International Journal of Computer Trends and Technology
ISSN: 2231 – 2803 / https://doi.org/10.14445/22312803/IJCTT-V70I10P101

Volume 70 Issue 10, 1-7, October 2022

Review Article

Study on Compression Methods for Quality Enhancement with Satellite Images

V. Sivasankar[1], P. Suresh Babu[2]

[1,2]*Department of Computer Science, Bharathidasan College of Arts and Science, Erode, India*

Received: 25 August 2022 Revised: 02 October 2022 Accepted: 13 October 2022 Published: 26 October 2022

Abstract - *Image processing is an essential technique for transforming an image into digital form for performing certain operations to attain useful information. Satellite image processing is an essential area in research and development with earth and satellite images taken by artificial satellites. The photographs are gathered in digital form and processed by computers to extract the information. Image enhancement increases the quality and information content before processing. Image compression is an essential step for processing large images through an encoder. Image pre-processing is carried out to improve image quality by minimizing undesired distortions for a particular application. Image segmentation is the method of dividing the digital image into multiple segments to enhance image quality. Many researchers carried out their research on image compression, pre-processing, and segmentation methods for image quality enhancement. But, the compression ratio and compression time were not improved by image quality enhancement. In order to address these problems, many image compression and filtering techniques are reviewed.*

***Keywords* -** *Image compression, Information, Pre-processing, Segmentation, Satellite image processing.*

1. Introduction

Image compression is an important feature in computer vision issues where image transmission is involved. Image compression algorithms are quite complex and difficult to run on hardware. Image compression is important in digital image processing for efficient image storage. Image compression saves storage space with minimal time consumption for fast transmission. Lossless compression allows the original data to be perfectly reconstructed from compressed data. Image compression minimized the image data redundancy. Image compression reduces the size in bytes of a digital image without reducing the image quality to an undesirable level.

This paper is organized as follows: Section 2 reviews the satellite image quality enhancement methods. Section 3 describes the existing satellite image quality enhancement methods. Section 4 portrays the simulation settings with the possible comparison between them. Section 5 discusses the limitation of existing satellite image quality enhancement. Section 6 concludes the paper.

2. Literature Review

Unified network architecture was designed in [1] to perform the task through a recurrent neural network (RNN) based image compression and three-dimensional (3D) reconstruction. The joint model provided image compression for 3D reconstruction. But, the designed architecture attained lesser performance for better compression rates.

An entropy minimization histogram emergence (EMHM) scheme was introduced in [2] to reduce the number of grayscales with nonzero pixel populations (GSNPP) to improve the image quality. However, the compression time was not minimized by the EMHM scheme.

A generative adversarial network (GAN) based prediction method termed MultiTempGAN was introduced in [3] for performing multitemporal image compression. The designed method described a lightweight GAN-based model to convert the reference image into the target image. But, the compression ratio was not improved by MultiTempGAN.

A deep multi-stage representation-based image compression (MSRIC) method was introduced in [4] with detailed information on shallow stages. However, efficient network architecture minimized the parameter volume and complexity of hierarchical hyper-prior for accurate entropy estimation.

A unique pixel-level multispectral (MS) very high resolution (VHR) image segmentation algorithm was introduced in [5] depending on variable-length multi-objective genetic clustering. But, the segmented images were not classified using ground truth information for change detection.

Convolutional Neural Network (CNN) was introduced in [6] for semantic segmentation of remote sensing images. Encoder-Decoder CNN structure and U-net were employed for multi-target semantic segmentation with remote sensing images. However, an improved SegNet was not used for multi-target semantic segmentation of remote sensing images.

A new domain adaptation algorithm was introduced in [7] to address the satellite and aerial imagery for region segmentation issues. Built-up area estimation was an essential component of human impact on the environment for urban population analysis. But, the segmentation time was not minimized.

A weakly supervised learning framework was designed in [8] to update deep learning model parameters and to suppose the hidden true vector label location. The designed framework labeled location errors in the vector representation to partially preserve the geometric properties. But, the designed method does not fully incorporate geometric properties of label location errors in vector representation.

An image-based two-phase data-driven framework was introduced in [9] for identifying and segmenting the landslide regions. An object detection algorithm was employed to identify the landslide location with satellite images. But, the error rate was not reduced by the image-based two-phase data-driven framework.

A new filter was introduced in [10] for image quality enhancement depending on the combination of the shock filter with the fourth-order diffusion equation. However, the designed filter was a semi-implicit scheme with harmonic means to remain inefficient and unstable.

An image compression technique was introduced in [11] to improve image quality and minimize bandwidth size transmission. But, the compression ratio was not improved by the designed technique.

3. Satellite Image Quality Enhancement Methods

Satellite image enhancement is essential in satellite image processing to improve the visualization of the features. Satellite images are captured from a long distance because of atmospheric barriers. Image enhancement is an enhancement of satellite image quality without knowledge about the source of degradation. Image compression is an essential step in image processing and computer vision pipelines. The compression is carried out to deliver the images with a high compression ratio. The evaluation criteria and compression goals are employed to perform the computer vision tasks with multi-view three-dimensional (3D) reconstruction.

3.1. Image Compression Optimized for 3D Reconstruction by Utilizing Deep Neural Networks

Compression in context was important when multi-view data was transmitted using limited resources. Unified network architecture was introduced to address the tasks jointly on recurrent neural network (RNN)-based image compression and three-dimensional (3D) reconstruction. The joint models carried out image compression for specific tasks of 3D reconstruction. The compressed image yielded better 3D reconstruction performance superior. The designed architecture increased compression rates where 3D reconstruction was possible. RNN-based image compression was carried out efficiently without additional cost to attain compression on top of the computation required for performing the 3D reconstruction task. RNN-based image compression was employed to compress the images used for 3D reconstruction. The compression was employed with negligible computation for image compression. The designed compression exceeded the 3D reconstruction performance attained from images compressed by JPEG-2000 across different medium to ultra-aggressive compression rates. The RNN-based basic component was employed for image compression and 3D reconstruction to demonstrate a generic concept with multi-task learning.

3.2. An Entropy Minimization Histogram Emergence Scheme and its Application in Image Compression

Image histograms are used in different image processing techniques like image enhancement, compression, and segmentation. An entropy minimization histogram emergence (EMHM) scheme was introduced to minimize the number of grayscales with nonzero pixel populations (GSNPP) without losing the image quality. Image entropy was reduced after histogram emergence, and entropy reduction gets maximized through EMHM. The reduction in image entropy was improved with a minimum average code word length per source symbol. The entropy of the source signal was determined to be consistent with Shannon's first theorem. EMHM minimized the code length of entropy codings like Huffman, Shannon, and arithmetic coding while preserving the image's subjective and objective quality. EMHM minimized an image entropy and the number of grayscale with a nonzero pixel population. The pixel population of grayscale with a greater pixel population difference was determined to minimize the entropy of the output image. EMHM was used to reduce the number of GSNPPs. Image entropy gets minimized for image compression. EMHM segmented the transformed images into blocks and quantified each block separately. The quantization operation minimized the GSNPP redundancy in every block and reduced the redundancy of the global image sufficiently. Entropy minimization was carried out for semi-supervised learning.

3.3. MultiTempGAN: Multitemporal Multispectral Image Compression Framework using Generative Adversarial Network

Multispectral satellites measure reflected energy from different regions on earth to generate multispectral (MS) images continuously. MS image was employed for the same region regarding the satellite revisit period. The images were gathered over the same region of multitemporal images at different times. The compression techniques were introduced based on the spectral and spatial correlation within MS images. A temporal correlation was determined between multi-temporal images. A new generative adversarial network (GAN) based prediction method termed MultiTempGAN for multitemporal MS image compression. The designed method described the lightweight GAN-based model that transforms the reference image to the target image. The generator parameters of MultiTempGAN were saved for reconstruction in the receiver system. MultiTempGAN included less number of parameters to provide efficiency in multitemporal MS image compression. MultiTempGAN attained the best metric values among techniques at a high compression ratio with convincing performances in change detection applications.

4. Performance Analysis of Satellite Image Quality Enhancement Methods

Experimental evaluation of existing compression-based quality enhancement techniques is implemented using Matlab software. The experiment of existing compression-based quality enhancement techniques is conducted using the Cardiovascular Disease dataset Satellite Image Classification taken from the Kaggle. The URL of the mentioned dataset is given as

https://www.kaggle.com/datasets/mahmoudreda55/satellite-image-classification. The dataset comprises dataset has 5631 images in jpg format. Result analysis is carried out with existing methods with parameters are,

- Compression ratio,
- Compression time and
- Space complexity

4.1. Measurement of Compression Ratio

Compression Ratio is defined as the ratio of the original image to the compressed data without considering original data precision. The compression ratio is formulated as,

$$Compression\ ratio = \frac{Uncompressed\ image\ size}{Compressed\ image\ size} \quad (1)$$

From (1), the compression ratio of different image sizes is attained. The technique is more efficient when the compression ratio is higher.

Table 1 describes the compression ratio for satellite image sizes ranging from 1 to 10. Compression ratio comparison takes place on the existing Unified network architecture, entropy minimization histogram emergence (EMHM) scheme, and generative adversarial network (GAN) based prediction method. Let us consider input as image 9 of 10.22KB size. The compression ratio of unified network architecture is 15. The compression ratio of the EMHM scheme and GAN-based prediction method are 13 and 10. The graphical representation of the compression ratio is illustrated in figure 1.

Table 1. Tabulation for Compression Ratio

Satellite Image Size	Image Size (KB)	Compression Ratio		
		Unified network architecture	EMHM scheme	GAN-based prediction method
Image 1	6.6	18	15	10
Image 2	4.48	20	17	12
Image 3	4.71	15	14	11
Image 4	4.56	12	10	8
Image 5	3.98	14	12	9
Image 6	19.94	11	8	6
Image 7	2.48	9	7	5
Image 8	7.85	12	10	8
Image 9	10.22	15	13	10
Image 10	2.11	18	16	15

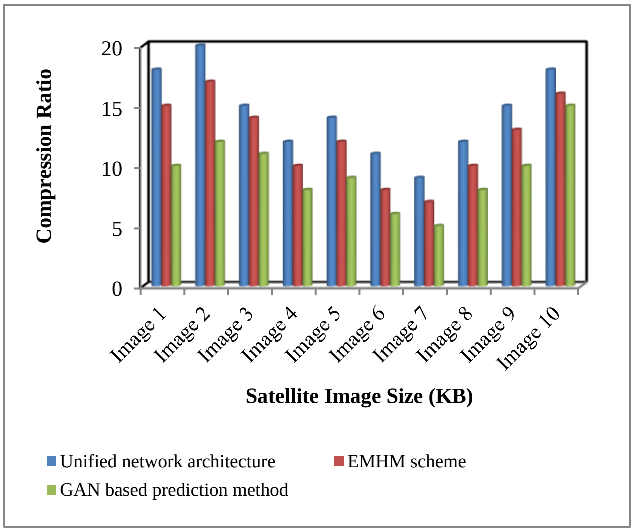

Fig. 1 Measurement of Compression Ratio

Fig. 1 describes the compression ratio for different satellite image sizes. The blue color cylinder represents the compression ratio of unified network architecture. The red and green color cylinders denote the compression ratio of the EMHM scheme and GAN-based prediction method correspondingly. It is clear that the compression ratio using unified network architecture is higher when compared to the EMHM scheme and GAN-based prediction method. It is due to the application of RNN-based image compression without additional cost to attain thecompression for performing 3D reconstruction tasks. This, in turn, helps to increase the compression ratio. As a result, the unified network architecture compression ratio is increased by 20% compared to the EMHM scheme and 57% compared to the GAN-based prediction method.

4.2. Measurement of Space Complexity

Space complexity is defined as the total amount of memory space consumed for storing the compressed image. The space complexity is computed in terms of kilobytes (KB) and formulated as,

$$Space_{Com} = N * memory\ for\ storing\ one\ compressed\ image) \quad (2)$$

From (2), the memory space needed for storing the compressed data is measured. $'N'$ denotes the number of satellite images. The method is said to be more efficient when the space complexity is lesser.

Table 2. Tabulation for Space Complexity

Number of Satellite Images (Number)	Space Complexity (KB)		
	Unified network architecture	EMHM scheme	GAN-based prediction method
10	31	17	25
20	33	18	27
30	36	20	29
40	39	22	31
50	42	25	33
60	45	30	35
70	48	33	38
80	51	35	41
90	54	38	45
100	57	41	48

Table 2 describes the space complexity of the number of satellite images ranging from 10 to 100. Space complexity comparison takes place on the existing Unified network architecture, entropy minimization histogram emergence (EMHM) scheme, and generative adversarial network (GAN) based prediction method. Let us consider the number of satellite images as 50; the space complexity of unified network architecture is 42KB. The space complexity of the EMHM scheme and GAN-based prediction method is 25KB and 33KB. The graphical representation of space complexity is described in figure 2.

Fig. 2 describes the space complexity for a different number of satellite images. The blue color cylinder represents the space complexity of unified network architecture. The red color cylinder and green color cylinder denote the space complexity of the EMHM scheme and GAN-based prediction method correspondingly.

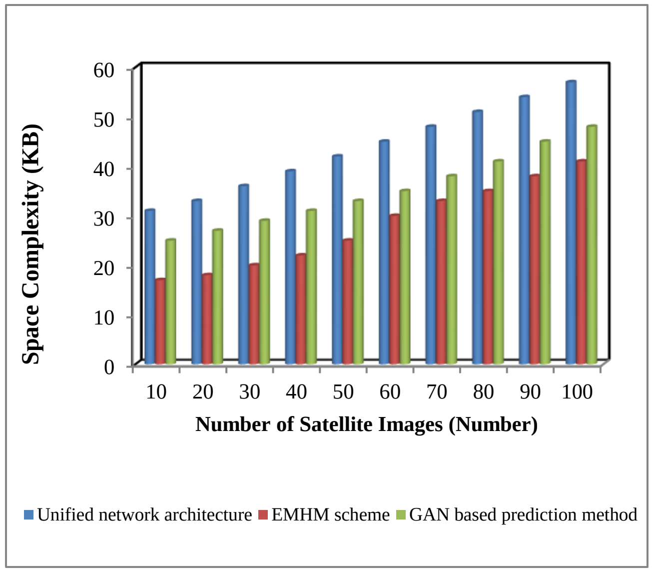

Fig. 2 Measurement of Space Complexity

It is observed that the space consumed using the EMHM scheme is lesser when compared to the unified network architecture and GAN-based prediction method. EMHM segmented the transformed images into blocks and computed each block individually. The quantization operation reduced the GSNPP redundancy in every block sufficiently. This, in turn, helps to reduce space complexity. Therefore, space consumption of the EMHM scheme is reduced by 37% compared to the unified network architecture and 22% compared to the GAN-based prediction method.

4.3. Measurement of Compression Time

The compression time ($Comp_{Time}$) is defined as the amount of time taken to compress the satellite image. The compression time is determined in terms of milliseconds (ms). It is formulated as,

$$Comp_{Time} = N * time\ consumed\ for\ compressing\ one\ image) \quad (3)$$

From (3), compression time for different image sizes is achieved. $'N'$ denotes the number of satellite images. The method is said to be more efficient when the compression time is lesser.

Table 3 illustrates the compression time to the number of satellite images ranging from 10 to 100. Compression time comparison takes place on the existing Unified network architecture, entropy minimization histogram emergence (EMHM) scheme, and generative adversarial network (GAN) based prediction method. Let us consider the number of satellite images as 70. The compression time of unified network architecture is 36ms. The compression time of the EMHM scheme and GAN-based prediction method is 34ms and 30ms. The graphical representation of compression time is illustrated in Fig. 3

Table 3. Tabulation for Compression Time

Number of Satellite Images (Number)	Compression Time (ms)		
	Unified network architecture	EMHM scheme	GAN-based prediction method
10	18	21	12
20	20	23	15
30	24	25	18
40	27	28	20
50	30	30	23
60	33	32	25
70	36	34	30
80	39	38	33
90	42	40	35
100	45	43	38

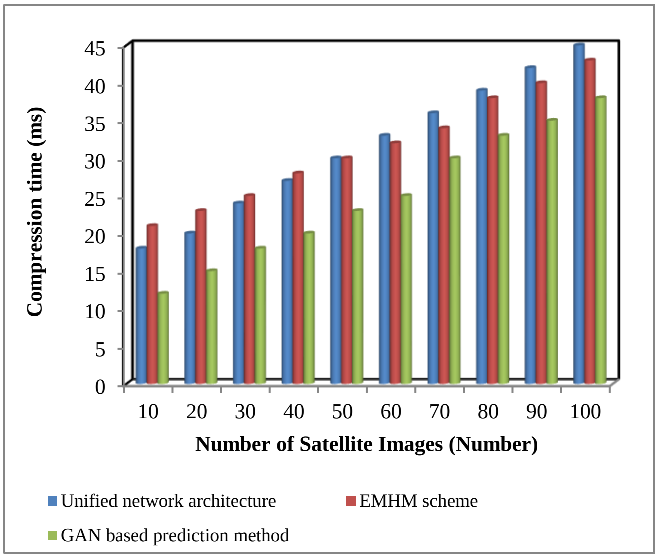

Fig. 3 Measurement of Compression Time

Fig. 3 describes the compression time for the different numbers of satellite images. The blue color cylinder represents the compression time of unified network architecture. The red and green color cylinders denote the compression time of the EMHM scheme and GAN-based prediction method correspondingly. It is observed that the compression time consumed using GAN based prediction method is lesser when compared to the unified network architecture and EMHM scheme. It is due to the application of MultiTempGAN with metric values at a high compression ratio for change detection applications. This, in turn, helps to reduce the compression time. Therefore, the compression time of GAN based prediction method is reduced by 22% compared to the unified network architecture and 23% compared to the EMHM scheme.

5. Discussion and Limitations of Satellite Image Quality Enhancement Methods

Unified network architecture was introduced to address the tasks jointly on RNN-based image compression and 3D reconstruction. The joint models carried out image compression for 3D reconstruction. The designed architecture attained lesser performance counter-intuitively obtained for better compression rate. The designed techniques must obtain a better and smooth performance curve across compression rates. EMHM scheme minimized the number of grayscales with nonzero pixel populations (GSNPP) without visible loss to improve the image quality. Image entropy is minimized after histogram emergence, and reduction in entropy gets increased using EMHM. The entropy of the source signal was determined according to the Shannon first theorem. The compression time was not minimized by the EMHM scheme at the required level.

A GAN-based prediction method performed multitemporal MS image compression. The designed technique described a lightweight GAN-based model to transform the reference image into the target image. The generator parameters of MultiTempGAN were saved for reconstruction purposes in the receiver system. However, the compression ratio was not improved by MultiTempGAN

5.1. Future Direction

The future direction of the satellite image quality enhancement methods is to improve the compression ratio and reduce time consumption by using machine learning and deep learning methods.

6. Conclusion

A comparative study of different satellite image quality enhancement methods is performed. From the study, the compression ratio was not improved by MultiTempGAN. In addition, the compression time was not minimized by the EMHM scheme at the required level. Unified network architecture attained a lesser compression rate with minimal space complexity. The wide experiment on conventional techniques estimates the result of different satellite image quality enhancement techniques and discusses its problems. From the result analysis, the research can be carried out using machine learning and ensemble learning techniques for efficient satellite image quality enhancement with compression ratio and less time consumption.

References

[1] Alex Golts and Yoav Y. Schechner, "Image Compression Optimized for 3D Reconstruction by Utilizing Deep Neural Networks", *Journal of Visual Communication and Image Representation, Elsevier*, pp. 1-16, 2021.

[2] Chong Chen, Yong-Liang Li and Lidong Huang, "An Entropy Minimization Histogram Emergence Scheme and Its Application in Image Compression," *Signal Processing: Image Communication, Elsevier*, vol. 99, pp. 1-15

[3] Ali Can Karaca, Ozan Kara and Mehmet Kemal Gullu, "Multitempgan: Multitemporal Multispectral Image Compression Framework Using Generative Adversarial Networks," *Journal of Visual Communication and Image Representation, Elsevier*, vol. 81, pp. 1-18, 2021.

[4] Zixi Wang, Guiguang Ding, Jungong Han and Fan Li, "Deep Image Compression with Multi-Stage Representation," *Journal of Visual Communication and Image Representation, Elsevier*, vol. 79, pp. 1-15, 2021.

[5] Ramen Pal, Somnath Mukhopadhyay, Debasish Chakraborty and Ponnuthurai Nagaratnam Suganthan, "Very High-Resolution Satellite Image Segmentation Using Variable-Length Multi-Objective Genetic Clustering for Multi-Class Change Detection," *Journal of King Saud University – Computer and Information Sciences, Elsevier*, pp. 1-13, 2022.

[6] Muhammad Alam, Jian-Feng Wang, Cong Guangpei, LV Yunrong and Yuanfang Chen, "Convolutional Neural Network for the Semantic Segmentation of Remote Sensing Images," *Mobile Networks and Applications, Springer*, vol. 26, pp. 200–215, 2021.

[7] Javed Iqbal and Mohsen Ali, "Weakly-Supervised Domain Adaptation for Built-Up Region Segmentation in Aerial and Satellite Imagery," *ISPRS Journal of Photogrammetry and Remote Sensing, Elsevier*, vol. 167, pp. 263-275, 2020.

[8] Zhe Jiang, Wenchong He, Marcus Stephen Kirby, Arpan Man Sainju, Shaowen Wang, Lawrence V. Stanislawski, Ethan J Shavers and E. Lynn Usery, "Weakly Supervised Spatial Deep Learning for Earth Image Segmentation Based on Imperfect Polyline Labels," *ACM Transactions on Intelligent Systems and Technology*, vol. 13, no. 2, pp. 1–20, 2022.

[9] Huajin Li, Yusen He, Qiang Xu, Jiahao Deng, Weile Li and Yong Wei, "Detection and Segmentation of Loess Landslides Via Satellite Images: A Two‑Phase Framework," *Landslides, Springer*, vol. 19, pp. 673 – 686, 2022.

[10] Simo Thierry, Welba Colince, Ntsama Eloundou Pascal and Noura Alexendre, "Shock Filter Coupled with a High-Order PDE for Additive Noise Removal and Image Quality Enhancement," *Array, Elsevier*, vol.12, pp. 1-18, 2021.

[11] C. Arunachalaperumal and S. Dhilipkumar "An Efficient Image Quality Enhancement Using Wavelet Transform," *Materials Today: Proceedings, Elsevier*, vol. 24, no. 3, pp. 2004-2010, 2020.

[12] Hafsa Ouchra, Abdessamad Belangour, Allae Erraissi, "A Comparative Study on Pixel-Based Classification and Object-Oriented Classification of Satellite Image," *International Journal of Engineering Trends and Technology*, vol. 70, no. 8, pp. 206-215, 2022. Crossref, https://doi.org/10.14445/22315381/IJETT-V70I8P221.

[13] Qinglan Fan, Ying Bi, Bing Xue and Mengjie Zhang, "Genetic Programming for Feature Extraction and Construction in Image Classification," *Applied Soft Computing, Elsevier*, vol. 118, pp. 1-18, 2022.

[14] Haoliang Yuan, Junyu Li, Loi Lei Lai, and Yuan Yan Tang, "Low-Rank Matrix Regression for Image Feature Extraction and Feature Selection," *Information Sciences, Elsevier*, vol. 552, pp. 214-226, 2022.

[15] Huafei Yu, Tinghua Ai, Min Yang, Lina Huang and Jiaming Yuan, "A Recognition Method for Drainage Patterns Using A Graph Convolutional Network," *International Journal of Applied Earth Observations and Geoinformation, Elsevier*, vol. 107, pp. 1-15, 2022.

[16] Mamata Wagh, Pradipta Kumar Nanda, "Rough Set and Otsu Approach Based Hybrid Image Classification Under Uneven Lighting Conditions," *International Journal of Engineering Trends and Technology*, vol. 69, no. 12, pp. 92-102, 2021. Crossref, https://doi.org/10.14445/22315381/IJETT-V69I12P211.

[17] Rashedul Islam, Md. Rafiqul Islam and Kamrul Hasan Talukder, "An Efficient ROI Detection Algorithm for Bangla Text Extraction and Recognition From Natural Scene Images," *Journal of King Saud University–Computer and Information Sciences, Springer*, vol. 79, pp. 20107–20132, 2020.

[18] B. Vidhya and R. Vidhyapriya, "Image Compression and Reconstruction by Examplar Based Inpainting Using Wavelet Transform on Textural Regions," *Cluster Computing, Springer*, vol. 22, pp. 8335–8343, 2019.

[19] Mohammed M. Siddeq and Marcos A. Rodrigues, "A Novel High-Frequency Encoding Algorithm for Image Compression," *EURASIP Journal on Advances in Signal Processing, Springer*, vol.2017, no. 26 , pp. 1-15, 2017.

[20] P.Svoboda,M.Hradis, D.Barina and P.Zemcik, "Compression Artifacts Removal Using Convolutional Neural Networks," *Journal of WSCG*, vol.24, no.2 , pp.63-72.

[21] Atif Nazir,Rehan Asharf and Taiha Hamdani, "Content Based Image Retrieval System by Using HSV Color Histogram, Discrete Wavelet Transform and Edge Histogram Descriptor," 2018.

[22] F.Artuger, F.Ozkaynak, Fractal, "Image Compression Method for Lossy Data Compression," *International Conference on Artificial Intelligence and Data Processing 2018.*

[23] Y.Vishnu Tej, M. James Stephen, PVGD. Prasad Reddy, Praveen Choppala, "A Novel Methodology for Denoising Impulse Noise in Satellite Images Through Isolated Vector Median Filter with K-Means Clustering," *International Journal of Engineering Trends and Technology*, vol. 70, no. 8, pp. 272-283, 2022. Crossref, https://doi.org/10.14445/22315381/IJETT-V70I8P229.

[24] Yumo Zhang, Zhanchuan Cai, "A New Image Compression Algorithm Based on Non-Uniform Partition and U-System," *IEEE Transaction on Multimedia*, vol. 23, 2021.

[25] Chandresh K Parmer and Prof.Kruti Pancholi, "A Review on Image Compression Techniques," *Journal of Information, Knowledge and Research in Electrical Engineering.*

[26] Gaurva Vijayvriya, Dr.Sanjay Silakari, Dr.Rajeev Pandey," A Survey: Various Techniques of Image Compression," *International Journal of Computer Science and Information Security,* vol. 11, no.10.

[27] Jagadish H. Pujar and Lohit M. Kadlaskar, "A New Lossless Method of Image Compression and Decompression Using Huffman Coding Techniques," *JATIT - Journal of Theoretical and Applied Information Technology*, pp. 18-22, 2012.

[28] Wencheng Wang, Zhenxue Chen, Xiaohui Yuan and Xiaojin Wu, "Adaptive Image Enhancement Method for Correcting Low-Illumination Images," *Information Sciences, Elsevier*, vol. 496, pp. 25-41, 2019.