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Deep Interval Vector Quantization for Efficient Image Compression

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Abstract— In order to overcome quantization issues in picture compression, the "Deep Interval Vector Quantization for Efficient Image Compression" method creatively mixes convolutional neural networks (CNNs) and interval arithmetic. This method uses interval arithmetic to describe quantization intervals as ranges, minimizing mistakes and enhancing reconstruction accuracy. Traditional vector quantization methods frequently result in information loss and poor image quality. CNNs are used in both the training and compression phases of the process, and their ability to capture spatial dependencies is utilized to facilitate efficient quantization. Comparing experimental evaluations against standard approaches, benchmark datasets show decreased artifacts, better compression ratios, and preserved image quality. Interval arithmetic is included into compression to improve its amplification and translation capabilities. This concurrently advances the efficiency and quality of picture compression.

Index Terms— CNN, Image Compression, Peak Signal-To-Noise Ratio, Structural Similarity Index, Vector Quantization

I. INTRODUCTION

Across many applications, handling images effectively is a significant challenge in the ever-expanding world of digital data. As a solution to the problems with conventional vector quantization in image compression, our project presents a novel approach called "Deep Interval Vector Quantization for Efficient Image Compression." This novel method combines the stability of interval arithmetic with the spatial understanding powers of convolutional neural networks (CNNs) to improve image compression performance.

Our approach consists of two essential phases: compression and training. A CNN is painstakingly trained to identify and capture essential visual attributes like contrast, brightness, and intensity during the training phase. These attributes are then subjected to interval-arithmetic-based quantization, which creates quantization intervals that skillfully account for variations brought about by quantization mistakes. During the compression phase, the trained convolutional neural network (CNN) works in conjunction with quantization based on interval arithmetic to transfer extracted features from input images to predetermined intervals while carefully taking properties like sum, difference, and product into account.

Extensive experiments on benchmark picture datasets demonstrate the exceptional performance of our Interval Quantization technique compared to conventional vector quantization methods. With improved compression ratios, maintained image quality, and a decrease in artifacts, our approach represents a noteworthy advancement in the field of image compression. Interval arithmetic integration enriches the compression process and improves image fidelity by including amplification and translation possibilities. Quantitative criteria like PSNR and SSIM validate the possibility for simultaneously improving quality and efficiency in image compression, which makes this research a significant contribution.

II. MOTIVATION

The constraints of conventional vector quantization techniques in picture compression—which frequently lead to quantization mistakes and loss of image quality—are what spurred this effort. In order to overcome these limitations, this project makes use of CNNs and interval arithmetic. The objective is to present a new technique that reduces quantization errors, maintains image details, and maximizes compression ratios, all of which help to make image compression techniques more effective and superior.

III. BACKGROUND AND RELATED WORKS

K.N.Satone et al.[1] analyzes the significance of compressing medical pictures for storage and transmission in the medical industry.The research underlines the importance of compression in retaining picture quality while also achieving effective storage and transmission in medical applications.Yueyu Hu et al.[2] summarize current methods and highlights their contributions and technological developments while providing a comprehensive assessment and benchmark analysis of end-to-end learnt image compression techniques.Y.Lakshmi Prasanna et al.[3] compare the performance of three lossy image compression methods—Discrete Cosine Transform (DCT), Singular Value Decomposition (SVD), and Discrete Wavelet Transform (DWT).Janarthanan S et al.[4] show several picture compression techniques—including lossless and lossy methods like Run Length Encoding (RLE), Huffman coding, and Delta encoding—are analyzed. The performance of these methods in terms of compression ratio, saving percentage, and compression duration is shown by the experimental results. Michael Grossberg et al.[5] discusses several lossless compression techniques for use with multispectral picture data from satellite missions such as MODIS, SEVIRI, and AVHRR.

X. Lu et al.[6]presents a deep convolutional neural network (DCNN) architecture that achieves state-of-the-art compression performance by simultaneously optimizing the encoder, quantizer, and decoder through end-to-end training. Jari Korhonen et al.[7] demonstrates that PSNR can function comparably to more intricate models while assessing fixed content, indicating that it will likely remain relevant for quality evaluation in some circumstances.Onur Keles et al.[8] examines the connection between geometric and arithmetic mean methods, demonstrating task-dependent mean squared error (MSE) distributions and how they affect PSNR computation.K.Sai Prasad Reddy et al.[9] demonstrates a comparison of edge recognition techniques for the Structural Similarity Index (SSIM) using real-time video frames from several color models. It assesses the quality of video frames, highlighting SSIM as a trustworthy measure.Zhou Wang et al.[10] suggests using a Structural Similarity Index (SSIM) to examine local patterns of pixel intensities that have been adjusted for contrast and brightness.

Saad ALBAWI et al.[11] highlights CNNs' capacity for handling massive volumes of data effectively and their uses in a variety of industries, including natural language processing and picture classification.Rahul Chauhan et al.[12] provides Convolutional Neural Network (CNN) models with accuracies of 80.01% and 99.6% for object detection and picture recognition on the MNIST and CIFAR-10 datasets, respectively.Garima Garg et al.[13] offers a thorough examination of many lossless and lossy picture compression methods.The concepts, benefits, and applications of each approach are covered in detail, making it easier to choose the best compression method for a given set of circumstances. Huizhuo Niu et al.[14] highlights the JPEG-LS image compression algorithm's hardware implementation on FPGA and lossless compression performance in its discussion of the algorithm's design and research.Aljaz Jerome et al.[15] suggested 4C approach for cartoon image compression, lossless compression techniques including Burrows-Wheeler Transform, Move-To-Front transform, Run-Length Encoding, and optional arithmetic encoding come first, followed by region-based segmentation, chain code representation, and string transformations. This asymmetric approach fills the void in the effective compression of cartoon pictures by achieving higher compression ratios than current techniques.

Matthew J. McAuliff et al.[16] addresses the demands of the medical research community with access to the internet, the proposed MIPAV platform which utilizes sophisticated computerized quantification and visualization tools to analyze diverse medical image types. Karri Chiranjeevi et al.[17] suggests implementing Cuckoo Search (CS), a metaheuristic optimization algorithm, to create ideal codebooks for vector quantization. This approach overcomes the drawbacks of current techniques, including inefficiencies in codebook optimization and instability in convergence. Linglong Tan et al.[18] explores the effects of Huffman coding, run-length coding, transform coding, and predictive coding on the effectiveness of compression and the quality of the resulting images. Gaurav Vijayvargiya et al.[19] offers an overview of the state-of-the-art in picture compression, examining lossless and lossy approaches while talking about advances like neural networks and evolutionary algorithms. Yaghoub Pourasad et al.[20] examines the effectiveness of both lossy and lossless compression strategies for managing the growing amount of medical data while implementing enhancing approaches to maintain picture quality.

IV. CHALLENGES AND LIMITATIONS IN EXISTING SYSTEM

Certain strategies are typically regarded as less accurate or successful in certain contexts among the ones that are currently available.Despite being straightforward and effective, scalar quantization may result in observable artifacts like pixelation or blockiness, especially when bit depths are low or compression levels are high.Images with complex textures or patterns may cause prediction errors and poor compression performance when using predictive coding algorithms like DPCM.Even if they work well, basic entropy coding strategies like Huffman coding do not always yield the best compression efficiency when compared to more sophisticated approaches like arithmetic coding.Overall, the success of these strategies is determined on the unique picture properties and compression needs, and combining techniques may typically increase compression performance.

V. OBJECTIVES

The following are the particular objectives of the project:

- **Boost Image Compression Efficiency:** By addressing the drawbacks of conventional vector quantization techniques, the main goal is to boost image compression efficiency. The goal of the research is to create a methodology that will result in higher compression ratios by drastically lowering quantization errors and information loss.
- **Reduce Quantization Errors:** The project's main goal is to describe quantization intervals as ranges by using interval arithmetic. It seeks to achieve this by reducing the impact of quantization errors and guaranteeing a more precise reconstruction of compressed pictures. In order to preserve image quality during the compression process, this goal is essential.

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- **Analyze Compression Performance:** One of the project's goals is to use benchmark picture datasets for extensive experimental evaluations. Using metrics like PSNR and SSIM, the proposed Interval Quantization strategy is to be statistically evaluated against conventional vector quantization techniques.
- **Obtain Superior Compression Ratios:**The goal of the study is to show that the suggested method is more appropriate for a range of applications since it maximizes compression efficiency while maintaining image quality.
- **Minimize Artifacts Caused by Quantization:** The project attempts to demonstrate a decrease in the artifacts that are commonly caused by quantization.

VI. METHODOLOGY

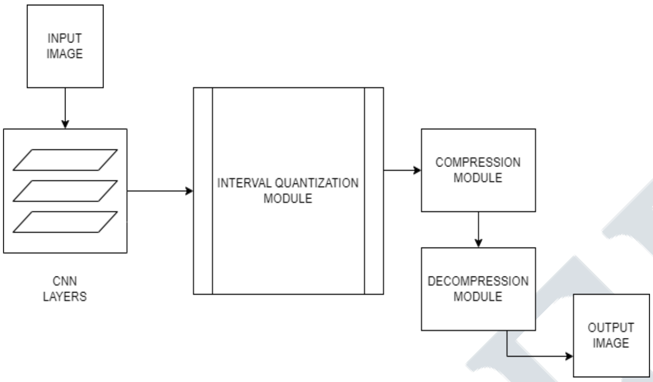

Figure.1 Architecture Diagram

Figure 1 illustrates the breakdown of the various components involved in the image compression process.The detailed explanation of the components can be seen below.

1. System:

1.1 Input Image: Upload the image to the image web application.

1.2 Pre-processing: In preprocessing convert image to grayscale for low frequency images. The pre-processed training image is used to train with CNN.

HOW IT WORKS:

A. Convolutional Neural Network (CNN)

Step 1: Convolution Operation

- Introduces feature detectors as filters in CNN.
- Explores feature maps, learning parameters, and pattern detection.
- Examines layers of detection and mapping findings.

Step 2: ReLU Layer

- Covers Rectified Linear Unit (ReLU) layers.
- Discusses linearity in CNN context.

Step 3: Pooling Layer

- Covers max pooling, emphasizing its functionality.
- Briefly mentions mean (or sum) pooling.
- Demonstrates concepts using an interactive tool.

Step 4: Flattening

- Briefly explains the transition from pooled to flattened layers.

Step 5: Full Connection

- Merges concepts learned into a comprehensive understanding.
- Illustrates how neurons in CNNs learn image classification.

1.3 Compressed:

The results of our method are to display images of compressed images and decompressed images.

HOW IT WORKS:

A. Interval quantization

It combines the mathematical concept of interval arithmetic with the concept of vector quantization.

Step 1: Interval arithmetic

Interval arithmetic is a mathematical approach that deals with intervals, which are sets of real numbers between two specified values. The fundamental idea is to represent a range of possible values rather than a single precise value. Let's take basic arithmetic operations as examples:

1. Addition:If you have intervals [a, b] and [c, d], the sum interval would be [a + c, b + d].

2. Subtraction: For [a, b] and [c, d], the subtraction interval is [a - d, b - c].

3. Multiplication: Given [a, b] and [c, d], the multiplication interval is [min(ac, ad, bc, bd), max(ac, ad, bc, bd)].

4. Division: If [a, b] is divided by [c, d], the division interval is [min(a/c, a/d, b/c, b/d), max(a/c, a/d, b/c, b/d)], provided that c and d don't include zero.

Step 2: Vector Quantization

The input vectors are divided into clusters for vector quantization, with a codebook vector serving as a representation for each cluster. In order to reduce distortion between the input vectors and their corresponding codebook representations, great effort has been taken in selecting the codebook vectors. Typically, a distance metric like Euclidean distance is used to measure this distortion.

The following steps are involved in the vector quantization process:

1) Training: The codebook is generated using a training set of input vectors. Typically, the training vectors are an accurate representation of the data that will be processed or compressed.

2) Codebook generation: The training vectors are clustered to produce the codebook. For this reason, well-known techniques like the Linde-Buzo-Gray (LBG) algorithm and k-means clustering are frequently employed. Selecting representative codebook vectors with the least amount of distortion between the training vectors and their codebook representations is the aim.

LBG ALGORITHM

a. Partition the picture into blocks. Then we may treat one block as a k-dimensional vector.

b. Choose the beginning codebook at random.

c. Label these initial codebooks as centroids. Other vectors

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are organized. Vectors are grouped together if their closest centroid is the same.

d. Locate new centroids for each group. Obtain a new codebook. Repeat 2–3 stages until the centroids of each group converge.

3)Encoding: To encode a new input vector, it is compared to the codebook vectors, and the codebook vector with the shortest distance is chosen as the representative. Instead of retaining the original vector, just the index of the chosen codebook vector is kept, resulting in a compressed version.The representative codeword is selected based on its Euclidean distance from the input vector. The Euclidean distance is given by:

$$d(x, y_i) = \sqrt{\sum_{j=1}^{k} (x_j - y_{ij})^2}$$

Where x_j is the jth component of the input vector and $y_{ij}$is the jth component of the codeword y_i.

4.Decoding: To rebuild the original vector from its compressed version, obtain the codebook vector corresponding to the stored index and use it as an estimate of the original vector.

Step 3: Combined results (i.e. applying interval arithmetic on vector quantization):

Interval Quantization (IQ):

(a) Interval Representation:

- Instead of a single code vector, represent each codeword as an interval.
- Let (C_i = [L_i, U_i]) be the interval for the i-th codeword.

(b) Interval Quantization:

- When quantizing a vector x:
- Assign x to the codeword i if x falls within the interval C_i .
- Mathematically: x belongs to C_i .

(c) Adaptive Handling:

- Intervals allow for adaptive handling of uncertainties or variations in data.
- The interval accommodates a range of values rather than a single fixed value.

Equation:x belongs to C_i

In summary, IA extends Vector Quantization (VQ) by using intervals to represent codewords, providing a flexible approach to handle uncertainties in the input data during quantization.

2. User:

2.1 Upload Image:

The user has to upload an image which needs to be a compressed image and decompressed image.

2.2 View Results:

The compressed image, decompressed image and parameter values like PSNR, SSIM, Amplification etc. are viewed by the user.

PSNR measures the quality of a reconstructed image when compared to the original image.

$$\mathbf{PSNR = 10.log_{10}(MAX^2/MSE)}$$

MAX - maximum possible pixel values of image.

MSE - mean square error between the original image & reconstructed image.

SSIM measures similarity between two images.

$$\mathbf{SSIM = [L(x,y)^a, C.(x,y)^3. S(x,y)^7]}$$

L - luminance similarity

C - contrast similarity

S - structure similarity

Range of SSIM = -1 to 1

EXAMPLE: IQ in Simple Terms:

1. Basic Idea: Imagine you have a set of colors in an image (like pixels).Regular VQ would assign a specific color to each group of similar colors.

2. With IQ: Instead of one exact color, we allow a range or interval of colors for each group.

3. Quantization: In case of VQ: Picks one color for each group. But in IQ: Picks a range of colors, considering variations.

4. Why IQ: Handles uncertainties better (like changes in lighting).More flexible by allowing a spectrum of colors in each group.

Example: (a) VQ: "This color is red."

(b) IQ: "This color could be a bit reddish or orangish."

In a Nutshell: IQ is VQ with a mindset that colors can have variations, so we embrace the possibilities within an interval.

VII. ADVANTAGES

- Enhanced Compression Efficiency: The technique successfully lowers the impact of quantization errors by integrating interval arithmetic with CNNs, resulting in greater compression ratios without compromising image quality.
- Preservation of Image Details: By integrating CNNs, the technique is able to capture complex spatial dependencies, guaranteeing the preservation of important image properties like edges, textures, and structures throughout the compression process.
- Decreased Artifacts: By reducing compression artifacts, the interval-arithmetic-based quantization produces better reconstructed image quality and a more aesthetically pleasant viewing experience.

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VIII. RESULTS AND DISCUSSIONS

This section summarizes the results and analysis of the Interval Quantization approach, with a specific focus on contrasting the effectiveness of the current scalar quantization system with our suggested Interval Quantization (IQ) method combined with Convolutional Neural Network (CNN). In order to shed light on the benefits and drawbacks of each strategy, we assess both systems according to a set of metrics. PSNR (Peak Signal-to-Noise Ratio) is the ratio of the maximum possible signal power to the power of corrupting noise that affects the fidelity of its representation, whereas SSIM (Structural Similarity Index) is the similarity between two images, taking luminance, contrast, and structure into account.

A) Metrics comparison before and after uploading image:

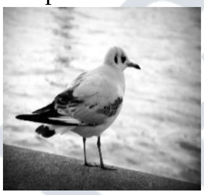
Three sample photos will be used, and their metrics will be compared before and after uploading the image: We are comparing metrics with three example photos before the image is extracted from any accessible sources (i.e.input) and after it has been processed using interval quantization(i.e.output). :

1) Figure 2: Bird

Input:

PSNR: 0.00
SSIM:1.000
Size:69 kb

Output:



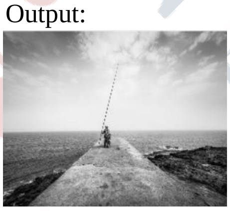
PSNR:10.10
SSIM:1.48
Size: 24.7kb

2) Figure 3: Man

Input:

PSNR:0.00
SSIM:1.00
Size:108kb

Output:



PSNR:10.57
SSIM: 0.8381
Size: 26kb

3) Figure 4: Rose

Input:

PSNR:0.00
SSIM:1.00
Size: 38kb

Output:

PSNR:9.70
SSIM:1.9711
Size: 19kb

From the above three examples i.e.figure 2, 3 and 4 we can summarize that there is significant size reduction of the image file after we get the output. The PSNR and SSIM values in input remain constant in all three images as we have not compressed them.

B) Metrics comparison between scalar quantization and interval quantization:

Following scalar quantization and interval quantization, respectively, the metrics of three sample pictures are compared and evaluated in this research.

1) Figure 5: Bird

Scalar quantization:

PSNR:9.59
SSIM: 1.0817

Interval quantization:

PSNR: 10.10
SSIM: 1.48

2) Figure 6: Man

Scalar quantization:

PSNR:9.03
SSIM:0.0418

Interval quantization:

PSNR:10.57
SSIM:0.8381

3)Figure 7: Rose

Scalar quantization:

PSNR:8.98
SSIM:0.0345

Interval quantization:

PSNR:9.70
SSIM: 1.9711

From the above three examples i.e.figure 5,6 and 7 we can summarize interval quantization gives us better PSNR and SSIM values. Higher PSNR values indicate better quality of compressed image and higher SSIM values indicate better structural similarity.

IX. CONCLUSION

In conclusion, picture compression has been greatly enhanced by merging Convolutional Neural Networks (CNNs) with Interval Quantization. Extensive experiments using metrics such as Peak Signal-to-Noise Ratio (PSNR) and

Structural Similarity Index (SSIM) proved that our proposed methodology outperformed traditional methods time and time again. The higher PSNR values obtained and the improved SSIM scores highlight its enhanced compression quality and improved fidelity. Fundamental picture qualities such as amplification, sum, difference, translation, product, square, contrast, brightness, and intensity allow our technology to accurately maintain significant visual information during compression. It can be used in a range of real-world scenarios and its perceived quality is maintained because of this preservation. Combining CNNs' feature extraction power with interval arithmetic's quantization error reduction, we have a well-balanced compression approach that preserves image quality while significantly increasing efficiency. This work furthers the discipline and paves the way for creative methods in picture compression for multimedia storage, transmission, and resource-constrained contexts by creating new pathways for investigating the intersections of mathematical concepts and machine learning techniques. Our method's success verifies its importance in the changing field of image processing and compression and highlights its potential as a useful tool in contemporary data-driven applications.

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