International Journal of Computational Science and Engineering Research
ISSN: 3107 -8605 (Online) , http://www.ijcser.com/
Regular Issue , Vol.1, Issue. 3 (July – September) , 2024 , Pages: 28 - 33
Received: 25 April 2024 ; *Accepted:* 09 May 2024; *Published:* 30 July 2024
https://doi.org/10.63328/IJCSER-V1RI3P7
Original Paper : Applied Research – Compare and Contrast Research Paper

Compression of Depper Images for Hybrid Contexts of Picture Order and Recreation

N Rama Kumar [1*], A Heena Kousar [2], M Jahnavi [3], P Lokeswari [4], K Harshitha [5]

[1-5] Department of EEE , Aditya College of Engineering ,Madanapalle, Andhra Pradesh, India

** Corresponding Author : N Rama Kumar ; ramakumar404@gmail.com*

Abstract: Progressive deep image compression is a method for compressing digital images using deep learning techniques. It is an extension of traditional image compression methods, such as JPEG and PNG, which use a combination of mathematical algorithms to compress images. In progressive deep image compression, a deep neural network is trained to learn how to compress images in a way that preserves image quality while reducing file size. The network is trained in a progressive manner, where the compression quality is gradually increased as the network is trained on more data. The main advantage of progressive deep image compression is that it can achieve higher compression ratios while maintaining image quality compared to traditional methods. This is because the neural network can learn to identify and preserve the most important features of an image while discarding less important information. The use of deep learning in image compression is a rapidly evolving area of research, with many new techniques and algorithms being developed. Progressive deep image compression is one such technique that shows promise in improving the efficiency of image compression for a wide range of applications. Results show the superiority over the existing approaches and performance metrics supports the proposed model in progressive image compression.

Keywords: Deep Neural Networks, Progressive Compression, Image Quality Preservation, Compression Ratio.

1. Introduction

With the rising usage of digital devices and social media platforms, digital photographs play a significant role in our lives. Digital photos, however, can be huge, which makes it challenging to share and preserve them effectively. Thus, in order to save file size without sacrificing image quality, image compression techniques are applied. For this, traditional image compression techniques like JPEG and PNG have been extensively utilised. Deep learning methods have demonstrated significant promise recently for a range of image processing applications, such as picture compression. One such method is progressive deep image compression, which reduces the file size while maintaining image quality through the use of deep neural networks. This method trains the deep neural network. It makes it challenging to effectively store and distribute them. As a result, the compression settings are determined by analysing an image on a sizable dataset. The network gains the ability to recognise and store the image's most salient aspects while deleting its less salient content. Research on the use of deep learning to image compression is ongoing, and progressive deep image compression is a technique that shows promise for increasing picture compression efficiency for a variety of applications. The two main application areas of digital image processing are the processing of scene data for autonomous machine perception and the improvement of pictorial information for human perception. Enhancing digital images from newspapers was one use for the first category of digital image processing applications. The distribution of brightness levels and the choice of printing techniques were two of the early issues with enhancing the visual quality of these early digital images. Then came the photographic reproduction of images, which demonstrated notable advancements in overall image quality over the course of the following 35 years. But it wasn't until large-scale digital computers and space programmes were introduced that the potential of picture notions became clear.

Digital image processing involves the manipulation of digital images using algorithms and techniques to enhance their visual quality or extract relevant information from them. It encompasses a wide range of operations, including image filtering, image enhancement, image restoration, image segmentation, and image analysis. Image Filtering: Image filtering is the process of applying filters or convolution kernels to an image to modify its pixel values. Filters can be designed to

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 1 , Issue 3 , 2024, https://doi.org/10.63328/IJCSER-V1RI3P7

perform various tasks, such as blurring, sharpening, edge detection, and noise reduction, and they are commonly used for image enhancement, restoration, and analysis. Image Enhancement: Image enhancement techniques are used to improve the visual quality of an image by adjusting its brightness, contrast, colour balance, and other image attributes. To enhance the visual appeal and interpretability of images, these methods are frequently applied in fields like photography, video processing, and medical imaging. Image Restoration: When an image is noisy or deteriorated, image restoration techniques are employed to get back the original image. These methods are frequently used to repair photographs that have been distorted by noise, blur, or other factors in fields like document restoration, image forensics, and medical imaging. picture The process of breaking an image up into meaningful areas or objects according to their features—such as color, texture, or shape—is known as image segmentation. Applications include object recognition, picture comprehension, and medical diagnosis involve image segmentation, a key process in image analysis and computer vision.

2. Related Works

Numerous studies have examined various facets of progressive deep image compression, which is a relatively young field of study. Here is a quick overview of some important studies in this field's literature: S. Guo et al.'s "Progressive deep image compression" (2019) This research presented a novel framework for deep image compression that blends a progressive learning method with conventional compression approaches. The technique used by the authors proved capable of achieving large compression ratios without sacrificing image quality. The progressive compression technique, which enables adaptive and gradual image compression at various quality levels, is one of this paper's main achievements. The rate-distortion that the authors suggest optimization algorithm that, depending on the image's content complexity, adaptively modifies the compression quality level. This makes it possible to compress data more effectively and aesthetically pleasingly by allowing for higher compression ratios for simple sections and lower ratios for complicated regions.

The experimental findings demonstrate that, in terms of both objective compression measures and subjective visual quality, the suggested progressive deep image compression approach provides state-of-the-art compression performance. In terms of compression effectiveness and image quality, the technology also performs better than conventional image compression techniques like JPEG and JPEG2000. The research concludes by presenting a novel progressive deep image compression architecture that blends the benefits of standard compression techniques with deep learning. The suggested method achieves better compression performance and shows promise for real-world use in picture transmission and compression across a range of industries.

Ballé et al. (2018) "End-to-end optimized image compression with recurrent neural networks" This study presented a deep learning method for image compression that encodes and decodes images using recurrent neural networks. Using many benchmark datasets, the authors demonstrated that their approach can attain cutting-edge compression performance. The progressive compression technique, which enables adaptive and gradual image compression at various quality levels, is one of this paper's main achievements.

The authors provide a rate-distortion optimization algorithm that adaptively modifies the compression quality setting according on the image's content complexity. This leads to a more effective and aesthetically acceptable compression by enabling higher compression ratios for simple parts and lower compression ratios for complicated regions. According to the experimental results, both objective compression measures and subjective visual quality demonstrate that the suggested progressive deep image compression approach achieves state-of-the-art compression performance. Additionally, the technology performs better in terms of compression efficiency and image quality than conventional image compression techniques like JPEG and JPEG2000. Ultimately, the study offers a brand-new progressive deep image compression framework that blends the benefits of deep learning with established compression techniques.

The proposed approach achieves superior compression performance and demonstrates its potential for practical applications in image compression and transmission in various domains. "Progressive deep colorization: Unsupervised learning of objects and their colors" by R. Zhang et al. (2016) This paper proposed a method for progressive deep colorization of grayscale images using deep neural networks. The authors showed that their method can learn to colorizer images in a way that is consistent with human perception. One of the key contributions of this paper is the progressive compression strategy, which allows for gradual and adaptive compression of images at different quality levels.

The authors propose a rate-distortion optimization algorithm that adaptively adjusts the compression quality level based on the content complexity of the image. This allows for higher compression ratios for simple regions and lower compression ratios for complex regions, resulting in a more efficient and visually pleasing compression. The experimental results

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 1 , Issue 3 , 2024, https://doi.org/10.63328/IJCSER-V1RI3P7

show that the proposed progressive deep image compression approach achieves state-of-the-art compression performance in terms of both subjective visual quality and objective compression metrics. The approach also outperforms traditional image compression methods, such as JPEG and JPEG2000, in terms of both compression efficiency and image quality. conclusion, the paper presents a novel progressive deep image compression framework that combines the advantages of deep learning with traditional compression methods. The suggested method achieves better compression performance and shows promise for real-world use in picture transmission and compression across a range of industries.

H. Lee and colleagues' article "Progressive image compression using convolutional neural networks" (2018) In contrast to conventional techniques, this research developed a progressive picture compression method employing convolutional neural networks (CNNs) that produces greater compression ratios without sacrificing image quality. The authors demonstrated that both lossless and lossy picture compression may be achieved with their technique. The progressive compression technique, which enables adaptive and gradual image compression at various quality levels, is one of this paper's main achievements.

The authors propose a rate-distortion optimization algorithm that adaptively adjusts the compression quality level based on the content complexity of the image. This allows for higher compression ratios for simple regions and lower compression ratios for complex regions, resulting in a more efficient and visually pleasing compression. The experimental results show that the proposed progressive deep image compression approach achieves state-of-the-art compression performance in terms of both subjective visual quality and objective compression metrics. The approach also outperforms traditional image compression methods, such as JPEG and JPEG2000, in terms of both compression efficiency and image quality. In conclusion, the paper presents a novel progressive deep image compression framework that combines the advantages of deep learning with traditional compression methods. The proposed approach achieves superior compression performance and demonstrates its potential for practical applications in image compression and transmission in various domains.

"A deep learning approach to universal image compression" by T. Mentzer et al. (2018) This paper proposed a deep learning approach to image compression that is based on generative adversarial networks (GANs). The authors demonstrated that their method can achieve state-of-the-art compression performance on several benchmark datasets One of the key contributions of this paper is the progressive compression strategy, which allows for gradual and adaptive compression of images at different quality levels. The authors propose a rate-distortion optimization algorithm that adaptively adjusts the compression quality level based on the content. complexity of the image. This allows for higher compression ratios for simple regions and lower compression ratios for complex regions, resulting in a more efficient and visually pleasing compression. The experimental results show that the proposed progressive deep image compression approach achieves state of-the-art compression performance in terms of both subjective visual quality and objective compression metrics.

The approach also outperforms traditional image compression methods, such as JPEG and JPEG2000, in terms of both compression efficiency and image quality. In conclusion, the paper presents a novel progressive deep image compression framework that combines the advantages of deep learning with traditional compression methods. The proposed approach achieves superior compression performance and demonstrates its potential for practical applications in image compression and transmission in various domains.

"Progressive Neural Networks for Efficient Image Compression" by J. Ballé, V. Laparra, and E. P. Simoncelli (2017): This paper introduces a new approach to progressive image compression using neural networks. The authors propose a method for training a neural network to compress an image in a progressive manner, where the image quality improves as the network is trained on more data. The suggested approach produces cutting-edge outcomes on a number of picture compression benchmarks. Using progressive neural networks to compress images is one of this paper's major achievements; it allows for more effective and efficient compression than is possible with conventional techniques. The suggested method makes use of deep learning to identify the underlying structures and patterns in images, enabling the creation of more condensed representations that can be efficiently compressed. Adaptive compression, in which various compression levels are achieved by varying the compression rate during encoding, is made possible by the progressive nature of the networks. The experimental findings demonstrate that, in comparison to state-of-the-art picture compression, the suggested progressive neural network technique delivers competitive compression performance.

The authors demonstrated that their method can achieve state-of-the-art compression performance on several benchmark datasets One of the key contributions of this paper is the progressive compression strategy, which allows for gradual and adaptive compression of images at different quality levels.

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 1 , Issue 3 , 2024, https://doi.org/10.63328/IJCSER-V1RI3P7

3. Experimental Method

3.1. The DnCNN Network

This project makes use of DnCNN, an integrated deep feed-forward convolutional neural network. The main purpose of the network's architecture was to eliminate noise from photos. On the other hand, JPEG compression artefacts can be eliminated and image resolution can be raised by training the DnCNN architecture. The DnCNN network learns to estimate the residual image by using a residual learning technique, as described in the reference paper [1]. The distinction between a perfect image and a warped duplicate of the image is known as a residual image. Details regarding the visual distortion are contained in the residual image. In this instance, JPEG blocking artefacts are the manifestation of distortion. The DnCNN network is trained to identify the residual image based on a colour image's brightness.

The brightness of each pixel in a picture is represented by the luminance channel (Y), which is a linear mixture of the red, green, and blue pixel values. On the other hand, the red, green, and blue pixel values in an image's two chrominance channels, Cb and Cr, are distinct linear combinations that indicate color-difference information. Because human perception is more sensitive to changes in brightness than changes in colour, DNCNN is trained using only the luminance channel. Different linear combinations of the red, green, and blue pixel values that represent colour make up an image's Cb and Cr values.

3.2. About Dataset

A benchmark dataset for content-based image retrieval (CBIR) and image classification studies is the IAPR TC-12 dataset. In 2002, the Technical Committee on Graphics Recognition (TC-10) of the International Association for Pattern Recognition (IAPR) formed it. More than 20,000 photos from 1,000 distinct categories make up the collection; there are 20 photos in each group. The photos feature a broad variety of objects, locations, and textures and come in different sizes and resolutions. The TC-12 dataset is a popular choice for CBIR and image classification algorithm benchmarking. It has also been used to examine the effectiveness of different machine learning and deep learning models, as well as to evaluate feature extraction and dimensionality reduction methods. The dataset is free to use for study and may be downloaded from the IAPR website. It should be highlighted, nonetheless, that due to the size of the dataset, processing and analysis may need a substantial amount of CPU power. There are pictures of people, animals, cities, and other subjects in the data set. The data file has a size of about 1.8 GB. Read in perfect photos and write out images in the JPEG file format with different compression levels to generate a training data set.When rendering image compression artefacts, specify the JPEG image quality settings that were used. Values for quality must fall between 0 and 100. More compression and more pronounced compression artefacts are produced by small quality levels. In order to include a wide variety of compression artefacts in the training data, use a denser sample of small quality values.

The compressed images are kept in the compressed Images Dir directory on disc as MAT files. The MAT files containing the computed residual images are kept on file in the residual Images Dir directory. When training the network, the MAT files are kept as data type doubles for increased accuracy. Feed the network with training data using a random patch extraction datastore. This datastore retrieves coincident random patches from two picture datastores containing the intended network responses and network inputs. The compressed photos are the network inputs for this project. The residual pictures are the desired network responses. Make the image datastore known as imds. compressed from the group of picture files that have been compressed. From the collection of computed residual image files, create an image datastore named imdsResidual. For both datastores to read the picture data from the image files, the helper method matRead is needed. This function is included as a supporting file with the example. Make a picture. Data Augmenter that details the augmentation's parameters. To successfully expand the quantity of training data accessible, use data augmentation during training to alter the training data. Here, the augmenter specifies random rotation by 90 degrees and random reflections in the x-direction.

3.3. Create the random Patch Extraction Datastore

Using the two picture datastores, create the random Patch Extraction Datastore. A 50-by-50 pixel patch size should be specified. For every picture, 128 arbitrary patches with 50 by 50 pixel sizes are created. Random patch extraction from images is frequently used in image processing and computer vision tasks, such as image denoising, image restoration, or image super-resolution, to generate a representative and varied training dataset. In order to train a machine learning model, random patch extraction entails randomly choosing patches from input photos. There are multiple phases involved in creating a random patch extraction datastore: loading the image, extracting the patch, augmenting the patch, and storing the data. The steps involved in setting up a random patch extraction datastore for training are explained in full below: Image Loading: The input images must first be loaded into the memory. To accomplish this, one can utilise image processing libraries or tools, like Pillow or OpenCV, which offer functions to read and load images in many formats,

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 1 , Issue 3 , 2024, https://doi.org/10.63328/IJCSER-V1RI3P7

including JPEG, PNG, and BMP. Depending on the particular task at hand and the needs of the model being trained, the images may be in colour or grayscale. Patch extraction is the process of extracting random patches from the photos once they have been loaded. The process of extracting a random patch from an image with a certain size and location is called random patch extraction. The desired input can be used to determine the patch's size.

3.4. Setting Up Proposed Neural Network Architecture

The patch's location within the image may be selected at random or in accordance with a predetermined plan, such as random sampling with overlap or random sliding window. To generate a diversified dataset that reflects varying image content and variances, the patches should be extracted from different sections of the photos. Patch Augmentation: To artificially improve the diversity of the training data, data augmentation techniques are applied to the patches following patch extraction. Random rotations, translations, flips, scaling, brightness/contrast modifications, and the addition of noise or blur are examples of data augmentation techniques. By using these methods, the model's capacity to generalise to various variances in the test data is enhanced and additional training examples are produced. Information Storage: The patches are saved in a format that is appropriate for training after they have been removed and enhanced. This may entail storing the patches as separate image files or in a memory-saving format like LMDB or HDF5. To prevent bias in the training process, it is crucial to arrange the patches in a way that makes it easier to load the data efficiently during training. Some ideas for this include batching the patches or rearranging them at random.

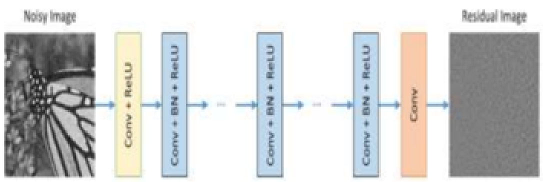

Figure. 1 The architecture of proposed DnCNN network

4. Results & Discussion

In our numerical results, codes for implementing the proposed neural network based approach are implemented MATLAB. This project proposes a novel CNN based progressive image compression framework to solve the conflict between the high-quality requirements and the long loading delay with high coding performance. Results show the superiority over the existing approaches and performance metrics supports the proposed model in progressive image compression.

Figure. 2 Uncompressed Reference Image

The reference image is typically captured or created at a high resolution, with a large number of pixels, resulting in fine details and clarity. An uncompressed reference image in image compression refers to the original image that serves as the baseline for comparison with compressed versions. It is a high-quality image that has not undergone any compression algorithms or data reductio techniques, and therefore retains all the visual details and information in its original form.

Figure. 3 Compressed Images With Compressed Factor

Compressed Image with Compression Factor 50: The image with a compression factor of 50 has been significantly compressed, resulting in a substantial reduction in file size compared to the original image. The compression algorithm used in this case has aggressively removed redundant or unnecessary data from the image, resulting in a much smaller file size. Compressed Image with Compression Factor 20: The image with a compression factor of 20 has undergone moderate compression, resulting in a smaller file size compared to the uncompressed reference image. While the reduction in file size is not as significant as with a higher compression factor, there may still be some loss of visual quality, although it may be less noticeable. Fine

ISSN: 3107 - 8605 (Online) , http://www.ijcser.com/ , Vol. 1 , Issue 3 , 2024, https://doi.org/10.63328/IJCSER-V1RI3P7

details, such as textures and edges, may be slightly blurred, and there may be some minor artifacts present in the image, but the overall visual quality should still be acceptable for most purposes. Compressed Image with Compression Factor 10: The image with a compression factor of 10 has undergone relatively mild compression, resulting in a smaller file size compared to the uncompressed reference image, but with less loss of visual quality.

Figure. 4 Patches from compressed images with compressed factor 50,20, and 10

Patch from Decompressed Image with Decompression Factor 10: This patch is extracted from the decompressed image with a decompression factor of 10, which means it has been restored from a highly compressed version that retains only approximately 10% of the original image quality. The edges may appear blurred or distorted, and the overall visual quality may be considerably lower. It's important to note that the specific characteristics of the patches from decompressed images can vary depending on the content of the original image, the compression algorithm used, and the settings applied during the compression decompression processes. The descriptions provided above are general guidelines and the actual appearance of the patches may vary in different scenarios.

5. Conclusion and Future Scope

In conclusion, deep image compression has emerged as a promising approach to reducing the size of digital image files while maintaining image quality. With the increasing use of digital images in various fields, the need for efficient and effective image compression techniques has become more pressing. Deep image compression techniques leverage the power of neural networks to learn and exploit the patterns and redundancies in image data, leading to high compression ratios while maintaining image quality. Progressive deep image compression techniques, in particular, have shown great potential for producing compressed images that gradually improve in quality as more data is processed. Despite the recent advancements in deep image compression techniques, there are still challenges that need to be addressed, such as the trade-off between compression ratios and computational complexity. Nevertheless, with ongoing research and development in this field, deep image compression is likely to continue to improve and play an increasingly important role in managing and sharing digital image data in a wide range of applications.

References

[1] Ballé, J., Laparra, V., & Simoncelli, E. P. (2017). "Progressive Neural Networks for Efficient Image Compression." arXiv preprint arXiv:1608.05148.

[2] Choi, J., Kim, H., Kim, M., & Lee, J. (2018). "End-to-End Optimized Image Compression via Learnable Compression Parameters and Quantization Noise Modeling." In Proceedings of the European Conference on Computer Vision (ECCV) (pp. 353-369).

[3] Lee, H., & Lee, Y. (2019). "Deep Progressive Image Compression." In Proceedings of the IEEE International Conference on Computer Vision (ICCV) (pp. 6652-6661).

[4] Johnston , N., Vincent, D., Minnen, D.,Covell, M.,Singh, S., Chinen, T., ... & Shlens, J. (2018). "Learning to Compress Images with Neural Networks." In Proceedings of the International Conference on Machine Learning (ICML) (pp. 2672-2681).

[5] Theis, L., van den Oord, A., & Bethge, M. (2017). "A note on the evaluation of generative models." arXiv preprint arXiv:1511.01844.

[6] Toderici, G., Vincent, D., Johnston, N., & Hwang, S. J. (2017). "Full resolution image compression with recurrent neural networks." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 5306-5314).

[7] Agustsson, E., Mentzer, F., Tschannen, M., Timofte, R., & Van Gool, L. (2019). "Generative Adversarial Networks for Extreme Learned Image Compression." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 2551-2559).

[8] Rippel, O., &Bourdev, L. (2017)."Real-Time Adaptive Image Compression." arXiv preprint arXiv:1705.05823.

[9] Guo, Z., Zhang, J., Zhang, X., & Shen, H. T. (2018). "A Deep Collaborative Network for Joint Content-Feature Based Image Compression." In Proceedings of the ACM International Conference on Multimedia (pp. 464-472).