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* **Corresponding author**.

vasu.ik1983@gmail.com

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A Novel Image Compression Algorithm Based on Autoencoder for Biometric Template Protection Scheme

R Vasuki[1]*, G Angeline Prasanna[2]

1 Research Scholar, Department of Computer Science, Karpagam Academy of Higher Education, Tamilnadu, Coimbatore, India
2 Assistant Registrar and Associate Professor, Department of Computer Application, Karpagam Academy of Higher Education, Tamilnadu, Coimbatore, India

Abstract

Objectives: To evaluate the proposed deep learning-based method for biometric template protection schemes with other existing image compression methods. **Methods:** In this study, four image compression methods such as JPEG_LS, Vector quantization (VQ), Run-length encoding (RLE), and the Autoencoder methods are implemented. The experimental results are compared with the different performance parameters that are applied over the CASIA I iris dataset possessing 756 images. **Findings:** The proposed autoencoder method algorithm offered enhanced results in terms of PSNR, SSIM, MSE, and CR when compared to other transform methods. The deep neural network-based autoencoder algorithm achieved the highest compression ratio of 89.05 percent, while the conventional algorithms achieved the highest image quality rate of 94.05 percent. **Novelty:** A novel autoencoder-based image compression model has been proposed in this study. The proposed Autoencoder (AE) method incorporates five stages like Initialization, Learning compression representations, Generation of chaotic sequence, Image encryption and decryption, and Image reconstruction. The generation of the chaotic sequence using the stochastic logistic map, as well as the learning compression representations contributes towards the novelty of this study.

Keywords: Image compression; Autoencoder; Runlength encoding (RLE); Vector quantization

1 Introduction

Currently, Data Compression (DC) technology is derived to satisfy the current requirements in terms of data quality, coding methods, data type, and applications to analyze the development of DC technology and its applications[(1)]. As storage and transmission capacity increases, the need for storage and transmission doubles. As a result, it does not address the problem of handling large amounts of data during transmission and storage. A deep-learning-based algorithm for image compression is proposed in this paper to address the aforementioned necessities and reduce the size of the data being stored or transmitted. By recognizing and making use of patterns that are present in the data, it compresses the original data. With a high CR, the obtained results were found superior to those of the existing techniques. The image compression techniques like JPEG_LS, VQ, RLE, and the proposed Autoencoder are used to compress the biometrics-acquired images. The actual context that determines when lossy or lossless image compression should be used, as well as the actual parameters for switching the image compression systems, are left to the implementer and use case.

1.1 Image Compression

By using image compression, it is possible to minimize the number of bytes in a graphics file without losing an acceptable level of image quality. By lowering file size, more images can be saved in a given quantity of memory or disc space. The image utilizes less bandwidth when downloaded from a website or sent over the Internet, which lowers network traffic and speeds up content delivery.

By functioning to make images smaller, the problem of lowering the amount of information needed to represent a digital image is addressed using image compression. It is a method for creating a more condensed image representation, which reduces the amount of space and bandwidth required for image storage and transmission. There will be some number of complimentary words in each image. The term redundancy indicates the most common way of copying information inside the images. It could be a pattern that appears repeatedly throughout the images, or it could be a pixel that appears repeatedly throughout the entire image. One or more of the three fundamental data redundancies, which are discussed below[2,3] can be removed to achieve compression.

1.2 Inter-Pixel redundancy

Adjacent pixels in an image are not statistically distinguishable. The image's correlation between adjacent pixels is responsible for this. Inter-pixel aggregation is the term for this kind of aggregation. Spatial aggregation is another name for this type of aggregation[4].

1.3 Coding redundancy

It involves comparing statistics from the actual source (in this case, the image or a modified version of its adjacent pixels) with variable-length codewords. Lookup tables (LUTs) are typically used to implement this type of reversible encoding[5].

1.4 Psycho-Visual redundancy

The psychophysical characteristics of human perception have shown that the human eye does not react to different types of visual data equally. The significance of different data varies. Most of the image coding techniques now in use include this type of redundancy. For instance, the DCT-based Algorithm is the foundation of the JPEG encoding standard.

2 Methodology

Image compression techniques can be extensively classified into lossy and lossless. Both have their own pros and cons. The original image quality is reproduced using a lossless method. The lossy method has advantages such as shorter processing time, higher compression ratio, and lower power consumption than the lossless method.

2.1 Lossless Compression

Lossless image compression seeks to indicate an image signal with the least number of bits while maintaining all its information, which speeds up transmission and reduces storage requirements[6]. Although this method reduces the file sizes, compared to lossy compression, the reduction is comparatively smaller. Most of the time, images, audio, and text are compressed with lossless compression. When image quality, words, or data loss (such as financial data) may be a problem, this is typically the method of choice for detailed product images, photo showcases, text files, and spreadsheet files. It does not reduce the file size nearly as much as lossy compression does, so it may not do much to improve download speeds, network bandwidth, or storage space. The general image formats here are BMP, GIF, PNG, and RAW. The algorithms utilized include Run-length encoding (RLE), Lempel-Ziv-Welch (LZW), Huffman coding, and Arithmetic encoding.

2.1.1 Run Length Encoding

RLE is a lossless data compression technique that stores streams of data as a single data value and counts rather than the original stream of data, which are cycles when the same data value appears in many successive data items. It is especially beneficial when data often repeats itself (Figure 1)[7]. The data are not deleted; rather, they are rearranged using frequency or data pairs. It works best with data that has multiple runs, like simple graphic images like icons, line graphs, Conway's Game of Life, animations, etc. RLE can likewise be utilized to indicate an early designs record design supported by CompuServe for packing highly contrasting images yet has been broadly replaced by their advanced Illustrations Trade Arrangement (GIF).

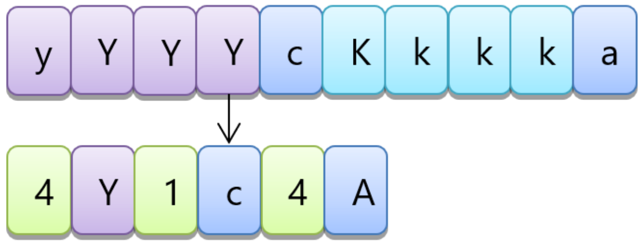

Fig 1. Representation of a typical Run Length Encoding

2.1.2 JPEG_LS

The need for efficient Continuous-tone image reduction with lossless and almost lossless quality was the motivation behind the creation of JPEG_LS. Modeling and encoding are the two distinct stages that make up this direct effect-based algorithm. Based on the LOCO-I algorithm, which makes use of residual prediction, residual modeling, and context-based coding[8], its fundamental method consists of two distinct and independent stages called modeling and encoding. The method is less difficult because of the use of more effective Colomb-like symbols for geometric distributions and the presumption that the predictive residuals have a two-sided geometric distribution. JPEG_LS's objective is to offer a low-complexity, high-quality standard for image compression that outperforms JPEG and more effectively converts the predictive residuals that are crucial to this encoding technique.

2.2 Lossy Compression

Lossy compression minimizes file size by permanently deleting certain information, particularly redundant information. Data from a file is removed during decompression, but the file is not returned to its initial condition. Because the data is irreversibly destroyed, this process is often referred to as irreversible compression. Data loss is possible since it cannot ensure that the data delivered and received will match perfectly. In a lossy algorithm, data that cannot be recovered later is deleted, which is why this occurs. The majority of pictures, audio files, and video files are compressed without loss. The general image formats here are JPEG and GUI. The algorithms utilized include Transform coding, DCT, DWT, and Fractal compression.

2.2.1 Vector Quantization

Signal vectors can be quantized using the effective coding method known as vector quantization (VQ). It is frequently used in voice and image coding, pattern recognition, and other aspects of signal and image processing. Codebook preparing (otherwise called codebook generation) and coding (i.e. code vector matching) are the two vital components of a VQ method. A training sequence's similar vectors are divided into clusters during the training step, and each cluster receives its own distinct representative vector, or code vector.

In the coding step, each input vector is then compressed by being replaced with the closest code vector that is determined by a direct cluster index[9]. The decoder then uses a channel to get the codebook's index (or address) of the matching code vector and uses that to get the same code vector from a matching codebook. After reconstruction, this is a copy of the matching input vector. As a result, rather than transmitting the code vector itself, compression is achieved by the transmission of its index.

2.3 Image Compression using Machine Learning (ML)

ML models are presently inevitable and filled nearly all applications under digital image processing, computer vision, and biometrics. Deep neural network's (DNN's) attractive feature extraction characteristic has solved a variety of traditional image processing challenges with significantly enhanced performance and economy. Epochs play a major role to train the model in DNNs[10]. It will be made to fetch real-world data. DNN-based approaches for image compression are proven to be very successful. Autoencoder comes under this approach[11,12].

2.3.1 Proposed Autoencoder-Based Image Compression model

An autoencoder is an unsupervised machine learning algorithm that uses backpropagation to ensure that the target values match the inputs. It is a type of ANN. Data can be converted from a high-dimensional space to a lower-dimensional space using this method, which is based on DL. It is used to reduce the size of the inputs into smaller representations. The compressed data is used to reconstruct the original data if necessary It is used in more demanding environments such as image coloring, dimensionality reduction, feature variation, denoising images, and watermark removal. It consists of three layers, namely Autoencoder, Code, and Decoder. The input is compressed by the network's encoder into a latent space representation. The dimensions of the input image are compressed and reduced by the encoder layer for encoding. The first image has been twisted to make the compacted rendition. The compressed input that is fed to the decoder is represented by the code portion of the network. After the image has been encoded, the decoder layer returns it to its original dimensions.

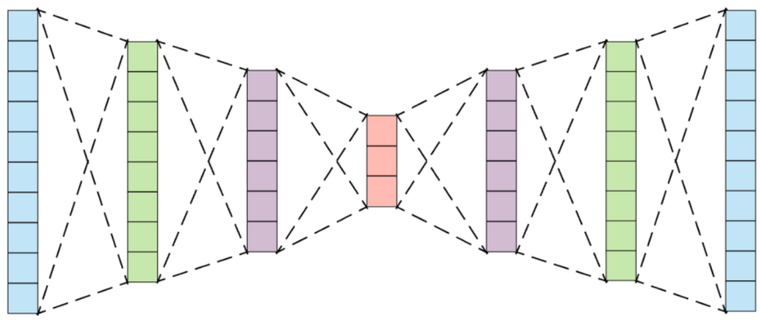

Fig 2. Schematic diagram of autoencoder-based image compression

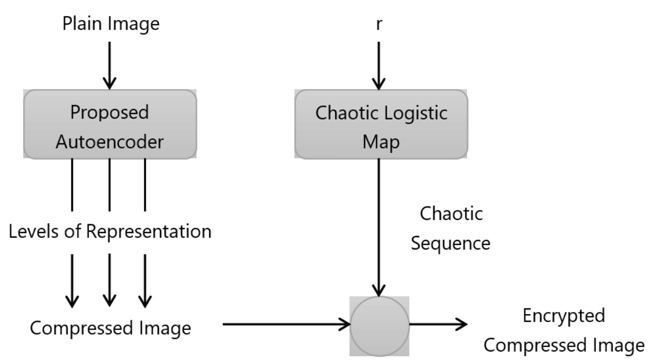

Fig 3. Block diagram of the proposed autoencoder-based image compression model

The layer of code that lies between the encoder and decoder is referred to as a bottleneck. This is a method that has been used to identify which parts of the perceived data are possessing important information and which can be ignored. The schematic diagram of the autoencoder-based image compression model is shown in Figure 2.

The image gets compressed utilizing the proposed Autoencoder (AE), and indeed the compressed image gets encrypted utilizing chaotic logistic map sequences. The methodology of the whole model is illustrated in Figure 3. The suggested model's detailed processes are outlined further below.

Step 1: Initialization

Inside the system, the second level would have fewer neurons than the input neurons to achieve fundamental image compression, as well as the third layer contains fewer neurons than the second level to achieve secondary image compression. These remaining fourth and fifth levels constitute duplicates of the second as well as first levels, respectively. This was assumed as well as demonstrated by a wide range of studies in the investigation of image processing using CNNs that because an image may be split them into a variety of parts and also the properties learned by CNN across different areas were comparable or even identical. The image is broken into identically sized segments. Each element is a test. A learning set is made up of all the parts from such a visual image. Variables throughout this data collection would be standardized as floating values within the range from 0 to 1 before getting entered into the algorithm for ease of processing in the proposed AE. This normalized data set is used to develop the algorithm. The ranges of learned attributes will be anti-normalized to result in the final outcome, which will consist of pixel values for one compressed image. The image is condensed using the dense approximation. The variable r is set to zero.

Step 2: Learning using the Proposed AE methodology

The activation function would be a linear transformation, and also the investigation employs the sigmoid function. We obtain a compressing approximation out of an unspecified hidden layer while developing the proposed AE algorithm. Such depiction would then be processed to generate an image. Since the result of the sigmoid function would be a floating value ranging from 0 and 1, it fits the conditions for initializing x0, that one of the target values is selected as x0. The former was picked for this present study.

Step 3: Generation of chaotic sequence

A series S is constructed using only a stochastic logistic map containing x0 and r, S=x1, x2, x3,..., xM, wherein M would be the length of the compressed images, for instance, when the compressed image may contain 1000*1000 pixels, M=1000*1000=1000000.

Step 4: Image encryption and decryption

The encrypting and decryption operations are explained below, wherein E represents the encoded image, C represents the plain images (the compressed images), S represents the series formed in step 3, and bitxor(-) represents a bit XOR operator, and the corresponding expressions for E and C are mathematically expressed below in equations 1 & 2,

$$\mathrm{E} = \mathrm{bitxor}(\mathrm{C}, \mathrm{S}) \tag{1}$$

$$\mathrm{C} = \mathrm{bitxor}(\mathrm{E}, \mathrm{S}) \tag{2}$$

Step 5: Reconstruction of Image

The Proposed AE methodology is used to reconstruct original compressed images. If the compressed images originate from either the level of h2, a model is rebuilt using just the levels of X, h1, and h2 and sharing the attributes gained in step 2. The compressed images are normalized as well as placed in the h2 level, while the outputs from the X levels represent the reconstructed images.

3 Results and Discussion

The selected algorithms are applied to numerous styles of iris images. The high-quality images typically used in image processing applications are a point of reference from which measurements may be made. At this point, the careful simulation of images' outcomes is offered. In the estimation of the solution, execution time plays a major role. The dataset description and sample test images are mentioned in Table 1 and Figure 4.

Attempts on stored reference patterns represent one of the riskiest challenges to biometric identification technologies. Such assaults are particularly dangerous since they may compromise security and privacy. Security measures to protect biometric patterns thus are an obligatory requirement [13,14]. According to the literature, a technique for developing a biometric template protection system should indeed be focussed on developing appropriate protection systems for each unsecured framework, resulting in the ideal balance between security and effectiveness when compared to every generic protection solution. Using this concept, Lahmidi et al [15] proposed in their research, a unique biometric template protection strategy that is effectively fitted to a well-established contemporary exposed biometric fragment database. The experiment results showed that their suggested approach achieved higher recognition accuracy when tested against established benchmarks like FVC 2002 DB1 and DB2.

Because of the excellent protection as well as reliability properties, biometric characteristics have drawn a great deal of attention and now are increasingly becoming employed in a variety of sectors. Nevertheless, many researchers have demonstrated that convolutional neural network-based biometric detection techniques pose significant privacy concerns. Ren et al. [16] suggested a biometric image compression algorithm that employs biometric image compression to address these issues. Furthermore, a fully reversible data-hiding biometric compression system with template protection is presented to secure the user's biometric template while retaining recognition performance. The experimental results revealed that the effectiveness of the suggested compression strategy, as well as the overall system for recognizing and protecting biometric features, is dependable as well as effective.

A biometric system should be simpler, adaptable, effective, as well as resistant to unauthorized users. Alamgir et al.[17] provided a modified biometric recognition method with greater effectiveness as well as optimized biometric template protection mechanisms in response to all of these requirements. This approach is made up of five parts: preprocessing, extraction of features, interruptible biometrics, categorization, and the bio-cryptosystem. After the preprocessing stage, the biometric texture area is retrieved from the original gesture. The biometric texture patterns are again processed using a data augmentation approach to derive discriminating features. Following that, the retrieved characteristics were examined using a data processing technique to generate a user-specific identifier. Ultimately, the multi-class linear support vector machine was employed to classify the individual gestures. The performance analysis of the biometric recognition system was done in terms of both detection and verification with the existing state-of-the-art approaches to demonstrate the superiority of the methodology.

In this present study, the evaluation results of different types of parameters are shown in Table 2. MSE, PSNR, CR, and BPP[18] based on equations (3) to (6) are the performance parameters that are utilized to find the effectiveness of the proposed model.

3.1 Performance Validation

This experimentation is carried out using the python Github algorithm. The proposed novel approach is experimented with using compression performance and reconstructed image quality. The techniques such as Autoencoders, JPEG_LS, RLE, and VQ are used for various comparisons. This study utilized a collection of 750 distinct benchmark iris images from the CASIA 1 dataset for the experimental analysis.

Table 1. Dataset Description

Image No.	Image Name	Dimensions	Original Size (KB)
1	002_1_1	320*280	88.5
2	002_1_2	320*280	88.5
3	002_1_3	320*280	88.5
4	002_1_4	320*280	88.5
5	002_1_5	320*280	88.5
6	002_1_6	320*280	88.5
7	002_1_7	320*280	88.5

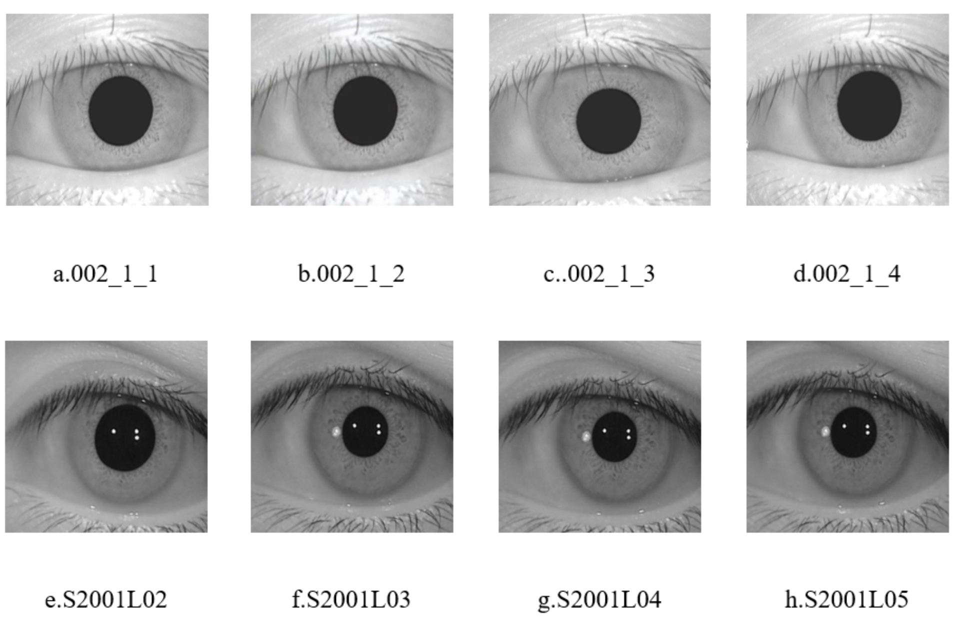

Fig 4. Sample Test images

The effectiveness of the compression algorithms is calculated in this study using a variety of performance indicators as discussed below.

3.1.1 Mean-Square Error (MSE)

MSE shows the total squared differences between the original and reduced images. MSE is mathematically expressed as in equation 3)

$$\mathrm{MSE} = \frac{\mathrm{a_a}\,(\mathrm{I_1}(\,\mathrm{m,n}) - \mathrm{I_2}(\,\mathrm{m,n}))^2}{\mathrm{MN}} \tag{3}$$

Here, M represents the rows of the input image, and N denotes the columns of the output image. The block first uses the aforementioned equation to calculate the MSE before calculating the PSNR.

3.1.2 Peak Signal-to-Noise Ratio (PSNR)

It indicates the error measurement of the peaks[19]. Therefore, PSNR can be mathematically denoted as per equation 4)

$$PSNR = 10\log_{10}\left[\frac{R^2}{MSE}\right] \tag{4}$$

3.1.3 Compression Ratio (CR)

The compression ratio is the proportion of the size of the original image to the size of the reconstructed images (CR). It can be calculated by equation 5)

$$\text{Compression Ratio (CR)} = \frac{\text{Original Im age Size}}{\text{Compressed Im age size}} \tag{5}$$

3.1.4. Bits Per Pixel (BPP)

BPP signifies the proportion of the entire size of the reconstructed images to the number of pixels it contains. BPP is expressed as per equation 6)

$$\mathrm{BPP} = \frac{\text{Compressed image size}}{\text{No. of pixel it contains}} \tag{6}$$

Table 2. Evaluation of Existing and Proposed Autoencoder methods for CR, PSNR, BPP, IQ

Image name	Before compression n1 (kB)	After compression n2 (kB)	Compression Ratio	Compression time	Image Quality	PSNR	BPP
Proposed Autoencoder method							
002_1_1	88.5	9.77	9.058341863	6 to 8 sec	95.00%	35.19634	0.000109
002_1_2	88.5	9.73	9.095580678	6 to 8 sec	95.00%	34.65754	0.000109
002_1_3	88.5	9.71	9.114315139	6 to 8 sec	95.00%	28.89891	0.000108
002_1_4	88.5	9.71	9.114315139	6 to 8 sec	95.00%	34.87707	0.000108
002_1_5	88.5	9.63	9.190031153	6 to 8 sec	94.00%	29.63809	0.000107
JPEG_LS Method							
002_1_1	15.8	9.06	1.74392936	14.5 sec	90.00%	42.0712	0.000101
002_1_2	45.5	10.2	4.460784314	14.5 sec	90.00%	41.1089	0.000113
002_1_3	37	10.8	3.425925926	14.5 sec	90.00%	40.4636	0.000120
002_1_4	36	10.5	3.428571429	14.5 sec	90.00%	41.0251	0.000117
002_1_5	35.9	10.4	3.451923077	14.5 sec	90.00%	41.0059	0.000116
RLE method							
002_1_1	4.41	4	1.1025	< 1 sec	82.00%	100	8.6395
002_1_2	4.41	4.1	1.075609756	< 1 sec	81.00%	100	8.8554
002_1_3	4.41	4.15	1.062650602	< 1 sec	80.50%	100	8.9634
002_1_4	4.45	4	1.1125	< 1 sec	80.50%	100	8.6395

Continued on next page

Table 2 continued

002_1_5	4.50	4.4	1.022727273	< 1 sec	80.50%	100	9.50344
VQ method							
002_1_1	257	47.1	5.456475584	34 sec	60.00%	35.32453	0.00018
002_1_2	257	46	5.586956522	35 sec	61.00%	35.27679	0.000175
002_1_3	257	48.1	5.343035343	36 sec	60.00%	35.30235	0.000183
002_1_4	257	47.3	5.433403805	35 sec	62.00%	35.37399	0.00018
002_1_5	257	46.7	5.503211991	36 sec	59.00%	35.36287	0.000178

3.2 Comparative Analysis of Autoencoder, JPEG_LS, RLE, and VQ

Figures 5, 6, 7 and 8 show the assessments of CR, Image Quality, PSNR, and BPP of the existing and proposed methods. The results indicated that the proposed method showed the highest compression ratio, better image quality, and better BPP when compared to the three existing methods. At the same time, the RLE algorithm has a high value in terms of PSNR and it takes below 1 second for compression.

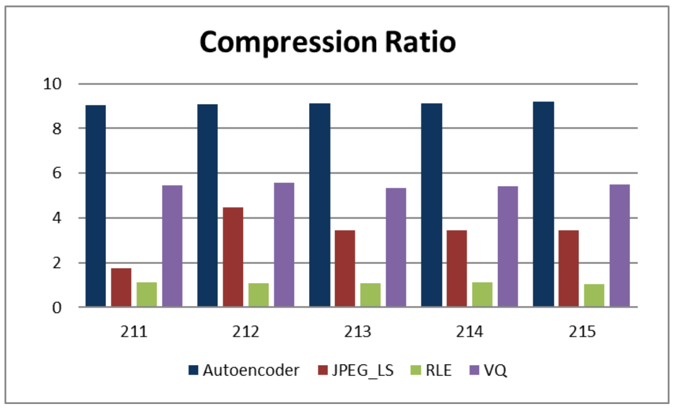

Fig 5. Compression Ratio Assessment

The average compression ratio for the proposed autoencoder method is 9.12, whereas the average compression ratios for JPEG_LS, RLE, and VQ are 3.30, 1.07, and 5.46 respectively. When compared to JPEG_LS, the proposed autoencoder method achieves a decent result in the compression ratio of 64.81 percent, RLE achieves a decent result in the compression ratio of 88.26 percent, and the VQ method achieves an enhanced result in the compression ratio of 40.13 percent. Also, for all the selected images the proposed autoencoder showed a compression ratio of 9.058341863, 9.095580678, 9.114315139, 9.114315139, and 9.190031153 which showed that there are not many irregularities in compression ratio, however, JPEG_LS, RLE, and VQ methods showed higher irregularities in compression ratios within the selected five images. The decoder layer precisely restores the image's original dimensions once it has been encoded, which led to a higher compression ratio when concerned with the proposed autoencoder method.

Similarly, the average image quality value of the proposed autoencoder method is 94.8% whereas the average image quality values of JPEG_LS, RLE, and VQ are 90%, 80.8%, and 60.4% respectively. The proposed autoencoder method clearly outperformed JPEG_LS by 5.06 percent, RLE by 14.76 percent, and the VQ method by 36.28 percent in terms of image quality.

Figure 7 shows the evaluation of PSNR for JPEG_LS, RLE, VQ, and the proposed autoencoder method. Figure 8 displays the BPP of the novel autoencoder method, JPEG_LS, and VQ. The average PSNR of the proposed autoencoder method is 32.65359 dB, the average PSNR for JPEG_LS is 41.13494 dB, the average PSNR of RLE is 100.00 dB, and the average PSNR of the VQ method is 35.328106 dB. The proposed autoencoder method showed better PSNR similar to JPEG_LS and VQ methods, whereas the RLE method depicted the highest PSNR. Figure 9 displays the average results of IQ, CR, PSNR, and BPP.

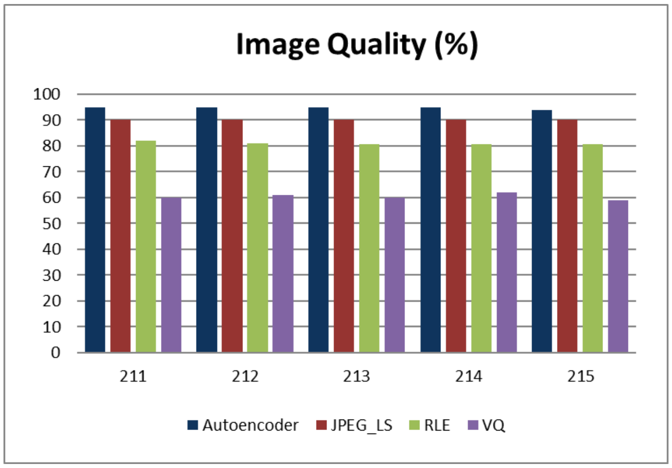

Fig 6. Evaluation of Image Quality

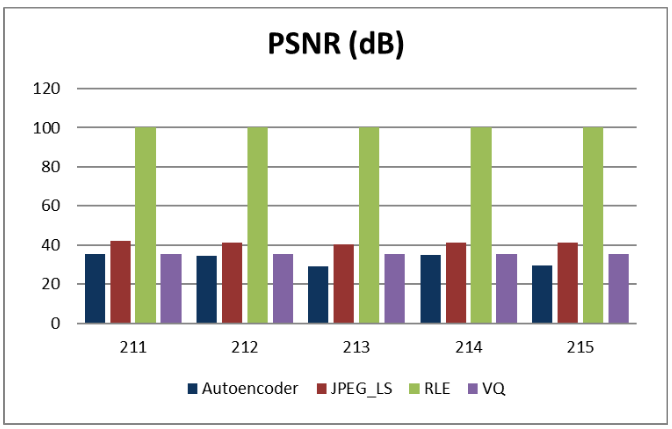

Fig 7. Assessment in terms of PSNR (dB)

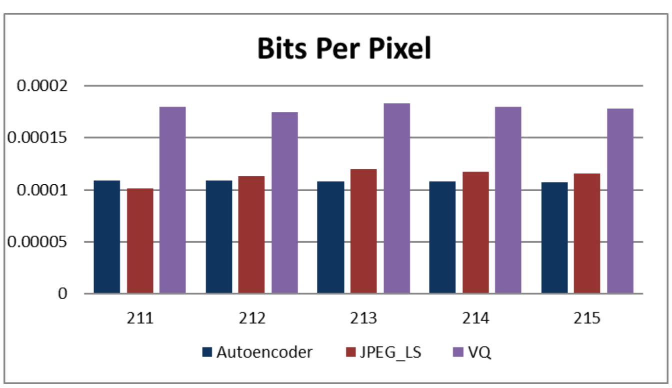

Fig 8. BPP Comparison of Autoencoder, JPEG_LS, and VQ

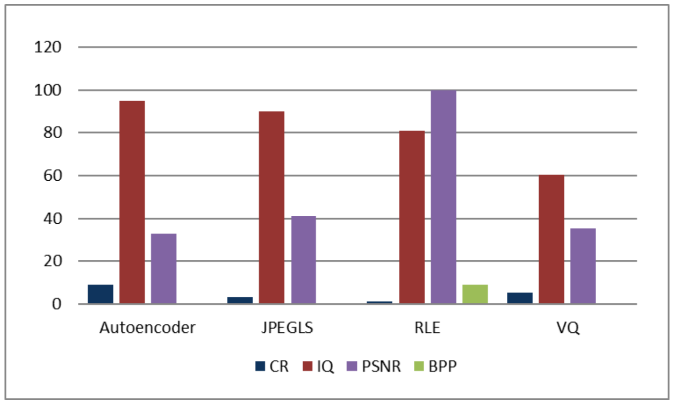

Fig 9. Average results of CR, IQ, PSNR, and BPP

4 Conclusion

Important image compression techniques like JPEG_LS, VQ, RLE, and Autoencoder's compression and decompression algorithms are discussed. Based on parameters like CR, MSE, PSNR, and BPP, this study presents an analysis of various image compression techniques for different images. According to the findings of this study, the autoencoder method that is proposed offered a higher compression ratio. Autoencoder achieves a higher compression ratio without losing any additional image information. Because it preserves most of the information while compressing it, it is better suited for several real-world applications. In order to achieve higher PSNR, an enhanced method will be further implemented in the future.

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