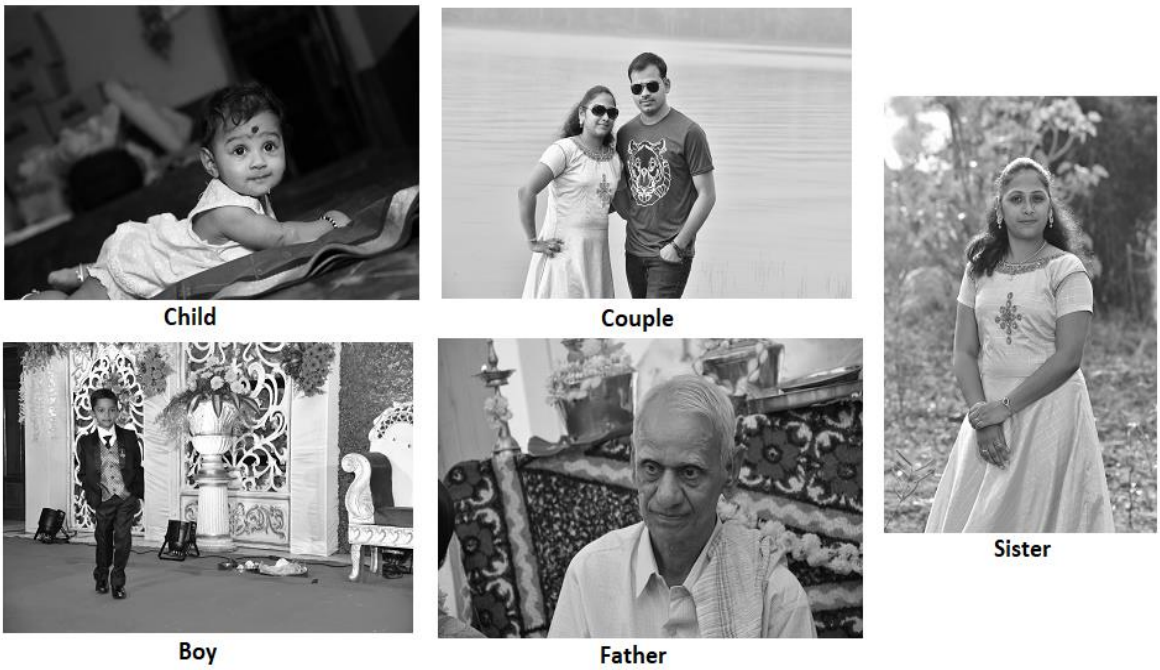

Fig. 7: Sample real-time test images used for experimentation

5.2 Vector Quantization and Encoding

Experiments carried out by considering the varied codebook sizes and block sizes. For every standard image a test is conducted to determine the effectiveness of the BVQ quantizer with a variable codebook and block sizes. Further compression using the Huffman encoding [9] technique demonstrates the excellent outcomes displayed from figure. (7 – 10). The compression ratios for each block size and codebook size are also included in the graphs. A significant proportion of the reconstructed image's quality is assessed by the PSNR and RMSE. One may observe that the RMSE significantly decreases as codebook size grows.

From all these flow graphs, it is concluded that the parameters (SSIM, CR, PSNR & RMSE) obtained for higher block sizes (64,32,16,8) which are almost similar to the minimum block size 4. Hence block size 4x4 is considered as ideal block size for experimentation.

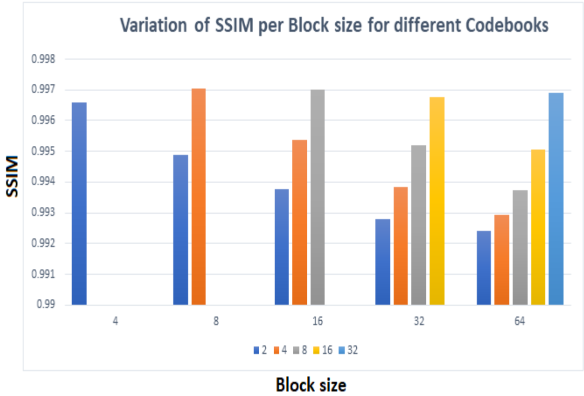

Fig. 7: Flow graph of SSIM per block size for different codebooks

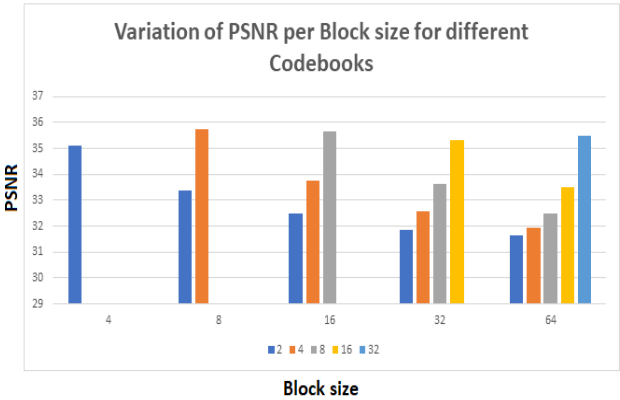

Fig. 8: Flow graph of PSNR per block size for different codebooks

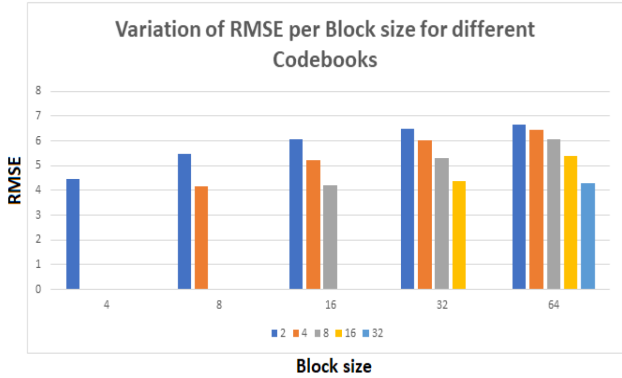

Fig. 9: Flow graph of RMSE per block size for different codebooks

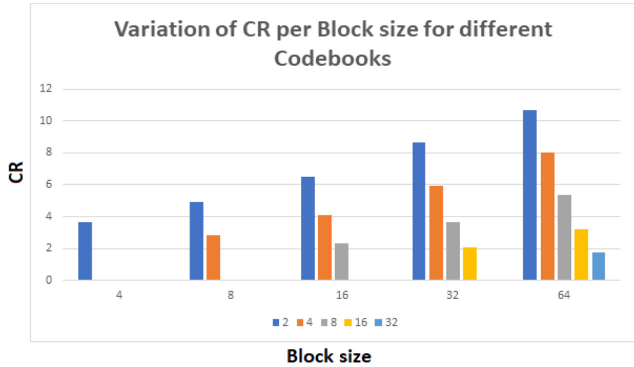

Fig. 10: Flow graph of CR per block size for different codebooks

5.3 Content Based Compression

The uniqueness of the proposed work is that, it performs compression by looking at the data. This is achieved by calculating variance at the local regions and making a decision before compression. This saves execution time and also controls degree of compression.

Table 2 displays the results of SSIM, PSNR, RMSE, Space Saving, CR and BPP of sample reconstructed images for standard test images. From the Table 2 it is concluded that image1 to image3 (*Foreman, Cameraman and Lena*) are compressed with high compression ratio. Since these images contains more similar intensity pixels (plainer information) which results in lesser block variance and reduced data size after compression. Whereas image4 to image6 (*Butterfly, Barbara and Boat*) are compressed with lower compression ratio. Since these images contains dissimilar intensity pixels (Edge information) which results in higher block variance and undergoes moderate or no compression. The accuracy of the reconstructed image is governed by the PSNR and RMSE. Figure 11. displays the sample original and reconstructed *Lena* test image.

Table 2: Assessment parameters obtained for standard images.

Image	Size in bytes	Data size after Compression in bytes	SSIM	PSNR	RMSE	% Of space saving	Compression ratio	Bits per Pixel (bpp)
Foreman	65536	17856	0.996591	35.10896	4.478082	72.753906	3.670251	0.880121
Cameraman	65536	17104	0.980048	26.274863	12.382178	73.901367	3.831618	0.888196
Lena	65536	19008	0.982070	29.10122	8.942921	70.996094	3.447811	0.973571
Butterfly	65536	27928	0.976427	25.36623	13.74766	57.385254	2.346606	0.985987
Barbara	65536	23832	0.981365	29.39468	8.645824	63.635254	2.749916	0.988455
Boat	65536	24672	0.976033	28.16342	9.962519	62.353516	2.65629	0.975373

(a) **(b)**

Fig. 11: (a) Sample original and **(b)** reconstructed standard test image

Table 3: Assessment parameters obtained for custom real-time images.

Image	Size in bytes	Data size after Compression in bytes	SSIM	PSNR	RMSE	% of space saving	Compression ratio	Bits per Pixel (bpp)
Child	7526400	519640	0.999686	44.831274	1.462098	93.095770	14.483873	0.656837
Couple	7312896	702240	0.996570	36.314714	3.897665	90.397238	10.413671	0.453147
Boy	7312896	1430680	0.996624	33.424249	5.436605	80.436205	5.111483	0.788924
Sister	7312896	1030696	0.996532	36.750182	3.707073	85.905775	7.095105	0.868477
Father	3053056	540768	0.998505	38.288726	3.105302	82.287649	5.645778	0.914778

(a) **(b)**

Fig. 12- (a) Sample original and **(b)** reconstructed real-time test image

5.4 Bulk image compression

The effectiveness of the suggested work is also evaluated by testing with custom real time images. These are high resolution images are captured using high end DSLR cameras. Table 3 shows the assessment parameters obtained for high resolution images.

From the Table 3 it is observed that, these images are too bulky and are compressed with higher compression ratios resulting in very minimal data size after compression. Hence the proposed work greatly saves storage memory. It is also found that higher PSNR, SSIM shows that the image is well reconstructed back from the minimal data. Figure 12. displays the sample original and reconstructed real-time test image.

5.5 Computation time analysis

Indicator for assessing compression techniques is the execution time in seconds. This section compares the proposed VQ method's implementation time to that of current existing methods [16]. Unless, the existing algorithms considers entire image for compression which increases the codebook size. By increasing the codebook, the quality of the resulting image is increased, but doing so increases the number of codeword and training vector comparisons, which intern increases computation time and results in a poor compression ratio. The proposed work implements block based lossy compression (BVQ) technique which takes only minimal codebook sizes for compression, thereby reduces the computation time and increases compression ratio. Table 4 shows the computation time (sec) of different test images for codebook size 16 and 32 using proposed BVQ and several existing [2-3] algorithms.

It is observed the algorithms such as Linde-Buzo-Gray algorithm (LBG) [27], Particle swarm optimization (PSO-LBG) [26], Quantum particle swarm algorithm (QPSO-LBG) [25], Honey bee mating optimization (HBMO-LBG) [28], Firefly algorithm (FA-LBG) [24], Bat algorithm (BA-LBG) [23], cuckoo search (CS-LBG) [14] and Pattern based masking algorithm (PBM-LBG) [3] has a high computational time compared to the proposed algorithm.

5.6 PSNR analysis

Table 5 shows the PSNR index of the proposed BVQ method and Linde-Buzo-Gray algorithm (LBG) [27], Firefly algorithm (FA-LBG) [24], Bat algorithm (BA-LBG) [23], Differential evolution algorithm (DE-LBG), Improved Particle swarm optimization (IPSO-LBG), Improved Differential evolution (IDE-LBG) and whale optimization algorithm [2]. compared with codebooks of sizes 8, 16, 32 and 64 for standard images.

The different existing methods such as LBG, FA-LBG, BA-LBG, DE-LBG, IPSO-LBG, IDE-LBG and whale methods [2] are considered for comparative analysis. The suggested method's greater PSNR index than current techniques implies that the proposed compression algorithm outperforms previous efforts. The suggested technique is less susceptible to image quality degradation, and the compressed image differs less from the original image [5]. The suggested approach and existing algorithms' analyses reveal that as the size of the codebook grows, so does the PSNR index. Figure 13 displays that the proposed BVQ algorithm is having greater PSNR value w.r.t the other algorithms.

Table 4: Computation time comparison of proposed compression with existing algorithms.

Codebook	**Size=16**								
Image	**LBG**	**PSO-LBG**	**QPSO-LBG**	**HBMO-LBG**	**FA-LBG**	**BA-LBG**	**CS-LBG**	**PBM-LBG**	**Proposed compression**
Lena	7.74	572.83	607.39	1202.47	1152.89	579.72	2288.09	10.76	**2.281631**
Pepper	8.91	487.58	493.46	1105.29	1040.35	630.45	3326.91	11.33	**2.608385**
Baboon	9.45	669.85	695.20	1983.13	1964.47	698.99	3031.07	10.73	**2.596582**
Gold hill	9.65	625.38	740.90	1158.51	1130.76	513.29	2480.96	10.66	**2.36307**
Barb	9.23	555.68	656.92	1567.50	1549.54	690.41	2811.52	9.88	**3.32327**
Codebook	**Size=32**								
Lena	8.77	510.89	530.52	1268.91	1184.69	572.90	2194.91	11.20	**3.896379**
Pepper	9.81	532.18	428.91	898.77	934.77	546.92	1713.64	11.49	**4.286584**
Baboon	8.89	468.13	497.97	1249.00	1243.72	549.35	2715.30	11.63	**4.982198**
Gold hill	7.71	476.65	538.47	1340.22	1299.81	480.46	2625.01	10.77	**4.70654**
Barb	10.04	423.94	474.93	1349	1320.16	422.79	2025.71	11.22	**4.216397**

Table 5: PSNR comparison of proposed compression with existing algorithms.

Codebook size	LBG	FA-LBG	BA-LBG	DE-LBG	IPSO-LBG	IDE-LBG	WHALE	Proposed work
8	22.874	23.186	23.52	24.72	24.718	24.964	25.138	**27.355334**
16	23.888	24.266	24.61	25.55	25.522	25.664	25.867	**28.268325**
32	23.984	25.062	25.104	26.63	26.608	26.778	26.982	**29.669651**
64	24.03	26.256	26.54	27.544	27.55	27.67	28.52	**32.394955**

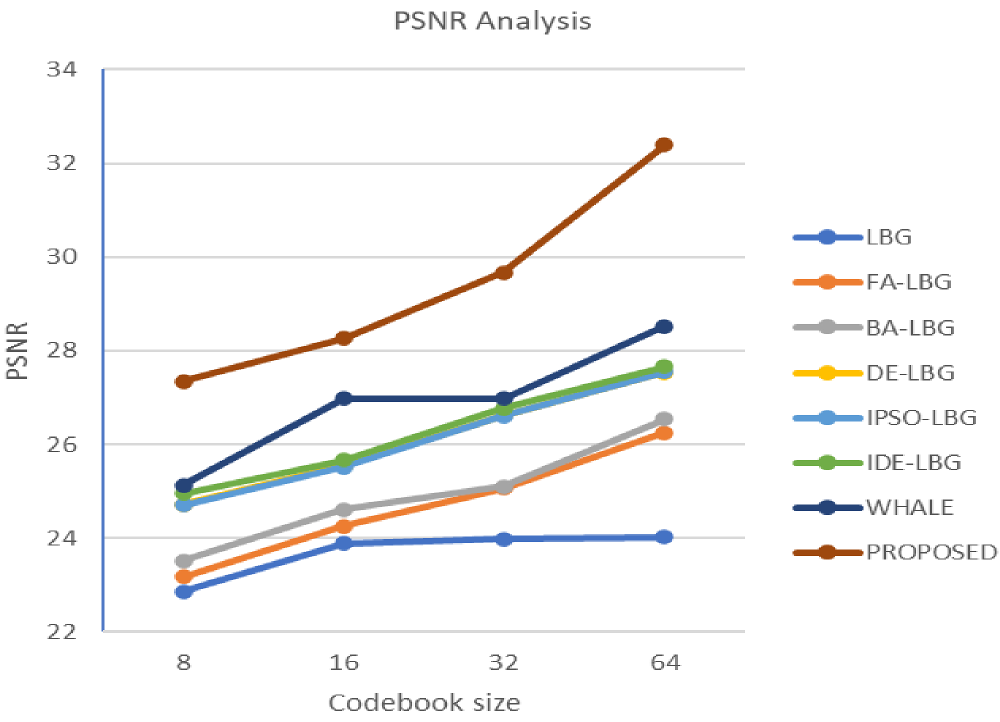

Fig. 13: Flow graph of PSNR Analysis per codebook size

5.7 Compression analysis

The usage of compression ratio is an essential criterion for assessing compression methods. The overall average compression percentage on all images may be determined to determine compression ratio. In the comparisons, the Firefly algorithm (FA-LBG) [24], Bat algorithm (BA-LBG) [23], Harris hawks' optimization (HHO) algorithm [21], Jellyfish search algorithm (JSA) [22] and whale optimization [2] were employed to calculate the compression percentage.

Table 6 shows the average percentage of compression on all standard images and is compared with existing techniques [2]. According to the analyses, the suggested technique increased the compression level by 24.38% compared to the whale optimization algorithm. Figure 14 displays comparison of compression percentage with the existing algorithms.

Table 6: Percentage of compression is compared with existing algorithms.

Techniques	Percentage of compression
FA	32.54
BA	34.81
HHO	38.34
JSA	39.68
Whale	42.75
Proposed	**67.13**

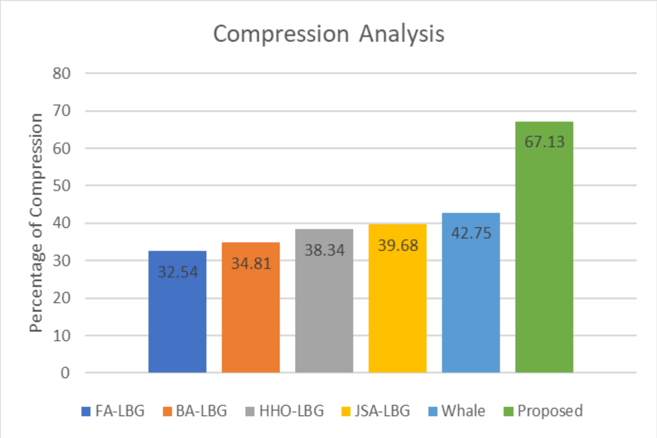

Fig.s 14: Flow graph of Compression Analysis

6. Conclusion

In this paper, content-based image compression by hybridizing discrete wavelet transform (DWT) and block vector quantization (BVQ) technique is proposed. Two level DWT is applied on the image, then each sub-band is divided into non-overlapping blocks and a decision is made for each block based on the block variance before going for quantization. This greatly increases number of discarded coefficients in the high frequency bands. The results conclude that, the number of discarded coefficients increases as the number of DWT levels increases which intern rises likelihood of obtaining a block of zeroes, making quantizer more efficient. The experimental results also shows that there was not too much distortion in the reconstructed image even after discarding some coefficients. The performance of the proposed work is also evaluated by testing with custom real time images. The experimental results show that, discarding less priority coefficients in the high frequency bands greatly increases compression ratio for real time bulk images.

The proposed work implements block vector quantization (BVQ) technique, where only minimal pixels in a block are considered for quantization at once. This technique greatly reduces the computation time and also increases compression ratio. Based on experimental results, it is illustrated that the proposed algorithm is more superior to BA-LBG, FA-LBG, QPSO-LBG, HBMO-LBG, PSO-LBG, PBM-LBG and LBG in terms of low computational time without compromising on PSNR and SSIM.

The PSNR index, which measures the effectiveness of image compression, outperforms a wide range of current exiting techniques. Study shows that the suggested technique compresses the PSNR index more than the conventional methods LBG, FA-LBG, BA-LBG, DE-LBG, IPSO-LBG, IDE-LBG and whale optimization methods. In image compression, percentage of compression and size are key aspects. Evaluations shown that the suggested method can reduce image size by as much as 67.13%. In novel techniques like whale optimization and JSA, the percentage of compressed images is 42.75% and 39.68%, respectively. The suggested approach provides a number of benefits. Its key benefit is that it successfully maintains the quality of compressed images, which is superior than the LBG, BA-LBG, DE-LBG, IPSO-LBG, and CS-LBG methods and increased the PSNR index.

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